Time Inconsistency and Alcohol Sales Restrictions *

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Abstract

Restrictions on alcohol sales hours or days are commonly used tools in order to reduce alcohol consumption. However, a forward looking consumer can buy in advance, thereby mostly undo the impact of the restriction. I study whether time inconsistent consumer preferences can provide a justification for restrictions on alcohol sales time. I estimate a demand model which allows a fraction of consumers to be time inconsistent, using scanner data of beer purchases and other shopping behavior. According to the estimation results, 20% of consumers are time inconsistent and they account for 64% of beer consumption. I find that Sunday sales restriction decreases weekend consumption by the same amount as a sales tax increase by 21 percentage points. In terms of consumer welfare, the sales restriction is preferable to the tax increase.

Keywords: behavioral economics, time inconsistent preferences, consumer demand, alcohol, public health policy.

JEL Codes: D03, D12, I18, L51, L66.

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1 Introduction

In most countries, a goal of public health policy is to limit alcohol consumption. One commonly used measure is to restrict the days when stores are allowed to sell alcohol. However, a forward looking consumer can buy in advance, thereby mostly undo the impact of the restriction. The literature provides evidence that some people might behave as if they are time inconsistent and alcohol consumption is a natural setting where we would expect to see evidence of time inconsistency.[1] In this paper, I study whether time inconsistent preferences can provide a justification for restrictions on alcohol sales time.

Consider a time inconsistent consumer. This is a person with a self-control problem. He enjoys a drink today, while promising himself that he will not be drinking tomorrow. But when tomorrow arrives, he repeats his behavior. He decides to drink again and hopes that he will drink less in the future.[2] For this person the regulation provides a commitment device that helps him to limit his consumption.

I estimate the fraction of consumers that behave as if they are time inconsistent and study the implications for policy. Specifically, I ask whether sales restrictions can be preferable to taxes in terms of consumer welfare. To answer the questions, first, I construct a model of alcohol purchasing, consuming, and storing that allows consumers to be time inconsistent and includes time consistency as a special case. Then I estimate the model, including consumers' time inconsistent discount factor, using scanner data of beer purchases and other shopping behavior. My data set is from a region with no sales restrictions and has information about the daily purchases of almost 500 households for up to three years. I use these estimates to evaluate policy. First, I calculate the impact of Sunday sales restriction on purchases. Then I find the tax rate that decreases purchases the same amount as Sunday sales restriction and compare consumer welfare with the sales restriction and the tax increase.

I identify time inconsistent behavior from dynamic purchasing patterns. Consider again the time inconsistent consumer. When he is in the store on Saturday and plans not to return the next day, then there are two important aspects of his behavior. First, on average he buys less for tomorrow than for current consumption, since he believes he wants to decrease his consumption in the future. Second, since he underestimates how much he wants to consume tomorrow, he sometimes returns to the store when he did not plan to. To summarize this,

[1] For an overview of research on time inconsistent discounting see Frederick, Loewenstein, and O'Donoghue (2002).

[2] We say that consumer who prefers a drink today to 5 dollars tomorrow, but reverses his decision when both offers are further postponed by a day, exhibits time inconsistent preferences regarding alcohol. This can be thought of as a special case of the definition that involves preference reversal over time.

we expect the time inconsistent consumer to purchase more for current consumption than for future consumption and more often to return to the store for additional purchases. Of course, in the data we only observe total purchases, and cannot separate inventory from the current consumption. However, I will show that we can partially distinguish these two, assuming optimizing behavior and variation in the shopping costs. This is so, since when the shopping cost in the future is high, the consumer is more likely to purchase inventory than in the periods when it is costless to purchase additional quantity later.

In the model that I will describe below, the motivation for storing inventory comes from shopping costs. That is, the consumer purchases for future consumption in order to avoid a shopping trip every time he would like to consume something. This is different from most of the storable good demand models (e.g. Hendel and Nevo (2006)). In those, the consumer wants to purchase for future consumption when the good is on sale and he expects the price to increase. The reason for not considering price changes in this paper, is that when I turn to the data I look at purchasing decisions in the short term horizon, over the weekend, and prices usually remain constant during this period. In the short term horizon, it is reasonable to expect that the main motivation for storing inventory comes from shopping costs. The role of shopping costs in the model is similar to the role of sales in Hendel and Nevo (2011). Namely, if future shopping costs are high, consumer may want to store inventory in order to avoid paying the high shopping cost.

Identification of time inconsistent preferences is based on two key assumptions. The first is that shopping costs are partially observable to the researcher. Specifically, I assume that when a consumer purchased a large shopping basket of goods other than beer, he was visiting a store for other reasons, and therefore his shopping cost for beer had to be relatively low. Second, I assume that shopping costs are uncorrelated with the daily preference shocks that determine the wish to consume beer on that day. That is, after controlling for observable characteristics that might affect beer demand (like day of the week and seasonal effects), I assume that shopping costs and preference shocks are not correlated.

According to the estimation results, 20% of consumers behave as if they are time inconsistent, having time inconsistent discount factor equal to 0.44. But since these consumers consume more beer, their share in the total beer consumption is much larger, namely 64%. This drives the welfare implications.

Using the estimated parameters of the model, I find the tax rate that decreases consumption the same amount as Sunday sales restriction. I then compare the sales restriction and the tax increase in terms of welfare. My goal here is to compare two policies that achieve the same change in behavior. The estimates imply that Sunday sales restriction leads to the same decrease in weekend consumption as an increase of sales tax by 21 percentage points.

In terms of welfare, the sales restriction is preferable to the tax increase. Note that the sales restriction has two effects. First, it increases costs by making it more inconvenient to buy. Second, for the time inconsistent consumers, it provides a commitment device. In comparison, taxes are more flexible in allowing consumers to choose when to decrease consumption. Therefore, time consistent consumers prefer taxes since they do not benefit from the commitment. However, the commitment effect for the time inconsistent consumers is large enough to compensate for the welfare loss from the sales restriction.

Then I ask which policy measure should be used when we want to limit heavy drinking. Public health policy is not only concerned about aggregate alcohol consumption, but specifically wants to decrease heavy drinking. I find that the Sunday sales restriction leads to a decrease in heavy drinking on weekends that could be achieved by 19 percentage points tax increase. Again, in terms of welfare, the sales restriction is preferred.

Finally, one should note that these estimates are based on only a small sample of consumers. Moreover, the sample is restricted to the consumers who regularly buy beer. The estimates might not well characterize consumers who buy beer less often or do not drink at all. Additionally, since the consumers are from a region where the beer regulation is more liberal, the estimates and results from the counterfactual policy experiment might not generalize to a wider population in other areas. Finally, one should note that the analysis here is based only on beer purchases in stores. When designing a policy, then substitutes like other types of alcohol and consumption in bars, should be taken into account.

This paper is related to the literature that studies alcohol markets and policy and specifically, the usefulness of sales restrictions in decreasing alcohol consumption. In the literature, the empirical evidence regarding the impact of alcohol off premise sales restrictions is mixed. The datasets used to measure the impact usually include some policy changes. But even in case of a policy change, it is difficult to identify the impact, since relaxing the sales restriction often is accompanied by changes in other restrictions and taxes. Moreover, the policy change itself usually is a political decision, taking place due to changes in voters preferences. Perhaps, the best dataset to study the impact of the sales restriction comes from a controlled policy experiment in Sweden. In 2000 in Sweden, in randomly chosen counties Saturday sales ban was lifted, while in the control counties the restriction remained in place for the following year and a half. Using data from this experiment, Norström and Skog (2003, 2005) find that total alcohol sales increased by 3 percent, and beer sales increased even more, by 8 percent. There are many other papers that have looked at changes in alcohol consumption associated with policy changes. But as said above, the results have been mixed, perhaps because the environment of the policy changes has been less controlled. For example, Stehr (2007) finds that after the repeal of Sunday sales bans in U.S., liquor but not beer sales increased. On the other hand, Bernheim, Meer, and Novarro (2012) also look at policy changes in US, Carpenter and Eisenberg (2009) look at policy changes in Canada, and they both find no effect on overall alcohol consumption.[3][4] In my dataset there is no policy change. But based on my estimates the sales restriction leads to a predicted decrease in weekend beer consumption by 38%. This implies that the impact on total consumption is somewhat larger than in the findings from the policy experiment in Sweden.

At a more general level, the paper is related to the literature that identifies time inconsistent preferences and then measures their empirical importance outside the lab. This literature has taken three different paths. First, there are papers that combine lab and field data. In those, the discount rate is learned using lab experiments, and then this is combined with the real world data about the individual. Examples include credit card usage (Meier and Sprenger, 2010), technology adoption (Tarozzi and Mahajan, 2011), and studying how present bias is related to income (Tanaka, Camerer, and Nguyen, 2010). Second, there are papers where the identification is based on policy experiments or discontinuities in policies or contracts. For example, Shapiro (2005); Mastrobuoni and Weinberg (2009); Hastings and Washington (2010) study food consumption before and after the arrival of social security paychecks, Della Vigna and Malmendier (2006) gym membership. Third branch of papers uses dynamic models to identify time inconsistent preferences. The settings include lifetime consumption-saving decisions (Laibson, Repetto, and Tobacman, 2007), unemployment and labor supply (Paserman, 2008; Fang and Silverman, 2009), mammography decisions (Fang and Wang, 2012). In this paper, I follow the last approach and identify time inconsistent discount rate from dynamic choices. My estimated time inconsistent discount factor (or sometimes called short-run discount factor), 44%, is seemingly lower than other studies have found (for an overview of the time inconsistent discount rate estimates see Frederick, Loewenstein, and O'Donoghue (2002); Laibson, Repetto, and Tobacman (2007)). But one should take

[3] In addition to studying the direct effect on consumption, many papers have looked at the impact on the indirect evidence on alcohol related harms and health like drunk driving, and traffic accidence, violence, and health conditions related to alcohol. For an overview see Popova, Giesbrecht, Bekmuradov, and Patra (2009).

[4] There is also some evidence on the heterogeneous impact on individuals. For example, Gruber and Hungerman (2008) looked at the impact of repealing Sunday restrictions on regular commerce, and found that it increased heavy drinking (consuming 6 or more drinks in one sitting in the past month) only among the individuals who before the repeal regularly attended church.

into account that most studies pool all consumers together and estimate a common time inconsistent discount factor. While according to my estimates most consumers have a discount factor equal to one, and only 20 percent discount at the higher rate. My estimates imply that time inconsistent consumers are important for the impact of the regulation.

This paper contributes to the literature on optimal regulation of "unhealthy" goods in case of time inconsistent consumers. In theoretical models, Gruber and Köszegi (2001) and O'Donoghue and Rabin (2006) find the optimal "sin" taxes in case of time inconsistent consumers who at the time of consumption underweigh the future costs. They find that the optimal tax rate is higher than with time consistent consumers.[5] All these papers look only at taxes and do not consider sales restrictions. The impact of sales restrictions on consumers who are not time consistent has been analyzed in a theoretical model by Beshears, Choi, Laibson, and Madrian (2006). [6] They show that when restricting sales is costless, sales restrictions are optimal.[7] They mention that the regulation comes with social costs, including increased inconvenience, which they do not include in their model, but due to those costs the welfare impact of the regulation becomes an empirical question. In my model, heterogeneous shopping costs capture this inconvenience, and the sales restriction is not necessarily the optimal policy, since in some situations it makes it more costly to purchase alcohol.

The rest of the paper is organized as follows. In section 2, I describe an illustrative example that captures the main ideas of the model that is later estimated and I derive some implications for consumer shopping behavior. In section 3, I discuss alcohol regulation in US, describe my data and look at the descriptive empirical evidence following the implications derived in section 2. Section 4 presents the model, 5 discusses estimation and 6 presents estimation results. In section 7, I do counterfactual policy analysis to evaluate the impact of the regulation. First, I study the impact of the sales restriction on quantity and welfare, and then compare this to the impact of taxes.

