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ABSTRACT

This thesis consists of three empirical papers on various topics, which are brought together under a broad umbrella of Applied Public Economics.

The first paper "Illicit Drug Seizures and Drug Consumption: Evidence from Italy" aims at uncovering causal links between cocaine seizures and cocaine-related hospital admissions by resorting to instrumental variables approach, using data on Italian provinces. Additionally, the study explores spatial interrelations between the variables of interest by adopting the SLX model. According to the results obtained, ignoring endogeneity leads to underestimating the effect of seizures on consumption by biasing the coefficient towards zero. Spatial relations were also found to be significant between seizures in key entry points and consumption in the rest of the country, as well as between seizures in adjacent provinces and consumption in a home province.

The second paper "Baby Bonuses and Household Consumption: Evidence from Russia" exploits a fertility-incentivizing reform that took place in Russia in 2007 to study the responses of eligible households in terms of consumption expenditure patterns. The peculiar design of the reform allows treating becoming eligible for the assistance as a positive wealth shock; therefore, the main focus of the paper is testing several theoretical predictions of the "wealth shocks" literature in a setting of a developing country. The results indicate the presence of liquidity constraints, as well as households resorting to consuming from wealth to smoothen consumption trajectories.

The third paper investigates causal links between problem drinking and depression by adopting a bivariate correlated random effects probit model, using individual-level data from the Russian Longitudinal Monitoring Survey (RLMS). According to the results, there is evidence of bidirectional causality between the two variables, although there are significant differences along the gender dimension: the impact of depression on alcohol abuse is present only in the female subpopulation. In addition, state dependence of alcohol abuse is higher among males. The study also provides estimates of potential effects of alcohol prices doubling on both depression and alcohol abuse: although a policy tackling problem drinking would be relatively more effective in reducing also depression in the males subpopulation, male alcohol abusers are found to be price-insensitive, whereas depression prevalence among females would decrease as a result of higher alcohol prices due to a lower probability of alcohol abuse.

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Foreword

This dissertation consists of three independent empirical papers in the field of applied public economics, with a particular focus on public health.

The choice of topics is motivated by several pressing issues of the modern society, on both global and local scales. Among such issues are illicit drug consumption and drug policies. Drug consumption is a worldwide concern that spares neither developed nor developing countries: while the former are typically the major consumers, the latter are the main production sites. In addition to negative health impacts, marginalization of addicted individuals and adverse effects on consumers' labour market outcomes and general well-being, high demand in the First World is fueling poverty, criminal activity and corruption in the source countries. An important step to challenge these interconnected issues on a global scale was made with the appearance in 1997 of the United Nations Office on Drugs and Crime, which is the leading unit in discussion, development and implementation of various drug policies on global and local levels. Although the problem is extremely relevant, there are substantial difficulties in properly assessing and predicting the effects of various anti-drug policies: typical issues of determining the causal effects and assessing external validity are aggravated by low data availability and quality, especially on disaggregated scale, due to the criminal nature of drug production and distribution. Attempting to overcome these difficulties to the extent possible, the first chapter investigates the impact of illicit drug seizures on drug consumption, in particular, for the provincial cocaine markets in Italy, providing the first evidence of a negative impact of confiscations on cocaine consumption. Incorporating spatial interrelations between provinces allows to capture significant interconnectedness among geospatial units: the results shed light on how cocaine seizures in key entry points affect consumption in the rest of the country, as well as on the impact of seizures in adjacent provinces on consumption in a home province. We hope that these findings could be of interest for policy-makers in taking decisions on funding enforcement activities, as well as for local forces in determining geographic allocation of law enforcement units.

A peculiar feature of the second chapter is that it relates to theoretical life-cycle literature, testing several predictions of wealth shocks impacts on current consumption. A distinct characteristic of the approach adopted is studying a positive wealth shock of microeconomic nature in a transition country (Russian) context: becoming eligible to a lump-sum non-cash assistance worth $10.000 with the birth of a second or higher order child. This assistance is a fertility incentivizing measure that came to action in Russia since 2007 and spurred a lot of public debate, as well as research aiming to estimate the effects of this policy on fertility and female employment. As opposed to this pool of studies, the analysis conducted in the second chapter suggests taking a different perspective by treating becoming eligible to the assistance as a positive wealth shock, in particular, a shock to the housing wealth, since the majority of eligible families choose to use these funds to improve housing conditions. According to the results, on average, households do not react to this wealth shock by increasing consumption, but more borrowing constrained households with low levels of wealth (tenants) do, which is in line with previous wealth effects literature. In addition, it appears that several policy changes, which allowed immediate utilization of the grant if a household was taking a mortgage, do not stimulate faster use of funds and their conversion into housing wealth. This finding may suggest that improving mortgage markets and increasing the level of trust in financial system can result in the households' higher propensity to convert the assistance into housing value. Finally, the study touches the issue of inequality, which is a huge concern for Russia and many other countries: it emerges that the policy has contributed to reducing housing wealth inequality; however, a vital question to be addressed in the future research is whether this decrease in wealth inequality will not be accompanied by a future increase in human capital inequality, since wealthier eligible households would opt for investing the funds into children's education.

The third chapter takes the reader back to the field of public health, this time with a focus on establishing causal links between alcohol abuse and depression, again in the Russian context. In the light of increasing prevalence of various types of mental disorders (the prevalence growth is especially fast in developing and transition countries), their high comorbidity, lengthy and costly treatment, and adverse impacts on physical health, productivity and numerous other outcomes, pinning down causal effects they have on each other becomes a relevant policy issue: having a proper estimate of the impacts, it will be possible to predict how effective a certain policy tackling one disorder would be in decreasing also the prevalence of the other. To reach the goal of capturing bidirectional causal links, a structural model with dynamic cross-spillovers is proposed. Although the adopted methodology is different from what was done in other studies, especially those in the fields of social epidemiology and psychiatry, from the qualitative perspective the results are quite in line with existing evidence, suggesting that depression causes alcohol abuse among females, but not among males, whereas the reverse causal link is significant in both subpopulations. This implies that for the male subpopulation, treating depression will not lead to a decrease in alcohol abuse, while a policy reducing alcohol abuse will have a spillover effect reducing the probability of being depressed. In addition, decreasing problem drinking at a given point in time will be more effective in reducing future probability of alcohol abuse for males than for females. Taken together these two facts suggest that an adequate policy able to reduce alcohol abuse has a good chance to diminish both problem drinking and depression for the male subpopulation in the long run. Therefore, the analysis conducted in the third chapter incorporates alcohol prices into the model, in order to find out whether taxation and other pricing policies can be effective from this perspective. However, according to the results, male alcohol abusers are price-insensitive; this last finding urges for measures other than price increases to be developed and adopted in the Russian environment in order to reduce hazardous drinking among males.

One of the most vital issues on the frontline of empirical research is addressing endogeneity and identifying causal links. Almost all processes that take place in the course of societal development and even more so individual choices are affected by such a large number of factors that applied work on virtually any topic has to solve the endogeneity problem if it wishes to pin down causality. These matters are also in the core of this dissertation, and a wide variety of tools are applied to be able to make inference about causal effects, and not just correlations. The empirical toolkit includes a reduced form instrumental variable approach embedded also into the spatial modelling framework when studying the impact of illicit drug seizures on drug consumption; a first-differenced specification to account for heterogeneity in households' tastes, preferences and other time-invariant unobserved characteristics when analyzing the response of current consumption to the wealth shock; and a bivariate nonlinear dynamic structural model with state dependence and correlated unobserved heterogeneity to investigate the causal links between alcohol abuse and depression.

Therefore, this study, motivated by hilghly relevant real world issues, contributes to the existing literature by shedding light on several causal interconnections within these topics. For each question of interest the appropriate methodological technique is chosen and tailored to the setting depending on the nature of the phenomenon and data availability. Although any approach has its limitations, we believe to have obtained a set of novel results and hope that these findings can not only be of interest for the academic audience, but also yield benefits to decision-makers and communities concerned with the abovementioned issues.

Illicit Drug Seizures and Drug Consumption: Evidence from Italy

Anastasia Arabadzhyan*

Abstract

This paper examines the impact of illicit drug seizures on drug consumption, using Italian province-year panel for the years 2010-2014. Specifically, we focus on cocaine market and aim to uncover the relationship and the causal effect of cocaine seizures on cocaine consumption proxied by cocaine-related hospitalization rates. The paper contributes to the existing literature in several ways. Firstly, we build a new panel dataset that has some favourable features as opposed to those used in the previous studies. Secondly, unlike the existing literature that barely touches the endogeneity issue, we address it by resorting to the instrumental variable estimation, using seaports turnover as an instrument for seizures. Our results suggest that there is a stable statistically significant negative relationship between cocaine seizures and cocaine consumption: on average, a one standard deviation increase in a province's cocaine seizures rate is associated with a 0.033 standard deviation decrease in related hospitalization rates; with an instrumental variables approach this effect reaches about 0.093 standard deviation. Finally, we also explore spatial interaction between provinces and find a negative relationship between seizures in key entry points and consumption in the rest of the country, as well as a negative relationship between seizures in adjacent provinces and consumption in a home province.

JEL classification: I18, C23, C26.
Keywords: illicit markets, drug consumption, anti-drug policies, fixed effects, endogeneity, spatial econometrics.

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1 Introduction

Drug consumption has been an important issue all over the world for several decades, not only because of the obvious adverse health effects, both directly from substance abuse and concomitant diseases, but also due to being a catalyst for other types of crimes. According to the United Nations World Drug Report of 2015, the total estimated number of illicit drug consumers has been growing from 2008 and reached 246 million worldwide in 2013, out of which 27.4 million were problem drug users.

In tackling the issue, the governments put in practice antidrug policies, which can be divided into two main directions: supply reduction and demand reduction. While both directions are generally considered important, in some countries there is a bias towards supply-side reduction measures (for instance, in the US the supply-side policies have always prevailed over the demand-side, occupying a larger share of the Office of National Drug Control Policy budget until recently). The large debate around supply reduction efficiency and the increasing evidence of its failure to decrease supply and/or adverse side effects (e.g. increase in violence (Dell, 2015) incentivized the turn to demand reduction, and also contributed to raising the discussion on decriminalization, depenalization and legalization issues. The evidence is controversial, and supply-side policies still account for about a half of the budgets in many countries[1]. This paper aims to provide another piece of evidence regarding one of the supply-reduction measures: drug seizures.

According to the general trend, consumption tends to rise together with the amounts seized (see UNODC et al. (2009)) on a world-wide and even country level. This fact is both intuitive and counterintuitive at the same time. On one hand, theory would suggest that if seizures decrease supply, ceteris paribus the amount consumed should also decrease. On the other hand, if seizures account for a very small share of the drug available in the market (which is more likely to be true on aggregated levels) then the rise in volumes seized should be viewed as a signal that the amount of drug available in the market is increasing. Thus, seizures are commonly perceived as an indicator of market size and not as an effective measure to reduce drug availability. This project makes an attempt to determine whether drug seizures, under certain circumstances, could actually be effective as a policy measure to reduce consumption, and are not only an indicator of the market size.

The paper is structured as follows. Section 2 provides a review of related literature and outlines how this study contributes to what has been done before, followed by Section 3, which discusses the motivation to use Italian data and to focus specifically on cocaine market, and Section 4 that motivates the choice of consumption proxy. In Section 5 we provide the baseline results and outline methodological challenges, which we tackle in Section 6 by proposing different instrumental variable approaches, and explore spatial interactions in Section 7. We then provide some robustness analysis in Section 6. Finally, Section 9 summarizes the findings and outlines directions for future research.

2 Literature review

Supply-side policies are very diverse and include crop eradication in producer countries, incarceration of drug dealers and players of higher hierarchical level, seizures of drugs on any

[1]The current study is focused on Italy; according to the 2012 figures, supply-reduction policies account for 43% of public expendiure related to illicit drugs (EMCDDA, 2012).

stage of production, seizures of property, transport, cash, sites, forfeiture of any other assets used for operating drug business, for synthetic drugs - imposing regulations on the main constituents market, etc.

Theoretically, the link between supply disruption and consumption should be prices: if the policy leads to a substantial shift in the supply curve, ceteris paribus it will lead to an increase in price and a decrease in the quantity consumed. Most of the existing empirical literature examines separately the two phases of the process: effect of the enforcement on price, and the relation between price and consumption. Concerning the price-consumption interconnection, the research commonly finds a negative relation. Schifano and Corkery (2008) report that crack cocaine death mentions are negatively correlated with prices. Caulkins (2001), Caulkins (2007), and Dave (2006) find that cocaine and heroin prices are negatively related to hospital admissions due to poisoning by cocaine and heroin. Brunt, Van Laar, et al. (2010) study the Dutch market and also find that lower cocaine prices are associated with higher numbers of addiction treatment and hospital admissions, whereas for amphetamine only the relation with addiction treatment was confirmed.

Weatherburn et al. (2003) and Smithson et al. (2004) investigate the effects of heroin shortage in Australia in late 2000. A large increase of heroin price was observed, while purity and consumption, measured by hospital admissions for overdoses, decreased as a result of the shortage. No substantial evidence of an increase in negative outcomes due to heroin users switching to other drugs was found, but a remarkable increase in methadone treatment program enrolments took place.

Other papers exploit the drop in prices due to decriminalization and legalization[2]. Model (1993) finds an increase of hospital admissions due to cannabis intoxication and a decrease of that from other types of drugs as a result of marijuana decriminalization in 12 US states between 1973 and 1978. M. Anderson et al. (2013) analyze the effect of medical marijuana legalization on traffic fatalities. They show that legalization was associated with a sharp decline in prices and also a decrease in traffic fatalities, which they attribute to the substitution effect: consumers moved from alcohol to marijuana and the net effect on traffic fatalities turned out to be negative. This evidence can be viewed as supportive of the prediction that illicit drugs consumption is in general negatively related to prices, and also depends on the quality expectations of consumers.

Most of these studies are analyzing the relation between purity-adjusted prices and health outcomes. Implementation of the supply-reduction strategies requires the policymaker to take into account purity. It is well-known that illicit drugs, especially hard drugs, are mixed with other substances and are never sold in absolutely pure form. If these adulterants adversely affect health outcomes, it could be the case that although per-pure-gram price rises, the actual price, not adjusted for purity but the one the consumers pay, does not change or increases only unsubstantially, so that the amount of deals stays the same, but while drug poisonings due to active substance will decrease, this positive effect might be offset by the increased damage due to adulterants. However, if cutting with poisonous agents was a common practice, the negative relationship between per-pure-gram prices and drug-related hospital admissions would not be as distinct as it appears from the studies mentioned above. While there

[2] There is mixed evidence on whether decriminalization leads to an increase in availability and decrease in prices: for instanse, Félix and Portugal (2017), analyzing the effect of drug decriminalization in Portugal in 2001 on prices for opiates and cocaine, find that no price decrease took place.

is some evidence that adverse substances are sometimes found in the samples (Brunt, Rigter, et al., 2009), it is important to note that consumers' demand, especially of non-dependent users, is sensitive not only to price, but also to quality given the price fixed (J. C. Cole et al., 2008). Even if consumers cannot observe quality before actually using drugs, the reputation mechanism plays a big role.

Galenianos et al. (2012) with their search-theoretic model for illicit drugs retail market show that enforcement, increasing the sellers' costs, may reinforce long run relationships and will not lead to a decrease in purity. Rose (2016) builds a theoretical model (as opposed to Galenianos et al. (2012), it allows sellers to choose purity and per-gram-price in each period) and also empirically assesses the effects of supply disruption on purity and prices. The model predicts that seizures result in dilution, which, in turn, reduces future demand. GMM estimation of a time-series for Washington DC confirmed that seizures negatively affect purity in the same period and the price in the future period. Testing the impact on consumption was not conducted due to absence of reliable consumption data.

Thus, the users could adjust their consumption depending on their quality expectations. Due to the fact that illicit drugs market is characterized by repeated purchases, reputation matters, which makes it unlikely for sellers to use adulterating substances that have immediate severe health effects (Coomber, 2006). This is supported by a review of empirical evidence on adulterants by C. Cole et al. (2011), according to which critically poisonous substances are rarely found in drug samples.

Regarding existing literature on the enforcement effect on prices, findings only partially support theoretical predictions, and results depend on the type of enforcement applied. For example, according to Kuziemko and Levitt (2004), harsher punishments for drug offenders are associated with higher drug prices. Dobkin and Nicosia (2009) study the effect of an exogenous policy change which imposed tough restrictions on distributors of ephedrine, one of the most common methamphetamine precursors. Analyzing monthly data on price, purity, related hospital admissions and methamphetamine use by arrestees in California's counties, they find that the policy led to the rise of price and a decrease in purity, hospital admissions and arrestees' consumption. Following this study, Cunningham and Finlay (2016) investigate the further state and federal interventions into the US precursor market and find that each subsequent intervention had a weaker effect on the market than the previous one. The effects on the prices and hospital admissions are significant but temporary. There is also a range of studies that try to capture the effect of enforcement on consumption without directly incorporating prices. Chaloupka et al. (1999) argue that sanctions for the possession of cocaine and marijuana have a negative impact on youth cocaine and marijuana use. On the contrary, sanctions for the sale, manufacture or distribution of cocaine and marijuana have little impact on youth consumption of these drugs. Callaghan et al. (2009) study precursor availability restrictions in Canada, in a setting similar to the one in Dobkin and Nicosia (2009). Having conducted time-series analysis on country-level monthly data, the authors conclude that, contrary to what was expected, those restrictions were associated with a rise in methamphetamine-related admissions.

Finally, to the best of our knowledge there is no empirical evidence of a robust negative relationship between drug seizures and consumption. DiNardo (1993), having constructed a state-year panel for the US, finds an insignificant positive interrelation between cocaine seizures and per-pure-gram price, also without any impact on consumption. Yuan and Caulkins (1998) study a national level monthly time-series and conclude that there is no Granger-causal relationship between seizures and cocaine and heroin prices. Similarly Wan et al. (2016) analyzing drug market in New South Wales, Australia via ARDL model, report generally insignificant or positive relation between seizures of cocaine, heroin, amphetamine substances and hospital admissions related to these substances.

Our paper contributes to the existing literature in several ways. First, a vast majority of studies uses the US STRIDE data, which is understandable because this dataset is large and provides information on price, purity and seizures. Using a different, not previously explored, dataset could provide new insights. This study is using data on drug seizures and hospital admissions in Italy to study the effect of supply disruption, measured by seizures, on consumption, proxied by hospital admissions, so the data on prices is not necessary to conduct the analysis. Some additional advantages and motivations to resort to the Italian case are provided in the next section. Second, the properties of these data allow overcoming an important drawback of a large part of the existing literature: aggregation among space and time masks the existing effects. For instance, Arkes et al. (2008) claims that drug markets are localized and prices and purity vary substantially among the US cities within the same region. The data we use allows disaggregation up to provincial level. Having a panel dataset has an obvious advantage over cross-sections as it makes it possible to observe the units over time and use internal instruments. Compared to time-series a panel allows for a more accurate inference of the model parameters (due to higher number of observations), and in our setting makes it possible to analyze spatial relationships between the variables of interest. This is a reasonable and necessary extension, since the phenomenon under investigation is clearly spatial by nature. Finally, unlike the existing literature that barely touches the endogeneity issue, we address it by resorting to the instrumental variable estimation, using seaports turnover as an instrument for seizures in the external instruments approach, which is compared with results yielded by Arellano-Bond and Spatial 2SLS methodologies.

3 Market peculiarities and key characteristics

The motivation to study the case of Italy is driven by several factors. Firstly, the prevalence of drug use is one of the highest in Italy among other European countries. According to data provided by the European Monitoring Centre for Drugs and Drug Addiction (EMCDDA), Italy ranks 4th in last year and last month prevalence among all adults aged 15-64, 3rd in last year prevalence among young adults (15-34) and 2nd in last month prevalence among young adults (use of any illegal drugs considered). Although the general trend of drug use is declining, in parallel the alarming tendency of increasing usage among the student population (aged 15-19) is observed (according to 2013 Italian National Report to EMCDDA). This makes drug consumption an important issue from the policy-makers point of view, requiring substantial budgets[3].

Secondly, a peculiar feature is Italy's geographic position: located at the center of the Mediterranean Sea and possessing a long coastline, Italy is an entry and transit area for the traffickers delivering drugs to Europe. This characteristic results in considerable quantities seized, which is necessary to capture the effect on consumption, and, importantly, makes the seizures less endogenous with respect to the local market features. From the technical point of view, a big advantage of Italian data is its availability and substantial spatial disaggregation level (up

[3] According to EMCDDA (2008), for 2008 the social cost of illicit drug use was estimated at EUR 6.5 billion, with law enforcement activities accounting for the largest share (43%), and the remainder divided between healthcare and social services (27%) and loss of productivity of drug users and people indirectly affected by drug use (30%).

to provinces), which is crucial, since the effects of the seizures, if any, are likely to be localized.

Throughout the paper we are focusing on the cocaine market, and this is also not by chance. Firstly, despite the fact that the prevalence of soft drugs (marijuana and hashish) use is much higher than that of hard drugs (cocaine and heroin), which makes the use of cannabioids a relatively more pressing policy issue, for the problem at hand it makes sense to focus on hard drugs markets, since the demand for hard drugs is more price-elastic. In his review of studies Gallet (2014) finds that price elasticity is smallest for marijuana, compared to cocaine and heroin. Although it is plausible that hard drug users are more addicted which should make their demand inelastic, they are also more experienced and often polydrug users and can find substitutes rather easily. If the demand is price-inelastic, seizures would have a negligible, if any, effect on consumption. Another possibility is that even though confiscations of marijuana and hashish do have an impact on street prices, users might find a way to substitute by resorting to home-growing, and so consumption will remain unaffected, while for cocaine and heroin it is not an issue. Secondly, when considering cocaine and heroin, the demand elasticity might be higher for cocaine, since it is less addictive than heroin, more expensive and is generally considered as a luxury good. Not surprisingly consumption expenditures on cocaine accounted for 43% of total 14.2 billion euros spent by Italians on all types of drugs in 2014[4]. Another reason for focusing on the market for cocaine rather than heroin is the abovementioned consideration on purity and adulterants/diluents present in the final product when it reaches the consumer. Although we cannot exclude completely the possibility that the seller might use harmful substances for dilution, this issue is much less of a concern for cocaine as compared to heroin. The avreage purity of cocaine is twice as high as that of heroin, and is around 60%[5]. Due to the fact that cocaine users are those who provide highest profits, the reputation mechanism in this market works very well. A series of papers summarizing the findings of Addiction and Lifestyles in Contemporary Europe: Reframing Addictions Project (ALICE RAP) provides interesting insights about peculiarities of cocaine and heroin markets in Italy. Tzvetkova et al. (2014) have inerviewed imprisoned drug dealers in Italy, discussing how dealers handle risks, customers, competitors, etc. It emerged that dealers prefer cocaine users to heroin users, because the latter have lower purchasing power, are likely to suffer from addiction, thus attracting unnecessary law enforcement attention and even willing to cooperate with them and denounce the dealer for a reward. Cocaine users, in contrast, were described as wealthy and easy to deal with. Moreover, as revealed by the study, by committing to quality cocaine dealers aim to maintain a regular pool of trustworthy customers who are ready to pay.

Before proceeding to the analysis, it may be useful to have some indication of whether the effects we are after are possible to capture, or the local markets are so resilient and flexible[6], that market participants do not change their behaviour and market outcomes are barely affected. The abovementioned study on dealers' business strategies sheds some light on this issue.

Dealers do appear to have several suppliers, which makes them more resistant towards supply disruption and allows adjustment within a short time lapse. However, since commitment to

[4]Estimation carried out by ISTAT and provided in 2017 Annual Report of Antidrug Policy Department. For a review of alternative estimates of Italian drug market size see Giommoni (2014).

[5]According to Annual Reports of Antidrug Policy Department for the years 2010-2014.

[6]As highlited in the literature, drug market players have the capability to adjust to temporary shocks very quickly and replace the lost resources (Caulkins and Reuter, 2010).

quality generally prevents sellers from cutting the drug below a certain level of purity[7], shortages, though not long-lasting, do occur. In the periods of lack of supply some dealers would take a vacation, switch off their phones and leave the city where they operate, others would ask the customers to wait or refer them to fellow dealers in other locations. One of the interviewees explicitly stated: *"If there is a seizure or a police operation, then the amount available decreases and prices go up"*. This qualitative evidence suggests that while local markets are resilient and adaptive, the theoretically predicted effect of law enforcement on prices is indeed present.

4 Consumption proxy

Due to illicit nature of the phenomenon under consideration, measuring drug consumption is a challenging task. While a direct measure does not exist, several proxies are commonly resorted to in the literature depending on the research objective. For a descriptive analysis of trends, survey data is used most often. However, this proxy is subject to the usual weaknesses of survey data, which are magnified by the sensitive nature of the issue. The two main surveys conducted in Italy are the General Population Survey and Student Population Survey where respondents are asked questions about their substance use habits. These, however, do not allow for substantial disaggregation and rigorous estimation of the *quantity* of the substance consumed. The questions typically asked are "Have you ever used ... ?", "Did you use ... in the previous month/year?" and "How many times, approximately, did you use ... in the past month/year?". These types of questions require the respondents to think retrospectively and fit their replies in the intervals provided for the answer.

A recent tool for measuring community-level drug consumption is wastewater analysis that in theory can provide daily estimates (though there might be concerns about precision[8]) of substances consumed in a given area by examining their residuals present in wastewater. The main disadvantage of this technique is its high cost, therefore, in practice, the equipment is installed in selected stations for a short period of time. In Italy, the analysis is conducted by the Mario Negri Institute in 17 Italian cities[9] and provides an estimate for the city-level consumption in a given year (the wastewater samples are taken during 1 week in a year). However, having only 17 spatial units in the sample is not sufficient to provide robust inference. We therefore resort to drug-related hospitalization rates as a proxy for drug consumption. The main advantages of this measure are objectivity, full coverage in the space dimension on a sufficiently disaggregated level (we chose provincial partition), and availability on yearly basis. The main disadvantages are relatively low numbers of hospital admissions (indeed, very few users are hospitalized, as compared to the total number of consumers) and ambiguity in relation to purity (if it is the case that diluents are harmful substances per se, seizures may result in hospitalization rates changing in the opposite direction). Since we are not trying to estimate the total amount of drug consumed or the total amount of users, which would be measured well by wastewater analysis and population survey respectively, but rather the con-

[7] Reputation plays a role at all dealing levels and, in fact, is not the only factor that explains preference for selling lower volumes of a more pure substance, rather than a cut drug in greater volumes. Important considerations are need for storage, labor required for repackaging (these are relevant for high quantity dealers) and time involved in selling, which are higher in the latter case and increase risks of being caught.

[8] For a critical analysis of sewage epidemiology see Nuijs et al. (2011).

[9] Refer to Zuccato, Castiglioni, Tettamanti, et al. (2011) and Zuccato and Castiglioni (2012) for the description of procedure and results, and Zuccato, Castiglioni, Senta, et al. (2016) for comparison of wastewater analysis with evidence from the abovementioned General Population Survey.

sumption response to the decrease of supply, the proxy we resort to is appropriate. Regarding the purity issue, the evidence from chemical analysis and drug dealers interviews suggests that the use of poisonous cutting agents in response to lack of supply, and even substantial increase in dilution per se[10], is highly unlikely. Thus, we believe that drug-related hospitalization rates, though having their own drawbacks, are the best proxy available to answer the question of interest.

5 Data and analysis

5.1 Data sources, variables and descriptive statistics

As data on cocaine street prices is not available on province-year level for Italy, this study resorts to the reduced form approach to investigate how cocaine seizures affect the dependent variable of interest: cocaine consumption.
The data on drug seizures is openly available on the Italian National Police website (poliziadistato.it). The province-level time-series are available from 2008 until the present moment (although there is an issue of data quality in the early and most recent years of collection and so the data from those years should be considered as provisionary) and contain information on the volume of seizures in kilograms for heroin, cocaine, marijuana, hashish, cannabis plants and amphetamines, as well as the number of operations, number of people arrested, released and not captured, and the number of minors and foreigners out of total number of persons denounced (the persons reported to the Judicial Authority for drug-related offences). Thus, the data would allow not only to identify the effect of drug seizures, but also control for the number of arrests and number of operations, which could be contaminating factors and need to be accounted for. The main independent variable of interest is seizures rate, which is expressed in tens of kilograms of cocaine seized in a given year in a given province per 100.000 inhabitants ($seizr$).

The main indicator for consumption are the most frequently used in the literature drug-related hospital admissions. Italian Ministry of Health, upon request, provides micro-level data on hospital admissions and dismissals by ICD-9 diagnosis codes; using these data we constructed the dependent variable: province-year cocaine-related hospital admission rate per 100.000 inhabitants (HAr). A range of other important variables is adopted as a set of province-level baseline controls: per capita income ($income$), unemployment rate ($unemp$), share of foreign residents ($foreign$), criminal associations crime rate ($crmr$), and the share of men aged 35-39 in the population ($men3539$), as this demographic category is the most prone to cocaine consumption.

The perfectly balanced province-year panel used in the analysis consists of 5 years (2010-2014) and 103 units (provinces), which yields 515 observations in total. Table 1 provides summary statistics for the selected variables.

