Networks and Immigrants' Economic Success*

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Abstract

This paper investigates how the presence of previous co-ethnic immigrants in the district of arrival affected employment opportunities, wage and human capital investment of recent immigrants to Germany. We analyze short and long run effects as we are able to follow new immigrants from their arrival in Germany over their working careers. A simple search model predicts that immigrants arriving in locations with larger co-ethnic networks are more likely to be employed after arrival. This positive effect, however, dissipates over time as those immigrants invest less in acquiring general human capital relative to those who arrived in locations with small co-ethnic networks. We match a recent survey on immigrants to Germany, which contains pre-migration information, with individual administrative panel data recording employment and earnings profiles of all workers in Germany. Applying panel analysis with a very large set of fixed effects and pre-migration controls we can isolate the causal impact of initial network size on post-migration outcomes. We also use a sample of refugees and ethnic Germans, who were assigned to an initial location by central policies, independently of their pre-migration characteristics, to validate our identification strategy. We find clear support for the predictions of our model: immigrants who arrive where large co-ethnic networks existed are more likely to be employed at first, but have a lower probability of investing in human capital. In the long-run they experienced lower wages.

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1 Introduction

The labor market success and the economic integration of new immigrants are fundamental steps towards incorporating them as productive actors in the economy, contributing to their success and to that of the host country. What is the role of co-ethnic immigrants in determining such economic success?[1] Do new immigrants benefit from their presence when they first arrive in the form of networks of contacts useful to find jobs and careers? Or are they hindered by it, as these networks limit new immigrants to informal channels missing the larger labor market and, possibly, discouraging the acquisition of general human capital and skills? How do the effects of migrating to a community with a large or a small number of co-ethnic immigrants differ between the short run and the long run? This paper answers these questions using survey data on recent immigrants to Germany from the IAB-SOEP Migration Sample matched with the universe of administrative records of the German social security archive (*Integrierte ErwerbsBiografie*, IEB in the following). The merged dataset includes pre-migration information on individual migrants, and allows us to follow them each year after arrival in Germany. It contains information on labor market, demographic and education variables. Our findings inform whether the policies promoting concentration or those encouraging dispersion of new immigrants are more conducive to their short and long-run success in the labor market, in the form of employment and wages.

The causal effect of the co-ethnic network size on immigrants' labor market success is not easy to assess. The main reason for that is that the size of the co-ethnic network itself affects the type of immigrants in the area and it is therefore correlated with observable and unobservable characteristics of new immigrants. Comparing post-migration outcomes of new immigrants in areas with large and areas with small co-ethnic networks would imply a comparison between different types of individuals and spurious correlations may arise. New immigrants tend to cluster where co-ethnic immigrants already are. This is a well established regularity both in the US (Cutler and Glaeser, 1997, Borjas, 1998), and in Germany (Glitz, 2014), the country of our study. Moreover, the tendency to cluster may vary across ethnicity and with immigrants characteristics. For instance, using social security data for Germany in 2008, Glitz (2014) computes measures of segregation and finds that Western Europeans,[2]

[1] We define "co-ethnic immigrants" as immigrants from the same country of origin.
[2] Excluding Italy, Greek, and Central Europe.

and Turks[3] were the groups with higher segregation indices. He also finds that less educated immigrants were more segregated than more educated ones. These facts are also confirmed by our data, as we will illustrate below.

In order to think more systematically about the role of co-ethnic networks in affecting the short and long-run employment and wage outcomes of new immigrants, we discuss a simple theoretical framework. Ours is a partial equilibrium search model, which illustrates the trade-off between employment and human capital investment after arrival in the destination country. Workers may receive employment offers through a formal search channel and an informal/network-based channel. How effective the latter is depends on the size of the local co-ethnic network. On the other hand, the effectiveness of the formal search method is affected by one's educational attainments. The key predictions of our model are that, while large co-ethnic networks have a positive effect on the chances of finding employment after arrival, over time immigrants who started in locations with small co-ethnic networks catch up and may have similar or higher employment probabilities and higher wages. The closing of the employment gap is due to the higher human capital investment of new immigrants in markets with small initial co-ethnic networks. For them, the incentive to increase their general human capital is higher and the cost is lower during the first period after immigration, because the opportunity cost of the foregone job search is lower. Therefore, our model suggests that it is important to distinguish the short run and the long run impact of co-ethnic networks on employment, wages and human capital. This distinction has not yet received much attention in the literature, partly for the lack of direct measures of human capital investment by immigrants, and partly because of a very limited availability of panel datasets following immigrants.

We investigate whether these simple predictions hold empirically. Our paper breaks new ground on three important empirical issues. First, we estimate the dynamic (short and long-run) effects of the size of the co-ethnic network at arrival on new immigrants' employment by taking advantage of the panel nature of our dataset.[4] Second, we analyze the investment in human capital of new immigrants after arrival as an additional outcome. This is a crucial margin to understand the differences in outcomes in the short-run after arrival and in the long run (six or

[3]Turkey stands out as the most segregated country also according to the dissimilarity index.

[4]To our knowledge Edin et al. (2003) is the only study shortly mentioning the dynamics of the network effect, though the paper focuses entirely on the static mechanism.

more years after arrival). To the best of our knowledge, there is no other study that investigates the role of co-ethnic networks on human capital investment of first-generation immigrants in the destination country.[5] Third, thanks to the novel survey data, we have direct information on job search methods and in particular on whether people have found jobs through personal contacts or through market/agency/internet search. Hence this study is one of the very rare cases in which we can check the "personal network" channel as way of finding a job and test if the predictions align with those of the model about the effect of co-ethnic networks.[6]

One aspect in which our paper makes crucial progress, relative to the existing literature, is related to the identification of a causal effect of network size on new immigrants' outcomes. As mentioned above the endogenous sorting of new immigrants across locations along observable and unobservable characteristics poses a big challenge. Location decisions depend on individual characteristics that may affect post-migration labor market outcomes. A first approach used in the literature for reducing the selection bias is measuring co-ethnic networks at a relatively broad local level. As pointed out by Bertrand et al. (2000), Cutler and Glaeser (1997) and Dustmann and Preston (2001), immigrants' location decisions are affected by the presence of co-ethnics in the specific district of residence (typically a city), but much less so by their presence in the larger region. Still the regional presence of co-ethnic networks may help job connections and it is used as explanatory variable. This strategy is helpful, but does not fully eliminate the problems of endogenous sorting. Recent papers, including Edin et al. (2003) and Damm (2009), have exploited a different strategy. Researchers have noticed that in some contexts the initial location of refugees, as dictated by national and international dispersal policies, has been almost random. These policies, by distributing individuals independently of their skills, human capital and labor characteristics, have generated quasi-experimental variation in the initial co-ethnic networks of refugees, which could be used to identify a causal effect on later outcomes. While limiting the attention to refugees is interesting and identification can be more credible, this group is very different from the rest of the immigrant population, limiting the external validity of such an ex-

[5] Investments in schooling and education are mentioned in other studies (for example in Edin et al. (2003) and Damm (2009)) as possible channels through which networks have an effect. They have never been studied directly, however, because of data limitations.

[6] A rare study analyzing the channels through which people find jobs and relating them to the size of one's network is Dustmann et al. (2016), where the network is defined at the firm level.

ercise.[7] Refugees come from traumatic situations, often experienced recent periods of non-employment and come from specific countries. This might not correspond to the experience of the majority of immigrants, usually attracted by family and employment opportunities. Our approach can improve on these methods for two reasons. First, the survey data provide us with pre-migration characteristics of immigrants such as pre-migration employment status, work experience, education level, language proficiency, and cognitive abilities. This allows us to control for several relevant characteristics (considered as unobservable in previous studies) and to test how pre-migration characteristics are correlated to their initial location and in particular to the size of the local co-ethnic network at arrival. Second, we can identify in our sample those individuals who were subject to central dispersal policies (refugees and ethnic Germans). By doing so we can evaluate how the estimated effect for the overall group, after controlling for several fixed effects and pre-migration characteristics, compares with the effects on such a randomly dispersed group, to see whether the two procedures give similar estimates and hence reinforce our claim to have effectively identified a causal effect.

Our three main empirical findings support the key predictions of our model. First, we find that immigrants in districts with larger initial co-ethnic networks are more likely to find employment within their first two years in Germany. Second, we find that this advantage fades away in the longer run and it is not present after around five years. Third, the likelihood that immigrants carry out human capital investments within two years since migration decreases with the size of co-ethnic network at arrival. As general human capital investment improves the opportunities on the labor market (in terms of wage and employment), the initial advantage in employment probability due to large-networks fades away over time. We also find some evidence that individuals in locations with small initial co-ethnic networks have higher wages in the long-run.

Even in our most conservative specification, controlling for district-year, country-year, and country-district fixed effects in order to absorb common shocks or local business cycle effects, and controlling for individual pre-migration characteristics, we find significant negative short-run effects on employment and positive short-run effects on human capital investment from large co-ethnic networks. We also find that, in the long-run, the employment advantage disappears and immigrants with smaller initial co-ethnic network have slightly higher wages, possibly because of larger invest-

[7] Table D.1 in Appendix D shows that in our dataset these differences are substantial.

ments in human capital. In addition, We find that immigrants with smaller initial ethnic networks are also less likely to find their job through referrals. These effects are largely driven by less educated immigrants, while for those with tertiary education the size of initial network does not seem to affect economic outcomes. Finally, when we restrict our analysis to the sample of refugees and *ethnic Germans* whose initial location was centrally determined by a dispersal policy,[8] we confirm similar effects of initial network on initial employment probability and on human capital investments. We also perform a series of robustness checks and falsification exercises, including a different definition of the geographic level at which we measure networks, a placebo-type exercise where we address possible concerns of the networks being a proxy for local labor market demand fluctuations, and changing our assumptions on the distribution of the residuals. Results from these exercises confirm our main results and the validity of our identification strategy.

The rest of the paper is organized as follows. In Section 2 we review the related literature and frame our contribution within it. In Section 3 we present our theoretical setup. Section 4 describes our data sources and presents some summary statistics; Section 6 discusses our estimation specification and results, including robustness checks and test for the determinants of initial location. Section 7 concludes.

2 Literature Review

Our paper is related to research on the effects of networks on job search and labor market outcomes. Much of this literature does not analyze immigrants per se, but focuses on the role of social networks on economic outcomes in general. Important theoretical contributions to the modeling of social networks and their effects on the labor market build on the seminal paper by Calvó-Armengol and Jackson (2004). Beaman (2012) develops a network model with multiple cohorts to investigate the relative importance of information transmission and competition in networks and their consequences on the labor market. Bayer et al. (2008) investigate the effect of living in the same city block on the likelihood of working together, finding an important role for referrals in the labor market. Goel and Lang (2009) show that networks may bring about additional job offers, thereby raising the observed wages of workers in jobs found through formal channels relative to those in jobs found through

[8]See Glitz (2012) for more details on the institutional background (Residence Allocation Act, *Wohnortzuweisungsgesetz*) for the allocation of ethnic Germans (*Aussliedler*) to local areas.

the network. Our model, which builds upon Goel and Lang (2009), combines a simple search model with the choice of human capital investment.[9] Several papers frame networks as alternative to the search in the general labor market. The network provides an advantage in the probability of a match but it may be limited by the specificity and cost of referrals. Galenianos (2013, 2014) are two theoretical examples of these models in which network and formal market coexist and different individuals use either of them depending on relative costs and benefits. Our model can be seen as a simple case within this line of inquiry.

As mentioned above, a number of papers use the initial dispersal of refugees across locations to achieve empirical identification of the effect of the co-ethnic networks on labor market outcomes. Edin et al. (2003) use data from a dispersal policy in Sweden and find positive effects of network size on earnings for less skilled immigrants. Edin et al. (2003) also point out that networks might have a positive effect on information and a negative effect on human capital acquisition. However, they are not able to investigate the empirical importance of that channel, because their data do not include any measure of human capital investment, and do not allow a dynamic analysis as they lack the panel dimension. Similarly, Damm (2009) investigates the effects of ethnic enclaves on labor market outcomes in Denmark. The paper takes advantage of a dispersal policy and also finds a large positive effect of ethnic enclaves on earnings after migration. On the other hand, Damm (2014) finds that socially deprived neighborhoods do not seem to affect labor market outcomes of refugee men. Lack of pre-migration information, and of panel data limit in this study the possibility of dynamic analysis and an assessment of how representative refugees are of other immigrants. Xie and Gough (2011) investigate the role of ethnic enclaves on labor market outcomes in the US, and find no evidence of a positive effect of ethnic enclaves on earnings of new immigrants. Hellerstein et al. (2011) look at the role of residential proximity on the chances that workers work at the same establishment.[10]

Recently, interesting work has been focused on the role of referrals for employment outcomes at the firm level. Dustmann et al. (2016) develop a model of job

[9]Pellizzari (2010) also develops a search model with a formal and an informal channel and match specific productivity.

[10]Using Danish administrative data, Bennett et al. (2015) investigate the role of attitudes as well as networks on educational attainments of teenagers with a migration background. Åslund et al. (2011) analyse the role of neighborhood characteristics on the school performance of immigrant children, using data from an exogenous refugee policy in Sweden. Using the mass migration wave to Israel as exogenous variation, Gould et al. (2009) look at the effects of high exposure to immigrants during elementary school on the long-term educational attainment of natives.

referrals by which current employees in a firm provide information on potential candidates, and test the main predictions of the model using information on ethnic origin of employees of a large metropolitan market in Germany. They find that firms tend to hire workers from ethnic groups that are already represented in the firm and that hiring through referrals pay higher wages and exhibits lower turnover. This suggests that network and referral may improve the quality of employer-employee matches. Similarly, Patacchini and Zenou (2012) analyze the effect of ethnic networks on job search methods, and they find results that confirm a positive role of networks on the probability of finding a job through referral. Analysis from our survey confirms these findings.

Our combination of data on the pre- and post-migration history of individual workers, plus the precise measures of co-ethnic network in the place of arrival and the presence of a group of immigrants whose initial location was determined by government officials independently of their characteristics, allows us to improve on the existing research. We believe that controlling for pre-migration features of immigrants is important for the identification of the effects of interest, and we claim better external validity compared to many previous studies, as we include all immigrants in our analysis. We also perform a full analysis of dynamic effects of networks from arrival throughout the working career of immigrants. Below, we describe the simple theoretical framework that guides our thinking of the tradeoffs involved.

3 Theoretical Framework

The model outlined below builds upon the basic structure of Montgomery (1991) and Goel and Lang (2009). The main goal of our framework is to illustrate the trade-off between search and human capital investments and it provides the key insight for our empirical predictions. Let us consider two periods, $t = 1, 2$. At the beginning of $t = 1$ the agent (new immigrant) enters the local economy with a certain level of human capital, which we take as exogenous. The level of human capital in periods 1 and 2 are denoted by h_1 and h_2. We should interpret human capital as the general set of skills that are valued in the host country labor market. The initial value of h is determined by its pre-migration level and its transferability. The size of co-ethnic network at the initial location is denoted as n_1. We denote a certain realization of h by $\bar{h}$ and a certain realization of n by $\bar{n}$. The first period is the arrival period in the destination country, and we assume that all individuals are initially unemployed.

