The impact of networks, segregation and diversity on migrants' labour market integration

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Authors: Thomas Horvath (WIFO), Peter Huber (WIFO)

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Authors: Thomas Horvath (WIFO), Peter Huber (WIFO)

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The impact of networks, segregation and diversity on migrants' labour market integration

Thomas Horvath (WIFO), Peter Huber (WIFO)

Contribution to the Project

The main contribution is to find out which migration policies are conducive of labour market integration of foreign born in a regional context.

The impact of networks, segregation and diversity on migrants' labour market integration

Thomas Horvath, Peter Huber[1]
Austrian Institute for Economic Research (WIFO)
Arsenal, Objekt 20
1030 Wien
e-mail: Huber@wifo.ac.at

Abstract
We analyse the role of ethnic networks, segregation and diversity of a region on migrants' success in integration into the host countries' labour markets. We find a robust negative impact of ethnic networks on unemployment probabilities of the foreign born and a positive one on employment probabilities. In addition a similarly robust positive impact of ethnic diversity on the unemployment probabilities and a negative one on employment probabilities is found. With respect to over-education our results are less robust, but in their majority point to a negative impact of ethnic networks on the probability of over-educated employment and an insignificant or positive impact of diversity. Segregation at the country level, by contrast, remains an insignificant determinant of both the probability of unemployment and of overeducated employment in most specifications and all three variables seem to be only very weakly correlated to the probability of being detached from the labour market and to the probability of being in education.

Jel Codes: D83, J71, R23

Keywords: Integration, Networks, Diversity

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Introduction

In most countries migrants are disadvantaged relative to natives in many areas of daily life. For example with respect to labour market integration migrants face substantially lower chances of being employed and higher ones of being unemployed than natives, and when employed also their jobs more often do not match their educational attainment than is the case among natives (see Algan et al. 2010, OECD 2007 and Hierländer et al. 2010 for recent cross-country evidence). Quite a few authors have therefore pointed out that this implies a potential waste of human resources through migration (e.g. Mattoo, Neagu, and Özden 2008) and have analysed the factors influencing the success of migrants in integrating into their host societies' labour markets. Among these factors – aside from the duration of stay in the host country (e.g. Borjas 2000) – regional influences and characteristics have featured prominently. One strand of this literature (e.g. Borjas 1995, Cutler and Glaeser 1997) analyses the impact of ethnic segregation on the economic outcomes of migrants, while another (e.g. Betrand et al. 1998, Patel and Vella 2007) emphasizes the role of ethnic networks. In both these literatures it has been noticed that from a theoretical perspective both networks and segregation could either enhance or hamper integration of migrants.

In this paper we are also interested in the role of ethnic networks and segregation on the integration success of foreign born. Our contribution to this literature is to present a detailed empirical analysis of the impact of the share of foreign born of the same ethnicity residing in the same region as the migrant and segregation on a country level on labour market integration of migrants in 15 countries of the EU. In addition to this we also analyse whether ethnic diversity in a region impacts on migrants' success in integrating into the host countries' labour markets. We argue that ethnic diversity may have either positive or negative effects on the labour market integration of foreign born. The reason for this is that on the one hand complementarities in productivity of different ethnicities may increase labour demand for the foreign born and thus increase chances of integration of migrants, while on the other hand diversity also increases the uncertainty with respect to the quality of migrants (e.g. with respect to skills or other productivity characteristics) and thus makes them more prone to statistical discrimination.

We use micro-data from the European labour force survey to empirically analyse how ethnic diversity and the share of foreign born of the same group of ethnicities residing in a (NUTS 2) region as well as segregation on a country level affect migrant's probability to successfully integrate into labour markets in terms of their probability of employment, unemployment or (for those employed) of being over-educated in a given job as well as on migrants probabilities to be detached from the labour market and to be in education. Distinguishing migrants by their region of birth as well as their duration of stay we derive for each migrant group measures of concentration and diversity at the regional level and of segregation at the national level for 15 EU countries. These measures are then used to explain migrants' probability of successful labour market integration in terms of their probability to be employed, unemployed, over-educated in employment, detached from the labour market and their probability to be in education.

In order to overcome potential biases caused by migrants' non-random location choice we apply fixed effects as well as instrumental variable estimation techniques. As instruments - following Betrand et al. (2000) and Culter et al. (2008) - we use predicted migrant group shares based on the distribution of individuals over different occupations across regions and the EU-wide occupation distribution of each migrant group.

We find a robust negative effect of ethnic networks on both the probability of a migrant to be unemployed and the probability to be overeducated and a positive one on the probability of employment. By contrast, diversity only has a robustly significant positive impact on the probability to be unemployed and a robustly negative one on the probability of employment. This indicates that migrant networks in general facilitate labour market integration but that diversity hampers it through negatively impacting on the selection of migrants into employment and unemployment. Country level segregation by contrast has no robust impact on any of the measures of labour market integration and for the probability of being detached from the labour market as well as for the probability to be in further education none of the variables of interest has a robust significant impact. Interestingly our results also suggest that female and EU migrants profit more from ethnic networks but more highly qualified migrants are more negatively affected by diversity.

Theory and previous Literature

Quite a few studies have analysed the impact of regional neighbourhood characteristics and their impact on individual outcomes before (see Durlauf et al. 2004 for a survey). In the field of migrant integration such studies have mostly focused on the role of migrant networks and enclaves on the success of migrants at integrating into host countries' labour markets. Thus with respect to migrant networks, starting from Caces (1987), it has been repeatedly argued that such networks are an important source of social capital, which allows migrants to mobilize resources (Portes 1995) that inter alia facilitate job matching and labour market integration. A large number of studies analysed the impact of the share of migrants of the same ethnicity residing in a region or neighbourhood on the labour market success of migrants (Patel and Vella 2007) and other economic outcome variables such as entrepreneurship (Toussaint-Comeau 2008) or welfare dependence (Bertrand et al. 1998). Many of these have found positive effects of migrant networks. At the same time, however, some authors (e.g. Pohjola, 1991, Betrand et al. 1998) argue that while migrant networks may initially facilitate integration, they may hinder it in the long run as they reduce incentives to invest into host country specific capital (such as language skills) or facilitate integration into welfare programs. Furthermore a number of contributions (e.g. Betrand et al., 1998, Borjas, 1995, Toussaint-Cammeau, 2008) also argue and present evidence that aside from network size also network quality (for instance measured by the share of same ethnicity persons having experience in a certain activity in the region) has a decisive impact on the effects of networks.

In a similar vein a related literature focuses on the impact of ethnic segregation on labour market outcomes of foreign born. This literature argues that while such segregation may initially facilitate labour market integration of migrants on account of providing ample contacts for newly arriving migrants, it may also hinder success in the long-run for the same reason as mentioned above. In contrast to the literature on migration networks, this literature, as recently pointed out by Cutler et al. (2008), has remained rather inconclusive in its findings. Early studies (e.g. Cutler and Glaeser 1997) find a negative impact of segregation on outcomes of minority group members, while later studies (e.g. Collins and Margo 2000) find no relationship or a reversed relationship and quasi experimental evidence (Piil Damm 2009, Edin et al. 2003) tends to find rather high positive effects of living in an enclave at least for newly arriving migrants.

One aspect of regional characteristics that has been neglected in much of this literature is the potential additional impact of ethnic diversity on migrant integration. This may be relevant because on the one hand a number of empirical examinations for EU regions show that higher ethnic diversity increases productivity and innovation in a region (Brunow and Brenzel 2012, Niebuhr 2010). This may increase labour demand for foreign born in ethnically diverse regions and may thus improve their employment chances. At the same time, however, to the degree that employers have inferior information on the productivity of migrants from smaller migrant groups, such migrant groups could more easily become victims of statistical discrimination. This may lead to them having higher unemployment rates and generally a worse labour market integration in more diverse regions.

To formalize this idea we consider a region in which potential migrants from a total of M countries (indexed by m) live. Labour from these groups is considered to be the only input to production. The productivity (q_i) of a worker (indexed by i) is assumed to be normally distributed with mean μ_m and variance σ_m and is unobservable to firms. Firms only observe group identity and a noisy signal ($\theta_{im} = q_m + \varepsilon_{im}$) that could for instance consist of information on education. We assume that the precision of this signal increases (or equivalently the variance of ε_{im} - which we refer to as $\sigma_{\varepsilon m}$ - decreases) with the share of persons of the respective migrant group residing in a region. This is equivalent to assuming that (given population size and the total share of migrants living in a region) signal quality is negatively related to ethnic diversity or that $\sigma_{\varepsilon m} = \sigma(div_r)$ with $\sigma^{'} > 0$.

As amply demonstrated in the literature on statistical discrimination (see Fang and Moro, 2010 for a survey), given the signal, expected productivity of a member of ethnic group m is given by:

$$E(q_m|\theta) = \frac{\sigma_m}{\sigma_m + \sigma_{\varepsilon m}}\theta + \frac{\sigma_{\varepsilon m}}{\sigma_m + \sigma_{\varepsilon m}}\mu_m \quad (1)$$

which is falling in the variance of the signal ($\sigma_{\varepsilon m}$) – or increasing in diversity – for workers with a high signal i.e. $\mu_m < \theta$ and increasing in the variance of this signal (or decreasing in diversity) for workers with a low signal $\mu_m > \theta$, so that for high signal quality expected productivity increases with better signal quality but decreases with signal quality for low signal workers. In consequence diversity should affect low ability workers more negatively than high ability workers.

Furthermore, to keep our line of argument as simple as possible, we also assume that labour is the only input to production and that the expected marginal product of a worker is positively influenced by the diversity of the economy (given by $y = \alpha(div_r)E(q_m|\theta)$ with $\alpha'(div_r) > 0$) and wages are assumed to be the same for all workers with the same observable characteristics (i.e.$w = w(\theta)$). Therefore all workers with signals such that:

$$w(\theta) \leq \alpha(div_r)E(q_m|\theta) = \alpha(div_r)\left[\frac{\sigma_m}{\sigma_m + \sigma_{\varepsilon m}}\theta + \frac{\sigma_{\varepsilon m}}{\sigma_m + \sigma_{\varepsilon m}}\mu_m\right] \quad (2)$$

will find employment in a job adequate for their signal quality. Defining $\bar{\theta}$ as the level of θ which solves equation (2) with strict equality and taking the implicit derivative it is easy to show that an increase in the diversity of a region has two effects on the labour market situation of migrants. First, due to the hypothesized increase in productivity in more diverse regions the critical signal level at which no employment in a job adequate for the level of qualification can be found unambiguously falls. This should lead to more diverse regions offering better chances of labour market integration to foreign born. At the same time with increasing diversity the signal quality $\sigma_{\varepsilon m}$ will fall. This in turn will increase the critical signal level at which no employment in a job adequate for the level of qualification can be found for a worker with $\theta > \mu_m$. This may lead to a negative net effect of higher diversity if the signal θ is sufficiently large relative to μ_m.

Data

In sum theoretical considerations suggest that aside from networks and segregation also higher regional diversity may have an impact on the labour market integration of foreign born. The sign of this impact, however, is ambiguous and may be non-linear in the degree of diversity in the region but is more likely to be negative for workers with lower measured ability. The main goal of the current paper is therefore to analyse how the three variables discussed above (networks, ethnic diversity and ethnic segregation) impact on the labour market outcomes of migrants in terms of unemployment and over-qualification. The data we use for this purpose is taken from the individual data provided in the scientific use files of the ELFS for the years 2004 to 2011.

This representative survey conducted in all EU27-countries asks respondents on their country of birth and (if born abroad) on their duration of stay in the respective country as well as on a number of demographic characteristics (such as age, gender, marital status number of children and many others) and their labour market status (which may be employed, unemployed and inactive) according to the standard ILO definitions. Furthermore, persons in paid employment for at least one hour in the week preceding the interview are interviewed on their workplace characteristics (e.g. branch of employment and occupation). From the data the number and structure of foreign born (according to a limited number of sending country groups) residing in a region of the EU27 countries as well as their employment status can therefore be calculated and occupations can be matched to educational attainment to allow measurement of education-job mismatch.

While this data therefore provides the necessary conditions for our research there are also a number of drawbacks. The first of these is that the German LFS does not ask the question on country of birth but only poses a question for nationality of the respondent. This leads us to have to exclude Germany from the analysis.[2] The second is that these data also contain only a sample of the households in the EU27 and is therefore subject to sampling error. In some countries, where only few foreign born reside, therefore samples are too small to allow for an analysis. Thus some of the new member states of the EU (Bulgaria, Romania, Slovenia and Poland) have to be omitted from the analysis. Other countries have only one region. This is not appropriate for our purpose since, as discussed below, our segregation measure is only available for countries with more than one region. We therefore also have to omit Cyprus, Denmark, Estonia, Latvia, Luxembourg, Lithuania and the Netherlands from the analysis. As a consequence our analysis can be conducted on a set of 15 EU countries covering 146 regions.

