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**Working Paper**

## Does residential segregation matter for the labor market performance of immigrants? Evidence from Germany

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**Does residential segregation matter  
for the labor market performance of  
immigrants? Evidence from Germany**

Sebastian Reil

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# **Does residential segregation matter for the labor market performance of immigrants? Evidence from Germany<sup>1</sup>**

by Sebastian Reil<sup>2</sup>

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Abstract: With the arrival of over one million asylum seekers in Germany in 2015, policy discussions opened whether refugees should be spread across the country or spatially concentrated in order to facilitate their integration in society. When an immigrant locates in a residential area with many natives or many foreigners he has access to different respective social networks which are important for the labor market performance. This paper uses the SOEP dataset to estimate which residential location decision via the networks leads to a better labor market performance. Findings show that residential concentration of immigration increases wages of new immigrants, but also raises their unemployment. Native wages are suppressed in an area with many foreigners.

Keywords: migration, residential segregation, labor market

*“Man hat Arbeitskräfte gerufen, und es kamen Menschen.” – Max Frisch (1965)*

*(English: “We asked for workers; we got people instead.”)*

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## 1. Introduction

With the arrival of around 1 million asylum seekers in Germany in 2015 the nexus between social and economic integration received increased attention (Sachverständigenrat 2015). Different policy proposals have been brought forward how to best integrate refugees into the society and the labor market. Whereas in political discourse the focus is often on how to achieve social integration and induce assimilation with the aim of maintaining the homogeneity of culture and values which characterize the nation state, in the science of economics the most interesting aspect is how successful immigrants are on the labor market and what determines their success.

The novelist and playwright Max Frisch famously wrote in 1965: “We asked for workers, and people came instead.” This realization that foreign workers are not only human capital or the production input labor (as commonly depicted in neoclassical theory) came late in most Western European societies. The guest workers recruited during the post-war economic boom were expected to fill temporary labor shortages and then return home (Constant and Massey 2005). But instead many stayed, founded families and became permanent parts of the society. Since then it is often assumed in political discourse that labor market integration helps social integration or might even be a necessary condition for social integration. This seems most likely to be true, but this study is interested in the reverse: Does social integration improve labor market success of immigrants? I test the hypothesis, which is widely adhered to in current political discourse, that more integration of immigration into mainstream German society, which is measured as living in the same neighborhood, will also help integration in an economic sense measured by higher wages and a lower probability of being unemployed.

There is an extensive literature on immigration and the labor market. The effect of immigration on native wages has been especially thoroughly researched (e.g. Card 1990; Friedberg 2001; Ottaviano and Peri 2007). A second strain of the literature focuses on the labor market success of immigrants in the host country and their performance and characteristics compared to natives (e.g. Chiswick 1978; Constant and Massey 2005; Beyer 2017). But the connection between social integration and labor market success and integration has been little researched in economics. As the quote from Max Frisch already indicated, it is important to also consider immigrants in their social dimension.

This study aims to understand the impact of social integration on labor market success. The native-foreigner composition of a residential area is taken as a starting point for integration

into (certain kinds of) social networks and the access they provide to the labor market. I estimate the effects of residential composition on labor market performance with a pooled OLS model using data of the German Socio-Economic Panel (SOEP). This dataset provides information on a wide range of variables tracking individuals since 1984 till 2015. This allows me to exploit information on income and employment status in relation to residential segregation. I am using historical data on immigrants due to availability issues. Nonetheless, refugees differ from immigrants that they are driven by push factors whereas regular immigrants are driven by pull – often labor market – factors. This leads to different selections in the characteristics of the people. I will account for that by a set of control variables described later.

As I estimate the direct effects of social integration indicator this will yield direct and straight forward policy conclusions on the integration strategies of refugees into German society and the German labor market. There has been a lot of discussion whether refugees should be concentrated in certain locations or more spread out across the country side, whether refugee children should be put together in special classes just for them or should be as mixed between the regular students as possible (Wößmann 2016; Geis and Orth 2016). Besides different standpoints in the discussion different federal states ('Bundesländer') have pursued different strategies so far.

Under usual circumstances it is considered unacceptable in a liberal democracy if the government forces on its citizens where to live in order to achieve a right mix of ethnic and cultural concentration.<sup>3</sup> But when dealing with forced migration it is common and legally possible to replace the free choice of residency with an allocated and enforced location of residency, ergo the insights of this study can be more easily translated into policy in respect with forced migration – refugees and asylum seekers – than when it comes to voluntary migration – labor migration and migration due to family reasons.

The next section reviews the relevant literature and provides further background. Sections on methodology and data description follow. The results of the regression analysis are presented in a separate section including a discussion of these results. The last section concludes.

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<sup>3</sup> There are exceptions like Singapore which has a state-run housing program that assures an even mixing of ethnic groups throughout the city-state.

## 2. Literature Review

### 2.1 Historical background

In order to better understand the literature and data presented it is helpful to understand the history of immigration to Germany<sup>4</sup>. Immigration has over time been driven by very different factors and happened in very different macroeconomic and political environments, hence the characteristics as well as the labor market success of different immigrant cohorts differs greatly.

Following Zimmermann (1995) there are four phases of migration in Europe since the Second World War:

1. The phase of war, adjustment and decolonialization in the direct aftermath of the Second World War. For Germany this phase was mainly characterized by the arrival of around 13 million expellees – ethnic Germans fleeing the ethnic cleansings in Eastern Europe and the former Eastern German territories (Glitz 2012).
2. A phase of labor migration starting in the 1950s until the first oil price shock in 1973. Guest workers were recruited from Southern Europe and Turkey to fill temporary labor shortages.
3. A phase of restrained migration following the oil price shock with virtually the only migration being family reunification which is guaranteed under European law.
4. The dissolution of socialism and afterwards leading to an East-West migration. The biggest source country was the former Soviet Union. Within this group ethnic German ‘Aussiedler’ constituted the biggest group (Glitz 2012).

Since 2010, net-immigration has been rising again which could lead to a potential future fifth phase (see Figure 1). The main reasons behind this are the EU East enlargement and the subsequent introduction of freedom of movement, the strong German labor market compared to the other Western European and especially Southern European economies (Bertoli et al 2013), and a sharp increase in the number of asylum seekers following the military interventions in Afghanistan, Iraq, Syria and Libya and the following destabilization of these regions.

Generally it can be assumed that more people want to immigrate to Germany than permitted. Jasso et al (2000) shows for the US that under such conditions shifts in the immigration policy will lead to changes in the number and skills of immigrants. There will also be losers and

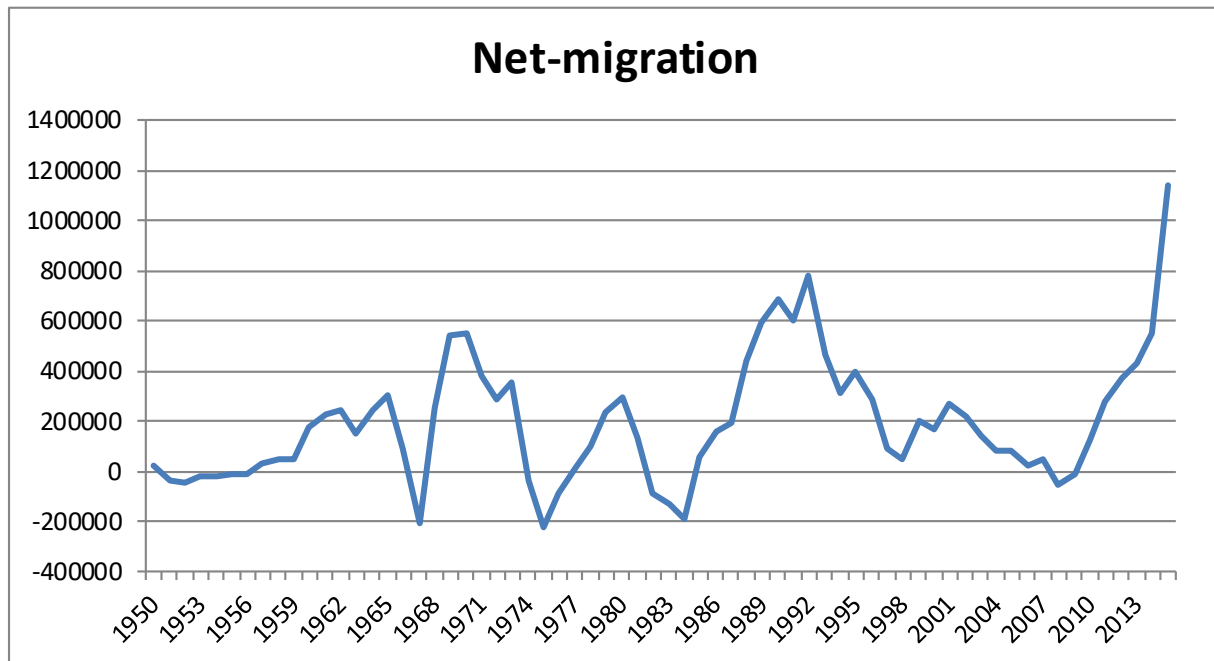
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<sup>4</sup> Before reunification Germany refers to West Germany



winner within the set of prospective immigrants with every policy change. That is one reason why it is important to understand the policy framework under which immigration took place as it affects the characteristics of the immigrants. Table A1 provides an overview over the different legal regimes under which immigration occurred to Germany.

Figure 1: Net-Migration to Germany



Source: Destatis (2017)

## 2.2 Labor market literature background to immigration

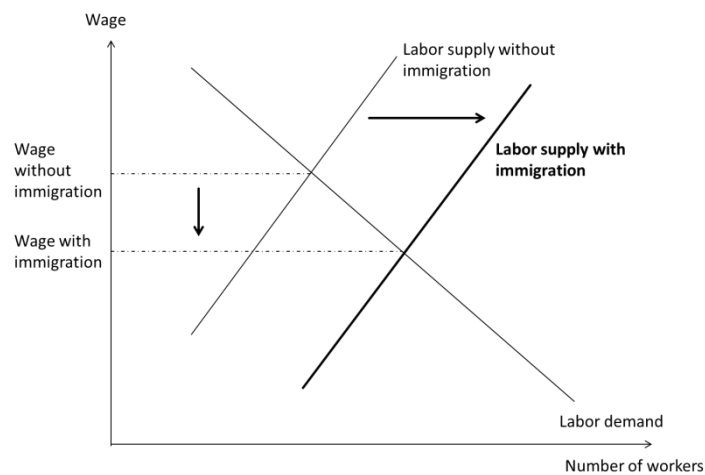
At the macro level, the function of the labor market is to provide a matching of supply and demand of labor and certain skills. Obstacles in this process will lead to a less efficient allocation of labor. Similarly, the increase in the extent of the (labor) market will improve the efficiency. Common estimations claim that the removal of all immigration restrictions around the world would lead to a more efficient matching of labor and skills in the global labor market and through this mechanism would lead to around a doubling in world GDP (The Economist 2016).

At the micro level, migration can generally be analyzed under the lens of cost-benefit considerations on the individual level. If the total benefits of moving from place A to place B outweigh the costs associated with this move the individual has a self-interest to move. Costs and benefits can be of pecuniary or non-pecuniary nature. So, risk, leaving family behind etc. are also entering the cost-benefit consideration. This viewpoint already suggests that young

people are more likely to migrate as they have more time to reap financial benefits after incurring the costs of moving (Constant and Massey 2005).

Much of the economic literature on migration has focused on the effect that immigration has on native wages. That is mainly due to the fact that this is of direct political interest and hence a straight forward research agenda. As shown in figure 2, a common hypothesis is that an outward shift in the supply curve of labor will lead to a fall in the price of labor which means lower wages. But in reality the model gets more complicated as the elasticity of the wage as well as the substitutability of the workers has to be considered.