There are two mechanisms through which workers receive job offers.[11] First, when searching for a job, there is a certain probability that the worker receives an offer through the *formal channel*.[12] We denote this probability by p_f and we assume that it depends positively on the human capital level of the individual, so that $\partial p_f(h)/\partial h > 0$, and that it does not depend on the size of the local network. Alternatively, when searching, the individual may receive an offer from the *network channel* (or informal channel) i.e. through the co-ethnic network, with a certain probability p_i, which depends positively on the size of the local co-ethnic network, such that $\partial p_i(\bar{n})/\partial n > 0$ and does not depend on the individual's human capital. Since p_i and p_f are probabilities, they are bounded between zero and one. We assume decreasing marginal returns for both channels, i.e. $\partial^2 p_i(n)/\partial n^2 < 0$ and $\partial^2 p_f(h)/\partial \bar{h}^2 < 0$.[13]

At the beginning of each period, the worker decides whether to search for a job or to invest in general human capital, engaging in activities that increase her human capital level h. If the individual looks for a job, she has some chances of getting an offer from either channel, as outlined above. We do not need to assume that wages are drawn from the same wage offer distribution in the formal and network channel. We restrict, however, wages drawn from either distribution to be always positive, we assume the two draws to be independent, and that the two wage offer distributions have overlapping support.[14] For convenience, we assume that those distributions do not change between period 1 and period 2. This assumption does not affect the key insights from our model. We denote the common cumulative distribution of wage offers obtained in the formal channel as $F_f(w)$. Correspondingly, wage offers in the network channel are drawn from $F_i(w)$. Instead of searching for a job, the individual can increase her human capital endowment. Her human capital after education is $\bar{h}' > \bar{h}$. We assume that $\bar{h}' = \bar{h} + A$ where A is a positive quantity. This is equivalent to assuming that human capital increase is independent from its

[11] A more general model is van den Berg and van der Klaauw (2006), where the intensity of the search is endogenous. For simplicity in our model the only endogenous choice is whether to search or to invest in human capital during the first period.

[12] One characterization of the "formal channel" would be a matching mechanism where applicants send applications with their resumes to employers or to an employment agency.

[13] We are not imposing the constraint that $p_f + p_i = 1$. This is because in our model an individual searching for a job can get either zero, one or two offers.

[14] This means that the highest possible offer from one of the two distributions cannot be lower that the lowest offer from the other distribution. In that case, there would be no gain in drawing two offers instead of one offer from the distribution with higher outcomes. This is a case we could easily handle, but we decided to assume it away because it does not deliver interesting insights.

initial level. Combined with $\partial^2 p_f(h)/\partial \bar{h}^2 < 0$, this assumption implies that investing in education has larger marginal effect on labor market perspectives of individuals with low initial levels of human capital. At the beginning of period 2, an agent that has chosen human capital accumulation in the previous period will be more likely to get offers through the formal channel, when compared to the previous period. Therefore, at $t = 2$ the agent will be less likely to be unemployed and will have a higher expected wage.[15]

The key decision for the agent is made at the beginning of period 1 and it is between searching for a job and investing in human capital.[16] If she searches for a job, she will have probability $p_f(\bar{h})$ to receive an offer through the formal channel, and probability $p_i(\bar{n})$ to receive an offer through the network channel. If she receives no offer, she remains unemployed, receives unemployment payments b_u and begins period 2 with the same level of human capital as in the first period $h_2 = h_1 = \bar{h}$. If she receives one offer, from either channel, she will accept it if higher than b_u and reject it otherwise.[17] If the agent receives two offers, she will accept the higher offer if it is higher than b_u, and reject both otherwise. If the individual decides to get education instead, she receives b_h in period 1 with certainty, and will have a higher level of human capital $h_2 = \bar{h}' > \bar{h}$, in period 2. This allows her to have more chances to receive an offer from the formal channel at $t = 2$. In the following, we assume that $b_u \geq b_h$ to allow for some costs of education.[18] Next, we postulate individual preferences and discuss the value functions for the different choices of the agent.

3.1 Preferences

Each agent only values consumption and discounts second period's outcomes at the rate $0 < \beta < 1$. We assume utility to be linear in consumption[19]

$$EU(c_1, c_2) = c_1 + \beta E(c_2) \tag{1}$$

[15] Because of the positive probability of receiving two offers, under the assumption of partially overlapping support of the two wage offer distributions. More on this below.

[16] A simple graphical representation of this decision is depicted in Figure A.1 in our Appendix.

[17] We assume b_u to be time invariant and that the agent has no utility from leisure, so the decision in the second period is equivalent to the one in the first period.

[18] While this assumption seems natural in this context, it is stronger than needed in our model, as we only need to assume that expected income is larger for those who look for a job at $t = 2$. None of the main propositions discussed below depend on this assumption.

[19] Implicitly we are assuming that individuals are endowed with one unit of "effort" (or time) each period and supply it to education or search/work.

As a standard two-period model, the solution is best described using backward induction. We start by illustrating possible payoffs at period 2. At $t = 2$, human capital investment will not occur as long as $b_u \geq b_h$. Therefore, all individuals search for a job at $t = 2$. If the agents acquired human capital in period $t = 1$, she will be able to search for a job with a higher probability of receiving an offer through the formal channel, as well as a higher probability of receiving two offers. If the agents searched in period 1, she will search again with a human capital endowment as in $t = 1$.[20]

3.2 Value functions

At the beginning of period $t = 2$, all individuals search for a job. If the agent has searched in period 1 (whether or not she found a job in that period) then $h_2 = h_1 = \bar{h}$, and her expected payoff from searching in period 2 is

$$\begin{aligned} S_2(\bar{n}, \bar{h}) =& b_u + p_i(1 - p_f) \int \max\{W_2(x_i) - b_u, 0\} dF_i(x_i) \\ &+ p_f(1 - p_i) \int \max\{W_2(x_f) - b_u, 0\} dF_f(x_f) \\ &+ p_i p_f \int \max\{W_2(x_i) - b_u, W_2(x_f) - b_u, 0\} dF_i(x_i) dF_f(x_f) \equiv \mathcal{S}(\bar{n}, \bar{h}) \end{aligned} \tag{2}$$

where for simplicity we omitted the dependence of p_i and p_f on network size $\bar{n}$ and human capital $\bar{h}$. Searching in period 2 means that the agent gets at least b_u, and has a certain probability that any of the wage offers she receives is higher than b_u, and in that case they will be accepted by the agent. The agent may instead enter period 2 after having invested in human capital in period $t = 1$. In this case her human capital is $\bar{h}' > \bar{h}$ and therefore the value of searching is $\mathcal{S}(\bar{n}, \bar{h}') > \mathcal{S}(\bar{n}, \bar{h})$ because of our assumption $\partial p_f/\partial h > 0$.[21]

At the beginning of period 1 the agent decides whether to make an educational investment or to search for a job immediately, and will do so taking account of the value of each possible state in period $t = 2$. If the agent decides to search for a job in period $t = 1$ given an initial network size of $\bar{n}$ and initial human capital level $\bar{h}$

[20] We assume separation rates at the end of each period to be equal to one so that it is easier to write down recursive value functions. None of our qualitative results depends on this assumption. In this version of the model, we are ignoring the possibility that working can generate human capital as well. As long as the growth in human capital is smaller when working than when in school, the main results of this model hold even for some learning by working.

[21] Under this assumption, it is trivial to show that $\partial S_2/\partial p_f > 0$.

the value function can be simply written as:

$$S_1(\bar{n}, \bar{h}) = \mathcal{S}(\bar{n}, \bar{h}) + \beta \mathcal{S}(\bar{n}, \bar{h}) = (1 + \beta)\mathcal{S}(\bar{n}, \bar{h}) \tag{3}$$

Because of the assumption of separation rates equal to one, the problem is recursive. A searching individual will get the value of being unemployed plus the difference between the value of unemployment and the value of employment, which depends on expected wages. At the beginning of period 1 the individual may instead decide to invest in human capital. The corresponding value function is

$$H_1(\bar{n}, \bar{h}) = b_h + \beta \mathcal{S}(\bar{n}, h') \tag{4}$$

Costs of education are incorporated in the flow of utility b_h.[22] Education increases the future employment possibilities of the individual, because of the newly acquired skills are useful to find a job in the host economy. Therefore, the lower the probability of finding a job through network or through formal channels in the first period and the higher β, the intertemporal discount rate, the more likely it is that an agent invests in human capital relative to searching at $t = 1$.

3.3 Employment and Human Capital Investment

The simple structure described above is sufficient to illustrate the main trade-off faced by the agent. Human capital investment increases employment and expected wages in the future, at the cost of foregoing current earnings. After observing her level of human capital and the size of the social network at the beginning of period 1, the individual decides whether to look for a job or to acquire human capital. The optimal decision between searching and acquiring human capital will be given by comparing $S_1(\bar{n}, \bar{h})$ and $H_1(\bar{n}, \bar{h})$. Next, we discuss how this optimal choice depends on the initial level of $\bar{n}$ and $\bar{h}$. We are able to make three simple predictions in a comparative statics exercises.

Proposition 1 *For each level of n_1 there is at most one "reservation" level of h_1 below which the agent will invest in human capital and above which the agent will search for a job in period 1.*
Discussion: see Appendix B.

[22]Results may be different for a risk-averse agent since returns to education are stochastic.

For a given level of n_1, both the value of searching and the value of investing in human capital are increasing concave functions of h_1. Under our assumptions, the relative first and second derivatives are such that the two curves $S_1(\bar{n}, h)$ and $H_1(\bar{n}, h)$ will intersect at most once in the h space.[23] Depending on functional form and support of h and n, corner solutions may exist: initial social networks n may be so large that the agent may find it optimal to search for a job irrespective of the level of h. Following Proposition 1, for a given level of social networks, individuals with higher human capital are going to be more likely to be employed in period 1, and less likely to invest in further human capital. Individuals with lower human capital, on the other hand, are expected to be more likely to get more education earlier and less likely to be employed earlier.

Proposition 2 *For each level of h_1 there is at most one "reservation" level of n_1 below which the agent will invest in human capital and above which the agent will search for a job in period 1.*
Discussion: see Appendix B.

The intuition for this is similar to that for Proposition 1. For a fixed value of $h_1 = \overline{h}$, $S_1(n, \overline{h})$ is increasing in the level of n_1, because n_1 positively affect offers' arrival rate via the network channel. It is only slightly more subtle to see why the value of human capital investment is lower at higher values of n_1. Let us imagine a case in which individuals with a very large social network decided to acquire further education in period 1. Despite the higher level of human capital, it would still be relatively likely that they get an offer in the informal sector compared to the formal sector, and therefore for them further human capital investment makes less of a difference.[24] Corner solutions may exist in this case as well: there might be levels of human capital that are high enough such that the agent searches for a job in period 1 for any possible level of social networks. Proposition 2 implies that the larger the size of co-ethnic networks, the less likely it is that the individual will get further education, and the more likely she will be employed in the first period. Conversely, individuals with small co-ethnic networks will be more likely to invest in education.

Proposition 3 *The magnitude of the effects of networks on employment and human capital investment are lower the higher is initial human capital endowment.*
Discussion: see Appendix B.

[23] We analyze the two functions S_1 and H_1 in more detail below and in Appendix B.
[24] These considerations are discussed in some more detail in Appendix B.

Individuals with higher initial human capital endowment h_1 are relatively more likely to find a job through the formal channel compared to individuals with the same networks but with lower initial human capital endowment. The marginal effect of network size in the value functions of individuals with initially high human capital is therefore going to be smaller. While qualitative effects of network size are unaffected, quantitatively we expect effects on employment to be larger for individuals with lower initial human capital endowment.[25]

Summarizing, based on our model we expect individuals with larger initial co-ethnic networks to be more likely to find employment after arrival. However, our model also predicts that the positive effect of network on employment probability decreases over time, because individuals with smaller co-ethnic networks "catch up" through human capital investment. Finally, the effects of network size on employment probability and, hence, on human capital investment after immigration are larger for individual with lower initial human capital. Figure 1 summarizes the main features of the equilibrium of our model. It plots the value functions of an individual, S_1 and H_1, as a function of initial network size. An individual with lower initial human capital $\underline{h}$ will optimally decide to invest in human capital if her initial network size is below $n_{\underline{h}}$, and she will search for a job if it is larger. This illustrates Proposition 2 above. The two thicker curves in Figure 1 are instead drawn for an individual with higher human capital $n_{\overline{h}} > n_{\underline{h}}$. Both S_1 and H_1 are higher (because at higher human capital levels the expected utilities are higher due to higher probability of job offers) and they also rotate clockwise (reflecting the fact that marginal effects of network size are smaller at higher levels of human capital, because offers are more likely to come from the formal channel, making networks less relevant for labor market outcomes as in Proposition 3). The new threshold for network size below which the individual will invest in human capital is now lower at $n_{\overline{h}}$, because the shift of the value function for search is larger than that of the value function for human capital investment.[26] This shift from $\underline{h}$ to $\overline{h}$ is an illustration of Proposition 1

[25]In order to make predictions concerning whether we expect individuals with low initial human capital or individuals with high initial human capital to be more likely to invest in it, we need to give some structure to the returns to human capital. If returns to human capital are smaller for individuals with high initial human capital endowment, which is the standard assumption in the literature and has support in our data, individuals with lower initial human capital are more likely to invest in its improvements. Results would be different if returns to human capital were larger for individuals with larger initial levels, which would be the case if the investment that immigrants choose were purely a way to make their existing human capital more productive in Germany. This would be close to the way in which Regets and Duleep (1999) think of this.

[26]We discuss the details of this in our Appendix.

above. The figure shows a range of intermediate network sizes for which individuals with lower levels of initial human capital invest, while individuals with higher levels of initial human capital search for a job in the first period.

3.4 Wages

In the paragraphs above, we have discussed the implications of our model for employment and human capital investment. Next, we look at the effects on observed wages, i.e. wages of those who are employed. Even if the distribution of wages from each channel (market and network) are given, the realized wage of an individual depends on the probability of getting competing offers. When an individual has a higher chance of receiving two offers, she also has a larger expected wage, but may not have a higher observed wage. Without additional assumptions on the wage distributions of the two channels, our model cannot deliver any predictions on relative observed wages at $t = 1$, because more chances to draw from a distribution can lower *observed* wages of the employed (although they would certainly increase expected earnings and employment rates). For the analysis below, we therefore make a further assumption. We assume that the wage offer distribution of the formal channel and that of the network channel have the same expected value.[27] Under this assumption, observed wages at $t = 1$ are a monotonically increasing function of n for a given initial level of human capital h: conditional on h_1, a higher $\bar{n}$ increases the likelihood of receiving two offers, which is associated with a higher expected wage.[28]

The relationship between initial network size and observed wages at $t = 2$ (conditional on a given initial human capital equal to h_1) is slightly more complicated. Assuming that initial human capital is low enough that an internal solution exists, at low levels of n_1, the individual will acquire human capital and enter period 2 with $h_2 > h_1$. Wages (conditional on working) at time $t = 2$ are then increasing in n_1 because larger social networks will increase the probability of receiving two offers. However, this effect exhibits a discontinuity at the level of social networks above which the individual does not invest in human capital at $t = 1$. If n_1 is high enough the individual will not find it profitable to invest in human capital at $t = 1$, then her wages at $t = 2$ will be discretely lower. Figure 2 depicts this relationship between wage in the second period and size of the network, graphically.[29]

[27] This rules out that a higher probability of receiving an additional offer depresses average wages.
[28] We expect this effect to be weak, especially when the probability of receiving any offer is low.
[29] Figure 2 is drawn under the assumption that the initial human capital level is low enough to

Under these assumptions we expect initial observed wages to be a monotonically increasing function of initial network size. On the other hand, the relationship between initial network size and long-term wages is non-monotonic. For changes in initial network size that are large enough and lead to changes in human capital accumulation decisions, individuals with larger network are expected to have lower wages in the long term. Similarly to the previous result, we expect this effect to be concentrated among those with relatively low initial human capital, for whom initial network size is more likely to matter for human capital decisions.[30]

3.5 Networks and Welfare

Our simple model describes the trade-off between searching for a job and investing in human capital, and relate it to the size of the initial co-ethnic network deriving some testable implications. Describing the welfare implications of different distributions of networks in the society is beyond the scope of this work. A brief discussion on the way in which networks may matter for individual and for social welfare can be useful, however. Taking our model at face value, networks unequivocally increase welfare. Networks may induce people to invest less in human capital, but that choice is optimal at the individual level and with rational, forward looking agents and no externalities also maximizes utilitarian social welfare. There are however realistic scenarios under which this may not be the case, and where larger networks may hurt social welfare, while increasing individual welfare. First, if we introduced progressive taxation, returns to education at the individual level would be lower than at the level of the society as a whole. Alternatively, if individual migrants discount the future more than the social planner, or if there were positive externalities from education there may be under-investment in human capital. To the extent in which these issues matter, individuals may be under-investing in general human capital (from the perspective of the social planner) and the under-investment would be more severe when there are large networks and for less educated people. In these cases, there would be an economic rationale for a government intervention that can encourage immigrants to distribute across locations (decreasing n), or that can favour search through the formal channel rather than through networks for new immigrants.[31]

make human capital investment at $t = 1$ optimal for low enough n.

