CSSR Research Proposal

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1 Introduction

In Western Europe alcohol is a commonly used medium for exhilaration. However, it is also known as a (if not *the most harmful*) drug (Nutt, King, and Phillips 2010), be it because of its toxic nature itself or the indirect consequences: The consumption of alcoholic beverages may on the one hand lead to behavioural changes and violent acts, as has been indicated by numerous studies (see e.g. Parker 1993; **???**; Stolle, Sack, and Thomasius 2009; **???**). On the other hand alcohol, if consumend regularly and over a longer period of time, does severe damage to individuals' health. It is therefore a policy concern not only to identify reasons and motivation for excessive alcohol consumption but also to develop measures to tackle this problem.

It is the aim of this paper to analyse both mentioned dimensions of the *challenge alcohol*. Using the example of all German federal states and time series data for different age groups from 2000 to 2014, we will [1] analyse the possible connection between medical diagnoses of alcohol misuse and possibly explanatory socioeconomic factors like gender, age, unemployment rate, education level, and regional economic performance. For this, we will take both short-term and long-term medical consequences of alcohol misuse into account by examining hospital health records on acute alcohol intoxication as well as on alcoholic liver disease. Besides the socio-economic factors mentioned above, we will [2] test the effect of recent policy measures on the German state level on alcohol consumption. The two cases we are going to examine are [a] the ban on alcohol night sales introduced in 2010 in the state of Baden-Wuerttemberg and [b] the prohibition of alcohol consumption in vehicles and stations of public transport in the federal city state of Hamburg, introduced in 2011.

With this approach, we aim to present an analysis that offers insights into both possible causes for alcohol misuse as well as the efficiency of policy measures designed to counter excessive drinking.

2 Related Literature

Our research proposal is inspired by the work of Marcus and Siedler (2015) who analysed *"The Effect of a Ban on Late-Night Off-premise Alcohol Sales on Alcohol-Related Hospital Stays in Germany"*. They find that the introduction of the alcohol night sales ban reduces alcohol-related hospitalizations among adolescents and young adults by about seven percent. In our analysis, we will not only try to replicate their work with the publicly available data sets. We are also going to build upon it – by differenciate between short-term and longer-term effects. The focus on socio-economic explanatory factors like economic performance for the alcohol abuse as such is based upon research done by e.g. Popovici and French (2013) and Ettner (1997). Focusing on the United States, the two studies found inconsistent results: While one sees "a positive and significant effect of unemployment on drinking behaviors and the findings are robust to numerous sensitivity tests" (Popovici and French 2013) the other argues that "non-employment significantly reduces both alcohol consumption and dependence symptoms, probably due to an income effect." (Ettner 1997) For the German case, Henkel (2000) finds a negative correlation between economic situation and alcohol and nicotine consumption.

3 Data

Our research health data origins from the German hospital diagnosis statistics from 2000 to 2014, obtained via the The Information System of the Federal Health Monitoring (GBE). The data is reported by hospitals to the state statistical bureaus and then aggregated by the Statistische Bundesamt Destatis. The data contains the aggregated numbers of hospital diagnoses for each German state by age group, gender and year. The diagnoses are published according to the WHO International Statistical Classification of Diseases and Related Health Problems (ICD-10).

The data is gathered via the online-interface of the GBE. Unfortunately the data provider neither provides an API nor a web-scrappable interface. Therefore we download the base tables manually by searching for the respective ICD-10 code, using the malleable tables to gather as much information in a single table and export them.

The identify alcohol-related health problems we use the diagnose F10 (Mental and behavioural disorders due to use of alcohol), its subdivision F10.0 (Acute intoxication) and F10.2 (Dependence syndrome), and K70 (Alcoholic liver disease). The diagnoses category F10.0 essentially captures short term effects of excessive drinking, and can be used as an indicator for binge drinking.[1] The categories F10.2 and K70 capture long-term effects of drinking as these diagnoses are consequences of regular drinking.

The advantages of this data is that they reflect a complete survey of all civilian hospitals in Germany for the time-frame of your investigation. Furthermore, the data is not self-reported by patients but gathered by a third party (the statistical bureau) there are no problems of self-reporting biases. For the case study of the Baden-Wuerttemberg's night sale prohibition we do also benefit from the availability of a longer time series as prior work on the issue (Marcus and Siedler (2015)). Finally, the state-year aggregation level does allows us to supplement to our analysis a wide variety of other freely available data, e.g. the level of alcohol sales, unemployment rates etc.

However, there are several serious limitations to the data we are using. First of all, the data set can only be exploited with strong limitations with sophisticated methods like panel data analysis. We only have access to data which is reported annually and by state.[2] Hence, for a panel data analysis we can only use 14 years and 16 states, which makes a total of 224 data point for each combination of diagnoses, age group and gender. We still think it is meaning full to work with the data as we will also use simpler but still insightful methods like multiple linear regression. Furthermore, our approach can easily be extended to more fine-grained data if it becomes available in the future. A second short coming is the lack of further patient information beyond their age and gender, e.g. socio-economic characteristics.