The spatial distribution of the hospitalization rates and volumes of cocaine seized is depicted in figures 1 and 2. While there is some overlap between high-consumption and high-seizures provinces, it is far from a perfect one. This may suggest that simultaneity on the cross-sectional level is not too extreme in the data at hand. Spatial distribution of other control variables is presented in subsection A.1 of the Appendix.

[10] In fact, increased dilution does not invalidate our proxy. If a drug is sold at the same price but is less pure since the amount of active substance is relatively lower, this should result in a decrease of related hospital admissions.

Table 1: Summary statistics (2010-2014)

Variable	Obs	Mean	Std. Dev.	Min	Max	P1	P10	P25	P50	P75	P90	P99
HAr	515	4.04	5.93	0	43.78	0	.32	.91	2.1	4.74	8.95	31.9
seizr	515	.72	3.89	0	47.11	0	0	.01	.06	.18	.57	21.19
income	515	12.96	2.89	7.28	20.25	7.84	8.77	10.01	13.68	15.21	16.11	18.43
unemp	515	10.7	5.22	2.69	27.81	3.73	5.28	6.8	9.15	13.45	18.53	25.66
crmr	515	1.4	2.2	0	31.04	0	.19	.52	.95	1.56	2.5	9.03
foreign	515	.07	.03	.01	.16	.01	.02	.04	.07	.1	.11	.14
men3539	515	.06	.1	0	1.3	0	.01	.02	.04	.07	.13	.45

In columns P1-P99 the corresponding percentiles are reported.

Figure 1: A map of cocaine-related hospitalization rates in provinces
(average for 2010-1014)

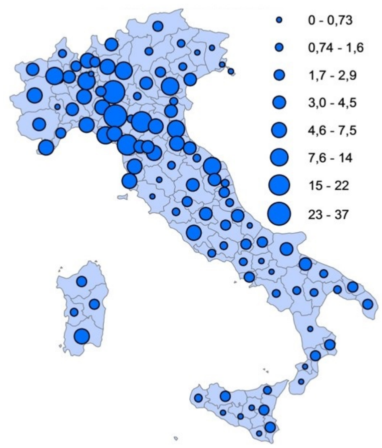
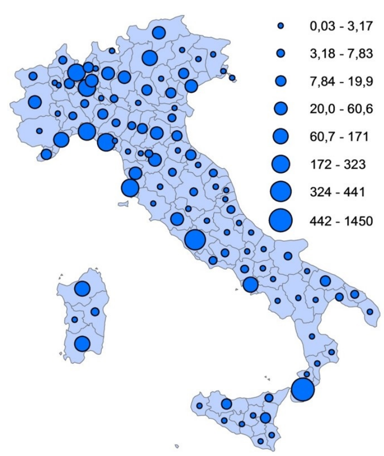


Figure 2: A map of kilograms of cocaine seized in provinces
(average for 2010-1014)



5.2 Baseline model

We assume that the partial equilibrium in a province market for cocaine is formed by the interaction of supply and demand, so that when there is a seizure substantial enough to shift the supply curve, per-pure-gram price rises and quantity consumed decreases[11]. A reduced-form equation for the quantity consumed, which we proxy by the rate of cocaine-related hospital admissions, takes the following form:

$$HAr_{it} = a_i + \tau_t + \gamma S_{it} + \delta X_{it} + \varepsilon_{it} \tag{1}$$

Here a_i is the province fixed effect, τ_t is the time (year) fixed effect which is common for all the provinces, S_{it} is the amount of drug seized in province i in year t per unit of population, X_{it} is a set of controls, and ε_{it} is the idiosyncratic disturbance. Our main coefficient of interest is γ.Before entering the discussion on the problem of endogeneity and its possible solutions, let us look at the results of the fixed-effects estimation of equation (1) presented in Table 2. The coefficient of seizures rate is negative and statistically significant at all conventional levels, and does not change in magnitude with inclusion of different controls. To the best of our knowledge, this is the first evidence of a stable and statistically significant negative relationship between cocaine seizures and consumption.

Table 2: Including various controls

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se	(7) b/se
seizr	-0.061***	-0.063***	-0.061***	-0.063***	-0.062***	-0.061***	-0.061***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)
income		1.074**		1.207**	1.212**	1.313**	1.311**
		(0.516)		(0.530)	(0.533)	(0.627)	(0.623)
unemp			0.011	0.041	0.036	0.046	0.045
			(0.038)	(0.038)	(0.038)	(0.038)	(0.037)
crmr					0.039	0.035	0.036
					(0.034)	(0.035)	(0.035)
foreign						29.582	29.533
						(47.671)	(47.631)
men3539							0.236
							(0.952)
constant	4.674***	-9.355	4.527***	-11.627	-11.690	-15.419	-15.393
	(0.164)	(6.698)	(0.558)	(7.042)	(7.064)	(11.119)	(11.070)
Obs	515	515	515	515	515	515	515
Nclust	103	103	103	103	103	103	103
R^2	0.076	0.083	0.076	0.084	0.086	0.088	0.089

* p<0.1, ** p<0.05, *** p<0.01. Cluster robust standard errors in parentheses.

While endogeneity of seizures and ways to tackle it will be discussed in the remaining sec-

[11] It is possible that enforcement activity makes consumers more cautious which in turn would affect demand. This impact would operate in the same direction, reinforcing the idea that more intense enforcement should be related to lower quantity consumed. However, the enforcement measure of interest considered in our analysis is the *volumes* seized, and it is unlikely that they have a clear effect on demand, since they are ambiguously linked to perceived enforcement presence.

tions, it is useful to comment on potential endogeneity of selected controls. At the individual level, income (as well as unemployment) and cocaine consumption are very likely to be related in both directions, so reverse causality would be an issue. However, here we are working with macro-level data and it is reasonable to believe that cocaine-related hospitalization rates (which are, in fact, rather low, as appears from Table 1) do not cause changes in province-level income or unemployment. Regarding the crime rate for criminal associations and the rate of foreign residents, it is possible that markets with expanding demand (provinces with higher cocaine-related hospitalization rates) attract more supply, which in the case of illicit drugs markets is tightly likned to organized crime and foreigners involved in the business (as required by trafficking and distribution networks). However, we believe that diffusion of criminal networks and their members' ethnicity are largely determined by other factors, such as historical routes and institutional quality, which change slowly and are unlikely to vary significantly from one year to another, while local drug consumption should play a smaller role; thus, though with caution, it is plausible to assume that the crime rates for criminal association and the rates of foreign residents are not driven by cocaine consumption in the local markets. Therefore, we argue that the list of controls in the baseline model is as exogenous as possible in the given setting.

At this point a brief discussion on the main drivers of results could be of interest. While the literature fails to find a significant negative relationship between seizures and consumption, we are able to capture it with our data. This could be explained by the substantial disaggregation in space and Italy's geographic features discussed in Section 3, which allows to observe very high volumes of cocaine seized in some provinces. Additionally, most of the provinces with exceptionally high cocaine seizure rates are not the ones with the highest hospitalization rates, which suggests that simultaneity problem is not as severe as often is in other settings, where due to data availability issues only big cities are considered. This could be an indication that the significant negative relationship is driven by provinces with high seizures rates: indeed, if they are excluded from the sample, the relationship becomes insignificant (see Column 1 vs. 2 in Table 3).

Table 3: Baseline on different subsamples

	(1) b/se	(2) b/se	(3) b/se	(4) b/se
seizr	-0.06***	-0.08	0.47*	-0.20***
	(0.01)	(0.19)	(0.26)	(0.05)
Controls	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs	515	465	210	255
Nclust	103	93	42	51
R^2	0.089	0.095	0.166	0.141

* p<0.1, ** p<0.05, *** p<0.01. Cluster robust standard errors in parentheses.

However, this does not mean that bulk seizures are the only drivers of the result, since simultaneity could still be responsible for masking the true relationship. To check if this is the case, we excluded the ten provinces with the highest average volumes seized and split the remaining sample into two parts: with higher and lower average consumption levels. Columns 3 and 4 of Table 3 provide results for high and low-consumption provinces respectively. While the negative relationship holds for low-consumption areas, enforcement in high-consumption areas is much more likely to be driven by local market conditions[12]. This finding provides evidence of reverse causality present in the data to a certain extent. In the remaining part of the paper we discuss other potential sources of endogeneity and propose ways to solve it.

5.3 Methodological challenges

The relationship discovered in the baseline model is likely to be biased due to endogeneity of seizures rate. With the data at hand endogeneity may emerge from all three possible sources, which are briefly described below:

1. Simultaneity: areas with higher consumption attract more enforcement. This may be partially alleviated by the inclusion of the fixed effects, but it would be unrealistic to assume that local market features, enforcement and their relationship are time-invariant. Some evidence of the presence of simultaneity bias was provided in the previous subsection.
2. Measurement error: since the data on purity is not available, errors in the measurement of pure substance seized are likely. However, this is less of a concern for bulk seizures, as wholesale seizures are generally high in purity[13]. We will assume that the "true" measure and the error in measurement, if present, are uncorrelated, leaving us with an attenuation bias that drives the coefficient towards zero.
3. Omitted variable bias: other variables, correlated with both seizures and hospitalization rates, may produce an upward or a downward bias of the seizures coefficient. Corruption, other enforcement activities, and seizures in other provinces may be relevant omitted variables. Most importantly, the actual amount of the drug available in the market is unobserved and therefore we do not know whether an increase in seizures is a signal of increased or decreased supply.

5.4 Solutions to methodological challenges

In the first attempt to alleviate endogeneity stemming from omitted variable bias we try including additional possibly relevant controls: corruption and other enforcement activities. For instance, arrests of drug sellers could influence consumption and would be positively related to seizures. Failing to account for this variable will produce a downward bias of the coefficient of interest and overstate the impact of seizures. On the other hand, corruption may be negatively related to seizures because corrupt officials would allow the traffickers and dealers to operate more freely and turn a blind eye to the growing levels of consumption. Omitting this variable would produce a bias towards zero.

The data from the Ministry of Interior allows us to control directly for the number of drug-related arrests and anti-drug operations: as evident from Column 2 of Table 4, including these enforcement measures does not alter the coefficient of the seizures rate as compared to the baseline case in Column 1, while they themselves are insignificant. These variables are

[12] We ran a similar check using quantile panel approach and obtained similar results: see subsection A.2 of the Appendix for details.

[13] Data on cross-country differences in prices and purity of cocaine at wholesale and retail levels are available from UNODC (https://data.unodc.org/)

endogenous themselves and were therefore not included in the baseline; a separate instrument would be needed for each one in order to identify their true coefficients. Nevertheless, it is crucial to show that their inclusion does not alter the coefficient of interest.

Regarding corruption, if it is thought of as a time-invariant feature then it is already controlled for by inclusion of the fixed effect. It is plausible, however, that corruption is not constant over time, which requires a time-variant measure of it. The best available province-level corruption proxy that is time-variant is an indicator constructed for the Institutional Quality Index for Italy, which is an index built in a similar manner to the World Government Indicator. This index consists of several dimensions: voice and accountability, government effectiveness, regulatory quality, rule of law, and corruption (Nifo and Vecchione, 2014). The corruption index is a composite measure and consists of three subindexes: number of crimes against the public administration relative to the number of public servants; the Golden-Picci Index (difference between the physically existing public infrastructure and the amounts of funds cumulatively allocated by the government to create these public works (Golden and Picci, 2005); and the share of overruled municipalities. The main drawback of this measure is that it is available only for the years no later than 2012; we therefore rerun the baseline on the 2010-2012 subsample (Column 3 of Table 4). The results in Columns 3 and 4 suggest that including the time-variant corruption proxy does not alter the coefficient of interest. Since the time-variant proxy is not available for the whole time span, it is not included in the baseline model.

Table 4: Controlling for corruption and other enforcement measures

	(1) b/se	(2) b/se	(3) b/se	(4) b/se
seizr	-0.061***	-0.060***	-0.035***	-0.035***
	(0.010)	(0.012)	(0.012)	(0.012)
corrup				-0.486
				(3.091)
arrest		-0.003		
		(0.003)		
oper		0.010		
		(0.007)		
constant	-15.306	-14.571	-6.467	-6.581
	(10.280)	(9.852)	(13.864)	(14.308)
Controls	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs	515	515	309	309
Nclust	103	103	103	103
R^2	0.089	0.110	0.039	0.039

* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Cluster robust standard errors in parentheses.

It is possible that other omitted variables and sources of endogeneity exist; instrumental variables are usually adopted to address this issue. In crime literature external instruments were traditionally applied, however, since finding an external instrument which is both exogenous and relevant is problematic, more and more studies resort to internal instruments, and provide evidence that they can even outperform their external counterparts (Bun, 2015, Bun et al., 2016). We compare results from both approaches, with cargo turnover rate in ports serving as an external instrument, and lags of seizures rates as internal instruments in the Arellano-Bond framework, as well as spatial lags of exogenous variables applying Spatial 2SLS to estimate a SAR model. Finally, we resort to spatial analysis that differs from traditional spatial econometrics approaches to explore the relationship between seizures in the main trafficking hubs and consumption in other provinces, as well as the relation between consumption in a given province and seizures in the adjacent provinces.

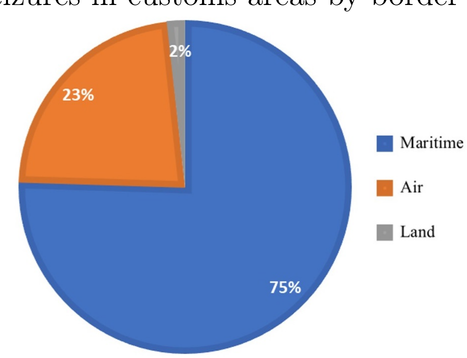
6 Instrumental variables estimation

In this section we propose several ways to instrument for the seizures variable: cargo turnover rate in western coast seaports (an external instrument), time lags of explanatory variables (internal instruments in the Arellano-Bond framework), and spatial lags of exogenous variables within a SAR model (internal instruments in the Spatial 2SLS framework).

6.1 External Instrument

The largest volumes seized and the highest variation in seizures rates occur either in high consumption areas (large local markets, such as Milan and Rome), or in logistically convenient trafficking points (here seizures are roughly exogenous with respect to local market conditions), which are mostly border areas and vital transportation knots (e.g. ports, airports, train stations). Figures 1 and 2 provide a visualization of the consumption and seizures patterns; while the highest hospitalization rates cluster in the North (the richest macro region), the largest amounts seized are observed in the border areas, in particular, in the western part of the country. Because maritime transportation is cheaper and allows for transporting much higher volumes of cargo than aerial, it is often preferred by the traffickers. Thus, it is not surprising that maritime seizures account for the majority of border seizures (Figure 3).

Figure 3: Distribution of seizures in customs areas by border type (average shares)



Since cocaine comes from the western part of the world where it is produced, ceteris paribus it is optimal to ship it to the Western coastline of the country (as compared to the Eastern). This is exactly why we observe very high amounts seized in the provinces that have maritime borders and are located in the West.

For these reasons, we adopt maritime cargo turnover rate[14] in the ports of 16 western

[14]Since all the variables in the baseline specification are expressed in terms of rates, for consistency we adopt a turnover rate measure, which is absolute cargo turnover in port(s) divided by the population of the province.

provinces[15] (Figure 4 depicts the centroids of selected provinces) as an instrument for seizures rates. As can be seen from the adjacent table, cocaine seizures in these ports amount for 60-80% of the country's total throughout the given period[16].

Figure 4: The 16 selected provinces and their share in total volume of cocaine seized

Table 5: Share of 16 selected provinces in total volume of cocaine seized

2010	2011	2012	2013	2014
60%	81%	65%	65%	75%

For the instrument to be valid, it should be relevant and exogenous. The cargo turnover rate in the selected provinces is strongly and positively associated with cocaine seizures (Column 2 of Table 5), confirming that the instrument is relevant.

Regarding the exogeneity of the instrument, the exclusion restriction builds upon two main assumptions:

1. Increased turnover implies increased customs vigilance. One of the obvious reasons to increase vigilance are taxation revenues: the customs would be interested to check whether all the goods on board are properly declared and all the necessary duties are paid. The authorities are also aware of the fact that higher freight turnover can make smuggling easier and respond correspondingly by increasing monitoring. Finally, it could be higher amount of cargo from specific source countries (e.g. Latin American region) that makes the authorities more cautious.

2. This intensification of enforcement translates into higher seizures and, conditional on covariates, only affects consumption through this channel. A potential threat to validity comes from the fact that cargo turnover rate can be viewed as a proxy for economic activity, and so can affect consumption not only through seizures, but also through income, for instance. If we believe that all the variables in our main equation are exogenous, this is not an issue, since we control for income and unemployment. Another potential threat is that higher turnover rate may be associated to higher volumes of cocaine transiting through the port (which is plausible if higher volumes of licit trade provide more opportunities for traffickers to smuggle). If the observed increase in seizures rates is not due to increased enforcement but to increased cocaine supply, the exclusion

[15]The total number of ports is larger than 16, however the data for port-level turnover exists only for the large ports, which also happen to be the main trafficking hubs. In fact, restricting the number of port provinces to 9 with the highest seizures yields identical results. We chose to keep the cargo values for all of the available western coast provinces since they are already very few, accounting for around 16% of the sample. For all other provinces the value of cargo is taken as zero. Data source: reports of Italian Port Association (assoporti.it).

[16]According to the yearly reports of the Central Directorate for the Antidrug Services (Ministry of Interior).

restriction does not hold. Yet, higher turnover implies lower speed of the process of going through the customs, which increases risks of being caught. Dell (2015) also points out that congestion costs at the bottlenecks, such as ports and terrestrial borders, play a big role and are accounted for in the traffickers' optimization problem for finding the optimal route. Additionally, as was mentioned in the previous point, the customs officials are perfectly aware of the fact that higher turnover may incentivize smuggling, which implies increased vigilance from their side: this increases probability of detection and decreases traffickers' expected payoffs. If this reasoning applies, it is plausible to believe that increased turnover rate does not imply higher amounts of drug entering the ports, therefore, the exclusion restriction holds.

Table 5 provides the results of a fixed effects estimation with the cargo turnover rate in the western coast ports used as an instrument. Column 1 has the baseline result and Columns 2 and 3 represent the first and the second stages respectively (variable *turnover_rate* stands for the cargo turnover rate). The coefficient of the seizures rate is about 2.8 times higher than that of the fixed effect baseline model and is significant at the 1% confidence level. Due to the instrument taking non-zero values only for the sixteen selected provinces, which are concurrently the ones with high volumes seized, this result is again driven by provinces with high seizures. However, an important difference is that we were now able to capture the variation in seizures that corresponds to the actual decrease in supply.

6.2 Internal instruments

Since the nature of the problem and lack of data prevent us from directly proving the validity of the assumptions made for the external instrument to satisfy the exclusion restriction, we resort to internal instruments and compare the results with those obtained using cargo turnover as an instrument. The Arellano-Bond methodology (Arellano and Bond, 1991) proposes using lags of the exogenous explanatory variables as instruments for the endogenous and predetermined ones. This approach is typically applied to first-differenced specifications with the lagged value of the dependent variable present in the right hand side of the equation. The lag is predetermined by construction, therefore in order to identify its coefficient additional moment conditions are necessary. These conditions are created by using lags of exogenous variables as instruments. Moreover, by the same means this approach also allows for identification of the coefficients of endogenous variables, if they are present. In our setting the empirical model is not concerned with the impact of consumption in the previous year on that of the current year, but there is an endogenous variable whose effect is of interest. Therefore, the relevance of internal instruments with respect to the seizures rate variable determines the choice of the lag depth of controls. Column 4 of Table 5 provides the results of the Arellano-Bond estimation of the equation in first differences:

$$\Delta HAr_{it} = \Delta HAr_{it-1} + \tau_t + \gamma \Delta S_{it} + \delta \Delta X_{it} + \Delta \varepsilon_{it} \tag{2}$$

The model passes formal tests but there appears to be a problem of weak instruments: the standard error of the seizures coefficient is quite high, yielding significance only at the 10% level, and insignificant estimate in some cases, depending on the instruments specification. However, the magnitude of the effect is similar to what was found with an external instrument.

6.3 SAR model

Finally, we apply the same principle and exploit spatial lags of exogenous variables as internal instruments. In classical spatial econometrics literature[17], both theoretical and applied, the main issue has been to identify the coefficient of the spatial lag of the dependent variable, although spatial components are present in those models in other forms as well (e.g. the Spatial Error Model accounts for the spatial component in the error terms, and the Spatial Durbin Model allows for spatial lags of both the dependent and the independent variables to be present). By analogy with the Arellano-Bond case, we apply the Spatial 2SLS methodology (Kelejian and Prucha, 1998) aiming to identify the point estimate of seizures, while the spatial lag of hospital admission rates is not the main focus[18]. Spatial interactions, however, are also of great interest, and we provide the corresponding analysis in Section 7.

We estimate a Spatial Autoregressive (SAR) model of the following form:

$$HAr_{it} = \rho WHAr + a_i + \tau_t + \gamma S_{it} + \delta X_{it} + \varepsilon_{it} \tag{3}$$

Here, in addition to spatial lag order and number of variables chosen as instruments, it is necessary to choose also the underlying spatial structure: the weight matrix W. Results presented in Column 5 of Table 5 are obtained with the second order contiguity row-standardized spatial matrix. As in the previous case, the obtained coefficient is marginally significant and sometimes insignificant depending on the spatial lags and type of W chosen, but point estimate is similar throughout different specifications and to the two previously obtained.

Table 5: Baseline FE and instrumental variable specifications

	FE	FS	IV	AB	SAR
	b/se	b/se	b/se	b/se	b/se
seizr	-0.061***		-0.177***	-0.176*	-0.172*
	(0.010)		(0.031)	(0.098)	(0.090)
turnover_rate		0.007**			
		(0.003)			
HAr_{t-1}				0.087	
				(0.12)	
$WHAr$					0.974**
					(0.438)
Controls	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs	515	515	515	515	515
Nclust	103	103	103	103	103

* p<0.1, ** p<0.05, *** p<0.01. Cluster robust standard errors in parentheses.

The results of the baseline model suggest that a one standard deviation increase in a province's cocaine seizures rate is associated with a 0.033 standard deviation decrease in related hospi-

[17]For an overview of different types of spatial models see Elhorst (2010).

[18]Inclusion of temporal/spatial lags is useful, since they possibly account for omitted variables. In our case these specifications can be viewed as robustness checks.

talization rates; with an instrumental variables approach this effect reaches a 0.093 standard deviation (the effects are calculated at the mean).

7 Spatial interactions

Until now we have been focusing on uncovering the relationship between cocaine consumption and seizures in a given province. However, it is clear that the observations are not independent in space: seizures in one province may also have an impact on its neighbours' consumption. Most importantly, seizures anywhere else are much more exogenous than those in the same province. In this section we aim to explore spatial interactions in two complementary ways: first we study how seizures in entry points affect consumption in other provinces, and then investigate the relationship between seizures in the neighbouring provinces and consumption in a given province in a more general way.

7.1 Relation to seizures in selected provinces

We return to the western coast provinces with high volumes of cocaine seized and analyze how seizures in these provinces affect consumption in the rest of the country[19]. We focus on the nine[20] western coast port provinces (Reggio Calabria, Roma, Livorno, Genova, Savona, La Spezia, Napoli, Sassari, and Cagliari) and study how consumption elsewhere responds to cocaine seizures in these provinces, estimating the following fixed effects specification:

$$HAr_{it} = a_i + \tau_t + \gamma_0 S_{it} + \gamma_1 Snearest_{it} + \gamma_2 Snearest_{it} * dist_i + \delta X_{it} + \varepsilon_{it} \tag{4}$$

Here $Snearest_{it}$ stands for seizures in one of the nine provinces that is closest to a given province i, and $Snearest * dist$ - interaction with distance[21] to that province. Columns 1 and 2 of Table 6 contain results for equation 4 without including interaction with distance, for the whole sample and for the case when the selected nine provinces are excluded, respectively. Without accounting for distance, seizures in the nearest port appear to be insignificant, and excluding the nine provinces yields an insignificant coefficient of the own seizures rate in the remaining subsample. Estimation results for the full equation are presented in Columns 3 and 4 of the table; accounting for distance yields significant estimates of γ_1 and γ_2, which are also jointly significant.

[19] In Section 8.2 we do several robustness checks and provide results of the same analysis but with alternative groups of provinces chosen as the key provinces that influence consumption everywhere else.

[20] Out of the 16 provinces whose port turnover was used as instrument, these nine provinces are the ones with the largest seizures, among the top 12 by average volumes seized, and are the drivers of the previous result.

[21] In Section 8.1 other distance/proximity measures are also explored.

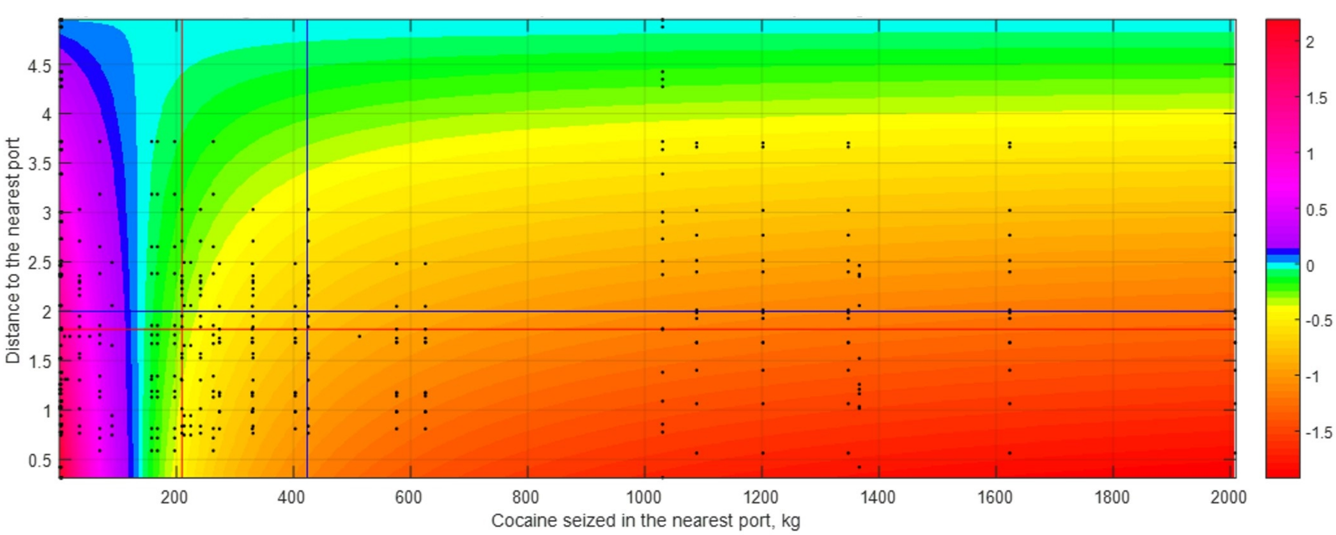
Table 6: Relation with seizures in the nine port provinces

	(1)	(2)	(3)	(4)	(5)	(6)
	b/se	b/se	b/se	b/se	b/se	b/se
seizr	-0.0603***	0.0465	-0.0573***	0.0407	-0.0608***	0.0499
	(0.0097)	(0.0987)	(0.0097)	(0.0910)	(0.0121)	(0.0998)
Snearest	-0.0001	-0.0001	-0.0010**	-0.0011**		
	(0.0003)	(0.0003)	(0.0005)	(0.0005)		
Snearest*dist			0.0004**	0.0004***		
			(0.0002)	(0.0002)		
Avg_dist					0.0000	-0.0000
					(0.0000)	(0.0000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	515	470	515	470	515	470
Nclust	103	94	103	94	103	94
R^2	0.089	0.087	0.098	0.097	0.089	0.087

* p<0.1, ** p<0.05, *** p<0.01. Cluster robust standard errors in parentheses.

In order to interpret the results we depict the effects predicted by the model on a color map (Figure 6). On the horizontal axis the volume of cocaine seized in the nearest port province is plotted with the maximum value corresponding to the maximum volume of yearly seizures in one of the nine provinces (Reggio Calabria) observed in the data. On the vertical axis is the distance to this province so that low values mean higher proximity. The dots represent the data points and red and blue lines correspond to the median and mean values respectively.

Figure 5: The total effect of seizures in nearest port province depending on the volume seized and distance



While it is true that higher volumes seized have a negative impact on consumption and it is more pronounced for the closer provinces, the relationship is reversed for relatively low seizure values. Our interpretation of this finding is that when the volumes seized are relatively low they are, in fact, mirroring supply, and so are positively related to consumption in the nearby provinces. However, when large volumes are seized, there is a decrease in the actual amount of cocaine available in the local markets which is substantial enough to decrease cocaine consumption.

For a province located at the mean, a 500 kilograms increase in cocaine seized in the nearest port (500 kilograms is one standard deviation of volumes seized in the selected nine provinces) corresponds to a decrease in the hospitalization rates by about 0.018 standard deviation. An analogous decrease would occur if an average province would have been located 40 kilometers closer to the nearest port province. For a mean value of kilograms seized in a nearest port, which is around 420 kilograms, the effect of such seizure varies from -0.46 for the closest possible province (about 35 kilometers) and becomes zero for the provinces located more than 180 kilometers from this nearest port.

