LUND UNIVERSITY
School of Economics and Management

Explaining differences in labour market outcomes between natives and immigrants in a European institutional context

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Bachelor Thesis (15 ECTS) – May 2018

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Abstract

In most European countries today, immigrants are doing worse than their native counterparts on the labour market, resulting in economically and socially undesirable outcomes. This thesis studies differences in labour market segregation for immigrants among European countries and explains how different institutional factors on the labour markets of Europe affect labour market segregation. More precisely, unemployment segregation and activity rate segregation is analyzed using a theoretical framework founded in previous research on the matter as well as prevalent labour market theory. This thesis uses statistical analyses at the aggregated level, as well as at the multi-level of micro and macro data, to compare four potential explanatory variables of activity rate gaps and unemployment rate gaps. These four variables are the share of immigrants with low education, the degree of union influence, the degree of wage compression and the degree of redistributive welfare schemes. The activity rate gap is found to be larger in countries with a high degree of redistributive welfare schemes. This segregating effect is found to be stronger for women than for men and to disappear for immigrants who are members of a union. The unemployment rate gap is also found to be larger in countries with a high degree of redistributive welfare schemes, but is also highly affected by the degree of influence from unions. This segregating effect is again found to disappear for immigrants who are members of a union, and in contrast to the activity rate gap, being female does not additionally increase the likelihood of being unemployed for immigrants. All explanatory variables have value in some specification but the share of immigrants with low education seems to be irrelevant in determining labour market segregation.

Keywords: Immigration, labour market segregation, labour market outcomes, activity rate gaps, unemployment rate gaps, insider–outsider theory, immigration surplus.

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1. Introduction

1.1 The immigrant surplus in relation to labour market outcomes

In almost all Western countries today, the differences in labour market outcomes between immigrants and natives are large and the immigrant populations of European countries tend to do much worse on the labour market than natives (Borjas 1995, 5; Jean et al. 2010, 15; Nannestad 2009). Theoretically, as Borjas (1995) discusses, there are both positive and negative effects of migration for native workers and tax payers. According to the most basic neo-classical framework, immigration will lead to a lowering of wages following the expansion of the labour force. Although native workers will receive lower wages, the overall effect will be an increase in national income for natives since the benefit of higher rental income for capital will succeed the loss resulting from lower wages. This effect is called the immigration surplus by Borjas (1995, 6).

In this basic model, the size of the immigration surplus will depend solely on the elasticity of the demand for labour. In the special case of a perfectly inelastic demand for labour, there would be no immigration surplus since wages would not change and the whole additional product would be distributed to the immigrants. In the special case of perfectly elastic demand for labour, the whole additional product would instead be distributed to the native population and captured as an immigration surplus. (Borjas 1995, 6)

However, if institutional arrangements prevent the labour market from clearing, the immigration surplus will be smaller than it would otherwise be and might even prove to be negative. As stated above, and as discussed by for example Slaughter and Swagel (1997, 3f.), labour market outcomes are less favourable for immigrants than for natives in the often highly regulated labour markets of Europe, possibly since wages are not allowed to adjust to market clearing conditions. This then leads to a smaller immigrant surplus, and as a result lower welfare, than would otherwise be the case.

Moreover, a segregated and ill functioning labour market have been shown to spill over into social segregation and unrest, with riots and terrorism as the most extreme cases (Algan et al 2010, 1f.). Unemployment and exclusion from the labour market have also been shown to reduce the wellbeing of a person (Clark and Oswald 1994, 655). Thus, to reform European labour markets in order to make them more integrating should be in the interest of society as well as in the interest of the individual immigrant struggling to find a job.

1.2 The situation of today

As mentioned above, the general situation in Europe for immigrants on the labour market is one of segregation and poor labour market outcomes. However, the situation is different among European countries. The activity rate gap[1] measures the difference in activity rates between natives and immigrants, where a larger number indicates higher segregation. As figure 1 shows, there are large differences among European countries in the activity rate gaps between natives and immigrants. In some countries, such as Luxembourg and Greece, the situation is better for immigrants than for natives.

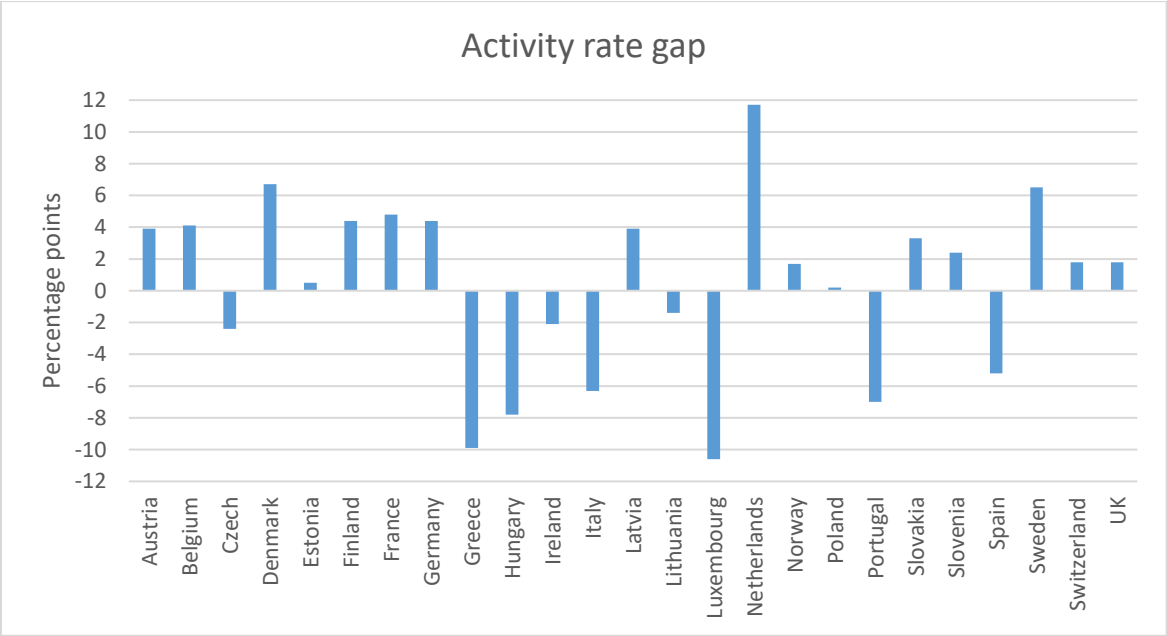

Figure 1. Country differences in the activity rate gap between natives and immigrants in 2015, age 15-64. Data from Eurostat 2018a.

The unemployment rate gap[2] is similar to the activity rate gap as it measures the difference in unemployment rates between natives and immigrants, where, again, a larger number indicates higher segregation. As figure 2 shows, there is a wide variety of outcomes when it comes to the unemployment rate gap as well. Although the unemployment rate gap is quite large for most countries, some countries, such as Belgium, Sweden, and Spain, experience substantially larger segregation in comparison to countries like Hungary, Lithuania and the UK.

[1] For a more detailed explanation, see section 2.1.
[2] Again, for a more detailed explanation, see section 2.1.

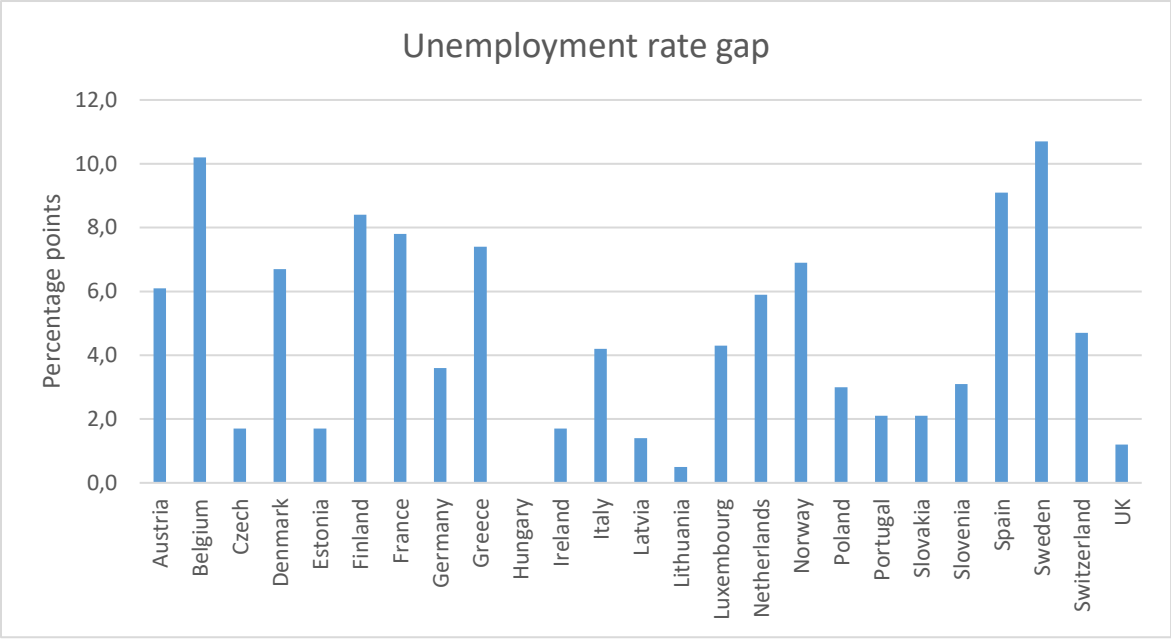

Figure 2. Country differences in the unemployment rate gap between natives and immigrants in 2015, age 15-64 years. Data from Eurostat 2018e.

Moreover, as can be seen in table 1, immigrants make up a substantial part of the population in most European countries. Furthermore, for the EU as a whole, 4 % of the population and 6 % of the workforce consists of non-EU immigrants (van Mol and de Valk 2016, 38). To conclude, given the large segregation in general and the current size of the immigrant share of the population in most European countries, research on how to reform labour markets to become more integrating is an important task for economists. The fact that the magnitude of segregation differs greatly among European countries makes it valuable to explain what constitutes the basis for discriminatory labour markets, and to point out what countries with large segregation can learn from those with less.

	Total		Born in another EU Member State		Born in a non-member country	
	(thousands)	(% of the population)	(thousands)	(% of the population)	(thousands)	(% of the population)
Belgium	1 876.7	16.5	876.5	7.7	1 000.2	8.8
Bulgaria	145.4	2.0	52.2	0.7	93.2	1.3
Czech Republic	465.1	4.4	181.4	1.7	283.6	2.7
Denmark	668.1	11.6	228.4	4.0	439.7	7.6
Germany	12 105.4	14.7	4 849.9	5.9	7 255.5	8.8
Estonia	192.5	14.6	20.1	1.5	172.4	13.1
Ireland	796.4	16.6	600.6	12.6	195.9	4.1
Greece	1 250.9	11.6	345.6	3.2	905.2	8.4
Spain	6 024.7	12.9	1 943.5	4.2	4 081.2	8.8
France (1)	8 155.7	12.2	2 220.7	3.3	5 935.0	8.9
Croatia	539.6	13.0	68.4	1.6	471.2	11.3
Italy(2)	6 054.0	10.0	1 837.6	3.0	4 216.3	7.0
Cyprus	173.8	20.3	113.8	13.3	60.0	7.0
Latvia	251.5	12.9	27.6	1.4	223.8	11.5
Lithuania	127.4	4.5	20.5	0.7	106.8	3.8
Luxembourg (2)	270.0	45.7	205.2	34.7	64.8	11.0
Hungary	513.6	5.2	321.9	3.3	191.7	2.0
Malta	69.6	15.1	33.7	7.3	35.9	7.8
Netherlands	2 137.2	12.5	580.6	3.4	1 556.6	9.1
Austria	1 649.0	18.8	739.6	8.4	909.4	10.4
Poland (1)(3)	651.8	1.7	220.9	0.6	431.0	1.1
Portugal	876.3	8.5	240.2	2.3	636.1	6.2
Romania	421.8	2.1	180.1	0.9	241.7	1.2
Slovenia	245.4	11.9	66.4	3.2	179.0	8.7
Slovakia	186.2	3.4	153.7	2.8	32.6	0.6
Finland	349.0	6.3	122.2	2.2	226.8	4.1
Sweden	1 783.2	17.8	540.4	5.4	1 242.8	12.4
United Kingdom	9 293.7	14.1	3 612.9	5.5	5 680.8	8.6
Iceland	46.1	13.6	31.4	9.3	14.7	4.4
Liechtenstein	24.6	65.2	8.3	21.8	16.4	43.3
Norway	799.8	15.2	351.2	6.7	448.6	8.5
Switzerland	2 391.5	28.4	1 414.2	16.8	977.3	11.6

Note: The values for the different categories of country of birth may not sum to the totals due to rounding.

(1) Provisional.
(2) Break in series.
(3) Estimate.

Table 1. Foreign born by country of birth, 1 January 2017. Source: Eurostat 2018b.

1.3 Research questions and objectives

An overarching purpose of this thesis is to be relevant for research and policy on how to best reform and improve the functioning of labour markets to better integrate immigrants. This is done by examining what determines the differences in labour market segregation among European countries and which features that bring about segregation.

The thesis is concerned with two aspects of labour market segregation for immigrants, namely, the activity rate and the unemployment rate. Thus, two different but equally important aspects of segregation are captured. First, by analyzing determinants of relatively higher inactivity among immigrants, factors that exclude immigrants from the labour force altogether can be found. Second, by analyzing what brings about relatively higher unemployment among immigrants, i.e. factors that act excluding within the labour force – making it harder for immigrants than for natives to find a job – can be found.

For a complex research field such as this, it is not feasible to include every potential explanation for labour market segregation. Therefore, this thesis is not about explaining all observed variation among European countries in labour market segregation. Rather, it is about analyzing the ceteris paribus effects in Europe of four variables on labour market segregation. The variables

are chosen in accordance with prevalent economic theory[3] in the field, as well as in accordance with previous research[4] on the matter, and are the following: the share of immigrants with low education, the degree of wage compression, the share of social spending as percentage of GDP and, finally, the degree of union influence on labour markets.

Consequently, the two research questions of this thesis are as follows:

1. What are the ceteris paribus effects of the share of immigrants with low education, the degree of wage compression, the share of social spending in percentage of GDP and the degree of union influence on activity rate gaps between natives and immigrants among European countries?

2. What are the ceteris paribus effects of the share of immigrants with low education, the degree of wage compression, the share of social spending in percentage of GDP and the degree of union influence on unemployment rate gaps between natives and immigrants among European countries?

As noted by Bergh (2014, 2), there has been little research done on cross-country differences regarding labour market segregation, despite the pressing need for labour market reforms in many countries. Previous research on the matter, to the best of the author's knowledge, has been concerned only with one period cross-country comparisons or with country-specific micro data. By utilizing both aggregated panel data stretching from 2008-2015, and combined micro and macro data, this thesis aims at giving a more complete picture of labour market segregation in Europe.

