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Does alcohol consumption lead to greater unemployment? The case of US

Bachelor thesis

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Prehlasujem na svoju česť, že som bakalársku prácu vypracoval samostatne a s použitím uvedenej literatúry.

Pavel Klečko

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Poďakovanie

Na tomto mieste by som sa rád poďakoval rodine a priateľke za podporu, hlavne krstnému za korekciu. Tiež by som sa rád poďakoval svojej školitelke Ing. Helene Chytilovej za jej komentáre, a pomoc pri vypracovaní tejto práce.

Abstract

The main objective of this thesis is to find the relationship between alcohol consumption and unemployment and explicitly how changes in alcohol consumption affect unemployment. In the theoretical part we will discuss basic factors related to the unemployment rate. Additionally, we will analyze the relationship between alcohol consumption and unemployment backed by relevant economic analysis including behavioral economics. We will study 3 states from the US (California, Georgia, Michigan). Many economists have proved that increased alcohol consumption increases unemployment, among others Johansson et al. (2000), MacDonald and Shields (2004), Terza (2002) or Popovici and French (2013). However, this research is based on micro data collected from surveys, while we will use the most available macro data in order to conduct analysis. We gathered data for our three between years 1987-2015. As the dependent variable we chose unemployment and for independent variables percentage change in GDP, inflation, average real income, state and federal expenditures on unemployment benefits, apparent per capita alcohol consumption, NASDAQ-100 index, proportion of people from ethnic groups, share of women and dummy variable crisis, which will be 1 in years of financial or economic crisis and 0 otherwise. We confirmed our hypothesis that increased alcohol consumption leads to a higher unemployment rate, mostly due to loss of productivity. Reversed causality that increased unemployment leads to higher alcohol consumption was denied.

Key words: Alcohol Consumption, Unemployment Rate, Determinants of Unemployment, Productivity Loss

JEL: C01, D9, E24, I15, I12, J24, J30

Abstrakt

Hlavným cieľom tejto práce je nájsť vzťah medzi alkoholom a nezamestnanosťou, a hlavne ako ju ovplyvňujú zmeny v konzumácii alkoholu. V teoretickej časti rozoberáme základné faktory ovplyvňujúce nezamestnanosť. Ďalej budeme analyzovať vzťah alkoholu a nezamestnanosti na základe relevantných ekonomických výskumov vrátane aplikovania behaviorálnej ekonómie. Budeme študovať tri členské štáty USA (Kalifornia, Georgia, Michigan). Mnoho ekonómov dokázalo že zvýšená spotreba alkoholu vedie k zvýšeniu nezamestnanosti, mimo iných Johansson et al. (2000), MacDonald and Shields (2004), Terza (2002) or Popovici and French (2013). Bohužiaľ, tieto výskumy pracujú s mikroekonomickými dátami zozbieraných z dotazníkov, zatiaľ čo my použijeme najnovšie makroekonomické dáta. Tie sme zozbierali pre roky 1987 až 2015. Ako vysvetľovanú premennú sme zvolili nezamestnanosť, a za vysvetľujúce premenné sme zvolili HDP, infláciu, priemerný reálny príjem, štátne a federálne výdaje na podporu v nezamestnanosti, zdanlivú spotrebu alkoholu na obyvateľa, NASADAQ-100 index, podiel ľudí z etnických skupín, podiel mužov a žien a dummy premennú kríza, ktorá nadobúda hodnotu 1 v dobe krízy a inak hodnotu 0. Potvrdili sme hypotézu, že zvýšená spotreba alkoholu vedie k vyššej miere nezamestnanosti, a to hlavne kvôli strate produktivity. Obrátená kauzalita tvrdiaca, že vyššia miera nezamestnanosti vedie k vyššej spotrebe alkoholu bola vyvrátená.

Kľúčové slová: Spotreba Alkoholu, Miera Nezamestnanosti, Determinanty Nezamestnanosti, Strata produktivity

JEL: C01, D9, E24, I15, I12, J24, J30

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Introduction

The relationship between alcohol and unemployment gains more attention with the recent boom of behavioral economics. Recent Nobel Peace Prize in Economics Sciences awarded to Richard Thaler proves that behavioral economics could be considered as rather complementary to standard mainstream economic theories. One of the interesting fields, where we can apply knowledge of behavioral economics is alcohol consumption and its relation to unemployment. Nevertheless, there are many other factors responsible for increased consumption of alcohol, such as mental illness, or just increased mental constrain and stress. Also increased alcohol consumption can lead to the increased probability of being unemployed. Terza (2002)

In recent decades, many analyses were aiming to explain unemployment on a micro or macro level. The main aim of this thesis is to analyze the relationship of alcohol consumption and unemployment on a macro level. There exists many studies, which analyze this phenomenon at microeconomic level Mullahy and Sindelar 1(996) Johansson et al. (2000) Terza (2002) MacDonald and Shields (2004), however only few studies, which do it at the macroeconomics level. As a result, significant value added of the thesis is not only analysis with the help of macroeconomic data, but also the inclusion of other factors potentially responsible for a higher probability of unemployment. Additionally, we examined the reversed causality, as strong endogeneity is suggested Popovici and French (2013).

In order to estimate these relationships, we needed an econometric model of unemployment, including as many variables as possible, with option to add alcohol consumption into it. We had problems with finding such a model, so instead we decided to combine together more models and approaches used before to explain unemployment factors. Although we could not incorporate all variables affecting unemployment rates, we are pretty confident that we included the bigger part of the strongest factors. We also added constructed variable crisis, as in the years of crisis the economy is at stagnation or recession and unemployment should rise rapidly, even the other factors are not as much and soon affected . At first we wanted to make a cross-time analysis of all states of the US, but due to the vastness of data, and the complicated econometric approach for such a model, we decided for ARMA[1] model, for 3 specific states of US.

[1] Autoregressive moving average model

We opted for California, Georgia and Michigan and used annual data from the period of 1987-2015, which includes 28 observations. We used 11 variables to estimate unemployment rates, including alcohol consumption, unemployment benefits, growth of real GDP per capita, growth of income, minimum wage, crisis, NASADAQ-100, inflation and ratio of males, Afro-Americans and Hispanics.

Results suggest that the relationship of increased alcohol consumption leads to higher unemployment, but is not as strong and “pure” as on a microeconomic level, but still remains in all states except for Georgia where we found strong arguments why it is the opposite as expected. Further examination of this relationship is still needed. We also denied endogeneity by the fact that our models for reversed causality were insignificant.

This thesis is organized as follows. In the first part we take a standard look at unemployment and alcohol consumption. In the second part we look at unemployment from the perspective of behavioral economy and psychology. The third part is devoted to delineation of determinants of unemployment. In the fourth part we discuss the findings on the relationship between alcohol and unemployment. Our hypothesis is formed in the fifth part. Chapter 6 and 7 are devoted to our data collection. In chapter 8, we discuss our constructed variables. Descriptive statistics of our dataset are available in chapter 9. Our model for unemployment is in chapter 10. Chapter 11 is devoted to reversed causality model. We discuss our results in chapter 12 followed by the conclusion in chapter 13.

1 Standard approach to alcohol-unemployment relationship

Alcohol severely reduces certain capabilities of humans. Alcohol usage before, or on the job, may result into increased risk of injury, and it is forbidden to be under influence of alcohol on the job by law in almost all countries. However, heavy drinkers may not be engaged with this fact, which may result into redundancies.

According to (Keynes 2016, p.280) “The employment function only differs from the aggregate supply function in that it is, in effect, its inverse function and is defined in terms of the wage-unit” This means that any aggregate shock will also affect the employment. In the recession the unemployment will rise, while during the recovery it will decrease.

As it is generally known, the majority of affected groups by unemployment is mostly from the lower income classes (or we can say that their previous wage was lower than average), with wages closer to minimum wage. This is caused mostly by the unexplainable ability of workers with a previous higher wage to find new job faster. This means that those with lower wages will be unemployed for a longer time. Also unskilled labor is easiest to replace, meaning that the job separation rate will be higher. During the recession companies would more likely start to decrease the wage, rather than selling some capital, and since there is a limit to minimum wage, they need to make people redundant sooner than higher paying industries. Of course there are cases in which this is not true, as the structural unemployment may occur during recessions for some higher paying industries, otherwise the ratio of workers from high and low paying industries that lost jobs due to recession should remain much higher than lower paying ones.

We can assume that people with lower income had lower investments into human capital compared to those with higher income as Mincer (1974) claims, that investments into human capital are one of major determinants of wage. Further they assume that people who prefer current highest utility over higher future ones (with high discounting of future) have lower investments into human capital. If they were looking forward they would be investing into their human capital more. This effect is diminishing as higher income groups had higher investments into human capital and are much more concerned about future utility (Mincer 1974). Of course there are some limitations in investing into human capital. For example, during college you has to pay study fees, books, living expenditures like rent or food and in most cases you cannot work a full-time job. One needs either to be supported by some source (parents) or take a loan. Some people may prefer to go to work immediately after high school if they miss the funding for college and have some job training to work than for let's say average wage.

Becker (1988) defines people with highest likelihood of becoming addicted as those who discount the future the most. This is caused by the fact that these individuals take high dosages of substances in present time, and therefore they need to consume an even bigger amount in future as the utility for each dosage decreases as users consumed more in past. (Becker 1988, p.694)

Becker and Murphy (1965) also state that we do not consume only money but we also consume time. To monetize the time, he simply sets the value of time as wage you could earn working. This means that lower the income, the cheaper the time is. With unemployment benefits high enough, it can happen that someone with a low income will have a higher utility if he stopped working (considering he has right to receive unemployment benefits), although his value of time will decrease. We can consider that heavy drinking consumes a lot of time, due to the time spent in pubs (or other), or simply by drinking/buying alcohol. Heavy drinking also consumes time by recovering from hangovers. If we apply here (Becker 1988) theory of time allocation, we can conclude that persons with lower income have enough time to start drinking more heavily, and that persons with high income would need to decrease their working hours in order to have enough time to recover from a hangover.

This is in line with Fisher (1995) as he claims that heavy drinking may negatively affect job productivity. This happens through increased lateness, early leaves, low performance and risk of on-the-job injury caused by a hangover, and overall lower physical and mental health (Fisher 1995.), (Klingemann and Gmel 2001). Such behaviors may result into redundancy, as these people with lower productivity will be the first one to be fired in all cases. Also the ones labeled as alcoholics are the first ones to be fired.

Heavy drinkers suffer from decreased job productivity, which results in the increased probability of being unemployed. Also, heavy drinkers have increased alcohol consumption due to previous alcohol consumption, which reduces their abilities even more. This applies to all income groups, but lower income groups have a higher chance of becoming addicted, as we suppose they prefer current utility over future one, as they had lower investments into the human capital. We also need to bear in mind that people from high paying industries may feel much more stress in their work (as they have probably more responsibility, and their loss of income would be much higher than compared to low paying industry), which is also a factor that increases alcohol consumption.

2 Behavioral and psychological approach to alcohol-unemployment relationship

Alcohol, even though is legal, is still a drug, which usage occurs sleep and lowers brain and nerve functions. This means that an employee under the influence of alcohol is worse at critical thinking, irresponsible, inaccurate a may forget things. (Klingemann and Gmel 2001) These facts increase the probability of losing the job. Ruhm (1995) suggests that increased stress and mental constrain (decreased mental health) may result in increased alcohol consumption, as many people consider alcohol as some bandage for such problems. He also states that being unemployed and facing lower income is a very stressful event which may lead to decreased mental health. This is in line with Hull (1981) as he states that alcohol is used for decreasing the self-awareness, which means it will numb physical or emotional pain.

Whelan (1994) and Clark, Georgellis, Sanfey (2001) came to the conclusion that 3 phases occurs after losing a job. The initial reaction is shock from losing your job and income. Optimism is the second phase, as you hope to find maybe an even better job than before and get your life straight. After unsuccessful phase 2 comes phase 3, which is deep depression from the fact you cannot find a job. The length of phase 2 is individual, but 3 months is the maximum duration of phase 2. According to Whelan (1994) phase 3 may result in substance (alcohol) abuse or suicide. Popovici and French (2013) also states that being unemployed increases alcohol consumption. They also say that being unemployed brings more stress, and even more stress for the ones whom have families dependent on their income, as they are worried how to secure their income.

Hull and Bond (1986) conducted that alcohol significantly impairs information processing and motor performance and improves mood and increases aggression. They also claim that these effects of alcohol usage may be considered badly by society and result in a decrease of social status.

MacKillop (2016) defines three cores of behavioral understanding of alcohol consumption. The first one is future discounting, which is defined as preference between lower current and higher later reward meaning. For example, if we made people to decide between 100$ immediately and 300$ after certain period of time which is lowers each time they do not agree until they do. People with higher alcohol consumption have much steeper hyperbolic discounting of future meaning they would prefer the 300$ later than the others. Heavy drinkers are in circle as they demand more and more alcohol due to decreasing reinforcing effect of alcohol, and their future discounting allows them to buy more, as future negative consequences are negligible for them compared to present utility from alcohol. Etiology may play a major role in future discounting, as it has been proved that family history of alcohol and drug use is associated with steeper future discounting. The second important thing is that only very high prices affect the amount of alcohol consumption. This is related to reinforcing the value of alcohol, because as the price of alcohol grows, the utility from alcohol grows too. As third he mentions that individuals differ between alcohol and non-alcohol reinforcement activities. Heavy drinkers will have higher proportion of alcohol reinforcement time relative to modest drinkers, even though they can have lower total alcohol consumption.

Saffer, Dave, Grossman (2012) examined the effect of prices and advertisement of alcohol on alcohol consumption. They suggest that heavy drinkers are much more responsible to advertisements relative to prices compared with modest drinkers. Therefore they suggest regulation on alcohol advertisements, rather than higher taxes on alcohol, as heavy drinkers are more problematic group than modest drinkers, although they are minority of drinkers.

Delaney, Harmon, Wall (2007) proved again that price or income is not the main variable of alcohol consumption. They claim that alcohol consumption is better explained by personality, or level of well-being.

Bickel, Madden, Petry (1998) examined future discounting in detail among the drug addicts. They have found that the addicted have future discounting higher by 80%. They also state that due to this very high discounting of future they will lose control of themselves, as they will abandon all their plans in order to secure current highest pleasure.

To summarize, we can say that alcohol users have a higher probability of losing a job, and those whose lost a job will start to drink more. A higher probability of losing a job is bound in this case with purely psychological aspect of alcohol usage, as reduced memory, incompetence, and addiction. Same holds for increased alcohol consumption as increased stress and mental constrain from losing job is often “solved”[2] by increased alcohol consumption. Also an increase in current alcohol consumption will lead to a future increased alcohol consumption.

