BEHAVIOURAL ECONOMICS ANALYSIS OF RECREATIONAL AND MEDICAL CANNABIS

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the degree of Doctor of Philosophy .

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Abstract

Cannabis is among the most widely used psychoactive substances in Canada and there is increasing need to examine the reinforcing effects of the substance. Hypothetical cannabis purchasing tasks have been used to describe the reinforcing value of psychoactive substances. The present body of research examined the utility of cannabis purchasing tasks for modelling recreational and medical cannabis use. It adds to the current body of literature by examining across units of consumption (hits vs grams), the impact of THC potency on recreational use, and the potential for cannabis to serve as a substitute for alcohol or prescription opioid medication. Data were collected from young adult recreational cannabis users (N = 250) and medical cannabis users recruited through a medical cannabis network (N = 410). Participants were presented with hypothetical purchasing tasks asking them how many units (hits or grams) of cannabis they would purchase at 17 price points (ranged $0.00 - $500). Recreational users were randomly assigned to low and high THC conditions. Demand curves were modelled using an Exponentiated Demand equation yielding five distinct metrics theorized to be associated with reinforcing value of cannabis which were compared to cannabis use variables and ratings of pain for medical users. Secondary purchasing tasks asked participants how many units of cannabis they would purchase with concurrently available alcohol and prescription pain medication at both static and varying prices. With respect to potency, there was no difference in demand characteristics across high and low THC cannabis among recreational users. With regard to unit of measurement, a clearer association between demand characteristics and cannabis use variables was apparent for grams of cannabis purchased than hits of cannabis for recreational cannabis. For medical cannabis users, more apparent associations between demand and cannabis use were evident

for hits purchased than grams. For both recreational and medical users, cannabis did not serve as a substitute for alcohol. For medical users, prescription pain medication may serve as a partial substitute for cannabis.

Lay Summary

Behavioral economics applies economic principles of demand to evaluate the reinforcing value of psychoactive substances, including cannabis. Recreational and medical cannabis users were invited to complete surveys asking how many units of cannabis, alcohol, and prescription opioid medication they would purchase at varying price levels. Results indicated that cannabis can be described using principles of demand. Additionally, the potency (i.e., %THC) of cannabis does not impact reinforcing value. Medical cannabis users readily purchase more hypothetical units of cannabis at low price points than recreational users. In addition, the substitutability of cannabis for alcohol and prescription pain medication was evaluated. Among recreational users, cannabis serves to complement alcohol, rather than substitute. In medical users, cannabis and alcohol purchases are largely independent. Among medical cannabis users, prescription opioid medication may serve as a partial substitute for cannabis when price of cannabis increases. Implications of these findings are discussed.

Preface

The present studies included in this dissertation consist of original and unpublished data. Kimberly Crosby was responsible for the conceptualization and design of the studies, overseeing the collection of data, data analysis and synthesis of findings, and writing the final dissertation.

Ethics approval was granted by the University of British Columbia's Behavioural Research Ethics Board. Ethics approval for Recreational Cannabis Use was assigned certificate numbers H17-03523 and H17-03519. Medical Cannabis Use was assigned certificate number H18-00316.

Table of Contents

List of Tables

List of Figures

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Dedication

For all those who take the scenic route to their destination.

Chapter 1: Introduction

Cannabis is among the most widely used psychoactive substances in Canada, with nearly 50% of Canadians reporting trying cannabis at least once in their lifetime (Health Canada, 2018). Canada is one of a handful of countries that have legalized cannabis for non-medical use at the federal level. The *Cannabis Act* was implemented October 17, 2018, legalizing the sale of cannabis for recreational purposes for all individuals aged 21 years and older. In the two years post legalization, the number of retail stores for recreational cannabis increased nearly eight-fold (Roterman, 2021). In 2018, the average price per gram for herbal cannabis was $9.69 per gram, increasing to $10.30 per gram by the fourth quarter of 2019 (Statistics Canada, 2020). Average advertised THC levels of legally available herbal cannabis has been estimated to be around 16% in Canada, ranging from 14-18% across provinces and territories (Mahamad et al., 2020). One year following the enactment of the *Cannabis Act*, cannabis edibles and concentrates became legal for sale in Canada, though a majority of consumers report primarily using dried cannabis flower. Recent estimates of adults suggest that 20% of Canadians 15 years and older reported using cannabis in the past three months (Roterman, 2021). In addition to prevalent recreational cannabis use, Canada hosts a large number of medical cannabis users, with over 250,000 medical client registrants as of March 2021(Health Canada, n.d.). This changing legal landscape has generated significant public interest in the potential harms and benefits of medical and recreational cannabis.

Given the major shifts in policy regarding the legalization of recreational cannabis, there is increasing public interest in the effect that increased access to and availability of cannabis will have on the use of alcohol and other drugs. As such, there is a growing field of research examining the substitutability of cannabis for alcohol and other drugs, and research examining the potential ability for cannabis to ameliorate the deleterious effects of alcohol abuse and prescription opioid use. In this vein, cannabis substitution can be conceptualized within a harm-reduction framework for reducing the harms associated with alcohol use (Mikuriya, 2004). Case-study and observational data suggest that cannabis may play a role in decreasing alcohol use and alleviating alcohol-related harms (Mikuriya, 1970, 2004). Cross-sectional data from medical cannabis users suggest a similar theme, such that patients report choosing cannabis instead of alcohol (Lucas et al., 2013; Reiman, 2009). However, cross-sectional data is limited in the scope and ability to examine behavioural aspects of substitution. Namely, cross-sectional studies typically rely on data that examine substitution based on a dichotomous "yes/no" question. Further research is required to examine the utility of cannabis as a behavioural and economic substitute for alcohol in different populations. Moreover, the reliance of previous studies on examining cannabis substitution with a single dichotomous question provides little explanation of contexts that might affect rates of substitution, such as potency of cannabis or price of available alternative psychoactive substances (e.g., alcohol, opioids). The proposed study seeks to add depth and detail on the substitution effect, examining at which prices individuals may choose to substitute cannabis for alcohol and pain medication.

Recent cross-sectional and observational research has identified that cannabis serves as a substitute for prescription medication in medical cannabis patients, and that patients actively choose cannabis over traditional medications (Lucas et al., 2013; Lucas & Walsh, 2017a; Reiman, 2009)**.** The primary reasons that substitution occurs are due to better symptom management, less withdrawal, and fewer side-effects (Lucas et al., 2013; Reiman, 2009). However, as with research examining cannabis substitution for alcohol, there is reliance on simple “yes/no” questions regarding substitution behaviours. Moreover, there is little research that compares recreational cannabis users to medical users, in terms of substitution for prescription medications and for alcohol. The proposed research seeks to increase our appreciation of the substitution effect in medical cannabis patients by applying behavioural economic techniques to examine substitution for prescription medication in medical cannabis users, and to supplement existing cross-sectional findings.

Historically, the distinction between medical and recreational cannabis users has been a legal one, following the legalization of cannabis for medical purposes. This traditional distinction implies that there exist unique differences between the two types of users. However, existing research suggests that there exists some overlap between medical and recreational users, and evidence suggests that many medical cannabis users report recreational use (Morean & Lederman, 2019; Turna et al., 2020). A 2016 study of nationally represented US adults reported approximately 36% of participants use cannabis for both medical and recreational purposes (Schauer et al., 2016). These findings highlight the inherent challenges of categorizing users as medical or recreational. Exclusively medical cannabis users may be more likely to report using high CBD strains of cannabis and use cannabis to treat chronic pain, while those reporting both medical and recreational purposes use to treat mental health symptoms (Turna et al., 2020) and high THC cannabis products (Morean & Lederman, 2019). The proposed research seeks to compare and contrast users on reinforcing efficacy of cannabis along traditional delineations of user groups in order to identify possible differences in reinforcing efficacy for cannabis as a marker of recreational or medical use.

In sum, increasing public interest in the legalization of cannabis and high rates of medical cannabis use suggest a need for research related to the reinforcement properties of cannabis. Further, there is a paucity of experimental research on the ability of cannabis to serve as a substitute for alcohol and other drugs. The proposed research has the potential to further inform the public and broader research community of the reinforcement properties of cannabis in both recreational and in medical users, and the potential ability of cannabis to serve as a substitute or complement for alcohol and other drugs. At a more practical level, the legalization and commercialization of cannabis makes the determination of the association between cost and consumption a research priority. In addition, the research will further contribute to the literature on the association between cannabis and alcohol use. It is a matter of public health to examine the potential risks and benefits of cannabis use and cannabis intoxication on alcohol craving and potential subsequent alcohol use behaviours.

1.1 Behavioural Theories of Choice

The early principles of behavioural choice were established by Edward Thorndike and his *law of effect*, which states that responses that are closely follow or accompanied by "satisfaction" (Thorndike, 1911, pp. 244) are more likely to occur in the future. As one of the provisional laws of learned behavior, the law of effect suggests that, for substance use, the pleasurable physical and psychological effects produced by psychoactive substances increase the likelihood of the future use of those substances. Indeed, Thorndike recognized that alcohol and opioids (i.e., morphine) were potential "satisfiers" for humans. Building from this theoretical foundation, B. F. Skinner developed operant conditioning, replacing the term "satisfaction" with "reinforcement". Further work established that behavior can be influence by various schedules of reinforcement, and the primary schedules of reinforcement include: fixed ratio (FR), variable ratio (VR), fixed interval (FI), and variable interval (VI).

1.1.1 Matching Law

The *matching* law, established by Richard Herrnstein (1970), was another early behavioural theory of choice that pertains to concurrent schedules of reinforcement, stemming from his laboratory work with animals. In his seminal experimental work, Herrnstein (1961) presented pigeons with two response keys, and responding to each key was reinforced with food on mutually independent and simultaneous variable interval (VI) schedules for each key. When the within-subject ratio of responding was plotted against the ratio of reinforcements for Key A, the resulting slope closely approximated a perfectly linear association (r = 1.0), with only an 8% discrepancy. When the absolute responses per hour are plotted against the absolute reinforcements per hour for both Key A and Key B, the same association emerges. The most remarkable conclusion of this study was that the relative frequency of responding matched the relative frequency of reinforcement across the two response keys, and that this occurred independently across both keys. Based this study and the work of others. Herrnstein (1970) proposed the matching law, denoted by the following equation:

$$\frac{B_1}{B_2} = \frac{FR_1}{FR_2}$$

In this simple equation, B_1 and B_2 denote responses (e.g., pecking) to options one and two, and FR_1 and FR_2 denote reinforcements (e.g., food pellets) from the same respective options. Put simply, the rate of responding matches the rate of reinforcement. Herrnstein's matching law produced two important concepts for theories of behavior (see Vuchinich &

Heather, 2003). First, allocation of behavior to option A could be altered by changing not only the rate of reinforcement of that option, but also by changing the rate of reinforcement of a second, concurrent option B. Moreover, Herrnstein suggested the possibility that qualitatively different reinforcers could be scaled against one another, providing an empirical account of the reinforcing value of one reinforcer relative to another.

Subsequent work conducted by Miller (1976) examined the matching law of choice across qualitatively different reinforcers. Using the same concurrent VI-VI schedule of reinforcement utilized by Herrnstein (1961), pigeons were exposed to pairs of food reinforcers across three conditions: 1) hemp vs. buckwheat; 2) wheat vs. buckwheat; and 3) hemp vs. wheat. Working under the assumption that pigeons would *allocate behavi*or (i.e., choice) according to the *value of each reinforcer* (i.e., food preference), the matching law would allow for the prediction about behavior across conditions. The results confirmed this hypothesis, and predicted allocations were similar to observed allocations, suggesting that matching theory holds for qualitatively different reinforcers.

Despite replications of Herrnstein's matching theory under a variety of conditions, there are a number of challenges associated with the matching law as applied to substance use. One such challenge is that the matching law for heterogeneous reinforcers does not always hold under certain conditions. This was illustrated in a study by Elsmore and colleagues (1980), which introduced an economic constraint to behavioural choice experiments. Baboons were offered two concurrent reinforcers: heroin or food corresponding to two response options. The economic constraint was the number of choice-trials the baboons had each day, operationalized as "income". In conditions with high income (i.e., many choice-trials per day), the daily total responses for both heroin and food were high;

however, as income decreased (i.e., fewer choice-trials per day), the number of responses for heroin dropped more rapidly than the number of responses for food. These findings suggest that when reinforcers are markedly different and choice is constrained by income or price, the strength of a reinforcer is not adequately measured by rate of responding (Hursh & Silberberg, 2008).

1.1.2 Relative Reinforcing Efficacy

Relative reinforcing efficacy (RRE) refers to the ability of a psychoactive substance to maintain self-administrative behavior (Bickel, Marsch, & Carroll, 2000). This property varies across substances, and allows for the ranking of substances according to reinforcing value (Katz, 1990). Moreover, this attribute is determined by a variety of factors, including biology, environment, context, availability of other drugs, and behavioural and pharmacological history (Stafford et al., 1998). Seminal studies of the RRE of psychoactive substances have traditionally taken the form of self-administration of drugs in animal models (e.g., Griffiths, Bradford, & Brady, 1979). Animal models provide a useful model for examining reinforcing efficacy of psychoactive substances as drugs that function as reinforcers in animals are similar to those that are commonly abused by humans (Schuster & Thompson, 1969). Traditionally, three concepts have been used to describe the RRE, including: 1) peak response rates when working for a drug; 2) breakpoint from progressive ratio schedules of reinforcement (Stretch et al., 1971); and 3) preference of one substance over another in situations where both are concurrently available (Griffiths et al., 1979; Katz, 1990).

A number of criticisms have been leveled at traditional methods for examining RRE. Namely, that the variety of procedures used to establish RRE often fail to converge.

Inconsistent results between measures of rate of responding and breakpoint in responding in PR schedules (Arnold & Roberts, 1997; Richardson & Roberts, 1996). This suggests that no single traditional account comprehensively describes the phenomenon of RRE, and each method may in fact, represent different aspects of a heterogeneous phenomenon. Moreover, traditional assessments of RRE indices are affected by the limitations that are germane to laboratory administration tasks, including ethical constraints on administration with human participants, as well as costly and time-consuming procedures and smaller samples sizes.

1.2 Behavioural Economics

Given the limitations of traditional accounts of RRE, behavior economics has been suggested as an alternative theoretical framework by Bickel and colleagues (2000). The behavioural economic framework combines principles of operant conditioning and choice preference with economic principles derived from consumer demand theory in an effort to provide a single, parsimonious theory of the reinforcing efficacy of psychoactive substances. Economic principles and theories related to consumer demand evince a natural overlap with aspects of operant psychology. Indeed, economics has been described as a “science of behavior” of humans suggesting its potential utility for studying behavior related to substance use (Hursh, 1984). Within the behavioural economic framework, *demand curves* are generated by plotting drug consumption across price, and can be examined for a variety of indices, including drug sensitivity to price. This theoretical framework suggests that each traditional measure of RRE refers to different aspects of behavioural economic demand curves (Bickel et al., 2000), and that demand curves more accurately characterize the reinforcing efficacy of psychoactive drugs. A number of researchers have independently concluded that economic concepts are particularly relevant to behavioural choice (Allison, 1979; Lea, 1978; Rachlin et al., 1976), suggesting that a behavioural economics paradigm may have unique contributions to make in the understanding of the reinforcing effects of psychoactive substances and self-administrative behavior in humans.

Hursh (1980) described four areas of importance related to reinforcers and economic theory: 1) behavioural experiments, such as those utilized in self administration studies, can be characterized using economic terms; 2) reinforcers can be distinguished from one another by a property known in economic theory as *elasticity of demand*; 3) reinforcers can act as substitutes and complements; and 4) no simple choice rule can accurately account for all choice behavior. Subsequent research suggests that economic theories can be successfully used to describe behavioural choice and administration of psychoactive substances, including aspects of RRE (Hursh, 1991). The present study proposes to examine elasticity of demand to identify possible substitution effects.

1.2.1 Demand Curves

The hallmark of behavioral economic analysis of behavior and substance use is the creating and examination of a *demand curve*, which describes consumption of a reinforcer as a function of price. The primary outcome variable of interest in behavioural economics analysis is consumption, which is analogous to rate of responding in operant conditioning, and the primary independent variable is price, which is conceptually similar to the FR requirement. From a demand curve, four of indicators of RRE can be derived: elasticity, intensity of demand, $P_{max,}$ and O_{max}.. (Bickel et al., 2000). *Elasticity of demand* is defined as "proportional change in consumption as a function of proportional change in price" (Bickel et al., 2000, pp. 47-48). When graphed in log-log scales (see Figure 1.1), elasticity is the absolute value of slope of the demand curve at any given point along the curve. When the slope > 1, a reinforcer is said to be elastic, such that even small changes in price is associated with proportional changes in consumption. When slope < 1, a reinforcer is considered inelastic, and changes in price do not affect changes in consumption. Typically, most reinforcers are said to be of mixed elasticity; inelastic at lower prices (i.e., not sensitive to changes in price) and elastic at higher prices (i.e., sensitive to changes in price) (Bickel et al., 2000). Intensity of demand is the consumption of a reinforcer at a given price point, typically analyzed as the consumption at the lowest price point tested. P_{max} refers to the highest price an individual is willing to pay for a reinforcer, and is also the point at which elasticity of demand shifts from inelastic to elastic. At this price point, rate of consumption begins to rapidly decrease. O_{max}, refers to the maximum consumption (maximal rate of responding) at P_{max}. (Hursh, 2000)

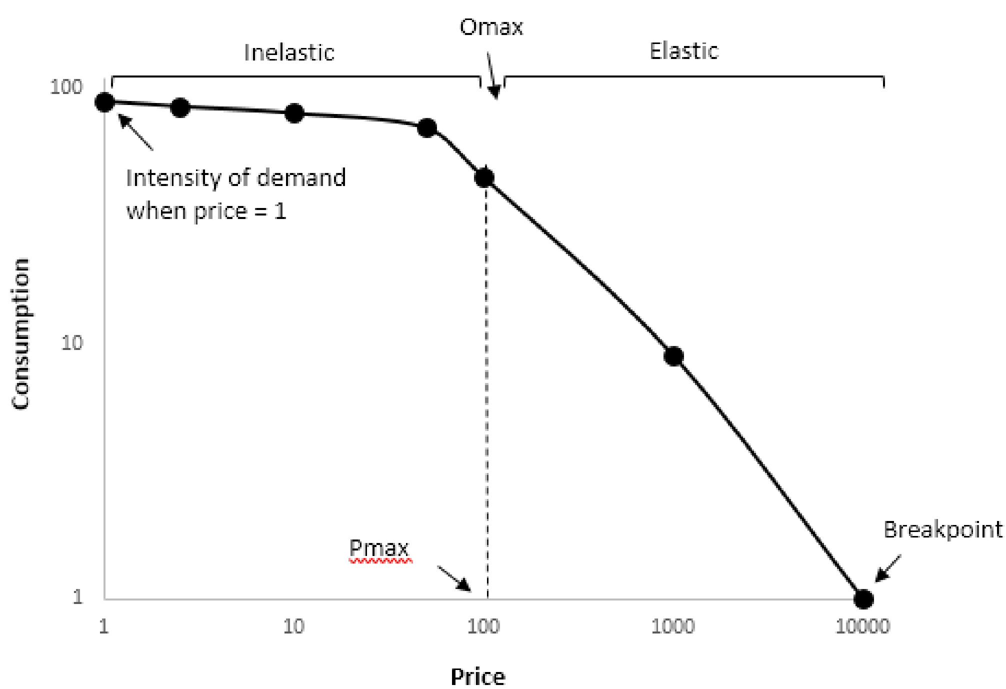


Figure 1.1 A hypothetical demand curve plotted in log-log coordinates

There is evidence to suggest that indices generated by demand curve analysis are related to traditional measures of RRE (Bickel et al., 2000). For example, in a study examining the RRE of cigarettes and money, P_{max} is strongly positively associated with PR breakpoint and O_{max} is analogous with peak response rate (Bickel & Madden, 1999; Bickel et al., 2000). This link between behavioural economic and traditional measures of RRE has been established in questionnaire simulation studies. In the seminal work by Jacobs and Bickel (1999), described in detail below, PR breakpoint was strongly associated with both P_{max} (r =.99) and elasticity of demand (Spearman rank order correlation coefficient (r =.82)). These findings suggest that behavioural economics paradigms accurately capture important indices of RRE.

In addition to examining single schedules of reinforcement, the behavioural economic framework can be extended to examine reinforcement under concurrent schedules (Bickel, DeGrandpre, & Higgins, 1995). Using principles of economic theory, reinforcers can be categorized along a continuum that describes three basic ways reinforcers may interact: substitutes, complements, and independent (DeGrandpre & Bickel, 1996). A reinforcer functions as a substitute when, as the price of Reinforcer A (e.g., butter) increases and its consumption subsequently decreases, consumption of Reinforcer B at a constant price (e.g., margarine) increases. A reinforcer acts as a complement when, as the price Reinforcer A (e.g., movie tickets) increases and consumption decreases, the consumption of a Reinforcer B (e.g., popcorn) at a constant price will also decrease. Finally, reinforcers are considered independent when, as the price of Reinforcer A increases with proportional decrease in consumption (e.g., movie tickets), the consumption of Reinforcer B (e.g., carrots) remains unaffected. The behavioural economic index that describes the way in which reinforcers interact is referred to as cross-price elasticity. Cross price elasticity is defined as the proportional change in consumption of a secondary reinforcer under conditions in which the price of a primary reinforcer is altered (Bickel et al., 1995). Specifically, it is the slope of the curve when consumption of the unchanged reinforcer is plotted in log-log coordinates against the price of the changed reinforcer.