Figure 2: Shift in the supply curve in the labor market



The two most important works on the impact of migration on native wages are Card (1990) and Friedberg (2001) who both exploit natural experiment situations with a sudden increase in the labor force due to immigration. Both of them do not find adverse effects on the wages or employment levels of the original residents.

According to Constant (2014) there are five mechanisms through which migrants can increase rather than lower wages: through immigrant entrepreneurs hiring natives, innovations of high skilled immigrants, filling labor shortages, technological adaption and occupational mobility, by rising demand other firms expand and hire more workers.

Ottaviano and Peri (2007) find that immigrants and natives are only imperfect substitutes. If immigrants are rather compliments instead of substitutes for native labor, the mechanism in figure 2 does not hold. Rather natives will experience employment gains. This would also mean that native and immigrant labor markets are two separated segments. So, the dynamics in these labor markets as well as the access to jobs in the separate labor markets might differ.

Since Chiswick (1978) it is commonly known that the typical pattern of immigrant wages is one with a lower starting point as comparable natives followed by a catch-up process. The most recent study of immigrants' labor market performance in Germany has been conducted by Beyer (2017). He finds that immigrants earn 20% less than comparable natives in the beginning. German language skills and having obtained a degree in Germany help to close this gap. Initially immigrants are less likely to participate in the labor market, but this gap closes fully after 20 years. But a gap in the likelihood of being unemployed still remains.

A previous study by Constant and Massey (2005) finds that the economic assimilation process of immigrants in Germany takes up to 23 years. Fertig and Schurer (2007) find that the economic assimilation processes are heterogeneous. For example the immigrant cohort from 1969-1973 fully caught up with natives in respect of annual earnings after 16 years whereas for the cohorts 1955-1968 and 1974-1987 they neither find significant initial wage differences nor significant later relative wage growth. While in the US a clear convergence pattern can be found, different studies on Germany do not find clear results. Some papers do not find any evidence for a catch-up whereas more recent studies do detect a catch up process. This suggests that the German labor market is less able to absorb immigrants according to their skills than in the US (Beyer 2017). A common reason for the (initial) wage penalty is so-called skill downgrading. For example immigrants in the UK tend to work jobs in lower socio-economic classifications than comparable natives (Dustmann et al 2013). A decline in the 'quality' of immigrants arriving in Germany in subsequent cohorts is found by Gathmann et al (2014). This finding is reproduced in other studies. For example, Beyer (2017) finds that since 2007 the 'quality' dropped additionally.

### *2.3 The role of social networks in immigration*

While all authors studied immigrants' labor market performance from a general perspective, questions on the role of social networks have not been addressed to the same extent. What do we know about how social integration of immigrants affects these processes of labor market performance? And which role do residential location and social networks play in this?

According to Newman (2003, p.5) "a social network is a set of people or groups of people with some pattern of contacts or interactions between them." Through information flows and trust in such a network a participant is able to access the network or location specific social capital. This plays an important role in accessing jobs in the labor market as information about open positions as well as trust can be facilitated through the network. The size of the

network is also relevant. For example, Mexican migrants in the US labor market are more likely to be employed and earn higher wages if they have an exogenously larger network (Munshi 2003).

Nearly one third of all jobs in Germany are filled via referrals. This is the most common way of filling an open position and significantly more common than filling jobs via announcements in newspapers or through the government employment agency through which respectively 1 out of 7 jobs get filled (Brenzel et al 2016). This already suggests the importance of social networks for accessing jobs. Additionally, low skilled positions rely even more on referrals. Also immigrants rely more on referrals than natives. Nearly half find their job through their network. The number is even higher for young and low-educated workers. Jobs acquired through networks also lead to better working conditions than jobs found through other ways (Drever and Hoffmeister 2008). Filling vacancies via social networks and referrals also helps to overcome information problems and so leads to higher productivity and higher wages (Dustmann et al 2016). But high skilled positions take a longer time to be filled and are more likely to be filled via more formal channels (Brenzel et al 2016). The motivation behind the spreading policies for refugees are that a better integration into native social networks will ease access to the labor market and hence foster a long-term stable integration into the society and labor market.

Sanders and Sernau (2002) conducted interviews with Asian immigrants in Los Angeles. They find that for low-skilled jobs the reliance of networks is more common. Immigrants who search for a job without using their network are more likely to find employment with an employer of the same ethnic group. Relying on networks can hence be a mechanism to access jobs outside the realm of the own ethnic group and to enter multiethnic labor markets which might be an additionally intended policy outcome.

There is a limited literature - mainly in sociology rather than in economics - that documents how immigrants enter the labor market via social networks. Khvorostianov and Remennick (2017) provide evidence that volunteering of immigrants can help social and economic integration. They analyze Soviet immigrants in Israel using an interview based methodology. Typically, the volunteers build social networks through their volunteering activities and these can in the long run lead to a new job. Kalter and Kogan (2014) document how ethnic German 'Aussiedler' and Jewish Quota refugees integrate into Germany via their respective different networks. A study of Vietnamese immigrant children in New Orleans, finds that ethnic solidarity helps the children to succeed. Maintaining traditional ethnic values of their

community or source country and integrating socially in the new host country are not exclusive to each other, but rather reinforce each other (Zhou and Bankston 1998). Ethnic support can also provide resources to help the academic success of the second generation of immigrants. Also bilingualism is an asset rather than an obstacle to integration (Zhou and Gatewood 2000).

#### *2.4 The role of residential networks*

Social networks are usually created between people who are in direct contact with each other. Residential location matters for the creation and the access to these networks. It is well documented that immigrants and minorities are often unevenly distributed across residential neighborhoods. An economic explanation for that can be provided by arguing about the existence of ethnic goods and that these can lead to residential segregation. Ethnic goods are characterized by consumption characteristics – in the broader sense - of an ethnic or immigrant group that differs from other parts of the society. This can, for example, be certain foods, newspapers in specific language, minority religious institutions etc.. For a minority group, concentrating in an enclave can provide better access to these ethnic goods (Chiswick and Miller 2005).

Areas with many immigrants in the US and Sweden are connected with a poorer quality of amenities like public schools (Andersson 1998; Cutler et al 2008). Studies analyzing the residential location of refugees in Denmark and Sweden show that living in an ethnic enclave increases the earnings of the refugees. In Sweden this is only true for low skilled refugees (Damm 2009; Edin et al 2003). Aslund (2005) shows that immigrants in Sweden tend to relocate to more immigrant-dense neighborhoods as their time in Sweden increases.

Political refugees that have been resettled to the US receive a forceful spatial allocation. Due to this they provide a quasi-experimental setup that circumvents sorting issues. Research shows that if social networks members arrived in the location one year earlier than the studied individual it increases the probability of being unemployed. But if network members arrived two years or more before, it improves the probability of being employed and increases hourly wages (Beaman 2012). This suggests that the size of the social network is not as important as how well it is settled into and connected in the location. Borjas (2000) analyzes ethnic enclaves and its impact on wage growth in the US. He finds that living in an ethnic enclave slows down wage growths.

Schüller (2016) suggests that enclave quality matters more than the size of the enclave. Higher income, education and employment levels in an ethnic enclave will have a positive effect of other member living there. Schüller documents that low-skilled immigrants benefit the most from living in enclaves whereas high-skilled immigrants may see their employment chances reduced.<sup>5</sup>

It is well known that in residential segregation between whites and blacks in the US is in a big part due to a phenomenon called “white flight” (Card et al 2008). US whites have an aversion towards living with black residents in an area. So, when the share of black residents reaches a certain threshold, whites will move out from the area. This leads to the observed high degree of ethnic residential segregation. If such mechanisms are at work, living in an ethnic enclave is not the choice of the individual member of the minority group due to e.g. labor market considerations but it is rather involuntarily imposed on them.

Additionally, it is important to stress that refugees are especially different than e.g. labor migration; the one is driven by a push factor whereas the other one by a labor market pull. Statistically speaking we can expect very different selection by characteristics into these different groups which make them hard to compare. Also between refugees we have different characteristics depending on the nature of the conflict. During political repression and persecution typically educated urbanites are targeted and fleeing the country whereas during a ground war potentially less educated peasants have to flee as well. Figure A2 provides an overview over the current stock of foreign population in Germany by nationality. This may differ from the actual migration movements as it does not include immigrants that took on German citizenship. Taking on citizenship is also differently difficult for different migrant groups.

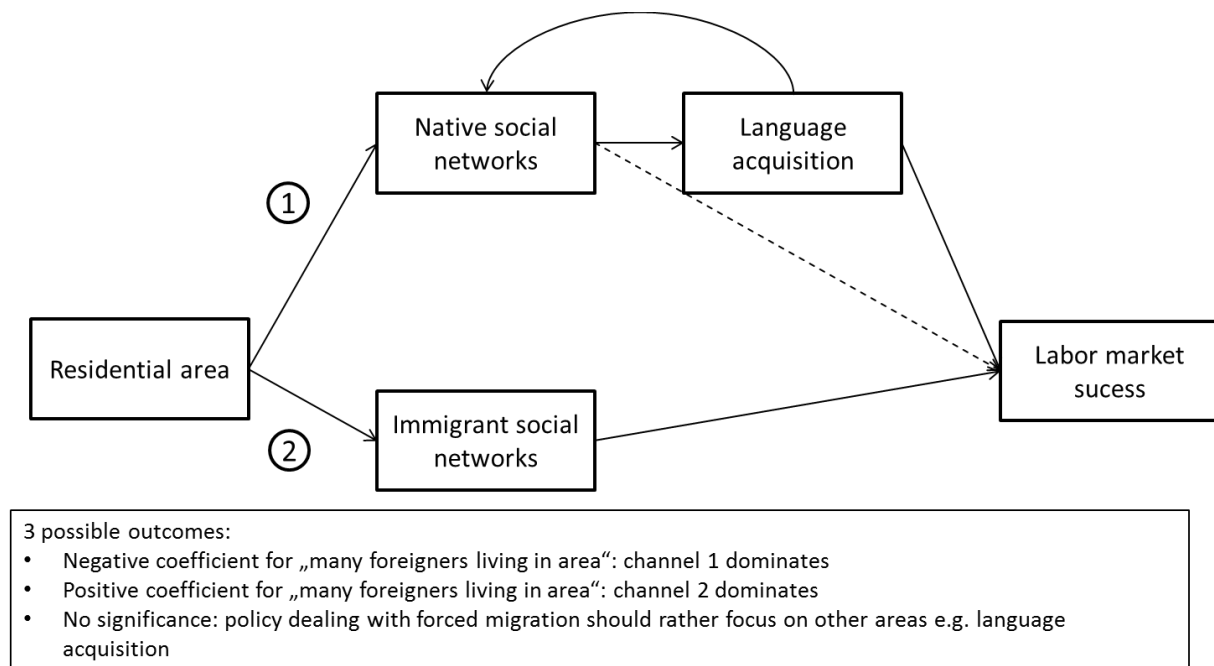
### *2.5 Hypothesis development*

It is reasonable to expect that the effects of residential composition on labor market performance will be indirect. For example if a recently arrived immigrant lives in an area with few other foreigners, he might improve his language skills faster and due to this earn a higher wage (see figure 3).

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<sup>5</sup> For this study I do not have detailed data on the level of the neighborhood. I use the information if many or few foreigners live in the residential area but I do not have data on the average education level there etc.

Figure 3: Scheme of mechanisms how social integration affects labor market integration



According to Keeley (2007) “we can think of social capital as the links, shared values and understandings in society that enable individuals and groups to trust each other and so work together.” Social integration can be seen as a way of immigrants being able to benefit of the social capital present in the host country. We can expect if immigrants integrate more into the native society they will benefit in the labor market by being able to tap more into existing social capital. There are also examples where the effect would be opposite if there are exclusive ethnic or immigrants social networks that provide big economic benefits, but require a degree of social exclusion to maintain the trust within this special group. This particularly matters for sectors with a low reliance on formal institutions or if there a separated immigrant and native labor markets. We know from Kalter and Kogan (2014) and Sowell (1981) that different migrant networks can be differently successful. A prominent example of a case where low integration into the native society is important for success are the diamond traders in Antwerp. By constituting an exclusive and separated group they are able to maintain a level of trust much higher than would be possible in an arms-length market (Aiyar 2014).

