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# Peers and Alcohol: Evidence from Russia

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**Abstract**

For the last twenty years Russia has confronted the Mortality Crisis- the life expectancy of Russian males has fallen by more than five years, and the mortality rate has increased by 50%. Alcohol abuse is widely agreed to be the main cause of this change. In this paper, I use a rich dataset on individual alcohol consumption to analyze the determinants for heavy drinking in Russia, such as the price of alcohol, peer effects and habits. I exploit unique location identifiers in my data and patterns of geographical settlement in Russia to measure peers within narrowly-defined neighborhoods. The definition of peers is validated by documenting a strong increase of alcohol consumption around the birthday of peers. With natural experiments I estimate the own price elasticity of the probability of heavy drinking. This price elasticity is identified using variation in alcohol regulations across Russian regions and over time. From these data, I develop a dynamic model of heavy drinking to quantify how changes in the price of alcohol would affect the proportion of heavy drinkers among Russian males and subsequently also affect mortality rates. I find that that higher alcohol prices reduce the probability of being a heavy drinker by a non-trivial amount. An increase in the price of vodka by 50% would save the lives of at least 40,000 males annually. Peers account for a quarter of this effect.

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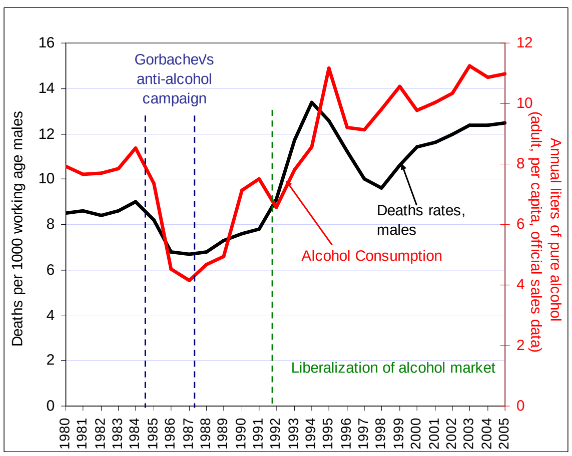
# 1 Introduction

Russian males are notorious for their hard drinking. The Russian (non-abstainer) male consumes an average of 35.4 liters of pure alcohol per year.[1] This amount is equivalent to the daily consumption of 6 bottles of beer or 0.25 liters of vodka. The most notable example of the severe consequences of alcohol consumption is the male mortality crisis – male life expectancy in Russia is only 60 years. This is 8 years below the average in the (remaining) BRIC countries, 5 years below the world average, and below that in Bangladesh, Yemen, and North Korea. High alcohol consumption is frequently cited as the main cause (see for example Treisman 2010, Leon et al. 2007, Nemtsov 2002, Bhattacharya et al. 2011, Brainerd and Cutler 2005).[2] Approximately one-third of all deaths in Russia are related to alcohol consumption (see Nemtsov 2002). Most of the burden lies on males of working age: more than half of all deaths in working-age men are accounted for by hazardous drinking (see Leon et al. 2007, Zaridze et al. 2009, and Figure 1 below).

Figure 1. Alcohol Consumption and Male Mortality Rate.




Source: WHO, Treisman (2010), Rosstat.

Surprisingly, no attempts have been made to quantify the effects of public policy on mortality rates, and there have been few efforts to identify the effects of public policy on alcohol consumption. Moreover, research that identifies the causal effect of price on alcohol consumption and mortality deals with only aggregate (regional-level) data.[3] However, the

[1]See the WHO Global Status Report On Alcohol And Health (2011). More than 90% of Russian males of working age are non-abstainers. Per-adult consumption estimates vary from 11 to 18 liters of pure alcohol per year. Official statistics that take into account only legal sales report 11 liters; however, expert estimates are 15-18 liters (see Nemtsov 2002, WHO 2011, report of Minister of Internal Affairs, http://en.rian.ru/russia/20090924/156238102.html).

[2]In comparison, the situation with female mortality is not so bad. Female life expectancy in Russia is 73 years – 5 years higher than world average, and 2 years above of average in the (remaining) BRIC countries. For health statistics, see https://www.cia.gov/library/publications/the-world-factbook/fields/2102.html.

[3]Regional-level analysis is done by Treisman (2010) and Bhattacharya et al. (2011).

use of disaggregated data is of particular interest because it allows disentangling the different forces that bear on individual decisions about drinking. Also, it allows an evaluation of the effect of policy on different subgroups.

My paper fills this gap. I utilize micro-level data on the alcohol consumption of Russian males to answer the following two key questions. First, how can we quantify the effects of a price increase for alcohol on the proportion of heavy drinkers and on mortality rates and social welfare? Second, how can we identify the effects of structural forces that influence alcohol consumption, and specifically peer effects and forward-looking assumptions on consumer behavior?

Peer effects are agreed to be very important for policy analysis because they produce a (social) multiplier effect. Recent literature emphasizes the importance of peers in making personal decisions, in particular whether to drink or not (see, for example, Akerlof and Kranton 2000, Card and Giuliano 2011, Cooley 2010, 2012, Gaviria and Raphael 2001, Krauth 2005, Kremer and Levy 2008, Moretti and Mas 2009). There are sound reasons to believe that peer influence is even stronger in Russia because of patterns of the dense geographical settlement inherited from the Soviet Union and the very low level of mobility in Russia. In my paper, I exploit unique location identifiers in the data to measure peers within narrowly-defined neighborhoods. This definition of peers is validated by documenting a strong increase in alcohol consumption around the birthday of peers.

This paper then introduces a model that incorporates these peer effects, and verifies the predictions of the model against both myopic and forward-looking assumptions on agent behavior. Although there is no consensus regarding which model is more true, most literature on policy analysis deals with only myopic assumptions.[4] At the same time, key consequences of alcohol consumption – on health, family, and employment status, for example – do not necessarily appear immediately, but rather increasingly manifest over the course of the next few years, or even much later in life (see Mullahy and Sindelar 1993, Cook and Moore 2000). Moreover, alcohol consumption forms a habit, and thus affects future behavior. Given this, one expects that individuals may behave in a forward-looking manner when determining current alcohol consumption (see rational addiction literature, Becker and Murphy 1988).[5] Possible mis-specification from omitting forward-looking agent assumptions might introduce a significant bias in estimates, and as such might result in incorrect predictions regarding proposed changes in the regulation of the alcohol industry.

[4]In my view, this happens because myopic models are easier to analyze. Besides in general these two models are hardly (or even simply not) distinguishable from the data. Thus, Rust (1994) shows that in a general set-up of dynamic discrete-choice model (with non-parametric utilities) the discounting parameter $\beta$ is not identified. Although today different identification results are stated, they all are obtained under certain restrictions on parameters (see for example Magnac and Thermar 2002, Fang and Wang 2010, Arcidiacono et al. 2007).

[5]Some studies find empirical evidence to support the rational addiction model (see Becker, Grossman, and Murphy 1991 , Chaloupka 2000, Arcidiacono et al. 2007). Other studies question this evidence (see Auld and Grootendorst 2004), or provide an alternative to a (fully) rational-model explanation of the evidence (see Gruber and Köszegi 2001).

In this paper, I employ recent developments in the econometric analysis of static and dynamic models of strategic interactions to model and estimate individual decision problems (for review, see Bajari et al. 2011a). Peer effects are modeled in the context of game with incomplete information. In my model, alcohol consumers use the demographic characteristics of peers to form beliefs about peers' unobservable decisions regarding drinking. This model is naturally extended to a dynamic framework, where consumers have rational expectations about future outcomes (see Bajari et al 2008, Aguirregabiria and Mira 2007, Berry, Pakes, and Ostrovsky 2007, and Pesendorfer and Schmidt-Dengler 2008).

In my estimates, I show the importance of peer effects for young age strata (below age 40). In addition, I find a non-trivial price elasticity for heavy drinking. To estimate the own price elasticity, I explore an exogenous variation in the price of alcohol that comes from changes in alcohol regulations across Russian regions and over time.

To illustrate these findings, I simulate the effect of an increase in vodka price by 50 percent on the probability of being a heavy drinker. A myopic model predicts that five years after introducing a price-raising tax, the proportion of heavy drinkers would decrease by roughly one-third, from 25 to 18 percent. The effect is higher for younger generations because of the non-trivial effect of a social multiplier. This cumulative effect can be decomposed in the following way: own one-period price elasticity predicts a drop in the share of heavy drinkers by roughly 4.5 percentage points, from 25 to 20.5 percent. In addition, peer effects increase the estimated price response by 1.5 times for younger generations. Further, the assumption that consumers are forward-looking increases the estimated cumulative effect by roughly an additional 30 percent.

Then, I simulate the consequences of a price-raising alcohol tax on mortality rates. I find a significant age heterogeneity in the effect of heavy drinking on the hazard of death: this effect is much stronger for younger generations. Increasing the price of vodka by 50 percent results in a decrease in mortality rates by one-fourth for males of ages 18-29, and by one-fifth for males ages 30-39, but with no effect on the mortality of males of older ages.

My results coincide with the regional-level analyses by Treisman (2010) and Bhattacharya et al. (2011), and with the micro-level analyses by Andrienko and Nemtsov (2006) and Denisova (2010). Treisman (2010) utilizes regional-level data for the period 1997-2006, and shows that the increase in heavy drinking resulted largely from an increase in the affordability of vodka. In 1990 – immediately before liberalization of the Russian alcohol market – the price of vodka relative to CPI was four times higher than in 2006. Treisman shows that demand for alcohol is (relatively) elastic, and that variations in vodka price closely match variations in mortality rates. Bhattacharya et al. (2011) use regional-level data from the period of Gorbachev's anti-alcohol campaign, and find that regions experiencing a higher intensity of the campaign also exhibited a higher drop in mortality rates. They argue that the surge in mortality that happened after Gorbachev's campaign can be explained (partly) by a mean reversion effect. Andrienko and Nemtsov (2006) and Denisova (2010) utilize micro-level data on alcohol consumption to reach similar conclusions. Andrienko and Nemtsov (2006) find a negative correlation between the price of alcohol and alcohol consumption. Denisova (2010) studies determinants of mortality in Russia, and finds a correlation between alcohol consumption and hazard of death.

Finally, I analyze the effect of a tax increase on social welfare. I find that when agents have bounded rationality (that is, do not take into account the effect of consumption on hazard of death), a raise in vodka price by 50 percent improves welfare. I find also that under certain assumptions on consumers utilities, a tax increases consumers welfare even for fully-rational agents.

This paper is organized as follows. In the following section I describe my data and the variables used in my analysis. Section 3 presents the model, section 4 presents estimation strategy. In Section 5, I discuss results. Section 6 discusses robustness checks. Section 7 concludes.

## 2 Data Description

Soviet Union left the legacy of the communist-style apartment blocks where people live in an (uncomfortably) close proximity. I exploit this feature and define peers using geographical locations.

Approximately 10% of Russian families live in dormitories and communal houses, where residents share kitchens and bathrooms.[6] A majority of the remaining, more fortunate, part of the population lives in a complex of several multi-story multi-apartment buildings, called a "dvor." These complexes have their own playgrounds, athletic fields, and ice rinks, and often serve as the place where people spend leisure time. The population of dvor vary in range from 100 to more than 2000 inhabitants. The most common dvors (so called khrushchevki) are relatively small-size dvors with population of about 300 people. Photo of typical dvor is presented in Figure A2 in the appendix. Dvors are the most popular place in Russia to find friends – the very low level of personal mobility in Russia means that most people live in the same place (and therefore the same dvor) for most of their lives.

In this study, I utilize data from the Russian Longitudinal Monitoring survey (RLMS)[7], which contains data on small neighborhoods where respondents live. The RLMS is a nationally-representative annual survey that covers more than 4,000 households (with be-

[6]See the RLMS web site, http://www.cpc.unc.edu/projects/rlms-hse/project/sampling

[7]Official Source name: "Russia Longitudinal Monitoring survey, RLMS-HSE," conducted by Higher School of Economics and ZAO "Demoscope" together with Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology RAS. (RLMS-HSE web sites: http://www.cpc.unc.edu/projects/rlms-hse, http://www.hse.ru/org/hse/rlms).

tween 7413 and 9444 individual respondents), starting from 1992. For every respondent in the survey, the RLMS identifies the census district in which he or she lives. The average population of census district in Russia is 300.[8] Typical census district in Russia contains one dvor or one multi-story building; this allows me to use information on neighborhood (and age) to successfully identify peer groups.[9]

The RLMS also has other advantages over existing data sets. It provides a survey of a very broad set of questions, including a variety of individual demographic characteristics, consumption data, and so on. In particular it includes data on death events, so I can identify the effects of drinking on mortality from micro-level data. Further, it contains rich data on neighborhood characteristics, including – critically – the price of alcoholic beverages in each neighborhood, allowing me to analyze individual price elasticity.

