ANALYZING THE IMPACT OF IMMIGRATION ON UNEMPLOYMENT IN EUROPEAN UNION MEMBER STATES, NORWAY, AND ICELAND

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Abstract

This paper analyzes the impact immigration has on unemployment in European Union member states, excluding Bulgaria, and Norway and Iceland in both 2005/2006 and 2011/2012. Given the importance of the current Syrian refugee crisis and political debates, particularly those featuring Eurosceptic politicians in various European nation states and those featured in the 2016 US Presidential campaign, about the impact immigration has on a nation state, we decided that it is vital that immigration's impact on unemployment is studied empirically. Our hypothesis was that immigration is positively correlated with unemployment in the short run (up to 3 years after immigration occurs). Our rationale for this was that a lot of adult immigrants are immediately added to the labour force, thereby increasing the labour force more quickly than if there was no immigration, while not all of these immigrants will be employed immediately upon arrival to a new country. This would increase the labour force by the number of adult immigrants, while the number of employed members in the labour force may not increase by the total number of adult immigrants, thereby increasing the unemployment rate. We ran a simple regression between immigration and unemployment and several multiple regressions that included other independent variables, including GDP growth, a binary variable for whether or not a country has a national minimum wage, and how much the countries spend on social welfare programs. All but one of these regressions suggest that increases in immigration in a country decrease unemployment in that country in the short run. After running a robustness test on a couple of our multiple regression models, including the only one that suggested that increases to immigration lead to increases in the unemployment rate, we determined that Model 2 was our best model. In this model log(immigration) is statistically significant at the 1% level and the coefficient on log(immigration) is negative. This suggests that our initial hypothesis was incorrect and that increased immigration in a nation state leads to a decrease in the unemployment rate in the short run.

I. Introduction

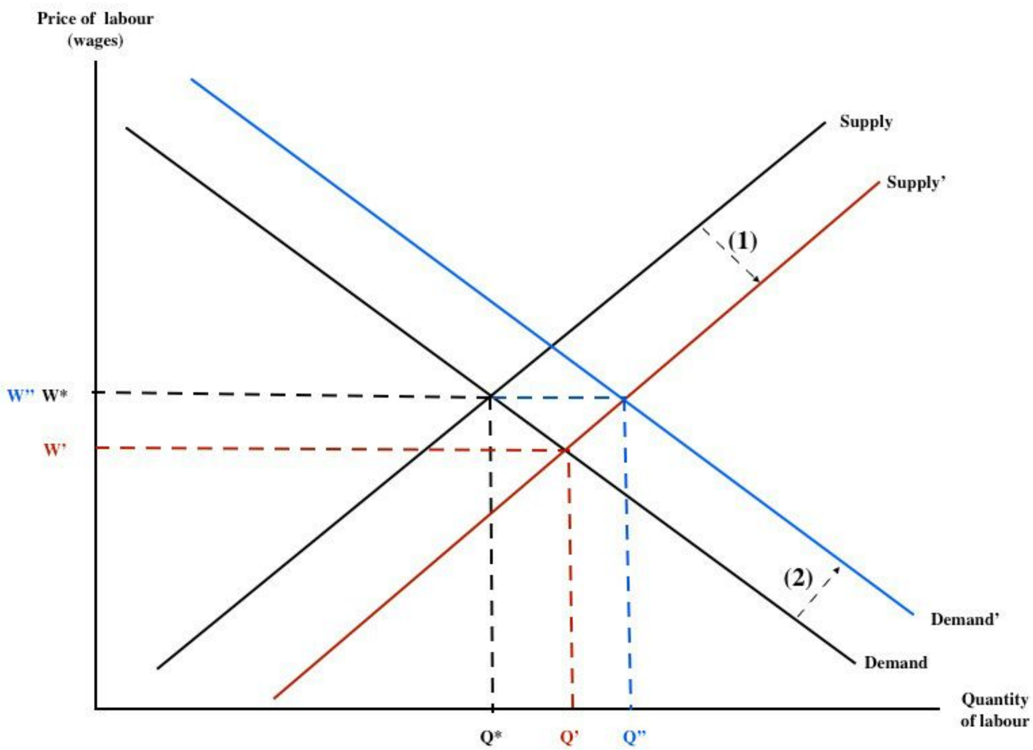
We chose to analyze the relationship between rates of immigration and the unemployment rates in a variety of European nation states. The Syrian refugee crisis coupled with the current Euro crisis and the increasing influence of Eurosceptic and protectionist politicians in the European Union make this topic exceedingly important. We believe that our study will provide useful insights into what impact increasing or decreasing immigration has on a nation state.

Our hypothesis is that immigration is positively correlated to unemployment in the short run (up to three years after the immigration flow). Unemployment is defined as the ratio of the number of people who are not employed and who are actively seeking employment to the total number of people in the labour force. Immigration increases the labour force at a higher rate than if there were no immigration. Since myriad immigrants to the European Union, Norway, and Iceland are adults they enter the labour force as soon as they enter the country, as opposed to newborn children who will enter it after they are sixteen years old.