1.2.2 Hypothetical Purchasing Tasks

Despite the advantages of the behavioural economic framework for modelling reinforcing efficacy, there are limitations for measuring actual drug consumption in humans, including studies that are lacking ethical muster, time-intensive, and costly. To address these limitations, researchers have begun to utilize hypothetical purchasing tasks, in which participants are presented with questionnaires and asked what quantity of drug they would purchase across varying price points. In these tasks, the hypothetical purchase amount is a proxy for drug consumption. A seminal study of a hypothetical purchase task was conducted with 17 opioid-dependent cigarette smokers (Jacobs & Bickel, 1999). Participants were presented with three questionnaires in which they were asked how many cigarettes or bags of heroin they would purchase across 15 price points (range $0.01-$1,120.00). In two questionnaires, participants were presented the option of purchasing either cigarettes or heroin. In the third questionnaire, both substances were available concurrently. Participants were instructed that everything that they hypothetically purchased was for consumption within a 24-hour period. The behavioural economic measures that were extracted for each participant included intensity of demand, overall elasticity of demand, P_{max}, and O_{max}; traditional measures of RRE extracted included progressive-ratio breakpoint, peak response rate, peak rate of self-administration, and preference. In general, this study demonstrated that hypothetical self-report data produced similar measures of behavioural economics through simulation using questionnaires. Moreover, the hypothetical purchase paradigm provides several advantages over in-person laboratory sessions, as it is less time-intensive, requires fewer resources, which facilitates data collection from a greater number of participants.

Research of the utility and applicability of hypothetical purchasing tasks continued with the development of the Alcohol Purchasing Task (APT; Murphy & MacKillop, 2006) modelled from Jacob and Bickel's (1999) demand curve analysis. This study examined the utility of a simulated purchasing task for examining behavioural economic RRE indices in 267 undergraduates who reported using alcohol. In the APT, participants were asked to indicate how many alcohol beverages they would hypothetically purchase across a range of 14 prices ($0-$9 per drink). In addition, participants were assessed for weekly alcohol consumption and alcohol-related problems. Demand curves yielded standard indices of RRE, including breakpoint, intensity of demand, elasticity of demand, P_{max}, and O_{max}. Consistent with prior research, breakpoint was positively associated with P_{max} and elasticity of demand. Correlations between RRE indices and self-report alcohol use patterns and alcohol-problems were examined. The number of alcoholic drinks consumed per week was positively associated with breakpoint, intensity of demand, and O_{max}. Alcohol-related problems were associated with intensity of demand and O_{max}. Moreover, RRE indices were significantly higher in individuals who reported heavy drinking, compared to lighter drinking counterparts. This suggests that alcohol has a greater reinforcing efficacy in heavy drinkers.

1.2.3 Cannabis Purchase Tasks

The seminal study examining the utility of using a computerized hypothetical cannabis purchasing task was conducted in 2014 (Collins, Vincent, Yu, Liu, L, & Epstein, 2014). The sample included 59 young adults (i.e., 18-25 years) who used cannabis at least 3 times per week. Participants were asked how many high-grade cannabis joints they would purchase for a 4-hour period at home at 16 escalating prices ranging from $0 to $160 per joint. Participants were instructed to imagine that they could not save the purchased joints for a later date. Data were also collected on cannabis use variables, including preferred method of self-administration, typical context of use, frequency and quantity used, symptoms of abuse and dependence, cannabis-used related problems, real-world purchasing patterns, and quantity typically smoked in a single session. In addition, researchers collected ecological momentary assessment (EMA) data on cannabis use within a two-week period, including EMA interviews prior to and following cannabis use sessions. Demand indices extracted included breakpoint, intensity of demand, O_{max}, P_{max}, and elasticity. Overall, the results suggest that demand for cannabis was inelastic between $0.00 and $13.00 per joint, but became elastic for higher prices, up to $160.00 per joint. The authors note that even at very high prices, some individuals continued to purchase cannabis joints. Indeed, the first breakpoint was $38.07/joint, suggest the reinforcing value of cannabis is strong, as the authours note that this is more than five times the average retail price per joint ($7.00). Additionally, results indicated that for self-report quantity of cannabis used, only O_{max} was significantly associated, suggesting that individuals who used more cannabis would have a higher peak expenditure rate for cannabis. With regard to EMA cannabis use data, intensity of demand and O_{max} were positively related to real-time quantity of joints used per session, suggesting individuals who used more cannabis in a two-week period also reported higher hypothetical consumption at lower prices and higher hypothetical maximum expenditures. Further, P_{max} and elasticity of demand were negatively related to quantity of cannabis consumed, suggesting that higher real-world consumption was related to a lower price point for maximum expenditure and that those who used more cannabis were most sensitive to changes in prices. This is noteworthy, as according to BE theory, it was expected that individuals who use more cannabis would be less sensitive to changes in price and would have higher maximum expenditure rates. The authours note that the extant literature is mixed on the association between price elasticity and real-world substance use, and highlight the need for additional research to clarify this point.

Further support for the self-report cannabis purchasing task was evident in a 2015 study of demand characteristics of cannabis (Aston et al., 2015). Aston and colleagues administered a self-report cannabis purchasing task to 99 non-treatment seeking, high frequency cannabis users, who reported using cannabis at least twice per week in the past month and at least weekly in the past 6 months. All participants were asked to abstain from cannabis and tobacco use for 12 hours prior to the session. Participants were administered a Marijuana Purchase Task (MPT), in which they were asked how many "hits" (10 hits/joint) of average quality cannabis they would purchase for a range of twenty-two different prices ($0-$10/hit). Five metrics of demand were extracted from the MPT: breakpoint, intensity of demand, elasticity of demand, P_{max}, and O_{max}. In addition, participants were queried on cannabis use variables, including initiation of cannabis use, past 60-day cannabis use, craving, typical quantity of use, preferred mode of self-administration, and monthly expenditure on cannabis. The authors establish convergent validity of demand indices by examining their associations with cannabis use variables. In particular, intensity of demand was negatively associated with age of initiation, positively associated with proportion of cannabis use days, and positively associated with subjective craving. O_{max} was associated with proportion of cannabis use days and with craving, and Elasticity was negatively associated with craving. These findings suggest that that intensity of demand is greatest for individuals with earlier age of initiation, frequent cannabis users, and those experiencing high levels of subjective craving. Moreover, frequent cannabis use and self-reported craving was associated with a higher peak-purchasing price. These findings are in contrast with those reported by Collins et al. (2014), highlighting the need for further clarification.

1.2.3.1 Experimental Manipulation of Cannabis Purchasing Tasks

Ongoing research in CPTs and behavioural economics of cannabis use has explored the ability to introduce experimental manipulation of the cannabis task, manipulating quality of cannabis and cannabis strain in the CPT vignettes presented to participants. Research using a web-based purchasing task examined demand indices for cannabis at varying qualities of cannabis (Vincent et al., 2017). In total, 2,531 participants were recruited from the website of a nonprofit cannabis lobbying group, and were restricted to young adult (i.e., 18-25) non-medical cannabis users (i.e., excluding those who used for medical purposes or were non-users). Participants completed a MPT for cannabis joints at a range of nine prices from $0 to $20/joint (defined as 0.5 grams, 5 bong hits, or 10 puffs), and completed three separate tasks for low, medium, and high-grade cannabis. Participants were instructed to imagine that they could stay at home and smoke cannabis during some free time, and that they were unable to save the joints for a later date. In addition, data were collected on preferred smoking methods, frequency of cannabis use, typical quantity of use (grams/week), and real-world purchasing behavior. The extracted demand curves indices included breakpoint, intensity of demand, O_{max}, P_{max}, and elasticity of demand. The authors noted, that regardless of quality, cannabis users are sensitive to changes in price, with hypothetical consumption decreasing as a function of price. For each grade of cannabis, intensity and Omax were positively correlated to quantity of cannabis used, suggesting that individuals using higher amounts of cannabis are likely to consume more cannabis at low prices and likely to pay higher peak prices for cannabis. However, important differences in demand indices were apparent across quality. In particular, P_{max} and intensity of demand, increased as perceived quality improved. This suggests that regardless of cost, consumption would vary based on quality. Moreover, higher breakpoints were evident at higher grades of cannabis, suggesting that individuals will spend more for higher quality cannabis. Ultimately, the results suggested that the reinforcing value of cannabis increased as the perceived quality of cannabis increased.

A recent study examined the impact of cannabis strain on hypothetical purchases of cannabis. In a cross-sectional survey of cannabis users, participants complete purchasing tasks for grams of both *indica* and *sativa* cannabis (Sholler et al., 2021). Demand curves were modelled for both tasks, yielding intensity and elasticity demand metrics. Notably, there was no difference between *indica* or *sativa* strains of cannabis, despite the participant-reported knowledge of the potential differences between the two. Nevertheless, the study is among one of the first to examine the suitability of comparing types of hypothetical cannabis purchasing tasks. To date, no research has examined the effect of THC potency on hypothetical purchases of recreational cannabis.

There exist a number of challenges with regard to assessing demand for hypothetical purchases of cannabis. In particular, there is no standardized unit for cannabis. Moreover, there are a number of different methods of administration, including inhalation and oral administration. Cannabis users are also more likely to use in a group, and therefore consumption may be measured in “hits” taken, rather than whole units. Indeed, the most recent studies conducted using hypothetical purchasing have used two different, yet related, metrics for units of cannabis: number of joints (Collins et al., 2014) and number of hits (Aston et al., 2015). Finally, cannabis is not purchased in the same units as it is administered. Those who purchase are likely to purchase in grams or ounces, and unlikely to administer an entire purchase in a single administration setting. Research examining the cannabis purchasing task using grams as the unit of measurement is limited. Two studies conducted by Amlung and colleagues have examined the impact of legality on purchases of grams of cannabis. Participants were invited to complete hypothetical purchasing tasks for grams of legal and illegal cannabis, both on their own and concurrently. In general, participants view legal cannabis as more valuable than illegal cannabis, with higher intensity, higher P_{max} price, and lower elasticity (Amlung et al., 2019; Amlung & MacKillop, 2019). Notably, these particular studies did not evaluate the associations between demand metrics and cannabis use variables such as frequency, quantity, or age of initiation. Other research examining the association between demand indices of grams of cannabis explored the link between demand for cannabis and driving after cannabis use (Patel & Amlung, 2019). The results suggest that individuals who report driving after cannabis use are likely to report greater cannabis demand for all demand indices. After controlling for age, sex, income, and problematic use, intensity of demand was the strongest predictor of driving after cannabis use. This study did not specifically examine the association between demand metrics and cannabis use variables but suggests that demand for grams of cannabis is associated with outcomes of cannabis use.

1.2.4 Cannabis Purchasing with Concurrently Available Other Substances

Few studies have examined the cross-price elasticities of cannabis and alcohol. This is a particularly important avenue of research, given the increasing scientific and public interest in the potential ability of cannabis to serve as a substitute for alcohol. A 2007 study used a hypothetical purchase task to examine the effects of price and quality on the behavioural economics of alcohol, amphetamine, cannabis, cocaine, and ecstasy in 40 nondependent polysubstance users (Goudie et al., 2007). Participants were asked to make hypothetical purchases of alcohol and illicit drugs based on a given price list. The quality of alcohol varied (i.e., normal vs strong) as did the quality of the illicit substances (e.g., poor quality cannabis, average quality cannabis, good quality cannabis). In addition, the prices varied according to quality, with higher unit prices for higher quality. Participants were asked to imagine that they had a set disposable income for a night out and given a price list and Monopoly money with which to purchase their choice of substances. Moreover, participants were asked the quantity of cannabis purchased in 1/8 oz units, rather than in "hits" or "joint". Due to differing methodology, demand indices were not presented, with the exception of overall elasticity. For poor and average quality cannabis, income had no significant effect on purchasing, however, for high quality cannabis, more disposable income was associated with increased units of cannabis purchased. The results suggest that available income may affect purchasing patterns of high-quality cannabis.

A recent examination of hypothetical purchases of concurrently available cannabis and alcohol among recreational cannabis users demonstrated the complementarity of the two substances (Dolan et al., 2020). Participants completed hypothetical purchasing tasks for hits of cannabis and standard drinks of alcohol, both single-item and cross-commodity. When both cannabis and alcohol were available for purchase, there was a reduction in demand intensity for both substances, compared to when each was available alone. When cannabis was presented with alcohol, alcohol elasticity rose (i.e., lower demand); however, the reverse association was not present. Moreover, the authours report that while complementarity was evident at the group level, many individual participants endorsed independent purchases of cannabis and alcohol. Further replication of the association between alcohol and cannabis purchases is warranted.

1.2.5 Modeling and Analyzing Demand Curves

Conventional analysis of demand curves generated with purchase tasks has been using one of two methods: 1) fitting a linear model with log transformed consumption prices; and 2) using a nonlinear model fit to each individual person, and then averaging derived parameter estimates ad hoc. However, there are a number of major limitations to these methods (Yu et al., 2014). First, purchase data almost always contains data points that include zero, and thus cannot be log transformed. Typically, zero values of price and consumption are replaced with small non-zero values, and then subsequently log transformed, ultimately altering the scale in which it was used, and potentially making some data points more influential. Moreover, log transformation fails to preserve the distance between two data points, thus distorting the data further. Using a nonlinear model fit to each person has been used to avoid this problem, and typically results in better fitting models and more robust parameter estimates. Fitting nonlinear models for each individual, however, does not take into account deviations from mean values, and results in an over-parameterized model. As such, recent methods have been developed to analyze overall model fit of demand curves for the sample to address these concerns.

An important aspect of BE analysis to examine the associations between BE indices and substance use variables of participants, namely examining individual demand curve models. To facilitate the examination of the association between BE indices and individual characteristics (i.e., demographics, substance use, motives), BE indices are obtained for each individual from the empirical demand curve. The BE indices include breakpoint, P_{max}, O_{max}, intensity of demand, and elasticity of demand. To estimate demand elasticity, the Exponential-Demand Equation (Hursh & Silberberg, 2008) provides an advantage over traditional linear models. This equation takes the form of:

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

Where Q_0 is the consumption when price is zero, and denotes the highest level of demand. Price is denoted by P. The rate constant α denotes elasticity. The value of k is set to a common constant. As such, as k is constant across the demand curve, and demand for a commodity will shift from inelastic to elastic as price increases, the most appropriate value for identifying demand is α, as it gives a single index of accelerating or decelerating demand. There are limitations to the Exponential-Demand Equation when examining purchasing tasks that include zeros, as zero cannot be represented on a logarithmic scale. Options for approaching this include only fitting non-zero consumption values or replacing them with small nonzero values (e.g., 0.01). However, on a logarithmic scale, even small differences can result in very large effects. An alternative equation proposed to model demand equations serves to address these issues, and is created by exponentiating the above equation. The proposed equation is known as the Exponentiated Demand Equation (Koffarnus et al., 2015):

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

1.3 Summary and Aims

In sum, there has been extensive research utilizing the behavioural economic framework to examine the relative reinforcing efficacy of several psychoactive substances. Moreover, research has identified that hypothetical substance purchasing tasks produce demand curves similar to those seen in laboratory administration. However, there are a number of gaps in the current literature. Though a small number of studies have examined hypothetical purchasing tasks of cannabis, all have instructed participants to imagine how many “hits” or “joints” they would purchase. Though this may reflect how some cannabis users may typically administer, this is not reflective of how cannabis is purchased in the real-world.

The present research seeks to validate the original purchasing task (i.e., using “hits”), but also seeks to extend the paradigm to examine purchasing patterns for grams of cannabis. Second, previous research has focused primarily on non-medical cannabis users for deriving demand curves, and no studies have examined the patterns of medical cannabis users. This proposal seeks to add to the growing body of literature aimed at identifying differences and similarities between non-medical and medical cannabis users by modelling demand of cannabis for medical cannabis users. Finally, while there exists an extant body of descriptive research of the substitution effect of cannabis, few behavioural studies have examined the ability of cannabis to serve as a substitute for alcohol, and no studies have examined the ability of cannabis to substitute for prescription medications. This proposal will add depth to the current research body of cannabis substitution. As such, this study has the following aims:

Aim 1. Replicate the findings of previous purchase tasks for "hits" of recreational cannabis available on a single schedule and examine how potency of cannabis can affect purchasing patterns.

Aim 2. Apply the behavioural economic framework to hypothetical purchases of "grams" of recreational cannabis available on a single schedule and examine how potency of cannabis can affect purchasing.

Aim 3. Extend the behavioural economic framework to medical cannabis users and characterize behavioural economics indices in this population.

Aim 4. Examine the substitution effect of cannabis for alcohol and pain medication in recreational and medical cannabis users.

Aim 5. Compare and contrast behavioural economics indices for cannabis use between medical and non-medical cannabis users

1.4 Hypotheses

Hypothesis 1. "Hits" of recreational cannabis will conform to behavioural economic principles as established by previous hypothetical purchasing tasks

Hypothesis 1a. Intensity of demand will be positively associated with frequency of cannabis use, quantity of cannabis used, regular years of use, and negatively associated to age of initiation

Hypothesis 1b. O_{max} will be positively associated with frequency of cannabis use, quantity of cannabis used, regular years of use, and negatively associated with age of initiation.

Hypothesis 1c. There will be significant group differences for behavioural economics indices across potency conditions, such that P_{max}, breakpoint, and intensity will be highest in the high THC condition.

Hypothesis 2. "Grams" of recreational cannabis will similarly conform to behavioural economic principles as outlined with hypothetical purchasing tasks using "hits" (i.e., similar associations with cannabis use variables)

Hypothesis 2a. Intensity of demand will be positively associated with frequency of cannabis use, quantity of cannabis used, and negatively associated to age of initiation

Hypothesis 2b. O_{max} will be positively associated with frequency of cannabis use, quantity of cannabis used, regular years of use, and negatively associated with age of initiation.

Hypothesis 2c. There will be significant group differences for behavioural economics indices across potency conditions, such that P_{max}, breakpoint, and intensity will be highest in the high THC condition.

Hypotheses 3. Cannabis for medical purposes will conform to behavioural economic principles in a fashion similar to that of non-medical users.

Hypothesis 3a. Intensity of demand will be positively associated with frequency of cannabis use, quantity of cannabis used, regular years of use, pain variables, and negatively associated to age of initiation

Hypothesis 3b. O_{max} will be positively associated with frequency of cannabis use, quantity of cannabis used, regular years of use, pain variables, and negatively associated with age of initiation.

Hypothesis 3c. The patterns of association described above will be consistent whether measured in “grams” or in “hits”

Hypothesis 4. Cannabis will act as a substitute for alcohol and for pain medication.

Hypothesis 4a. As the price of alcohol increases, hypothetical purchases of alcohol will decrease, and purchases of cannabis will increase.

Hypothesis 4b. As the price of pain medication increases, hypothetical purchases of pain medication will decrease, and purchases of cannabis will increase.

Hypothesis 5. There will be group differences between medical and recreational cannabis users in behavioural economics indices.

Hypothesis 5a. Medical cannabis users will report higher intensity, O_{max}, P_{max}, and breakpoint values compared to recreational cannabis users.

Hypothesis 5b. Medical cannabis users will be more sensitive to changes in price than recreational cannabis users.

Chapter 2: Method

2.1 Participants

A power analysis was conducted using G*Power to identify the ideal sample size for combined recreational and medical cannabis users. The analysis suggests that to observe a medium effect size f = .25, a total sample of 160 would be required at sufficient statistical power (β =.80) and appropriate Type I error rate (.05). As such, the studies would require approximately 160 combined medical and recreational to facilitate comparisons among groups.

The recreational cannabis sample recruited 252 participants who endorsed cannabis use from the undergraduate sample at the University of British Columbia in Kelowna BC. Recruitment was conducted via SONA systems, and participants were compensated for course credit. This population is appropriate to sample for this study, as the highest rates of cannabis use are reported by young adults (age 18-25). Eligible participants were 18 years or older, fluent in English, and reported past month cannabis use. Descriptive statistics are presented in Table 2.1.

Table 2.1 Demographic and substance use descriptive for recreational cannabis users

	mean (SD); N (%)	
	Low THC (N=75)	High THC (N=81)
Age	19.50 (1.54)	19.63 (1.68)
Male	31 (41%)	34 (42%)
Caucasian	54 (72%)	55 (68%)
Cannabis Use		
Days of Use (Past Month)	7.92 (9.79)	8.54 (10.96)
Days of Use (Past Week)	2.03 (2.33)	1.89 (2.52)
Frequency per day		
Weekday	0.83 (1.70)	0.96 (2.53)
Weekend	1.44 (2.85)	1.50 (2.53)
Age of First Use	16.18 (1.68)	16.96 (1.81)
Quantity/Session (g)	0.31 (0.40)	0.43 (0.44)

The medical cannabis sample (N = 410) was recruited from medical cannabis dispensaries in Canada. Recruitment took place through web advertisement, providing a link that participants could access online. The advertisement was disseminated through a medical cannabis organization in Canada. To participate in the study eligible participants had to be 18 years or older, fluent in English, and reporting medical cannabis use for pain-related conditions. Compensation was the opportunity to be enrolled in a draw for a $20 Amazon gift card. Descriptive statistics are presented in Table 2.2. Means and standard deviations for pain-related variables are presented in Table 2.3.

Table 2.2 Demographic and cannabis use information for medical cannabis users

	mean (SD); N (%)
Age	44.56 (14.71)
Male	45(54%)
Caucasian	74 (89%)
Cannabis Use	
Days of Use (Past Month)	26.49 (7.69)
Days of Use (Past Week)	5.93 (2.05)
Frequency per day	
Weekday	3.67 (4.83)
Weekend	4.64 (5.65)
Age of First Use	18.09 (7.87)
Quantity/Session (g)	0.48 (0.55)

Table 2.3 Means and standard deviations for pain-related variables

	mean (SD)
PNRS (past week)	
Current	4.35 (2.24)
Worst Pain	7.15 (2.02)
Least Pain	3.42 (1.85)
Average Pain	5.24 (1.84)
Pain relief	6.59 (2.76)
Pain Interference	
General Activity	6.00 (3.14)
Mood	5.71 (3.05)
Walking	4.62 (2.96)
Normal Work	5.67 (3.39)
Relations	4.30 (2.98)
Sleep	5.70 (3.13)
Enjoyment of Life	5.85 (2.98)

PNRS = Pain Numeric Rating Scale

2.2 Measures

Cannabis Use Variables. The Daily Sessions, Frequency, Age of Onset, and Quantity of Cannabis Use Inventory (DFAQ-CU; Cuttler & Spradlin, 2017) was used to measure important cannabis use variables. The DFAQ-CU is a 41-item measure designed to assess frequency, age of onset, and quantity of cannabis used by respondents. A total of 24 items are used to assess cannabis use variables: Eleven of the items measure frequency of cannabis use, 4 items assess age of onset, and 9 items assess quantity of cannabis. The remaining 17 items are used to establish skip logic and to establish adequate screening. The measure has adequate reliability, with Cronbach's alpha coefficients between .69 and .95 (Cuttler & Spradlin, 2017). The variables of interest were past week use, past month use, number of sessions per day, quantity of cannabis used per session, and age of first use.