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[5] Papers with similar findings include Gruber and Kőszegi (2004), Haavio and Kotakorpi (2011).

[6] Bernheim and Rangel (2004) also consider a somewhat similar setting when studying addiction and cue-triggered decision making, which is not hyperbolic discounting but still deviates from time consistent preferences. They analyze supply disruptions (which include sales restrictions) and find that this could be a benefitial policy measure.

[7] In their model, restricting sales at suitable times provides a costless commitment device. That is, the sales restriction does not change long term self's payoff and eliminates the choices of the short term self. Thereby, the restriction provides a way for the long term self to maximize his payoff.

2 Illustrative Example

In this section, I describe an illustrative example of alcohol demand when a consumer uses time inconsistent discounting. It is useful to look at the example before going to the model in Section 4, which carries the same ideas and describes the same trade offs. The example provides a simple way of mapping the data to the the structural parameters that describe consumer preferences. I present that mapping in Section 3.3 after describing my data.

There are two time periods when a consumer makes decisions. In each period $t = 1, 2$, the consumer simultaneously decides whether to shop for alcohol, whether to consume alcohol, and whether to store inventory. The consumer receives an instant payoff d_t if he consumes one unit of alcohol, and zero otherwise, where d_t is distributed with uniform distribution on the interval $[0, 1]$. Uniform distribution is assumed here in order to present the implications on simple figures. It is easy to relax, and the implications do not depend on it. Unit demand assumption simplifies the analysis here, but is also relaxed later in the model. Alcohol consumption is associated with a cost p, and consumer bears this cost in the future. In addition to that, shopping is also costly. There is a shopping cost C_t, which varies over time, and can take one of two values, Low $= 0$ or High $= C^H > 0$. The variation in the shopping costs over time could, for example, capture the following situation. The consumer sometimes is visiting a store for other reasons than alcohol. While in the store, the shopping cost for alcohol is relatively low. But at other times, when there are no stores close by, then shopping cost for alcohol is large. All uncertainty, regarding instant payoffs (d_1, d_2) and shopping costs (C_1, C_2), is realized before period one. If the consumer is indifferent between storing inventory or not, then he chooses not to store.

Consider the quasi-hyperbolic discounting framework (Laibson, 1997), which is sometimes called $\beta - \delta$ model, where β is the time inconsistent discount factor and δ is the time consistent exponential discount factor. Then payoff in period 1 of a consumer who were to purchase and consume one unit in each period equals

$$d_1 - C_1 + \beta\delta \left[d_2 - C_2 - p - \delta p \right]. \tag{1}$$

The payoff of the same consumer in period 2 if he were to purchase and consume in that period, takes the form

$$d_2 - C_2 - \beta\delta p. \tag{2}$$

To see the role of time inconsistent discounting, consider the situation where consumer has the same instant payoff in both periods $d_1 = d_2 = d$ and costless shopping $C_1 = C_2 = 0$. Then a time consistent consumer ($\beta = 1$) either consumes in both periods or in neither, depending on whether $d > \delta p$. But time inconsistent consumer ($\beta < 1$) could consume in period one as $d > \beta\delta p$ and believe that he will not consume in period two as $d < \delta p$. However, when period two arrives, he will purchase and consume.[8]

In the rest of the paper, I assume that there is no time consistent discounting ($\delta = 1$). This setup is meant to capture a short time frame. A suitable time period here is a day. Therefore, the effect of any reasonable yearly discount factor is negligible.

In this setup, shopping costs provide the only incentive to buy inventory. Consumer purchases inventory only when shopping is costly in the future. In all other situations, demand is static. Since consumer knows his current and next period shopping costs, he conditions his behavior on those. Hence, the pairs of shopping costs that each can be either Low (L) or High (H) define four states. In states LH and HH, shopping cost is high in period two, therefore, in period one, consumer might buy inventory for period two. In states LL and HL, demand is static.

Comparing demand in different states allows to identify time inconsistent behavior. First, in state LH, we would expect those with low discount factor to buy more often than other consumers. This is so, since in this state in addition to the current consumption consumer buys inventory for next period. A time inconsistent consumer expects that he wants to consume less in the future, but his payoff changes when the second period arrives. Therefore, in the second period, he might return to the store. To clarify this, consider the consumer payoffs. In period one, he buys one unit for current consumption if $d_1 > \beta p$, and another unit for future consumption if $d_2 > p$. Note that he uses a higher threshold for the second period instant payoff. Recall his first period payoff function, Equation (1), where he weights the instant benefit and future cost of consumption equally when both realize in the future, but in case of current consumption, he discounts only the cost. In the second period, he compares his payoff from consumption $d_2 - \beta p$ to the shopping cost C^H. If the discount factor is low enough, there exists a region of the second period instant payoff values $\beta p + C^H < d_2 < p$, that are low enough, so that the consumer did not buy inventory, but high enough, so that he will buy in the second period. The timing of purchases depending on the instant payoff values is summarized by Figure 2b.

Second, time inconsistent consumer purchases less for the future than for current consumption. To see this is, it is useful to first look at the static demand. I denote by Q the

[8] I assume that time inconsistent consumer is unware of his future time inconsistency problem. In the literature, this consumer is often called time inconsistent naive consumer.

static demand (expected quantity purchased without inventory) as a function of the current period shopping cost. Note that with unit demand this equals the probability of purchasing. Consider states LL and HL. In these states, each period consumer buys only for current consumption, since next period shopping cost is low and therefore he has no incentive to store inventory. He will purchase when his payoff from alcohol $d - \beta p$ is larger than the cost of shopping C. This determines the static demand as a function of shopping cost: $Q(C) = 1 - \beta p - C$. In state LH, decision problem is dynamic and consumer stores inventory. Time Consistent consumer's expected demand in this situation is just twice his static demand $2Q^{TC}(L) = 2(1-p)$. But Time Inconsistent consumer is less likely to buy inventory than for the current consumption. If his discount factor is not too low $\beta > \frac{p-C_H}{p}$, then his expected demand equals the sum of his own static demand and Time Consistent Consumers static demand $Q^{TIC}(L) + Q^{TC}(L) = (1-\beta p) + (1-p) < 2Q^{TIC}(L)$. Time Inconsistent consumer with very low discount factor, such that the high shopping cost does not prevent him from shopping next period, he will purchase additional quantity next period.

Comparison of demand in these two states LL and LH helps to pin down the the discount factor. Namely, if the discount factor is not too low, then

$$\frac{Prob(x_1 = x_2 = 0|LL)}{Prob(x_1 = x_2 = 0|LH)} = \beta \tag{3}$$

On Figure 2 which describes purhcases in these states as a function of instant payoffs, we see that β can be measured by the relative size of area denoted by B. If the discount factor is low enough, such that the high shopping cost does not prevent consumer from shopping next period, then the fraction gives us only the upper bound for the discount factor:

$$\frac{Prob(x_1 = x_2 = 0|LL)}{Prob(x_1 = x_2 = 0|LH)} = \begin{cases} \frac{(\beta p)^2}{\beta p^2} = \beta & \text{if } \beta > \frac{p-C_H}{p} \\ \frac{(\beta p)^2}{\beta p(\beta p + C^H)} \geq \beta & \text{if } \beta < \frac{p-C_H}{p} \end{cases} \tag{4}$$

Note that whenever the fraction is lower than one, then consumer is time inconsistent. The intuition comes directly from the definition of present biased preferences. Time inconsistent consumer wants to consume less when he chooses consumption for the future compared to when he chooses his current consumption.

Finally, we can identify the remaining parameters of the example from the static demand. High shopping cost can be measured by comparing the difference in the static demand with low and high shopping costs. Recall that the static demand as function of shopping cost equals $Q(C) = d - \beta p - C$. For example, in state LL and HL, demand in static. Therefore, comparison of the purchases in the first period in these states identifies the shopping cost as described on Figure 3 and:

$$Prob(x_1 > 0|HL) - Prob(x_1 > |LL) = Q(C^H) - Q(0) = C^H \tag{5}$$

When we have learned the value of the discount factor β from above, then static demand gives us the value of parameter p. For example, we could measure it by purchases in state LL:

$$Prob(x_1 > 0|LL) = Q(0) = 1 - \beta p \tag{6}$$

3 Institutional Background, Data, and Descriptive Analysis

3.1 Institutional Background

In U.S., as well as in other countries, public health agenda includes objectives to decrease alcohol consumption.[9] One of the policy measures suggested is to restrict the hours and days when retail stores can sell alcohol. For example, in 2010, 193 member states of World Health Organization adopted a resolution WHA63.13 on a global strategy to reduce the harmful use of alcohol. The strategy is meant to provide guidance to the member states and among the policy measures suggested, it includes (on page 14) "regulating days and hours of retail sales".[10]

In U.S., most states limit the days and hours alcohol can be sold in stores. Several states, and many local governments do not allow alcohol sales on Sundays and evenings. But during the past decade, several states have repealed the sales restrictions. While in 2001, fifteen states did not allow off-premise beer sales on Sunday, by 2011 five of those states had repealed the ban. The states which repealed the ban, are Delaware, Pennsylvania, and Massachusetts in 2003, and Rhode Island, and Virginia in 2004. Note that there are several exceptions to the state level beer sales restrictions. First, most states have permitted local governments to overrule the state's sales restriction. Second, some states regulate beer sales based on alcohol

[9] U.S. objectives for Healthy People 2020:
http://healthypeople.gov/2020/topicsobjectives2020/pdfs/HP2020objectives.pdf
World Health Organization's Global Status Report on Alcohol and Health 2011:
http://www.who.int/substance_abuse/publications/global_alcohol_report/msbgsruprofiles.pdf

[10] Source: http://www.who.int/substance_abuse/alcstratenglishfinal.pdf

content, banning only sales of beer with alcohol content more than 3.2% alcohol per weight (APW).[11]

Restrictions on alcohol sales time go back to the prohibition area, when alcohol sales was not allowed at all. It is argued that the main reason for lifting the restriction has been the hope to increase tax revenues. But as noted above, public health agendas stress that restrictions on sales time are important policy tools in reducing alcohol consumption. Therefore, in popular press, public health officials have voiced concern that repealing the sales bans has negative health consequences.

The dataset used in this paper is from Eau Claire county in Wisconsin, therefore let's look more closely at alcohol consumption and alcohol policy in this region. Wisconsin is a rather liberal state in terms of alcohol policy and there are no restrictions on selling beer on Sundays. During the time period of interest, in 2005 – 2007, most statistics describing alcohol consumption in Wisconsin were somewhat higher than US average. According to Wisconsin Epidemiological Profile on Alcohol and Other Drug Use, 2010.:

- Per capita alcohol consumption in Wisconsin was higher than US average. Namely, 2.9 – 3.0 gallons of ethanol per capita per year compared to 2.2 – 2.3 as US average.
- Heavy drinking was more prevalent among adults in Wisconsin than US average: 7 – 8% compared to 5% as the US average.[12]
- The prevalence of alcohol dependence and abuse among age 12 and older, was 9% in Wisconsin vs 8% in US on average.
- Age adjusted death rate from alcohol related causes is the same in Wisconsin as the US average, both being 7.4.[13]
- But specifically in Eau Claire county, alcohol related death rates are lower than in Wisconsin on average.
    - Age adjusted rate of alcohol related liver cirrhosis deaths per 100 000 population was about the same in Wisconsin (4.1 – 4.2) as the US average (4.0 – 4.1). For

[11] 3.2% alcohol per weight (APW) is equivalent to about 4.0% alcohol per volume, which is the usual measure reported on the bottle.

[12] The Centers for Disease Control and Prevention defines heavy drinking as more than two drinks per day for men and more than one drink per day for women.

[13] Rate is calculated as the number of deaths per 100 000 population. That is, rate equals 10, means 10 deaths of this cause for 100 000 people.

the combined time period 2000 –2008, in Eau Claire country it was 2.9, which is lower than Wisconsin average 4.2.