Finally, we check if local markets are supplied by more than one key province. As was revealed in the study by Tzvetkova et al. (2014), dealers at all levels usually have multiple suppliers; therefore, we adopt a measure that takes into account proximity to all of the key provinces: $Avg\_dist = \sum_{i=1}^{9} S_i * dist_i$, which is the sum of seizures in all the nine selected provinces, weighted by distances. We estimate equation 4 with the Avg_dist variable instead of $Snearest$ and $Snearest * dist$. According to the results presented in Columns 5 and 6 of Table 6, the variable is not significant; it does not imply, however, a contradiction with the qualitative evidence from drug dealers' interviews: the interchangeability of suppliers might be present on the local level but not on the country level. This is quite reasonalble, since due to the illegal nature of the business long-distance travelling is minimized to reduce risks. Thus, while dealers may resort to several suppliers, most or all of these suppliers might be sourced through the same major entry point. Another reason could be the tight interconnection between drug business and organized crime[22]; in certain cases local markets are clearly divided between groups and subgroups so that freedom to choose a supplier may be limited.

7.2 The SLX model

In this final section we make an attempt to account for spatial interactions in a more unified way. Differently from what has been done in most of the spatial econometric literature, we adopt an SLX model which was originally proposed by Gibbons and Overman (2012) and further developed in the applied direction by Halleck Vega and Elhorst (2015). They highlight that the SLX approach is more flexible in modelling spatial spillover effects as compared to other spatial econometrics models (SAR, SEM, SAC, SDM), and should be preferred or at least taken as a point of departure in empirical analysis when there is no underlying theory suggesting to opt for a particular specification (as in Ertur and Koch, 2007). In our setting an SLX model is the most intuitive choice; one would be interested in the relationship between consumption in a given province and seizures in neighboring provinces, rather than focusing on the relationship between consumption in a given province and that of the neighbours. In fact, seizures in neighbouring provinces are an important variable per se that should be included since it is potentially related to both seizures and consumption in a given province, and at the same time is much more exogenous than own province seizures. Additionally, an

[22] Another interesting feature of drug markets in Italy is the coexistence of two business models: a vertically integrated monopoly is present in the areas where Camorra is in power, while rather free competition is common for northern areas where no dominating criminal group exists.

advantage of the SLX approach is that it allows to parameterize the spatial weight matrix W, while other models do not. Most commonly W is chosen based on the geographical proximity of units since generally neighboring units are interrelated with each other. However, in specific contexts this assumption seems too restrictive, and so Halleck Vega and Elhorst (2015) suggest parameterizing W unless there is a theory suggesting a particular W be adopted (as in Buonanno et al., 2012).

The SLX specification in our case will take the following form:

$$HAr_{it} = a_i + \tau_t + \beta S_{it} + \theta WS + \delta X_{it} + \varepsilon_{it}, \tag{5}$$

where WS is the spatial lag of seizures rates. Following Halleck Vega and Elhorst, we adopt an inverse distance spatial weight matrix, with zeros on the main diagonal and the off-diagonal elements taking value $w_{ij} = 1/d_{ij}$, normalized by maximum eigenvalue. In the course of estimation the matrix is parameterized in the following way:

$$w_{ij} = 1/d_{ij}^{\gamma} \tag{6}$$

where γ is an additional parameter that is also estimated, together with β, θ, δ and the fixed effects. The estimate of γ will provide an understanding of how fast the effects actually fade away with distance.

We also make an attempt to extend the external IV approach and use the spatial lag of cargo turnover rate as an additional instrument. Table 7 is organized as follows. Columns 1 and 2 contain results of the baseline and IV estimate[23] from Section 6; in Column 3 we used two variables as instruments for the seizures rate: the previously adopted cargo turnover in key ports and its spatial lag, and the point estimates are quite similar. Column 4 contains the output from the pure SLX model estimation where all variables are considered exogenous, with the seizures spatial lag point estimate equal to -0.39. This last result is similar to the one obtained when the seizures rate in own province is treated as endogenous and instrumented with cargo turnover only (Column 5). Though marginally significant, in line with our expectations the coefficient is negative, indicating that higher seizures in adjacent provinces are associated with a decrease in hospitalization rates in a given location. Next, Column 6 represents the IV estimation of the SLX equation with endogenous S, now instrumented with both $turnover\_rate$ and $W\_turnover\_rate$. Interestingly, the point estimate of WS jumps drastically, by more than 10 times, as compared to previous cases which could suggest that it is also endogenous. To take this possibility into account, we estimated the SLX model treating both seizures in own province and spatial lag as endogenous, instrumenting them with cargo turnover and its spatial lag (Column 7). The point estimate of WS is now -1.09, which seems more reasonable as compared to the previous case.

Given these point estimates, we can quantify the relationships and the effects. The baseline SLX model suggests that a one standard deviation increase in WS is associated with a 0.036 standard deviation decrease in local consumption. This finding is very similar to the relationship with seizures rate in own province, where the effect is 0.033. The magnitude of the effect of a one standard deviation increase in WS implied by results in Column 6 is the highest and reaches a 0.37 standard deviation decrease in hospitalization rates, while a point estimate in

[23] A slight difference of results with respect to those previously obtained is due to using 9 key provinces as opposed to 16. This is done because in the current section we now use 2 instruments, so that reduction in the first instrument's variation is compensated by adopting its spatial lag.

Column 7 implies this effect to be 0.1.

Table 7: SLX model

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se	(7) b/se
seizr	-0.061***	-0.162***	-0.198***	-0.062***	-0.159***	-0.191***	-0.155***
	(0.010)	(0.029)	(0.035)	(0.010)	(0.030)	(0.067)	(0.036)
Wseizr				-0.390*	-0.416*	-5.989**	-1.093*
				(0.219)	(0.217)	(2.922)	(0.602)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
γ			0.63	1.01	1.01	0.15	1.09
Obs	515	515	515	515	515	515	515
Nclust	103	103	103	103	103	103	103
R^2	0.089	0.062	0.040	0.094	0.070	0.070	0.046

* p<0.1, ** p<0.05, *** p<0.01. Cluster robust standard errors in parentheses.

Whether the spatial lag of seizures should be considered as endogenous itself is debatable. In the abovementioned paper, Vega and Elhorst suggest to test for endogeneity of the spatial lag by regressing the dependent variable on the residuals from the first step. However, this test may yield illogical results (e.g. indicating that WS is endogenous and S itself is exogenous - in fact, this is what they get in their case, and suggest to opt for a model with the spatial lag treated as exogenous; interestingly, with our data we obtained the same outcome). From the formal testing point of view, the model in Column 6 outperforms other specifications that have been presented by substantially improving both the strength and exogeneity of the instrument set. Another thing worth noting is that in this specification the optimal value of γ was estimated to be 0.15. This is in line with what we show in the following section, suggesting that the effects of seizures in neighbouring provinces fade with distance much slower than a plain inverse distance function would suggest.

8 Robustness checks

8.1 Different distance functions

Table 8 below provides results of estimating equations with distance interactions (eq. 4) for the full (Columns 1-3) and restricted (Columns 4-6) samples using inverse instead of plain distances. The results are different from what was obtained before: seizures in the nearest port are still insignificant and their interaction with inverse distance is negative and marginally significant, and these two variables are not significant jointly. The average weighted by distance is now negative and marginally significant. It appears that plain inversion punishes distance too much, assuming the effect of port province seizures to be less far-reaching than it really is. This would also explain why the Avg_invd coefficient has the same sign and significance level as the $Snearest * invd$: since the effect decays rapidly with distance, the most relevant constituent of the average weighted by distance is still the nearest port province.

Table 8: Using inverse distances as a proximity measure

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se
seizr	-0.060***	-0.061***	-0.061***	0.046	0.032	0.036
	(0.010)	(0.010)	(0.011)	(0.099)	(0.088)	(0.092)
Snearest	-0.000	0.000		-0.000	0.000	
	(0.000)	(0.000)		(0.000)	(0.000)	
Snearest*invd		-79.828*			-83.877*	
		(41.491)			(45.082)	
Avg_invd			-35.219*			-36.083*
			(20.397)			(20.842)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	515	515	515	470	470	470
Nclust	103	103	103	94	94	94
R^2	0.089	0.096	0.093	0.087	0.095	0.091

* p<0.1, ** p<0.05, *** p<0.01. Cluster robust standard errors in parentheses.

With a different proximity measure, that allows the decay not to diminish as fast as a pure inverse would suggest, the results are very similar to the plain distance case. Tables 9 and 10 contain estimation outputs using $distance^{-0.05}$ and $exp^{-alpha*distance}$ proximity measures respectively.

Table 9: Using $distance^{-0.05}$ as a proximity measure

	(1) b/se	(2) b/se	(3) b/se	(4) b/se
seizr	-0.059***	0.033	-0.030	0.045
	(0.010)	(0.086)	(0.033)	(0.097)
Snearest	0.017**	0.019**		
	(0.007)	(0.007)		
Snearest*$dist^{-0.05}$	-0.032**	-0.034**		
	(0.013)	(0.014)		
avg_$dist^{-0.05}$			55.034	65.987
			(51.760)	(81.927)
Controls	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs	515	470	515	470
Nclust	103	94	103	94
R^2	0.100	0.099	0.090	0.088

* p<0.1, ** p<0.05, *** p<0.01. Cluster robust standard errors in parentheses.

Table 10: Using exponential discounting with $alpha = 10^{-6}$

	(1) b/se	(2) b/se	(3) b/se	(4) b/se
seizr	-0.057***	0.040	-0.062***	0.048
	(0.010)	(0.090)	(0.010)	(0.099)
Snearest	0.004**	0.005***		
	(0.002)	(0.002)		
Snearest*$e^{-alpha*d}$	-0.006**	-0.006***		
	(0.002)	(0.002)		
avg_$e^{-alpha*d}$			-0.000	-0.000
			(0.000)	(0.000)
Controls	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs	515	470	515	470
Nclust	103	94	103	94
R^2	0.099	0.098	0.089	0.087

* p<0.1, ** p<0.05, *** p<0.01. Cluster robust standard errors in parentheses.

8.2 Different key province groupings

Here we provide the results of the spatial analysis in terms of relation to seizures in key provinces using slightly different groupings. In Section 7 we used nine provinces of the western coast.

Table 11: Relation to seizures in top-9 provinces by average amount seized

	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se
seizr	-0.0602***	-0.0634	-0.0615***	-0.0639	-0.0585***	-0.0642
	(0.0102)	(0.1099)	(0.0105)	(0.1054)	(0.0125)	(0.1105)
Snearest	-0.0001	-0.0000	-0.0009*	-0.0011**		
	(0.0003)	(0.0003)	(0.0005)	(0.0005)		
Snearest*dist			0.0004**	0.0005**		
			(0.0002)	(0.0002)		
Avg_dist					0.0000	0.0000
					(0.0000)	(0.0000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	515	470	515	470	515	470
Nclust	103	94	103	94	103	94
R^2	0.089	0.095	0.096	0.105	0.089	0.095

* p<0.1, ** p<0.05, *** p<0.01. Cluster robust standard errors in parentheses.

Table 11 contains results of estimating equation 4 for the top nine provinces by average yearly amount of cocaine seized (full sample used in odd columns, and excluding these top nine provinces in even columns). Since the majority of seizures take place in the western coastline provinces with ports, the top nine group is very similar to the original nine ports group, with the exceptions of Milan and Varese now replacing Savona and Cagliari. Perhaps, this is the reason why the results are almost the same: both signs and absolute values of the point estimates are identical to those in the baseline nine ports case.

Table 12 contains the results for the top nine provinces by average seizures *rates* selected as a key province group. In this grouping, as compared to the nine ports case, we have Varese, Trento and Pisa instead of Roma, Cagliari and Napoli. It appears that absolute volumes, rather than rates, are more relevant in determining which provinces' seizures have an impact on consumption in the rest of the country.

Table 12: Relation to seizures in top-nine provinces by seizure rates

	(1) hapop b/se	(2) hapop b/se	(3) hapop b/se	(4) hapop b/se	(5) hapop b/se	(6) hapop b/se
seizr	-0.0615***	0.1701	-0.0611***	0.1607	-0.0591***	0.0186
	(0.0103)	(0.2769)	(0.0108)	(0.2763)	(0.0125)	(0.0891)
Snearest	-0.0004*	-0.0004	-0.0006	-0.0008		
	(0.0002)	(0.0003)	(0.0006)	(0.0008)		
Snearest*dist			0.0001	0.0001		
			(0.0002)	(0.0002)		
Avg_dist					0.0000	0.0000
					(0.0000)	(0.0000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	515	470	515	470	515	470
Nclust	103	94	103	94	103	94
R^2	0.093	0.085	0.093	0.086	0.089	0.081

* p<0.1, ** p<0.05, *** p<0.01. Cluster robust standard errors in parentheses.

9 Conclusion

Studying illicit markets is facinating but intrinsically difficult. Due to the clandestine nature of the phenomenon, our knowledge of it, at least at the general public level, is very limited. Currently existing and openly available data is sparse and often of low quality. This hinders the possibility to rigorously study many policy-relevant questions and implies that any results obtained should be treated with caution. This paper is concerned with studying the relationship and effects of law enforcement, specifically illicit drug seizures, on drug consumption, proxied by drug-related hospital admission rates, using the case of the cocaine market in Italy. To the best of our knowledge, our results are the first evidence of a stable negative relationship between cocaine seizures and cocaine consumption. Contrary to existing studies, we tackle the endogeneity of seizures by implementing the instrumental variable approach, using both internal and external (western coast provinces' cargo turnover in ports) instruments. According to our findings, a one standard deviation increase in cocaine seizure rates leads on average to a decrease in hospitalization rates by about 3.3% in the baseline case and by 10% of a standard deviation if endogeneity is properly addressed. However, this result is driven by a relatively small group of provinces with high volumes of cocaine seized. In order to explore how those bulk seizures affect consumption in the rest of the country, we conduct the spatial interactions analysis by studying how cocaine consumption relates to seizures in seaport provinces. Our results suggest that when seizures in the nearest port province are large enough, their impact on consumption elsewhere is negative and more pronounced for closer units. Finally, we resort to an SLX model to investigate how cocaine consumption is related to seizures in the neighbouring provinces in general. The results vary depending on the exact specification but all suggest that the relationship is negative and at least as considerable in magnitude as the relationship with the seizures in own province.

These results are not only the first evidence of spatial interrelations between seizures and consumption, but may also be suggestive from the policy implications point of view. Specifically, we find that a province with 500.000 residents that is within a 130 kilometer distance (we consider it as being closely positioned) to a key port province on average exhibits a larger decrease in cocaine consumption from additional 50 kilograms seized in the port province than if that same amount was seized in the province itself. In other words, given that provinces in close proximity to the key port provinces greatly benefit from larger quantities seized in ports, a policy-maker who allocates enforcement resources on a country level and wishes to minimize consumption levels should shift the forces further away from the ports (with ports still being the main enforcement centers), rather than locating them right next to the port provinces. If that was the strategy currently adopted by the authorities, we would have observed that an increase in cocaine volumes seized in the port provinces is associated with a decrease in seizures rates in adjacent provinces. However, we do not find evidence in support of this in the data, and it may suggest that there is a potential to further decrease the overall levels of cocaine consumption by relocating enforcement from the provinces that are close neighbours of port provinces to those units that are further away.

There are several possible directions for future research. Firstly, in this work we focused on cocaine markets. Studying markets for other types of drugs may provide insights into whether seizures of heroin, hashish and marijuana are related to consumption of those drugs in a similar way as was discovered for the cocine market. Additionally, incorporating all types of drugs in a single empirical model would allow to investigate their substitution/complementarity for Italian users. Secondly, the unique Italian setting potentially allows to study the effectiveness of law enforcement on differently organized drug markets (but located within the same country): the mafia-controlled vertically integrated monopoly with strict rules for the participants and the relatively free competition in the areas with no dominating criminal group present. Finally, similar analysis on cross-country level might provide insights for antidrug supply-side policies on a global scale.

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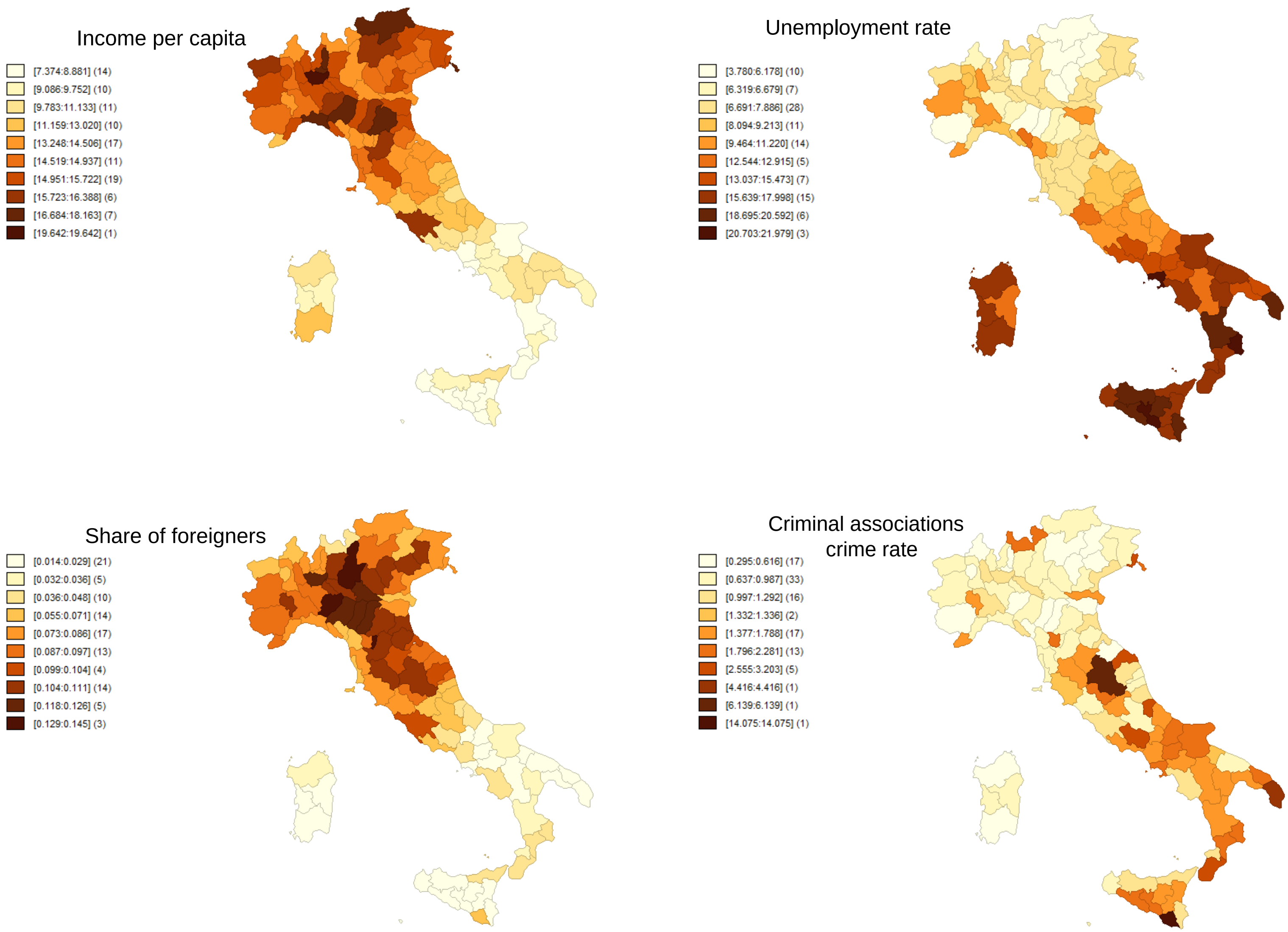
Appendix

A.1 Spatial patterns of control variables (averaged over 2010-2014)

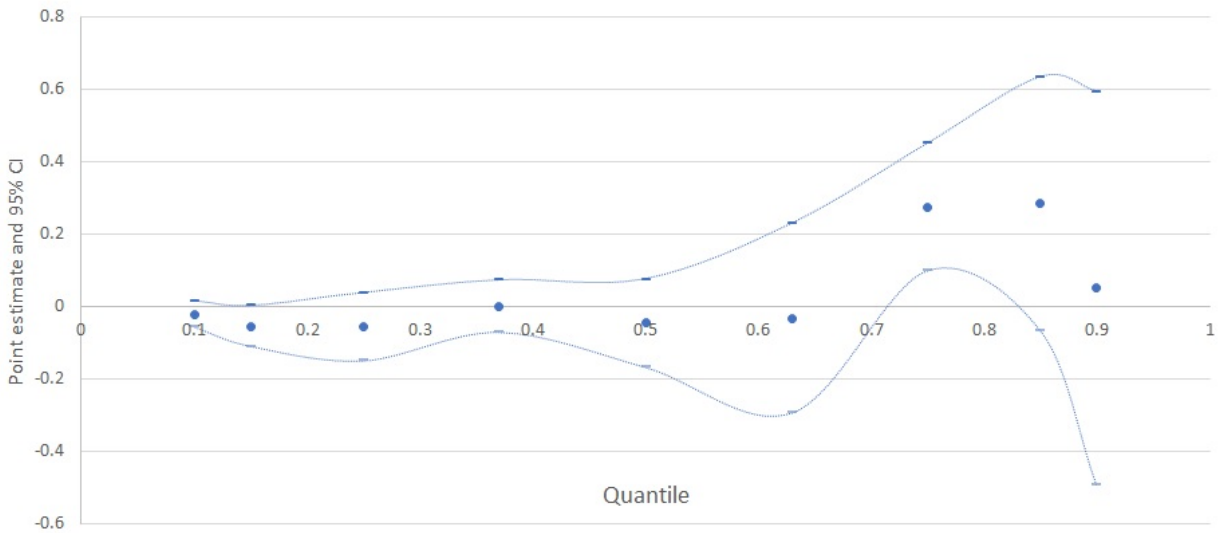


A.2 Quantile panel estimation

Apart from running a baseline model on subsamples with high and low consumption levels (Table 3), we also adopt quantile regression technique for panel data (Powell, 2014) to investigate whether seizures rates and consumption are interrelated in a different way for units located in different parts of consumption distribution.

In order to apply this methodology, we within-normalize all the right handside variables, so that $X_{it}^{new} = \frac{X_{it} - \bar{X}_{it}}{sd(X_{it})}$ (note that the obtained coefficients should not be interpreted in the same way as in the baseline FE regression), and run the quantile panel estimation using adaptive MCMC optimization with 20.000 draws. The figure below depicts the resulting point estimates of the normalized seizures rates coefficients, together with 95% confidence intervals, for a range of quantiles (from 0.1 to 0.9).

Figure 6: Coefficient of seizures rates for different quantiles of consumption distribution



The qualitative result is the same as that obtained with a sample split: the coefficient of seizures rate is negative for lower consumption quantiles and positive for high quantiles, which is indicating the presence of endogeneity of seizures in high-consumption areas.

Baby Bonuses and Household Consumption: Evidence from Russia

Anastasia Arabadzhyan*

Abstract

This paper studies the response of the Russian households' consumption expenditures to becoming eligible for maternity capital assistance: a lump-sum non-cash grant worth about $10.000, which mothers of the second and higher order child born after the 1st of January 2007 are allowed to invest in housing, children's education or retirement fund; in most of the cases this financial support becomes accessible only after the eligibility-granting child reaches three years of age. Through the prism of the wealth effects literature, we view becoming eligible to the assistance as experiencing a positive wealth shock, which, unlike negative shocks, is an uncommon event in developing countries. Our results suggest that, on average, households' consumption expenditure patterns do not change in response to becoming eligible for the assistance; however, this null average effect masks important heterogeneities: households with particularly low levels of wealth (tenants) do react to becoming eligible by increasing consumption of nondurable goods. We also find strong evidence of consumption smoothing by consuming from wealth, which was observed in partial liquification periods, when the government allowed withdrawing small amounts in cash during economic downturns: households actively consumed from the assistance to smooth consumption in occurrence of negative income shocks. Finally, we document the presence of liquidity constraints: housing wealth of eligible households mostly increases three years after the child was born, only when the assistance becomes available to purchase housing without getting a loan.

JEL classification: H31, H53, J13, J18.
Keywords: fertility, household consumption, wealth shocks, consumption smoothing.

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1 Introduction and motivation

Due to low fertility rates the Russian federal government launched a pro-natalist policy measure in 2007. Once in a lifetime a woman who gives birth to or adopts a second or consecutive child is eligible to "maternity capital" assistance (around $10,000 in 2007, adjusted for inflation on yearly basis) which can be obtained after the child reached three years of age and only in no-cash form (to avoid parents spending money on random purposes) for the following needs: invested in children's education, housing (buying a new house or taking a mortgage) or put on the mother's pension account. The program is, obviously, quite costly: the share of related expenditures in total government expenditures has increased from 1% in 2010 to 2.2% in 2016[1], however, whether the policy was successful in reaching its goals is questionable.

Virtually from the very beginning of the program there has been a lot of discussion around its effects, design and general adequacy. Given that the liabilities due to the program are very large, many claim that its effects are too small: families tend to reschedule births, but do not increase the desired number of children. Others insist that it is the design that causes inefficiency: for majority of cases it is necessary to wait three years after the eligibility-granting child is born; restricting the ways of the use of the assistance also diminishes its subjective value for the families. Current discussions on demographic policies primarily touch upon maternity capital program: among the recent suggestions were turning to cash and allowing families to withdraw the full amount of assistance, and extensive expansion by granting the assistance to families with the first-order newborn child.

The current study aims to capture the responses of Russian households to becoming eligible to the assistance in terms of their consumption expenditure patterns. This would not only be highly relevant from the policy-makers' point of view, but also relate to the wide strand of the wealth shock literature: the peculiarity of our approach is treating becoming eligible to the assistance as a positive wealth shock, so that households are expected to change their consumption expenditure patterns even before the assistance is fully accessible (three years after the second or higher order child was born) to be spent on any of the ways specified by the law. In addition to testing responses to the wealth shock, we investigate whether households exhibit smoothing behaviour and consume from wealth in the periods of economic downturns, and whether and when they tend to execute their right for the grant by converting it into housing value.

The remaining of the paper is organised as follows. Section 2 locates our study in the existing literature and highlights main contributions, Section 3 describes in detail the design of the policy and its evolution. Section 4 introduces data and the baseline empirical specification, which is estimated in Section 5 along with other specifications. Finally, Section 6 concludes the paper.

2 Related literature and contribution

There is no doubt that policy-makers, as well as the general public, would be interested in estimating the cost-efficiency of such a program. However, pure effects of this policy are very difficult to pin down because it was not the only fertility-incentivizing reform that came into action since 2007: in addition to the introduction of maternity capital, the government has also increased child benefits and parental leave benefits. In principle, there is interest in assessing

[1] According to the data of the Pension Fund of Russia and the Ministry of Finance.

the impact of the full package of reforms on fertility. Regarding households' decisions to have one more child, Chirkova (2013) estimates a binary choice model of fertility exploiting the variation in the financial incentives and concludes that the probability to have a second child has increased after 2007, with the magnitude of the effect depending on the gender of the first child. Slonimczyk and Yurko (2014) resort to a structural dynamic programming model of fertility and labor force participation. They find that long-run fertility increased by about 0.15 children per woman with increases in birth rates being larger among women who are married or cohabiting with a spouse and women with lower potential earnings. While increasing fertility, the policy did not have disemployment effects. Additionally, no significant differences were found when grouping women by observable skill levels, rural and urban areas of residence and employment status. Apart from these obvious variables of interest, the policy could have affected many other outcomes worth investigating. Given that the funds are supposed to be spent on housing, children's education or retirement funds, the second set of outcomes that the policy should have affected are housing wealth, expenditures on housing and expenditures on education. Mukanova (2018) uses a mix of matching and difference-in-difference methodologies to study the effect of becoming eligible to the assistance on housing expenditures (rent, municipal services, construction materials) and education expenditures. She finds that eligibility decreases housing expenditures at the year of second child's birth by 18% and by approximately 35% three years after, and increases education expenditures by 63% at the year of the second child's birth.

Although our study is close to the abovementioned ones and could also be of interest for policymakers, our main contribution lies in treating becoming eligible to the assistance as a wealth shock. Eligibility to maternity capital could have had an impact on household's consumption patterns even before it was allowed to spend the funds. For example, keeping in mind that there is a substantial sum of money available to invest in improving housing conditions in the future, the household might spend its current income differently (save less than they would if were not eligible) and increase expenditure of other kinds: buy a car, or increase consumption of non-durable goods such as food and clothing. Differently from the vast majority of existing studies that focus on the impact of child benefits on fertility decisions and maternal labour supply (Brugiavini et al. (2013), Cohen et al. (2013), Milligan (2005), González (2013)) and child health and well-being (Milligan and Stabile (2009), Milligan and Stabile (2011)), we focus on households' consumption response to being eligible to the assistance. The most closely related papers would be that of González (2013), where she also investigates if households' total expenditures changed at the point when families became eligible for payment, and does not find the effect; and Stephens Jr and Unayama (2015) who use a basic life-cycle/permanent income hypothesis framework to analyse the impact of child benefits on household wealth accumulation. In line with the model's predictions, they find that higher cumulative benfits received increase current assets, higher future benfit payments lower asset holding, these effects systematically vary over the life cycle, and that there is heterogeneity in responses of liquidity constrained and unconstrained households. Differently from their setting, in our case we are interested in response of consumption to a wealth shock, rather than response of wealth to an income shock. To the best of our knowledge existing literature on consumption in Russian context focuses on consumption responses to income shocks rather than to wealth shocks (Stillman, 2001). An extremely important feature of our setting is that it allows to study households' responses to a *positive* wealth shock.

