Migrant Networks and Job Search Outcomes: Evidence from Displaced Workers

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Abstract

This paper investigates how immigrants' job search outcomes are affected by the labor market outcomes of workers from the same country of origin they are connected to. Connections are identified based on having worked for the same firm in the past. Using matched employer-employee micro data from Italy and an instrumental variables approach, I show that an increase in the employment prospects of socially connected workers improves immigrants' job search outcomes. The paper also sheds light on the different mechanisms generating the social effect and it highlights the role of migrant networks in explaining immigrant segregation.

Keywords: Migration, Job Displacements, Networks

JEL Classification: J61, J63

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1 Introduction

Social networks play a key role for immigrant job seekers for several reasons. First, as migrants are often *newcomers* in the labor market, personal contacts help them overcome information asymmetries generally affecting inexperienced workers. Second, members of minority communities are more cohesive and they are more likely to help other members of the same community. In addition, immigrants may systematically rely on personal contacts while unemployed as many of them come from low-income countries where social networks are one of the major sources of job information and support (Munshi 2003). Figure 1 plots the share of private sector employees who received information about their current job through their acquaintances across a number of European countries.[1] On average more than one third of the workers in Europe report that they have obtained their current job through *informal channels*, i.e. through friends or relatives (Pellizzari 2010); this share becomes higher when immigrant workers are considered: in Italy for instance, about 42% of immigrants found their current job through personal contacts, compared to a figure for natives of 31%.

Many studies find that non-native individuals tend to interact mainly with individuals of the same ethnicity (Bandiera, Barankay and Rasul 2008; Bertrand, Luttmer and Mullainathan 2000; Marmaros and Sacerdote 2006) and that recent immigrants typically locate where earlier immigrants from the same sending country live and work, giving rise to ethnic clusters (Card 2009). Individuals from the same country of origin provide valuable information and support, in turn possibly leading to positive labor market outcomes. In particular, employed network members might provide information on job openings (Calvo-Armengol and Jackson 2004) or directly refer workers to their employers (Montgomery 1991; Dustmann, Glitz and Schoenberg 2010), eventually increasing the arrival rate of job offers (Goel and Lang 2010).[2]

A higher employment rate among network members though might also have the opposite effect, as greater network support could reduce job search effort, resulting in longer unemployment

[1] Data come from The European Community Household Panel, which is a longitudinal dataset covering 15 countries of the European Union for the period 1994-2001. Several countries, like Luxembourg, Sweden, Finland, Austria and Denmark are excluded from the sample as they are not covered in all the waves. The precise question asked in this survey is: *"By what means were you first informed about your current job?"*. Respondents then have six mutually exclusive alternatives, which include *"Friends, family or personal contacts"*.

[2] Workers, both employed and unemployed, often use their personal contacts to acquire information about job vacancies; similarly, firms tend to rely on employee referrals as they reduce information uncertainties when screening new job applicants (Ioannides and Loury 2004).

duration. General equilibrium effects might also be at work, due to competition in the labor market, possibly offsetting the potential benefits stemming from clustering (Beaman 2012). Ultimately, segregation might reduce the pace of integration and lead to poor labor market outcomes, as it may lower the speed at which immigrants learn host country skills and language or reduce the incentives to relocate to areas where labor demand is stronger (Lazear 1999; Edin, Fredriksson and Aslund 2003; Boeri, De Philippis, Patacchini and Pellizzari 2011).

Whether overall an increase in the employment prospects of socially connected individuals improves or harms job search outcomes among the unemployed remains an open question. This work precisely addresses this issue by focusing on immigrant networks and estimating the effect of changes in the current employment rate of past co-workers from the same country of origin on unemployed individuals' job search outcomes. For this exercise I use matched employer-employee micro data from the administrative records of the Italian Social Security Administration (INPS), which cover the universe of private non-agricultural dependent employment relationships between January 1975 and December 2001.

Identifying the effect of social networks on workers' job search outcomes poses fundamental identification issues. First, because of task and job specialization along country of origin lines and because of geographical clustering, migrants from the same country tend to be exposed to similar labor demand shocks, a classic case of correlated effects (Moffitt 2001). A positive correlation between a worker's employment status and the employment rate of his co-workers may be driven for example by shocks affecting only specific groups in the same occupation or working in the same local labor market. Second, migrants who tend to cluster with employed individuals might be systematically different; for example, being the ones most benefiting from group membership, a classic case of endogenous group formation, possibly leading to biased estimates of social effects. Finally, reflection plagues any credible attempt to identify social effects (Manski 1993; Moffitt 2001; Soetevent 2006).

In order to get causal estimates of the effect of social networks, I focus on displaced workers as their decision to work is arguably exogenous. For each of these workers I define a *network* as the group of past co-workers from the same country of origin in the five years preceding the displacement. I then instrument each network member's employment status by his own displacement episode up to the month before the pivotal worker's displacement episode. A well-established body of literature shows that job loss episodes have long-lasting consequences on employment (von Wachter and Bender 2007). As long as past displacements are uncorrelated with a worker's characteristics, both those that affect or are correlated with socially connected individuals' latent employment outcomes and those affecting the propensity to form a group, this instrumental variable approach will lead to consistent estimates of the effect of interest.

Empirical findings show that, among immigrants who lost the job, a 10 percentage point increase in the current employment rate of previous co-workers from the same country of origin raises the probability of re-employment within 36 months by 5.7 percentage points. Separate regressions for low skilled and unexperienced immigrants show that these categories of workers gain the most from the support of past co-workers. The social effect is significant only for immigrants coming from non-OECD countries, where formal labor markets are less developed and where non-market institutions are likely to be prevalent. Further, the magnitude of the social effect increases after the second year following the lay-off: networks appear to constitute an important resort particularly for immigrants with limited access to employment opportunities (Datcher Loury 2006)

Interestingly, I find no evidence of any effects of changes in the employment rate of past co-workers from countries of origin other than the workers' own. Moreover results show that even among natives there is a positive effect of the network employment rate, however this effect is significantly smaller than the one found for immigrants, suggesting that migrants tend to rely more on their acquaintances in job search than natives.

The analysis of post-displacement outcomes sheds light on the different mechanisms behind the estimated network effect. I show that when the network employment rate increases by 10 percentage points, the probability that displaced migrants find a job within 36 months since job loss in *connected* cities and firms, i.e. firms or cities in which at least one past co-worker has ever worked, increases by 7.9 and 5.1 percentage points respectively. These last findings are consistent with the interpretation that migrant networks facilitate the job search of displaced members by providing them with information about job vacancies.

I find a positive correlation between the degree of workplace segregation, measured by the dissimilarity and isolation indexes, and the magnitude of the social effect across different countries of origin: immigrants who benefit more from the employment status of their co-workers are also the ones who experience relatively higher levels of segregation in the labor market.

The rest of the paper is structured as follows: Section 2 describes the data and it provides summary statistics. Section 3 discusses the research design and the identification issues. Section 4 reports the main results and a set of robustness checks. Section 5 analyses post displacement outcomes of displaced migrant workers. Finally, Section 6 concludes.

2 Data and Summary Statistics

The data used in this paper are matched employer-employee micro data from the administrative records of the Italian Social Security Administration (INPS) for the Italian region of Veneto. The data cover the universe of private non-agricultural dependent employment relationships between January 1975 and December 2001.[3] This dataset has been used by a number of other papers; among others, Card, Devicienti and Maida (2011) test the degree of rent sharing by workers in Italy.[4]

Veneto is one of the twenty-one Italian regions (administrative divisions corresponding roughly speaking to USA states) encompassing seven provinces (roughly a USA county) and 581 towns.[5] As of 2011, Veneto had a population of about 4.9 million, accounting for about 8% of the total Italian population and 9% of national GDP.[6]

The primary unit of observation in the data is a firm-worker match per calendar year. In other terms, for each employment relationship, there are as many observations in the data as the number of calendar years over which this relationship spans. In each calendar year, there can be multiple observations by individual, as individuals can hold more than one job, whether simultaneously or sequentially, during the same year. The data provide information about start

[3] Although the data primarily include private sector workers, they also contain information on public sector workers who have fixed term contracts, such as substitute teachers, health professionals and nurses.

[4] Using a similar version of this dataset that encompasses only two provinces, Cingano and Rosolia (2011) assess the strength of information spillovers of past co-workers' employment status on unemployment duration of displaced workers.

[5] This dataset contains 7675 municipalities as workers originally observed in Veneto may be subsequently employed in any Italian municipalities outside Veneto. As of 2011, in Italy there were about 8,200 municipalities.

[6] Veneto is located in the north east of the Italy, the major municipalities, in terms of population, are Venice (270,000 inhabitants), Verona (263,000 inhabitants) and Padua (214,000 inhabitants). The most industrialised cities are Verona, Vicenza, Padua, Treviso, characterized by small firms, operating in different areas of manufacturing: food products, wood and furniture, leather and footwear, textiles and clothing, gold jewelery. Venice and Rovigo are instead specialized in energy, chemical and metal processing. Tourism also plays an important role in the region's economy: Veneto is the first region in Italy in terms of tourist presence, accounting for one-fifth of Italy's foreign tourism. Tattara and Anastasia (2003) provide a report on Veneto's economy.

and end dates of any employment relationships, the total yearly compensation, the number of working weeks, the type of contract (part-time vs. full time), worker's occupation, age, gender, and municipality of residence at the time of the first job in Veneto, sector of activity (at the 3 digit level) and the municipality where the firm is located.[7] The INPS data also provide detailed information on country of birth (overall, 154 countries).[8]

The data exclude self-employed individuals or those employed in family businesses for which registration at INPS archive is not required. Both workers and firms in the data are individually identifiable and can be followed over time. Workers originally observed in Veneto who are subsequently employed anywhere else in Italy are also followed in the data. The absorbing state hence includes non-employment, death, movements to other countries (including the home country for non-natives), self-employment, public sector employment and informal employment. The original dataset includes information on around 3.6 million workers for a total number of approximately 12.5 million employment relationships in more than 1.1 million firms.

2.1 Immigrants in Veneto's Labor Market

While being one of the largest sources of immigration to the USA and the rest of America in the early twentieth century and a traditional source of internal migration up to the 1970, Veneto has witnessed a large influx of international migrants in the last thirty years, currently being one of the favored destinations among international migrants to Italy. Between 1990 and 2001, the number of immigrants in the population increased almost three-fold, from around 50,000 to more than 140,000 out of a total population of 3.5 millions. In 2001 the share of migrant population in Veneto was about 4%, well above the national average of 2.3% (Anastasia, Gambuzza and Rasera 2001; Venturini and Villosio 2008).