– Alcohol related motor vehicle injury rates are lower in Eau Claire county than in Wisconsin on average. In 2007, 75 per 100 000 population in Eau Claire county vs 99 in Wisconsin on average.

– The death rate from other alcohol-attributable causes is 13.9 in Eau Claire county vs 18.6 in Wisconsin on average, for the combined time period 2000 –2008.

3.2 Data

I use consumer level scanner data provided by SymphonyIRI Group, Inc.[14] For each day and each consumer, the consumer panel includes the quantity of beer purchased, the time of all shopping trips, including the ones when beer was purchased, purchases of other goods, and consumer characteristics. In addition to the panel data on consumers, there is price data that is obtained separately from stores. The dataset is from Eau Claire county in Wisconsin and covers time period from 2005 to 2007.

In this paper, I restrict attention to the consumers who purchase beer rather regularly. A household in a given year is included in the sample if it: (1) reported purchases in at least 26 weeks; (2) purchased beer at least on 10 weeks. Households can be different over the years. If a household satisfies these criteria one year, but not on the others, then it is included in the sample only that year. There are altogether almost 500 households that satisfy these criteria for at least one year. Table 1 displays descriptive statistics of these households.

The median household has two members and a total income of $80,000. A quarter of households include a male who does not work full time. Half of the households include a full time working female. There are children in 27% of households.

On a median weekend shopping trip, household spends $30. On a median weekend shopping trip when household purchases beer, then it spends $11 dollars on beer and purchases 24 bottles/cans. Figure 4 presents the histogram of beer purchases. Average price per bottle is $ 0.715.[15] Beer demand is higher in the summer and it is affected by public holidays. Figure 5 presents beer purchases by calendar week, and most of the holidays are easily recognizable from the graph: including Superbowl Sunday, Memorial Day Weekend, Labor Day Weekend,

[14]For more detail on this data, see Bronnenberg, Kruger, and Mela (2008). Note that Information Resources, Inc. ("IRI") has changed its name to SymphonyIRI Group, Inc.

[15]The price is based on store sales data and calculated as weighted average of the prices in grocery stores, the prices are weighted by the quantities. Then median of those prices is taken over all shopping trips.

Thanksgiving, Christmas.

3.3 Descriptive Analysis

The general intuition supported by the example in section 2 is that Time Inconsistent consumer buys more often. To see who are the consumers who behave this way, I examine the frequency of buying beer regressed on various household characteristics. In regressions in Table 2, the dependent variable in the first two columns is an indicator for purchasing beer conditional on a beer purchase the previous day. In the last two columns, dependent variable is purchasing at least twice (two days) from Friday to Sunday, conditional on having purchased at least once in those days.

The consumer characteristic that is strongly correlated with the frequency of beer purchases, is a measure for the likelihood of purchasing goods on display (in the end aisle). Purchasing goods on display probably captures consumer impulsivity. I construct the measure as the share of weeks the consumer purchased goods on display from the total number weeks that consumer purchased the same category of goods. I calculate this share for both beer and salted snacks. I look at salted snacks since this is a category where one expects consumers to make impulsive decisions.

Demographic characteristics do not have much explanatory power in explaining the frequency of beer purchases. Single member households and households with a male who neither works full time nor is retired tend to purchase beer more frequently. The effects are significant in the regressions for purchasing more than once from Friday to Sunday, but not in the regressions for purchasing on two consequtive days. All other household characteristics are also insignificant, including female working more than 35 hours, income per household member, indicator for female head of household, highest education obtained by the household heads.

In this dataset, beer is usually bought with other goods, consumer seldom purchases only beer. In the following, I assume that shopping costs are related to other purchases. Specifically, I assume that when consumer purchased other goods worth more than half of that paid for beer, the shopping cost is Low, and otherwise it is High. These shopping cost pairs define four states. Beer purchases in these states are presented in Table 3.

The illustrative example in section 2 provides a simple way to map data to the structural parameters that describe consumer behavior. According to Equation 3, we can find the discount factor from Table 3, by comparing the purchases in the state where consumer buys only for current consumption (LL) to that where he buys inventory (LH). Let's look at the last row of probabilities in the table, the probability of purchasing beer neither in period 1 nor 2, and let's compare states LL and LH. That gives discount factor equal to $\frac{0.644}{0.712} = 0.904$.

Other parameters of the example can also be learned from Table 3. According to Equation 5, the value of high shopping cost is given by the difference of the probability of buying in period 1 in states where the shopping cost is low and that where it is high, namely LL and HL, and hence equals $0.238 - 0.023 = 0.215$. Knowing the discount factor, we learn parameter p from Equation 6.

The illustrative example in section 2 also gave testable implications. One of the implications was that consumer buys more when he buys for current consumption (state LL) than for future consumption (state LH). To test the implication, I regress the total quantity bought during a weekend on week and household characteristics. Results are in Table 4. The estimates show that while controlling for observable characteristics, consumer buys less in weeks with High Shopping Cost (when he purchases fewer other goods). Again, none of the demographic characteristics of the households have much explanatory power in explaining the variation in the quantity.

4 Model

The model in this section has the same main ideas and the same implications for consumer behavior as the illustrative example presented in Section 2. The main differences are that here, unit demand assumption is relaxed and costs depend on price. I proceed to present the model, and then derive the equations which desribe consumer behavior. Those equations will be used in the next section for the structural estimation.

Setup: There are two goods, alcohol and a composite good, and two time periods, when consumer makes decisions. Each period $t = 1, 2$, consumer simultaneously decides how much alcohol to purchase x_t, how much to consume q_t and how much inventory to store for next period i_t. In the third period, consumer consumes the composite good. Price p is known to consumer and remains constant during these periods. The model is meant to describe decisions in a short time frame. A suitable time period is a day.

Purchasing alcohol has a cost per shopping trip. The shopping cost can take one of two values $C_t \in \{Low, High\}$, where $Low = 0$, $High = C^H > 0$. The value of the shopping cost does not depend on the quantity purchased. Storing is costless, but if indifferent, then consumer chooses not to store any inventory.

Consumer payoff from consuming q_t is affected by a random preference shock η_t that affects marginal utility and decreases the wish to consume. I assume that the preference shocks η_t is independently and identically distributed on $[0, \infty)$, according to a distribution with cumulative density function F. Utility is quasilinear in money and logarithmic in the amount of alcohol consumed $\log(q_t + \eta_t)$.

The uncertainty regarding consumption shocks (η_1, η_2) and shopping costs (C_1, C_2) realizes before period one. That is, from the consumer's perspective there is no uncertainty in the model, but for the econometrician, consumption shocks are unobserved.

Discounting: Consumer discounting is exactly the same as in the example. I consider discounting in the quasi-hyperbolic discounting framework (Laibson, 1997), sometimes called $\beta - \delta$ model, where β is the time inconsistent discount factor and δ is the time consistent exponential discount factor.

I restrict attention to the case, where there is no time consistent discounting ($\delta = 1$). Although, the assumption is restrictive, relaxing it, would not much change the results regarding the time inconsistent discount factor β. This is so, since the time period here is a day, and therefore any reasonable yearly discount factor would be more or less negligible. In the rest of the paper, discount factor always means time inconsistent discount factor.

I look at at two types of consumers who differ by their time inconsistent discount factor β. A Time Consistent (TC) consumer has the time inconsistent discount factor $\beta = 1$, and hence weights all current and future payoffs equally. A Time Inconsistent (TIC) consumer has $\beta < 1$, and hence discounts current payoff less than future payoffs. I assume that the time inconsistent consumer is unaware of his future time inconsistency problem, meaning that he incorrectly believes that he becomes time consistent in the future. In the literature, this is called the naive time inconsistent agent. An alternative would be to assume that the time inconsistent consumer is aware of his present biased discounting. In the literature, that is called the sophisticated time inconsistent agent. The share of sophisticated agents among the time inconsistent agents has been estimated in the literature, and found to be close to zero Fang and Wang (2012). Therefore, in the case of time inconistent consumers, I proceed with restricting attention only to naive consumers and will point out what would change if a consumer were aware of his present biasedness.

Consumer optimization problem: At period t, each consumer chooses his optimal alcohol consumption q_t, alcohol purchases x_t, and alcohol inventory i_t, given price p, current and future shopping costs, and current and future alcohol consumption shocks. Consumer has the following payoff function:

$$U_t(p, i_t, \beta) = \log(q_t + \eta_t) - \beta\alpha p x_t + \beta U_{t+1}(p, i_{t+1}, \beta = 1) - C_t \cdot 1[x_t > 0]$$

where η_t is alcohol consumption shock, α is marginal utility of income, and C_t is shopping cost. Payoff function U_t also depends on the current and future consumption shocks and shopping costs, and the parameters of the model, but I omit those to shorten the notation. I write U_{t+1} specifically at the point where discount factor equals one, to draw attention to the fact that discounting is time inconsistent. With time consistent discounting, we do not expect payoffs that are one or two periods away to be weighted equally, if a payoff one period away is weighted less than the current payoff.

Note that consumer discounts the price of alcohol, but not the positive payoff he receives from consuming alcohol. This is based on the assumption that consumption of the composite good takes place in the third period. The assumption is meant to capture the idea that at the moment of purchasing alcohol, one compares the cost to the the opportunity to buy alternative goods in the future.[16]

Optimization problem in period t is:

$$\begin{aligned} \max_{q_t, x_t, i_{t+1}} \ & U_t(p, i_t, \beta) \\ \text{s.t.} \ & U_3(p, i_3, \beta) = \alpha p i_3 \\ & q_t + i_{t+1} \leq x_t + i_t \\ & i_1 = 0 \end{aligned}$$

Similar to the illustrative example, the shopping cost pairs (either low or high) define four possible states. In short, the states are denoted by LL, HL, LH, HH. When the future shopping cost is low, then demand is static, that is, consumer does not buy inventory. I denote the static demand (expected quantity bought without inventory) given the current period shopping cost $C \in \{0, C^H\}$, by Q. The static demand equals

$$Q(C) = \int_0^{\frac{\Lambda(C)}{\beta\alpha p}} \left(\frac{\Lambda(C)}{\beta\alpha p} - \eta \right) dF(\eta),$$

where $\Lambda : [0, \infty) \to [0, 1]$ is such that $\Lambda^{-1}(x) = x - \log(x) - 1$. Note that Λ is decreasing and

[16]Note that the time inconsistent discounting modeled in this way is similar to the temptation goods in Banerjee and Mullainathan (2010).

$\Lambda(0) = 1$. Note that in order to purchase, benefits from consumption must be large enough to cover the shopping cost. This is not restrictive when shopping cost equals zero. But when shopping cost is high demand is lower due to the high shopping cost.

A consumer stores inventory only when shopping cost is high next period, that is, in states LH and HH. First, consider the state where shopping cost is low in period one and high in the second period. It is useful compare this state with the one where shopping costs were low in both periods. Time Consistent consumer buys the same total amount in both states

$$E(x_1^{TC}) = \begin{cases} Q^{TC}(L) & \text{in } LL \\ 2 \cdot Q^{TC}(L) & \text{in } LH \end{cases}, \qquad E(x_2^{TC}) = \begin{cases} Q^{TC}(L) & \text{in } LL \\ 0 & \text{in } LH \end{cases}$$

where $Q^{TC}(L)$ is his static demand with Low shopping cost. Time inconsistent consumer buys less, when he buys for next period compared to when he buys for the current period. If the discount factor is not too low, then:

$$E(x_1^{TIC}) = \begin{cases} Q^{TIC}(L) & \text{in } LL \\ Q^{TIC}(L) + Q^{TC}(L) & \text{in } LH \end{cases}, \quad E(x_2^{TIC}) = \begin{cases} Q^{TIC}(L) & \text{in } LL \\ 0 & \text{in } LH \end{cases}$$

where his static demand with Low shopping cost is $Q^{TIC}(L)$, and his inventory is $Q^{TC}(L) < Q^{TIC}(L)$. Let's summarize the consumer behavior in state LH. For the time consistent consumer shopping cost determines only the time of the shopping trips, but it has no impact on the total quantity. When it is costly to shop in the second period, but not in the first, then consumer just chooses his inventory equal to his second period optimal consumption. In case of time inconsistent consumer, shopping cost decreases his total quantity bought.