Dependent Variables

Among the many variables in which differences between natives and foreign born exist we are particularly interested in unemployment, employment and education-job mismatch as well as in the probability to be detached from the labour market and the

[2] We give preference to data on country of birth rather than nationality because the later would lead to distortions on account of different naturalization laws across countries.

probability to participate in education beyond the compulsory level. In the ELFS employment and unemployment is measured according to the ILO/EU definition so that an internationally comparable measure of these two variables is provided in the data. Furthermore, the ELFS also asks respondents on whether they attended any training in the four weeks preceding the interview and whether persons aged older than 16 participated in education or training at the time of the interview. From these data it is therefore possible to construct measures of whether a person is detached from the labour market (which we consider to be the case when the person is neither employed nor in training or education), or in full time education[3] at the time of the interview.

Table 1: Correspondence of major occupation groups (ISCO-88) and required education levels (ISCED-97)

ISCO-88 Major groups	Required education level according to OECD (2007)	
1: Legislators, senior officials and managers	High-skilled	ISCED 5,6
2: Professionals		ISCED 5,6
3: Technicians and associate professionals		ISCED 5,6
4: Clerks	Medium-Skilled	ISCED 3,4
5: Service workers and shop and market sales workers		ISCED 3,4
6: Skilled agricultural and fishery workers		ISCED 3,4
7: Craft and related trades workers		ISCED 3,4
8: Plant and machine operators and assemblers		ISCED 3,4
9: Elementary occupations	Low-skilled	ISCED 0,1,2
(0: Armed forces)	No assignment	

Source: OECD (2007)

In addition to these variables we also include the probability of job-education mismatch in our analysis, because recent evidence shows that even when employed foreign born disproportionately often have jobs that do not match their skill levels (OECD 2007, Hirländer et al. 2010) and that such job-education mismatch often causes substantial income loss to natives (McGuinness 2006) and even more so to foreign born (Nielsen, 2011). To

3A person who is a student or apprentice in regular education during the last 4 weeks is considered as being in full time education.

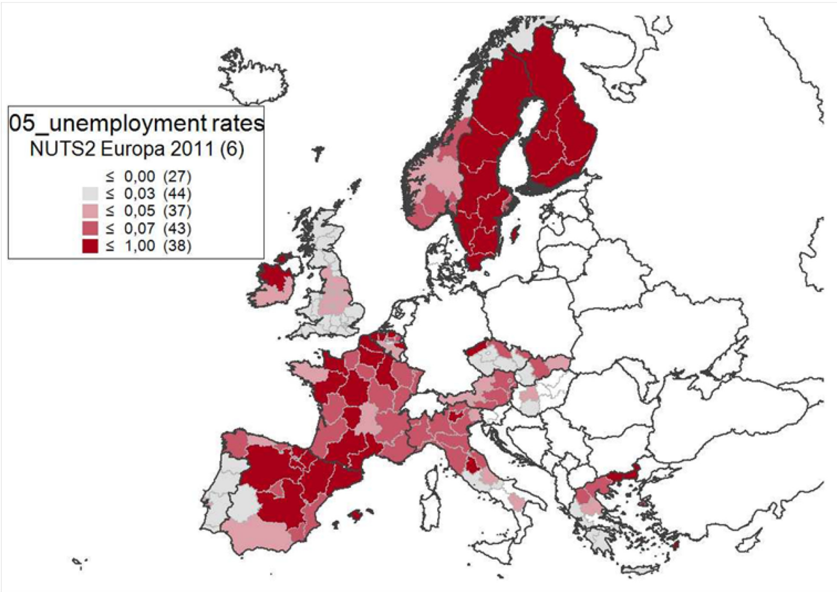
measure this education-job mismatch we follow OECD (2007) and use the link between the standard international taxonomy of educational attainment (ISCED) and the international classification of occupations (ISCO) at the 1 digit level suggested by OECD (2007) (see table 1).[4] According to this link high education levels (i.e. ISCED 5 and 6) are required from legislators, senior officials and managers as well as professionals and technicians and associate professionals. Low education levels (ISCED 0, 1 and 2) are required for elementary occupations and all other occupations are associated with intermediate education levels.

Based on these reference levels, education-job mismatch is measured by comparing a persons' highest completed education to that required in her/his occupation. A person is over-educated if educational attainment is higher than required for his/her occupation and under-educated if educational attainment is lower than required for the occupation. Over- and under-education are thus characteristics of the employee relative to his/her occupation: Highly educated workers cannot be under-educated (as there are no occupations requiring higher educational attainment than high education) and less educated workers cannot be over-educated (since there are no occupations requiring education lower than low education).

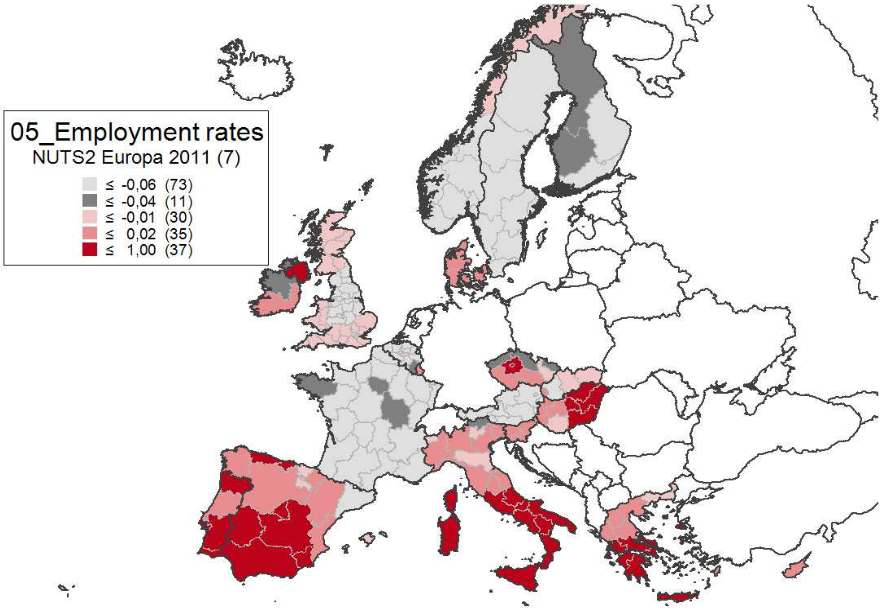
[4] Chiswick and Miller (2012) provide a recent discussion of the pro's and con's of alternative measures of over-education and Huber (2011) compares the chosen measure to some alternatives. The use of this measure – aside being justified on pragmatic grounds, as it is the only one available – is also justified because it provides an internationally comparable measure that is highly correlated with both more disaggregated analyses and with measures based on realized job matches (Hartog 2000).

Figure 1: Differences in unemployment and employment rates between foreign born and natives across NUTS2 regions (average 2004 to 2011)

Unemployment rates



Employment rates

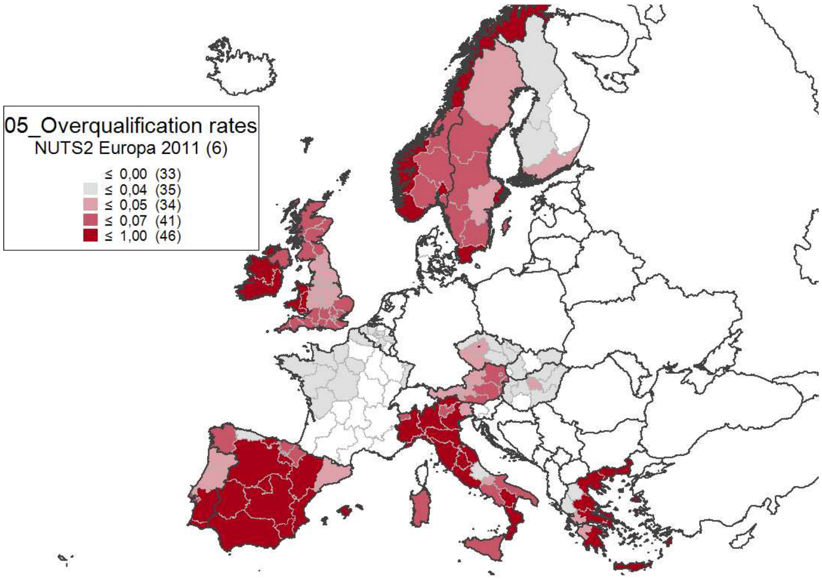


Source: EUROSTAT LFS 2004 to 2011, own calculation.

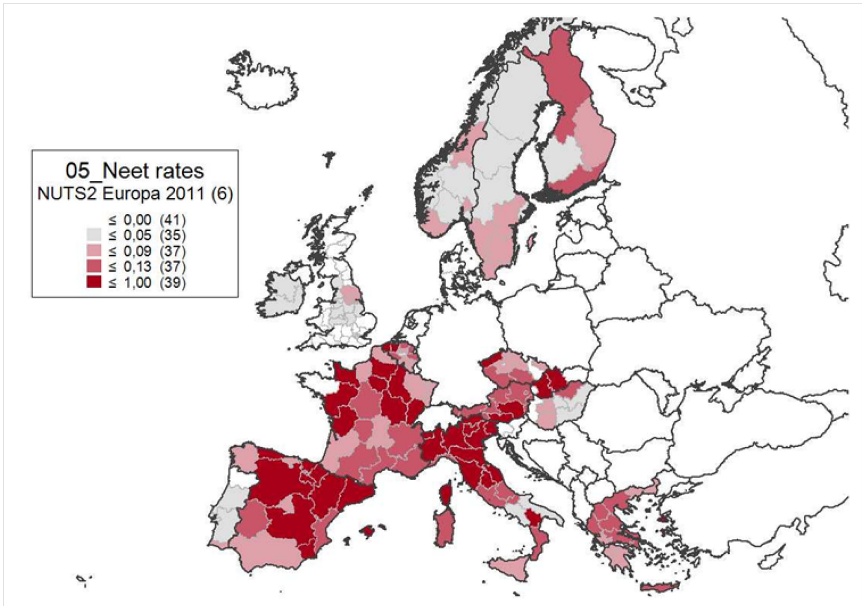
In constructing these variables we focus on the active aged foreign born (16 to 65 years old) population. The reason for this is that this group can be expected both to still be active in the labour market and is also the most relevant for analysis when considering further education (beyond compulsory education).

Figure 2: Differences in over-education rates and share of persons detached from the labour market between foreign born and natives across NUTS2 regions (average 2004 to 2011)

Over-education rates

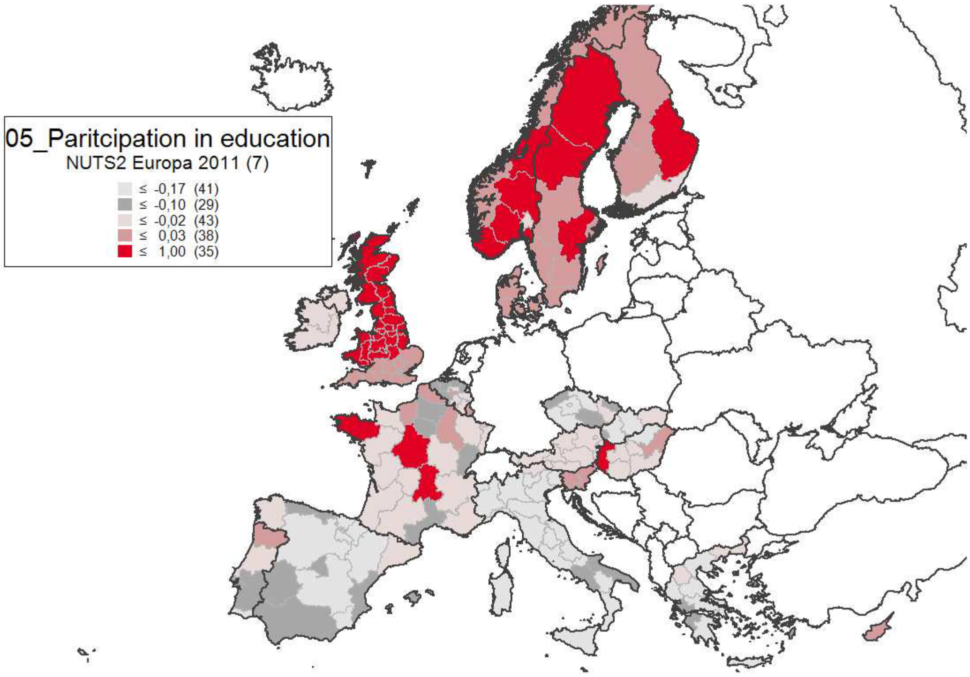


Share of persons detached from the labour market[1)]



Source: EUROSTAT LFS 2004 to 2011, own calculation. 1) Share of persons detached from the labour market = persons that are neither employed nor in education or training.