[3] For more details, see section 2.
[4] For more details, see section 3.

2. Theory

2.1 Measuring labour market outcomes

The concept of labour market outcomes is not a uniform one, with a standardized set of important parameters to be measured. Thus, labour market outcomes can be measured in many ways and the relative performances of groups will therefore depend on which measurements that are incorporated into the analysis. As mentioned previously, this thesis is only concerned with two important separate measures, that capture two different aspects of the functioning of labour markets.

First, there is the unemployment rate, defined as the number of people without employment divided by the total labour force. The labour force, also called the active part of the population, consists of those in working age, commonly defined as those aged 15-64 years, that are either employed or actively looking for a job, the latter being the unemployed part of the labour force. A higher unemployment rate indicates that a larger number of people are searching for a job, but are unable to find one. (Bosworth, Dawkins and Stromback 1996, 394ff.)

Second, there is the activity rate, which is the number of people in the labour force divided by the total population of working age (Bosworth, Dawkins and Stromback 1996, 396f.). A higher activity rate indicates that a higher proportion of the population is active on the labour market, either by being employed or unemployed. A lower activity rate, in turn, indicates that more people are not participating in the labour market.

The differences in unemployment rates and activity rates between groups can be defined, respectively, as the unemployment rate gap and the activity rate gap. A gap between two groups different from zero indicates differences in labour market outcomes between the groups and hence labour market segregation. This thesis is concerned with the differences in labour market outcomes between natives and immigrants, and thus the unemployment rate gap and the activity rate gap between natives and immigrants. For the purpose of this thesis, the unemployment rate gap will be defined as;

(1) Unemployment rate gap = Unemployment rate of immigrants – Unemployment rate of natives,

and the activity rate gap will de defined as;

(2) Activity rate gap = Activity rate of natives – Activity rate of immigrants.

As is shown in equation (1) and (2), an unemployment rate gap and/or an activity rate gap > 0 indicates segregation between immigrants and natives, and a larger gap indicates larger segregation. Reversely, an unemployment rate gap and/or activity rate gap < 0 indicates that immigrants are doing better than natives on the labour market. To construct the two measures this way makes it easy to interpret and to compare them with each other since a larger number always indicates larger segregation. This is also in line with similar previous research, e.g. Bergh (2014, 4).

2.2 Theoretical explanations for unemployment and participation on the labour market

2.2.1 The standard neoclassical model of labour market supply

To understand why disequilibriums such as unemployment arises, it is often useful to first try to find a theoretical setting in which they do not exist. This can be done by applying the most basic neoclassical model on the labour market. The neoclassical model of the labour market treats the labour market as a perfectly competitive market where the households sell labour to the firms in order to be able to consume goods. However, there is also a cost associated with work, namely the opportunity cost of leisure. Thus, households optimize their utility by choosing the number of hours worked in such a way that the marginal utility of leisure is equal to the marginal utility of goods/consumption, given the current market wage. (Bosworth, Dawkins and Stromback 2010)

The lowest wage at which the individual is willing to supply labour is called the reservation wage and is an important concept in labour supply models. The specific reservation wage will depend on the individual's preferences, but any rate below the reservation wage will lead to the individual choosing not to participate in any exchange on the labour market, i.e. will turn the individual inactive. It is important to note that unemployment, as defined in the previous section, by assumption cannot exist in this model since everyone can find work at the going wage rate of the market, which in turn can be set as low as needed for the market to clear. (Bosworth, Dawkins and Stromback 2010)

However, since large groups of people remain unemployed, the model implies that labour markets are not allowed to clear at the equilibrium wage. Introducing a more realistic set of circumstances, as is done below, changes the picture and helps explain why unemployment arises and why activity rates differ among countries as well as between groups.

2.2.2 Introducing heterogeneity in productivity and level of education among workers

As shown by Mincer (1991, 5ff.), low-educated workers experience much greater risk of unemployment and inactivity, both as an increase in turnover and higher exposure to unemployment, compared to highly educated workers. This is due to several factors on both the demand and supply side of the labour market (Mincer 1975, 83-90). On the demand side, firms are more prone to invest in searching for highly educated workers, physical capital can more easily substitute low-skilled workers than high-skilled, and final consumer demand is in general less volatile in sectors with high-skilled workers. On the supply side, highly educated enjoy higher market earnings leading to changed preferences of allocation between leisure and labour, since productivity will be relatively higher in market activities compared to nonmarket activities. As shown by Bowen and Finegan (1966, 578), educational level is linked to labour force participation in a similar way, where the highly educated are more likely to be part of the labour force compared to low-educated individuals. Moreover, with education and higher market earnings being positively correlated, as discussed in the next section, the low-skilled workers are more prone to be impacted by wage compression and social spending.

In most Western countries, the relative level of human capital for immigrants in comparison to natives, or the quality of immigrants, as Wright and Maxim (1993, 339) put it, has declined[5] for each cohort since the 1970s (Borjas 1990, 7; Jean et al. 2010, 4f.; van Mol and de Valk 2016, 36f.). Moreover, as Chiswick (1978, 899f.) argues, the lack of country-specific human capital among immigrants, i.e. cultural and institutional knowledge, is also important in explaining why immigrants often earn lower wages than natives when first arriving.

Thus, to conclude, given the effects of being low-skilled on unemployment and inactivity, and the fact that a large share of today's immigrants are low-skilled workers, the education level of the immigrant share of the population can be an important factor in explaining both the activity rate gap and the unemployment rate gap between immigrants and natives.

2.2.3 Pricing out low-wage jobs

The level of wage compression is a factor that differs among the European countries as can be seen in figure 3. The figure shows the 2015 Gini-coefficient of equivalized disposable income

[5] For an explanation of why, see section 3.1.

for a number of European countries, where a number of 0 indicates perfect equality and a number of 100 indicates perfect inequality.

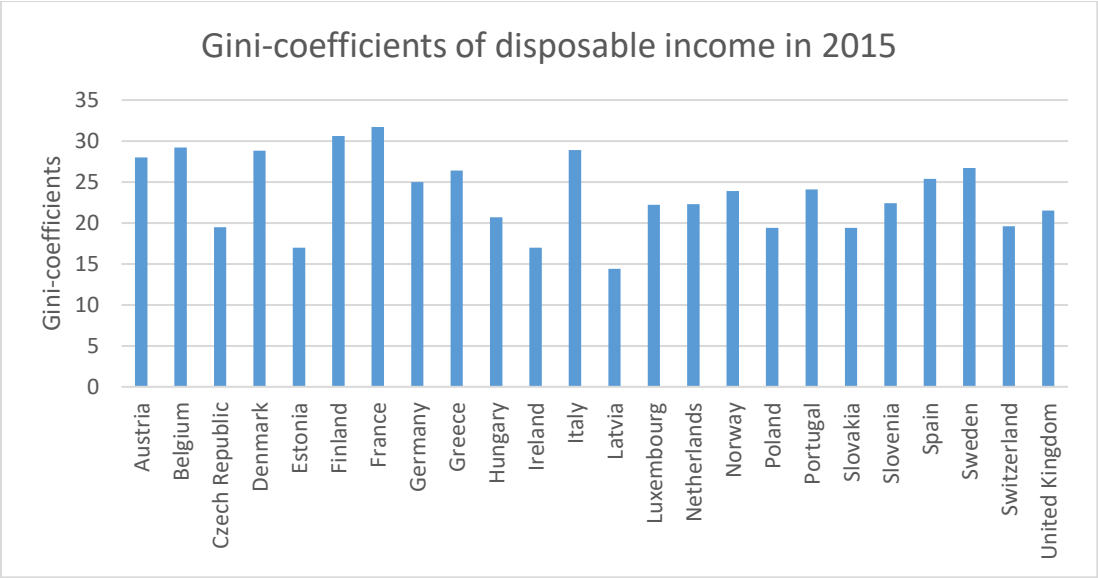

Figure 3. Gini-coefficients of disposable income in 2015. Data from Eurostat 2018c.

A high compression of wages does not necessarily lead to higher unemployment and lower activity rates at all. If it is the result of a very homogenous population, equality will simply be the product of similar productivity levels and preferences. However, as is discussed by Nonneman (2007, 5), a lot of the wage compression in European countries comes from centralized collective labour agreements and high de facto minimum wages. This in turn leads to low-paid jobs being priced out of the market since wages are not allowed to fall to market clearing levels. For low-productive marginal groups, this leads to unemployment or inactivity since they cannot compete with the more productive workers by offering to work at lower wages. Immigrants, often being low-skilled and lacking the cultural knowledge of the country, should therefore be more affected by a high wage compression than the average native worker, which in turn should influence the unemployment rate gap and activity rate gap. Indeed, as shown by e.g. Wright and Maxim (1993, 338), immigrants tend to earn less than natives. Holding all else constant, this should lead to larger segregation in countries with a high level of wage compression.

At the supply side of the labour market, there are ways of pricing out low-wage jobs as well, namely by increasing reservation wages so that they are higher than the going market wage of low-skilled workers. Simplified, reservation wages are determined by the individual's preferences regarding leisure and consumption. For marginal groups such as immigrants, if the level

of social transfers is larger than – or rather just not sufficiently small[6] in comparison to – the going wage rate, the rational utility maximizing choice is to remain unemployed or not participate in the labour market at all. Thus, by offering an alternative income other than that received from work, low-paid jobs might be priced out of the market leading to higher unemployment and inactivity in groups with lower wages. (Bosworth, Dawkins and Stromback 2010)

In Western countries, immigrants have gone from being less prone than natives to receive public assistance in the 1970s to become more prone to receive public assistance (Borjas 1995, 4; Nannestad 2004). Moreover, as implied by the discussion above, the level of public spending on welfare should matter for groups like immigrants, who theoretically should be more responsive to non-work-related income. As can be seen in figure 4, the level of social spending varies among European countries and countries with a high level of social spending should also experience a higher level of segregation, ceteris paribus.

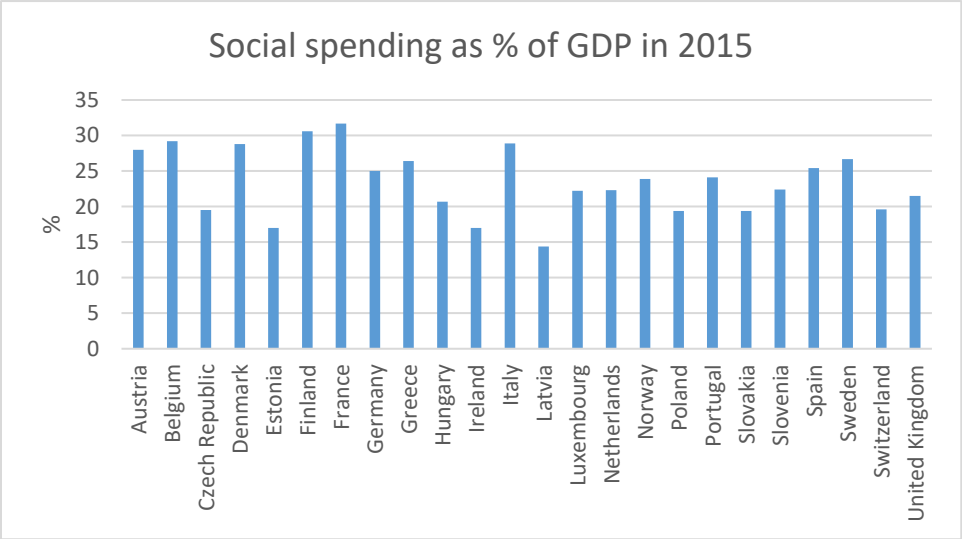

Figure 4. Social spending as percent of GDP in 2015. Data from: OECD 2018b.

2.2.4 The insider–outsider theory

As Lindbeck and Snower (2001, 165) discuss, the turnover costs of replacing one worker with another give the insiders, those who already are employed, market power. The insiders can then use this market power to limit recruitment of new personnel in order to push up wages and decrease their own risk of unemployment (Lindbeck and Snower 2001, 175f.). This context also

[6] I.e. sufficiently small given the individual's preferences regarding leisure and consumption of goods. Given that work, disputedly, is seen as a bad, it may be rational for the individual not to work and receive welfare benefits instead, although total consumption of goods may be lower.

gives a partial explanation for the occurrence of unions on labour markets, and explains why large union influence on the labour market may hurt marginal groups, especially a group such as immigrants, who are not yet rooted on the labour market when arriving in the new country. By acting collectively through a union, the insider agents can get extra leverage since firms would be unwilling to replace the whole high-wage work force at once, due to the very high turnover costs that would incur (Lindbeck and Snower 2001, 175f.). The union does not need to go as far though as to threaten with mass termination. By engaging in – or threatening to engage in – strikes, work-to-rule activities and picket lines, unions can incur costs on firms who do not follow the interests of insider workers (Lindbeck and Snower 2001, 177).

Moreover, unions often hold significant political power. Therefore, and as is often seen in reality in countries with strong labour unions, they can often successfully lobby for their special interests, such as employment security and other policies, at the political level that increase turnover costs for firms (Lindbeck and Snower 2001, 177). Among those policies are high social spending and increases in low-wage levels, which strengthen the power of insiders at the cost of firms and outsiders. Thus, the insider–outsider theory is linked to a higher wage compression and a higher degree of social spending and they may reinforce each other. For marginal groups such as immigrants, who have also been found to be less likely to be members of unions (Migration Policy Institute 2004), a high degree of union power could thus, ceteris paribus, explain why some countries experience larger segregation between natives and immigrants than others. As can be seen in figure 5, there are large differences among European countries in the influence of unions, measured as the rate of collective bargaining agreements on the labour market. Thus, the differences in segregation among European countries may partially be explained by the differences in union power.

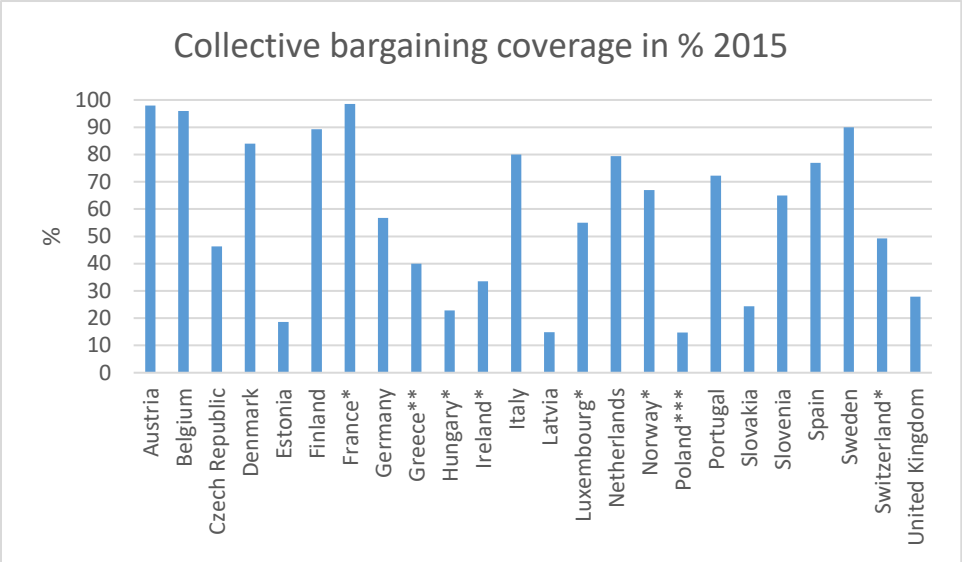

Figure 5. Collective bargaining coverage in % 2015. * Data from 2014, ** data from 2013, *** data from 2012. Data from: OECD 2018a.