Finally, consider the state where shopping costs are high in both periods. In this state, consumer also stores inventory and now the shopping costs decrease consumption of both types of consumers. That is, time consistent consumer correctly predicts his next period preferences and behavior, but high shopping cost sometimes prevents him from purchasing. For details see Appendix A.

5 Identification and Estimation

5.1 Identification

5.1.1 Identification with observable shopping costs

I make the following assumptions regarding consumption shocks.

Assumption 1. *Consumption shocks for beer η_{int} are independently and identically distributed across consumers i, weeks n and days t, conditional on observable time and consumer characteristics Z_{int}, according to log-normal distribution with parameters $\mu + \kappa Z_{int}$ and σ.*

Specifically, I assume that

$$\begin{aligned} E\left[\log \eta_{int}\right] &= \mu + \kappa_1 \cdot Sunday_{nt} + \kappa_2 \cdot Summer_n + \kappa_3 Income_i \\ &\quad + \kappa_4 PreviousPurchase_{in} \end{aligned} \tag{7}$$

where Sunday is a dummy variable, Summer is dummy variable for dates from Memorial Day to Labor Day weekends, Income is household's income, and Previous Purchase is a dummy variable indicating a beer purchase earlier during the same week.

Regarding shopping costs I assume here that it is observable whether shopping cost is zero or not.

Assumption 2 (Observable Shopping Costs)**.** *If consumer purchases a large quantity of other goods together with beer, then his shopping cost equals zero. Otherwise shopping cost equals C^H.*

Suppose that for each consumer for many pairs of time periods, we observe his quantity of beer purchased and prices (even when he did not purchase anything), and suppose we observe whether shopping cost equals zero or not. Then using the model and the data, we want to identify discount factor β, marginal utility from income α, shopping cost C^H, and parameters of the consumption shock distribution μ and σ. We can identify all these for each consumer separately, using higher order moments of demand in four states that are defined by shopping costs (High and Low shopping costs in two periods).

The parameters of the distribution of consumption shocks F and $(\beta\alpha)$ are identified from static demand using data on quantities and prices. To do that the following equation at different quantities is used:

$$Prob(x_t > K|LL) = F\left(\frac{1}{\beta\alpha p} - K\right), \quad K \geq 0 \tag{8}$$

Identification of discount factor β is based on the same idea as equation 3 in the example. Namely, we compare purchases in a state where demand is static and that where consumer is predicted to buy inventory for the 2nd period: states LL and LH. When we have already learned the distribution of consumption shocks F as described above, then by combining equation (8) and

$$Prob(x_1 = 0|LH) = \left[1 - F\left(\frac{1}{\beta\alpha p}\right)\right]\left[1 - F\left(\frac{1}{\alpha p}\right)\right] \tag{9}$$

we can identify both α and β separately. High shopping cost C^H is identified by the comparison of purchases in states where demand is static but shopping cost varies: states HL and LL. Namely, equation

$$Prob(x_1 > 0|HL) = F\left(\frac{\Lambda(C^H)}{\beta\alpha p}\right) \tag{10}$$

identifies the value of shopping cost C^H, since Λ is strictly monotone in C^H.

5.1.2 Identification with partly unobservable shopping costs

Next let's relax the assumption of observable shopping costs, by substituting Assumption 2 with the following.

Assumption 3 (Partly Unobservable Shopping costs)**.** *If consumer purchases a large quantity of other goods together with beer, then his shopping cost equals zero. Otherwise shopping cost equals zero with probability γ and C^H with problability $1-\gamma$.*

Let's denote by $\widehat{CC}$ the state corresponding to observables. For example, $\widehat{LL}$ denotes large purchases of other goods in both periods. Then the following relationships hold:

$$Prob(.|\widehat{LL}) = Prob(.|LL)$$

$$Prob(.|\widehat{HL}) = \gamma Prob(.|LL) + (1-\gamma)Prob(.|HL)$$

$$Prob(.|\widehat{LH}) = \gamma Prob(.|LL) + (1-\gamma)Prob(.|LH)$$

$$Prob(.|\widehat{HH}) = \gamma^2 Prob(.|LL) + (1-\gamma)^2 Prob(.|HH) + \gamma(1-\gamma)^2 Prob(.|LH) + \gamma(1-\gamma)^2 Prob(.|HL)$$

Because $Prob(.|\widehat{LL}) = Prob(.|LL)$, we can identify $(\beta\alpha), \mu, \sigma$ from $Prob(.|\widehat{LL})$ like before. Knowing the above, and if shopping cost is large enough $C^H > 0$ such that there exist a price at which $Prob(x_1 > 0|p, LL) = 1$ and $Prob(x_1 = 0|p, HL) = 1$, then the demand at this range of prices identifies γ from $Prob(.|\widehat{HL})$. Knowing γ, and looking at $Prob(.|\widehat{HL})$ at lower prices identifies C^H. Knowing γ, we can identify β from $Prob(.|\widehat{LH})$ as in the previous section.

5.2 Estimation

I estimate parameters of the model using the following data. For consumer i and over time period pairs indexed by $n = 1, \ldots, N$, we observe beer prices $(p_{11}, p_{12}, \ldots, p_{N1}, p_{N2})$, purchased beer quantities $(x_{11}, x_{12}, \ldots, x_{N1}, x_{N2})$, and by either assumption 2 or 3 shopping costs $(C_{11}, C_{12}, \ldots, C_{N1}, C_{N2})$.[17] Beer is treated as a homogeneous product and quantity of beer is measured in bottles/cans. The price of beer is the average price across all products from all supermarkets in this area that are included in the dataset. In the aggregation the prices are weighted by the quantity sold. Let's denote the above data by Y.

I estimate the share of time inconsistent consumers $1-\rho$, their discount factor β, and other parameters $\theta = (\alpha, C^H, \mu, \sigma)$ from a mixture model by ML using EM algorithm. Contribution of consumer i with a given discount factor to the likelihood is presented in Appendix B. To summarize that, each consumers contribution to the likelihood is the sum of likelihoods in each state. I use data on quantities in states LL, HL, LH, but only probability of buying in state HH.

In the Log-likelihood, consumer i is time consistent (TC) with probability ρ and time inconsistent with probability $1 - \rho$. Since consumer type is unobservable, the log-likelihood is an expectation over the unobservable consumer type:

$$\log L = E\left[\sum_i \log\left(1[i \text{ is } TC]\rho L_i(1, \theta, Y) + [1 - 1[i \text{ is } TC]]\,(1-\rho)L_i(\beta, \theta, Y)\right)\middle| Y\right] \quad (11)$$

where $1[i \text{ is } TC]$ is an indicator function for time consistent consumer, and $L_i(1, \theta, Y)$ and $L_i(\beta, \theta, Y)$ are consumer i's contributions to the likelihood if he were time consistent and time inconsistent respectively. We can rewrite the above log-likelihood after taking the expectation as:

$$\log L = \sum_i \left[\rho_i \log \rho + \rho_i \log L_i(1, \theta, Y) + (1-\rho_i)\log(1-\rho) + (1-\rho_i)\log L_i(\beta, \theta, Y)\right] \quad (12)$$

[17] The assumptions gave that it is observable when consumer has shopping cost equal to zero. That is, he is in the store buying other goods, and can costlessly buy beer.

where ρ_i denotes the conditional expectation:

$$\begin{aligned} \rho_i &= E\left(1[i \text{ is } TC] \right| \rho, \beta, \theta, Y) = Prob_i(TC|\rho, \beta, \theta, Y) \\ &= \tfrac{\rho L_i(1,\theta,Y)}{\rho L_i(1,\theta,Y)+(1-\rho)L_i(\beta,\theta,Y)} \end{aligned} \tag{13}$$

I estimate the parameters using EM algorithm, which is just an iterative ML estimation.[18] In the following part of the section, I describe the procedure. I maximize (12) over ρ, β and θ using the following steps. First, I fix some initial values for ρ, β and θ. Then in step 2, given these parameter values and data, for each consumer i, I calculate his probability of being time consistent, ρ_i, according to equation (13) using Bayesian updating. In step 3, I substitute these consumer specific probabilities ρ_i-s into equation (12) to obtain new estimates of β, θ and ρ by ML. The maximization problem in step 3, can be separated in the following way:

$$(\hat{\beta}, \hat{\theta}) = \arg\max_{\beta,\theta} \sum_i \left[\rho_i \log L_i(1, \theta, Y) + (1 - \rho_i) \log L_i(\beta, \theta, Y)\right] \tag{14}$$

$$\hat{\rho} = \frac{1}{I} \sum_{i=1}^{I} \rho_i \tag{15}$$

where I denotes the number of consumers. Then using the new parameter estimates from (14) and (15), I go back to step 2 and calculate new ρ_i-s. I iterate over steps 2 and 3 until convergence.

6 Estimation Results

Table 5 presents estimates of the parameters of the model. According to the estimation results of the baseline model in Column 1, 20% of consumers are time inconsistent, having a time inconsistent discount factor equal to 0.44. The estimate from the baseline model implies an annualized discount rate 0.36 if we continue to assume that time consistent discount factor equals one, $\delta = 1$.[19]

My estimate of time inconsistent discount factor is in the range that previous studies have found. Most other studies estimate a common discount factor for all consumers. I allow two types of consumers, either with discount factor equal to 1 or with discount factor $\beta < 1$. Hence, my estimate of β is the discount factor for the especially present biased

[18]Note that I could also maximize the likelihood function directly.
[19]The annualized discount rate equals $-\log(\beta\delta)$.

group of consumers. Many recent studies using data from various topics, estimate a common time inconsistent discount factors to be from 0.5 to 0.9. For example, based on savings and consumption decisions; Laibson, Repetto, and Tobacman (2007) estimate $\beta = 0.7$, and Brown, Chua, and Camerer (2009) from 0.6 to 0.7; Fang and Wang (2012) estimate β to be from 0.56 to 0.71 based on mammography decisions; Tanaka, Camerer, and Nguyen (2010) in experiments in Vietnam get β to be from 0.74 to 0.89. Frederick, Loewenstein, and O'Donoghue (2002) provide an extensive overview of discount rate estimates based on both field and lab studies and the general conclusion in the literature seems to be that discount rates can take a wide range of values, from slightly negative values to plus infinity.

Although, only a small percentage of consumers are estimated to be time inconsistent, they account for a larger share in total beer consumption. According to the estimates from the baseline model, 20% of consumers are time inconsistent. But since time inconsistent consumers consume more beer, their share in the total beer consumption is much larger, namely 64%. This drives the welfare implications.

For time inconsistent consumers discount factor β directly corresponds to the imaginary price reduction. That is, when buying for current period, then for time inconsistent consumers the effective price is just 0.44 of the regular price. Which also implies that if government could discriminate and tax time inconsistent consumers, he can offset the present biased discounting.

Price elasticity of beer according to my baseline estimates equals - 2.57 for time consistent consumers and -2.12 for time inconsistent consumers. The elasticity is calculated as discussed in Appendix C according to equation (20). It is calculated for static demand for the state when shopping cost equals zero. The elasticity should be interpreted as a percentage change in average quantity as price changes and it is calculated at the median price value.[20]

The estimated alcohol own price elasticity is higher than found in most of the literature. In the literature, based on aggregate data alcohol demand is usually estimated to be inelastic.[21] Using micro data and allowing heterogeneous price responses, several studies have found that those consumers who drink more, respond less to price. Manning, Blumberg, and Moulton (1995) study how price elasticity varies with the level of drinking (measured in volume). For a median drinker they estimate price elasticity to equal - 1.19, but price responsiveness is lower for those who drink a lot. Ayyagari, Deb, Fletcher, Gallo, and Sindelar (2012) estimate price elasticity for two groups of consumers in a mixture model. For the group of consumers

[20] In the calculation I use scaled prices (the actual price of the bottle divided by ten), since these are the prices used in the estimatation.