Figure 3: Difference in education participation rates between foreign born and natives across NUTS2 regions (average 2004 to 2011)



Source: EUROSTAT LFS 2004 to 2011, own calculation.

Figures 1 to 3 show the regional distribution of the difference in unemployment, over-education, employment, and education participation rates as well as in the share of persons detached from the labour market between the foreign born and natives by NUTS2 regions for the average of the years 2004 to 2011 in the ELFS. According to these figures the regions where foreign born are most disadvantaged relative to natives in terms of unemployment rates are located in the South of Europe (Spain and Greece) but also in the North of the EU (i.e. Finland and Sweden). The largest differences in employment rates between natives and foreign born are, by contrast, found in southern Spain and Italy, but also in Greece and eastern Hungary.

The largest differences in over-education rates between foreign born and natives are found in Spain, northern and central Italy, Greece, and Ireland, while differences between natives and foreign born in terms of detachment from the labour market are spatially more dispersed but tend to be high in northern Spain and Italy as well as southern Austria and western Slovakia. Finally, differences in participation rates in full-time education between foreign born and natives are highest in the Nordic countries and in the UK. This therefore suggests that aside from unemployment, over-qualification and detachment rates from the labour market being markedly higher among the foreign born than among natives in most EU regions (and employment as well as participation in education rates being lower), there is also a spatial pattern to these differences, which seems to be closely related to the extent of recent migration in particular when over-education is considered. The three countries with the highest over-education rates among the foreign born (Spain, Ireland and UK) are also countries that have experienced a substantial inflow of migrants (in particular from the NMS) recently.

Explanatory Variables

Our central explanatory variables of interest are first of all the share of population born in the same country group and living in the same NUTS 2 region as the migrant considered. We consider this a proxy of migrants' same ethnicity networks in the region. Second of all we are interested in the ethnic diversity of the region. We measure this in two alternative ways: First following Brunow and Brenzel (2012), Easterly and Levine (1997) and Alesina et al., (2002) diversity is measured by the fractionalization index. This is calculated as:

$$div_{rt} = 1 - \sum_{m=1}^{M} {s_{mrt}}^2 \qquad (4)$$

where s_{mrt} is the share of population of ethinicity group m (of M groups in total), residing in region r at time t. This index is therefore distributed on the interval between 0 and $1 - 1/M^2$ with 0 indicating no diversity and $1 - 1/M^2$ the maximum diversity possible.

Second, since the fractionalisation index puts a very strong emphasis on large migrant groups (as pointed out by Gold and Dohse (2013)), while our theory suggests stronger effects for small groups we also use the Shannon index as an alternative measure of diversity. This is given by:

$$H_{rt} = -\sum_{m=1}^{M} s_{mrt} \ln(s_{mrt}) \quad (5)$$

This index takes on the value of 1/M when all ethnic groups are equally represented in a region and declines with the inequality of the distribution of ethnicities in a region. It reaches zero when only one ethnicity resides in a region.

In addition we also include ethnic segregation of a group in a certain country as measured by the dissimilarity index used by Cutler et al (2008). This is calculated as:

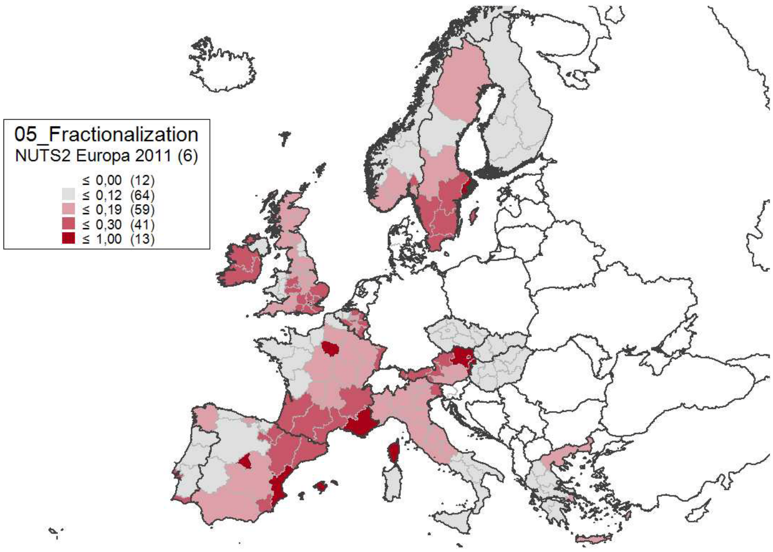
$$Dis_{rt} = \frac{1}{2}\sum_{r=1}^{R} \left|\frac{s_{rm}}{s_{cm}} - \frac{s_{ro}}{s_{co}}\right| \quad (5)$$

where s_{rm} is the population share of migrant group m residing in region r, s_{cm} is the population share of the same group in the respective EU country and s_{ro} and s_{co} is the population share of all other groups in the region and the country, respectively. This index takes on values between zero and one. A value of zero indicates that the respective ethnicity is distributed across the regions in the same way as the overall population in the country and a value of one indicates that all of the ethnicity resides in regions where no other ethnicity lives and thus signalling complete segregation.

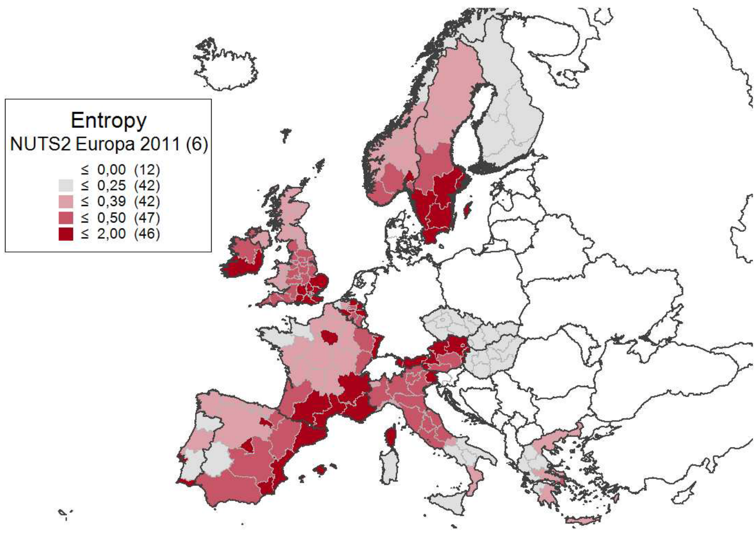
For the calculation of these indexes as well as the population share of the same ethnicity the ELFS provides the possibility to differentiate between 8 groups of migrants. These are migrants from other EU15 countries, NMS, other European Countries, North Africa and the near East, other African countries, Asia, South America and the rest of the world.

Figure 4: Fractionalisation and Shannon index according to ELFS data (average 2004 to 2011)

Fractionalisation Index



Shannon Index



Source: EUROSTAT LFS 2004 to 2011, own calculation.

Both the fractionalisation index as well as the Shannon index are particularly high in southern Spain and France, northern Austria, southern Sweden and also southern UK (see Figure 4). The lowest diversity regions, by contrast, are located in EU member states that joined the EU in 2004 (the Czech Republic, Slovakia, Hungary and Romania) as well as in Finland, which as a rule also have a rather low share of foreign born living in their regions. Furthermore, these two indexes are also highly correlated although in individual regions (such as parts of Ireland and southern Spain) they lead to slightly different results (see figure 4 and Dohse and Gold, 2013 for a detailed description).

Figures A1 to A4 in the appendix augment this information by data on the share of foreign born of a certain sending country group residing in a particular region. These data largely confirm prior expectations. The share of migrants from EU-15 countries residing in a region is largest in central and southern France, northern Austria and in the Scandinavian countries and thus reflects the high migration from Germany to Austria and between Scandinavian countries. By contrast, the share of migrants from other EU-member states in the population is highest in Spain, northern Italy and Austria but also in Ireland. This reflects the migration trends that have characterized European east-west migration since the fall of the iron curtain and the accession of these countries to the EU in 2004, respectively 2007.

In addition migrants from other European countries often reside in Austria, Italy and Greece but also (on account of a large share of Russians) in the Baltic countries, while migrants from northern Africa and the near East mostly settle in the south of Spain and in large parts of France, but also in the south of Sweden. Asians are concentrated in the UK and the Scandinavian countries, while south Americans mostly live in Spain and Portugal.

Furthermore, other African migrants are an important share of the population in Portugal (on account of Portuguese speaking colonies in Africa), but also in the South of the UK and North of France.

Table 2 shows the segregation index. As could be expected - migrants from EU15 as well as other European countries and the NMS are less segregated groups of migrants in most countries, while the smaller groups of migrants from other African countries and Asia as well as from South-America are often among the most segregated groups in their respective receiving countries. When considering the segregation index across all 146 regions migrants from Asia are the most segregated, while migrants from the EU15 countries are least segregated just after natives.

Table 2: Segregation by sending country groups

	Native	EU-15	NMS	other Europe	north Africa and Near East	other Africa	Asia	South America	rest of the world
AT	0.139	0.125	0.228	0.124	0.235	0.252	0.278	0.152	0.145
BE	0.282	0.292	0.336	0.253	0.427	0.314	0.251	0.278	0.386
CZ	0.151	0.269	0.142	0.281	0.287	0.302	0.283	0.34	0.342
ES	0.223	0.203	0.312	0.207	0.247	0.276	0.324	0.269	0.254
FI	0.183	0.085	0.304	0.214	0.255	0.296	0.203	0.142	0.217
FR	0.274	0.193	0.304	0.307	0.304	0.349	0.404	0.339	0.395
GR	0.168	0.212	0.232	0.163	0.385	0.312	0.468	0.233	0.233
HU	0.173	0.266	0.188	0.17	0.302	0.302	0.422	0.332	0.338
IE	0.013	0.077	0.033	0.109	0.113	0.069	0.094	0.014	0.042
IT	0.160	0.102	0.234	0.201	0.23	0.281	0.276	0.161	0.258
NO	0.200	0.146	0.188	0.152	0.354	0.248	0.301	0.267	0.23
PT	0.278	0.167	0.464	0.197	0.392	0.413	0.447	0.239	0.259
SE	0.142	0.119	0.216	0.136	0.17	0.239	0.128	0.204	0.242
SK	0.186	0.276	0.178	0.302	0.37	0.318	0.334	0.332	0.358
UK	0.319	0.234	0.225	0.44	0.33	0.357	0.282	0.334	0.473
EU-wide	0.327	0.345	0.359	0.454	0.452	0.375	0.43	0.403	0.518

Source:: European labour force survey, own calculations.

Table 3: Means of individual level controls by sending country group

	Native	EU-15	NMS	other Europe	north Africa and Near East	other Africa	Asia	South America	rest of the world	Overall
Share own group	0,91	0,04	0,02	0,03	0,05	0,04	0,04	0,02	0,05	0,81
Dissimilarity Index	0,22	0,19	0,24	0,21	0,28	0,34	0,29	0,29	0,27	0,23
Fractionalization	0,17	0,26	0,24	0,23	0,28	0,31	0,30	0,30	0,27	0,18
Entropy	0,36	0,65	0,50	0,50	0,66	0,63	0,65	0,57	0,58	0,38
Share unemployed	0,09	0,09	0,09	0,08	0,10	0,08	0,07	0,09	0,12	0,09
Share Female	0,50	0,52	0,55	0,53	0,46	0,49	0,51	0,56	0,55	0,50
Age 15-19	0,09	0,04	0,05	0,07	0,04	0,06	0,04	0,05	0,08	0,08
Age20-24	0,09	0,06	0,11	0,09	0,06	0,09	0,09	0,08	0,10	0,09
Age 25-29	0,10	0,09	0,20	0,13	0,10	0,12	0,14	0,13	0,15	0,10
Age 30-34	0,11	0,11	0,19	0,15	0,12	0,15	0,16	0,15	0,18	0,11
Age 35-39	0,11	0,14	0,14	0,15	0,13	0,15	0,15	0,15	0,15	0,11
Age 40-44	0,11	0,14	0,10	0,13	0,13	0,14	0,12	0,13	0,13	0,11
Age 45-49	0,11	0,12	0,08	0,11	0,12	0,11	0,11	0,11	0,09	0,11
Age 50-54	0,10	0,11	0,06	0,08	0,11	0,09	0,09	0,09	0,06	0,10
Age 55-59	0,10	0,11	0,04	0,06	0,11	0,06	0,06	0,07	0,04	0,10
Age 60-64	0,09	0,10	0,03	0,04	0,08	0,03	0,04	0,05	0,02	0,08
Low education	0,37	0,35	0,27	0,45	0,55	0,36	0,38	0,23	0,40	0,37
Medium Education	0,41	0,35	0,54	0,38	0,27	0,35	0,35	0,38	0,39	0,41
High Education	0,22	0,30	0,19	0,17	0,17	0,29	0,27	0,39	0,20	0,22
Share married	0,51	0,56	0,55	0,65	0,67	0,53	0,67	0,50	0,49	0,52

Source: European labour force survey, own calculations

Furthermore, there are also some important differences in demographic characteristics between different migrant groups in the EU (table 3). These apply in particular to age, educational status and gender. Migrants from the rest of the world (which inter alia include many of the developed OECD countries of America and Oceania) are the most highly educated group of migrants in the EU and together with migrants from other EU countries, the near middle East Africa and Asia have a higher share of tertiary educated migrants than natives. Migrants from the NMS, by contrast, disproportionately often have an intermediary education, while North African, South American migrants and migrants from other European (non-EU) countries belong to the less qualified migrant groups in the EU. Migrants from the NMS are also more often female than natives, while migrants from North Africa are more often male. One common theme is that migrants irrespective of their sending region are underrepresented among the youngest (i.e. the 15 to 19 year olds) and oldest (60 to 64 year olds) age groups in the population.