3 Other factors affecting unemployment rate

As we want to enrich the pool of known factors of unemployment by alcohol consumption, we need to gather this pool on good empirical basis a following chapters contain. Following chapters contain recapitalization of known determinants of unemployment other than alcohol.

3.1 Unemployment benefits

It is known that unemployment benefits and unemployment rates are closely related as with higher unemployment benefits the opportunity cost of being unemployed rises. Also with higher minimum wage, there is chance that some companies will need to raises their wages, and this may result in redundancies. According to Meyer (1988) the ratio of unemployment benefits and previous wages, together with the duration of unemployment benefits affects the unemployment rate. As those whose previous income is higher than unemployment benefits will try to find new a job as soon as possible due to loss of income and some unobserved ability to be better at job finding than those with lower incomes. Those whose previous income was lower than their unemployment benefits will feel a moral hazard of not returning to work as long as they have unemployment benefits. This means the longer and higher unemployment benefits are, the higher the unemployment rate. Hagedorn (2013) in his research concludes that extending unemployment benefits raises the pressure on increase in equilibrium wages, and this results in an increase in unemployment rates, as companies need to raise wages, and some of them reduce their expenditures by decreasing the workforce.

Moffitt and Nicholson (1982) further supports that increasing or extending unemployment benefits is positively affecting (increasing) the unemployment rate. Therefore we can expect that with increase of unemployment benefits the unemployment rate will rise.

[2] Alcohol is not solution for them in ordinary way, but it reduces pain and stress

3.2 Economic growth

With an increase in employment, the aggregate output should rise[3] as the economy should produce more. Therefore with higher economic growth, more job opportunities should appear and the unemployment rate shall be lower. With lower economic growth or negative growth lower amount of job opportunities will appear and unemployment rate will increase.

Okun (1970) states, that one point reduction of unemployment shall increase the output of the economy by 3 points. This relationship was re-examined by many researchers. For example Lee (2000) tried to apply Okun´s law in countries of OECD, since Okun was using US data only. He found that Okun´s law was not as “powerful” as in the US, but still applied. He suggested that this may be caused by different economic structures of various states. Another research was done by Ball, Leigh, Lougani (2013). They have collected data for the US and 20 important countries to examine Okun´s law. They have fully confirmed the law. They also stated that “It is rare to call a macroeconomic relationship a “law.” Yet we believe that Okun’s Law has earned its name. It is not as universal as the law of gravity (which has the same parameters in all advanced economies), but it is strong and stable by the standards of macroeconomics. Reports of deviations from this Law are often exaggerated. Okun’s Law is certainly more reliable than a typical macro relationship like the Phillips curve, which is constantly under repair as new anomalies arise in the data.”(Ball, Leigh, Lougani 2013, p.21)

To conclude, we can expect a positive correlation between changes in unemployment rates and changes in economic growth, however it may be shortsighted to analyze this relationship only from a point of unemployment and product, as both of these are influenced by many other factors.

3.3 Growth of income

The relationship between growth in wages and unemployment has been examined for centuries, starting with Phillips (1958) whom claims that there is a negative correlation between wage growth and the unemployment rate. This claim was further confirmed by more research, for example by Aaronson et al. (2000). They also

[3] Of course we cannot forgot, that economic growth can be also caused by other factors, like positive shocks or advance in technologies

suggested that according to newer data, the relationship is not as tight as suggested at first, because there are more determinants of unemployment than just wage growth, but we can still expect that lower unemployment rate will be observed together with higher growth of wages (income), as higher wages forces people to find a job sooner, or to work more hours, as opportunity costs rises.

3.4 Changes of minimum wage

A raise of the minimum wage should result in increased pressure on equilibrium wages. Also it may occur to some companies that their wages are lower than the new minimum wage, and therefore they need to increase them instantly. The increased pressure on equilibrium wages and the need of increasing the wages results in increased variable costs of companies(higher payroll), which they may solve by decreasing the work force. Brown, Gilroy, Kohen (1982) has come with the conclusion that the minimum wage effect depends on the composition of population, as results differ across adults and teenagers. Teenage employment is decreasing while minimum wage is growing, while adults are not affected. Similar behaviors affect high and low paying industries, where low paying industries behave as teenagers while high paying industries are not affected. This research is in line with older one by Mincer (1976). He too found a negative effect of increasing minimum wages on employment. On the other hand Card and Krueger (1993) conducted analysis for New Jersey´s fast foods chains in 1992 when the minimum wage increased from $4.25 to $5.05 per hour. Considering fast foods as a low paying industry (wage was set to minimum wage, or slightly above), they came to opposite results as Brown, Gilroy, Kohen (1982). They divided fast foods into two groups. First group had their wage lower than the new minimum wage, and second group had it already high enough. In both cases the employment is increased by the same amount holding the wages ceteris paribus. To conclude these works we can say that effect of minimum wages depends on the length of the examined period. Brown, Gilroy, Kohen (1982) and Mincer (1976) both proved the negative effect of minimum wage on employment in long term relationships, while Card and Krueger (1993) proved the opposite. The difference in outcomes can be also caused by the time period used as this relationship could evolve, because in recent years we could observe that the minimum wage was growing much more and at a much faster pace than it grew in 70´s or 80´s. Also we may consider fast food chains as a unique industry, but we can still expect that in the future, the minimum wage will decrease employment.

3.5 Inflation

Friedman (1977) adapted Keynes´s Phillips curve, and agreed on variation between inflation and unemployment in the short run. However he argued that in the long run the unemployment rate will always be leading to natural unemployment rate. Therefore governments can only set the inflation level. However in the short term there is a substitution between inflation and unemployment rates, which means that increases in inflation can lead to lower unemployment rates. On the other hand, newer researches suggests more complicated relationship between inflation and unemployment rate, but as simple outliner of the fact that increased inflation can lead to higher unemployment rate the Friedman (1977) theory is sufficient.

3.6 Demographic composition of population

3.6.1 Gender

Due to biological differences, and also because of women's position in society in the last century, the man works more. According to Albanesi and Sahin (2018), the difference between the amount of men and women is decreasing. They observed two gender gaps. One for the ratio of employed men and women and second one for the ratio of unemployed men and women. They observed that the gaps are in their time series of 1970-2005 slowly closing. However the gap still remains. According to this work we can assume that with the higher male ratio comes lower unemployment rates. These claims are supported also by Azmat, Guell, Manning (2006). They claim that most of OECD countries have an unemployment rate gender gap, as more females are unemployed compared to males. To conclude, we can expect that with higher ratios of men we will observe lower unemployment rates.

3.6.2 Race and Hispanic origin

According to Farley (1987), racial discrimination still remains as one of the main sources of black unemployment, and their disadvantage to find jobs compared to the white population. This applies also to Hispanics, but this discrimination is not as strong. Social class also plays a role for both races but it is much stronger for Hispanics. Sundstrom (1992) states, that Afro-American unemployment was always higher than general. He explained it for men by fact that Afro-American males concentrated in occupations with higher unemployment rates, but also because of racial discrimination. On the other hand, for women, there was found a big difference in within-occupation. He assumes that this is caused by racial discrimination.

To the same conclusions, but this time for Hispanics only came DeFreitas (1986) as he was not examining the Afro-Americans. He claims that we can observe relative higher unemployment among Hispanics in comparison to whites.

To sum up we can state that we can observe higher unemployment rates for Afro-Americans and Hispanics than for whites in general and therefore we can expect higher unemployment rates, with higher relative population of Afro-Americans or Hispanics. This difference can be either caused by racial discrimination or by concentration of these racial groups into industries with higher unemployment rates than average.

4 Recent studies on alcohol and unemployment

First, we examine economic costs of alcohol consumption. Research done by Bouchery et al. (2011) provides us interesting results. They have analyzed costs for health care, productivity losses, and other effects (e.g., property damage) in 2006 in the US. They defined productivity loss as "When alcohol-related sickness, disability, death, or incarceration prevents an individual from engaging in his or her normal expected productive activities, this represents a loss of potential productivity—work that could and would have been done, but wasn't because of excessive drinking."(Bouchery et al. 2011, p.518) They have estimated excessive drinking costs in 2006 to be around 223.5 billions[4] of dollars. 72.2% of this amount was due to productivity loss.

Additionally, Mullahy and Sindelar (1996) analyzed around 15000 observations from a 1988 Alcohol Survey of the National Health Interview Survey from the US. They have applied the ordinary least square method and method of instrumental variables. For men, the results from both methods suggests that problem drinking increases the likelihood of being unemployed, and more people with a higher probability of being unemployed will be projected in higher unemployment rates. Although in IV[5] method, the estimators were much bigger. In the case of women, the OLS method suggested that for women the relationship worked the other way, but when they controlled unobserved heterogeneity through IV method, they gained same results

[4] US billion = 1.000.000.000
[5] Instrumental variables

as in mens models. They claimed that this is caused by fact that for women, being in work is not always preferred state. However, results were statistically insignificant for women. Still, the study approached the problem of alcohol and unemployment with the help of innovative modeling.

Johansson at al. (2000) has proved again that increased alcohol consumption leads to decreased probability of being employed, this time for Finland. They also found again that males suffer from this disadvantage far more than females do.

Terza (2002) followed Mullahy and Sindelar (1996) in similar manner. He improved the method of IV used by them, by dealing with non-linearity directly and not through Taylor estimation. He came to the conclusion that he supports the qualitative finding of Mullahy and Sindelar (1996), that problem drinking increases the probability of being unemployed, but his results are all statistically significant, and the effect is much bigger.

MacDonald and Shields (2004) examined the relationship between alcohol and unemployment in England. They used data from Health Survey of England to show that people with drinking problems, (in this case we consider them as heavy-drinkers), have a higher chance of becoming unemployed. They proved that heavy-drinkers have 7 to 31% higher probability of being unemployed. Also they have found that problem drinking is more related to physical and psychological aspects of heavy drinking rather than amount of alcohol drunk. This is caused by different individual´s tolerance to alcohol.

Popovici and French (2013) examined the effect of being unemployed on alcohol consumption. Method of IV was used again. With 43093 respondents in 2001, 2002 and 34653 respondents in 2004, 2005, they had one of the biggest respondents' databases. They claim that job loss leads to an increase in alcohol consumption due to many factors. Mental strain can be increased due to job loss, and alcohol may be used to relieve this strain. The mental strain will be even higher for persons from families, which are reliant to theirs income. Shame can too increase this mental pressure. It also appears that these effects are dominant to income effect in alcohol consumption, as with missing money; subject will just substitute for cheaper alcohol.

In summary, we can claim that it was proved on a micro level that increased alcohol consumption leads to a higher chance of being unemployed. We can also claim that being unemployed leads to higher alcohol consumption. This means that we can observe endogeneity problem as this relationship works both ways according to gathered literature. A higher chance of being unemployed is mostly caused by decreased productivity resulting from, increased lateness, sickness (health problems caused by increased amount of alcohol consumed), injury, not showing to work, leaving early and low performance all resulting from alcohol abuse and hangovers. Higher alcohol consumption of the unemployed is caused by a variety of psychological factors like shock or shame of losing job, the stress coming from the need of finding a new job, and maintaining current income, fear of the future due to uncertainty, etc. Of course employed can start drinking due to psychological factors too as they can be under pressure due to for example tight work schedule and deadlines.

5 Hypotheses

Our main hypothesis in this thesis is that increased alcohol consumption leads to higher unemployment rates on macro level. We based this hypothesis on many findings on microeconomic level revised in Chapter 4 (Mullahy and Sindelar 1996), (Johansson et al. 2000), (Terza 2002), (MacDonald and Shields 2004). We conclude that if alcohol consumption increases, there is bigger probability that a higher ratio of population becomes heavy drinkers thus their chance of being unemployed increases resulting in higher unemployment rates. Also in light of Popovici and (French 2013), the endogeneity is questionable on a macro level, as they proved that unemployment can lead to greater alcohol consumption on micro data due to many psychological aspects, mainly due to increased mental constrain. To confirm or confute the endogeneity, we constructed a secondary hypothesis that higher unemployment rate leads to greater alcohol consumption.

6 Data

6.1 Data restrictions by time

We gathered data for three states including California, Georgia and Michigan for period of 1987 – 2015. The USA weren´t measuring GDP per state until 1987, and since GDP is on of crucial factors in our analysis, we could not conduct our empirical investigation for earlier time period.

The end of year 2015 is available due to the dataset of the last publication of NIH[6] on apparent alcohol consumption per capita.

6.2 Data restrictions by space

We gathered data for three states including California, Georgia and Michigan for a period of 1987 – 2015. We have chosen these states due to many factors. At first we wanted to do a cross-time analysis of all states, but vastness of data and difficult econometric approach to such analysis forced us to opt for some states with specific features, just to sketch the macro relationship of alcohol and unemployment rates. The main reasons why we chose California are that it has the highest GDP from all states, which should result in low unemployment. Also one of the biggest Hispanic community's lives here, and again according to chapter 4, this should increase the unemployment rate. California has also one of the highest unemployment benefits, which are crucial for this model. We suppose higher the unemployment benefits, the more money unemployed have to buy alcohol. Factors that spoke for Georgia are one of the biggest Afro-American communities, which should have the same effect as Hispanics in California. Georgia also has one of the lowest unemployment benefits. As further mentioned in the data section, Georgia´s minimum wage is lower than the Federal, resulting in the Federal one to apply. Also they have one of the lowest unemployment benefits. These statistics should be crucial, as we can assume that Georgians have lower incomes compared to most of the US. Additionally, it was hit badly by 2007-2010 economic crisis. Apart from that we wanted to include a southern US state in our sample. Michigan´s position was not the main factor, which made us to opt for this state, but it was the fact that it´s car industry was almost destroyed during last economic crisis 2007-2010. It is also crucial that Michigan has a very different climate from California or Georgia, and also different demographics of races.

7. Data collection

All the collected data is annual data if not mentioned otherwise, also all data is collected per state if not mentioned otherwise. Most of the data is accessible online, however we had to make special request regarding LAUS data. We used only reliable sources of data like state databases.