Our rationale is that as the labour force increases, new jobs have to be created in order to keep the unemployment rate low. These jobs will be created as a nation state's population grows, regardless of whether it is due to domestic population growth or immigration because the added people will begin to consume a variety of goods and services. This increase in consumption will eventually require the creation of new jobs. This adjustment is not instantaneous and may take a few years. Since most adult immigrants will be added to the labour force immediately, while not all adult immigrants will have a job upon their arrival to a new nation state, the unemployment rate will increase in the short-run while returning to pre-immigration levels in the long-run.

The figure below shows the effect of a supply shock in labour. As an initial effect, the supply curve shifts down (1) due to an increase in the number of workers. The job market can sustain this shift only if the wage of all workers go down; it can have a new equilibrium at (Q', W'). The problem, however, is that the labour market is quite rigid, especially in Europe, which means that the wages will not easily decrease; therefore, instead of a wage decrease there will be an increase in unemployment. After a few years, new jobs will be created due to the increase in aggregate demand brought by the immigrants. This will shift demand up (2), and wages and unemployment will go back to a level similar to the pre-immigration level while output will increase.

Figure 1: Basic Model for Supply and Demand of Labour



II. Literature Review

Before delving into a discussion of scholarly studies that are relevant to our project, it is worth describing what we believe our contribution to the existing literature includes. As was mentioned before, increasing amounts of attention and debate have been dedicated to the coverage of the current Syrian refugee crisis. This, coupled with the political arguments of various Eurosceptic and national political parties, eventually inspired our desire to examine what impact immigration has on a nation state's unemployment. Our contribution will be significant to the literature because it analyzes a previously unexamined combination of regions (the European Union plus Norway and Iceland) and time period (2011/2012 in addition to 2005/2006). This, coupled with our unique methods, will add a new voice to the scholarly examination of what impact immigration has on a nation-state. It is critical that new studies and new voices are added to the already existing conversation and we are confident that our paper will serve as a unique, if relatively minor, voice in that conversation.

Jean and Jimenez (2011) used data from seventeen European countries, New Zealand, and the United States from 1984 to 2004 in order to assess the effect of immigration on unemployment in OECD countries. The strength of their analysis lies in the fact that they divided the population into different levels of skills so that they could assess the effect that the number of immigrants of a certain level of skills has on identically skilled natives' employment. They also try to find out if the effect of immigration on unemployment varies with different labour market policies, like employment protection legislation and replacement rate of unemployment benefits. Their findings show that there is no effect of immigration in a certain year on unemployment five years later; neither on the aggregate level nor in the different categories of skills. However, they find that a change in immigration has a temporary effect on unemployment on the aggregate level and a slightly lesser effect on the skills level. As for the different policies, they cannot find a statistically significant effect of the employment protection legislation on how immigration affects unemployment. A higher replacement rate of unemployment benefits increases the impact because it will increase the reservation wage of natives while immigrants, who in the first years after their arrival will probably not be eligible for unemployment benefits, will have a very low reservation wage. Their analysis also unveils the different impacts for different age categories. They find that unemployment of native workers under the age of 40 is more affected by immigration than that of native workers over the age of 40, which is actually not affected at all.

This analysis is a complete and broad analysis of the subject: not only do Jean and Jimenez (2011) analyze the aggregate effect we will try to assess, but they also break this effect down to different categories of skill, age, and policies, which gives a more detailed idea of the effect as a whole. The analysis could however be broadened by taking into account not only male but also female workers, and by then breaking down the effect of immigration on unemployment for women and for men.

The OECD (2015) analyzed data on the total changes in unemployment and immigration levels from the pre-crisis period, 2007-2010, and the recovery period, 2011-2014, to assess the relative success or failures of the market in accommodating migrants. In this assessment, they take into account labour market trends among the native-born and migrant population, which include poverty levels (due to long-term unemployment), types of employers hiring migrants, and integration policy. During the recovery period, employment rates for migrants on average increased by 1.3% across all OECD countries. However, for natives of these countries, the unemployment rate was unaffected. European OECD countries account for approximately a 2.1 million person increase from 2013 and 2014 in those who are employed, which includes both foreign- and native-borns. Older migrants tend to have an easier time finding jobs, while those with higher levels of education fare better in European OECD countries rather than in the United States. Policy measures aim to level the playing field between migrants and native-borns by increasing funding for education programs for foreign-borns, which increase qualifications and basic skills. Another disparity between migrants and natives is the issue of poverty:

from the years 2006-2012 the rate of poverty among migrants increased from 27% to 29%, and the poverty rate for employed migrants increased from 15% to 17% during that time. However, the overall market outcomes for immigrants have been relatively stable or increasing. Those with more skills have seen more job opportunities because of the emphasis on lifelong learning, though the jobs available have been more selective in choosing their employees.

Galloway and Jozefowicz (2008) analyzed panel data from 26 labour market regions from 1996 until 2003. Their study measures immigration as a year-to-year change in the foreign population and they paid particular attention to immigrants of non-Western origin. They utilized a variety of variables to describe local labour markets, including occupation shares, the percentage of workers in low- and high-skilled jobs, the percentage of female workers, how many part-time employees there were, labour force participants over the age of 55, educational attainment of workers, and population density. They note that by the end of the 20th century about 1.5 million people (roughly 10% of the Netherlands' population) with a foreign birthplace lived in the Netherlands. This has caused various Dutch politicians and the Dutch public to be concerned about what impact immigrants, particularly non-Western immigrants, will have on their economy.