Immigrant networks can be useful due to easier access and ethnic solidarity for new arriving immigrants. Also if discrimination against immigrant is high in the normal labor market, a push into a separate labor market relying on immigrant networks can occur. Downsides of immigrant specific social networks are that they can hinder integration into the host country

native society. This can slow down language acquisition and learning host country specific skills and knowledge. It could also be possible that many high-status positions are only available via well established (native) social networks. Hence by not integrating into the native networks these positions will remain out of reach. This should have a lowering impact on wages. But it does not have to be that integrating into one kind of networks excludes the other. As Zhou and Bankston (1998) show it can be possible to maintain strong ties with other home country immigrants and integrate into the host society.

So, all in all there is no rigorous economic study yet for Germany that links integration into social networks by residential location to economic integration into the labor market. In this study I aim to take the first step in closing this gap. I will test the hypothesis underlying current policy proposals which is that a spreading of immigrants between natives – by facilitating integration into native social networks - leads to better access to the labor market than concentration in residential enclaves, and that it leads to higher wages and lower unemployment. As the networks itself are not observed in the data, I use the residential composition as proxy and arrive at the following testable hypothesis:

**Hypothesis:**

*Living in an area with few other foreigners leads to higher wages and lower unemployment for immigrants than when living in an area with many other foreigners.*

### 3. Methodology

I will measure labor market performance in two different ways. First, I analyze the hourly wages that immigrants earn. Second, I analyze the probability of being unemployed. Using two different independent variables provides a more thorough test of the hypothesis.

The theoretical background for analyzing wages realized in the labor market has been provided by Mincer (1974). Mincer presents an economic model that explains wages by years of schooling and experience. After linearizing the model we have a testable linear econometric model of log-wages:

$$\ln Y = \beta_0 + \beta_1 S + \beta_2 t + \beta_3 t^2 + \varepsilon \quad (1)$$



where Y is income, S years of schooling and t work experience in years. This - the so-called Mincer earnings function - is the starting point for the equation that I will estimate. I proceed by adding a migrant dummy for persons born outside of Germany, years since arrival (YSA) and years since arrival squared to capture nonlinearities. I also add controls.

$$\ln Y = \beta_0 + \beta_1 S + \beta_2 t + \beta_3 t^2 + \beta_4 \text{migrant} + \beta_6 \text{YSA} + \beta_7 \text{YSA}^2 + \beta \text{controls} + \varepsilon \quad (2)$$

Equation (2) is my expanded version of the Mincer wage equation that suffers less from omitted variable bias and that can differentiate between migrants and natives. In this basic framework I will now add the independent variable of “foreigners in area” (FA), defined as whether more or less than half of the families in the area are foreign or native, and an interaction effect between FA and migrant. Additionally I add year dummies ( $\alpha$ ) as otherwise macroeconomic conditions and policy which both change over time will disturb the estimation.

$$\ln Y = \alpha + \beta_0 + \beta_1 S + \beta_2 t + \beta_3 t^2 + \beta_4 \text{migrant} + \beta_6 \text{YSA} + \beta_7 \text{YSA}^2 + \beta_7 \text{FA} + \beta_8 \text{FAxmigrant} + \beta \text{controls} + \varepsilon \quad (3)$$

I will estimate this equation (3) in different variations: with a pooled OLS, a fixed effect and a random effects model to see which one fits the data better.

The second step will be to repeat the exercise but now estimate the probability of being unemployed using a logit model. It is important to keep in mind that not being unemployed is not the same as being in employment. There are also students, retirees and housewives to name a few examples who are not in employment but also not unemployed. I use unemployment status instead of employment (labor force status ‘working’) as it is less biased by demographics and as unemployment of immigrants is typically of higher political concern. But generally the same outcomes should be expected by using labor force status (see e.g. Beyer 2017). I estimate the following equation:

$$\Pr(U_{i,t} = 1) = \frac{\exp(\alpha + \beta X)}{1 + \exp(\alpha + \beta X)} = \frac{\exp(\alpha + \beta_0 + \beta_1 S + \beta_2 t + \beta_3 t^2 + \beta_4 \text{migrant} + \beta_6 \text{YSA} + \beta_7 \text{YSA}^2 + \beta_7 \text{FA} + \beta_8 \text{FAxmigrant} + \beta \text{controls})}{1 + \exp(\alpha + \beta_0 + \beta_1 S + \beta_2 t + \beta_3 t^2 + \beta_4 \text{migrant} + \beta_6 \text{YSA} + \beta_7 \text{YSA}^2 + \beta_7 \text{FA} + \beta_8 \text{FAxmigrant} + \beta \text{controls})} \quad (4)$$

where U=1 if the person is unemployed in this year. It is expected that the general findings are the same as in the wage equation. However, it could be that unemployment is spatially unevenly distributed and immigrants are also spatially unevenly distributed. So if

neighborhoods with more immigrants also have more unemployment, the effect of “living in an area with many foreigners” could be stronger on unemployment than on wages.

It is reasonable to assume that where people live matters for their social interaction and integration into social networks and hence the social capital that people are able to utilize. The residential location also determines which jobs are within a geographical reach. But the commuting perimeter can typically be bigger than the perimeter of the social networks. One is automatically confronted with the people living in the same area which suggests that residential location matters for accessing social networks. If this mechanism also extends to labor market performance will be assessed later.

Whether a neighborhood is rural or urban can make a difference as it can make a neighborhood geographically more separated or connected. But for the analysis conducted here, the data is self-reported by the participants of the survey. They are being asked: “How many foreigner families live in your residential area?” What constitutes the extent of the residential area is due to the judgement of the individual participant. Due to privacy reasons the data does not identify where the participant lived, so it is not possible to construct further information about the neighborhood.

According to the hypothesis “many foreigners in area“ interacted with immigrant should have a negative sign for wages and a positive sign for unemployment. The overall effect for an immigrant living in an area with few foreigners compared to living in an area with many foreigners is expected to be positive for wages and negative for unemployment .

This hypothesis can either be supported, the opposite effect can be detected or no significance can be found at all (also see figure 3).

#### **4. Data Description**

I use data of the German Socio-Economic Panel (SOEP) in the version 32 which covers the years 1984 till 2015. The SOEP is a household survey conducted by the German Institute for Economic Research (DIW) Berlin. It started out with 12,000 participants in 1984. New sets of participants have since been added to on the one hand compensate for participants exiting the sample and adjust to new socio-economic realities and demands of researchers. So for

example an extra set of East-German participants has been added in 1989, a sample of high income earners in 2002 and a new immigrant sample in 2013. The SOEP aims to represent the people living in Germany. So, already from 1984 on it includes foreigners in the sample. Certain minority groups like immigrants are overrepresented in order to have sufficient sample sizes for researchers conducting studies on these groups.<sup>6</sup>

I obtained from the SOEPlong dataset the following variables:

Hourly wages: I use current gross labor income in Euros (p<sub>glabgro</sub>) and actual weekly working hours (p<sub>gtatzeit</sub>) to calculate hourly wages. A month is assumed to have 4.33 weeks. I transform the hourly wages to log-hourly wages to get a normally distributed variable.

Unemployment status: This variable captures if a person is registered as unemployed.

Working: This variable is used as an alternative specification for the previous variable. It captures if a person's labor force status is "working".

Years of education: This variable measures how many years a person spend in school and further full-time education.

Years of experience: Number of years of full-time work experience.

Immigrant dummy: Everyone born outside of Germany is attributed a dummy value of 1. Büchel and Frick (2004) show that second generation immigrants are very similar to 'natives'. Given the findings of previous studies I expect this dummy to have a negative sign for the wage regression.

Years since arrival: I use information on the year of immigration to calculate the number of years an immigrant is living in Germany. This variable is expected to have a positive sign and the squared variable a negative sign leading to a concave catch-up process.

Foreigners living in residential area: The dummy variable takes the value of 1 if the respondents indicated that about half or more of the families are foreign. This question was part of the household survey and was hence asked by all SOEP participants – natives and immigrants. This question was only part of the survey in 6 years (1986, 1994, 1999, 2004, 2009, 2014). This reduces the sample to 84,788 observations that include this variable.

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<sup>6</sup> For a more detailed description of SOEP see Wagner et al (2007)

According to the hypothesis this is expected to have a negative sign. Also the interaction with immigrant is expected to have a negative sign.

East German: A person who lived in 1989 in the German Democratic Republic (GDR) is assigned a dummy value of 1.

Marital status: Persons married or in civil union are assigned a dummy value of 1, whereas singles, divorced person and widows are assigned a 0.

Female: A dummy for women is included. All persons are assigned to either male or female.

Trained for job: This dummy takes a value of 1, if the person received specific training for the job he or she is currently doing.

Fulltime job: A dummy for full-time positions is included to differentiate between full and part-time jobs.

Good German speaking skills: A dummy is included for persons reporting to have good or very good German speaking skills. As this variable has a high number of missing variables it has its problems regarding its relevance.

Good German writing skills: A dummy is included for persons reporting to have good or very good German writing skills. As this variable has a high number of missing variables it has its problems regarding its relevance.

Industry: I add dummies for the different industries according to the NACE classification.

I restrict my dataset to persons aged 16 to 70. I also drop all individuals that are not (potentially) part of the labor force. This includes everyone in education, military or community service, on maternity leave or retired. I also drop individuals that did not provide information on their labor force status.

## **5. Descriptive Results**

The dataset has 70,092 observations (which include information on foreigners living in area) of natives and 14,696 observations of immigrants. In figure 4, I plot the distributions of hourly and log-hourly wages of natives and immigrants. It can already be seen that the mode

of immigrant wages is slightly skewed to the left while the right-tail is also bigger for natives. A similar picture shows for immigrants living in an area with few other foreigners compared to immigrants living in an area with many other foreigners. The wage distribution for those with many foreigners in the area is moved to the left. The trend is the same for natives but not as pronounced. The unemployment rate of the immigrants in the sample is substantially higher compared to natives with 12.90% and 5.50% respectively (see table 1).