Figure 2 plots the evolution of foreign workers presence in Veneto since 1975 based on INPS

[7]The dataset is composed of three archives: a *"worker"* archive in which all the time invariant characteristics of the workers are included, such as the date and the country of birth, the gender and the municipality of residence at the time he started to work in Veneto; a *"job"* archive, in which information on the employment relationships is provided. Whenever an employment relationship changes, because of an upgrade or switch from part time to full time, a new record is created. The third archive contains information on the firm, its industry code (3-digit), the municipality in which the firm is located and its post code. If a firm changes location or sector of activity a new record is created.

[8]The data only refer to foreign born individuals, including legal immigrants with a work permit currently employed as formal employees. The data exclude all the undocumented migrants working in Italy, which are estimated to account for about 10% to 40% of the regular foreign workforce (Venturini and Villosio 2008). See Appendix B for a brief summary of immigration policies in Italy.

data: the share of migrants among formal non-agricultural private sector employees in Veneto started increasing rapidly after 1990, the highest increase being between 1995 and 2000, following two large regularizations of illegal immigrants. This pattern is in line with immigration trends in Italy: from 1970 to 2000 the number of foreign workers has increased from about 150.000 to 1.3 million.[9]

Figure 2 also shows that the origin of immigrants has varied significantly over the period considered: the share of immigrants from EU15 countries has decreased (from about 47% in 1975 to 16% in 2001), while the share of immigrants from the Balkans and North Africa has increased, the most numerous immigrants' groups in 2001 being Moroccans, citizens of former Yugoslavia and Albanians, respectively with shares equal to 12.7%, 9.4% and 7.3%.

Table 1 presents averages over the entire period of the main variables in the dataset by immigration status (migrants vs. natives). Immigrants represent about 7 percent of the individuals in the sample.[10] Since migration to Veneto is a recent phenomenon, most foreign workers appear in the last years of observation, partly explaining why the average length of employment spells is shorter among migrants than natives. About 58% of migrants who ever worked in Veneto are present in the last year of the dataset (the corresponding figure for natives is 45%), and the average length of the spell is half the one for natives. The shorter duration of job matches among migrants however is also indicative of migrants switching jobs more frequently. Indeed transition rates show that migrants have both higher exit and entry rates from and into employment than natives: the monthly exit rate for natives is 1.7% while for migrants this is 3.2%. Entry rates for natives and immigrants are respectively 1.68% and 3.14%, suggesting that immigrants are more mobile in the labor market and tend to end up in more precarious jobs than natives.

Table 1 also reports information on the gross weekly wage; values are expressed in real terms (Euros of 2003) and are comprehensive of all payments including overtime and bonuses. Immigrants' weekly wages are lower than natives' by about 29 Euros, roughly 4%.

Migrants tend to be employed in low skilled occupations and in smaller firms, which pay lower wages and have fewer restrictions in firing decisions.[11] 72% of migrants are blue collars workers

[9] For an extensive review of immigration trends to Italy see Ministero dell'Interno (2007).

[10] According to Venturini and Villosio (2008), in 2001 in Italy there were 1.4 million foreign workers, representing about 6% of the total workforce. This share in the northern regions was higher than the national average, being equal to 7.3%.

[11] In Italy a law regulating employment relationships, the "Chart of Workers' Rights" (*Law No. 300: Statuto*

compared to 63% of natives; the average number of co-workers in the sample is 213 for migrants and 481 for natives. Immigrants are more likely to work for firms in which other migrants are also employed: the number of foreign co-workers is 26 for migrants and 13 for natives.

Table 2 explores key characteristics of firms and municipalities in the data. Veneto firms are in general very small: the average firm size is equal to about seven employees.[12]

The Table also reports values of two measures of segregation of migrants: the *dissimilarity* and the *isolation* indexes.[13] The dissimilarity index, also known as the Duncan index of segregation, tells us whether immigrants are evenly distributed over firms or municipalities. The index is defined as:

$$DI = \frac{1}{2}\sum_{i=1}^{N} |\frac{Migrants_i}{Migrants_{Total}} - \frac{Natives_i}{Natives_{Total}}|,$$

where i is the unit of analysis, i.e. the firm or the municipality of work, $Migrants_i$ is the number of all immigrants employed in unit i, $Migrants_{Total}$ is the number of all migrant workers in the population; $Natives_i$ is the number of Italian workers in unit i and $Natives_{Total}$ represents the total Italian workforce in the dataset. This index reports the share of migrant workers that would have to move to different firms (or cities) in order to produce a distribution that matches the one of natives. It ranges from zero, when all the units have the same relative number of migrants and natives, to one, i.e. complete segregation. Following Cutler, Glaeser and Vigdor (1999), values of this index higher than 0.6 imply high levels of segregation.

However, even if migrants evenly work in firms and cities relative to natives, it does not mean that they frequently interact with natives. For instance, immigrants can be evenly distributed among firms but have few contacts with natives if their share in the overall population is relatively large. The *isolation* index measures the exposure of migrants to natives, it indicates the amount of potential contacts and interactions between immigrants and natives within firms or cities. The

del Lavoratori) of 1970, introduced norms that restrict firing decisions of firms with more than 15 employees. In case of unfair dismissals, firms are forced to take back the displaced employee and to pay him his full wage before the lay-off. Moreover firms are fined up to 200% of the displaced workers' original wage for the delayed payment of contributions.

[12]Italy is characterized by a multitude of small firms and few big companies; the Italian average firm size is equal to 10.5 employees (Bartelsman, Scarpetta and Schivardi 2003).

[13]Segregation is defined as the degree to which two or more groups live or work separately from one other (Massey and Denton, 1988).

index is defined as:

$$II = \frac{\sum_{i=1}^{N}(\frac{Migrants_i}{Migrants_{Total}} * \frac{Migrants_i}{Workforce_i}) - \frac{Migrants_{Total}}{Workforce}}{1 - \frac{Migrants_{Total}}{Workforce}},$$

where i is the unit of analysis and $Workforce_i$ is the number of all the workers in unit i irrespectively of the country of origin. The first term in the numerator, $E = \sum_{i=1}^{N}(\frac{Migrants_i}{Migrants_{Total}} * \frac{Migrants_i}{Workforce_i})$, is the typical *exposure* index (Massey and Denton 1988), which has been adjusted by subtracting the share of migrants in the total working population of Veneto, i.e. $\frac{Migrants_{Total}}{Workforce}$. Indeed, when immigrants in the population are few it would be impossible for them to be completely isolated, this adjustment then eliminates the effect arising from the overall size of the migrant population. The adjusted exposure index has eventually been rescaled by $1 - \frac{Migrants_{Total}}{Workforce}$ so that we get a measure of *isolation* ranging between zero and one. Typically, values of this index higher than 0.3 suggest that immigrants are highly isolated (Cutler Glaeser and Vigdor 1999).

From Table 2 there is evidence of low segregation at municipality level, with a Duncan index equal to 0.25, meaning that about one fourth of the all migrants would have to move municipality in order to produce a distribution that matches that of the natives. The index substantially increases when the unit of analysis is the firm: more than half of migrant workers have to switch firm in order to have no segregation at the firm level. The same pattern applies to the isolation index, the level of exposure significantly increases when the unit of analysis is the firm, being the index equal to 0.27. In sum, despite the relatively low level of residential segregation, immigrants seem to be highly segregated at the firm level.

Figure 3 further explores segregation at the city level separately by country of birth; in this figure only the most numerous groups are included. Segregation increases when the Duncan index is separately computed by country of origin. The least segregated migrants come from France (25.2%) while the most segregated are from Ghana (45.3%). Dissimilarity between minority groups is also high: for example, workers from former Morocco are equally segregated from Italians (32.7%) as they are from Yugoslavians (31.9%).

2.2 Closing Firms and Displaced Workers

In the rest of this section I focus on displaced workers, i.e., those who lost their job because of a firm closure. Overall 16% of the firms do not survive to the last year of observation.[14] Closing firms are in general smaller than the rest as they employ on average 4.8 employees.

Of the 261,399 migrants ever observed in data in the period 1975-2001, 16,857 were laid off because of a firm closure. Some of them were displaced more than once, giving a total of 18,267 displacement episodes. Relative to the entire sample of workers, displaced workers are younger, more likely to be female, earn lower wages and more likely to be employed in unskilled occupations. Compared to natives, migrants have a higher propensity to be displaced: the share of workers displaced every month, i.e. the transition from employment to non employment due to firm closure, is 0.14% among migrants and 0.10% among natives. Not only is the monthly displacement rate higher for migrant workers but, conditional on displacement, re-employment probabilities are lower: among displaced workers 49% of the natives find a job in the first 3 months following a firm closure, while the same figure for migrants is 46%.

Figure 4 explores the effect of displacement episodes on subsequent employment probabilities of migrant displaced workers. It plots the coefficients of a regression in which the employment probability is a function of individual characteristics, such as age and gender, as well as time exposure dummies for each of the 36 months before and after the closure.[15] While there is no clear pattern before the displacement episode, Figure 4 shows a strong persistence of displacement, on subsequent employment outcomes; even after 36 months, the probability of finding a job is negatively affected by the firm closure. Regressions are run separately for immigrants and natives: the persistence of the displacement effect does not vary by immigration status, however it seems that natives recover slightly faster than migrants after job loss. For both immigrant and native workers the consequences of displacements on successive labor market performances are long lasting.

[14] A firm closure is recorded whenever a firm shuts down; in the dataset a specific variable indicates the (monthly) date at which a firm stops its business and thus disappears from the sample. This variable also distinguishes between real closure and other events affecting a firm's business other than closures, such as changes in the name and in the organization, breaks up, mergers and acquisitions.

[15] The estimated equation is $y_{its} = \alpha + \sum_{k=-36}^{+36} \delta_k D_{ik} + \lambda_i + u_{its}$. D_k are dummies for a worker's time exposure for each month t before and after displacement, i.e. $D_k = I[t - s > k]$, where s is the displacement date. All regressions include individual fixed effects, standard errors are robust.

3 Empirical Strategy

This section presents a linear-in-means model in which the re-employment probabilities of unemployed workers depend on the both employment rate and the observed characteristics of network's members:

$$y_{it} = \beta_0 + \beta_1 \overline{y}_{-it} + \overline{\mathbf{x}}'_{-it}\beta_2 + \mathbf{x}'_{it}\beta_3 + u_{it} \tag{1}$$

where y_{it} is a dummy variable equal to one if worker i is in employment at time t; $\overline{y}_{-it}$ denotes the network's employment rate at time t and $\mathbf{x}$ is a vector of individual characteristics. For each individual i, a *network* is defined as the group of past co-workers from the same country of origin in the five years preceding the displacement.

The coefficient β_1 captures the endogenous social interaction effect. Least squares estimates of this coefficient can be biased because of correlated effects i.e. the presence of institutional environments or common unobserved individual characteristics that lead to spurious correlations among group members' behaviors. This is for example the case of aggregate supply and demand shocks that equally affect workers from the same country of origin or those in a specific local labor market.