Galloway and Jozefowicz (2008) got all of their regional data from the Centraal Bureau voor Statistiek (CBS). They use Pischke and Velling's 1997 version of an econometric equation that measures the impact immigration has on regional unemployment rates. They ultimately find that their immigration variable has a positive and statistically significant coefficient associated with it in relation to the unemployment rate. They also found that immigrants of Western origin had little to no statistical impact on the unemployment rate and that the non-Western population in a region posed no statistically significant effect on the unemployment rate volatility. That being said, they mention that an increase in the foreign population in the Netherlands has an unfavorable impact on regional unemployment rate volatilities. The educational attainment of immigrants has a significant impact on the change in the unemployment rates in the Netherlands and it increased the overall fit of the equation they used. They conclude that a selective immigration policy of some kind is a good strategy for the Netherlands.

These articles, Galloway and Jozefowicz (2008), Jean and Jimenez (2011) and the 2015 OECD report, are representative of portions of an ever-expanding academic conversation about immigration and the impact it has on various nation-states. Each of these studies examine different categories of immigrants, dividing them into groups based on age, skill or educational attainment. Our study examines what macro-impact immigration has on unemployment in our selected region, thereby lending our study a unique voice amongst these studies. Each of these studies find that immigration has a relatively small, though significant, impact on unemployment. As we will discuss later, our findings seem to be at odds with some of the findings of these articles, particularly the Galloway and Jozefowicz piece. We ultimately found that immigration is negatively correlated with unemployment while Galloway and Jozefowicz find that it has a slightly positive correlation with unemployment. This being said, it should be noted that the Galloway and Jozefowicz piece focuses on regional and local unemployment rates, thereby differentiating their findings from our own. Our initial hypothesis utilizes the rationale of the Galloway and Jozefowicz piece, but we ultimately found that our initial hypothesis was incorrect in our selected region and for our selected time period. That aside, the OECD (2015) report does note that immigration during any given year has little to no lasting impact on unemployment 5 years after it takes place. This supports our idea that immigration has a short run impact on unemployment and that the unemployment rate will eventually return to pre-immigration levels in the long run, holding other factors constant. We will utilize the understandings provided by these studies, but we will also be sure to accurately depict our findings and note any differences between our findings and the articles' findings.

III. Data

Our analysis aims to uncover the effect of immigration on unemployment in European countries (list in Table 5, Appendix A). The data we use comes from Eurostat, which is the database of the European Commission. To do this, we will use a log-log model, which will give us the effect of a change of immigration on a change in unemployment (it will tell us the percentage change of unemployment when immigration is increased by a certain percentage). We therefore use the log of unemployment as our dependent variable. We chose to take unemployment one year after a certain flow of immigration, because immigrants aren't taken into account as part of the labour force as soon as they set foot in the host country. One year leaves enough time for the whole data to be adapted more accurately to the immigration flow. In order to give more weight to our analysis, we made two models at two different periods: 2011-12 and 2005-06. We chose the first period because, being quite recent, there is data to be found about most of the actual EU member states. At the same time, it is preceding the beginning of the European migrant crisis, an exogenous immigration shock that could have an unwanted effect on our analysis. The second period is six years earlier. We chose this timespan of six years because it is wide enough for the job market and economic conditions to be quite different to what they will be later, and it is the earliest we could go without losing to many data points and reducing our sample too much. This time period also comes directly before the major worldwide recession, in which the combination of the housing market collapse coupled with the stock market crash created powerfully negative effects on the global economy.

Our independent variable is the log of the total number of immigrants that came to every European country in 2011 or 2005 divided by the total population of the country on January 1, 2011 or 2005. Immigrants are defined in our data as "people undertaking an immigration," which "denotes the action by which a person establishes his or her usual residence in the territory of a Member State for a period that is, or is expected to be, of at least 12 months." Dividing the number of immigrants by the population comes from the fact that the level of unemployment is a rate related to the size of the population, so it's only logical to do the same with immigration.

To better understand the results of our research, we have various independent variables in the multiple regressions. The variables chosen represent various factors that we deem both historically and statistically significant in placing a value on the effect of a change in immigration on unemployment rates. We used the following variables: GDP growth rate, minimum wage and social protection (see Table 6, Appendix A). We decided to use GDP growth over GDP per capita because we think that in Europe, where there are no big discrepancies in GDP per capita, GDP growth is a better indicator of economic well-being. Our minimum wage variable is a dummy variable. A value of one is placed for countries with national minimum wages in 2011, while a value of zero is used for countries without a mandatory national minimum wage. Adding a dummy variable for minimum wage allows us to observe the potential differences in unemployment given whether or not a country has a legally binding minimum wage. We also use the multiplication of our minimum wage and log of immigration variable in order to reveal an effect of the minimum wage on the coefficient of immigration. Social protection is an aggregate measure of expenditures on social protection as a percentage of GDP. This includes expenditures on health, unemployment, and funding for the retired and/or disabled.