Figure 4: Density plots of hourly wages

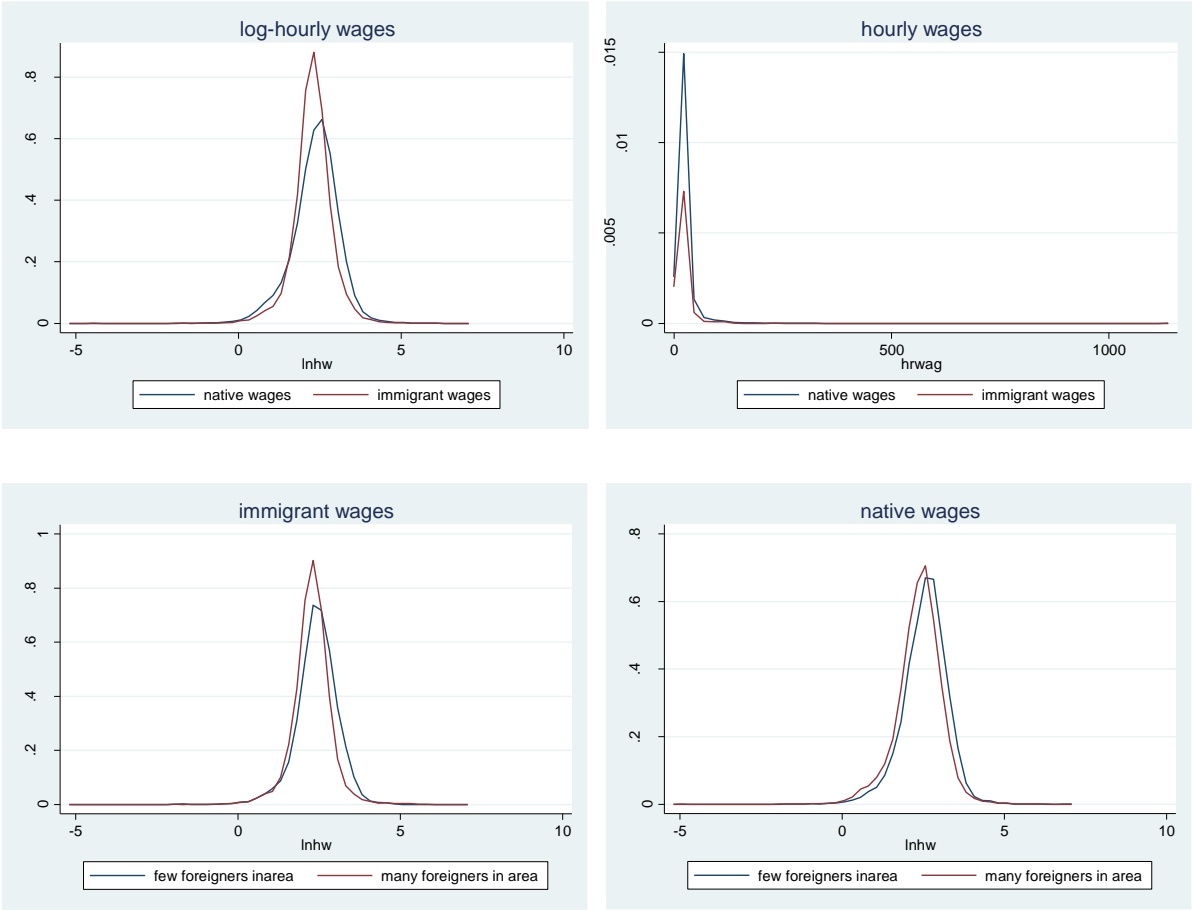


Table 1 shows the raw mean hourly-wage gaps for the most recent year, 2015. Immigrants earn on average about 20% less than natives. Natives have an average net hourly wage of 17.00€ and immigrants of 13.65€. This wage gap is smaller than the one between men and women (24.37%). The native-immigrant wage gap is slightly higher for men than for women. For comparison, former East Germans have a 13% lower wage (see table 1).

Table 1: Raw mean wage and unemployment gaps in 2015 (in Euros)

Total population			Total population			Women		
Hourly wages		Gap	Hourly wages		Gap	Hourly wages		Gap
Natives	Immigrants		Men	Women		Natives	Immigrants	
17.00	13.65	19.71%	18.51	14.00	24.37%	14.56	11.91	18.20%
(17.15)	(10.85)		(20.15)	(9.91)		(10.27)	(8.11)	

Men			Former East – West Germans		
Hourly wages		Gap	Hourly wages		Gap
Natives	Immigrants		West	East	
19.56	15.19	22.34%	16.65	14.47	13.09%
(21.91)	(12.60)		(17.22)	(8.83)	

Unemployment (in the sample) in 2015	
Natives	Immigrants
5.50%	12.90%

Hourly wages (in overall sample)		
Few foreigners in area	Many foreigners in area	Gap
15.78	13.14	16.73%
(17.35)	(12.71)	

	Hourly wages (in overall sample)		
	Few foreigners in area	Many foreigners in area	Gap
Native	16.10 (18.24)	13.44 (12.94)	16.52%
Immigrants	13.67 (9.50)	11.64 (11.42)	14,85%

Unemployment rates (in overall sample)	
Few foreigners in area	Many foreigners in area
6.03%	7.15%

	Unemployment rates (in overall sample)		
	Few foreigners in area	Many foreigners in area	Gap (percentage points)
Native	5.46%	6.42%	0.96
Immigrants	9.51%	10.40%	0.89

Source: SOEP; own calculations; as in sample, not weighted towards the real population.  
(standard deviation in brackets)

Areas with few foreigners living in them see higher hourly wages compared to areas with many foreigners. But this gap is higher for natives than for immigrants. Unemployment is also higher in areas with many foreigners. Again the gap is bigger for natives than for immigrants.

Additionally, the descriptive data suggests that there might be sorting of immigrants into areas with few and many foreigners based on education. Immigrants living in areas with few other foreigners have on average 1.4 additional years of education.

## **6. Regression Results and Discussion**

### *6.1 Results*

I start out by first estimating equation (2) without controls – the expanded Mincer wage equation. The coefficients are reported in column (1) of Table 2. The results reproduce common findings in immigration economics. I then add my variables of interest: a dummy for “many foreigners living in the area” and an interaction effect between “many foreigners living in the area” and being an immigrant. In column (3) I expand the model by including more control variables. I then add year dummies and industry dummies in column (4). After these standard pooled OLS regressions I also conduct a fixed effects and a random effects estimation – reported in the appendix A3. The Hausman test suggest against the use of the random effects model. The fixed effects model cannot be used due to the time invariance of the “immigrant” variable. The pooled OLS from column (4) also performs the best in terms of R-squared.

In table 3 I use unemployment as dependent variable. As unemployment is a binary measure I use a logit model to estimate my coefficients. I expand the number of variables in the same way as for the wage regressions. 1986 is the reference year in column (3). The further analysis will refer to the full model in column (3). For the unemployment estimation I do not use the industry dummies, trained for job dummy and fulltime dummy. These would always lead to a probability of being unemployed of 0 as these variables are conditional on being employed.

Table 2: Wage regressions

VARIABLES	(1) lnhw	(2) lnhw	(3) lnhw	(4) lnhw
Years of education	0.0987*** (0.000392)	0.0940*** (0.000883)	0.0810*** (0.000865)	0.0642*** (0.000907)
Years of experience	0.0494*** (0.000290)	0.0496*** (0.000650)	0.0369*** (0.000682)	0.0330*** (0.000654)
Years of experience^2	-0.000860*** (7.50e-06)	-0.000853*** (1.68e-05)	-0.000641*** (1.66e-05)	-0.000571*** (1.59e-05)
Immigrant	-0.0527*** (0.00965)	-0.196*** (0.0252)	-0.339*** (0.0244)	-0.248*** (0.0235)
Years since arrival	0.00684*** (0.000914)	0.0128*** (0.00211)	0.0135*** (0.00197)	0.0118*** (0.00191)
Years since arrival^2	-1.20e-05 (1.96e-05)	-0.000115*** (4.40e-05)	-0.000117*** (4.11e-05)	-0.000166*** (3.97e-05)
Foreigners in area		-0.132*** (0.00574)	-0.168*** (0.00538)	-0.0350*** (0.00784)
Foreigners in area X Immigrant		0.0565*** (0.0153)	0.131*** (0.0148)	0.112*** (0.0143)
East German			-0.339*** (0.00538)	-0.345*** (0.00523)
Married			0.140*** (0.00487)	0.125*** (0.00467)
Female			-0.0492*** (0.00497)	-0.0428*** (0.00510)
Trained for the job			0.198*** (0.00473)	0.187*** (0.00460)
Fulltime			0.178*** (0.00598)	0.202*** (0.00590)
Good German speaking skills			0.0378 (0.0316)	-0.0471 (0.0302)
Good German writing skills			0.0254 (0.0328)	-0.0142 (0.0312)
Constant	0.713*** (0.00530)	0.908*** (0.0131)	1.001*** (0.0130)	0.372*** (0.0232)
Time Dummies	No	No	No	Yes
Industry Dummies	No	No	No	Yes
Observations	317,590	57,884	57,884	54,511
R-squared	0.281	0.302	0.391	0.460

Standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1



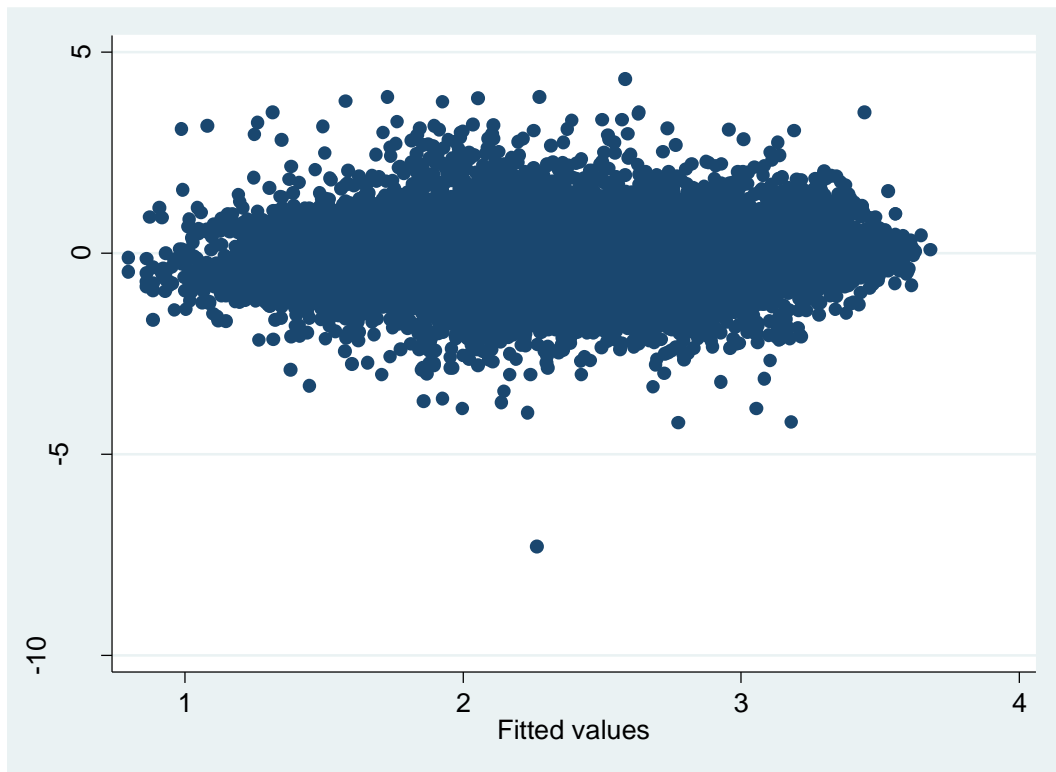
Table 3: Unemployment regressions

VARIABLES	(1) unempl	(2) unempl	(3) unempl
Immigrant	0.226*** (0.0343)	1.202*** (0.125)	1.271*** (0.124)
Years of education	-0.182*** (0.00672)	-0.205*** (0.00721)	-0.214*** (0.00734)
Years of experience	-0.0114*** (0.00370)	-0.0113*** (0.00392)	-0.00947*** (0.00392)
Years of experience^2	0.000100 (9.58e-05)	6.63e-05 (9.97e-05)	2.96e-05 (9.96e-05)
Foreigners in area	0.0217 (0.0345)	0.140*** (0.0393)	0.306*** (0.0539)
Foreigners in area X Immigrant		-0.271*** (0.0881)	-0.267*** (0.0882)
Years since arrival		-0.0463*** (0.00958)	-0.0465*** (0.00959)
Years since arrival^2		0.000907*** (0.000200)	0.000817*** (0.000202)
East German		1.113*** (0.0331)	1.056*** (0.0336)
Married		-0.322*** (0.0306)	-0.364*** (0.0308)
Female		-0.115*** (0.0299)	-0.115*** (0.0299)
Good German speaking skills		-0.352* (0.184)	-0.472*** (0.178)
Good German writing skills		0.658*** (0.187)	0.570*** (0.180)
1994			0.608*** (0.0633)
1999			0.497*** (0.0659)
2004			0.672*** (0.0628)
2009			0.484*** (0.0662)
2014			0.762*** (0.0716)
Constant	-0.458*** (0.0864)	-0.435*** (0.0933)	-0.998*** (0.109)
Observations	80,887	80,391	80,391

Standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

Figure 5: Residuals of model (4) table 2



Plotting the residuals of the model in column (4) in table 2 shows no systematic error in the model (Figure 5). This model even has a higher R-squared in explaining hourly wages than previous studies e.g. Beyer (2017). This suggests that adding a dummy for the number of foreigners living in the area in order to capture effects of social network integration is a valuable improvement of an econometric wage model.