In an attempt to control for such correlation, regressions include a set of controls for observed workers' and environment characteristics, such as nationality, time and municipality of first work in Veneto. As long as the network measure is worker-specific, it is possible to compare re-employment probabilities of individuals with different network employment rates who are otherwise identical because of their country of origin and the initial location of work.

Another source of potential endogeneity arises from non-random sorting: agents might self-select into reference groups according to unobservable characteristics that simultaneously influence group membership and individual behavior.

Finally, reflection might lead to biased OLS estimates. In a network composed of two workers, i and j, i's behavior will influence j's behavior and vice versa, implying that OLS estimates of equation (1) will pick up more than the causal effect of j's on i's behavior (Manski 1993).

The identification of the endogenous effect is still possible by means of instrumental variables, where the instrument is an exogenous variable affecting j's outcome variable directly and i's outcome only through the endogenous social interaction. Following a well-established literature that shows long-term effects of displacement (von Wachter and Bender 2007), in the rest I use past co-workers' displacement episodes as an instrument for their current employment status. In particular, I instrument a network member's employment status by his own displacement episode between the time the connection with pivotal worker i was established and the month before the pivotal individual's displacement episode.

In practice I augment equation (1) with a dummy variable z_{it} equal to one if an individual was ever displaced up to period t. Clearly, because I restrict the sample to pivotal individuals i who have been displaced, the variable z_{it} is equal to one in the main equation. The first stage equation then takes the following expression:

$$\overline{y}_{-it} = \gamma_0 + \gamma_1 \overline{z}_{-it} + \mathbf{x'}_{it}\gamma_2 + \overline{\mathbf{x}}\mathbf{'}_{-it}\gamma_3 + e_{it} \tag{2}$$

where $\bar{y}_{-it}$, the network employment rate, is regressed on the fraction of network members who were ever displaced between the time they first worked with individual i and time t.

This instrumental variable estimate of the social interaction effect will be consistent if, as it seems plausible, firm closures are uncorrelated with a worker's characteristics that simultaneously affect both his and his network members' latent employment outcomes. Under this assumption, the instrumental variable approach will eliminate any residual endogeneity arising from unobserved network's characteristics.

4 The Effects of Networks: Empirical Results

In the rest of the analysis, I focus on networks that are created at most five years before the displacement. Because of this, I drop the first five years of observation in the dataset (1975 to 1979) hence focusing on job loss episodes that occur not earlier than January 1980. Displacements occurring in the last three years (1999 to 2001) are also excluded so that workers can be followed for up to 36 months after job loss.[16]

In order to solve for the reflection problem, I define the dependent variable y_{it} in equation (1) as a dummy variable equal to one for non-employment spells starting at t which are concluded

[16] If a worker experienced more than one closure, I only consider the first episode, as the subsequent episodes are likely to be correlated with the first one.

within a given time span (e.g. 36 months); while $\bar{y}_{-it}$, the network employment rate, is the share of network members employed at the time of i's displacement episode. The instrumental variable, $\bar{z}_{-it}$, is thus the share of network members that have experienced a firm closure between the time they first met worker i, up to the month before worker i's displacement episode. This instrument is thus worker specific and it solves any potential reverse causality issue: since contemporaneous firm closures may be correlated, the instrument only considers job loss experienced by group members before individual i's displacement episode.

Eventually, the sample analyzed is composed of 10,738 workers who experienced a firm closure between January 1980 and December 1998. Excluding closures occurring in 1999, 2000, and 2001 decreases the sample size to 14,317. Moreover, by dropping closures happening in the first 5 years of the dataset, the number of displaced immigrants becomes equal to 13,194. Finally, workers who experienced a closure while they were employed at the same time in another firm are excluded from the sample of displaced workers.

4.1 Baseline Specification

Table 3 reports estimation results of model (1) and (2); controls include age, country of origin, and gender dummies for worker i plus the averages of the same variables for network's members and a set of dummies for the size of the network. In addition, dummies for the month of displacement are added to the regressions. Standard errors are clustered by country of origin.[17]

Column (1) of Table 3 reports baseline IV estimates: the endogenous interaction coefficient, β_1, is positive and statistically significant at 1% level; this result suggests that past co-workers' employment status has thus a positive effect on the displaced workers' probability of finding a job in the 36 months after firm closure. This first specification includes month of displacement dummies; column (2) of the same Table additionally controls for the interaction between country of birth and the month of displacement, accounting for unobservable shocks that equally affect migrants from the same country that have been laid off at the same time. As country specific shocks are absorbed, the coefficient of interest falls in magnitude and significance but it remains

[17] This is the most restrictive specification: clustering at country level increases standard errors and it thus affects the significance of the coefficients. A less restrictive specification by country of origin interacted with the month of displacement has been tested in the regressions: the magnitude of standard errors decreases. The tables only report standard errors clustered by country of origin.

positive and statistically significant.

Consistent with Figure 4, first stage regression estimates confirm the strong predictive power of the instrument; the bottom rows of Table 3 show that these estimates are very precise, being the value of the F-test (40.74) reasonably high.[18]

To further account for endogenous location choices, column (3) includes the interaction between nationality, date of displacement and the first municipality of work in Veneto; in practice I am comparing two individuals from the same country of origin, who started working in the same municipality and who have experienced a firm closure at the same time. Within-country and within-municipality comparisons control for any spurious correlation due to unobservables that affect all individuals from the same country that started working in the same local labor market.[19]

The empirical evidence shows that social spillovers still persist: as more restrictive controls are added both the significance and the magnitude of the endogenous effect increase. The more members employed in the network at the time of displacement, the higher the re-employment probability of displaced co-workers within 36 months following firm closure. The coefficient of the social effects tells that a 10 percentage point increase in the network employment rate raises the probability of finding employment within 36 months after job-loss by 5.7 percentage points. In other words, a one standard deviation rise, i.e. about 28 percentage points, in the network employment rate leads to a 34 percentage point increase in the 36 months re-employment probability.[20]

Social networks have thus a beneficial effect on re-employment probabilities of their displaced group members. Moreover, estimates of the endogenous effect are significant and positive in every specification adopted.

OLS regressions are presented in Appendix A: coefficients are always smaller than the ones reported in Table 3, suggesting that OLS estimates are downward biased. One possible explanation for this bias could be negative sorting into groups: high ability immigrants tend not to rely

[18]Coefficients of the first stage regressions exhibit a positive sign because of the way the regression's sample is constructed.

[19]Because of non-random sorting, controls for the first city of work should be less endogenous with respect to subsequent cities, including the one of displacement.

[20]In other terms, one more additional worker employed in a displaced worker's group at the time of displacement increases his chances of finding a job in the next 36 months following a firm closure by 12 percentage points.

on their co-national past coworkers. The next subsection aims at exploring the heterogeneity of the network effect by running separate regressions according to displaced workers' characteristics.

4.2 Heterogeneity of the Network Effect

Results in the first three columns of Table 3 impose that the social effect is constant across different types of migrant workers; however, it is reasonable to think that this network effect differs according to workers' characteristics, such as experience and tenure in the labor market.

As highlighted by several studies (Edin, Fredriksson and Aslund 2003), less experienced immigrants are more prone to rely on their acquaintances, being thus the ones who benefit the most from the help of their co-workers. In order to test this hypothesis, I run separate regressions in which the sample of displaced workers is split according to their occupation and tenure at the time of displacement.

In columns (4) and (5) the sample is divided on the basis of the occupation of the pivotal individuals at the time of firm closure. Blue collar workers are analyzed in column (4), they represent about 70% of the whole sample; while in column (5) I retain occupations other than blue collars, such as white collars and managers, accounting for the remaining 30% of displaced migrants.

Estimates indicate that immigrants employed in *unskilled* occupations are the only ones for which the endogenous social interactions are positive and significant: the coefficient of the network employment rate is equal to 0.54 and statistically significant at 5% level. There is no significant effect for other categories of workers, as shown by results in column (5).

To further explore the heterogeneity of the network effect, I focus on migrants' tenure in the Italian labor market. I define *low-tenured* immigrants those who have been employed less than 20 months prior the job loss, i.e. the median of the distribution of months in employment. The coefficient in column (6) is still positive and it increases in both significance and magnitude: a 10 percentage point raise in the network employment rate increases the 36 month re-employment probability of low tenured immigrants by about 9 percentage points. There is no significant effect for more experienced workers, as shown in column (7).

Immigrants' use of their acquaintances may also vary depending on their country of origin. Whenever labor markets function imperfectly, non-market institutions, such as social networks, may emerge in order to contrast market failures. Personal contacts then represent the major source of job information and support for immigrants coming from less developed countries. Workers from those countries may systematically rely on their social networks also in the host country. I therefore split the sample in two subgroups depending on whether a worker's country of origin is an OECD member state. The coefficient of the network employment rate is positive and significant only when regressions are run for non-OECD countries; this result suggests that workers from least developed countries make a wide use of their personal contacts even after they moved to Italy.

Regressions in Table 3 only analyze the network effect on re-employment probabilities within 36 months following a lay-off. However this effect may vary according to the time window considered. Figure 5 plots re-employment probabilities of displaced individuals in each of the 36 months following the displacement; because of censoring, the graph does not include displaced workers who have not found a job within 36 months, i.e. about 27% of the sample. Almost 30% of displaced migrants found a job within the very first month of unemployment, while only a small portion of workers are still non-employed after the first year following the lay off.

Figure 6 reports coefficients of the network employment rate from 36 regressions in which the dependent variable is, in turn, the cumulative re-employment probability from one to 36 months after job loss. As in column (3) of Table 3, I control for the interaction between the country of origin, the time of displacement and the first city of work; standard errors are clustered by country. The vertical lines in the graph depict the 95% confidence intervals.

The estimated coefficients actually change according to the different time intervals considered: they are always positive but they become statistically significant only after the 22nd month since job loss. The effect appears particularly high within the first months following the displacement even though it is not statistically significant. After the 22nd month, the social effect stays positive and significant up to the 36th month.

One possible interpretation of these results is that immigrants use their personal contacts as a *last resort* when they are not able to find a job through the formal channel. However a delayed effect of networks can be explained by the fact that networks are particularly helpful for immigrants with limited access to employment opportunities, as shown in Table 3. Low-skilled and unexperienced workers are the ones who struggle the most after firm closure, hence they may take long time to find a job.[21]

In order to further investigate this issue I look at the timing of the social effect separately for workers with low and high tenure in the labor market. If networks represent a last resort in job search, I should not observe any differences in the timing of the network employment rate effect between the two groups. Figures 7, plots the coefficients of the network employment rate on the cumulative re-employment probabilities from one to 36 months after job loss for low and high tenured workers respectively.[22] Regression coefficients exhibit different values and patterns for the two groups. Low tenured workers gain from a higher employment status of their past co-workers after the first 15 months since job loss; conversely, high tenured only benefit from the employment status of their co-workers in the very first months after firm closure, the effect for this type of employees however is never significant. The interpretation of networks as a last resort seems to be not supported by these results; on the contrary, the delayed effect of networks can be interpreted as a composition effect: low skilled displaced workers are the ones who need more time to find a job and, at the same time, they are also the ones who rely more on their personal contacts while looking for a job.