In order to have a properly structured multiple regression model, every Gauss-Markov Assumption needs to be upheld in our tests. The first assumption analyzes whether the model is linear in parameters, which is shown in the results section. The second assumption ensures that random sampling occurs, which is the case in our study because we took all European countries that had available data on Eurostat, without choosing on the basis of their unemployment or immigration level. The third assumption states that the variables must not be perfectly correlated and that the expected value of the independent variables should not equal zero. We tested our variables for collinearity among one another and did not find perfect collinearity; and, as seen in the summary statistics tables, none of our variables have an expected value of zero. The fourth assumption explains the zero conditional mean, which states that the error term (given any value for the explanatory variables) have an expected value of zero. Finally, the fifth assumption concerns homoskedasticity: the variance of the error term is constant given any value of the independent variables. There is no guaranteed method to uphold both the fourth and fifth assumptions, so we include several multiple regression models to reduce bias in our models and test for the statistical significance of our coefficients. We also tried to keep the number of independent variables small, because we have a small sample.

Table 1: Summary Statistics for 2011-12

Variable	**Obs**	**Mean**	**Std. Dev**	**Min**	**Max**
unemployment 2012	29	10.34	5.30	3.2	24.8
immigration ratio 2011	29	0.88	0.79	0.09	4.00
GDP growth rate 2011	29	1.82	2.90	-8.9	7.6
Minimum wage 2011 (dummy)	29	0.69	0.47	0	1
Social protection expenditures 2011	29	24.3	5.37	14.8	32.8

Table 2: Summary Statistics for 2005-06

Variable	**Obs**	**Mean**	**Std. Dev**	**Min**	**Max**
unemployment 2006	25	6.82	2.72	2.9	13.9
immigration ratio 2005	25	0.99	0.95	0.03	3.33
GDP growth rate 2005	25	4.08	2.58	0.7	10.7
Minimum wage 2005 (dummy)	25	0.64	0.49	0	1
Social protection expenditures 2005	25	21.61	5.33	12.3	30.4

IV. Results

The simple regression model for 2011 examines the effects of a change in immigration on unemployment, which is shown as a change in unemployment. The following model was constructed:

$$\mathbf{log(\boldsymbol{unemp})} = \beta_0 + \beta_1 \mathbf{log(\boldsymbol{imm})} + \boldsymbol{u},$$

which produced the following results:

$$\log(unemp) = 2.109 - 0.267 \log(imm), \quad \text{for 2011-12}$$

indicating a negative relationship between percent changes in unemployment and percent changes in immigration. Table 5 shows results of tests for the years 2011-2012. From an economic perspective, the coefficient on the change in immigration suggests that a 1% increase in the immigration ratio is followed by a 0.267% decrease in unemployment. Though this is not a very strong effect, it is still quite considerable. The t-tests conducted on this model indicate a decidedly negative correlation at the 5% level of significance. However, the R^2 value for the simple regression is small which suggests, as we expected, that our estimated model is far from a perfect predictor of the actual model.

Incidentally, the R^2 values for each multiple regression model do not surpass 0.5, indicating that every one of our estimated models do not entirely represent perfect predictors of the actual model.

For 2005-06, we have the results:

$$\log(unemp) = 1.750 - 1.760 \log(imm)$$

suggesting a negative here again a negative correlation between changes in immigration and changes in unemployment. Immigration this time has a much greater impact on unemployment: a 1% percent increase of the immigration ratio leads to a 1.760% percent decrease in unemployment. The t-tests (Table 6) for this model indicate significance for the coefficient of the log of immigration at the 1% level. However, the R^2 value for this regression is low with a value of 0.33, denoting little closeness of fit between the actual model and estimated model. In fact, for each regression in this time period, the R^2 values do not surpass a value of 0.43.

For our first multiple regression model, we added *GDP growth* as an independent variable in order to account for the economic differences between countries in the sample. Thus, we used the following template:

$$\mathbf{log(\boldsymbol{unemp})} = \beta_0 + \beta_1 \mathbf{log(\boldsymbol{imm})} + \beta_2 \boldsymbol{GDPgrowth} + \boldsymbol{u},$$

which produced results:

$$\log(unemp) = 2.211 - 0.275 \log(imm) - 0.058 GDPgrowth, \text{ in 2011-12}$$

illustrating a negative relationship between both percent changes in immigration and GDP growth on percent changes in unemployment. We find that as GDP growth increases by one percentage point, unemployment decreases by 5.8% with a significance level of 5%. This is not surprising: economic growth leads to the creation of jobs and thus increases unemployment significantly. Our coefficient on immigration did not change much from the first to the second model, but it gained in significance, at it is now statistically significant at 1%. This suggests that GDP growth is a relevant explanatory variable and adds significance to our regression. Additionally, GDP growth is significant at the 5% level for each multiple regression in the 2011-2012 models, and its coefficient varies very little from one model to another.

For 2005-06 we have the results:

$$\log(unemp) = 1.876 - 0.194 \log(imm) - 0.033 GDPgrowth$$

showing a negative relationship between both changes in immigration and GDP growth with changes in unemployment. According to the results, if GDP growth increases by one percentage point, unemployment decreases by 3.3%. Adding GDP growth to the model decreased the coefficient on immigration nearly tenfold, and it increases its significance even further than before. The coefficient on GDP growth however was found to not be significant at any level; it is therefore less clear than in the 2011-2012 model as to whether this is an important improvement of the model.