I find that the amount of foreigners living in the area has a significant effect on wages and unemployment for immigrants as well as for natives. Column (4) in table 2 is the preferred model as for the wage regressions as it provides the best model fit with the highest R-squared. The sign of the “many foreigners in area” dummy is negative, but the interaction with “immigrant” is positive leading to an overall positive effect of “many foreigners area” for immigrants. So, the hypothesis that location in areas with few foreigners will help the labor market performance has to be rejected. This supports the opposite of the hypothesis that immigrants enter the labor market via immigrant social networks. The reverse seems to be true for natives: having many foreigners in the area reduces wages. So natives are also expected to enter the labor market via native social networks. “Sticking with your own kind” seems to help wages. Theory would say that group specific social capital and social networks which provide access to jobs in the labor market are the underlying reason behind that. Living

in an area with many foreigners reduced the average native wage by 3.5%; for an immigrant it increases the wage by 7.7%, which reduces the initial immigrant penalty of 24.8% (see below in 6.2). Table 3 shows that immigrants have a significant higher probability of being unemployed. Many foreigners in an area increases the probability of being unemployed for both natives and immigrants. The interaction between “foreigners in area” and immigrant is significant and lowers the probability of being unemployed. But the interaction effect does not fully compensate the stand-alone negative effect of “foreigners in area”.

Another indirect finding is that where people live does matter for how they enter the labor market. Otherwise we would not be able to find the significance as described above. Their residential location influences their membership in social networks and/or gives direct access to certain jobs. Due to poor data availability I am not able to assess the role that language acquisition plays in this process. This will be left to further research.

### 6.2 Discussion: Wages

Using the model from column (4) of table 2 the effect of a change in foreigners in area from few to many for an immigrant while all the rest remains constant can be determined as follows:

$$\begin{aligned} & \frac{\Delta \ln wage}{\Delta \text{foreigners in area}} \\ & = \text{coefficient of many foreigners in area dummy} \\ & + \text{coefficient of many foreigners in area dummy interacted with immigrant} \\ & = -0.0350 + 0.112 = 0.077 \end{aligned}$$

Hence, an immigrant’s hourly wage is expected to increase by 7.7% if he would move from an area with few foreigners to an area with many foreigners all else constant.

The analogous analysis for a native goes as follows:

$$\frac{\Delta \ln wage}{\Delta \text{foreigners in area}} = \text{coefficient of many foreigners in area dummy} = -0.0350$$

A native’s wage is expected to decrease by 3.5% if he would move from an area with few foreigners to an area with many foreigners all else constant.

Table 4: The effect of “foreigners in area” on natives and immigrant hourly wages

Change in lnwages with changes in Dmig and forinarea; rest constant:

	Few Foreigners in area (forinarea==0)	Many foreigners in area (forinarea==1)
Native (Dmig==0)	0 (baseline)	-0.0350
Immigrant (Dmig==1)	-0.248	-0.248 -0.0350 +0.112= -0.171

In percentage changes on hourly wages:

	Few Foreigners in area (forinarea==0)	Many foreigners in area (forinarea==1)
Native (Dmig==0)	0% (baseline)	-3.5%
Immigrant (Dmig==1)	-24.8%	-24.8% -3.5% +11.2%= -17.1%

Dmig: Immigrant dummy

forinarea: Dummy for many foreigners living in the area

Table 4 shows the effect of the variables “immigrant” and “foreigners in area” have on wages. The results control for characteristics such as education and experience. The wages for the immigrant refer to the first year in Germany. The dynamic effects are analyzed at a later stage. A native in an area with few foreigners receives the highest wage. Benchmarked against this, an immigrant receives a penalty of 24.8%. This penalty decreases to 17.1% if he locates in an area with many foreigners. For a native his wage decreases by 3.5% if he is located in an area with many foreigners. This is also visually represented in figure 6. Immigrants relatively gain by being located in an area with many foreigners while natives’ wages are suppressed.

Figure 6: Wage difference to a comparable native in an area with few foreigners (in %) (static at the first year in Germany of the immigrant)

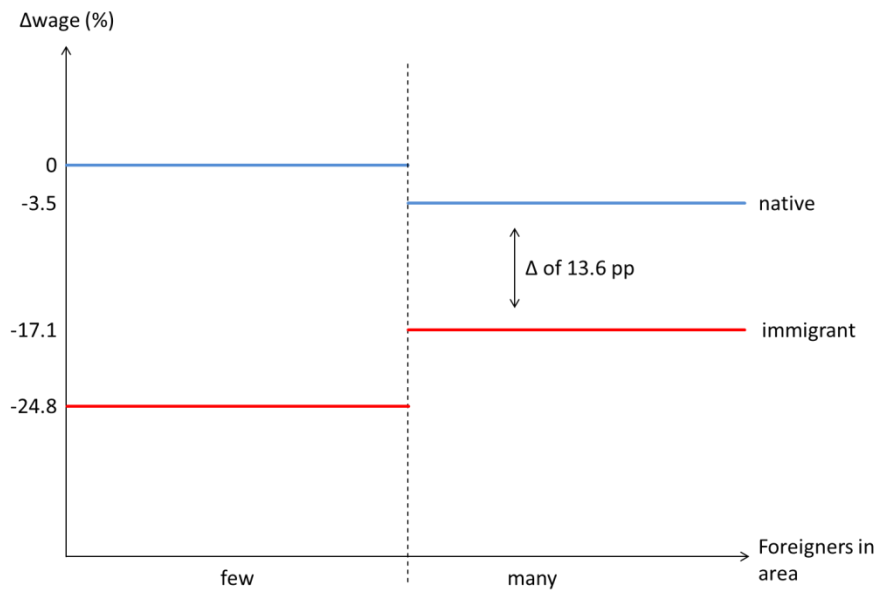
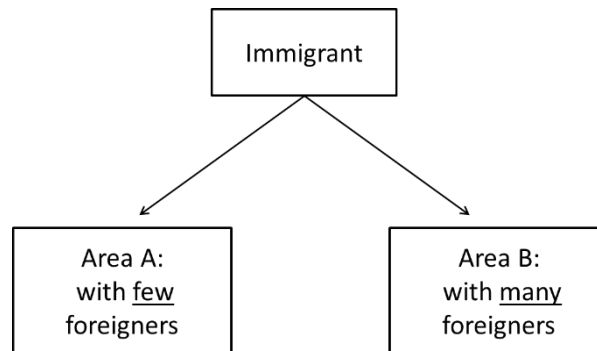


Figure 7: Location decision of an immigrant



A new arriving immigrant faces a location decision or in special cases the government faces the decision where to locate immigrants. This is shown in Figure 7 above.

If the immigrant chooses Area A he will earn 24.8% less than a comparable native in this area. If he chooses Area B he will make 17.1% less than a comparable native in Area A and 13.6% less than a comparable native in Area B (all numbers for the first year since immigration). But the descriptive statistics suggest that the decision in which area to locate is not completely independent. For example, immigrants who chose Area A have on average 1.4 more years of education than immigrants who chose Area B which alone already leads to an around 9% increase in the hourly wage. Also, table A10 shows that the years of education, being trained for the job and being married increase the chances of being located in an area with few foreigners.

What will be the effect on natives if an area with few foreigners turns into an area with many foreigners due to immigration? The wages of the natives might suffer as the regression analysis suggests a drop of 3.5% in the hourly wage (Table 2 column (4)). But as the regression analysis does not analyze actual changes over time but just observes people either living here or there this has to be taken with caution. It is reasonable to assume, that the old social networks can be maintained after the ethnic composition of the neighborhood changed. To analyze these mechanisms in more detail will be left for further research.

Figure 8: Assimilations paths: Wage difference (%) of an immigrant to a comparable native..

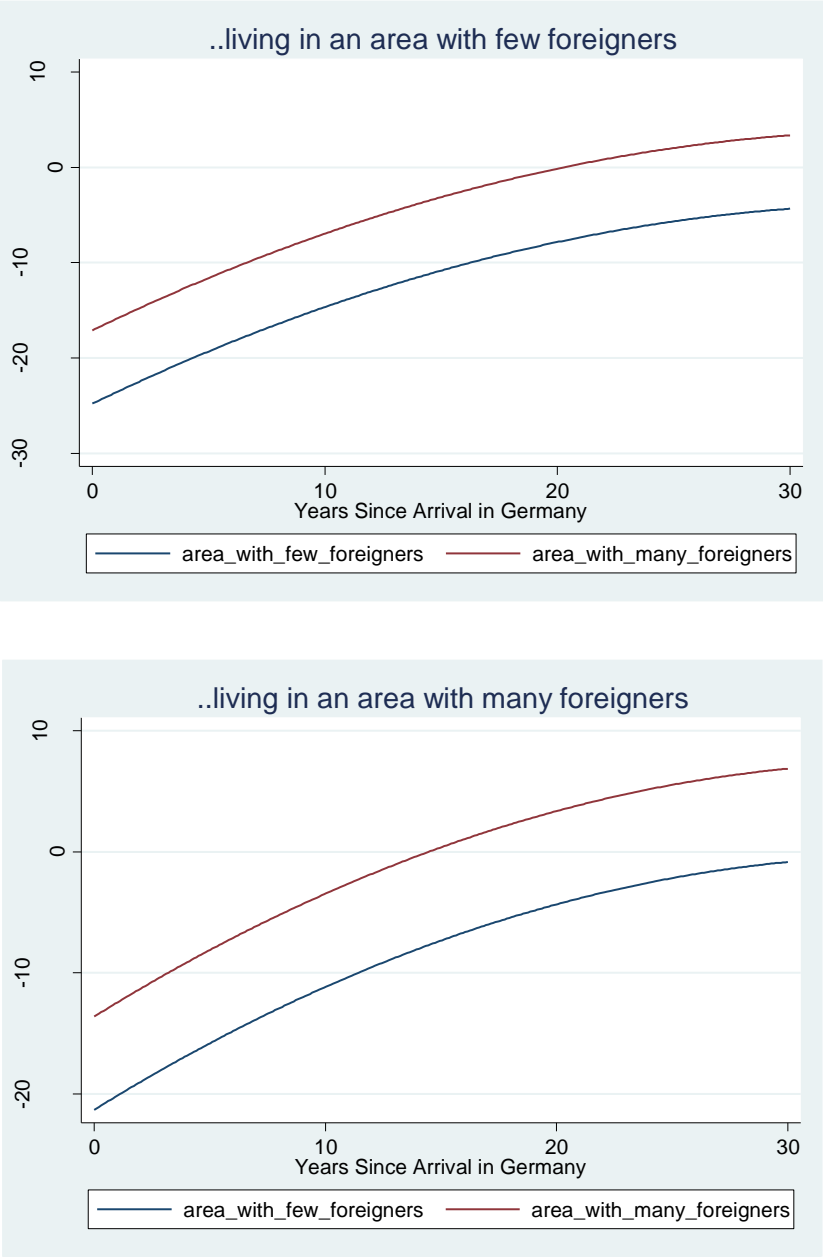


Figure 8 shows the dynamics over the years following immigration. It plots the assimilation paths for an immigrant over the years since arrival. (More detailed description of how the curves have been calculated can be found in the appendix A9.)