My study utilizes rounds 5 through 16 of RLMS over a time span from 1994 to 2007, except 1997 and 1999.[10] The data cover 33 regions – 31 oblasts (krays, republics), plus Moscow and St. Petersburg. Two of the regions are Muslim. Seventy-five percent of respondents live in an urban area. Forty three percent of respondents are male. The percentage of male respondents decreases with age, from 49% for ages 13-20, to 36% for ages above 50. The data cover only individuals older than 13 years.

The RLMS data have a low attrition rate, which can be explained by low levels of labor mobility in Russia (See Andrienko and Guriev 2004). Interview completion exceeds 84 percent, lowest in Moscow and St. Petersbug (60%) and highest in Western Siberia (92%). The RLMS team provides a detailed analysis of attrition effects, and finds no significant effect of attrition.[11]

My primary object of interest for this research is males of ages between 18 and 65. The threshold of 18 years is chosen because it is officially prohibited to drink alcohol before this age. The resulting sample consists of 29554 individuals*year points (2937 to 3742 individuals per year). Summary statistics for primary demographic characteristics are presented in Table 3.

[8] RLMS team indicates that population of census districts in RLMS survey is in range between 250 and 400 people. There are 459,000 census districts in Russia (data on 2010 census). This number implies that average population of census district is 310 people (including females, youth and elderly). This number in turn implies, that average population of peer group is 21 (adult males in the same age strata).

[9] Later in the paper I provide a check confirming that this definition of peers has ground.

[10] I do not utilize data on rounds earlier than round 5 because they were conducted by other institution, have different methodology, and are generally agreed to be of worse quality. Rounds 17 -19 that currently available are also not used in my paper because of two reasons. First, these rounds no longer contain identifiers of neighborhoods, therefore I can not identify peers groups. Second, regional legislature was unified after year 2007, therefore I do not have instruments for alcohol price for these rounds (that cover years 2008, 2009 and 2010).

[11] See http://www.cpc.unc.edu/projects/rlms-hse/project/samprep

## 2.1 "Peers" Definition

I define "peers" as those who live in one neighborhood (school district) and belong to the same age stratum. Applying this definition, I constructed peer groups. The median number of people in a group is 5; the lower 1% is 2, the upper 90% is 20, and largest number is 66. On average, I have 835 peer groups (each with 2 or more peers) per year. The distribution of the number of peers per peer group is shown in Table 4.

To verify the reliability of my measures, I provide the following test: I correlate log (the amount of vodka consumption) with a dummy variable if a person has a birthday in the previous month, and with averages of the birthday dummy variables across peers.[12] Vodka is the most popular alcoholic beverage to serve on birthdays, compared to beer and for males also to wine. Results for both regressions are positive and statistically significant. Regression suggests that a person's consumption of vodka increases by 16% if his birthday is during the previous month, and by 6% if there was a birthday of one of his peers (in a group of 5 peers). The results are robust if I eliminate household members from the sample of peers.[13]

Table 1. Birthdays and Alcohol Consumption.

| | All peers | | Without household members | |
|---|---|---|---|---|
| | log(vodka) | +1 birthday in group of 5 | log(vodka) | +1 birthday in group of 5 |
| $\frac{\sum_{peers} I(birthday)}{(N-1)}$ | 0.227 | 0.057 | 0.212 | 0.053 |
| | [0.086]*** | [0.021]*** | [0.086]** | [0.021]*** |
| $I(birthday)$ | 0.161 | 0.161 | 0.161 | 0.161 |
| | [0.053]*** | [0.053]*** | [0.053]*** | [0.053]*** |
| Year*month FE | Yes | Yes | Yes | Yes |
| Observations | 35995 | 35995 | 35995 | 35995 |

* significant at 10%; ** significant at 5%; *** significant at 1%

## 2.2 Alcohol consumption variable

Although the negative health and social consequences of hard drinking are widely recognized, there is no evidence for negative consequences from moderate drinking. Thus, I concentrated on an analysis of the personal decision to drink "hard" or not. I use a dummy variable that equals 1 if a person belongs to the top quarter of alcohol consumption (among

[12] The specifications of the regressions are as follows:
$Log(1+vodka)_{it} = \alpha_1 + \alpha_2 I(birthday)_{it} + \varepsilon_{it}$,
$Log(1+vodka)_{it} = \zeta_1 + \zeta_2 \sum_{j \in peers} I(birthday)_{jt}/(N-1) + \varepsilon_{it}$,
where *vodka* stands for amount of vodka have drunk last month (in milliliters).

[13] The results are robust using a different measure of vodka consumption. There is no effect (or a small negative effect) of peer birthdays on the consumption of other goods, such as tea, coffee, or cigarettes (see Table A1 in the appendix).

males of working age). Alcohol consumption is measured as the reported amount of pure alcohol consumed the previous month.[14]

However, alcohol consumption reporting in the RLMS suffers from the common problem of all individual-level consumption surveys: it is significantly under-reported.[15] So, to offer an indication of the actual level of alcohol consumption corresponding to the threshold of being a "heavy drinker," I correlate the reports of consumption from the RLMS data with official sales data as a benchmark for average levels of alcohol consumption.

The threshold level for being a "heavy drinker" is 2.6 times the mean alcohol consumption (including women and the elderly) in the RLMS sample. If I take mean alcohol consumption from official sales data (11 liters of pure alcohol per year per person), I can determine that the actual threshold is equivalent to an annual consumption of 29 liters of pure alcohol. This amount corresponds to a daily of consumption of 5 bottles (0.33 liters each, 1.66 liters total) of beer, or 0.2 liters of vodka. If I use (more reliable) expert estimates as a benchmark, then the threshold corresponds to daily consumption of 7 bottles of beer, or 0.29 liters of vodka.

In the Robustness section, I present the results of regressions, where alternative measures of alcohol consumption are used.

# 3 Model

As I already mentioned in introduction, most of the literature that studies demand for alcohol beverages deals with reduced-form (non-structural) approach of estimation of elasticity (see Leung and Phelps, 1993, Cook and Moore, 2000 for literature review).

In my paper I use formal model to directly model consumer's choice. This approach that can be viewed as complimentary to existing literature has some advantages.

First, the use of non-structural approach makes it hardly possible to distinguish between forward-looking and myopic consumers. Indeed, the estimation of demand using regression of quantity on price implies that consumers are myopic. However, as I already discussed above, there is no a priory agreement which assumption on consumer behavior, myopic or forward-looking, should be used in the analysis of consumer drinking behavior. My model allows me to directly model and to estimate consumer choice under both assumptions, and thus to establish bounds on estimates that come from different models.

Besides, this approach allows me to quantify the effect of government policy on some

[14] Sometimes a high level of monthly average alcohol consumption is not as harmful for health as one-time binge drinking (with a relatively low average level otherwise). Still, the measure I choose indicates that heavy drinking has huge adverse effect on health (see hazard of death regression).

[15] This is the common problem of all individual-level surveys that study alcohol consumption. Reported threshold level corresponds to reported amount drinking of more 150 grams of pure alcohol per month. A summary statistics and age profiles for reported amounts of alcohol consumption are shown in Table 3 and Figure A1 in the appendix.

key economic policy outcomes, like consumer health and welfare, and to decompose the effect of policy for such important factors for personal decision-making, like social multiplier and "habit" multiplier. With my model I can calculate magnitudes of these multipliers. In particular I show that these multipliers together have the same magnitude as own price elasticity.[16]

Finally, although my model does put structure on consumer choice, it's estimation results still can be easily comparable with reduced form estimates. Indeed, my model can be analyzed using standard 2SLS approach under certain assumptions on consumer utility and beliefs, such as myopia, linear beliefs, and uniform distribution of private utility shocks (see Bajary et al 2011).

I model consumer's behavior and his/her interaction with peers using discrete game with incomplete information set up.

I discretize consumer choice set of how much to drink on two choices, whether to drink hard or not. I use this discretization because only hard drinking is agreed to be harmful for health (see for example Cook and Moor, 2000). The effect of moderate drinking on health is ambiguous: for example moderate drinking is associated with lower chance of heart diseases, such as coronary heart disease.

My second assumption is incomplete information. The game with incomplete information implies that consumer does not know payoffs of other players. In context of "drinking game" it implies that when one starts drinking in a party, she (he) does not know exactly how much her (his) peers value drinking today and how much her (his) peers will drink up to the end of the day. Depending on some random factors, like problems with girl-(boy-) friends or parents, stress on a work or in school, one can value drinking differently and may end up drinking a lot or just one shot. Although consumers do not know exactly, they do guess on how much peers will drink using information that they know about peers, like personal demographic characteristics, previous level of alcohol consumption etc. These guesses (beliefs) are consistent with observed equilibrium behavior, and can be estimated from using data on consumers choices and consumers demographic characteristics.

The set-up of the model is as follows.

There are N peers in an (exogenously-given) peer group: $i = \{1, ..., N\}$. In every period of time $t$ consumers simultaneously choose an action, $a_{it}$. The set of actions, $a_{it}$ is binary: whether to drink hard $a_{it} = 1$ or not, $a_{it} = 0$.

The expected present value of consumer utility consists of current per period utility, $\pi_{it}(a_{-it}, a_{it}, s_t)$, discounted expected value function, $\beta E(V_{it+1}(s_{t+1})|a_{-it}, a_{it}, s_t)$, and a stochastic preference shock, $e_{it}(a_{it})$:

$$U(a_{-it}, a_{it}, s_t) = \pi_{it}(a_{-it}, a_{it}, s_t) + \beta E(V_{it+1}(s_{t+1})|a_{-it}, a_{it}, s_t) + e_{it}(a_{it})$$

[16]This result holds for men below age 40. Besides I find that demand elasticity is significantly higher for younger cohorts because of presence of social multiplier.

Per-period utility and private preference shock of not (heavy) drinking are normalized to zero: $\pi_{it}(a_{it}=0)=0$ and $e_{it}(a_{it}=0)=0$.

Private preference shocks of drinking, $e_{it}(1)$, have i.i.d. logistic distribution. Private preference shocks stay for personal tastes for heavy drinking, tolerance to alcohol and other factors that observable for the consumer, but unobservable for researcher and for other peers in the group.

Further, I will consider two different assumptions on $\beta$, that $\beta=0$ (for myopic consumers) and $\beta=0.9$ (for forward-looking consumers).

For the case of forward-looking consumers I assume that consumers have an infinite time planning horizon, and that the transition process of state variables is Markovian. This implies that expectations for future periods depend on only a current-period realization of state variables and consumer choice of action. Finally, I restrict equilibrium to be a Markov Perfect Equilibrium, so that a consumer's strategy is restricted to be a function of the current state variables and the realization of a random part of utility (private preference shock). These assumptions ensure identification, and are common in dynamic-choice models. For myopic consumers the model is static, such that none of the assumptions described above is needed.

I also assume that the per-period utility from (heavy) drinking has the linear parametrization:

$$\pi_{it}(a_{-it},a_{it}=1,s_t)=\delta\frac{\sum_{-i}I(a_{jt}=1)}{N-1}+\gamma habit_{it}+\Gamma' D_{it}+\Upsilon' G_{-it}+\rho_{mt}$$

Thus, $\pi_{it}(a_{-it},a_{it}=1,s_t)$ depends on average peer alcohol consumption, habits $(a_{i,t-1})$[17], a set of personal demographic characteristics ($D_{it}$), (sub) set of peers characteristics $G_{-it}$ and municipality*year invariant factors $\rho_{mt}$.

The set of personal demographic characteristics $D_{it}$ includes weight, education, work status, lagged I(smokes), I(Muslim), health status, age, age squared, marital status, size of family and log(family income). The (sub) set of peers characteristics $G_{-it}$ that stands for so-called exogenous effects includes share of Muslims, share of peers with college education, share of unemployed.[18] I include municipality*year invariant factors $\rho_{mt}$ to account for price, weather and other factors that affect a consumer utility, and that (I assume) vary only on the municipality*year level.

[17] I define state variable $habit_{it}$ as follows. Let state variable $habit_{it}=0$ if $age_{it}<18$(years) and let transition process of $habit_{it}$ be defined in following way: $habit_{it}(S_{t-1},a_{i,t-1})=a_{i,t-1}+\varphi_{i,t}$ if $age_{it}\geq 18$, where $a_{i,t-1}$ is consumer's equilibrium choice of action in previous period, and $\varphi_{i,t}$ is (negligible) smoothing noise. $\varphi_{i,t}$ is added to ensure existence of equilibrium. With this definition of habits, the model satisfies assumptions required for MPE (see for example, Assumptions AS, IID and CI-X in Aguirregabiria and Mira, 2007 or Bajari et al 2010). A Markov perfect equilibrium (MPE) in this game is a set of strategy functions $a^{\star}$ such that for any consumer $i$ and for any $\{S_t, e_{it}\}$, where $S_t=U_{j\in\{i,-i\}}\{habit_{jt}, D_{jt}, G_{nt}, \rho_{mt}\}$ we have that $a_i^{\star}(S_t,e_{it})=b(S_t,e_{it},a^{\star}_{-i})$.

