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Peer Effects in Alcohol Consumption: Evidence from Russia's Beer Boom

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Abstract: Starting around 1996, Russia witnessed a strong growth in beer consumption, leading to a fivefold growth in average beer consumption and making beer the most important alcoholic drink today. We use survey data from the Russian Longitudinal Monitoring Survey (RLMS) to analyze individual determinants of beer drinking. Using both lagged and simultaneous measures to establish lower and upper bounds on the peer effect, we show that the decision to drink beer is strongly influenced by the average behavior of the individual's peer group. We find that this peer effect may account for one-third to one-half of the rise of beer in Russia.

Keywords: peer effects, Russia, alcohol, beer consumption, dynamic linear probability model

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1. Introduction

In many contexts, individual choices depend on the behavior of peers. An extensive empirical literature has documented such peer effects in a variety of settings, including investment decisions among university professors (Duflo and Saez, 2002), crime rates (Glaeser et al., 1996), adolescent overweight (Trogdon et al., 2008) and academic performance among university students (Sacerdote, 2001).[2] The existence of peer effects is important for policy-makers because it implies a social multiplier (Glaeser et al., 2003). An exogenous shock or a policy measure will not only change some individual's behavior directly, it will also indirectly affect the behavior of their peers. Therefore, knowledge of the existence and magnitude of peer effects is essential in order to evaluate the effects of exogenous shocks or policy interventions. In particular, peer effects have been documented in health contexts, e.g. for obesity (Blanchflower et al., 2009; Christakis and Fowler 2007) and for cigarette and alcohol use (Ali and Dwyer, 2010; Christakis and Fowler, 2008, 2010; Kremer and Levy, 2008).

This paper studies the role of peer effects in the rapid adoption of beer as the dominant alcoholic beverage in Russia. Until recently, beer consumption in Russia was negligible. However, in recent years beer consumption has grown spectacularly. Between 1996 and 2007, beer consumption in Russia more than quintupled, from 15 liters per capita to 80 liters per capita. As a result, Russia is now the third largest beer market in the world, accounting for 6% of global beer production and consumption. Both in volume and value, beer is now the most important alcoholic drink in Russia. We document the rapid growth in beer consumption and show that it is not the result of existing consumers drinking larger quantities. Rather, the rise of beer is due to a larger number of people turning to beer. For an understanding of the Russian beer boom, it is

[2] For a popular introduction to the wide literature on peer effects and social interactions, see Christakis and Fowler (2009).

thus necessary to study the individual decision to drink beer or not. Using data from the Russian Longitudinal Monitoring Survey, we analyze the determinants of this choice. Our results indicate that peer effects played a central role in persuading consumers to start drinking beer. In contrast, changes in prices and incomes seem to have played only a minor role. Understanding patterns of alcohol consumption behaviors is especially important in the case of Russia, where alcoholism is a major public health problem and alcohol is thought to be the cause of approximately one-quarter of all deaths (Brainerd and Cutler, 2005; Nemtsov, 2002; Treisman, 2010). Studying the determinants of alcohol consumption patterns is necessary in order to arrive at effective policy interventions to limit the negative health impacts of alcohol abuse.

The remainder of the paper is structured as follows. The next section discusses the extraordinary growth of beer consumption in Russia since the mid-1990s and shows that the rise of beer is the result of larger numbers of beer drinkers, not of higher consumption per beer drinker. The third section discusses our methodology and dataset. Our empirical analysis is presented in the fourth section. We interpret the magnitude of our estimated peer effects in the fifth section, and the sixth section concludes.

2. The Russian Beer Boom

For more than thirty years, from the 1960s through the 1980s and the early 1990s, per capita beer consumption in the Soviet Union and Russia fluctuated between 15 and 25 liters per capita – considerably lower than in the rest of Europe. However, since the mid-1990s consumption has increased dramatically (**Figure 1**). Between 1996 and 2007 beer consumption grew from 15 liters per capita to around 80 liters. Consumption levels are now at a level similar to the EU average, and Russia has become the world’s third largest beer market, after China and the US but ahead of Germany, the UK or Brazil (Colen and Swinnen 2011).

These developments are remarkable given the fact that Russia was traditionally a spirits-drinking country. Using data from the Russian Longitudinal Monitoring Survey (RLMS), introduced in more detail below, **Error! Reference source not found.** shows that as recently as 1994, 77% of Russians identified themselves as vodka-drinkers whereas only 28% reported drinking beer. However, by 2001, the proportion of beer drinkers (60%) had overtaken the share of vodka drinkers (57%). Between 1994 and 2007 the share of beer in total alcohol consumption increased from 51% to 79%, while the share of vodka decreased from 39% to 13% (Treml 1997; Euromonitor 2010b). Beer has also become the most popular drink in terms of money spent, occupying almost half of total sales in the alcoholic beverages market (Euromonitor 2010a). After its remarkable rise in past years, beer is now the dominant alcoholic drink in Russia.

Increased aggregate beer consumption is driven by growth in the number of beer drinkers rather than growth in individual consumption levels. Figure 2, based on **Error! Reference source not found.**, shows the fraction of beer drinkers and vodka drinkers over time.[3] The fraction of beer drinkers increased from roughly 30% in 1994 to more than 60% in 2008, while the fraction of vodka drinkers fell from more than 75% to less than 60%. On the other hand, Figure 3 shows self-reported monthly consumption volumes of beer over time together with the median level of consumption reported.[4] Although these numbers should be treated with caution because of possible underreporting, there is no evidence of an upward trend in quantities consumed per drinker. The median reported intake remains constant at 2.5 liters of beer per month per beer drinker. Hence, the Russian beer boom seems to be driven by changes on the extensive margin (more people turning to beer) rather than changes on the intensive margin (beer drinkers consuming larger quantities).

[3] These fractions have been calculated using the sampling weights provided by the RLMS.
[4] This variable is computed by multiplying a survey question on the quantity normally consumed "per occasion" with a question on the normal number of days in a month the respondent drank alcohol.

The adoption of beer among Russian consumers is widespread and not limited to a specific gender, region or age group. Figure 4 shows the fraction of beer drinkers among men and women over time. While the fraction of female beer drinkers is always about 20 percentage points lower than the fraction of male beer drinkers, both show a similar trend over time. Thus, the increase in beer drinking is not limited to men only.

Figure 5 shows the fraction of beer drinkers in eight Russian regions over time. In a country as dispersed as Russia, it seems reasonable to expect large variations in consumption patterns between different regions. Surprisingly, however, the regional fraction of beer drinkers follows the same pattern everywhere. Even though at any point in time there is considerable variation across regions, all regions experienced an upward trend in the number of beer drinkers. In 1994, for instance, the fraction of beer drinkers varied from somewhat less than 20% in the Volga-Vyatski and Volga region to around 35% in the Moscow and St. Petersburg region. In 2001, the regional fraction of beer drinkers varies between some 50% (Volga-Vyatski and Volga) and almost 70% (Ural). From 2001 onwards, regional averages remain within this band, although there is some variation over time.

Likewise, the spread of beer is not limited to a single age group. Figure 6 shows the fraction of beer drinkers by birth cohort over time, where we have divided the sample into those born before 1940, those born between 1941 and 1960, those born between 1961 and 1980, and those born after 1980.[5] The fraction of beer drinkers in each younger cohort is at least ten percentage points higher than in the preceding birth cohort. Yet, apart from this level effect, there is a strong increase in beer consumption among all cohorts. In the pre-1940 cohort, the fraction of beer drinkers increases from around 10% in the mid-1990s to more than 30% in 2003.

[5] The results for the post-1980 cohort are only reported from 2001 onwards. The median age of this cohort increases steadily from 17 years in 2001 to around 21 years at the end of the period. Our analysis only includes respondents age 15 or older.

Although there is some decline afterwards, the fraction of beer drinkers in the oldest cohort remains above 20%, or twice the level of the mid-1990s. A similar increase is present among the pre-1960 and pre-1980 cohorts.

As these graphs make clear, the spectacular growth in beer consumption in Russia is the result of an increase in the number of beer drinkers, and not in their average intake levels. Moreover, the rising popularity of beer is not confined to men only, or to a specific region or age group. These findings suggest that an individual-level analysis of the decision to drink beer is needed in order to explain the rise of beer in Russia.

3. Methodology and Data

To study the determinants of beer consumption in Russia, we estimate a linear probability model for beer drinking with a measure of peer behavior as one of the explanatory variables. Estimation of peer effects poses some well-known difficulties. Therefore, we first discuss issues related to the identification of peer effects and the strategy adopted here. Next, we discuss econometric issues related to the inclusion of a lagged dependent variable in order to capture possible habit formation. Finally, we present our dataset and the definition of variables used in our analysis.

3.1 Identification of Peer Effects

Identifying the role of social interactions on individual behavior is far from trivial. As emphasized by Manski (1993), an observed correlation between peer behavior and individual behavior may be due to three reasons (Table 2). First, the correlation may indeed be the result of peer *choices* influencing individual behavior (which Manski labeled *endogenous effects*); these constitute the peer effects we are most interested in. However, the correlation may also be due to common shocks (groups of consumers experiencing the same price shocks, for instance) or nonrandom selection of peers (people with similar preferences may seek each other's company, thus creating a false impression of peer effects). Manski referred to this as *correlated effects*. Third, the correlation may be the result of group *characteristics* (such as the average income or education level in the peer group) influencing individual behavior, which Manski called *contextual effects*. Disentangling these three effects is a major concern in the literature on social interactions (Manski, 1993; Brock and Durlauf, 2007). The importance of addressing these issues is shown by Cohen-Cole and Fletcher (2008) who demonstrate that it is possible to find 'peer effects' for acne, height and headaches – phenomena where peer effects seem highly unlikely – if group characteristics are not included or selection issues are not properly taken into account.

The strategy adopted in this paper is to use both a simultaneous and a lagged measure of peer behavior, providing an upper bound and a lower bound on the peer effect. Our lagged measure in particular mitigates the risk of common shocks driving the results. In addition, we use time dummies in all specifications in order to capture nation-wide shocks. Our measures of peer behavior are based on an exogenous definition of the peer group which avoids selection issues. To disentangle the influence of group behavior and group characteristics, we include group-level averages of all individual covariates. Moreover, we control for additional group-level characteristics and our specifications include individual fixed effects (which also capture any group-level fixed effects).

Our two measures of peer behavior are the simultaneous and lagged fraction of beer drinkers in the peer group. A simultaneous measure will tend to pick up unobserved transitory shocks affecting all members of the peer group at the same time (common shocks), giving the false impression of a peer effect (or overstating the true extent of the peer effect). Hence, simultaneous measures of peer behavior may lead to upward biased estimates of the peer effect.

For this reason, it would seem appropriate to use lagged peer behavior.[6] On the other hand, the use of lagged peer behavior may lead to an underestimate of the true size of the peer effect. In our dataset, based on yearly observations, the use of lagged peer behavior implicitly assumes that individuals update their expectations of peers' behavior with a one-year lag. It seems reasonable that belief updating is faster in reality, in which case our lagged measure is not an accurate proxy for individuals' beliefs about peer behavior. In addition, as the RLMS dataset does not contain data for 1997 and 1999, the lagged measures used as explanatory variables for 1998 and 2000 are based on behavior observed two years earlier. Our lagged measure thus captures peer behavior with considerable measurement error, which leads to attenuation bias. Hence, while the simultaneous measure of peer behavior may lead to an upward bias in our estimates of the peer effect, the lagged measure may lead to a downward bias. For this reason, we perform our empirical analysis using both measures, establishing an upper bound and a lower bound on the actual peer effects.