Pain Variables. Intensity of current pain was assessed using the pain Numeric Rating Scale (NRS). The pain NRS is a visual analog scale (VAS) on which a respondent indicates a value between 0 ("no pain") and 10 ("worst possible pain") that best describes the intensity of their current pain. In addition to intensity of current pain, a modified version of the Brief Pain Inventory (Cleeland, 1989) was included. This is a brief, 9-item measure designed to assess intensity of pain, effectiveness of treatments or medications, and general interference of pain on daily activities. Participants are asked to rate on a 10-point scale, the intensity of pain, effectiveness of pain relief, and interference from pain across a variety of domains of daily living.

Demographics. Finally, participants were presented with questions related to demographics, including, age, gender and race/ethnicity.

2.3 Procedure

2.3.1 Own-Price Demand

Participants were presented with four distinct cannabis purchase tasks (CPTs). Purchase tasks were presented in accordance with the recommendations for hypothetical purchase tasks provided by Roma and colleagues (2016). In the first task, participants were presented with a vignette, and asked to imagine how many "hits" of cannabis they would purchase across a variety of purchase prices. The use of "hits" for the first task was chosen, as previous research suggests that this is the most ideal utilization of the purchase task (Aston et al., 2015). In addition, "hits" rather than joints or grams is the most likely method of administration, particularly for individuals who use infrequently. Previous studies on cannabis purchase tasks have employed a varying number of escalating price points (i.e., price density) for participants to purchase at, including nine (Vincent et al., 2017). 16 (Collins et al., 2014), and 22 (Aston et al., 2015). Results from the previous studies suggest that the highest average maximum expenditure (O_{max}) per cannabis joint ranges from $11.00 (Vincent et al., 2017) to $139.00 (Collins et al., 2014). Recommendations for general hypothetical purchasing tasks suggest that the minimum required number of price points is nine, with a more optimal number being 17 (Roma et al., 2016). As such, the tasks included 17 price points, to avoid potential burnout. Participants were presented with each price in a randomized order, to allow for a check on consistency of responding. To evaluate the effects of potency on demand indices and RRE of cannabis, participants were randomized into one of two conditions: high THC (>%20) and low THC (<12%). In each of the two conditions participants were presented with the following vignette:

> "Imagine a typical day when you would use marijuana. You have the typical amount of money available to purchase marijuana. You have not used marijuana, alcohol, or any other drugs before making this decision. Think about how many "hits" (e.g., one hit from a joint, one puff of a bong/pipe) of marijuana you would purchase for a typical day. How many "hits" of marijuana would you purchase at the following

> prices per hit: $0, $0.05, $0.10, $0.25, $0.50, $1, $2, $3, $5, $10, $20, $40, $60, $80, $100, $250, and $500."

In the second CPT participants were presented with a similar vignette and asked to imagine how many grams of cannabis they would purchase across a variety of purchase prices for a typical month. Given the wide disparity in previously reported maximum prices and the lack of research on the validity of a CPT using grams, this study employed a wide range of prices to present to participants. In the two conditions, participants were given the following vignette:

> "Imagine a typical day when you would purchase marijuana. You have the typical amount of money available to purchase marijuana. You have not used marijuana, alcohol, or any other drugs before making this decision. Think about how much marijuana you would purchase (in grams) on a typical purchasing day. This is the only source of marijuana available. How many grams of marijuana would you purchase at the following prices per gram: $0, $0.05, $0.10, $0.25, $0.50, $1, $2, $3, $5, $10, $20, $40, $60, $80, $100, $250, and $500."

2.3.2 Cross-Price Demand

The third set of CPTs examined the cross-price elasticity of demand for cannabis and alcohol. In addition, these purchase tasks were utilized to determine if cannabis can serve as a substitute for or complement to alcohol and vice versa. Participants were presented with two tasks: in each task, participants were provided with a vignette with two choices, alcohol or cannabis. Alcohol was presented as a standard drink (e.g., 12-ounce can of beer, 5-ounce glass of wine, 1.5-ounce hard liquor shot, or a mixed drink with one shot). Cannabis was indicated as per gram. In the first task, the price for cannabis varied, while the price of alcohol remained unchanged. The price of cannabis (per gram) was presented as $1.00, $4.00, $8.00 or $15.00, while the price of alcohol remained constant ($5.00). For each of the four price points, participants were asked how many grams of cannabis and how many standard drinks they would purchase. Participants were presented with a random sequence of the four price conditions, to avoid priming and to provide a consistency check on responding. In the second task, the price of cannabis (per gram) remained constant ($8.00) while the price of alcohol varied. Alcohol price was presented as: $1.00, $5.00, $10.00, or $15.00. Participants read the following vignette:

> "Imagine a typical night out or night off on which you use marijuana or alcohol. You have the typical amount of money available to purchase marijuana or alcohol. This is the only source for cannabis or alcohol. You cannot retain and sell any marijuana or alcohol at a later date. How many grams of marijuana and how many standard drinks would you purchase at the following prices for a typical month?
>
> Marijuana: $1.00, $3.00, $8.00, $15.00 per gram
>
> Standard Drink: $5.00 ea. "

Finally, the fourth CPT examined the cross-price elasticity for pain medication. As with the third CPT, participants were presented with a random sequence of four price conditions of cannabis (in grams), and a constant price for pain medication in the first task; cannabis was presented as: $1.00, $3.00, $8.00, $15.00 per gram, while prescription pain medication was presented as unchanged at $5.00 per pill. In the second purchase task, pain medication was presented as: 1.00, $3.00, $8.00, $15.00 per pill, and cannabis remained unchanged at $8.00 per gram. Due to low responding in recreational cannabis users for pain medication use, these analyses for pain medication and cannabis was limited to the medical sample only. The vignette is presented below:

> "Imagine a typical evening in which you would marijuana or prescription opioid medication for pain. You have the typical amount of money available to purchase marijuana or prescription opioid pills. You cannot retain and sell any marijuana or opioid pills at a later date. How many grams of marijuana and how many prescription opioid pills would you purchase at the following prices for a typical month?
>
> Marijuana: $1.00, $3.00, $8.00, $15.00 per gram
>
> Pills: $5.00 ea.

Chapter 3: Analytic Plan

3.1 Identification of Nonsystematic Data

Prior to analyses, the observed indices of demand for each participant were analyzed to identify nonsystematic data. Nonsystematic data derived from purchase tasks are demand curves that do not systematically vary by price (Stein et al., 2015). They may be caused by inconsistent, invariant, or non-responding to price. These issues arise for a number of reasons, including task inattention/fatigue or participant error. Identification of nonsystematic data is important, as they may compromise subsequent parameter estimates. Nonsystematic data may also indicate a potentially important property of the study sample or population that is worthy of exploration. Nonsystematic data of this nature may be excluded from further model building. Models may then be compared to each other for overall fit. The proposed study will utilize a three-criterion algorithm to identify nonsystematic data proposed by Stein and colleagues (2015) and described below. The algorithm defines three specific criteria for identifying nonsystematic data: trend, bounce, and reversals from zero.

Based on economic theory and the law of demand, the trend criterion refers to the tendency for participants to respond less as the price for the commodity increases. As such, it would be expected that the amount consumed (i.e., ‘hits’, grams) generally reduces as the price moves from the lowest to the highest price. The algorithm is capable of identifying data that do not follow this general trend, exposing instances of zero change in consumption or increases of consumption. The relative change in quantity purchased (ΔQ) is calculated using the following formula for each participant:

$$\Delta Q = \frac{logQ_1 - logQ_n}{logP_n - logP_1}$$

where Q_1 refers to the quantity purchased at the first price and Q_n refers to the quantity purchased at the last price point. P_1 and P_n refers to the first and last price point, respectively. To accommodate zero prices, which cannot be log transformed, a constant of 0.01 will be added to all zero values. In accordance with Stein et al. (2015), ΔQ for each participant was compared against a criterion detection limit (X = 0.025). Any value below this criterion suggests nonsystematic responding in with regard to *trend*, and warrants further consideration.

Where the *trend* criterion measures general effects of price on responding, the *bounce* criterion refers to local variability in response to changes in price (Stein et al., 2015). While it is expected that a general decrease will occur, individual variability in participant response patterns may affect purchasing responses. This may occur due to participant inattention, or may arise from the randomized order in which participants are presented each price. The primary assumption of the *bounce* criterion assumes that relatively few increases in quantity purchased occur for each local price increment. To calculate *bounce* (*B*), each participant's data should first be inspected for price-to-price increases in consumption that exceed 25% of consumption at the lowest price point (i.e., "jumps"). *B* may then be calculated by dividing the number of the observed jumps, by the total number of price points minus one:

$$B = \frac{\#\ of\ jumps}{(\#\ of\ price\ points - 1)}$$

Each B value is then compared against a criterion detection limit (X = 0.10), and anything above will be flagged as nonsystematic for further examination.

The final criterion reversal from zero refers to instances in which participants resume purchasing after they have already ceased purchasing at a given price. The most commonly used metric to identify this type of responding is the breakpoint, or the price at which consumption becomes zero. As per Stein et al. (2015), participant responding may be classified as nonsystematic if, after two instances of zero consumption at incremental prices, a nonzero instance of consumption occurs at a higher given price. Reversals from zero may occur, particularly when prices are presented in a randomized order, and cases of such should be carefully considered.

3.2 Model Fit and Deriving BE Indices

To examine the overall model fit, demand characteristics were modelled using a nonlinear exponentiated equation of demand:

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

. This model will be calculated using previously established methods in the BE literature (Koffarnus et al., 2015). Individual BE indices (P_{max}, O_{max}, elasticity, intensity of demand, breakpoint) will be obtained from both the individual purchasing plots and derived from the nonlinear model. This is referred to as the over-parameterized model. When purchase data are plotted, as demonstrated in Figure 1.1, these data are obtained from the individual plots. In addition, formulaically derived BE indices are available from the nonlinear model, including P_{max}, O_{max}, and overall elasticity.

3.3 Hypothesis Testing

Hypothesis 1a, 2a, 3a. Spearman's rho was used to examine the association of intensity of demand with the following substance use variables in non-medical cannabis users: frequency of cannabis use, typically quantity of cannabis used, number of years of regular use, and age of cannabis use initiation. I expect that intensity of demand will be positively correlated with frequency, quantity, and number of years of regular use. I expect that intensity of demand will be negatively correlated with age of initiation.

*Hypothesis 1b, 2b, 3b*Spearman's rho was used to examine the association of both $O_{max\ emp}$ and $O_{max\ der}$ with the following substance use variables in non-medical cannabis users: frequency of cannabis use, typically quantity of cannabis used, number of years of regular use, and age of cannabis use initiation. I expect that O_{max} will be positively correlated with frequency, quantity, and number of years of regular use, and negatively correlated with age of initiation.

Hypotheses 1c, 2c, 3c. Welch's F test was used to examine group differences across THC conditions for non-medical cannabis users. This will consist of four distinct one-way ANOVAs, with potency condition (i.e., high and low THC) serving as the independent variable, and $P_{max\ emp}$, $P_{max\ der}$, breakpoint, and intensity serving as the dependent variables. It was expected that those in the high THC condition will report higher values for all dependent variables, compared to the low THC condition.

Hypothesis 4a, 4b, 4c. To examine cross price elasticity of cannabis and alcohol/prescription medication, data were plotted in accordance with previously established methods of demand analysis for concurrent schedules (e.g., Petry, 2001; Sumnall, 2004). Demand was calculated by plotting the line of best fit and establish slope. In particular, two indices of demand can be calculated: own-price elasticity (E_{own}) and cross-price elasticity (E_{cross}). E_{cross} values are indicative of a substance's ability to serve as a substitute (i.e., ≥ 0.2), complement (i.e., ≤ -0.2), or independent drug (i.e., between -0.2 and 0.2) (Bickel, DeGrandre, & Higgins, 1995). Repeated measures analysis of variance will be used to analyze changes in purchases across price conditions. Overall significant *F* tests will be followed by simple contrasts to examine differences between particular price points.

Hypothesis 5a. To examine differences between medical and non-medical cannabis users on BE indices, Welch's F test of group differences was used, with type of use serving as the independent variable, and the following BE indices serving as dependent variables: $P_{max\ emp}$, $P_{max\ der,}$ $O_{max\ emp}$ and $O_{max\ der}$, breakpoint, and intensity of demand. It was predicted that the values of all BE indices will be elevated in the medical cannabis user type.

Hypothesis 5b. To examine the difference between medical and non-medical cannabis users on sensitivity to changes in price, I will use one-way ANOVA, with elasticity of demand serving as the dependent variable. I expect that medical cannabis users will be more sensitive to changes in price than non-medical users.

Chapter 4: Recreational Results

4.1 Recreational Cannabis

4.1.1 Hypothetical purchases of "hits" of recreational cannabis

Hypothesis 1 examined whether "hits" of recreational cannabis would conform to behavioural economic principles that have been previously established in the literature. A total of 250 cannabis users responded to the online survey. 29 were removed due to missing responses. Extreme responses of >1000 hits purchased were considered non-legitimate and were eliminated from subsequent analysis (N=2). Next, the data were examined for non-systematic responding (N = 219), and respondents who passed all three criteria (i.e., trend, bounce, reversal from zero) were retained. In total, 52 respondents failed to pass all three criteria; 26 failed a single criterion, 16 failed two criteria, and 9 failed all three criteria. In total, 167 respondents were retained this way. Participants with nonsystematic data did not significantly differ from systematic responders on age, gender, or ethnicity. Finally, raw purchase task data were examined for outliers, using Z = 3.29 as a criterion. Outliers were recoded to one unit above the next non-outlying value to retain maximum data. Descriptive data for the purchasing tasks for low and high THC conditions are presented in Table 4.1 and 4.2 respectively. There were no significant differences between groups on age, frequency of use, sessions per day, quantity, or age of initiation.

Table 4.1 Means, medians, standard deviations, proportion of zero responses, and range of hypothetical purchases of "hits" of low THC recreational cannabis

Price ($)	Mean (# hits)	Median (#hits)	SD	PropZeros	Min	Max
0	12.96	6	17.61	0	1	71
0.05	11.14	6	15.64	0.01	0	71
0.1	8.87	6	8.73	0.03	0	39
0.25	7.72	5	6.92	0.03	0	32
0.5	6.22	5	4.91	0.04	0	22
1	4.41	3	3.65	0.08	0	17
2	3.18	2	2.98	0.18	0	11
3	2.33	1	2.42	0.3	0	10
5	1.33	1	1.73	0.47	0	7
10	0.51	0	1.15	0.71	0	6
20	0.2	0	0.67	0.89	0	4
40	0.08	0	0.42	0.96	0	3
60	0.05	0	0.32	0.97	0	2
80	0.03	0	0.23	0.99	0	2
100	0.01	0	0.11	0.99	0	1
250	0.01	0	0.11	0.99	0	1
500	0.01	0	0.11	0.99	0	1

Note: PropZeros = Proportion of zero responses

Table 4.2 Means, medians, standard deviations, proportion of zero responses, and range of hypothetical purchases of "hits" of high THC recreational cannabis

Price ($)	Mean (# hits)	Median (#hits)	SD	PropZeros	Min	Max
0	12.40	8	14.74	0	1	55
0.05	9.90	5	12.52	0.07	0	52
0.1	8.59	5	10.23	0.08	0	46
0.25	7.40	5	7.94	0.09	0	33
0.5	5.69	4	5.92	0.14	0	24
1	4.70	3	5.74	0.22	0	24
2	3.29	2	4.32	0.33	0	18
3	2.18	1	3.07	0.41	0	14
5	1.33	0	2.27	0.54	0	10
10	0.67	0	1.49	0.75	0	7
20	0.32	0	1.02	0.85	0	6
40	0.15	0	0.66	0.94	0	4
60	0.08	0	0.38	0.95	0	2
80	0.02	0	0.15	0.98	0	1
100	0	0	0	1	0	0
250	0	0	0	1	0	0
500	0	0	0	1	0	0

Note: PropZero = Proportion of Zero responses

To examine overall *model fit*, demand indices were generated from both observed values and generated using the exponentiated demand equation and fit aggregated around the mean with *k* set to a value of 2. This was determined by testing model fits for three different k values (Table 4.3). All three models had similar levels of fit, and *k* = 2 was selected on the basis of prior research and best fit (Koffernus et al., 2015). The models for both high and low THC were of excellent fit. Demand curves are presented graphically in Figures 4.1 and 4.2.

Table 4.3 Model fit for "hits" of recreational cannabis

	Low THC			High THC		
	k = 2	*k* =3	*k* = 4	*k* = 2	*k* = 3	*k* = 4
Intensity	12.96	12.96	12.96	12.40	12.40	12.40
Q_{0d}	11.27	11.1358	11.0785	10.41	10.2902	10.239
Alpha	0.0198	0.0122	0.0089	0.0187	0.0115	0.0084
EV	0.18	0.16	0.14	0.19	0.17	0.15
R^2	0.97	0.96	0.96	0.96	0.96	0.96

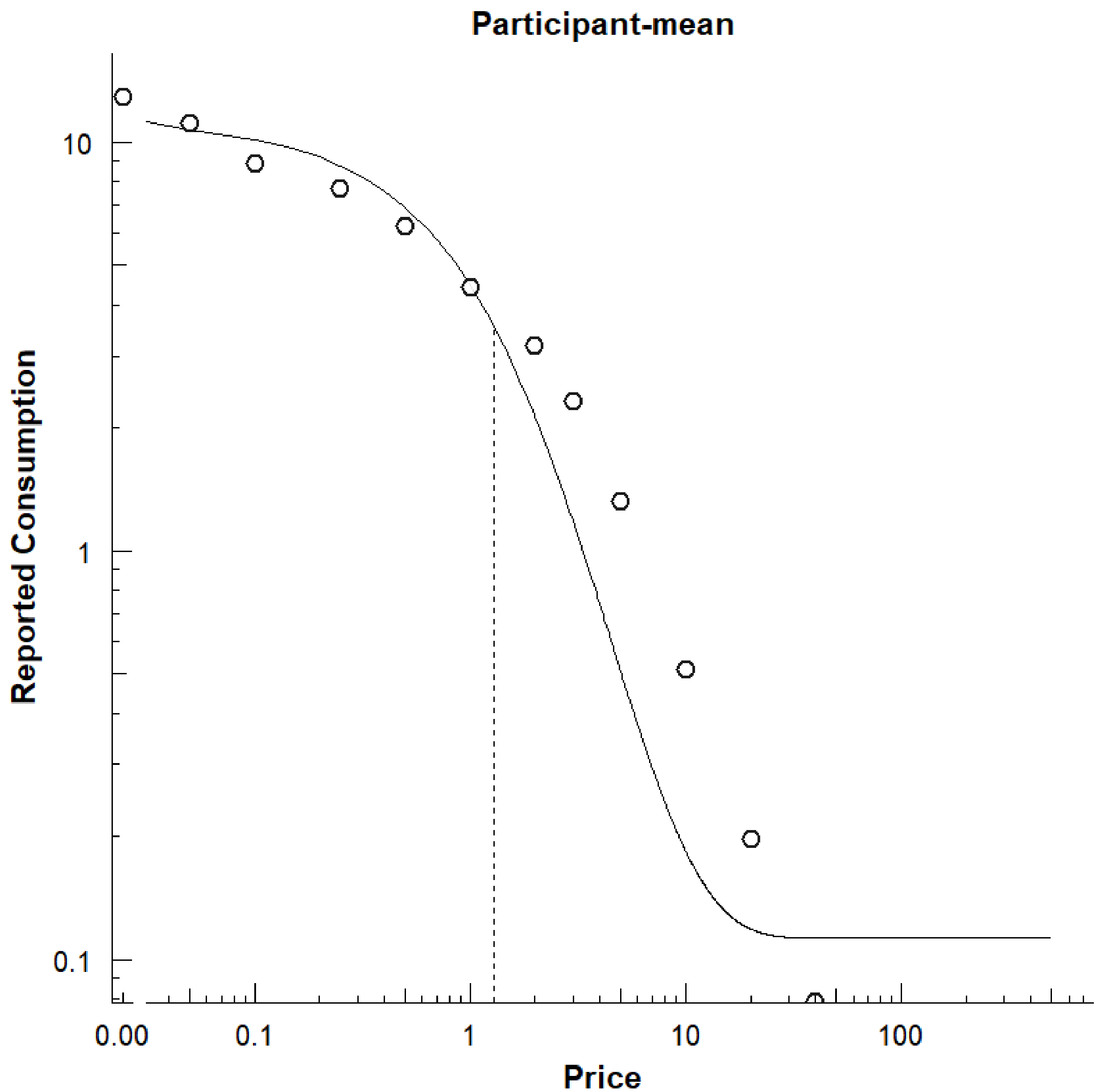


Figure 4.1 Demand curve for "hits" of low THC recreational cannabis aggregated around the mean