[18] Exclusion restriction requires that subset $G_{-it}$ does not contain all set of demographic variables. It seems to be reasonable assumption: for example, consumer does not have higher utility when she/he drinks with peers with different weight, different marital or health status. Actually my estimates show that consumer does not have any preferences about $G_{-it}$: all coefficients in $\Upsilon'$ are insignificant.

Subscripts $i$, $t$, $m$ stand for individual, year, and municipality; subscript $-i$ stands for other individuals within the same peer group.

I assume a game with an incomplete information set up.[19]

Consumers do not observe peer choices and do not observe realization of peer private shocks, $e_{it}(a_{it})$. They form expectations of other peer actions. The expectations are based on consumer (consistent) beliefs of what peers do. These beliefs depend on a set of state variables, observed by consumers. In my case, beliefs are based on (own and peers') set of variables $S_{i,-i,t} = U_{j\in\{i,-i\}}\{habit_{jt}, D_{jt}, G_{nt}, \rho_{mt}\}$.

Thus, a consumer expected (over beliefs) per-period utility from drinking:

$$E_{e_{-i}}\pi_{it}(a_{-it}, a_{it} = 1, s_t) = \delta\overline{\sigma_{jt}(a_{jt} = 1|S_{i,-i,t})} + \gamma habit_{it} + \Gamma' D_{it} + \Upsilon' G_{-it} + \rho_{mt}$$

The term $\overline{\sigma_{jt}(a_{jt} = 1|S_{i,-i,t})} = \dfrac{\sum_{-i}\sigma_{jt}(a_{jt} = 1|S_{i,-i,t})}{N-1}$, where $\sigma_{jt}(a_{jt} = 1|S_{i,-i,t})$ stands for the consumer's $i$ belief of what player $j$ will do. I follow this notation throughout this paper.

Finally, a consumer chooses to drink hard if his or her expected present value of the utility from (heavy) drinking is greater than the utility from not drinking:

$$\begin{aligned} E_{e_{-i}}\pi_{it}(a_{-it}, a_{it} &= 1, s_t) + \beta E(V_{it+1}(s_{t+1})|a_{-it}, a_{it} = 1, s_t) + e_{it}(a_{it} = 1) \\ &> \beta E(V_{it+1}(s_{t+1})|a_{-it}, a_{it} = 0, s_t) \end{aligned}$$

In the following section, I discuss the estimation procedure for two parametrization of the discount factor, $\beta = 0$ and $\beta = 0.9$. Case $\beta = 0$ refers to "myopic" consumers, while $\beta = 0.9$ refers to "forward-looking" consumers.

To simplify the exposition of the model and estimation, I start with the less-technical case, the myopic consumer model.

# 4 Estimation

## 4.1 Myopic consumers

Myopic consumers maximize only current per-period utility, $\pi_{it}(a_{-it}, a_{it}, s_t)$, and thus discount their future utilities with discount factor $\beta = 0$.[20]

Estimation of the model proceeds in two steps. These steps are similar to the standard 2SLS regression procedure.

[19] In both games with complete and incomplete information consumers do not observe actions of others if they make their decisions simultaneously. Within game with an incomplete (rather than complete) information set-up consumers do not know payoffs of other players because these payoffs include private preference shocks $e_{it}(1)$.

[20] The expected utilities of myopic consumer are as follows: $E_{e_{-i}}U_{it}(0) = 0$, and $E_{e_{-i}}U_{it}(1) = \delta\overline{\sigma_{jt}(a_{jt} = 1|S_{i,-i,t})} + \gamma habit_{it} + \Gamma' D_{it} + \Upsilon' G_{-it} + \rho_{mt} + e_{it}(1)$

On the first stage, I estimate beliefs $\hat{\sigma}_{jt}(a_{jt}=1|S_{i,-i,t})$ as a (arbitrary) function of state variables $S_{i,-i,t}$.[21]

On the second stage, I estimate the remaining parameters of utility function by plugging estimated beliefs in the following logit regression:

$$\begin{aligned} I(heavy\,drinker)_{it} &= \sum_k \delta_k I(age\,strata=k)\overline{\hat{\sigma}_{jt}(a_{jt}=1|S_{i,-i,t})} \\ &\quad +\gamma habit_{it}+\Gamma' D_{it}+\Upsilon' G_{-it}+\rho_{mt}+e_{it} \end{aligned}$$

I assume age heterogeneity in peer effects, so I estimate $\delta$ separately for every age stratum.

Parameters of the model are identified under the assumption that the utility of one consumer does not depend on subset of peer demographic characteristics, and that random components of personal utility are independent of peer demographic characteristics (see Bajari et al. 2005 for proof). I discuss the robustness of my results in the Robustness section.

#### 4.1.1 Estimation of the price elasticity

To estimate elasticity, I employ following strategy.

I assume that all price variation is captured on a municipality*year level. I obtain the municipality*year fixed effects component of utility $\hat{\rho}_{mt}$, and then regress $\hat{\rho}_{mt}$ on a log of the relative price of cheapest vodka in neighborhood.

$$\hat{\rho}_{mt}=\theta log(Price)_{mt}+u_{mt}$$

I use data on regional regulation of the alcohol market to instrument the price variable. I use following variables as instruments: I(regional government imposes tax on producers), I(regional government imposes tax on retailers), I(regional government imposes additional measure to controls for alcohol excise payments).[22] The latter measure is a popular tool in Russia because it controls the tax evasion of sellers of alcoholic beverages.

[21] The expression for first stage is as follows: $I(a_{jt}=1)_{it}=H(s_{it})'\zeta+\varepsilon_{it}$, where $I_i$ =$I(a_{it}=1)$, $H(s_{it})$ is a set of Hermite polynomials of state variables $s_{it}$ (for a discussion of non-parametric regression with Hermite polynomials see Ai and Chen (2003)). That is, $H(s_{it})$ contains set of Hermite polynomials up to the third degree of $S_{i,-i,t}=U_{j\in\{i,-i\}}\{habit_{jt},D_{jt},G_{nt},\rho_{mt}\}$. In addition it includes interactions of state variables $U_{j\in\{i,-i\}}\{habit_{jt},D_{jt},G_{nt}\}$. I do not extend the set of polynomials to a larger degree or include a larger set of interactions because of dimensionality problem. One important implication of this strategy is that $\rho_{mt}$ appears in $H(s_{it})$ only once: this happens because the dummy variable structure of fixed effects implies that $\rho^k_{mt}=\rho_{mt}$. Still, $\rho_{mt}$ will account for any variable (in any power) that varies only on municipality*year level.

[22] As a rule, regional regulations are imposed because of two reasons. First, regulations are popular tool to increase regional budget revenues: excise tax and license tax are two of the very few taxes that go directly into the regional budget. Second, regional regulations are imposed in the result of the lobbying of local firms and/or tollbooth corruption (see Yakovlev 2008, Slinko et al. 2005). This implies that the introduction of new regulation is generally not motivated by public health reasons.

## 4.2 Forward-looking consumers

Here I present an estimation strategy for forward-looking consumers (with $\beta = 0.9$).

Literature on the estimation of dynamic discrete models originated in 1987, after the seminal work of Rust (1987). During the last 20 years, tremendous progress has been made in this field. Further work significantly simplified the estimation procedure (Holtz and Miller 1993), discussed identification restrictions (Rust 1994), and extended dynamic discrete choice to the estimation of dynamic discrete games (Bajari et al. 2011, Aguirregabiria and Mira 2002, Berry, Pakes, and Ostrovsky 2007, and Pesendorfer and Schmidt-Dengler 2008). For excellent surveys of dynamic discrete models, see research by Aguirregabiria and Mira (2010) and Bajari et al. (2011b).

My estimation procedure follows Bajari et al. (2007). Compared to many other studies, the estimation strategy proposed by Bajari et al. has three advantages. First, this estimation procedure does not require the calculation of a transition matrix on the first stage. Avoiding this calculation decreases errors of estimation. Second, this estimation strategy allows using sequential procedure estimation, wherein every step of estimation has closed-form solutions. This means that one can avoid mistakes and problems related with finding a global maximum using a maximization routine. Finally, this estimation procedure does not require discretization of variables. This flexibility of estimation routine allows me to work with the same extensive set of explanatory variables as in the myopic (static) model, and thus makes these two models comparable.

The idea of this estimation is as follows. After applying two well-known relationships – Hotz-Miller inversion and expression for Emax (ex ante Value function) function – the choice-specific Bellman equation

$$V_{it}(a_{it}, s_t) = E_{e_{-i}}\pi_{it}(a_{-it}, a_{it} = 1, s_t) + \beta E(V_{it+1}(s_{t+1})|a_{it}, s_t)$$

can be rewritten as two moment equations (for derivation see Proof A1 in the appendix):
Bellman equation for $V_i(0, s_t)$

$$\begin{aligned} V_{it}(0, s_t) = \beta E_{t+1}(log(1 + exp(log(\sigma_{it+1}(1)) - log(\sigma_{it+1}(0))|s_t, a_{it} = 0) \\ + \beta E_{t+1}(V_{it+1}(0, s_{t+1})|s_t, a_{it} = 0) \end{aligned} \quad (1)$$

Bellman equation for $V_i(1, s_{it})$

$$\begin{aligned} log(\sigma_{it}(1)) - log(\sigma_{it}(0)) + V_{it}(0, s_t)_i = \pi_{it}(a_{-it}, a_{it} = 1, s_t, \theta) \\ + \beta E_{t+1}(V_{it+1}(0, s_{t+1}) - log(\sigma_{it+1}(0))|a_{it} = 1, s_t) \end{aligned} \quad (2)$$

These two equations together with a moment condition on choice probabilities

$$E(I(a_i = k)|s_t) = \sigma_{it}(k|s_t),\, k \in \{0,1\} \tag{3}$$

form the system of moments I estimate in next section.

#### 4.2.1 Estimation of utility parameters

A shortcut of the estimation procedure is as follows.

The first step resembles the first step in the estimation of the myopic model: I obtain estimates of beliefs (choice probabilities) $\widehat{\sigma_{it}(0)}$ and $\widehat{\sigma_{it}(1)}$. On the second step, I estimate $V_{it}(0,s)$ as a (arbitrary) function of state variables $S_{i,-i,t}$ by solving a sample equivalent of moment condition (1). On final step, I estimate $\pi(1,s)$ by solving sample equivalent of moment condition (2).[23]

#### 4.2.2 Estimation of price elasticity

Here, I follow a procedure similar to that employed in the myopic case.

To simplify description of the procedure, I start with estimation of elasticity under assumption that government changes price without changing consumers expectations over future price movement.

To calculate elasticity in this case, I obtain municipality*year fixed effects components $\hat{\rho}_{mt}(\pi)$, $\hat{\rho}_{mt}(EV1)$, $\hat{\rho}_{mt}(EV0)$ of my estimates of per-period utility of drinking $\pi_{it}(a_{-it}, a_{it} = 1, s_t)$, and conditional expectation of future Value function, $\beta E(V_{it+1}(s_{t+1})|a_{it} = 1, s_t)$, and $\beta E(V_{it+1}(s_{t+1})|a_{it} = 0, s_t)$. Then I calculate the aggregate effect of fixed effect components, $\hat{\rho}_{mt}$:

$$\hat{\rho}_{mt} = \hat{\rho}_{mt}(\pi) + \hat{\rho}_{mt}(EV1) - \hat{\rho}_{mt}(EV0)$$

and then regress $\hat{\rho}_{mt}$ on log of the relative price of the cheapest vodka in neighborhood (with the same set of instruments as in myopic case):

$$\hat{\rho}_{mt} = \theta log(Price)_{mt} + u_{mt}$$

This estimation procedure relies on assumption that consumers, when form their expectations over future prices, use the rule of price motion guessed from their previous

[23] On the second step I find $V_i\widehat{(0,s_t)} = H(s_{it})'\hat{\mu}$ by finding $\hat{\mu}$ that solves equation $I(a_{it} = 0)[H(s_{it})'\hat{\mu}] = \beta I(a_{it} = 0)[(log(1 + exp(log(\widehat{\sigma_{it+1}(1)}) - log(\widehat{\sigma_{it+1}(0)})) + H(s_{it+1})'\hat{\mu}]$ , where $H(s_{it})$ is a set of Hermite polynomials of state variables $s_{it}$. On final step, I estimate $\pi(1,s)$ by solving for $\hat{\theta}$ equation $I(a_{it} = 1)[s_t'\hat{\theta} + V_{it}\widehat{(0,s_t)} + log(\widehat{\sigma_{it}(1)}) - log(\widehat{\sigma_{it}(0)})] = \beta I(a_{it} = 1)[(log(1 + exp(log(\widehat{\sigma_{it+1}(1)}) - log(\widehat{\sigma_{it+1}(0)})) + V_{it}\widehat{(0,s_{t+1})}]]$. This sequential estimation procedure is not efficient. One can improve efficiency by solving three moment conditions altogether. In this case, however, there is no closed-form solution, and so one will face computational difficulties related to the problem of finding the (correct) global maximum of the GMM objective function with many variables.

experience. In Russia, the price of alcohol is volatile, and the rule of price motion demonstrates significant mean reversion (see Table A2). Therefore, estimation above implies that consumers believe that current increase in price comes before it's future decrease. If government increases price permanently, and can credible commit that price will not decrease in future, then expectations of consumers should be corrected.