For our third model, we added the binary variable *minimum wage*. It is well known in economic literature that a minimum wage can have negative effect on unemployment because it drive out of the job market low-productivity workers who would have been willing to work for a low wage. We also think that adding the minimum wage will have an effect on the coefficient on immigration, because a minimum wage might attract more immigrants. We used the following model:

$$\mathbf{log(\boldsymbol{unemp})} = \beta_0 + \beta_1\,\mathbf{log(\boldsymbol{imm})} + \beta_2\,\boldsymbol{GDPgrowth} + \delta_0\,\boldsymbol{minwage} + \boldsymbol{u},$$

which produced the following results:

$$\log(unemp) = 2.02 - 0.208\log(imm) - 0.057\,GDPgrowth + 0.315\,minwage, \text{ in 2011-12}$$

again showing a negative correlation between both percent changes in immigration and GDP growth on unemployment in the EU Region. Minimum wage has, as expected a positive relationship to percent changes in unemployment: countries with a national minimum wage have a 31.5% higher unemployment rate on average than countries without a national minimum wage. Accounting for the minimum wage lowers the effect of immigration on unemployment by approximately 0.07 percentage points. The coefficient on minimum wage only has a statistical significance of 10%, and adding this variable to the model decreased the significance of the coefficient on immigration from 1% to 5%.

For 2005-06 we have the result:

$$\log(unemp) = 1.808 - 0.170\log(imm) - 0.047\,GDPgrowth + 0.215\,minwage,$$

specifying a positive relationship between minimum wage and changes in unemployment, and a negative correlation between both changes in immigration and GDP growth and changes in unemployment. This model suggests that countries with a national minimum wage have a 21.5% unemployment rate in average than countries without one. Adding minimum wage in the model doesn’t change the coefficients on immigration and GDP growth by much. Nonetheless, the coefficient on minimum wage is not significant at any level, while the coefficient on immigration is again significant at the 1% level and the significance level of the coefficient on GDP growth improves to 10%.

In the next model, we test if the minimum wage has an effect not only on the average unemployment rate but also on the coefficient on immigration. We therefore add the variable *minwage*log(immigration)* to our regression:

$$\mathbf{log(\mathit{unemp})} = \beta_0 + \beta_1\, \mathbf{log(\mathit{imm})} + \beta_2\, \boldsymbol{GDPgrowth} + \delta_0\, \boldsymbol{minwage}^*\mathbf{log(\mathit{imm})} + \boldsymbol{u}$$

which produced results:

$$\log(unemp) = 2.015 - 0.014 \log(imm) - 0.055 GDPgrowth + 0.299\, minwage - 0.222 minwage * log(imm)$$

It suggests that countries with a required minimum wage have on average 29.9% higher unemployment and that immigration has a 22.2 percentage-point higher effect on unemployment than in countries without a national minimum wage. However, we can see that in this regression, the significance level of the coefficient on immigration dropped very low, and our multiplied variable has a very low significance too. This suggests that there is very high collinearity between *log(imm)* and *minwage*log(imm)* which indicates that this model is biased.

For 2005-06, we get:

$$\log(unemp) = 1.793 - 0.300 \log(imm) - 0.039 GDPgrowth + 0.211\, minwage - 0.151 minwage * log(imm),$$

which means that countries with a minimum wage have on average 21.1% higher unemployment and that immigration has a 15.1 percentage points higher effect on unemployment than in countries without a minimum wage. The coefficient on immigration is greater, but is also loses statistical significance to 10% as compared to 1% in the previous regression; this is most likely due to the aforementioned multicollinearity. Our added variable, *minwage*log(imm)*, has no statistical significance at all. From the results from 2011-12 and 2005-06, we decide to drop our last variable and continue our regression without it.

In the final model, we add an explanatory variable to account for social protection within each country. The estimated model was as follows:

$$\mathbf{log(\mathit{unemp})} = \beta_0 + \beta_1\, \mathbf{log(\mathit{imm})} + \beta_2\, \boldsymbol{GDPgrowth} + \beta_3\, \boldsymbol{minwage} + \beta_4\, \boldsymbol{socprot} + \boldsymbol{u},$$

which produced the following results:

$$\log(unemp) = 2.276 + 0.197 \log(imm) - 0.063\, GDPgrowth + 0.278\, minwage + 0.009\, socprot$$

in 2011-12, displaying a positive relationship between changes in unemployment and every other variable except for GDP growth. Our last added variable indicates that increasing the percentage of social protection expenditure to GDP by one percentage point leads to a 0.9% increase in unemployment. Adding this variable does not affect the coefficients on GDP growth and minimum wage by much. However it changes the coefficient on immigration from negative to positive. This regression suggests that when immigration increases by 1%, unemployment increases by 0.197%, which is the positive effect we expected before the writing of this research paper. In this case, changes in immigration are significant only at the 10% level. Though minimum wage and social protection measurements are positively correlated to changes in unemployment, neither are significant at any level.