The problem of non-random selection of peers is avoided by taking a definition of the peer group that is exogenous to individuals' preferences for beer. In our analyses, we define an individual's peer group based on location, defined by the sites included in the RLMS survey. As argued by Yakovlev (2012), a large part of the population in Russia lives in a complex of multi-story apartment buildings known as a "dvor". These complexes often have common playgrounds and recreational fields and serve as the center of social life for most inhabitants. As Yakovlev (2012) notes, the RLMS definition of a site typically contains only few dvors, which implies that the location-based definition of peers used here captures the relevant peer group.

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[6] In addition, we may prefer lagged peer behavior over simultaneous peer behavior on theoretical grounds. In settings with peer effects, multiple equilibria are possible. Dependence on simultaneous peer behavior would then imply that all individuals have perfect information on the preference distribution of the peer group *and* use the same equilibrium selection rule to coordinate on one of the multiple equilibria (Brock and Durlauf, 2001). These seem rather strong assumptions. By contrast, it is more natural to assume people have adaptive expectations, basing their estimates of peer behavior on observed peer behavior in the recent past.

Thus, our empirical strategy provides lower-bound and upper-bound estimates of the peer effect using an exogenous definition of the peer group and controlling for peer group characteristics, unobserved individual (and hence also group-level) fixed effects, and common (nationwide) shocks.

A separate problem highlighted by Manski (1993) is the 'reflection problem'. In a linear model, the explanatory variable of interest (the average behavior of the group) is itself a linear function of the other explanatory variables (group-level characteristics and the group-level average of individual characteristics). This causes the regressors to be linearly dependent, and no identification is possible. However, this particular problem only occurs with linear models (e.g. a regression of individual weight or BMI on group-level averages to measure contagion in obesity). With non-linear models, the average behavior of the group cannot be a linear function of the other regressors, and the reflection problem disappears (Blume and Durlauf, 2005). We note here that using a linear probability model to analyze a binary choice does not give rise to this reflection problem. What causes the reflection problem is the linear dependence of the average group *behavior* on the other covariates. In the case of binary choice, there is no such linear dependence, and the reflection problem does not arise. A linear probability model assumes a linear relationship between the *probability* and the covariates, but it does not imply a linear relationship between actual behavior and covariates, and thus avoids the reflection problem.[7]

3.2 Habit formation

The individual decision to drink beer is likely to be influenced both by unobserved individual tastes and attitudes and by previous experiences. For this reason, we would like to control for

[7] To see this, suppose that for an individual some covariate (e.g. income) increases, thus increasing his individual probability from 0.2 to 0.4. Since this does not change his behavior, there is no linear dependence of group behavior on the group-level average of covariates. However, this example does not depend on the specific form of the probability model; thus, linear probability models also avoid the reflection problem.

past consumption behavior in our estimations. However, the combination of unobserved heterogeneity and state dependence leads to a number of well-known econometric difficulties (we refer to the appendix for a discussion). In order to avoid these issues, we opt to perform our empirical analysis using a linear probability model with a lagged dependent variable, which we estimate using standard dynamic panel data techniques (i.e. dynamic GMM). This approach has the advantage that it allows us to control for both individual fixed effects and state dependence in a computationally easy way and with a minimum of extra assumptions on the data-generating process.

In a dynamic linear probability model, the probability of a positive outcome is assumed to be a linear function of the lagged dependent variable, observable covariates and an individual-level (unobserved) fixed effect. The model is treated as a regular dynamic panel data model using dynamic GMM (Arellano and Bond, 1991; Arellano and Bover, 1995). By using a suitable transform (most commonly first-differencing) the fixed effect is removed. However, this step introduces endogeneity into the model, as the first-differenced lagged dependent variable will be correlated with the first-differenced error term. This endogeneity is then addressed by using lags of the dependent variable as instruments, and the model is estimated using GMM. In our specific case, we use the forward orthogonal deviation transform developed by Arellano and Bover (1995) instead of first differencing because of the unbalanced nature of our panel. In an unbalanced panel, first differencing leads to a cascade of missing values. By contrast, instead of subtracting the previous period values, the forward orthogonal deviation subtracts the average of all *available* future values. In a balanced panel, this approach is numerically identical to first differencing, but in an unbalanced panel this approach improves efficiency by avoiding the loss of information inherent in first differencing (Roodman, 2009). The dynamic linear probability approach has been used by Bernard and Jensen (2004) in their analysis of firm entry into exporting and by Chay and Hyslop (1998), who use it as a robustness check for their nonlinear models and conclude that this approach provides an attractive alternative to more complicated methods.

3.3 Data and Variables

The data used in our analysis is the Russian Longitudinal Monitoring Survey (RLMS).[8] The RLMS is a nationally representative survey organized annually since 1992 (except in 1997 and 1999), covering a large number of respondents (typically more than 8,000 per round) and providing valuable information on all aspects of life in Russia. Our analysis uses rounds 5 to 17, spanning the years 1994-2008. Following common practice, we do not use earlier rounds due to concerns about data quality. We focus on individuals age 15 or older. The dataset covers 171 communities (sites) across Russia, divided among eight regions (Moscow and St. Petersburg, Northern and Northwestern, Central and Central Black-Earth, Volga-Vyatski and Volga, North Caucasian, Ural, Western Siberian, and Eastern Siberian and Far Eastern).[9] Around three quarters of the sample lives in an urban setting. Some 43% of our respondents are male. Depending on the specification used, our sample varies between 6,000 and 16,000 individuals and between 25,000 and 57,000 observations (N x T). Summary statistics of our variables are presented in Table 3.

Our outcome variable is an indicator equal to one if the individual drank beer in the 30 days preceding the interview. In some specifications, we include a similar variable for vodka consumption. Our dataset includes three variables related to prices of alcoholic beverages. The real price of beer is based on the community-level price data included in the RLMS. In each

[8]The RLMS is organized by the Carolina Population Center at the University of Carolina (Chapel Hill) and by the Higher School of Economics in Moscow. More information regarding the survey can be found at www.cpc.unc.edu/projects/rlms-hse.
[9] A map of the villages and regions can be found at the RLMS website.

community surveyed, the lowest and highest prices for several consumption goods were recorded. We use the lowest price recorded as our measure for the prices of beer and vodka.[10] Real prices are calculated using CPI data for Russia taken from the World Development Indicators (World Bank, 2012), using the CPI of 1995 as benchmark. We also compute the relative price of beer versus vodka at the community level, defined as the price of beer divided by the price of vodka.

As individual covariates, we use age, gender, personal income, educational status, employment status, marital status, and television ownership. Our personal income variable is the log of real income. This variable is constructed using the real value of household expenditures (calculated by the RLMS). The value of household expenditures has been divided by the square root of household size to arrive at equivalent income at the individual level. Taking the logarithm of this value then gives us our income measure. The RLMS contains several variables on educational status. We construct an indicator variable equal to one if the individual has followed some extra education (be it a professional course, a technical training, a university degree or similar programs). Including separate indicators for different educational levels leaves the fundamental results unchanged while giving little information on the effects of different education levels. As our measure for employment status, we use an indicator equal to one if the individual is unemployed. Likewise, marital status is measured by an indicator equal to one if the individual is married. We include an indicator variable for TV ownership as a measure of exposure to commercials.

[10] Alternatively, it is possible to compute prices from household level data on purchases of goods, which are both recorded in quantities and in total expenses. However, in general there is a lot of noise in these data since both quantities and expenses may be measured with error. We use the minimum price at the community level, since this variable has the best correlation with household level prices. The highest recorded price is less informative, because the most expensive brand may be an outlier. This is less of an issue if we use the lowest price since this price is bounded from below.

Based on the community-level information included in the RLMS, we construct several indicator variables representing whether the community can receive TV signals, whether the community has access to cable TV, and whether there are movie theaters and video halls. We also include as variables the number of restaurants and cafeterias. In addition, we include community-level averages of individual covariates.

4. Empirical Results

4.1 Baseline Estimates

The first column of Table 4 presents a baseline estimate without peer effects. As covariates we use the full set of individual-level controls, the community-level averages of these individual characteristics, and time dummies. All standard errors are clustered at the community level. There is evidence of a moderate income effect, with a 1% increase in income translating into an increase of around one percentage point in the probability of drinking beer. The coefficients on the three price variables are not significantly different from zero and small in absolute terms. We find a negative effect of drinking vodka, which reduces the likelihood of drinking beer with almost nine percentage points.[11] The likelihood of drinking beer decreases in age. Combining the linear and quadratic effect of age implies that the extra effect of age is zero at age 19. Compared to this baseline, an individual aged 40 is almost 14 percentage points less likely to drink beer; someone 50 years old is 26 percentage points less likely, and at age 60 the negative effect of age is minus 41 percentage points. Thus, there seems to be a strong negative effect of age. None of the other covariates seem to play an important role in explaining beer drinking. There is, however, strong evidence for a time trend. Using 1995 as the baseline year, the time dummies

[11] Clearly, the decision to drink beer and the decision to drink vodka are not taken independently, and hence this variable may be endogenous. However, repeating our analysis without the indicator for vodka consumption leaves our results basically unchanged. (These results are not reported here but are available from the authors upon request.)

clearly pick up the upward trend in beer drinking, with individuals in 1996 having a two percentage points higher likelihood of drinking beer, all the way up to a 35% points higher probability near the end of our sample period. As this baseline estimate shows, the rapid increase in beer consumption in Russia cannot be explained solely by prices and income changes.

4.2 Peer Effects

In the second column of Table 4, we add our "lower bound" measure of peer effects (the lagged fraction of other people in the community drinking beer) as a covariate. This coefficient is strongly significant and relatively large: compared to a community where nobody is drinking beer, living in a community where everybody is drinking beer increases the individual likelihood of beer-drinking with 17 percentage points. The coefficients of the other covariates do not change noticeably after including the peer effect: there is still evidence of a negative effect of age, a modest income effect and a negative impact of vodka drinking, but no evidence of an impact of prices. However, the coefficients of the year dummies have declined in magnitude, indicating that the peer effect indeed accounts for part of the observed increase in beer consumption.

The third column of Table 4 uses our simultaneous measure of peer behavior to establish an upper bound on the peer effect. This coefficient is considerably larger than our lower bound estimate and implies that compared to a community where nobody drinks beer, living in a community where everyone drinks beer increases the individual likelihood of drinking beer with 45 percentage points. As in the second column, other coefficients do not change noticeably with respect to the baseline estimate, with the exception of the time dummies. Compared to the baseline estimate, inclusion of the simultaneous measure of peer behavior decreases the magnitude of the time dummies by half, again indicating that peer effects explain a large part of the evolution of beer consumption over time.

In the fourth and fifth column, we add extra covariates accounting for time-variant community characteristics. We add a measure of vodka consumption among peers similar to our measure of beer consumption. Moreover, to control for the possibility that "supply-side" factors drive our results, we include as variables the number of cafeterias and the number of restaurants in the community. In order to capture the effect of advertising, we include indicator variables for whether there is a movie theatre or a video hall in the community, whether the community has TV reception, and whether it has cable access.