To estimate price elasticity in this case, I make two simplifying assumptions on the price transition process and on the parametrization of the choice-specific value functions.

First, I assume that the price-transition process is independent of all other state variables and personal choice of action, and that it follows the AR rule of motion: $log(p_{i,t+1}) = \phi_0 + \phi_1 log(p_{it}) + \omega_{it}$, where $E(\omega_{it}|p_{it}) = 0$. Second, I assume the following parametrization of the choice-specific Value functions: $V_{it}(S_t, a_{t-1} = j) = \vartheta_j log(p_t) + V_{it}(\{S_t/p_t\})$, where $j \in \{0,1\}$, and $\{S_t/p_t\}$ is set of state variables excluding price.

Under these assumptions price elasticity can be estimated from regression of modified fixed effect component $\widetilde{\rho}_{mt}$:[24]

$$\widetilde{\rho}_{mt} = \hat{\rho}_{mt}(\pi) + \frac{1}{\widehat{\phi}_1}(\hat{\rho}_{mt}(EV1) - \hat{\rho}_{mt}(EV0))$$

on log of the relative price of the cheapest vodka in neighborhood:

$$\widetilde{\rho}_{mt} = \theta ln(Price)_{mt} + u_{mt}$$

Again I use the same set of instruments as in myopic case.

# 5 Results

Estimates of per-period utility parameters are shown in Table 2 below, and in Tables 5 through 7 at the end of paper.

In both specifications (myopic and forward-looking consumers), I find that peers have a strong effect on younger generations, with the effect decreasing with increasing age. For the two youngest strata, the effect is statistically significant. For myopic consumers, $\widehat{\delta}$ equals to 1.355, 0.688, 0.039, and 0.09 for ages 18-29, 30-39, 40-49, and 50-65 respectively. For forward-looking consumers, $\widehat{\delta}$ equals to 0.932, 0.456, 0.128, and 0.214 for ages 18-29, 30-39, 40-49, and 50-65 respectively.

The myopic model allows for an immediate statistical interpretation of the coefficients: an increase in peer average alcohol consumption of 0.2 (corresponding to a situation in which one out of five peers in a group becomes a heavy drinker) will increase the probability of becoming a heavy drinker for the "mean" person in age group 18-29 by 5.4 percentage

[24]See note 1 in appendix top for proof.

points, and for "mean" person in age group 30-39 by 2.8 percentage points. The forward-looking model does not allow immediate statistical interpretation; to evaluate how an increase in peer alcohol consumption affects consumer decision, one must know not only the consumer per-period utility, but also have an expectation of the consumer's future value function. In Table 6, I present point estimates of the marginal utility and marginal value function of peers, evaluated at the mean value of other state variables. Table 6 shows that in the forward-looking model, marginal value function (of peers) does not differ much from marginal per-period utility. The predicted marginal value function for the youngest age stratum is smaller than the marginal utility of myopic consumers.

The per-period (indirect) marginal utility of myopic consumers with respect to log(price) is equal to -0.79 and -0.85 for myopic and forward-looking consumers respectively. For a myopic consumer with mean level of all demographic characteristics, this coefficient implies that, for example, an increase in the price of vodka by 10% will lead to a decrease in the probability of heavy drinking by 6.5 percentage points (from 0.25 to 0.185). To evaluate the effect of a change in price on forward-looking consumers, one must know not only the consumer per-period utility, but also have an expectation of the consumer future value function. The per-period marginal value function of consumers with respect to log(price) is equal to -1.42.[25] This number implies a higher elasticity for forward-looking consumers - an increase in the price of vodka by 50% leads to a decrease in the probability of becoming a heavy drinker by 11.2 percentage points.

Table 2. Consumer's utility parameters. Point estimates.

| | Myopic | Forward-looking | |
|---|---|---|---|
| | Per-period utility | Per-period utility | Value function |
| Log(vodka price) | -0.79*** | -0.85*** | -1.05*** |
| peer effect, $\widehat{\delta}$: | | | |
| age 18-29 | 1.355*** | 0.932*** | 0.961*** |
| age 30-39 | 0.688*** | 0.456 *** | 0.609*** |
| age 40-49 | 0.039 | 0.128 | 0.073 |
| age 50-59 | 0.09 | 0.214 | 0.18 |
| Habit: lag I(heavy drinker) | 1.27*** | 1.234*** | |

Note: * significant at 10%** significant at 5%;*** significant at 1%
Bootstrapped standard errors are clustered on municipality*year level

The description of utility parameters above does not offer a full picture of what happens with consumer decisions regarding heavy drinking when the price of alcohol changes. One needs to calculate new equilibrium consumption levels after the price has changed, as well

[25]Elasticity is calculated under assumption that a price increase is permanent. In case if government can not commit that change in price is permanent, the elasticity is -0.97. For description of calculation procedure see Appendix.

as to take in account that the change in price will have an effect on future consumption through a change in habits. To evaluate the response of a consumer to a price change, I evaluate the cumulative effect of own elasticity, the peer effect, and the effect of a change in habits (and other state variables). To do this, I simulate consumer response to a permanent fifty percent increase in price for the 5-year period after the price change.

Figure 2 illustrates the decomposition of the cumulative response to change in price for males age 18-29. Dashed lines show the effect of a price increase on myopic consumers for three situations: in a model where peer effects and habit formation are included, in a model without peer effects, and in a model without habit formation. The difference in effects refers to the effect of the social multiplier and of the "habit multiplier." Solid lines show the effect of a price-increasing tax for forward-looking consumers. The forward-looking model predicts a decrease in the proportion of heavy drinkers by 8 percentage points, from 22.5% to 14.5% over five years. The myopic model predicts a (slightly) smaller decrease of 7.5 percentage points, from 22.5% to 15%. Taking into account only peer effects or only habit formation leads to a prediction of smaller changes: 5.3 percentage points versus 5.6 percentage points. Finally, own price elasticity results in a one-time change of 4.3 percentage points, which is approximately half of the cumulative effect.

Figure 2. Effect of tax on Pr(heavy drinker), age 18-29.

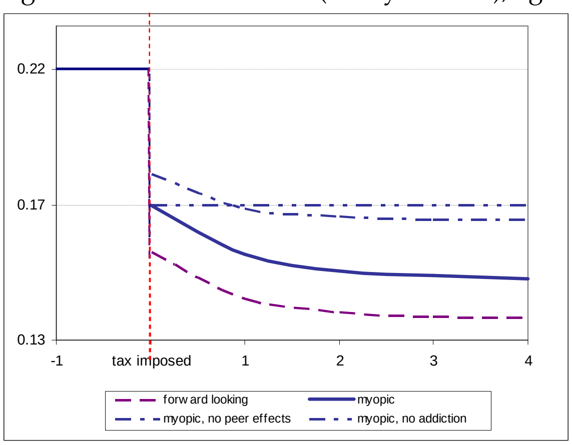
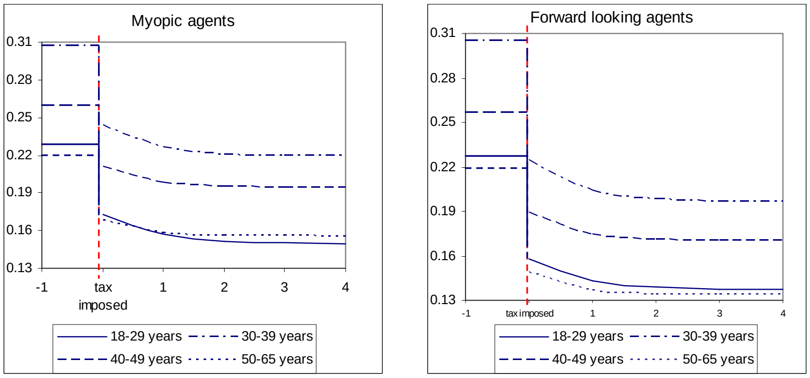



Figure 3 below illustrates the simulated effect of an increase in price for myopic and forward-looking consumers in different age strata. Overall, five years after the introduction of a price-raising tax, the proportion of heavy drinkers will decrease by one-third. The effect is higher for younger generations because of the non-trivial social multiplier.

In the model with forward-looking assumptions on consumer behavior, the predicted magnitude of change in the proportion of heavy drinkers is 1.75 times higher. The difference in the effect of a price-raising tax on different age strata is not large, because of smaller differences in estimated peer effects.

Figure 3. Effect of a 50% tax on Pr(heavy drinker) in different age cohorts.




In my second experiment, I model the effect of a change in vodka price on mortality rates.

To do this I estimate the effect of heavy drinking on death rates using the hazard specification

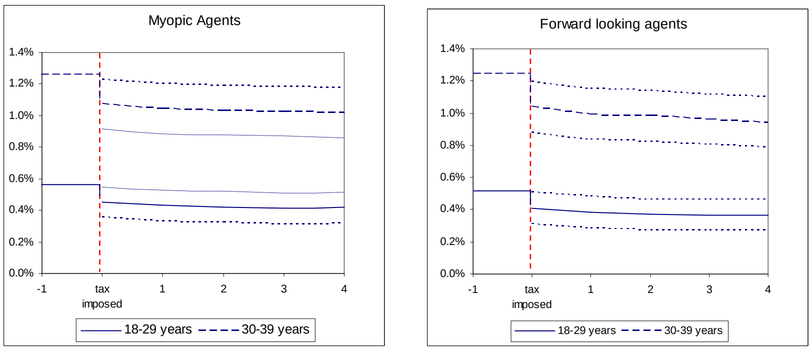
$$\lambda(t,x) = exp(x\beta)\lambda_0(t)$$

where $\lambda_0(t)$ is the baseline hazard, common for all units of population. I use a semi-parametric Cox specification of baseline hazard. Explanatory variables includes I(heavy drinker), I(smokes), log of family income, I(diseases), weight, current work status, and educational level. I allow heavy drinking to have a heterogeneous (by age stratum) effect on hazard of death. Younger males are more likely to be engage in hazardous drinking, which increases hazard rates. For younger people, other factors that affect hazard of death – such as chronic diseases – play a smaller role, and so the relative importance of heavy drinking as a factor of mortality is high.

Results of the estimation are presented in Table 8. The effect of heavy drinking is highly heterogeneous by age. The hazard of death for heavy drinkers age 18-29 is 7.4 times higher than for other males of the same age. The hazard of death for heavy drinkers in age 30-39 is 4.5 times higher. There is no difference between hazard rates for heavy drinkers and non-heavy drinkers age 40-65. It is worth noting that these estimations are done for a relatively-short period of 12 years, and so do not capture very long run consequences of alcohol consumption.

Figure 4 shows the simulated effect of increasing the price of alcohol on mortality rates for males of the youngest age strata. The simulated effect (in case of myopic consumers) of introducing a 50 percent tax is a decrease in mortality rates by one-fourth (from 0.55% to 0.4%) for males age 18-29 years, and by one-fifth (from 1.23% to 1.02%) for males age 30-39 years. There is no effect on the mortality of males of older ages. In other words, a 50 percent increase in the price of vodka would save 40,000 (male) lives annually. This is a lower bound (in magnitude) estimate of the effect: under "forward looking" assumption the effect of this policy is more than 55,000 saved lives.

Figure 4. Effect of 50% tax on mortality rates.




In my final experiment, I model the effect of tax policy on consumer welfare.

In both the forward-looking and myopic models presented above, consumers have bounded rationality: they do not take into account the effect of heavy drinking on hazard of death.[26] Within these models, tax corrects a negative externality that appears from the bounded rationality of consumers. The welfare effect of the 50 % tax is as follows. The tax results in a 30% loss in consumer surplus. At the same time, the tax saves 40,000 young male lives annually, which is 0.055% of the working-age population. The rough estimation of the value of their lives is the present value of the GDP that they generate. With time discount $\beta = 0.9$ value of saved lives equals to 0.55% of GDP, which is more than the size of the whole alcohol industry in Russia (0.48% of GDP). This speculative calculation suggests that a 50% tax is actually likely to be smaller than optimal one.[27]

Besides, my model, under certain assumptions of utilities, implies that the effect of a vodka tax on consumer surplus would be positive even for fully-rational consumers, forward-looking consumers who take into account the hazard of death associated with heavy drinking. The model I describe in the main body of my paper implies that peer effects and the effect of habits are positive: all other things being constant, a consumer has higher utility if he or she drank within the previous period and if he or she has peers that are heavy drinkers. These forces, however, can equally run a consumer utility to the negative. First, quitting heavy drinking is costly. Second, a consumer who decides not to drink may suffer from the fact that peers are drinking – the consumer may experience peer pressure, or consumer may suffer if no peer wishes to participate in alternative (to drinking) activities, such as playing soccer or doing other sports.[28]Thus, in the Robustness

[26]I analyze the model where consumers do take in account the effect of drinking on hazard of death in the appendix (table A2, column 2). Results are similar to those of forward looking model in main body of text (with slightly lower magnitude).