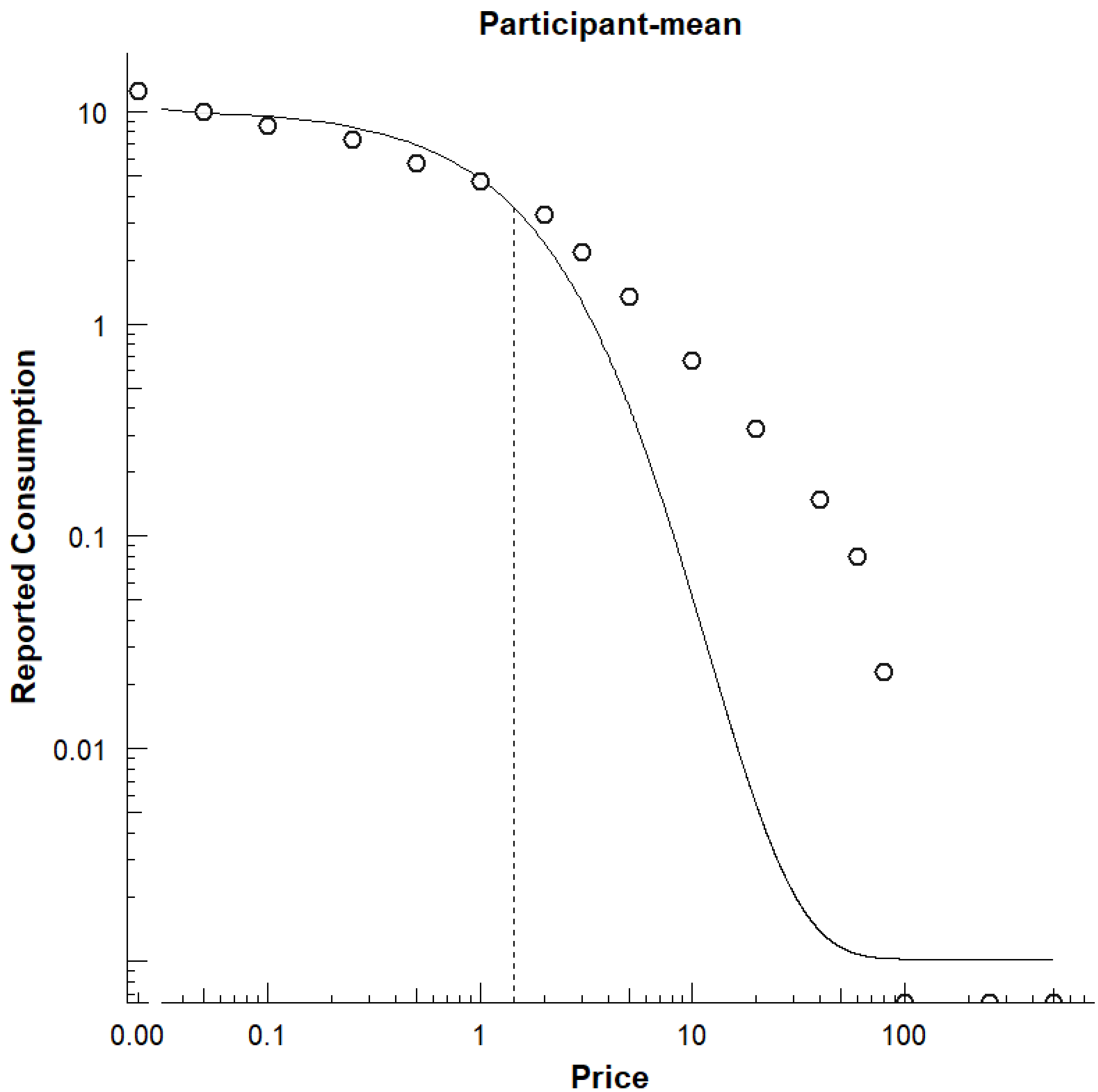


Figure 4.2 Demand curve for "hits" of high THC recreational cannabis aggregated around the mean

Next, to examine the association between *individual* demand indices and substance use, demand curves were fit for each participant (i.e., over-parameterized model), yielding observed and derived indices of demand. For six respondents, the models failed to converge, and thus were excluded from further analysis. These data are presented in Table 4.4.

Table 4.4 Individual demand indices for “hits” of recreational cannabis

	Mean (SD)	
Demand Indices	Low THC (N=75)	High THC (N=81)
Breakpoint - observed	12.32 (14.15)	14.89 (21.52)
Intensity - observed	13.11 (17.69)	12.75 (15.18)
Intensity - derived	13.25 (17.72)	12.79 (14.98)
O_{max} - observed	18.26 (58.85)	14.90 (26.95)
O_{max} - derived	9.30 (15.022)	9.69 (15.37)
P_{max} - observed	12.35 (57.58)	7.18 (13.59)
P_{max} - derived	4.37 (7.83)	3.87 (5.19)
Alpha	0.0568 (0.1731)	0.0890 (0.2950)
EV	0.36 (0.58)	0.38 (0.60)

Note: EV = Essential Value

Spearman’s rho bivariate correlation was used to examine the association between demand indices and cannabis use variables and to test Hypothesis 1. Given numerous deviations from normality, a robust non-parametric test was used to examine potential linear associations among variables. Hypothesis 1a predicted that intensity of demand would be positively associated with frequency of cannabis use, quantity of cannabis used, regular years of use, and negatively associated with age of initiation. For low THC (Table 4.5), Intensity of demand was associated with past week (r_s = .30, 95% CI [.076, .502], p = .008), and month use at the trend level (r_s = .23, 95% CI [-.006, .438], p = .049). Intensity for low THC was also positively associated with quantity of cannabis used per session (r_s = .47, 95% CI [.042, .748, p = .029). For high THC (Table 4.6), intensity was positively associated with number of cannabis use sessions on weekdays (r_s = .27, 95% CI [.047, .468], p = .015) and weekends (r_s = .28, 95% CI [.056, .475], p = .012). Intensity was also related to quantity of cannabis used per session (r_s = .51, 95% CI [.137, .761], p = .009). Hypothesis 1b stated that O_{max} will be positively associated with frequency of cannabis use, quantity of cannabis used, regular years of use, and negatively associated with age of initiation. In the low THC condition, O_{max} was unrelated to any cannabis use variables. In the high THC condition, the model derived O_{max} was positively related to quantity of cannabis used (r_s = .42, 95% CI [.012, .702], p = .039). Hypothesis 1c predicted significant group difference across behavioural economics indices such that higher values were expected for the high THC conditions. There were no significant group differences across any of the indices.

Table 4.5 Spearman's rho bivariate correlations for demand indices and cannabis use variables for "hits" of low THC recreational cannabis

	Breakpoint	Intensitye	Intensityd	Omaxe	Omaxd	Pmaxe	Pmaxd	Alpha
Past Week Use	.07	.30**	.29**	.01	.03	-.04	-.16	-.03
Past Month Use	.11	.23*	.22	-.01	.07	-.01	-.11	-.07
Sessions/weekday	.10	.12	.10	.05	.09	-.02	.01	-.09
Sessions/weekend	.14	.22	.20	.03	.08	.03	-.07	-.08
Age of Initiation	.04	.06	.11	.13	.13	.17	.01	-.07
Quantity/Session	-.11	.47*	.50*	.22	.25	-.11	-.02	-.25

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

Age of Initiation and Quantity per session N =22

Table 4.6 Spearman's rho bivariate correlations for demand indices and cannabis use variables for "hits" of high THC recreational cannabis

	Breakpoint	Intensitye	Intensityd	Omaxe	Omaxd	Pmaxe	Pmaxd	Alpha
Past Week Use	.01	.19	0.17	.05	0	-.09	-.13	0
Past Month Use	-.02	.14	0.13	.03	-.02	-.09	-.08	.02
Sessions/weekday	-.03	.27*	.26*	.07	.06	-.14	-.07	-.06
Sessions/weekend	.09	.29*	.26*	.16	.10	-.01	-.05	-.1
Age of Initiation	-.04	-.01	.02	.08	.06	-.02	.01	-.09
Quantity/Session	.23	.51**	.48	.38	.42*	.06	.01	-.42*

Note: * $p < .05$; ** $p < .01$. Age of Initiation and Quantity/Session N = 25

4.1.2 Hypothetical purchases of "grams" of recreational cannabis

In total, there were 252 responses to the survey. A total of 30 participants were removed due to incomplete data. Very extreme values (>1000 grams purchased) were considered to be non-legitimate responding and were excluded (12 and 9 for low and high THC respectively). A total of 222 (111 each condition) were retained this way. The purchasing data were examined for outliers, and extreme values were recoded to one unit higher than the next non-outlying value. Next, data were examined for unsystematic responding. For low THC, 67 passed all three criteria; 16 failed one, 12 failed two, and 3 failed all three checks. For high THC, 74 passed all three criteria; 12 failed one, 12 failed two, and 3 failed all three**.** Failures were removed from further analysis. Descriptive statistics for low and high THC are presented in Tables 4.7 and 4.8 respectively.

Table 4.7 Means, medians, standard deviations, proportion of zero responses, and range of hypothetical purchases of "grams" of low THC recreational cannabis

Price ($)	Mean (# grams)	Median (#grams)	SD	PropZeros	Min	Max
0	23.29	6	34.62	0	0.25	100
0.05	17.99	6	27.35	0.01	0	100
0.1	18.57	6	28.79	0.01	0	100
0.25	17.35	5	27.71	0.01	0	100
0.5	16.21	5	26.97	0.01	0	100
1	14.02	5	24.50	0.03	0	100
2	10.79	4	20.17	0.07	0	100
3	8.23	3	16.08	0.10	0	100
5	4.62	2	7.67	0.13	0	50
10	1.95	1	2.74	0.25	0	14
20	0.71	0	1.42	0.64	0	8
40	0.18	0	0.69	0.90	0	5
60	0.07	0	0.32	0.94	0	2
80	0.04	0	0.21	0.96	0	1
100	0	0	0	1	0	0
250	0	0	0	1	0	0
500	0	0	0	1	0	0

Note: PropZeros = Proportion of zero responses

Table 4.8 Means, medians, standard deviations, proportion of zero responses, and range of hypothetical purchases of "grams" of high THC recreational cannabis

Price ($)	Mean (# grams)	Median (#grams)	SD	PropZeros	Min	Max
0	23.87	10	34.28	0	0.12	101
0.05	19.75	10	29.6	0.10	0	101
0.1	17.76	8	26.9	0.10	0	100
0.25	14.86	7.5	21.06	0.10	0	81
0.5	12.77	6	18.34	0.11	0	81
1	9.99	5	12.23	0.11	0	51
2	8.15	5	11.08	0.12	0	51
3	5.83	3	7.43	0.18	0	30
5	3.74	2	5.62	0.21	0	29
10	2.42	1	5.5	0.36	0	29
20	0.49	0	1.06	0.67	0	5
40	0.27	0	0.86	0.81	0	5
60	0.07	0	0.29	0.92	0	2
80	0.05	0	0.2	0.93	0	1
100	0	0	0.02	0.97	0	0.12
250	0	0	0.02	0.97	0	0.12
500	0	0	0.02	0.97	0	0.12

Note: PropZeros = Proportion of zero responses

As with "hits" purchasing data, "grams" data were examined for *overall model fit* aggregated around the mean. Three models were tested for varying *k* values (i.e., 2, 3, and 4). Demand and fit indices are presented in Table 4.9. As with previous analysis, the overall fit of the exponeniated demand model were excellent for both low and high THC. Based on model testing, *k* was set at 2 for demand curbe modelling. Demand curves are presented in Figures 4.3 and 4.4.

Table 4.9 Model fit for "grams" of recreational cannabis

	Low THC (n = 67)			High THC (n = 73)		
	k = 2	k =3	k = 4	k = 2	k = 3	k = 4
Intensity	23.29	23.29	23.29	23.87	23.87	23.87
Q_{0d}	19.92	19.83	19.79	19.97	19.78	19.70
Alpha	0.0038	0.0024	0.0018	0.0066	0.0041	0.0030
EV	0.93	0.80	0.71	0.53	0.47	0.42
R^2	0.99	0.99	0.98	0.97	0.96	0.96

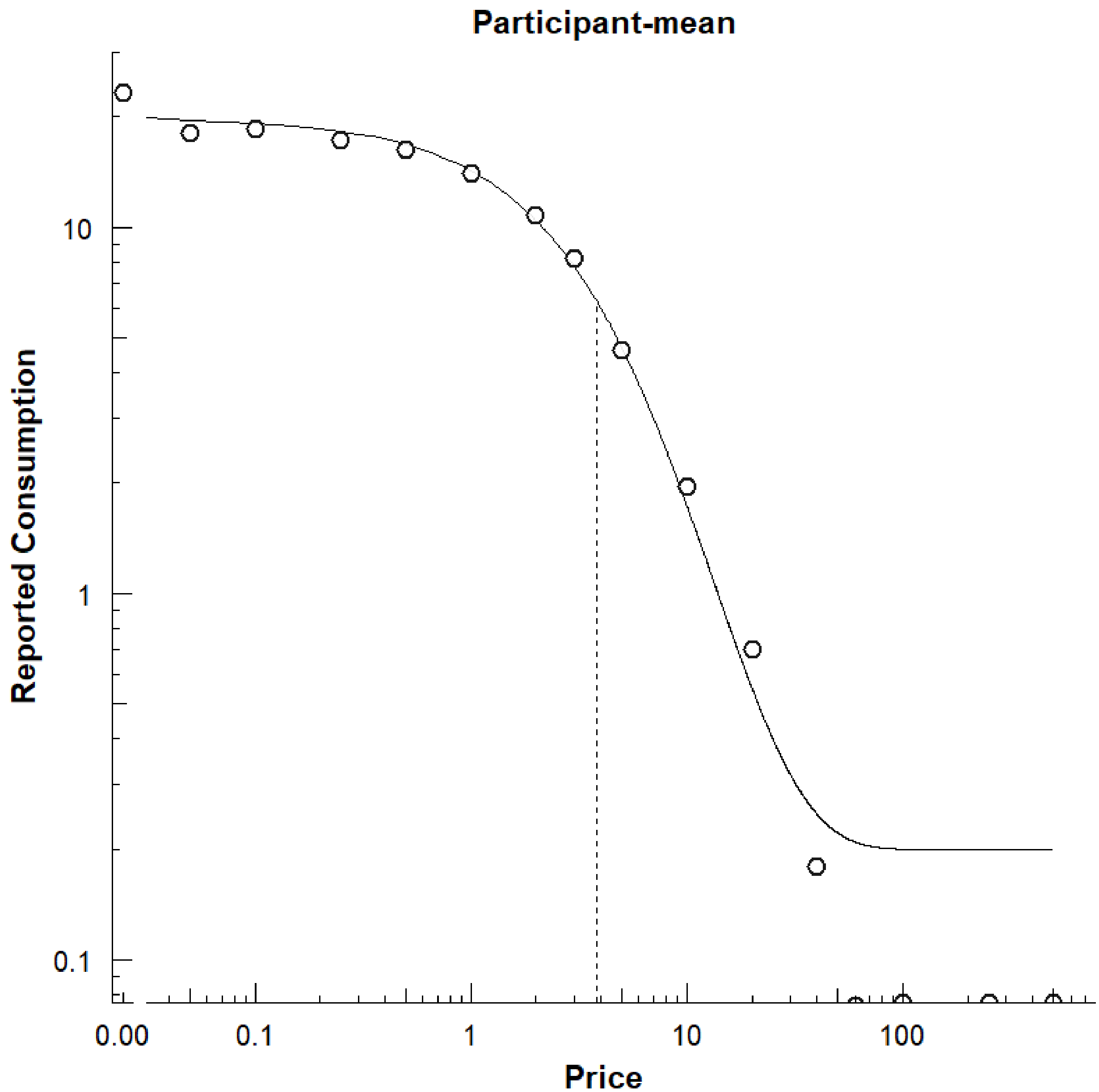


Figure 4.3 Demand curve for "grams" of low THC recreational cannabis aggregated around the mean

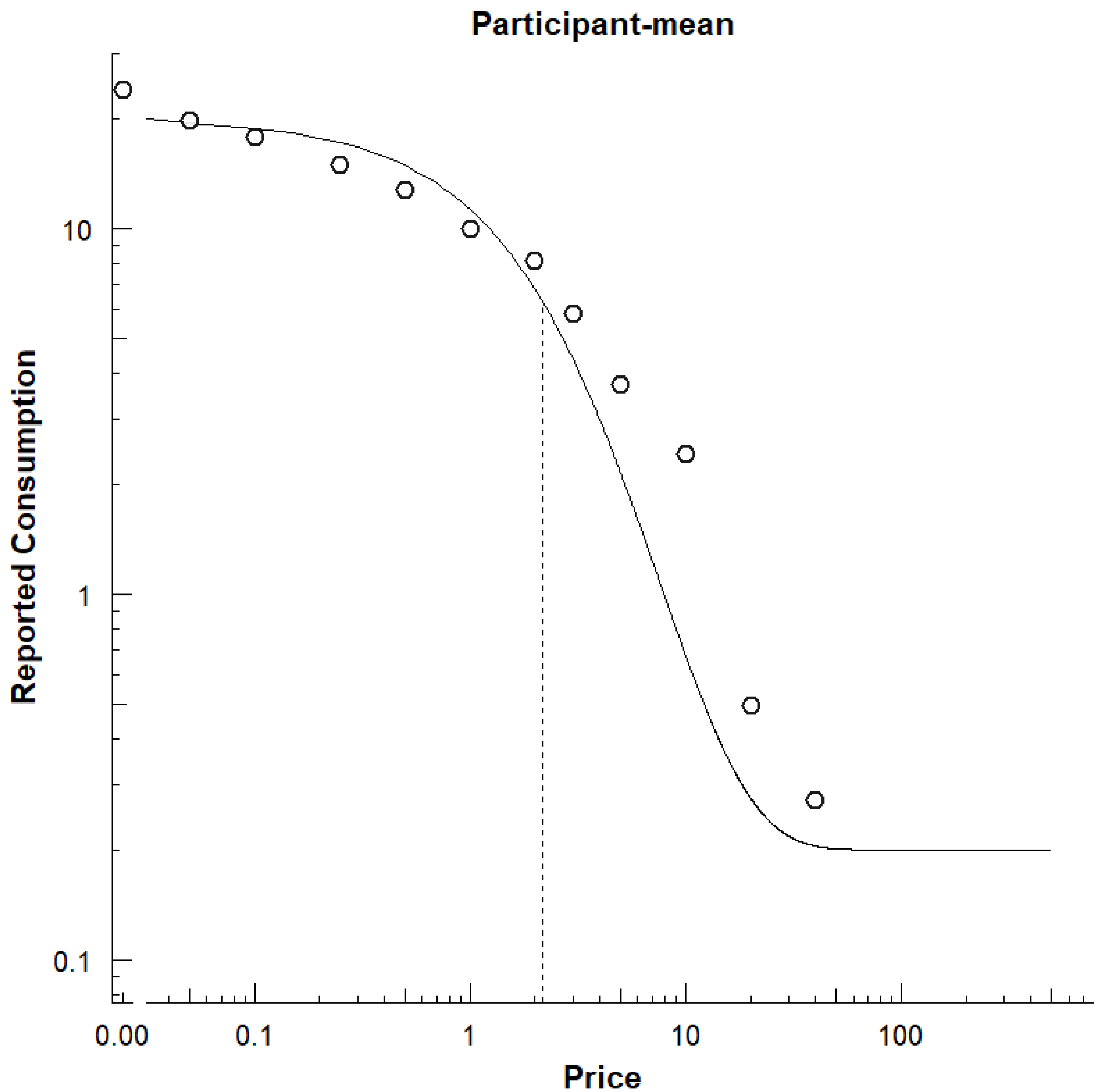


Figure 4.4 Demand curve for "grams" of high THC recreational cannabis aggregated around the mean

To explore associations between individual demand indices and cannabis use variables, the exponentiated demand equation was fit for each individual participant, yielding observed and derived demand indices. Overall, the model failed to converge for 8 participants, who were excluded from analysis, as the demand characterisitics were unreliable estimates.. Individual demand characteristics are presented below in Table 4.10.

Table 4.10 Individual demand indices for "grams" of recreational cannabis

	Mean (SD)	
Demand Indices	Low THC (N=66)	High THC (N=66)
Breakpoint - observed	28.23 (22.56)	28.98 (24.51)
Intensity - observed	23.63 (34.77)	26.11 (35.31)
Intensity - derived	23.87 (35.21)	25.59 (35.14)
O_{max} - observed	37.74 (56.39)	43.80 (62.51)
O_{max} - derived	32.91 (54.33)	30.75 (42.68)
P_{max} - observed	11.80 (14.86)	20.55 (61.98)
P_{max} - derived	8.88 (8.19)	10.58 (14.15)
Alpha	0.0383 (0.1634)	0.01401 (0.0004)
EV	1.28 (2.11)	1.20 (1.67)

Note: EV = Essential Value

Hypothesis 2 stated that "grams" of recreational cannabis will similarly conform to behavioural economic principles as outlined with hypothetical purchasing tasks using "hits" (i.e., similar associations with cannabis use variables). This was tested by examining bivariate associations among demand indices and cannabis use variables, and Spearman's rho was used. Analyses are presented for low and high THC in Tables 4.11 and 4.12 respectively. Hypothesis 2a predicted that intensity of demand would be positively related to cannabis use variables. In the low THC condition, intensity was positively related with past week (r_s = .27, 95% CI [.027,

.490], p = .026) and past month cannabis use at a trend level (r_s = .25, 95% CI [-.004, .466], p = .047). In the high THC condition, intensity of demand was related to past week use (r_s = .41, 95% CI [.179, .600], p < .001), past month use (r_s = .41, 95% CI [.180, .601], p < .001), number of weekday sessions (r_s = .42, 95% CI [.193, .610], p < .001), and number of weekend sessions (r_s = .48, 95% CI [.263, .654], p < .001). Intensity was unrelated to age of initiation or quantity. Hypothesis 2b stated that O_{max} would be positively associated with frequency of cannabis use and quantity of cannabis used, and negatively associated with age of initiation. In the low THC condition, O_{max} was associated with past week (r_s = .39, 95% CI [.157, .583] p = .001) and past month use (r_s = .38, 95% CI [.139. .571], p = .002). O_{max} was also related to number of sessions per weekend (r_s = .40, 95% CI [.164, .587], p < .001). In the high THC condition, O_{max} was positively associated with past week use (r_s = .40, 95% CI [.160, .587], p = .001), past month use (r_s = .45, 95% CI [.223, .629], p < .001), weekday sessions (r_s = .45, 95% CI [.221, .627], p < .001), and weekend sessions (r_s = .55, 95% CI [.350, .706], p < .001). There were no associations between demand indices and age of initiation or quantity of cannabis used per session, however sample size was small due to participant nonresponding. Hypothesis 2c predicted significant group differences for demand indices. Pairwise comparisions revealed that there were no significant differences between THC conditions for all demand indices.