Using our lagged measure of peer behavior, the dummy for TV reception is large and significant, indicating that if a community is able to receive TV signals, the individual likelihood of drinking beer increases by thirteen percentage points. None of the other variables seem to play a role. The coefficient on peer behavior decreases somewhat in magnitude (to 0.14), although it is still large and significant. When using the simultaneous measure of peer behavior, none of the extra community-level variables play a role. The coefficient on peer behavior remains practically unchanged at 0.44. The dummy for TV reception is negligible in this case. Hence, there is some evidence that TV reception plays a role, although in any case this cannot explain away the observed peer effect.[12]

4.3 Habit Formation

In order to account for the possibility of habit formation, we next turn to including a lagged dependent variable in our regression. As discussed in the previous section, the combination of

[12] Similar results (not reported here) are obtained if we include an indicator for whether there is a fastfood restaurant in the community.

fixed effects and a lagged dependent variable introduces endogeneity into the model, biasing not only the lagged dependent variable but the estimates of the other coefficients as well. A dynamic GMM estimation is needed to arrive at consistent estimates. However, it is possible to get a first idea of the magnitude of state dependence using simpler techniques. If a lagged dependent variable is used in a panel context, pooled OLS has an upward bias, while a fixed-effects estimation has a downward bias (Roodman, 2009). Thus, the correct coefficient on the lagged dependent variable must lie between the lower bound provided by the fixed-effects estimate (presented in the first column of Table 5**Table 5**) and the upper bound provided by the OLS estimate (second column of Table 5). Based on these estimates, we see that drinking beer in the previous period has an effect on beer-drinking today of somewhere between a decrease of the likelihood with 5 percentage points and an increase with 35 percentage points.

Table 6 presents our GMM estimates using the lagged measure of peer effects. As explained in the previous section, we use the Arellano-Bond estimator with a forward orthogonal deviations transform. All specifications are estimated using two-step GMM with Windmeijer-corrected standard errors (Windmeijer, 2005; Roodman, 2009). The different columns report specifications using different lags as instruments; thus, column (1) reports the specification using lag 1 and higher, while column (2) reports results using lag 2 and higher, and so on.

Based on the diagnostic tests for autocorrelation, we reject the specifications in the first two columns. The Arellano-Bond estimator relies on the use of lagged levels of the endogenous variable as an instrument for the transformed endogenous variable. However, this depends on the assumption of no autocorrelation in the error term (apart from that induced by the presence of fixed effects). More specifically, there should be no autocorrelation of order 2 in the differenced errors.[13] The Arellano-Bond test for autocorrelation, assuming a null of no autocorrelation, is reported at the bottom of Table 6. The hypothesis of no autocorrelation is rejected at all conventional significance levels for columns (1) and (2). Moreover, the Hansen test indicates that instruments are not valid.[14]

The results in columns (3), (4) and (5) are comparable; all three indicate that after controlling for habit formation there is evidence of a peer effect while, in fact, habit formation is not significantly different from zero. The three specifications pass the test for no autocorrelation of degree 2 in differenced residuals. However, for columns (3) and (4) (using lags 3 and higher, and using lags 4 and higher respectively), the Hansen test indicates that instruments may not be valid. The specification in column (5) passes all diagnostic tests. Although using lags 5 and higher may lead to a considerable loss of information, estimates are comparable with those in column (3) and (4). In columns (3) to (5), the coefficient on lagged peer behavior varies between 0.12 and 0.26, comparable in size to our earlier results (0.14 to 0.17, see Table 4). Results indicate that the income effect is around 2% (that is, a one percent increase in income increases the likelihood of beer-drinking with two percentage points). The coefficient on vodka-drinking is similar to that in earlier specifications. Again, with the exception of the time dummies and a negative concave effect of age, none of the other variables appear to play a role.

Table 7 reports similar GMM results using our simultaneous measure of peer behavior. Our estimate of the peer effect is remarkably robust across specifications. Again, diagnostic tests

[13] In difference GMM, the difference transform induces serial correlation of order 1 in the first-differenced errors. Hence, to check for serial correlation in *levels*, one needs to check for second-order serial correlation in *differences*. For the case of orthogonal deviations considered here, the transform induces correlation of all orders in the transformed errors. Hence, even for the orthogonal deviations case, the test is run on differenced residuals (Roodman, 2009).

[14] In addition to being rejected on the grounds of correlation in the error terms, our specification in column (2) gives a coefficient for the lagged dependent variable which is outside the interval established by our OLS and FE estimates.

reject the first two specifications. The Hansen test indicates that instruments may not be valid in column (3) and (4), while column (5) (using lags 5 and earlier) passes all diagnostic tests. In columns (3) to (5), estimates are similar (with the exception of the coefficient on habit formation, which changes sign but which is not significant in any of the three models). In these specifications, our peer effect is estimated to be between 0.44 and 0.48. Again, the income effect is around 2%, vodka-drinking reduces the likelihood of beer-drinking with around 8 percentage points, and there is a negative effect of age, consistent with earlier specifications. Our GMM estimates thus show little evidence for habit formation while leaving our results on the role of peer effects and other covariates basically unchanged.

4.4 Robustness Checks

In Table 8 we present a number of robustness checks. In column (1) and (2), we restrict our sample to those communities for which we have at least 30 observations to compute the average behavior of the peer group. Our estimated peer effect in both cases increases. Thus, it seems likely that our findings are not driven by outliers (caused by peer behavior computed from a small number of observations). Rather, our measures of the peer effect are valid, but the measurement error when less than 30 observations are used leads to an attenuation bias.

One concern with the previous specifications may be that the identification of the peer effect is entirely due to data from the second half of our observation period. In that case, our results would not be able to shed light on the strong increase in beer consumption in Russia between 1995 and 2002. To address this, we split the sample into two time periods. Columns (3) and (4) present results for the period 1995-2002 (when the growth in beer consumption was strongest), while columns (5) and (6) present results for the period 2003-2008 (during which beer consumption remained roughly stable). Our simultaneous measure of peer effects does not differ markedly between the two periods. Our lagged measure of peer effects differs between the two periods, but is larger in the first period (0.14) than in the second period (0.05), in which case it is no longer statistically significant. Thus, peer effects indeed seem to have been at work between 1995 and 2002.

5. Discussion

Our empirical analysis points to the existence of a robust and important peer effect in beer consumption in Russia. The lower bound of this peer effect, given by our lagged measure of peer behavior, varies between 0.14 and 0.26 in different specifications on our full sample. The upper bound of the peer effect, given by our simultaneous measure of peer behavior, varies between 0.44 and 0.48.

These estimates are in line with the empirical literature on peer effects. Ali and Dwyer (2010) study peer effects in alcohol consumption among adolescents. They find that the marginal effect of the peer group on the likelihood of drinking is between 0.16 and 0.45 in different specifications. The estimated peer effect on the intensity of drinking is between 0.24 and 0.41 across different specifications. Trogdon et al. (2008) look at peer effects on individual's body-mass index using a sample of high-school children around 16 years old. They find a marginal effect of mean peer weight of 0.30. Using an instrumental variable approach, the marginal effect increases to 0.52. Powell et al. (2005) find evidence of peer effects in cigarette use among high school students. He estimates a peer effect of 0.58. Similarly, Lundborg (2006) finds a marginal effect of peer behavior of 0.56 for binge drinking, 0.47 for smoking and 0.16 for illicit drug use among a sample of Swedish high-school students. In contrast with these rather high estimates of peer effects in alcohol and cigarette use, Gaviria and Raphael (2001) find marginal effects of 0.15 for alcohol drinking and 0.13 for smoking among a sample of high-school students age 16.

They estimate a marginal effect of peer behavior for drug use of 0.24. Thus, estimates of the marginal effect of peer behavior on individual behavior range from 0.13 to 0.56 across different contexts and using different methods. Our own estimates are in line with these results.

Apart from having a reliable point estimate, we would like to know the relative importance of peer effects in explaining the rise of beer in Russia. Because of our binary dependent variable, traditional measures of the goodness-of-fit such as R^2 are not informative. One approach would be to compare the predicted behavior based on our specifications with actual consumption behavior. However, because of the elimination of individual fixed effects in our empirical approach, it is not possible to derive meaningful predictions from these estimates.

To get some idea of the importance of peer effects, rather than comparing the statistical fit of models, we may look at the magnitude of the coefficients on the time dummies. Because of the strong growth of beer consumption over time, these dummies "soak up" much of the unexplained increase over time in our baseline model. In a sense, these dummies are a "black box" capturing the unexplained increase in beer consumption. The explanatory power of other models compared to our baseline model without peer effects can then be evaluated by the decline in magnitude of the time dummies. A large decline in magnitude of the time dummies relative to the baseline estimate would indicate that peer effects account for a large part of the observed increase in beer consumption over time.

Figure 7 plots the estimated coefficients of the time dummies of our baseline model and our specifications using lagged and simultaneous peer behavior (columns (1)-(3) from Table 4). These time dummies give the relative increase in the probability of beer drinking as against the baseline year 1995. As can be seen from a comparison of Figure 7 with Figure 2, the time dummies in our baseline model closely mimic the evolution of the fraction of beer drinkers over time. For instance, in 1995 the fraction of beer drinkers was 26%, while in 2001 the fraction of beer drinkers was 60%, an increase of 34 percentage points. The coefficient of the 2001 dummy in our baseline model is 32%. Thus, the time dummies in our baseline model indeed capture the trend in beer consumption over time.

Compared to the baseline model, the coefficients on the time dummies decline by about half when our measures of peer behavior are added. Although there is still an upward trend in the time dummies between 1995 and 2002 (the period we are most interested in), peer effects clearly explain a large part of the increase in beer consumption over time. For 2001, the coefficient on the time dummy is 21% if lagged peer behavior is used, and 16% if simultaneous peer behavior is used, as compared to a baseline estimate of 32%. Including peer effects thus decreases the 2001 time dummy with between one-third and one-half. Similar results obtain for the other time dummies. These results indicate that peer effects potentially explain one-third to one-half of the observed increase in beer consumption in Russia.

6. Conclusion

Between 1996 and 2007, Russian patterns of alcohol consumption underwent a dramatic change. While beer consumption had been practically non-existent before the mid-1990s, per capita consumption in Russia increased from 15 liters to 80 liters in the span of a decade. Understanding this transition is important for policy makers, given widespread problems of alcohol abuse and alcohol-related health problems in Russia.

This paper analyzed the determinants of beer consumption in Russia during the remarkable rise of beer. We documented how the increase in beer consumption is not driven by higher consumption levels per drinker, but rather by an increase in the fraction of beer drinkers. Relying on an extensive Russian panel dataset, our empirical analysis shows that beer consumption was not influenced by changes in relative prices of beer and vodka. There is evidence of a positive income effect, and a negative effect of age. Moreover, people drinking vodka are less likely to drink beer. However, our most interesting result concerns the influence of peer effects. In line with a large literature demonstrating the importance of the behavior of a peer group in shaping individual choices, our results show that the fraction of people drinking beer in an individual's community positively influences this individual's likelihood of drinking beer. Our empirical analysis avoids the traditional pitfalls of estimating peer effects by relying on an exogenous definition of the peer group, and including controls for group-level characteristics, individual-level fixed effects (and thus also group-level fixed effects), and time dummies. Moreover, we use two measures of peer behavior to establish an upper bound and a lower bound on peer effects. Our lower bound estimate varies between 0.14 and 0.26 while our upper bound varies between 0.44 and 0.48 across specifications. We show that these estimates are robust to controlling for habit-formation (using dynamic panel data models), exclusion of communities with small numbers of observations, and splitting up the sample into two time periods (although our lagged measure of peer behavior does not indicate strong peer effects after 2002). By comparing the magnitude of the time dummies across specifications, we show that peer effects probably account for one-third to one-half of the rise of beer in Russia.