The horizontal line at 0 is the benchmark which is the comparable native. The first figure is for the case that the comparable “benchmark” native lives in an area with few foreigners, in the second figure the comparable “benchmark” native lives in an area with many foreigners. The blue lines represent the wage difference of an immigrant, living in an area with few other foreigners, to a comparable native over the years that the immigrant is living in Germany. The red lines are the wage of an immigrant, living in an area with many other foreigners, relative to a comparable native over the years that the immigrant is living in Germany. The blue line in the first figure and the red line in the second figure show the assimilation path of immigrants to comparable natives in the same kind of area (in terms of foreigners living there).

The wage of an immigrant living in an area with many other foreigners converges to the level of a comparable native living in an area with few foreigners after 20 years. It converges to the level of a comparable native living in an area with many foreigners after around 14 years. The wages of foreigners living in an area with few other foreigners never converge to the levels of comparable natives no matter where these natives live. Within an area with few foreigners, natives always maintain a premium. Within an area with many foreigners, immigrants catch up to comparable natives within 14 years. When extrapolating the trend immigrants actually earn a premium of around 7% after 30 years. Only 15 percent of the immigrants in the sample have “years since arrival” of 30 or more. So, the extrapolation has to be seen with caution.

### *6.3 Discussion: Unemployment*

The regressions on unemployment as presented in table 3 model (3) produce different results. The coefficients all have the signs in line with findings from the wage regressions. But the interaction effect does not fully compensate for the ‘many foreigners in area’ effect. Having many foreigners in the residential area increases the probability of being unemployed, also for immigrants. With every additional year in the country, the probability of being unemployed decreases. One possible explanation is that as the overall wage level in the immigrant labor market is lower, implicit and explicit minimum wages have a stronger effect on crowding out employment. Over the years in Germany immigrants can expect a higher hourly wage and hence employment becomes more attractive and the probability of being unemployed goes down.

It is surprising that even though the regression analysis, which accounts for observed characteristics, showed that living with many foreigners helps the labor market performance of immigrants measured in wages, the descriptive statistics in Table 3 show that immigrants living in areas with many foreigners actually earn lower wages and are more likely to be unemployed than their counterparts in areas with fewer foreigners. This suggests that more productive immigrants sort themselves into areas with fewer foreigners even though they forego a significant wage premium that they would earn if they would tap into the immigrant social networks in an immigrant neighborhood. The results from Table A10 show that more educated, married and immigrants who are especially trained for the job they do are sorting themselves into areas with fewer other foreigners.

It is also possible that the spatial concentration of people is not so much along ethnic lines, but along lines of blue and white collar workers. This would explain the before mentioned sorting. Immigration into Germany has typically been skewed towards blue collar workers. This started with the hiring of guest workers for the heavy industry. First, labor force participation rates for foreigners were extremely high as they just came for the job. But now we observe that in working class neighborhoods with many foreigners, unemployment rates of immigrants are unusually high. This might be due to the structural change. The heavy industry declined and most of the jobs in these industries for which cheap immigrant labor was recruited disappeared (Bade 2000).

#### *6.4 Robustness*

Going from the model in column (3) to the full model in column (4) in table 2 which includes time and industry dummies the immigrant penalty shrinks as does the “foreigners in area” effect leading to an overall positive effect of “foreigners in area” for immigrants. The immigrant dummy penalty gets smaller after adding the industry dummies. This suggests that immigrants are more often employed in lower paying industries. So, model (3) overestimates the immigrant penalty. When introducing the time dummies the “foreigners in area” effect gets smaller leading to an overall positive effect for immigrants of living in an area with many foreigners. Without accounting for the different years, the overall effect was negative for immigrants due to a bigger effect of “foreigners in area”. A probable reason why accounting for the years is important is that the immigrant labor market is more vulnerable for economic cycles than the native labor market. Since the start of the guest worker recruitments immigrant labor has been seen as a way to fill labor shortages in unattractive positions. These are also more vulnerable during a downturn. So in an area with many foreigners the labor market will



suffer more during a down turn than in areas with few foreigners. (Also see the reduced full model (4) once without industry dummies and once without time dummies in the appendix A11.)

I also tried religion and nationality as further controls, but these were not significant and did not improve the model fit and are hence excluded from the model. I further test whether my findings are robust by experimenting with a few variations of the model. In table A8, I present the results when estimating whether a person has a labor force status of “working” with a logit model instead of if a person is unemployed. There can be differences in the classification of unemployed and working. The unemployment statistics can be misleading if there is a high number of discouraged workers who gave up on finding a job. The results for “working” as dependent variable are consistent with the previous findings. “Many foreigners in area” has a significant and negative effect on the probability of being in work. But the interaction between immigrant and foreigners in the area is not significant.

Next, I use 6 different dummies for the amount of foreigners in the area going from none to all (see Tables A4-A5). Not all dummies are significant and the model fit stays similar. So, I chose the model specification in Table 2 for a clearer interpretation. But when assessing unemployment in Table A5 all “foreigners in area” dummies are significant, but the interactions are not significant.

In table A6 I re-estimate model (4) of Table 2 with time lags of 2 years, 5 years, 10 years and 15 years for the “foreigners in area variable”. None of the lagged variables and their interactions are significant which suggests that the original model in Table 2 is correct. The effect of “foreigners living in area” on wages seems to be instantaneous and not lagged over time. In table A7 I repeat the same procedure for model (3) of table 3. The results are the same with again no significance for the lagged variables. This indicates that using the non-lagged specification is the right model choice.

### *6.5 Limitations and Further Research*

The results have the following limitations: The variable “foreigners in area” is self-reported and hence lacks objectivity. The variable also only captures all foreigners. So, I cannot determine how many of them are of the same nationality or the same language group as the new immigrant. I also do not have information on other characteristics of the neighborhood such as rural or urban, average income level, average education level etc. As the dataset did not allow the use of panel methods, unobserved individual characteristics are not accounted

for in the results. Also, there might be a degree of endogeneity between wages and the number of foreigners in an area. In this study I test the impact that “foreigners in area” has on wages (and unemployment). It is assumed that the effect works through social networks and access to network specific social capital. But reverse causality can lead to problems in the analysis. Reverse causality would mean that the hourly wage influences the location decision, whether to live in an area with many or few foreigners. Higher earning people often have a preference to live in certain areas which are typically different from working class neighborhoods with a bigger foreign population. So higher income could lead to a preference to live in an area with fewer foreigners for natives as well as for immigrants. But it is reasonable to believe that this effect is not only driven by wages but rather by education. So, rich people do not only like to live close to other rich people, rather rich people are typically higher educated and like to be around other highly educated people out of personal preference as well as that they can share certain public amenities like theaters, galleries etc. more easily. By accounting for many control variables – including education - the distortion due to reverse causality should be minimized.

A more detailed analysis of the sorting process of immigrants into different areas as well as the role of language acquisition in residential location and social networks are left for further research. It would also be interesting for further research to gather more detailed data on residential composition to differentiate between foreigners of the own nationality and other nationalities. The effect of migrant networks is probably underestimated as it takes all foreigners living in an area together. The positive links are probably stronger for members of the same language group or nationality living there. Additional questions for future research are: which are the defining characteristics of a group that fosters strong network ties? Is it nationality, language, religion or something else? If in the future data on enclave quality and on refugees become available, it will interesting to account for enclave quality as well as to repeat the analysis with data on refugees to see whether there will be differences.

## *6.6 Policy Implications*

The labor market integration of refugees is foremost a political decision. Despite the UN 1951 Refugee Convention guaranteeing the right to wage-labor and self-employment, refugees are in most countries effectively barred from taking up work in the formal sector (Asylum Access 2014). Most Western European countries followed a similar approach by actively discouraging the labor market integration of refugees (Martín 2017). This is mainly due to political opportunism, as deterrent for potential asylum applicants and to make a potential

future repatriation easier. But since the record arrival of asylum seekers in 2015 there has been a shift towards policies that facilitate easier labor market integration. As time in exile for refugees is typically fairly long – the UNHCR (2012) reports an average time in exile of 20 years – many countries abandoned the idea of a fast repatriation and started to think of integration instead (Martín 2017).

The findings of this study can therefore not predict the labor market performance and integration of immigrants and refugees as this is dominated by policy, but it can help to design better policies by providing insights into how concrete instances of residential location and social integration affect labor market success.

I do not find evidence that policies that support a spreading of migrants would help their labor market performance. On the contrary being located in an area with many other foreigners increases immigrant wages and leads to a faster convergence to the wage levels of comparable natives. But there can of course be reasonable arguments under different considerations for spreading policies. Policies to encourage the spreading of migrants are expected to have a negative effect on their wages, but might help the chance of getting in employment. On the other hand native wages might suffer if the share of foreigners increases in a neighborhood and hence decreases the size of the native social network. Effectively this leads to a policy dilemma without straight forward recommendations on what would be best to do.

## **7. Conclusion**

I estimated the impact of “foreigners living in the same residential area” on immigrants’ wages using a pooled OLS model and the impact on unemployment using a logit model. Many foreigners in the same residential area have a positive impact on wages of immigrants, but increase their probability of being unemployed. For natives, the effect is reversed: many foreigners in area lowers wages and increases the probability to be unemployed even more than for immigrants. These results reject the hypothesis that a spreading of refugees will lead to a better labor market performance and instead support that immigrants mainly enter the labor market via migrant social networks. It also provides evidence that the residential location matters for access to the labor market. But average wages in areas with many immigrants are still lower due to a sorting of higher productive immigrants into areas with

fewer foreigners. Policy proposals for an even spreading of refugees to support integration cannot be supported with empirical evidence in respect to labor market performance. On the other hand, a policy dilemma remains as natives' wages suffer from a high share of foreigners living in the residential area.

## Appendix:

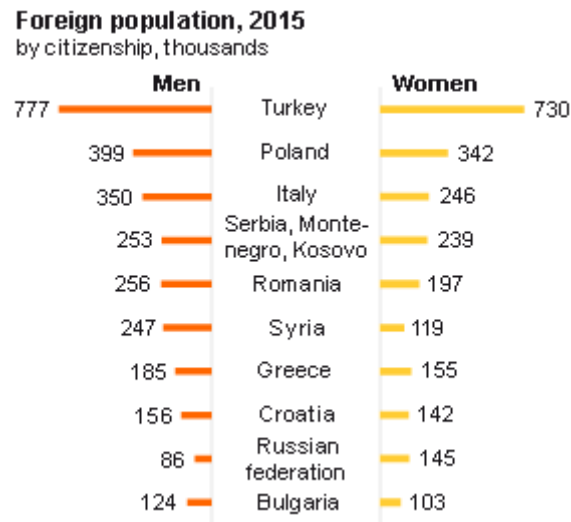
Table A1: Different legal regimes of migration and their characteristics (selection bias)

<b>Legal regime of immigration</b>	<b>Legal German term</b>	<b>Explanation</b>
Expellees	Vertriebene	Ethnic Germans who fled ethnic cleansing in Eastern Germany; partially better educated than the natives in the rural areas where they settled (e.g. Semrad 2015)
(East German) refugees	Flüchtlinge	People who moved from the Soviet occupation zone to the Western zones or later the GFR
“Aussiedler”	Aussiedler; since 1993 Spätaussiedler	Ethnic Germans from Eastern Europe resettled to Germany
Guest workers	Gastarbeiter	Southern European men who were hired on temporary contracts to fill labor shortages in the industry
Family reunification	Familienzusammenführung	Mainly wives and children of the guest workers
Asylum	Asyl	Politically persecuted individuals; often high educated
Tolerated	Geduldet	People who do not fulfil the criteria for asylum but are granted temporary stay due to unsafe conditions in the origin country
War time protection	Kriegszeitschutz	Similar to tolerated; both typically consist of populations fleeing a ground war and are hence often less educated than political refugees
Quota refugees	Kontingentflüchtlinge	Soviet Jews, previously also Vietnamese
EU Blue Card	Blaue Karte EU	EU-wide policy aimed at attracting high-skill immigration; 38.000 since