Table 4.11 Spearman's rho bivariate correlations for demand indices and cannabis use variables for "grams" of low THC recreational cannabis

	Breakpoint	$Intensity_e$	$Intensity_d$	$Omax_e$	$Omax_d$	$Pmax_e$	$Pmax_d$	Alpha
Past Week Use	.27*	.27*	.27*	.39**	.37**	.11	.04	-.37**
Past Month Use	.27*	.25*	.24*	.38**	.34**	.12	.05	-.34**
Sessions/weekday	.16	.08	.08	.20	.26*	.10	.17	-.26*
Sessions/weekend	.33**	.20	.19	.40**	.40**	.24*	.23	-.40**
Age of Initiation (N =18)	.11	.17	.05	.12	.14	.14	.11	-.14
Quantity/Session (N=18)	-.02	.19	.24	.22	.20	-.16	-.26	-.20

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

Table 4.12 Spearman's rho bivariate correlations for demand indices and cannabis use variables for "grams" of high THC recreational cannabis

	Breakpoint	$Intensity_e$	$Intensity_d$	$Omax_e$	$Omax_d$	$Pmax_e$	$Pmax_d$	Alpha
Past Week Use	.14	.42**	.41**	.40**	.36**	-.09	-.11	-.36**
Past Month Use	.20	.42**	.40**	.45**	.38**	.02	-.10	-.38**
Sessions/weekday	.23	.43**	.42**	.45**	.40**	.08	-.40	-.40**
Sessions/weekend	.29*	.49**	.46**	.55**	.47**	.09	-.09	-.47**
Age of Initiation (N=22)	-.28	-.15	-.09	.00	.12	-.30	.25	-.12
Quantity/Session (N=22)	-.03	.39	.45*	.40	.33	-.16	-.17	-.33

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

4.2 Medical Cannabis

4.2.1 Hypothetical purchases of “hits” of medical cannabis

A total of 410 participants responded to the online survey. 108 respondents did not endorse past six-month cannabis use, and as such, were excluded from further analysis. Next, data were examined for complete responses for purchasing data, and 189 were removed for incomplete responses. Data were then examined for extreme responses and outliers. Extreme responses of >1000 hits were considered to be non-legitimate responses (N=11) and were excluded from further analysis. All other responses (N=102) were examined for outliers using standard scores, using Z = 3.29 as criterion and winsorised to one unit higher than the next non-outlying value (Tabachnik & Fidell, 2013). Finally, responses were examined for unsystematic responding. In total, 19 cases failed to pass all three criteria determining systematic responding; 2 cases failed all three, 10 cases failed two criteria, and 7 failed a single criterion. In keeping with recommendations and past research, only cases that passed all three criteria (N=83) were retained for demand curve analysis. Non-systematic respondents did not differ from systematic respondents in terms of age, gender, or ethnicity. Descriptive statistics for purchasing data are presented in Table 4.13.

Table 4.13 Means, medians, standard deviations, proportion of zero responses, and range of hypothetical purchases of "hits" of medical cannabis

Price ($)	Mean (# hits)	Median (#hits)	SD	PropZeros	Min	Max
0	33.63	15	43.41	0	1	163
0.05	24.71	10	30.09	0.02	0	102
0.1	20.58	10	24.34	0.04	0	93
0.25	16.70	10	19.76	0.04	0	78
0.5	12.46	7	15.29	0.06	0	62
1	6.98	5	8.06	0.16	0	32
2	3.86	2	4.66	0.30	0	18
3	2.45	1	3.17	0.40	0	13
5	1.41	0	2.16	0.54	0	9
10	0.66	0	1.49	0.70	0	7
20	0.17	0	0.62	0.89	0	4
40	0.02	0	0.15	0.98	0	1
60	0.02	0	0.15	0.98	0	1
80	0.01	0	0.11	0.99	0	1
100	0.01	0	0.11	0.99	0	1
250	0.01	0	0.11	0.99	0	1
500	0.01	0	0.11	0.99	0	1

Note: PropZeros = Proportion of zero responses

Demand indices were generated from both observed values and generated using the exponentiated demand equation and fit aggregated around the mean. To compare to recreational users, *k* was fixed at 2 in to facilitate comparison (Koffernus et al., 2015). Model characteristics presented in Table 4.14. The demand curve is presented in Figure 4.5.

Table 4.14 Model fit and characteristics for "hits" of medical cannabis

	Estimate
Intensity	33.63
Q_{0d}	29.47
Alpha	0.0157
EV	0.2254
R^2	0.97

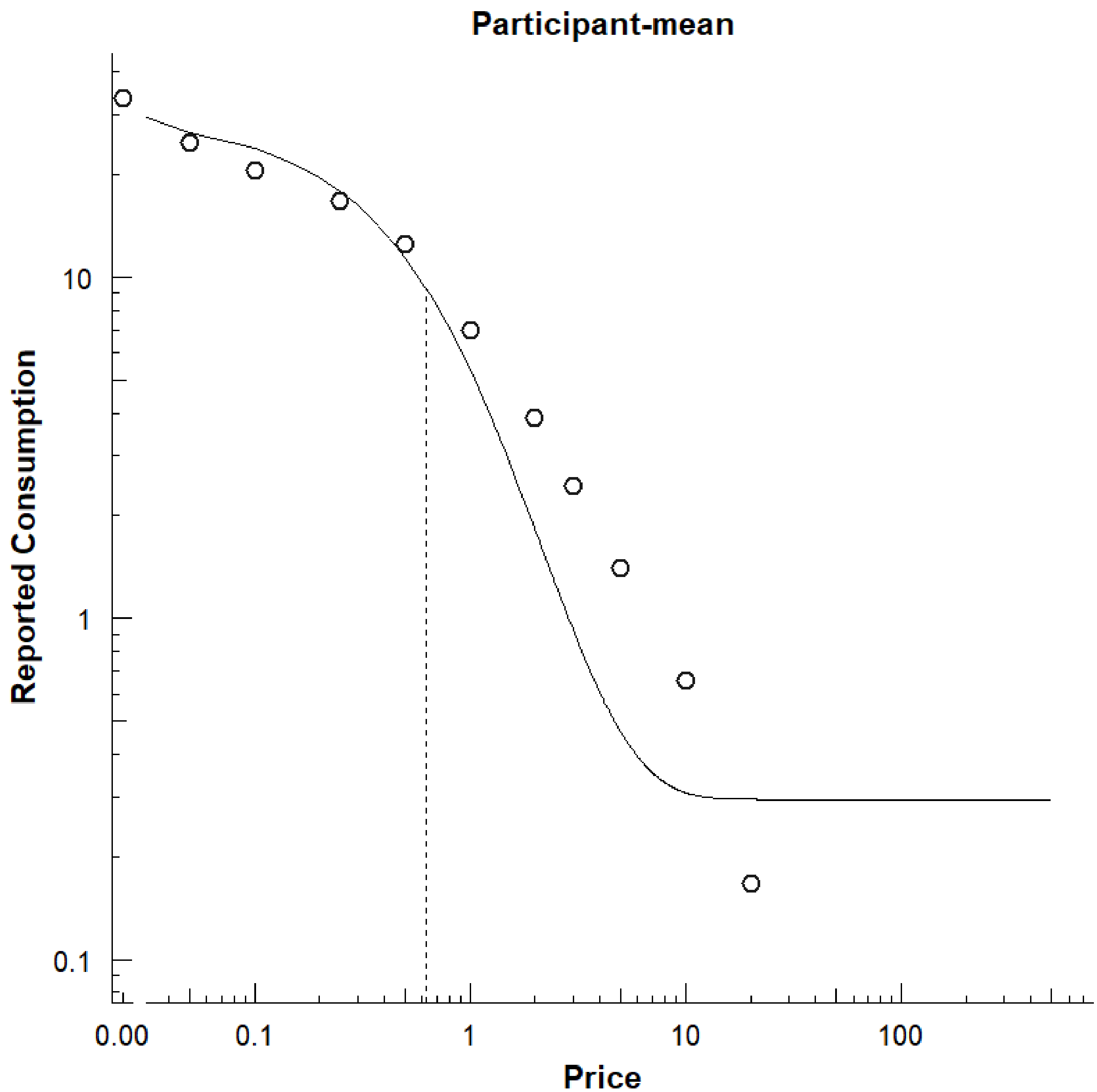


Figure 4.5 Demand curve for "hits" of medical cannabis aggregated around the mean

Next, individual demand indices were calculated for each individual using the exponentiated demand equation. These data are presented in Table 4.15. For two participants, the model failed to converge, given that they did not indicate any consumption for cannabis at prices higher than zero, and were subsequently dropped for subsequent analysis.

Table 4.15 Individual demand indices for "hits" of medical cannabis

Demand Indices	Estimates	SD
Breakpoint - observed	11.59	13.78
Intensity - observed	31.83	41.42
Intensity - derived	32.38	40.33
O_{max} - observed	20.36	55.78
O_{max} - derived	12.22	13.36
P_{max} - observed	10.95	55.55
P_{max} - derived	3.89	6.14
Alpha	0.0247	0.0327
EV	0.48	0.52

Note: EV = Essential Value

The data were examined for normality. Given the numerous instances of deviation from normality, Spearman's rho, a non-parametric test was used to examine associations between demand indices and substance use characteristics and to test Hypothesis 3. These analyses are presented in Table 4.16. A significant positive correlation emerged between breakpoint and age of initiation, such that higher breakpoint values were associated with older age of first-time cannabis use. Hypothesis 3a predicated that intensity of demand would be associated with cannabis use variables. Indeed, intensity was associated with increased past week use (r_s = .35, 95% CI [.112, .543], p = .004), past month use (r_s = .26, 95% CI [.012, .472], p = .035), weekday sessions (r_s = .44, 95% CI [.215, .614], p < .001), and weekend sessions (r_s = .41, 95% CI [.185, .594], p < .001). Intensity of demand was also positively related to quantity of cannabis use (r_s = .39, 95% CI [.154, .589], p = .001). There was a negative association between intensity and age of initiation (r_s = -.29, 95% CI [-.503, -.044], p = .018), such that high intensity tended to be associated with lower age of first cannabis use. With regard to Hypothesis 3b, that O_{max} would be related to cannabis use variables, O_{max} was positively associated with the number of weekday (r_s = .39, 95% CI [.161, .578], p < .001) and weekend sessions (r_s = .38, 95% CI [.151, .571], p = .001). O_{max} was unrelated to other substance use variables.

Finally, the demand indices were compared with measures of pain (Table 4.17). There were no associations between any demand index and current pain ratings. Pain relief was unrelated to intensity or O_{max}, however it was negatively associated with breakpoint (r_s = -.36, 95% CI [-.599, -.062], p = .016), such that participants reporting lower ratings of pain relief were more likely to have higher price points before they stopped purchasing. There were no significant associations among pain-related interferences and any demand index.

Table 4.16 Spearman rank order correlation coefficients for demand indices and cannabis use variables for "hits" of medical cannabis

	Breakpoint	$Intensity_e$	$Intensity_d$	$Omax_e$	$Omax_d$	$Pmax_e$	$Pmax_d$	Alpha
Past Week Use	.08	.35**	.36**	.18	.16	.01	-.10	-.16
Past Month Use	-.01	.26*	.26*	.18	.18	.01	-.02	-.18
Sessions/weekday	.11	.44**	.44**	.39**	.36**	.04	-.08	-.36**
Sessions/weekend	.09	.42**	.41**	.38**	.37**	.01	-.06	-.36**
Age of Initiation	.19	-.29*	-.29*	.01	.03	.16	.25*	-.03
Quantity/session	.01	.39**	.39**	.19	.15	-.16	-.19	-.15

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

Table 4.17 Spearman rank order correlation coefficients for demand indices and pain variables for "hits" of medical cannabis

	Breakpoint	$Intensity_e$	$Intensity_d$	$Omax_e$	$Omax_d$	$Pmax_e$	$Pmax_d$	Alpha
Current Pain	-.16	.01	.01	-.11	-.14	-.15	-.09	.14
Worst pain past week	-.13	-.03	-.03	-.18	-.17	-.14	-.06	.17
Least pain past week	-.10	-.02	-.04	-.05	-.14	-.11	-.07	.14
Average pain past week	-.11	-.04	-.05	-.14	-.22	-.13	-.10	.22
Pain relief	-.36*	.13	.16	-.21	-.21	-.27	-.35*	.21
Pain interference with:								
General Activity	-.01	.21	.19	.12	.06	-.05	-.09	-.06
Mood	-.04	.18	.16	.08	-.02	-.09	-.14	.02
Walking Ability	-.13	.16	.17	-.05	-.09	-.19	-.17	.09
Normal Work	-.05	.10	.09	.10	.02	-.06	-.04	-.02
Relationships	.07	.10	.07	.12	.12	-.03	.07	-.12
Sleep	-.01	.16	.15	.06	.05	-.10	-.06	-.05
Enjoyment of Life	-.05	.08	.06	.02	-.06	-.07	-.05	.06

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

4.2.2 Hypothetical purchases of "grams" of medical cannabis

A total of 302 respondents endorsed past 6-month cannabis use, and as such, were considered for further analysis. Next, data were examined for complete purchasing data for *grams* of cannabis purchased, and 188 were excluded for lacking complete responses. Data were then examined for extreme responses and outliers. Extreme responses of > 1000 grams were considered non-legitimate responses (N = 13), and subsequently excluded. All other responses were examined for outlier using Z = 3.29 as criterion and winsorised to one unit higher than the next non-outlying value (Tabachnik & Fidell, 2013). Next, the data (N = 101) were examined for unsystematic responses using the three criteria. Of the responses, the majority passed all three criteria (N = 83), and were retained for demand curve analysis. Five respondents failed a single criterion, and 12 respondents failed two criteria, and one failed all three. Means, standard deviations and other descriptive statistics can be found in Table 4.18.

Table 4.18 Means, medians, standard deviations, proportion of zero responses, and range of hypothetical purchases of "grams" of medical cannabis

Price ($)	Mean (# grams)	Median (#grams)	SD	PropZeros	Min	Max
0	31.87	10	43.54	0	0.12	153
0.05	25.98	10	33.99	0.01	0	104
0.1	24.44	10	33.11	0.04	0	103
0.25	22.6	10	30.81	0.04	0	100
0.5	20.38	8	28.02	0.04	0	100
1	14.75	7	18.11	0.06	0	62
2	11.45	5	14.2	0.07	0	52
3	10.08	4	14.01	0.08	0	52
5	7.10	3	9.26	0.11	0	31
10	3.19	1	4.53	0.25	0	16
20	0.86	0	1.99	0.66	0	9
40	0.35	0	1.05	0.83	0	6
60	0.12	0	0.48	0.93	0	3
80	0.05	0	0.27	0.96	0	2
100	0.02	0	0.12	0.98	0	1
250	0	0	0.03	0.99	0	0.25
500	0	0	0.03	0.99	0	0.25

Note: PropZeros = Proportion of zero responses

Next, demand indices were obtained from both observed values and generated using the exponentiated demand equation, fit around the mean, with *k* set at 2 to allow comparisons to recreational users. Model characteristics presented in Table 4.19. The demand curve is presented in Figure 4.6.

Table 4.19 Model fit and characteristics for “grams” of medical cannabis

	Estimate
Intensity	31.87
Q_{0d}	26.95
Alpha	0.0036
EV	0.97
R^2	0.97

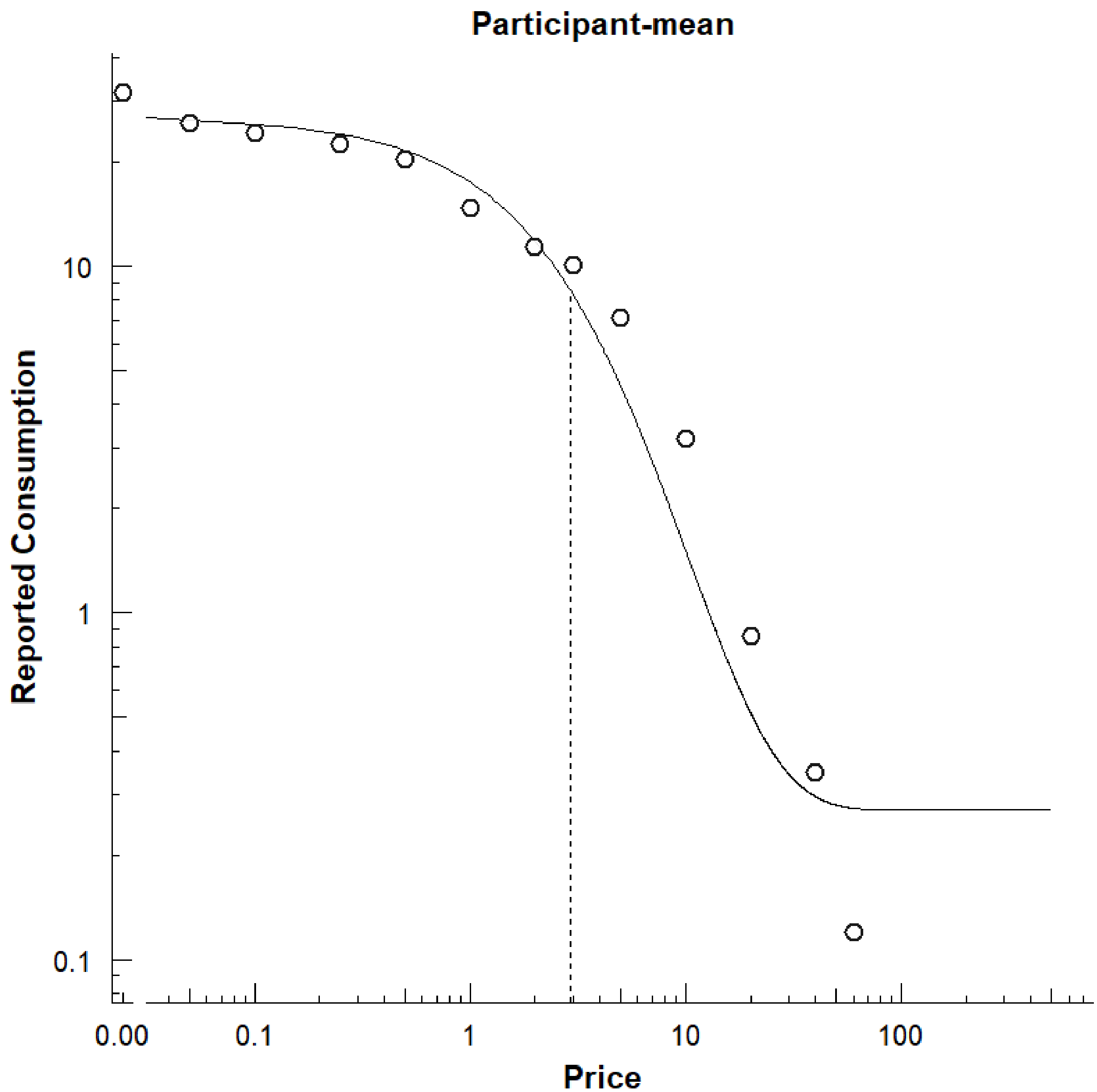


Figure 4.6 Demand curve for "grams" of medical cannabis aggregated around the mean

Next, individual demand indices were calculated for each respondent using the observed values, as well as the model generated by the exponentiated demand equation. These means and standard deviations for these data are presented in table 4.20. For one respondent, the model failed to converge. As with the previous respondents that failed to converge, this was due to the participant indicating only purchasing when price = 0, and therefore did not produce meaningful purchasing data. This respondent was excluded from further analysis.

Table 4.20 Individual demand for "grams" of medical cannabis

Demand Indices	Estimates	SD
Breakpoint - observed	30.21	32.37
Intensity - observed	31.65	43.76
Intensity - derived	31.78	42.46
O_{max} - observed	51.57	56.41
O_{max} – derived	44.90	54.37
P_{max} - observed	17.59	55.48
P_{max} - derived	12.96	16.13
Alpha	0.0203	0.0513
EV	1.74	2.11

Note: EV = Essential Value

To examine the association between individual demand characteristics and substance use variables, Spearman's rho was used. Given numerous deviations from normality, this non-parametric test was used to examine monotonic associations between demand indices and substance use variables. These data are presented in Table 4.21. Intensity was positively associated with number of sessions of cannabis use for both weekday (r_s = .29, 95% CI [.057, .490], p = .013) and weekends (r_s = .30, 95% CI [.069, .499], p = .010). O_{max} was positively associated with number of weekend session (r_s = .25, 95% CI [.019, .461], p = .030).

Finally, demand indices were analyzed for associations with pain-related variables. These are presented in Table 4.22. Intensity of demand was unrelated to any pain ratings. O_{max} was negatively associated with worst past week pain at a trend level (r_s = -.25, 95% CI [-.466, .004],

p = .047). With regard to pain interference, breakpoint was negatively associated with pain interference in normal work (r_s = -.28, 95% CI [-.492, -.030], p = .025) and enjoyment of life (r_s = -.27, 95% CI [-.486, -.022], p = .029), such that individuals reporting higher breakpoints report lower levels of pain interference in these areas. Intensity was negatively related to pain interference in relationships (r_s = -.32, 95% CI [-.524, -.073], p = .010). Respondents who reported higher purchases at zero were more likely to report lower levels of pain interference in their relationships. O_{max} was negatively associated with pain interference in relationships (r_s = -.29, 95% CI [-.500, -.040], p = .020) and enjoyment of life (r_s = -.27, 95% CI [-.487, -.024], p = .028), such that higher maximum expenditure was related to lower levels of interference in these areas. O_{max} was negatively associated with pain interference in normal work, however only at a trend level (r_s = -.25, 95% CI [-.467, .003], p = .046).