[30]For individual with high levels of initial human capital, the discontinuity shown in Figure 2 is either much further to the left or not there at all.

[31]The large share of immigrants relying on social networks for employment may in part by the result of limited opportunities in the “formal” channel.

4 Data

Our primary dataset is the IAB-SOEP Migration Sample, a large survey of immigrants to Germany conducted in two waves that took place in 2013 and 2014, respectively. The survey over-samples recent immigrants, who arrived in Germany after 1994. We use the sub-sample of the survey that has been linked to the social security data (IEB), selecting only foreign born in the age rage 15-65.[32] As a consequence, for each individual included in the analysis, we are able to observe several pre-migration characteristics and the entire labor market history after migration to Germany. The data on employment and wages are from administrative records and they cover the period 1975-2013. A person is considered in employment if she ever works within the year.[33] We also look at the wage, measured as real hourly wage of the longest full time working spell per year excluding all spells of apprenticeship, or marginal employment. Our measure of human capital investment comes from the survey data, because it is not available from the administrative data. The survey provides a full account of each year spent in education as each individual is asked retrospectively to fill a life-long calendar in and to report for each year, starting from age 15 up to 65, whether in that year she was in education.[34] We use this information to reconstruct an individual life-long panel of spells of education and we merge this to the individual administrative records.[35]

The variable capturing the co-ethnic network size at arrival for each immigrant, is the number of workers by nationality[36] as share of total employment in each German district.[37] This share is calculated using the full registry of workers in Germany (IEB). The number of German districts is 404, with an average size of

[32]The survey is targeted to individuals with any migration background, including second generation. For details on this dataset see the Appendix C.

[33]We check the robustness of our results to this criterion by using alternative definitions of employment (Table D.5). The results are robust to defining an individual as employed if she works at least 25, 50, or 75 percent of the year, or on June 30 (used as a cutoff date).

[34]This variable is derived from the survey biography section. Unfortunately we can not distinguish the type of education, but, given our selected age range, we argue that school episodes play a minor role. In addition, individuals reporting at the time of the survey to be still in school are excluded from the sample as well as individuals reporting to have entered Germany as students.

[35]To limit recall bias, we use administrative data as well, and set the variable to zero whenever the person in the corresponding year is found to be working for at least 50 percent of the time.

[36]Due to sample size considerations, we group them into eight country groups: Western countries including Western Europe, Eastern Europe, South-Eastern Europe, Turkey, USRR, Asia and Middle East, Africa, Central and South America.

[37]For each individual, we define the living district as the one corresponding to the longest spell within the year, and impute this information from the workplace district in case of missing values.

65,801 workers per district and a median size of 42,643. Our sample of immigrants is distributed across 227 districts. Our network measure has an average size of 0.011 with a standard deviation of 0.015 and an highest value of 0.11. The immigrants with the highest value of the average co-ethnic network size are those from Western Europe (0.033) followed by Turkish immigrants (0.027), and South-Eastern European immigrants (0.019).[38]

4.1 Descriptive Statistics

Table 1 reports summary statistics for some of the main variables we use in our empirical analysis. The top panel of this table reports statistics for panel variables, where each individual has more than one record, taking simple averages. The variable $Netw_{d0}$ is the measure for the size of the co-ethnic network at time of arrival (described above). People are employed (for at least one day within the year) in 68.8 percent of the individual-year observations.[39] The average wage per hour earned in the sample is around 8.6 Euros for full time workers. Individuals in the sample are investing in education, i.e. spending some time in school or training, in 4.3 percent of the individual-years. Confirming that education and training are particularly common when an immigrant first arrives, the share of individual-year in education is higher during the early years in Germany. Twelve percent among recent immigrants in Germany for two years or less was in school part of the year, but that percentage was only equal to 2 percent for immigrants in Germany for at least six years (see Table D.2).[40] Symmetrically, employment rate increases over time since first arrival. During the first two years only 48 percent of individuals work, while after 10 years more than 76 percent is employed (see Table D.2). Our panel is unbalanced, the average number of years since migration observed is 7.57, whereas the median value is 6 years. Around 23 percent of observations are relative to individuals who have been zero to two years in Germany, 21 percent has been three to five years, and 56 percent has been in the country six years and above. Our sample is relatively young at 37 years of age on average.

The bottom panel of Table 1 lists averages of time-invariant individual characteristics, relative to ethnicity, country of origin and pre-migration characteristics. These

[38] This ranking is in line with Glitz (2014).

[39] This share is down to 56.4 percent if we consider as employed only those working for at least 50 percent of the days within the year.

[40] There is also a stark difference by age, since those investing the most are those in the age bracket 15-20 (Table D.3).

data are obtained from the IAB-SOEP immigrant survey. Our sample consists of 933 foreign born individuals[41] in working age (15-65 years old), who are linked to the registry data. Among those immigrants, we select individuals whose date of arrival reported in the survey is within three years of their first appearance in the registry data, which collects information on employment and labor market outcomes. Since unfortunately we do not have information on the district of arrival from the survey, we take the district of first registration in the administrative data as capturing the place of first arrival of the new immigrant.[42] In addition to the standard characteristics, such as gender, age, and region of origin, we include a set of pre-migration characteristics that we use throughout the analysis: education, working experience, language proficiency, and employment status one year before migration. The survey data also reports the job search method for the first job found in Germany as well as a measure of self-assessed over-qualification in the current job.[43] Our sample reflects the fact that people are relatively young when they first migrate. The average age at migration was 30.50, and the median 29. An interesting fact emerging from the summary statistics for our data is that 57.8 percent of the immigrant sample found the first job in Germany through personal contacts.[44] This percentage is much higher and equal to 66.5 percent is we only consider the low skilled immigrants (those with at most lower secondary schooling, which corresponds in the German educational system to be in school until 18 year old). The information on job search method is very interesting and it is rarely recorded in datasets. It will allow us to test the importance of local co-ethnic networks in finding job through personal referral. Fi-

[41] Using country of birth to identify immigrants is a much more precise definition, and this represents an improvement with respect to all previous papers using German administrative data, which can only identify immigrants via nationality. This is particularly important for Germany, where the group of ethnic Germans, one of the biggest among immigrants, is entitled to receive the German nationality by law. To the best of our knowledge, Dustmann et al. (2016) is the only study partially exploiting this definition of immigrant.

[42] Our results are robust to restricting the analysis to only individuals whose year of arrival corresponds exactly to the first year in the registry data (55 percent), which we find reassuring. There are also cases in which the individual appears in the administrative data before the last migration year. In those cases we consider as year of arrival the first appearance in the registry data if the person appears working at least once in the subsequent years.

[43] This last variable is available only for those working at the time of the survey.

[44] The question asked is the following: "How did you find the first job in Germany?". The possible answers are: through the Federal Employment Office, through an employment office in my own country, through an employment agency in my home country, through an employment agency for foreigners, through a private job agency, through a job advertisement in the newspaper, through a job advertisement on the internet, through friends/acquaintances/relatives, through business relationships in Germany, I was self-employed in my first job. We consider the category through friends/acquaintances/relatives as contacts.

nally, 41.4 percent of those currently working report to have a degree higher than the level of schooling required for that job, which may suggest a certain degree of "downgrading" whereby individuals are matched to jobs that do not require the skills they have.

5 Empirical Specification and Identification

In order to estimate the effect of the size of the co-ethnic network at arrival on the employment and human capital investment of new immigrants we adopt the following linear estimating equation:

$$Y_{id_0t} = \alpha + \beta \mathbf{X_{it}} + \gamma_0 Netw_{d_0} + \gamma_1 Netw_{d_0} \times Ysm_{it} + \eta Ysm_{it} + \delta_{d0} + \psi_{t0} + \theta_c + \epsilon_{it} \quad (5)$$

Where Y_{id_0t} is an outcome for individual i in year t who first arrived in district d_0. In our main regressions the variable Y will be, alternatively, a dummy for being employed or a dummy for being in school or training. $\mathbf{X_{it}}$ is a vector of individual characteristics and it includes a gender dummy, age, age squared, age at migration and its square, and a set of pre-migration characteristics (education, working experience, employment, and language proficiency), which are time-invariant. The variable $Netw_{d_0}$ captures the size of the co-ethnic network (previous working immigrants from the same country as share of total employment) in the district of arrival, with d_0 described as above. The term δ_{d0} captures a set of district-of-arrival fixed effects and θ_c captures a set of country-of-origin fixed effects. The term ψ_{t0} is a year of arrival fixed effects. The variable Ysm_{it} is a dummy that indicates the years since migration of the individual. In the main analysis we use three dummies for "years since migration": $(Ysm0-2)_{it}$, $(Ysm3-5)_{it}$ and $(Ysm6+)_{it}$, denoting the first two years, years 3-5 and more than five years from arrival, respectively. We also experiment with a more flexible specification by interacting the network size with yearly dummies (since arrival).

The non-random initial location of immigrants may bias the estimates of the coefficients of interest ($\gamma's$) if unobserved individual characteristics, affecting employment and human capital investments are also correlated with the initial size of the co-ethnic network. Controlling for pre-migration characteristics (usually not observed but available in our data) and including district and country of origin fixed effects, which absorb systematic differences in economic performance across cities and ethnic groups, alleviates this issue substantially. In our main specification, we estimate equation (5) using OLS regressions and absorbing location specific effects and pre-migration characteristics among the controls. Hence we only exploit differences in the choice of the initial co-ethnic network unrelated to pre-migration characteristics and we exploit variation only within district and country-of-origin over time. Moreover, we estimate equation (5) alternatively on all immigrants and on the restricted sample, which should be unaffected (or much less affected) by endogenous initial sorting. The restricted sample consists of people moving to Germany as refugees and asylum seekers and of ethnic Germans moving during the period when the Residence Allocation Act was in place. Due to institutional arrangements both of these groups were subject to a dispersal policy implemented by a central authority who was not aware of their individual characteristics and hence could not consider them in choosing their initial location. Ethnic Germans (*Aussiedler*) were immigrants with German ethnicity from Eastern Europe. Upon application they were granted a visa, and registered with a central authority. Those without a job (which comprised the vast majority of them) were distributed to one of the 16 federal states according to pre-specified state quotas. The further allocation to districts was regulated within each federal state, according to state-specific allocation. We could not find any evidence that individual skills and abilities of the immigrant played a role in the decision of the authorities. Similarly, refugees were re-settled by the central authority and their distribution across districts was performed to disperse them evenly and without knowledge of the refugee economic abilities and skills. This restricted sample is much smaller, consisting of 297 individuals, around one third of which are asylum seekers, and two thirds Ethnic Germans.

The comparison between the estimates in the overall sample and those in the restricted sample indicates whether a possible bias, induced by immigrant sorting, still exists in the sample that decided their own location even after controlling for district effects, country of origin effects and individual controls. If most of the omitted variable bias is eliminated by this strategy the full sample estimation should produces similar coefficient as the restricted sample one. This would be a sign that the identified coefficient is consistent with causal interpretation. Considering the whole sample of immigrants, we also test whether pre-migration individual characteristics included as controls in the main analysis, are correlated with co-ethnic network size and how this correlation is reduced when we include different sets of fixed effects. Both checks reassure us that omitted variable and selection concerns are effectively addressed by our method and do not produce significant bias. In addition, in the most demanding specifications, we control for a full battery of two-way fixed effects: country of origin by year of arrival, year of arrival by district of arrival, and country of origin by district of arrival fixed effects. In order to do this, we need to rely on estimated fixed effects from an external sample of immigrants obtained from administrative data, since the small sample size does not allow to estimate them reliably in our sample. Give this constraint we can implement this strategy only for the employment regression, since we don't have an external sample from administrative data with information on human capital investments.

6 Results

6.1 Employment

The main empirical results are illustrated in Tables 2 and 3. All of the tables described in this section use the same notation. The estimates in the row $Netw_{d0}$ contain the coefficient on the size of the co-ethnic network in the district of arrival. The network variables that we use throughout the analysis are standardized (to have mean zero and standard deviation one) so as to interpret the coefficients more easily. Our estimates measure the impact of an increase in the size of co-ethnic network by one standard deviation on the outcome in the initial years (0-2) after arrival. The interaction terms (Netw_{d0}xYsm3-5) and (Netw_{d0}xYsm6+) show the coefficients on the interaction of the network size with a dummy that is equal to three to five years from arrival, or six and more years from arrival, respectively.

The dynamic effects of the initial co-ethnic network on employment are estimated using a linear probability regression where the probability of being employed in each year, measured as a dummy equal to one if the individual ever worked in a year, is the dependent variable. Results are reported in Table 2 below. In column 1 we only include the network size measure, not interacted with time-since-arrival dummies. This column is most similar to the type of "static" estimates previously presented in the literature (e.g. Edin et al., 2003 and Damm, 2009). It reveals that on average, a larger size of the co-ethnic network at arrival increases significantly the probability of employment. Then in columns 2 and 3 we include the year since arrival interactions and we control for pre-migration characteristics, base controls and fixed effects (district, year and country of origin). In column 4 we control for the average wage in the district as indicator of the local productivity. In column 5 we restrict the estimates to the sample of refugees and ethnic Germans (denoted as sample R) which approximates more closely the condition of initial random distribution of immigrants across districts. Columns 6 and 7 show our estimates where fixed effects (district, year and country of origin) are estimated on a large external sample of immigrants taken from administrative data and column 8 and 9 include externally estimates of two-way fixed effects (country by district, district by year, country by year). The inclusion of two-way fixed effects is extremely demanding, as it absorbs all the district-year specific variation that could have affected employment of immigrants, leaving only variation across ethnic groups over time as identifying variation. The estimates are overall consistent with the basic prediction of our model: social networks have significantly positive effects on the probability of being employed and this effect is significant in the first two years after arrival. When we do not include dummies for years since arrival, we obtain a positive estimate on the network size equal to 0.041, which implies an increase of the probability of working by 4.1 percentage points (relative to an average employment rate of 68.8 percent) for an increase in the network by one standard deviation.