Such analysis would be closest to the spirit of empirical literature that estimates wealth effects on consumption, and bases on theoretical background found, for instance, in Deaton (1992). To illustrate, we resort to a standard life-cycle model (particularly, in notation of Carroll (1997)): a household lives for T periods and maximizes utility over the remainder of its lifetime by choosing a level of consumption in each period:

$$\max_{C_{t+\tau}} E_t \sum_{\tau=0}^{T-t} \left(\frac{1}{1+\delta}\right)^{\tau} u(C_{t+\tau})$$

$$s.t. \quad \underbrace{X_t}_{\text{gross wealth}} = \underbrace{(1+r)(X_{t-1}-C_{t-1})}_{\text{net wealth}} + \underbrace{Y_t}_{\text{current labor income}}$$

Under no uncertainty (only for the purpose of representation simplicity; a model with uncertainty does not have a closed-form solution) and assuming $\delta = r$, the solution of the model will be given by:

$$C_t = k_t \left[X_t + \sum_{\tau=1}^{T-t} \left(\frac{1}{1+r}\right)^{\tau} Y_{t+\tau} \right] \tag{7}$$

where k_t can be interpreted as annuity of lifetime wealth or marginal propensity to consume, and equal to:

$$\left(\frac{r}{1+r}\right) \left[\frac{1}{1-\left(\frac{1}{1+r}\right)^{T-t+1}} \right]$$

From equation (7) it is clear that household's consumption is tightly related to wealth, and a positive wealth change is expected to be accompanied by an increase in current consumption.

Therefore, the current study contributes to the vast literature that sheds light on the relation between wealth shocks and consumption (e.g. Campbell and Cocco (2007), Case et al. (2005), Christelis, Georgarakos, et al. (2015), Paiella and Pistaferri (2017), Bottazzi et al. (2017)). A survey study by Paiella (2009) provides an overview of time-series and micro-econometric evidence on the relationship between stock and housing wealth and consumer spending. These two factors are the most frequently investigated, since financial market and housing prices shocks are plausibly exogenous and unanticipated by individuals, which makes it convenient to use such shocks as a source of exogenous variation to uncover the effects of wealth changes on consumption. In this case, however, we face a peculiar kind of shock to a household's wealth: a shock that is not determined by macroeconomic dynamics, but results from a second or higher order birth. One may argue that eligibility is highly endogenous. First, we note that even the abovementioned macroeconomic shocks are not completely free from endogeneity issues. Co-movements in house and stock prices and consumption are driven in part by common macro-factors and not by causal link (Attanasio et al., 2009); constructing a portfolio and changing its' composition is a choice, based on the investor's expectations about future changes in the components' value, etc. Secondly, while a decision to give birth to another child is still more endogenous than decisions made conditional on macroeconomic environment, high levels of uncertainty and low levels of trust towards government and financial institutions in Russia[2] make the population treat any promises with caution, feeling safe only when all the official documents that grant eligibility are at hand. This implies that anticipation effect is unlikely to be present.

[2]These peculiar features of contemporary Russia are typically attributed to severe shocks the country experienced in the 1990s (see, for example, Shlapentokh (2006) and Spicer and Pyle (2000)).

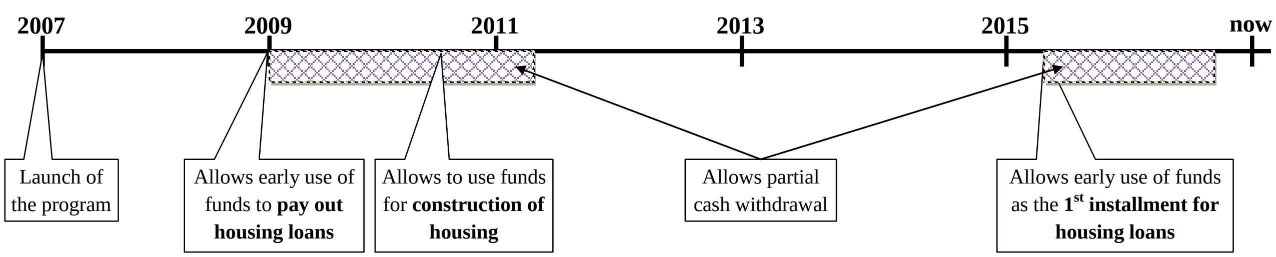
3 Policy design

In this section we describe in more detail the design of the policy, as well as other fertility-incentivizing measures which were adopted simultaneously.

The maternity capital program was launched on the 1st of January in 2007. Acording to the new law, families, who adopted or gave birth to a second or consecutive child in 2007 or later, were eligible to the government assistance of approximately $10.000 (adjusted for inflation on the yearly basis[3]; at the moment, due to severe depreciation of the ruble in the past years, in dollar terms the assistance would account for about $8.000 - roughly 70% of per capita GDP). The peculiarity is that this assistance is available solely in the non-cash form. To avoid careless spending, the initial version of the law allowed the assistance to be invested in three not mutually exclusive ways: housing, children education or mother's retirement fund. Moreover, the assistance was available only after the child that granted eligibility to the household turned three years of age. The coordinator of the program is the Pension Fund of Russia, which is responsible for issuing certificates for eligible families who decided to apply, and for transferring the funds to entities that provide related services (i.e. housing, education) according to the needs of those families, who decided to activate the certificate.

Several significant changes have been made since the law was first enacted (see Figure 7 below). Firstly, beginning in January 2009 the funds can be used for mortgage payments immediately after the birth of the eligible child (i.e. without the three year waiting period); from May 2015 it is also allowed to use the maternity capital assistance as a first installment for housing loans. Secondly, since August 2010 the funds can also be used for construction of housing (previously it was allowed to use for acquiring housing only). Finally, from 2009 until March 2011, maternity capital certificate holders were allowed to withdraw 12.000 rubles (around $400) in cash; from May 2015 until March 2016 - 20.000 rubles.

Figure 7: Timeline of changes of the maternity capital policy



From 2007 until 2015, the Pension Fund has issued certificates to 6.7 million families[4], 50% of families have spent the whole sum of assistance; about the same share accounts for certificates requested for the purpose of improving housing conditions. 1360 billion rubles was spent in total in all the years of the program until 2015 (which would be a considerable $2.7 billion per year), over 90% of these funds were used for the purpose of improving housing conditions. In addition to the assistance being a non-cash deposit, the latter fact is another reason why it is plausible to think of becoming eligible for the assistance as of an increase in wealth, rather than increase in income: in most of the cases the money is converted into housing, increasing

[3]until 2015

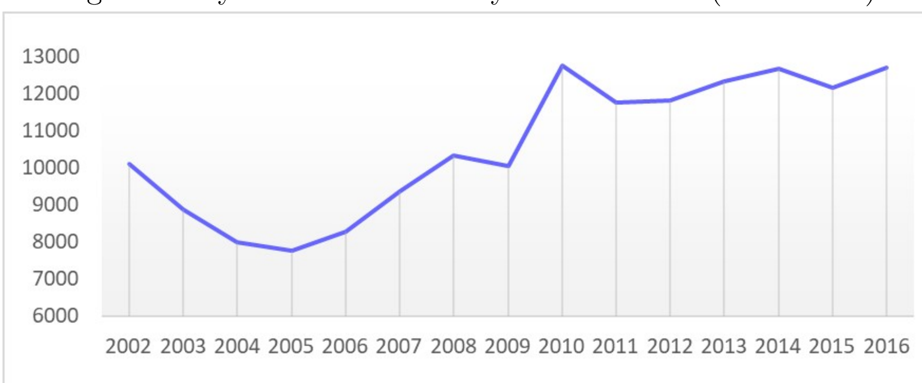
[4]These are families who applied for the certificate, not the total number of eligible families. As estimated in 2013, from 2007 until 2013 around 90% of eligible families have actually applied for the certificate.

households' housing wealth.

It is worth highlighting that since the amount of the assistance is fixed, it would have different value for households in different regions. To illustrate we picked several random real estate ads and calculated the share of the price that maternity capital assistance could cover. In 2017, for a decent 75 m^2 apartment in Moscow suburbs the grant would have covered only 7.4% of the price; for an apartment of the similar size in Barnaul - 21% of the price; for a 50 m^2 house with a land plot of 1200 m^2 in a village in Irkutsk Oblast' - 54% of the price.

In parallel to the maternity capital assistance, several other fertility-incentivizing measures came into action. These were related to an increase in various types of benefits: child benefits (in terms of monthly payments[5]) and maternity leave benefits. Maternity leave in general cases comprises 140 days, split equally before and after the child's birth; the amount to which eligible (employed) women are entitled to is calculated based on average yearly earnings and is restricted by a maximum value that is updated every year. Figure 8 shows the dynamics of the real value (in 2001 prices) of the maximum amount of maternity leave benefit: as evident from the graph, it has been raising gradually since 2005. Child benefits are another type of

Figure 8: Dynamics of maternity leave benefits (real values)

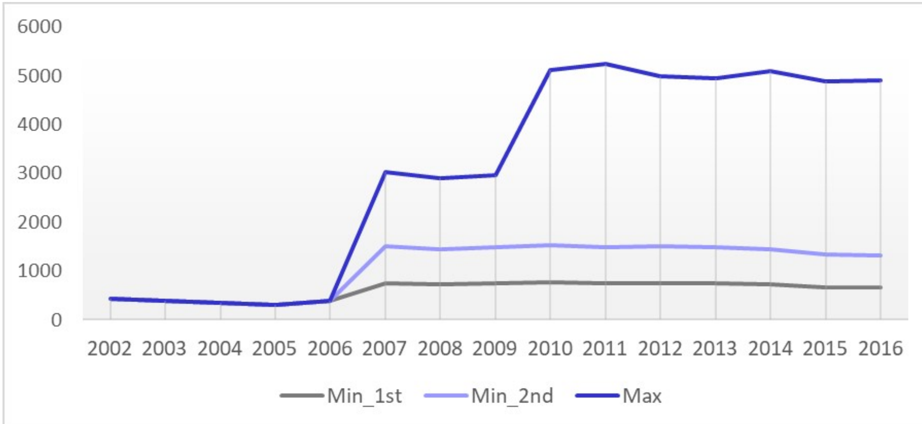


transfer that a woman can receive in addition to the maternity leave, and is paid until the child reaches 1.5 years of age. Prior to 2007 these benefits were fixed and of a relatively low amount. However, since 2007 substantial changes were introduced: these benefits were calculated as a share (40%) of the mother's salary, with predefined minimum and maximum amounts. The dynamics of child benefits real values is depicted in Figure 9. Not only has the reform increased maximum amount available, but has also set minimum amounts that differ by birth order. Other studies argue that these amounts are relatively low and only a small fraction of employed women have earnings that fall in the range where distinction by birth order plays a role. However, another novelty of the reform was to introduce these child benefits for non-employed women, who now became eligible to the minimum amount. Therefore, the benefits became higher for non-employed and low-paid mothers, and even more so for higher order births.

For our research question these differences are non-negligible. For instance, in 2006 a low-paid mother would receive a monthly child benefit that would have accounted for about 6.9% of an average monthly income per person. In 2007 the same woman would have received an amount that would comprise about 12% of an average monthly per capita income, and about 24% if she gave birth to a second or higher order child. While it could be argued that it is still

[5]Mothers are also entitled to a lump-sum benefit at birth. This benefit, however, did not exhibit substatial dynamics at the 2007 cut-off.

Figure 9: Dynamics of child benefits (real values)



insufficient to stimulate a family to give birth to another child, these differences do play a role when it comes to current consumption, which is the focus of our analysis, preventing us from resorting to a difference-in-difference approach which is invalid in the presence of confounding factors. Table 22 in the Appendix provides evidence of higher expenditures on durable and non-durable goods by households with two or more kids in the post-reform period. However, the difference-in-difference specification used does not allow to distinguish various channels: the pure wealth effect, the impact of increased amounts of child benefits, and the effects related to direct use of the assistance (e.g. an increase in durable expenditures triggered by moving to a new apartment purchased with the use of the funds). In the next section we describe the methodology adopted to capture specifically the wealth shock impact on various consumption expenditures.

4 Data and methodology

4.1 Defining the sample

We conduct the analysis using the Russia Longitudinal Monitoring Survey (RLMS) which collects data on both individual and household levels, allowing to evaluate household-level expenditures on various types of goods and services. Selected expenditures are classified into the following categories:

- Non-durable consumption expenditures (food, convenience goods, clothes);
- Durable consumption expenditures (furniture, cars, home appliances, etc);
- Expenditures on travelling and entertainment;
- Expenditures on medical services.

All expenditures are converted into real values (in 2001 prices). Figures 10-13 in Appendix depict the dynamics of real expenditures for the selected categories: it is evident that with the exception of medical goods and services, all other expenditures exhibit a substantial drop in 2009 with the major financial crisis, and also in 2015 as a result of anti-Russian sanctions following 2014 Crimea events.

For the purposes of our analysis we compose the final sample so that it satisfies several criteria. Firstly, for the reasons described in the previous section, we focus on households in the post-reform period, covering years 2007-2017. Secondly, given that household composition plays a huge role with respect to expenditure patterns, for the purpose of studying responses to the wealth shock, only households with kids are included in the sample to make it more homogeneous[6]. Finally, there is an issue of defining a proper control group. Note that by construction a household's eligibility status changes from 0 to 1 with an arrival of a newborn child, so, there is no control group that would have households that become eligible without a newborn child appearing in the family. If this issue is ignored, it will not be possible to distinguish the response of consumption expenditures to a wealth shock from that to arrival of a newborn. As a consequence, the sample is further restricted to households with newborns. Next, there are two possibilities for control groups: households with a first newborn child, and households with a second order newborn, which, however, are not eligible for the assistance (extended families, remarried, etc). Regarding the first group, the main disadvantage is that such households have different demographic characteristics which may result in different preferences over goods, and also less experience in managing related expenditures. This latter feature implies that households with an experienced mother, for whom the newborn child is of second or higher order, are likely to increase their consumption expenditures of non-durable goods by a lower amount than their less experienced counterparts. The second control group could partially alleviate these concerns: extended families are likely to have some stock of semi-durable goods (e.g. child clothing), or have another mother with a child present, who could share her experience in managing expenditures with the mother who has just given birth. A serious disadvantage is that this second control group is low in numbers and may also differ from eligibles in demographic and socio-economic dimensions. Table 13 provides summary statistics by subsamples: for the treated (eligible) households and the two control groups. Indeed, as was suspected, neither of the control groups is a perfect match for the treated: the first group has less family members, more educated household head and higher income, while the second one - more family members, less educated and older household head. Some of this differences may be spurious and result from a small sample size, but in any case it is important to keep those differences in mind when interpreting the findings.

Table 13: Descriptive statistics for treated and control groups

	Eligible	Control 1	Control 2
Observations	395	425	57
Number of family mmbers	4.4	3.8	5.8
HH head age	34.5	34.2	40.2
HH head emp	0.85	0.83	0.74
HH head is female	0.07	0.09	0.16
HH head educ	0.25	0.32	0.12
Income per person	2641	3413	2443
Tenant	0.10	0.15	0.05
Urban	0.66	0.76	0.53

Highlited are characteristics that are significantly different for control groups at 5% level.

[6] In addition, the sample is restricted to consist of households that have not moved houses when their eligibility status switched from 0 to 1.

4.2 Empirical specification

Following Banks et al. (2012) and Bottazzi et al. (2017), we consider a first-differenced equation:

$$\Delta C_{it}^k = \alpha^k + \beta^k \Delta Elig_{it} + \gamma^k \Delta X_{it} + \delta_t^k + \epsilon_{it}^k \quad (8)$$

where C_{it}^k is expenditure on category k by household i in year t; X_{it} is a set of controls: demographic composition of the household (number of children and adults in different age groups), real household income, characteristics of the household head (age, sex, education, employment status), and regional macroeconomic variables (unemployment rate and average real wage); $Elig_{it}$ is eligibility indicator, which is equal to 1 if there is a mother of at least two siblings and at least one of them was born in 2007 or later, and 0 otherwise[7]; δ_t^k are year fixed effects. The coefficients of interest are β - households average response in terms of consumption expenditures to having become eligible to the assistance. Taking the equation in differences allows controlling for the household fixed effect: it is plausible to think that when the policy was announced households have consequently updated their tastes for children, which since then stayed time-invariant as no other substantial policy changes were in place; therefore, the β coefficient has also a causal interpretation[8].

In the following section we present results of esimating the first-differenced equations, using the two different control groups defined above, as well as a mixed control group (combining the two).

5 Results

5.1 Responses to the wealth shock

Tables 14, 15 and 16 contain the results of estimating equation (8) for the four categories of consumption expenditures using the first, second and mixed control groups respectively.

From Table 14 it appears that households which become eligible increase their non-durable consumption by a lower amount than their counterparts with the first-order newborn: this may reflect the learning effect and the semidurables stock availability described in the previous section[9]. As regards expenditures on durable goods, eligible households increase these more than non-eligible ones; however, this may be a result of another child present in the household: for instance, if the second child is entering pre-school or primary school in the same year, it will be associated with increased spending on related goods[10]. Table 15 contains estimation results for the second control group, which has higher number of kids and may partly mitigate the learning effect that is at play for the first control group, but is low in numbers. Contrary to what should be expected in accordance with the theory, households that have experienced a wealth shock do not increase their current consumption more than their untreated counterparts: the coefficient of *elig* variable is insignificant for all the expenditure categories. While it could

[7]Since there is no data on actual program uptake, the only feasible way to proceed is to use meeting the eligibility criteria indicator.

[8]Assumig that the control groups are properly defined.

[9]This result is driven by expenditures on child clothing: as opposed to households with the first-order newborn, eligible households do not have to spend as much on child clothing for the newborn if they have usable clothing items left from the first child.

[10]We find evidence in support of this hypothesis by taking a step back and running the estimation on different constituents of durable expenditures category. The results suggest that the main drivers of larger durable consumption increase for eligible families are expenditures on home appliances, books and sports equipment.

Table 14: Control group 1: 1st order newborn

	D.nondur	D.durables	D.trav	D.medical
	b/se	b/se	b/se	b/se
elig	-683.7*	1303**	5.60	29.4
	(382.9)	(534.4)	(57.6)	(34.4)
D.income	0.18***	0.07	0.02***	0.006*
	(0.03)	(0.05)	(0.005)	(0.003)
HH demographic composition	Yes	Yes	Yes	Yes
HH head's characteristics	Yes	Yes	Yes	Yes
regional macro	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes
constant	2507*	-177.4	-303.9*	12.7
	(1336)	(1493)	(165.8)	(97.6)
Obs	595	722	750	746

Significance levels: * p<0.1, ** p<0.05, *** p<0.01

Table 15: Control group 2: 2nd child, noneligibles

	D.nondur	D.durables	D.trav_ent	D.medical
	b/se	b/se	b/se	b/se
elig	-789.7	866.2	70.6	28.0
	(799.8)	(1198)	(106.8)	(71.7)
D.income	0.19***	0.06	0.022***	0.004
	(0.05)	(0.07)	(0.007)	(0.005)
HH demographic composition	Yes	Yes	Yes	Yes
HH head's characteristics	Yes	Yes	Yes	Yes
regional macro	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes
constant	3433**	-2637	-429.7*	184.4
	(1731)	(2180)	(254.6)	(134.6)
Obs	341	406	420	414

Significance levels: * p<0.1, ** p<0.05, *** p<0.01

be a problem of the low number of observations, combining two control groups and estimating the equation adding the indicator of having two or more kids in the household (2^{+}kids) yields the same results (Table 16).

There are several possible explanations to the observed null response of current expenditure to the wealth shock. First, eligible households may have higher level of indebtedness (since they are typically at a further life cycle stage than households with one child, for instance), which will force them to allocate a more considerable share of the budget to debt repayment,

Table 16: Mixed control group

	D.nondur	D.durables	D.trav_ent	D.medical
	b/se	b/se	b/se	b/se
elig	-1188	1283	73.8	38.8
	(771.3)	(949.1)	(98.4)	(68.2)
D.2^{+}kids	612.1	-29.1	-83.4	-4.81
	(758.5)	(932.4)	(95.7)	(68.2)
D.income	0.19***	0.08	0.022***	0.005
	(0.03)	(0.05)	(0.005)	(0.003)
HH demographic composition	Yes	Yes	Yes	Yes
HH head's characteristics	Yes	Yes	Yes	Yes
regional macro	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes
constant	2486**	-707.1	-341.8*	37.7
	(1252)	(1400)	(159.5)	(93.2)
Obs	642	776	803	799

Significance levels: * p<0.1, ** p<0.05, *** p<0.01

sacrificing current consumption. To see whether this is the case, we perform a check regressing the indicator of having taken a loan in the past 12 months and in the past 3 months on the same set of variables; according to the results, there is no evidence that households which became eligible are more likely to have borrowed than their counterparts (see Table 23 in the Appendix). Another explanation could be that the change in consumption expenditures happens not when the family obtains the certificate which formalizes their eligibility status, but when the eligibility-granting child is conceived or even sooner. This hypothesis is tested by using the first and second order leads of eligibility indicator in equation 8. The results are presented in Table 24 in the Appendix and indicate that a positive response of consumption expenditures to positive changes in future wealth is not present. However, one may extend this reasoning by claiming that since all households are informed about the existence of the policy, the future changes in wealth are anticipated, and according to the permanent income hypothesis, rational consumers should not respond to anticipated changes in wealth. However, in the presence of credit market imperfections, liquidity constraints and precautionary savings there is still room for excess sensitivity. To test this theoretical prediction, we now make a distinction between homeowners and tenants. The latter are characterized by low levels of wealth and are presumably more liquidity constrained, since they do not have an option for using real estate as a collateral. Moreover, those would be the households whom we would expect to be more sensitive to becoming eligible for maternity capital assistance, since for them it would be the most valuable. In contrast, households that are satisfied with their living conditions may not intend to convert the assistance into housing value and postpone the decision on how to spend it to the future. Therefore, we add the *tenant* indicator and its interaction with the *elig* dummy variable to the baseline specification, obtaining the following equation:

$$\Delta C_{it}^{k} = \alpha^{k} + \beta_{0}^{k} \Delta Elig_{it} + \beta_{1}^{k} tenant_{it} + \beta_{2}^{k} \Delta Elig_{it} \times tenant_{it} + \gamma^{k} \Delta X_{it} + \delta_{t}^{k} + \epsilon_{it}^{k} \quad (9)$$

Table 17 contains results of estimating equation (9) for non-durable and durable consumption categories. While eligible households in general increase their non-durable consumption by

Table 17: Homeowners vs tenants

	D.nondur	D.nondur	D.nondur	D.durables	D.durables	D.durables
	b/se	b/se	b/se	b/se	b/se	b/se
elig	-1136	-1143	-1366*	1069	1067	818.5
	(758.7)	(761.2)	(769.9)	(956.5)	(957.5)	(978.2)
tenant		-375.9	-1376**		-185.2	-1213
		(568.1)	(751.6)		(711.3)	(865.5)
elig × tenant			2395**			2575
			(1082)			(1776)
D.2^{+}kids	541.2	534.0	466.4	269.6	263.7	220.2
	(737.0)	(738.8)	(740.5)	(948.2)	(949.8)	(950.5)
D.income	0.19***	0.19***	0.19***	0.08*	0.08*	0.09*
	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)
HH demographic composition	Yes	Yes	Yes	Yes	Yes	Yes
HH head's characteristics	Yes	Yes	Yes	Yes	Yes	Yes
regional macro	Yes	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes	Yes
constant	2480**	2549**	2647**	-666.9	-622.6	-507.3
	(1253)	(1257)	(1263)	(1397)	(1418)	(1411)
Obs	643	643	643	777	777	777

Significance levels: * p<0.1, ** p<0.05, *** p<0.01

lower amount as compared to non-eligibles, eligible tenants increase their non-durable consumption more than other households (the interaction coefficients are jointly significant at the 10% significance level), which is in line with theoretical predictions. Therefore, we conclude that the null average response of becoming eligible to the assistance conceals important heterogeneities among households across the liquidity constraints dimension: more constrained households which value the assistance more are found to exhibit higher levels of current expenditure in response to the wealth shock. This result is in line with those from other empirical studies (Cooper (2013), Aladangady (2017)), which find that the increase in spending in response to an increase in housing value is driven by borrowing constrained households.

5.2 Consumption smoothing

In this subsection we check another theoretical prediction, which suggests that consumers tend to exhibit smoothing behaviour to balance their consumption trajectory by consuming from wealth. We exploit partial liquification periods in 2009, 2010 and 2015, which allowed to withdraw a small amount of the assistance in cash form, and add corresponding dummy variables to the basic specification:

$$\Delta C^k_{it} = \alpha^k + \beta^k_0 Elig_{it} + \beta^k_1 Elig09_{it} + \beta^k_2 Elig10_{it} + \beta^k_3 Elig15_{it} + \gamma^k \Delta X_{it} + \delta^k_t + \epsilon^k_{it} \quad (10)$$

where $Elig09, Elig10$ and $Elig15$ are dummy variables equal to 1 when a household is eligible in the corresponding year (in other words, interaction terms of eligibility indicator and year

Table 18: Consuming from wealth

	HHs with kids			HHs with 2 and more kids		
	D.nondur	D.durables	D.food	D.nondur	D.durables	D.food
	b/se	b/se	b/se	b/se	b/se	b/se
elig	-84.7	-68.1	-65.7**	7.20	-325.4*	-91.0**
	(98.5)	(125.3)	(31.0)	(138.7)	(184.8)	(43.9)
elig09	-46.9	1807**	14.8	-68.8	2587***	232.2
	(456.4)	(719.6)	(134.1)	(548.1)	(839.8)	(170.3)
elig10	-376.4	-750.0	-77.8	-216.6	-717.9	-71.3
	(376.3)	(511.2)	(150.2)	(526.3)	(630.4)	(184.0)
elig15	161.2	-422.6	226.3**	-272.3	8.03	316.3*
	(276.2)	(356.8)	(87.8)	(517.3)	(621.5)	(172.3)
2^{+}kids	151.0**	195.2**	2.48			
	(76.2)	(94.2)	(22.5)			
D.income	0.155***	0.132***	0.037***	0.162***	0.121***	0.041***
	(0.010)	(0.014)	(0.003)	(0.017)	(0.022)	(0.005)
HH demographic composition	Yes	Yes	Yes	Yes	Yes	Yes
HH head's characteristics	Yes	Yes	Yes	Yes	Yes	Yes
regional macro	Yes	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes	Yes
constant	298.799	-298.965	51.060	446.013	163.513	-42.516
	(201.893)	(269.188)	(64.981)	(418.988)	(508.124)	(136.706)
Obs	15305	19090	17960	5247	6617	6202
Nclust	4396	4942	4736	1713	1981	1862

Significance levels: * p<0.1, ** p<0.05, *** p<0.01

dummies). Table 18 contains estimation results for equation (10) for durable, non-durable, and expenditures on food in the 2007-2017 period for two subsamples: households with kids and households with two or more kids. In parallel with the previous estimation of the wealth shock response, these correspond to using two control groups: a mixed control group (ineligible households with both only one child and several children), and control group 2 (ineligible households with two or more kids) respectively. As evident from the table, households tend to behave as consumption smoothers, in line with theoretical predictions. Specifically, in 2009 the assistance allowed eligible households to have significantly higher expenditures on durable goods than other households (note a drastic dip of average expenditures on durable goods in 2009: Figure 11 in the Appendix). Despite the fact that we do not find smoothing behaviour for the aggregate non-durable category, it appears that in 2015 eligible households spent more specifically on food as compared to non-eligible households. The null result for 2010 for all categories could arise from the fact that households rushed to withdraw cash as soon as the temporary liquification period from January 2009 until March 2011 was announced.

5.3 Housing wealth and liquidity constraints

Finally, we investigate whether and how being eligible for the assistance translates into housing wealth. As a first approximation, from column (1) of Table 19 it is evident that eligible households have higher housing value than other households, but this can be explained by the number of eligible households increasing with time.

Table 19: Housing wealth in the post-reform period

	(1)	(2)	(3)	(4)
	b/se	b/se	b/se	b/se
elig	0.35**			
	(0.15)			
2^{+}kids		0.08	0.05	
		(0.16)	(0.15)	
post2007		0.36**		
		(0.15)		
2^{+}kids × post2007		0.22		
		(0.17)		
post2010			0.36**	0.40***
			(0.15)	(0.15)
2^{+}kids × post2010			0.27*	
			(0.16)	
age3^{+}				-0.08
				(0.15)
age3^{+} × post2010				0.46***
				(0.15)
income	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
HH demographic composition	Yes	Yes	Yes	Yes
HH head's characteristics	Yes	Yes	Yes	Yes
regional macro	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes
constant	-4.02***	-4.06***	-4.06***	-3.96***
	(0.27)	(0.24)	(0.24)	(0.24)
Obs	52620	50622	50622	53147
Nclust	12334	12220	12220	12441

To make columns (2) and (3) more comparable, non-eligible households with two and more kids in post-2007 period are excluded from the sample. Significance levels * p<0.1, ** p<0.05, *** p<0.01

Therefore, as a second approximation, a difference-in-difference equation 11 is estimated on the sample covering the time span from 2001 to 2017:

$$H_{it} = \alpha + \beta_1 2^{+}kids + \beta_2 post\_reform + \beta_3 2^{+}kids \times post\_reform + \gamma X_{it} + \delta_t + \epsilon_{it} \quad (11)$$

Here H_{it} is self-reported housing wealth in 100.000 rubles in real terms, $2^{+}kids$ is an indicator equal to 1 if there are two or more children in the household, $post_reform$ is a variable equal to 1 if an observation belongs to the post-reform period, $2^{+}kids \times post\_reform$ is their interaction, and X_{it} is the usual set of controls. Column (2) reports the results of estimating equation 11 with the original post-reform cut-off (2007). We see, however, that the coefficient of the interaction term is positive but not statistically significant. This may already suggest that translation of eligibility to housing wealth does not happen immediately. We then run the same equation setting the post-reform cut-off at 2010: this is the year when the first eligibles could get the full access to the assistance (eligibility-granting child born in 2007 would reach three years of age in 2010). In this specification the coefficient is positive and significant at the 10% level. Although this indicates that housing wealth of households with two and more kids improved in the post-reform period, it appears that households prefer to wait until the assistance can be used to purchase their own housing without taking a loan.