		2012, many of them former international university students (Hanganu and Heß 2016)
--	--	--

NB: The available data does not identify the legal regime under which people immigrated

Figure A2: Chart of current stock of immigrants by nationality; Source: Destatis (2017)



A3: Wage regressions (Table 2): Fixed and Random effects model

VARIABLES	(1) lnhw	(2) lnhw
pgbilzeit	0.0543*** (0.00363)	0.0664*** (0.00106)
pgexpft	0.0287*** (0.00161)	0.0351*** (0.000675)
pgexpft2	-0.000615*** (2.68e-05)	-0.000604*** (1.63e-05)
o.Dmig	-	
ysa	-0.00498 (0.00314)	0.00883*** (0.00188)
ysa2	-4.97e-05 (6.19e-05)	-0.000137*** (3.94e-05)
forinarea	-0.00432 (0.0101)	-0.0317*** (0.00734)
Dmigxarea	0.0432* (0.0246)	0.110*** (0.0138)
o.east	-	

married	0.0768*** (0.00846)	0.115*** (0.00494)
o.fem	-	
trforjob	0.135*** (0.00747)	0.182*** (0.00477)
fulltime	0.186*** (0.00895)	0.203*** (0.00584)
o.speaking	-	
o.writing	-	
Dmig		-0.197*** (0.0236)
east		-0.349*** (0.00652)
fem		-0.0379*** (0.00610)
speaking		-0.0559* (0.0311)
writing		-0.00947 (0.0321)
Constant	0.633*** (0.0568)	0.372*** (0.0249)
Time Dummies	Yes	Yes
Industry Dummies	Yes	Yes
Panel Method	FE	RE
Observations	54,511	54,511
R-squared	0.343	
Number of pid	31,572	31,572

Standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A4: Wage regressions with 6 categories of “foreigners in area”

VARIABLES	(1) lnhw	(2) lnhw	(3) lnhw
pgbilzeit	0.0987*** (0.000392)	0.0929*** (0.000879)	0.0803*** (0.000865)
pgexpft	0.0494*** (0.000290)	0.0501*** (0.000646)	0.0368*** (0.000679)
pgexpft2	-0.000860*** (7.50e-06)	-0.000865*** (1.67e-05)	-0.000641*** (1.65e-05)
Dmig	-0.0527*** (0.00965)	-0.203*** (0.0672)	-0.399*** (0.0634)
ysa	0.00684*** (0.000914)	0.0126*** (0.00210)	0.0134*** (0.00197)

ysa2	-1.20e-05 (1.96e-05)	-0.000113*** (4.37e-05)	-0.000114*** (4.10e-05)
2.hlj0004		0.00455 (0.00854)	-0.00143 (0.00801)
3.hlj0004		-0.140*** (0.00890)	-0.0719*** (0.00847)
4.hlj0004		-0.0356*** (0.0115)	0.0295*** (0.0108)
5.hlj0004		0.173*** (0.0102)	0.202*** (0.00957)
6.hlj0004		0.0537*** (0.0130)	0.163*** (0.0123)
1b.hlj0004#0b.Dmig		0 (0)	0 (0)
1b.hlj0004#1.Dmig		0.0136 (0.0652)	0.175*** (0.0614)
2o.hlj0004#0b.Dmig		0 (0)	0 (0)
2.hlj0004#1.Dmig		0.0115 (0.0646)	0.167*** (0.0608)
3o.hlj0004#0b.Dmig		0 (0)	0 (0)
3.hlj0004#1.Dmig		0.157** (0.0656)	0.231*** (0.0616)
4o.hlj0004#0b.Dmig		0 (0)	0 (0)
4.hlj0004#1.Dmig		0.0907 (0.0669)	0.146** (0.0628)
5o.hlj0004#0b.Dmig		0 (0)	0 (0)
5.hlj0004#1.Dmig		-0.0460 (0.0663)	0.0311 (0.0622)
6o.hlj0004#0b.Dmig		0 (0)	0 (0)
6o.hlj0004#1o.Dmig		0 (0)	0 (0)
east			-0.320*** (0.00554)
married			0.140*** (0.00487)
fem			-0.0485*** (0.00495)
trforjob			0.198*** (0.00471)
fulltime			0.184*** (0.00597)
speaking			0.0371 (0.0316)
writing			0.0294 (0.0327)
Constant	0.713***	0.833***	0.862***



	(0.00530)	(0.0134)	(0.0133)
Observations	317,590	57,884	57,884
R-squared	0.281	0.313	0.396

Standard errors in parentheses  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

VARIABLES	(4) lnhw	(5) lnhw	(6) lnhw
pgbilzeit	0.0641*** (0.000909)	0.0545*** (0.00363)	0.0663*** (0.00106)
pgexpft	0.0330*** (0.000654)	0.0288*** (0.00161)	0.0351*** (0.000675)
pgexpft2	-0.000571*** (1.59e-05)	-0.000618*** (2.69e-05)	-0.000606*** (1.63e-05)
Dmig	-0.288*** (0.0599)		-0.233*** (0.0588)
ysa	0.0115*** (0.00191)	-0.00454 (0.00314)	0.00876*** (0.00188)
ysa2	-0.000159*** (3.97e-05)	-5.84e-05 (6.21e-05)	-0.000133*** (3.94e-05)
2.hlj0004	0.00359 (0.00764)	-0.0282*** (0.00923)	-0.00661 (0.00722)
3.hlj0004	-0.0328*** (0.00815)	-0.0383*** (0.0105)	-0.0362*** (0.00787)
4.hlj0004	-0.00426 (0.0109)	-0.0255* (0.0134)	-0.00699 (0.0103)
5.hlj0004	0.0657*** (0.0127)	-0.0281 (0.0194)	0.0486*** (0.0124)
6.hlj0004	0.0387*** (0.0149)	-0.00925 (0.0223)	0.0308** (0.0145)
1b.hlj0004#0b.Dmig	0 (0)	0 (0)	0 (0)
1b.hlj0004#1.Dmig	0.165*** (0.0578)	-0.0665 (0.112)	0.143** (0.0566)
2o.hlj0004#0b.Dmig	0 (0)	0 (0)	0 (0)
2.hlj0004#1.Dmig	0.135** (0.0572)	-0.0299 (0.111)	0.133** (0.0559)
3o.hlj0004#0b.Dmig	0 (0)	0 (0)	0 (0)
3.hlj0004#1.Dmig	0.162*** (0.0581)	0.0297 (0.112)	0.164*** (0.0568)
4o.hlj0004#0b.Dmig	0 (0)	0 (0)	0 (0)
4.hlj0004#1.Dmig	0.0770 (0.0592)	-0.0866 (0.113)	0.0624 (0.0578)
5o.hlj0004#0b.Dmig	0 (0)	0 (0)	0 (0)

5.hlj0004#1.Dmig	0.0199 (0.0585)	-0.0444 (0.115)	0.0234 (0.0573)
6o.hlj0004#0b.Dmig	0 (0)	0 (0)	0 (0)
6o.hlj0004#1o.Dmig	0 (0)	0 (0)	0 (0)
east	-0.337*** (0.00542)		-0.342*** (0.00666)
married	0.126*** (0.00467)	0.0785*** (0.00847)	0.116*** (0.00494)
fem	-0.0424*** (0.00509)		-0.0377*** (0.00609)
trforjob	0.187*** (0.00460)	0.135*** (0.00747)	0.182*** (0.00477)
fulltime	0.203*** (0.00589)	0.186*** (0.00894)	0.203*** (0.00584)
speaking	-0.0350 (0.0303)		-0.0474 (0.0311)
writing	-0.00955 (0.0312)		-0.00574 (0.0321)
1994.syear	0.256*** (0.00943)	0.374*** (0.0121)	0.271*** (0.00806)
1999.syear	0.348*** (0.00941)	0.507*** (0.0153)	0.361*** (0.00826)
2004.syear	0.462*** (0.00881)	0.654*** (0.0187)	0.471*** (0.00807)
2009.syear	0.472*** (0.00898)	0.718*** (0.0221)	0.488*** (0.00834)
2014.syear	0.526*** (0.0114)	0.858*** (0.0282)	0.552*** (0.0109)
Constant	0.352*** (0.0228)	0.662*** (0.0587)	0.361*** (0.0245)
Industry Dummies	Yes	Yes	Yes
Panel Methods	No	FE	RE
Observations	54,511	54,511	54,511
R-squared	0.461	0.344	
Number of pid		31,572	31,572

Standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A5: Unemployment regressions with 6 categories of “foreigners in area”

VARIABLES	(1) unempl	(2) unempl	(3) unempl
Dmig	0.226*** (0.0351)	1.055** (0.480)	1.192** (0.480)
pgbilzeit	-0.180*** (0.00676)	-0.203*** (0.00722)	-0.211*** (0.00734)

pgexpft	-0.0112*** (0.00371)	-0.0107*** (0.00392)	-0.00847** (0.00392)
pgexpft2	9.86e-05 (9.60e-05)	6.42e-05 (9.98e-05)	2.30e-05 (9.97e-05)
2.hlj0004	-0.202*** (0.0415)	-0.279*** (0.0525)	-0.275*** (0.0526)
3.hlj0004	0.0937** (0.0432)	-0.214*** (0.0533)	-0.212*** (0.0538)
4.hlj0004	0.190*** (0.0561)	-0.0677 (0.0678)	-0.219*** (0.0710)
5.hlj0004	-0.216*** (0.0582)	-0.424*** (0.0707)	-0.893*** (0.0883)
6.hlj0004	-0.406*** (0.0921)	-0.780*** (0.0982)	-1.246*** (0.112)
1b.hlj0004#0b.Dmig		0 (0)	0 (0)
1b.hlj0004#1.Dmig		-0.296 (0.477)	-0.320 (0.477)
2o.hlj0004#0b.Dmig		0 (0)	0 (0)
2.hlj0004#1.Dmig		-0.0639 (0.476)	-0.179 (0.475)
3o.hlj0004#0b.Dmig		0 (0)	0 (0)
3.hlj0004#1.Dmig		-0.0837 (0.478)	-0.295 (0.479)
4o.hlj0004#0b.Dmig		0 (0)	0 (0)
4.hlj0004#1.Dmig		-0.136 (0.484)	-0.349 (0.485)
5o.hlj0004#0b.Dmig		0 (0)	0 (0)
5.hlj0004#1.Dmig		0.280 (0.483)	0.278 (0.483)
6o.hlj0004#0b.Dmig		0 (0)	0 (0)
6o.hlj0004#1o.Dmig		0 (0)	0 (0)
ysa		-0.0466*** (0.00960)	-0.0455*** (0.00962)
ysa2		0.000909*** (0.000201)	0.000798*** (0.000203)
east		1.122*** (0.0344)	1.081*** (0.0352)
married		-0.311*** (0.0307)	-0.354*** (0.0309)
fem		-0.112*** (0.0299)	-0.113*** (0.0299)
speaking		-0.344* (0.185)	-0.528*** (0.175)
writing		0.646***	0.501***

		(0.187)	(0.177)
1994.syear			0.578*** (0.0635)
1999.syear			0.458*** (0.0661)
2004.syear			0.639*** (0.0631)
2009.syear			0.451*** (0.0665)
2014.syear			0.999*** (0.0733)
Constant	-0.405*** (0.0823)	-0.137 (0.0923)	-0.541*** (0.102)
Observations	80,887	80,391	80,391

Standard errors in parentheses  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A6: Time lags: wage