[21] For an overview of alcohol price elasticity estimates see Wagenaar, Salois, and Komro (2009).

who drink more, they estimate price elasticity to be close to zero, for rest of the consumers (which is about 75% all consumers) estimated price elasticity equals -1.6. My estimates imply a similar result. Time inconsistent consumers drink more and respond less to price.

Estimated shopping cost from the baseline model equals about $11. Remember that the shopping cost can take two values, either zero or this estimated higher value, and therefore the average shopping cost is lower. There are somewhat similar shopping cost values estimated in the literature. For example, Erdem, Imai, and Keane (2003) estimate ketchup demand and find that for the most popular size (32 ounce) ketchup, their estimated shopping cost is slightly higher than a typical price of the product.

In Table 5 in columns 2 to 4 , beer consumption shocks are modeled according to equation (7). The model in column 2, includes Sunday and Summer dummies. The model in column 3, adds household income. Column 4, includes dummy for for beer purchases earlier during the same week. The main parameter estimates are very similar across all these models.

The model is not well suited to take into account beer purchases for big social events. Therefore, for robustness check I exclude holidays from the sample. The estimation results of the same models but with the smaller sample of holidays excluded are in Table 6. The estimated share of time consistent consumers is now somewhat higher 0.82 and discount factor is even lower 0.38.

Finally, I use the alternative assumption regarding shopping costs, Assumption 3, according to which shopping costs are partially unobservable. The estimation results with the alternative assumption are in Table 7, where column 1 presents results with the full sample, and column 2 with the smaller sample where holidays are excluded. I estimate the share of Low shopping costs γ to be 0.12. The estimated share of time consistent consumers is now lower, 0.76, and discount factor is higher, 0.7. The higher discount factor estimate and higher shopping cost estimate are expected. Since in some of the cases where consumer showed behavior that earlier was attributed to time inconsistent discounting, is now attributed to low shopping costs.

7 Counterfactual Analysis

7.1 Sunday Sales Restriction

In this section, I consider a counterfactual experiment where alcohol sales is prohibited on Sundays. In the model, the restriction is equivalent to increasing the second period shopping cost. I introduce a total ban on the second period sales, $C_2 \to \infty$. I assume that the distribution of first period shopping costs remains unchanged.This is of course restrictive to assume that in response to alcohol sales restriction, consumers don't change their general shopping behavior, that is time when they buy other goods. The assumption is suitable for consumers for whom alcohol perhaps is not that important in their weekly shopping basket, and who have other constraints that determine their weekly shopping schedule.

For the time consistent consumer, restricting sales in the second period has any impact only due to shopping costs. That is, only when shopping in the first period is costly, does the sales restriction reduce his demand. That is described on Figure 8a, which presents percentage decrease in consumption as a function of shopping cost parameter C^H with and without sales restriction. Without shopping costs, the time consistent consumer stores all the inventory that he otherwise would have bought in the second period. With shopping costs, his demand with the sales restriction is lower, exactly due to those weeks when it is costly for him to buy on Saturdays.

For the time inconsistent consumer, the sales restriction reduces demand for two reasons. First, the shopping costs, which is the same as for the time consistent consumer above. The second reason is that when he has to plan ahead, then he buys less. Note that even without shopping costs, the restriction still decreases his consumption due to the second effect. To see how the decrease in consumption is related to shopping cost in the first period see Figure 8b. Note that for time inconsistent consumers the impact of the restriction is relatively larger when shopping costs are small. This is so, since high shopping cost itself provides a partial commitment device. This effect can be seen as a discontinuity in the decrease in consumption on Figure 8b.

For the welfare analysis, one first has to clarify how should we think of time inconsistent consumer's welfare. Here, I take the common approach in the literature and consider the long-term self's welfare (see for example, O'Donoghue and Rabin (2006)). This is expressed by the time consistent consumer payoff.

The welfare impact of the decrease in consumption is different for the two types of consumers. For the time consistent consumer, any decrease in consumption lowers his welfare. Hence, with the restriction he is worse off than without it. But for the time inconsistent consumer, a decrease in consumption can increase his welfare. This is so, since without the restricion his consumption was actually larger than his long term self welfare maximizing quantity. Altogether, this implies that the sales restriction can increase total consumer welfare by helping time inconsistent consumers to make better decisions. Their welfare increase comes at the expense of time consistent consumers.

With the current shopping cost distribution, sales restriction decreases the weekend consumption of time consistent consumers by 25%. As expected, on time inconsistent consumers the impact is much larger, their consumption decreases by 46%. This leads to a decrease in aggregate consumption by 38%. In terms of welfare, the estimates imply that the sales restriction increases time inconsistent consumer welfare. Rembember that the restriction always decreases time consistent consumer welfare, as long as shopping costs are not zero. The overall effect on consumer welfare is positive. That is, even though, it decreased time consistent consumers' welfare, the increase in time inconsistent consumers' welfare was larger.

7.2 Comparison With Sales Tax

Alcohol is regulated mainly because it is considered to be a good with negative externality. The externality includes both direct costs for the society like drunk driving and indirect costs like alcohol consumers' health problems. Due to these costs the socially optimal level of alcohol consumption is lower than the private optimum. Current paper does not consider the externality from alcohol, and cannot find the alcohol consumption level that is optimal taking into account the externality. But we can ask the question which policy instrument should we use to decrease consumption in this case.

In the standard model, economic theory tells us that we can obtain the first best solution using Pigouvian taxes, distortionary taxes that equate the social payoff with the private one. But the question is what is the optimal policy tool in case of time inconsistent consumers. Specifically, I ask whether taxes are welfare improving compared to the sales restriction in achieving the same decrease in consumption. First, I look at the aggregate consumption and find the tax rate that leads to the equivalent consumption decrease as the sales restriction. Then I compare the welfare impact of this tax rate and the sales restriction.

Health policy is not only concerned about aggregate consumption, but specifically wants to limit heavy drinking. In this dataset a proxy for heavy drinking is large purhcases. Specifically, I define a large purchase as at least 13 bottles of beer. I will do a similar exercise as above for the tax rate that leads to the same decrease in the share of these large purchases as the sales restriction.

Let's first compare a sales tax and the sales restriction in terms of the impact on aggregate consumption. Figure 9 shows that restricting sales on Sunday, leads to a decrease in weekend consumption by 38%. The same decrease in consumption can be achieved by increasing the sales tax by 21 percentage points. On Figure 10, similar comparison is done for large purchases. Restricting sales on Sunday leads to a decrease in large purchases by 32%. The same decrease in large purchases can be achieved by increasing sales tax by 19 percentage points. Much lower tax is needed to decrease large purchases among time consistent consumers.

Having found the tax rates that are equivalent to the sales restriction in terms of decreasing consumption, consider the welfare. Figure 11a graphs the decrease in time consistent consumer welfare due to these policies. Note that both the sales restriction and taxes decrease time consistent consumer's welfare. Suppose all consumers were time consistent, and consider whether to restrict sales or increase taxes in order to reduce their consumption. If all consumers were time consistent, the sales restriction would reduce consumption the same amount as a 11 percentage point tax increase. This tax rate is slightly welfare improving compared to the sales restriction. If we were to take into account tax revenues, taxes would become even more preferable for time consistent consumers. But in case of time inconsistent consumer, whose welfare is described on Figure 11b, both the sales restriction and taxes improve his welfare. In terms of the impact on consumption, the sales restriction was equivalent to a 30 percentage point tax increase. In terms of consumer welfare, the sales restriction is preferable. But note that this does not take into account tax revenues.

Finally, consider the aggregate consumer welfare, including also tax revenues. Figure 12 presents the aggregate consumer welfare with the sales restriction and a tax increase, where a common tax rate is applied to both types of consumers. It shows that the sales restriction increases aggregate consumer welfare. Taxes are almost welfare neutral when we do not take into account tax revenue. But when we include tax revenue, then taxes also increase aggregate consumer welfare.

We saw above that we can achieve the same reduction in alcohol consumption using either taxes or the sales restriction. When we compare the policies that achieve the same reduction in consumption, then in terms of the aggregate consumer welfare, the sales restriction is preferable to taxes. This is so, even if we take into account tax revenue. As discussed above, the sales restriction has two effects. First, for both types of consumers, it increases costs by making it more inconvenient to buy. But for time inconsistent consumers, it also has a positive effect, as it provides them a commitment device. In comparison, taxes are more flexible in allowing consumers to choose when to decrease consumption. Since time consistent consumers do not benefit from commitment, they prefer the tax increase. However, according to the estimates, the commitment effect for the time inconsistent consumers is large enough to compensate for the welfare loss from the sales restriction.

8 Conclusions

I provided a model where sales restrictions decrease consumption if consumers are time inconsistent or shopping is costly. Using scanner data of beer purchases, I estimated the fraction of time inconsistent consumers to be 20%, and they account for 64% of beer consumption. I found that restricting sales on Sunday leads to a decrease in weekend consumption that can be achieved by increasing sales tax by 21 percentage points. But the sales restriction is welfare improving compared to the tax increase. Although, taxes are more flexible in allowing consumers to choose when to decrease their consumption, but the sales restriction provides a commitment device for time inconsistent consumers allowing them to improve their welfare. Apparently, the second effect more than balances the increase in costs associated with the sales restriction. The implication of this analysis is that with a significant share of time inconsistent consumers, the alcohol sales restrictions may be a good health policy tool.

The analysis presented here could be extended to take into account other potential reasons why sales restrictions decrease consumption, for example, storing costs. To better understand the impact of sales restrictions on consumption, data from policy experiments should be used. Future research should also look at time inconsistent behavior in consumption of other unhealthy goods, for example, the importance of time inconsistent preferences for obesity.

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A State with High Shopping Costs

Consider the state where shopping costs are high in both periods. The quantity that consumer purchases for period t consumption equals $\frac{1}{\beta\alpha p} - \eta_t$ if consumer buys it in period t, and it equals $\frac{1}{\alpha p} - \eta_t$ if consumer stores it as inventory in period $t-1$. If consumer purchases something in period one, then he buys inventory, if $\eta_2 < \frac{1}{\alpha p}$. Let's now look at when consumer purchases something. Let's first consider the case, where discount factor is not too low. The consumption shock realizations, where consumer purchases in period one and two, are described on Figure 6 and given with the following equations.

$$Prob(x_1 > 0, x_2 = 0|HH) = \int_0^{\infty} \int_0^{\bar{\eta}_1(\eta_2)} dF_{\eta_1}(\eta_1) dF_{\eta_2}(\eta_2) \tag{16}$$

and

$$Prob(x_1 = 0, x_2 = 0|HH) = \int_{\frac{\Lambda(C^H)}{\beta\alpha p}}^{\infty} \int_{\bar{\eta}_1(\eta_2)}^{\infty} dF_{\eta_1}(\eta_1) dF_{\eta_2}(\eta_2) \tag{17}$$

$$Prob(x_1 = 0, x_2 > 0|HH) = \int_0^{\frac{\Lambda(C^H)}{\beta\alpha p}} \int_{\bar{\eta}_1(\eta_2)}^{\infty} dF_{\eta_1}(\eta_1) dF_{\eta_2}(\eta_2) \tag{18}$$

where

$$\bar{\eta}_1(\eta_2) = \begin{cases} \frac{\Lambda(C^H)}{\beta\alpha p} & \frac{1}{\alpha p} < \eta_2 \\ \frac{\Lambda\left[C^H - \beta\Lambda^{-1}(\alpha p \eta_2)\right]}{\beta\alpha p} & \frac{\Lambda(C^H)}{\alpha p} < \eta_2 < \frac{1}{\alpha p} \\ \frac{\Lambda((1-\beta)C^H)}{\beta\alpha p} & \eta_2 < \frac{\Lambda(C^H)}{\alpha p} \end{cases}$$

When discount factor is low enough, then in addition to the above, demand in the second period may be positive as described on Figure 7.