When we estimate the effect interacted with year of arrival, we learn that, for the first two years such an increase in probability of employment is much larger (about 10.6 percentage point) and that the effect vanishes after around five years.[45] The results hold also when we include the full set of pre-migration characteristics and fixed effects (column 3) and also when we include the average wage by district-year (column 4). These controls should capture individual characteristics affecting employment probability and the local labor demand conditions. Both could be correlated to the outcomes and to the sorting into initial networks of different size.[46] The results hold when we perform the analysis on the restricted sample of asylum seekers and ethnic Germans (column 5), which is consistent with the idea that the omitted variable bias is not significant. However, due to the drastic reduction in the sample size, the effect is imprecisely estimated. One reasons may be that the fixed effects that we include are too many to be estimated with precision in the small sample of surveyed immigrants. Therefore we replicate the analysis on both samples using

[45]The yearly effect for the full sample and including all controls as in column 3 is reported in the top-left panel of Figure 3.

[46]An even better control for labor demand factors would be the unemployment rate by district and year. Due to administrative changes in the registry data, we don't have this information for the aggregate data at district level for the years before 1999.

pre-estimated country, year of arrival and district of arrival fixed effects (columns 6 and 7).[47] In addition we use all possible two-way fixed effects (country of origin by year of arrival, year of arrival by district of arrival, and district of arrival by country of origin) also estimated out of sample in columns 8 and 9, which represent the most demanding specifications. It is reassuring to see that the coefficients on all the network and interaction variables are quite similar to those estimated in columns 4 and 5. Moreover the standard error of the estimates is smaller as in columns 8 and 9, in spite of estimating a very large number of two-way fixed effects, we do not use any of the degree of freedom from the immigrant sample to estimate those. The results remain significant adopting different levels of clustering. In the tables we report the clustering at the individual level (in parenthesis) as well as the more conservative clustering at the district level (in square brackets).[48]

6.2 Human Capital Investments

Differences in employment rate associated to large initial networks disappear as if some off-setting factors were at work for individuals starting their experience in places with smaller co-ethnic networks. Our survey includes information on the full history of human capital investment in Germany measured each year. We analyze whether there is a systematic relationship between social networks and investment in human capital. The main results of this regressions are presented in Table 3, where we find relatively strong evidence of a negative association between the size of the initial network and the probability of investing in human capital. Having a bigger network in the first two years after arrival by one standard deviation corresponds to a reduction by 2.7 percentage points in the probability of investing in human capital (column 2). The respective "static" effect is still negative and significant, however much lower in magnitude, corresponding to a reduction by 1 percentage point (column 1).[49] This may be driven by the fact that immigrants with better initial

[47] The external estimation sample is a sample of 176,387 randomly drawn individuals with non German nationality from the 2 percent IEB registry, corresponding to 1,569,520 person-year observations. The estimated regression includes, in addition to the mentioned fixed effects: gender, education, age and age squared. We estimate these fixed effects and then we import them into the main sample as additional regressors. For all regressions where we use predicted fixed effects, we obtain the standard errors using 500 bootstrap replications. The education variable is imputed using the algorithm IP1 developed by Fitzenberger et al. (2005).

[48] The reported significant levels refer to the individual clustering.

[49] To the best of our knowledge this is the first estimate in the literature of the effect of co-ethnic networks at arrival on human capital investment of immigrants.

co-ethnic networks are more likely to work and less likely to pursue more education in Germany. Results are robust to the inclusion of controls for pre-migration characteristics (column 3), as well as to the inclusion of average wage at the district-year level (column 4). In addition, they are robust and even stronger when we replicate the analysis for the restricted sample of refugees and ethnic Germans (column 5), corresponding to a reduction by 7.5 percentage points in the probability of investing in human capital. In this case, the effect is much larger for restricted sample and this could be due to the fact that refugees and ethnic Germans were on average less educated than the full sample.[50]

6.3 Effects by Education Group

Table 4 (columns 1-3) breaks down the main sample by pre-migration educational attainments.[51] The first three columns replicate the estimates on the network and its interactions with years since migration, with employment as dependent variable, but separately by education group. We find that the overall positive initial effect of network on employment is driven by low skilled, followed by medium skilled and it is not present for highly educated immigrants. We also find that, as in Table 2, the effect disappears around six years after arrival. Figure 3 shows that allowing for yearly interactions and plotting the effect by year, the positive coefficient converges to 0 after about 4-5 years. For less educated immigrants the effect of co-ethnic network in job finding is substantial. Moving to a district with one standard deviation larger co-ethnic network at arrival corresponds to 15 percentage point higher probability of being employed. As for the full sample, also for the less educated immigrants this effect disappears 4 years since migration. The network effects is still positive, though significantly lower (8 percentage points for each increase by one standard deviation) for immigrants with intermediate levels of schooling. It evens its sign and it is not significantly different from zero level for high skilled.

Columns 4-6 of Table 4 investigate the relationship between network size and human capital investment for individuals with different initial education. Results are

[50]We cannot replicate the analysis adding pre-estimated two-way fixed effects as for the employment regressions, because of the lack of a comparable sample with information on human capital investment.

[51]In all our analysis, the breakdown by education is always obtained considering the education before moving to Germany. Three education categories are considered: low skill corresponding to at most lower secondary school, medium skill corresponding to some form of vocational study, and high skill corresponding to University or higher degree.

again driven by low and medium skilled workers, which is consistent with our very simple model, and absent for highly educated. Taken together, our findings suggest that, after arrival, less educated immigrant workers in places with large co-ethnic networks find employment with larger probability. The benefit of networks, however, dissipates over time. Our model suggests that this may be because individuals in location with smaller networks invest more in human capital and in the long-run have the same probability of being employed as the group that started with larger co-ethnic network. Short-run effects on employment probability and human capital investment are larger for the low and medium educated. In the first two years after arrival they experience lower probability of going back to school by 3.4-3.3 percentage points if they land in a district with one standard deviation larger co-ethnic networks. This difference, however, disappears after 4-5 years.[52] In the sample of high skilled, the effect is close to zero in magnitude and not statistically significant.

6.4 Wage Effects

Table 5 analyzes the impact of network on wages. In the first column we present the coefficients estimated on the full (1) and restricted (2) samples. Then column 3-5 show the results separating individuals with low, medium and high education. When we consider the full sample of immigrant workers (Table 5, column 1) we do not detect any significant effect on wages, in the short or in the long run. We detect, however, a negative effect on the restricted sample in the short term (column 2), which is substantial in magnitude (17.5 percent, or a log difference of 0.192), and significant at 5% level. The negative effect for this sample decreases but persists also in the long term (15.1 percent percent, or a log difference of 0.164), and also statistically significant. Once we break down the sample by different skill groups (column 3-5), the evidence suggests a negative effect of the initial network only for the low skilled, and this corresponds to a long-term reduction of 10.3 percent (a log difference of 0.109) percent in hourly wage by letting the network size rise by one standard deviation (column 3), which is also strongly statistically significant. Differently from the effect on employment, the effect on wage for less educated persists beyond the short-term: in the first two years since migration the reduction in hourly wages for a one-standard-deviation larger network corresponds to 7.5 percent (a log difference of

[52] For the yearly effects see Figure 4.

0.078), and the wage level is still 10.3 percent lower after 6 or more years.[53] Such an effect is consistent with the hypothesis that initial network-generated job referrals imply somewhat lower quality jobs relative to "formal channel" referrals. Once in these jobs individuals miss on general human capital accumulation and their wage progression is not as fast as elsewhere, hence they maintain this initial disadvantage.

According to the predictions of our simple theoretical setup, larger initial networks should be associated with slightly higher observed wages, due to the higher probability of receiving two job offers and picking the one with higher wage. This prediction, which relies on a larger number of assumptions compared to those for employment and human capital investment, is not supported by our empirical results for the low skilled. One possible explanation, also developed theoretically by Bentolila et al. (2010), is that there is matching specific heterogeneity in productivity across formal and informal channel. In particular, finding a job through the informal channel may associated with a penalty due to imperfect matching.[54] Indeed, if we postulated wage offers through the informal channel to be on average lower than those of the formal channels, this is the result that we would get.

In alternative to the specification shown with only three time-periods since migration, we also experiment with a more flexible specification, where we include yearly dummies for each of the three outcomes: employment, human capital investment, and wage. The results are in line with the previous specification, we report them graphically in Figure 3, 4, and 5. In particular it is evident how the dynamics of the network effect unravels. The positive effect on employment is only in the short term and it is associated with a response in the flow of human capital, in the short run, which produces a permanent difference in general human capital levels (in favor of immigrants with smaller initial co-ethnic networks) and in wages.

In the simple model developed above, jobs found through networks and through the formal channel are not systematically different from each other. In a more

[53]The literature provides mixed evidence about the effect of social networks on wages also for the general population. Starting with the seminal work of Granovetter (1973), where the quality of the match depends on how close the person is to the social contact, similarly other more recent papers found mixed results. Loury (2006) finds that the wage effect varies according to the low- high-wage offer contacts, whereas Pellizzari (2010) shows that the positive effect on wages of finding the job through the informal channel rises when the efficiency of the matching process in the formal channel increases, in that firms become more selective in hiring through the informal channel. Looking at the effect of co-ethnic networks in Denmark on earnings, in turn Damm (2009) finds a substantial positive effect, equivalent to 18 percent, irrespective of the skill level.

[54]From our descriptive evidence we learn that the first job found through the network is unconditionally associated with a 18 percent lower wage than jobs found through other methods.

general setup one might expect that networks of immigrants, could be particularly good in generating referrals for jobs that do not require a lot of formal education in smaller companies and market niches. These jobs may be more easily available and they are passed onto co-nationals, but they may also provide limited potential of upward career and be an imperfect match for the specific abilities of a new immigrant (see Bentolila et al. (2010) for an example of the theoretical underpinning). We investigate this mechanism by analyzing whether the larger probability of employment associated to larger co-ethnic networks is also accompanied by a larger "mismatch" on the job. We construct a measure of job mismatch from the information in the survey. Individuals are asked about the type of education required for the current occupation and this information is compared to the education effectively held by individuals. Individuals are classified as overqualified when the education level required is lower than their level of education and a dummy is associated to individuals being overqualified. Given that this information is only available for the current job, we estimate the same specification 5 as in the rest of the analysis, but using only one cross section for each individual. Moreover we pool all individuals, and we estimate the effect of a "low education dummy" (first row)[55] of the initial co-ethnic network (second row) and of the additional effect of the network on less educated (third row) in specifications that include progressively more pre-migration controls and fixed effects. The estimated coefficients should be interpreted as the impact of initial co-ethnic network size on the probability of being over-qualified in the current job. Results are presented in Table 6. We find statistically significant and economically large effects, for the interaction of initial network and the dummy for less skilled. This group was more likely to be employed in district with larger networks, and our hypothesis is that this is due to the network referral effect in job finding. That group is also more likely to be in a job for which they are over-qualified. For low-skilled individuals the increase in the initial network size by one standard deviation corresponds to a 11 percentage points higher likelihood of being over-qualified for the current job. This magnitude translates into 26 percent of the average (41.4 percent) and it is robust for the standard specification (column 1), as well as controlling for pre-migration characteristics (column 2), for the average wage at district-year of arrival (column 3), or for past cognitive skills (column 4), measuring the self-reported past test score in math. There is no significant effect of initial network size for the medium and high skilled, the excluded category.

[55]Education is measured before migration.

6.5 Networks and Job Search Methods

The employment and human capital regressions analyzed above include a dynamic dimension, which plays an important role. There is an initial trade off between working and accumulating human capital and looking only at the short-run or average effects would miss the long-run impacts. Regressions estimated in previous papers portray a static effect of co-ethnic networks on the labor market effects of immigrants and summarize in one coefficient such effect. Usually, those papers include a discussion on the possible channels at work but only at the speculative level.[56] One implicit assumption that is usually made is that workers in a location with larger co-ethnic network obtain job referrals from it, i.e. using an informal search method. This is the main channel through which networks may be effective. Often, however, results are consistent with other possible channels, including, among others, differential labor market demand that is correlated with network size or quality.

In most datasets, it is not possible to directly observe whether and how search behavior is affected by social networks. In our dataset, instead, we have direct information on the way an individual has found her first job in Germany. This unique information allow us to investigate the effect of co-ethnic networks at arrival on the type of job search method used to find the first job in Germany. Table 7 uses as dependent variable a dummy for having found the first job in Germany through "personal contacts" and estimates a similar specification as Table 6, in that we use the cross-section of immigrants, control for their initial characteristics, and estimate the impact of initial network size.[57] There is a strong positive association between initial network size and the likelihood that the first job in Germany was found through personal contacts, and this is shown in column 1 of 7. Columns 2-4 show that this overall effect is entirely driven by immigrants with low education. For a less educated immigrant one standard deviation increase in the co-ethnic network size at arrival corresponds to 9.6 percentage points higher likelihood of having found the first job through contacts (the value is calculated as -0.009+0.096 percentage points, the coefficient on the main effect and interaction with less educated). This magnitude

[56] Dustmann et al. (2016) is a notable exception. The authors use German administrative data to evaluate the effect of within-firm ethnic networks on wage growth and firm turnover. They use the same survey that we use to show how the within-firm ethnic networks affect the probability of finding the job through contacts.

[57] Personal contacts refer in the questionnaire to friends, relatives, or acquaintances. We use the same specification as in estimating the effect on over-qualification, since we have a single cross-section for each individual.

corresponds to 15 percent of the average (57.7 percent) and it holds when we include the usual controls and the average wage at district-year of arrival. Table 8 presents the results from similar regressions (the main results of Table 7 (column 3) are presented in column 1 for comparison) where the dependent variables are dummies equal to one if an individual has found a job using online advertising (column 2) or if she used the employment agency (column 3). The positive effects of network size on the probability of finding the first job via personal contacts are confirmed by other specifications that include three education categories. The findings imply that for low skilled individuals, networks tend to replace employment agency and internet resources as the main source of successful job referrals.[58]

6.6 Falsification Exercise and Robustness Checks

In our main specification, we calculate network size as the share of employed individuals from the own country group in the district of arrival.[59] A possible concern with our findings is that they may be driven by the prevalence of immigrants in the area and that networks of individuals from the same origin country is simply acting as a proxy for that. Moreover, the size of the immigrants population in a certain district can simply be correlated with strong labor demand conditions in that location. Hence, in Table 9 we perform a placebo-type analysis where we investigate the specific role of co-ethnic network, as opposed to that of the generic share of immigrants. In columns 2 and 4 of Table 9 we use as explanatory variable the number of all immigrants, excluding co-nationals, as share of the employment of a district as explanatory variable in Netw_{d0}. Columns 1 and 2 show the estimates of the network variable and its interactions for the employment regressions: column 1 reports the baseline estimates and column 2 uses the share of foreign born excluding the co-nationals in the same district. The estimates of column (2) are not significantly different from zero, and of very small magnitude. This finding is consistent with our view that co-ethnic networks are the determinant of the employment effect, rather than local labour market demands (proxied by a general measure of immigration).