Table 4.21 Spearman correlation coefficients for demand indices and cannabis use variables for "grams" of medical cannabis

	Breakpoint	$Intensity_e$	$Intensity_d$	$Omax_e$	$Omax_d$	$Pmax_e$	$Pmax_d$	Alpha
Past Week Use	.12	.08	.08	.08	.14	.12	-.05	-.14
Past Month Use	-.05	.01	.01	-.01	.06	.03	-.02	-.06
Sessions/weekday	-.08	.29*	.29*	.19	.20	-.03	-.14	-.20
Sessions/weekend	.01	.30*	.29*	.25*	.29**	-.01	-.08	-.29**
Age of Initiation	.06	-.21	-.19	.05	.18	.13	.19	-.14
Quantity/session	.01	.24	.23	.15	.14	-.12	-.11	-.18

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

Table 4.22 Spearman correlation coefficients for demand indices and pain variables for "grams" of medical cannabis

	Breakpoint	$Intensity_e$	$Intensity_d$	$Omax_e$	$Omax_d$	$Pmax_e$	$Pmax_d$	Alpha
Current Pain	-.10	.07	.07	-.03	-.06	-.04	-.18	.06
Worst pain past week	-.17	-.08	-.08	-.25*	-.23	-.11	-.13	.23
Least pain past week	-.21	.10	.10	.01	.02	-.25*	-.14	-.02
Average pain past week	-.20	.13	.12	-.12	-.15	-.15	-.35**	.15
Pain relief	-.27	.17	.17	-.14	-.11	-.14	-.34*	.11
Pain interference with:								
General Activity	-.14	-.12	-.11	-.09	-.10	-.16	-.04	.10
Mood	-.17	-.04	-.04	-.13	-.12	-.19	-.13	.12
Walking Ability	-.11	-.01	.01	-.04	-.06	-.09	-.14	.06
Normal Work	-.28*	-.16	-.16	-.25*	-.24	-.24	-.08	.24
Relationships	-.07	-.32*	-.31*	-.29*	-.24	-.08	.04	.24
Sleep	-.16	-.11	-.11	-.23	-.22	-.14	-.10	.22
Enjoyment of Life	-.27*	-.10	-.11	-.27*	-.28*	-.23	-.22	.28*

4.3 Substituting Cannabis for Alcohol and Prescription Opioid Pills

4.3.1 Purchases of concurrently available cannabis and alcohol in recreational users

Of the 250 initial respondents, 240 indicated alcohol use in the past 6 months. One response was removed due to extreme responding (>1000 grams/drinks). Three respondents were excluded due to missing data. Data were examined for outliers, and any identified were recoded to one unit higher than the next non-outlying value. Means and standard deviations for drug purchases are presented in Table 4.23. As cannabis prices increased (Figure 4.7), purchases of cannabis significantly decreased ($F_{3,233} = 21.66$, $p < .01$. To calculate own price elasticity, the data were plotted on log-log coordinates, and a simple regression was conducted to determine elasticity of demand ($E_{own} = -0.88$). Elasticity of demand was determined to be inelastic. Alcohol purchases were unaffected by cannabis price and remained constant as the price of cannabis varied ($E_{cross} = -0.006$; $F_{3,233} = 2.51$, $p > .05$), suggesting that alcohol purchases were independent of cannabis.

Table 4.23 Means and standard deviations for units of recreational cannabis and alcohol purchased at increasing cannabis prices and fixed alcohol price

Price of Cannabis	Alcohol	Cannabis
$1.00	8.39 (10.71)	9.25 (18.60)
$3.00	8.05 (9.69)	5.25 (9.80)
$8.00	8.24 (10.61)	2.04 (3.48)
$15.00	8.19 (10.60)	0.83 (1.71)

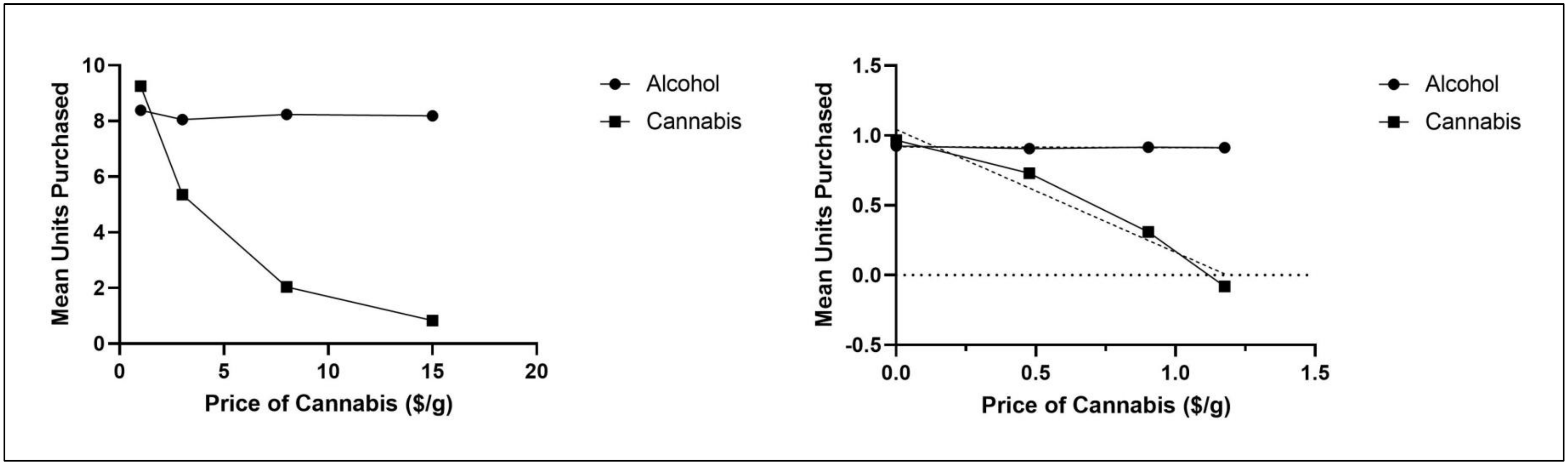


Figure 4.7 Mean units of cannabis and alcohol purchased as the price of recreational cannabis increases and alcohol remains fixed

Left panel depicts raw mean consumption values. Right panel depicts purchasing plotted on log-log coordinates with elasticity.

Means and standard deviations for purchases of cannabis and alcohol are presented in Table 4.24. When the price of cannabis was fixed, and alcohol price increased, purchases of alcohol significantly decreased (E_{own} = -0.63, $F_{3,233}$ = 46.40, p < .01). In addition, as alcohol price increased, purchases of cannabis also decreased (E_{cross} = -0.24; $F_{3,233}$ = 8.55, p < .01), suggesting that cannabis serves as a complement to alcohol, rather than as a substitute. This is depicted in Figure 4.8.

Table 4.24 Means and standard deviations for units of cannabis and alcohol purchased at increasing alcohol prices and fixed cannabis price

Price of Alcohol	Alcohol	Cannabis
$1.00	13.24 (17.42)	3.74 (6.94)
$5.00	6.74 (8.67)	3.00 (4.76)
$10.00	3.40 (5.64)	2.27 (3.69)
$15.00	2.39 (5.37)	1.96 (3.14)

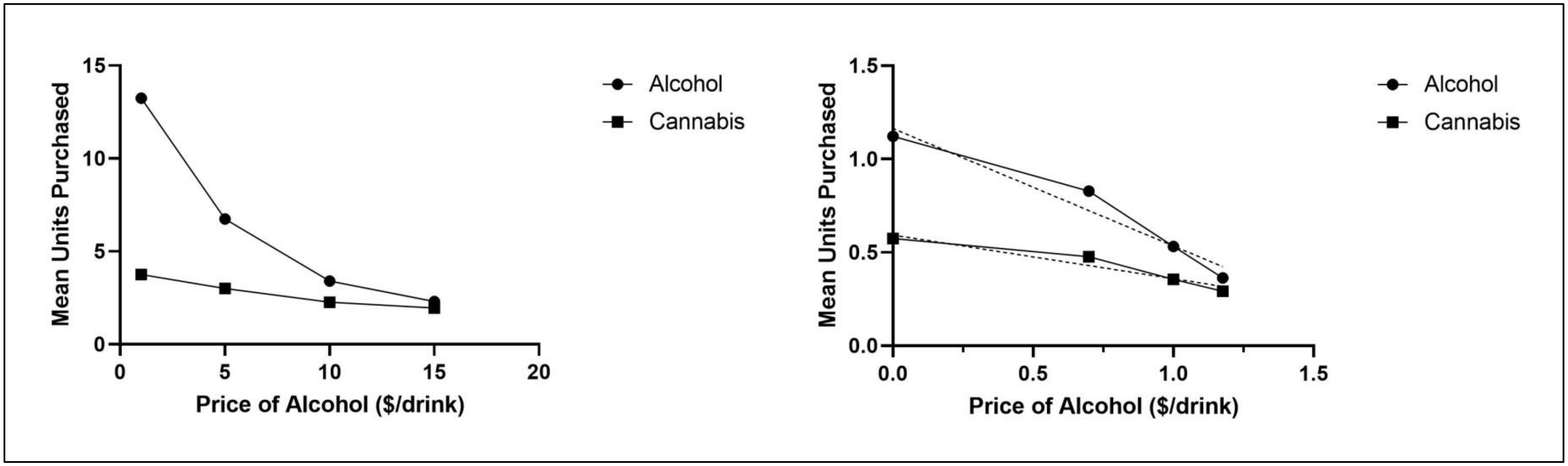


Figure 4.8 Mean units of cannabis and alcohol purchased as the price of alcohol increases and cannabis remains fixed

Left panel depicts raw mean consumption values. Right panel depicts purchasing plotted on log-log coordinates with elasticity

4.3.2 Purchases of concurrently available cannabis and alcohol in medical users

Of the 302 respondents who endorsed cannabis use, 165 indicated concurrent alcohol use and were invited to complete the concurrent cannabis-alcohol use hypothetical purchasing task. 69 were removed due to incomplete responses. Data were examined for extreme values, and outliers were recoded to one unit higher than the next non-outlying value.

Next, the elasticity of cannabis purchases was examined at varying price points for cannabis at a fixed alcohol price point ($5.00/drink) (Table 4.25). The expenditure and demand curves are presented in Figure 4.9. Cannabis purchases decreased significantly as its own price increased ($F_{3,94} = 15.38$, $p < .01$). $E_{own} = -0.46$, indicating inelastic demand. Changes in the price of cannabis did not significantly affect the purchases of alcohol ($E_{cross} = -0.02$; $F_{3,94} = 1.23$, $p > .05$). Elasticity of demand was not significantly different from zero and purchases of alcohol were independent of purchases of cannabis.

Table 4.25 Means and standard deviations for units of medical cannabis and alcohol purchased at increasing cannabis prices and fixed alcohol price

Price of Cannabis	Alcohol	Cannabis
$1.00	6.23 (9.83)	29.34 (40.16)
$3.00	6.04 (9.78)	22.87 (31.30)
$8.00	5.88 (9.81)	14.99 (21.60)
$15.00	6.00 (9.75)	7.89 (12.21)

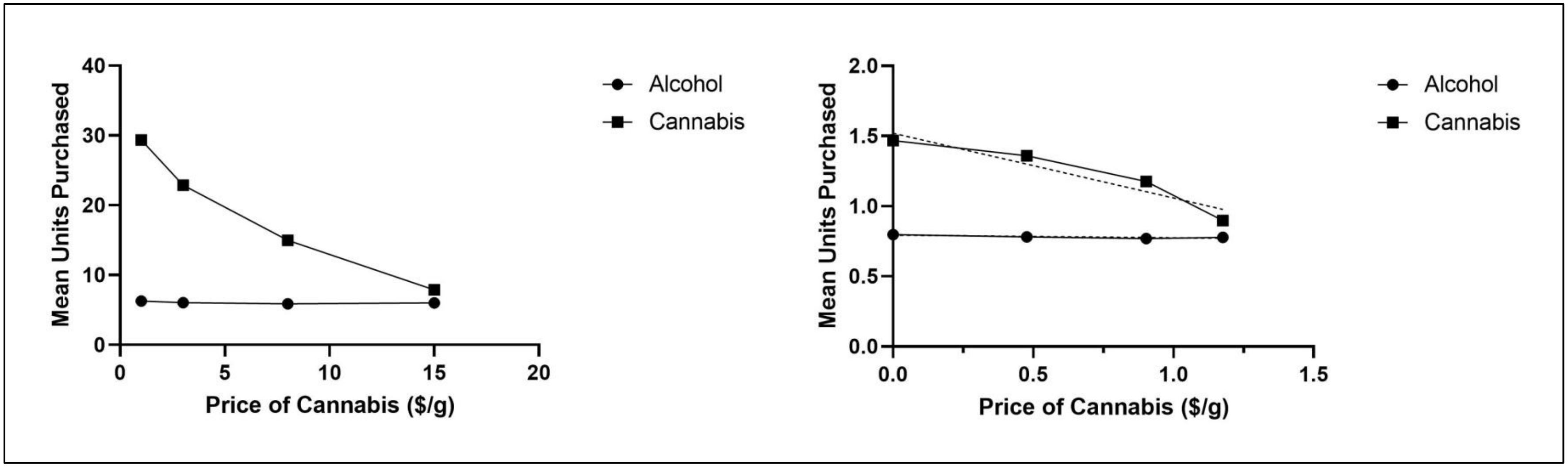


Figure 4.9 Mean units of medical cannabis and alcohol purchased as the price of cannabis increases and alcohol remains fixed

Left panel depicts raw mean consumption values. Right panel depicts purchasing plotted on log-log coordinates with elasticity.

Elasticity of cannabis and alcohol was also assessed at fixed cannabis price points ($8.00/gram) and increasing alcohol prices (Table 4.26). The consumption and demand curves are presented in Figure 4.10. As the price of alcohol increased, purchases of alcohol decreased (E_{own} = -0.44; $F_{3,94}$ = 9.84, p < .01). The price of alcohol did not affect cannabis purchases (E_{cross} = 0.002; $F_{3,94}$ = 0.20, p > .05), suggesting that purchases of cannabis are independent of purchases of alcohol.

Table 4.26 Means and standard deviations for units of medical cannabis and alcohol purchased at increasing alcohol prices and fixed cannabis price

Price of Alcohol	Alcohol	Cannabis
$1.00	11.31 (18.94)	12.00 (16.80)
$5.00	7.50 (13.15)	12.01 (16.80)
$10.00	4.79 (10.10)	12.05 (16.82)
$15.00	3.21 (8.02)	12.09 (16.87)

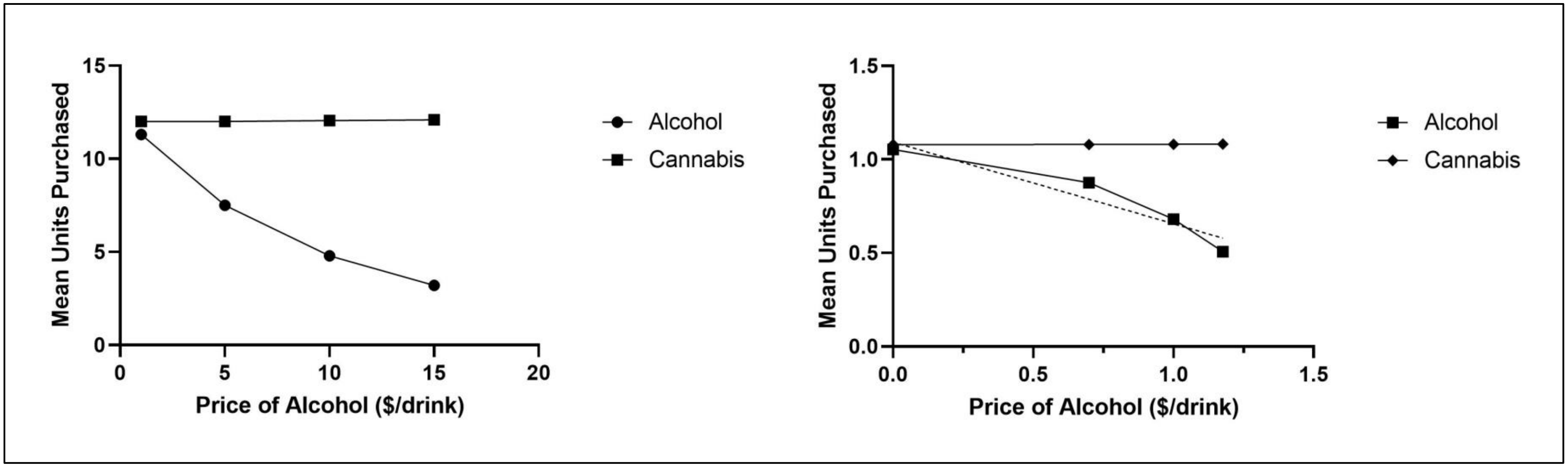


Figure 4.10 Mean units of medical cannabis and alcohol purchased as the price of alcohol increases and cannabis remains fixed

Left panel depicts raw mean consumption values. Right panel depicts purchasing plotted on log-log coordinates with elasticity.

4.3.3 Purchases of concurrently available cannabis and prescription opioid pills in medical users

In total, 89 respondents reported using prescription opioid pain relievers in the past six months and were selected for further substitution analysis. Forty responses were excluded due to incomplete purchasing data, and two respondents were excluded due to non-systematic responding. The remaining data were examined for extreme values, and all outlying values were winsorized to one unit higher than the next non-outlying value.

First, purchasing patterns were examined using fixed opioid prescription medication prices ($5/pill) and varying cannabis prices (per gram). Means and standard deviations for purchasing task are detailed in Table 4.27. The consumption and demand curves are presented in Figure 4.11. As the price of cannabis increased, the number of grams of cannabis purchased decreased (E_{own} = -0.64; $F_{3,44}$ = 9.55, $p < .01$). Given that own-price elasticity of demand was between 0 and -1, cannabis demand is considered inelastic. As the price of cannabis increased and prescription opioid prices remained constant, purchases of prescription opioids increased significantly (E_{cross} = 0.11; $F_{3,44}$ = 3.53, $p < .05$). Using simple planned contrasts with $1.00/gram as the reference group, purchases of opioids when cannabis was $15.00/gram were significantly higher than purchases of opioids when cannabis was $1.00/gram ($F_{1,46}$ = 4.72, $p <$ .05). There were no significant differences in price for the $3.00 and $8.00 cannabis price points. Given that cross price elasticity was a positive value, this suggests that prescription opioid pills may function as a partial substitute for cannabis (Hursh & Roma, 2016).

Table 4.27 Means and standard deviations for units of medical cannabis and prescription opioid pills purchased at increasing cannabis prices and fixed opioid price

Price of Cannabis	Prescription Opioid Pills	Cannabis
$1.00	8.34 (17.11)	39.78 (52.54)
$3.00	8.15 (17.43)	26.93 (31.96)
$8.00	9.40 (18.23)	15.18 (18.30)
$15.00	11.26 (18.82)	6.48 (9.61)

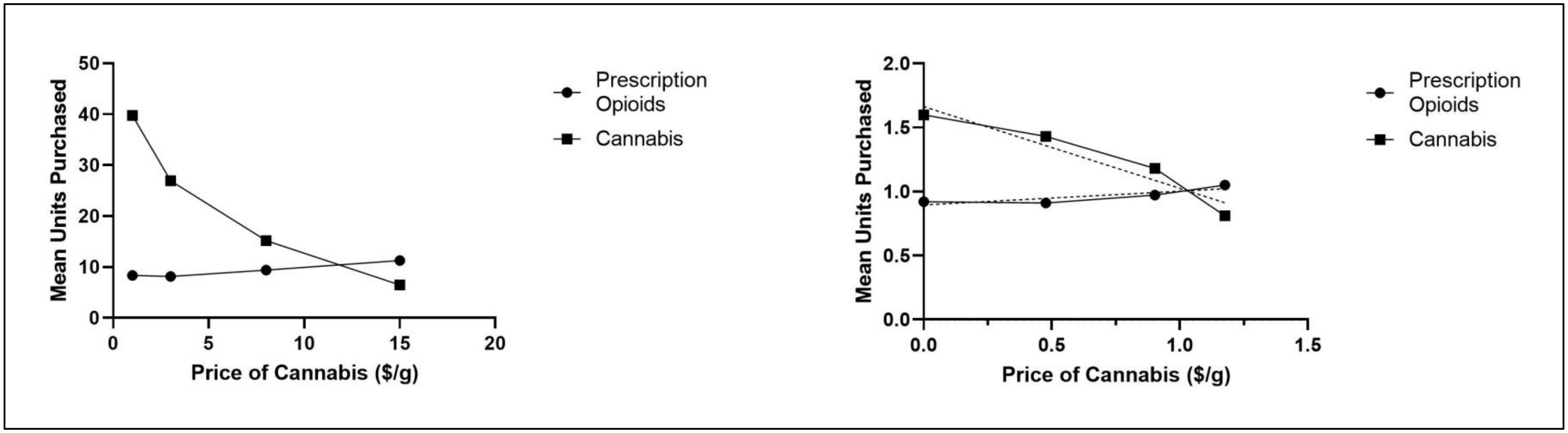


Figure 4.11 Mean units of medical cannabis and prescription opioid pills purchased at increasing cannabis prices and fixed opioid price

Left panel depicts raw mean consumption values. Right panel depicts purchasing plotted on log-log coordinates with elasticity.

Next, purchases of cannabis and prescription opioid pills were examined for fixed cannabis prices ($8.00/gram) and varying prices for prescription medication (Table 4.28). As the price of prescription pills increased, the number of pills purchased decreased (E_{own} = -0.46; $F_{3,44}$ = 5.05, p < .01). Purchases of pills were significantly lower at $3 ($F_{1,46}$ = 15.02, p < .01), $8 ($F_{1,46}$ = 13.98, p < .01), and $15 ($F_{1,46}$ = 7.83, p < .01). As own-price elasticity was between 0 and -1, purchases of prescription medication was largely inelastic. Cannabis purchases did not change as a result of increasing prices of prescription opioid medication (E_{cross} = 0.02; $F_{3,44}$ = 1.86, p > .05), suggesting that purchases of cannabis were independent of prescription opioids. Consumption and demand curves are presented in Figure 4.12.