3. Previous research

3.1 Patterns of migration in Europe

The patterns of migration in Europe, i.e. both intra-European migration and migration to and from Europe, has shifted a lot during the last 70 years. After the Second World War, the countries of Northwestern Europe experienced very high economic growth and domestic workers were increasingly turning to better paid and more productive white-collar jobs (van Mol and de Valk 2016, 32). During this period of rapid growth, as is discussed by Boyle et al. (1998), the labour market in low-wage sectors experienced large excess demand since the domestic labour pool was limited in numbers, and increasingly unwilling to work in the low-wage sector. As a result, the governments of Northwestern Europe implemented policies to attract temporary guest workers, mainly from southern Europe and North Africa. These regions experienced lower economic growth and lower productivity increases and the labour markets were instead characterized by excess supply. Thus, migration helped to solve the emergent imbalances on the labour markets across Europe and was beneficial to all countries (Van Mol and de Valk 2016, 33). However, the countries of Eastern Europe were not subject to the same migration policies since the political differences between Eastern and Western Europe made it infeasible (Van Mol and de Valk 2016, 34).

Following the oil crisis of 1973, the European economies experienced great restructuring resulting in less need for unskilled labour. This prompted the governments of Northwestern Europe to impose much stricter laws on immigration, which in turn led to less intra-European migration and less labour migration (Van Mol and de Valk 2016, 35). In the two following decades, following a period of economic growth in Southern Europe, non-European immigration instead increased leading to a significant share of non-European immigrants in Europe, many of whom were refugees (Van Mol and de Valk 2016, 37). However, following the collapse of the USSR and the incorporation of former communist countries into the European Union, migration from Eastern Europe to Western Europe has also increased (Van Mol and de Valk 2016, 42f.). To conclude, given the heterogenous composition of migration in Europe over time, the results of this study cannot be generalized to all immigrants or time periods in European history, but should rather be seen as concerned with the composition of the immigrant stock and migration patterns of today's Europe.

3.2 Previous studies on segregation regarding labour market outcomes

Overall, there exists a number of studies examining gaps in labour market outcomes between immigrants and natives. Nannestad (2007, 520f.) discusses the moral hazard problems with immigrants in redistributive welfare states and shows a positive relation between the level of welfare benefits and unemployment segregation in Western countries. The article further discusses the evidence for negative self-selection of low-quality immigrants to countries with a high degree of welfare benefits, but finds no conclusive evidence in either direction. Moreover, as Algan et al. (2010, 23ff.) show in their comparative study of labour market outcome gaps in France, Germany and the UK, immigrant women tend to be more segregated than immigrant men on the labour market. This is however contradicted by Fleischmann and Dronker (2010), who find no gender effect on labour market outcomes for immigrants.

Algan et al. (2010) also find that regardless of ethnicity, immigrants did worse on the labour market than their native counterparts in the UK, but that Pakistani, Black Africans and Bangladeshi men experienced much larger segregation than for example white immigrants. In France, the overall situation for immigrants is the same as in the UK[7] with the exception of immigrants from Southern Europe, who are doing better than their native counterparts. However, the segregation of immigrants from e.g. Northern Europe is much smaller than the segregation of African and Eastern Europeans. In Germany[8], immigrants other than EU16 experience worse labour market outcomes than their native counterparts. To conclude, Algan et al. (2010) find that immigrants almost always are worse off on the labour market than natives, but that the level of segregation varies a lot between different immigrant groups.

Fleischmann and Dronker (2010), who analyze the unemployment rate gap in 13 Western European countries using a multilevel approach, find that both individual characteristics as well as country-specific institutional factors matter in explaining the unemployment rate gap. At the individual level, being a child of a mixed parentage with one parent being an immigrant and the other a native born increased the likelihood of unemployment whereas being a second-generation immigrant did not increase the likelihood of being unemployed. Moreover, a high parental level of education can be seen to decrease unemployment segregation, but being highly educated does not, interestingly (Fleischmann and Dronker 2010). At the country-level, the size of

[7] Different categorizations of immigrants are used however, making a straightforward comparison more difficult.
[8] Again, the categories differ from the ones used for the two other countries in the paper.

the low-status job segment, as well as a low native unemployment level in the destination country, showed significant positive relations with more successful integration, and they also find that, contrary to most other research on the matter, welfare regimes of the destination countries did not matter for unemployment segregation (Fleischmann and Dronker 2010). Country-specific factors in the origin countries that seem to affect integration positively, according to the study, are political freedom and stability, as well as higher GDP per capita. As the authors discuss, this might reflect the differences in migration motivation between groups, where those emigrating from less stable countries are more likely to be refugees, a group that usually has less favourable labour market outcomes (Fleischmann and Dronker 2010).

Moreover, they find that coming from a Muslim majority country has a negative impact on the likelihood of being employed, something that may be explained through direct or indirect discrimination of Muslims in Europe, but might as well be explained by the fact that many Muslim immigrants come from politically unstable countries, and thus, that coming from a Muslim country act as a proxy for the already discussed factor of political stability (Fleischmann and Dronker 2010). Overall, immigrants from other Western European countries tend to have similar labour market outcomes as natives while non-Western European immigrants tend to do worse. Furthermore, Bergh (2014) who, similarly to this thesis, analyzes the unemployment rate gap and the employment rate gap, but in the OECD countries using one period cross-country data, mainly finds that unemployment gaps are bigger in countries with strong unions, and that the employment gap is bigger in countries with more generous safety nets, just as predicted by theory.

When it comes to the effect immigration has on labour market outcomes for natives in the host country, Friedberg and Hunt (1995), as well as Slaughter and Swagel (1997) find that the effects are negligible in Western countries in general. Even those in the native population that should be most affected by immigration, such as low-skilled workers, are not significantly affected by immigration (Friedberg and Hunt 1995, 42). This might be explained by the low employment rates among immigrants in general as discussed above, and a side effect of a more integrating labour market might be to impact labour market outcomes for natives to a higher degree, especially those who are the closest substitutes to immigrant workers. However, since immigrants tend to be net beneficiaries of social transfers, as mentioned in section 2.2.3, the indirect costs of migration through higher government expenditures may still impact native workers disposable income negatively, despite immigration having no significant direct effect on wages or employment.

3.3 Contributions of this study

This thesis will try to bridge the gap in knowledge regarding labour market segregation by using both aggregated panel data and by combining micro-and macro data for a large number of countries, in contrast to the literature presented above. To the author's best knowledge, previous studies on labour market segregation are either concerned with one period cross-country data at the aggregated level, with many countries included, or with larger data sets of micro or multilevel data but with significantly less countries and time periods involved. Thus, by combining both panel data and combined micro and macro data, a new approach of analyzing labour market segregation is used. By performing two different forms of regressions, using partly different kinds of data, this thesis has the advantage of being able to compare the results of the two methodological approaches. Moreover, by analyzing two different but interacting measures of labour market segregation, it is possible to see how the explanatory variables affect these two forms of segregation differently. Furthermore, as one period cross-country analyses – with a large array of possible explanations – are very sensitive to omitted variable bias, using panel data might be a better choice of empirical strategy in analyzing data at the aggregated level (Dougherty 2016, 529).

4. Methodology

4.1 Data

This thesis investigates segregation in labour market outcomes in Europe, using as many European countries as possible in the analysis to get more generalizable results. However, since far from all European countries have sufficient data for statistical analyses of this kind, countries with no data on the variables analyzed, or countries that yield very unbalanced panels, are excluded. Thus, in total, 25 countries[9] are included in the analysis.

4.1.1 Aggregated data

For the aggregated data analysis, all variables are measured using aggregated country data from 2008 through 2015. The two dependent variables in equation (1) and (2) are constructed using data from the data bases of Eurostat, the statistical office of the European Union. The unemployment rate data is gathered from their lfsa_urgacob data base (Eurostat 2018e) and the data on activity rates is gathered from their lfsa_argacob data base (Eurostat 2018a), with all numbers being calculated for the population aged 15-64 years, following common practice in measuring labour market outcomes.

The aggregated data on Gini-coefficients, as a measurement of wage compression, is also from Eurostat, using the ilc_d12 data base with Gini-coefficients going from 0, meaning perfect equality, to 100, meaning perfect inequality (Eurostat 2018c). Moreover, the level of low-educated immigrants comes from the Eurostat data base edat_lfs_9912 and is defined as the share of the immigrant population aged 15-64 years with less than upper secondary education[10] (Eurostat 2018d). The rate of collective bargaining, used as a measurement of union influence on the labour market, comes from the labour data base of the Organization for Economic Co-operation and Development (OECD) and shows the share of employees covered by collective agreements (OECD 2018a). Furthermore, social spending as share of GDP comes from the OECD society data base and measures the share of social expenditures – comprised of cash benefits, direct in-kind provision of goods and services and tax breaks with social purposes – in relation to GDP (OECD 2018b).

[9] The countries included are Austria, Belgium, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland and the UK.
[10] I.e. below ISCED 3.

4.1.2 Disaggregated data

The data at the micro-level comes exclusively from the European Social Survey (ESS), which is an academically driven survey at the cross-country European level, started in 2001 (ESS 2018). ESS conducts interviews every two years in more than 30 countries where they ask about attitudes, beliefs and how people behave, and the results can be acquired by applying for access to their data base. The data used in this thesis comes from round 4, 5, 6 and 7, meaning data from 2008, 2010, 2012 and 2014, respectively.

All respondents outside of the 15-64 years of age range are dropped so that the analysis follows common practice for measuring labour market outcomes. For the dependant binary variables inactive and unemployed, respondents who did not actively look for a job, nor were employed, are coded as 1 for inactive, whereas respondents either actively looking for job or working are coded as 0. In the regressions using unemployed as the dependent variable, all those coded as 1 for inactive are dropped so that the sample only contains people in the labour force, and those actively looking for a job are coded as 1 for unemployed whereas those employed are coded as 0.

The control variable for being highly educated is created by coding respondents with less than upper secondary education as 0 and respondents with at least upper secondary education as 1. The control variable female is constructed by coding all males as 0 and all females as 1. Finally, the control variable for being a member of a union is created by coding those who were members of a union as 1 and those who were not members with 0.

4.2 Econometric application and estimation issues

Since this thesis uses two different kinds of data sets, it is necessary to use two different kinds of econometric applications. The econometric applications and estimation issues regarding the two kinds of data will therefore be explained below in two different sub-sections.

4.2.1 Panel data analyses

First, for the panel data analyses, using both cross-sectional as well as time series dimensions, the dependent variables for measuring the unemployment rate gap and the activity rate gap are defined as in equation (1) and (2) respectively, found in section 2.1 above. The data is analyzed both by performing bivariate regressions with each explanatory and dependent variable, as well as regressing each of the dependent variables on all four explanatory variables in multivariate

regressions. Using the notation with i as referring to the unit of observation, and t as referring to the period of time, the data will be analyzed by running regressions according to the following econometric function:

$$(3)\ y_{i,t} = \alpha + \boldsymbol{\beta}\mathbf{X}_{i,t} + \varepsilon_{i,t}\ ,$$

where y is the dependent variables unemployment rate gap and activity rate gap, α is the intercept, $\boldsymbol{\beta}$ is the vector of coefficients measuring the marginal effects, $\mathbf{X}$ is the matrix containing the observed explanatory variables and ε is the error term.

Using a random effects model as compared to a fixed effects model on panel data has the benefits of enjoying more degrees of freedom, and of capturing characteristics that remain constant over time for each individual (Dougherty 2016, 539f.; Wooldridge 2013, 492f.). However, if the model does not perfectly explain the dependent variable, as would be unrealistic regarding the analyses in this thesis, the error term ε will partly consist of the unobserved explanatory variables affecting y. For a random effects model to be appropriate, these unobserved effects must be distributed independently of the explanatory variables (Wooldridge 2013, 496). With institutions often influencing each other in a mutually dependent fashion, this is unlikely to hold. Thus, to allow for unobserved heterogeneity bias, a fixed effect model is used. Nevertheless, to empirically test this hypothesis, a Hausman test is carried out before each multivariate regression to test if the random effects differ systematically from the fixed effects estimates, something that would confirm the hypothesis of unobserved heterogeneity bias (Dougherty 2016, 540). Moreover, for a random effects model to be appropriate, the observations should also be described as randomly drawn from some given population (Dougherty 2016, 539f.; Wooldridge 496f.) This can hardly be the case for this sample consisting of certain European countries, which again makes the fixed effects model used in this thesis the more appropriate choice.

Moreover, the proposed test for autocorrelation in panel data by Wooldridge (2002, 282f.) is carried out before all regressions to assess whether or not to use robust standard errors to correct for autocorrelation. If autocorrelation is detected, Huber-White robust standard errors are used, which allows for both autocorrelation and for possible heteroscedasticity. Thus, no test is carried out for heteroscedasticity if autocorrelation is found. If not, the modified Wald test for heteroscedasticity is used as proposed by Laskar and King (1997) and if heteroscedasticity is

found, Huber-White robust standard errors are used that, as mentioned, allows for heterogeneity. Otherwise, normal standard errors are used since they will be more efficient, as discussed by Hinkley and Wang (1991).

4.2.2 Combined micro and macro data

The second kind of data analysis consists of both individual specific data and aggregated data. To analyze what brings about segregation in labour market outcomes, being unemployed as compared to employed and being out of the labour force as compared to being in the labour force, are used as dependent variables. Being unemployed is thus coded as 1 whereas being employed is coded as 0 in the regressions, using unemployed as the dependent variable. Only individuals that are reportedly in the labour force, i.e. are either employed or actively looking for a job, are included. In the case of analyzing labour force participation, being inactive on the labour market is coded as 1 and being active is coded as 0.