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Appendix: *Unobserved Heterogeneity and State Dependence*

The individual decision to drink beer is likely to be influenced both by unobserved individual tastes and attitudes and by previous experiences. However, the combination of unobserved heterogeneity and state dependence leads to a number of well-known econometric difficulties. In order to avoid these issues, we opt to perform our empirical analysis using a linear probability model with a lagged dependent variable, which we estimate using standard dynamic panel data techniques, discussed in the paper.

A limitation of the linear probability model is that it may result in predicted probabilities outside the unit interval. For this reason, researchers often prefer using nonlinear models. However, nonlinear models have several drawbacks in the present context because of the combination of unobserved heterogeneity and state dependence. First, since the decision to drink beer may depend on unobservable tastes and attitudes which are possibly correlated with observable covariates, it seems appropriate to apply a fixed effects estimator. Including fixed effects is not possible in several nonlinear panel data models, since there exists no general analogue to the "within transformation" used in linear models. For instance, there is no fixed effects estimator for the probit model. For this reason, researchers generally use random effects specifications, thus assuming no correlation between unobserved heterogeneity and observed covariates. In contrast, there exists a fixed effects logit estimator, but inclusion of state dependence in this model is not straightforward. Although the dynamic fixed effects conditional logit estimator developed by Honoré and Kyriazidou (2000) does not require assumptions about unobserved heterogeneity or the initial conditions, their approach has several drawbacks. First, their estimator needs at least four periods of data, which greatly reduces our sample. Second, identification depends on individuals who experienced little or no change in explanatory variables during the last two time periods, which implies that a lot of information is lost. (Specifically, in the presence of discrete covariates such as marital status, the approach depends on those individuals for whom the discrete covariates did not change at all during the last two time periods.) Third, the approach does not allow the inclusion of time dummies and does not allow the calculation of partial effects (Wooldridge, 2005).

Because of the difficulties involved in estimating dynamic binary choice models with fixed effects, researchers usually work with dynamic random effects models. However, in combination with random effects, the inclusion of state dependence leads to the so-called "initial conditions problem", which results from the assumption that unobserved heterogeneity is uncorrelated with covariates. To use an example from Wooldridge (2005), suppose we are interested in studying the dynamics of earnings for recent college graduates using data going back to their first job out of college. In this case, the random effects specification for the dynamic model assumes that graduates' earnings in their first year are uncorrelated with unobserved individual characteristics such as ability or motivation, which is clearly unrealistic. Under the assumption of random effects, a "naive" estimate would therefore attribute a large impact to the initial period (graduates' earnings in their first job), while the effect is in reality due to unobserved characteristics. Researchers typically address this issue by adding extra assumptions to a nonlinear random effects estimator (see Chay and Hyslop, 1998 and Wooldridge, 2005). However, these approaches, apart from adding extra assumptions, all require that unobserved heterogeneity is uncorrelated with observable characteristics. Hence, nonlinear models have difficulties accommodating the presence of state dependence and unobserved heterogeneity which may be correlated with observable covariates. For these reasons, we opt to use a dynamic linear probability model as outlined in the paper.

Table 1. Fraction of Beer Drinkers and Vodka Drinkers in Russia

Year	Beer Drinkers	Vodka Drinkers
1994	28%	77%
1995	26%	77%
1996	30%	74%
1998	39%	70%
2000	51%	63%
2001	60%	57%
2002	59%	55%
2003	58%	54%
2004	57%	51%
2005	55%	52%
2006	61%	50%
2007	60%	49%
2008	59%	51%

Source: RLMS, authors' own calculations using sampling weights

Table 2. Three Explanations for Observed "Peer Effects"

Manski (1993)	Explanation	Empirical strategy adopted
Endogenous effects	Influence of group *behavior* on individual behavior (peer effect)	Measured by average behavior at group level (lagged and simultaneous measure)
Correlated effects	Common shocks	- Lagged peer measure - Time dummies
	Nonrandom selection	Exogenous definition (location-based)
Contextual effects	Influence of group *characteristics* on individual behavior	- Group-level average of individual covariates - Additional group-level covariates - Individual FE (control for group FE)

Table 3. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Drinks Beer	72571	0.51	0.5	0	1
Drinks Vodka	72755	0.58	0.49	0	1
Real Price of Beer	109835	3.17	1.27	1.2	22.06
Real Price of Vodka	113185	13.6	4.28	3.2	42.38
Price of Beer / Price of Vodka	107872	0.25	0.11	0.08	1.14
% of Beer Drinkers	72517	0.51	0.19	0.00	1.00
Lagged % of Beer Drinkers	54747	0.50	0.19	0.00	1.00
Individual Characteristics					
Age	131409	43.3	18.68	14.08	102.67
Male	132076	0.43	0.5	0	1
Log of Real Income	126599	8.35	0.88	1.88	12.56
Higher Education	132388	0.66	0.47	0	1
Unemployed	126660	0.04	0.2	0	1
Married	132388	0.6	0.49	0	1
Owns a Television	132388	0.92	0.28	0	1
Community Characteristics					
Average Age	132388	43.29	3.88	30.77	87.92
% of Men	132388	0.43	0.04	0	0.67
Log of Average Income	132388	8.65	0.49	5.33	10.81
% of Higher Educated	132388	0.66	0.12	0	1
Unemployment Rate	132388	0.04	0.03	0	0.37
% of Married People	132388	0.6	0.08	0	1
TV Signal Reception	120827	0.97	0.16	0	1
Cable Access	110171	0.71	0.45	0	1
Number of Cafeterias	109531	68.79	149.12	0	1300
Number of Restaurants	112943	18.57	61.36	0	770
Movie Theater	120807	0.8	0.4	0	1
Video Hall	110196	0.51	0.5	0	1

Table 4. Results

Dependent Variable: Respondent Drinks Beer (Linear Probability Model)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Baseline Regression	Lagged Peer Behavior	Simultaneous Peer Behavior	Lagged Peer Behavior	Simultaneous Peer Behavior
Lagged % of Beer Drinkers		0.172***		0.142***	
		(0.0379)		(0.0425)	
% of Beer Drinkers			0.446***		0.444***
			(0.0285)		(0.0304)
Log of Real Income	0.0141***	0.0198***	0.0136***	0.0258***	0.0182***
	(0.00394)	(0.00515)	(0.00392)	(0.00573)	(0.00429)
Real Price of Vodka	-0.000524	0.00199	-0.000180	0.00285	0.000119
	(0.00202)	(0.00262)	(0.00116)	(0.00273)	(0.00132)
Real Price of Beer	-0.00285	-0.00982	-0.00114	-0.0194*	-0.00190
	(0.00682)	(0.0102)	(0.00425)	(0.0109)	(0.00475)
Price of Beer / Price of Vodka	-0.0407	0.0909	-0.0351	0.157	-0.0173
	(0.0818)	(0.106)	(0.0476)	(0.123)	(0.0615)
Drinks Vodka	-0.0872***	-0.0863***	-0.0864***	-0.0854***	-0.0828***
	(0.00734)	(0.00790)	(0.00732)	(0.00902)	(0.00790)
Age	0.00320	0.0131	0.00630	0.00921	0.00331
	(0.00667)	(0.0107)	(0.00609)	(0.0137)	(0.00836)
Age Squared	-0.000167***	-0.000125***	-0.000164***	-0.000141***	-0.000176***
	(2.49e-05)	(3.94e-05)	(2.44e-05)	(4.62e-05)	(3.03e-05)
Higher Education	0.00695	0.00975	0.00856	0.0122	0.00777
	(0.00777)	(0.00936)	(0.00781)	(0.0105)	(0.00828)
Unemployed	-0.00603	-0.0180	-0.00469	-0.0200	-0.00836
	(0.00882)	(0.0128)	(0.00871)	(0.0143)	(0.0102)
Married	0.00451	0.00329	0.00389	0.00380	0.00701
	(0.00894)	(0.00918)	(0.00865)	(0.0108)	(0.00963)
Owns a television	0.00797	0.0154	0.0105	0.0204	0.0124
	(0.0127)	(0.0169)	(0.0126)	(0.0190)	(0.0140)
Log of Avg Income	0.00501	0.0159	-0.00214	-0.00609	-0.0135
	(0.0128)	(0.0170)	(0.00784)	(0.0176)	(0.00958)
Average Age	-0.0107	-0.00645	-0.00650	0.000356	-0.00680
	(0.0156)	(0.0186)	(0.0114)	(0.0191)	(0.0115)
Average Age, squared	0.000173	0.000130	0.000140	4.32e-05	0.000142
	(0.000165)	(0.000196)	(0.000122)	(0.000197)	(0.000123)
% of Men	0.00309	-0.134	-0.0820	-0.0932	-0.0441
	(0.140)	(0.179)	(0.0904)	(0.192)	(0.0990)
% of Higher Educated	0.0260	-0.00519	0.0237	-0.0199	0.0263
	(0.0751)	(0.0852)	(0.0516)	(0.0936)	(0.0517)
Unemployment Rate	0.0296	-0.0313	0.00845	-0.0598	-0.0327
	(0.100)	(0.126)	(0.0701)	(0.144)	(0.0798)
% of Married People	0.0432	-0.00471	0.000796	-0.00811	-0.0166
	(0.0635)	(0.0772)	(0.0422)	(0.0806)	(0.0441)
Year: 1996	0.0246*	0.0204	0.00673	0.0323	0.0122

	(0.0143)	(0.0200)	(0.0115)	(0.0278)	(0.0159)
Year: 1998	0.127***	0.0949**	0.0575**	0.125**	0.0718**
	(0.0291)	(0.0440)	(0.0239)	(0.0560)	(0.0308)
Year: 2000	0.252***	0.183***	0.124***	0.220***	0.146***
	(0.0355)	(0.0556)	(0.0319)	(0.0738)	(0.0413)
Year: 2001	0.324***	0.206***	0.156***	0.267***	0.189***
	(0.0415)	(0.0660)	(0.0376)	(0.0862)	(0.0499)
Year: 2002	0.323***	0.179**	0.152***	0.256**	0.194***
	(0.0512)	(0.0789)	(0.0449)	(0.100)	(0.0590)
Year: 2003	0.325***	0.159*	0.151***	0.248**	0.196***
	(0.0545)	(0.0861)	(0.0491)	(0.111)	(0.0647)
Year: 2004	0.311***	0.138	0.142**	0.230*	0.194***
	(0.0618)	(0.0984)	(0.0551)	(0.126)	(0.0728)
Year: 2005	0.309***	0.123	0.136**	0.217	0.190**
	(0.0676)	(0.107)	(0.0598)	(0.139)	(0.0803)
Year: 2006	0.344***	0.138	0.152**	0.238	0.214**
	(0.0730)	(0.116)	(0.0648)	(0.150)	(0.0877)
Year: 2007	0.351***	0.124	0.156**	0.238	0.225**
	(0.0826)	(0.129)	(0.0728)	(0.166)	(0.0983)
Year: 2008	0.348***	0.108	0.150*		
	(0.0897)	(0.138)	(0.0783)		
Lagged % of Vodka Drinkers				0.0809*	
				(0.0422)	
% of Vodka Drinkers					0.0221
					(0.0236)
Number of Cafeterias				-5.46e-05	-1.30e-06
				(5.58e-05)	(2.78e-05)
Number of Restaurants				3.93e-05	-9.19e-05
				(0.000117)	(5.64e-05)
Movie Theater				-0.0244	-0.0177
				(0.0217)	(0.0111)
Video Hall				0.0140	0.0130**
				(0.0109)	(0.00614)
TV Signal Reception				0.131***	0.0345
				(0.0325)	(0.0390)
Cable Access				-0.0106	-0.00417
				(0.0114)	(0.00631)
Constant	0.440	-0.159	0.215	-0.187	0.338
	(0.433)	(0.557)	(0.332)	(0.622)	(0.395)
Observations	56,876	35,024	56,857	27,966	46,148
Number of individuals	16,067	10,128	16,063	8,999	14,442
Overall R2	0.136	0.0129	0.156	0.0978	0.158
Clusters	153	150	150	148	150