[6] National Institutes of Health

7.1 Unemployment rate

We took the unemployment rate from the Local Area Unemployment Statistics known as LAUS. The unemployment rate was measured monthly with annual averages, which is presented by Bureau of Labor Statistics to determinate annual unemployment rate in each state. As it is easier to deal with data from (FRED 2018) we opted for them, as they use the LAUS data, but in much more approachable form. They use a basic definition of unemployment rate known as:

$$Unemployment\ rate = \frac{Unemployed}{Labor\ force} * 100\%\ (1)$$

7.2 Alcohol consumption

We used the latest surveillance report of NIH "Apparent per capita alcohol consumption: national, state, and regional trends, 1977–2015". They measured the average amount of ethanol consumed per capita over 21 years. They also measured alcohol consumption in three categories, spirits, wine and beer, but we decided to take into account only alcohol consumption of all alcoholic beverages. We do not think that different alcoholic beverages have different influences on macroeconomic level, as we cannot observe what certain groups of population currently consume. Beer, wine and spirits are close substitutes and the only main difference is taste and volume of alcohol. Since we measured the amount of ethanol drunk, we do not see a point in splitting alcohol consumption into the groups.

7.3 Income

Similarly the income is measured by real personal income per capita. The reason why we chose per capita variables is that we want to compare three states with different sizes of population. If we were taking into consideration just one state, we could work with real personal income. The source of data is U.S. Bureau of Economic Analysis (2018). The important thing to be mentioned about real income per capita in the US is that not only income from working (wage) is counted, but also other means of income. Whole income per capita corresponds from wages, investment, interest and other income.

7.4 NASDAQ-100 index

One of the factors that may have effect on unemployment rates is the stock market, as stock markets reflects how well is the economy doing. The best way to capture how well the stock is performing is choosing one of the stocks markets indexes. For our purpose we chose the NASADAQ-100 which is defined as a basket of the 100 largest, most actively traded US companies listed on the NASDAQ stock exchange. This index does not include the financial sector (commercial and investments banks, etc). It is constructed on a modified capitalization methodology, which means that individual weights are set according to market capitalization. Influence of the largest companies is constrained. To accomplish this, they review the index quarterly, and adjust the weights if needed.

We have chosen NASADAQ-100 from all available stock market indexes, because from its definition, it is clear that this index can clearly capture the state of the economy. As in recessionary times, the index should have slower or negative growth. Other available indexes, captures financial companies (whose growth on the stock market is a result of good investments, not growth of a company by building new factories, increasing their production, etc. and opening new work places, although growth of financial firms also brings some growth of jobs, it is negligible compared to other industries). Data set is downloaded from (FRED 2018).

7.5 Inflation

We decided to work with the national inflation rate due to many factors. One of the main reasons was that state inflation levels started to be measured in 1996, which is a bit too late for our data set, as it is suggested to work with at least 20-30 observations when dealing with time series. We also think that it is better to use the Federal level of inflation, rather than not using inflation at all, as the federal inflation rate is measured by all states. We must consider the fact, that this inflation is blurred. The data is downloaded from (FRED 2018). They defined inflation according to Laspeyres index: "To calculate the index, price changes are averaged with weights representing their importance in the spending of the particular group. The index measures price changes (as a percent change) from a predetermined reference date." (FRED 2018)

7.6 GDP

As mentioned in previous sections, in our model we will take into account the growth rate of GDP, since this number should be most related with unemployment rates. To eliminate other elements that can influence this number, like inflation, or the size of population we work with growth rate of real GDP per capita. Also it is necessary to emphasize, the technique of measuring the GDP changed in 1997 due to a change from SIC[7] to NAICS[8] codes. The difference between them is defined by (U.S. census bureau, 2018) as "NAICS codes provide a greater level of detail about a firm's activity than SIC codes. NAICS includes 1,170 industries and SIC includes 1,004 industries. There are 358 new industries recognized in NAICS, 250 of which are services producing industries. Additionally, NAICS codes are based on a consistent, economic concept, while SIC codes are not. For NAICS codes, establishments that use the same or similar processes to produce goods or services are grouped together. Industries under the SIC codes were grouped together based on either demand or production. Unlike SIC codes, the NAICS codes were developed by the U.S. federal government in cooperation with Canadian and Mexican statistical agencies. Because both Canada and Mexico use NAICS for their industry classifications, government and business analysts are now able to compare directly industrial production statistics collected and published in the three North American Free Trade Agreement countries. Additionally, NAICS provides for increased comparability with the International Standard Classification System (ISIC, Revision 3), developed and maintained by the United Nation" Since they used both techniques in 1997, we still can work with growth rate, although it is a bit blurred, due to higher GDP measured by SIC code. For example SIC real GDP per capita in California in 1997 was 41345 dollars while the NAICS come up with only 31924 dollars. The source of data for all three states was U.S. Bureau of Economic Analysis (2018).

7.7 Minimum wage

We will work with state minimum wage if it is higher than the federal one. The reason behind this is the Federal Fair Labor Standards Act, by which most people are covered by federal minimum wage if the state minimum wage is lower. It would be impossible to apply state and federal minimum wages at one time, as we miss data on

[7] Standard Industrial Classification
[8] North American Industry Classification System

how much people were exactly covered by minimum wage of each type. We can only claim that the vast majority according to laws is covered by the federal minimum wage. In Georgia, the Federal minimum wage is always higher, so in Georgia we use the Federal minimum wage. In Michigan we can observe that except of a few observations, the Federal minimum wage is lower than state minimum wage. To smooth this out we decided to construct our own minimum wage series for Michigan. More on Michigan´s minimum wage time series construction in Chapter 8.2. Data is retrieved from (Department of Labor statistics, 2018).

7.8 Demographics

Demographic statistics such as sex, race and Hispanic origin comes from CPS[9]. We measured only Afro-Americans, due to other races being too small, or unimportant. According to the methodology of CPS the Hispanics are not a race but origins. All are measured in rates again due to the different size of populations in each state. Since CPS is decennial, we had to smooth these variables at an annual basis. The method of smoothing of these variables is described in the next chapter.

7.9 Unemployment benefits

We decided to work with the total sum paid on unemployment benefits rather than the sum of how much people should receive. In macro models, we cannot model individuals; hence the total sum paid by states is for our purpose the best, as it still captures the size of unemployment benefits and changes to it. As a bonus it captures the length of unemployment benefits too, as it is the total sum paid per year. Also it would be impossible to apply some rule to our model on how high the unemployment benefits were according to law. There are too many variables that influence the individual unemployment benefits, and they are more consistent for calculation with micro data. We ended with the total sum paid on unemployment benefits in nominal billion dollars. This includes all expenditures on the unemployed, from the subsidies paid, to other unemployment benefits like new job training, food stamps, housing support, child support. We could not make it to total sum paid on unemployment benefits per capita or unemployed, because this would cause certain unsolvable[10] econometric problems. The source of data is (US government spending, 2018).

[9] Current Population Survey

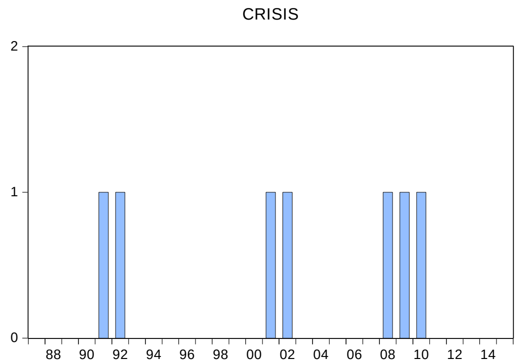
[10] When the unemployment rate is explained by unemployment benefits per capita, we can observe almost perfect multicollinearity.

8 Constructed variables

8.1 Crisis

The first discussed constructed variable is the dummy variable crisis. We considered three crises in our analysis. As earliest we will take the 90´s US recession, caused by raising interest rates and simultaneous presence of oil shocks. Oil shocks were a result of war in Middle-East and the prices of gas increased rapidly. Since the crisis was in during years 1990-1991 we need to take into account the time that passed before companies started firing and taking back employees, so we set years 1991-1992 as crisis years, or at least those years of crisis that affected unemployment as we can observe lagging of unemployment behind development of production. As second crisis we will take the dot-com bubble. This happened in 2000 but again we will tag year 2001 and 2002 as the crisis year. Last crisis is the great recession in 2007- 2009 but again we will take 2008-2010 as crisis years. The following graph displays this variable which is identical across all the states. We hope that this variable will explain the growing unemployment rate during the years of crisis.

Graph 1: Dummy variable crisis



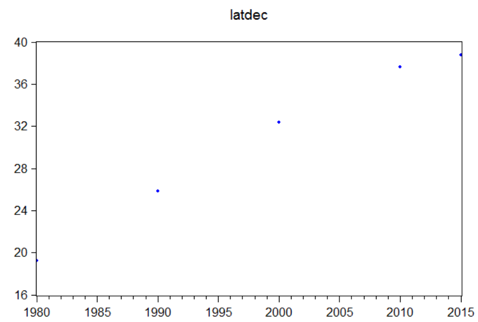
Source: Author´s own calculations

8.2 Spline variables

Sex, race and Hispanic origin are constructed variables too, since they have been only measured in ten years cycles. To solve this, we used a method of interpolation in EViews. For correct use of this function, the appropriate shape of these variables has to be determined, (either linear or cubic). According to other annual graphs, from other states, we identified that all demographic variables have a cubic shape, so we used cubic spline as the method of interpolation. The second problem is that the value at the start and end of the time line needs to be outlined. To solve this, we used as starting data the

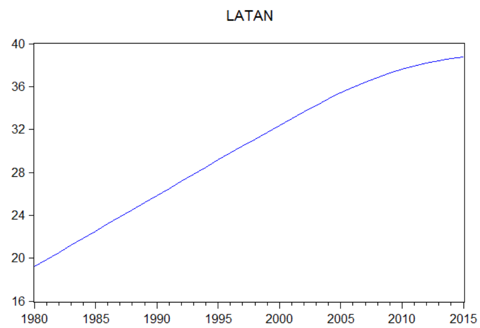
1980 CPS and after our interpolation, we cut the values at the year 1987. It was not a problem to acquire the end year 2015, since they started to collect this type of data more annually. The following graphs describe what we did for the size of the Hispanic population in California. Figure 1 shows data collected for the years 1980, 1990, 2000, 2010 and 2015. Figure 2 shows our series with cubic spline interpolation.

Figure 1: Collected data for Hispanic origin in CA



Source: Author´s own illustration

Figure 2: Interpolated data for Hispanic origin in CA



Source: Author´s own illustration and calculation

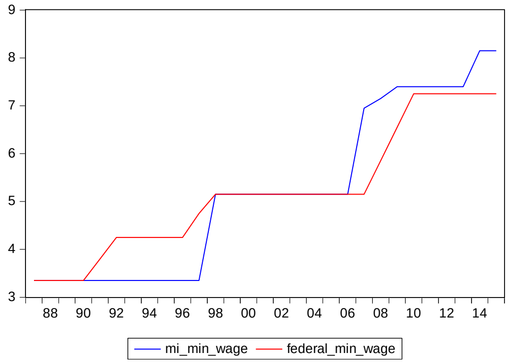
The rates gathered through this process may not reflect with a hundred percent accuracy the exact rates during those years, but will capture the trends in change, which is more important for us than exact rate. We used the same approach with respect to all other demographic variables. Figures and tables of other variables are in appendix.

8.3 Michigan minimum wage

As mentioned before, the Fair Labor Standards Act says that "if state minimum wage is lower than federal, than the federal one applies in the most of cases."[11] In Georgia, the state minimum wage is always lower than federal, so this does not constitute a problem, but as figure 3 shows, in the beginning of our time series, the state minimum wage is lower than the Federal in Michigan. We have dealt with this by creating our own time series of minimum wage in Michigan. This time series consists of the higher values of Michigan and the Federal minimum wage for each year.

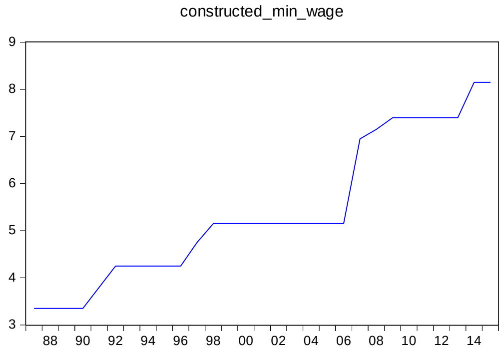
[11] https://www.dol.gov/whd/regs/compliance/hrg.htm

GRAPH 3: Michigan and Federal minimum wage



Source: Author´s own illustration

GRAPH 4: Michigan constructed minimum wage



Source: Author´s own illustration and calculation in eViews

9 Description statistics

The most important fact within these statistics is that inflation in 2009 was -0,4, which means that in fact we have seen deflation in that year. We can also observe rapid growth of NASADAQ-100 index, with minimum of nearly 400 and maximum over 4000. A very interesting aspect is that we can see big differences in all state-specific variables except for alcohol consumption, which is almost on the same level in all states. This may suggest that alcohol consumption behaves according to some trend consistent with the character of population or it may be pure coincidence. But as this is further observable in all US states, we believe that it is not coincidence.

The following tables illustrates basic statistics of variables used in the model for California, Georgia and Michigan.