The general explanatory variables are the same as in the panel data analyses except for the micro-level dummy variable "immigrant" coded as 1 if respondent is foreign born and 0 if the respondent was born in the country. However, utilizing the benefits of more detailed micro data, three different control dummy variables, explained further below, are used in separate regressions. Since the thesis is concerned with binary dependent variables, a binary choice model called the linear probability model is used. The model assumes that the probability of y=1, called p, is a linear function of a set of explanatory variables (Dougherty 2016, 367f.). Using the notation with i as referring to the unit of observation, the following econometric function can thus be specified:

$$(4)\ p_i = p(y_i = 1) = \alpha + \boldsymbol{\beta}\mathbf{X_i} + \gamma\delta_i + \boldsymbol{\theta}_i\mathbf{X}\delta_i + \varepsilon_i\ ,$$

where α is the intercept, $\boldsymbol{\beta}$ is a vector of coefficients, $\mathbf{X}$ is the matrix containing the explanatory variables at the aggregated level and ε is the error term. δ is the interactive dummy variable "immigrant" and γ is a coefficient measuring the marginal effect of δ on y. However, the measurement of the coefficients of the interactive term $\mathbf{X}_i\delta_i$, labeled $\boldsymbol{\theta}$, is what this thesis really is interested in, since it measures the additional marginal effect of each of the explanatory variables for an immigrant as compared to a native. It is these coefficients of additional marginal effects for immigrants that are displayed in table 3 and 5 below in section 5.1 and 5.2, respectively.

Moreover, certain individual specific characters, pointed out to be important by theory and/or previous literature, are added in further regressions following the same econometric function specified in equation (4), but with the added control variable. Three categorical dummy variables are used for this purpose. The first control variable is level of education, coded as 1 if the respondent has completed upper secondary education (ISCED 3 or more), and 0 if not. Second, gender is controlled for with being female coded as 1 and being male coded as 0. Third, being member of a union is controlled for with being a current member of a union coded as 1 and not being a member coded as 0.

As discussed by Dougherty (2016, 368ff.), the linear probability model can be problematic for two reasons. The disturbance term will not be normally distributed and will not be continuous, yielding a heteroscedastic distribution. To allow for heteroscedasticity, only Huber- White robust standard errors are used for all the regressions with combined micro and macro data. Moreover, the predicted probabilities are not constrained between 0 and 1 but can take on values beyond the appropriate interval. To correct for this, models such as logit or probit can be used instead (Dougherty 2016, 372-380). However, as discussed by Greene (2011), the linear probability model estimates the conditional expectations of outcome and has a very straightforward interpretation, as compared to the logit or probit model where the results are very hard to interpret. The linear probability model is still therefore widely used among economists since the benefits of interpretability of the estimates of the model as compared to logit or probit models often outweigh the negative effects. This is shown by e.g. Ejrnæs, Holm and Karlsson (2014), who measure the share of published articles using the linear probability model in the Quarterly Journal of Economics from 2007 through 2011. They find that the linear probability model is used in nine percent of all empirical articles (including articles using non-categorical dependent variables), and that it is thus a popular econometric tool for economists.

5. Results

5.1 The activity rate gap

Table 2 shows the results from the panel data regressions, A1-A5 in appendix A, with activity rate gap as the dependent variable. As table C1-C5 in appendix C shows, autocorrelation could not be rejected at the 5 % significance level for any of the bivariate regressions, nor for the multivariate regression with all four explanatory variables, when preforming the Wooldridge test for autocorrelation. Therefore, Huber-White robust standard errors were used, which also allowed for potential heteroscedasticity. Moreover, as discussed in section 2, it is reasonable to assume that there exists endogeneity in the regressors. The Hausman tests confirmed this for the multivariate analysis. Thus, in accordance with both theory and the regression diagnosis carried out, fixed effects regressions were chosen to correct for misspecification of the model. The results from the Hausman test is found in table C6 in appendix C.

As can be seen from table 2, an R-squared of 0.1059 means some variation can be explained by the model. However, with no explanatory variable significant even at the 10 % significance level in the bivariate regressions, nor at the multivariate regression, the model proves to be poor in explaining labour market segregation regarding labour force participation according to the data.

Variables	(1)	(2)	(3)	(4)	All variables
1. Low-educated immigrants	0,1222407				-0.0199531
	(0,1118367)				(0.0454096)
2. Union influence		-0.0162617			0.0006542
		(0.0408014)			(0.0454096)
3. Social spending			0,1423431		0.0225871
			(0,160858)		(0.1953999)
4. Gini-coefficient				0,4021417	-0.285863
				(0,245392)	(0.2215663)
Constant	-3.899249	0.0113526	-3.608344	-12.22646	-9.105978
	(3.255659)	(2.464838)	(3.749852)	(7.180048)	(11.19001)
Observations	194	142	192	200	136
R-squared	0.0014	0.0565	0.0192	0.1318	0.1059

Table 2. Regressing the activity rate gap on panel data from 2008-2015 using aggregated data. Robust standard errors in parentheses. ***P<0.01, **P<0.05, *P<0.1.

However, when looking at table 3, which shows the results from the more elaborate regressions B1-B20 in Appendix B, the model proves to do much better. To be precise, the table displays the additional marginal effect of being an immigrant for the likelihood of being inactive. At the bivariate level of analysis, both the degree of social spending and the Gini-coefficient are significant at the 1 % significance level. An increase in social spending with one percentage point can be shown to additionally increase the probability of being inactive for an immigrant in comparison to a native born by 0.27 percent. Likewise, an increase in the Gini-coefficient by one unit can be shown to additionally decrease[11] the probability of being inactive for an immigrant in comparison to a native born by 0.35 percent. In the multivariate analysis, the effect of the Gini-coefficient for segregation is no longer significant even at the 10 % significance level. The marginal effect of social spending however has grown to 0.49 percent and is still significant, although at the 5 % significance level. Rather surprisingly, the marginal effect of the share of low-educated immigrants can be shown to be negative at the 1 % significance level. Clearly, this contradicts the theoretical arguments made in section 2.2.2.

[11] Note that, since a larger Gini-coefficient means less wage compression, the negative sign of the coefficient is exactly what is predicted by theory.

Moreover, as predicted by theory, the results are weakened substantially when controlling for if the immigrant is highly educated. No variable is any longer significant, except for the share of immigrants that are low-educated, which is significant at the 5 % significance level. However, the sign of the coefficient is in the non-predicted direction. In this case though, the negative sign of the coefficient is less unreasonable since a highly educated immigrant should not be affected negatively by the share of low-educated immigrants. When instead controlling for if the respondent is female, wage compression and especially the degree of social spending can be seen to have an even larger effect than before. The degree of social spending is significant at the 1 % significance level in the bivariate analysis as well as in the multivariate analysis, whereas wage compression is significant at the 1 % significance level in the bivariate analysis but only at the 10 % significance level in the multivariate analysis. Finally, when controlling for if the respondent is a union member, there is no longer any significant effect at all.

Variables	(1)	(2)	(3)	(4)	All variables	One variable only	All variables	One variable only	All variables	One variable only	All variables
1. Low-educated immigrants	-0.0004243 (0.0003775)				-0.0023269*** (0.0009569)	0.0000497 (0.0004044)	-0.0022155** (0.0009886)	-0.0002278 (0.0005301)	-0.002169 (0.0013692)	0.0008175 (0.0008399)	0.0006078 (0.0020019)
2 Union influence		0.0000518 (0.000235)			0.0001741 (0.0005485)	0.0002599 (0.00025)	0.0006718 (0.0005774)	-0.0000813 (0.0003349	-0.0006601 (0.0007812)	0.0003539 (0.0004571)	0.0004678 (0.0010956)
3.Social spending			0.0026987*** (0.0010436)		0.0049067** (0.00221136)	0.001818* (0.0010983)	0.0022828 (0.0022857)	0.0047669*** (0.0014836)	0.0105187*** (0.003044)	-0.0011099 (0.0018641)	-0.001485 (0.0039127)
4. Gini-coefficient				-0.003454*** (0.001258)	-0.0026851 (0.0023073)	0.0006119 (0.0013299)	0.0022665 (0.0024286)	-0.0048967*** (0.0018)	-0.0060393* (0.0033219)	0.0033795 (0.00209)	0.0031074 (0.0042576)
Constant	0.3075071*** (0.0036821)	0.3137209*** (0.0044405)	0.3214538*** (0.0079341)	0.2229294*** (0.0109464)	0.3612177*** (0.0213788)		0.3846317*** (0.0219108)		0.4708771*** (0.0309717)		0.1276748*** (0.0382309
Observations	116 774	81 816	118 237	122 599	79 105		68 304		41 430		13 326
R-squared	0.0003	0.0004	0.0002	0.0005	0.0008		0.0026		0.0016		0.0102
Controls	No	No	No	No	No	Highly Educated	Highly Educated	Female	Female	Union member	Union member

Table 3. Combined micro and microdata. Dependent variable: Inactive. The table displays the additional marginal effect of each variable for immigrants compared to natives. Robust standard errors in parentheses. ***P<0.01, **P<0.05, *P<0.1.

5.2 The unemployment rate gap

Table 4 shows the results from the panel data regressions at the aggregated level with unemployment rate gap as the dependent variable. The separate regressions can be seen in appendix A in table A6-A10. Here, just as with the panel data regressions regarding the activity rate gap, autocorrelation could not be rejected at the 5 % significance level when performing Wooldridge tests for autocorrelation, as can be seen in tables C7-C11 in appendix C. Therefore, Huber-White standard errors, are used in all of the regressions summarized in table 4. Moreover, just as in the case of the activity rate gap, endogeneity among the regressors is likely to be an issue and a fixed effects model should be used for the regressions. This is also confirmed by the Hausman test carried out. The results of this test can be found in table C12 in Appendix C.

Variables	(1)	(2)	(3)	(4)	All variables
1. Low-educated immigrants	-0,1032431				0.0132057
	(0,0695686)				(0.0666948)
2. Union influence		-0,1320606**			-0.1080246**
		(0,0554929)			(0.044357)
3. Social spending			0,5732481***		0.4906572***
			(0,179173)		(0.1459941)
4. Gini-coefficient				0,103811	0.0975924
				(0,16031)	(0.1398057)
Constant	7.50226***	12.24988***	-9.014501**	1.280428	-3.740957
	(2.074827)	(3.417639)	(4.212338)	(4.692885)	(6.732159)
Observations	186	138	184	191	133
R-squared	0.3349	0.3842	0.3891	0.0154	0.0505

Table 4. Regressing the unemployment rate gap on panel data from 2008-2015 using aggregated data. Robust standard errors in parentheses. ***P<0.01, **P<0.05, *P<0.1.

As can be seen in table 5, with the results from table B21-B40 in Appendix B, in contrast to the regressions at the aggregated level for the activity rate gap, there are significant results at the 1 % significance level and at the 5 % significance level. The degree of social spending can be seen to increase segregation in unemployment by 0.57 units in the bivariate analysis, and by 0.49 units in the multivariate analysis, for every increase in social spending by one percentage point. The rate of collective bargaining, serving as a proxy for union power, is also significant,

but at the 5 % significance level. However, the negative sign of the coefficient is rather surprising, since it is the opposite of what the insider–outsider theory predicts and opposite to previous research mentioned in section 3.

As can be seen in table 5, the results for the more elaborate regressions with combined micro and macro data, are a bit different. For all the regressions summarized in table 5, White-Huber robust standard errors were used to allow for potential heteroscedasticity. In the bivariate analysis, the share of low-educated immigrants was shown to be statistically significant at the 1 % significance level, but the effect is rather small. For every increase by one percentage point in the share of immigrants that is low-educated, the additional probability for an immigrant to be unemployed as compared to a native born is 0.09 percent. In the multivariate analysis, the marginal effect is no longer significant even at the 10 % significance level, and the sign of the coefficient is now negative.

Moreover, the degree of social spending is significant at the 1 % significance level in the bivariate analysis, where an increase in social spending by one percentage point increases the probability of an immigrant being unemployed, as compared to a native born, by 0.34 percent. In the multivariate analysis however, the degree of social spending is shown to have no significant effect. Rather surprisingly, and in contrast to previous research and theory, a lower degree of wage compression is shown to increase the probability of an immigrant being unemployed as compared to a native born by 0.58 percent for each unit increase. The perhaps most interesting result in table 5 is the impact of union power on segregation in regard to unemployment. In contrast to the results from the analysis of purely aggregated data, using a larger and more detailed data set shows that an increase in the rate of collective bargaining by one percentage point increases the probability of an immigrant being unemployed, as compared to a native born, by 0.1 percent in the bivariate analysis, and by 0.16 percent in the multivariate analysis. Both results are statistically significant at the 1 % significance level.

When controlling for if the respondent is highly educated, all variables are still significant either at the bivariate or the multivariate level of analysis, just as in the case of no controls, and the marginal effects are very similar to the regressions with no controls. When instead controlling for if the respondent is female, no variable is significant apart from the degree of wage compression, which is significant at the 10 % significance level in the multivariate analysis with a marginal effect of 0.51 percent. This is in contrast to the results presented in table 3 with inactivity as the dependent variable and shows that the segregation effects of a high degree of social

spending may be larger for immigrant women than for men when deciding to participate or not on the labour market, but that immigrant women already participating are not that much affected at all. Finally, just as in table 3, when controlling for if the respondent is a union member, the marginal effects are smaller in general, and insignificant even at the 10 % significance level for all variables in the multivariate analysis.

Variables	(1)	(2)	(3)	(4)	All variables	One variable only	All variables	One variable only	All variables	One variable only	All variables
1. Low-educated immigrants	0.0009496***				-0.001215	0.0011266***	-0.0010295	0.0000852	-0.0014628	0.0012932*	0.0024859
	(0.0003443)				(0.0008631)	(0.000364)	(0.0008829)	(0.0004754)	(0.0012046)	(0.0007606)	(0.0020695)
2 Union influence		0.0009509***			0.0015605***	0.0009656***	0.001737***	0.000542*	0.0010327	0.0004301	-0.0003279
		(0.0002042)			(0.00048)	(0.0002169)	(0.0004971)	(0.0002899)	(0.0006697)	(0.0003475)	(0.0009333)
3.Social spending			0.0033833***		0.0016461	0.0028257***	-0.0002101	0.0022073*	0.0028156	0.0025929*	0.0010137
			(0.0009057)		(0.0017551)	(0.000929)	(0.0018563)	(0.0012473)	(0.0025195)	(0.0015324)	(0.0033621)
4. Gini-coefficient				0.0010266	0.0058129***	0.0019806*	0.0073674***	0.0008448	0.0050574*	0.0005935	-0.0000653
				(0.0011114)	(0.0020406)	(0.0011506)	(0.0021305	(0.0015446)	(0.0028063)	(0.0016956)	(0.0035244)
Constant	0.0720806***	0.0850988***	0.0786924***	-0.0841706***	-0.1053575***		-0.0595431***		-0.0750828***		-0.0828465***
	(0.0027843)	(0.0032077)	(0.005702)	(0.0080443)	(0.0154198)		(0.0155155)		(0.0223207)		(0.0198779)
Observations	82 562	57 663	83 577	86 534	55 871		50 227		27 082		11 670
R-squared	0.0033	0.003	0.0029	0.0010	0.0113		0.0087		0.0125		0.0089
Controls	No	No	No	No	No	Highly Educated	Highly Educated	Female	Female	Union member	Union member

Table 5. Combined micro and microdata. Dependent variable: Unemployed. The table displays the additional marginal effect of each variable for immigrants compared to natives. Robust standard errors in parentheses. ***P<0.01, **P<0.05, *P<0.1

6. Discussion

The statistical analyses carried out in this thesis confirm that gaps in labour market outcomes between immigrants and natives can be explained at least partly by institutional factors as suggested by previous economic literature and theory. However, educational attainment seems not to matter for labour market segregation. If anything, a larger pool of less educated immigrants can be seen to improve integration. This is in line with the previous results of e.g. Bergh (2014) and Fleischmann and Dronker (2010), but clearly in contrast to the theoretical framework of this thesis. One possible explanation for this dubious result might be that the chosen variable is a measurement of the proportion of low-educated immigrants only, i.e. the measurement is not relative to the education level of natives. Since the theory predicts a higher probability of being inactive for those with a relatively low education level, it depends on both the immigrant and the native level of education in each country. This is not captured in the measurement of education level used, nor in the studies previously mentioned.