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5. Fixed Effects and OLS Estimates

Dependent Variable: Respondent Drinks Beer (Linear Probability Model)

VARIABLES	(1) FE with Lagged Dep. Var. (Biased Downwards)	(2) OLS with Lagged Dep. Var. (Biased Upwards)	(3) FE with Lagged Dep. Var. (Biased Downwards)	(4) OLS with Lagged Dep. Var. (Biased Upwards)
Drank Beer in Previous Period	-0.0538***	0.353***	-0.0525***	0.350***
	(0.00972)	(0.00835)	(0.00954)	(0.00836)
Lagged % of Beer Drinkers	0.196***	0.286***		
	(0.0381)	(0.0312)		
% of Beer Drinkers			0.466***	0.477***
			(0.0354)	(0.0225)
Log of Real Income	0.0199***	0.00661**	0.0191***	0.00663**
	(0.00517)	(0.00329)	(0.00513)	(0.00320)
Real Price of Vodka	0.00215	-0.00113	0.00306*	0.000299
	(0.00261)	(0.00190)	(0.00184)	(0.00131)
Real Price of Beer	-0.0105	0.000957	-0.0103	-0.00138
	(0.0101)	(0.00699)	(0.00766)	(0.00481)
Price of Beer / Price of Vodka	0.0944	-0.0163	0.109	0.0275
	(0.106)	(0.0718)	(0.0792)	(0.0532)
Drinks Vodka	-0.0856***	-0.0179**	-0.0860***	-0.0184**
	(0.00788)	(0.00720)	(0.00774)	(0.00709)
Age	0.0139	-0.0103***	0.0125	-0.0102***
	(0.0108)	(0.000975)	(0.0105)	(0.000976)
Age Squared	-0.000135***	4.21e-05***	-0.000135***	4.10e-05***
	(4.12e-05)	(1.10e-05)	(4.04e-05)	(1.09e-05)
Higher Education	0.0104	-0.00813	0.0115	-0.00702
	(0.00950)	(0.00564)	(0.00964)	(0.00570)
Unemployed	-0.0183	-0.0111	-0.0167	-0.0103
	(0.0129)	(0.0108)	(0.0126)	(0.0108)
Married	0.00392	0.0327***	0.00686	0.0342***
	(0.00928)	(0.00553)	(0.00910)	(0.00539)
Owns a television	0.0151	0.0344*	0.0148	0.0321*
	(0.0170)	(0.0181)	(0.0167)	(0.0177)
Log of Avg Income	0.0155	-0.00244	0.00532	-0.00404
	(0.0172)	(0.0103)	(0.0121)	(0.00713)
Average Age	-0.00646	-0.00164	-0.00514	-0.00142
	(0.0189)	(0.00822)	(0.0158)	(0.00527)
Average Age, squared	0.000133	8.23e-06	0.000130	3.76e-05
	(0.000199)	(8.58e-05)	(0.000168)	(5.45e-05)
% of Men	-0.131	-0.0246	-0.163	-0.0162
	(0.180)	(0.0968)	(0.140)	(0.0697)
% of Higher Educated	-0.00524	0.0545	0.00332	0.0407

	(0.0860)	(0.0489)	(0.0708)	(0.0323)
Unemployment Rate	-0.0374	-0.00497	-0.0465	-0.00174
	(0.126)	(0.126)	(0.0970)	(0.0785)
% of Married People	-0.00195	-0.0243	-0.0193	-0.0218
	(0.0785)	(0.0478)	(0.0638)	(0.0329)
Year: 1996	0.0189	0.0447***	-0.00698	0.0181
	(0.0198)	(0.0165)	(0.0162)	(0.0110)
Year: 1998	0.0930**	0.133***	0.0254	0.0634***
	(0.0441)	(0.0224)	(0.0393)	(0.0159)
Year: 2000	0.184***	0.187***	0.0885*	0.0966***
	(0.0559)	(0.0164)	(0.0529)	(0.0125)
Year: 2001	0.210***	0.166***	0.101	0.0723***
	(0.0661)	(0.0157)	(0.0627)	(0.0113)
Year: 2002	0.184**	0.119***	0.0946	0.0502***
	(0.0792)	(0.0182)	(0.0735)	(0.0132)
Year: 2003	0.164*	0.118***	0.0773	0.0506***
	(0.0867)	(0.0152)	(0.0836)	(0.0122)
Year: 2004	0.142	0.104***	0.0681	0.0482***
	(0.0991)	(0.0182)	(0.0934)	(0.0131)
Year: 2005	0.127	0.111***	0.0499	0.0486***
	(0.107)	(0.0165)	(0.102)	(0.0129)
Year: 2006	0.140	0.154***	0.0505	0.0736***
	(0.117)	(0.0165)	(0.111)	(0.0125)
Year: 2007	0.127	0.136***	0.0451	0.0653***
	(0.130)	(0.0168)	(0.123)	(0.0127)
Year: 2008	0.111	0.128***	0.0323	0.0571***
	(0.140)	(0.0168)	(0.132)	(0.0132)
Constant	-0.168	0.424**	-0.141	0.315**
	(0.565)	(0.195)	(0.491)	(0.135)
Observations	35,024	35,024	35,027	35,027
Number of individuals	10,128		10,130	
Overall R2	1.04e-06		0.0164	
Clusters	150	150	150	150

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6. Results Dynamic GMM Using Lagged Peer Behavior

Dependent Variable: Respondent Drinks Beer (Linear Probability Model)

VARIABLES	(1) Dynamic GMM (Arellano-Bond using FOD)	(2) Dynamic GMM (Arellano-Bond using FOD)	(3) Dynamic GMM (Arellano-Bond using FOD)	(4) Dynamic GMM (Arellano-Bond using FOD)	(5) Dynamic GMM (Arellano-Bond using FOD)
L.drbeer	0.0881***	0.422***	0.118	-0.134	-0.201
	(0.0116)	(0.113)	(0.143)	(0.175)	(0.175)
Lagged % of Beer Drinkers	0.133***	-0.0151	0.119*	0.230***	0.261***
	(0.0293)	(0.0594)	(0.0702)	(0.0834)	(0.0840)
% of Beer Drinkers					
Log of Real Income	0.0199***	0.0190***	0.0201***	0.0206***	0.0203***
	(0.00500)	(0.00512)	(0.00495)	(0.00500)	(0.00507)
Real Price of Vodka	0.00203	0.00127	0.00180	0.00276	0.00279
	(0.00202)	(0.00212)	(0.00202)	(0.00206)	(0.00209)
Real Price of Beer	-0.0110	-0.00732	-0.00966	-0.0131	-0.0135
	(0.00784)	(0.00813)	(0.00784)	(0.00810)	(0.00828)
Price of Beer / Price of Vodka	0.109	0.0925	0.0975	0.115	0.117
	(0.0816)	(0.0858)	(0.0807)	(0.0811)	(0.0820)
Drinks Vodka	-0.0850***	-0.0904***	-0.0870***	-0.0835***	-0.0832***
	(0.00695)	(0.00739)	(0.00714)	(0.00730)	(0.00736)
Age	0.00901	0.00496	0.0123	0.0171	0.0170
	(0.0116)	(0.0124)	(0.0114)	(0.0117)	(0.0116)
Age Squared	-0.000104***	-4.27e-05	-0.000100**	-0.000151***	-0.000163***
	(3.44e-05)	(3.56e-05)	(4.28e-05)	(5.07e-05)	(5.25e-05)
Higher Education	0.0145	0.00795	0.0122	0.0145	0.0127
	(0.0118)	(0.0119)	(0.0118)	(0.0123)	(0.0126)
Unemployed	-0.0168	-0.0149	-0.0174	-0.0192	-0.0191
	(0.0146)	(0.0154)	(0.0144)	(0.0142)	(0.0142)
Married	-0.00471	-0.00685	-0.00291	0.00138	0.00356
	(0.0119)	(0.0116)	(0.0118)	(0.0125)	(0.0129)
Owns a television	0.0152	0.0158	0.0153	0.0136	0.0142
	(0.0170)	(0.0180)	(0.0168)	(0.0167)	(0.0170)
Log of Avg Income	0.0192	0.0231*	0.0197	0.0175	0.0172
	(0.0134)	(0.0139)	(0.0133)	(0.0135)	(0.0138)
Average Age	-0.00579	-0.00488	-0.00615	-0.00727	-0.00730
	(0.0152)	(0.0153)	(0.0151)	(0.0157)	(0.0161)
Average Age, squared	0.000120	9.59e-05	0.000124	0.000146	0.000150
	(0.000166)	(0.000168)	(0.000165)	(0.000170)	(0.000175)
% of Men	-0.141	-0.165	-0.153	-0.126	-0.116

	(0.123)	(0.123)	(0.122)	(0.127)	(0.130)
% of Higher Educated	-0.0336	-0.0207	-0.0198	-0.0190	-0.0206
	(0.0680)	(0.0665)	(0.0673)	(0.0705)	(0.0727)
Unemployment Rate	0.0249	0.0589	0.0142	-0.0240	-0.0554
	(0.118)	(0.125)	(0.119)	(0.119)	(0.121)
% of Married People	0.0138	-0.0153	0.00276	0.0181	0.0238
	(0.0668)	(0.0660)	(0.0670)	(0.0705)	(0.0726)
Year: 1996	0.0264	0.0357*	0.0242	0.0163	0.0152
	(0.0176)	(0.0198)	(0.0180)	(0.0178)	(0.0177)
Year: 1998	0.108***	0.116***	0.0981***	0.0873**	0.0907**
	(0.0379)	(0.0407)	(0.0371)	(0.0374)	(0.0375)
Year: 2000	0.201***	0.189***	0.180***	0.181***	0.187***
	(0.0565)	(0.0608)	(0.0539)	(0.0542)	(0.0541)
Year: 2001	0.222***	0.186**	0.194***	0.211***	0.223***
	(0.0674)	(0.0730)	(0.0648)	(0.0656)	(0.0655)
Year: 2002	0.188**	0.145*	0.160**	0.185**	0.199***
	(0.0783)	(0.0850)	(0.0755)	(0.0767)	(0.0766)
Year: 2003	0.177**	0.135	0.144*	0.163*	0.177**
	(0.0892)	(0.0966)	(0.0854)	(0.0864)	(0.0862)
Year: 2004	0.158	0.117	0.121	0.138	0.152
	(0.0999)	(0.108)	(0.0955)	(0.0964)	(0.0961)
Year: 2005	0.146	0.107	0.107	0.121	0.135
	(0.110)	(0.119)	(0.105)	(0.106)	(0.106)
Year: 2006	0.161	0.127	0.120	0.130	0.145
	(0.121)	(0.131)	(0.116)	(0.116)	(0.116)
Year: 2007	0.149	0.108	0.102	0.116	0.133
	(0.133)	(0.143)	(0.126)	(0.127)	(0.127)
Year: 2008	0.134	0.0911	0.0826	0.0973	0.116
	(0.144)	(0.155)	(0.137)	(0.138)	(0.138)
Observations	24,896	24,896	24,896	24,896	24,896
Number of individuals	7,156	7,156	7,156	7,156	7,156
AR(1)-test p-value	0.0000	0.0000	7.97e-05	0.0324	0.0638
AR(2)-test p-value	0.00282	0.000547	0.377	0.450	0.248
Hansen test DF	65	54	44	35	27
Hansen test p-value	0.00219	0.0473	0.0450	0.0455	0.256