Empirical strategy

For our baseline analysis we relate the explanatory variables to the measures of labour market integration in a linear probability model, in which – aside from networks, segregation and diversity – we also include the duration of stay of the respective migrant in the respective country. The reason for this is that this variable has been shown to be the uniformly most important individual level determinant of labour market integration of foreign born (e.g. Borjas 2000, Chiswick 1978). Furthermore, we also control for gender, age, marital status and the highest level of educational attainment of migrants, since these variables have been shown to be important predictors of both the probability to be unemployed as well as the probability to be over-educated in the current job (e.g. Verdugo and Verdugo 1989). In addition we also include for each outcome variable its corresponding regional aggregate rate in the period under consideration (i.e. unemployment, over-education, employment, detachment from the labour market and education participation rates) to account for time varying changes in labour market conditions of regions. Finally, also a full set of sending country, region and year fixed effects is included to control for all effects stemming from (time invariant) sending country or region characteristics and common business cycle effects. The baseline specification of the linear probability model therefore reads:

$$y_{i(m)rt} = \alpha_0 + \alpha_1 share_{mrt} + \alpha_2 div_{rt} + \alpha_3 seg_{mct} + \alpha_1 dur_{i(m)rt} + \beta X_{i(m)rt} + \gamma Z_{rt} + \rho + \mu + \tau + \zeta_{i(m)rt} \quad (6)$$

Where $y_{i(m)rt}$ is a variable that takes the value of one if the migrant (i) from sending country (m), residing in region (r) at time (t) – depending on the specification analysed - is unemployed, overqualified, employed, detached from the labour market or in full time education and zero else. $share_{mrt}$, div_{rt}, seg_{mct}, are the share of same origin migrants residing in the region, ethnic diversity and segregation while $dur_{i(m)rt}$ is the duration of residence of the migrant from sending country group m in the respective country and $X_{i(m)rt}$ are individual level while Z_{rt} are time varying regional characteristics. ρ, μ and τ, finally, are region, sending country and time fixed effects, respectively.

There are a number of methodological issues involved in estimating specifications such as equation (6) (see: Dujardin and Goffette-Nagot 2010). The most important of these is probably endogeneity of the measures of networks, segregation and diversity. This may arise either from omitted variables bias or from the fact that migrants are likely to choose their region of residence according to where their chances of integration are highest. As pointed out by for instance Bertrand et al. (2000) with respect to the first of these problems, using data from more than one time period that allows controlling for region of residence, sending country and time fixed effects should do away with many of the missing variable problems that plague standard cross-sectional analyses on this topic.

This is, however, unlikely to deal with the endogeneity of the choice of regions of residence. Dujardin and Goffette-Nagot (2010) in their summary suggest a number of ways to deal with this issue. Aside from quasi experimental techniques or the use of sibling data, for which we do not have the necessary data, these consist of focusing on a group of persons that is unlikely to have had a choice in their original location decision. One such group could for instance be persons, who moved to a particular country as children and whose location decision was therefore taken by their parents. This route unfortunately is not open to us since the ELFS does not provide information on the circumstances under which migrants moved to their country of residence and focusing only on those that arrived at a very young age would lead to a very low number of observations and would shift the focus of our study on only very young migrants.

A second approach would be to rely on the cross-country variation in dependent variables as for instance in Cutler and Glaeser (1997), who argue that endogeneity bias can be minimized by considering whether more segregated cities in aggregate have better labour market outcomes for certain ethnic groups. This approach, however, can only be used in the case of certain variables (such as the segregation variable where we use this method by focusing only on the between country variation in segregation) and also requires rather strong assumptions on the comparability of segregation measures across regions. As a consequence our preferred identification strategy is to apply instrumental variables. Here we follow Betrand et al. (2000) and Cutler et al. (2008) and use a prediction of the share of foreign born by applying their occupational structure across NUTS2 regions of Europe as an instrument.

The validity of the instrumental variable estimation approach rests on the assumption that the instrument chosen fulfils the exclusion restriction – i.e. the instrument should affect the outcome variable of interest only via its effect on the endogenous variable without affecting the outcome variable directly. In our case the instrument is derived as the predicted share of each migrant group that would be observed within each region based on the EU wide distribution of the migrant groups across occupations and the prevalence of these occupations within each region. While these predicted shares are highly correlated with actual shares observed within regions they are unlikely to affect individual workers labour market prospects within regions since they are based on EU wide occupation structures.

Results

Tables 4 and 5 show linear probability model estimation results from OLS and IV regressions for the probability of unemployment, employment, to be over-educated, to be detached from the labour market and to be in full time education for the full sample of migrants when using the Shannon and the fractionalisation index as a measure of diversity, respectively. In these estimations observations are weighted by so as to represent the total population and standard errors are cluster corrected by region and year.

The results of the OLS estimates with respect to both networks and diversity are very similar irrespective of whether the fractionalisation or Shannon index is used. Both specifications indicate a significant negative impact of migrant networks (i.e. the share of own ethnicity migrants residing in the region) on the probability of a foreign born to be unemployed and a positive one on the probability of a foreign born to be employed. For the probability to be detached from the labour market or to be in education this variable remains insignificant. Diversity is significantly negatively correlated with the probability of employment but significantly positively with both the probability of overeducated employment and unemployment of the foreign born, irrespective of whether the fractionalisation or the Shannon index is used to measure it. In addition when using the Shannon index diversity significantly increases the probability of a foreign born to be detached from the labour market or in full time training, while when using the frationalisation index, diversity has no impact on these two variables.

For the segregation index OLS results, however, differ slightly between the two specifications. When using the fractionalisation index as a measure of diversity, segregation is significantly negatively correlated with the probability of being employed and of being overeducated but weakly significantly positively with the probability to be detached from the labour market. When using the entropy index as a measure of diversity, by contrast, an additional positive significant effect of segregation on the participation in education of the foreign born is added.

These results, however, have to be interpreted with care, since they do not account for the potential endogeneity of the settlement structure of the foreign born. Once we instrument for the share of foreign born of the same ethnicity, segregation and diversity by their predicted values on the basis of the occupation structure of foreign born from their respective region in a country, the negative impact of segregation and diversity on the probability of overeducated employment disappears when using fractionalisation as a measure of diversity and is reduced to a weakly significantly negative impact of segregation when using the Shannon index. The share of own ethnicity migrants residing in the region, by contrast, emerges as a significant negative determinant of the probability of overeducated employment in both specifications. The coefficient for this variable suggests that a 1 percentage point increase in the share of population of same ethnicity migrants in a region reduces the probability of overeducated employment of foreign born by 0.8 to 0.9 percentage points. By contrast, the share of foreign born of the same ethnicity, segregation and diversity all remain insignificant in the IV-estimates of the probability to be detached from the labour market as well as for the probability to be in full time education.

The unemployment and employment equations, by contrast, are more robust. Here both the share of the own ethnicity group residing in the same region as well as diversity remain to be significant for the probability of unemployment and employment of foreign born while segregation turns insignificant for both measures of diversity. According to the point estimates of the parameters a 1 percentage point increase in the share of same ethnicity migrants residing in the same region reduces the unemployment probability of foreign born by 0.7 to 0.8 percentage points, while a unit increase in the fractionalisation or the Shannon index increases this probability by 0.2 percentage points. Similarly, the point estimates in the employment probability equation imply that a 1 percentage point increase in the share of same ethnicity migrants increases the employment probability of a foreign born by 1.0 to 1.3 percentage points, while a unit increase in diversity reduces this probability by 0.3 to 0.7 percentage points, depending on the measure of diversity used.

Table 4: OLS and IV estimates for the sample of all migrants using fractionalisation as a measure for diversity

Independent Variable	P(unemployed)	P(overeducated)	P(employed)	P(neet)	P(participation in education)
			OLS Regressions		
Share own group	-0.29***	-0.04	0.40***	-0.05	0.12
	(0.073)	(0.105)	(0.087)	(0.138)	(0.139)
Segregation	0.00	-0.21***	-0.11***	0.08*	0.09
	(0.025)	(0.049)	(0.032)	(0.045)	(0.057)
Fractionalization	0.16**	-0.23**	-0.45***	0.13	0.17
	(0.067)	(0.110)	(0.093)	(0.143)	(0.146)
Female	0.03***	0.09***	-0.20***	0.07***	0.04***
	(0.003)	(0.005)	(0.004)	(0.005)	(0.006)
Medium education	-0.03***		0.08***	-0.08***	0.06***
	(0.002)		(0.005)	(0.006)	(0.006)
High Education	-0.05***	0.17***	0.14***	-0.12***	0.07***
	(0.003)	(0.007)	(0.008)	(0.009)	(0.015)
Years of residency	-0.00***	-0.01***	0.01***	-0.01***	0.01***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Married	-0.01**	-0.02***	-0.04***	0.28***	-0.23***
	(0.003)	(0.004)	(0.004)	(0.011)	(0.007)
Observations	577,002	304,812	822,101	128,029	128,029
R-squared	0.074	0.153	0.191	0.156	0.292
			IV- Regressions		
Share own group	-0.72***	-0.83***	1.29***	-0.52	0.03
	(0.217)	(0.287)	(0.221)	(0.377)	(0.373)
Segregation	-0.10	-0.29	0.18	0.17	-0.29
	(0.168)	(0.190)	(0.177)	(0.244)	(0.249)
Fractionalization	0.22**	-0.05	-0.65***	0.04	0.22
	(0.090)	(0.156)	(0.123)	(0.181)	(0.182)
Female	0.03***	0.09***	-0.20***	0.07***	0.04***
	(0.003)	(0.005)	(0.004)	(0.005)	(0.006)
Medium education	-0.03***		0.08***	-0.08***	0.06***
	(0.002)		(0.005)	(0.006)	(0.006)
High Education	-0.05***	0.17***	0.14***	-0.12***	0.07***
	(0.003)	(0.007)	(0.008)	(0.010)	(0.014)
Years of residency	-0.00***	-0.01***	0.01***	-0.01***	0.01***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Married	-0.01**	-0.02***	-0.04***	0.28***	-0.23***
	(0.003)	(0.004)	(0.004)	(0.011)	(0.008)
Observations	577,002	304,812	822,101	128,029	128,029
R-squared	0.053	0.109	0.175	0.126	0.260

Source: European labour force survey, own calculations. All estimations include age-group, region (NUTS2), sending country group and year dummies. Additional controls are the region specific unemployment and over-education rates. Standard errors are clustered at the region and year level. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively. Instruments are predicted shares of nationality based on national occupation structure. P(neet)=probability to be neither employed nor in education or training. First stage F-Statistics larger than 10 for all instruments in all specifications.