4.3 Effects of Other Groups

So far *networks* have been defined as groups of co-national past co-workers, relying on the assumption that immigrants tend to interact mainly with workers from the same country of origin. This section investigates whether co-workers from different nationalities provide the same valuable information in job search; in particular, I test if the employment status of past co-workers other than co-nationals affects the 36-month re-employment probability of displaced migrants.

Table 4 presents estimates from regressions in which the re-employment probability of a displaced worker depends on the employment rate of past co-workers from other countries of origin. The first two columns of the Table focus on groups composed of immigrants from other foreign countries (i.e. *non-nationals*), while in the last two columns networks only include native

[21] Figure A1 in the Appendix plots re-employment probabilities of displaced individuals in each of the 36 months following the displacement by tenure in the labor market. Among low tenured displaced workers 41% do not find a job, while the same figure for high tenured is about 25%.

[22] Table A4 in the Appendix reports regressions' coefficients and standard errors of Figures 6 and 7.

past co-workers (i.e. *Italians*).[23] IV regressions include average characteristics of past co-workers, as well as dummies for the size of the network. Controls are the interaction between the country of origin, the month of displacement and the first city of work.

The estimate of the effect of non-national co-workers' employment status on the individuals' re-employment probability is positive but not significant in column (1), where I only include the interaction between the country of origin and the month of displacement. When I additionally control for endogenous location choices, i.e. column (2), the sign of the coefficient turns negative but it is still not significant. It is also interesting to notice that the coefficients of the employment rate of the non-nationals are always smaller in magnitude than the ones of the co-nationals found in Table 3. These results indicate that there is no evidence of significant social interactions among co-workers of different nationalities; further, the negative sign for the coefficient in column (2) suggests that immigrants, who used to be co-workers but from different nationalities, rather compete for the same job vacancies.

Columns (3) and (4) of Table 4 analyze networks composed of Italian past co-workers. Regressions still compare two individuals from the same country of origin, who have experienced a firm closure at the same time, however the network does not include any migrant past co-workers. Results are similar to the ones found when non-nationals are taken as reference group: the coefficient of the social effect is positive but not significant. As more restrictive controls, i.e. the first city of work, are added, the sign of the coefficient turns negative but it is still not significant. Interestingly, the estimated coefficients when the reference group is only composed of Italians are always smaller than the ones found when immigrants are included in the reference group. This difference in magnitude may indicate that interactions between natives and immigrants are occasional, either because of preferences (or tastes) or because they end up working in different occupations or firms. First stage regressions again confirm that the instrument has a strong predictive power, which is particularly performing when natives are considered as a reference group.[24]

[23] From now onwards I will refer to co-workers from the same country of origin of the pivotal displaced worker as *co-nationals*, the ones from different countries of origin (excluding Italians) as *non-nationals* and *Italians* for the natives past co-workers.

[24] Table A3 in Appendix A provides supplementary robustness checks. I first run regressions in which I include a control for the industry of displacement: estimates of the social effect stay significant and positive when network members are co-workers from the same country of origin; not significant effects are found for other network members, both foreigners and natives. Moreover I run regressions in which I simultaneously include the network

Results in Table 4 might also be considered as a test validating the identification assumptions developed in Section 3. Indeed, estimates in Table 3 may still be driven by omitted characteristics that simultaneously affect individual i's probability of finding employment and his co-workers' probability of displacement rather than a genuine social effect; for instance, if low ability individuals self select into firms with a high probability of closure, the identification assumption would be invalid, as firm closures affecting group members could be correlated with unobserved characteristics of the pivotal displaced individual.

Past co-workers from other countries are likely to share the same unobserved characteristics as co-national co-workers but they are unlikely to provide valuable information in job search; finding a significant positive effect also for co-workers from different nationalities would suggest sorting along unobservables, possibly driving the estimates of social effects among co-nationals in Table 3.

Regressions in Table 4 produce not significant coefficients in any specifications adopted: the positive social effect found for co-national networks is not biased by omitted variables affecting workers that have worked together in the same firm. If there were sorting, generating spurious correlation leading to a significant network effect as in Table 3, then the effect of non-national past co-workers would have been significant. These results then confirm the validity of the instrument used, which manages to solve potential biases coming from the endogenous group formation.

4.4 Social Effects among Natives

In previous Sections I only focus on interactions among immigrants, however Figure 1 shows that in every European labor market native workers also rely on their personal contacts while looking for a job. Moreover, previous studies report that a positive network effect exists among natives too; Cingano and Rosolia (2012), using a reduced version of these data, provide evidence of significant and robust network effects on unemployment duration of native workers. Similarly, Glitz (2013) using data on employees in Germany, finds a strong positive effect of a higher employment rate in a worker's network on his re-employment probability after displacement.

employment rate of co-national, non-national and native past co-workers: only the coefficient of network members from the same country of origin is positive and statistically significant.

This section explores whether endogenous interactions take place among natives and how this social effect compares to the one found for immigrants. Columns (5) and (6) of Table 4 provides IV estimates of the effect of the employment rate of network members on the 36 month re-employment probability of a sample of native displaced workers. Controls include age and gender dummies for worker i plus the averages of the same variables for network's members and a set of dummies for the size of the reference group.[25] In column (5), only dummies for the month of displacement are added to the regressions.

The effect is positive and significant: a 10 percentage point increase in the employment rate of past co-workers increases re-employment probability of displaced native workers by about one percentage point. A higher employment rate of past co-workers is beneficial also for displaced native workers. When more restrictive controls are added to the regressions (column 6), i.e. dummies for the first city of work, the effect does not change in significance and it slightly increases in magnitude, being now the coefficient equal to 0.109.

The existence of a positive social effect for natives is in line with findings in Cingano and Rosolia (2012): they found that a one standard deviation increase in the network employment rate reduces unemployment duration by almost 8%.

From these results, we can draw two conclusions that are consistent with the empirical evidence of Figure 1. First, social interactions take place among Italian employees, suggesting that also native co-workers interact and help each others in job search. Second, immigrants rely more on the help of their acquaintances than natives: the size of the network employment rate coefficient for immigrants is higher the size of the one for natives, i.e. 0.57 versus 0.11.

[25] Country of origin dummies are included but automatically dropped in the regressions as all the displaced individuals are Italian workers and thus share the same nationality. Standard errors are thus clustered by the date of displacement.

5 Network Mechanisms and Segregation: Empirical Analysis of Post-Displacement Outcomes

5.1 Possible Mechanisms behind the Social Effect

This last section attempts to shed light on the possible mechanisms behind the estimates of the social effect previously found. Among several possible explanations, a positive network effect can arise from two different channels: *information* and *norms* (Bertrand Luttmer and Mullainathan 2000).

According to the information story (Calvo-Armengol and Jackson 2004), the more people employed in the network, the higher the probability of finding a job as the arrival rate of job offers increases. If employed, network members are better informed about job vacancies in firms or municipalities in which they work; moreover, employed members are also more likely to share their sources of job information, such as previous or current employers, with unemployed members. Therefore the higher the employment rate of the network, the lower the competition within the network for job openings and thus the higher the arrival rate of offers for displaced migrants.

Similarly, social norms can lead to a positive network effect on re-employment probabilities: as more members of the network are employed, unemployment may turn into a social stigma hence pushing displaced workers to rapidly exit from unemployment. A high network employment rate then may act as a sort of peer pressure on displaced migrants.

Table 5 provides estimates of the of the network employment rate on different outcome variables such as the firm and the municipality in which displaced immigrants find job after firm closure. Investigating where displaced immigrants end up after the displacement episode helps us understanding the mechanism behind the social effect.

The first outcome variable looks at firms in which the pivotal worker is re-employed after his own displacement. Firms are divided into two groups: firms in which at least one member of the network, i.e. a co-national past co-worker, has ever worked before individual i's displacement episode, i.e. *connected firms*; and firms in which no past co-worker has ever been employed, i.e. *non-connected firms*.[26]

[26]The econometric specification controls for the interaction of the country of origin, month of displacement

In column (1) of Table 5, the dependent variable is the probability of working in a connected firm; the coefficient is positive and significant at 10% level implying that a 10 percentage point increase in the network employment rate increases the chances of displaced workers of finding a job in connected firms by 5.4 percentage points. In column (2) the outcome variable is the probability of finding a job in non connected firms: the coefficient is still positive but not significant and it is also smaller in magnitude than the one found in column (1). Note that these coefficients sum up to the net total effect found in column (3) of Table 3, i.e. 0.574.[27]

Past co-workers may also hear about job openings in municipalities in which they currently work or in which they have worked in the past; thus, they may help their unemployed network members by placing them in municipalities in which they have a connection. Regressions reported in Columns (3) and (4) of Table 5 look at the effect of the network employment rate on the municipality in which the displaced migrant is employed after job loss; in column (3) the dependent variable is the probability of working in a *connected* municipality, where at least one past co-worker has ever been employed. Results are strongly positive and significant at 1% level, the coefficient of the social spillovers predicts that a 10 percentage point increase in the network employment rate increases the probability of working in connected cities by 7.9 percentage points. Conversely, the estimate of the network employment rate on the probability of finding a job in a non-connected municipality is negative but not significant.

The last columns of Table 5 investigate the effect of past co-workers' employment status on the probability of working in industries in which displaced immigrants have a connection, i.e. in which at least one network member has worked in the past. Again, the effect is positive and significant: stronger networks will help unemployed immigrants to get a job in *connected* industries.

As the employment rate of the network raises, displaced migrants are more likely to work after job loss in firms, municipalities and industries in which past co-workers have a connection. These results are consistent with the information transmission story. Each network has a pool of

and the first city of work. As in the previous section, the employment rate of network members is instrumented with displacement episodes experienced by group members before worker i's job loss. With respect to regressions in Table 3, only the dependent variable has changed therefore first stage regressions are the same as the ones reported in column (3) of Table 3.

[27]If a worker does not find a job within 36 months since job loss, both outcome variables, the probability of finding a job in connected and in non-connected firms, take a value equal to zero.

job information's sources, represented by connected workplaces; as more people in the network are employed, the higher the probability of hearing about job vacancies and the higher the probability that employed members will pass this information to the unemployed.

Interpreting these results through the lenses of the social norm channel is more difficult; this story predicts that as the employment rate of network increases, immigrants will exit the unemployment faster. There is no implication about the place of work in which displaced migrants will find a job. In addition, the social norm theory is not consistent with the delayed effect of the social effect found in Figure 6.