Table 1: California basic descriptive statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Sum	Sum Sq. Dev.	Observations
CAALC	2,354828	2,27	3	2,16	0,218397	68,29	1,335524	29
CABEN	8,919655	7,87	24,55	1,59	5,778198	258,67	934,8519	29
CABLCK	6,730574	6,591224	7,539447	6,152686	0,484576	195,1867	6,574796	29
CAGDP	1,624138	1,7	5,9	-5	2,633934	47,1	194,2531	29
CAINC	29594,62	28432	46766	16082	9390,601	858244	2.47E+09	29
CALAT	32,4465	33,01276	38,79	23,83969	4,824136	940,9484	651,624	29
CAM	49,84321	49,79178	50,07337	49,67	0,147981	1445,453	0,613156	29
CAMINW	5,972414	6,25	9	3,35	1,857782	173,2	96,63793	29
CAUR	7,272414	6,7	12,1	4,9	2,113544	210,9	125,0779	29
NASDAQ100	1898,607	1845,38	4945,55	374,43	1227,796	55059,59	42209524	29
INFLATION	2,7	2,8	5,4	-0,4	1,243555	78,3	43,3	29

Source: Authors own calculation in eViews,

Table 2: Georgia basic descriptive statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Sum	Sum Sq. Dev.	Observations
FEDMINW	5,193103	5,15	7,25	3,35	1,307241	150,6	47,84862	29
GAALC	2,126897	2,12	2,48	1,95	0,133259	61,68	0,497221	29
GABEN	0,690862	0,58	1,86	0,22	0,443571	20,035	5,509135	29
GABLCK	28,90552	28,8764	31,72	26,75661	1,530453	838,2601	65,58402	29
GAGDP	1,134483	1,7	4,6	-4,9	2,402569	32,9	161,6255	29
GAINC	24943,31	25717	36342	12998	7148,448	723356	1.43E+09	29
GALAT	5,550579	5,743529	9,35	1,23563	2,889942	160,9668	233,8495	29
GAM	48,87311	48,85872	49,19415	48,40621	0,235347	1417,32	1,550874	29
GAUR	5,927586	5,3	10,4	3,6	1,891125	171,9	100,1379	29
INFLATION	2,7	2,8	5,4	-0,4	1,243555	78,3	43,3	29
NASDAQ100	1898,607	1845,38	4945,55	374,43	1227,796	55059,59	42209524	29

Source: Authors own calculation in eViews

Table 3: Michigan basic descriptive statistics

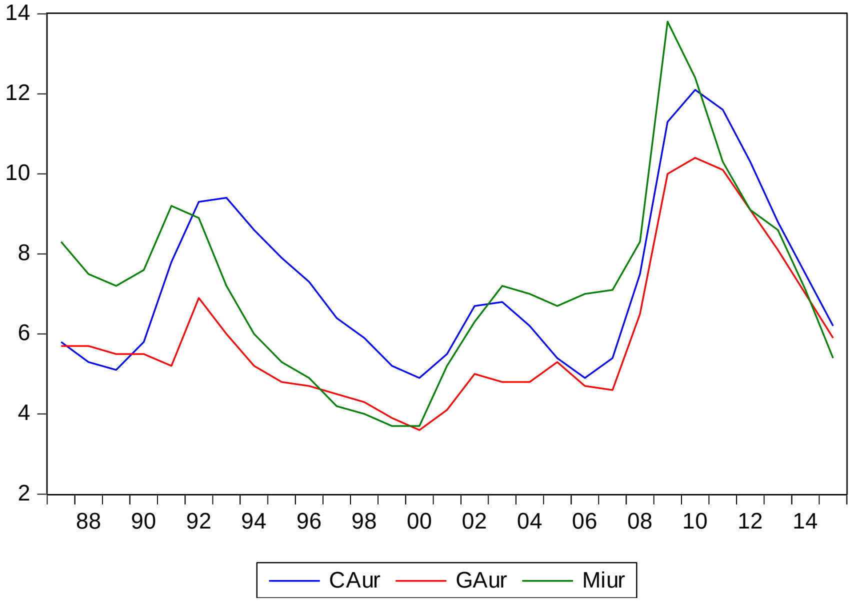
	Mean	Median	Maximum	Minimum	Std. Dev.	Sum	Sum Sq. Dev.	Observations
INFLATION	2,7	2,8	5,4	-0,4	1,243555	78,3	43,3	29
MIALC	2,21069	2,19	2,51	2,05	0,120503	64,11	0,406586	29
MIBEN	2,058621	1,88	6,88	0,83	1,289304	59,7	46,54454	29
MIBLCK	14,1109	14,17809	14,21133	13,66611	0,148066	409,2161	0,613855	29
MIINC	25762,72	26790	38127	13897	7085,72	747119	1.41E+09	29
MILAT	3,386953	3,382663	4,9	1,982875	0,943235	98,22165	24,91137	29
MIM	48,90892	49,04519	49,16	48,52759	0,216414	1418,359	1,31138	29
MIMINW	5,412069	5,15	8,15	3,35	1,55326	156,95	67,55328	29
MIUR	7,213793	7,1	13,8	3,7	2,374075	209,2	157,8145	29
NASDAQ100	1898,607	1845,38	4945,55	374,43	1227,796	55059,59	42209524	29
MIGDP	1,072414	1,4	8,2	-8	3,28828	31,1	302,7579	29

Source: Authors own calculation in eViews

9.4 Unemployment rate

The following graph illustrates the unemployment rate in all three states. We can see three amplitudes of different sizes. These were created by economic depressions. Otherwise we can see a small declining trend along the whole period, because if we took the local minimums, each one further in time is lower. This does not apply on local maximums however. Different sizes of amplitudes may be caused by variety of crises that happened. We can also see the differences across these states. It is interesting to compare the size of unemployment in Michigan compared to other states during 2008-2012.

Figure 5: The unemployment rates in states

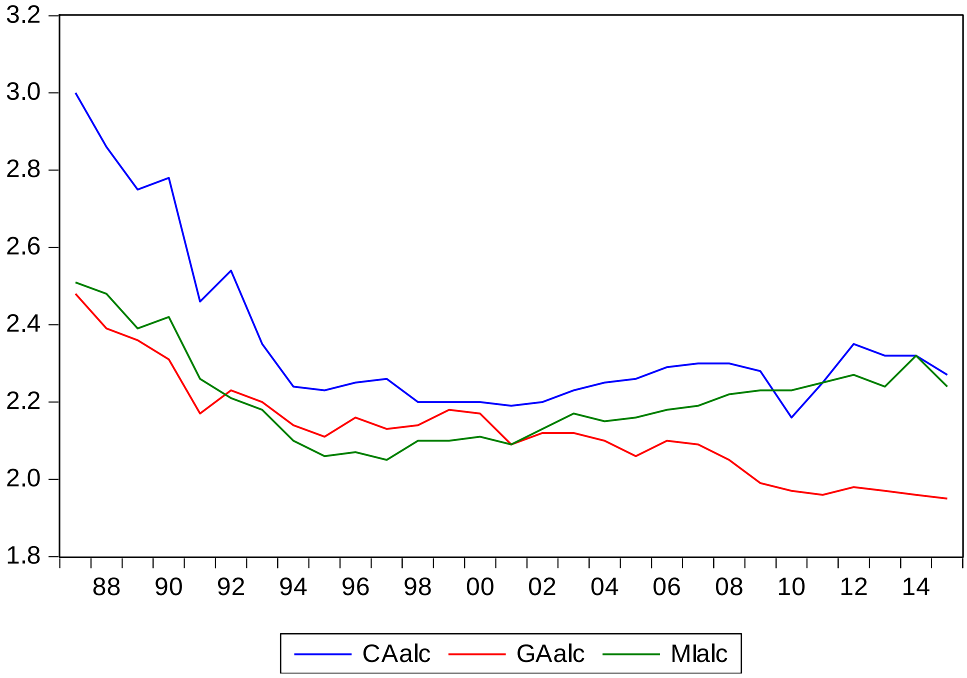


Source: Author´s own illustration

9.5 Alcohol consumption

The following figure 6 describes alcohol consumption in all three states. We can see a small declining trend again, with few or more smaller amplitudes. The most unexpected is development of CAalc in 2007-2011. We are uncertain whether this decline in alcohol consumption, is based on a decrease in income during these years, or an other effect is responsible for this development. The change in alcohol consumption due to lower income would not make big sense, due to thr years in beginning of our time series where we can observe growing income together with decreasing alcohol consumption. But if we think about alcohol as luxury good, it can make great sense to stop consuming these in crisis years as some way of insuring yourself, that in case you became unemployed, you would still have some money to survive. On the other hand it can be just some random change due to some trends or changes in laws.

Figure 6: Apparent alcohol consumption per cappita in all states



Source: Author´s own illustration

10 Model

Since nobody tried to apply theory of alcohol consumption and unemployment rates on macro data before, we wanted to use ordinary least square regression. Due to serial problems with autocorelation, we decided to follow few studies like Collins (2009), Dobre and Alexandru (2008) and also advances described by Brooks (2008) to use ARMA model here. Mostly according to Brooks (2008) we think that this model will bring us BLUE[12] results rather than any other model. We will apply the identical model on all three states. This will not only show us if the alcohol consumption has any influence on umeployment rates, but also we we will be able to identify various effects (such as a different relationship between alcohol consumption and unemployment rates, or different size) across chosen states.

Our model looks as follows:

$$\log(Ur) = c + \beta_1 \log(alc) + \beta_2 \log(ben) + \beta_3 blck + \beta_4 GDP + \beta_5 \log(inc) + \beta_6 lat + \beta_7 m + \beta_8 minw + \beta_9 crisis + \beta_{10} inflation + \beta_{11} \log(nasdaq100) \quad (2)$$

[12] the best linear unbiased estimator

In the case of variables like unemployment rates, alcohol consumption, unemployment benefits, average income or the NASDAQ-100, we used log() function, because we are more interested in changes of these variables, rather than the value. The GDP is already expressed in percentual change, so we do not need to put it in log(). We hope that this adjustment will bring us more accurate results.

10.1 Stationarity and cointegration

Before testing our models, we need to verify that we are working with stationary variables. Stationary variables are those, whose parameters are constant in time. In other words, their parameters, such as mean and variance are not influenced by the time. We made a KPSS test on all our variables. The following tables show stationariy of variables. Those which were found non-stationary, are in first differences in our models. This approach can make our model more inaccurate, but we had to use first differences in order to secure stationarity of variables. We had a problem with variables “caalc” and “miben”. As KPSS tests shows, they are stationary only on 10% level. We decided to consider these variables as non-stationary and put them in first difference too.

Table 4: stationarity of variables

Variable	California	Georgia	Michigan
alc	stat*	non-stat	non-stat
ben	non-stat	non-stat	stat*
blck	non-stat	non-stat	non-stat
gdp	non-stat	Stat	stat
inc	non-stat	non-stat	non-stat
lat	non-stat	non-stat	non-stat
m	non-stat	non-stat	non-stat
minw	non-stat	non-stat	non-stat
ur	non-stat	non-stat	non-stat
inflation	non-stat	non-stat	non-stat
nasdaq	non-stat	non-stat	non-stat

*stationary on 10% only, non-stationary on 5% and 1%
Source: own illustration

10.2 ARMA

AR models are dealing with autoregresive processes. These models count with the fact that for example the size of income is dependable on previous levels of income. Such models can eliminate the autoregresion. MA models are dealing with unobservable shocks or mini shocks, white noise, and other unobservable variables. “By combining the AR(p) and MA(q) models, an ARMA(p,q) model is obtained. Such a model states that the current value of some series Y depends linearly on its own previous values plus a combination of current and previous values of a white noise error term."(Brooks 2008)[13] First we deployed simple LM test of serial corelation, on our OLS model. After finding the autocorelation, we examined each variable through the corelogram. After this analysis we found out that most autocorelating variable is real income per capita, which autocorelated up to lag 5. Most of the variables however showed only autocorelation up to lag 2 or lag 3. Correlograms are available in appendix. We decided to include 5 lags in our ARMA model, according to our corelogram analysis. This may not be ideal, but it is in line with Brooks (2008). After this adjustment our ARMA model looks as follows:

$$\log(Ur) = c + \beta_1 \log(alc) + \beta_2 \log(ben) + \beta_3 blck + \beta_4 GDP + \beta_5 \log(inc) + \beta_6 lat + \beta_7 m + \beta_8 minw + \beta_9 crisis + \beta_{10} inflation + \beta_{11} \log(nasdaq100) + \beta_{12} AR(1) + \beta_{13} AR(2) + \beta_{14} AR(3) + \beta_{15} AR(4) + \beta_{16} AR(5) + \beta_{17} MA(1) + \beta_{18} MA(2) + \beta_{19} MA(3) + \beta_{20} MA(4) + \beta_{21} MA(5) \quad (3)$$

This model will be further adjusted to fit each state. This means that any ARMA parts with very low statistical significance will be eliminated from our model.[14]

10.3 Economic analysis of independent variables

Expected effects of independent variables describes are summarized in the Table 5 below.

[13] Brook Chris, Introductory Econometrics for Finance, 2008 , Cambridge university press, ISBN-13 978-0-511-39848-3
[14] We have choosen the ML method, because we did not find any heteroskedasticity which should be dealth with GLS method
AR- autoregressive model
MA- moving average model

Table 5: expected effects of independent variables on unemployment rate

Variable	Effect
Alcohol consumption	Positive
Unemployment benefits	Positive
Black population	Positive
GDP	Negative
Real income per capita	Positive
Latino and Hispanic population	Positive
Man in population	Negative
Minimum wage	Unknown
Crisis	Positive
Inflation	Negative
NASADAQ-100	Negative

Source: Author´s own illustration

Alcohol consumption: with higher alcohol consumption comes more absent days at work, reduced productivity, and probability of decrease of social status. With all these the probability of losing the job increases. For this reasons we think the effect of alcohol consumption will be **positive.**

Unemployment benefits: with higher unemployment benefits comes higher opportunity cost of returning to work. This may results that some people with low wage, can have higher utility after being made redundant, as they have high unemployment benefits and utility from bigger amount of free time. Therefore we expect positive effect on unemployment rate.

Afro-American population: reasons to claim positive relationship are job market discrimination and lower investment in human capital on average, where both should lead to higher unemployment rates. These claims are supported by many researchers as mentioned in the theoretical part of this thesis, for example Farley (1987) or Sundstrom (1992).

Latino and Hispanic population: lower level of human capital, and job market discrimination should be the main reason for positive relationship as we observed with Afro-Americans.

Real GDP per capita: GDP represents the size of the economy, so when GDP grows, the economy grows too, so there should be more free jobs, meaning lower unemployment rates.

Real income per capita: as income grows, people increase their working hours up to the certain amount, from which they work less with increasing income. We claim that most of the people are always in front of this point. The only thing that can obscure the positive relationship is non-working incomes like returns on bonds etc. Due to US policy, these are counted into individual incomes. In case that income from other actions is higher than income from working, this variable can have also negative effect on unemployment rates.

Men in population: we claim that the employment rate is higher among men, so when the ratio of men increases the unemployment rate should fall.

Minimum wage: with higher minimum wage comes higher opportunity cost of staying jobless. Even less educated and inexperienced can find a better job with minimum wage increases, so they should be more motivated to find job. We must also mention the other side of raising the minimum wage. Some companies may not afford as many employees as before, so this can also increase unemployment rates. The effect of minimum wage on unemployment is not straightforward.

Crisis: crisis can have only positive relationship with unemployment rates. If unemployment rates decreased during crisis, than it is not crisis. We must take in account the lagging of unemployment rate behind crisis, but we solved this during the construction of the dummy variable crisis.

Inflation: with increasing prices people should demand more work, so with increasing inflation, unemployment should decrease.

NASDAQ-100: represents the performance of stock market, meaning how well is stock market going, meaning higher index = higher profits. People earning more money on financial markets will reduce their working time, or stop working, for this we claim there is negative relationship. On the other hand the stock market index like NASDAQ-100 can be seen as “benchmark” of economy. This means the better is the economy performing, the bigger the growth of index and vice versa. We think that second effect is much stronger than the first one, therefore we claim a positive relationship.