For 2005-06, we have the result:

$$\log(unemp) = 1.770 - 0.170\,\log(imm) - 0.045\,GDPgrowth + 0.218\,minwage + 0.001\,socprot,$$

which reveals a positive correlation between both social protection and minimum wage with changes in unemployment, while changes in immigration and GDP growth show a negative relationship. The coefficient on social protection suggests that a one-percentage point increase in social expenditures leads to a 0.1% increase in unemployment. Unlike in 2011-12, the sign of the coefficient on immigration doesn't change with the addition of social protection expenditures in the model; in fact it even stays exactly the same. Its statistical significance decreases by a little bit, but is still very high, as the coefficient has still a 1% level significance. The t-test indicates that the coefficient on social protection however is not significant at any level, like the one on minimum wage.

Table 3: Results and Statistical Inference for 2011-2012

2011-2012					
log(unemployment)					
Independent variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
log(immigration)	-0.267** (-2.60)	-0.275*** (-2.86)	-0.208** (-2.10)	-0.014 (-0.05)	0.197* (-1.93)
GDP growth		-0.058** (-2.18)	-0.057** (-2.23)	-0.055** (-2.11)	-0.063** (-2.19)
Minimum wage			0.315* (1.87)	0.299* (1.74)	0.278 (1.50)
min. wage x log(immigration)				-0.222 (-0.74)	
Social protection					-0.009 (-0.50)
intercept	2.109*** (22.85)	2.211*** (22.47)	2.02*** (14.53)	2.015*** (14.35)	2.276*** (4.30)
R^2	0.20	0.32	0.41	0.42	0.41

n	29	29	29	29	29
Significance level: * = 10 %, ** = 5%, * = 1%**					

Table 4: Results and Statistical Inference for 2005-2006

2005-2006					
log(unemployment)					
Independent variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
log(immigration)	-0.176*** (-3.35)	-0.194*** (-3.61)	-0.170*** (-3.08)	-0.300* (-1.83)	-0.170*** (-2.98)
GDP growth		-0.033 (1.29)	-0.047* (-1.75)	-0.039 (-1.38)	-0.045 (-0.94)
Minimum wage			0.215 (1.46)	0.211 (1.42)	0.218 (1.32)
min. wage x log(immigration)				0.151 (0.85)	
Social protection					0.001 (0.05)
Intercept	1.750*** (24.91)	1.876*** (15.71)	1.808*** (14.44)	1.793*** (14.08)	1.770** (2.28)
R^2	0.33	0.37	0.43		0.43
n	25	25	25		25
Significance level: * = 10 %, ** = 5%, *** = 1%					

V. Robustness Test

Our last model takes into account the existence of a national minimum wage and level of expenditures in social protection. Both variables have individually no statistical significance at 10%, neither in 2011-12 nor in 2005-06. In order to determine if we should keep them in our regression, we did an F-test on both years. Our restricted model is Model 2, and our unrestricted model is Model 5 for 2011-12 and Model 4 for 2005-06.

For 2011-12, we have residual sum of squares of 4.37 for the restricted and 3.79 for the unrestricted model. We have q=2 restrictions and n-k-1 = 24. This gives us a critical value of:

F(2,24) = 3.40,

which is higher than our value:

F = 1.84.

For 2005-05, we have a residual sum of squares of 2.17 for the restricted and 1.97 for the unrestricted model. Again, we have q=2 restrictions and n-k-1 = 19. This gives us a critical value of

F(2,19) = 3.52,

which again is higher than our value:

F = 0.96.

For both years, we fail to reject the null hypothesis, which is that minimum wage and social protection are both equal to zero. Thus, it seems like we should take both variables out of the model, as they are significant neither individually nor jointly. This would leave us with Model 2, which is actually the model in which immigration, the variable that really interests us, has the highest statistical significance.

VI. Conclusion

Given the results of our robustness test, we have concluded that Model 2 is the best representation of the relationship between immigration and unemployment in our selected region for 2011/2012 and 2005/2006. This aside, it is worth noting that all but one of our regression models, including simple and multiple, suggest that there is a negative correlation between immigration and unemployment. In Model 2, log(immigration) is not only negative, but it is significant at the 1% level. It is also worth mentioning that log(immigration) is statistically significant at least at the 10% level in all but one of our models, and that it is statistically significant at the 5% or 1% levels in Models 1, 2 and 3. Given this, we are confident that immigration is a major driver of a nation state's unemployment rate. We are also confident that our results, particularly Model 2, suggest that immigration is negatively correlated with unemployment. Our regressions, most notably Model 2, seem to suggest that as immigration increases in a nation state that it is likely that the same nation state will see a decrease in its unemployment rate. This rebukes our initial hypothesis and calls into question some of the political dogmas associated with how immigration affects a nation's economic well-being. All of this said, our results pertain to impacts in the short run and for a limited region of the world. Without extrapolating our results to other parts of the world, our conclusion given our analysis is that immigration is negatively correlated with unemployment in the short run in European Union member states, excluding Bulgaria, and Norway and Iceland for the years 2011/2012 and 2005/2006.