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7. Results Dynamic GMM Using Simultaneous Peer Behavior

Dependent Variable: Respondent Drinks Beer (Linear Probability Model)

VARIABLES	(1) Dynamic GMM (Arellano-Bond using FOD)	(2) Dynamic GMM (Arellano-Bond using FOD)	(3) Dynamic GMM (Arellano-Bond using FOD)	(4) Dynamic GMM (Arellano-Bond using FOD)	(5) Dynamic GMM (Arellano-Bond using FOD)
L.drbeer	0.0863***	0.384***	0.0901	-0.118	-0.199
	(0.0115)	(0.106)	(0.138)	(0.176)	(0.185)
Lagged % of Beer Drinkers					
% of Beer Drinkers	0.445***	0.403***	0.443***	0.473***	0.482***
	(0.0298)	(0.0342)	(0.0354)	(0.0389)	(0.0411)
Log of Real Income	0.0191***	0.0184***	0.0194***	0.0196***	0.0194***
	(0.00497)	(0.00507)	(0.00492)	(0.00497)	(0.00503)
Real Price of Vodka	0.00282	0.00173	0.00263	0.00371*	0.00384*
	(0.00201)	(0.00212)	(0.00203)	(0.00211)	(0.00216)
Real Price of Beer	-0.0105	-0.00554	-0.00940	-0.0133	-0.0140
	(0.00776)	(0.00813)	(0.00794)	(0.00834)	(0.00859)
Price of Beer / Price of Vodka	0.121	0.0902	0.110	0.133	0.137*
	(0.0806)	(0.0849)	(0.0803)	(0.0815)	(0.0828)
Drinks Vodka	-0.0854***	-0.0902***	-0.0869***	-0.0839***	-0.0836***
	(0.00690)	(0.00730)	(0.00708)	(0.00726)	(0.00731)
Age	0.00833	0.00561	0.0120	0.0155	0.0156
	(0.0116)	(0.0123)	(0.0112)	(0.0114)	(0.0114)
Age Squared	-0.000107***	-5.35e-05	-0.000108**	-0.000150***	-0.000164***
	(3.43e-05)	(3.50e-05)	(4.23e-05)	(5.04e-05)	(5.31e-05)
Higher Education	0.0155	0.00956	0.0135	0.0151	0.0132
	(0.0117)	(0.0118)	(0.0117)	(0.0121)	(0.0124)
Unemployed	-0.0161	-0.0143	-0.0167	-0.0178	-0.0181
	(0.0145)	(0.0152)	(0.0142)	(0.0141)	(0.0141)
Married	-0.00255	-0.00492	-0.000989	0.00314	0.00588
	(0.0118)	(0.0115)	(0.0118)	(0.0124)	(0.0129)
Owns a television	0.0153	0.0156	0.0154	0.0138	0.0142
	(0.0170)	(0.0178)	(0.0168)	(0.0168)	(0.0170)
Log of Avg Income	0.0100	0.0151	0.00989	0.00704	0.00615
	(0.0133)	(0.0138)	(0.0134)	(0.0136)	(0.0138)
Average Age	-0.00465	-0.00447	-0.00536	-0.00653	-0.00666
	(0.0150)	(0.0146)	(0.0149)	(0.0156)	(0.0162)
Average Age, squared	0.000117	9.87e-05	0.000126	0.000150	0.000156
	(0.000163)	(0.000160)	(0.000162)	(0.000170)	(0.000176)
% of Men	-0.178	-0.223*	-0.190	-0.153	-0.134

	(0.124)	(0.124)	(0.124)	(0.129)	(0.132)
% of Higher Educated	-0.0300	-0.0287	-0.0156	-0.00587	-0.00587
	(0.0682)	(0.0667)	(0.0678)	(0.0706)	(0.0728)
Unemployment Rate	0.0224	0.0627	0.00462	-0.0381	-0.0740
	(0.118)	(0.124)	(0.119)	(0.121)	(0.123)
% of Married People	-0.0151	-0.0522	-0.0244	-0.00374	0.0105
	(0.0669)	(0.0664)	(0.0683)	(0.0719)	(0.0742)
Year: 1996	0.00438	0.0180	0.00101	-0.00998	-0.0133
	(0.0175)	(0.0200)	(0.0188)	(0.0192)	(0.0194)
Year: 1998	0.0430	0.0544	0.0320	0.0196	0.0213
	(0.0379)	(0.0406)	(0.0373)	(0.0378)	(0.0379)
Year: 2000	0.103*	0.0851	0.0819	0.0865	0.0952*
	(0.0567)	(0.0608)	(0.0538)	(0.0540)	(0.0538)
Year: 2001	0.105	0.0536	0.0786	0.105	0.123*
	(0.0676)	(0.0738)	(0.0661)	(0.0679)	(0.0681)
Year: 2002	0.0850	0.0141	0.0589	0.100	0.124
	(0.0782)	(0.0865)	(0.0781)	(0.0816)	(0.0824)
Year: 2003	0.0763	0.00449	0.0440	0.0821	0.105
	(0.0891)	(0.0978)	(0.0875)	(0.0902)	(0.0906)
Year: 2004	0.0691	-0.00410	0.0331	0.0701	0.0944
	(0.0997)	(0.109)	(0.0970)	(0.0995)	(0.0998)
Year: 2005	0.0537	-0.0153	0.0162	0.0498	0.0741
	(0.110)	(0.120)	(0.106)	(0.108)	(0.108)
Year: 2006	0.0573	-0.00778	0.0161	0.0465	0.0701
	(0.121)	(0.131)	(0.116)	(0.117)	(0.117)
Year: 2007	0.0494	-0.0267	0.00356	0.0406	0.0685
	(0.132)	(0.143)	(0.127)	(0.129)	(0.129)
Year: 2008	0.0378	-0.0419	-0.0126	0.0257	0.0545
	(0.144)	(0.155)	(0.137)	(0.139)	(0.139)
Observations	24,894	24,894	24,894	24,894	24,894
Number of individuals	7,155	7,155	7,155	7,155	7,155
AR(1)-test p-value	0.0000	0.0000	8.72e-05	0.0305	0.0813
AR(2)-test p-value	0.00359	0.000831	0.481	0.501	0.273
Hansen test DF	65	54	44	35	27
Hansen test p-value	0.00240	0.0483	0.0408	0.0264	0.200

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8. Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)
	Lagged Peer Behavior	Simultaneous Peer Behavior	Lagged Peer Behavior	Simultaneous Peer Behavior	Lagged Peer Behavior	Simultaneous Peer Behavior
VARIABLES	Obs>30	Obs>30	1995-2002	1995-2002	2003-2008	2003-2008
Lagged % of Beer Drinkers	0.199***		0.136*		0.0529	
	(0.0693)		(0.0757)		(0.0509)	
% of Beer Drinkers		0.546***		0.422***		0.394***
		(0.0395)		(0.0473)		(0.0387)
Log of Real Income	0.0162***	0.0113**	0.0402***	0.0286***	0.00157	0.000670
	(0.00578)	(0.00444)	(0.00813)	(0.00478)	(0.00706)	(0.00630)
Real Price of Vodka	0.00412	-0.000524	0.00298	-7.63e-06	-0.00114	-0.00314
	(0.00313)	(0.00130)	(0.00277)	(0.00146)	(0.00379)	(0.00232)
Real Price of Beer	-0.0119	0.00363	-0.0184	-0.00123	0.00488	0.00899
	(0.0121)	(0.00534)	(0.0130)	(0.00568)	(0.0162)	(0.0102)
Price of Beer / Price of Vodka	0.110	-0.0610	0.148	-0.0496	0.0131	-0.0869
	(0.131)	(0.0539)	(0.123)	(0.0744)	(0.160)	(0.0935)
Drinks Vodka	-0.0843***	-0.0850***	-0.0537***	-0.0587***	-0.0928***	-0.100***
	(0.00889)	(0.00867)	(0.0125)	(0.0102)	(0.00937)	(0.00786)
Age	0.0199	0.00724	0.0512***	0.0267***	0.00723	0.0159
	(0.0134)	(0.00654)	(0.0147)	(0.00948)	(0.0171)	(0.0126)
Age Squared	-0.000117**	-0.000166***	-0.000305***	-0.000331***	-0.000196**	-0.000136**
	(4.60e-05)	(2.77e-05)	(8.13e-05)	(5.15e-05)	(7.77e-05)	(6.41e-05)
Higher Education	0.00506	0.00980	-0.0366	0.00298	0.0321**	0.0171
	(0.00993)	(0.00870)	(0.0221)	(0.0165)	(0.0158)	(0.0112)
Unemployed	-0.0233	-0.00295	-0.00917	-0.00387	-0.0240	-0.00247
	(0.0139)	(0.00939)	(0.0235)	(0.0144)	(0.0207)	(0.0158)
Married	0.00217	0.00376	-0.0430***	-0.0153	0.0366**	0.0201
	(0.00976)	(0.00988)	(0.0162)	(0.0141)	(0.0165)	(0.0131)
Owns a television	0.00147	0.0130	-0.0213	-0.00625	0.0329	0.0335*
	(0.0204)	(0.0153)	(0.0304)	(0.0207)	(0.0235)	(0.0194)
Log of Avg Income	0.00311	-0.0177*	0.0237	0.00321	0.0411**	0.0224*
	(0.0220)	(0.00961)	(0.0264)	(0.0130)	(0.0208)	(0.0115)
Average Age	-0.184***	-0.116***	-0.0140	-0.0242	-0.0118	0.0270
	(0.0593)	(0.0382)	(0.0328)	(0.0219)	(0.0318)	(0.0205)
Average Age, squared	0.00213***	0.00138***	0.000203	0.000328	0.000203	-0.000250
	(0.000682)	(0.000438)	(0.000350)	(0.000233)	(0.000354)	(0.000232)
% of Men	-0.138	-0.183	-0.355	-0.0588	0.0899	-0.134