5.2 Networks and Segregation

The last part of this work analyses whether networks push immigrants to cluster together in the same local labor markets. Previous results show that immigrants pass information to their unemployed network members about job vacancies in *connected* workplaces. This result may also suggest that as the network employment rate rises, so do the probability of being employed in firms in which other immigrants from the same country of origin are employed, eventually increasing the level of segregation.

To further explore this issue, Table 6 reports a set of regressions in which the dependent variable is the probability of finding a job in firms in which at least one migrant worker is employed. I then distinguish between workers from the same country of origin and workers of different foreign nationalities.

The first column reports results from a regression in which the dependent variable is the probability that a displaced migrant ends up working with at least one co-worker (new or past) from the same country of origin in the 36 months after his own displacement episode. The coefficient is positive and significant: as the network employment rate increases by 10 percentage points, the probability of ending up working with at least one co-national coworker increases by 7.7 percentage points. In column (2) I explore whether the network employment rate has any effects on the probability of finding a job in firms in which no co-national worker is employed, the effect is negative but not statistically significant.[28]

This positive effect may be due to the fact that immigrants are employed in firms that

[28]Note that the two coefficients sum up to the network effect found in column (3) of Table 3.

systematically hire foreign workers; column (3) then looks at the probability of finding a job in firms in which at least one immigrant, who is either a new or a past co-worker of a different nationality, is employed; the effect of the network employment rate is positive but not significant; it is also smaller in magnitude than the coefficient in column (1). Again, the effect on the probability of finding a job in firms in which no immigrant from other nationalities is employed is not significant and very small in magnitude.

A higher network employment rate then increases the probability that displaced immigrants will be employed by firms in which other immigrants from the same country of origin work, potentially increasing the level of segregation at the workplace.

I thus explore whether the use of networks by immigrants can explain immigrant segregation and clustering in the workplace. First, I compute for each nationality the dissimilarity index at firm level over the period 1980-2001, which is defined as:

$$DI_g = \frac{1}{2}\sum_{i=1}^{N} |\frac{Migrants_{g,i}}{Migrants_{g,Total}} - \frac{Workforce_{-g,i}}{Workforce_{-g,Total}}|,$$

where i is the firm and g is the country of origin. $Migrants_{-g,i}$ is the number of immigrants from country g employed in firm i; $Workforce_{-g,i}$ is the number of workers, natives and immigrants other than the ones belonging to group g (i.e. $-g$), in unit i. $Workforce_{-g,Total}$ represents the total workforce in the dataset but immigrants from group g. The dissimilarity index gives me a measure of firm segregation for every immigrants' sending country. I then plot these dissimilarity values with the estimated coefficients of the network employment rate from regressions of model (1) and (2) separately run for each country of origin. Figure 7 shows a positive relationship between the social effect and the degree of dissimilarity by nationality: immigrants that are positively affected by the employment status of their co-national co-workers are also the ones who are highly segregated.

Similarly, Figure 8 explores the relationship between the network effect and another measure of segregation: the isolation index; this is again computed for every single sending country and it is defined as:

$$II_g = \frac{\sum_{i=1}^{N}(\frac{Migrants_{g,i}}{Migrants_{g,Total}} * \frac{Migrants_{g,i}}{Workforce_i}) - \frac{Migrants_{g,Total}}{Workforce}}{1 - \frac{Migrants_{g,Total}}{Workforce}},$$

where i again is the unit of analysis and g is the country of origin. $Workforce_i$ is the number of all the workers in unit i irrespectively of the country of origin.

The Figure suggests that whenever immigrants are largely exposed to other workers from the same country of origin, the magnitude of the network effect increases. Clearly this analysis does not have any causal implications; at this stage it is hard to tell whether the effect of network increases because of segregation. For instance the social effect may increase because social ties are tighter in segregated migrant communities; on the other hand, immigrants, who largely rely on networks, end up working in segregated firms. These findings however provide evidence of the positive correlation between the use of networks and segregation: the network effect increases for immigrants belonging to migrant groups that are relatively segregated in the Veneto labor market.

6 Concluding Remarks

The aim of this work has been to provide consistent estimates of the causal effect of past co-workers employment status on displaced immigrants' job search outcomes. Using matched employer-employee micro data from the administrative records of the Italian Social Security Administration (INPS), I show that an increase in the employment prospects of socially connected workers improves immigrants' job search outcomes.

To deal with several identification issues, I use displacement episodes of past co-workers as an instrument for their current employment status. As long as firm closures are uncorrelated with a worker's characteristics that affect both his and his network's labor market outcomes, this instrumental variable approach will lead to consistent estimates of the effect of interest. To further account for correlated effects, such as labor demand and supply shocks, controls for the time of displacement, the country of origin and the first municipality of work are included in the regressions.

The paper offers three key findings. First, the net effect of migrant networks on re-employment probabilities is positive: a 10 percentage point increase in the network employment rate raises the probability of finding employment within 36 months after job loss by 5.7 percentage points. The effect of past co-workers from the same country of origin is positive and significant in any specifications adopted. The social effect becomes negative and not significant when I consider as a reference group past co-workers from different countries; I take this last finding as a validation of the empirical strategy.

Second, the network effect is particularly relevant for immigrants with limited job offers in the labor market, such as low skilled and low tenured workers. Moreover, estimates show that the magnitude of the social effect increases after the 20th month of job search: immigrants at the bottom of the skills distribution are the ones who rely more on the help of their past co-workers.

Third, the analysis of post-displacement outcomes shows that employed network members provide displaced co-workers with information about job vacancies in cities and firms in which they have worked, i.e. *connected* workplaces. The information transmission mechanism described by Calvo-Armengol and Jackson (2004) seems to be the prevailing one: the higher the employment rate of the network, the lower the competition within the network for the same sources of job information.

This work also presents evidence of the positive correlation between the magnitude of the network effect and the level of immigrant workplace segregation. As the network employment rate increases, displaced migrant workers are more likely to find a job in firms in which at least one immigrant of the same nationality is employed, potentially increasing the level of exposure to co-workers from the same country of origin.

The evidence of a positive social effect suggests that interactions between employees coming from the same country of origin are an important channel through which migrants find a job. However networks can eventually push immigrants to cluster into the same workplaces.

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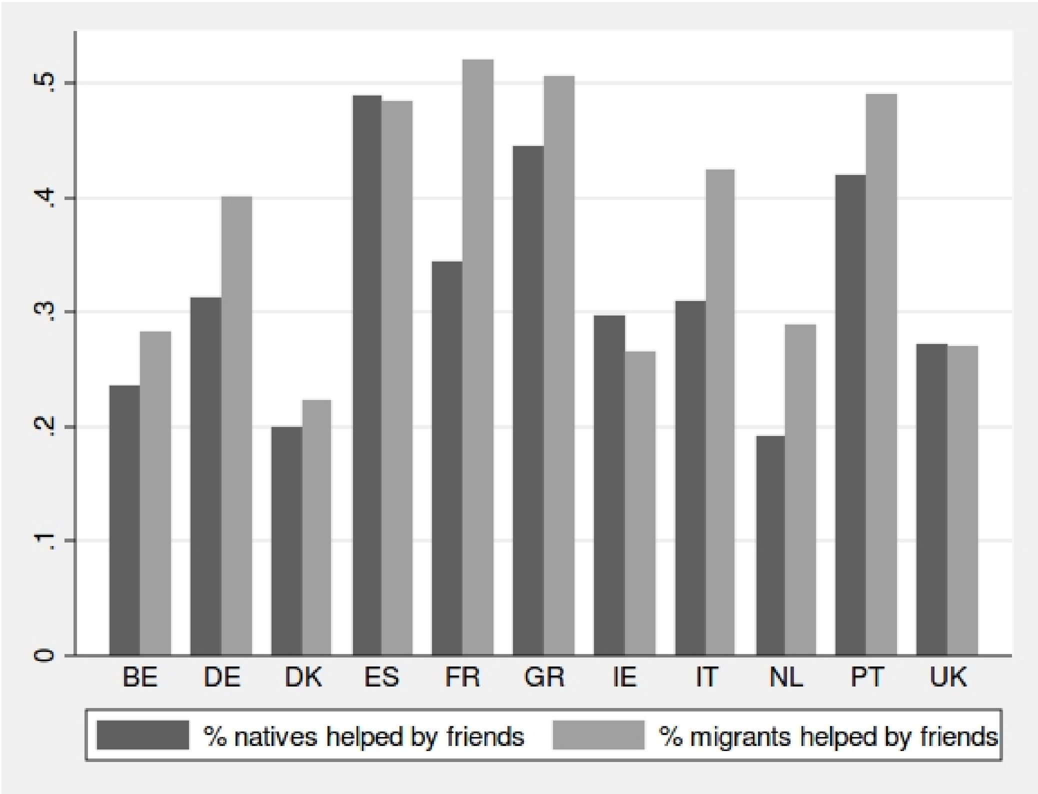
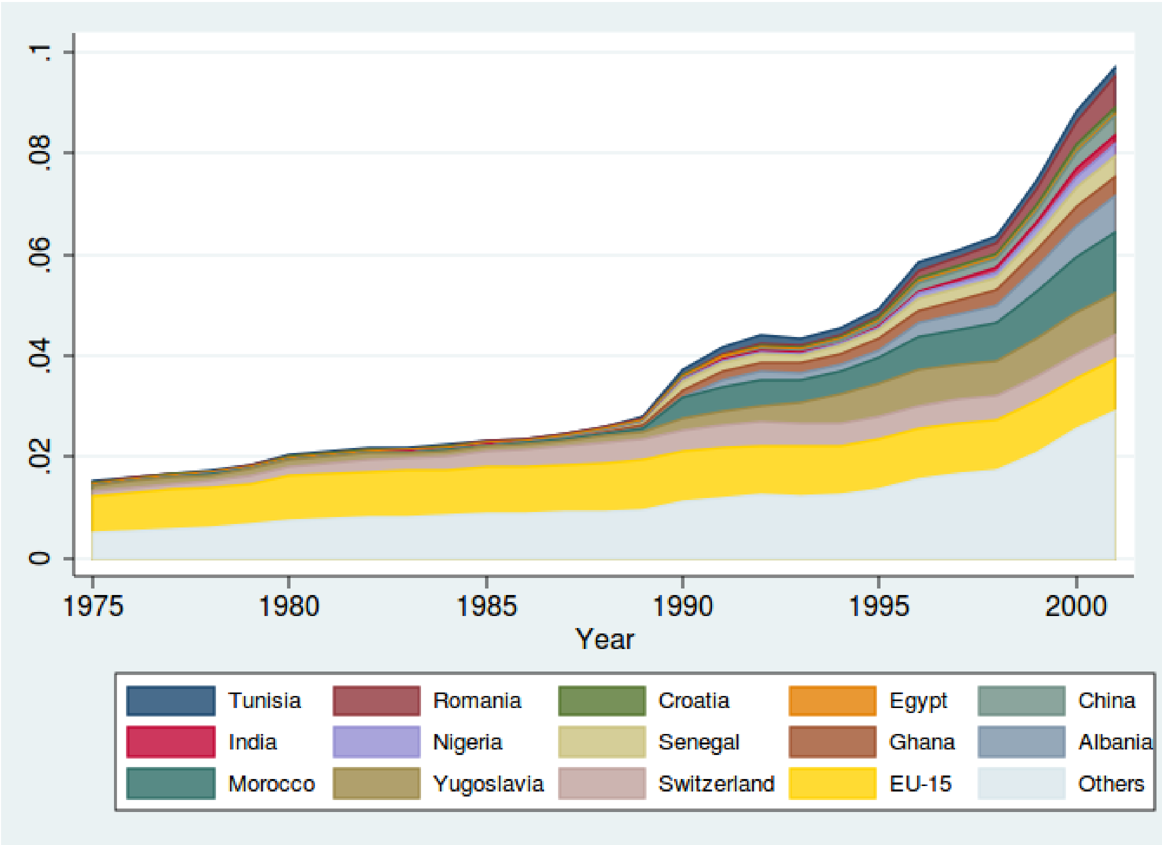
Tables and Figures