10.4 Model for California

We will briefly summarize the results of our ARMA regression model for California. Detailed economic interpretation will be available in chapter 12, after conducting the model for all three states.

Model for California looks as follows:

$$\log(Ur) = c + \beta_1 \log(alc) + \beta_2 \log(ben) + \beta_3 blck + \beta_4 GDP + \beta_5 \log(inc) + \beta_6 lat + \beta_7 m + \beta_8 minw + \beta_9 crisis + \beta_{10} inflation + \beta_{11} \log(nasdaq100) + \beta_{12} AR(1) + \beta_{13} AR(2) + \beta_{14} AR(3) + \beta_{15} AR(4) + \beta_{16} AR(5) \quad (4)$$

The MA part was removed since we did not find any evidence of MA process[15] in our model. This was done, by simply adding MA processes to the model, and observing if they were statistically significant. Outputs of these regressions are available in appendix. Following table shows results of our regression. Our model describes 94,5 % of the dependable variable, and is statistically significant at level of 1 se statistically significant variables on level of 10% are *caalc*, *cainc* and cam. *Cainc* and cam are even statistically significant at level of 5% and cam even on level of 1%. From this we can clearly see that men ratio is probably the most important factor that influences the unemployment rate among our chosen variables. *Caalc* coefficient is 1,65, which means that if alcohol consumption increases by 1%, than the first difference of unemployment rate grows by 1,65%. The same thing is happening for *cainc* with coefficient of growth -3,5 % and *cam* with 2,69 %. Other variables have been proved statistically insignificant. This does not mean that they do not influence unemployment rate at all, but their influence is much lower than of those statistically significant. Other important thing about our model for California is that all statistically significant variables have the same direction as determined in economic analysis of this model except for Cam. Albanesi and Sahin (2018) and Azmat, Guell, Manning (2006) concluded opposite relationship in contrast with our results. This can be explained by technique of measuring amount of unemployed, as many unemployed women can be missed from this statistic. *Cainc* has in the end negative effect on unemployment as suggested by Phillips (1958) and Aaronson at al. (2000). This can happen for many reasons explained above. For example, according to Becker (1965) higher wage means that free time is more expensive so people might start working more. Reasons for negative effect of *cablck* and *calat* are unknown. The negative effect may be caused simply by the fact that these variables are not statistically significant, or by adjustments we made to these variables

[15] MA process – moving-average process is used to capture unobserved white noise error terms or random shocks
NIH- National Institutes of Health

during interpolating processes as these results are opposite to Farley (1987). The unimportance of *crisis* is also surprise. Initially, we thought that ratio of men and *crisis* will be significant in all models. The most important finding is the positive relationship between alcohol and unemployment rate .To conclude, this model supports initial hypothesis of positive effect of alcohol consumption on the rate of unemployment and is in line with Mullahy and Sindelar (1996), Johansson et al. (2000), Terza (2002) and MacDonald and Shields (2004).

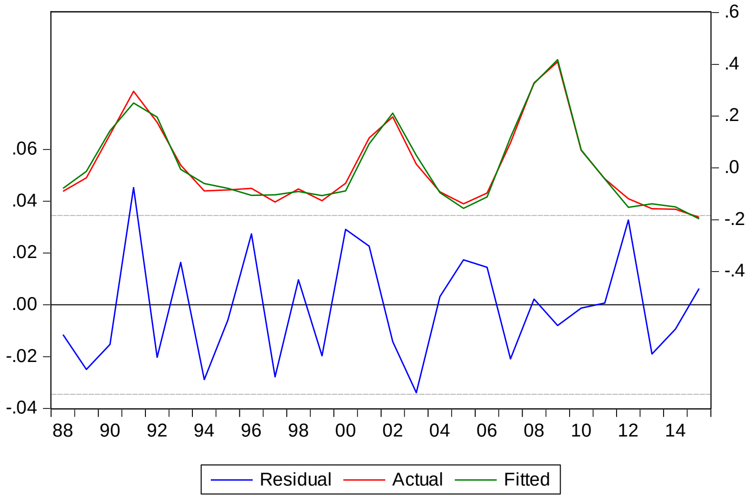
Table 6: ARMA regression of California model

Variable	**Coefficient**	**Std. Error**	**Prob.**
C	0.186491	0.083738	0.0501
D(LOG(CAALC))	1.147876	0.357201	0.0093
D(CABEN)	0.007982	0.014516	0.5945
D(CABLCK)	-2.099998	0.742756	0.0179
D(CAGDP)	0.007884	0.011975	0.5251
D(LOG(CAINC))	-4.411628	0.685667	0.0001
D(CALAT)	-0.267308	0.192331	0.1947
D(CAM)	3.968476	0.820072	0.0007
D(CAMINW)	0.157390	0.074473	0.0607
CRSIS	0.209394	0.088474	0.0395
D(INFLATION)	-0.001946	0.032198	0.9530
D(LOG(NASDAQ100))	0.099350	0.082033	0.2537
R-squared	**0.980920**	**F-statistic**	**30.24208**
Adjusted R-squared	**0.948485**	**Prob(F-statistic)**	**0.000002**

Source: Author´s own illustration and calculation

Figure 7 illustrates actual and fitted values. Fitted values represent 95,36% of actual values, which is a very high number. We can say that our model for California worked out very well.

Figure 7: Representation of actual and fitted values California



Source: Author´s own illustration

10.5 Model for Georgia

We will again briefly summarize the results of our ARMA regression model for Georgia. Detailed economic interpretation will be available in chapter 12, after conducting the model for all three states. Model for Georgia looks as follows:

$$\log(Ur) = c + \beta_1 \log(alc) + \beta_2 \log(ben) + \beta_3 blck + \beta_4 GDP + \beta_5 \log(inc) + \beta_6 lat + \beta_7 m + \beta_8 minw + \beta_9 crisis + \beta_{10} inflation + \beta_{11} \log(nasdaq100) + \beta_{12} AR(1) + \beta_{13} AR(2) + \beta_{14} AR(3) + \beta_{15} AR(4) + \beta_{16} AR(5) \qquad (5)$$

The MA part was again removed. No evidence of MA process has been found. Detailed evidence of no MA process is available in appendix. Following table shows results of our regression. Our model describes 94,53 % of dependable variable and it is statistically significant at level of 1%. Statistically significant variables on level of 10% are *galat, gam, gahdp, fedminw* . On level of 5% and also 1% only *fedminw, gam* and *galat* are significant. *Gablck* and *gaalc* have the opposite relationships as we conducted in our economic analysis. *Gablck* has a negative effect on unemployment rate. This may be caused by fact, that Georgia has one of the biggest Afro-American populations in the US, therefore our findings in theoretical part, that Afro-Americans are being discriminated in the job market Fearley (1987) may not apply here, or at least the discrimination is not as strong as in other states. According to Lindquist and Cockerham (1999), the southerners are less prone to heavy drinking episodes and many of Southerners are abstinent. This may be the source of the opposite relationship between alcohol consumption and unemployment rate than we expected in our hypothesis, as the increased alcohol consumption, is just general increase, and moderate drinkers become heavy drinkers. In times of crisis the first difference of the unemployment rate grows by 0,05%. If the first difference of any other significant variables grows by 1, than first difference of unemployment rate grows by 0,33% in case of *galat*, by -0,72% in case of gam, and finally by 0,23% in case of *fedminw*. Positive effect of increased men ratio is in line with Albanesi and Sahin (2018) and Azmat, Guell, Manning (2006). Negative effect of *galat* is again opposite to findings of Fearley (1987) as in model for California. For minimum wage we came to the same conclusion as Brown, Gilroy, Kohen (1982) or Mincer (1976), that increase in minimum wages results in increased unemployment.

Finding the effect of alcohol is our primary task here, and since the *gaalc* is not statistically significant, we decided that this is the main reason of opposite coefficient than we expected. On the other hand, this can be caused by different acceptance of alcohol in Southern states according to Lindquist and Cockerham (1999).

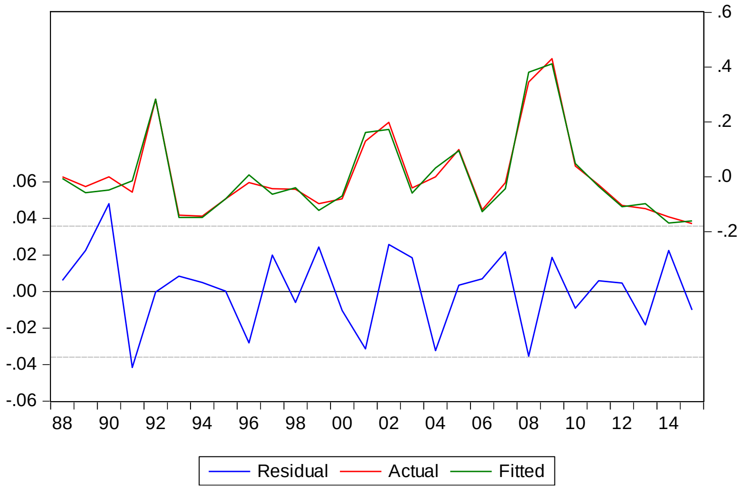
Table 7: ARMA regression of Georgia model

Variable	**Coefficient**	**Std. Error**	**Prob.**
C	-0.053195	0.056883	0.3717
D(LOG(GAALC))	-2.424317	0.806956	0.0132
D(GABEN)	0.016333	0.033511	0.6365
D(GABLCK)	-0.341249	0.187614	0.0990
D(GAGDP)	0.009666	0.002853	0.0069
D(LOG(GAINC))	-0.932366	0.794349	0.2677
D(GALAT)	0.333157	0.040447	0.0000
D(GAM)	-0.723496	0.131880	0.0003
D(FEDMINW)	0.229947	0.022551	0.0000
CRISIS	0.058464	0.017137	0.0066
D(INFLATION)	-0.007082	0.014716	0.6407
D(LOG(NASDAQ100))	-0.107388	0.054401	0.0766
R-squared	**0.979745**	**F-statistic**	**28.45335**
Adjusted R-squared	**0.945312**	**Prob(F-statistic)**	**0.000003**

Source: Author´s own illustration and calculation

Following figure shows us actual and fitted values by our model. Fitted values represents 94,45% of actual values. We can say that our model for Georgia worked very well as for the California before.

Figure 8: Representation of actual and fitted values Georgia



Source: Author´s own illustration

10.6 Model for Michigan

Again we will briefly summarize the results of our ARMA regression model for Michigan. Detailed economic interpretation will be available in chapter 12, after conducting the model for all three states. Model for Michigan looks as follows:

$$\log(Ur) = c + \beta_1 \log(alc) + \beta_2 \log(ben) + \beta_3 blck + \beta_4 GDP + \beta_5 \log(inc) + \beta_6 lat + \beta_7 m + \beta_8 minw + \beta_9 crisis + \beta_{10} inflation + \beta_{11} \log(nasdaq100) + \beta_{12} AR(1) + \beta_{13} AR(2) + \beta_{14} AR(3) + \beta_{15} AR(4) + \beta_{16} AR(5) \quad (6)$$

The MA part was again removed, due to no evidence of MA process. Evidence is again available in appendix, as before. Following table shows us the results of regression. This model describes 98% of dependable variable, and it is statistically significant at level of 1%. *Miminw* is significant at level of 5%. All other variables are significant at level of 1%. Estimated effect of all independent variables matches those outlined in economic analysis before except for inflation. In times of *crisis* the first difference of unemployment rate changes by 0,16% which matches with our theory. Unemployment rate increases by 5,59% for every increase in alcohol consumption by 1%. This further confirms our primary hypothesis that increase in alcohol consumption leads to increase of unemployment rate. An increase in the first difference of unemployment benefits by 1 leads to an increase in unemployment rate by 0,03%. This is in light of research done by Hagedorn at al. (2013) and Meyer (1998). Increase of first difference of *miblck* leads to increase of first difference of unemployment rate by

8,52%, this relationship has same direction as suggested by Farley (1987). For every increase in the first difference of growth rate of GDP by 1% the unemployment rate shall fall by 0,03% which is lower than expected by Lee (2000) or Ball, Leigh, Lougani (2013) but the relationship still holds. Real income comes here again with negative relationship as increase in first difference of real income per capita by 1% leads to lower first difference of unemployment rate by 7,51% and is in line with Phillips (1958) and Aaronson et al. (2000). In case of *Milat*, for each increase of the first difference by 1%, we can observe increase in first difference of unemployment rate by 22,84%. It does not make sense that 1% increase of such a small group would lead to such a high unemployment rate growth. A most probable explanation we can consider that the relative small size of Hispanics in Michigan just randomly correlated with the unemployment rate. We can also consider that Hispanics moved here to work illegally and therefore the unemployment rate rised, as population got bigger and they were working illegally. However, we consider this less probable. Last possible explanation is that Hispanics grew in Michigan rapidly together with rapid growth unemployment due to cheap housing. Growth of first difference of *mim* by 1 lead to increase of unemployment rate by 3,03%. We again gathered result opposite to Albanesi and Sahin (2018) and Azmat, Guell, Manning (2006). As Michigan is the first model in which the inflation statistically significant we hoped for results according to Friedman (1977), percent changes in unemployment and inflation will be almost the same, but we proved that for each increase of the first difference of inflation by 1 we can observe 0,03% rise in unemployment, which means that we estimate quite the opposite relationship as it seems that the bigger the inflation growth, the lower the unemployment growth.

Finally, an increase in the first difference of *NASDAQ100* by 1% lead to change in unemployment rate by -0,14%. We are again mostly interested in alcohol consumption. The results of Michigan model are in line with the ones for California regarding alcohol consumption and also in line with Mullahy and Sindelar (1996) Johansson et al. (2000) Terza (2002) MacDonald and Shields (2004). They confirm our primary hypothesis. However we are bit skeptical about our results from the Michigan model, as we suspect that we have undetected some econometric problem, which is causing that all independent variables are significant, although we detected them in reversed causality only.