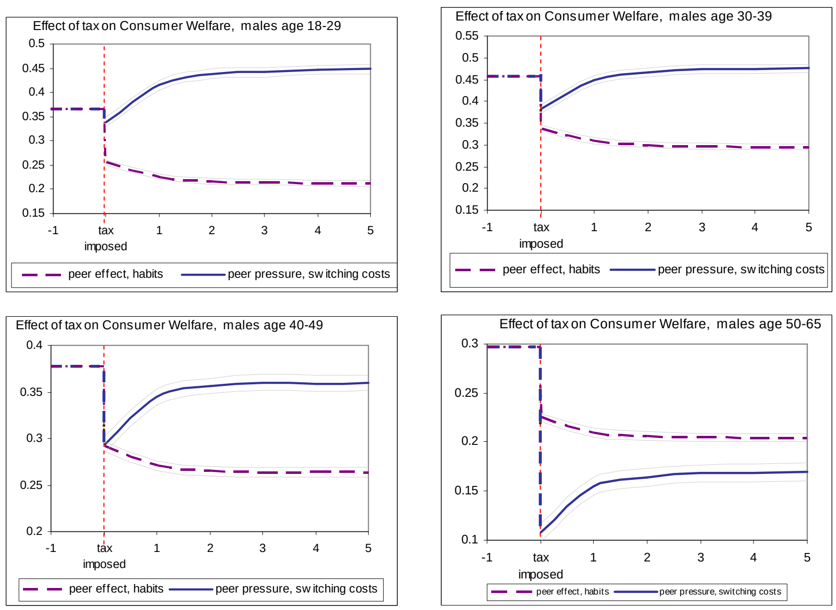
[27]My model does not take into account that the tax almost certainly saves other lives (children, females, the elderly), decreases crimes committed under alcohol intoxication, decreases car accidents, and so on.

[28]In this case, a consumer per-period choice specific utilities are as follows:

section I find that peer decisions matter for a consumer if he or she decide to do physical training. These alternative assumptions on utilities, although barely distinguishable from the data, have different implications for the analysis of consumer welfare.[29] In this case, a 50% tax on vodka results in an increase in the consumer welfare of young males below age 40.[30]

Figure 5 below illustrates this point.

Figure 5. Effect of tax policy on Consumer Welfare.




The final point I want to discuss is my finding that estimations of utilities and response functions, although different, do not differ dramatically in the myopic and forward-looking models. A possible explanation of this phenomenon is as follows. During the lengthy period in my analysis, Russia was in period of transition. This time people were uncertain about the future, and in particular about the realization of state variables such as future alcohol prices, future career, and income. In the context of my model, this may imply that consumers expectations about future Value function are noisy, possibly not correlating with current state variables or having a strong effect on consumer decision. In this case, even if in reality consumers are forward-looking, an estimated "myopic" indirect utility may be a good enough approximation of the choice-specific Value function. Table A2 in

$\pi_{it}(0) = -\delta \overline{I(a_j = 1|S_{i,-i,t})} - \gamma a_{i,t-1}$, $\pi_{it}(1) = \Gamma' D_{it} + \Upsilon' G_{-it} + \rho_{mt}$

[29]In "myopic" case peer effect and peer pressure jointly are not identified. One can identify only difference between them. In "forward-looking" case they are identified under additional assumptions. See proof of identification results in the appendix (Proof A3). In appendix I provide results of estimation for the following model: $\pi_{it}(0) = \delta \overline{\sigma(a_j = 1|S_{i,-i,t})} + \gamma a_{i,t-1}$, $\pi_{it}(1) = \alpha \overline{\sigma(a_j = 1|S_{i,-i,t})}$. Point estimates of $\delta$, $\gamma$ and $\alpha$ are -1.373, -1.141, 0.114 correspondingly (see Table A9b).

[30]Determining this optimal tax rate is a question for my future research.

Appendix illustrates this point. My data implies that in this case consumers should expect a significant mean reversion in price movement. According to column 2 of Table A2, a 10% change in price today leads to only a 4% change in the expected price next year.

# Robustness

In this section I provide several robustness checks for my results.

### Reduced-form elasticity estimates

Table A3 in the appendix presents reduced-form elasticity estimates from linear 2SLS regression.

$I(heavy\,drinker)_{it} = \alpha + \theta log(vodka\,price)_{mt} + \Gamma' D_{it} + \rho_t + e_{it}$

The price of vodka is instrumented by the same set of regulatory variables described above. Results are consistent with my estimates: reduced-form elasticity is 1.5 times higher than the own-price elasticity from my model, and represents the cumulative effect of own-price elasticity and the social multiplier.

### Linear in means peer effect

In this section I provide a robustness check for my estimates of peer effects on the two younger age groups.

The results of my estimations can be contaminated if (i) peers have the same with consumer unobservable shocks that affect their choice, and (ii) these unobservable shocks are independent of the set of peers demographic characteristics (see Manski, 1993)[31].

I check the validity of my results using a non-structural, linear in means assumption for

[31] The naïve approach of analyzing peer effects that was dominant prior to Manski's paper analyzed only the (residual) correlation between individual choice and the average choice of people from a reference group. Manski's primary critique of this approach was that parameters of interest were not identified – the effects would be contaminated by common unobservable factors, non-random reference group selection, the endogeneity of other group members' choices (correlated effects), and the influence of group characteristics (rather than group choice) on individual behavior (contextual effects). In contrast to endogenous peer effects, both contextual effects and correlated effects do not produce a social multiplier.

Different identification approaches have been proposed to solve the problems introduced in Manski's critique. The primary approaches in the empirical labor literature are the random assignment of peers (see Kremer and Levy 2008, Katz et al. 2001) and finding the exogenous variation of peer characteristics (see Gaviria and Raphael 2001, Card and Giuliano, 2011). Glaeser, Sacerdote, and Scheinkman (2002) and Graham (2008) use structural models to infer the magnitude of peer effects from aggregate statistics. Krauth (2005) employs a structural approach to directly model endogenous choice and correlated effects.

peer effects. The main regression specification is the following:

$$I_{it}(heavy\ drinker) = \sum_k \delta_k I(age\ strata = k)\overline{I(heavy\ drinker)} +$$
$$\gamma I_{it-1}(heavy\ drinker) + \Gamma' D_{it} + \Upsilon' G_{-it} + \rho_{mt} + e_{it}$$

where $\overline{I(heavy\, drinker)}$ is instrumented by average (across peers) demographic characteristics.[32]

Table A4 the appendix presents IV regression results, as well as the results of different robustness checks. After correcting for the difference in the magnitude of coefficients of the logit and linear probability models, the results have the same magnitude as the myopic model.[33]

First, I present estimates of peer effects using average peer demographic characteristics as instruments. I estimate the model using the entire sample and also separately for different age strata, and for sub-samples without the two regions with a Muslim majority (the Tatarstan and Karachaevo-Cherkessk republics). I verify the robustness of my results by including different sets of fixed effects. Results are similar to those elsewhere in this paper.

I then check the robustness of my results by using the demographic characteristics of the fathers of peers, rather than of the peers themselves, as instruments in my regression. The fathers of peers likely do not face shocks in common with the consumer. Finally, I verify the robustness of my results by estimating IV regression on only a sub-sample of respondents who just returned from military service. These people are likely not to face shocks common to their peers. All estimates have the same magnitude, and most of them are statistically significant.

I also employ alternative measures of alcohol-consumption frequency as a measure of alcohol consumption. I use a dummy (who drinks two-or-more times per week, so is in the top 21% of drinkers) as an indicator for a heavy drinker, from which I get similar results with a slightly lower magnitude (see Table A4 in the appendix). In addition, I check the model by applying a similar strategy to tea, coffee, and cigarette consumption, and to hours of physical training. I find no evidence that peers affect either tea, or coffee consumption. At the same time, I find a positive and statistically-significant (for younger groups) peer effect on the personal decision to undertake physical training (see Table A5 in the appendix). The effect of peers on smoking is marginally significant for two age strata.

[32] One can show that, under the assumption that beliefs are linear, the structural model I describe in the main body of this paper can be rewritten as a 2SLS regression with average peer demographics used as instruments. To simplify exposition of material, I do not follow structural specification. Within this structural framework, every particular set of instruments potentially changes the model itself. For example, I should add additional game with fathers to the model if I wanted use paternal demographics as instrumental variables.

[33] To compare coefficients in the logit model (Table 5) with those in the linear probability model (Table A4) one need to multiply coefficients in Table A4 on 5.3. To compare marginal effects of LPM and logit regression, one need to divide coefficients in LPM on $p(1-p)$, where $p$ is the probability of being a heavy drinker. In our case $(p(1-p))^{-1} = 5.3$.

**Robustness of dynamic model assumptions**

First, I verify the robustness of the results of the dynamic model under different normalizations of utility: in contrast to the myopic case, the dynamic model's estimator of parameters depends on the chosen normalization. I normalize the utility of heavy drinking to be 0. Results qualitatively are the same, with slightly higher own price elasticity , and a slightly lower magnitude of peer effects (see table A6 in the appendix). In addition, I check the results of the model by allowing all parameters of utilities to vary by age cohort. Utility estimates are similar to those described above (see Table A6 in the appendix).

Second, I did not model that consumers probably correctly estimate their hazard of death, and so I now take this into account. I verify the robustness of results after accounting for this factor. In this robustness experiment, a consumer has discounting factor $\beta\lambda(t,s)$, where hazard rates depends on state variables, and also on a consumer's decision about heavy drinking. Results of this estimation are presented in Table A6 in in the Appendix. Again, utility parameters do not differ from those shown above, because actual hazard of death is very small, especially for young generation.

Finally, I re-estimate the model under the assumption that unobserved utility $e_{it}(1)$ has a uniform (rather than logistic) distribution. The evaluation of moment equations that I use to estimate utility parameters relies largely on the functional form of logistic distribution. To check the robustness of my results against different distributional assumptions, I re-estimate the model with the assumption that $e_{it}(1)$ has U[-1,0] distribution, so that the moment condition can be rewritten in the following way (for the derivation of moment conditions, see Proof A2 in the appendix):

$$E[V_{it}(0,s_t) - \beta V_{it+1}(0,s_{t+1}) + \sigma_{it}(1) + \beta\sigma^2_{it+1}(1) + \pi_{it}(a_{-it},1,s_t,\theta)|a_{it}=1,s_t)] = 0$$

$$E[V_{it}(0,s_t) - \beta V_{it+1}(0,s_{t+1}) + \beta\sigma^2_{it+1}(1)|a_{it}=0,s_t] = 0$$

$$E(I(a_{it}=k)|s_t) = \sigma_{it}(k|s_t)\ ,\ k\in\{0,1\}$$

Table A6 in the appendix presents the results of estimations for both myopic and forward-looking consumers. Again, results qualitatively are similar, although in this specification, the price elasticity of forward-looking consumers is twice as high as that for myopic consumers.

Finally, I estimate the primary specification of the dynamic model separately for every stratum. Results are presented in Table A7 in the appendix. The magnitude of peer effects is slightly lower in this case.

**Habits versus unobserved heterogeneity**

To provide evidence that the observable correlation between current and lagged level of consumption is driven not by only individual heterogeneity, but also by habit formation, I estimate an instrumental variable regression:

$$I_{it}(heavy \quad drinker) = \alpha + \gamma I_{it-1}(heavy \quad drinker) + \Gamma' D_{it} + \rho_i + \delta_t + e_{it}$$

I use personal demographic characteristics (including current health status) to control for observed individual heterogeneity, and individual fixed effects to control for unobserved heterogeneity. I use lagged health status as an instrument for lagged $I(heavy\, drinker)$. Results of regression are presented in Table A8 in Appendix. Table A8 shows results of regressions with lagged $I(heavy\, drinker)$ as well as results of regressions with average across two and three lags of $I(heavy\, drinker)$. Regression results suggest that habits are important, with the same magnitude as elsewhere in my paper.

### Extension

In this section, I provide an informal toy test of which model, myopic or forward-looking, does the better job of explaining my data.

To start, it is worth noting that the seminal result of Rust (1994) states that in general, set-up cannot identify the discounting parameter. One must impose a strong parametric restrictions in order to obtain identification from the model. Therefore, this informal test should be treated at most as only suggestive. In main text of this paper, I use a sequential procedure of estimation for my parameters, which provides little guidance regarding which $\beta$ is better in describing my data. To provide an informal test I first simplify my model, and then use maximum likelihood with the nested fixed-point estimation algorithm described by Rust (1987) instead of the sequential algorithm described above.

In my toy model I assume that consumer utility depends on a simplified model with only two variables - habits (lag of I(heavy drinker)) and beliefs about peer actions, $\overline{\hat{\sigma}(a_j = 1|S_{i,-i,t})}$. Table A9 in the appendix shows the level of log likelihood functions, as well as estimated peer effects and the effect of habit for different age strata. Log likelihood for both models is almost the same, with a slightly-higher likelihood in the myopic model for young generations, and a slightly-higher likelihood in the forward-looking model for the oldest generation.