VII. References

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Appendix

Appendix A. Data and variable descriptions

Table 5. Countries used

Belgium	*France**	*Hungary*	*Slovenia*
Czech Republic	*Croatia**	*Malta*	*Slovakia*
Denmark	*Italy*	*Netherlands*	*Finland*
Germany	*Cyprus*	*Austria*	*Sweden*
Estonia	*Latvia*	*Poland*	*United Kingdom*
Ireland	*Lithuania*	*Portugal*	*Iceland*
*Greece**	*Luxembourg*	*Romania**	*Norway*
Spain	*only in 2011/12		

Table 6. Variables description

log(unemployment)	log of the unemployment rate (as a percentage) in 2012/2006
log(immigration)	log of the number of immigrations/total population (ratio expressed as a percentage) in 2011/2005
GDP growth	growth rate of the country's GDP (as a percentage) in 2011/2005
minimum wage	= 1 if the country has a national minimum wage in 2011/2005
*minimum wage * immigration*	multiplications of the two variables *log(immigration)* and *minimum wage*
social protection	expenditures in social protection as a percentage of GDP in 2011/2005

Appendix B. STATA Regression Outputs

Figure 2: Simple Regression of Unemployment on Immigration (2011-12 then 2005-06)

```
. regress lunemp limm

      Source |       SS           df       MS      Number of obs   =        29
-------------+----------------------------------   F(1, 27)        =      6.76
       Model |  1.29340446         1  1.29340446   Prob > F        =    0.0149
    Residual |  5.16740349        27  .191385314   R-squared       =    0.2002
-------------+----------------------------------   Adj R-squared   =    0.1706
       Total |  6.46080795        28  .230743141   Root MSE        =    .43748

------------------------------------------------------------------------------
      lunemp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        limm |  -.2671511   .1027647    -2.60   0.015    -.4780068   -.0562953
       _cons |   2.108595   .0922979    22.85   0.000     1.919216    2.297975
------------------------------------------------------------------------------
```

```
. regress lunemp limm

      Source |       SS           df       MS      Number of obs   =        25
-------------+----------------------------------   F(1, 23)        =     11.21
       Model |   1.1401547         1   1.1401547   Prob > F        =    0.0028
    Residual |  2.33869116        23  .101682224   R-squared       =    0.3277
-------------+----------------------------------   Adj R-squared   =    0.2985
       Total |  3.47884586        24  .144951911   Root MSE        =    .31888

------------------------------------------------------------------------------
      lunemp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        limm |  -.1764857   .0527048    -3.35   0.003    -.2855139   -.0674575
       _cons |   1.750636   .0702869    24.91   0.000     1.605236    1.896036
------------------------------------------------------------------------------
```

Figure 3: Model 2 (2011-12 then 2005-06)

```
. regress lunemp limm GDP

      Source |       SS           df       MS      Number of obs   =        29
-------------+----------------------------------   F(2, 26)        =      6.24
       Model |  2.09483588         2  1.04741794   Prob > F        =    0.0061
    Residual |  4.36597207        26  .167922003   R-squared       =    0.3242
-------------+----------------------------------   Adj R-squared   =    0.2723
       Total |  6.46080795        28  .230743141   Root MSE        =    .40978

------------------------------------------------------------------------------
      lunemp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        limm |  -.2753427   .0963325    -2.86   0.008    -.4733569   -.0773284
 GDPgrowth2~e |  -.0583621   .0267148    -2.18   0.038    -.1132751   -.0034491
       _cons |   2.211362   .0984243    22.47   0.000     2.009048    2.413676
------------------------------------------------------------------------------
```

```
. regress lunemp limm GDP

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(2, 22)      =    6.60
       Model |  1.30398653     2  .651993266           Prob > F      =  0.0057
    Residual |  2.17485932    22  .098857242           R-squared     =  0.3748
-------------+------------------------------           Adj R-squared =  0.3180
       Total |  3.47884586    24  .144951911           Root MSE      =  .31442

------------------------------------------------------------------------------
      lunemp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        limm |  -.1939969   .0537183    -3.61   0.002    -.3054017   -.082592
GDPgrow~2005 |  -.0331098   .0257194    -1.29   0.211    -.0864486   .0202291
       _cons |   1.875775   .1193825    15.71   0.000     1.628191   2.123359
------------------------------------------------------------------------------
```

Figure 4: Model 3 (2011-12 then 2005-06)

```
. regress lunemp limm GDP minwagedummy

      Source |       SS       df       MS              Number of obs =      29
-------------+------------------------------           F(3, 25)      =    5.72
       Model |  2.62997743     3  .876659143           Prob > F      =  0.0040
    Residual |  3.83083052    25  .153233221           R-squared     =  0.4071
-------------+------------------------------           Adj R-squared =  0.3359
       Total |  6.46080795    28  .230743141           Root MSE      =  .39145

------------------------------------------------------------------------------
      lunemp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        limm |  -.2079772   .0988314    -2.10   0.046    -.4115242   -.0044301
GDPgrowth2~e |  -.0569473   .0255308    -2.23   0.035    -.1095291   -.0043655
minwagedummy |   .3153812   .1687633     1.87   0.073    -.0321933    .6629556
       _cons |   2.020002   .1390161    14.53   0.000     1.733693    2.306311
------------------------------------------------------------------------------

. regress lunemp limm GDP minwagedummy

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(3, 21)      =    5.33
       Model |  1.50427995     3  .501426651           Prob > F      =  0.0069
    Residual |   1.9745659    21  .094026948           R-squared     =  0.4324
-------------+------------------------------           Adj R-squared =  0.3513
       Total |  3.47884586    24  .144951911           Root MSE      =  .30664

------------------------------------------------------------------------------
      lunemp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        limm |  -.1694209    .055029    -3.08   0.006    -.2838599   -.0549818
GDPgrow~2005 |  -.0469327   .0268117    -1.75   0.095    -.1026906    .0088253
minwagedummy |   .2149239   .1472575     1.46   0.159    -.0913149    .5211627
       _cons |   1.808343   .1252613    14.44   0.000     1.547848    2.068838
------------------------------------------------------------------------------
```