Columns 3 and 4 perform an equivalent falsification test on the relationship between network size and human capital investment. Column 3 presents our orig-

[58] It is worth noting here that the results of these regressions do not refer to the relative time spent searching. Rather, they concern only the successful search method, because our question on job search methods refers to the first job found in Germany. Therefore, we do not know whether and to what extent other search methods have been used.

[59] Throughout the empirical analysis we consider the last migration episode.

inal results. In column 4 as above we define networks simply as the share of non co-national foreign born in the local employment. Here again, effects are not significantly different from zero, and much lower in magnitude. The results of this exercise are consistent with the idea that the mechanism operates at the level of the co-ethnic network. In Appendix D we perform an additional robustness check running the main regressions and including as additional regressor a measure of cognitive skills, measuring the self-reported past test score in math.[60] (Table D.4). All our main results are confirmed, both on employment (columns 1 and 2) as well as on human capital (columns 3 and 4).

6.7 Initial Location Decision

Our survey includes a rich set of information on pre-migration characteristics: education, employment, working experience, language proficiency, and cognitive ability. In this section, rather than simply using them as controls, we use them to test the initial sorting of immigrants across locations, which provides an idea of the potential endogeneity concerns for our estimates. In particular, while initial characteristics of immigrants can be correlated with the size of co-ethnic networks at arrival, because different people have different preferences for networks, we like to test whether this correlation survives the inclusion of district, country of origin and year fixed effects. To the extent that the correlation between the pre-migration characteristics and the size of network is weak once we condition on our set of fixed effects, this would imply that, conditionally on them, individual unobservable characteristics do not explain the initial location. Our assumption is that the vector of pre-migration characteristics is also a good proxy for unobserved characteristics. If it does not strongly determine the initial selection, omitted variable bias is likely not to be too large. This test of orthogonality is new to this literature and it is generally not possible with social security data alone, because in those no information about pre-migration variables is available. Testing the conditional orthogonality of initial co-ethnic network and individual characteristics is not a perfect test of randomness but it is informative, and certainly a significant step in checking that the correlation between pre-migration characteristics and network size does not drive the results.

[60]We have decided not to include this measure in our main regressions because we would lose around 29 percent of our sample. This drastic sample restriction is due to the fact that the relative question is asked only in the second wave of the survey, and almost all our sample comes from the first wave. For the details about the data structure see Section C of the Appendix.

A similar exercise is carried out in Guryan et al. (2009) to test the orthogonality of predetermined student characteristics and average class characteristic. The exercise consists in regressing the initial network size variable on all pre-migration variables (Table 10), first without other controls (column 1), then adding country-of-origin, arrival year, and arrival district fixed effects (column 2 and 3). While significant correlation exists, showing in particular that large initial co-ethnic networks are associated with less educated immigrants (negative correlation with medium and high education) and workers with lower work experience, it also turns out that, once we control for the fixed effects, none of the pre-migration variables is correlated with the initial network size, neither individually, nor jointly. This exercise shows that, once we condition on district, year of arrival, and country fixed effects, there is no remaining correlation between any of our pre-migration characteristic and the choice of the initial network. Given this evidence, we can argue that, once we include a full set of fixed effect dummies, our results are only marginally affected by sorting, under the assumption that pre-migration variables are good proxies for unobserved characteristics potentially related to selection and labor market outcomes.

Finally, we check that our results are robust to different geographical levels at which one can measure co-ethnic networks. Our specifications throughout the paper uses the district level, while in robustness checks we use municipalities (the number of municipalities in Germany is around 12,000), we try to replicate the main analysis at this lower aggregation. The results show that the main estimated effects are robust to this different definition of the network as can be seen in Table D.6 of Appendix D (other papers also use small units such as Bayer et al. 2008 who use Census blocks, whereas Schmutte 2015 considers small neighborhoods).

7 Concluding Remarks

This paper looks at co-ethnic networks of immigrants in Germany, and their role in helping the economic success of new immigrants. In particular, we investigate how co-ethnic networks at arrival may affect employment and human capital investments of immigrants soon after arrival, as well as in the following years. We develop a very simple search model where individuals search through two channels, formal and informal, and co-ethnic networks help individuals find employment by providing referrals. Such a model predicts an initial lower probability of employment for individuals with smaller initial co-ethnic networks. Over time, our model predicts convergence to similar employment probability and possibly higher wages for those who arrived in small co-ethnic networks because of the effects of human capital investment.

Our main dataset is a novel survey of immigrants to Germany, which we merged to the social security archive to reconstruct the entire individual labor market history of immigrants, as well as their district of arrival in Germany. Our empirical evidence is consistent with the main implications of our model: individuals with larger ethnic networks are more likely to be employed soon after their arrival, but are less likely to invest in human capital and are not more likely to be employed several years after arrival. In addition, the initial co-ethnic network exerts a negative long run effect on wages and on the quality of the job matching. Higher initial networks increase the likelihood of being overqualified in the job. These effects are larger and more strongly significant for initially less educated immigrants.

Identifying the effect of co-ethnic networks on human capital investment of recent immigrants is a new contribution of this paper, and it suggests that, while positive overall, co-ethnic networks may give a larger initial boost that attenuates over time and can cause under-investment in human capital. Previous empirical estimations of network effects for immigrants such as Edin et al. (2003) and Damm (2009) emphasized only the employment effect. As they found a positive impact of networks on that, they argued that dispersal policies have high costs for immigrants, worsening their labor market outcomes. The implications from our results, however, suggest a more complex story. While in the short-run employment probability may be increased by the presence of co-ethnic networks, dynamically they may reduce human capital accumulation and lower the quality of the match and wages. Ignoring those effects may result in overestimating the negative effects of dispersal policies.

Possibly, however, the most important contribution of this study is to be able to identify with greater confidence the causal effect of co-ethnic network on several different outcomes of immigrants in the short and in the long run. We are bringing better data (inclusive of pre-migration characteristics), better identification strategy (based on panel regressions and dispersal policies), and higher external validity (by including all immigrants) to this literature.

Tables and Figures

Table 1: Summary Statistics

	Time Variant Variables		
Variable	Mean	Std. Dev.	N
Netw_{d_0}	0.012	0.018	12230
Employment	0.688	0.463	12230
Human Capital Investment	0.043	0.204	12175
Real Hourly Wage	8.508	4.005	4814
Year since Migr:0-2	0.227	0.419	12230
Year since Migr:3-5	0.214	0.410	12230
Year since Migr:6+	0.559	0.497	12230
Low Edu	0.382	0.486	12230
Med Edu	0.393	0.489	12230
High Edu	0.225	0.418	12230
Age	37.028	10.450	12230
	Individual Variables		
West	0.105	0.307	933
East Eu	0.129	0.335	933
Turkey	0.064	0.245	933
South and East EU	0.202	0.401	933
USSR	0.427	0.495	933
Asia	0.047	0.212	933
Africa	0.020	0.141	933
Central and South America	0.006	0.080	933
First Job Found through Contacts	0.578	0.494	824
Low Edu	0.409	0.492	933
Pre Migration Edu: Medium	0.346	0.476	933
Pre Migration Edu: High	0.244	0.430	933
Pre migration Employment	0.726	0.446	929
Pre migration Language Proficiency	0.115	0.319	930
Pre migration work Experience	10.245	9.716	933
Age at Migration	30.504	9.895	933
Overqualified in current Job	0.414	0.493	650

Source: IAB-SOEP Migration Sample linked to IEB.

Table 2: Network at Migration and Employment

	Dependent Variable: Employment (dummy)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Netw_{d_0}	0.041***	0.106***	0.106***	0.102***	0.097	0.099***	0.103**	0.092***	0.106**
	(0.012)	(0.021)	(0.022)	(0.022)	(0.075)	(0.014)	(0.047)	(0.013)	(0.048)
Netw_{d_0}xYsm3-5		-0.076***	-0.074***	-0.074***	-0.070	-0.071***	-0.072	-0.073***	-0.073
		(0.016)	(0.016)	(0.016)	(0.061)	(0.016)	(0.065)	(0.016)	(0.065)
Netw_{d_0}xYsm6+		-0.098***	-0.098***	-0.100***	-0.101	-0.105***	-0.119	-0.102***	-0.117
		(0.016)	(0.017)	(0.017)	(0.062)	(0.018)	(0.074)	(0.018)	(0.075)
		[0.023]	[0.025]	[0.024]	[0.062]	[0.026]	[0.071]	[0.026]	[0.072]
Individuals	933	933	926	926	297	926	297	925	297
Obs	12230	12230	12121	12121	4240	12121	4240	12107	4240
R^2	0.141	0.233	0.236	0.236	0.376	0.107	0.183	0.108	0.191
Mean Dep. Var	0.688				0.655				
Base Contr.	yes	yes	yes	yes	yes	yes	yes	yes	yes
Pre-Migration Contr.	no	no	yes	yes	yes	yes	yes	yes	yes
Single FEs	no	yes	yes	yes	yes	no	no	no	no
Single FEs (predicted)	no	no	no	no	no	yes	yes	no	no
Double FEs (predicted)	no	no	no	no	no	no	no	yes	yes
Mean Wage	no	no	no	yes	no	no	yes	no	no
Sample	full	full	full	full	R	full	R	full	R

Note: The dependent variable is an indicator for employment. All network variables are standardized: the relevant coefficient corresponds to the effect of an increase by one standard deviation. Base controls: gender, current age and age at migration (and its sq.), education, country of origin fixed effects (8 groups), year at migration fixed effects, and district at migration fixed effects. Pre-migration controls: employment, language proficiency, education, working experience. Sample R: includes only those who migrated to Germany as asylum seekers, or ethnic Germans migrating in the period covered by the law of random allocation. In column (6)-(7) we include the following predicted fixed effects, that we estimated using an external sample of immigrants: year of arrival, district of arrival, and country group. In column (8)-(9) we include the following externally predicted fixed effects: year of arrival-district of arrival, country-year of arrival, country-district of arrival. All predicted fixed effects are obtained using a random sample of 174,581 immigrants from IEB data. The estimating regression included the following regressors: education, age and its squared, and gender. Standard errors in parenthesis are clustered at individual level in column (1)-(5), and are further obtained with 500 bootstrap replications in column (6)-(9). Significance level: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Standard errors in square brackets refer to the respective estimates with clustering at district of arrival level.

Table 3: Network at Migration and Investment in Human Capital

Dependent Variable: Investment in Human Capital (dummy)					
	(1)	(2)	(3)	(4)	(5)
$Netw_{d_0}$	-0.008**	-0.027***	-0.028***	-0.027***	-0.075***
	(0.004)	(0.009)	(0.009)	(0.009)	(0.026)
	[0.003]	[0.009]	[0.010]	[0.010]	[0.027]
$Netw_{d_0}$xYsm3-5		0.011	0.011	0.011	0.033
		(0.008)	(0.009)	(0.009)	(0.020)
		[0.009]	[0.009]	[0.009]	[0.021]
$Netw_{d_0}$xYsm6+		0.030***	0.030***	0.030***	0.061***
		(0.009)	(0.009)	(0.009)	(0.019)
		[0.010]	[0.010]	[0.010]	[0.021]
Individuals	933	933	926	926	297
Obs	12175	12175	12083	12083	4233
R^2	0.141	0.204	0.206	0.206	0.327
Mean Dep. Var	0.043				0.061
Base Contr. and FEs	yes	yes	yes	yes	yes
Pre-Migration Contr.	no	no	yes	yes	yes
Mean Wage	no	no	no	yes	no
Sample	full	full	full	full	R

Note: The dependent variable is an indicator for being in education. All network variables are standardized: the relevant coefficient corresponds to the effect of an increase by one standard deviation. Base controls: gender, current age and age at migration (and its sq.), education, country of origin fixed effects (8 groups), year at migration fixed effects, and district at migration fixed effects. Pre-migration controls: employment, language proficiency, education, working experience. Sample R: includes only those who migrated to Germany as asylum seekers, or ethnic Germans migrating in the period covered by the law of random allocation. Standard errors in parenthesis are clustered at individual level with * $p<0.10$, ** $p<0.05$, *** $p<0.01$. We report standard errors clustered at district level in square brackets.

Table 4: Network at Migration, Employment and Human Capital Investment by Education

Dep. Var.	Work/Not Work			HC Investment		
Education	Low	Medium	High	Low	Medium	High
	(1)	(2)	(3)	(4)	(5)	(6)
Netw_{d_0}	0.150***	0.080*	0.003	-0.034**	-0.033***	0.006
	(0.027)	(0.041)	(0.059)	(0.016)	(0.010)	(0.026)
	[0.033]	[0.041]	[0.073]	[0.018]	[0.011]	[0.023]
Netw_{d_0}xYsm3-5	-0.082***	-0.094***	-0.043	0.021	0.014*	0.010
	(0.025)	(0.033)	(0.030)	(0.014)	(0.008)	(0.019)
	[0.024]	[0.036]	[0.035]	[0.015]	[0.007]	[0.021]
Netw_{d_0}xYsm6+	-0.122***	-0.079***	-0.070*	0.043***	0.030***	0.018
	(0.024)	(0.030)	(0.041)	(0.014)	(0.011)	(0.019)
	[0.029]	[0.030]	[0.051]	[0.016]	[0.011]	[0.021]
Individuals	378	321	227	378	321	227
Obs	5244	4176	2701	5223	4176	2684
R^2	0.314	0.296	0.360	0.330	0.147	0.211
Mean Dep. Var	0.677	0.699	0.689	0.058	0.024	0.045
Sample	full	full	full	full	full	full

Note: The dependent variable is an indicator for employment (column 1-3), or a indicator for being in education (column 4-6). Education is measured before migration. Low education refers to lower secondary education. Medium and high refer to upper secondary, and tertiary education, respectively. All network variables are standardised: the relevant coefficient corresponds to the effect of an increase by one standard deviation. Controls include base controls and pre-migration controls. Base controls: gender, current age and age at migration (and its sq.), country of origin fixed effects (8 groups), year at migration fixed effects, and district at migration fixed effects. Pre-migration controls: employment, language proficiency, education, working experience.
Standard errors in parenthesis, clustered at individual level, * p<0.10, ** p<0.05, *** p<0.01. We report standard errors clustered at district level in square brackets.

Table 5: Network and Wages

Dependent Variable: Hourly Wage (log)					
	(1)	(2)	(3)	(4)	(5)
$Netw_{d_0}$ (a)	-0.004	-0.192**	-0.078**	0.054	-0.164
	(0.031)	(0.084)	(0.035)	(0.057)	(0.155)
	[0.033]	[0.105]	[0.039]	[0.069]	[0.148]
$Netw_{d_0}$xYsm3-5	-0.026*	0.059*	-0.020	-0.051*	-0.013
	(0.015)	(0.035)	(0.020)	(0.030)	(0.025)
	[0.015]	[0.036]	[0.018]	[0.028]	[0.027]
$Netw_{d_0}$xYsm6+ (b)	-0.036*	0.028	-0.031	-0.005	-0.076**
	(0.018)	(0.045)	(0.024)	(0.036)	(0.035)
	[0.016]	[0.046]	[0.020]	[0.033]	[0.036]
Individuals	654	215	264	229	161
Obs	4814	1618	2038	1730	1046
R^2	0.492	0.637	0.595	0.609	0.706
(a)+(b)==0 (p-value)	0.155	0.033	0.001	0.338	0.127
Mean Dep. Var	8.508	7.759	7.702	7.742	11.346
Base Contr. and FEs	yes	yes	yes	yes	yes
Pre-Migration Contr.	yes	yes	yes	yes	yes
Sample	full	R	Low edu	Med edu	High edu

Note: The dependent variable is the (log) real hourly wage. Sample: individuals working at least once within the year, only full time workers are considered. Spells of apprenticeship, and marginal employment are excluded. Education is measured before migration. Low education refers to lower secondary education. Medium and high refer to upper secondary, and tertiary education, respectively. All network variables are standardised: the relevant coefficient corresponds to the effect of an increase by one standard deviation. Controls include base controls and pre-migration controls. Base controls: gender, current age and age at migration (and its sq.), country of origin fixed effects (8 groups), year at migration fixed effects, and district at migration fixed effects. Pre-migration controls: employment, language proficiency, education, working experience.
Standard errors in parenthesis, clustered at individual level, * $p<0.10$, ** $p<0.05$, *** $p<0.01$. We report standard errors clustered at district level in square brackets.