VARIABLES	(1) Lnhw (2 years lag)	(2) Lnhw (5 years lag)	(3) Lnhw (10 years lag)	(4) Lnhw (15 years lag)
pgbilzeit	0.0623*** (0.00116)	0.0611*** (0.00122)	0.0624*** (0.00168)	0.0640*** (0.00263)
pgexpft	0.0287*** (0.000855)	0.0233*** (0.000932)	0.0179*** (0.00138)	0.0152*** (0.00219)
pgexpft2	-0.000491*** (2.03e-05)	-0.000359*** (2.15e-05)	-0.000275*** (3.01e-05)	-0.000232*** (4.60e-05)
ysa	0.0139*** (0.00293)	0.0119*** (0.00358)	0.0100 (0.00650)	0.0213* (0.0127)
ysa2	-0.000241*** (5.92e-05)	-0.000180*** (6.58e-05)	-0.000122 (0.000107)	-0.000303 (0.000193)
Dmig	-0.115** (0.0490)	-0.140** (0.0613)	-0.284** (0.113)	-0.399* (0.217)
lag2forinarea	0.00873 (0.0114)			
lag2forinareaxdmig	-0.0494 (0.0394)			
east	-0.345*** (0.00653)	-0.330*** (0.00697)	-0.323*** (0.00963)	-0.317*** (0.0154)
married	0.0978*** (0.00599)	0.0707*** (0.00632)	0.0720*** (0.00898)	0.0732*** (0.0137)
fem	-0.0702*** (0.00648)	-0.0925*** (0.00698)	-0.102*** (0.00978)	-0.0929*** (0.0152)
trforjob	0.147*** (0.00577)	0.138*** (0.00613)	0.131*** (0.00839)	0.136*** (0.0127)
fulltime	0.176*** (0.00775)	0.113*** (0.00831)	0.129*** (0.0115)	0.132*** (0.0180)

o.speaking	-	-	-	-
o.writing	-	-	-	-
1996.year	0.232*** (0.0100)			
2001.year	0.300*** (0.00988)			
2006.year	0.371*** (0.00946)			
2011.year	0.425*** (0.00976)			
lagforinarea		0.0180 (0.0122)		
lagforinareaxdmig		-0.0369 (0.0439)		
1999.year		0.199*** (0.0102)		
2004.year		0.291*** (0.0101)	0.105*** (0.0122)	
2009.year		0.318*** (0.00958)	0.116*** (0.0123)	0.0741*** (0.0151)
2014.year		0.421*** (0.0102)	0.238*** (0.0120)	0.192*** (0.0158)
lag10forinarea			0.00533 (0.0163)	
lag10forinareaxdmig			0.0827 (0.0670)	
lag15forinarea				-0.00969 (0.0237)
lag15forinareaxdmig				0.0269 (0.0887)
Constant	0.480*** (0.0294)	0.710*** (0.0325)	0.978*** (0.0451)	0.985*** (0.0666)
Observations	32,858	27,051	14,269	6,692
R-squared	0.409	0.394	0.360	0.337

Standard errors in parentheses  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A7: Time lags: unemployment

VARIABLES	(1) unempl (2years)	(2) unempl (5 years)	(3) unempl (10 years lag)	(4) unempl (15 years lag)
Dmig	0.805*** (0.283)	0.641* (0.388)	-1.825** (0.775)	-3.086* (1.738)
pgbilzeit	-0.212*** (0.0101)	-0.215*** (0.0119)	-0.195*** (0.0154)	-0.203*** (0.0256)

pgexpft	-0.00812 (0.00534)	-0.0198*** (0.00654)	-0.0291*** (0.00910)	-0.0387** (0.0150)
pgexpft2	0.000137 (0.000130)	0.000297* (0.000155)	0.000396* (0.000207)	0.000565* (0.000328)
lag2forinarea	-0.0600 (0.0778)			
lag2forinareaxdmig	-0.225 (0.232)			
ysa	-0.0198 (0.0164)	0.0184 (0.0232)	0.141*** (0.0457)	0.203** (0.101)
ysa2	0.000518 (0.000326)	-0.000306 (0.000429)	-0.00213*** (0.000766)	-0.00307** (0.00156)
east	1.124*** (0.0442)	1.108*** (0.0525)	1.048*** (0.0732)	0.840*** (0.122)
married	-0.455*** (0.0413)	-0.489*** (0.0484)	-0.574*** (0.0649)	-0.714*** (0.102)
fem	-0.174*** (0.0399)	-0.244*** (0.0482)	-0.352*** (0.0665)	-0.500*** (0.113)
o.speaking	-	-	-	-
o.writing	-	-	-	-
1996.year	0.519*** (0.0727)			
2001.year	0.322*** (0.0756)			
2006.year	0.539*** (0.0717)			
2011.year	0.109 (0.0801)			
lagforinarea		-0.0470 (0.0932)		
lagforinareaxdmig		-0.243 (0.281)		
1999.year		0.990*** (0.0954)		
2004.year		1.185*** (0.0951)	0.265*** (0.0898)	
2009.year		0.919*** (0.0968)	-0.00152 (0.0976)	0.389*** (0.128)
2014.year		0.647*** (0.106)	-0.289*** (0.102)	-0.0182 (0.145)
lag10forinarea			-0.0880 (0.120)	
lag10forinareaxdmig			0.322 (0.449)	
lag15forinarea				-0.0587 (0.193)
lag15forinareaxdmig				0.526 (0.761)
Constant	-0.578***	-0.996***	0.0344	0.123

	(0.148)	(0.183)	(0.235)	(0.386)
Observations	48,695	38,187	20,631	9,504

Standard errors in parentheses  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A8: Working as dependent variable

VARIABLES	(1) working	(2) working	(3) working
Dmig	-0.0513** (0.0219)	-0.696*** (0.0862)	-0.685*** (0.0862)
pgbilzeit	0.173*** (0.00375)	0.182*** (0.00390)	0.180*** (0.00396)
pgexpft	0.0960*** (0.00219)	0.0989*** (0.00235)	0.0992*** (0.00235)
pgexpft2	-0.00245*** (5.52e-05)	-0.00268*** (5.77e-05)	-0.00269*** (5.77e-05)
forinarea	-0.246*** (0.0207)	-0.271*** (0.0230)	-0.175*** (0.0329)
Dmigxarea		-0.00247 (0.0593)	-0.0192 (0.0597)
ysa		0.0599*** (0.00668)	0.0606*** (0.00669)
ysa2		-0.00134*** (0.000139)	-0.00137*** (0.000139)
east		-0.274*** (0.0211)	-0.271*** (0.0216)
married		-0.331*** (0.0189)	-0.335*** (0.0190)
fem		-0.791*** (0.0190)	-0.794*** (0.0190)
speaking		0.595*** (0.130)	0.538*** (0.131)
writing		-0.181 (0.133)	-0.211 (0.134)
1994.syear			0.00111 (0.0341)
1999.syear			0.0479 (0.0343)
2004.syear			-0.0444 (0.0321)
2009.syear			0.130*** (0.0337)
2014.syear			0.159*** (0.0398)
Constant	-1.227*** (0.0502)	-0.532*** (0.0541)	-0.634*** (0.0615)

Observations	80,887	80,391	80,391
	Standard errors in parentheses		
	*** p<0.01, ** p<0.05, * p<0.1		

#### A9: Assimilation paths

The wage difference in percentage points for an immigrant over time follow the following forms:

For an area with few foreigners:

$$\Delta wage = \beta_{Immigrant} + \beta_{YSA} + \beta_{YSA^2}$$

For an area with many foreigners:

$$\Delta wage = \beta_{Immigrant} + \beta_{YSA} + \beta_{YSA^2} + \beta_{foreignersinarea} + \beta_{interaction\ for\ in\ area\ \&\ immigrant}$$

The betas are the coefficients of the model (4) in table 2. The following Stata code uses these values to plot the presented graphs:

```
//plot the NEW assimilation path
```

```
//b_Dmig+b_ysa*ysa+b_ysa2*ysa2 (+b_forinarea +b_interaction)
```

```
//Wage difference to a comparable native living in an area with few foreigners
```

```
twoway function area_with_few_foreigners=100*(-0.248+0.0118*x-0.000166*(x^2)), range (0 30) ||
function area_with_many_foreigners=100*(-0.248+0.0118*x-0.000166*(x^2)-0.0350+0.112), range (0
30) xtitle(Years Since Arrival in Germany) ytitle(Wage difference in %) title(..living in an area with few
foreigners)
```

```
//Wage difference to a comparable native living in an area with MANY foreigners
```

```
twoway function area_with_few_foreigners=100*(-0.248+0.0118*x-0.000166*(x^2)+0.0350), range (0
30) || function area_with_many_foreigners=100*(-0.248+0.0118*x-0.000166*(x^2)+0.112), range (0 30)
xtitle(Years Since Arrival in Germany) ytitle(Wage difference in %) title(..living in an area with many
foreigners)
```



Table A10: What determines if a migrant lives with many other foreigners or with few other foreigners? Logit model

VARIABLES	(1) forinarea
pgbilzeit	-0.166*** (0.00912)
pgexpft	0.0221*** (0.00647)
pgexpft2	-0.000337** (0.000166)
ysa	0.0207*** (0.00736)
ysa2	-0.000542*** (0.000151)
east	0.137 (0.208)
married	-0.684*** (0.0498)
fem	-0.0773 (0.0529)
trforjob	-0.311*** (0.0559)
fulltime	0.0311 (0.0567)
Constant	3.410*** (0.142)
Observations	13,478

Standard errors in parentheses  
 \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A11: Model (4) wage regressions with only time or industry dummies

VARIABLES	(1) lnhw	(2) lnhw
pgbilzeit	0.0725*** (0.000846)	0.0718*** (0.000932)
pgexpft	0.0352*** (0.000658)	0.0345*** (0.000678)
pgexpft2	-0.000623*** (1.60e-05)	-0.000583*** (1.65e-05)
Dmig	-0.308*** (0.0235)	-0.271*** (0.0244)
ysa	0.0155*** (0.00191)	0.00930*** (0.00198)
ysa2	-0.000222*** (3.97e-05)	-5.78e-05 (4.12e-05)

forinarea	-0.0481*** (0.00791)	-0.158*** (0.00532)
Dmigxarea	0.137*** (0.0144)	0.113*** (0.0147)
east	-0.369*** (0.00528)	-0.320*** (0.00534)
married	0.127*** (0.00471)	0.137*** (0.00483)
fem	-0.0548*** (0.00479)	-0.0410*** (0.00529)
trforjob	0.184*** (0.00457)	0.200*** (0.00477)
fulltime	0.229*** (0.00583)	0.153*** (0.00605)
speaking	-0.0793*** (0.0307)	0.0630** (0.0312)
writing	0.000677 (0.0317)	0.0102 (0.0324)
Constant	0.629*** (0.0149)	0.773*** (0.0224)
Time dummies	Yes	No
Industry dummies	No	Yes
Observations	57,884	54,511
R-squared	0.434	0.418

Standard errors in parentheses  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A12: Time dummies of table 2 model (4)

VARIABLES	(1) lnhw
pgbilzeit	0.0642*** (0.000907)
pgexpft	0.0330*** (0.000654)
pgexpft2	-0.000571*** (1.59e-05)
Dmig	-0.248*** (0.0235)
ysa	0.0118*** (0.00191)
ysa2	-0.000166*** (3.97e-05)
forinarea	-0.0350*** (0.00784)
Dmigxarea	0.112*** (0.0143)
east	-0.345***

	(0.00523)
married	0.125***
	(0.00467)
fem	-0.0428***
	(0.00510)
trforjob	0.187***
	(0.00460)
fulltime	0.202***
	(0.00590)
speaking	-0.0471
	(0.0302)
writing	-0.0142
	(0.0312)
1994.syear	0.257***
	(0.00942)
1999.syear	0.351***
	(0.00939)
2004.syear	0.466***
	(0.00877)
2009.syear	0.476***
	(0.00894)
2014.syear	0.548***
	(0.0105)
Constant	0.372***
	(0.0232)
Industry Dummies	Yes
Observations	54,511
R-squared	0.460

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Standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

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