## 6 Conclusion

Over the past twenty years, the life expectancy of male Russian citizens has fallen by more than five years, and the mortality rate has increased by fifty percent. Now, male life expectancy in Russia is only 60 years, below that in Bangladesh, Yemen, and North Korea. Heavy alcohol consumption is widely agreed to be the main cause of this change.

In this paper, I present a dynamic model of heavy drinking behavior that accounts for the presence of peer effects and habit formation in order to quantify the effect of public policy (specifically, higher taxation) on the number of heavy drinkers and on mortality rates

First, I find that the probability of being a heavy drinker is (relatively) elastic with respect to the price of alcohol. Second, I find that peers play a significant role in the decision-making of Russian males below age 40. Presence of social multiplier results in significantly higher elasticity of alcohol consumption for younger cohorts. Finally, I find that the assumption that consumers are forward-looking gives me higher estimates of price elasticity compare to "myopic" case.

To illustrate this finding, I simulate the effect on heavy drinkers of increasing the price of vodka by 50%. The myopic model predicts that five years after introducing a price-raising tax, the proportion of heavy drinkers will decrease by roughly one-third – from 25 to 18 percentage points. The effect is higher for young generations because of the non-trivial effect of the social multiplier. This cumulative effect can be decomposed in following way: own one-period price elasticity predicts a drop in the proportion of heavy drinkers by roughly 4.5 percentage points, from 25 to 20.5 percent. In addition, peer effects and habit formation, and a forward-looking assumption, increase the estimated price elasticity by 1.9 times for younger generations, and by about 1.4 times for the older generation. In a model with forward-looking consumers, the effect of a change in price is higher by roughly 30 percent.

With this established, I simulate the effect on mortality rates of this increase in the price of alcohol. I find significant age heterogeneity in the effect of heavy drinking on the hazard of death: the hazard is much stronger for younger generations. The lower bound of simulated effect of introducing a 50% tax is as follows: tax leads to a decrease in mortality rates by one-fourth for males age 18-29 years, and by one-fifth for males age 30-39 years (with little effect on the mortality of males of older ages). In terms of actual numbers, a 50% tax on the price of vodka will save 40,000 (male) lives annually, or 1% of young male adult lives in six years.[34]

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[34]These numbers are elaborated for myopic consumers, and so give the lower bound of the effect of tax on mortality and share of heavy drinkers.

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## Tables

Table 3. Summary statistics.

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Panel data (males) | | | | | |
| I(Drunk more than 150 gr last month) | 41261 | 0.285 | 0.451 | 0 | 1 |
| Log(family income) | 41395 | 2.681 | 3.848 | -10.37 | 8.79 |
| Age | 41395 | 38.77 | 13.04 | 18 | 65 |
| Age squared | 41395 | 1674 | 1064 | 324 | 4225 |
| I(diseases) | 41379 | 0.137 | 0.343 | 0 | 1 |
| I(big family) | 41395 | 0.485 | 0.500 | 0 | 1 |
| Lag I(heavy drinker) | 32515 | 0.284 | 0.451 | 0 | 1 |
| Lag I(Smokes) | 32530 | 0.651 | 0.477 | 0 | 1 |
| I(works) | 40734 | 0.713 | 0.452 | 0 | 1 |
| I(college degree) | 41391 | 0.429 | 0.495 | 0 | 1 |
| I(Muslim) | 41395 | 0.088 | 0.283 | 0 | 1 |
| Weight | 37956 | 75.87 | 13.25 | 35 | 250 |
| I(big family) | 41395 | .455 | .498 | 0 | 1 |
| Liters of pure alcohol drunk last month | 41261 | 0.114 | 0.143 | 0 | 2.69 |
| I(physical training) | 41395 | 0.137 | 0.344 | 0 | 1 |
| I(drink tea) | 22104 | 0.966 | 0.181 | 0 | 1 |
| I(drink coffee) | 22098 | 0.698 | 0.459 | 0 | 1 |
| Survival regression data | | | | | |
| Death cases, total population | 25697 | 0.058 | 0.226 | 0 | 1 |
| Death cases, male, >17 years | 10894 | 0.078 | 0.259 | 0 | 1 |
| Drunk more than 150 gr last month | 10895 | 0.250 | 0.433 | 0 | 1 |
| Smokes | 10900 | 0.701 | 0.458 | 0 | 1 |
| Health evaluation (5 = good, 1 = bad) | 10881 | 2.690 | 0.648 | 1 | 5 |
| Married | 10307 | 0.645 | 0.479 | 0 | 1 |
| University education | 10900 | 0.588 | 0.492 | 0 | 1 |
| Weight | 10627 | 74. 78 | 12.65 | 36 | 215 |

Table 4. Distribution of # of peers in peer groups.

| # of peers | (Peer group)-level data | | | Individual - level data | | |
|---|---|---|---|---|---|---|
| in peer group | Freq. | Percent | Cum. % | Freq. | Percent | Cum. % |
| 2 | 3,373 | 37.98 | 37.98 | 6,746 | 18 | 17.71 |
| 3 | 2,383 | 26.83 | 64.81 | 7,149 | 19 | 36.48 |
| 4 | 1,253 | 14.11 | 78.92 | 5,012 | 13 | 49.64 |
| 5 | 653 | 7.35 | 86.27 | 3,265 | 8.57 | 58.21 |
| 6 | 326 | 3.67 | 89.94 | 1,956 | 5.14 | 63.35 |
| 7 | 174 | 1.96 | 91.9 | 1,218 | 3.2 | 66.55 |
| 8 | 129 | 1.45 | 93.36 | 1,032 | 2.71 | 69.26 |
| 9 | 66 | 0.74 | 94.1 | 594 | 1.56 | 70.82 |
| 10 | 46 | 0.52 | 94.62 | 460 | 1.21 | 72.02 |
| 11 | 57 | 0.64 | 95.26 | 627 | 1.65 | 73.67 |
| 12 | 37 | 0.42 | 95.68 | 444 | 1.17 | 74.84 |
| 13 | 28 | 0.32 | 95.99 | 364 | 0.96 | 75.79 |
| 14 | 28 | 0.32 | 96.31 | 392 | 1.03 | 76.82 |
| 15 | 22 | 0.25 | 96.55 | 330 | 0.87 | 77.69 |
| 16 | 31 | 0.35 | 96.9 | 496 | 1.3 | 78.99 |
| 17 | 19 | 0.21 | 97.12 | 323 | 0.85 | 79.84 |
| 18 | 17 | 0.19 | 97.31 | 306 | 0.8 | 80.64 |
| 19 | 17 | 0.19 | 97.5 | 323 | 0.85 | 81.49 |
| 20 and more | 222 | 2.5 | 100 | 7,050 | 18.51 | 100 |
| Total | 8,881 | 100 | | 38,087 | 100 | |

Note: 3642 peers groups that contain 1 peer are excluded

Table 5. Consumer utility parameters.

| | Agent's (per-period) Utility | |
|---|---|---|
| | $\beta = 0$ | $\beta = 0.9$ |
| peer effect, $\widehat{\delta}$: | | |
| age 18-29 | 1.355 | 0.932 |
| | *[0.273]**** | *[0.263]**** |
| age 30-39 | 0.688 | 0.456 |
| | *[0.158]**** | *[0.166]**** |
| age 40-49 | 0.039 | 0.128 |
| | *[0.182]* | *[0.178]* |
| age 50-59 | 0.090 | 0.214 |
| | *[0.229]* | *[0.206]* |
| Habit: Lag I(heavy drinker) | 1.270 | 1.234 |
| | *[0.039]**** | *[0.038]**** |
| Log (family income) | 0.004 | 0.003 |
| | *[0.011]* | *[0.01]* |
| *Age* | 0.120 | 0.079 |
| | *[0.016]**** | *[0.013]**** |
| *Age squired* | -0.001 | -0.001 |
| | *[0.0002]*** | *[0.0003]**** |
| *Weight* | 0.007 | 0.005 |
| | *[0.001]**** | *[0.001]**** |
| *I(diseases)* | -0.096 | -0.093 |
| | *[0.062]** | *[0.042]*** |
| *I(big family)* | -0.002 | -0.010 |
| | *[0.038]* | *[0.024]* |
| *Lag I(smokes)* | 0.505 | 0.429 |
| | *[0.037]**** | *[0.035]**** |
| *I(work)* | -0.241 | -0.222 |
| | *[0.039]**** | *[0.042]**** |
| *I(college degree)* | -0.147 | -0.127 |
| | *[0.068]*** | *[0.062]**** |
| *I(Muslim)* | -0.263 | -0.186 |
| | *[0.09]**** | *[0.094]**** |
| *municipality*year FE* | *Yes* | *Yes* |
| *Peers mean characteristics* | *Yes* | *Yes* |
| Observations | 25042 | 25042 |

Note: Bootstrapped standard errors in brackets

* significant at 10%;** significant at 5%;*** significant at 1%

Table 6. Marginal utility of peers

| | Myopic consumers | Forward looking consumers | |
|---|---|---|---|
| | MU ($du/d\overline{\sigma(a_j=1)}$) | MV ($dV/d\overline{\sigma(a_j=1)}$) | MU ($du/d\overline{\sigma(a_j=1)}$) |
| age 18-29 | 1.355 | 0.961 | 0.932 |
| age 30-39 | 0.688 | 0.609 | 0.456 |
| age 40-49 | 0.039 | 0.073 | 0.128 |
| age 50-59 | 0.09 | 0.18 | 0.214 |

Table 7. Estimates of price elasticity

| | Myopic consumers | Forward looking consumers | | First stage |
|---|---|---|---|---|
| | MU (du/dlogP) | MV (dV/dlogP) | MU (du/dlogP) | log(vodka price) |
| log(vodka price) | -0.79 | -1.05 | -0.85 | |
| | [0.244]*** | [0.293]*** | [0.23]*** | |
| I(excise) | | | | 0.137 |
| | | | | [0.050]*** |
| I(tax-producers) | | | | 0.135 |
| | | | | [0.039]*** |
| I(tax-retail) | | | | 0.117 |
| | | | | [0.037]*** |
| Constant | -0.245 | 1.324 | 1.196 | 0.4 |
| | [0.174] | [0.224]*** | [0.175]*** | [0.028]*** |
| Year FE | yes | yes | yes | yes |
| Observations | 25042 | 25042 | 25042 | 25042 |
| F-stat (clustered errors) | 9.75 | 9.75 | 9.75 | 9.75 |
| F-stat | 724 | 724 | 724 | 724 |
| J-test, p-value | 0.97 | 0.61 | 0.45 | |

Note: Second stage: bootsraped standard errors in brackets;

First stage: Robust standard errors, clustered at regionXyear level in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8. Mortality and heavy drinking.

| | all males | | all males | |
|---|---|---|---|---|
| | coefficient | hazard ratio | coefficient | hazard ratio |
| I(heavy drinker) age 18-29 | 1.993 | 7.337 | | |
| | [0.519]*** | | | |
| I(heavy drinker) age 30-39 | 1.541 | 4.669 | | |
| | [0.357]*** | | | |
| I(heavy drinker) age 40-49 | -0.031 | 0.969 | | |
| | [0.324] | | | |
| I(heavy drinker) age 50-64 | 0.108 | 1.114 | | |
| | [0.243] | | | |
| I(heavy drinker), age18-64 | | | 0.39 | 1.477 |
| | | | [0.147]*** | |
| Log (family income) | -0.322 | 0.725 | -0.321 | 0.725 |
| | [0.016]*** | | [0.016]*** | |
| I(diseases) | 0.34 | 1.405 | 0.365 | 1.441 |
| | [0.128]*** | | [0.128]*** | |
| Lag I(smokes) | 0.561 | 1.527 | 0.563 | 1.756 |
| | [0.099]*** | | [0.099]*** | |
| I(college degree) | -1.504 | 0.222 | -1.53 | 0.217 |
| | [0.228]*** | | [0.228]*** | |
| Weight | -0.002 | 0.998 | -0.001 | 0.999 |
| | [0.003] | | [0.003] | |
| I(work) | -0.299 | 0.742 | -0.29 | 0.748 |
| | [0.134]** | | [0.133]** | |
| Observations | 7735 | | 7735 | |

Standard errors in brackets; * significant at 10%** significant at 5%;*** significant at 1%

## Appendix

Figure A1. Alcohol consumption: age profile

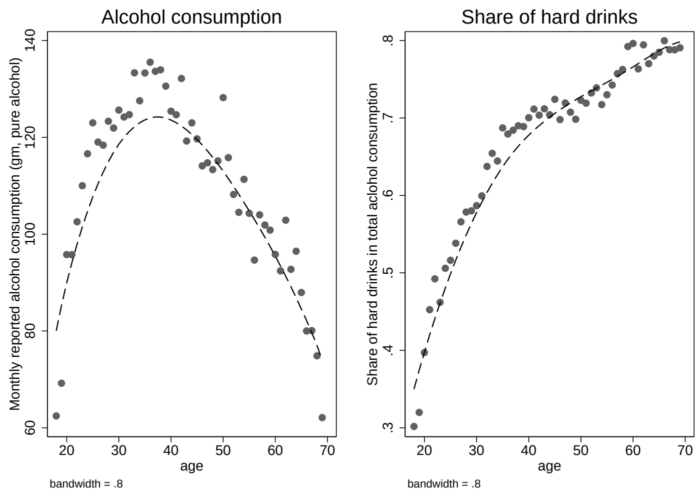


Figure A2. Typical dvor ("khrushevka") in Russia.