B Contribution of Consumer i to the Log-Likelihood

The log-likelihood of observing the purchases of consumer i can be separated into the log-likelihoods of states: $\log L_i = \sum \log L_i^S$. Moreover, in all the states where the shopping cost is low in the 2nd period, the likelihood can be separated even further. In states $S = LL, HL$, decision problem is static, and therefore x_{1n} and x_{2n} are independent. So, in these states, probabilities can be separated across periods $t = 1, 2$: $\log Prob(x_{1n}, x_{2n}|S) = \log Prob(x_{1n}|S) + \log Prob(x_{2n}|S)$.

I will not try to match the exact quantities, but instead quantity intervals, defined by the following ordered points $X_0 = 0 < \cdots < X_K = \infty$ indexed by k. For now, I take $K = 3$. The thresholds I choose separately for each state. Specifically, the first threshold is the 25th percentile of the distribution of quantities purchased in the first period (that includes only strictly positive quantities). The second threshold is the median of the same distribution. In both states LL and LH, the quantity thresholds are 12 and 24 bottles of beer.

The likelihood in states LL, HL can be written as:

$$\log L_i^S = \sum_{n=1}^{N} 1[s] \sum_{t=1,2} \{1[x_{tn} = 0] \cdot \log Prob(x_{tn} = 0|C_t) + \sum_{k=1}^{K} 1[X_{k-1} < x_{tn} \leq X_k] \cdot \log Prob(X_{k-1} < x_{tn} \leq X_k|C_t) \Bigg\}, \quad S = LL, LH$$

where

$$Prob(x_{tn} = 0|C_t) = 1 - \Phi(\frac{\log \Lambda(C_t) - \log \beta\alpha p_{tn} - \mu}{\sigma})$$

and

$$Prob(X_{k-1} < x_{tn} < X_k|C_t) = \Phi\left(\frac{\log \max\{\frac{\Lambda(C_t)}{\beta\alpha p_{tn}} - X_{k-1}, 0\} - \mu}{\sigma}\right) - \Phi\left(\frac{\log \max\{\frac{\Lambda(C_t)}{\beta\alpha p_{tn}} - X_k, 0\} - \mu}{\sigma}\right)$$

In state LH I will try to match quantities only in the first period, and for the second period match only the indicator of buying or not. The likelihood in state LH is:

$$\begin{aligned}\log L_i^{LH} = &\sum_{n=1}^{N} 1[LH] \cdot \{1[x_{1n} = 0, x_{2n} = 0] \cdot \log Prob(x_{1n} = 0, x_{2n} = 0|LH) \\ &+ \sum_{k=1}^{K} 1[X_{k-1} < x_{1n} \leq X_k, x_{2n} = 0] \cdot \log Prob(X_{k-1} < x_{1n} \leq X_k, x_{2n} = 0|LH) \Bigg\} \\ &+ \sum_{n=1}^{N} 1[LH] \cdot \{1[x_{1n} = 0, x_{2n} > 0] \cdot \log Prob(x_{1n} = 0, x_{2n} > 0|LH) \\ &+ \sum_{k=1}^{K} 1[X_{k-1} < x_{1n} \leq X_k, x_{2n} > 0] \cdot \log Prob(X_{k-1} < x_{1n} \leq X_k, x_{2n} > 0|LH) \Bigg\}\end{aligned}$$

In the last state, I match only the probability of buying in each period:

$$\log L_i^{HH} = \sum_{n=1}^{N} 1[HH] \cdot \{1[x_{1n} = 0, x_{2n} = 0] \cdot \log Prob(x_{1n} = 0, x_{2n} = 0|HH)$$
$$+ 1[x_{tn} > 0, x_{2n} = 0] \cdot \log Prob(x_{1n} > 0, x_{2n} = 0|HH)$$
$$+ 1[x_{1n} = 0, x_{2n} > 0] \cdot \log Prob(x_{1n} = 0, x_{2n} > 0|HH)$$
$$+1[x_{1n} > 0, x_{2n} > 0] \cdot \log Prob(x_{1n} > 0, x_{2n} > 0|HH)\}$$

In case of partially unobservable shopping costs the likelihood is extended by including parameter γ as described in Section 5.1.2 where identification was discussed.

C Price Elasticity

I calculate price elasticity in the state where shopping costs are low in both periods. That is the price elasticity in case of static demand and low shopping cost. There are different ways how, to think about elasticity here. I look at the percentage change in the average quantity (expected demand) as price changes. Since the expected quantity equals:

$$E(q) = \int_0^{\frac{1}{\alpha p}} \left(\frac{1}{\beta \alpha p} - \eta \right) dF(\eta) \tag{19}$$

the percentage change in the quantity equals

$$\frac{\partial E(q)}{\partial p} \frac{p}{E(q)} = -\frac{1}{\beta\alpha p} \cdot \frac{F\left(\frac{1}{\beta\alpha p}\right)}{E(q)} = -\frac{1}{\beta\alpha p} \cdot \frac{F\left(\frac{1}{\beta\alpha p}\right)}{\frac{1}{\beta\alpha p} F\left(\frac{1}{\beta\alpha p}\right) - \int_0^{\frac{1}{\alpha p}} \eta dF(\eta)} = -\frac{1}{1 - \beta\alpha p \cdot \frac{\int_0^{\frac{1}{\beta\alpha p}} \eta dF(\eta)}{F\left(\frac{1}{\beta\alpha p}\right)}}$$
$$= -\frac{1}{1 - \beta\alpha p \cdot \frac{\exp(\mu + \frac{1}{2}\sigma^2)\left[1 - \Phi\left(\frac{\mu + \sigma^2 + \log \beta\alpha p}{\sigma}\right)\right]}{\Phi\left(\frac{-\log \beta\alpha p - \mu}{\sigma}\right)}} \tag{20}$$

The absolute value of the elasticity is decreasing in $(\beta\alpha)$. Therefore, the lower is the discount factor, the less consumer reacts to price changes. This also implies that time inconsistent consumer is less price sensitive than time consistent consumer. Note how the elasticity changes with the parameters of consumption shock distribution. The absolute value of the elasticity is increasing in μ and decreasing in σ.

Tables and Figures

Table 1: Summary statistics

	mean	sd	min	max	median
Household demographic characteristics					
Household's income ($10,000)	8.2	2.7	<1	>10	8.0
Family size	2.6	1.2	1	6	2.0
Includes non-fulltime working male	0.248	0.433	0	1	0
Includes fulltime working female	0.503	0.501	0	1	1
Includes children	0.274	0.446	0	1	0
Shopping trip characteristics					
Quantity (number of bottles/cans) bought	23.541	15.947	1	270	24
Price ($)	0.710	0.019	0.667	0.750	0.715
Total expenditure ($)	42.984	42.888	0.010	1064.978	29.678
Total beer expenditure when purchasing ($)	12.723	7.561	0.540	135.580	11.390

Note: In case of household demographic characteristics, an observation is a household. In case of shopping trip characteristics, an observation is a shopping trip on weekends.

Table 2: Frequency of beer purchases and household's characteristics

	(1)	(2)	(3)	(4)
Share of Items Purchased on Display	0.289*	0.236***	0.208**	0.194***
	(0.153)	(0.086)	(0.088)	(0.067)
Single Person Household		0.103		0.105*
		(0.063)		(0.058)
Male Not Working Full Time		0.015		0.061**
		(0.026)		(0.027)
HH Characteristics	No	Yes	No	Yes
Day and Seasonal Variables	Yes	Yes	Yes	Yes
R-squared	0.027	0.071	0.013	0.034
N	24284	24284	19897	19897

Note: Dependent variable in the first two columns is indicator for purchasing beer conditional of a beer purchase on the previous day. In the last two columns, dependent variable is purchasing at least twice (two days) from Friday to Sunday, conditional on having purchased at least once. An observation in the first columns is a household-day pair. An observation in the last two columns is a household-week pair. *Male not working full time* is an indicator for households that have a male household head who neither works full time nor is retired. All regressions include *Day and seasonal variables* like dummy for Summer, and dummy for the 4th of July, and the first two regressions include dummy for Monday. *Household characteristics* include female working more than 35 hours, income per household member, indicator for female head of household, highest education obtained by the household heads. Standard errors are clustered at household level and are included in paranthesis.

Table 3: Probability of purchasing beer in the following periods

	LL	HL	LH	HH
Period 1	0.238	0.023	0.275	0.019
Period 2	0.165	0.231	0.016	0.013
Periods 1 and 2	0.047	0.005	0.004	0.001
Neither 1 nor 2	0.644	0.750	0.712	0.969
Number of Obs	3649	8338	9822	21418

Table 4: Total quantity bought during a weekend, in states LL and HL

	(1)	(2)
High Shopping Cost	-0.071***	-0.065***
	(0.021)	(0.010)
Price	-0.003	-0.264
	(0.340)	(0.316)
Consumer Fixed Effects	No	Yes
HH Characteristics	Yes	No
Seasonal Variables	Yes	Yes
R-squared	0.011	0.169
N	12948	12948

Note: Dependent variable is total quantity bought during a weekend. Sample includes states LL and LH. An observation a household-week pair. *High Shopping Cost* is an indicator for state LH. All regressions include *Seasonal variables* like dummy for Summer, and dummy for the 4th of July. *Household characteristics* include female working more than 35 hours, income per household member, indicator for female head of household, highest education obtained by the household heads, an indicator for households that include a male household head who neither works full time nor is retired, an indicator for single person households. Standard errors are clustered at household level and are included in paranthesis.

Table 5: Structural model parameter estimates

	(1)	(2)	(3)	(4)
Share of time consistent consumers ρ	0.805	0.808	0.807	0.804
	(0.021)	(0.024)	(0.021)	(0.021)
Discount factor β	0.438	0.438	0.437	0.438
	(0.011)	(0.011)	(0.011)	(0.011)
Marginal utility of income α	0.453	0.448	0.448	0.451
	(0.010)	(0.019)	(0.010)	(0.009)
High shopping cost C^H	0.524	0.498	0.498	0.509
	(0.043)	(0.071)	(0.041)	(0.040)
μ	0.059	0.143	0.236	0.263
	(0.030)	(0.047)	(0.048)	(0.049)
σ	1.168	1.155	1.150	1.162
	(0.047)	(0.076)	(0.045)	(0.043)
Sunday κ_1		-0.080	-0.075	-0.075
		(0.025)	(0.025)	(0.025)
Summer κ_2		-0.130	-0.130	-0.129
		(0.021)	(0.020)	(0.020)
Income κ_3			-0.012	-0.013
			(0.004)	(0.004)
Earlier Purchase κ_4				-0.051
				(0.021)

Note: The beer consumption shock distribution in columns 2-4 is given by equation (7). The model in column 2 includes dummy variables for Sunday and Summer, column 3 includes household income and column 4 includes a dummy variable that indicates a beer purchase earlier during the same week. Asymptotic standard errors are included in paranthesis.