Figure 1: Share of employees who found their current job through personal contacts



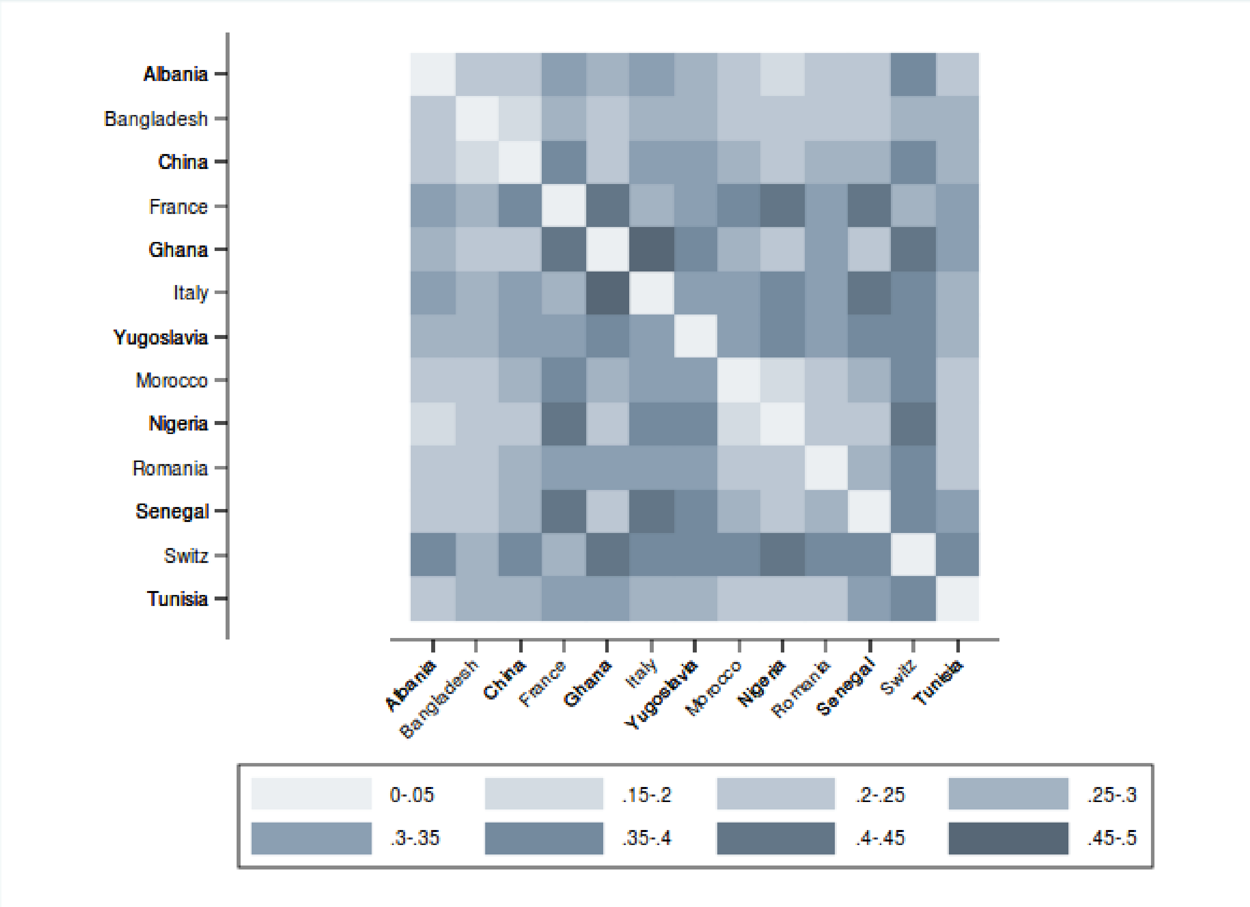
Notes: author's calculations on ECHP data for the period 1994-2001. The sample includes private sector dependent employees aged 16-64; Luxembourg, Sweden, Finland, Austria and Denmark are excluded from the analysis as they are not covered in all the waves. The precise question asked in this survey is: *"by what means were you first informed about your current job?"*. Respondents then have six different alternatives, which include *"friends, family or personal contacts"*.

Figure 2: Share of migrant workers in Veneto, 1975 - 2001



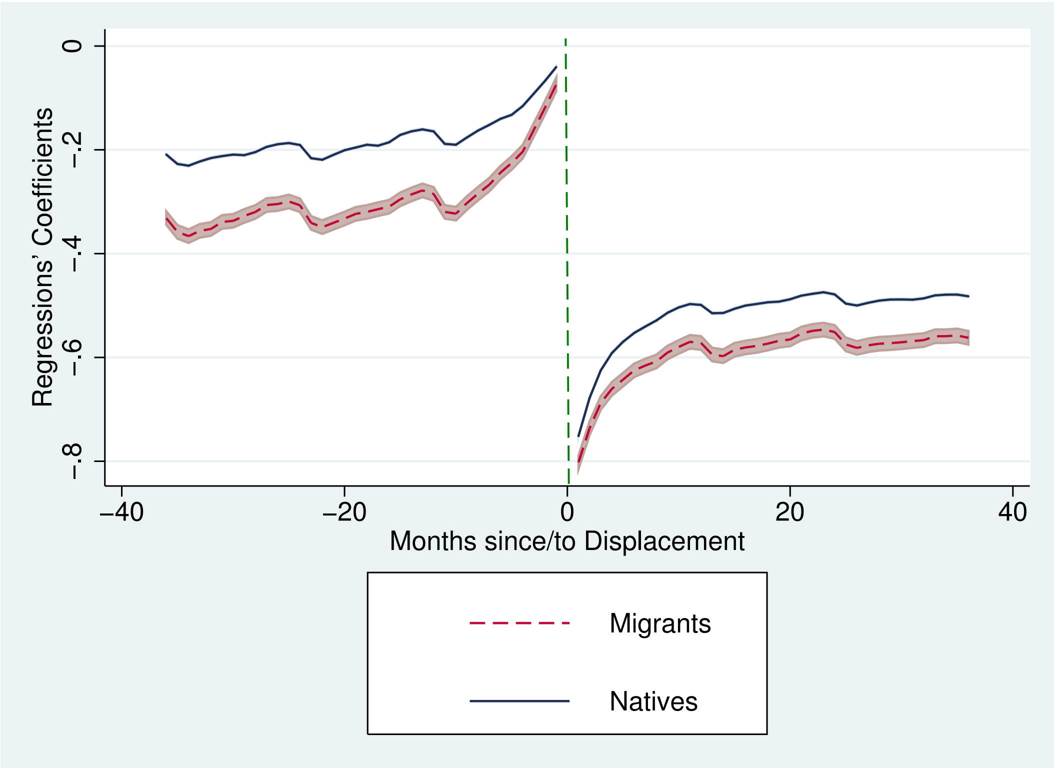
Notes: author's calculations on INPS data for the period 1975 - 2001. Each shaded area represents the share of immigrants from the corresponding country of origin on the overall population.

Figure 3: Duncan index of segregation at municipality of work level



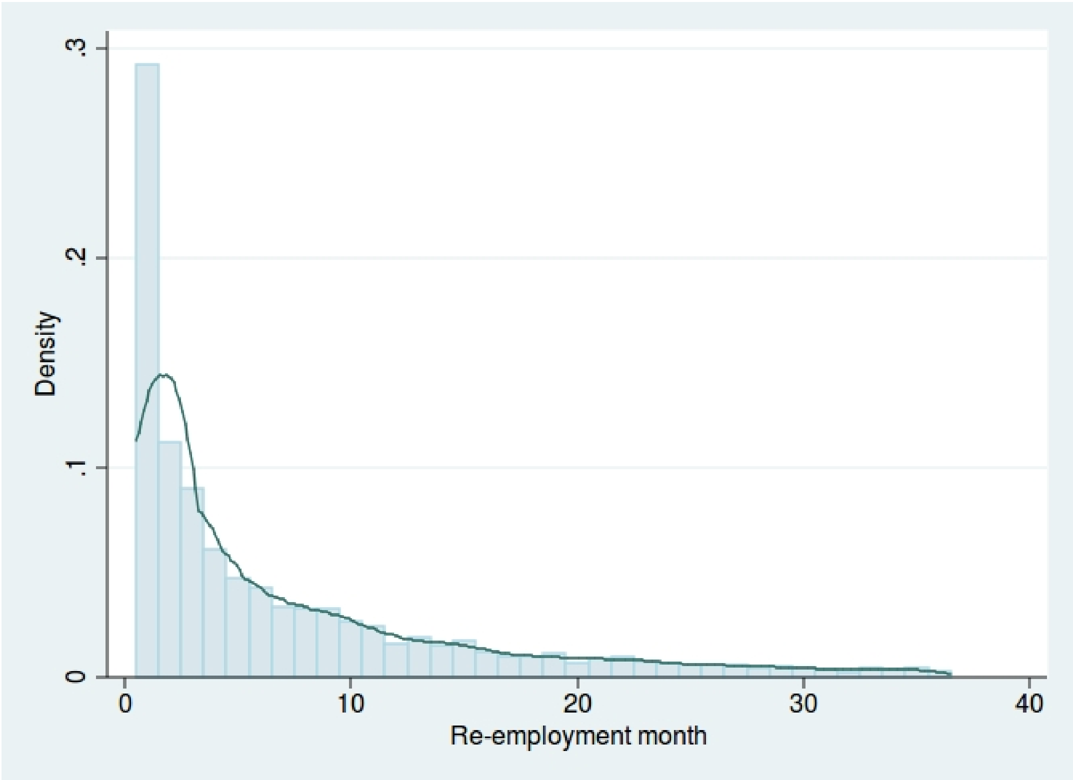
Notes: this Figure is based on INPS data for the period 1975-2001. Each square in the *heat map* represents the value of the dissimilarity index of each country of origin from anyone other.