Regarding the inactivity rate gap, no variable was significant at the aggregated level of analysis. This was rather unexpected since previous research, e.g. Berg (2014), found that countries with more generous safety net levels experienced higher segregation in labour force participation. However, since labour market policy seldom changes drastically from one year to another, the cross-country variations are much larger than the country-specific changes over time. The relatively small span of years, stretching from 2008-2015, is therefore a weakness when doing a fixed effects regression. When available, a larger data set spanning over more time periods would be of interest to future researchers on the matter, since it would probably significantly increase the robustness of the results. Still, in order not to inflate the results by misspecification of the model, something this kind of research arguably should be sensitive to, only the fixed effects results are reported in table 2.

Indeed, the results from the regressions using combined micro and macrolevel data, with a lot more observations, show that there are significant effects of having a more redistributive welfare system on labour market segregation regarding labour force participation, just as shown by Bergh (2014) and Nannestad (2007). Thus, there is support for supply effects of social transfers for immigrants' likelihood of being in the labour force. By altering the reservation wages through non-market income, the incentives are weakened for participating on the labour market leading to lower activity rates for immigrants than for natives. That these effects are connected to lower productivity levels among immigrants than compared to the general native can be seen

in the overall smaller coefficients and the loss of significance for social spending even at the 10 % significance level when controlling for if the respondent is highly educated. To be honest, it could also be a sign of self-selection bias where those respondents more interested in having a career are more likely to go through higher education. Either way though, this has important implications for migration policy and cost-benefit analyses of migration.

When instead controlling for if the respondent is female or not, one can see that the effects of a high degree of social spending, but also of a high compression of wages, are more segregating for immigrant women than for men. This confirms what has been found in previous studies, namely that the segregation effect of increasing reservation wages is not evenly distributed among immigrant women and men but that immigrant women are more negatively affected than immigrant men. This is well in line with previous research mentioned above and could probably be explained by a higher degree of breadwinning culture in many non-European countries as compared to in European countries, as discussed by e.g. Bergh (2014, 9).

The rate of collective bargaining could not be shown to significantly affect the activity rate gap in any of the regressions carried out. However, when controlling for if the respondent is a union member, no variable is any longer significant. This gives strong indirect support for the insider–outsider theory since only immigrants that are non-union members show signs of labour force participation segregation.

When turning to the unemployment rate gap instead, there are significant results on the aggregated level of analysis. However, as was previously mentioned regarding the panel data regressions with the activity rate gap as the dependent variable, the rather small time series, stretching over a span of only eight years, means that there is little variation within countries. Again, data covering larger periods of time would be interesting and would probably give more robust result, especially when doing fixed effects regressions, since variations in the explanatory variables within each country would probably be greater.

Here as well, social spending can be seen to increase the labour market outcome segregation, both at the bivariate and multivariate level of analysis, further confirming the importance of non-market income for reservation wages, and the effect it has for labour market outcomes for marginal groups such as immigrants. Strong union influence, on the other hand, seems to decrease the unemployment rate gap, contradictory to the findings of Bergh (2014) and the insider–outsider theory.

However, in the more elaborate regressions using both micro and macro data, the effect of unions for immigrants, in regard to unemployment segregation, instead shows a significantly positive relationship between a high degree of union influence and unemployment segregation. This gives strong support for the insider–outsider theory and confirms that strong unions are partly to blame for the observed labour market outcome segregation in Europe. This is further confirmed, just as in the case of the activity rate gap, by controlling for if the respondent is a member of a union, with all significance then gone for every variable in the regression with all four explanatory variables. In the regressions with one explanatory variable, the p-values and the coefficients are smaller for the variables low-educated immigrants and social spending. But most important of all, the strong effect of union influence on unemployment segregation is now gone and the coefficient is negative, although insignificant, further supporting the insider–outsider theory.

Both social spending and the share of low-educated immigrants can be seen to increase unemployment segregation in the bivariate analysis, but both variables are insignificant and the coefficients small or negative in the multivariate analysis. The degree of wage compression seems to affect unemployment segregation negatively, which is very surprising and in conflict to both previous studies and the theoretical framework of this thesis. When controlling for if the respondent is highly educated, the results are very similar to the regressions with no control variable. The result is rather surprising – maybe with the exception for union influence since the insider–outsider theory is less dependent on education level – and in contrast to what could have been expected from theory and previous research such as Mincer (1991), who shows that unemployment and a low education are correlated.

Another interesting result, and to be contrasted with the results for activity rate segregation, is the less segregating effects of the explanatory variables on unemployment for immigrant women than for immigrants in general. This is however well in line with previous research such as Flesischmann and Dronker (2010) and Van der Lippe and Van Dijk (2002), showing that whether or not to participate on the labour market is highly influenced by gender, whereas the likelihood of unemployment typically is not affected by gender.

In conclusion, all independent variables carry some explanatory power in explaining segregation of labour market outcomes in Europe, except for the share of low-educated immigrants. For further research, it would certainly be interesting to study the effects of the share of relatively uneducated immigrants in relation to the average educational attainment among natives.

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Appendix A – Regression outputs from regressions with aggregated data only

This appendix shows the regression outputs from Stata from the regressions run using aggregated panel data. Tables A1-A5 show the output from the regressions with the variable activity rate gap as dependent variable. A summary of these regression results can be found in table 2 in the thesis above. The results of the corresponding regression diagnostic, run prior to these regressions, can be found in Appendix C below, in tables C1-C6. Tables A6-A10 shows the output from the regressions with the unemployment rate gap as the dependent variable. A summary of these regressions results can be found in table 4 in the thesis above. The results from the corresponding regression diagnostic, run prior to these regressions, can be found in tables C7-C12 in Appendix C below.

```
Fixed-effects (within) regression               Number of obs      =       142
Group variable: ID                              Number of groups   =        25

R-sq:  within  = 0.0036                         Obs per group: min =         2
       between = 0.1063                                        avg =       5.7
       overall = 0.0565                                        max =         8

                                                F(1,24)            =      0.16
corr(u_i, Xb)  = -0.3138                        Prob > F           =    0.6945

                                 (Std. Err. adjusted for 25 clusters in ID)
```

Actrategap	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
Union	-.0162167	.0408014	-0.40	0.695	-.1004268	.0679933
_cons	.0113526	2.464838	0.00	0.996	-5.075824	5.098529
sigma_u	5.9897688					
sigma_e	1.4612385					
rho	.9438286	(fraction of variance due to u_i)				

Table A1. Output from egressing the activity rate gap on rate of collective bargaining.

Author's note: As can be seen, the rate of collective bargaining has no significant effect on the activity rate gap. The corresponding regression diagnostic output can be found in table C1 in Appendix C.

```
Fixed-effects (within) regression               Number of obs      =       194
Group variable: ID                              Number of groups   =        25

R-sq:  within  = 0.0225                         Obs per group: min =         3
       between = 0.0004                                        avg =       7.8
       overall = 0.0014                                        max =         8

                                                F(1,24)            =      1.19
corr(u_i, Xb)  = -0.2928                        Prob > F           =    0.2852

                                 (Std. Err. adjusted for 25 clusters in ID)
------------------------------------------------------------------------------
             |               Robust
  Actrategap |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       Eduim |   .1222407   .1118367     1.09   0.285    -.1085789    .3530604
       _cons |  -3.899249   3.255659    -1.20   0.243     -10.6186    2.820101
-------------+----------------------------------------------------------------
     sigma_u |  6.1469868
     sigma_e |  2.1116419
         rho |  .89444699   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Table A2. Output from regressing the activity rate gap on the share of immigrants with low education.

Author's note: As can be seen, the variable has no significant effect on the activity rate gap. The corresponding regression diagnostic output can be found in table C2 in Appendix C.

```
Fixed-effects (within) regression               Number of obs      =       192
Group variable: ID                              Number of groups   =        24

R-sq:  within  = 0.0072                         Obs per group: min =         8
       between = 0.0207                                        avg =       8.0
       overall = 0.0192                                        max =         8

                                                F(1,23)            =      0.78
corr(u_i, Xb)  = 0.0444                         Prob > F           =    0.3854

                                 (Std. Err. adjusted for 24 clusters in ID)
------------------------------------------------------------------------------
             |               Robust
  Actrategap |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      Socexp |   .1423431    .160858     0.88   0.385    -.1904171    .4751033
       _cons |  -3.608344   3.749852    -0.96   0.346     -11.3655    4.148815
-------------+----------------------------------------------------------------
     sigma_u |  5.9188597
     sigma_e |  2.1167269
         rho |  .88660735   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Table A3. Output from regressing the activity rate gap on the share of social spending in percentage of GDP.

Author's note: As can be seen, the variable has no significant effect on the activity rate gap. The corresponding regression diagnostic output can be found in table C3 in Appendix C.

```
Fixed-effects (within) regression               Number of obs      =       200
Group variable: ID                              Number of groups   =        25

R-sq:  within  = 0.0319                         Obs per group: min =         8
       between = 0.1670                                        avg =       8.0
       overall = 0.1318                                        max =         8

                                                F(1,24)            =      2.69
corr(u_i, Xb)  = -0.5718                        Prob > F           =    0.1143

                                 (Std. Err. adjusted for 25 clusters in ID)
```

Actrategap	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
GINI	.4021417	.245392	1.64	0.114	-.1043225	.9086059
_cons	-12.22646	7.180048	-1.70	0.102	-27.04535	2.592425
sigma_u	6.6681261					
sigma_e	2.0764611					
rho	.91160147	(fraction of variance due to u_i)				

Table A4. Output from regressing the activity rate gap on the Gini-coefficient.

Author's note: As can be seen, the variable has no significant effect on the activity rate gap. The corresponding regression diagnostic output can be found in table C4 in Appendix C.

```
Fixed-effects (within) regression               Number of obs      =       136
Group variable: ID                              Number of groups   =        24

R-sq:  within  = 0.0295                         Obs per group: min =         2
       between = 0.1159                                        avg =       5.7
       overall = 0.1059                                        max =         8

                                                F(4,23)            =      0.59
corr(u_i, Xb)  = -0.4775                        Prob > F           =    0.6730

                                 (Std. Err. adjusted for 24 clusters in ID)
```

Actrategap	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
Union	.0006542	.0454096	0.01	0.989	-.0932827	.094591
Eduim	-.0199531	.0513309	-0.39	0.701	-.1261392	.086233
Socexp	.0225871	.1953999	0.12	0.909	-.3816285	.4268026
GINI	.285863	.2215663	1.29	0.210	-.1724817	.7442078
_cons	-9.105978	11.19001	-0.81	0.424	-32.25428	14.04232
sigma_u	6.2927146					
sigma_e	1.4374499					
rho	.95040715	(fraction of variance due to u_i)				

Table A5. Output from regressing the activity rate gap on the rate of collective bargaining, the share of immigrants with low education, the share of social spending in percentage of GDP and the Gini-coefficient.

Author's note: As can be seen, no variable has any significant effect on the activity rate gap. The corresponding regression diagnostic output can be found in table C5 and C6 in Appendix C.

```
Fixed-effects (within) regression               Number of obs      =       138
Group variable: id                              Number of groups   =        24

R-sq:  within  = 0.2245                         Obs per group: min =         2
       between = 0.5850                                        avg =       5.8
       overall = 0.3842                                        max =         8

                                                F(1,23)            =      5.66
corr(u_i, Xb)  = -0.9272                        Prob > F           =    0.0260

                                 (Std. Err. adjusted for 24 clusters in id)
------------------------------------------------------------------------------
             |               Robust
   Unemplgap |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       Union |  -.1320606   .0554929    -2.38   0.026    -.2468564   -.0172648
       _cons |   12.24988   3.417639     3.58   0.002     5.179956     19.3198
-------------+----------------------------------------------------------------
     sigma_u |  6.3043783
     sigma_e |  1.3323397
         rho |  .95724673   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Table A6. Output from regressing the unemployment rate gap on the rate of collective bargaining.

Author's note: As can be seen, the variable is significant at the 5 % significance level. The corresponding regression diagnostic output can be found in table C7 in Appendix C.

```
Fixed-effects (within) regression               Number of obs      =       186
Group variable: id                              Number of groups   =        25

R-sq:  within  = 0.0355                         Obs per group: min =         2
       between = 0.4800                                        avg =       7.4
       overall = 0.3349                                        max =         8

                                                F(1,24)            =      2.20
corr(u_i, Xb)  = -0.8117                        Prob > F           =    0.1508

                                 (Std. Err. adjusted for 25 clusters in id)
------------------------------------------------------------------------------
             |               Robust
   Unemplgap |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       Eduim |  -.1032431   .0695686    -1.48   0.151    -.2468256    .0403394
       _cons |    7.50226   2.074827     3.62   0.001     3.220028    11.78449
-------------+----------------------------------------------------------------
     sigma_u |   4.071143
     sigma_e |  1.4061435
         rho |  .89341856   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Table A7. Output from regressing the unemployment rate gap on the share of immigrants with low education.

Author's note: As can be seen, the variable has no significant effect on the unemployment rate gap. The corresponding regression diagnostic output can be found in table C8 in Appendix C.

```
Fixed-effects (within) regression               Number of obs      =       184
Group variable: id                              Number of groups   =        24

R-sq:  within  = 0.2591                         Obs per group: min =         4
       between = 0.4385                                        avg =       7.7
       overall = 0.3891                                        max =         8

                                                F(1,23)            =     10.24
corr(u_i, Xb)  = -0.1724                        Prob > F           =    0.0040

                                 (Std. Err. adjusted for 24 clusters in id)
------------------------------------------------------------------------------
             |               Robust
   Unemplgap |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      Socexp |   .5732481    .179173     3.20   0.004     .2026005    .9438957
       _cons |  -9.014501   4.212338    -2.14   0.043    -17.72839   -.3006162
-------------+----------------------------------------------------------------
     sigma_u |  2.2643804
     sigma_e |  1.2359718
         rho |   .7704559   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Table A8. Output from regressing the unemployment rate gap on the share of social spending in percentage of GDP.

Author's note: As can be seen, the variable is significant at the 1 % significance level. The corresponding regression diagnostic output can be found in table C9 in Appendix C.