Table 4.28 Means and standard deviations for units of medical cannabis and prescription opioid pills purchased at increasing opioid prices and fixed cannabis price

Price of Pills	Prescription Opioid Pills	Cannabis
$1.00	17.02 (30.11)	14.23 (18.82)
$3.00	12.34 (23.9)	14.53 (18.71)
$8.00	6.06 (12.47)	15.40 (18.58)
$15.00	4.81 (11.54)	15.02 (18.61)

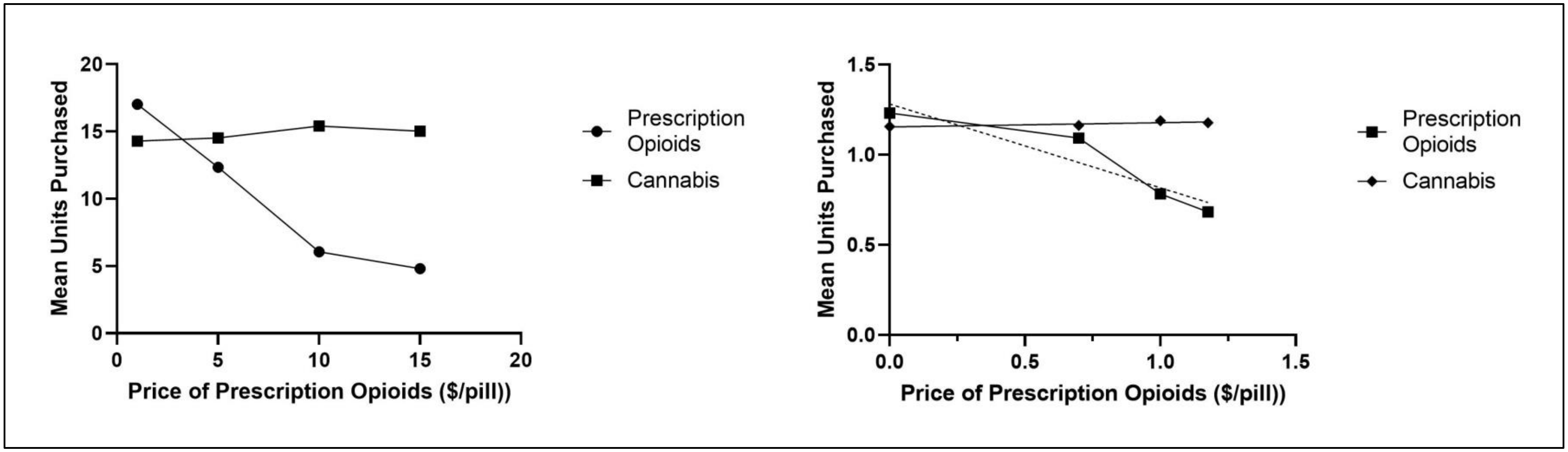


Figure 4.12 Mean units of medical cannabis and prescription opioid pills purchased at increasing opioid prices and fixed cannabis price

Left panel depicts raw mean consumption values. Right panel depicts purchasing plotted on log-log coordinates with elasticity.

4.4 Comparing medical cannabis users to recreational users

4.4.1 Demographic differences

To examine differences among medical and recreational users, one-way ANOVA was conducted with group (i.e., low THC recreational, high THC recreational, and medical) was used as the independent variable. Dependent variables included age, past month use, past week use, sessions/weekday, sessions/weekend, age of initiation, and quantity/session. Given unequal variances between groups, Welch's F test was used as a more robust analysis, with Bonferroni adjustment for multiple comparisons ($p < .007$). Follow-up comparisons were conducted using Games-Howell method (when group size > 50) and Dunnett's T3 when group size <50).

There was a significant overall omnibus test for group differences for age (*Welch's* $F_{2,135.25}$= 105.19, $p < .001$). Pair-wise comparisons revealed that medical users (M = 44.35, SD = 14.75) were significantly older than low THC (M = 19.51, SD = 1.54) and high THC recreational users (M = 19.54, SD = 1.66). There were significant group differences for past month use (*Welch's* $F_{2,150.27}$ = 107.64, $p < .001$). Medical cannabis users (M = 26.43, SD = 7.73) reported a higher number of days of past month use than both low THC (M = 7.92, SD = 9.79) and high THC groups (M = 8.38, SD = 10.98). Similarly, there were group differences for past week cannabis use (*Welch's* $F_{2,150.76}$ = 79.65, $p < .001$), such that medical users reported more frequent past week use (M = 5.91, SD = 2.06) than the low (M = 2.03, SD = 2.33) and high THC groups (M = 1.87, SD = 2.52). For weekday sessions, there were significant differences between groups (*Welch's* $F_{2,133.29}$ = 10.64, $p < .001$). Indeed, medical cannabis users reported more use-sessions per day (M = 3.43, SD = 4.44) than the low (M = 0.82, SD = 1.70) and high THC groups (M = 0.93, SD = 2.45). In the same vein, there were group differences for number of weekend sessions (*Welch's* $F_{2,132.76}$ = 9.49, $p < .001$). The medical sample reported more sessions per weekend (M

= 4.44, SD = 5.37) than low (M = 1.44, SD = 2.85) and high THC groups (M = 1.47, SD = 2.45). There were no significant group differences in age of initiation of cannabis use (*Welch's* $F_{2,70.22}$ = 2.72, $p > .05$) among medical (M = 18.20, SD = 7.88), low THC (M = 16.18, SD = 1.68), and high THC groups (M = 17.04, SD = 1.73). Similarly, there were no group differences in quantity of cannabis used per session (*Welch's* $F_{2,51.05}$ = 1.21, $p > .05$) among medical (M = 0.46, SD = 0.54), low THC (M = 0.31, SD = 0.40), and high THC groups (M = 0.50, SD = 0.65).

4.4.2 Differences in demand characteristics

To examine the differences recreational cannabis users on measures of demand of "hits" of cannabis, one-way ANOVA was conducted, with type of user (low THC recreational, high THC recreational; and medical) serving as the grouping variable, and each of the demand indices serving as the dependent variables. Given that the assumption of homogeneity of variance was violated, Welch's F test was used as a more robust analysis, with a Bonferroni adjustment. For significant omnibus *F* tests, Games-Howell multiple comparisons test was used to examine differences between users. Comparisons are depicted graphically in Figure 4.13.

For intensity of demand (observed), the omnibus F-test was significant (*Welch's* $F_{2,144.03}$ = 7.81, $p < .001$). Intensity in medical users (M = 31.83, SD = 41.15) was significantly larger than in low THC recreational (M = 13.11, SD = 17.69) and high THC recreational users (M = 12. 75, SD = 15.18). Similarity, there were significant group differences for model-derived estimate of intensity (*Welch's* $F_{2,143.93}$ = 8.63, $p < .001$), such that medical users reported larger estimates (M = 32.38, SD = 40.33) than low (M = 13.25, SD = 17.72) and high THC (M = 12.79, SD = 14.98) groups. There were no group differences among users for Breakpoint, O_{max},or P_{max}. Similarly, there were no overall group differences in sensitivity to change in price (i.e., alpha and EV).

For the demand characteristics in the “grams” hypothetical purchasing task, medical cannabis users were compared with low and high THC recreational cannabis user groups. There were no significant overall tests of group differences for any of the demand characteristics (depicted in Figure 4.14).

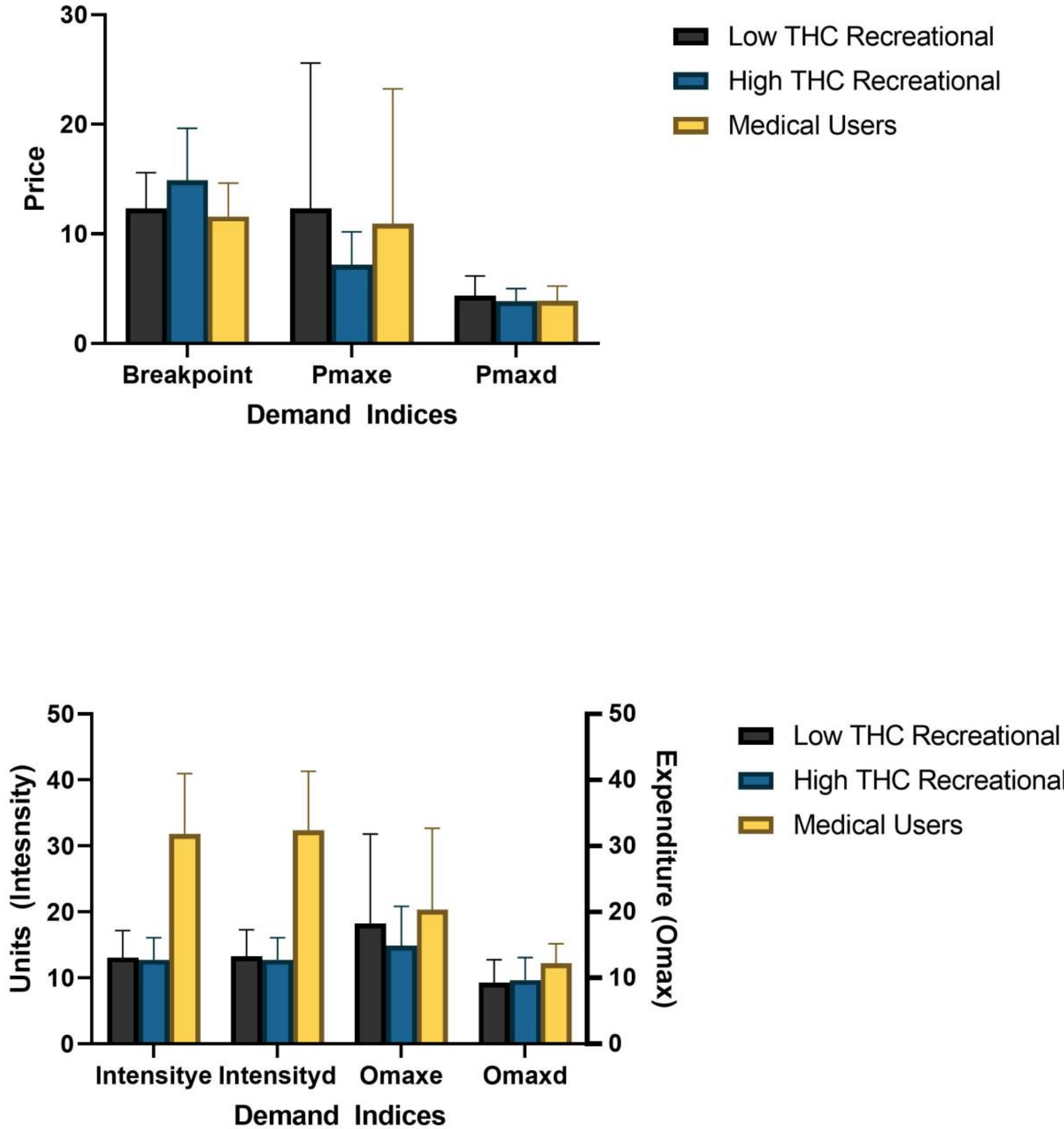
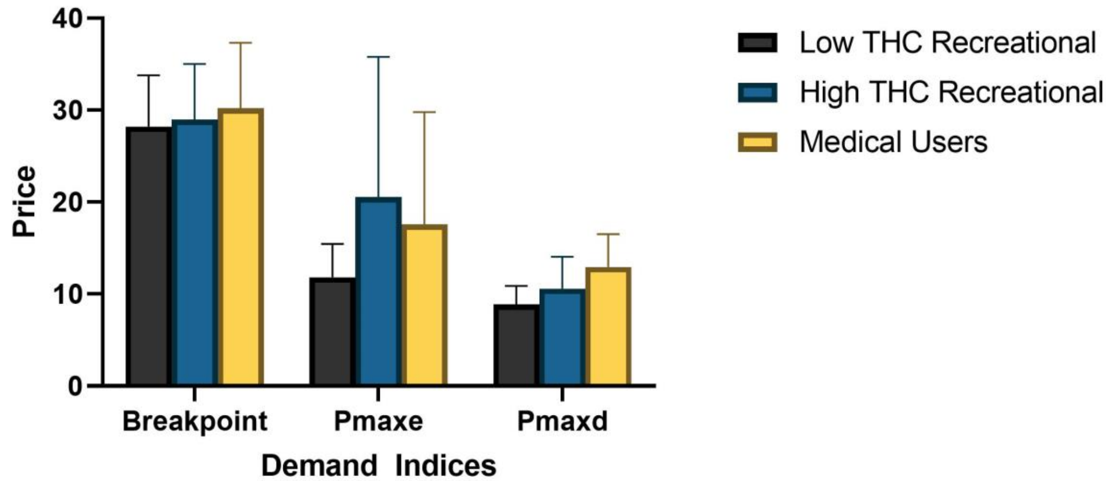


Figure 4.13 Comparison of demand indices for "hits" of cannabis with 95% CIs



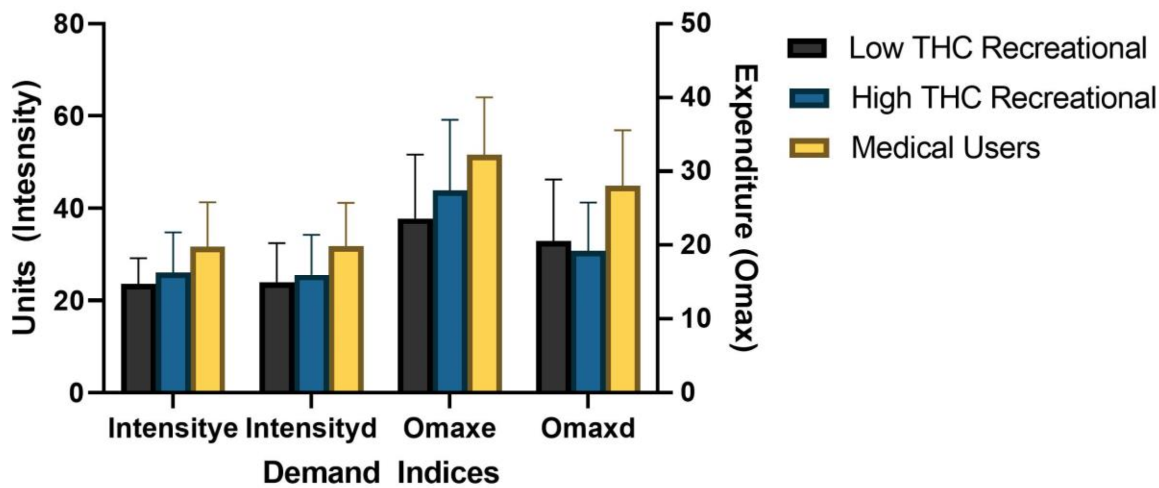


Figure 4.14 Comparison of demand indices for "grams" of cannabis with 95% CIs

Chapter 5: Discussion

5.1 Recreational Cannabis

5.1.1 Hits of Recreational Cannabis

The first aim of the present study was to replicate previous findings using “hits” of cannabis as a commodity in a hypothetical purchase task across two different potencies of cannabis. As expected, purchasing patterns for hits of cannabis adhered to demand models such that purchases decreased as price increased. Demand curves were modelled for both high and low THC cannabis, yielding five demand indices: breakpoint, intensity, O_{max}, P_{max}, and alpha.

In attempting replication of previous research, demand indices for “hits” of cannabis purchased were compared to cannabis use variables. Our findings were generally consistent across demand characteristics. Specifically, we hypothesized that intensity of demand would be positively correlated with frequency of use, quantity of use, and negatively associated with age of initiation (H1a). This hypothesis was partially confirmed. Intensity of demand was positively associated with past week and past month cannabis use for the low THC condition, providing partial support for the hypothesis that intensity of demand would be associated with frequency of use. This is consistent with previous research that has demonstrated the association between intensity of demand (i.e. the number of hits of cannabis purchased at the lowest price), and the number of cannabis use days in the past month (Aston et al., 2015, 2017; Dolan et al., 2020; Strickland et al., 2017, 2019; Teeters et al., 2019). Intensity for high THC cannabis is associated with more frequent use per day, and not associated with past week or month use. Individuals who report more sessions per day were more likely to purchase large numbers of hits of high THC cannabis at unrestrained cost. This suggests that potency of THC may impact the association between *intensity of demand* and frequency of cannabis use. Intensity of demand was also positively associated with quantity of cannabis used per session in both conditions, consistent with hypothesis 1a. Respondents who reported purchasing a larger number of hits of cannabis at the lowest cost were more likely to report using higher quantities of cannabis in each session. This is generally consistent with previous research that has demonstrated that quantity of cannabis used positively associated with intensity (Dolan et al., 2020; Strickland et al., 2019). Age of initiation (i.e., number of years of use) was not associated with intensity of demand. This is in contrast to previous research demonstrating a negative association between intensity and age of initiation (Aston et al., 2015).

The next step for replication of results from prior research using "hits" of cannabis involved examining the association between O_{max} and cannabis use variables. Model derived O_{max} was correlated with quantity of cannabis used per session for the high THC condition but was not correlated with other cannabis use variables in either the high or low THC conditions. Perhaps more importantly, observed O_{max} was unrelated to any cannabis use variables for their condition. This was unexpected, as previous research has demonstrated the positive association between O_{max} and number of cannabis use days (Aston et al., 2015).

The divergent findings for intensity of demand and O_{max} may be explained in part by the theory that they may represent separate aspects of demand. Indeed, a recent study examining the latent factor structure of demand indices suggest two distinct, underlying factors (Aston et al., 2017); persistence (i.e., sensitivity to changes in price) and amplitude (i.e., purchases at unconstrained price, usually the lowest price point). They reported that O_{max}, P_{max}, breakpoint, and elasticity load primarily on persistence, whereas intensity of demand loads primarily on amplitude. Moreover, these two distinct factors are differentially associated with cannabis use variables, such that persistence is more likely to be associated with quit attempts and cognitive expectancies of use, and amplitude is more likely associated with frequency of use and expectation of positive outcomes of cannabis use (i.e., social/sexual facilitation, relaxation/tension reduction). Another reason for lack of predicted associations may be due in part to small effect sizes. A recent meta-analysis suggests that intensity of demand tends to be more strongly associated with cannabis use variables than elasticity, and that elasticity may in fact represent a less important valuation variable than intensity (Strickland et al., 2020). This meta-analysis also suggests that P_{max}, breakpoint, and elasticity are small effects, and as such were perhaps undetectable in the present study. In general, in the present research, intensity of demand appears to be a consistently more important demand index when considering associations among demand and cannabis use.

Finally, it was expected that potency of THC would impact demand of cannabis such that demand characteristics would be higher for high THC cannabis than low THC cannabis. This was not supported. There were no significant differences across conditions for any of the demand indices, suggesting that participants did not view high THC cannabis as more rewarding than low THC. This is the first study to exam potency of presented cannabis in a hypothetical purchasing task. These findings are surprising in the context of the reinforcing potential of THC. Human studies examining the impact of potency on self-administration of cannabinoids suggest that THC content plays a role in the reinforcing effects of the drug, such that individuals actively choose higher THC doses over lower (see Justinova et al., 2005). Moreover, research examining the real-world price of cannabis available from retailers indicates that THC is positively associated with higher prices (Smart et al., 2017) and willingness to pay (Shi et al., 2019). This correlation was not observed in the present research. Previous research examining the effect of quality of cannabis on demand indices suggested that as quality of cannabis increased, the intensity of demand also increased; however, there was no indication that quality of cannabis is associated with THC content (Vincent et al., 2017). Other hypothetical purchasing task research comparing *indica* and *sativa* cannabis strains have similarly found no difference in *intensity of demand* or elasticity (Sholler et al., 2021). While participants report being aware of the different perceived effects commonly associated with each strain, demand metrics were unaffected by strain. One proposed reason for this finding may be that individual cannabis-use preferences may vary according to context (e.g., going to a party vs. preparing to go to bed). It is possible that similar context matters for participants when consuming high THC and low THC strains, and as such, differences in reinforcing or rewarding properties of high and low potency cannabis in specific contexts may have been obscured.

5.1.2 Grams of Recreational Cannabis

Following replication of established CPT protocols, the second aim of the present study sought to model demand curves when participants were queried on how many grams – rather than hits - of cannabis they would buy. This may reflect a more ecologically valid method, as cannabis is typically purchased in grams, and not individual hits. As with the “hits” CPT, there were no significant differences across high or low THC cannabis conditions for any of the demand characteristics.

Hypotheses for the grams CPTs were similar to the hits hypotheses such that it was predicted that intensity of demand for grams would be positively associated with frequency of cannabis use and quantity of cannabis used and negatively related to age of initiation of use. This hypothesis was partially supported. Intensity of demand was associated with past week and past month use for both high and low THC conditions. Intensity was also positively associated with the number of times used per day in the high THC condition but not the low THC condition. This is partially consistent with previous research of hypothetical purchasing of hits of cannabis. Intensity of demand was associated with quantity of cannabis used in the high THC condition, and not in the low THC condition. This is consistent with previous work that has indicated that *intensity* is related to grams of cannabis used per week (Vincent et al., 2017) or number of joints per episode of use (Collins et al., 2014). Intensity of demand was unrelated to age of initiation. Overall, intensity of demand emerged as a possible predictor of frequency and quantity of cannabis use, particularly for high THC strains.

It was predicted that O_{max}, peak expenditure of grams of cannabis, would be positively related to frequency and quantity of cannabis use and negatively related to age of initiation (H2b). Partial support for this hypothesis was confirmed. O_{max} was associated with past month and past week use for both high and low THC conditions. O_{max} was positively related to the number of sessions per days in both high THC and low THC. O_{max} was unrelated to age of initiation or quantity of cannabis used in either condition, running contrary to predictions; however this may have been impacted by power, as the sample responding to these questions was small.