Table 6: Parameter estimates with a sample that excludes holidays

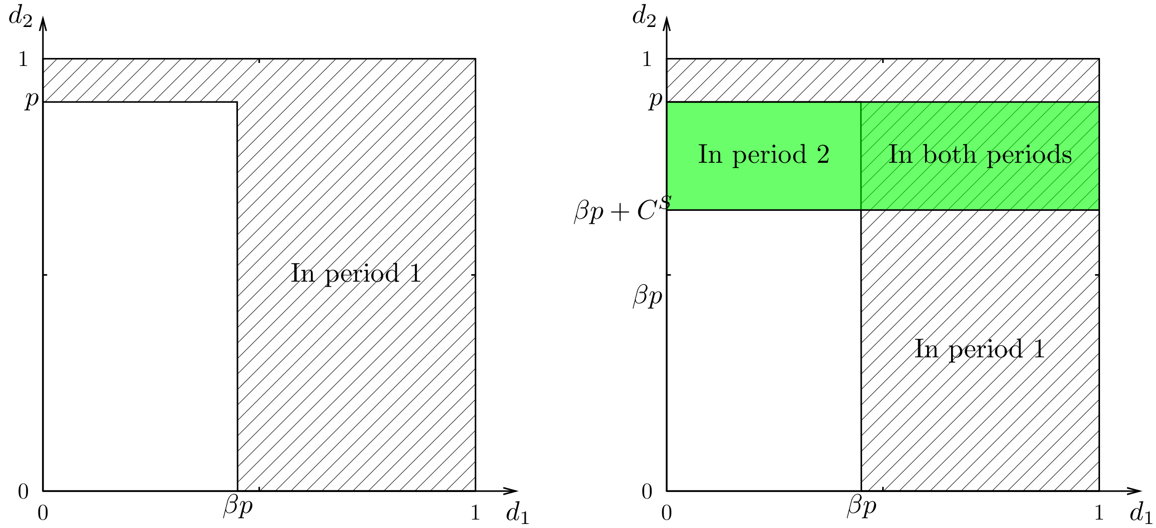
	(1)	(2)	(3)	(4)
Share of time consistent consumers ρ	0.817	0.820	0.817	0.814
	(0.021)	(0.021)	(0.021)	(0.021)
Discount factor β	0.377	0.377	0.377	0.380
	(0.013)	(0.014)	(0.013)	(0.013)
Marginal utility of income α	0.477	0.474	0.473	0.475
	(0.010)	(0.010)	(0.010)	(0.010)
High shopping cost C^H	0.641	0.613	0.609	0.620
	(0.053)	(0.054)	(0.052)	(0.052)
μ	0.192	0.278	0.374	0.413
	(0.044)	(0.053)	(0.067)	(0.070)
σ	1.328	1.320	1.309	1.321
	(0.057)	(0.059)	(0.054)	(0.054)
Sunday κ_1		-0.096	-0.089	-0.090
		(0.034)	(0.033)	(0.033)
Summer κ_2		-0.126	-0.126	-0.123
		(0.029)	(0.028)	(0.029)
Income κ_3			-0.013	-0.014
			(0.005)	(0.005)
Earlier Purchase κ_4				-0.074
				(0.028)

Note: Mixture model estimates with a sample that excludes weeks with holidays. The beer consumption shock distribution in columns 2-4 is given by equation (7). The model in column 2 includes dummy variables for Sunday and Summer, column 3 includes household income and column 4 includes a dummy variable that indicates a beer purchase earlier during the same week. Asymptotic standard errors are included in paranthesis.

Table 7: Parameter estimates from mixture model with partly unobservable shopping costs

	(1)	(2)
Share of time consistent consumers ρ	0.759	0.770
Discount factor β	0.700	0.668
Marginal utility of income α	0.177	0.196
High shopping cost C^H	1.746	1.440
μ	0.196	0.146
σ	0.371	0.414
Share of low shopping costs γ	0.119	0.118

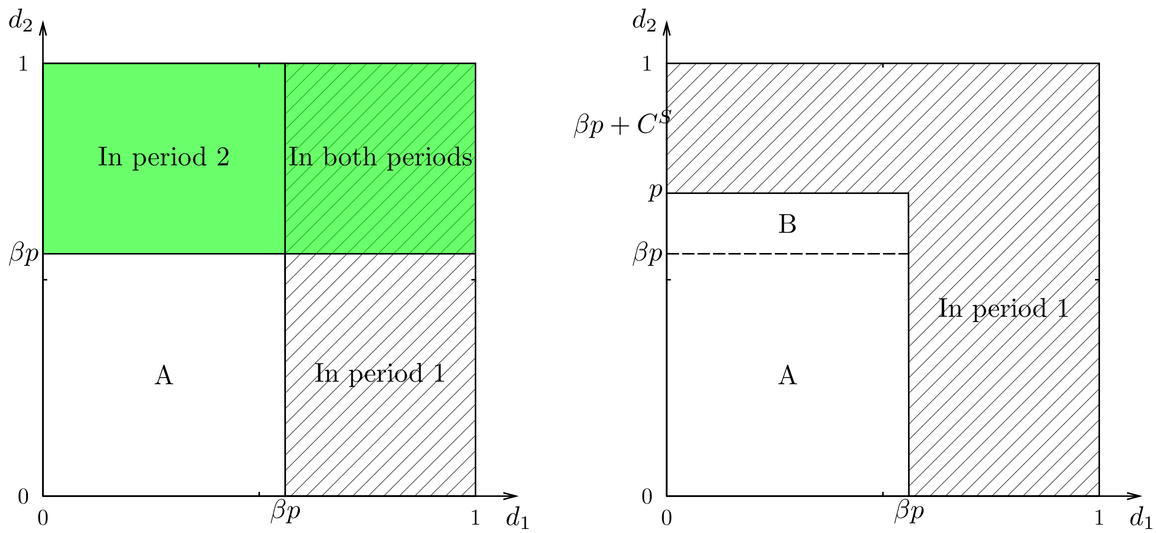
Note: Mixture model estimates using Assumption 3. Model 1 is estimated with the full sample, and model 2 with the smaller sample where holidays are excluded.



(a) Period 1

(b) Period 2

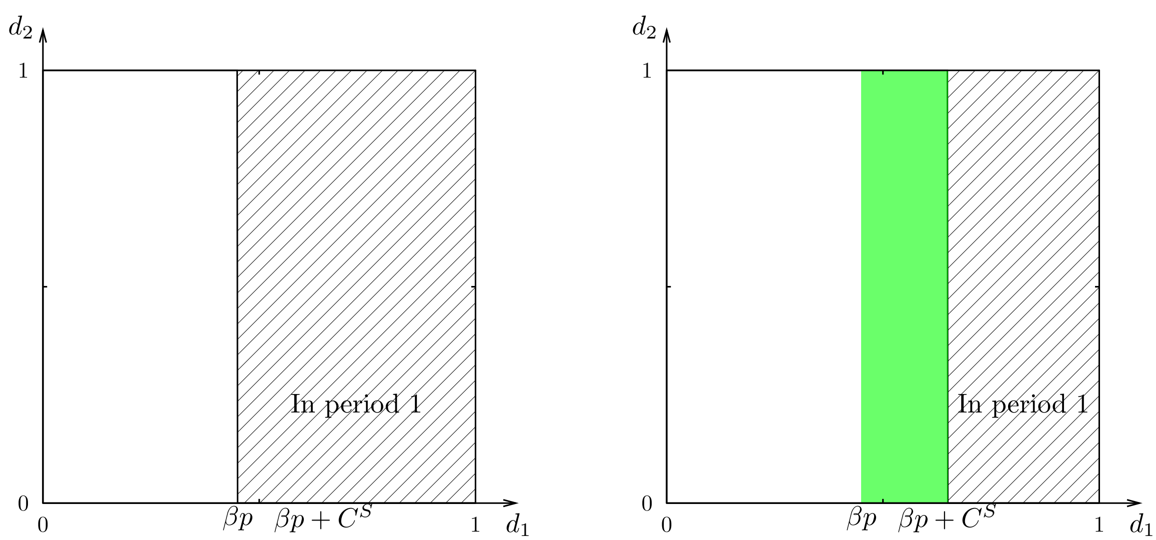
Figure 1: Example: Timing of purchases in state LH



(a) LL

(b) LH

Figure 2: Example: Purchases in state LL and LH



(a) Low shopping cost (state LL)

(b) High shopping cost (state HL)

Figure 3: Example: Demand in period one, when second period shopping cost is low

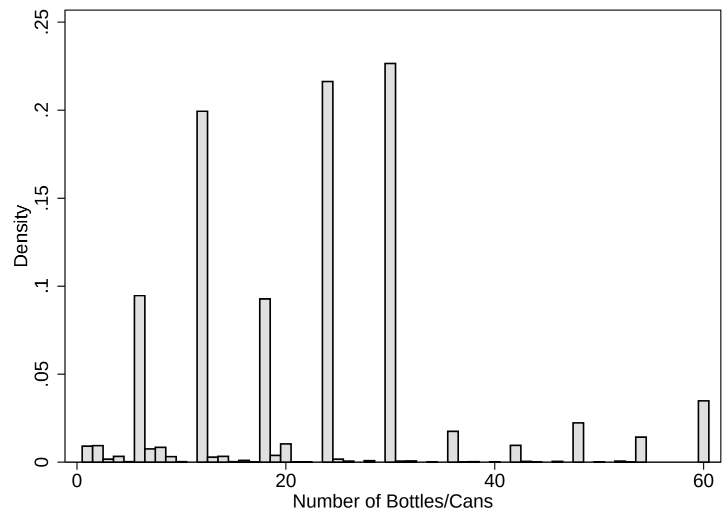


Figure 4: Histogram of beer purchases on Weekends. (Note: Only purchases up to 60 bottles are included.)

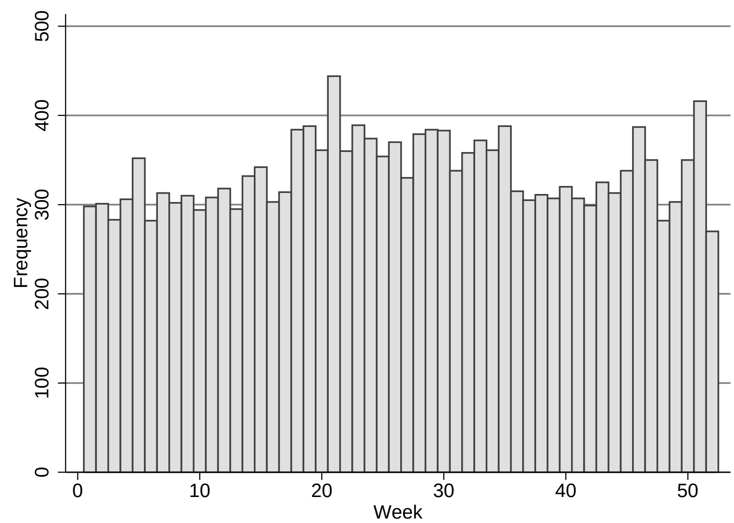


Figure 5: Distribution of calendar weeks when beer is purchased

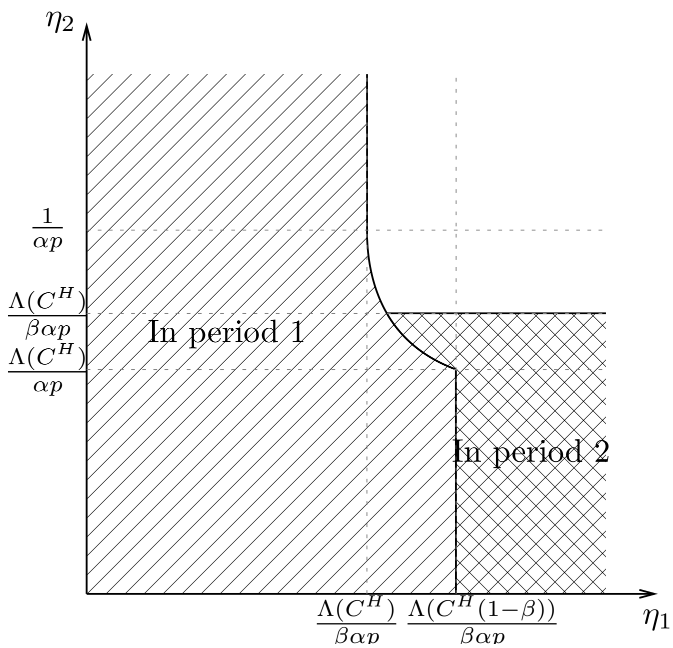


Figure 6: Probability of purchasing in period 1 and 2 when shopping costs are high both periods and discount factor is high