Figure 4: The effect of displacements episodes on employment probabilities



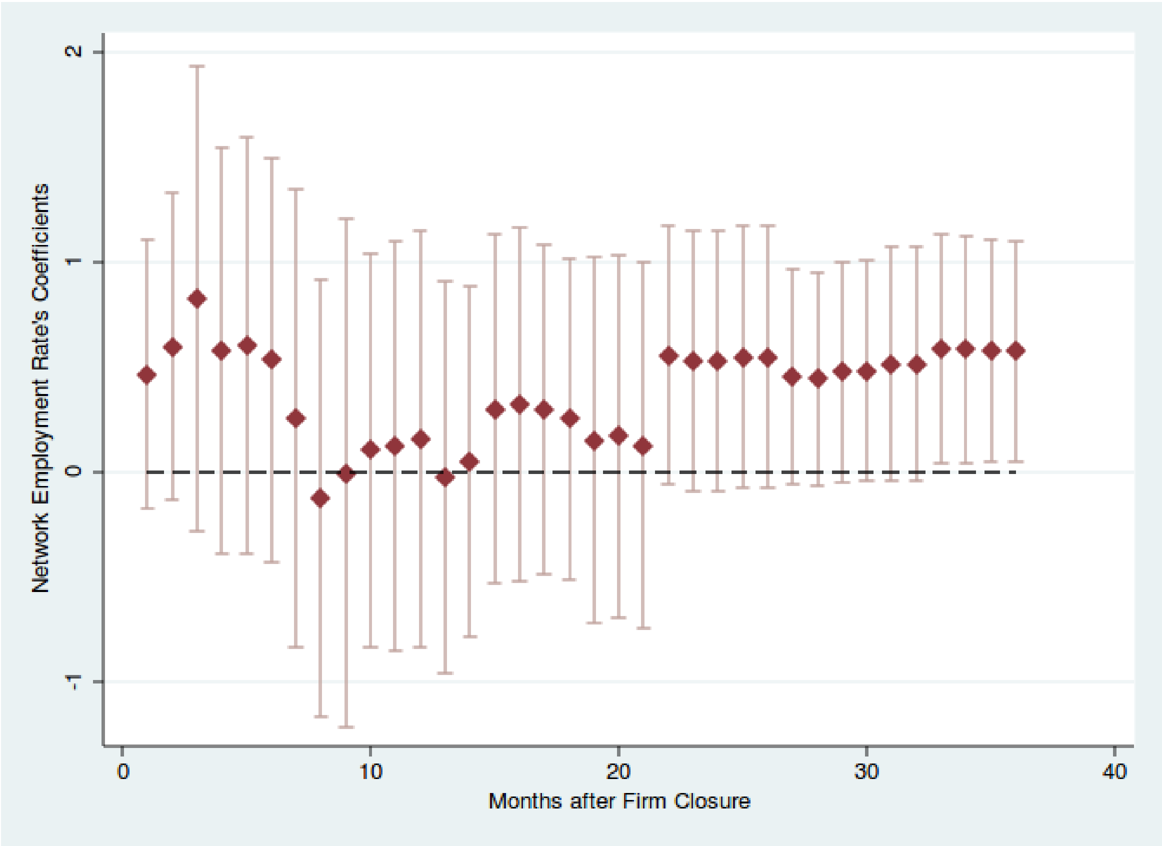
Notes: the sample includes displaced workers only. I control individual fixed effects. The estimated equation is $y_{its} = \alpha + \sum_{k=-36}^{+36} \delta_k D_{ik} + \lambda_i + u_{its}$. D_k are time exposure dummies for each of the 36 months before and after the closure. i.e. $D_k = I[t - s > k]$, where s is the displacement date; two separate sets of regressions have been run for migrants and natives. Standard errors are robust. The shaded areas in the figure represent the 95% level confidence intervals.

Figure 5: Re-employment probabilities by month (up to 36 months)



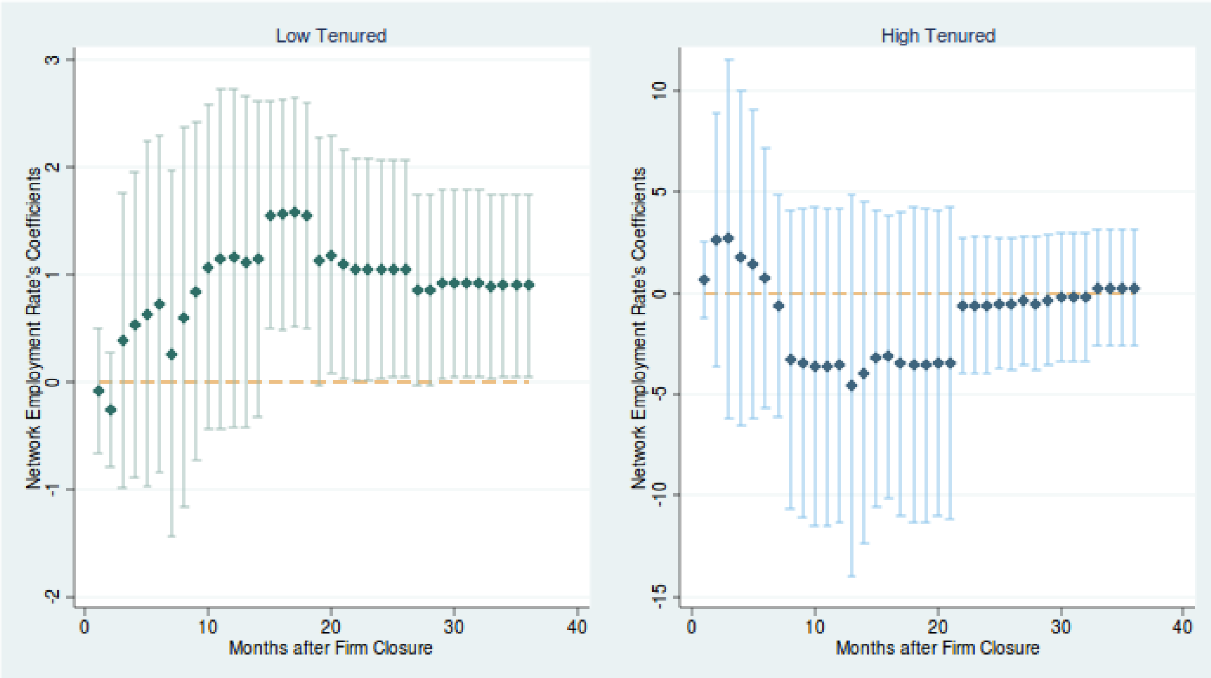
Notes: author's calculations on INPS data for the period 1980- 2001. Closures occurred after December 1998 and before January 1980 are excluded from the analysis. The percentage of the sample individuals censored is about 27%. The blue line plots the Kernel density function.

Figure 6: Timing of the social effect



Notes: the coefficients are estimated using equations (1) and (2), where the dependent variable is the probability of finding a job by each of the 36 months following job loss. Standard errors are clustered by country of origin; controls include age and gender dummies, nationality, time of displacement and the interaction between the first city of work, nationality and time of displacement. The vertical bars in the figure represent the 95% level confidence intervals.

Figure 7: Timing of the social effect by tenure in the labor market

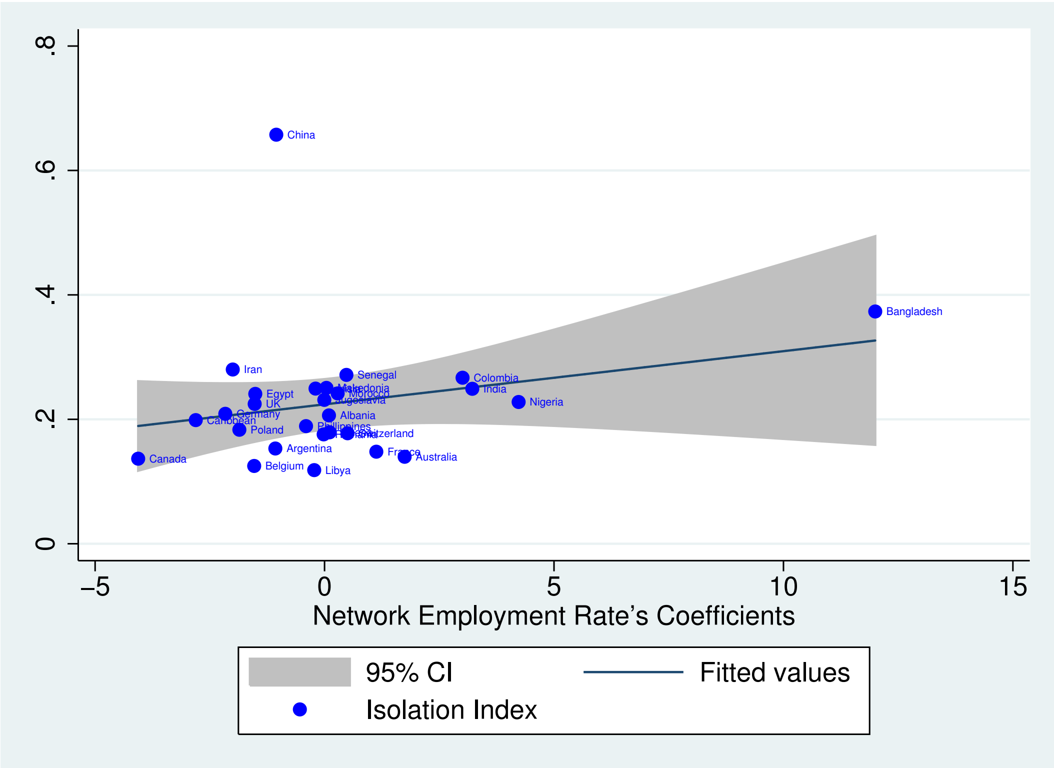


Notes: the coefficients are estimated using equations (1) and (2), where the dependent variable is the probability of finding a job by each of the 36 months following job loss. Standard errors are clustered by country of origin; controls include age and gender dummies, nationality, time of displacement and the interaction between the first city of work, nationality and time of displacement. A worker is defined as *low tenured* if he has a number of months in employment below the median. The vertical bars in the figure represent the 95% level confidence intervals.

Figure 8: Social effect and the index of dissimilarity by country of origin

Notes: the coefficients are estimated for each sending country using equations (1) and (2), where the dependent variable is the probability of finding a job within 36 months following job loss. Standard errors are robust; controls include age and gender dummies, and time of displacement dummies.