Source: www.photographer.ru (Petr Antonov)

Table A1. Consumption of goods and birthday.

| | I(drink vodka) | I(smokes) | I(drink tea) | I(drink coffee) |
|---|---|---|---|---|
| All peers | | | | |
| $\frac{\sum_{peers} I(birthday)}{(N-1)}$ | 0.042 | -0.029 | -0.01 | -0.013 |
| | [0.015]*** | [0.015]* | [0.007] | [0.019] |
| $I(birthday)$ | 0.028 | 0.025 | -0.002 | 0.008 |
| | [0.009]*** | [0.009]*** | [0.005] | [0.012] |
| Year*month FE | Yes | Yes | Yes | Yes |
| Observations | 39534 | 39515 | 20450 | 20444 |
| Without household members | | | | |
| $\frac{\sum_{peers} I(birthday)}{(N-1)}$ | 0.039 | -0.028 | -0.008 | -0.015 |
| | [0.015]** | [0.015]* | [0.007] | [0.019] |
| $I(birthday)$ | 0.028 | 0.026 | -0.002 | 0.007 |
| | [0.009]*** | [0.009]*** | [0.005] | [0.012] |
| Year*month FE | Yes | Yes | Yes | Yes |
| Observations | 35995 | 35977 | 18253 | 18247 |

* significant at 10%; ** significant at 5%; *** significant at 1%

Table A2. Lag (Log vodka price) is not a good predictor for current Log(Vodka Price)

| | $log(vodka\,price)_t$ | $log(vodka\,price)_t - log(vodka\,price)_{t-1}$ |
|---|---|---|
| $log(vodka\,price)_{t-1}$ | 0.392 | |
| | [0.039]*** | |
| $log(vodka\,price)_{t-1}$ | | -0.419 |
| $-log(vodka\,price)_{t-2}$ | | [0.052]*** |
| Year FE | NO | NO |
| Region FE | NO | NO |
| Observations | 36307 | 28403 |
| R-squared | 0.18 | 0.19 |

Robust standard errors clustered at municipalityXyear level are in brackets
* significant at 10%; ** significant at 5%; ***significant at 1%

Table A3. Reduced form elasticity estimates. 2SLS regression.

| | Individual-level, 2SLS | |
|---|---|---|
| | 1st stage | 2nd stage |
| | log(vodka price) | I(heavy drinker) |
| log(vodka price) | | -0.338 |
| | | [0.133]** |
| I(excise) | 0.051 | |
| | [0.018]*** | |
| I(tax, producers) | 0.084 | |
| | [0.016]*** | |
| I(tax, retail) | 0.034 | |
| | [0.016]** | |
| Log (family income) | 0.022 | 0.007 |
| | [0.002]*** | [0.003]** |
| Age | 0 | 0.013 |
| | [0.001] | [0.001]*** |
| Age squired | 0 | 0 |
| | [0.000] | [0.000]*** |
| Weight | -0.001 | 0.001 |
| | [0.000]*** | [0.000]*** |
| I(diseases) | 0.009 | -0.013 |
| | [0.007] | [0.009] |
| I(big family) | -0.033 | -0.029 |
| | [0.010]*** | [0.010]*** |
| Lag I(smokes) | 0.026 | 0.127 |
| | [0.007]*** | [0.009]*** |
| I(work) | 0.018 | -0.017 |
| | [0.011]* | [0.009]* |
| I(college degree) | 0.028 | -0.021 |
| | [0.010]*** | [0.011]* |
| I(Muslim) | -0.31 | -0.215 |
| | [0.078]*** | [0.054]*** |
| Year FE | YES | YES |
| Constant | 0.521 | 0.032 |
| | [0.034]*** | [0.067] |
| Observations | 33193 | 33103 |
| R-squared | 0.31 | |
| F-test | | 154.62 |
| F-test (robust st.errors) | | 9.58 |
| J-test, p-val | | 0.12 |

Standard errors clustered at neighborhood level in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table A4. Linear in means peer effects. Robustness checks under different specification.

| | I(heavy drinker) | | | | | |
|---|---|---|---|---|---|---|
| | | | age 18-55 | | | |
| | IV-1 | IV-2 | IV-3 | IV-4 | OLS-1 | OLS-2 |
| Peer effect, $\widehat{\delta}$: | | | | | | |
| age 18-29 | 0.264 | 0.297 | 0.242 | 0.255 | 0.193 | 0.119 |
| | [0.04]*** | [0.05]*** | [0.04]*** | [0.09]*** | [0.03]*** | [0.02]*** |
| age 30-39 | 0.194 | 0.218 | 0.181 | 0.16 | 0.17 | 0.111 |
| | [0.03]*** | [0.04]*** | [0.03]*** | [0.065]** | [0.02]*** | [0.01]*** |
| age 40-49 | 0.063 | 0.089 | 0.053 | 0.063 | 0.121 | 0.057 |
| | [0.030]** | [0.037]** | [0.031]* | [0.059] | [0.02]*** | [0.01]*** |
| age 50-59 | -0.005 | 0.015 | -0.022 | 0.009 | 0.088 | 0.03 |
| | [0.033] | [0.041] | [0.033] | [0.056] | [0.02]*** | [0.016]* |
| Demographics | Yes | Yes | Yes | Yes | Yes | Yes |
| Munic*year FE | Yes | Yes | Yes | | | Yes |
| Individual FE | | | | Yes | | |
| Year FE | | | | Yes | | |
| Muslim region excluded? | | | Yes | | | |
| Instruments | Peers 1 | Peers 2 | Peers 1 | Peers 1 | | |
| Observations | 29554 | 29554 | 27400 | 29554 | 29923 | 29923 |
| F-test | 79.9 | 36.29 | 72.02 | 17.02 | | |
| J-test, p-value | 0.22 | 0.13 | 0.26 | 0.02 | | |
| | | age18-29 | | | | |
| | IV-5 | IV-6 | IV-7 | IV-8 | | |
| Peer effect, $\widehat{\delta}$: | 0.211 | 0.197 | 0.225 | 0.359 | | |
| | [0.09]** | [0.136] | [0.14]* | [0.180]** | | |
| Demographics | Yes | Yes | Yes | Yes | | |
| Munic*year FE | Yes | Yes | Yes | Yes | | |
| Just came from military service? | | | | Yes | | |
| Instruments | Peers 1 | Fathers 1 | Fathers 2 | Peers 1 | | |
| Observations | 7750 | 8152 | 8152 | 149 | | |
| F-test | 34.24 | 16.52 | 28.97 | 6.85 | | |
| J-test, p-value | 0.06 | 0.4 | 0.86 | 0.17 | | |

Standard errors clustered at municipality*year in brackets.

* significant at 10%; ** significant at 5%, *** significant at 1%

Instrument set: Peers: (1) average demographics (2) average demographics without lag I(heavy drinker)

Instrument set: Peer fathers: (1) average demographics (2) average demographics-subset

Table A5. Linear in means peer effects. Peer effects for different products/activities.

| | Peer effect | | | |
|---|---|---|---|---|
| year | age 18-29 | age 30-39 | age 40-49 | age 50-64 |
| I(drink tea) | -0.016 | -0.016 | -0.003 | -0.006 |
| I(drink coffee) | 0.02 | 0.055 | 0.055 | 0.057* |
| I(smoking) | 0.016 | 0.021* | 0.014 | 0.018* |
| I(physical training) | 0.14*** | 0.127*** | 0.141*** | 0.073 |
| I(Drink 2 days/week) | 0.195*** | 0.118*** | -0.014 | 0.009 |

* significant at 10%; ** significant at 5%, *** significant at 1%

Table A6. Forward looking consumers. Point estimates of utility parameters. Different robustness checks.

| | Utility parameters | | | |
|---|---|---|---|---|
| Utility parameters: | | | | |
| Peer effect, $\widehat{\delta}$: | | | | |
| age 18-29 | 0.644 | 0.948 | 0.198 | 0.358 |
| age 30-39 | 0.201 | 0.49 | 0.132 | 0.321 |
| age 40-49 | -0.031 | 0.152 | 0.014 | 0.052 |
| age 50-59 | 0.051 | 0.253 | -0.008 | 0.019 |
| Habit: lag I(heavy drinker) | 1.34 | 1.23 | 0.262 | 0.261 |
| Elasticity: | | | | |
| log(vodka price) | -2.39 | -0.858 | -0.157 | -0.51 |
| Normalization | U(drink)=0 | U(not drink)=0 | U(not drink)=0 | U(not drink)=0 |
| Forward looking? | Yes | Yes | Myopic | Yes |
| Distribution of private shocks | Logistic | Logistic | Uniform[-1.0] | Uniform[-1.0] |
| Discounted by hazard of death | No | Yes | No | No |
| Demographics | Yes | Yes | Yes | Yes |
| Municipality*year FE | Yes | Yes | Yes | Yes |
| Peers mean characteristics | Yes | Yes | Yes | Yes |

Note: In first column I revert signs of coefficients on opposite.

Table A7. Point estimates of utilities for forward looking consumers. Separate regression for every age strata.

| | age: 18-29 | age: 30-39 | age: 40-49 | age: 50-65 |
|---|---|---|---|---|
| Peer effects, $\widehat{\delta}$ | 0.793 | 0.558 | 0.001 | 0.143 |
| Habit: lag I(heavy drinker) | 1.074 | 1.338 | 1.38 | 1.441 |

Table A8. Habits versus unobserved heterogeneity.

| | Y | | | | | |
|---|---|---|---|---|---|---|
| | log(1+alcohol consumption) | | | I(heavy drinker) | | |
| Mean(Lag Y, LagLag Y, LagLagLag Y) | 0.423 | | | 0.666 | | |
| | [0.207]** | | | [0.323]** | | |
| Mean(Lag Y, LagLag Y) | | 0.472 | | | 0.901 | |
| | | [0.233]** | | | [0.462]* | |
| Lag Y | | | 0.313 | | | 0.604 |
| | | | [0.235] | | | [0.497] |
| I(health problems) | -0.006 | -0.005 | -0.007 | -0.01 | -0.001 | -0.009 |
| | [0.002]** | [0.003]* | [0.003]*** | [0.010] | [0.015] | [0.013] |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographics | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 33812 | 33810 | 33735 | 33814 | 33814 | 33814 |
| Number of individuals | 5814 | 5814 | 5814 | 5814 | 5814 | 5814 |
| F-test for instruments (with robust se) | 19 | 14.9 | 14.78 | 9.77 | 6.02 | 4.82 |

Note: Instruments are Mean(Lag X, LagLag X, LagLagLag X), Mean(Lag X, LagLag X), and Lag X correspondingly, where X stands for I(health problems).
Robust standard errors, clustered on individual level, are in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table A9a. Log likelihoods for different betas. Rust's (NFP) approach.

| | age 18-29 | age 30-39 | age 40-49 | age 50-65 |
|---|---|---|---|---|
| $\beta$=0 | | | | |
| Lag I(heavy drinker) | 1.407 | 1.42 | 1.425 | 1.466 |
| Peer effect | 1.399 | 0.98 | 0.866 | 0.757 |
| Log Likelihood | -3555.43 | -3723.54 | -3877.12 | -3591.9 |
| $\beta$=0.9 | | | | |
| Lag I(heavy drinker) | 1.432 | 1.42 | 1.425 | 1.468 |
| Peer effect | 1.257 | 0.767 | 0.673 | 0.596 |
| Log Likelihood | -3556.5 | -3723.52 | -3877.1 | -3591.34 |

Table A9b. Peer effects vs Peer pressure. Rust approach.

| | age 18-29 |
|---|---|
| $\beta$=0.9 | |
| Lag I(heavy drinker), $\gamma$ | -1.373 |
| Peer effect, $\alpha$ | 0.114 |
| Peer pressure, $\delta$ | -1.141 |
| Log Likelihood | -3554.9 |

Note: In this case, a consumer per-period choice specific expected utilities are as follows:
$\pi_{it}(0) = \delta\overline{\sigma(a_j = 1|S_{i,-i,t})} + \gamma a_{i,t-1}$, $\pi_{it}(1) = \alpha\overline{\sigma(a_j = 1|S_{i,-i,t})}$.
$\overline{\hat{\sigma}_{jt}(a_{jt} = 1|S_{i,-i,t})}$ is discretized to set {0.2, 0.4, 0.6. 0.8, 1}.