```
Fixed-effects (within) regression               Number of obs      =       191
Group variable: id                              Number of groups   =        25

R-sq:  within  = 0.0045                         Obs per group: min =         4
       between = 0.0147                                        avg =       7.6
       overall = 0.0154                                        max =         8

                                                F(1,24)            =      0.42
corr(u_i, Xb)  = -0.2623                        Prob > F           =    0.5234

                                 (Std. Err. adjusted for 25 clusters in id)
------------------------------------------------------------------------------
             |               Robust
   Unemplgap |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        GINI |    .103811     .16031     0.65   0.523    -.2270526    .4346745
       _cons |   1.280428   4.692885     0.27   0.787    -8.405211    10.96607
-------------+----------------------------------------------------------------
     sigma_u |  3.0865888
     sigma_e |  1.4519882
         rho |    .818804   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Table A9. Output from regressing the unemployment rate gap on the Gini-coefficient.

Author's note: As can be seen, the variable has no significant effect on the unemployment rate gap. The corresponding regression diagnostic output can be found in table C10 in Appendix C.

```
Fixed-effects (within) regression               Number of obs      =       133
Group variable: id                              Number of groups   =        23

R-sq:  within  = 0.3936                         Obs per group: min =         2
       between = 0.2421                                        avg =       5.8
       overall = 0.0505                                        max =         8

                                                F(4,22)            =      4.17
corr(u_i, Xb)  = -0.6574                        Prob > F           =    0.0115

                                 (Std. Err. adjusted for 23 clusters in id)
```

Unemplgap	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
Eduim	.0132057	.0666948	0.20	0.845	-.1251109	.1515223
Union	-.1080246	.044357	-2.44	0.023	-.2000154	-.0160339
Socexp	.4906572	.1459941	3.36	0.003	.1878839	.7934305
GINI	.0975924	.1398057	0.70	0.492	-.1923468	.3875317
_cons	-3.740957	6.732159	-0.56	0.584	-17.7026	10.22069
sigma_u	4.1020432					
sigma_e	1.2027424					
rho	.92083612	(fraction of variance due to u_i)				

Table A10. Output from regressing the unemployment rate gap on the rate of collective bargaining, the share of immigrants with low education, the share of social spending in percentage of GDP and the Gini-coefficient.

Author's note: As can be seen, the rate of collective bargaining is significant at the 5 % significance level, and the share of social spending in percentage of GDP is significant at the 1 % significance level. Other variables are insignificant. The corresponding regression diagnostic output can be found in tables C11 and C12 in Appendix C.

Appendix B – Regression outputs for regressions with combined micro and macro data

This appendix shows the regression outputs from Stata from the regressions run using combined micro and macro data. Huber- White robust standard errors are used for all regressions in this Appendix. Tables B1-B20 show the output from the regressions with the variable inactive, as the dependent variable. A summary of these regression results can be found in table 3 in the thesis above. Tables B21-B40 show the output from the regressions with unemployed as the dependent variable. A summary of these regression results can be found in table 5 in the thesis above.

```
Linear regression                                      Number of obs =  116774
                                                       F(  3,116770) =   11.05
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0003
                                                       Root MSE      =  .45507
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0016529	.0125394	-0.13	0.895	-.0262298	.0229241
Eduim	-.0004393	.0001147	-3.83	0.000	-.0006641	-.0002146
immigrant#c.Eduim						
1	-.0004243	.0003775	-1.12	0.261	-.0011642	.0003155
_cons	.3075071	.0036821	83.51	0.000	.3002903	.3147239

Table B1. Output from regressing inactive on being immigrant and the share of immigrants with low education.

Author's note: As can be seen, the share of low-educated immigrants is not significant in explaining the relatively higher probability for an immigrant of being inactive.

```
Linear regression                                      Number of obs =   81816
                                                       F(  3, 81812) =   11.05
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0004
                                                       Root MSE      =  .45606
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0245498	.0158936	-1.54	0.122	-.0557011	.0066015
Union	-.0002679	.0000663	-4.04	0.000	-.0003979	-.000138
immigrant#c.Union						
1	.0000518	.000235	0.22	0.826	-.0004088	.0005124
_cons	.3137209	.0044405	70.65	0.000	.3050176	.3224242

Table B2. Output from regressing inactive on being immigrant and the rate of collective bargaining.

Author's note: As can be seen, the rate of collective bargaining is not significant in explaining the relatively higher probability for an immigrant of being inactive.

```
Linear regression                                      Number of obs =  118237
                                                       F(  3,118233) =    8.97
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0002
                                                       Root MSE      =  .45516
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0774084	.0242655	-3.19	0.001	-.1249684	-.0298484
Socexp	-.0011676	.00034	-3.43	0.001	-.0018339	-.0005012
immigrant#c.Socexp						
1	.0026987	.0010436	2.59	0.010	.0006532	.0047442
_cons	.3214538	.0079341	40.52	0.000	.305903	.3370046

Table B3. Output from regressing inactive on being immigrant and the share of social spending as percentage of GDP.

Author's note: As can be seen, the share of social spending in percentage of GDP is significant at the 1 % significance level in explaining the relatively higher probability for an immigrant of being inactive.

```
. regress inactive i.immigrant##(c.GINI), vce(robust)

Linear regression                                      Number of obs =  122599
                                                       F(  3,122595) =   20.01
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0005
                                                       Root MSE      =  .45556
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	.0840697	.0373662	2.25	0.024	.0108325	.1573069
GINI	.0025075	.0003746	6.69	0.000	.0017732	.0032417
immigrant#c.GINI						
1	-.003454	.001258	-2.75	0.006	-.0059196	-.0009883
_cons	.2229294	.0109464	20.37	0.000	.2014746	.2443842

Table B4. Output from regressing inactive on being immigrant and the Gini-coefficient.

Author's note: As can be seen, the Gini-coefficient is significant at the 1 % significance level in explaining the relatively higher probability for an immigrant of being inactive.

```
Linear regression                                      Number of obs =   79105
                                                       F(  9, 79095) =    7.44
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0008
                                                       Root MSE      =  .45531
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	.0124247	.0714246	0.17	0.862	-.127567	.1524164
Union	-.0008806	.0001642	-5.36	0.000	-.0012025	-.0005587
Eduim	.0015373	.0003199	4.81	0.000	.0009103	.0021644
Socexp	.0007334	.000628	1.17	0.243	-.0004975	.0019643
GINI	-.0025879	.0007086	-3.65	0.000	-.0039767	-.0011991
immigrant#c.Union						
1	.0001741	.0005485	0.32	0.751	-.000901	.0012492
immigrant#c.Eduim						
1	-.0023269	.0009569	-2.43	0.015	-.0042025	-.0004513
immigrant#c.Socexp						
1	.0049067	.0021136	2.32	0.020	.000764	.0090493
immigrant#c.GINI						
1	-.0026851	.0023073	-1.16	0.245	-.0072073	.0018372
_cons	.3612177	.0213788	16.90	0.000	.3193155	.40312

Table B5. Output from regressing inactive on being immigrant, the share of low-educated immigrants, the rate of collective bargaining, the share of social spending as percentage of GDP and the Gini-coefficient.

Author's note: As can be seen, social expenditure and the share of low-educated immigrants are significant at the 5 % significance level in explaining the relatively higher probability for an immigrant of being inactive.

```
Linear regression                                      Number of obs =  102334
                                                       F(  3,102330) =   31.21
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0009
                                                       Root MSE      =  .44047
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0005066	.0132174	-0.04	0.969	-.0264125	.0253994
Eduim	-.0011228	.0001212	-9.27	0.000	-.0013603	-.0008853
immigrant#c.Eduim						
1	.0000497	.0004044	0.12	0.902	-.0007429	.0008423
_cons	.2961026	.0038133	77.65	0.000	.2886286	.3035765

Table B6. Output from regressing inactivity on immigrant and share of immigrants with low education, controlled for if respondent is highly educated.

Author's note: As can be seen, the share of low-educated immigrants is insignificant in explaining the relatively higher probability for an immigrant of being inactive when controlled for if the respondent is highly educated.

```
Linear regression                                      Number of obs =   70948
                                                       F(  3, 70944) =   37.83
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0016
                                                       Root MSE      =    .442
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0249054	.0167466	-1.49	0.137	-.0577286	.0079178
Union	-.0007065	.0000682	-10.35	0.000	-.0008403	-.0005728
immigrant#c.Union						
1	.0002599	.00025	1.04	0.299	-.0002301	.0007499
_cons	.3103493	.0045276	68.55	0.000	.3014753	.3192233

Table B7. Output from regressing inactivity on immigrant and rate of collective bargaining, controlled for if respondent is highly educated.

Author's note: As can be seen, the share of low-educated immigrants is insignificant in explaining the relatively higher probability for an immigrant of being inactive when controlled for if the respondent is highly educated.

```
Linear regression                                      Number of obs =  103778
                                                       F(  3,103774) =    2.96
                                                       Prob > F      =  0.0310
                                                       R-squared     =  0.0001
                                                       Root MSE      =  .44095
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0430274	.0255601	-1.68	0.092	-.0931247	.00707
Socexp	-.0009841	.0003447	-2.85	0.004	-.0016597	-.0003085
immigrant#c.Socexp						
1	.001818	.0010983	1.66	0.098	-.0003346	.0039706
_cons	.2869985	.0080518	35.64	0.000	.2712172	.3027799

Table B8. Output from regressing inactivity on immigrant and share of social spending as percentage of GDP, controlled for if respondent is highly educated.

Author's note: As can be seen, the share of social spending as percentage of GDP is significant at the 10 % significance level in explaining the relatively higher probability for an immigrant of being inactive when controlled for if the respondent is highly educated.

```
Linear regression                                      Number of obs =  108004
                                                       F(  3,108000) =    3.70
                                                       Prob > F      =  0.0112
                                                       R-squared     =  0.0001
                                                       Root MSE      =  .44176
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0215474	.03924	-0.55	0.583	-.0984573	.0553625
GINI	.0011593	.0003922	2.96	0.003	.0003905	.001928
immigrant#c.GINI						
1	.0006119	.0013299	0.46	0.645	-.0019947	.0032186
_cons	.2326679	.0113839	20.44	0.000	.2103555	.2549803

Table B9. Output from regressing inactivity on immigrant the Gini-coefficient as percentage of GDP, controlled for if respondent is highly educated.

Author's note: As can be seen, the Gini-coefficient is insignificant in explaining the relatively higher probability for an immigrant of being inactive when controlled for if the respondent is highly educated.

```
Linear regression                                      Number of obs =   68304
                                                       F(  9, 68294) =   19.80
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0026
                                                       Root MSE      =   .4406
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0943483	.0751328	-1.26	0.209	-.2416086	.0529119
Eduim	.0012563	.0003274	3.84	0.000	.0006146	.001898
Union	-.001641	.0001673	-9.81	0.000	-.001969	-.001313
Socexp	.0044176	.0006536	6.76	0.000	.0031365	.0056987
GINI	-.0054969	.0007377	-7.45	0.000	-.0069428	-.0040509
immigrant#c.Eduim						
1	-.0022155	.0009886	-2.24	0.025	-.0041531	-.000278
immigrant#c.Union						
1	.0006718	.0005774	1.16	0.245	-.0004599	.0018035
immigrant#c.Socexp						
1	.0022828	.0022857	1.00	0.318	-.0021971	.0067627
immigrant#c.GINI						
1	.0022665	.0024286	0.93	0.351	-.0024935	.0070265
_cons	.3846317	.0219108	17.55	0.000	.3416867	.4275768

Table B10. Output from regressing inactive on being immigrant, the share of low-educated immigrants, the rate of collective bargaining, the share of social spending as percentage of GDP and the Gini-coefficient, controlled for if the respondent is highly educated.

Author's note: As can be seen, the share of low-educated immigrants is significant at the 5 % significance level in explaining the relatively higher probability for an immigrant of being inactive when controlled for if the respondent is highly educated.

```
Linear regression                                      Number of obs =   61101
                                                       F(  3, 61097) =    3.29
                                                       Prob > F      =  0.0197
                                                       R-squared     =  0.0002
                                                       Root MSE      =  .47478
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	.0116708	.0175265	0.67	0.505	-.0226812	.0460228
Eduim	-.0004492	.0001621	-2.77	0.006	-.000767	-.0001315
immigrant#c.Eduim						
1	-.0002278	.0005301	-0.43	0.667	-.0012668	.0008112
_cons	.3560805	.0051982	68.50	0.000	.3458921	.3662689

Table B11. Output from regressing inactivity on immigrant and share of immigrants with low education, controlled for if the respondent is female.

Author's note: As can be seen, the share of low-educated immigrants is insignificant in explaining the relatively higher probability for an immigrant of being inactive when controlled for if the respondent is female.

```
Linear regression                                      Number of obs =   43033
                                                       F(  3, 43029) =    3.63
                                                       Prob > F      =  0.0123
                                                       R-squared     =  0.0003
                                                       Root MSE      =  .47588
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	.0059834	.02263	0.26	0.791	-.0383718	.0503386
Union	-.0002891	.0000934	-3.09	0.002	-.0004723	-.000106
immigrant#c.Union						
1	-.0000813	.0003349	-0.24	0.808	-.0007376	.000575
_cons	.3643631	.0062291	58.49	0.000	.352154	.3765722

Table B12. Output from regressing inactivity on immigrant and rate of collective bargaining, controlled for if the respondent is female.

Author's note: As can be seen, the rate of collective bargaining is insignificant in explaining the relatively higher probability for an immigrant of being inactive when controlled for if the respondent is female.

```
Linear regression                                      Number of obs =   61936
                                                       F(  3, 61932) =   11.87
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0006
                                                       Root MSE      =  .47472
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.1053288	.0344569	-3.06	0.002	-.1728644	-.0377932
Socexp	-.0028045	.0004858	-5.77	0.000	-.0037567	-.0018522
immigrant#c.Socexp						
1	.0047669	.0014836	3.21	0.001	.0018591	.0076748
_cons	.4070406	.0113094	35.99	0.000	.3848742	.429207

Table B13. Output from regressing inactivity on immigrant and share of social spending as percentage of GDP, controlled for if the respondent is female.

Author's note: As can be seen, the share of social spending is significant at the 0.1 % significance level in explaining the relatively higher probability for an immigrant of being inactive when controlled for if the respondent is female.

```
Linear regression                                      Number of obs =   64511
                                                       F(  3, 64507) =   10.21
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0005
                                                       Root MSE      =  .47472
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	.1465591	.0536532	2.73	0.006	.0413988	.2517194
GINI	.0028588	.0005308	5.39	0.000	.0018185	.0038991
immigrant#c.GINI						
1	-.0048967	.0018	-2.72	0.007	-.0084247	-.0013687
_cons	.2596392	.0155843	16.66	0.000	.229094	.2901845

Table B14. Output from regressing inactivity on immigrant and the Gini-coefficient, controlled for if the respondent is female.