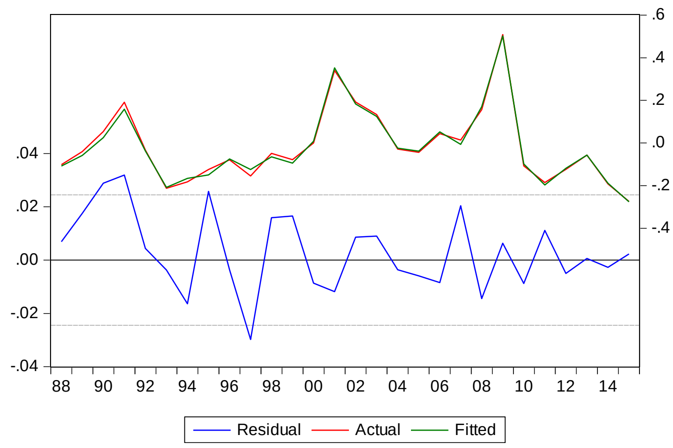
Table 8: ARMA regression of Michigan model

Variable	Coefficient	Std. Error	Prob.
C	-6.759456	0.122832	0.0000
LOG(MIALC)	5.596743	0.122326	0.0000
D(MIBEN)	0.025663	0.003288	0.0000
D(MIBLCK)	8.521498	0.125230	0.0000
MIGDP	-0.028372	0.001676	0.0000
D(LOG(MIINC))	-7.505740	0.174320	0.0000
D(MILAT)	22.84210	0.301669	0.0000
D(MIM)	3.037328	0.135398	0.0000
D(MIMINW)	-0.061659	0.014163	0.0014
CRISIS	0.162044	0.008090	0.0000
D(INFLATION)	0.031964	0.007781	0.0021
D(LOG(NASDAQ100))	-0.142498	0.017725	0.0000
R-squared	**0.992620**	**F-statistic**	**79.11754**
Adjusted R-squared	**0.980074**	**Prob(F-statistic)**	**0.000000**

Source: Author´s own illustration and calculation

Following figure show us actual and fitted values. Fitted values represents 98% of actual values, what is again a pleasant result.

Figure 9: Representation of actual and fitted values Michigan



Source: Author´s own illustration

10.7 Econometric verification of models

In order to consider our models correct, we had to check the Gaus-Markov theorem. This means we had to check if our models do not contain autocorrelation, heteroscedasticity or multicollinearity. Because we were working with time series we needed to apply also a cointegration test. All tests were fine except autocorrelation, which is solved by the ARMA model, and we also discovered cointegration in reversed causality model for Michigan. Results are available in the appendix.

11 Model for reversed causality

Since we are working with the same series as in the models before, we do not have to do any test, or ARMA adjusting. Everything is just set. We will only remove the variables, which we seem to have nothing in common with alcohol consumption according to theoretical part. We will also skip the reversed causality model for Michigan as we detected cointegration. There are many ways to look at reasons for increased alcohol consumption. In light of our theoretical part, we assume according to Becker, that the unemployed have higher chances of becoming addicted to alcohol, as their income falls and they are also in very stressful situations.

Popovici and French (2013) exanimated this reversed causality, and came to the conclusion, that on micro data, the unemployed simply starts to drink more. Even if they cannot afford their usual drinks anymore, they will substitute them for cheaper ones. In the end our model looks as follows:

$$\mathrm{d}(\log(alc)) = c + \beta_1\,\mathrm{d}(\log(ur)) + \beta_2\,\mathrm{d}(\log(ben)) + \beta_3 d(GDP) + \beta_4\mathrm{d}(\log(inc)) + \beta_5 d(m) + \beta_6 d(minw) + \beta_7 crisis + +\beta_8 AR(1) + \beta_9 AR(2) + \beta_{10} AR(3) + \beta_{11} AR(4) + \beta_{12} AR(5) \quad (7)$$

11.1 Economic analysis

Table 12: Summary of expected effects of independent variables on alcohol consumption

Variable	Effect
Unemployment rate	Positive
Unemployment benefits	Positive
GDP	Unknown
Real income per capita	Positive
Man in population	Positive
Minimum wage	Positive
Crisis	Positive

Source: own illustration

Unemployment rate: as mentioned in the theoretical part of this thesis, being unemployed can lead to spending your free time drinking since you have unlimited amount of free time. Your only problem is money.

Unemployment benefits: the higher the unemployment benefits the more money for your drinking, as mentioned above.

GDP: the GDP can have positive effect due to higher income with higher GDP

Real income per capita: with more money you can buy more alcohol. According to consumer behavior, increased income leads to greater consumption.

Man in population: due to biological differences, man can drink more alcohol in general. Therefore we expect that with higher ratio of men more alcohol will be drunk.

Minimum wage: again as mentioned above, higher minimum wages means higher income which can result in higher alcohol consumption.

Crisis: we expect that during the years of crisis, people drink more due to increased stress, and other problems coming with the economic crisis.

11.2 Reversed causality results

The result for California explains 14,65% of dependent variable and is insignificant even at level of 10%. Concluding this findings, we do not have to interpret the model further, as we failed to explain the dependent variable.

Table 13: result of reversed causality model California

Variable	Coefficient	Std. Error	Prob.
D(LOG(CAUR))	0.029065	0.119013	0.8106
C	-0.025512	0.022230	0.2704
D(CABEN)	0.001248	0.002719	0.6533
D(CAGDP)	-0.002413	0.002766	0.3977
D(LOG(CAINC))	0.651196	0.511819	0.2240
D(CAM)	-0.447020	0.391075	0.2722
D(CAMINW)	-0.049198	0.015748	0.0075
CRSIS	-0.008322	0.025646	0.7504
R-squared	**0.557457**	**F-statistic**	**1.356566**
Adjusted R-squared	**0.146525**	**Prob(F-statistic)**	**0.288981**

Source: Author´s own illustration and calculation

The results of Georgia ARMA regression explains 18,84% of dependent variable and is not statistically significant even at level of 10%. In the light of these results, we can conclude that we failed to explain alcohol consumption.

Table 14: result of reversed causality model Georgia

Variable	Coefficient	Std. Error	Prob.
C	-0.006691	0.021937	0.7648
D(LOG(GAUR))	-0.018506	0.087669	0.8359
D(GABEN)	0.003091	0.022872	0.8944
GAGDP	0.001639	0.002878	0.5781
D(LOG(GAINC))	-0.054223	0.481971	0.9120
D(GAM)	-0.096282	0.309696	0.7605
D(FEDMINW)	0.003481	0.037646	0.9276
CRISIS	-0.006736	0.023070	0.7746
R-squared	**0.383821**	**F-statistic**	**0.670822**
Adjusted R-squared	**-0.188344**	**Prob(F-statistic)**	**0.760738**

Source: Author´s own illustration and calculation

As none of models were proven statistically significant, and since the alc has high probability, we claim there is no reversed causality.

12 Results

As mentioned before, in this chapter, we will economically interpret our results more thoroughly

12.1 Alcohol consumption

Our first hypothesis of positive effect of increased alcohol consumption on unemployment rate was confirmed by the California and Michigan models. In Georgia, we found the opposite relationship even if it was proven statistically insignificant. According to Lindquist and Cockerham (1999) we may take in mind that southerners should not suffer from heavy drinking, and most of them are abstainers. This raises two questions. First one is why is the apparent alcohol consumption per capita in Georgia is the same as in other states? We can answer this by the fact that those who drink alcohol, simply consume much more per capita. Based on this question we can form a second one. Can the opposite relationship caused by fact, that southerners do not suffer from productivity loss due to hangover, because, those who drink tend to drink more and are used to that? We could not figure this out, as we think that one work is not enough to supply us with powerful enough arguments for southern states, although we think that we are not far from the truth. Our results suggest that our primary hypothesis that increased alcohol consumption increases the probability of being unemployed, and therefore unemployment rate on macro level is true, as proved before on micro data by Mullahy and Sindelar (1996), Johansson et al. (2000), Terza (2002) and MacDonald and

Shields (2004). Our results are also in line with MacKillop (2016), alcohol steepens future discounting so employed people may start to have reduced productivity due to higher alcohol consumption (not showing to work, late arrivals,..), as they will not take the threat of redundancies as big as before. They will also prefer current reinforcing effect of alcohol rather than having hangover, which may result again in redundancy. The unemployed drinkers will prefer to stay unemployed and to drink more, rather than possibility of working again and having a wage in future due to their higher discounting of future.

As we have to take the results of the Michigan model with slight reserve, we can conclude with 100% certainty only that our second hypothesis, of increase in unemployment rates leads to greater alcohol consumption was denied. Maybe only one of our two models for reversed causality showed us this, but none of the models is statistically significant even at level of 10% which means, we have not succeeded in explaining the alcohol consumption by our variables. Many of the works have proven the opposite, for example Popovici and French (2013). We need to imply again that we tried to prove this relationship on macro data. In line with our results where we found unemployment rates statistically insignificant in reversed causality models for California and Georgia we stick to the theory that at least on macro levels, the alcohol should be considered as a "normal consumable good", whose consumption is affected by many factors, starting from free time, income to social status, mood and other variables, Ruhm (1995) and Whelan (1994). These variables are not observable in macro data, and this may be the main reason why our results were insignificant. We also think that the amount of alcohol bought by the unemployed on a state level is negligible. If we consider that the entire population legally allowed to drink is roughly the size of work force, then change of preferences in 1% of group cannot have big effect. However our models for reversed causality were not significant even on 10% level, so all these are just pure guesswork as it would be hard to determine macro models of consumption of alcoholic beverages, as there are many types and brands, trends and marketing campaigns.

12.2 Other determinants of unemployment

The reason for including other known determinants of unemployment were to obtain a full model of unemployment and then to implement alcohol consumption into it. We were inspired by various models introduced in determinants of unemployment rates before. Again we will not interpret the Michigan model. We expected that same independent variables will be proved statistically significant in our models. We also did not expect that all independent variables would be proven significant since putting all these variables together would take a much more complicated model. Our goal was not to find an exact model for unemployment rates, but to find some model that is good at explaining unemployment rates and then adding alcohol consumption. The only variable significant to both models was the ratio of man. This is explained by the so called "unemployment gap" suggested by Albanesi and Sahin (2018) and Azmat, Guell, Manning (2006), that amount of unemployed females is bigger than males. They also suggest that a second gap is in employment where we can observe that men are more hold more jobs. However our expectations were not met with variable crisis. We expected variable crisis to explain the amplitudes of unemployment rates in the years of crisis. It did not even help when we made a new dummy variable for each crisis. We think that different significant variables are based on different type of economies of each state, as California has one of the best economies in US while Georgia is not even in the top 10. Also demographics and "mentality"[16] are different across different states and they may also play a major role.

12.3 Possible improvements of the model

As mentioned above, we came across cointegration in the Michigan model for reversed causality. The Engle-Granger test showed us that there is cointegration, but after we removed cointegrating variables, we did not get rid of cointegration. This problem can be solved by using Johanssen cointegration test, which requires at least 30 observations and we only have 28. Due to this reason it would be great to do this analysis again in 2020 with more than 30 observations.

Another weak side of this thesis is that we did not want to work with cross-time analysis. In order to obtain an universal model of unemployment and alcohol

[16] Mentality as some type of behaviour followed by majority of population in state

consumption for all states this should be the next step. Such analysis can further prove a positive relationship between alcohol consumption and unemployment on macro level.

It can be also interesting to replace unemployment rates by job separation rates, as this may suggest if really with increased alcohol consumption more people lose their job.

It is also strange that crisis was not proved significant in California and Georgia. We have even tried a different size of lag of the unemployment behind product. We suspect that this fact could be caused by an inadequate modeling of dummy variable crisis.

Conclusion

This thesis tries to support the hypothesis that increased alcohol consumption leads to higher unemployment rates at an aggregate level. This proved to be true many times on microeconomic levels by Mullahy and Sindelar (1996), Johansson et al. (2000), Terza (2002), and MacDonald and Shields (2004). According to our knowledge, very few studies exist at macroeconomic levels. As a result, our study is almost pioneering on aggregate levels. Also we wanted to solve the endogeneity by examination of inverse relationship that an increase in unemployment rate leads to higher alcohol consumption supported by Popovici and French (2013). We collected data for period of 1987-2015 for Michigan, Georgia and California. Estimation is performed by universal model defined by equation (3).

We fitted each state to this model. We extended the model, which was previously used by Collins (2009) by adding more independent variables like alcohol consumption, or income and also by removal of insignificant variables.

Results suggest that our primary hypothesis was confirmed and we can observe even on macro level increase in unemployment rate with increasing alcohol consumption. This means that if bigger part of population starts to drink more (increased apparent alcohol consumption per capita) then all these people have increased probability of losing job (mostly due to lost productivity, and other psychological factors related to heavy drinking. All this is in line with our theoretical part of recent studies on alcohol and unemployment Bouchery et al. (2011), Mullahy and Sindelar (1996). Results are also in line with MacKillop (2016) as he claims that heavy drinkers have higher discounting of future, and more impulsiveness behavior. Therefore they fall in circle of alcohol consumption as they constantly increase their alcohol consumption due to lower effect of alcohol caused by previous higher consumption than usual. Together with their higher discounting of future and impulsiveness, it results in fact that they hold low values for any future events, like finding a job and receiving paycheck later. Also, they value current events relatively more, so as result "curing" hangover with more booze is better option according to them, than get sober and go to work or try to find a job (in case they are unemployed). We also refused the secondary hypothesis, that increase in unemployment leads to higher alcohol consumption. This is in contrast with the study of Popovici and French (2013), but we need to mention again that their analysis was based on microeconomic data, whereas ours is on macroeconomic data. We suggest that on macroeconomics level, the remaining trend of decreasing alcohol consumption simply nullifies the increased amount of alcohol drunk by the newly unemployed. If you compare the size of the employed and the unemployed, it is obvious that the behavior of the majority (employed) will have a bigger influence than behavior of the minority.

This study confirms that increased alcohol consumption leads to higher unemployment rates caused by negative effects of alcohol usage. However, the results are not final as we modeled 3 out of 51 states, and in Georgia we found the opposite relationship. Maybe well explained by specificity of Southerners, but still existing. More complex cross-time analysis on all states should be done in order to finally confirm or refute this hypothesis, and to bring unified determinants of unemployment.

Appendix

Appendix contains lists of shortcuts used in models, figures of how we modeled the rest of the demographic variables and econometric tests, and outputs of our regressions.