Table 5: OLS and IV estimates for the sample of all migrants using the Shannon Index as a measure for diversity

Independent Variable	P(unemployed)	P(overeducated)	P(employed)	P(NEET)	P(participation in education)
			OLS Regressions		
Share own group	-0.29***	-0.04	0.39***	-0.05	0.06
	(0.072)	(0.105)	(0.086)	(0.140)	(0.081)
Seggrgation	0.00	-0.21***	-0.11***	0.08*	0.11***
	(0.025)	(0.049)	(0.032)	(0.045)	(0.034)
Shannon Index	0.08**	-0.11**	-0.20***	0.06	-0.01
	(0.033)	(0.051)	(0.044)	(0.351)	(0.038)
female	0.03***	0.09***	-0.20***	0.07***	0.03***
	(0.003)	(0.005)	(0.004)	(0.005)	(0.003)
Medium education	-0.03***		0.08***	-0.08***	0.05***
	(0.002)		(0.005)	(0.006)	(0.004)
High Education	-0.05***	0.17***	0.14***	-0.12***	0.06***
	(0.003)	(0.007)	(0.008)	(0.010)	(0.007)
Years of residency	-0.00***	-0.01***	0.01***	-0.01***	0.00***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Married	-0.01**	-0.02***	-0.04***	0.28***	-0.11***
	(0.003)	(0.004)	(0.004)	(0.011)	(0.004)
Observations	577,002	304,812	822,101	128,029	234,503
R-squared	0.074	0.153	0.191	0.156	0.349
			IV-Regressions		
Share own group	-0.77***	-0.87***	1.02***	-0.53	0.05
	(0.210)	(0.278)	(0.206)	(0.361)	(0.220)
Seggrgation	-0.13	-0.31*	0.10	0.16	-0.06
	(0.163)	(0.186)	(0.171)	(0.232)	(0.152)
Shannon Index	0.21***	0.03	-0.28***	0.04	0.04
	(0.050)	(0.106)	(0.072)	(0.122)	(0.068)
female	0.03***	0.09***	-0.20***	0.07***	0.03***
	(0.003)	(0.005)	(0.004)	(0.005)	(0.003)
Medium education	-0.03***		0.08***	-0.08***	0.05***
	(0.002)		(0.005)	(0.006)	(0.004)
High Education	-0.05***	0.17***	0.17***	-0.12***	0.03***
	(0.003)	(0.007)	(0.007)	(0.010)	(0.007)
Years of residency	-0.00***	-0.01***	0.01***	-0.01***	-0.00
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Married	-0.01**	-0.02***	-0.02***	0.28***	-0.15***
	(0.003)	(0.004)	(0.004)	(0.011)	(0.005)
Observations	577,002	304,812	822,101	128,029	234,503
R-squared	0.052	0.109	0.139	0.126	0.314

Source: European labour force survey, own calculations. All estimations include age-group, region (NUTS2), sending country group and year dummies. Additional controls are the region specific unemployment and over-education rates. Standard errors are clustered at the region and year level. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively. Instruments are predicted shares of nationality based on national occupation structure. P(neet)=probability to be neither employed nor in education or training. First stage F-Statistics larger than 10 for all instruments in all specifications.

The control variables in all these specifications as well as in all other specifications presented below are well in line with the theoretical expectations and the results in the previous literature. They suggest that more highly educated foreign born have a lower unemployment probability and a lower probability to be detached from the labour market as well as a higher employment probability and a higher probability to be in education but also a higher probability of overeducated employment. Female migrants all else equal have a (0.03 percentage point) higher unemployment and a 0.1 to 0.2 percentage point lower employment probability and a 0.09 percentage point higher probability to be overeducated in their employment than males, while they have a 0.07 percentage points higher probability to be detached from the labour market and a 0.04 percentage point higher probability to be in full time education. Married migrants are less often unemployed and less often overeducated, but also less often employed and in education and thus more often detached from the labour market. Finally, for all dependent variables the labour market integration is better for foreign born with a longer duration of stay in the host country. An extra 10 years of stay reduces the unemployment, over-education and detachment from the labour market probabilities of foreign born by around 0.1 percentage points each, and increases the probability of employment and to be in education by about the same amount.

Table 6 extends these results in a number of ways.[5] First, we interact migrant networks, segregation and diversity with the duration of stay of the respective migrant because a number of studies (e.g. Borjas 1995) argue that networks and segregation are particularly beneficial to recent migrants but may be harmful for integration of established migrants. As can be seen from the columns labelled (1) in table 6 this hypothesis is largely rejected for the unemployment specification and for the specification focusing on the

[5] This table reports results using fractionalization as diversity measure. Table 6a in the appendix augments this with results using the Shannon index.

probability to be detached from the labour market as well as for the specification for participation in education. In all these specifications (except for the unemployment equation when the Shannon index is used as a measure of diversity) the interactions of our key dependent variables with years of residence remain insignificant. These specifications, however, reconfirm our finding of a significant negative impact of migrant networks on the unemployment risk and a positive one on the employment probability as well as the finding of insignificant effects of these variables on the probability to be detached from the labour market and the participation in education. Although the impact of ethnic networks increases substantially in size in the unemployment regression both these variables remain significant in this specification. In the detachment from the labour market and participation in education equations both variables remain to be insignificant and their size is also less influenced by the inclusion of duration of stay interaction.

In the over-education and the employment equations, by contrast, some evidence for a diminishing positive effect of network size on migrants with an increasing duration of residence in the respective country can be found. The coefficient of the interaction term of the share of own ethnicity migrants residing in the region and the duration of stay has a significantly positive impact on the rate of over-education and a negative one on the employment probability. Established migrants living in regions with a large share of migrants of the same ethnicity, therefore, profit less from these networks with an increasing duration of stay in terms of their over-education and employment probability. In addition the interaction of diversity with duration of stay has a significantly positive impact on the employment probability. Foreign born with a longer duration of stay suffer less under diversity in terms of employment than foreign born with a shorter duration of stay.

Second, we include a squared term for the measure of diversity in the regression to test for a potentially nonlinear impact of diversity on labour market outcomes of foreign born. In this specification results slightly disagree depending on which measure of diversity is used. When the fractionalisation index is used this hypothesis is rejected for the unemployment and the participation in education equation on account of the insignificance of the squared fractionalisation index. When the Shannon index is used this applies to all equations but the unemployment and over-education equation.

For over-education and unemployment in the case when the fractionalisation index is used (as well as for unemployment and over-education when the Shannon index is used), however, the estimated coefficient for the squared diversity indicates an increasingly negative effect of diversity on labour market integration in low diversity regions (i.e. is negative for unemployment and over-education and positive for the employment probability). For the probability to be detached from the labour market, however, the significant coefficient for the squared fractionalisation index indicates that the probability to be detached from the labour market is increasing in fractionalisation. This result, however, has to be interpreted with some care on account of the insignificance of the main effect in this specification.

Third, we extend our baseline specification by including interactions between networks and the share of employed of the same ethnicity to control for effects of migrant network quality highlighted for instance in Cutler et al. (2005). The idea here is that migrants

Table 6: IV estimates for the sample of all migrants alternative specifications using fractionalisation as a measure for diversity

	P(Unemployed)			P(Overeducated)			P(Employed)			P(neet)			P(Education)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Share own group	-1.82**	-0.72***	3.51***	-3.22***	-0.83***	-0.23	3.66***	1.07***	-8.57***	-1.57	-0.52	1.85**	0.17	0.07	3.40***
	(0.899)	(0.217)	(0.424)	(1.064)	(0.286)	(0.590)	(0.879)	(0.214)	(0.582)	(1.072)	(0.377)	(0.725)	(0.658)	(0.226)	(0.542)
Segregation	0.01	-0.10	-0.11	0.15	-0.28	-0.29	0.14	0.12	0.14	0.21	0.17	0.13	-0.13	-0.04	-0.06
	(0.417)	(0.168)	(0.178)	(0.407)	(0.189)	(0.191)	(0.448)	(0.174)	(0.223)	(0.499)	(0.244)	(0.253)	(0.306)	(0.155)	(0.155)
Fractionalization	0.29**	0.24*	0.29***	0.03	0.14	-0.05	-0.84***	-0.85***	-0.64***	0.07	-0.20	0.05	0.02	-0.12	-0.06
	(0.134)	(0.142)	(0.090)	(0.201)	(0.217)	(0.157)	(0.158)	(0.206)	(0.113)	(0.223)	(0.266)	(0.174)	(0.134)	(0.170)	(0.117)
Fractionalization^2		-0.03			-0.47**			0.45*			0.54*			0.25	
		(0.162)			(0.217)			(0.265)			(0.273)			(0.211)	
share own group X share employed			-7.18***			-1.01			16.44***			-4.06***			-5.61***
			(0.853)			(1.080)			(1.203)			(1.245)			(0.954)
female	0.03***	0.03***	0.03***	0.09***	0.09***	0.09***	-0.20***	-0.20***	-0.20***	0.07***	0.07***	0.07***	0.03***	0.03***	0.03***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Medium education	-0.03***	-0.03***	-0.03***				0.07***	0.08***	0.08***	-0.08***	-0.08***	-0.08***	0.00	0.05***	0.05***
	(0.002)	(0.002)	(0.002)				(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.004)	(0.004)
High Education	-0.05***	-0.05***	-0.05***	0.18***	0.17***	0.17***	0.14***	0.17***	0.17***	-0.12***	-0.12***	-0.12***	-0.11***	0.03***	0.03***
	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.010)	(0.010)	(0.010)	(0.004)	(0.007)	(0.007)
Years of residency	-0.00	-0.00***	-0.00***	-0.00	-0.01***	-0.01***	0.01	0.01***	0.01***	-0.01	-0.01***	-0.01***	0.05***	-0.00	-0.00
	(0.009)	(0.001)	(0.001)	(0.009)	(0.001)	(0.001)	(0.010)	(0.001)	(0.001)	(0.011)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
Married	-0.01**	-0.01**	-0.01***	-0.02***	-0.02***	-0.02***	-0.04***	-0.02***	-0.01***	0.28***	0.28***	0.28***	0.06***	-0.15***	-0.15***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.011)	(0.011)	(0.011)	(0.007)	(0.005)	(0.005)
Share own X Years	0.15			0.33***			-0.33***			0.18			-0.03		
of residency	(0.094)			(0.111)			(0.091)			(0.126)			(0.078)		
Frac. X Years	-0.01			-0.01			0.04**			-0.01			-0.01		
of residency	(0.015)			(0.017)			(0.015)			(0.021)			(0.013)		
Segreg. X Years	-0.01			-0.04			-0.01			-0.00			0.01		
of residency	(0.038)			(0.036)			(0.039)			(0.046)			(0.029)		
Observations	577,002	577,002	577,002	304,812	304,812	304,812	822,101	822,101	822,101	128,029	128,029	128,029	234.503	234,503	234,503
R-squared	0.051	0.053	0.055	0.106	0.109	0.109	0.172	0.139	0.144	0.125	0.126	0.126	0.332	0.314	0.315

Source: European labour force survey, own calculations. All estimations include age-group, region (NUTS2), sending country group and year dummies. Additional controls are the region specific unemployment and over-education rates. Standard errors are clustered at the region and year level. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively. P(neet)=probability to be neither employed nor in education or training. First stage F-Statistics larger than 10 for all instruments in all specifications.

located in regions where a large share of their co-ethic workers are employed, all else equal, are likely to have better information on job opportunities and are thus more likely to find employment which matches their educational attainment than migrants located in regions where many of their co-ethic workers are not-employed. According to the results a higher network quality significantly reduces the probability of unemployment as well as the probability of being detached from the labour market but also significantly reduces the probability of participation in education and higher network quality also increases the probability to find employment, irrespective of the measure of diversity used. With respect to the probability to find a job matching education levels higher network quality, by contrast, do not have a significant impact.

Finally, in table 7, we extend further on these results by considering the impact of networks, segregation and diversity on different subgroups of the migrant population.[6] Here we differentiate first of all between EU and non-EU migrants, because the differences in legal standards in the mutual recognition of skills between EU and non-EU migrants may lead to differences in the effects of networks, segregation and diversity on migrant integration. Second, we differentiate between male and female migrants to analyse potential gender differences in effects and fourth, we differentiate between workers of different education levels because our theoretical considerations suggest that the probability of diversity having a negative impact on integration success is higher for low ability workers than for high ability workers.

[6] In this table we focus on results using the fractionalisation index. Results using the Shannon index are reported in the appendix (table 7a).