To test this hypothesis the following equation is estimated:

$$H_{it} \quad = \quad \alpha + \beta_1 age3^+ + \beta_2 post2010 + \beta_3 age3^+ \times post2010 + \gamma X_{it} + \delta_t + \epsilon_{it} \tag{12}$$

where $age3^+$ is a dummy variable equal to 1 if a household has two or more kids with the second or higher order child of three years of age or older, $post2010$ is a variable equal to 1 if an observation belongs to the post-2010 period, and $age3^+ \times post2010$ is the interaction of the two. As appears from column (4) of Table 19, there is a positive and statistically significant relation with eligibility-granting child being three years of age or older and housing wealth.

Table 20: Change in housing wealth depending on the age of the eligibility-granting child

	(-2) b/se	(-1) b/se	(0) b/se	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se
ΔAge_Elig	-0.06	0.10	0.15	-0.17	0.06	0.30*	-0.17	-0.11	-0.10
	(0.13)	(0.12)	(0.12)	(0.14)	(0.11)	(0.16)	(0.13)	(0.15)	(0.13)
D.income	0.00**	0.00**	0.00**	0.00**	0.00**	0.00**	0.00**	0.00**	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HH demographic composition	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH head's characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
regional macro	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
constant	0.72**	0.73**	0.72**	0.73**	0.72**	0.72**	0.72**	0.72**	0.72**
	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)	(0.29)
Obs	4635	4635	4635	4635	4635	4635	4635	4635	4635
Nclust	1111	1111	1111	1111	1111	1111	1111	1111	1111

Estimating equation 13 on the sample of ever-eligible households. The dependent variable is the yearly change in housing wealth, while every column differs with respect to how ΔAge_Elig is specified: in column (-2) the variable ΔAge_Elig is equal to 1 if a household will become eligible in 2 years and 0 otherwise; in column (0) ΔAge_Elig is equal to 1 if a newborn is present (eligibility-granting child aged 0); in column (3) ΔAge_Elig is equal to 1 if eligibility-granting child is three years old, and so on. Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Next, we investigate whether eligible households have a preference for the timing of converting their eligibility status into housing wealth by estimating an equation of the form:

$$\Delta H_{it} \quad = \quad \alpha + \beta_0 \Delta Age\_Elig_{it} + \gamma \Delta X_{it} + \delta_t + \epsilon_{it}, \tag{13}$$

where $\Delta Age\_Elig_{it} = \mathbb{I}\{\text{age of eligibility-granting child}_{it} = j\}$, $j = (-2; 6)$. Therefore, a separate regression is run for each value of j from -2 (two years before the eligibility-granting child was born) to 6 (eligibility-granting child turned six years old). Table 20 contains estimation results: for most of the cases the coefficient of ΔAge_Elig is insignificant, however, as emerges from column (3), there is a positive though marginally significant change in housing wealth when the child turns exactly three years of age. This may suggest not only that the majority of eligible households prefer to buy their own housing avoiding taking loans, but also that they are prone to do so as soon as possible.

Finally, we test whether policy changes that occured in 2009, 2010 and 2015 (allowing using funds immediately to pay out housing loans, allowing using funds not only for purchasing and mortgage repayment, but also for construction of new housing, and allowing immediate use of funds as a first installment of housing loans) had a significant impact on housing wealth. Such modifications could have loosen the liquidity constraints for households with low levels of wealth, stimulating them to improve their housing conditions right after becoming eligible instead of waiting three years. To see whether this is the case, the following specification was estimated:

$$\begin{aligned} \Delta H_{it} = \alpha + \beta_0 \Delta Elig_{it} + \beta_1 \Delta Elig_{it} \times post2009 + \beta_2 \Delta Elig_{it} \times post2010 \\ + \beta_3 \Delta Elig_{it} \times post2015 + \gamma \Delta X_{it} + \delta_t + \epsilon_{it} \end{aligned} \tag{14}$$

Table 21: Changes in housing wealth and liquidity constraints

	full sample b/se	ever-eligible HHs b/se
D.elig	0.46	0.48
	(0.28)	(0.31)
elig09	-0.56	-0.41
	(0.77)	(0.79)
elig10	0.11	-0.13
	(0.72)	(0.75)
elig15	0.21	0.31
	(0.24)	(0.25)
D.income	0.00***	0.00**
	(0.00)	(0.00)
HH demographic composition	Yes	Yes
HH head's characteristics	Yes	Yes
regional macro	Yes	Yes
year FE	Yes	Yes
constant	0.47***	0.72**
	(0.08)	(0.29)
Obs	34238	4635
Nclust	8400	1111

Significance levels: * p<0.1, ** p<0.05, *** p<0.01

Here $\Delta Elig_{it} \times post2009$ is a term that equals 1 if a household's eligibility status has changed in 2009 or later, $\Delta Elig_{it} \times post2010$ equals 1 if eligibility status has changed in 2010 or later, etc. As appears from Table 21, a change of eligibility status is not immediately followed by an increase in housing value, independently from the time when this change took place. Therefore, in the time-span under scrutiny, the households on average were reluctant to opt for an immediate use of funds via mortgages.

The main conclusion that follows from this set of exercises is that housing wealth typically increases when the eligibility granting child reaches three years of age, and not earlier. This is evidence of liquidity constraints present, which force the households to wait until they can access the funds to purchase their own house without taking a mortgage. We suppose that these constraints are self-imposed: households can borrow, but are reluctant to do so because of fear of indebtedness, high levels of uncertainty about future incomes and low level of trust for financial institutions.

6 Conclusions

This paper aims to study the relationship between positive wealth shocks and consumption expenditures of the Russian households by exploiting a peculiar pro-natalist policy launched in 2007, which granted mothers of the second and higher order child born after the 1st of January 2007 with a non-cash deposit (maternity capital) worth about $10.000. While the vast majority of the wealth shock literature exploits macroeconomic fluctuations of asset prices to study the relationship between financial and housing wealth and current consumption, our approach is substantially different as the wealth shock under consideration is of microeconomic nature. We argue that although becoming eligible for the assistance is endogenous in a sense that it results from a household's choice to have one more child, and hence is also anticipated by the households, specific institutional characteristics of the Russian environment, such as low levels of trust in financial and government institutions, create both actual and self-imposed liquidity constraints and also mitigate anticipation to a certain extent. Another difficulty that was encountered stemmed from the fact that introduction of maternity capital assistance was not the only reform that came to action in 2007: changes in child benefits with differences by birth order created a confounding factor which is non-negligible for our main variables of interest. To overcome this issue, the analysis of consumption expenditures response was conducted using data from the post-reform period only. In addition to the wealth shock response, the paper studies whether households exhibit smoothing behaviour and consume from wealth in the periods of economic downturns, and whether and when they tend to execute their right for the grant by converting it into housing value.

Our study yielded several findings. First, while on average we do not find an increase in non-durable consumption expenditures as a response to the positive wealth shock, there is evidence of such a response for households with particularly low levels of wealth and, as a consequence, high levels of liquidity constraints (tenants). This may result from the fact that becoming eligible for the assistance is more valuable for these households than for those who own their own property: the possibility to improve housing conditions may have even been a driver of self-selection into the program. Next, we observe that eligible households took the temporary opportunity to withdraw certain amounts of cash to smooth consumption of food and durable goods, in particular in the periods of economic downturns of 2009 and 2015. Finally, we find evidence of liquidity constraints playing a role in the housing market. The major increases in housing value are observed after the eligibility-granting child reaches three years of age, when the assistance becomes available to purchase housing without taking a loan. Despite the fact that policy changes of 2009 and 2015 were aimed to broaden the possibilities to spend the funds, allowing to use them also to pay out housing loans without waiting until the eligibility-granting child reaches three years of age, and to use them as the first installment for the housing loans respectively, it did not have a significant impact on housing wealth: households which became eligible in 2009 and later still do not improve their housing conditions in the same year they became eligible. While the measures were meant to stimulate households to resort to mortgages, the majority of households still prefer to wait until the assistance can be used for purchasing housing without taking a loan. Given that the banks are willing to issue a line of credit specifically on the maternity capital assistance, we see these liquidity constraints as self-imposed.

Regarding the direction of future research, a question worth investigating is the impact of the policy on inequality. Wealth inequality in particular is a concern for contemporary Russia: in 2015, the top 1% of the wealthiest possesed 43% of wealth (Alvaredo et al., 2018). Concerning housing wealth, with the data at hand we find that housing wealth inequality has decreased in the post-2007 period for all groups of households, and more so for households with two or more children (see subsection A.4 in the Appendix). While the reform contributed to achieving a more equal distribution of housing wealth, its prospective impacts on other dimensions of inequality are unclear. Specifically, it is possible that the reform will fuel the increase of human capital and income inequality. Given that households with low levels of wealth are often also ones with low levels of income, their choice to convert all the assistance into housing will not allow them to invest it in children's education. Meanwhile, eligible households who do not have a need to improve housing conditions are free to spend the grant on education. This may result in the future increase of income inequality, which has already been on rise: the Gini Index increased from 0.27 in 1985 to 0.45 in 2015 (Novokmet et al., 2018). However, the assessment of the reform's impact on various dimensions of inequality requires obtaining data on labour market outcomes of children whose parents invested the assistance in their higher education.

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Appendix

A.1 Dynamics of real expenditures, income and housing value

Figure 10: Dynamics of non-durable goods expenditures (real values)

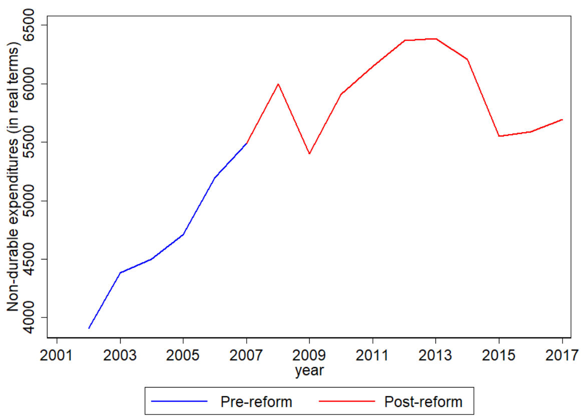


Figure 11: Dynamics of durable goods expenditures (real values)

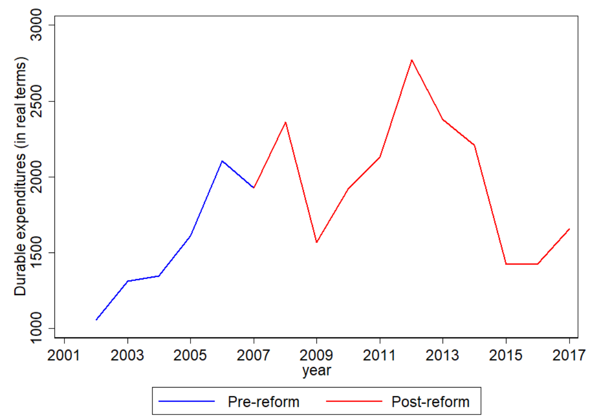


Figure 12: Dynamics of medical expenditures (real values)

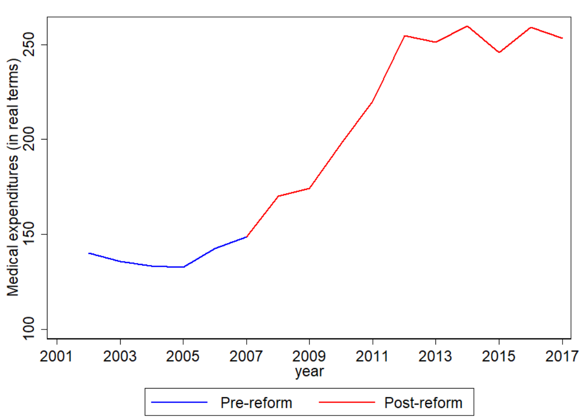


Figure 13: Dynamics of travelling and entertainment expenditures (real values)

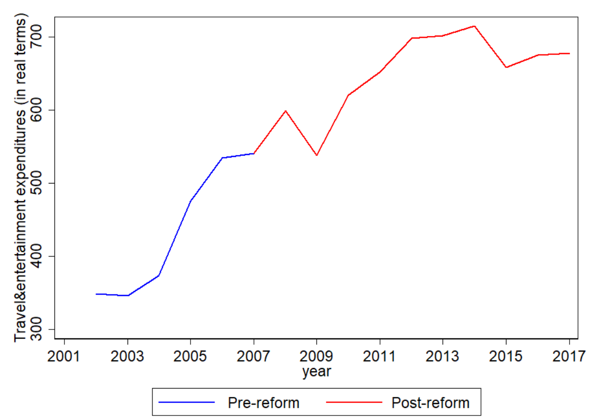


Figure 14: Dynamics of real housing wealth

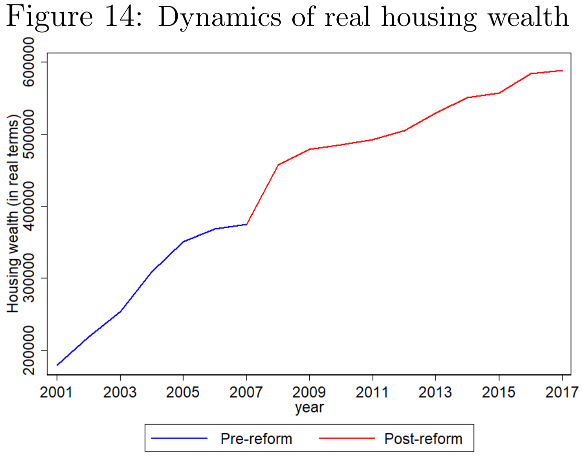
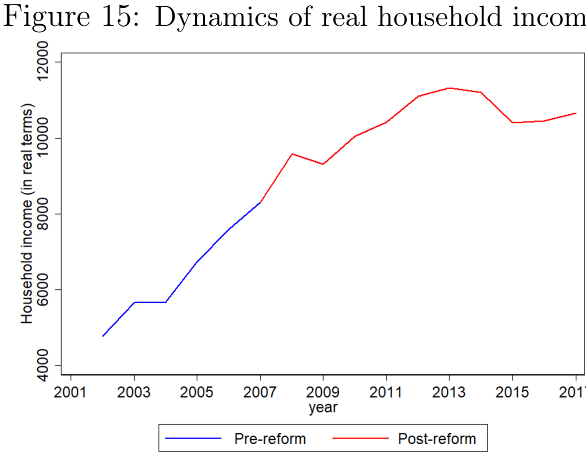


Figure 15: Dynamics of real household income



A.2 Pro-natalist reforms of 2007 and consumption expenditures

In this section we perform a difference-in-difference estimation to evaluate how the whole package of pro-natalist reforms which came to action in 2007 has affected consumption expenditures of households with two and more children - the group that benefited most from the policy. The following equation

$$C_{it}^k = \alpha^k + \beta_1^k 2^+ kids + \beta_2^k post2007 + \beta_3^k 2^+ kids \times post2007 + \gamma^k X_{it} + \delta_t^k + \epsilon_{it}^k$$

is estimated on the full sample (all households) and on a subsample comprising only households with children. As appears from Table 22, households with two and more kids indeed spend more than in the pre-reform period, in particular on nondurable and durable goods categories. This holds for both control groups used. While the reform as a whole had a positive impact on

Table 22: Consumption expenditures in the post-reform period

	Full sample				Households with children			
	nondur	durables	trav_ent	medical	nondur	durables	trav_ent	medical
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
2^+kids	-1888.01***	-547.50***	-54.30*	-20.45**	-792.13***	-282.16	117.85***	-9.37
	(154.36)	(155.10)	(28.29)	(10.16)	(183.28)	(179.59)	(31.51)	(12.19)
post2007	-340.40***	-92.22	-38.14**	36.86***	110.85	-238.48	-55.18	29.87*
	(88.91)	(81.23)	(15.26)	(8.89)	(211.89)	(193.04)	(34.57)	(15.86)
2^+kids ×	1048.74***	419.97**	39.51	-6.24	565.21***	605.75***	-53.61	-0.71
post2007	(164.10)	(164.93)	(30.54)	(10.67)	(178.03)	(187.36)	(32.83)	(11.87)
income	0.28***	0.17***	0.04***	0.01***	0.29***	0.19***	0.05***	0.01***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
HH demographic composition	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH head's characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
regional macro	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
constant	723.44***	442.72***	207.57***	-15.16	1788.16***	1336.51***	385.89***	-32.15
	(140.84)	(129.29)	(23.77)	(12.39)	(379.20)	(336.95)	(59.24)	(25.88)
Obs	62477	73400	73819	73455	21717	25012	25293	25378
Nclust	13672	14428	14445	14466	6176	6594	6617	6628

Significance levels: * p<0.1, ** p<0.05, *** p<0.01

consumtion expenditures, the channels of influence are multiple: higher nondurable expenditure is likely to be a result on the larger amount of cash benefits in the post-reform period, whereas larger expenditures on durable goods can be driven by both child benefits increase and higher propensity of (eligible) households to improve their housing conditions, which is accompanied by purchasing various durable items.

A.3 Indebtedness and response to future wealth changes

Here we check whether eligible households are more likely to be burdened by higher indebtedness, which may be affecting their current consumption expenditures, estimating the following equation:

$$Loan_{it} \quad = \quad \alpha + \beta \Delta Elig_{it} + \gamma \Delta X_{it} + \delta_t + \epsilon_{it}$$

on the same sample and control groups described in Section 4. Two dependent variables are used: a 0-1 indicator of whether a household has taken a loan in the 12 months prior to the interview, and a similar indicator of having taking a loan in 3 months prior to the interview. As follows from Table 23, for none of the control groups used there is any difference between eligible and non-eligible households along this dimension.

Next we investigate whether eligible households react to a future change in wealth: this

Table 23: Loans

	Control group 1		Control group 2		Control group 3	
	P_{loan}12m	P_{loan}3m	P_{loan}12m	P_{loan}3m	P_{loan}12m	P_{loan}3m
	b/se	b/se	b/se	b/se	b/se	b/se
elig	0.05	-0.02	-0.03	0.00	0.01	0.01
	(0.04)	(0.02)	(0.08)	(0.03)	(0.07)	(0.03)
D.kids2					0.03	-0.03
					(0.07)	(0.03)
D.income	0.00	0.00	-0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
constant	0.26**	0.13*	0.25	0.24**	0.26**	0.13*
	(0.13)	(0.07)	(0.17)	(0.11)	(0.12)	(0.07)
HH demographic composition	Yes	Yes	Yes	Yes	Yes	Yes
HH head's characteristics	Yes	Yes	Yes	Yes	Yes	Yes
regional macro	Yes	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	779	779	433	433	835	835
Nclust	729	729	431	431	781	781

Significance levels: * p<0.1, ** p<0.05, *** p<0.01

implies that the response in terms of consumption expenditures occurs prior to the arrival of the newborn, at the time of conception or sooner. To check if this is the case, the following equations are estimated:

$$\Delta C^k_{it} \quad = \quad \alpha^k + \beta^k Elig_{it+1} + \gamma^k \Delta X_{it} + \delta^k_t + \epsilon^k_{it}$$

$$\Delta C^k_{it} \quad = \quad \alpha^k + \beta^k Elig_{it+2} + \gamma^k \Delta X_{it} + \delta^k_t + \epsilon^k_{it}$$

on the same samples as the baseline equation for all the consumption categories considered. According to results presented in Table 24, there is no evidence of an increase of consumption expenditures by households who are expecting to become eligible in the next one or two years.

Table 24: Consumption expenditures in pre-eligibility periods

	D.nondur	D.durables	D.trav_ent	D.medical	D.nondur	D.durables	D.trav_ent	D.medical
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
				Control group 1				
elig_{t+1}	-390.49	-1129.14*	12.31	-18.41				
	(406.38)	(660.20)	(66.09)	(35.17)				
elig_{t+2}					422.05	1167.13	-4.77	-8.93
					(477.30)	(834.72)	(74.33)	(37.45)
Obs	475	554	574	584	352	415	435	439
Nclust	449	526	542	553	341	403	421	424
				Control group 2				
elig_{t+1}	284.55	-343.87	124.15	87.06				
	(982.55)	(1552.40)	(147.97)	(76.45)				
elig_{t+2}					1069.03	953.45	-248.85**	113.66
					(993.54)	(1126.32)	(120.82)	(103.82)
Obs	282	330	349	351	227	271	293	291
Nclust	281	329	348	350	226	270	292	290
				Control group 3				
elig_{t+1}	160.48	-1230.86	-39.84	108.37				
	(880.13)	(1380.06)	(156.78)	(76.42)				
$\text{D.2}^{+}\text{kids}_{t+1}$	-573.25	155.14	76.63	-127.47				
	(850.69)	(1335.39)	(158.47)	(77.89)				
elig_{t+2}					715.34	70.89	-108.07	47.96
					(952.96)	(1033.29)	(138.67)	(95.87)
$\text{D.2}^{+}\text{kids}_{t+2}$					-164.08	972.01	63.55	-53.12
					(918.28)	(979.05)	(143.71)	(93.55)
Obs	504	592	611	620	379	449	472	475
Nclust	477	561	576	587	366	436	456	458

All regressions include household income in real terms, the set of household demographic composition variables, household head characteristics, regional marcoeconomic variables and year fixed effects. Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$

A.4 Housing wealth inequality

In this section we present preliminary evidence of the changes in housing wealth inequality that could be attributed to the policy effects. Since the vast majority of eligible households that execute their right for assistance choose to improve housing conditions, it could have affected the distribution of housing wealth. Figures 16 and 17 depict Lorenz curves for housing wealth distribution for two groups of households: with two or more children and with the only child or no kids. As follows from the visual inspection, the distribution of housing wealth among families with two or more kids is more unequal that among the rest of the households, but the gap decreased in the post-reform period. Furthermore, figures 18 and 19 provide evidence that housing wealth distribution became less unequal with time for both subsamples. However, already from these graphs it is apparent that the decrease in inequality in the post-reform period was larger for households with two and more kids than for the rest.

Figure 16: Pre-reform Lorenz curves

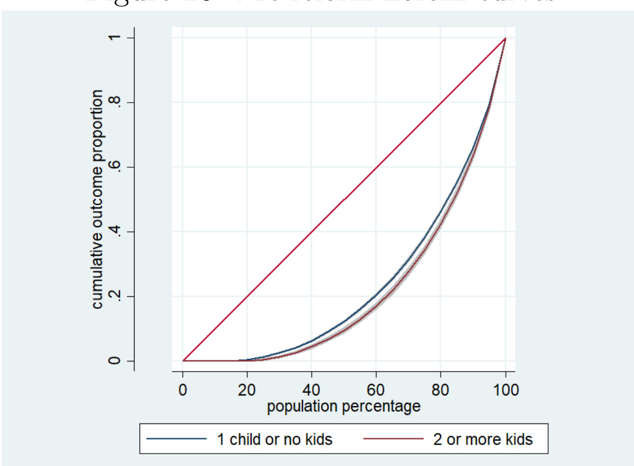


Figure 17: Post-reform Lorenz curves

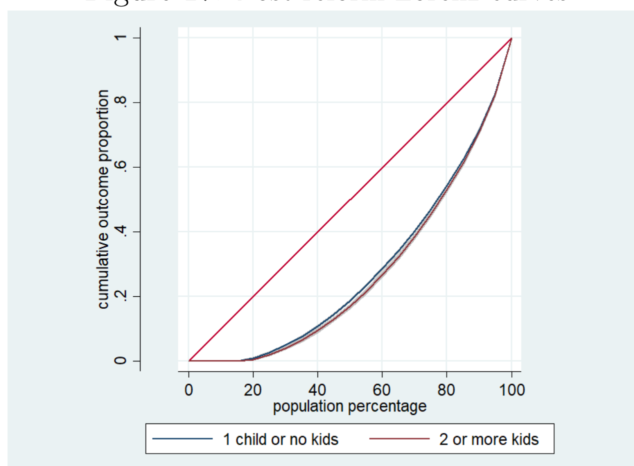


Figure 18: Pre- and post-reform Lorenz curves (1 child or no kids)

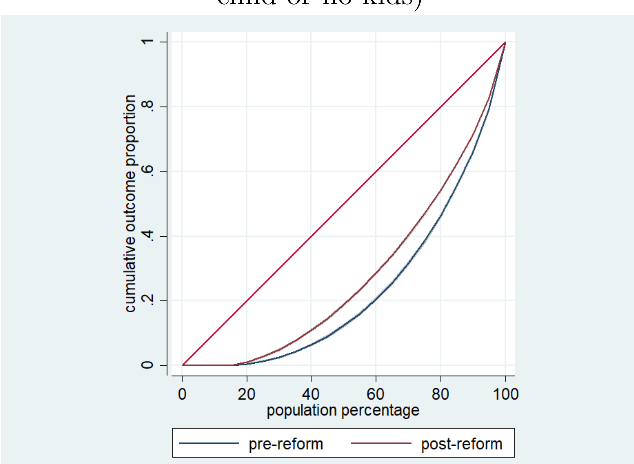
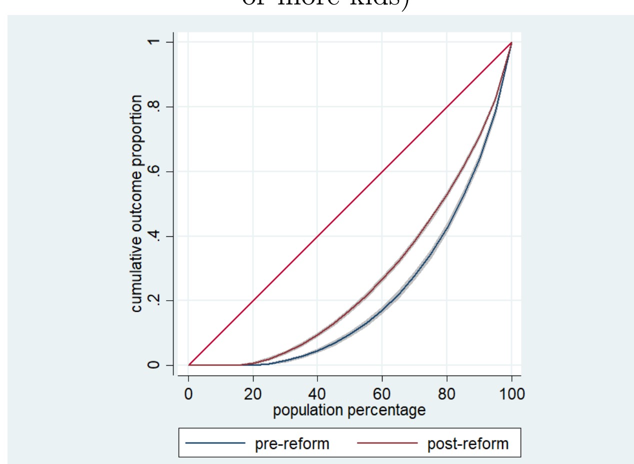
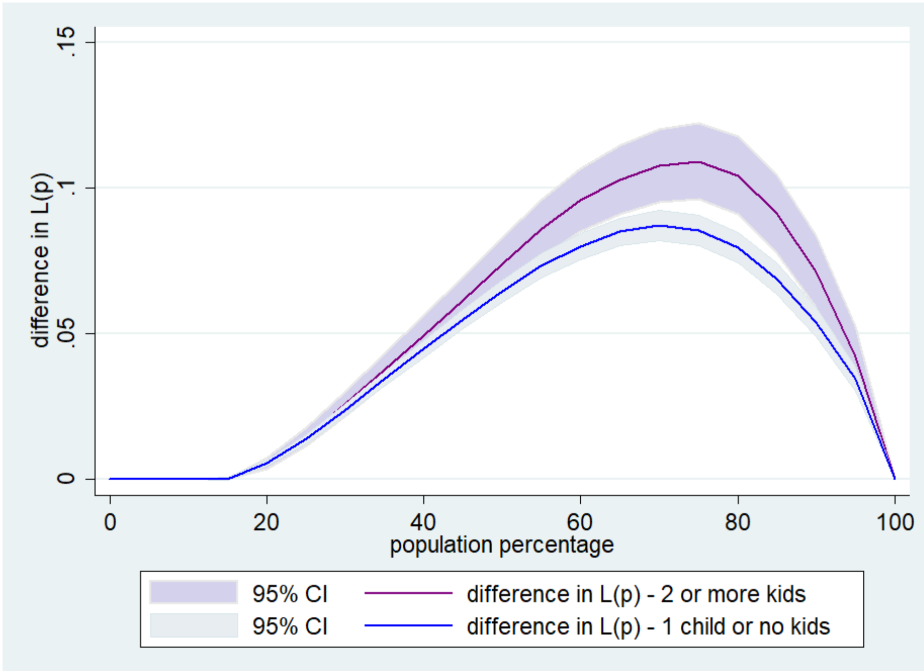


Figure 19: Pre- and post-reform Lorenz curves (2 or more kids)



This is further confirmed in Figure 20, which plots the differences (post-reform − pre-reform) between Lorenz curve ordinates from figures 18 and 19. Virtually for each value of the population percentage the difference in L(p) is larger for households with two and more kids than the rest. This allows to conclude that the policy has contributed to reducing inequality in the distribution of housing wealth.