List of shortcuts for variables

Table 15: List of shortcuts used for states

California	Ca
Gerogia	Ga
Michigan	Mi

Source: Author´s own illustration

Table 16: List of shortcuts used for variables

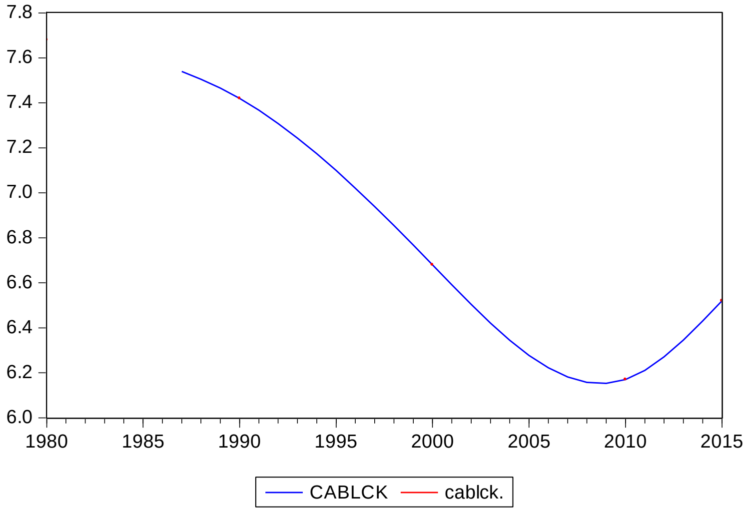
Alcohol consumption	alc	Minimum wage	Minw
Unemployment benefits	ben	Crises	crsis
Ratio of Afro-Americans	blck	Inflation	inflation
Ratio of Hispanics	lat	Nasdaq-100	nasdaq100
Growth of GDP	gdp	Autoregressive part	AR
Real income per capita	inc	Auto moving average part	AM
Ratio of men	m		

Source: Author´s own illustration

Interpolated variables

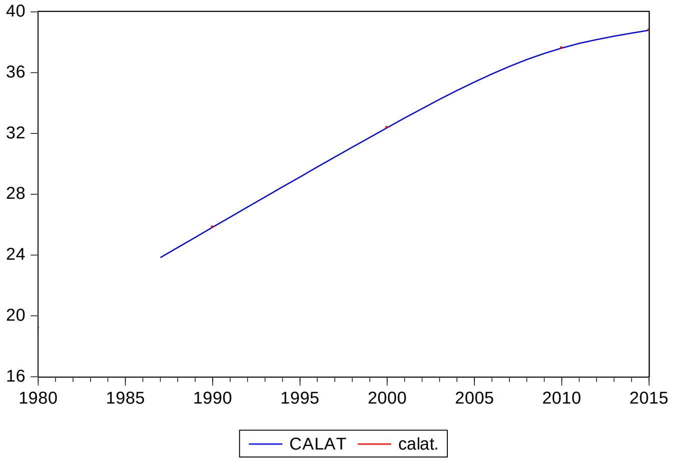
Red dots represent our data sample, and blue lines are our variables after interpolating. We did not include years of 1980-1987 for variables after interpolating as these years were not used in our analysis.

Figure 10: California, Afro-Americans



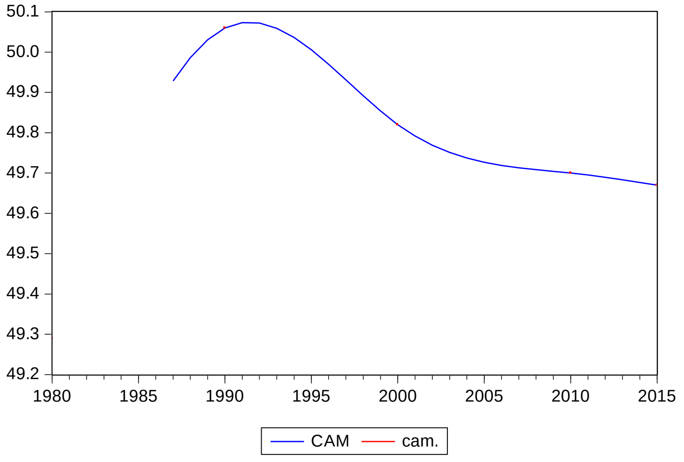
Source: Own illustration

Figure 11: California, Hispanics



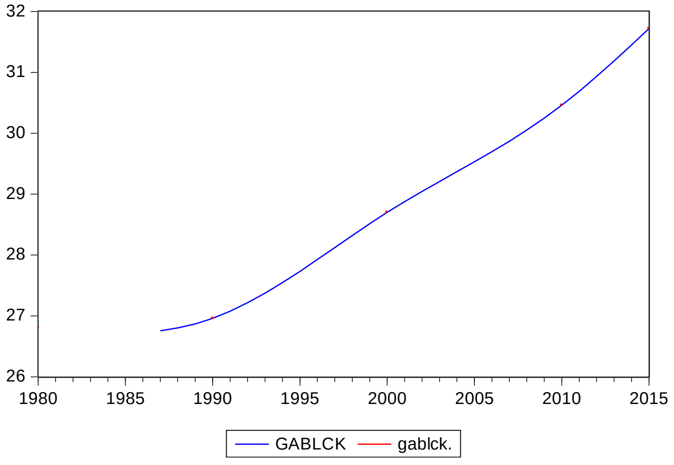
Source: Own illustration

Figure 12: California, men



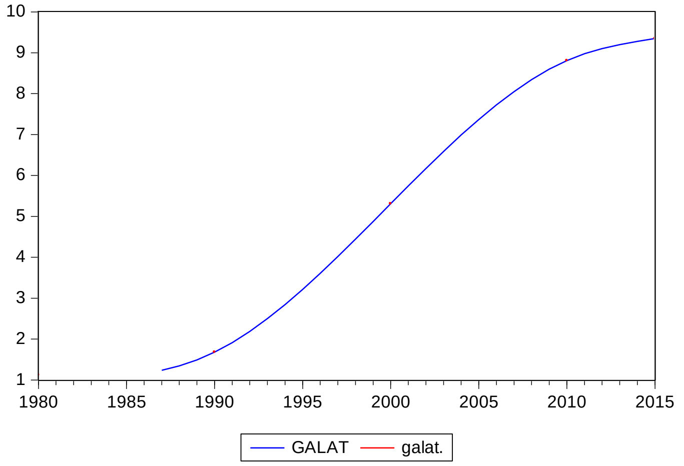
Source: Own illustration

Figure 13: Georgia, Afro-Americans



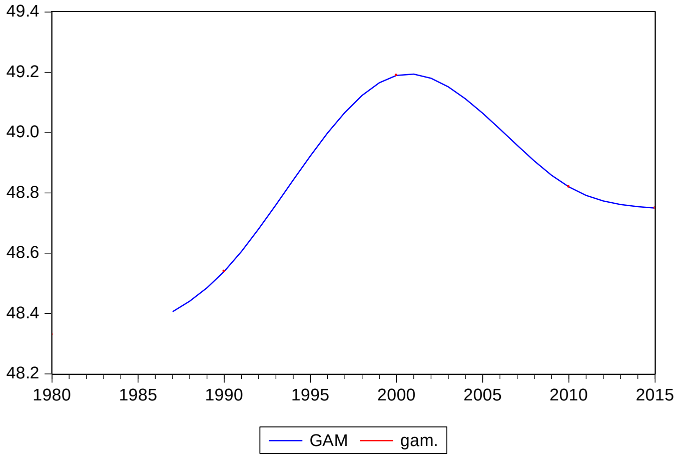
Source: Own illustration

Figure 14: Georgia, Hispanics



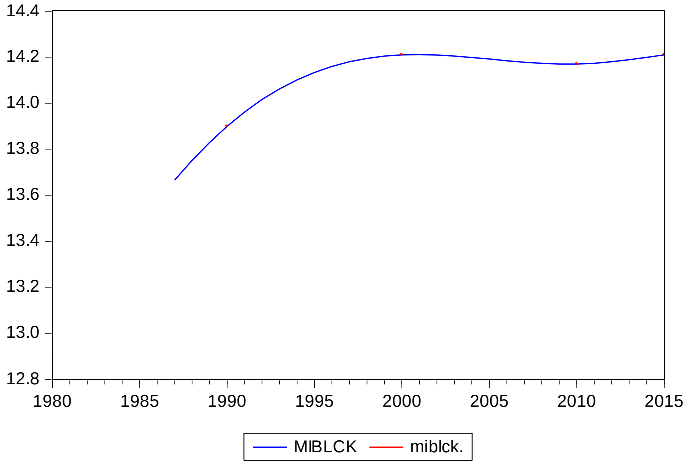
Source: Own illustration

Figure 15: Georgia, men



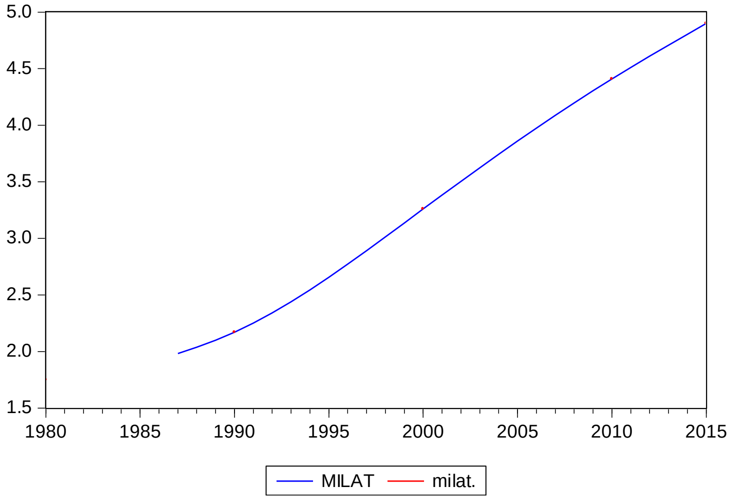
Source: Own illustration

Figure 16: Michigan, Afro-Americans



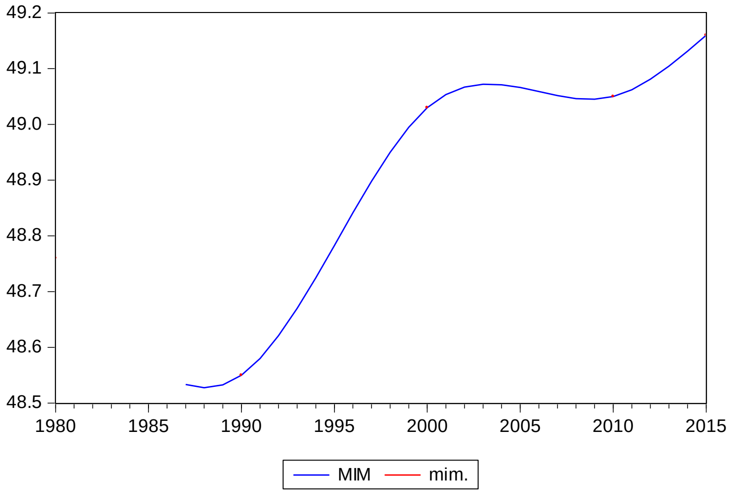
Source: Own illustration

Figure 17: Michigan, Hispanics



Source: Own illustration

Figure 18: Michigan, men



Source: Own illustration

Econometric verification

Heteroscedasticity tests

Table 17: Heteroskedasticity, California

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	1.583865	Prob. F(11,16)	0.1956
Obs*R-squared	14.59586	Prob. Chi-Square(11)	0.2018
Scaled explained SS	1.587401	Prob. Chi-Square(11)	0.9995

Source: Own illustration and calculation

Table 18: Heteroskedasticity, Georgia

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	0.608379	Prob. F(11,16)	0.3964
Obs*R-squared	8.257510	Prob. Chi-Square(11)	0.4901
Scaled explained SS	0.781601	Prob. Chi-Square(11)	0.9998

Source: Own illustration and calculation

Table 19: Heteroskedasticity, Michigan

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	1.771861	Prob. F(11,16)	0.1447
Obs*R-squared	15.37689	Prob. Chi-Square(11)	0.1659
Scaled explained SS	1.739272	Prob. Chi-Square(11)	0.9992

Source: Own illustration and calculation

Cointegration tests

Following tables contains results of Engle-Granger cointegration tests, null hypothesis for these test is that cointegration is present.

Table 20: Cointegration test, California

Dependent	tau-statistic	Prob.*
CAALC	-5.641805	0.3001
CABEN	-5.527661	0.3413
CABLCK	-4.227045	0.8048
CAGDP	-5.684198	0.2875
CAINC	-4.969464	0.5357
CALAT	-5.051043	0.5093
CAM	-4.971883	0.5488
CAMINW	-5.646288	0.2987
CRISIS	-6.010704	0.2030
INFLATION	-6.069317	0.1900
NASDAQ100	-1.918954	0.9999

Source: own illustration and calculation

Table 21: Cointegration test, Georgia

Dependent	tau-statistic	Prob.*
FEDMINW	-4.544240	0.7847
GAALC	-5.017201	0.6193
GABEN	-5.872355	0.3148
GABLCK	-4.684428	0.7349
GADEBT	-6.145426	0.2398
GAGDP	-8.319838	0.0144
GAINC	-4.758372	0.7122
GALAT	-5.874577	0.3206
GAM	-4.530814	0.7869
CRISIS	-5.277408	0.5283
NASDAQ100	-6.053339	0.2637
INFLATION	-5.673662	0.3774

Source: own illustration and calculation

Table 22: Cointegration test, Michigan

Dependent	tau-statistic	Prob.*
MIALC	-5.803720	0.3357
MIBEN	-6.015396	0.2739
MIBLCK	-4.830886	0.6868
MIGDP	-7.115477	0.0767
MIINC	-4.285631	0.8603
MILAT	-5.398762	0.4788
MIM	-4.009505	0.9150
MIMINW	-5.189978	0.5504
MIUR	-6.374882	0.1874
NASDAQ100	-5.977853	0.2908
INFLATION	-5.932588	0.3036
CRISIS	-6.215218	0.2228

Source: own illustration and calculation

Cointegration tests for reversed causality models

Table 23: Cointegration test for reversed causality, California

Dependent	tau-statistic	Prob.*
CABEN	-5.369366	0.3881
CABLCK	-4.040898	0.8575
CAGDP	-6.285376	0.1474
CAINC	-4.428787	0.7388
CALAT	-4.280854	0.7881
CAM	-3.998047	0.8684
CAMINW	-4.687771	0.6472
CAUR	-5.215451	0.4428
CRISIS	-5.883353	0.2334
NASDAQ100	-5.450715	0.3663
INFLATION	-6.649557	0.0976

Source: own illustration and calculation

Table 24: Cointegration test for reversed causality, Georgia

Dependent	tau-statistic	Prob.*
FEDMINW	-5.485385	0.4479
GABEN	-5.793677	0.3388
GABLCK	-4.464296	0.8054
GADEBT	-4.681403	0.7359
GAGDP	-7.425400	0.0509
GAINC	-4.027241	0.9117
GALAT	-5.644362	0.3872
GAM	-4.758576	0.7121
GAUR	-5.664160	0.3868
NASDAQ100	-6.684995	0.1426
INFLATION	-5.197607	0.5476
CRISIS	-5.591116	0.4177

Source: own illustration and calculation

Table 25: Cointegration test for reversed causality, Michigan

Dependent	tau-statistic	Prob.*
INFLATION	-5.936563	0.3025
MIBEN	-9.641827	0.0075
MIBLCK	-3.601065	0.9690
MIDEBT	-4.843668	0.6790
MIGDP	-5.668015	0.3990
MIINC	-3.923551	0.9308
MILAT	-4.909761	0.6550
MIM	-4.778110	0.7024
MIMINW	-5.225847	0.5370
MIUR	-6.947409	0.0951
NASDAQ100	-5.906783	0.3111
CRISIS	-5.360233	0.4984

Source: own illustration and calculation

Autocorrelation

Due to vastness of variables (39 tables), we decided to include only few of correlograms to show autocorrelation.