## Note 1. Calculation of Price elasticity.

Remind that, I assume that the price-transition process is independent of all other state variables and personal choice of action, and that it follows the AR rule of motion:

$log(p_{i,t+1}) = \phi_0 + \phi_1 log(p_{it}) + \omega_{it}$, where $E(\omega_{it}|p_{it}) = 0$, i.e. $\frac{\partial E_p(log(p_{t+1}))}{\partial log(p_t)} = \phi_1$

Second, I assume the following parametrization of the Value function:

$$V_{it}(S_t, a_{t-1} = j) = \vartheta_j log(p_t) + V_{it}(\{S_t/p_t\}),$$

where $j \in \{0,1\}$, and $\{S_t/p_t\}$ is set of state variables excluding price.

Under these assumptions,

$$\frac{\partial}{\partial log(p_t)}[E(V_{it+1}(S_{t+1})|1,S_t) - E(V_{it+1}(S_{t+1})|0,S_t)] = (\vartheta_1 - \vartheta_0)\frac{\partial E_p(log(p_{t+1}))}{\partial log(p_t)}$$

Without a commitment on price stability, $\frac{\partial E_p(log(p_{t+1}))}{\partial log(p_t)} = \phi_1$. Once the government can commit that the price will not revert, then $\frac{\partial E_p(log(p_{t+1}))}{\partial log(p_t)} = 1$, and therefore

And

$$\begin{aligned}\frac{\partial Value\,function}{\partial log(p_t)} = \quad & \frac{\partial}{\partial log(p_t)}[E_{e_{-i}}\pi_{it}(a_{-it}, a_{it} = 1, s_t)] \\ & + \frac{\partial}{\partial log(p_t)}[E(V_{it+1}(S_{t+1})|1,S_t) - E(V_{it+1}(S_{t+1})|0,S_t)] \\ & = \frac{\partial \rho_{mt}(\pi)}{\partial log(p_t)} + \frac{1}{\phi_1}(\frac{\partial \rho_{mt}(EV1)}{\partial log(p_t)} - \frac{\partial \rho_{mt}(EV0)}{\partial log(p_t)})\end{aligned}$$

Proof A1

Derivation of moment conditions, model with forward looking assumption (with$\beta$=0.9).
consumer choice specific value function is

$$V(a_{it},s_t) = E_{e_{-i}}\pi_{it}(a_{-it},a_{it},s_t) + \beta E(V_{it+1}(s_{t+1})|a_{it},s_t)$$

where $E(V_{it+1}(s_{t+1})|a_{it},s_{it})$ is ex ante value function (or so called Emax function):

$$V_{it+1}(s_{t+1}) = E_{e_{it+1}}(max_{a_{it+1}}[V(a_{it+1},s_{t+1})_{it+1} + e_{it+1}(a_{it+1})])$$

To derive moment conditions for my further estimation I will use two well-known relationships. Both of these relationship based on properties of logistic distribution of private utility shock (random utility component).

First relationship, is called Hotz-Miller inversion (see Hotz and Miller, 1993):

$$V(1,s_t)_i - V(0,s_t)_i = log(\sigma_{it}(1)) - log(\sigma_{it}(0))$$

Second equation states relationship between Emax function and choice specific value functions:

$$V(s_t) = log(exp(V(0,s_t)) + exp(V(1,s_t)))$$

Applying these relationships to equation for value function:

$$\begin{aligned} V(a_{it},s_t) &= \pi_{it}(a_{-it},a_{it},s_t,\theta) + \beta E(log(exp(V(0,s_{t+1})) + exp(V(1,s_{t+1}))|a_{it},s_t) \\ &= \pi_{it}(a_{-it},a_{it},s_t,\theta) + \beta E(log(exp(V(0,s_{t+1})) + exp(V(0,s_{t+1}))\sigma_{it+1}(1)/\sigma_{it+1}(0))|a_{it},s_t) \\ &= \pi_{it}(a_{-it},a_{it},s_t,\theta) + \beta E(V(0,s_{t+1}) - log(\sigma_{it+1}(0))|a_{it},s_t) \end{aligned}$$

When put $a_{it} = 0$, and $a_{it} = 1$ in equation above I have:

Moment condition on $V_i(0,s_{it})$:

$$V_i(0,s_{it}) = \beta E_{t+1}[log(1 + exp(log(\sigma_{it+1}(1)) - log(\sigma_{it+1}(0)) + V_i(0,s_{it+1})|s_t,a_{it} = 0]$$

Moment condition on $V_i(1,s_{it})$:

$$\begin{aligned} V(1,s)_{it} &= log(\sigma_{it}(1)) - log(\sigma_{it}(0)) + V(0,s)_{it} \\ &= \pi_{it}(a_{-it},a_{it} = 1,s_t,\theta) + \beta E_{t+1}(V(0,s_{t+1}) - log(\sigma_{it+1}(0))|a_{it} = 1,s_t) \end{aligned}$$

These two equations, together with moment equation on choice probabilities

$$E(I(a_i = k)|s_t) = \sigma_i(k|s_t),\ k \in \{0,1\}$$

form system of moments I estimated:

$$E[\pi_{it}(a_{-it},a_{it} = 1,s_t,\theta) + V_i(0,s)_{it} - \beta V(0,s_{t+1}) + log(\sigma_{it}(1)) - log(\sigma_{it}(0)) + \beta log(\sigma_{it+1}(0))|a_{it} = 1,s_t)] = 0$$

$$E[V_i(0,s_t) - \beta V(0,s_{t+1}) + \beta log(\sigma_{it+1}(0))|a_{it} = 0,s_t] = 0$$

$$E(I(a_i = k)|s_t) = \sigma_i(k|s_t),\ k \in \{0,1\}$$

## Proof A2

Derivation of moment conditions with assumption of uniform distribution of unobserved component of utility: $e_{it}(1)$ is distributed uniformly on [-1,0], $e_{it}(0)$ is normalized to 0.

I use the same notation I used in Proof A1. To derive moment conditions for my estimation I will use "uniform" analogs of relationships I discussed in Proof A1:

First lemma establishes relationship between choice probability and choice specific value functions:

Lemma 1

$V(1,s)_{it} - V(0,s)_{it} = \sigma_{it}(1)$

Proof:

$$\begin{aligned} Pr(1) &= Pr(V(1,s)_{it} + e_{it}(1) > V(0,s)_{it} + e_{it}(0)) \\ &= Pr(e_{it}(0) - e_{it}(1) < V(1,s)_{it} - V(0,s)_{it} = V(1,s)_{it} - V(0,s)_{it} \end{aligned}$$

Second lemma states relationship between Emax function and choice specific value functions:

Lemma 2

$V(s) = V(0,s)_{it} + (V(1,s)_{it} - V(0,s)_{it})^2$

Proof:

$$\begin{aligned} V(s) &= E_{e1}(max(V(1,s)_{it} + e_{it}(1), V(0,s)_{it})) \\ &= Pr(V(1,s)_{it} + e_{it}(1) > V(0,s)_{it})[V(1,s)_{it} + E(e_{it}(1)|e_{it}(1) > V(0,s)_{it} - V(1,s)_{it})] \\ &+ Pr(V(1,s)_{it} + e_{it}(1) < V(0,s)_{it})V(0,s)_{it} \\ &= (V(1,s)_{it} - V(0,s)_{it})[V(1,s)_{it} + (V(0,s)_{it} - V(1,s)_{it})/2] \\ &+ (1 - V(1,s)_{it} + V(0,s)_{it})V(0,s)_{it} \\ &= V(0,s)_{it} + (V(1,s)_{it} - V(0,s)_{it})^2/2 \end{aligned}$$

Applying these relationships to equation for value function:

$$\begin{aligned} V(a_{it}, s_t) &= \pi_{it}(a_{-it}, a_{it}, s_t, \theta) + \beta E(Emax|a_{it}, s_t) \\ &= \pi_{it}(a_{-it}, a_{it}, s_t, \theta) + \beta E(V(0, s_{t+1}) + (\sigma_{it+1}(1))^2|a_{it}, s_t)/2 \end{aligned}$$

When put $a_{it} = 0$, and $a_{it} = 1$ in equation above I have:

Moment condition on $V_i(0, s_{it})$:

$$V_i(0, s_{it}) = \beta E_{t+1}((\sigma_{it+1}(1))^2/2 + V_i(0, s_{it+1})|s_t, a_{it} = 0)$$

Moment condition on $V_i(1, s_{it})$:

$$\begin{aligned} V(1,s)_{it} &= \sigma_{it}(1) + V(0,s)_{it} \\ &= \pi_{it}(a_{-it}, a_{it} = 1, s_t, \theta) + \beta E_{t+1}(V_i(0, s_{t+1}) + (\sigma_{it+1}(1))^2/2|a_{it} = 1, s_t) \end{aligned}$$

These two equations, together with moment equation on choice probabilities

$$E(I(a_i = k)|s_t) = \sigma_i(k|s_t),\ k \in \{0,1\}$$

form system of moments:

$$E[\pi_{it}(a_{-it}, a_{it} = 1, s_t, \theta) + V_i(0,s)_{it} - \beta V_i(0, s_{t+1}) + \sigma_{it}(1) + \beta(\sigma_{it+1}(1))^2/2|a_{it} = 1, s_t)] = 0$$

$$E[V_i(0, s_t) - \beta V_i(0, s_{t+1}) + \beta(\sigma_{it+1}(1))^2/2|a_{it} = 0, s_t] = 0$$

$$E(I(a_i = k)|s_t) = \sigma_i(k|s_t),\ k \in \{0,1\}$$

## Proof A3

Lemma

Let $z_{it}$ be a state variable that enters both in $\pi_{it}(1)$ and in $\pi_{it}(0)$:

$\pi_{it}(0) = \rho_0 z_{it}$

$\pi_{it}(1) = \rho_1 z_{it} + \Gamma' S_{it} + e_{it}(1)$

then

i) In myopic model $\rho_0$ and $\rho_1$ are not identifiable

ii) In forward looking model, $\rho_0$ and $\rho_1$ are identifiable iff there is no $f(s_t, z_{it})$ such that

$f(s_t, z_{it}) - \beta * E[f(s_{t+1}, z_{it+1})|a_{it} = j, s_t, a_{-it}] = \phi_j * z_{it}$ for $j \in \{0,1\}$

Proof

i) In myopic model agent decides to drink if

$\pi_{it}(1) - \pi_{it}(0) = (\rho_1 - \rho_0) z_{it} + \Gamma' S_{it} + e_{it}(1) > 0$

Then for any number $b$ , pairs$(\rho_1, \rho_0)$ and $(\rho_1 + b, \rho_0 + b)$ are observationally equivalent.

ii)$\Rightarrow$ From the data we know population parameters $\sigma(0)$ and $\sigma(1)$ and operators $E_{t+1}(.|1)$, $E_{t+1}(.|0)$.

In case of forward looking consumer value function is fully characterized by two equations:

$$V(0_{it}, s_t) = \rho_0 z_{it} + \beta E_{t+1}(exp(V(0,s) - log(\sigma(0))|0_{it}, s_t) \quad (4)$$

$$V(0_{it}, s_t) + log(\sigma(1)/(\sigma(0)) = \rho_1 z_{it} + \pi_{it}(a_{-it}, a_{it}, s_t, \theta) + \beta E_{t+1}(V(0,s) - log(\sigma(0)))|1, s_t) \quad (5)$$

Suppose that exists another pair$V(0_{it}, s_t)', \rho'_j$ for which these two equations hold

Define $\Delta_j = \rho'_j - \rho_j$, $f(s_t, z_{it}) = V(0_{it}, s_t) - V(0_{it}, s_t)'$

Equations above imply

$f(s_t, z_{it}) - \beta * E[f(s_{t+1}, z_{it+1})|a_{it} = j, s_t, z_{it}] = \Delta_j * z_{it}$, so contradiction.

$\Leftarrow$

Assume that $\exists f(s_t, z_{it}) : f(s_t, z_{it}) - \beta * E[f(s_{t+1}, z_{it+1})|a_{it} = j, s_t, a_{it}] = \phi_j * z_{it}$

and let $V(0_{it}, s_t), \rho_j$ is solution of equations above. Then $V(0_{it}, s_t)', \rho'_j$, such as $V(0_{it}, s_t)' = f(s_t, z_{it}) + V(0_{it}, s_t)$, and $\rho'_j = \rho_j + \phi_j$ will be solution of equations (4) and (5).

•

Note: Example where we can not identify $\rho_1$ and $\rho_0$.

If there are $\phi_j$, such that $E(z_{it+1}|a_{it} = j, s_t) = \zeta + \phi_j * z_{it}$, then we can not identify$\rho_0$ and $\rho_1$ simultaneously.

Proof:

Let $V(0_{it}, s_t)' = V(0_{it}, s_t) + z_{it} + \zeta/(1-\beta)$ and $\rho'_j = \rho_j + 1 - \beta\phi_j$ , and we have that equations (4) and (5) above hold for new$V(0_{it}, s_t)', \rho'_j$