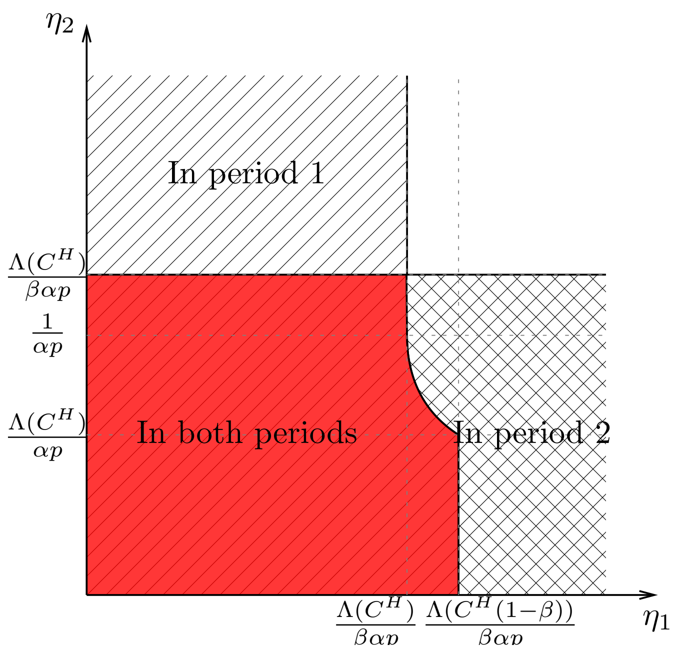
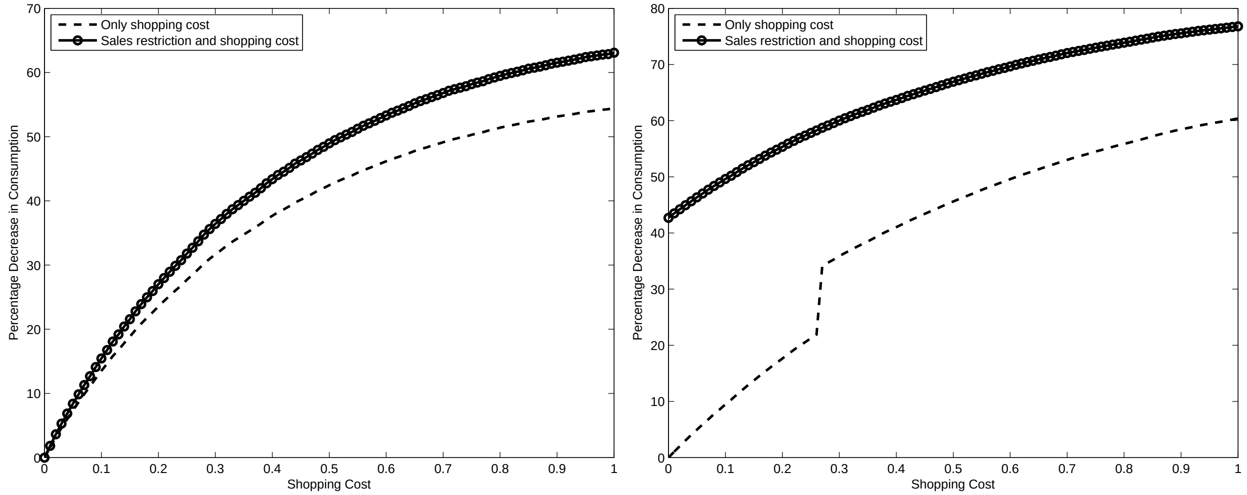


Figure 7: Probability of purchasing in period 1 and 2 when shopping costs are high both periods and discount factor is low



(a) Time consistent

(b) Time inconsistent

Figure 8: Decrease in consumption due to shopping costs and the sales restriction

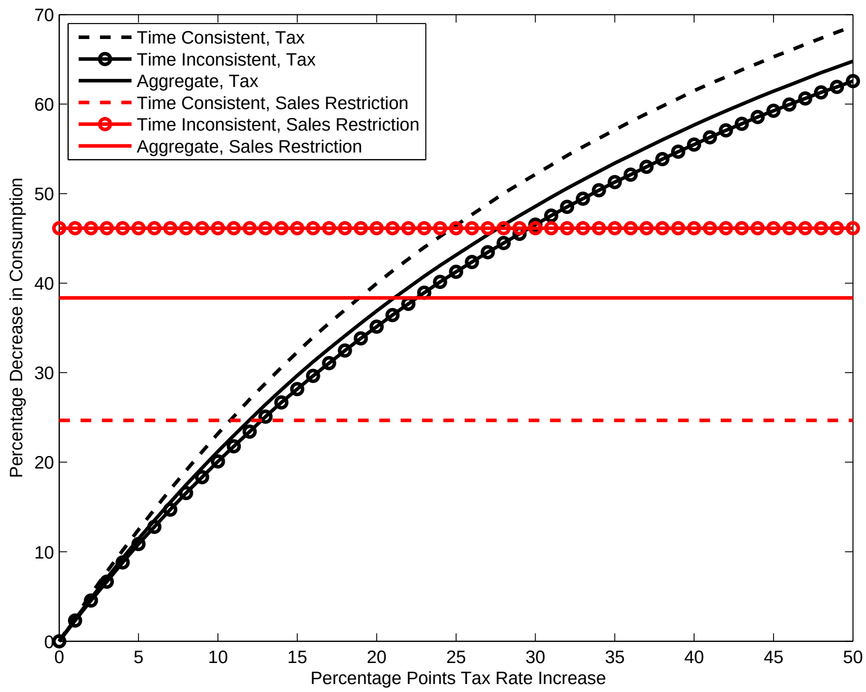


Figure 9: Decrease in aggregate consumption in case of sales restriction and taxes

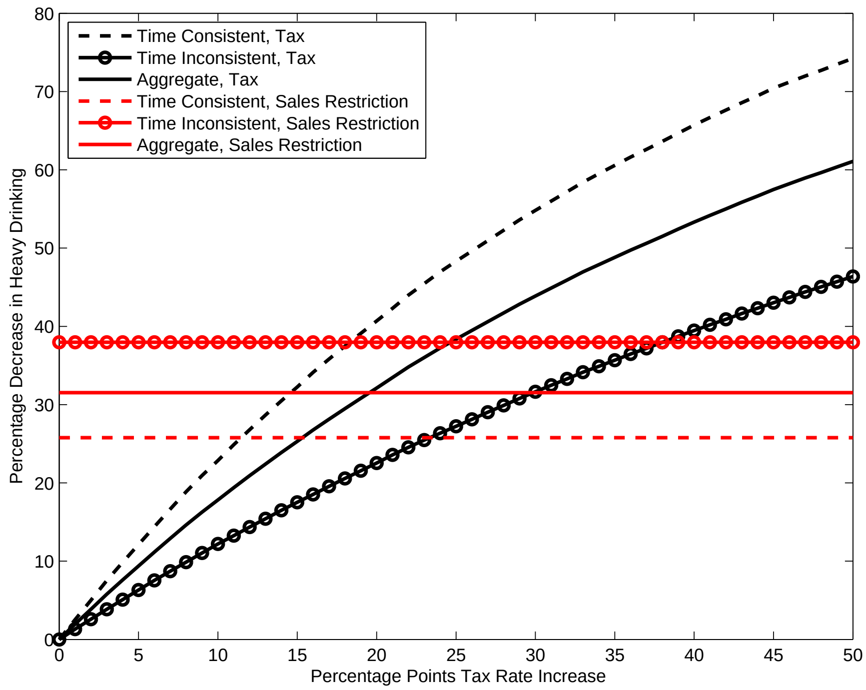
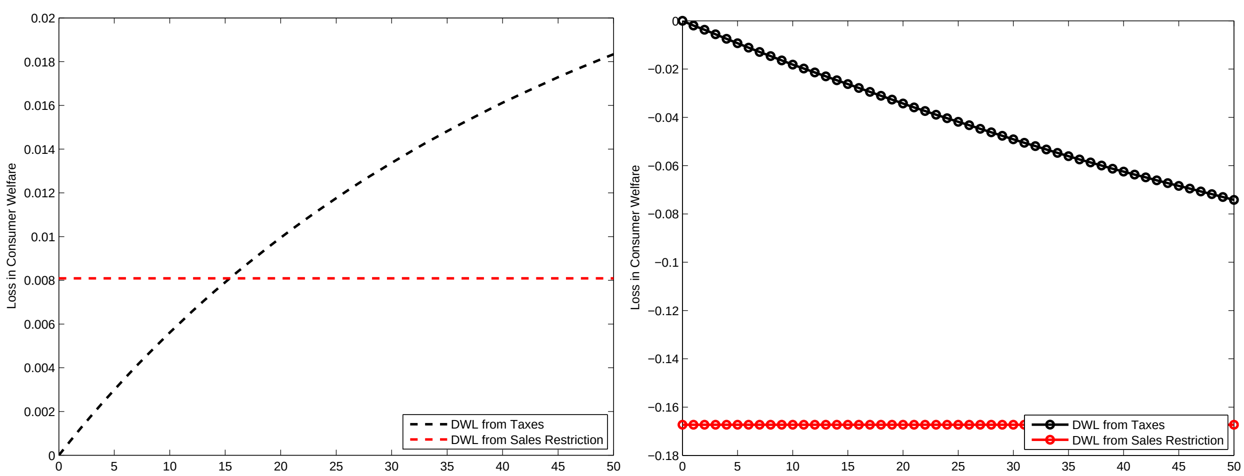


Figure 10: Decrease in large purchases in case of sales restriction and taxes



(a) Time consistent

(b) Time inconsistent

Figure 11: Decrease in consumer welfare due to the sales restriction and taxes

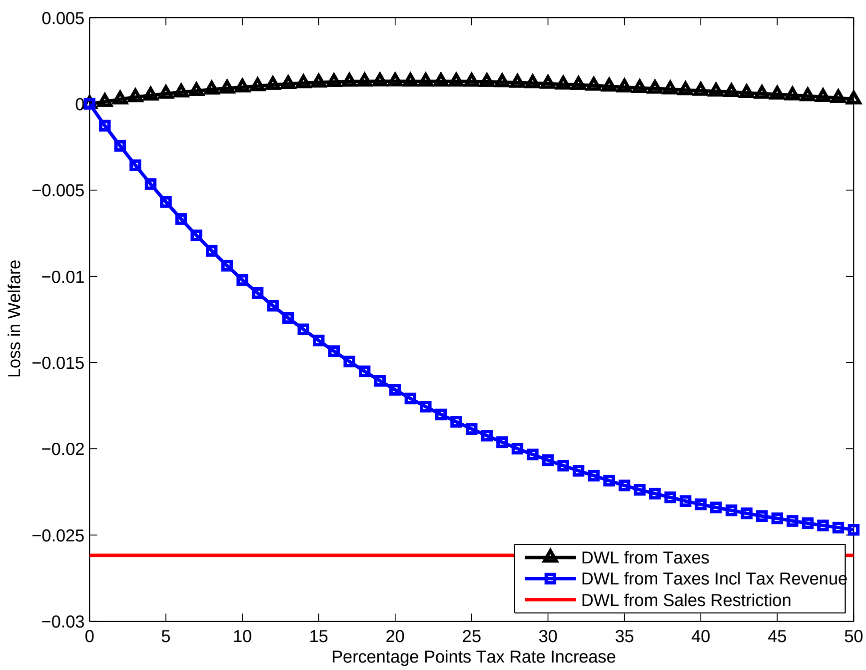


Figure 12: Decrease in aggregate consumer welfare due to the sales restriction and taxes