Table 26: Correlogram for *caalc*:

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.754	0.754	18.270	0.000
		2	0.593	0.055	29.970	0.000
		3	0.432	-0.074	36.431	0.000
		4	0.217	-0.237	38.119	0.000
		5	0.143	0.137	38.881	0.000
		6	-0.013	-0.211	38.888	0.000
		7	-0.077	0.065	39.133	0.000
		8	-0.101	-0.021	39.565	0.000
		9	-0.116	0.074	40.172	0.000
		10	-0.143	-0.202	41.146	0.000
		11	-0.180	-0.011	42.772	0.000
		12	-0.184	-0.037	44.553	0.000

Source: own illustration and calculation

Table 27: Correlogram for *gaalc*:

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.780	0.780	19.539	0.000
		2	0.623	0.036	32.448	0.000
		3	0.490	-0.015	40.765	0.000
		4	0.355	-0.081	45.305	0.000
		5	0.284	0.068	48.324	0.000
		6	0.196	-0.070	49.831	0.000
		7	0.113	-0.055	50.354	0.000
		8	0.072	0.030	50.578	0.000
		9	0.077	0.108	50.848	0.000
		10	0.063	-0.040	51.035	0.000
		11	0.024	-0.087	51.065	0.000
		12	0.001	0.002	51.065	0.000

Source: own illustration and calculation

Table 28: Correlogram for *mialc*:

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.803	0.803	20.681	0.000
		2	0.621	-0.066	33.509	0.000
		3	0.446	-0.089	40.401	0.000
		4	0.188	-0.359	41.671	0.000
		5	0.034	0.092	41.714	0.000
		6	-0.099	-0.088	42.098	0.000
		7	-0.232	-0.094	44.307	0.000
		8	-0.282	-0.029	47.714	0.000
		9	-0.300	0.017	51.755	0.000
		10	-0.309	-0.061	56.258	0.000
		11	-0.297	-0.108	60.658	0.000
		12	-0.303	-0.132	65.505	0.000

Source: own illustration and calculation

Table 29: Correlogram for *cainc*:

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.893	0.893	25.622	0.000
		2	0.798	-0.002	46.801	0.000
		3	0.710	-0.011	64.220	0.000
		4	0.611	-0.103	77.641	0.000
		5	0.517	-0.038	87.669	0.000
		6	0.432	-0.025	94.950	0.000
		7	0.342	-0.071	99.731	0.000
		8	0.242	-0.122	102.23	0.000
		9	0.139	-0.105	103.10	0.000
		10	0.036	-0.089	103.16	0.000
		11	-0.055	-0.037	103.31	0.000
		12	-0.139	-0.054	104.33	0.000

Source: own illustration and calculation

Table 30: Correlogram for *gainc*:

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.896	0.896	25.763	0.000
		2	0.799	-0.018	47.007	0.000
		3	0.711	-0.005	64.499	0.000
		4	0.618	-0.079	78.215	0.000
		5	0.517	-0.092	88.234	0.000
		6	0.427	-0.018	95.364	0.000
		7	0.333	-0.084	99.888	0.000
		8	0.235	-0.082	102.26	0.000
		9	0.135	-0.096	103.08	0.000
		10	0.039	-0.075	103.15	0.000
		11	-0.054	-0.066	103.30	0.000
		12	-0.135	-0.037	104.26	0.000

Source: own illustration and calculation

Table 31: Correlogram for *miinc*:

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.886	0.886	25.190	0.000
		2	0.782	-0.013	45.536	0.000
		3	0.688	-0.009	61.896	0.000
		4	0.588	-0.079	74.337	0.000
		5	0.486	-0.074	83.185	0.000
		6	0.396	-0.015	89.310	0.000
		7	0.310	-0.042	93.235	0.000
		8	0.217	-0.091	95.258	0.000
		9	0.129	-0.057	96.010	0.000
		10	0.046	-0.058	96.113	0.000
		11	-0.032	-0.052	96.163	0.000
		12	-0.107	-0.061	96.765	0.000

Source: own illustration and calculation

Outputs of regression

Following tables contains outputs of our regressions.

Table 32: Output of regression for California

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.186491	0.083738	2.227086	0.0501
D(LOG(CAALC))	1.147876	0.357201	3.213526	0.0093
D(CABEN)	0.007982	0.014516	0.549876	0.5945
D(CABLCK)	-2.099998	0.742756	-2.827307	0.0179
D(CAGDP)	0.007884	0.011975	0.658419	0.5251
D(LOG(CAINC))	-4.411628	0.685667	-6.434069	0.0001
D(CALAT)	-0.267308	0.192331	-1.389831	0.1947
D(CAM)	3.968476	0.820072	4.839179	0.0007
D(CAMINW)	0.157390	0.074473	2.113381	0.0607
CRSIS	0.209394	0.088474	2.366742	0.0395
D(INFLATION)	-0.001946	0.032198	-0.060427	0.9530
D(LOG(NASDAQ100))	0.099350	0.082033	1.211086	0.2537
AR(1)	-2.026412	0.275954	-7.343290	0.0000
AR(2)	-2.809729	0.479001	-5.865805	0.0002
AR(3)	-2.664130	0.603376	-4.415374	0.0013
AR(4)	-1.803611	0.421951	-4.274460	0.0016
AR(5)	-0.768385	0.316284	-2.429414	0.0355
SIGMASQ	0.000471	0.000336	1.401241	0.1914

R-squared	0.980920	Mean dependent var	0.002382
Adjusted R-squared	0.948485	S.D. dependent var	0.160055
S.E. of regression	0.036328	Akaike info criterion	-3.221234
Sum squared resid	0.013197	Schwarz criterion	-2.364817
Log likelihood	63.09727	Hannan-Quinn criter.	-2.959419
F-statistic	30.24208	Durbin-Watson stat	2.378138
Prob(F-statistic)	0.000002		

Source: own illustration and calculation in eViews

Table 33: Output of regression for Georgia

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.013878	0.054696	-0.253722	0.8049
D(LOG(GAALC))	-2.258651	0.848788	-2.661032	0.0239
D(GABEN)	0.018029	0.041584	0.433555	0.6738
D(GABLCK)	-0.427949	0.182237	-2.348307	0.0408
GAGDP	0.005825	0.001773	3.284427	0.0082
D(LOG(GAINC))	-1.304978	0.784844	-1.662723	0.1273
D(GALAT)	0.285939	0.032360	8.836069	0.0000
D(GAM)	-0.740746	0.124871	-5.932106	0.0001
D(FEDMINW)	0.255222	0.026059	9.794118	0.0000
CRISIS	0.060536	0.021809	2.775698	0.0196
D(INFLATION)	-0.006137	0.018546	-0.330899	0.7475
D(LOG(NASDAQ100))	-0.160383	0.043665	-3.673029	0.0043
AR(1)	-2.299758	0.362578	-6.342799	0.0001
AR(2)	-3.345693	0.596490	-5.608971	0.0002
AR(3)	-3.169354	0.642558	-4.932398	0.0006
AR(4)	-1.881412	0.581573	-3.235041	0.0089
AR(5)	-0.714804	0.285376	-2.504783	0.0312
SIGMASQ	0.000459	0.000290	1.581181	0.1449

R-squared	0.979135	Mean dependent var	0.001232
Adjusted R-squared	0.943665	S.D. dependent var	0.151081
S.E. of regression	0.035859	Akaike info criterion	-3.210160
Sum squared resid	0.012859	Schwarz criterion	-2.353743
Log likelihood	62.94224	Hannan-Quinn criter.	-2.948345
F-statistic	27.60469	Durbin-Watson stat	2.720727
Prob(F-statistic)	0.000004		

Source: own illustration and calculation in eViews

Table 34: Output of regression for Michigan

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-6.759456	0.122832	-55.03025	0.0000
LOG(MIALC)	5.596743	0.122326	45.75263	0.0000
D(MIBEN)	0.025663	0.003288	7.805145	0.0000
D(MIBLCK)	8.521498	0.125230	68.04651	0.0000
MIGDP	-0.028372	0.001676	-16.92652	0.0000
D(LOG(MIINC))	-7.505740	0.174320	-43.05733	0.0000
D(MILAT)	22.84210	0.301669	75.71913	0.0000
D(MIM)	3.037328	0.135398	22.43254	0.0000
D(MIMINW)	-0.061659	0.014163	-4.353372	0.0014
CRISIS	0.162044	0.008090	20.02963	0.0000
D(INFLATION)	0.031964	0.007781	4.107850	0.0021
D(LOG(NASDAQ100))	-0.142498	0.017725	-8.039513	0.0000
AR(1)	-3.339504	0.394216	-8.471264	0.0000
AR(2)	-5.539117	0.941664	-5.882264	0.0002
AR(3)	-5.317561	1.161781	-4.577075	0.0010
AR(4)	-2.963475	0.779637	-3.801099	0.0035
AR(5)	-0.805631	0.322117	-2.501055	0.0314
SIGMASQ	0.000214	0.000126	1.692561	0.1214

R-squared	0.992620	Mean dependent var	-0.015352
Adjusted R-squared	0.980074	S.D. dependent var	0.173423
S.E. of regression	0.024480	Akaike info criterion	-3.698303
Sum squared resid	0.005993	Schwarz criterion	-2.841886
Log likelihood	69.77624	Hannan-Quinn criter.	-3.436488
F-statistic	79.11754	Durbin-Watson stat	1.887495
Prob(F-statistic)	0.000000		

Source: own illustration and calculation in eViews

Reversed causality

Table 35: Output of regression for California

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LOG(CAUR))	0.044651	0.160092	0.278910	0.7847
C	-0.025670	0.023627	-1.086459	0.2970
D(CABEN)	0.000699	0.003192	0.218869	0.8302
D(CAGDP)	-0.001980	0.004595	-0.430927	0.6736
D(LOG(CAINC))	0.696325	0.569539	1.222610	0.2432
D(CAM)	-0.473017	0.381271	-1.240630	0.2367
D(CAMINW)	-0.053408	0.020321	-2.628243	0.0209
CRSIS	-0.008636	0.030799	-0.280403	0.7836
D(INFLATION)	0.002200	0.008127	0.270736	0.7908
AR(1)	-0.024445	0.206515	-0.118367	0.9076
AR(2)	0.275798	0.229821	1.200055	0.2515
AR(3)	-0.099859	0.359993	-0.277391	0.7858
AR(4)	-0.005985	0.230726	-0.025941	0.9797
AR(5)	0.671729	0.342137	1.963335	0.0714
SIGMASQ	0.000529	0.000243	2.178990	0.0483

R-squared	0.565068	Mean dependent var	-0.009958
Adjusted R-squared	0.096679	S.D. dependent var	0.035508
S.E. of regression	0.033748	Akaike info criterion	-3.515276
Sum squared resid	0.014806	Schwarz criterion	-2.801595
Log likelihood	64.21386	Hannan-Quinn criter.	-3.297097
F-statistic	1.206408	Durbin-Watson stat	2.056461
Prob(F-statistic)	0.370415		

Source: own illustration and calculation in eViews

Table 36: Output of regression for Georgia

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.006691	0.021937	-0.305018	0.7648
D(LOG(GAUR))	-0.018506	0.087669	-0.211086	0.8359
D(GABEN)	0.003091	0.022872	0.135135	0.8944
GAGDP	0.001639	0.002878	0.569452	0.5781
D(LOG(GAINC))	-0.054223	0.481971	-0.112502	0.9120
D(GAM)	-0.096282	0.309696	-0.310891	0.7605
D(FEDMINW)	0.003481	0.037646	0.092477	0.9276
CRISIS	-0.006736	0.023070	-0.291961	0.7746
AR(1)	-0.212237	0.507579	-0.418137	0.6822
AR(2)	-0.048706	0.429552	-0.113388	0.9113
AR(3)	0.208897	0.400043	0.522186	0.6097
AR(4)	0.335146	0.598255	0.560206	0.5842
AR(5)	-0.312933	0.448217	-0.698173	0.4965
SIGMASQ	0.000239	9.65E-05	2.482608	0.0263

R-squared	0.383821	Mean dependent var	-0.008587
Adjusted R-squared	-0.188344	S.D. dependent var	0.020075
S.E. of regression	0.021884	Akaike info criterion	-4.440125
Sum squared resid	0.006705	Schwarz criterion	-3.774023
Log likelihood	76.16175	Hannan-Quinn criter.	-4.236491
F-statistic	0.670822	Durbin-Watson stat	2.063666
Prob(F-statistic)	0.760738		

Source: own illustration and calculation in eViews

Insignificance of MA part

We decided to show just probability of MA parts in each model. With adding additional MA lags, the probability of previous decrease, therefore there is no need to show results for models including just one or two MA lags.

Table 37: Probability of MA part, California

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(1)	-0.997282	3.298918	-0.302306	0.7712
MA(2)	-0.999967	12.45726	-0.080272	0.9383
MA(3)	0.997251	9.130182	0.109226	0.9161

Source: own illustration and calculation

Table 38: Probability of MA part, Georgia

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(1)	1.000000	516.2980	0.001937	0.9985
MA(2)	-1.000000	772.9071	-0.001294	0.9990
MA(3)	-1.000000	1271.679	-0.000786	0.9994

Source: own illustration and calculation

Table 39: Probability of MA part, Michigan

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(1)	-0.948219	60.07425	-0.015784	0.9878
MA(2)	-0.949013	1.773291	-0.535171	0.6091
MA(3)	0.997650	61.98726	0.016094	0.9876

Source: own illustration and calculation

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