Figure 20: Lorenz dominance for the two subsamples



Problem Drinking and Depression
State Dependence, Unobserved Heterogeneity and Dynamic Cross-Effects

Anastasia Arabadzhyan*

Abstract

The tight link between alcohol abuse and depression has been an object of interest for medical and social scientists for a very long time. Although problem drinking and depressed state are highly correlated, establishing causality between these variables is not a trivial task. The aim of this study is to uncover causal links between alcohol abuse and depression by estimating a structural model and separately identifying the contributions of state dependence and unobserved heterogeneity. Using individual-level data from the Russian Longitudinal Monitoring Survey (RLMS) for the years 2011-2016, we jointly model depression and problem drinking and estimate a bivariate dynamic correlated random effects probit model via Maximum Simulated Likelihood, allowing for correlation of both time-invariant and stochastic components of the error terms. The results suggest that unobserved individual heterogeneity is not only an important determinant of both variables of interest but is also correlated among them, which implies that individuals with high intrinsic proneness to depression are more prone to problem drinking. Additionally, we find that causal links between the two variables are bidirectional, but the impact of problem drinking on depression is stronger and larger in magnitude than that of depression on alcohol abuse, especially for males. However, male problem drinkers turn out be insensitive to price changes, which urges for alternative policies to be developed to tackle male alcohol abuse and explains very moderate impacts of doubling alcohol price on the prevalence of depression through decreasing the share of problem drinkers in the population. The effect of such a price increase on both alcohol abuse and depression amounts to about 6-6.7% decrease in disability-adjusted lifeyears in three year time, which corresponds to 65.000 disability-adjusted lifeyears per year on the country level.

JEL classification: I18, C35, C54.
Keywords: alcohol abuse, depression, public policy, unobserved heterogeneity, maximum simulated likelihood, bivariate probit model.

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1 Introduction and motivation

The tight link between substance use and mental health has been an object of interest for medical and social scientists for a very long time. Consumption of alcohol, tobacco and other substances does not only exhibit high level of comorbidity with mental disorders, but can lead to addiction to the substance, so that the patient would be diagnosed with dependence, which is classified as a mental disorder per se. The discussion on the causal links between substance use and mental health gave rise to two main streams of thought. According to the self-medication hypothesis (SMH), psychological distress is a crucial determinant in using, becoming dependent upon, and relapsing to addictive substances (Khantzian, 1997). The opponents of SMH claim that while this channel is not irrelevant, investigating the reverse causal link deserves the same, if not more, attention, since substance misuse often preceeds further deterioration of mental state. As pointed out by Frances (1997), an alternative explanation would be that individuals with intrinsically high proneness to mental disorders such as anxiety, depression and psychosis also have high level of predisposition to substance abuse.

As it becomes evident from the broad literature, mental health plays a huge role in determining individuals' educational choices (Cornaglia et al., 2015), labour market outcomes (Chatterji et al., 2011, Fletcher, 2013, Johar and Truong, 2014), and other variables. Substance use is also one of those variables of interest. However, most of the studies that investigate the link between substance use and mental health cannot claim to identify the causal link between the two phenomena. A notable exception is the work of Mentzakis et al. (2016). Having at disposal a cross-sectional sample of individuals from former-Soviet Union countries, the authors use alcohol-related advertising as an instrument for excessive alcohol consumption, which allows them to document a significant impact of drinking on mental health; applying an OLS without instrumenting for problem drinking leads to an underestimation of the effect.

Mental health problems have been aknowleged as one of the most pressing public health issues in developed countries, with the use of antidepressants rocketing in the richer part of the world in the past decade[1]. The prevalence of mental disorders is on rise in developing countries as well. In fact, possibly due to the lack of an adequate timely treatment, societal losses from mental illness, and in particular, depressive disorders, are highest in developing and transition countries. Table 25 provides a ranking of top-10 countries by the years lost to disability or death due to selected causes that are the focus of this study: depressive disorders and alcohol use disorders.

While among the countries with highest depression burden we do find Australia, the US, and Portugal, the majority of the list consists of developing countries. A similar picture appears for alcohol-induced disorders. Two other observations emerge from this evidence. Firstly, 50% of the top-10 countries most burdened by depression are also among the top-10 suffering from alcohol use disorders. This is another indication of the tight interconnection between depression and alcohol abuse. Secondly, all these countries that enter both rankings are post-Soviet states. Given their institutional and cultural backgrounds similarity, an investigation of causal links between alcohol abuse and depression using the data from one of these countries may be valuable from the point of view of the others' policy-makers as well.

The aim of this paper is multifold. Broadly speaking, our focus is the interconnection between

[1]See OECD (2017), p.191.

Table 25: Top-10 countries by disability-adjusted life years (DALY) for depressive and alcohol-induced disorders, per 1000 inhabitants.

	Depressive disorders			Alcohol-induced	
1	Ukraine	11.07	1	Russia	12.63
2	Brazil	10.46	2	Estonia	10.31
3	Estonia	10.31	3	El Salvador	9.29
4	Australia	9.83	4	Belarus	8.10
5	Lithuania	9.70	5	Latvia	7.81
6	Belarus	9.51	6	Lithuania	7.54
7	Cuba	9.51	7	Moldova	6.76
8	US	9.50	8	Finland	6.46
9	Russia	9.42	9	Ukraine	5.98
10	Portugal	9.39	10	Mongolia	5.68

Source: WHO (2015). DALY is a measure of overall disease burden, expressed as the number of years lost due to ill-health, disability or early death.

alcohol abuse[2] and one of the dimensions of mental health - depression. First, we wish to study the formation of depressed state and the choice to abuse alcohol in a non-linear framework, disentangling state dependence from unobserved individual heterogeneity. This is already a challenging task with specific data and methodological requirements. However, it can be insightful from the policy-makers' point of view: whether a certain state or choice is largely determined by its past value or by individuals' intrinsic heterogeneous characteristics determines the potential of policies to impact future states or choices by affecting them today. Our second goal is to establish causal links between depressed state and alcohol abuse. Finally, we conduct a policy simulation exercise to quantify the potential effects of an increase in alcohol prices.

The remaining of the paper is organised as follows. Section 2 locates our study in the existing literature and highlights main contributions, Section 3 describes theoretical and empirical frameworks that we build our analysis on. Section 4 introduces the data and discusses the problem drinking indicators used in the analysis, the results of which are presented in Section 5, followed by robustness analysis and application of a different methodology in sections 6 and 7. The policy simulation exercise is conducted in Section 8, and Section 9 concludes the paper.

2 Related literature and contribution

Both alcohol abuse and depression are of interest for economists due to their impacts on a wide range of relevant socio-economic outcomes. Alcohol abuse may affect individuals' performance in the labour market (Böckerman et al., 2017), income (Jayathilaka et al., 2016), lead to family dissolution (Ostermann et al., 2005) and unequal gender distribution of household resources (Menon et al., 2018); parental drinking may affect childrens' educational attainment (Mangiavacchi and Piccoli, 2018), decrease parents' time spent doing child care (Giannelli et al., 2013), and so on. Similarly, depression can have negative impacts with respect to labour market outcomes (Peng et al., 2016), engagement into criminal activities (D. M. Anderson et al., 2015), and parental depression affects childrens' health (Dahlen, 2016).

[2]Throughout the paper the terms "alcohol abuse" and "problem drinking" will be used as synonyms.

The issue of separating the inputs of true state dependence and individual heterogeneity has also received much attention from the scholars; in health economics, one of the first applications can be found in a series of papers by Contoyannis, Jones, and Rice (2004b), Contoyannis and Jones (2004), Contoyannis, Jones, and Rice (2004a). With respect to mental health and substance use existing studies tend to focus on either of the issues. For example, Christelis and Sanz-de-Galdeano (2011) jointly model the decision to smoke and the intensity of smoking, using panel data for ten European countries. They find that even after accounting for unobserved heterogeneity, smoking habits tend to be very persistent, however, some cross-country differences in the strength of persistence exist. Gilleskie and Strumpf (2005) study a similar question but focusing on US adolescents and also incorporate prices into the analysis. According to their findings, price increases can influence future behaviour by reducing the current number of smokers. With respect to alcohol consumption, Browning and Collado (2007) use household-level data to estimate demand systems and account for both state dependence and unobserved heterogeneity and provide evidence of alcohol being a habit-forming good. Among the studies that use individual-level data, Deza (2015) investigates the stepping-stone effects between alcohol, marijuana and hard drugs use among US youth and finds that these effects are indeed present, and state dependence and unobserved heterogeneity are important determinants of drugs and alcohol consumption patterns. A study very closely related to ours would be that of Fergusson et al. (2009), where the authors study causal links between alcohol abuse and dependence and major depressive disorder amoung young New Zealanders via a structural model and conclude that the causal link goes from alcohol to depression, and not vice versa.

Concerning related literature on depression, Contoyannis and Li (2017) use a depression index as an outcome variable and study persistence of adolescent depression in a quantile fixed effects framework. They find that the main driver of youth depression in US is unobserved heterogeneity, while true state dependence is relatively low. In contrast, Roy and Schurer (2013) find evidence of substantial persistence in depression, although in a different setting (Australian general population) and applying the system GMM methodology. While some studies attempt to model health outcomes and substance use simultaneously, they do not account for either state dependence (Yen et al., 2010), or unobserved heterogeneity (Blaylock and Blisard, 1992).

Our work contributes to the current literature by modelling alcohol abuse and depression jointly, allowing for several ways that these variables may be interconnected. This enables us not only to separate true state dependence and individual heterogeneity but also to uncover bidirectional causal links between alcohol abuse and depression, which are overlooked by existing literature (this distinguishes our approach from that of Mentzakis et al. (2016), who resort to a reduced form model, and so are only able to capture the immediate impact of problem drinking on mental health, but not the reverse). Differently from Fergusson et al. (2009), who develop a structural model in a linear framework, we work within a non-linear world given that the depression indicator available in the data is binary: Fergusson et al. (2009) employ a small sample of young New Zealanders below age 25 with very detailed measures of alcohol-induced disorder and major depression, whereas our study is based on the general population survey with very limited options for the depression variable. Additionally, we aim to provide estimates of direct and indirect effects of a policy intervention that increases alcohol prices: the direct effect would imply problem drinking decreasing in response to price, whereas the indirect effect would quantify a decrease in the prevalence of depressed state among population achieved through reduction of alcohol abuse. To reach these goals, we propose a dynamic bivariate probit model with correlated time-invariant and time-variant idiosyncratic components, therefore jointly modelling alcohol abuse and formation of depressed state. Our methodology and general setting are similar to those of Humphreys et al. (2014), who study the impact of physical exercise on health outcomes, Haan and Myck (2009), who model the mutual links between non-employment and self-reported health, Hajivassiliou and Ioannides (2007), who investigate the interaction between liquidity constraints and the mode of employment of the household head, and Hajivassiliou and Savignac (2016), where the methodology is applied to study the impact of financial constraints on firms' decisions to invest in R&D.

3 Methodology

3.1 Theoretical background and empirical specification

Alcohol abuse is described via the Additive Random Utility Model (ARUM) framework. Suppose that at each period of time t an individual maximizes his per-period utility choosing whether to abuse alcohol or not. Let U_t^* denote the utility that an individual obtains **from abusing alcohol** at each period t:

$$U_t^* = \underbrace{h(A_{t-1}, D_{t-1}, Z_t, \eta^a)}_{V_t \text{ - deterministic part of utility}} + \underbrace{\xi_t}_{\text{random component of utility}},$$

Overall utility can be decomposed into two parts: the deterministic component V_t and a transitory component ξ_t. The deterministic component is a function of several variables: A_{t-1} - alcohol abuse choice in the previous period, D_{t-1} - the depressed state in the previous period, Z_t - demographic and socio-economic characteristics, and η^a - the unobserved time-invariant heterogeneity component.

Analogously, utility that the individual obtains from **not** abusing alcohol at each period t is:

$$\bar{U}_t^* = \bar{V}_t + \bar{\xi}_t.$$

While U_t^* and $\bar{U}_t^*$ are not observed directly, the final choice of the individual is observed and takes the form:

$$A_t = \begin{cases} 1, & \text{if } U_t^* > \bar{U}_t^* \\ 0, & \text{otherwise} \end{cases}$$

Following the literature, we make a normalization assumption and set the deterministic part $\bar{V}_t$ to 0. In this formulation, V_t represents the difference between the mean utility of abusing alcohol versus not abusing in period t.

For each individual i this yields an empirical model of the form:

$$\begin{aligned} U_{it}^* &= \underbrace{\gamma^a A_{it-1} + \delta^a D_{it-1} + Z_{it}\beta^a + \eta_i^a}_{V_{it}} + \underbrace{\xi_{it}^a}_{\xi_{it} - \bar{\xi}_{it}} \\ A_{it} &= \mathbb{I}\{U_{it}^* > 0\} \end{aligned}$$

with $\mathbb{I}\{.\}$ denoting an indicator function. We then postulate that the persons' depression production function at each period is shaped in the following fashion:

$$D_t^* = f(A_{t-1}, D_{t-1}, X_t, \eta^d) + \xi_t^d,$$

where, similarly to the utility function described above, A_{t-1} and D_{t-1} are lagged values of alcohol abuse choice and the *observed* depressed state, X_{it} are relevant demographic and socio-economic characteristics (which in principle may differ from those entering the utility function), η^d - time-invariant individual-specific factors, ξ_t^d - stochastic component. The observed depression state may take values 0 (not depressed) or 1 (depressed) defined as

$$D_t = \begin{cases} 1, & \text{if } D_t^* > 0 \\ 0, & \text{otherwise} \end{cases}$$

In terms of underlying latent regression we obtain:

$$\begin{aligned} D_{it}^* &= \gamma^d D_{it-1} + \delta^d A_{it-1} + X_{it}\beta^d + \eta_i^d + \xi_{it}^d, \\ D_{it} &= \mathbb{I}[D_{it}^* > 0] \end{aligned}$$

Under this formulation we allow both variables to affect each other: depression state in the previous period contributes to the individual's choice whether to abuse alcohol or not in the following period, and this choice contributes to his next depression state, which, in turn, affects the subsequent choice, and so on[3]. Our final target is estimating the parameters of the stochastic structures determining two discrete endogenous variables, disentangling true state dependence from unobserved heterogeneity. To do this the variables of interest are allowed to depend on their lagged value. In the case of alcohol abuse, the lagged value captures the addictiveness of alcohol, or the strength of the habit, whereas the lagged value of depressed state captures its very persistent nature.

Given all of the above we arrive at a system of dynamic simultaneous equations model:

$$\begin{cases} D_{it} = \mathbb{I}\{\gamma^d D_{it-1} + \delta^d A_{it-1} + X_{it}\beta^d + \eta_i^d + \xi_{it}^d > 0\} \\ A_{it} = \mathbb{I}\{\gamma^a A_{it-1} + \delta^a D_{it-1} + Z_{it}\beta^a + \eta_i^a + \xi_{it}^a > 0\} \end{cases} \tag{15}$$

To proceed, some further distributional assumptions are necessary. Specifically, the time-invariant individual component, representing intrinsic individual heterogeneity (the random effect), is assumed to be normally distributed, $\eta^j \sim (0, \sigma_{\eta^j}^2)$ with $j \in (d, a)$, while idiosyncratic shocks have a standard normal distribution, $\xi^j \sim (0, 1)$, $j \in (d, a)$.

At this point a brief discussion on what state dependence and unobserved heterogeneity could actually represent may be useful. As was mentioned before, the lagged dependent variable is expressing persistence of depressed state in the first equation, and the impact of habits in the second one. The random effects, representing individual heterogeneity, are the individual's intrinsic proneness to depression (η^d) and being susceptible to alcohol abuse (η^a). These two features are very likely to be correlated. For instance, it is plausible that an individual who experienced abuse in childhood, that formed his vulnerability to depression, was at the same time observing their parents' high rates of alcohol consumption, and got acquainted with the substance at an early age, which formed his tastes that stayed with him for the rest of his life. Failing to account

[3] At this point a question on whether cross-spillovers should enter in the lagged or contemporaneous form (or both) may arise. There are several reasons for using their lagged form. First, as shown by Lewbel (2007), adding both cross-spillovers in the contamporaneous form within a non-linear framework leads to the model's incoherency and incompleteness, making identification of the structural parameters impossible. This concern is not present if only one of the cross-spillovers is represented by its contemporaneous value, but then there is a need to make an arbitrary assumption on which one of the two it should be, which we prefer to avoid. Finally, some data features are also suggesting to opt for the lagged cross-spillovers: while alcohol consumption quantitative data refers to the 30 days prior to the interview, the question on depression refers to the past 12 months, which precludes modelling depression as a function of alcohol abuse in the same period. Due to all of the above we prefer the most rigorous and prudent approach, allowing for cross-spillovers in dynamic (lagged) fashion only.

for correlation in time-invariant unobservables may lead to spurious results indicating causality between the lagged or contemporaneous consumption choices and depression state. Therefore, we allow these individual heterogeneity terms to be correlated, so that the correlation coefficient $\rho_\eta = corr(\eta^a, \eta^d)$ can be estimated. The time-specific shocks are also allowed to be correlated, with $corr(\xi^a_{it}, \xi^d_{it}) = \rho_\xi$. This would describe a situation when an individual is hit by two shocks that affect both his probability of being depressed and probability of abusing alcohol. For example, experiencing an impact of a stressor such as losing a job attributes to being depressed, and if an individual starts spending the time freed up with other unemployed peers whose pastime involves excess alcohol consumption out of pure boredom, the individual is more likely to increase his own consumption of alcohol due to exposure to the peer effect.
The covariance structure of the composite error terms $\epsilon^j_{it} = \eta^d_i + \xi^j_{it}$, $j \in (d, a)$ is described as:

$$cov(\epsilon^d_{it}, \epsilon^a_{is}) = \begin{cases} \rho_\eta \sigma_{\eta^a} \sigma_{\eta^d} + \rho_\xi, & \text{if } \ s = t \\ \rho_\eta \sigma_{\eta^a} \sigma_{\eta^d}, & \text{if } \ s \neq t \end{cases} \tag{16}$$

The sample likelihood will then take the following form:

$$L = \prod_{i=1}^{N} \int_{\eta^d} \int_{\eta^a} \left\{ \prod_{t=1}^{T} P_{it}(\eta^d, \eta^a) \right\} f_2(\eta^d, \eta^a; \mu_\eta) d\eta^d d\eta^a, \tag{17}$$

with μ_η denoting the covariance of the random effects terms η^d and η^a. Because the random effects error terms are assumed to have a bivariate joint density, the joint probability of the observed outcomes is:

$$P_{it}(\eta^d, \eta^a) = \Phi^2 \left\{ h^d_{it}(\gamma^d D_{it-1} + \delta^d A_{it-1} + X_{it}\beta^d + \eta^d_i), h^a_{it}(\gamma^a A_{it-1} + \delta^a D_{it-1} + Z_{it}\beta^a + \eta^a_i), h^d_{it} h^a_{it} \rho_\xi \right\}, \tag{18}$$

with $\Phi^2\{.\}$ denoting the bivariate normal cumulative distribution function, and h^d_{it} and h^a_{it} representing indicators such that for $J_{it} \in \{D_{it}, A_{it}\}$ and $j \in \{d, a\}$

$$h^j_{it} = \begin{cases} 1, & \text{if } \ J_{it} = 1 \\ -1, & \text{otherwise} \end{cases} \tag{19}$$

Because (17) does not have a closed form solution, Maximum Simulated Likelihood will be applied to integrate out the random effects error terms, allowing to estimate the bivariate binomial probit model, specified in system (15).

3.2 Correlated random effects and Initial conditions

Until now it was assumed that the time-invariant effects are random, which implies that by assumption they are independent from the observable covariates included in the equations. Since in the current setting this assumption is very likely to be violated, we follow the literature and adopt a correlated random effects approach (Chamberlain, 1984), parametrizing time-invariant effects η^j and allowing them to be correlated with regressors X_{it} and Z_{it} in a time-invariant manner, so that:

$$E[\eta^d_i | \quad X_{i1}, ..., X_{iT}] \quad = \bar{X}_{i.}\theta^d, \tag{20}$$

$$E[\eta^a_i | \quad Z_{i1}, ..., Z_{iT}] \quad = \bar{Z}_{i.}\theta^a \tag{21}$$

This device introduces time-averaged sample means $\bar{X}_{i.}$ and $\bar{Z}_{i.}$ as additional regressors to the first and second equations of system (15).

Under the full stochastic structure assumed here there is no need to instrument for the lagged dependent variables, as it should be done in a linear framework (typically by resorting to Arellano-Bond or Blundell-Bond approaches). However, it is necessary to specify the distribution of the initial conditions. The "initial condition" problem in non-linear dynamic random effects models arises due to the fact that the starting point of a survey is not the beginning of the stochastic process: we only observe individuals at several consecutive points in time, and the values of alcohol abuse and depression documented in the beginning of time span covered by the sample had already been affected by both time-invariant characteristics of the individual, as well as their past choices of alcohol abuse and depression states. As shown by Heckman (1981), treating initial conditions as exogenous when they are not leads to inconsistent estimators.

There are two approaches to dealing with this issue. The first one was proposed in Wooldridge (2005) and implies modelling the distribution of the unobserved heterogeneity conditional on the initial value and any exogenous explanatory variables, for instance, for depression random effect we assumed a density function $g(\eta_i^d|D_{i0}, A_{i0}, X_i; \psi)$, which in a probit setting is convenient to be thought of as a normal probability density function. The main advantage of this solution is that it is easy to implement, since it results in a likelihood function based on the joint distribution of the observations conditional on the initial period ones. In other words, it is executed by simply adding the initial values of dependent variables as separate regressors in both equations. Due to its simplicity, Wooldridge's approach is very often adopted in the literature; however, there are two important drawbacks. Firstly, from the technical point of view, it reduces the number of observations entering the likelihood function, since the initial period values have to enter the equations as separate regressors. While this is not a big issue in long panels, in our case we have a panel of a moderate size in the time dimension -six consecutive years, which should be considered borderline when applying the described procedure. Secondly, there is a conceptual weakness of the approach. Although it does allow for dependence between the random effect and the initial value, it assumes the former is conditional on the latter. However, as was mentioned above, it is reasonable to believe that it should be the opposite: e.g. an individual's inherited and time-invariant proneness to be depressed determines the path of D_{t^*} that the researcher does not observe, and therefore, determines the D_0 that is the first observed value. This issue is dealt with in the second approach, which was suggested in Heckman (1981). Unlike in the previous case, it implies specifying a conditional density for the initial value, given observable and unobservable charachteristics: $f(D_{i0}|\eta_i^d, \eta_i^a, X_i; \phi)$. Therefore, a separate equation for the initial period has to be specified:

$$\begin{aligned} D_{i0} &= \mathbb{I}\{X_{i0}\beta_0^d + \nu_d^d\eta_i^d + \nu_a^d\eta_i^a + \xi_{i0}^d > 0\}, && (22)\\ A_{i0} &= \mathbb{I}\{Z_{i0}\beta_0^a + \nu_a^a\eta_i^a + \nu_d^a\eta_i^d + \xi_{i0}^a > 0\} && (23) \end{aligned}$$

with ν representing the loading parameters of individual heterogeneity terms. X_{i0} and Z_{i0} include the initial period values of covariates (demographic and socio-economic variables that are assumed to be strictly exogenous). The main disadvantage of the Heckman approach is that it is not as easy to implement from the technical point of view, as that of Wooldridge.

In our analysis we are going to resort to Wooldridge's approach to account for initial conditions, and then contrast the results with those obtained with initial conditions a-la Heckman. Following Devicienti and Poggi (2011) and Kano (2008), for our bivariate setting we insert the values of D and A observed in the initial period as additional regressors in both equations, when estimating the specification with initial conditions a-la Wooldridge. Together with the means of explanatory variables inserted in line with the correlated random effects approach, the final specification becomes:

$$\begin{cases} D_{it} = \mathbb{I}\{\gamma^d D_{it-1} + \delta^d A_{it-1} + X_{it}\beta^d + \bar{X}_{i.}\theta^d + D_{io} + A_{io} + \eta_i^d + \xi_{it}^d > 0\} \\ A_{it} = \mathbb{I}\{\gamma^a A_{it-1} + \delta^a D_{it-1} + Z_{it}\beta^a + \bar{Z}_{i.}\theta^a + D_{io} + A_{io} + \eta_i^a + \xi_{it}^a > 0\} \end{cases} \tag{24}$$

4 Data

We are going to use the data from the Russian Longitudinal Monitoring Survey (RLMS) that is a series of nationally representative surveys designed to monitor the effects of Russian reforms on the health and economic welfare of households and individuals in the Russian Federation. The data is collected on both household and individual level, and alongside with general demographic and socio-economic characteristics includes detailed monitoring of individuals' health status and dietary intake, precise measurement of household-level expenditures and service utilization, and collection of relevant community-level data, including region-specific prices and community infrastructure data.

4.1 Variables of interest

The variables of particular interest for our study are the indicator for depression, which comes from an answer to a "yes/no" question on whether an individual has been experiencing a depressed state in the past 12 months[4], and an indicator, or a range of indicators of alcohol abuse. In fact, alcohol abuse is not a trivially defined concept, as it may take different forms for different individuals, therefore, being a subjective measure to a certain extent. Therefore, assessing whether an individual is abusing alcohol or not may require measures in several dimensions.

For example, the US National Survey on Drug Use and Health (NSDUH) contains a wide range of questions based on criteria specified in the Diagnostic and Statistical Manual of Mental Disorders, including the amount of alcohol consumed, frequency of drinking, social context, attitudes towards drinking and its consequences. However, in most longitudinal and even cross-sectional surveys that are not designed specifically with the purpose of analysing substance use and abuse the questions related to alcohol consumption are realtively few. For instance, the Health in Times of Transition (HITT) study, which was designed to collect and analyse health-related data in CIS countries, uses the CAGE questionnaire (Ewing, 1984), that consists of four questions, to construct the problem drinking indicator. A possible disadvantage of this approach is that these questions are mostly subjective[5]. A more comprehensive yet concise approach is the Alcohol Use Disorders Identification Test (AUDIT) developed by a World Health Organization-sponsored collaborative project to determine if a person may be at risk for alcohol abuse problems (Saunders et al., 1993). The test contains ten questions that comprise those from CAGE but also introduces questions to determine frequency and typical volume of alcohol intake. Regarding the RLMS data, it does not offer a ready-to-use problem drinking indicator, but contains an extensive list of alcohol-related questions: grams of each specific type of alcohol consumed in the last 30 days (in days when the respondent consumed alcohol), number of days this beverage was consumed in the last 30 days, frequency of drinking in the last 30 days (a categorical variable). The survey

[4]With all possible drawbacks of such a measure, this is the only indicator available on a sufficiently long timespan.

[5]The CAGE questionnaire contains the following questions: Have you ever felt you needed to Cut down on your drinking? Have people Annoyed you by criticizing your drinking? Have you ever felt Guilty about drinking? Have you ever felt you needed a drink first thing in the morning (Eye-opener) to steady your nerves or to get rid of a hangover?

also asked the respondents whether they think their alcohol consumption is a source of trouble at work, causes family issues or health problems, but those questions were only asked in 2008, 2009 and 2012, therefore we will not be able to use them in our analysis. There is, however, a set of questions on the social context and typical mode of drinking: whether an individual drinks alcohol as a guest, at home, in public places, restaurants, while eating or without food. Using these data and having consulted existing psychological and economic studies which propose various measures of alcohol abuse, we define several indicators:

1. Binge-drinker. A person is defined as a binge-drinker, if their pure alcohol consumption in the last month was higher than the 80th percentile for a pool of subjects of the same gender, but the individual reports to have been drinking *rarely*: once a week or less, in the past 30 days. We follow Yakovlev (2018) and calculate the total volume of pure alcohol intake converting the grams of different types of beverages consumed using the formula: Q(pure alcohol) = 0.4Q(hard drinks) + 0.12Q(dry wine) + 0.15Q(fortified wine) + 0.05(beer). Although the cutoff may seem arbitrary, using a relative measure allows to define individuals who drink "too much", given cultural peculiarities and genetic traits, specific for the given subject pool (this is the reason why different countries have different definitions of riskless drinking (IARD, 2018)). The relative measure allows to evaluate if an individual drinks "too much" as compared to all other individuals of the same gender (socially acceptable drinking habits differ drastically for males and females).
2. Heavy-drinker. A person is defined as a heavy drinker if, like in the previous case, their monthly alcohol intake is in the upper quintile but they report to have been drinking *frequently*: more often than once a week in the past 30 days. This type of indicator will capture not those who may drink a lot occasionally, but those who do so often, and are therefore likely to suffer from alcohol dependence.
3. Frequent-drinker. We define a person as a frequent drinker if they report having consumed alcohol more then once a week during the past month. This measure has an advantage of being less affected by shocks that create noise in the binge-drinker indicator (e.g. a "special occasion" when an individual consumed a very high amount of alcohol, which is not their typical level of consumption).
4. No-food drinker. Those individuals who reported having consumed some alcohol in the past month are asked several questions about the mode of drinking. Although there is no question on whether an individual tends to drink alone or with others, there is an indicator of whether an individual consumes alcohol without food.
5. Composite problem-drinking indicator. Based on the univariate analysis conducted using the abovementioned indicators, we combine those that proved to be most related to depression (heavy drinking and drinking without food) and calculate *score* as a sum of individual problem-drinking indicators:

   $$score = \mathbb{I}\{Top20\%\ \ per\_occasion = 1\} \ + \ \mathbb{I}\{frequent\_dr = 1\} \ + \ \mathbb{I}\{alcnofood = 1\},$$

   and then define a problem drinker with a binary variable $problem\_dr$ such that:

   $$problem\_dr = \begin{cases} 1, & \text{if } \ score \geqslant 2 \\ 0, & \text{otherwise} \end{cases}$$

Both depression indicator and alcohol abuse are therefore represented by binary variables. While detailed data for alcohol use is mostly available for every wave of the survey, the depression variable appears only in selected waves: for the years 2003-2004 and 2011-2016. Given that our question of interest requires a panel with consecutive observations, we focus on the 2011-2016 time span.