Overall, the patterns of associations between demand characteristics and cannabis use variables was more robust for both conditions in the grams CPTs than in the hits CPTs. This is among the first replication studies examining grams rather than hits of cannabis. While the specific pattern of associations differed across hits or grams CPTs, the direction of associations was similar, and intensity of demand emerged as the most consistent predictor of cannabis use.

The findings regarding hits vs grams of cannabis demonstrates the importance of considering unit of measurement of cannabis in CPTs. Different measurement units may indicate wholly different types of purchasing patterns (Aston & Cassidy, 2019; Aston & Meshesha, 2020). Indeed, it has been suggested that the two types of purchasing tasks are difficult to compare (Aston & Meshesha, 2020). This study examined both "hits" and "grams" CPTs, and the findings reflect the inherent difficulty in directly comparing demand indices and provide further evidence that they may represent unique purchasing patterns. Indeed, raw intensity values were much lower for hits of cannabis purchased than grams of cannabis purchased, reflecting the potential impact of the time frame presented to participants, as participants are more likely to view consuming hits in short time periods, and decisions about purchasing grams of cannabis may reflect longer time periods. Moreover, the expected patterns of associations were more apparent in grams CPTs than in hits CPTs. Identifying standard units of cannabis has been a longstanding issue in research and developing safe-use guidelines for cannabis users (Volkow & Weiss, 2020). Proposals for standard units focus primarily on specific methods of use, such as joints (Kögel et al., 2017), which is criticized for being unable to account for other methods of ingestion including pipe or bong smoking/vaporization, cannabis concentrates, and edibles and does not take into consideration the substantial heterogeneity of strains (Freeman & Lorenzetti, 2020).

5.2 Medical Cannabis

5.2.1 Hits of Medical Cannabis

Though there exists a developing body of research examining BE and demand curve analysis for recreational cannabis, there is a growing need to apply similar approaches to medical cannabis use (Aston & Meshesha, 2020). The third aim of this study, and subsequent hypotheses, examined behavioural economic principles of demand in a sample of medical cannabis users. First, demand curves were modelled for medical cannabis users using "hits" of cannabis in the hypothetical purchasing tasks yielding demand characteristics in a similar fashion to models generated for recreational users.

Consistent with hypotheses, intensity of demand was associated with frequency of cannabis use, frequency of use within a single day, and quantity of cannabis used. In addition, it was negatively associated with age of initiation, such individuals who began cannabis use at a younger age were more likely to report higher rates of purchasing at unconstrained price. This is consistent with recreational cannabis use research using hits of cannabis as a unit of consumption in hypothetical purchasing tasks. Intensity of demand was also negatively associated with age of initiation, such that individuals who purchased more when cannabis was free are more likely to have a younger age of initiation. In addition, quantity of cannabis used was associated with intensity of demand. These findings are generally consistent with research examining the association of demand indices and cannabis use variables in non-medical cannabis users (Aston et al., 2015, 2017; Dolan et al., 2020; Strickland et al., 2017, 2019; Teeters et al., 2019).

These findings are a slight departure from the previously examined demand metrics for hits of recreational cannabis in the present body of work, which did not yield expected patterns of associations. Similarly, it was predicted that O_{max} would be associated with cannabis use variables. This was only partially supported, and O_{max} was positively related to number of cannabis use sessions for weekdays and weekend days, such that individuals reporting higher hypothetical expenditure reported using more cannabis in a single session.

It was expected that level of pain severity, pain relief, and pain interference would be associated with demand characteristics (H3). This hypothesis was generally not supported. Intensity of demand and O_{max} were unrelated to any pain variable for hits CPTs. One explanation is that it is possible that the association between pain and demand characteristics is a non-linear relationship, and thus not captured by the current analyses. Previous research examining cannabis use demand in persons living with HIV suggest that intensity of demand is affected by pain severity, such that intensity was higher for those reporting mild or moderate pain than those reporting no pain or severe pain (Greenwald et al., 2021). The current study's sample size did not allow for such fine-grained analyses, and future studies should examine the unique association between pain and demand for cannabis.

5.2.2 Grams of Medical Cannabis

We predicted that the pattern of associations of demand characteristics observed in hits CPT for medical cannabis would be replicated in the grams CPT (Hypothesis 3c). The pattern of associations observed for hits of medical cannabis was only partially replicated for grams of medical cannabis. Intensity of demand was positively associated with number of weekday and weekend sessions, and unrelated to any other cannabis use variables. O_{max} was positively associated with number of sessions for weekends only.

Similar predictions for pain variables were made, such that pain severity and interference would be associated with demand characteristics. This was largely not confirmed. Intensity of demand was unrelated to current, worst, least, or average pain in the past week. With regard to daily interference of pain, intensity was negatively associated with pain interfering with relationships and socializing. Indeed, participants reporting greater pain interference from relationships were more likely to report lower unrestrained consumption. Intensity was unrelated to any other interference variables. Maximum expenditure (O_{max}) was negatively associated with pain interference in normal work, sleep, and enjoyment of life, such that lower maximum expenditure was related to greater interference in these areas.

5.3 Cannabis Substitution

5.3.1 Concurrent Alcohol and Cannabis Use

A prominent aim of the present study was to examine the potential substitutability of cannabis for alcohol in both recreational and medical users. The hypothesis that cannabis would serve as a substitute for alcohol was not confirmed. Indeed, as the price of alcohol increased and cannabis price remained constant, purchases of grams of cannabis decreased along with purchases of standard drinks of alcohol. These findings suggest that cannabis may serve as complement to alcohol, rather than a direct substitute, as long as cannabis prices are stable. Indeed, the reverse was not apparent, such that when the price of cannabis decreased and alcohol price was fixed, alcohol purchases did not decrease. This suggests that though cannabis may complement alcohol, the reverse is not true, and alcohol purchases remain largely independent of cannabis purchasing patterns. A recent behavioural economic study examined the interaction between cannabis and alcohol use by completing hypothetical purchasing tasks of standard alcohol drinks and "puffs" of cannabis (Dolan et al., 2020). Findings from this study suggest that cannabis and alcohol serve as complements to one another, when examined at group level. However, the authors note that there exists significant variability among individuals when it comes to making purchases, and recognized that all three patterns of concurrent use emerged (i.e., complement, substitution, independent purchasing). This suggests that the association between cannabis and alcohol is highly varied across individuals and that the decision about whether or not cannabis and alcohol are substitutes for one another varies from person to person.

A potential factor affecting results for recreational users may be the impact of legality and availability of cannabis. Though the present recreational data were collected post-legalization of recreational cannabis in Canada, participants did not actively choose to use cannabis over alcohol. However, the average age of recreational cannabis users was approximately 19, whereas the minimum age requirement for legal purchases of recreational cannabis in Canada is 21. It may be that, due to being underage for purchasing cannabis but not for alcohol, young adult recreational users do not have consistent legal access, and therefore are less likely to have the opportunity to substitute. Moreover, given the younger age of the sample, they may be less likely to have extensive experience with cannabis and are therefore less familiar with the effects.

Alternatively, there may be additional variables that impact an individual's choice to use cannabis as a substitute or a complement to alcohol. An important factor that may impact the ability of cannabis to serve as a substitute or complement that was not assessed was motive for use. Indeed, emerging research suggests that, among university students, using cannabis to cope affected whether or not cannabis was a self-reported substitute or a complement (O'Hara et al., 2016). Indeed, substitution is more likely among individuals who use cannabis or alcohol to cope with stressful events. Among individuals who do not use drugs or alcohol to cope, cannabis is more likely to serve as a complement. One potential explanation for the findings of the present study may be that, overall, the sample was less likely to use either cannabis or alcohol as a coping mechanism, and more likely to use for fun, relaxation, experimentation, or for social reasons. Future research examining substitution effects in BE frameworks should include motives for use of cannabis and alcohol, to identify patterns of substitution.

The hypothesis that cannabis would act as a substitute for alcohol in medical cannabis was not observed. When alcohol prices were fixed and cannabis prices increased, cannabis purchasing decreased, and alcohol purchases remained constant. Indeed, the varying price of cannabis did not impact purchases of alcohol. The reverse was also true, such that the price of alcohol did not impact purchases of cannabis. As alcohol price increased (and cannabis price remained constant), alcohol purchases decreased, and cannabis purchases remained unchanged. As with recreational use, this runs contrary to descriptive research examining self-reported substitution. Cross-sectional studies routinely report that medical cannabis users self-report replacing alcohol with cannabis (Lucas et al., 2013, 2016b, 2019; Lucas & Walsh, 2017b). Moreover, there is evidence that initiation of medical cannabis use is associated with a reduction of alcohol use (Lucas et al., 2020; Piper et al., 2017). Users who substitute are more likely to report using medical cannabis two or more times a day, are more likely to be employed, and more likely to have significant health problems (Hayat & Piper, 2020). This suggests that there are important factors that impact the substitution of alcohol, including demographics, familiarity with cannabis, frequency of cannabis use, and health-related factors. Policy evaluation and population-level studies of medical cannabis laws demonstrate mixed evidence, with some evidence that legalization reduces alcohol sales (Baggio et al., 2020) and some that legalization does not affect alcohol purchases (Veligati et al., 2020). There exists significant heterogeneity among individuals using cannabis that may impact these findings, including demographic differences, cannabis product variety, methods of consumption. Moreover, epidemiological studies of medical cannabis laws do not specifically target medical cannabis users, making the substitution phenomenon difficult to characterize at the macro-level. Taken together, the research suggests substantial variability among medical cannabis users in their decision to substitute, and further research is required to evaluate characteristics that affect substituting cannabis for alcohol.

5.3.2 Concurrent Prescription Opioid and Cannabis Use

The present study sought to examine the potential of cannabis to serve as a substitute for prescription opioid use in medical cannabis users. The fourth aim of the study was to compare purchases of cannabis when prescription pain medication was concurrently available. It was predicted that as the price of pain medication increased, pill purchases would decrease, and cannabis purchases would increase to compensate (Hypothesis 4b). This particular association was not observed; indeed, as the price of pain medication increased, purchases of pills decreased, but cannabis purchases remained unchanged. However, in the reverse situation, as the price of cannabis increased, purchases of opioid pills increased slightly. Indeed, there was a significant increase in the number of pills purchased when cannabis was $1.00/gram vs. when cannabis was $15.00/gram. Though overall cross-price elasticity did not meet the threshold of previously established research (Sumnall et al., 2004), the overall positive value of elasticity suggests that opioid pills may serve as a *partial* substitute (Hursh & Roma, 2016) for cannabis, when cannabis prices become too high. These findings are partially consistent with existing cross-sectional research that demonstrates that medical cannabis users report substituting prescription opioids with cannabis (Boehnke et al., 2019; Corroon et al., 2017; Lucas et al., 2016a; Lucas & Walsh, 2017a; Reiman et al., 2017)..

There is a growing body of research evaluating the effect of medical cannabis on opioid use among pain patients. Medical cannabis patients self-report decreasing opioid use following initiation of medical cannabis use (Boehnke et al., 2016). This may be particularly true for individuals who do not respond to traditional pain medications. A longitudinal study examining the effectiveness of cannabis for treating pain among patients who do not respond to first or second line analgesics found that use of cannabinoid medicines was associated with a 44%

reduction in opioid use 6 months post baseline (Haroutounian et al., 2016). A review of policy-level evaluations concluded that medical cannabis authorization is associated with a decrease in prescription opioid use, mortality rate, and hospitalizations as well as cost-savings for prescription medications that can be substituted with cannabis (Vyas et al., 2018). Moreover, enrollment in medical cannabis programs has been linked to decreases in daily opioid usage among pain patients (Barlowe et al., 2019; Vigil et al., 2017). This reduction of opioid use may also extend beyond prescription opioid medications. For example, among individuals who use injection opioids, daily cannabis use was associated with faster injection cessation than those who used cannabis less frequently (Reddon et al., 2020). The finding from the present body of work that increasing prices of cannabis may lead to increases purchases of prescription pain medication highlights the importance of affordability and availability of cannabis, particularly with regard to the ongoing opioid crisis

5.4 Differences between Recreational and Medical Cannabis Users

The fifth aim of this study was to compare medical cannabis users to recreational users, to examine potential differences between groups for demand indices. Indeed, it was posited that there would be significant group differences between medical and recreational cannabis users for demand indices. This hypothesis was partially borne out. In the “hits” tasks, there were significant group differences for intensity of demand, such that medical users reported significantly higher purchases of “hits” of cannabis when price was $0.00/hit. There were no significant group differences, however, for breakpoint, P_{max}, O_{max}, or alpha.

In the “grams” CPT, there was a significant group difference for O_{max}, but only when comparing medical cannabis users to the low THC condition. Indeed, there was no significant difference in O_{max} between the medical and high THC recreational cannabis condition.

Additionally, there were no group differences among users for breakpoint, P_{max}, alpha, or intensity of demand. The lack of substantial group differences suggests that cannabis largely adheres to a similar behavioural economic framework for medical users as it does with recreational users. Additionally, previous reported theories suggest that medical cannabis users may be more likely to report “constant demand” or be less sensitive to changes in price than recreational users and more willing to pay higher prices for cannabis (Aston & Meshesha, 2020). This suggestion was largely not observed; indeed, medical cannabis users demonstrated that they were sensitive to changes in price. Moreover, there were no differences in maximum price that participants were willing to pay (P_{max}), nor were there group differences in breakpoint prices. These findings suggest that behavioural economic principles of demand are consistent across user groups.

Past descriptive research suggests that there are significant differences among cannabis use patterns between medical and recreational users (Hakkarainen et al., 2019; Lin et al., 2016). Indeed, medical users are more likely to use daily, less likely to meet criteria for alcohol or other illicit substance use disorders, and have worse overall health. Moreover, medical users likely diverge from recreational users for reasons or motive for use, more likely to use cannabis to alleviate pain or anxiety (Bohnert et al., 2018) while recreational users are more likely to use for enjoyment, to alleviate boredom, or to experience altered perception (Lee et al., 2009). Ultimately, however, the reinforcing effect, as observed using behavioural economic demand indices, suggest that while users may vary in use characteristics or motives, the reinforcing value of cannabis is more similar between groups than it is different.

5.5 Strengths, Limitations, and Future Directions

There exist a number of strengths of the present study that highlight the importance of ongoing research using behavioural economic models of cannabis use. First, this study examined demand indices across both hits and grams cannabis purchasing tasks (CPTs). Important differences may exist across paradigms and suggest that purchasing patterns can be conceptualized as state-like or trait-like. Second, at the time of writing, this is the first study to examine a behavioral economic framework among medical cannabis users, and to compare and contrast demand indices across user groups. Third, few studies have used demand analysis to examine the substitution effect of cannabis for alcohol and for prescription pain medication.

A limitation of this study exists in the methods and data analysis used to examine substitution of cannabis for alcohol and for prescription medication. The field of behavioural economics and use of CPTs for cannabis is an emerging area of research, and as such is rapidly changing. There are a variety of different methods for quantifying and examining demand. Indeed, recent studies have used more fine-grained and sensitive analysis to examine the substitution effect of legal cannabis for illegal cannabis use (Amlung & MacKillop, 2019). Future research should include substitution CPTs that use more price points, and use purchasing tasks for single schedule alcohol-only and prescription medication-only, in addition to cross-price purchasing tasks.

A possible limitation of the findings among the recreational sample is the use of university-attending students. Research suggests that attending university or college may impact substance use trajectories for young adults. For example, young adults (age 18) who use cannabis more than once a week are less likely to enroll in post-secondary education (Homel et al., 2014), suggesting that the current sample may not include the highest frequency cannabis users among young adults. In addition, the average age of the recreational sample was considerably lower than the medical sample, and may not be representative of the average Canadian recreational cannabis user.

A significant concern and potential limitation is the difficulty in discerning medical use from recreational use among some of those who use cannabis. Although medical users were conceptualized as distinct from recreational users, it is likely that medical cannabis users may use cannabis recreationally as well as for medical reasons. Similarly, non-medical cannabis users may use cannabis in a therapeutic manner, in addition to or instead of recreational purposes. This blend of cannabis is difficult to tease apart in self-report data. Indeed, research examining medical and recreational use suggests among self-identified medical cannabis users, 80% report using for both medical and recreational purposes (Turna et al., 2020). Future research CPTs for medical samples may wish to qualify and differentiate between medical and recreational purchasing scenarios in vignettes presented to patients. In addition, ecological momentary assessment (EMA) may be useful for differentiating between number of medical vs recreational sessions when examining cannabis use variables and their association to demand indices.

From a methodological standpoint, purchasing tasks may have been worded in a way that was confusing for participants. For example, in the grams CPT, participants were not given a timeline for which to consider their purchases, rather they were asked how much they would purchase on a typical day that they buy cannabis. It is likely that recreational and medical users purchase varying amounts over a time period (e.g., one month), and this may have impacted the number of grams purchased. In addition, participants were asked to complete a relatively large number of tasks, potentially eliciting some exhaustion or boredom. It is worth noting that a sizeable to large proportion of participants either did not provide complete purchasing data, or failed the criteria for systematic reporting for data (33% recreational users, 73% medical users)

A primary statistical limitation concerns the issue of potential alpha inflation associated with multiple comparisons. In order to minimize the impact of familywise error and protect against Type I error, while simultaneously preserving findings and limiting Type II error, results are presented with 95% confidence intervals and exact p values for significant findings. Findings were reported at trend level if significance was below .05 and if the confidence interval contained zero.

Future research may wish to extend the purchasing task paradigm to other methods of cannabis use. This study used herbal cannabis as the cannabis product available for purchase, however users may report alternative methods, including cannabis edibles or beverages, or cannabis concentrates. While dried cannabis flower is the most commonly used cannabis product in Canada, 39% of users report using at least one other product such as oil cartridges, hashish/kief, liquid concentrates, solid concentrates, edibles, or other liquids (Rotermann, 2019). Type of cannabis product has the potential to affect the perceived rewarding value of the product. For example, compared to inhaled cannabis, orally ingested cannabis has a delayed onset and an extended duration of action (Blake & Nahtigal, 2019). Moreover, cannabis edibles sold by retailers are often mislabeled with regard to THC content (Vandrey et al., 2015), potentially making it difficult for consumers to accurately judge dose. With regard to substituting cannabis for alcohol, future research may wish to examine the utility of cannabis beverages to substitute for alcoholic ones, as these may be viewed by users as more similar products.

5.6 Conclusion

The present body of work represents a comprehensive examination of hypothetical purchasing tasks as applied to recreational and medical cannabis use. From a methodological perspective, the findings highlight the importance and impact of differing units of measurement, for both recreational and medical cannabis users. Indeed, among recreational cannabis users, cannabis purchasing tasks (CPTs) that used "grams" of cannabis as the unit of measurement demonstrated more robust associations among demand indices and cannabis use variables than CPTs that used the "hits" of cannabis as the unit of measurement. This was particularly evident for the high THC condition CPT. However, this observation was reversed for medical cannabis users, with the "hits" CPTs yielding a more robust association among intensity of demand and cannabis use variables than was observed in the "grams" CPTs. A possible explanation for this difference may have to do with demographic and use differences between recreational and medical cannabis users. For example, medical cannabis users reported using more frequently (past month, past week, sessions/day) than recreational cannabis users.

This is the first study to examine cannabis potency in an experimentally manipulated CPT. There were no differences in demand indices between those in the low or high THC potency conditions. This was largely surprising, as it was expected that higher potency cannabis would be viewed as more rewarding than lower THC cannabis. A potential explanation is that reasons for cannabis use and context of use may impact the perceived value of either high or low THC cannabis. Moreover, quality of cannabis, rather than potency may impact the value of cannabis as a commodity. Previous research evaluating CPTs and the impact of quality suggest that demand indices vary according to quality of cannabis offered in the task (Vincent et al., 2017). Research examining the meaning of quality cannabis to users suggests that the rewarding nature of cannabis may be impacted by characteristics other than potency. For example, in a survey of cannabis users in Florida, Czechia, Spain, and Australia noted that participants preferred strains that were milder in nature with lower potency (Belackova, 2020), suggesting that high THC strains that produce undesirable side effects may be less rewarding for consumers. The present research provides support that potency of THC alone is not a determinant of the reinforcing value of cannabis and suggests that there are other important qualities of cannabis strains that users may consider when purchasing cannabis.

Previous research has identified the need to examine CPTs for medical cannabis users, as they may differ from recreational cannabis patients in important ways. In particular, it has been suggested that medical cannabis users may be less sensitive to changes in price, and there more likely to report consistent demand across price points. The results of the present body of work suggest that perhaps medical and recreational cannabis users are more similar than they are different. While medical users may report purchasing more units of cannabis at unrestrained cost, they do not differ from recreational cannabis users in other demand characteristics, including breakpoint, maximum expenditure, or maximum price. Moreover, there were no differences between medical and recreational users for sensitivity to change in price. In addition, when unit of measurement is given as “grams” of cannabis, rather than hits, there are no differences between recreational and medical cannabis users on any demand index. Taken together, the findings suggest that the reinforcing value of cannabis is more similar than it is different among these two user groups.

From a clinical perspective, the findings of the present body of work examined the potential utility of cannabis to service as a substitute for alcohol and other drugs. Overall, cannabis was found to not be a substitute for alcohol for either recreational or medical cannabis users. Among recreational users, alcohol purchases are largely unaffected by cannabis prices. Cannabis, however, may sometimes serve as a complement to alcohol for recreational users, as purchases of cannabis were affected by increasing prices of alcohol. Among medical cannabis users, the independence of alcohol and cannabis purchases is clear; the purchase of cannabis is not impacted by the price of alcohol, and vice versa. An important clinical finding is the impact of cannabis prices on prescription pain medication purchases in the medical cannabis sample. In particular, as the price of cannabis increased and prescription pain medication costs remained stable, purchases of pills increased. These findings are particularly salient given the ongoing opioid epidemic and taken with extant research demonstrating that medical cannabis users reporting choosing cannabis over other medications, suggest that the affordability of cannabis may impact the decision to use cannabis over prescription opioid medications.

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