	(0.367)	(0.169)	(0.268)	(0.141)	(0.267)	(0.141)
% of Higher Educated	0.189	0.147*	0.102	0.137*	-0.000668	-0.0235
	(0.152)	(0.0830)	(0.139)	(0.0735)	(0.112)	(0.0637)
Unemployment Rate	-0.0637	0.0187	-0.127	-0.115	0.0646	0.170
	(0.198)	(0.107)	(0.254)	(0.116)	(0.197)	(0.128)
% of Married People	-0.0796	0.0320	0.0260	-0.0517	-0.0185	0.0129
	(0.127)	(0.0525)	(0.131)	(0.0747)	(0.116)	(0.0729)
Year: 1996	0.0157	0.00745	-0.00323	0.00599		
	(0.0233)	(0.0123)	(0.0244)	(0.0150)		
Year: 1998	0.0468	0.0378	0.0236	0.0466		
	(0.0513)	(0.0256)	(0.0530)	(0.0334)		
Year: 2000	0.144**	0.0984***	0.0717	0.109**		
	(0.0681)	(0.0357)	(0.0660)	(0.0483)		
Year: 2001	0.158*	0.122***	0.0760	0.133**		
	(0.0845)	(0.0424)	(0.0772)	(0.0563)		
Year: 2002	0.106	0.114**	0.0324	0.117*		
	(0.0996)	(0.0499)	(0.0931)	(0.0662)		
Year: 2003	0.0797	0.113**				
	(0.110)	(0.0550)				
Year: 2004	0.0494	0.107*			-0.0118	-0.0187
	(0.125)	(0.0610)			(0.0180)	(0.0136)
Year: 2005	0.0169	0.0970			-0.0182	-0.0388
	(0.136)	(0.0654)			(0.0316)	(0.0241)
Year: 2006	0.0349	0.117			0.00303	-0.0379
	(0.150)	(0.0714)			(0.0480)	(0.0350)
Year: 2007	0.00436	0.115			0.00211	-0.0500
	(0.167)	(0.0796)			(0.0629)	(0.0484)
Year: 2008	-0.00157	0.112			-0.00332	-0.0681
	(0.178)	(0.0861)			(0.0807)	(0.0608)
Constant	3.574**	2.654***	-1.305	-0.0660	0.357	-0.801
	(1.356)	(0.827)	(0.938)	(0.628)	(0.952)	(0.632)
Observations	27,836	44,976	14,065	25,988	20,959	30,869
Number of individuals	7,810	12,470	6,089	10,486	7,696	11,236
Overall R2	0.0317	0.148	0.0498	0.107	0.0892	0.00951
Clusters	40	39	139	139	145	145

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 1. Beer Consumption Per Capita in Russia, 1960-2007