Table 7: IV estimates for different subgroups using fractionalisation as a measure for diversity

	Region of birth		Gender		Education level		
	EU	NONEU	Female	Male	Low	medium	high
			P(Unemployment)				
Share own group	-1.54***	-0.65*	-1.16***	-0.45*	-0.89**	-0.18	-0.91**
	(0.419)	(0.358)	(0.304)	(0.261)	(0.346)	(0.282)	(0.358)
Segregation	0.29*	-0.12	-0.11	-0.07	-0.32	0.10	0.02
	(0.164)	(0.258)	(0.227)	(0.192)	(0.320)	(0.180)	(0.274)
Fractionalization	0.38***	0.21	0.31***	0.15	0.37**	0.16	0.05
	(0.120)	(0.132)	(0.115)	(0.115)	(0.150)	(0.109)	(0.122)
Observations	215,062	361,940	266,835	310,167	196,350	236,130	144,522
R-squared	0.038	0.053	0.051	0.061	0.064	0.043	0.028
			P(Overeducated employment)				
Share own group	2.31***	-2.49***	-0.96**	-0.76**		-0.63*	-0.06
	(0.502)	(0.640)	(0.431)	(0.366)		(0.344)	(0.440)
Segregation	0.00	-1.31***	-0.39	-0.24		-0.11	-0.03
	(0.176)	(0.439)	(0.258)	(0.258)		(0.204)	(0.314)
Fractionalization	-0.33*	0.25	0.02	-0.13		-0.33	0.17
	(0.181)	(0.263)	(0.223)	(0.167)		(0.219)	(0.175)
Observations	135,563	169,249	147,771	157,041		182,476	122,336
R-squared	0.133	0.081	0.117	0.089		0.074	0.131
			P(employed)				
Share own group	2.46***	1.17***	1.86***	0.63**	1.03***	0.63**	1.52***
	(0.486)	(0.364)	(0.294)	(0.288)	(0.320)	(0.285)	(0.433)
Segregation	-0.39**	0.22	0.16	0.05	0.44	-0.27	0.05
	(0.189)	(0.265)	(0.233)	(0.209)	(0.288)	(0.187)	(0.310)
Fractionalization	-0.82***	-0.72***	-0.45***	-0.74***	-0.76***	-0.63***	-0.34*
	(0.160)	(0.162)	(0.139)	(0.153)	(0.159)	(0.142)	(0.180)
Observations	297,834	524,267	440,486	381,615	325,928	318,772	177,401
R-squared	0.101	0.152	0.136	0.195	0.165	0.088	0.057
			P(neet)				
Share own group	-2.11*	-0.43	-0.72	-0.26	-0.54	-0.53	-1.35
	(1.132)	(0.592)	(0.481)	(0.567)	(0.488)	(0.594)	(1.931)
Segregation	0.47	0.16	0.00	0.45	0.11	0.19	-0.17
	(0.320)	(0.378)	(0.332)	(0.348)	(0.379)	(0.342)	(0.929)
Fractionalization	-0.08	0.16	0.13	-0.02	0.11	0.17	-0.52
	(0.348)	(0.256)	(0.222)	(0.292)	(0.299)	(0.226)	(0.541)
Observations	39,244	88,785	65,358	62,671	74,551	46,655	6,823
R-squared	0.048	0.155	0.200	0.026	0.162	0.079	0.090
			P(participation in education)				
Share own group	-0.15	-0.28	0.05	0.06	-0.19	0.37	-0.02
	(0.452)	(0.368)	(0.268)	(0.348)	(0.313)	(0.333)	(0.672)
Segregation	0.25	-0.29	0.16	-0.20	-0.44*	0.41**	0.14
	(0.153)	(0.247)	(0.180)	(0.235)	(0.253)	(0.187)	(0.390)
Fractionalization	0.38**	-0.07	-0.02	-0.01	0.13	-0.10	0.00
	(0.178)	(0.155)	(0.143)	(0.160)	(0.157)	(0.173)	(0.252)
Observations	76,903	157,600	124,702	109,801	111,493	91,431	31,579
R-squared	0.292	0.317	0.317	0.313	0.478	0.171	0.077

Source: European labour force survey, own calculations. All estimations include age-group, region (NUTS2), sending country group and year dummies. Additional controls are the region specific unemployment and over-education rates, gender, years of residence, education dummies and marital status dummy. Standard errors are clustered at the region and year level. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively. P(neet)=probability to be neither employed nor in education or training. First stage F-Statistics larger than 10 for all instruments in all specifications.

The results suggest that EU migrants profit more from networks but also suffer more from diversity in terms of unemployment and employment than non EU-migrants. An increase of the share of same ethnicity migrants residing in the same region by 1 percentage point reduces the unemployment probability by 1.5 to 1.6 percentage points and increases the employment probability by 2.5 to 2.9 percentage points for EU migrants (depending on the measure of diversity used), but reduces the unemployment probability by only 0.7 percentage points and increases the employment probability by 1.2 to 1.3 percentage points for non-EU migrants. Similarly, a unit increase in diversity increases the unemployment probability significantly only for EU migrants, while it reduces employment probability of EU migrants by 0.8 percentage points (for the fractionalisation index) or 0.4 percentage points (for the Shannon index) but only 0.7 or 0.3 percentage points for non EU-migrants. Segregation of the own group, by contrast, impacts negatively on the employment probability and positively on the unemployment probability of EU migrants, only.

With respect to over-education the effects of migrant networks go in opposite directions for these two groups of migrants. A higher share of own ethnic migrants increases the probability of overeducated employment for EU migrants but reduces it for non-EU migrants. Furthermore the fractionalisation index as well as the Shannon index have a significant (negative) impact on the probability of overeducated employment only for EU-migrants, while for non-EU migrants segregation insignificantly increases the overeducated employment risk. For the other two dependent variables analysed (the probability to be detached from the labour market and the probability to be in education) by contrast slight differences arise depending on the measure of diversity used. When the fractionalisation index is used differences are limited to a weakly significantly negative impact of networks on the probability to be detached from the labour market and a significantly positive one of fractionalisation on the probability to be in education for EU migrants. When the Shannon index is used, by contrast, the significantly positive effect of diversity negative impact of networks on the probability to be detached from the labour market for EU-citizen the significantly positive effect of diversity on the probability to be in full time education is stronger for EU migrants. In addition in this specification the share of own ethnic migrants has a negative significant effect on the participation in education.

Also women profit more from networks in terms of unemployment and employment than males and they also face significantly lower over-qualification risks when living in regions where a higher share of co-ethnics reside than males, while gender specific results for diversity are not robust across measures of diversity (in the case of the fractionalisation index women suffer more, in the case of the Shannon index the opposite is found) and none of the variables of interest is significant in the detachment from the labour market and participation in education equation either for men or for women, except for a significant positive impact of the Shannon index on the probability to be in education.

More able migrants - consistently with theoretical expectations more able migrants (i.e. those with a higher education) - are also less strongly affected by diversity than low skilled migrants in terms of unemployment, employment and over-education (although for over-education these coefficients mostly remain insignificant). Migrant networks, however, reduce unemployment probabilities significantly only for the most highly educated and the least educated migrants and also have the strongest significant positive effects on the employment probability of these two groups. Finally, segregation significantly increases the probability to be in education for medium skilled migrants but weakly significantly reduces this probability for the least skilled migrants when the fractionalisation index is used as a measure of diversity.

Table 8: IV estimates for the sample of all migrants excluding segregation

	P(unemployed)	P(overeducated)	P(employed)	P(neet)	P(participation in

					education)
Share own group	-0.65***	-0.56***	1.07***	-0.17**	0.06
	(0.120)	(0.159)	(0.213)	(0.078)	(0.133)
Fractionalization	0.21**	-0.08	-0.65***	0.04	-0.02
	(0.087)	(0.153)	(0.124)	(0.036)	(0.108)
Female	0.03***	0.09***	-0.20***	0.02***	0.03***
	(0.003)	(0.005)	(0.004)	(0.001)	(0.003)
Medium education	-0.03***		0.08***	-0.01***	0.05***
	(0.002)		(0.005)	(0.001)	(0.004)
High Education	-0.05***	0.17***	0.17***	-0.03***	0.06***
	(0.003)	(0.007)	(0.007)	(0.001)	(0.007)
Years of residency	-0.00***	-0.01***	0.01***	-0.01***	0.00***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Married	-0.01**	-0.02***	-0.02***	-0.02***	-0.11***
	(0.003)	(0.004)	(0.004)	(0.001)	(0.004)
Observations	577,002	304,812	822,101	822,101	234,503
R-squared	0.053	0.109	0.139	0.053	0.332

Source: European labour force survey, own calculations. All estimations include age-group, region (NUTS2), sending country group and year dummies. Additional controls are the region specific unemployment and over-education rates. Standard errors are clustered at the region and year level. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively. P(neet)=probability to be neither employed nor in education or training. First stage F-Statistics larger than 10 for all instruments in all specifications.

Finally since one could be concerned about the insignificance of the segregation variable in most of our specifications, which may be due to the fact that this is measured only at the national level and the consequently low number of observations for this variable, in table 8 we report results of our baseline specification when excluding these variables.[7] This change does not alter results significantly and does not provide for further insights. As previously unemployment risks significantly reduce and employment chances substantially increase with a higher share of co-ethnics residing in a region. Similarly unemployment risks significantly increase and employment chances significantly decrease with increasing diversity and over-education and detachment from the labour market risks reduce with a higher share of co-ethnics residing in a region, but are unaffected by diversity.

[7] Table 8a repeats these results when using the Shannon index as a measure of diversity.

Summary

In this paper we were interested in the role of ethnic networks, segregation and diversity of a region on the integration success of foreign born. Our contribution to the literature is to present a detailed empirical analysis of the impact of foreign born in the same region and segregation on a country level on labour market integration of migrants in 15 EU countries and to also analyse the impact of diversity as a determinant to a migrants' success in integration into the host countries' labour markets. We argue that from a theoretical point of view ethnic diversity may have either positive or negative effects on labour market integration of foreign born. The reason for this is that on the one hand complementarities in productivity of different ethnicities may increase labour demand for the foreign born and increase their chances of integration, while on the other hand diversity also increases the uncertainty with respect to the quality of migrants of a particular sending country group.

Our results indicate a rather robust negative impact of ethnic networks on unemployment probabilities of the foreign born and a positive one on employment probabilities. In addition they also suggest a similarly robust positive impact of ethnic diversity on the unemployment probabilities and a negative one on employment probabilities. In regions where many migrants of the same ethnicity reside foreign born have lower unemployment and higher employment rates, while in ethnically more diverse regions, all else equal, unemployment among foreign born is higher and employment lower. With respect to over-education our results are slightly less robust, but in their majority point to a negative impact of ethnic networks on the probability of over-educated employment and an insignificant or positive impact of diversity. Segregation at the country level, by contrast, remains an insignificant determinant of both the probability of unemployment and of

overeducated employment in most specifications and all three variables seem to be only very weakly correlated to the probability of being detached from the labour market or the probability of being in education full time.

Furthermore the results suggest that higher network quality in a region (i.e. the share of employed same ethnicity migrants living in a region) increases employment prospects of migrants and reduces their unemployment chances. In addition migrants living in regions with a large share of migrants of the same ethnicity profit less from networks in terms of their over-education and employment probability but also suffer less from higher diversity in terms of employment the longer their increasing duration of stay. EU migrants profit more from networks but also suffer more from diversity in terms of unemployment and employment than non EU-migrants, while with respect to over-education rates the effects of migrant networks go in opposite directions for these two groups of migrants. In addition women profit more from networks in terms of unemployment, employment and over-education than males, while gender specific results for the impact of diversity are less robust. Finally, and consistent with theoretical expectations, more able migrants (i.e. those with a higher education) are less strongly affected by diversity than low skilled migrants both in terms of unemployment and over-education and migrant networks reduce unemployment rate disparities significantly for the most highly educated and the least educated migrants, while for medium skilled migrants over-education rates are weakly significantly reduced by the presence of co-ethnic networks.

From a policy perspective these results therefore indicate a number of policy trade-offs with respect to migrant integration and regional development. The first of these arises from the fact that (as shown in the literature) while diversity may have a beneficial impact on economic development of a region through increased productivity and innovation, it also has an unfavourable impact on the integration in particular of newly arriving migrants. The second arises from the fact that while large same ethnicity networks may foster integration of newly arriving migrants it hinders long term integration. Given these policy trade-offs, we would argue that rather than focusing on settlement policies to improve migrant integration a more efficient policy mix may consist of allowing migrants to settle anywhere, while at the same time providing additional aid with integration (e.g. through language training) to migrants in areas where either the share of same ethnicity is very high (to avoid long term disintegration, while at the same time reaping the short term benefits from integration) or which have very high diversity (to reap the growth benefits from diversity in terms of productivity and innovation, while at the same time improving integration).