4.2 Descriptive statistics

The full sample[6] contains data on roughly 6300 adult individuals over 6 years, resulting in more than 31000 individual-year observations (the first period is lost due to inclusion of lags). Table 26 provides basic descriptive statistics and definitions of the variables used. The average prevalence of depressed state in the general population is 11%[7], frequent drinkers comprise about 7% of the sample, while roughly 10% report consumping alcohol without food. By definition that we adopted, binge-drinkers are the top quintile of the gender-specific alcohol intake distribution, who drink rarely: those comprise 15% of the sample. This could be viewed as evidence of Russians being typical "northern style" drinkers: consuming large amounts of alcohol on a single occasion. Heavy drinkers, whom we defined as those whose drinking style may signal alcohol dependence, comprise about 6% of the sample.

Table 26: Summary statistics (2011-2016)

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
depr12m	Depressed in the past 12 month	31,600	0.11	0.32	0	1
per_occasion	Pure alcohol intake on a single occasion (grams)	31,600	44.59	77.36	0	1700
avg_daily	Pure alcohol intake per day (grams)	31,600	5.08	16.55	0	1002
binge	Binge-drinker indicator	31,564	0.15	0.36	0	1
heavy	Heavy-drinker indicator	31,564	0.06	0.23	0	1
frequent_dr	Frequent-drinker indicator	31,564	0.07	0.26	0	1
alcnofood	If consumes alcohol without food	31,551	0.1	0.3	0	1
age	Age	31,600	48.75	16.52	18	102
kidssmall	If has kids younger than 18 y/o	31,600	0.35	0.48	0	1
city	If lives in a city	31,600	0.61	0.49	0	1
married	If married	31,600	0.58	0.49	0	1
college	If has a college degree	31,600	0.26	0.44	0	1
female	If female	31,600	0.6	0.49	0	1
curwrk	If is currently working	31,600	0.56	0.5	0	1
muslim	If muslim	31,600	0.06	0.24	0	1
smokes	If smokes	31,600	0.29	0.45	0	1
lowincome	If household income is lower than that of 40% of HHs within sampling unit and year	31,600	0.41	0.5	0	1

Regarding persistence of the main variables of interest and crude transition probabilities from problem drinking to depression and vice versa, it emerges from Table 41 in Appendix that all variables are quite persistent, with probabilities of 1-1 transitions ranging from 32 to 48% for different alcohol-abuse measures and 44% for depression variable. Concerning cross-transitions, the probabilities of being depressed in period t are slightly higher if alcohol abuse was observed in $t-1$, with the difference being almost negligible for the *binge* and $freq\_dr$ measures, but reaching more than 2 pp. if alcohol-without-food consumption and a composite measure are used as a problem-drinking indicator. In the case of depression-alcohol transitions, the picture is more obscure: for some measures (heavy and frequent drinkers) the difference is negligible and even reverse: the probability of being a heavy or frequent drinker is marginally higher if in the previous period depression was not observed. On the other hand, again for no-food drinkers and problem drinkers, conditional on having observed depression in the previous period, the probability of alcohol abuse in subsequent period is higher. This may be suggestive of the asymmetric nature

[6]Using a fully balanced sample may lead to erroneous conclusions if attrition is related to the outcome variables. Subsection A.4 of the Appendix provides evidence that the results obtained are likely to be understating the true effects, thus being a prudent estimate.

[7]This figure is in line with the Russian Ministry of Health estimate of depression prevalence in the general population: about 10.4% for the year 2012.

of the interrelations between problem-drinking and depression: the spillover from alcohol abuse to depression appears to be more pronounced than the reverse.

5 Results

5.1 Univariate and bivariate analysis

Before estimating the system of equations (24), we begin with estimating the two equations separately, as simple dynamic random effect probit models, for the depression variable and for each of the problem drinking measures. To adopt the correlated random effects aproach the time means of the variables *smokes*, *lowincome* and *married* are also included among the covariates. The initial conditions problem is solved in the Wooldridge's fasion by inserting the initial values of the dependent variables as separate covariates into both equations. Tables 27, 28, 29 and 30 contain results of the estimations.

Table 27: Binge-drinker indicator (univariate case)

	depr	binge-drinker
$depr_{t-1}$	0.371***	0.006
	(0.040)	(0.041)
$binge_{t-1}$	0.009	0.211***
	(0.039)	(0.034)
$depr_o$	1.05***	-0.009
	(0.057)	(0.056)
$binge_o$	-0.003	0.984***
	(0.050)	(0.044)
Soc.-dem. controls	✓	✓
CRE controls	✓	✓
constant	-2.065***	-3.620***
	(0.165)	(0.169)
NT	31410	31410
N	6282	6282
σ_η	0.86	0.81
ω	0.43	0.39

Table 28: Heavy drinker indicator (univariate case)

	depr	heavy-drinker
$depr_{t-1}$	0.371***	0.06
	(0.040)	(0.066)
$heavy_{t-1}$	0.117*	0.244***
	(0.061)	(0.056)
$depr_o$	1.05***	-0.077
	(0.057)	(0.056)
$heavy_o$	0.098	1.67***
	(0.074)	(0.089)
Soc.-dem. controls	✓	✓
CRE controls	✓	✓
constant	-2.068***	-3.375***
	(0.165)	(0.264)
NT	31410	31410
N	6282	6282
σ_η	0.86	1.04
ω	0.43	0.52

The variables used are described in Table 26. Initial conditions are accounted for by inserting initial values of both dependent variables in both equations. In the framework of the CRE approach, the means of *smokes*, *lowincome* and *married* are also included in the equations. σ_η stands for the estimated parameter of the standard deviation of the heterogeneity term; ω is a ratio $\frac{\sigma_\eta^2}{\sigma_\eta^2+1}$ and represents the relevant importance of individual heterogeneity in explaining total variance of the error term. Significance levels: * p<0.1, ** p<0.05, *** p<0.01

First, we note that all the variables exhibit persistence: own lags are highly significant, and even the point estimate of depression lag is almost the same, independently of which type of alcohol abuse variable was included. Secondly, it emerges that different indicators adopted provide different results. Specifically, binge-drinking does not prove to be related to depression in either direction; being a frequent or heavy drinker affects depression in the next period, but the reverse does not occur; finally, consuming alcohol without food has proven to have the strongest bidirectional link with depression. These results are very much in line with the analysis of persistence

Table 29: Frequent-drinker indicator (univariate case)

	depr	frequent drinker
$depr_{t-1}$	0.371***	0.054
	(0.040)	(0.063)
$frequent_{t-1}$	0.111**	0.241***
	(0.056)	(0.051)
$depr_o$	1.05***	-0.089
	(0.057)	(0.094)
$frequent_o$	0.091	1.645***
	(0.068)	(0.081)
Soc.-dem. controls	✓	✓
CRE controls	✓	✓
constant	-2.075***	-3.021***
	(0.165)	(0.25)
NT	31410	31410
N	6282	6282
σ_η	0.86	1.06
ω	0.43	0.53

Table 30: No-food drinker indicator (univariate case)

	depr	no-food drinker
$depr_{t-1}$	0.380***	0.104**
	(0.040)	(0.051)
$alcnofood_{t-1}$	0.114**	0.132***
	(0.048)	(0.043)
$depr_o$	1.05***	0.097
	(0.056)	(0.071)
$alcnofood_o$	0.196***	1.313***
	(0.059)	(0.060)
Soc.-dem. controls	✓	✓
CRE controls	✓	✓
constant	-2.075***	-1.455***
	(0.165)	(0.189)
NT	31245	31245
N	6249	6249
σ_η	0.86	0.917
ω	0.42	0.457

The variables used are described in Table 26. Initial conditions are accounted for by inserting initial values of both dependent variables in both equations. In the framework of the CRE approach, the means of *smokes*, *lowincome* and *married* are also included in the equations. σ_η stands for the estimated parameter of the standard deviation of the heterogeneity term; ω is a ratio $\frac{\sigma_\eta^2}{\sigma_\eta^2+1}$ and represents the relevant importance of individual heterogeneity in explaining total variance of the error term. Significance levels: * p<0.1, ** p<0.05, *** p<0.01

discussed above. Finally, the results suggest that individual heterogeneity is indeed important, with σ_η^2 accounting for about 43% of the total variance of the depression variable and 39-53% of the alcohol abuse variables.

These findings were used as guidance for construction of the composite problem-drinking indicator, which was described in detail in Section 4. We then estimate both univariate and bivariate models, now allowing for correlation between both individual heterogeneity and transitory shocks of the two processes. The outcomes of the estimations are presented in Table 31.

First, as regards univariate analysis, our problem-drinker indicator is in bidirectional relationship with depression. Moving to bivariate estimation, it is evident that the relationship still holds, even after correlations between the error terms are also accounted for. Both correlation coefficients turn out to be significant and positive, indicating that modelling the two processes in the bivariate framework is a correct choice. In the rest of the paper the remaining analysis is carried out using this composite problem-drinking measure.

It is important to highlight that while the signs of the structural parameters obtained are indicative of the direction of cross-spillover effects, the values of the parameters are not enough to elicit anything about the impacts magnitudes. To assess the latter, we move to the next section and calculate Average Partial Effects (APEs).

Table 31: Univariate and bivariate estimation with a composite problem drinking indicator

	Univariate		Bivariate	
	depr	problem_dr	depr	problem_dr
$depr_{t-1}$	0.380***	0.122**	0.437***	0.106*
	(0.040)	(0.054)	(0.040)	(0.059)
$problem\_dr_{t-1}$	0.105**	0.198***	0.104*	0.288***
	(0.051)	(0.047)	(0.055)	(0.046)
$depr_o$	1.03***	-0.043	0.98***	-0.008
	(0.057)	(0.077)	(0.055)	(0.072)
$problem\_dr_o$	0.186***	1.446***	0.190***	1.348***
	(0.063)	(0.068)	(0.061)	(0.064)
Soc.-dem. controls	✓	✓	✓	✓
CRE controls	✓	✓	✓	✓
constant	-2.104***	-2.725***	-2.116***	-2.591***
	(0.165)	(0.215)	(0.159)	(0.199)
σ_{η^d}	0.86***		0.82***	
σ_{η^a}		0.93***	0.89***	
ρ_η			0.09**	
ρ_ϵ			0.08**	
NT	31085	31085	31085	
N	6217	6217	6217	

The variables used are described in Table 26. Initial conditions are accounted for by inserting initial values of both dependent variables in both equations. In the framework of the CRE approach, the means of *smokes*, *lowincome* and *married* are also included in the equations. σ_η stands for the estimated parameter of the standard deviation of the heterogeneity term; ρ_η and ρ_ϵ correspond to the estimated correlation parameters of the time-invariant and time-variant heterogeneity components respectively. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

5.2 Average Partial Effects (APEs)

Following Devicienti and Poggi (2011), we resort to Wooldridge (2005) and firstly calculate predicted probabilities of being depressed and being a problem drinker keeping lagged dependent variables at specific values, and then average the predictions across the sample. This becomes clear when illustrated by an example. When we wish to calculate APE of being depressed in $t-1$; for a simpler (univariate) case, the procedure is the following. In the first step, the model is estimated and the vector of coefficients $\hat{\beta}_1$ is obtained. Next, we obtain predicted probabilities P_1 and P_0 setting D_{t-1} to 1 and to 0 respectively, for the whole population, keeping all other variables as they are: the linear predictions are corrected for the estimated distribution of unobserved heterogeneity and inserted into the standard normal cumulative distribution function to obtain probabilities. Therefore, we get:

$$P_i = \Phi\left(\frac{x_{it}\hat{\beta}_1}{\sqrt{1+\sigma^2_{\eta^d}}}\right),$$

where D_{t-1} is among x_{it} and equals 1 for $i = 1$ and 0 for $i = 0$ for all observations. The difference between P_1 and P_0 is the average partial effect of being depressed in the previous period on the probability of being depressed in the current period, measured in percentage points.

In the bivariate case it is possible to obtain APEs in a similar fashion for individual equations, but also the APEs on the joint probability of being depressed and being a problem-drinker. In the latter case we resort to bivariate normal cumulative density function, which includes one additional parameter: correlation between stochastic shocks. Table 32 contains results of the calculations of APEs for three cases: the univariate case, the bivariate case for individual equations, and the APE on the joint probability of being depressed and being a problem-drinker. The first case is interesting not only for comparison with the bivariate model, but also because it allows for calculation of standard errors of the partial effects via bootstrapping (for the bivariate case it turned out to be unfeasible due to tremendous computational power needed).

Table 32: Average Partial Effects (APE) of lags and cross-lags (in percentage points)

Univariate	depr	problem_dr	Bivariate	depr	problem_dr
$depr_{t-1}$	5.6^{***}	1.1^{**}	$depr_{t-1}$	6.8	1
$problem\_dr_{t-1}$	1.4^{**}	1.8^{***}	$problem\_dr_{t-1}$	1.4	2.9

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

As evident from the table, being depressed in the previous period results in about 6 pp. higher probability of being depressed in the next period. The number is more moderate for the problem-drinkinig state dependence: the causal effect amounts for about 2 pp. The cross-spillovers are even less pronounced, and the APE of being a problem drinker in the previous period increases the joint probability of both being a problem drinker and being depressed by only 0.5 pp. This suggests that the immediate effects of decreasing the probability of abusing alcohol are very moderate; however, in the long-run they may be more pronounced.

5.3 Incorporating prices

We now incorporate prices into the analysis in order to see how sensitive problem-drinkers could be to a tax-raising or any other policy that will result in a price increase for alcohol beverages. The data provides community-level per-gram prices of different types of alcohol, which we convert into the price per unit of pure alcohol by using weights:

$$price = 0.05 \times p_{beer} + 0.12 \times p_{wine} + 0.15 \times p_{fwine} + 0.4 \times p_{spirits}$$

In the second step the prices are transformed into real values by abjusting for the community-level CPI, which we construct following Yakovlev (2018). The resulting price variable is then inserted only in the alcohol-abuse equation. Our setting allows us to do it directly without further adjustments to resolve the endogeneity problem: given that problem-drinkers are a small fraction of the population, it is implausible that their choices may affect prices. Table 33 contains results of the estimation for both univariate and bivariate cases, using a composite problem-drinking indicator and including price among covariates.

While all the structural parameters remain of the same signs and magnitudes, the price variable turns out to be significant at the 10% level and negative, as expected. Therefore, although the relationship with prices is not very strong, it is still present, suggesting that problem-drinkers are also responsive to price changes.

Table 33: Univariate and bivariate estimation with a composite problem drinking indicator, including prices

	Univariate	Bivariate	
	problem_dr	depr	problem_dr
$depr_{t-1}$	0.122**	0.436***	0.107*
	(0.054)	(0.040)	(0.059)
$problem\_dr_{t-1}$	0.198***	0.104*	0.288***
	(0.047)	(0.055)	(0.046)
$depr_o$	-0.045	0.98***	-0.009
	(0.077)	(0.055)	(0.072)
$problem\_dr_o$	1.445***	0.190***	1.347***
	(0.068)	(0.061)	(0.064)
$price$	-0.029*		-0.031*
	(0.017)		(0.017)
Soc.-dem. controls	✓	✓	✓
CRE controls	✓	✓	✓
constant	-2.725***	-2.116***	-2.591***
	(0.215)	(0.159)	(0.199)
σ_{η^d}		0.82***	
σ_{η^a}	0.93***	0.89***	
ρ_η		0.09**	
ρ_ϵ		0.08**	
NT	31085	31085	
N	6217	6217	

The variables used are described in Table 26. Initial conditions are accounted for by inserting initial values of both dependent variables in both equations. In the framework of the CRE approach, the means of *smokes*, *lowincome* and *married* are also included in the equations. σ_η stands for the estimated parameter of the standard deviation of the heterogeneity term; ρ_η and ρ_ϵ correspond to the estimated correlation parameters of the time-invariant and time-variant heterogeneity components respectively. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

6 Robustness checks

In this section we report results of various robustness checks. Firstly, a natural curiosity is to check whether the findings hold for different subpopulations, for instance, if considering separately males and females. Men and women have different habits and different drinking abilities, as well as the attitudes towards male and female alcohol abuse are very different. In fact, even with regard to depression, gender differences are quite pronounced: as in many traditionalist countries, in Russia it is considered acceptable to admit being depressed for women but not for men, since depression is oftentimes considered as evidence of weakness and self-indulgence[8] (Rogacheva, 2012).

[8] In this respect differential misreporting, in particular, underreporting of depression for males and alcohol abuse for females may take place. Given that the model as already computationally demanding, incorporating misclassification error may be extremely time consuming, if not infeasible. However, the important thing is that underreporting implies a downward bias of the state dependence parameter, and is likely to not affect the cross spillovers (Deza, 2015). Thus, we note that our estimates are prudent and are underestimating the true effects.

Table 34 provides evidence on the distribution of the average and per-occasion pure alcohol consumption for males and females.

Table 34: Pure alcohol intake per occasion and average daily intake: percentiles by gender

			Males		Females	
percentile	per_occasion	avg_daily	per_occasion	avg_daily	per_occasion	avg_daily
1%	0	0	0	0	0	0
5%	0	0	0	0	0	0
10%	0	0	0	0	0	0
25%	0	0	0	0	0	0
50%	0	0	40	2.66	0	0
75%	60	4	120	10.66	30	1.43
90%	140	13.3	200	26.66	80	5.1
95%	200	24	270	42.66	117.5	8.36
99%	345	66.66	430	105	203	24

Table 35: Bivariate model estimation on subsamples (by gender)

	Males		Females	
	depr	problem_dr	depr	problem_dr
$depr_{t-1}$	0.377***	0.080	0.444***	0.103
	(0.074)	(0.092)	(0.046)	(0.079)
$problem\_dr_{t-1}$	0.18**	0.351***	0.016	0.129*
	(0.080)	(0.059)	(0.080)	(0.076)
$depr_o$	1.226***	-0.165	0.893***	0.045
	(0.107)	(0.125)	(0.064)	(0.095)
$problem\_dr_o$	0.168**	1.345***	0.162*	1.383***
	(0.084)	(0.068)	(0.091)	(0.104)
Soc.-dem. controls	✓	✓	✓	✓
CRE controls	✓	✓	✓	✓
σ_{η^d}	0.83***		0.82***	
σ_{η^a}	0.88***		0.92***	
ρ_η	-0.07		0.24***	
ρ_ϵ	0.08*		0.06	
NT	12160		18925	
N	2432		3785	

The variables used are described in Table 26. Initial conditions are accounted for by inserting initial values of both dependent variables in both equations. In the framework of the CRE approach, the means of *smokes*, *lowincome* and *married* are also included in the equations. σ_η stands for the estimated parameter of the standard deviation of the heterogeneity term; ρ_η and ρ_ϵ correspond to the estimated correlation parameters of the time-invariant and time-variant heterogeneity components respectively. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

It is clear that males consume substantially more than females both on average and on a single occasion. Apart from the reasons mentioned above, such a drastic gap stems also from difference in tastes/habits (females are main consumers of wines in Russia, while males traditionally prefer hard drinks).

Table 35 presents results of the bivariate model estimation for males and females. It emerges that the finding on the cross-spillover from alcohol abuse to depression is mainly driven by the males subsample. The reverse causal link, while present in the whole population, appears to be insignificant in the subpopulations considered; this may, however, be attributed to decreased power due to lower number of observations. Another curious result arises from the obtained correlation coefficients. Recall that in the full sample we obtain both positive and significant correlation terms (see Table 31). First, we note that correlation between unobserved time-invariant heterogeneity seems to be driven by the female subsample; in fact, this link appears to be so strong that it substantially lowers the importance of the lagged dependent variable in the problem-drinking equation. Therefore, for females, unobserved heterogeneity seems to be the key factor that explains not only the observed correlation between alcohol abuse and depression, but in the large part also the correlation between past and present hazardous drinking style.

Table 36: Excluding potentially endogenous variables

	Exog.controls		Baseline	
	depr	problem_dr	depr	problem_dr
$depr_{t-1}$	0.447***	0.111*	0.436***	0.107*
	(0.039)	(0.059)	(0.040)	(0.059)
$problem\_dr_{t-1}$	0.105*	0.292***	0.104*	0.288***
	(0.055)	(0.046)	(0.055)	(0.046)
$depr_o$	1.000***	-0.002	0.98***	-0.009
	(0.055)	(0.077)	(0.071)	(0.072)
$problem\_dr_o$	0.201***	1.346***	0.190***	1.347***
	(0.061)	(0.064)	(0.061)	(0.064)
$price$		-0.029*		-0.031*
		(0.017)		(0.017)
Exog. controls	✓	✓	✓	✓
Endog. controls			✓	✓
CRE controls	✓	✓	✓	✓
σ_{η^d}	0.82***		0.82***	
σ_{η^a}	0.88***		0.89***	
ρ_η	0.10**		0.09**	
ρ_ϵ	0.08**		0.08**	

The variables used are described in Table 26. Initial conditions are accounted for by inserting initial values of both dependent variables in both equations. In the framework of the CRE approach, the means of *smokes*, *lowincome* and *married* are also included in the equations (only *smokes* for the model omitting potentially endogenous controls). σ_η stands for the estimated parameter of the standard deviation of the heterogeneity term; ρ_η and ρ_ϵ correspond to the estimated correlation parameters of the time-invariant and time-variant heterogeneity components respectively. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

In contrast, for males correlation between stochastic shocks proves to be significant, while that of time-invariant heterogeneity terms does not. This suggests that males should be the subpopulation that would benefit most from a policy aimed at decreasing alcohol abuse prevalence.

Another important feature our results should have is robustness to exclusion of potentially endogenous variables. In the list of controls included in the equations, some variables might not be strictly exogenous, which will invalidate the results (for the full list of assumptions and detailed explanations see subsection A.1 of the Appendix). A standard way to check whether violation of strict exogeneity leads to wrong conclusions is to compare results with and without including problematic variables. Table 36 contains both the baseline outcomes and the ones omitting potentially endogenous variables (*married*, *college*, *curwrk*, *lowincome*). As evident from the table, the outcomes remain very similar, therefore, we conclude that results are robust to potential violation of strict exogeneity assumption.

7 Heckman's solution to initial conditions problem

A possible explanation to small magnitudes of state dependence and spillover effects could be a relatively short time dimension of the sample. Inserting the values at the onset of the time span as separate regressors may result in "overcontrolling" for the initial conditions. Taking this and the considerations described in Section 3, we extend the analysis and apply Heckman's approach to initial conditions by defining a separate equation for each of the two variables at the initial period, as represented by (22) and (23). This allows using more data, as the 2011 observations now also enter the likelihood function. Table 37 provides results of estimating bivariate model via Heckman's approach, for the baseline case, and controlling for strictly exogenous variables only.

It appears that the results are qualitatively similar to those of the baseline case, and also robust to excluding potentially endogenous variables. However, the spillover effect of alcohol abuse on depression is now estimated with higher precision than that of the opposite direction, indicating that the link running from problem drinking to depression is more pronounced than the reverse. In line with this finding are the average partial effects implied by the new model (Table 38): the causal impact of being depressed in the previous period on the probability of abusing alcohol in the current period is 0.9 pp., while the reverse spillover effect is estimated to be 1.7 pp. The results also suggest that being depressed in the previous period leads to the 9.6 pp. higher probability of being depressed in the current period, while abusing alcohol in the previous period leads to the 3.8 pp. higher probability of being depressed in the current period. The magnitudes of state dependence for both variables are larger than in the baseline case (with initial conditions a-la Wooldridge), which implies these values being equal to 6.8 and 2.9 respectively[9] (Table 32). To understand the drivers of this difference we again run separate analysis dividing the sample by gender (Table 39). This time prices are also included in the analysis. It appears that the structural parameters are now estimated with higher precision: both cross-spillovers are now significant for females at the 5% level, and the coefficient of problem drinking cross-spillover for males is significant at 1% level. This indicates that the concern about the sample size was indeed valid, and provides robust evidence of substantial gender differences manifesting themselves in the relationship between alcohol abuse and depression.

First, we note that for females both cross-spillovers are present, while for males there is evidence of the causal impact of alcohol abuse on depression, but not the reverse. In order to see how

[9] While these average partial effects are small in magnitude, one may be concerned whether they could be biased upwards due to autocorrelation in the error terms which is not accounted for in the current specification. We show in subsection A.5 of the Appendix that it is not the case.

Table 37: Bivariate model with Heckman's initial conditions

	Full specification		Exog.controls	
	depr	problem_dr	depr	problem_dr
$depr_{t-1}$	0.553***	0.097*	0.564***	0.102*
	(0.038)	(0.057)	(0.039)	(0.057)
$problem\_dr_{t-1}$	0.116**	0.362***	0.116**	0.365***
	(0.052)	(0.046)	(0.052)	(0.046)
price		-0.035 **		-0.035**
		(0.017)		(0.017)
Exog. controls	✓	✓	✓	✓
Endog. controls	✓	✓		
CRE controls	✓	✓	✓	✓
σ_{η^d}	0.86***		0.87***	
σ_{η^a}	1.05***		1.05***	
ρ_η	0.11***		0.12***	
ρ_ϵ	0.08**		0.08**	
NT	37146		37146	
N	6191		6191	

The variables used are described in Table 26. Initial conditions are accounted for by specifying conditional densityies for the initial values (Heckman solution). In the framework of the CRE approach, the means of *smokes*, *lowincome* and *married* are also included in the equations. σ_η stands for the estimated parameter of the standard deviation of the heterogeneity term; ρ_η and ρ_ϵ correspond to the estimated correlation parameters of the time-invariant and time-variant heterogeneity components respectively. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 38: APEs of lags and cross-lags (in percentage points) implied by the model with Heckman's initial conditions

	depr	problem_dr
$depr_{t-1}$	9.6	0.9
$problem\_dr_{t-1}$	1.7	3.8

the effects differ in magnitude across subpopulations, average partial effects were estimated (Table 40). While the effect of the lagged depression variable on the current probability of being depressed is similar for men and women, state dependence for the problem drinking variable is much more pronounced for males than for females: abusing alcohol in the previous period leads to the probability of doing so in the current period being 7.2 pp. higher for males and only 1.7 pp. higher for females. This implies, in line with the previous findings, that males are the subpopulation who would benefit most from a policy tackling problem drinking, as it would be more effective in decreasing future alcohol abuse than for females, taking into account that cross-spillovers from alcohol to depression are of the same magnitude for both subpopulations. Finally, considering prices as a potential tool to which policy-makers may resort to, we find that male problem drinkers are not price sensitive, whereas their female counterparts are (Table 39). Further investigation suggested that this result is driven by the fact that males, unlike females, react to an increase of alcohol prices by increasing the amount of moonshine consumed (see subsection A.3 of the Appendix). Therefore, pricing policies would only impact the female subpopulation.

Table 39: Bivariate model with Heckman's initial conditions (by gender)

	Males		Females	
	depr	problem_dr	depr	problem_dr
$depr_{t-1}$	0.606***	0.074	0.522***	0.170**
	(0.072)	(0.090)	(0.046)	(0.074)
$problem\_dr_{t-1}$	0.253***	0.424***	0.178**	0.250***
	(0.077)	(0.060)	(0.073)	(0.075)
price		-0.009		-0.065**
		(0.022)		(0.026)
Soc.-dem. controls	✓	✓	✓	✓
CRE controls	✓	✓	✓	✓
σ_{η^d}	0.81***		0.86***	
σ_{η^a}	1.05***		0.99***	
ρ_η	-0.08		0.09*	
ρ_ϵ	0.08*		0.11***	
NT	14556		22590	
N	2426		3765	

The variables used are described in Table 26. Initial conditions are accounted for by specifying conditional densities for initial values (Heckman solution). In the framework of the CRE approach, the means of *smokes*, *lowincome* and *married* are also included in the equations. σ_η stands for the estimated parameter of the standard deviation of the heterogeneity term; ρ_η and ρ_ϵ correspond to the estimated correlation parameters of the time-invariant and time-variant heterogeneity components respectively. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 40: APEs of lags and cross-lags
(in percentage points) for males and females

Males	depr	problem_dr
$depr_{t-1}$	8.9	$1.2^{\times}$
$problem\_dr_{t-1}$	3.2	7.2

Females	depr	problem_dr
$depr_{t-1}$	9.8	1.1
$problem\_dr_{t-1}$	3.1	1.7

$^{\times}$ the structural parameter is insignificant.

8 Policy simulation

In this section we present results of a policy simulation excercise that aims to predict how an increase in prices would change the probability of being depressed through affecting the probability to be a problem-drinker. Specifically, we consider a case when the price of a pure alcohol unit twofolds and remains at this level for several periods. Given that average partial effects of lags and cross-lags were found to be moderate, we expect the effects of the policy to be of small magnitude, especially for the model with Wooldridge initial conditions. We first execute the analysis for the full population sample for the baseline case with Wooldridge initial conditions and for the second case with initial conditions a-la Heckman.