Figure 5: Model 4 (2011-12 then 2005-06)

```
. regress lunemp limm GDP minwagedummy minwageimm

      Source |       SS           df       MS      Number of obs   =        29
-------------+----------------------------------   F(4, 24)        =      4.35
       Model |  2.71600918         4  .679002295   Prob > F        =    0.0087
    Residual |  3.74479877        24  .156033282   R-squared       =    0.4204
-------------+----------------------------------   Adj R-squared   =    0.3238
       Total |  6.46080795        28  .230743141   Root MSE        =    .39501

------------------------------------------------------------------------------
      lunemp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        limm |  -.0136856   .2800192    -0.05   0.961    -.5916169    .5642457
GDPgrowth2~e |  -.0547817   .0259276    -2.11   0.045    -.1082937   -.0012698
minwagedummy |    .298593   .1717924     1.74   0.095    -.0559691    .6531552
  minwageimm |  -.2224792   .2996185    -0.74   0.465    -.8408613     .395903
       _cons |   2.015446   .1404145    14.35   0.000     1.725644    2.305247
------------------------------------------------------------------------------
```

```
. generate minwageimm = minwagedummy*limm

. regress lunemp limm GDP minwagedummy minwageimm

      Source |       SS           df       MS      Number of obs   =        25
-------------+----------------------------------   F(4, 20)        =      4.12
       Model |  1.57236963         4  .393092407   Prob > F        =    0.0135
    Residual |  1.90647623        20  .095323811   R-squared       =    0.4520
-------------+----------------------------------   Adj R-squared   =    0.3424
       Total |  3.47884586        24  .144951911   Root MSE        =    .30875

------------------------------------------------------------------------------
      lunemp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        limm |  -.3004253   .1646103    -1.83   0.083    -.6437963    .0429457
GDPgrow~2005 |  -.0392976   .0284674    -1.38   0.183    -.0986795    .0200844
minwagedummy |    .210713   .1483533     1.42   0.171    -.0987465    .5201725
  minwageimm |   .1509471   .1786014     0.85   0.408    -.2216089    .5235032
       _cons |   1.793425   .1273514    14.08   0.000     1.527774    2.059075
------------------------------------------------------------------------------
```

Figure 6: Model 5 (2011-12 then 2005-06)

```
. regress lunemp limm GDP minwagedummy SPR

      Source |       SS           df       MS      Number of obs   =        29
-------------+----------------------------------   F(4, 24)        =      4.23
       Model |  2.66972304         4  .667430761   Prob > F        =    0.0099
    Residual |  3.79108491        24  .157961871   R-squared       =    0.4132
-------------+----------------------------------   Adj R-squared   =    0.3154
       Total |  6.46080795        28  .230743141   Root MSE        =    .39744

------------------------------------------------------------------------------
      lunemp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        limm |  -.1977827   .1023822    -1.93   0.065    -.4090891    .0135237
GDPgrowth2~e |  -.0634417   .0289752    -2.19   0.039    -.1232436   -.0036397
minwagedummy |   .2788047   .1862174     1.50   0.147    -.1055291    .6631386
     SPR2011 |  -.0088267   .0175967    -0.50   0.621    -.0451444     .027491
       _cons |   2.275886   .5292901     4.30   0.000     1.183485    3.368287
------------------------------------------------------------------------------
```

```
. regress lunemp limm GDP minwagedummy SPR

      Source |       SS       df       MS              Number of obs =      25
-------------+------------------------------           F(4, 20)      =    3.81
       Model |  1.50453089     4  .376132724           Prob > F      =  0.0185
    Residual |  1.97431496    20  .098715748           R-squared     =  0.4325
-------------+------------------------------           Adj R-squared =  0.3190
       Total |  3.47884586    24  .144951911           Root MSE      =  .31419

------------------------------------------------------------------------------
      lunemp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        limm |  -.1698718   .0570892    -2.98   0.007    -.2889578   -.0507858
GDPgrow~2005 |  -.0449577   .0478446    -0.94   0.359    -.1447597    .0548443
minwagedummy |   .2182792   .1649089     1.32   0.201    -.1257147    .5622732
     SPR2005 |   .0013045    .025874     0.05   0.960    -.0526677    .0552768
       _cons |   1.769699   .7771286     2.28   0.034     .1486371    3.390761
------------------------------------------------------------------------------
```