Author's note: As can be seen, the Gini-coefficient is significant at the 1 % significance level in explaining the relatively higher probability for an immigrant of being inactive when controlled for if the respondent is female.

```
Linear regression                                      Number of obs =   41430
                                                       F(  9, 41420) =    7.66
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0016
                                                       Root MSE      =  .47547
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	.051795	.1046734	0.49	0.621	-.1533672	.2569572
Eduim	.0026389	.0004587	5.75	0.000	.0017399	.003538
Union	-.0012179	.0002361	-5.16	0.000	-.0016807	-.0007552
Socexp	-.0019218	.0009029	-2.13	0.033	-.0036916	-.0001521
GINI	-.0029629	.0010138	-2.92	0.003	-.0049499	-.0009758
immigrant#c.Eduim						
1	-.002169	.0013692	-1.58	0.113	-.0048527	.0005147
immigrant#c.Union						
1	-.0006601	.0007812	-0.84	0.398	-.0021912	.0008711
immigrant#c.Socexp						
1	.0105187	.0030444	3.46	0.001	.0045516	.0164858
immigrant#c.GINI						
1	-.0060393	.0033219	-1.82	0.069	-.0125503	.0004716
_cons	.4708771	.0309717	15.20	0.000	.4101719	.5315823

Table B15. Output from regressing inactive on being immigrant, the share of low-educated immigrants, the rate of collective bargaining, the share of social spending as percentage of GDP and the Gini-coefficient, controlled for if the respondent is female.

Author's note: As can be seen, the share of social spending as percentage of GDP is significant at the 0.1 % significance level in explaining the relatively higher probability for an immigrant of being inactive when controlled for if the respondent is highly educated.

```
Linear regression                                      Number of obs =   24228
                                                       F(  3, 24224) =   26.18
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0027
                                                       Root MSE      =  .32279
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0421204	.0262279	-1.61	0.108	-.0935288	.0092881
Eduim	.001829	.0002335	7.83	0.000	.0013713	.0022866
immigrant#c.Eduim						
1	.0008175	.0008399	0.97	0.330	-.0008287	.0024637
_cons	.0622727	.0073834	8.43	0.000	.0478007	.0767447

Table B16. Output from regressing inactivity on immigrant and share of low-educated immigrants, controlled for if the respondent is a union member.

Author's note: As can be seen, the share of low-educated immigrants is insignificant in explaining the relatively higher probability for an immigrant of being inactive when controlled for if the respondent is a union member.

```
Linear regression                                      Number of obs =   13449
                                                       F(  3, 13445) =   33.67
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0060
                                                       Root MSE      =  .32825
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0448032	.0308744	-1.45	0.147	-.1053214	.015715
Union	.0010776	.0001174	9.18	0.000	.0008475	.0013076
immigrant#c.Union						
1	.0003539	.0004571	0.77	0.439	-.0005422	.0012499
_cons	.0482006	.0083171	5.80	0.000	.031898	.0645033

Table B17. Output from regressing inactivity on immigrant and rate of collective bargaining, controlled for if the respondent is a union member.

Author's note: As can be seen, the rate of collective bargaining is insignificant in explaining the relatively higher probability for an immigrant of being inactive when controlled for if the respondent is a union member.

```
Linear regression                                      Number of obs =   24340
                                                       F(  3, 24336) =   54.26
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0062
                                                       Root MSE      =  .32211
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	.0132323	.044966	0.29	0.769	-.0749039	.1013684
Socexp	.0066799	.000547	12.21	0.000	.0056078	.0077521
immigrant#c.Socexp						
1	-.0011099	.0018641	-0.60	0.552	-.0047637	.0025438
_cons	-.0452761	.0132548	-3.42	0.001	-.0712563	-.0192959

Table B18. Output from regressing inactivity on immigrant and share of social spending, controlled for if the respondent is a union member.

Author's note: As can be seen, the share of social spending is insignificant in explaining the relatively higher probability for an immigrant of being inactive when controlled for if the respondent is a union member.

```
Linear regression                                      Number of obs =   24536
                                                       F(  3, 24532) =   17.76
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0018
                                                       Root MSE      =  .32253
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.1071926	.0579808	-1.85	0.065	-.2208384	.0064532
GINI	-.0044301	.000629	-7.04	0.000	-.0056629	-.0031972
immigrant#c.GINI						
1	.0033795	.00209	1.62	0.106	-.000717	.007476
_cons	.2404438	.0175744	13.68	0.000	.2059969	.2748907

Table B19. Output from regressing inactivity on immigrant and share of social spending, controlled for if the respondent is a union member.

Author's note: As can be seen, the Gini-coefficient is insignificant in explaining the relatively higher probability for an immigrant of being inactive when controlled for if the respondent is a union member.

```
Linear regression                                      Number of obs =   13326
                                                       F(  9, 13316) =   17.38
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0102
                                                       Root MSE      =  .32833
```

inactive	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.1217892	.1247341	-0.98	0.329	-.3662858	.1227075
Eduim	.0009133	.0005795	1.58	0.115	-.0002226	.0020491
Union	-.0002415	.0003053	-0.79	0.429	-.0008399	.0003568
Socexp	.0067588	.0010778	6.27	0.000	.0046461	.0088714
GINI	-.0064488	.0012808	-5.04	0.000	-.0089593	-.0039382
immigrant#c.Eduim						
1	.0006078	.0020019	0.30	0.761	-.0033162	.0045318
immigrant#c.Union						
1	.0004678	.0010956	0.43	0.669	-.0016798	.0026153
immigrant#c.Socexp						
1	-.001485	.0039127	-0.38	0.704	-.0091545	.0061844
immigrant#c.GINI						
1	.0031074	.0042576	0.73	0.465	-.0052381	.0114529
_cons	.1276748	.0382309	3.34	0.001	.0527368	.2026129

Table B20. Output from regressing inactive on being immigrant, the share of low-educated immigrants, the rate of collective bargaining, the share of social spending as percentage of GDP and the Gini-coefficient, controlled for if the respondent is a union member.

Author's note: As can be seen, all variables are insignificant in explaining the relatively higher probability for an immigrant of being inactive when controlled for if the respondent is a union member.

```
Linear regression                                      Number of obs =   82562
                                                       F(  3, 82558) =   64.42
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0033
                                                       Root MSE      =   .2836
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	.0189792	.0110402	1.72	0.086	-.0026596	.0406179
Eduim	.0003856	.000089	4.33	0.000	.0002111	.00056
immigrant#c.Eduim						
1	.0009496	.0003443	2.76	0.006	.0002749	.0016244
_cons	.0720806	.0027843	25.89	0.000	.0666233	.0775378

Table B21. Output from regressing unemployed on being immigrant and the share of immigrants with low education.

Author's note: As can be seen, the share of low-educated immigrants is significant at the 1 % significance level in explaining the relatively higher probability for an immigrant of being unemployed.

```
Linear regression                                      Number of obs =   57663
                                                       F(  3, 57659) =   37.69
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0030
                                                       Root MSE      =  .28451
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.012501	.0132141	-0.95	0.344	-.0384007	.0133988
Union	-7.57e-06	.0000479	-0.16	0.874	-.0001014	.0000862
immigrant#c.Union						
1	.0009509	.0002042	4.66	0.000	.0005506	.0013511
_cons	.0850988	.0032077	26.53	0.000	.0788118	.0913859

Table B22. Output from regressing unemployed on being immigrant and the rate of collective bargaining.

Author's note: As can be seen, the rate of collective bargaining is significant with a p-value <0.000 in explaining the relatively higher probability for an immigrant of being unemployed.

```
Linear regression                                      Number of obs =   83577
                                                       F(  3, 83573) =   57.14
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0029
                                                       Root MSE      =  .28417
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0287366	.020728	-1.39	0.166	-.0693632	.0118901
Socexp	.0002301	.0002449	0.94	0.347	-.0002498	.0007101
immigrant#c.Socexp						
1	.0033833	.0009057	3.74	0.000	.0016081	.0051584
_cons	.0786924	.005702	13.80	0.000	.0675164	.0898683

Table B23. Output from regressing unemployed on being immigrant and the share of social spending as percentage of GDP.

Author's note: As can be seen, social spending as percentage of GDP is significant with a p-value <0.000 in explaining the relatively higher probability for an immigrant of being unemployed.

```
Linear regression                                      Number of obs =   86534
                                                       F(  3, 86530) =  213.11
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0084
                                                       Root MSE      =  .28328
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	.0158393	.0324303	0.49	0.625	-.0477238	.0794024
GINI	.0057957	.0002827	20.50	0.000	.0052416	.0063498
immigrant#c.GINI						
1	.0010266	.0011114	0.92	0.356	-.0011517	.0032048
_cons	-.0841706	.0080443	-10.46	0.000	-.0999373	-.0684039

Table B24. Output from regressing unemployed on being immigrant and the Gini-coefficient.

Author's note: As can be seen, the Gini-coefficient is insignificant regarding the relatively higher probability for an immigrant of being unemployed.

```
Linear regression                                      Number of obs =   55871
                                                       F(  9, 55861) =   56.99
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0113
                                                       Root MSE      =   .2825
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.2298343	.0635874	-3.61	0.000	-.3544659	-.1052027
Eduim	.0009619	.0002337	4.12	0.000	.0005038	.00142
Union	-.000549	.0001173	-4.68	0.000	-.000779	-.000319
Socexp	.0026506	.0004216	6.29	0.000	.0018243	.003477
GINI	.004553	.0005244	8.68	0.000	.0035252	.0055807
immigrant#c.Eduim						
1	-.001215	.0008631	-1.41	0.159	-.0029067	.0004767
immigrant#c.Union						
1	.0015605	.00048	3.25	0.001	.0006196	.0025013
immigrant#c.Socexp						
1	.0016461	.0017551	0.94	0.348	-.0017939	.0050861
immigrant#c.GINI						
1	.0058129	.0020406	2.85	0.004	.0018134	.0098124
_cons	-.1053575	.0154198	-6.83	0.000	-.1355804	-.0751346

Table B25. Output from regressing unemployed on being immigrant, the share of low-educated immigrants, the rate of collective bargaining, the share of social spending as percentage of GDP and the Gini-coefficient.

Author's note: As can be seen, the rate of collective bargaining and the Gini-coefficient are both significant at the 1 % significance level in explaining the relatively higher probability for an immigrant of being unemployed.

```
Linear regression                                      Number of obs =   75343
                                                       F(  3, 75339) =   51.07
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0030
                                                       Root MSE      =  .27252
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	.0130493	.0114643	1.14	0.255	-.0094206	.0355192
Eduim	.0001337	.0000908	1.47	0.141	-.0000443	.0003116
immigrant#c.Eduim						
1	.0011266	.000364	3.10	0.002	.0004132	.0018401
_cons	.0725188	.0028034	25.87	0.000	.0670242	.0780134

Table B26. Output from regressing unemployed on immigrant and share of immigrants with low education, controlled for if respondent is highly educated.

Author's note: As can be seen, the share of low-educated immigrants is significant at the 1 % significance level in explaining the relatively higher probability for an immigrant of being unemployed, when controlled for if the respondent is highly educated.

```
Linear regression                                      Number of obs =   52011
                                                       F(  3, 52007) =   34.79
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0030
                                                       Root MSE      =  .27297
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0130339	.0138815	-0.94	0.348	-.0402417	.0141739
Union	-.0001151	.0000483	-2.38	0.017	-.0002098	-.0000204
immigrant#c.Union						
1	.0009656	.0002169	4.45	0.000	.0005405	.0013907
_cons	.0841085	.0032246	26.08	0.000	.0777882	.0904288

Table B27. Output from regressing unemployed on immigrant and the rate of collective bargaining, controlled for if respondent is highly educated.

Author's note: As can be seen, the rate of collective bargaining is significant with a p-value <0.000 in explaining the relatively higher probability for an immigrant of being unemployed, when controlled for if the respondent is highly educated.

```
Linear regression                                      Number of obs =   76350
                                                       F(  3, 76346) =   49.48
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0028
                                                       Root MSE      =  .27325
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0175318	.0212962	-0.82	0.410	-.0592723	.0242087
Socexp	.0002779	.0002419	1.15	0.251	-.0001962	.0007521
immigrant#c.Socexp						
1	.0028257	.000929	3.04	0.002	.0010048	.0046466
_cons	.0705799	.0056327	12.53	0.000	.0595398	.08162

Table B28. Output from regressing unemployed on immigrant and the share of social spending as percentage of GDP, controlled for if respondent is highly educated.

Author's note: As can be seen, the share of social spending as percentage of GDP is significant at the 1 % significance level in explaining the relatively higher probability for an immigrant of being unemployed, when controlled for if the respondent is highly educated.

```
Linear regression                                      Number of obs =   79294
                                                       F(  3, 79290) =  143.12
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0064
                                                       Root MSE      =  .27301
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0130383	.0333722	-0.39	0.696	-.0784477	.0523711
GINI	.0045301	.0002873	15.77	0.000	.0039669	.0050933
immigrant#c.GINI						
1	.0019806	.0011506	1.72	0.085	-.0002745	.0042357
_cons	-.0533457	.008155	-6.54	0.000	-.0693295	-.0373619

Table B29. Output from regressing unemployed on immigrant and the Gini-coefficient, controlled for if respondent is highly educated.

Author's note: As can be seen, the Gini-coefficient is significant at the 10 % significance level in explaining the relatively higher probability for an immigrant of being unemployed, when controlled for if the respondent is highly educated.

```
Linear regression                                      Number of obs =   50227
                                                       F(  9, 50217) =   38.14
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0087
                                                       Root MSE      =  .27083
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.2477139	.066241	-3.74	0.000	-.377547	-.1178807
Eduim	.0008724	.0002345	3.72	0.000	.0004128	.0013321
Union	-.0006296	.0001175	-5.36	0.000	-.0008599	-.0003994
Socexp	.0028112	.0004264	6.59	0.000	.0019755	.0036469
GINI	.00289	.0005345	5.41	0.000	.0018424	.0039376
immigrant#c.Eduim						
1	-.0010295	.0008829	-1.17	0.244	-.0027599	.000701
immigrant#c.Union						
1	.001737	.0004971	3.49	0.000	.0007627	.0027113
immigrant#c.Socexp						
1	-.0002101	.0018563	-0.11	0.910	-.0038484	.0034283
immigrant#c.GINI						
1	.0073674	.0021305	3.46	0.001	.0031917	.0115431
_cons	-.0595431	.0155155	-3.84	0.000	-.0899536	-.0291325

Table B30. Output from regressing enemployed on being immigrant, the share of low-educated immigrants, the rate of collective bargaining, the share of social spending as percentage of GDP and the Gini-coefficient, controlled for if the respondent is highly educated.

Author's note: As can be seen, the rate of collective bargaining and the Gini-coefficient are both significant at the 0.1 % significance level in explaining the relatively higher probability for an immigrant of being inactive, when controlled for if the respondent is highly educated.