As already mentioned, our analysis will be supplemented by data from other sources. We are in particular using indicators for the state level. They include the populations, the population density, unemployment rates of different age groups, the state gdp and beer sales by state. We are collecting this data from different statistics provided by *Destatis*.

[1] In contrast to Marcus and Siedler (2015) and Wicki and Gmel (2011) we do not include T51 (Intoxination due to alcohol) as its covers the consumption of pure ethanol and its number are relatively small.

[2] In principle there is more fine-grained data available, even down to the individual level. But to get access to the data we would have to use the paid services of the Forschungsdatenzentrum.

4 Empirical strategy

We want to make a two stage analysis of short and long-term alcohol-related hospitalizations (ARH)[3]. First, a multiple regression for a better understanding of factors correlated to high rates of hospitalizatons. This analysis will show how characteristics of states and individuals are correlated to the number of ARH. The simple multiple regression model for one year t looks like this:

$$ARH_s = \alpha_0 + \alpha_1 \cdot GDP_s + \alpha_2 \cdot UR_s + \alpha_3 \cdot B_s + \alpha_4 \cdot PD_s + \epsilon_s \tag{1}$$

Where *GDP* stands for the states GDP level, *UR* for the states unemployment rate, *B* for the beer consumption in the state and *PD* for the population density. The regression will be conducted for the aggregated number for all age groups and than for specific age-groups making use of the age-group specific unemployment rate. Based on the idea that individuals adapt to their circumstances and are more reactive to changes than to actual levels we will analysis ARH difference:

$$\Delta ARH_{s,t} = \beta_1 \cdot \Delta GDP_{s,t} + \beta_2 \cdot UR_{s,t} + \beta_3 \cdot \Delta B_{s,t} + \epsilon_{s,t} \tag{2}$$

The populations density drops out of the equation as their levels can be assumed to be stable over the short time period of 14 years. In contrast to the multiple regression on levels, the difference approach highlights how changes in hospitalizations are correlated to changes in state indicators.

In the second step of our analysis we are looking at the effect of the night sales ban on alcohol in Baden-Wuerttemberg. To measure the effect of the ban we use the difference-in-difference (DD) approach. As the ban was only introduced in Baden-Wuerttemberg, this state will be the treatment group. All other states are in the control group. This distinction can be justified by the fact that most alcohol regulation is done on the federal level with the exception of sales hour regulation and campaigns.[4] The ban was introduced in 2010, which is captured by the treatment dummy. We further assume there are no dynamic effects, which is reasonable as patients are registered when their treatment begins:[5]

$$ARH_{s,t} = \gamma_0 + \gamma_1 \cdot BAN_{s,t} + \gamma_2 \cdot POST_t + \gamma_4 \cdot BW_s + \epsilon_{s,t} \tag{3}$$

where *BAN* is a dummy variable for the night-sale-prohibition, *POST* a dummy for the time after the treatment began and *BW* a dummy to indicate the treatment group. Since were are reengenieering Marcus and Siedler (2015) here, we will limit the DD application to ARH by young people (15-25). Furthermore, to check for further robustness of the result we are comparing short-term ARH (F10.0), which should show an effect according to Marcus and Siedler (2015), and long-term ARH (K70/F10.2) which should not be affected in the short term by the treatment.

As the DD approach crucially depends on the common-trend assumption, we can incorporate control variables which capture different trends. Due to the small sample size we are limited on the number of control variables we can add and decided only to control for youth unemployment (*YUR*):

$$ARH_{s,t} = \delta_0 + \delta_1 \cdot BAN_{s,t} + \delta_2 \cdot POST_t + \delta_3 \cdot BW_s + \delta_4 \cdot YUR_s + \epsilon_{s,t} \tag{4}$$

Finally, we are refining our DD approach further by turning it into a panel:

[3] ARH is normalized by the state population and denoted in hospitalizations per 100.000 inhablitants.

[4] The night-sale ban in Baden-Wuerttenberg has been the most prominent alcohol policy in 2010. There have also been general changes to opening hours as during this time the competency was transfered to the states and media campaigns. As we only have annual data we are not fully able to distnguish between these treatments, but we assume that they are outweigthed by the night-sales ban.

[5] Even if they would be registered in consecutive reporting periods, the stay of patients for short-term ARH (F10.0) is in average 2,1 days and for long-term ARH 10,7 days (K70) and 11,4 days (F10.2) in 2014 making the dynamic effect insignificantly small.

$$ARH_{s,t} = \theta_0 + \theta_1 \cdot BAN_{s,t} + FED_t + c_s + \theta_2 \cdot YUR_s + \epsilon_{s,t} \quad (5)$$

This model includes time-invariant heterogeneity of states c and time-specific shocks *FED* affecting all states, e.g. a change in a federal law. This model can be estimated by using dummies for the time-periods and first-differencing or fixed-effects to address the unobserved heterogeneity of states.

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