Figures 21 and 22 depict the dynamics of the probability of being depressed (equivalently, the share of depressed persons in the population) in response to the price increase for these two cases respectively. As expected, the changes in the probability of being depressed are very small:

Figure 21: Depression prevalence in response to an increase in alcohol prices (Wooldridge ICs)

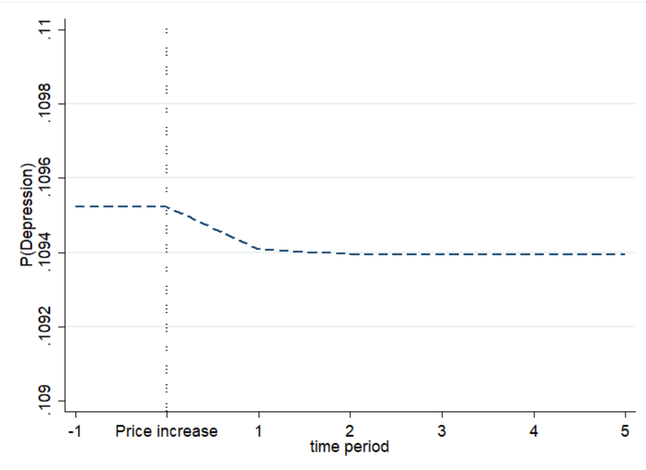


Figure 22: Depression prevalence in response to an increase in alcohol prices (Heckman ICs)

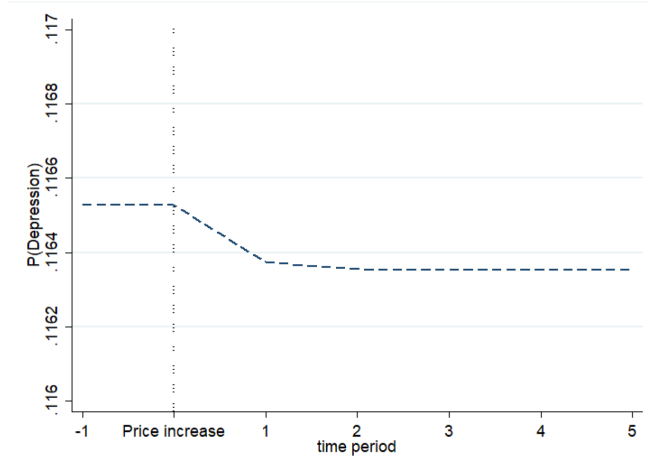


Figure 23: Share of problem drinkers in response to an increase in alcohol prices (Wooldridge ICs)

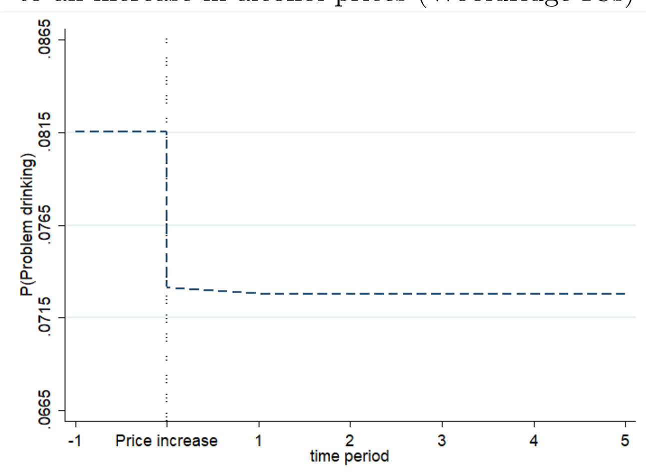
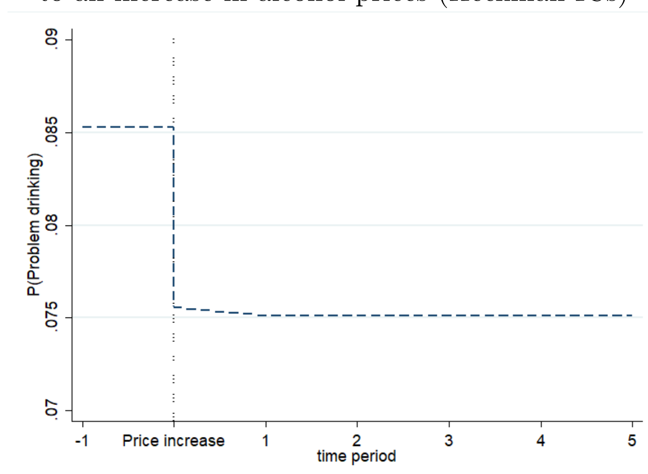


Figure 24: Share of problem drinkers in response to an increase in alcohol prices (Heckman ICs)



from 10.952% to 10.939% for the first case and from 11.653% to 11.635% for the second case. These changes in percentage points are equivalent to a decrease in shares of depressed population by 0.12% and 0.15% respectively. The implied impacts on problem-drinking are larger: the probability decreases from 8.153% to 7.279% and from 8.526% to 7.510% for the baseline and Heckman's cases respectively, which is equivalent to a decrease in the alcohol abuse prevalence in the population by 10.72% and 11.91%. The main drop in the share of problem-drinkers is the direct response to the price change and is observed in the same period when the price increase takes place, while the role of habit is small, so further decreases are marginal. For the same reason the main decrease in depression prevalence occurs in the period following the price change, due to a spillover effect, and fades out in the following periods.

We then explore heterogeneity in policy responses by gender, conducting the same analysis for males and females separately using the models with Heckman's initial conditions, since they allowed estimating the parameters with higher precision. Figures 25 and 26 depict the probability responses for males (right axes) and females (left axes). Recall that males were found to be insensitive to price changes, therefore the dynamics of the probability depicted in the graph for males would have a very large confidence interval[10], indicating the changes are indistinguishable from zero.

Figure 25: Depression prevalence in response to an increase in alcohol prices (by gender)

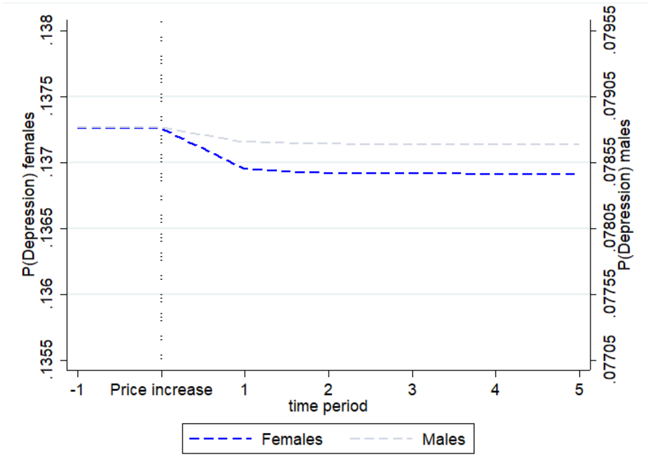
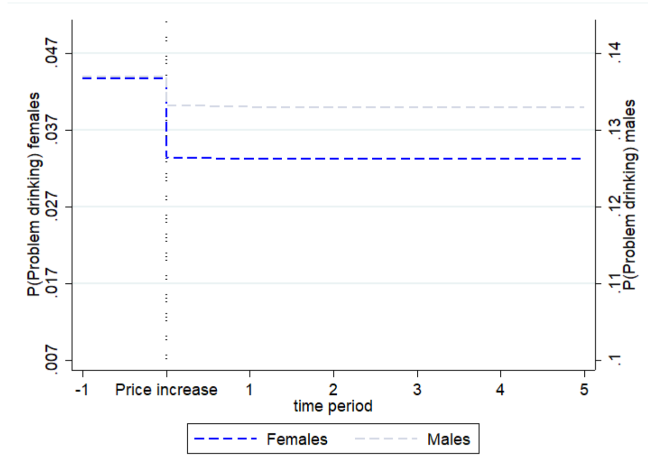


Figure 26: Share of problem drinkers in response to an increase in alcohol prices (by gender)



As evident from the figures, the effects found for the whole population are driven by female subpopulation. The share of problem-drinkers across females decreases from 4.379% to 3.321%, which in relative terms corresponds to quite a substantial decrease by 24.16%. The drop in the probability of being depressed, however, is moderate: from 13.726% to 13.691%, which is equivalent to about 0.25% decrease in the depression prevalence. Lastly, we try to understand how effective would a price increase be in affecting depression in the males population, *had they been as price-sensitive as females.* An alternative way to think about this experiment is to predict the effect of another policy that in relative terms is as efficient in decreasing alcohol abuse among males as prices are in reducing problem drinking among females. Figures 27 and 28 depict and compare the dynamics of depression and alcohol abuse prevalence among males and females adding a hypothetical counterfactual scenario, under which some policy managed to instantly decrease the males' probability of problem drinking by about 23.65%, from 13.703% to 10.462%.

The results suggest that depression prevalence in males would be more responsive to the same instant relative decrease of problem drinking prevalence (by 23.65%): a hypothetical effect of such a policy would be an observed decrease in depression prevalence among males from 7.882% to 7.773%, which in relative terms amounts for about 1.4%.

Finally, it is important to highlight that although the effects seem to be of small magnitude, they should not be thought of as negligible, given that they do matter from a country perspective. Back of the envelope calculations suggest that doubling alcohol prices will decrease the amount of disability-adjusted lifeyears by 6.7-6.9% in three year time, which corresponds to 65.000 disability-adjusted lifeyears per year on the country level.

[10]To obtain proper confidence intervals it is necessary to bootstrap the standard errors of the predicted values; given very large computational costs of obtaining results for a single estimation, it was not possible to calculate confidence intervals for the predictions.

Figure 27: Depression prevalence in response to an increase in alcohol prices (by gender), adding a counterfactual for males

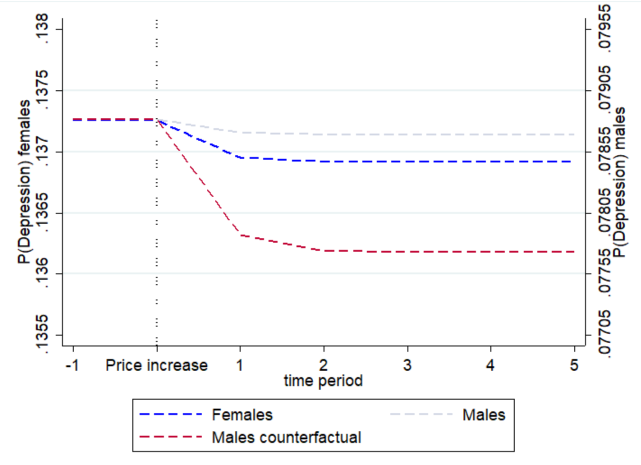
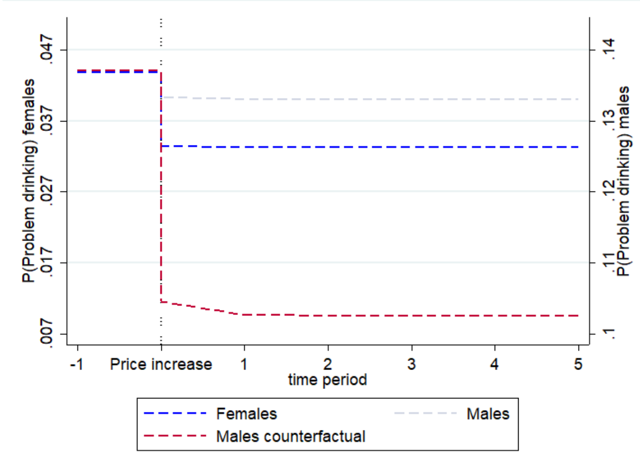


Figure 28: Share of problem drinkers in response to an increase in alcohol prices (by gender), adding a counterfactual for males



9 Conclusions

This paper aims to investigate causal relationship between alcohol abuse and depression using individual-level data from the Russian Longitudinal Monitoring Survey for the years 2011-2016. Having analyzed a range of qualitative and quantitative alcohol consumption variables and their relation with depressed state, we constructed a composite problem-drinking indicator, which loads on frequent binge drinking and consuming alcohol without food. To account for correlation between individual heterogeneity and stochastic shocks in the two dynamically interconnected processes, we adopt a bivariate dynamic correlated random effects probit model, including lags and cross-lags of our variables of interest, contrasting the results obtained with the Wooldridge vs Heckman approach to initial conditions problem.

According to the results, which are quite similar independently of the methodology adopted for the initial conditions, unobserved individual heterogeneity is not only an important determinant of both depression and problem drinking, but is also correlated among them, which implies that individuals with high intrinsic proneness to depression are more prone to alcohol abuse, in line with the literature on social epidemiology and psychology. We find evidence of biderectional causal links between depression and problem drinking in the general population, but the impact of problem drinking on depression is stronger and larger in magnitude than that of depression on alcohol abuse. These interrelations are highly heterogeneous across males and females. We find that dynamic spillover from problem drinking to depression is present in both subpopulations, while the reverse is significant only for females: therefore, we do not find support for the self-medication hypothesis in the males subsample. In addition, our analysis revealed that while the causal effect of alcohol abuse on depression is of the similar magnitude for both males and females, problem drinking state dependence is higher for males. This implies that depression in the male population should be affected by changes in probability of alcohol abuse more than that in the female population. However, estimating the model for male and female subpopulation separately reveals that male alcohol abusers are not price sensitive, which can be explained by the fact that men, as opposed to women, tend to substitute marketed alcohol with moonshine.

Therefore, the outcomes of the policy simulation excersise for the general population, where we predict the dynamics of the two variables in response to a permanent doubling of alcohol prices, are largely driven by the female subpopulation. According to the results, prevalence of depression and problem drinking in the general population decrease by 0.12% and 10.7% respectively if Wooldridge's approach to initial conditions is adopted, and by 0.15% and 11.9% respectively if that of Heckman is used. If only the female subsample (for which the exercise is valid) is considered, these effects amount to 0.25% and 24.16% respectively. In a hypothetical case where some policy manages to achieve the same relative decrease in problem drinking prevalence among males, a potential decline in depression prevalence in the male subpopulation would reach 1.4%. While these figures are small in magnitude, we emphasize that, as shown in Section 6 and in the Appendix, the estimates obtained are the most prudent possible and are likely to underestimate the true effects. In order to improve on this dimension, we intend to extend the model such that it would allow for autocorrelated errors and support unbalanced panels.

These results highlight that policy-makers should consider adopting different policies to tackle alcohol abuse among males and females: while price increases are effective for women, a different policy should be developed to decrease male alcohol abuse. Given that male problem drinking in Russia is a severe threat to public and social health and longevity, our results urge for policies other than taxation and pricing to be adopted. If such a policy package could be developed and be effective in decreasing alcohol abuse prevalence across males, a more profound reduction in depression prevalence will also be observed. Lastly, although the effects of alcohol price increase found in this study might be considered very small, they do matter from a country perspective. Back of the envelope calculations suggest that doubling alcohol prices will decrease the amount of disability-adjusted lifeyears due to depressive and alcohol-induced disorders by 6.7-6.9% in three year time, which corresponds to 65.000 disability-adjusted lifeyears per year on the country level.

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Appendix

A.1 Critical assumptions

To obtain consistent estimates, the following assumptions must hold (notation $D(.)$ denotes "distribution"):

1. The Random Effects assumption: $D(\eta_i|x_i) = D(\eta_i)$, meaning that the heterogeneity term η and other covariates must be fully independent. To make this assumption more plausible, we resort to the Correlated Random Effects framework, which allows η and x to be correlated in a time-invariant fashion, by assuming a parametric model: $E(\eta_i|x_{i1}, x_{i2}...x_{iT}) = \bar{x}_{i.}$, where $\bar{x}_{i.}$ are the means of time-variant covariates. Therefore, the means of time-variant covariates enter the list of regressors, and $D(\eta_i|x_i) = D(\eta_i)$ is relaxed to $D(\eta_i|x_i) = D(\eta_i|\bar{x}_i)$.
2. Strict Exogeneity: $D(y_{it}|x_{i1}, ...x_{iT}, \eta_i) = D(y_{it}|x_{it}, \eta_i)$. This implies that x_{it+h} do not react to unanticipated changes in y_{it}. Is it true for all the covariates that enter the equation? Most likely, no: abusing alcohol or falling into depressed state may result in subsequent family dissolution, job loss, decrease of income, etc. However, note that strict exogeneity is required to hold conditional on the unobserved heterogeneity term η. Given that CRE formulation applies (see previous point), the link between η and $\bar{x}$ is allowed. For example, $\bar{x}$ could be interpreted as individual's "taste" for marriage; then the link between proneness to alcohol abuse and "taste" for marriage is accounted for. Still, it is possible that a shock in y_{it} will result in a change in x_{it+s}. In order to see if this might affect the results, we run a robustness check, estimating the model without those variables which are potentially not strictly exogenous.
3. Dynamic Completeness: $D(y_{it}|x_{it}, y_{it-1}, \eta_i) = D(y_{it}|x_{it}, y_{it-1}, x_{it-1}, y_{it-2}, ..., x_{i1}, y_{i0}, \eta_i)$. This implies that only one lag of y_{it} and only current values of x_{it} are sufficient to capture all the distributional dynamics. In principle, it is possible that some lagged values of x_{it} are also meaningful to include in the specification: e.g. a divorce may be a trigger for depression in the future period. The same logic of CRE partially alleviating this concern applies also for this point.
4. Conditional Independence: conditional on x_{it} and η_i, y_{it} is independent over time. In other words, the errors must be serially uncorrelated. This is a strong assumption and becomes more plausible with the inclusion of the lagged dependent variable.
5. Distributional and Normalization assumptions: for identification it is standard to assume that $\bar{V}_t = 0$, that both time-invariant and stochastic shocks are normally distributed with mean 0, and the latter with $\sigma = 1$.

A.2 Transition probabilities

Table 41: Stylized facts

Panel A: depression and alcohol abuse persistence	
$P(Y_{i,t}^{depr} = 1 \mid Y_{i,t-1}^{depr} = 1)$	44.17
$P(Y_{i,t}^{depr} = 1 \mid Y_{i,t-1}^{depr} = 0)$	7.46
$P(Y_{i,t}^{binge} = 1 \mid Y_{i,t-1}^{binge} = 1)$	32.55
$P(Y_{i,t}^{binge} = 1 \mid Y_{i,t-1}^{binge} = 0)$	6.42
$P(Y_{i,t}^{heavy} = 1 \mid Y_{i,t-1}^{heavy} = 1)$	44.57
$P(Y_{i,t}^{heavy} = 1 \mid Y_{i,t-1}^{heavy} = 0)$	3.28
$P(Y_{i,t}^{freq\_dr} = 1 \mid Y_{i,t-1}^{freq\_dr} = 1)$	47.81
$P(Y_{i,t}^{freq\_dr} = 1 \mid Y_{i,t-1}^{freq\_dr} = 0)$	3.89
$P(Y_{i,t}^{alcnofood} = 1 \mid Y_{i,t-1}^{alcnofood} = 1)$	44.76
$P(Y_{i,t}^{alcnofood} = 1 \mid Y_{i,t-1}^{alcnofood} = 0)$	5.83
$P(Y_{i,t}^{problem\_dr} = 1 \mid Y_{i,t-1}^{problem\_dr} = 1)$	47.22
$P(Y_{i,t}^{problem\_dr} = 1 \mid Y_{i,t-1}^{problem\_dr} = 0)$	5.08
Panel B: Cross-transitions from alcohol abuse to depression	
$P(Y_{i,t}^{depr} = 1 \mid Y_{i,t-1}^{binge} = 1)$	11.79
$P(Y_{i,t}^{depr} = 1 \mid Y_{i,t-1}^{binge} = 0)$	11.4
$P(Y_{i,t}^{depr} = 1 \mid Y_{i,t-1}^{heavy} = 1)$	12.16
$P(Y_{i,t}^{depr} = 1 \mid Y_{i,t-1}^{heavy} = 0)$	11.39
$P(Y_{i,t}^{depr} = 1 \mid Y_{i,t-1}^{freq\_dr} = 1)$	11.97
$P(Y_{i,t}^{depr} = 1 \mid Y_{i,t-1}^{freq\_dr} = 0)$	11.39
$P(Y_{i,t}^{depr} = 1 \mid Y_{i,t-1}^{alcnofood} = 1)$	13.57
$P(Y_{i,t}^{depr} = 1 \mid Y_{i,t-1}^{alcnofood} = 0)$	11.21
$P(Y_{i,t}^{depr} = 1 \mid Y_{i,t-1}^{problem\_dr} = 1)$	13.33
$P(Y_{i,t}^{depr} = 1 \mid Y_{i,t-1}^{problem\_dr} = 0)$	11.17
Panel C: Cross-transitions from depression to alcohol abuse	
$P(Y_{i,t}^{binge} = 1 \mid Y_{i,t-1}^{depr} = 1)$	9.83
$P(Y_{i,t}^{binge} = 1 \mid Y_{i,t-1}^{depr} = 0)$	8.64
$P(Y_{i,t}^{heavy} = 1 \mid Y_{i,t-1}^{depr} = 1)$	5.47
$P(Y_{i,t}^{heavy} = 1 \mid Y_{i,t-1}^{depr} = 0)$	5.84
$P(Y_{i,t}^{freq\_dr} = 1 \mid Y_{i,t-1}^{depr} = 1)$	6.81
$P(Y_{i,t}^{freq\_dr} = 1 \mid Y_{i,t-1}^{depr} = 0)$	7.34
$P(Y_{i,t}^{alcnofood} = 1 \mid Y_{i,t-1}^{depr} = 1)$	11.54
$P(Y_{i,t}^{alcnofood} = 1 \mid Y_{i,t-1}^{depr} = 0)$	9.7
$P(Y_{i,t}^{problem\_dr} = 1 \mid Y_{i,t-1}^{depr} = 1)$	9.61
$P(Y_{i,t}^{problem\_dr} = 1 \mid Y_{i,t-1}^{depr} = 0)$	8.98

A.3 Substitution with moonshine

In order to find out why male problem drinkers are not price sensitive, we study the relationship between moonshine (homemade liquor) consumption and alcohol prices by estimating an equation of the form:

$$grams\_moon_{it} = \alpha_i + \beta_j price_{jt} + \gamma X_{it} + \delta_t,$$

separately for male and female subsamples. Here $price_{jt}$ are real prices for j-th of the three most common alcohol drinks: vodka, beer, table wine; and the weighted by alcohol content price of all available alcohol drinks (the price variable used in baseline models). Other variables include: individual fixed effect (α_i), year fixed effect (δ_t), and socio-demographic controls (X_{it}). As appears from Table 42, for male subpopulation moonshine consumption is in positive relationship with prices for marketed alcohol. Therefore, we conclude that males are willingly substituting marketed alcohol with homemade alternative. In contrast, it is not the case for female subpopulation. These results provide an explanation for male problem drinkers being price-insensitive, as opposed to their female counterparts.

Table 42: Moonshine consumption and alcohol prices

	Males				Females			
$Price_{vodka}$	2.823**				0.226			
	(1.227)				(0.420)			
$Price_{beer}$		12.107**				-0.748		
		(5.749)				(1.077)		
$Price_{wine}$			1.693				-0.076	
			(1.178)				(0.240)	
$weighted$				1.448**				-0.152
				(0.717)				(0.206)
Soc.-dem. cont.	✓	✓	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs	12145	12145	12145	12145	18900	18900	18900	18900
Nclust	2429	2429	2429	2429	3780	3780	3780	3780

The dependent variable is grams of moonshine typically consumed on a drinking day in the last 30 days prior to the interview. Prices of alcohol beverages are in real terms. The sample used is the same balanced sample employed in the baseline analysis. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

A.4 Discussion on attrition

A very important point deserving discussion is the impact of attrition bias on our results. Adopting a model with initial condition a-la Wooldridge requires a balanced sample; however, it is very likely that participants who drop out of the sample are more prone to both depression and alcohol abuse. To have an idea about how severely attrition could have altered our conclusions, we conduct a following check: assuming exogenous initial conditions, estimate univariate correlated random effects probit model for depression and problem drinking on the full sample and the balanced one.

Table 43: Univariate estimation with exogenous initial conditions
(full vs balanced sample)

	Full		Balanced	
	depr	problem_dr	depr	problem_dr
$depr_{t-1}$	0.909***	0.109***	0.577***	0.135***
	(0.028)	(0.031)	(0.042)	(0.050)
$problem\_dr_{t-1}$	0.120***	0.864***	0.163***	0.484***
	(0.030)	(0.037)	(0.045)	(0.051)
Soc.-dem. controls	✓	✓	✓	✓
CRE controls	✓	✓	✓	✓
constant	-2.021***	-2.725***	-2.106***	-2.688***
	(0.081)	(0.215)	(0.161)	(0.215)
σ	0.62	0.65	0.83	0.96
ω	0.28	0.30	0.41	0.47
NT	62820	62820	31085	31085
N	19711	19711	6217	6217

The variables used are described in Table 26. Initial conditions are treated as exogenous. In the framework of the CRE approach, the means of *smokes*, *lowincome* and *married* are also included in the equations. σ stands for the estimated parameter of the standard deviation of the heterogeneity term; ω is a ratio $\frac{\sigma^2}{\sigma^2+1}$ and represents the relevant correlation parameters of the time-invariant and time-variant heterogeneity components respectively. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

First, note that results for balanced sample will differ from those obtained in the first two columns of Table 31 due to a different treatment of initial conditions. Taking initial conditions as exogenous should lead to an upward bias of state dependence and cross-effects. Therefore, we will compare the results of correlated random effects probit with exogenous initial conditions obtained on a full sample versus the balanced one, and assume that the revealed difference will pertain independently of the model type (univariate, bivariate, with initial conditions a-la Wooldridge or a-la Heckman).

The estimation output is presented in Table 43. Structural parameters are indeed different among subsamples, and unobserved heterogeneity accounts for a larger share of variance in the balanced sample than in the unbalanced one. To obtain a more rigorous evidence, average partial effects were also calculated. As appears from Table 44, estimated level of state dependence is about two times higher in the unbalanced sample. The cross-spillover effects, however, are of similar magnitude. Therefore, our results are likely to understate the true effects, thus being a prudent estimate.

Table 44: APEs of lags and cross-lags
(in percentage points) for full and balanced sample

Full	depr	problem_dr
$depr_{t-1}$	18	1.2
$problem\_dr_{t-1}$	1.8	13

Balanced	depr	problem_dr
$depr_{t-1}$	9.5	1.3
$problem\_dr_{t-1}$	2.3	5.2

A.5 Autocorrelated errors

One of the crucial assumptions outlined in A.1 is conditional independence, implying that errors must be serially uncorrelated in order to obtain consistent estimates. For the moment we do not incorporate autocorrelated errors in the bivariate model, but instead do a simple check to understand whether and to which extent ignoring this issue biases the resulting estimate by estimating univariate equations in (25), accounting for autocorrelation in the error terms as in (28):

$$\begin{cases} D_{it} = \mathbb{I}\{\gamma^d D_{it-1} + \delta^d A_{it-1} + X_{it}\beta^d + \bar{X}_{i.}\theta^d + \eta_i^d + \xi_{it}^d > 0\} \\ A_{it} = \mathbb{I}\{\gamma^a A_{it-1} + \delta^a D_{it-1} + Z_{it}\beta^a + \bar{Z}_{i.}\theta^a + \eta_i^a + \xi_{it}^a > 0\} \end{cases} \tag{25}$$

$$D_{i0} = \mathbb{I}\{X_{i0}\beta_0^d + \nu_d^d\eta_i^d + \xi_{i0}^d > 0\}, \tag{26}$$

$$A_{i0} = \mathbb{I}\{Z_{i0}\beta_0^a + \nu_a^a\eta_i^a + \xi_{i0}^a > 0\} \tag{27}$$

$$\xi_{it}^j = \rho_j\xi_{it-1}^j + u_{it}^j, j = a, d \tag{28}$$

Table 45 contains estimation results. An alarming sign would be if we found a positive and significant autocorrelation parameter ρ, as it would lead to an upward bias of the structural parameters of interest. However, this is not the case. For depression variable the autocorrelation parameter is *negative*, which, in fact, suggests that our estimate is biased downwards, whereas in the problem drinking equation ρ turned out to be insignificant at all conventional significance levels (z-test p-value = 0.7), and the state dependence parameter now lost significance, which is another indicator of misspecification. Therefore, we conclude that error terms for alcohol abuse equation do not exhibit autocorrelation, while negative autocorrelation in the depression equation suggests that our estimate of state dependence is a prudent one.

Table 45: Univariate equations with autocorrelated errors

	depr	problem_dr
$depr_{t-1}$	0.624***	0.109**
	(0.105)	(0.051)
$problem\_dr_{t-1}$	0.152***	0.285
	(0.047)	(0.175)
Soc.-dem. controls	✓	✓
CRE controls	✓	✓
constant	-2.105***	-2.858***
	(0.164)	(0.237)
σ_{η^j}	0.85***	1.09***
ρ_j	-0.12**	-0.04
NT	37146	37146
N	6191	6191

The variables used are described in Table 2. Initial conditions are accounted for by specifying conditional densities for the initial values (Heckman solution). In the framework of the CRE approach, the means of *smokes*, *lowincome* and *married* are also included in the equations. σ_η stands for the estimated parameter of the standard deviation of the heterogeneity term; ρ_j corresponds to the estimated AR(1) parameters of the error terms ξ. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.