```
Linear regression                                      Number of obs =   40127
                                                       F(  3, 40123) =   44.50
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0041
                                                       Root MSE      =  .28152
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	.0409948	.0152302	2.69	0.007	.0111433	.0708463
Eduim	.0009588	.0001261	7.60	0.000	.0007117	.0012059
immigrant#c.Eduim						
1	.0000852	.0004754	0.18	0.858	-.0008466	.001017
_cons	.0542724	.003837	14.14	0.000	.0467518	.0617929

Table B31. Output from regressing unemployed on immigrant and share of immigrants with low education, controlled for if respondent is female.

Author's note: As can be seen, the share of low-educated immigrants is insignificant in explaining the relatively higher probability for an immigrant of being unemployed, when controlled for if the respondent is female.

```
Linear regression                                      Number of obs =   28114
                                                       F(  3, 28110) =   16.29
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0024
                                                       Root MSE      =  .28712
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	.0092646	.0189699	0.49	0.625	-.0279172	.0464465
Union	.0001372	.0000667	2.06	0.040	6.35e-06	.000268
immigrant#c.Union						
1	.000542	.0002899	1.87	0.062	-.0000263	.0011104
_cons	.0783886	.0044061	17.79	0.000	.0697524	.0870248

Table B32. Output from regressing unemployed on immigrant and the rate of collective bargaining, controlled for if respondent is female.

Author's note: As can be seen, the rate of collective bargaining is significant at the 10 % significance level in explaining the relatively higher probability for an immigrant of being unemployed, when controlled for if the respondent is female.

```
Linear regression                                      Number of obs =   40669
                                                       F(  3, 40665) =   25.32
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0025
                                                       Root MSE      =  .28256
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0061756	.0285192	-0.22	0.829	-.0620738	.0497226
Socexp	.0008168	.0003434	2.38	0.017	.0001436	.0014899
immigrant#c.Socexp						
1	.0022073	.0012473	1.77	0.077	-.0002373	.004652
_cons	.06459	.0079438	8.13	0.000	.0490201	.08016

Table B33. Output from regressing unemployed on immigrant and the share of social spending as percentage of GDP, controlled for if respondent is female.

Author's note: As can be seen, the share of social spending as percentage of GDP is significant at the 10 % significance level in explaining the relatively higher probability for an immigrant of being unemployed, when controlled for if the respondent is female.

```
Linear regression                                      Number of obs =   42362
                                                       F(  3, 42358) =   91.22
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0073
                                                       Root MSE      =  .28159
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	.0160456	.0452424	0.35	0.723	-.0726304	.1047217
GINI	.0054364	.0004002	13.59	0.000	.004652	.0062207
immigrant#c.GINI						
1	.0008448	.0015446	0.55	0.584	-.0021826	.0038721
_cons	-.0750827	.0114462	-6.56	0.000	-.0975174	-.052648

Table B34. Output from regressing unemployed on immigrant and the Gini-coefficient, controlled for if respondent is female.

Author's note: As can be seen, the Gini-coefficient is insignificant in explaining the relatively higher probability for an immigrant of being unemployed, when controlled for if the respondent is female.

```
Linear regression                                      Number of obs =   27082
                                                       F(  9, 27072) =   29.98
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0125
                                                       Root MSE      =  .28495
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.1974701	.0907511	-2.18	0.030	-.375347	-.0195932
Eduim	.0020303	.0003339	6.08	0.000	.0013757	.0026848
Union	-.0006925	.0001678	-4.13	0.000	-.0010214	-.0003636
Socexp	.001392	.0006079	2.29	0.022	.0002004	.0025836
GINI	.0037412	.0007485	5.00	0.000	.0022741	.0052083
immigrant#c.Eduim						
1	-.0014628	.0012046	-1.21	0.225	-.0038238	.0008982
immigrant#c.Union						
1	.0010327	.0006697	1.54	0.123	-.0002801	.0023454
immigrant#c.Socexp						
1	.0028156	.0025195	1.12	0.264	-.0021227	.007754
immigrant#c.GINI						
1	.0050574	.0028063	1.80	0.072	-.0004432	.010558
_cons	-.0750828	.0223207	-3.36	0.001	-.1188325	-.031333

Table B35. Output from regressing unemployed on immigrant, the share of low-educated immigrants, the rate of collective bargaining, the share of social spending as percentage of GDP and the Gini-coefficient, controlled for if respondent is female.

Author's note: As can be seen, the Gini-coefficient is significant at the 10 % significance level in explaining the relatively higher probability for an immigrant of being unemployed, when controlled for if the respondent is female.

```
Linear regression                                      Number of obs =   21357
                                                       F(  3, 21353) =   33.64
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0054
                                                       Root MSE      =  .18973
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0094039	.0231051	-0.41	0.684	-.0546916	.0358839
Eduim	.00113	.0001406	8.04	0.000	.0008544	.0014057
immigrant#c.Eduim						
1	.0012932	.0007606	1.70	0.089	-.0001976	.002784
_cons	-.000388	.0042078	-0.09	0.927	-.0086357	.0078596

Table B36. Output from regressing unemployed on immigrant and share of immigrants with low education, controlled for if respondent is a union member.

Author's note: As can be seen, the share of low-educated immigrants is significant at the 10 % significance level in explaining the relatively higher probability for an immigrant of being unemployed, when controlled for if the respondent is a union member.

```
Linear regression                                      Number of obs =   11786
                                                       F(  3, 11782) =   31.86
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0070
                                                       Root MSE      =  .18198
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	.0034192	.0224404	0.15	0.879	-.0405676	.0474061
Union	.000531	.0000615	8.64	0.000	.0004105	.0006516
immigrant#c.Union						
1	.0004301	.0003475	1.24	0.216	-.0002511	.0011112
_cons	-.0051699	.0039082	-1.32	0.186	-.0128307	.0024908

Table B37. Output from regressing unemployed on immigrant and the rate of collective bargaining, controlled for if respondent is a union member.

Author's note: As can be seen, the rate of collective bargaining is insignificant in explaining the relatively higher probability for an immigrant of being unemployed, when controlled for if the respondent is a union member.

```
Linear regression                                      Number of obs =   21458
                                                       F(  3, 21454) =   62.22
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0092
                                                       Root MSE      =  .18916
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0310037	.0356739	-0.87	0.385	-.1009273	.0389199
Socexp	.0039123	.0003295	11.87	0.000	.0032665	.0045582
immigrant#c.Socexp						
1	.0025929	.0015324	1.69	0.091	-.0004107	.0055964
_cons	-.0612627	.0076301	-8.03	0.000	-.0762182	-.0463072

Table B38. Output from regressing unemployed on immigrant and the share of social spending as percentage of GDP, controlled for if respondent is a union member.

Author's note: As can be seen, the share of social spending as percentage of GDP is significant at the 10 % significance level in explaining the relatively higher probability for an immigrant of being unemployed, when controlled for if the respondent is a union member.

```
Linear regression                                      Number of obs =   21637
                                                       F(  3, 21633) =   10.24
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0022
                                                       Root MSE      =  .18919
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	.0152794	.0468813	0.33	0.744	-.0766115	.1071702
GINI	-.0006089	.0003453	-1.76	0.078	-.0012857	.0000679
immigrant#c.GINI						
1	.0005935	.0016956	0.35	0.726	-.0027301	.003917
_cons	.0513233	.0096259	5.33	0.000	.0324558	.0701908

Table B39. Output from regressing unemployed on immigrant and the Gini-coefficient, controlled for if respondent is a union member.

Author's note: As can be seen, the Gini-coefficient is insignificant in explaining the relatively higher probability for an immigrant of being unemployed, when controlled for if the respondent is a union member.

```
Linear regression                                      Number of obs =   11670
                                                       F(  9, 11660) =   11.70
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.0089
                                                       Root MSE      =  .18251
```

unemployed	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
1.immigrant	-.0449301	.1068931	-0.42	0.674	-.2544585	.1645984
Eduim	-.000338	.0003325	-1.02	0.309	-.0009898	.0003137
Union	.0005185	.0001632	3.18	0.001	.0001985	.0008384
Socexp	.0019627	.0005894	3.33	0.001	.0008074	.003118
GINI	.0014743	.0006578	2.24	0.025	.0001848	.0027638
immigrant#c.Eduim						
1	.0024859	.0020695	1.20	0.230	-.0015706	.0065424
immigrant#c.Union						
1	-.0003279	.0009333	-0.35	0.725	-.0021574	.0015015
immigrant#c.Socexp						
1	.0010137	.0033621	0.30	0.763	-.0055767	.007604
immigrant#c.GINI						
1	-.0000653	.0035244	-0.02	0.985	-.0069738	.0068432
_cons	-.0828465	.0198779	-4.17	0.000	-.1218106	-.0438825

Table B40. Output from regressing unemployed on being immigrant, the share of low-educated immigrants, the rate of collective bargaining, the share of social spending as percentage of GDP and the Gini-coefficient, controlled for if the respondent is a union member.

Author's note: As can be seen, all variables are insignificant in explaining the relatively higher probability for an immigrant of being unemployed when controlled for if the respondent is a union member.

Appendix C – Various regression diagnostic outputs

In this appendix, various regression diagnostic outputs from Stata will be presented. The outputs in tables C1-C6 are from the tests performed before the regressions giving the regression outputs in tables A1-A5 in appendix A, and the outputs in tables C6-C12 are from the tests performed before the regressions giving the regression outputs in tables A6-A10 in appendix A.

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      15) =     18.146
           Prob > F =      0.0007
```

Table C1. Wooldridge test for autocorrelation regressing the activity rate gap on the rate of collective bargaining.

Author's note: P-value = 0.0007< 0.05. HO stating no autocorrelation is thus rejected and Huber-White robust standard errors are used. The corresponding regression output can be found in table A1 in Appendix A.

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      23) =     14.724
           Prob > F =      0.0008
```

Table C2. Wooldridge test for autocorrelation regressing the activity rate gap on the share of immigrants with low education.

Author's note: P-value = 0.0008<0.05. HO stating no autocorrelation is thus rejected and Huber-White robust standard errors are used. The corresponding regression output can be found in table A2 in Appendix A.

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      23) =     17.451
           Prob > F =      0.0004
```

Table C3. Wooldridge test for autocorrelation regressing the activity rate gap on the share of social spending as percent of GDP.

Author's note: P-value = 0.0004<0.05. HO stating no autocorrelation is thus rejected and Huber-White robust standard errors are used. The corresponding regression output can be found in table A3 in Appendix A.

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      24) =     17.150
           Prob > F =      0.0004
```

Table C4. Wooldridge test for autocorrelation regressing the activity rate gap on the Gini-coefficient.

Author's note: P-value = 0.0004<0.05. HO stating no autocorrelation is thus rejected and Huber-White robust standard errors are used. The corresponding regression output can be found in table A4 in Appendix A.

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      14) =     19.241
           Prob > F =      0.0006
```

Table C5. Wooldridge test for autocorrelation regressing the activity rate gap on the rate of collective bargaining, the share of immigrants with low education, the share of social spending in percentage of GDP and the Gini-coefficient.

Author's note: P-value = 0.0006<0.05. HO stating no autocorrelation is thus rejected and Huber-White robust standard errors are used. The corresponding regression output can be found in table A5 in Appendix A.

	Coefficients (b) fixed	(B) .	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
Union	.0006542	.0230992	-.0224451	.0123461
Eduim	-.0199531	-.0470872	.0271341	.0229692
Socexp	.0225871	.0586598	-.0360728	.0473921
GINI	.285863	.1350508	.1508123	.0781547

```
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(4) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       10.27
                Prob>chi2 =      0.0361
```

Table C6. Hausman test regressing the activity rate gap on the rate of collective bargaining, the share of immigrants with low education, the share of social spending in percentage of GDP and the Gini-coefficient.

Author's note: P-value = 0.0361<0.05. HO stating difference in coefficients not systematic can thus be rejected. This further proves the fixed effects model to be the correct specification for the data. The corresponding regression output can be found in table A5 in Appendix A.

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      15) =      6.921
           Prob > F =      0.0189
```

Table C7. Wooldridge test for autocorrelation regressing the unemployment rate gap on the rate of collective bargaining.

Author's note: P-value = 0.0189<0.05. HO stating no autocorrelation is thus rejected and Huber-White robust standard errors are used. The corresponding regression output can be found in table A6 in Appendix A.

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      22) =     13.511
           Prob > F =      0.0013
```

Table C8. Wooldridge test for autocorrelation regressing the unemployment rate gap on the share of immigrants with low education.

Author's note: P-value = 0.0013<0.05. HO stating no autocorrelation is thus rejected and Huber-White robust standard errors are used. The corresponding regression output can be found in table A7 in Appendix A.

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      22) =      9.925
           Prob > F =      0.0046
```

Table C9. Wooldridge test for autocorrelation regressing the unemployment rate gap on the share of social spending in percentage of GDP.

Author's note: P-value = 0.0046<0.05. HO stating no autocorrelation is thus rejected and Huber-White robust standard errors are used. The corresponding regression output can be found in table A8 in Appendix A.

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      23) =     16.449
           Prob > F =      0.0005
```

Table C10. Wooldridge test for autocorrelation regressing the unemployment rate gap on the Gini-coefficient.

Author's note: P-value = 0.0005<0.05. HO stating no autocorrelation is thus rejected and Huber-White robust standard errors are used. The corresponding regression output can be found in table A9 in Appendix A.

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      14) =      6.966
           Prob > F =      0.0194
```

Table C11. Wooldridge test for autocorrelation regressing the unemployment rate gap on the rate of collective bargaining, the share of immigrants with low education, the share of social spending in percentage of GDP and the Gini-coefficient.

Author's note: P-value = 0.0194<0.05. HO stating no autocorrelation is thus rejected and Huber-White robust standard errors are used. The corresponding regression output can be found in table A10 in Appendix A.

	Coefficients (b) fe	(B) re	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
Eduim	.0132057	.0419822	-.0287765	.0319812
Union	-.1080246	-.0453041	-.0627206	.0156538
Socexp	.4906572	.589727	-.0990698	.0609437
GINI	.0975924	.0597048	.0378876	.1104575

```
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(4) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       23.96
                Prob>chi2 =      0.0001
```

Table C12. Hausman test regressing the unemployment rate gap on the rate of collective bargaining, the share of immigrants with low education, the share of social spending in percentage of GDP and the Gini-coefficient.

Author's note: P-value = 0.0001<0.05. HO stating difference in coefficients not systematic can thus be rejected. This further proves the fixed effects model to be the correct specification for the data. The corresponding regression output can be found in table A10 in Appendix A.