Table 6: Network at Migration and Over-qualification in the current Job

	(1)	(2)	(3)	(4)
Low Edu_{t0}	-0.252***	-0.259***	-0.255**	-0.263**
	(0.096)	(0.100)	(0.101)	(0.120)
	[0.113]	[0.121]	[0.122]	[0.144]
Netw_{d_0} (a)	-0.012	-0.012	-0.015	-0.037
	(0.046)	(0.046)	(0.046)	(0.053)
	[0.051]	[0.050]	[0.049]	[0.058]
Netw_{d_0}xLow Edu_{t0} (b)	0.108***	0.105**	0.106**	0.120**
	(0.041)	(0.042)	(0.042)	(0.048)
	[0.047]	[0.049]	[0.049]	[0.056]
Individuals	647	642	642	521
R^2	0.616	0.624	0.624	0.645
(a)+(b)==0 (p-value)	0.009	0.013	0.017	0.061
Mean Dep. Var	0.414			
Base Controls	yes	yes	yes	yes
Pre-Migration Controls	no	yes	yes	yes
Average Wage at Dist_{t0}xYear_{t0}	no	no	yes	no
Past Cognitive Skill	no	no	no	yes

Note: The dependent variable is an indicator for being overqualified in the current job. All network variables are standardised: the relevant coefficient corresponds to the effect of an increase by one standard deviation. Base controls: gender, current education, age at migration (and its sq.), country of origin fixed effects (8 groups), year at migration fixed effects, and district at migration fixed effects. Pre-migration controls: employment, language proficiency, education, working experience. Past cognitive skill: self-reported test score in math. Robust standard errors in parenthesis, * $p<0.10$, ** $p<0.05$, *** $p<0.01$. We report standard errors clustered at district level in square brackets.

Table 7: Network at Migration and first Job in Germany found through Contacts

	(1)	(2)	(3)	(4)
Low Edu_{t0}		0.077	0.110	0.109
		(0.050)	(0.069)	(0.069)
		[0.054]	[0.078]	[0.078]
Netw_{d_0} (a)	0.053***	-0.009	-0.012	-0.009
	(0.016)	(0.050)	(0.049)	(0.050)
	[0.016]	[0.053]	[0.051]	[0.052]
Netw_{d_0}xLow Edu_{t0} (b)		0.096**	0.093**	0.092**
		(0.044)	(0.044)	(0.044)
		[0.041]	[0.042]	[0.042]
Individuals	819	819	816	816
R^2	0.012	0.382	0.391	0.391
(a)+(b)==0 (p-value)		0.053	0.068	0.062
Mean Dep. Var.	0.578			
Base Controls	no	yes	yes	yes
Pre-Migration Controls	no	no	yes	yes
Average Wage at $\text{Dist}_{t0}\text{xYear}_{t0}$	no	no	no	yes

Note: The dependent variable is an indicator for finding the first job in Germany through contacts (friends/acquaintances/relatives). All network variables are standardised: the relevant coefficient corresponds to the effect of an increase by one standard deviation. Base controls: gender, age at migration (and its sq.), country of origin fixed effects (8 groups), year at migration fixed effects. Pre-migration controls: employment, language proficiency, education, working experience. Robust standard errors in parenthesis, * p<0.10, ** p<0.05, *** p<0.01. We report standard errors clustered at district level in square brackets.

Table 8: Network at Migration and methods of finding the first Job in Germany

Method	Contacts	Internet	Empl. Agency
	(1)	(2)	(3)
Low Edu_{t0}	0.110	-0.061	0.002
	(0.069)	(0.057)	(0.052)
Netw_{d_0} (a)	-0.012	-0.033	0.044
	(0.049)	(0.041)	(0.033)
Netw_{d_0}xLow Edu_{t0} (b)	0.093**	-0.047	-0.045
	(0.044)	(0.039)	(0.030)
Individuals	816	816	816
R^2	0.391	0.355	0.379
(a)+(b)==0 (p-value)	0.068	0.36	0.984
Mean Dep. Var	0.578	0.194	0.195

Note: The dependent variable is an indicator for different methods of finding the first job in Germany, the method varying according to the heading. All network variables are standardised: the relevant coefficient corresponds to the effect of an increase by one standard deviation. Controls include base controls and pre-migration controls. Base controls: gender, age at migration (and its sq.), country of origin fixed effects (8 groups), year at migration fixed effects. Pre-migration controls: employment, language proficiency, education, working experience. Robust standard errors in parenthesis, * p<0.10, ** p<0.05, *** p<0.01.

Table 9: Falsification Test: Network of all Other Immigrants

Dependent variable:	Employment		Human Capital	
Network:	Baseline	Other	Baseline	Other
	(1)	(2)	(3)	(4)
Netw_{d_0}	0.106***	-0.008	-0.028***	0.002
	(0.022)	(0.037)	(0.009)	(0.013)
Netw_{d_0}xYsm3-5	-0.074***	-0.012	0.011	-0.001
	(0.016)	(0.014)	(0.009)	(0.007)
Netw_{d_0}xYsm6+	-0.098***	-0.025	0.030***	0.001
	(0.017)	(0.015)	(0.009)	(0.008)
Individuals	926	926	926	926
Obs	12121	12121	12083	12083
R^2	0.236	0.230	0.206	0.203

Note: The dependent variable is an indicator for employment (column 1-2), and an indicator for being in education (column 3-4). In column (2) and (4) the network variable is computed using all immigrants in the district of arrival excluding those from the country of origin of the individual. Controls include base controls and pre-migration controls. Base controls: gender, age at migration (and its sq.), country of origin fixed effects (8 groups), year at migration fixed effects, and district at migration fixed effects. Pre-migration controls: employment, language proficiency, education, working experience. All network Variables are standardised: the relevant coefficient corresponds to the effect of an increase by one standard deviation. Standard errors in parenthesis, clustered at individual level, * p<0.10, ** p<0.05, *** p<0.01.

Table 10: Test of Network Sorting

Pre-Migration Variable	(1)	(2)	(3)
Language	0.105	-0.051	-0.048
	(0.101)	(0.069)	(0.082)
	[0.120]	[0.079]	[0.095]
Employment	-0.091	0.008	0.052
	(0.074)	(0.049)	(0.054)
	[0.071]	[0.049]	[0.063]
Work Experience	-0.012***	0.001	-0.001
	(0.003)	(0.002)	(0.003)
	[0.003]	[0.002]	[0.003]
Education: Medium	-0.166***	-0.001	0.003
	(0.064)	(0.052)	(0.057)
	[0.060]	[0.050]	[0.053]
Education: High	-0.098	-0.002	0.036
	(0.073)	(0.056)	(0.066)
	[0.078]	[0.066]	[0.083]
Cognitive Ability			-0.063
			(0.047)
			[0.053]
Individuals	921	921	741
R^2	0.042	0.781	0.793
All Coefficients = 0 (p-value)	0.000	0.975	0.638
District of arrival	no	yes	yes
Year of arrival	no	yes	yes
Country of origin	no	yes	yes

The dependent variable is the network at migration.
Robust standard errors in parenthesis: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. We report standard errors clustered at district level in square brackets.

Figure 1: Searching for a job and human capital investment

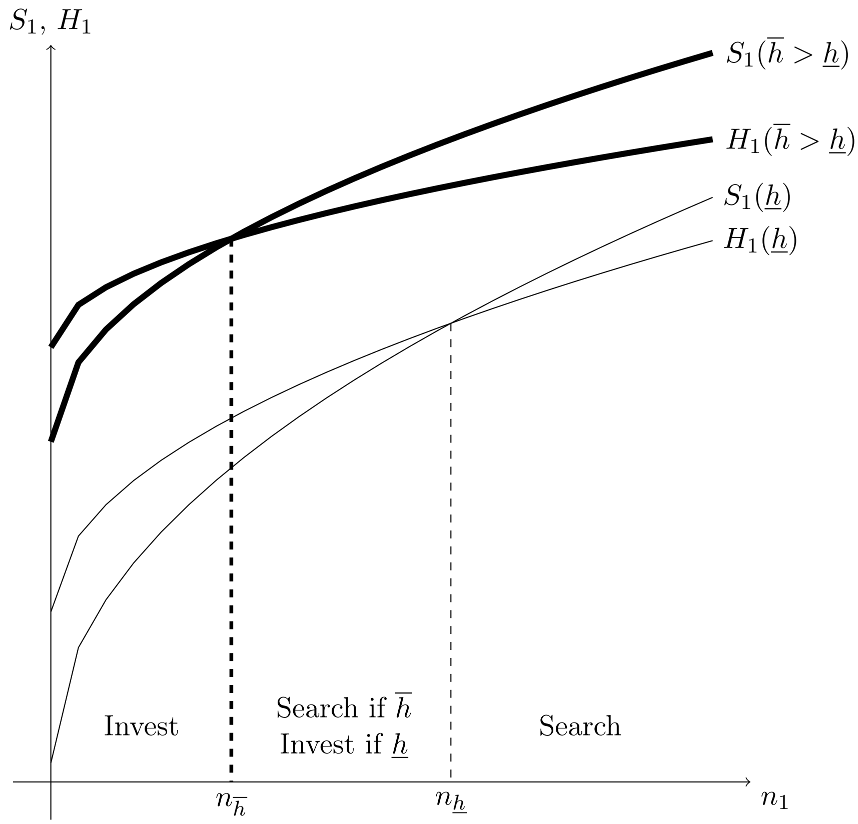


Figure 2: Wages at $t = 2$ for a given level of initial human capital

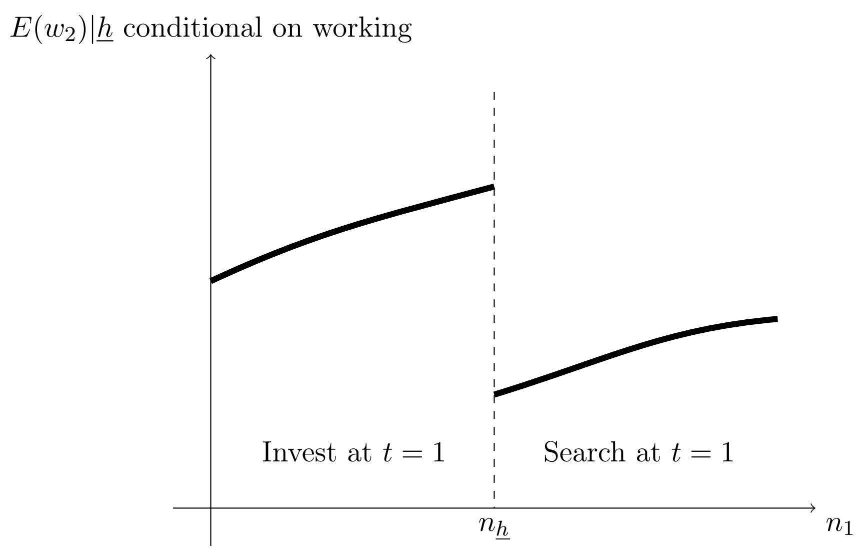
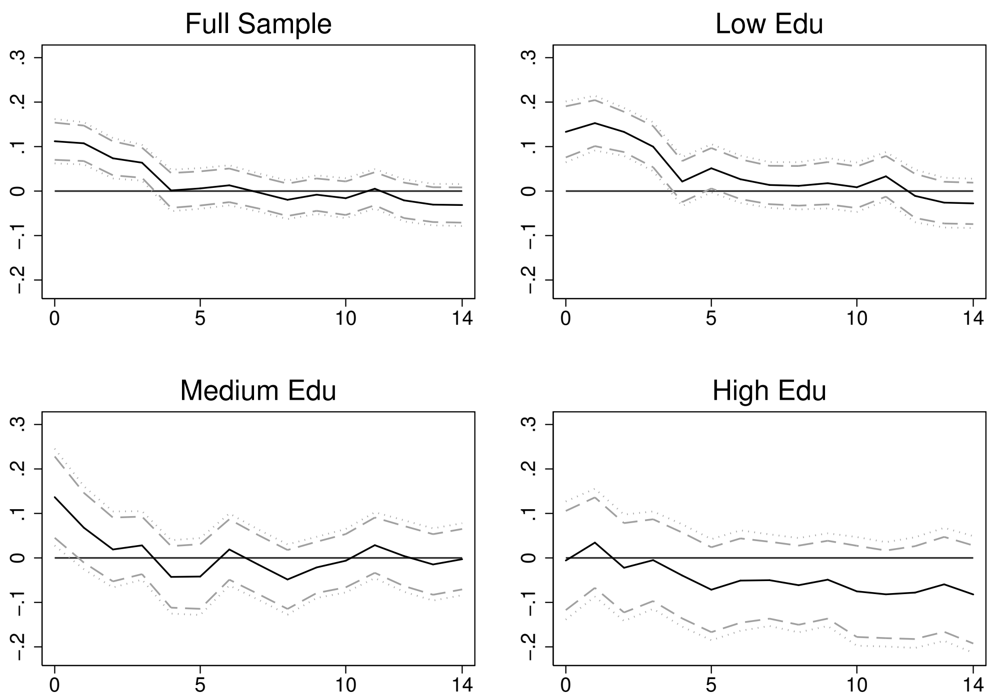
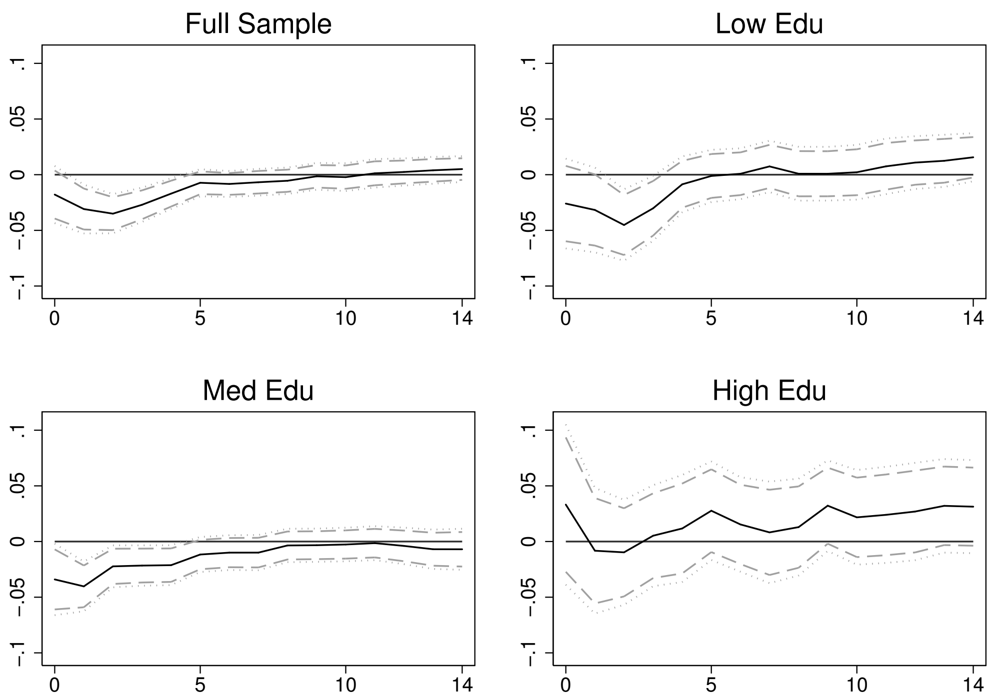