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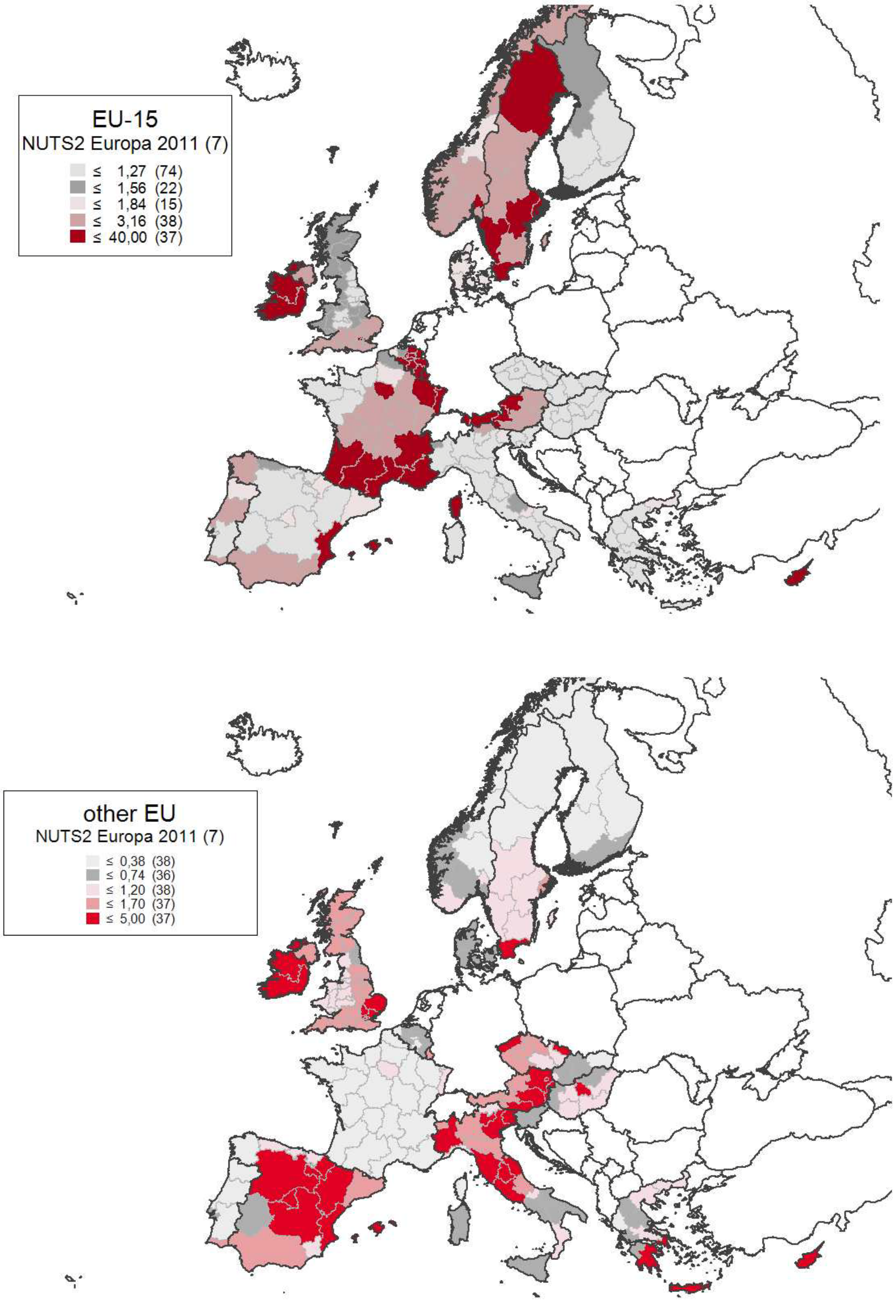
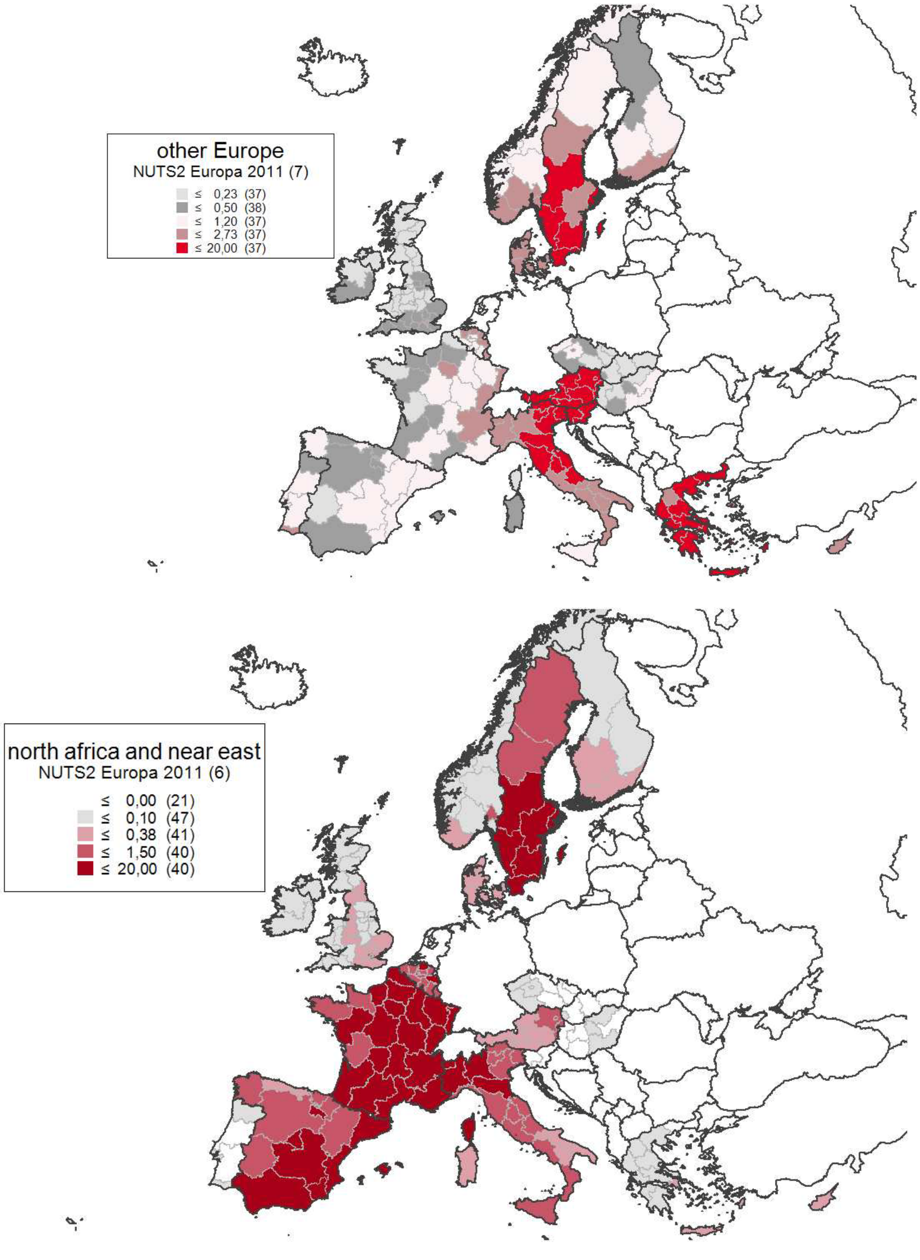
Figure A1 Regional distribution of foreign born from other EU15 and other NMS countries (average 2004 to 2011)



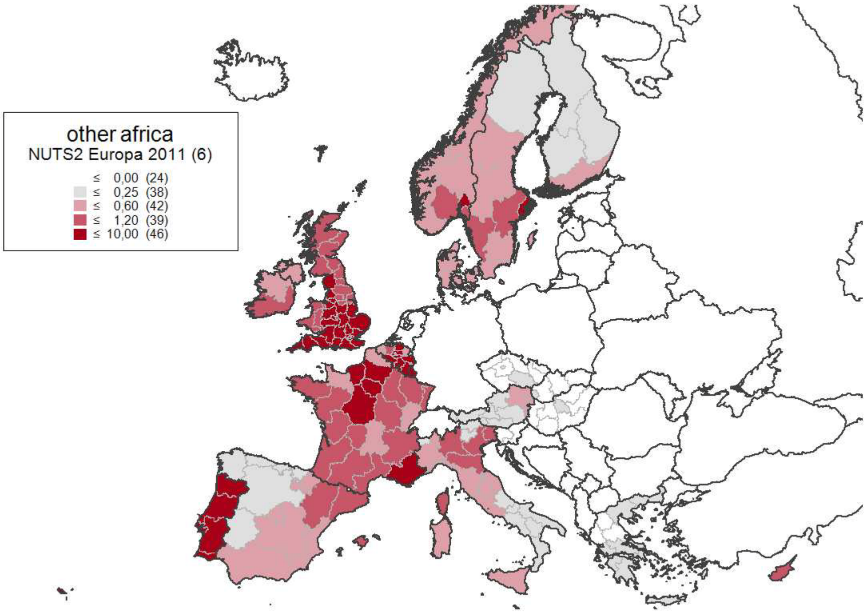
Source: EUROSTAT LFS 2004-2011

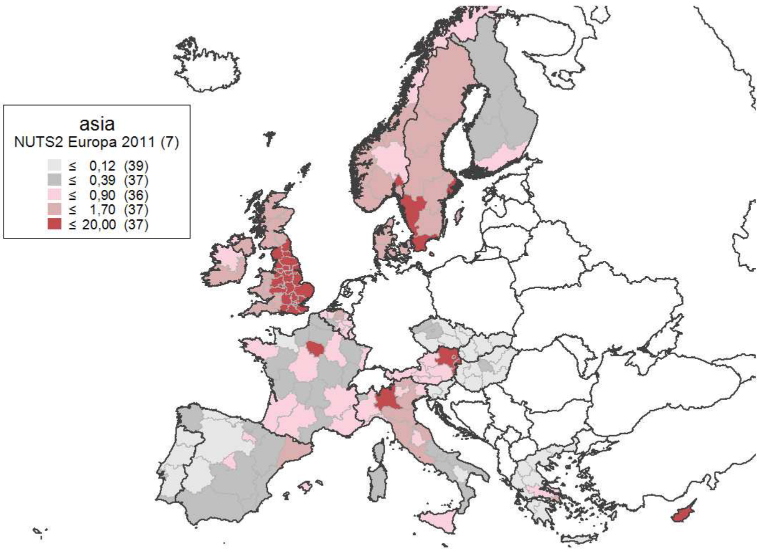
Figure A2: Regional distribution of foreign born from other European and other North African and near East countries (average 2004 to 2011)



Source: EUROSTAT LFS 2004-2011

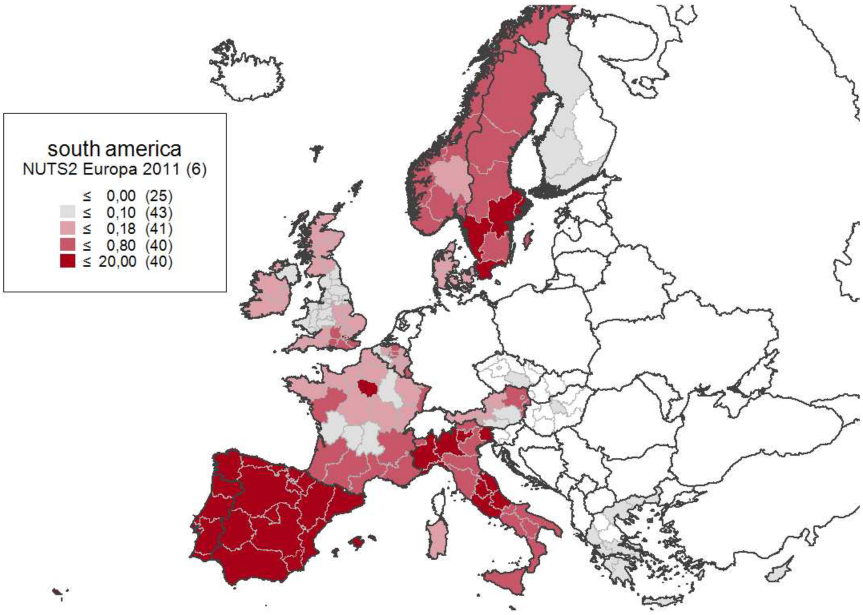
Figure A3: Regional distribution of foreign born from other African and Asian countries (average 2004 to 2011)

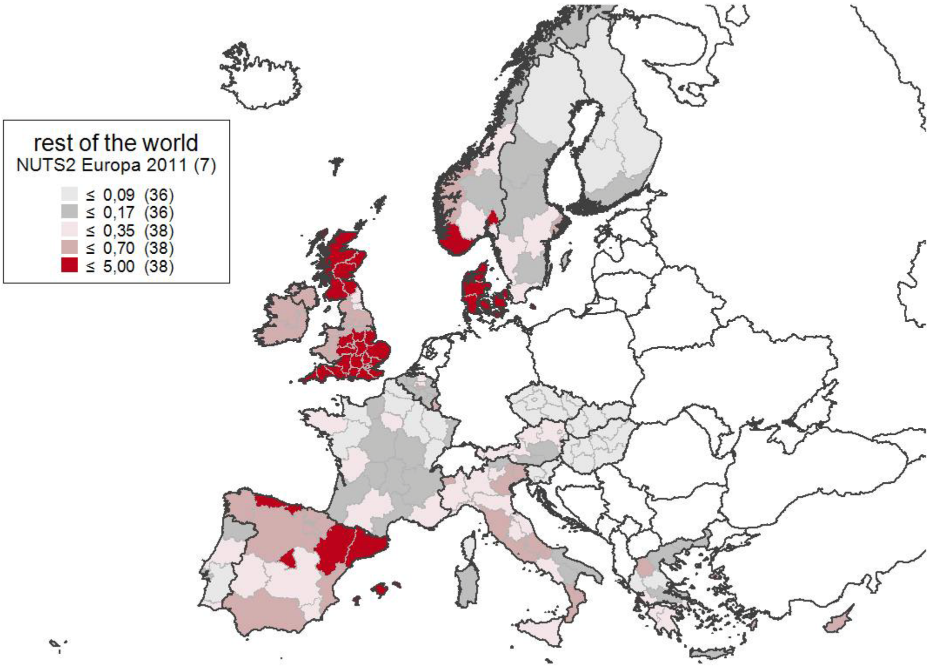




Source: EUROSTAT LFS 2004-2011

Figure A4: Regional distribution of foreign born from South America and the rest of the world (average 2004 to 2011)