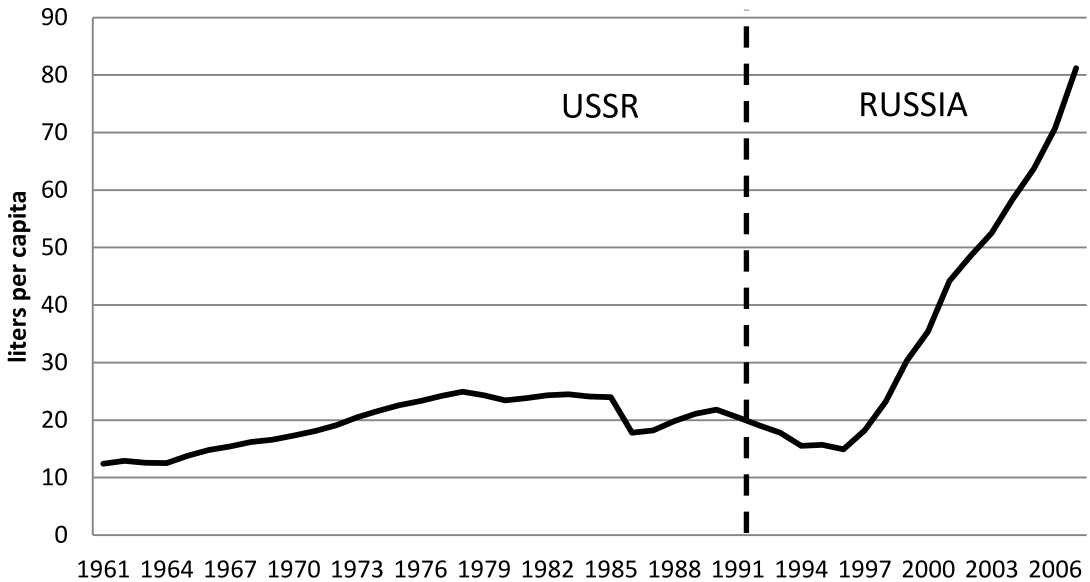

Figure 2. Fraction of Beer Drinkers and Vodka Drinkers Over Time

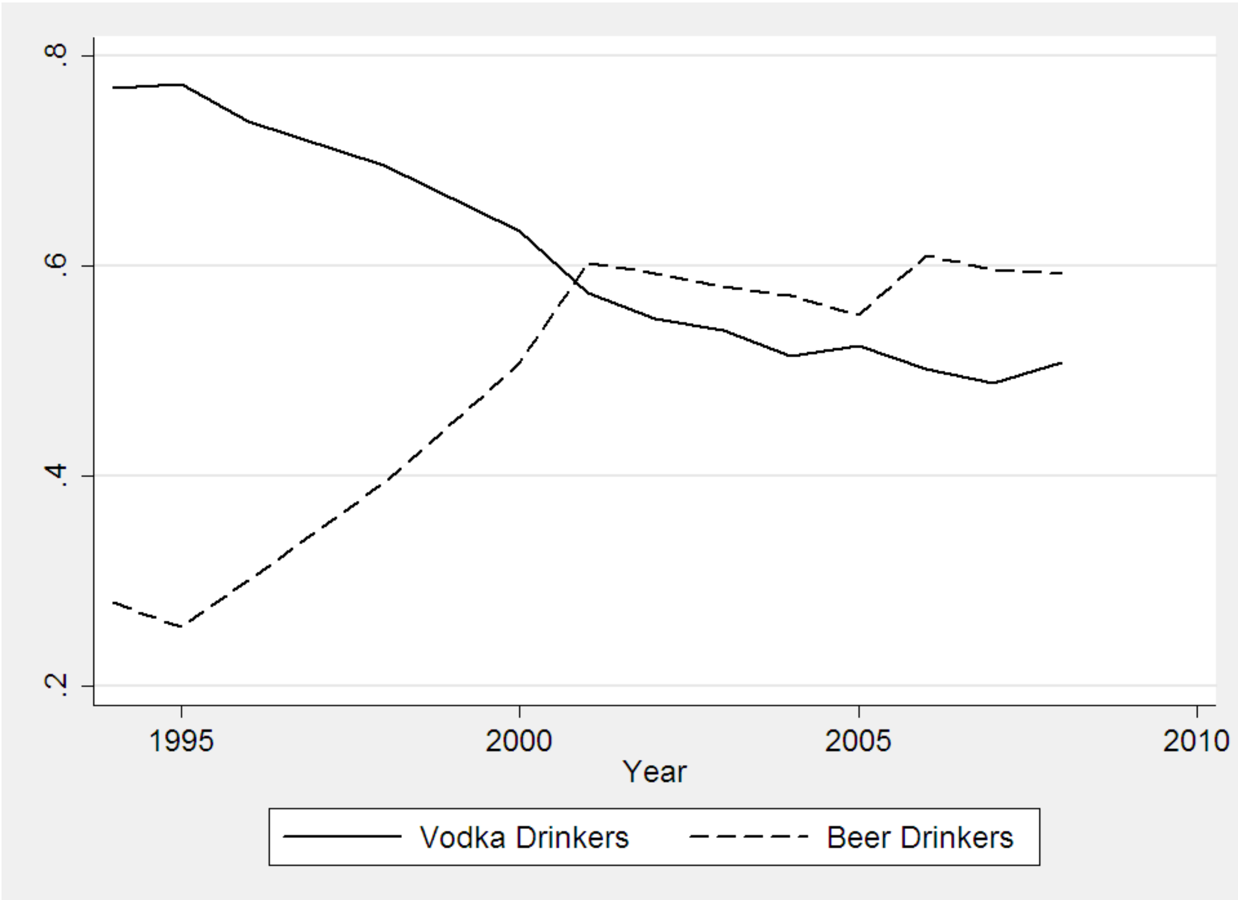

Figure 3. Monthly Volume of Beer Consumption

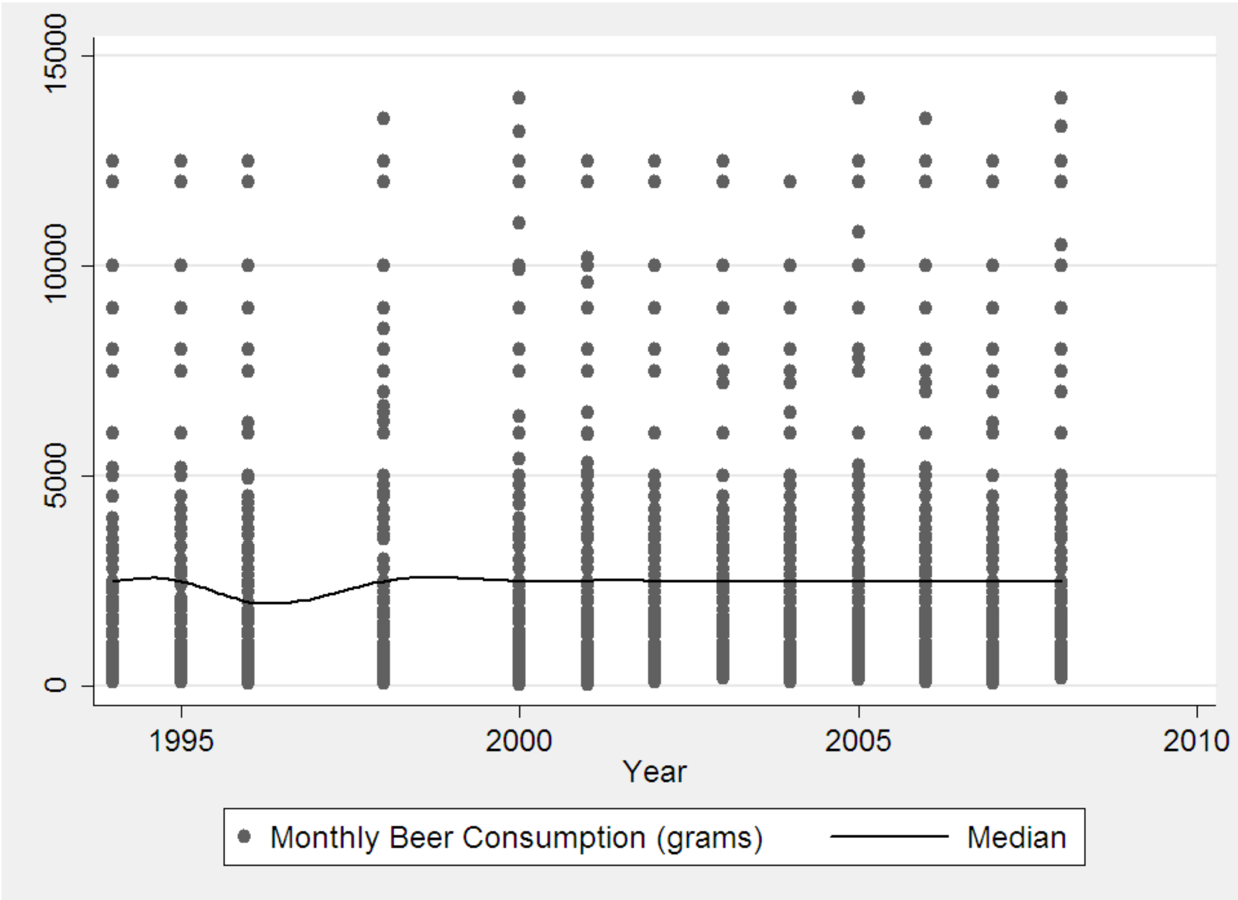

Figure 4. Gender Differences in Beer Consumption

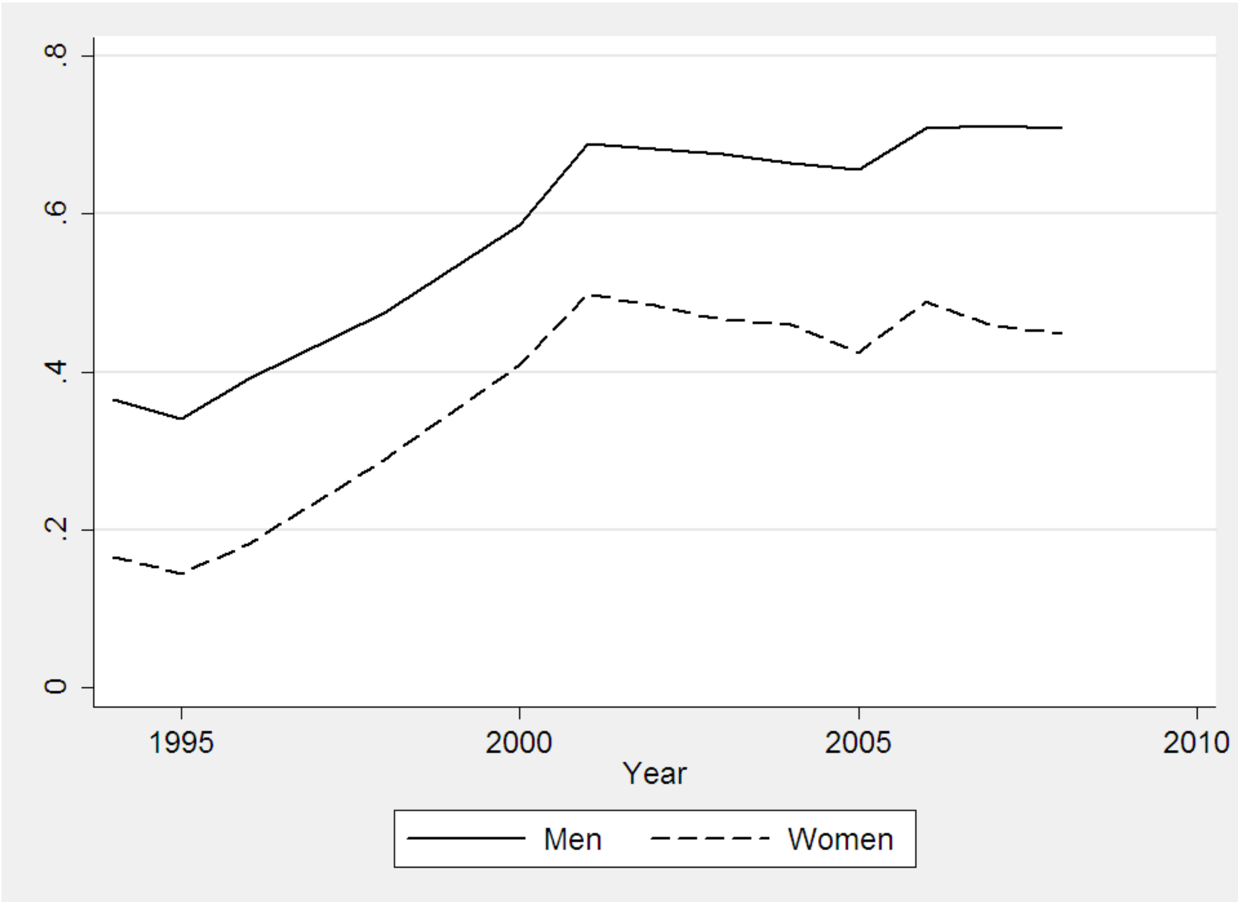

Figure 5. Fraction of Beer Drinkers per Region

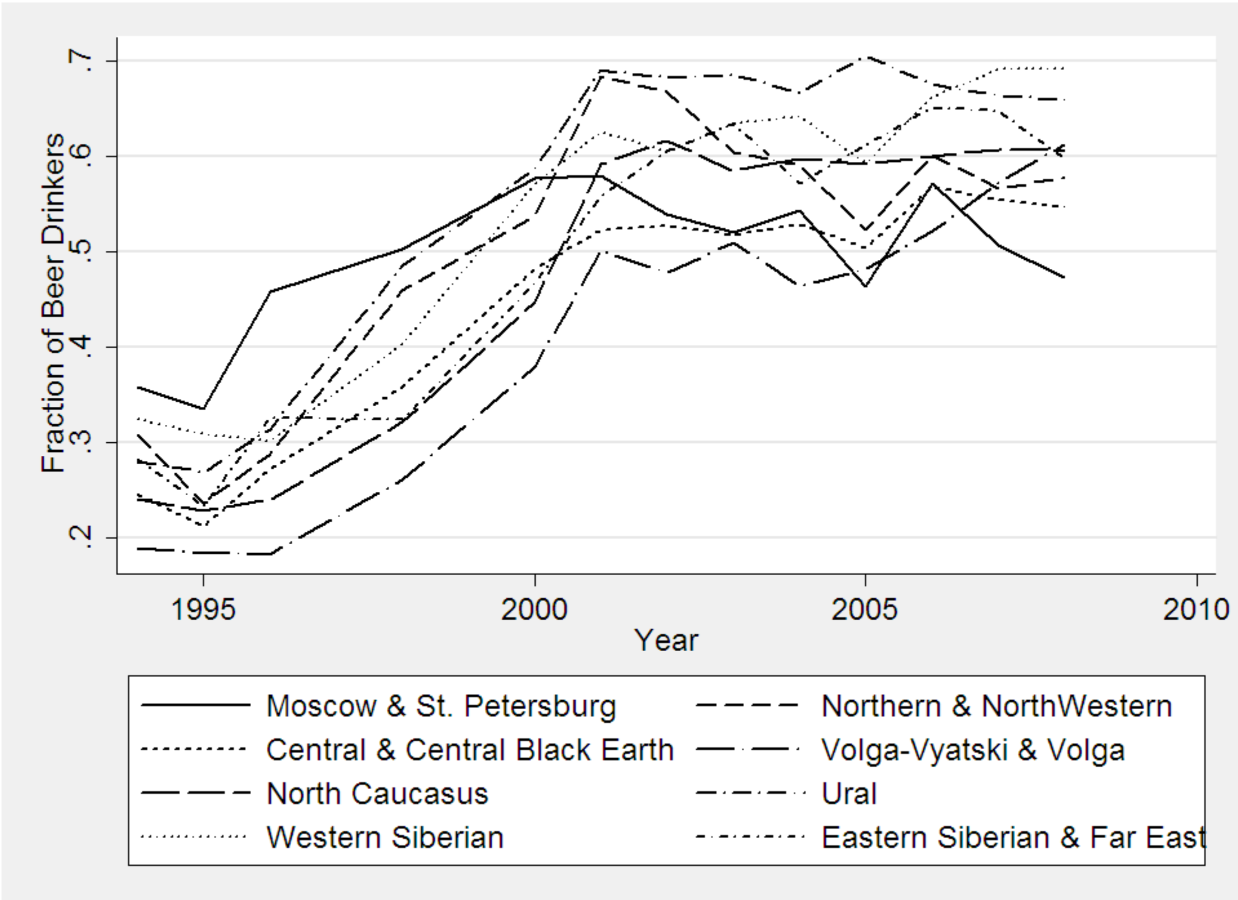

Figure 6. Fraction of Beer Drinkers per Cohort

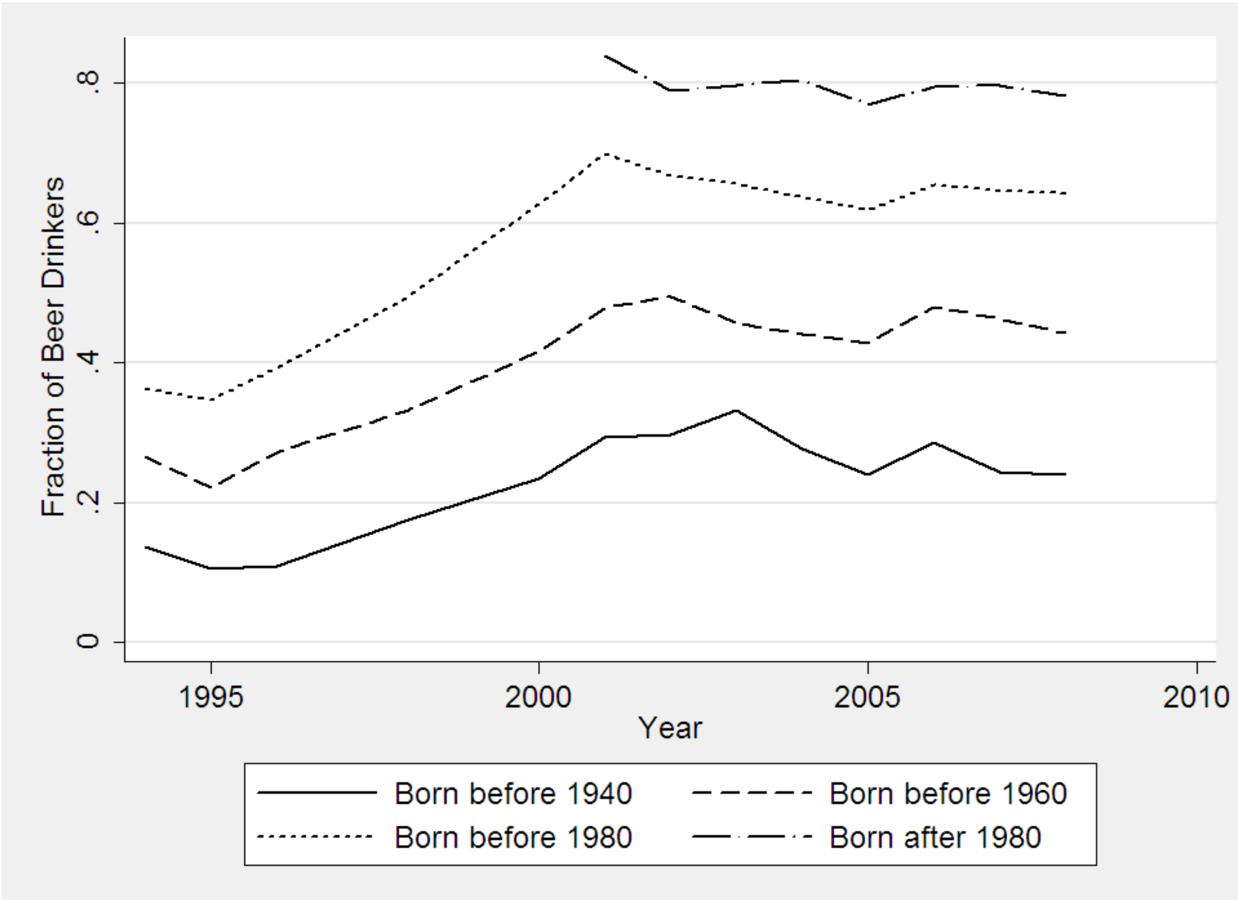

Figure 7. Pattern of Time Effects With and Without Peer Effects