Figure 3: Effect of Network at Migration on Employment



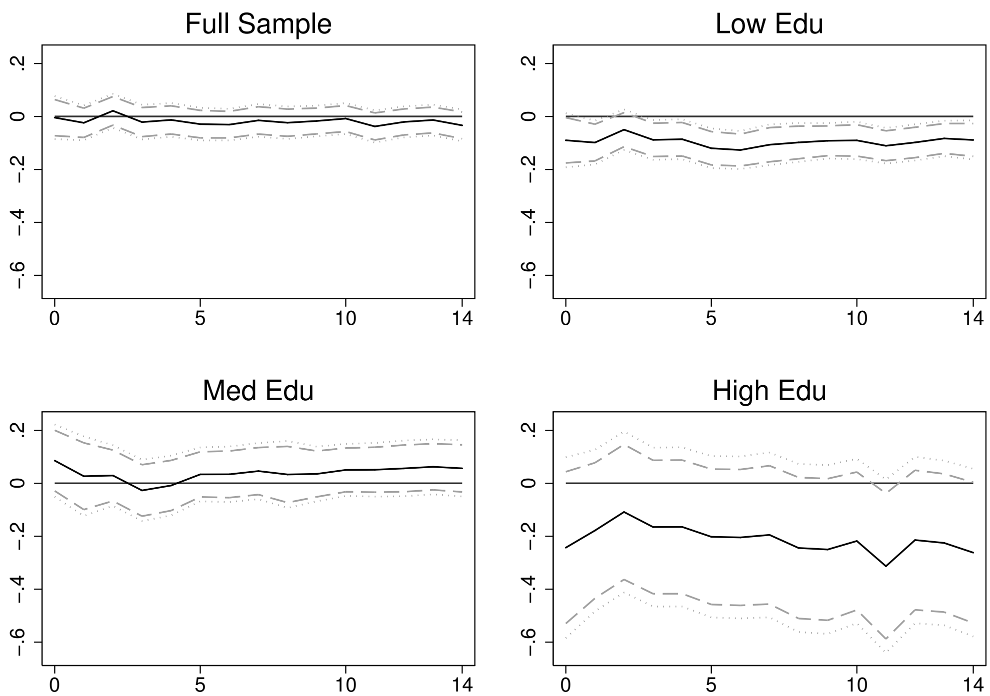
Note: the graphs report the coefficients of the network effect interacted with years since migration as well as confidence intervals (5 percent and 10 percent). The dependent variable is an indicator for employment defined as in Table 2. The estimated regression corresponds to the specification (5), where we use yearly dummies for years since migration. Standard errors are clustered at individual level. Controls: current age and age at migration (and their squared), language and education before migration, work experience before migration, employment before migration, gender, country, district and year at arrival fixed effects.

Figure 4: Effect of Network at Migration on Human Capital Investment



Note: the graphs report the coefficients of the network effect interacted with years since migration as well as confidence intervals (5 percent and 10 percent). The dependent variable is a indicator for being in education defined as in Table 3. The estimated regression corresponds to the specification (5), where we use yearly dummies for years since migration. Standard errors are clustered at individual level. Controls: current age and age at migration (and their squared), language and education before migration, work experience before migration, employment before migration, gender, country, district and year at arrival fixed effects.

Figure 5: Effect of Network at Migration on (log) hourly Wage



Note: the graphs report the coefficients of the network effect interacted with year since migration as well as confidence intervals (5 percent and 10 percent). The dependent variable is the (log) of hourly wage defined as in Table 5. The estimated regression corresponds to the specification (5), where we use yearly dummies for each year since migration. Standard errors are clustered at individual level. Controls: current age and age at migration (and their squared), language and education before migration, work experience before migration, employment before migration, gender, country, district and year at arrival fixed effects.

References

Åslund, Olof, Per-Anders Edin, Peter Fredriksson, and Hans Grönqvist (2011). Peers, Neighborhoods, and Immigrant Student Achievement: Evidence from a Placement Policy. *American Economic Journal: Applied Economics 3*(2), 67–95.

Bayer, Patrick, Stephen L. Ross, and Giorgio Topa (2008). Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes. *Journal of Political Economy 116*(6), 1150–1196.

Beaman, Lori A. (2012). Social Networks and the Dynamics of Labour Market Outcomes: Evidence from Refugees Resettled in the U.S. *The Review of Economic Studies 79*(1), 128–161.

Bennett, Patrick, Lisbeth La Cour, Birthe Larsen, and Gisela Waisman (2015, jul). Negative Attitudes, Network and Education. *Copenhagen Business School Working Paper 01-2015*.

Bentolila, Samuel, Claudio Michelacci, and Javier Suarez (2010). Social Contacts and Occupational Choice. *Economica 77*(305), 20–45.

Bertrand, Marianne, Erzo F P Luttmer, and Sendhil Mullainathan (2000). Network effects and welfare cultures. *The Quarterly Journal of Economics 115*(3), 1019–1055.

Borjas, George J. (1998). To Ghetto or Not to Ghetto: Ethnicity and Residential Segregation. *Journal of Urban Economics 44*(2), 228–253.

Calvó-Armengol, Antoni and Matthew O. Jackson (2004). The Effects of Social Networks on Employment and Inequality. *American Economic Review 94*(3), 426–454.

Cutler, David M. and Edward L. Glaeser (1997). Are Ghettos Good or Bad? *The Quarterly Journal of Economics 112*(3), 827–872.

Damm, Anna Piil (2009). Ethnic Enclaves and Immigrant Labor Market Outcomes: Quasi-Experimental Evidence. *Journal of Labor Economics 27*(2), 281–314.

Damm, Anna Piil (2014). Neighborhood quality and labor market outcomes: Evidence from quasi-random neighborhood assignment of immigrants. *Journal of Urban Economics 79*(C), 139–166.

Dustmann, Christian, Albrecht Glitz, Uta Schönberg, and Herbert Brücker (2016, oct). Referral-based Job Search Networks. *The Review of Economic Studies*, forthcoming.

Dustmann, Christian and Ian Preston (2001). Attitudes to Ethic Minorities, Ethnic Context and Location Decisions. *Economic Journal 111*(470), 353–73.

Edin, Per-Anders, Peter Fredriksson, and Olof Åslund (2003). Ethnic Enclaves And The Economic Success Of Immigrants - Evidence From A Natural Experiment. *The Quarterly Journal of Economics 118*(1), 329–357.

Fitzenberger, Bernd, Aderonke Osikominu, and Robert Völter (2005). Imputation rules to improve the education variable in the IAB employment subsample. *FDZ Methodenreport No. 3/2005*.

Galenianos, Manolis (2013). Learning About Match Quality and the Use of Referrals. *Review of Economic Dynamics 16*(4), 668–690.

Galenianos, Manolis (2014). Hiring through referrals. *Journal of Economic Theory 152*(C), 304–323.

Glitz, Albrecht (2012, jan). The Labor Market Impact of Immigration: A Quasi-Experiment Exploiting Immigrant Location Rules in Germany. *Journal of Labor Economics 30*(1), 175–213.

Glitz, Albrecht (2014, aug). Ethnic segregation in Germany. *Labour Economics 29*, 28–40.

Goel, Deepti and Kevin Lang (2009). Social Ties and the Job Search of Recent Immigrants. *NBER Working Paper 15186*.

Gould, Eric D., Victor Lavy, and M. Daniele Paserman (2009). Does Immigration Affect the Long-Term Educational Outcomes of Natives? Quasi-Experimental Evidence. *Economic Journal 119*(540), 1243–1269.

Granovetter, Mark (1973). The Strength of Weak Ties. *American Journal of Sociology 78*(6), 1360–1380.

Guryan, Jonathan, Kory Kroft, and Matthew J. Notowidigdo (2009). Peer Effects in the Workplace: Evidence from Random Groupings in Professional Golf Tournaments. *American Economic Journal: Applied Economics 1*(4), 34–68.

Hellerstein, Judith K., Melissa McInerney, and David Neumark (2011). Neighbors and Coworkers: The Importance of Residential Labor Market Networks. *Journal of Labor Economics 29*(4), 659–695.

Loury, Linda Datcher (2006). Some Contacts Are More Equal than Others: Informal Networks, Job Tenure, and Wages. *Journal of Labor Economics 24*(2), 299–318.

Montgomery, James D (1991). Social Networks and Labor-Market Outcomes: Toward an Economic Analysis. *The American Economic Review 81*(5), 1408–1418.

Patacchini, Eleonora and Yves Zenou (2012). Ethnic networks and employment outcomes. *Regional Science and Urban Economics 42*(6), 938–949.

Pellizzari, Michele (2010). Do Friends and Relatives Really Help in Getting a Good Job? *Industrial and Labor Relations Review 63*(3), 494–510.

Regets, Mark C. and Harriet Orcutt Duleep (1999). Immigrants and Human-Capital Investment. *American Economic Review 89*(2), 186–191.

Schmutte, Ian M (2015). Job referral networks and the determination of earnings in local labor markets. *Journal of Labor Economics 33*(1), 1–32.

van den Berg, Gerard J and Bas van der Klaauw (2006). Counseling And Monitoring Of Unemployed Workers: Theory And Evidence From A Controlled Social Experiment. *International Economic Review 47*(3), 895–936.

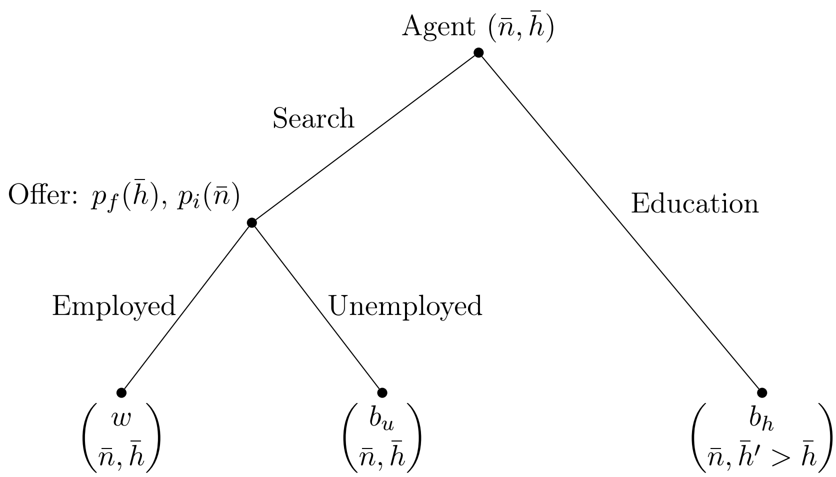
Xie, Yu and Margaret Gough (2011). Ethnic Enclaves and the Earnings of Immigrants. *Demography 48*(4), 1293–1315.

Appendices

A Job Search vs. Human Capital investment decision

Figure A.1 summarizes the decision of the individual at $t = 1$.[61]

Figure A.1: Sketch of decisions and outcomes in period $t = 1$



B Analytical Discussion of Propositions

Section 3 above presents three Prepositions, which constitute three main implications of our simple model, which we then compare to what we find in our empirical exercise. In this short appendix we present a slightly more structured discussions as a way to motivate those prepositions. Prepositions 1 and 2 are looking at the main comparative statics exercises of our model one at a time. Here, we focus on the same direction as Proposition 2 only, but from there we will outline everything that is at work here.

Proposition 2 concerns the effects of a changing level of n_1 on the choice of our agent between searching and human capital investment, taking h_1 as given. Here we will therefore look at the derivatives with respect to n and then look at the effects of changing h on outcomes as a comparative statics exercise. In order to evaluate the

[61] We borrow the graphical structure of a game tree for clarity, although there is no strategic interaction here.

effects of initial network size on the $t = 1$ choice between human capital investment (H_1) and searching for a job (S_1), let us look at the first derivative of these functions with respect to n.

$$\frac{\partial H_1}{\partial n_1} = \beta \left(\frac{\partial \mathcal{S}(h')}{\partial n_1} \right) \tag{B.1}$$

Let us now look at the first derivative of the S_1 function with respect to n_1.

$$\frac{\partial S_1}{\partial n_1} = (1+\beta) \left(\frac{\partial \mathcal{S}(\bar{h})}{\partial n_1} \right) \tag{B.2}$$

Clearly in order to sign the above two derivatives we need to sign $\frac{\partial \mathcal{S}(h)}{\partial n_1}$, which is what we do next. In order to mantain the notation relatively compact let us define:

$$\int \max\{x_i - b_u, 0\} dF_i(x_i) \equiv \mathcal{A} \tag{B.3}$$

$$\int \max\{x_f - b_u, 0\} dF_f(x_f) \equiv \mathcal{B} \tag{B.4}$$

$$\int \max\{x_i - b_u, x_f - b_u, 0\} dF_i(x_i) dF_f(x_f) \equiv \mathcal{C} \tag{B.5}$$

We can now write

$$\begin{aligned} \frac{\partial \mathcal{S}(h)}{\partial n} &= \frac{\partial p_i}{\partial n}(1 - p_f(h))\mathcal{A} - p_f(h)\frac{\partial p_i}{\partial n}\mathcal{B} + \frac{\partial p_i}{\partial n} p_f(h)\mathcal{C} \\ &= \frac{\partial p_i}{\partial n}\left[(1 - p_f(h))\mathcal{A} + p_f(h)(\mathcal{C} - \mathcal{B})\right] \end{aligned} \tag{B.6}$$

Now, under our assumption that the two distributions have common support, the the extent that probabilities are positive $\mathcal{C} > \mathcal{B}$ (if the common support assumption does not hold, this equation would hold as weak inequality). In other words, the value of drawing twice from two distributions that partially overlap, and picking the higher outcome is strictly better (in expectations) compared to only drawing from one of those distributions. Therefore, $\frac{\partial \mathcal{S}(h)}{\partial n} > 0$. This implies that both the value of searching and the value of human capital investment increase in n_1 i.e. the value of the initial network. The outcome from searching is positively affected by networks, which make it more likely to find a job and increase expected wage (because of the increased probability of drawing two offers and picking the higher one in that case).