Source: EUROSTAT LFS 2004-2011

Table 6a: IV estimates for the sample of all migrants – alternative specifications using Shannon Index as a measure for diversity

	P(unemployed)			P(overeducated)			P(employed)			P(NEET)			P(participation in education)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Share own group	-1.97**	-0.77***	3.52***	-2.45**	-0.63**	-0.13	3.44***	1.22***	-7.75***	-1.60	-0.54	1.85**	0.13	-0.02	2.90***
	(0.871)	(0.210)	(0.429)	(1.096)	(0.286)	(0.591)	(0.846)	(0.212)	(0.550)	(1.019)	(0.361)	(0.723)	(0.633)	(0.213)	(0.527)
Segregation	-0.07	-0.12	-0.14	0.34	-0.19	-0.20	0.05	0.13	0.15	0.20	0.16	0.11	-0.16	-0.08	-0.10
	(0.414)	(0.163)	(0.174)	(0.448)	(0.197)	(0.200)	(0.448)	(0.172)	(0.213)	(0.486)	(0.233)	(0.242)	(0.301)	(0.147)	(0.147)
Entropy	0.24***	0.29***	0.23***	0.06	0.22	0.07	-0.32***	-0.26**	-0.24***	0.06	-0.04	0.08	0.04	0.03	0.01
	(0.065)	(0.079)	(0.049)	(0.126)	(0.157)	(0.105)	(0.085)	(0.123)	(0.058)	(0.132)	(0.197)	(0.126)	(0.073)	(0.106)	(0.068)
Entropy²		-0.09**			-0.17**			0.02			0.09			-0.01	
		(0.039)			(0.070)			(0.072)			(0.094)			(0.053)	
share own gr.			-7.27***			-0.87			15.30***			-4.10***			-4.92***
X share empl.			(0.862)			(1.092)			(1.140)			(1.243)			(0.955)
female	0.03***	0.03***	0.03***	0.10***	0.10***	0.10***	-0.20***	-0.20***	-0.20***	0.07***	0.07***	0.07***	0.03***	0.03***	0.03***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Medium education	-0.03***	-0.03***	-0.03***				0.07***	0.08***	0.08***	-0.08***	-0.08***	-0.08***	0.05***	0.05***	0.05***
	(0.002)	(0.002)	(0.002)				(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
High Education	-0.05***	-0.05***	-0.05***	-0.17***	-0.17***	-0.17***	0.14***	0.14***	0.14***	-0.12***	-0.12***	-0.12***	0.06***	0.06***	0.06***
	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.010)	(0.010)	(0.010)	(0.007)	(0.007)	(0.007)
Years of residency	-0.01	-0.00***	-0.00***	-0.00	-0.01***	-0.01***	0.01	0.01***	0.01***	-0.01	-0.01***	-0.01***	0.00	0.00***	0.00**
	(0.009)	(0.001)	(0.001)	(0.009)	(0.001)	(0.001)	(0.009)	(0.001)	(0.001)	(0.010)	(0.001)	(0.001)	(0.007)	(0.001)	(0.001)
Married	-0.01**	-0.01**	-0.01***	-0.02***	-0.02***	-0.02***	-0.04***	-0.04***	-0.04***	0.28***	0.28***	0.28***	-0.11***	-0.11***	-0.11***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.011)	(0.011)	(0.011)	(0.004)	(0.004)	(0.004)
Share own X Years	0.16*			0.25**			-0.31***			0.18			-0.02		
of residency	(0.090)			(0.114)			(0.086)			(0.118)			(0.075)		
Frac. X Years	-0.01			-0.00			0.01**			-0.00			-0.00		
of residency	(0.006)			(0.008)			(0.007)			(0.009)			(0.006)		
Segreg. X Years	0.00			-0.06			-0.00			-0.00			0.01		
of residency	(0.037)			(0.040)			(0.039)			(0.044)			(0.029)		
Observations	577,002	577,002	577,002	314,555	314,555	314,555	822,101	822,101	822,101	128,029	128,029	128,029	234,503	234,503	234,503
R-squared	0.051	0.052	0.055	0.093	0.095	0.094	0.173	0.175	0.180	0.125	0.126	0.126	0.332	0.332	0.333

Source: European labour force survey, own calculations. All estimations include age-group, region (NUTS2), sending country group and year dummies. Additional controls are the region specific unemployment and over-education rates. Standard errors are clustered at the region and year level. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively. Instruments are predicted shares of nationality based on national occupation structure. P(neet)=probability to be neither employed nor in education or training. First stage F-Statistics larger than 10 for all instruments in all specifications.

Table 7a: IV estimates for different subsamples using Shannon Index as a measure for diversity

	Region of birth		Gender		Education level		
	EU	NONEU	Female	Male	Low	medium	high
	P(unemployed)						
Share own group	-1.63***	-0.74**	-1.13***	-0.53**	-0.92***	-0.20	-0.95***
	(0.427)	(0.339)	(0.296)	(0.254)	(0.335)	(0.273)	(0.347)
Segregation	0.28*	-0.19	-0.10	-0.13	-0.36	0.09	-0.01
	(0.162)	(0.244)	(0.222)	(0.186)	(0.312)	(0.174)	(0.265)
Entropy	0.27***	0.24***	0.13*	0.25***	0.30***	0.12*	0.09
	(0.091)	(0.062)	(0.078)	(0.069)	(0.083)	(0.065)	(0.081)
Observations	215,062	361,940	266,835	310,167	196,350	236,130	144,522
R-Squared	0.038	0.053	0.051	0.060	0.063	0.043	0.028
	P(Overeducated employment)						
Share own group	3.04***	-2.37***	-0.73*	-0.57		-0.41	0.18
	(0.540)	(0.628)	(0.435)	(0.369)		(0.344)	(0.480)
Segregation	0.12	-1.29***	-0.26	-0.18		-0.01	0.09
	(0.186)	(0.443)	(0.261)	(0.272)		(0.218)	(0.347)
Entropy	-0.32**	0.18	0.17	-0.06		-0.05	0.28**
	(0.134)	(0.155)	(0.124)	(0.133)		(0.125)	(0.143)
Observations	139,336	175,219	152,182	162,373		187,730	126,825
R-Squared	0.122	0.066	0.086	0.086		0.062	0.097
	P(employed)						
Share own group	2.87***	1.25***	1.75***	0.63**	1.29***	0.70**	1.67***
	(0.479)	(0.349)	(0.282)	(0.275)	(0.316)	(0.280)	(0.413)
Segregation	-0.35**	0.21	0.08	0.05	0.43	-0.23	0.10
	(0.177)	(0.255)	(0.226)	(0.200)	(0.282)	(0.180)	(0.300)
Entropy	-0.43***	-0.30***	-0.05	-0.41***	-0.43**	-0.30***	-0.12
	(0.112)	(0.083)	(0.093)	(0.087)	(0.094)	(0.081)	(0.102)
Observations	297,834	524,267	440,486	381,615	325,928	318,772	177,401
R-Squared	0.163	0.179	0.136	0.195	0.201	0.131	0.093
	P(neither employed in education or training)						
Share own group	-2.50**	-0.37	-0.70	-0.27	-0.53	-0.65	-0.92
	(1.126)	(0.559)	(0.467)	(0.550)	(0.468)	(0.574)	(1.798)
Segregation	0.41	0.20	0.02	0.44	0.12	0.12	0.04
	(0.315)	(0.356)	(0.321)	(0.339)	(0.364)	(0.327)	(0.859)
Entropy	0.35	0.00	0.02	0.02	0.02	0.31	-0.62
	(0.266)	(0.139)	(0.194)	(0.164)	(0.163)	(0.195)	(0.476)
Observations	39,244	88,785	65,358	62,671	74,551	46,655	6,823
R-Squared	0.047	0.155	0.200	0.026	0.162	0.079	0.092
	P(participation in education)						
Share own group	-1.40**	-0.25	-0.44	-0.06	-0.28	-0.38	-0.51
	(0.635)	(0.329)	(0.271)	(0.286)	(0.314)	(0.286)	(0.342)
Segregation	0.12	-0.00	-0.14	0.20	0.08	-0.05	-0.15
	(0.152)	(0.203)	(0.170)	(0.173)	(0.232)	(0.170)	(0.192)
Entropy	0.35***	0.17**	0.08	0.24***	0.14	0.28***	-0.01
	(0.121)	(0.072)	(0.086)	(0.085)	(0.089)	(0.089)	(0.116)
Observations	76,903	157,600	124,702	109,801	111,493	91,431	31,579
R-Squared	0.127	0.202	0.256	0.099	0.222	0.146	0.143

Source: European labour force survey, own calculations. All estimations include age-group, region (NUTS2), sending country group and year dummies. Additional controls are the region specific unemployment and over-education rates. Standard errors are clustered at the region and year level. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively. Instruments are predicted shares of nationality based on national occupation structure. First stage F-Statistics larger than 10 for all instruments in all specifications.

Table 8a: IV estimates for sample of all migrants excluding segregation using Shannon index as a measure for diversity

	P(unemployed)	P(overeducated)	P(employed)	P(neet)	P(participation in education)
Share own group	-0.67***	-0.68***	-0.58***	0.94***	0.09
	(0.119)	(0.229)	(0.157)	(0.117)	(0.136)
Entropy	0.21***	0.04	-0.28***	0.03	0.04
	(0.050)	(0.121)	(0.105)	(0.071)	(0.068)
Female	0.03***	0.07***	0.09***	-0.20***	0.03***
	(0.003)	(0.005)	(0.005)	(0.004)	(0.003)
Medium education	-0.03***	-0.08***		0.08***	0.05***
	(0.002)	(0.006)		(0.005)	(0.004)
High Education	-0.05***	-0.12***	0.17***	0.17***	0.03***
	(0.003)	(0.009)	(0.007)	(0.007)	(0.007)
Years of residency	-0.00***	-0.01***	-0.01***	0.01***	-0.00
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Married	-0.01**	0.28***	-0.02***	-0.02***	-0.15***
	(0.003)	(0.011)	(0.004)	(0.004)	(0.005)
Observations	577,002	128,029	304,812	822,101	234,503
R-squared	0.053	0.126	0.109	0.139	0.315

Source: European labour force survey, own calculations. All estimations include age-group, region (NUTS2), sending country group and year dummies. Additional controls are the region specific unemployment and over-education rates. Standard errors are clustered at the region and year level. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively. Instruments are predicted shares of nationality based on national occupation structure. P(neet)=probability to be neither employed nor in education or training. First stage F-Statistics larger than 10 for all instruments in all specifications.

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Project Information

Welfare, Wealth and Work for Europe

A European research consortium is working on the analytical foundations for a socio-ecological transition

Abstract

Europe needs a change: The financial crisis has exposed long neglected deficiencies in the present growth path, most visibly in unemployment and public debt. At the same time Europe has to cope with new challenges ranging from globalisation and demographic shifts to new technologies and ecological challenges. Under the title of Welfare, Wealth and Work for Europe – WWWforEurope – a European research consortium is laying the analytical foundations for a new development strategy that enables a socio-ecological transition to high levels of employment, social inclusion, gender equity and environmental sustainability. The four year research project within the 7th Framework Programme funded by the European Commission started in April 2012. The consortium brings together researchers from 33 scientific institutions in 12 European countries and is coordinated by the Austrian Institute of Economic Research (WIFO). Project coordinator is Karl Aiginger, director of WIFO.

For details on WWWforEurope see: www.foreurope.eu

Contact for information

Kristin Smeral

WWWforEurope – Project Management Office

WIFO – Austrian Institute of Economic Research

Arsenal, Objekt 20

1030 Vienna

wwwforeurope-office@wifo.ac.at

T: +43 1 7982601 332

Domenico Rossetti di Valdalbero

DG Research and Innovation

European Commission

Domenico.Rossetti-di-Valdalbero@ec.europa.eu

Partners

WIFO	Austrian Institute of Economic Research	WIFO	Austria
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