What can help us in the direction of understanding how n_1 may affect our individual's decision is to compare these two derivatives. We therefore compare $\frac{\partial \mathcal{S}(h')}{\partial n_1}$

with $\frac{\partial \mathcal{S}(\bar{h})}{\partial n_1}$ where $h' > \bar{h}$ because of our assumption of positive returns to investment in human capital. Let us write down the cross derivative of $\mathcal{S}$ with respect to n (since network size is constant over time we can ignore the subscript) and h.

$$\begin{aligned} \frac{\partial^2 \mathcal{S}(h)}{\partial n \partial h} &= -\frac{\partial p_i}{\partial n}\frac{\partial p_f}{\partial h}\mathcal{A} - \frac{\partial p_i}{\partial n}\frac{\partial p_f}{\partial h}\mathcal{B} + \frac{\partial p_i}{\partial n}\frac{\partial p_f}{\partial h}\mathcal{C} \\ &= \frac{\partial p_i}{\partial n}\frac{\partial p_f}{\partial h}(\mathcal{C} - \mathcal{A} - \mathcal{B}) \end{aligned} \tag{B.7}$$

Under our assumption that both wage distribution have only nonnegative outcomes $\mathcal{C} < \mathcal{A} + \mathcal{B}$. This directly implies that $\frac{\partial \mathcal{S}^2(h)}{\partial n \partial h} < 0$, which in turn means that $\frac{\partial \mathcal{S}(h')}{\partial n} < \frac{\partial \mathcal{S}(\bar{h})}{\partial n}$. In words, when individuals have high levels of human capital, in our setup the marginal effect of network size on search outcomes is (positive but) smaller. Since $\beta > 0$ this means that $\frac{\partial \mathcal{S}}{\partial n} > \frac{\partial H_1}{\partial n}$. This result, together with the results on second derivative we move to next, helps us analyse the comparative statics of the choice outlined by our model intuitively and graphically, and thereby confirm what we state in our Propositions.

We now know that both the value of human capital investment and the value of searching for a job are monotonically increasing in n_1 for a given level of h_1. We next look at the second derivative of the same two functions.

$$\frac{\partial^2 H_1}{\partial n^2} = \beta\left(\frac{\partial^2 \mathcal{S}(h')}{\partial n^2}\right) \tag{B.8}$$

and

$$\frac{\partial^2 S_1}{\partial n^2} = (1+\beta)\left(\frac{\partial^2 \mathcal{S}(\bar{h})}{\partial n^2}\right) \tag{B.9}$$

so we need to sign the terms in brackets in order to sign there derivatives and compare them. We evaluate that term for a generic h so that we can then investigate how it is affected by the level of h.

$$\begin{aligned} \frac{\partial^2 \mathcal{S}(h)}{\partial n^2} &= \frac{\partial^2 p_i}{\partial n^2}(1 - p_f(h))\mathcal{A} - p_f(h)\frac{\partial^2 p_i}{\partial n^2}\mathcal{B} + \frac{\partial^2 p_i}{\partial n^2}p_f(h)\mathcal{C} \\ &= \frac{\partial^2 p_i}{\partial n^2}(1 - p_f(h))\mathcal{A} + \frac{\partial^2 p_i}{\partial n^2}p_f(h)(\mathcal{C} - \mathcal{B}) < 0 \end{aligned} \tag{B.10}$$

because of our assumptions on the second derivative and because $\mathcal{C} > \mathcal{B}$ as discussed above. So both our functions (human capital investment and search values as a function of network size, given initial human capital level) have negative second derivatives.

In order to accurately draw those functions and in particular to evaluate whether the single-crossing result we stated in our propositions 1 and 2, it is useful to look at whether and how the magnitude of this second derivative depends on h.

For this, it is useful to rewrite the equation above as

$$\frac{\partial^2 \mathcal{S}(h)}{\partial n^2} = \frac{\partial^2 p_i}{\partial n^2}\mathcal{A} + \frac{\partial^2 p_i}{\partial n^2}\left(\mathcal{C} - \mathcal{A} - \mathcal{B}\right) p_f(h) \tag{B.11}$$

The first term of equation (B.11) above is unaffected by h. The second term is positive because $\frac{\partial^2 p_i}{\partial n^2} < 0$ and $\mathcal{C} - \mathcal{A} - \mathcal{B} < 0$. Since $\frac{\partial p_f(h)}{\partial h} > 0$, the overall derivative is increasing in h (it is less negative for larger values of h).

We are now ready to compare the second derivatives of the human capital investment and job searching functions above:

$$\begin{aligned} \frac{\partial^2 S(h')}{\partial n^2} &> \frac{\partial^2 S(\bar{h})}{\partial n^2} \\ \beta \frac{\partial^2 S(h')}{\partial n^2} &> (1+\beta)\frac{\partial^2 S(\bar{h})}{\partial n^2} \end{aligned} \tag{B.12}$$

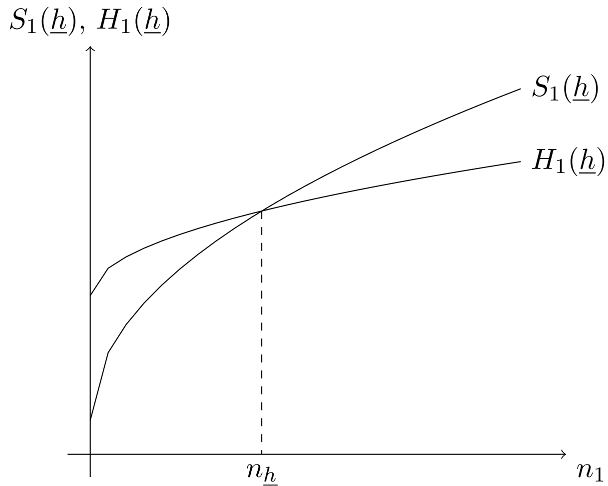
where the second line follows from the fact that both second derivatives are negatives and β is positive. Therefore,

$$\frac{\partial^2 H_1}{\partial n^2} > \frac{\partial^2 S_1}{\partial n^2} \tag{B.13}$$

In words, we found that both the value function for human capital investment and the that for job search are monotonically increasing concave functions of network size (for a given level of human capital initial endowment), we found that both first and second derivatives are smaller (in absolute value) for the human capital investment function. With the information above, we can relatively accurately draw the S_1 and the H_1 curves on a chart, which lets us evaluate the content of Propositions 1 and 2.

To the left of the intersection point $n_{\underline{h}}$ in Figure B.2 the individual will decide to invest in human capital, because it give higher utility in expectations. To the right of it (i.e. for larger size of initial social network) she will decide to search for a job. Figure B.2 is drawn for a certain human capital $\underline{h}$, following out findings above concerning sign and relative size of first and second derivative of our functions. However, the relative position of the two curves depend on the level of initial human capital and on other parameters. For example, under certain parameter configurations there

Figure B.2: Value of search and of human capital investment for a given level of human capital



may be a corner solution where h is sufficiently high that the the value of search is higher than the value of human capital investment even on the vertical axis. In this case, the agent will decide to look for a job at $t = 1$ for all levels of n_1.

From the Figure B.2 above we can also investigate the effects of changing h_1 on the equilibrium values. Since each curve on the chart below is drawn for a certain level of h, curves will shift as we let h vary. Symmetrically to our analysis for n above, it is very easy to show that

$$\frac{\partial S_1}{\partial h} > \frac{\partial H_1}{\partial h} \tag{B.14}$$

while both derivatives are positive, the S_1 curve reacts more than the H_1 curve to changes in h. Looking back at Figure B.2 this means that, under our assumptions, as we increase h the equilibrium value of n that will make our individual indifferent between searching for a job and acquiring human capital in period 1 will be lower. If we compare two individuals with the same social network but with different levels of initial human capital, the individual with higher initial human capital is more likely to start looking for a job earlier.

In the discussion above, we provided intuition for the claims made in Propositions 1 and 2. We next look at what our discussions on derivatives above implies for

Proposition 3, which refers to the cross derivative of the H_1 and S_1 functions, which is negative. Based on equation (B.7) above, at higher levels of h the effect of network on both curves is smaller is magnitude, and therefore equilibrium values move less (in response to changes in n) at higher levels of h, which is what Proposition 3 states.

C Linking Survey and Social Security Data

The IAB-SOEP Migration Sample is a new longitudinal survey of individuals with migration background in Germany. The survey is carried out jointly by the Institute for Employment Research (IAB) and the German Socio Economic Panel (GSOEP). The survey has a panel structure, the first wave was carried out in 2013 and the second wave in 2014. The starting sample consisted of around 5,000 individuals, and the second wave added a further refreshment sample of 275 individuals due to the sample attrition between the first and the second wave. Part of the original sample (the head of household) was drawn from the German Social Security Archive (IEB), therefore the head of households are individuals who have been at least once part of the labor force or registered as benefits recipient. All family members were also interviewed. A subsample of the original survey sample is then linked to the social security data (IEB), using a personal identifier. Due to data protection, respondents are required to give their prior consent for the record linkage by signing a document. The overall approval rate amounts to around 50 percent. The final linked sample consists 2,089 in individuals: 2,028 from the first wave and 61 from the refreshment sample of the second wave. Our sample consists in 933 individuals: 922 from the first wave and 17 from the second wave. This sample is obtained excluding second generation migrants, those with missing information in the variables of interest, those entering as student or still in education at the time of the survey.

D Additional Tables

Table D.1: Comparing refugees and non refugees in survey data (share)

	Refugees	Not Refugees	P-value
Pre migration Employment	0.519	0.442	0.001
Pre Migration Edu: Low	0.572	0.692	0.000
Pre Migration Edu: Medium	0.246	0.158	0.000
Pre Migration Edu: High	0.182	0.150	0.077
Pre migration Language: Good	0.130	0.060	0.000
Current Language: Good	0.581	0.473	0.000

Source: IAB/SOEP Migration Sample (first and second wave). P-value: significant difference between two samples.

Table D.2: Employment and Human Capital Investment over Time (Share)

Years since Migration	Work	In Education
0-2	0.480	0.119
3-5	0.717	0.040
6-9	0.757	0.020
10+	0.763	0.011
Total	0.688	0.044

Note: Data sources: IAB-SOEP Migration Sample linked to IEB data.

Table D.3: Human Capital Investment by Age (Share)

Age	In Education
15-20	0.439
21-30	0.062
31-40	0.020
41-65	0.012
Total	0.043

Note: Data sources: IAB-SOEP Migration Sample linked to IEB data.

Table D.4: Robustness. Control for Cognitive Skills

Dependent variable:	Employment		Human Capital	
	(1)	(2)	(3)	(4)
Netw_{d_0}	0.106***	0.094***	-0.028***	-0.029***
	(0.022)	(0.023)	(0.009)	(0.010)
	[0.028]	[0.026]	[0.010]	[0.010]
Netw_{d_0}xYsm3-5	-0.074***	-0.081***	0.011	0.008
	(0.016)	(0.017)	(0.009)	(0.009)
	[0.019]	[0.017]	[0.009]	[0.009]
Netw_{d_0}xYsm6+	-0.098***	-0.092***	0.030***	0.030***
	(0.017)	(0.017)	(0.009)	(0.009)
	[0.025]	[0.021]	[0.010]	[0.010]
Individuals	926	752	926	752
Obs	12121	9771	12083	9716
R^2	0.236	0.249	0.206	0.209

Note: The dependent variable is an indicator for employment (column 1-2), and a indicator for being in education (column 3-4). Past cognitive ability refers to an indicator for self-reported test score in Maths when in school. Controls include base controls and pre-migration controls. Base controls: gender, age at migration (and its sq.), country of origin fixed effects (8 groups), year at migration fixed effects, and district at migration fixed effects. Pre-migration controls: employment, language proficiency, education, working experience. All network variables are standardised: the relevant coefficient corresponds to the effect of an increase by one standard deviation. Standard errors in parenthesis, clustered at individual level, * p<0.10, ** p<0.05, *** p<0.01. We report standard errors clustered at district level in square brackets.

Table D.5: Robustness. Network at Migration and Employment. Different definition of employment

	Dependent Variable: Employment (dummy)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Netw_{d_0}$	0.106***	0.097***	0.089***	0.089***	0.086***	0.097	0.088	0.093	0.149**	0.085
	(0.022)	(0.023)	(0.023)	(0.023)	(0.022)	(0.075)	(0.068)	(0.078)	(0.070)	(0.079)
$Netw_{d_0}$xYsm3-5	-0.074***	-0.063***	-0.058***	-0.054***	-0.048***	-0.070	-0.019	-0.015	-0.013	0.007
	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.061)	(0.047)	(0.048)	(0.048)	(0.052)
$Netw_{d_0}$xYsm6+	-0.098***	-0.084***	-0.075***	-0.066***	-0.067***	-0.101	-0.062	-0.049	-0.030	-0.025
	(0.017)	(0.016)	(0.017)	(0.016)	(0.017)	(0.062)	(0.061)	(0.060)	(0.051)	(0.063)
Individuals	926	926	926	926	926	297	297	297	297	297
Obs	12121	12121	12121	12121	12121	4240	4240	4240	4240	4240
R^2	0.236	0.250	0.268	0.274	0.258	0.376	0.379	0.397	0.394	0.375
Mean Dep. Var	0.687	0.632	0.563	0.492	0.564	0.652	0.608	0.549	0.480	0.544
Cut-off working days (%)		25	50	75			25	50	75	
Work at 30^{th} June					yes					yes
Sample	full	full	full	full	full	R	R	R	R	R

Note: The dependent variable is an indicator for employment. All network variables are standardized: the relevant coefficient corresponds to the effect of an increase by one standard deviation. Controls include base controls and pre-migration controls. Base controls: gender, age at migration (and its sq.), country of origin fixed effects (8 groups), year at migration fixed effects, and district at migration fixed effects. Pre-migration controls: employment, language proficiency, education, working experience. Sample R: includes only those who migrated to Germany as asylum seekers, or Ethnic Germans migrating in the period covered by the law of random allocation. Standard errors in parenthesis are clustered at individual level with * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table D.6: Robustness. Network defined at District vs Municipality

Network level:	District				Municipality			
Dependent variable:	Employment		Human Capital		Employment		Human Capital	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Netw$_{d_0}$	0.106***	0.106***	-0.028***	-0.028***	0.067***	0.067**	-0.029***	-0.029***
	(0.022)	(0.028)	(0.009)	(0.010)	(0.024)	(0.028)	(0.009)	(0.010)
Netw$_{d_0}$xYsm3-5	-0.074***	-0.074***	0.011	0.011	-0.073***	-0.073***	0.016**	0.016**
	(0.016)	(0.019)	(0.009)	(0.009)	(0.017)	(0.018)	(0.008)	(0.008)
Netw$_{d_0}$xYsm6+	-0.098***	-0.098***	0.030***	0.030***	-0.091***	-0.091***	0.037***	0.037***
	(0.017)	(0.025)	(0.009)	(0.010)	(0.018)	(0.023)	(0.008)	(0.009)
Individuals	926	229	926	229	926	398	926	398
Obs	12121	12121	12083	12083	12121	12121	12083	12083
R^2	0.236	0.236	0.206	0.206	0.285	0.285	0.242	0.242
Cluster	I	D	I	D	I	M	I	M

Note: the dependent variable is an indicator for employment, and an indicator for being in education according to the heading. Controls include base controls and pre-migration controls. Base controls: gender, age at migration (and its sq.), country of origin fixed effects (8 groups), year at migration fixed effects, and district at migration fixed effects. Pre-migration controls: employment, language proficiency, education, working experience. Base controls: gender, age at migration (and its sq.), country of origin fixed effects (8 groups), year at migration fixed effects, and district at migration fixed effects (column 1-4), or municipality at migration fixed effects (column 5-8). All network variables are standardised: the relevant coefficient corresponds to the effect of an increase by one standard deviation. Standard errors in parenthesis, are clustered as denoted in the Table note. "I" denoted the individual level, and "D" denotes the district level, "M" denotes municipality level, * p<0.10, ** p<0.05, *** p<0.01.