Figure 9: Social effect and the index of isolation by country of origin



Notes: the coefficients are estimated for each sending country using equations (1) and (2), where the dependent variable is the probability of finding a job within 36 months following job loss. Standard errors are robust; controls include age and gender dummies, and time of displacement dummies.

Table 1: Descriptive statistics

	Total	Natives	Migrants
Panel a: All workers			
Number of individual workers	3,604,399	3,339,177	265,222
Number of job matches	12,561,479	11,711,885	849,594
% Workers in the last year of the dataset (2001)	45.53	44.53	58.15
Duration of employment spells (months)	31.16	32.24	16.21
% Male	59.11	58.55	66.17
Age	33.40	33.46	32.06
Gross weekly wage (2003 euros)	683.04	684.27	655.76
Number of co-workers ever worked with	461.07	480.77	213.04
Number of migrant co-workers ever worked with	13.72	12.75	25.93
Occupation:			
% Blue collars	63.16	62.84	71.71
% White collars	29.92	30.19	22.71
% Managers	1.25	1.25	1.08
Transitions (monthly rates):			
Exit rate from employment	1.7	1.65	3.2
Entry rate into employment	1.68	1.62	3.14
Panel b: Displaced workers			
Number of displacement episodes	403,368	385,101	18,267
Number of workers ever displaced	354,073	337,216	16,857
% Workers displaced every month	0.10	0.10	0.14
Characteristics at time of displacement:			
% Male	51.08	50.66	59.88
Age	30.89	30.88	30.99
% Blue collars	67.16	66.82	74.28
% White collars	19.81	19.92	17.55
% Managers	0.27	0.27	0.29
Gross weekly wage (2003 euros)	543.95	545.36	514.26
Probability of having a job after 3 months	49.05	49.17	46.21
Probability of having a job in 4 to 9 months	13.21	13.17	14.15
Probability of not having a job after 9 months	28.95	28.9	29.97

Notes: The table reports averages for the period 1975-2001 based on INPS data. Displaced workers' characteristics refer to the values at the time of displacement.

Table 2: Firms and municipalities characteristics

Firms:	
Number of firms	1,121,748
Firm Size	6.87
% Migrant workers	4.26
% Firms in the first year of the dataset (1975)	14.15
% Firms in the last year of the dataset (2001)	24.10
Months in the dataset	142.16
% Firms ever closed	16.32
% Firms closed every month	1.16
Closed firms' size	4.81
Duncan index by migrant status (Firm Level)	0.63
Isolation index by migrant status (Firm Level)	0.27
Municipalities:	
Number of Municipalities	7675
Municipality working population	218.14
Share of Migrants	4.79
Duncan index by migrant status (Municipality Level)	0.25
Isolation index by migrant status (Municipality Level)	0.03

Notes: The table reports summary statistics for the period 1975-2001 based on INPS data. Values for the Duncan and the Isolation indexes are averages across the period 1975-2001.

Table 3: Probability of re-employment in the 36 months after firm closure - IV Regressions

	All workers			Occupation		Tenure		Country of Origin	
				Blue collars	Others	Low	High	non-OECD	OECD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Network Employment Rate	0.407***	0.318*	0.574**	0.543**	0.283	0.899**	0.258	0.587**	2.551
	(0.134)	(0.168)	(0.266)	(0.267)	(1.789)	(0.433)	(1.463)	(0.253)	(4.100)
First Stage Regressions:									
Network Displacement Rate	0.321***	0.278***	0.533***	0.549***	0.551	0.714***	0.159	0.535***	0.139
	(0.045)	(0.043)	(0.125)	(0.120)	(0.691)	(0.181)	(0.158)	(0.131)	(0.352)
F-Test	51.35	40.74	18.05	42.49	0.63	15.59	1.02	16.60	0.16
Controls:									
Age and Gender Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Network Size Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nationality*Time	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nationality*Time*Municipality	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,738	10,738	10,738	7,635	3,103	5,457	5,281	6,285	4,453

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$; standard errors in brackets are clustered by country of origin; age dummies are defined as: 15-24, 25-34, 35-44, 45-54, 55-64, 65+. The instrumental variable is the share of network members displaced before the pivotal worker's displacement episode. *Low Tenure* is a dummy variable that is equal to one if the pivotal worker has a number of months in employment below the median. *OECD* is a dummy indicating workers whose country of origin was a member of the OECD as of 2001, i.e. Australia, Austria, Belgium, Canada, Czech Republic Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Korea Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States.

Table 4: Probability of re-employment in the 36 months after firm closure - Cross-group effect and effect on Italians

	Outcome of Displaced Immigrants				Outcome of Displaced Natives	
	Ref. Group: Other Countries		Ref. Group: Italians		Ref. Group: Italians	
	(1)	(2)	(3)	(4)	(5)	(6)
Network Employment Rate	0.048	-0.127	0.032	-0.089	0.095**	0.109**
	(0.129)	(0.282)	(0.062)	(0.098)	(0.039)	(0.045)
First Stage Regressions:						
Network Displacement Rate	0.307***	0.474**	0.577***	0.645***	0.292***	0.255***
	(0.048)	(0.181)	(0.017)	(0.092)	(0.009)	(0.009)
F-Test	40.08	6.83	1147.56	49.56	988.36	906.56
Controls:						
Age and Gender dummies	Yes	Yes	Yes	Yes	Yes	Yes
Network Size Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Nationality*Time	Yes	Yes	Yes	Yes	Yes	Yes
Nationality*Time*Municipality	No	Yes	No	Yes	No	Yes
Observations	10,738	10,738	10,738	10,738	223,936	223,936

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$; standard errors in brackets are clustered by country of origin; age dummies are defined as: 15-24, 25-34, 35-44, 45-54, 55-64, 65+. The instrumental variable is the share of network members displaced before the pivotal worker's displacement episode. In columns (1) and (2) networks members are past co-workers from other foreign countries of origin; in columns (3) and (4) the reference group is composed of Italian past co-workers. Columns (5) and (6) analyze Italian displaced workers, networks are composed of Italian past co-workers only; for this reason country of origin dummies are automatically dropped in the regressions; standard errors are thus clustered by the date of displacement.

Table 5: Post-displacement outcomes

	Firms		Municipalities		Industries	
	connected	non-connected	connected	non-connected	connected	non-connected
	(1)	(2)	(3)	(4)	(5)	(6)
Network Employment Rate	0.508*	0.066	0.789***	-0.216	0.819*	-0.246
	(0.275)	(0.344)	(0.196)	(0.251)	(0.432)	(0.260)
Controls:						
Age and Gender dummies	Yes	Yes	Yes	Yes	Yes	Yes
Network Size Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Nationality*Time*Municipality	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,738	10,738	10,738	10,738	10,738	10,738

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$; standard errors in brackets are clustered by country of origin; age dummies are defined as: 15-24, 25-34, 35-44, 45-54, 55-64, 65+. The instrumental variable is the share of group members displaced before the pivotal worker's displacement episode. *Connected* Firms/Municipalities/Industries are dummies equal to one if the displaced worker finds a job in Firms/Municipalities/Industries in which at least one past co-worker from the same country of origin has ever worked, before the pivotal individual's displacement episode. *Non-connected* Firms/Municipalities/Industries are dummies equal to one if the displaced worker finds a job in Firms/Municipalities/Industries which no past co-worker from the same country of origin has ever worked.

Table 6: Network effect and segregation

	Probability of working in 36 months after job loss with			
	Co-national	No co-national	Non-national	No non-national
	(1)	(2)	(3)	(4)
Network Employment Rate	0.779*	-0.205	0.540	0.034
	(0.483)	(0.393)	(0.393)	(0.379)
Controls				
Age and Gender dummies	Yes	Yes	Yes	Yes
Network Size Dummies	Yes	Yes	Yes	Yes
Nationality*Time*Municipality	Yes	Yes	Yes	Yes
Observations	10,738	10,738	10,738	10,738

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$; standard errors in brackets are clustered by country; age dummies are defined as: 15-24, 25-34, 35-44, 45-54, 55-64, 65+; the instrumental variable is the share of network members displaced before the pivotal worker's displacement episode. the dependent variables are: column (1), the probability of meeting at least one co-worker (new or past) from the same country of origin in the 36 months after the displacement. Column (2), the probability of not meeting any co-worker from the same country of origin. Column (3), the probability of working with at least one co-worker of other foreign nationalities, either past or new co-worker. Column (4), the probability of not meeting any co-workers from a different foreign country of origin.

Appendix A: Supplementary Tables

Table A1: Networks characteristics

	Mean	Std. Dev.	Min.	Max.
Panel a: Displaced Immigrants				
Re-employment within 36 months	0.669	0.470	0	1
Network's Size:				
Same Country	10.104	37.189	0	228
Other Foreign Countries	5.733	18.098	0	304
Natives	13.967	56.716	0	823
Network Employment Rate:				
Same Country	0.124	0.277	0	1
Other Foreign Countries	0.207	0.329	0	1
Natives	0.209	0.291	0	1
Network Displacement Rate:				
Same Country	0.017	0.101	0	1
Other Foreign Countries	0.032	0.131	0	1
Natives	0.112	0.213	0	1
Panel b: Displaced Natives				
Re-employment within 36 months	0.709	0.454	0	1
Network's Size:	107.413	442.496	0	15,772
Network Employment Rate:	0.380	0.285	0	1
Network Displacement Rate:	0.091	0.138	0	1

Notes: Author's calculations on INPS Data

Table A2: OLS regressions

	Reference Group: Same Country of Origin			
	(1)	(2)	(3)	(4)
Network Employment Rate	0.205***	0.138***	0.115	0.113
	(0.024)	(0.032)	(0.298)	(0.327)
Controls:				
Age and Gender Dummies	Yes	Yes	Yes	Yes
Network Size Dummies	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Nationality*Time	No	Yes	Yes	Yes
Nationality*Time*Municipality	No	No	Yes	Yes
Nationality*Time*Municipality*Industry	No	No	No	Yes
Observations	10,738	10,738	10,738	10,738

Notes: * p<0.10, ** p<0.05, *** p<0.01; standard errors in brackets clustered by country; age dummies are defined as: 15-24,25-34,35-44, 45-54, 55-64, 65+.

Table A3: Robustness checks

Network Employment Rate:	(1)	(2)	(3)	(4)
Same Country of Origin	0.312*			0.586**
	(0.178)			(0.281)
Other Foreign Country of Origin		0.089		-0.375
		(0.324)		(0.324)
Natives			-0.366	-0.122
			(0.277)	(0.186)
Controls:				
Age and Gender Dummies	Yes	Yes	Yes	Yes
Network Size Dummies	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Nationality*Time	Yes	Yes	Yes	Yes
Nationality*Time*Municipality	Yes	Yes	Yes	Yes
Nationality*Time*Municipality*Industry	Yes	Yes	Yes	No
Observations	10,738	10,738	10,738	10,738

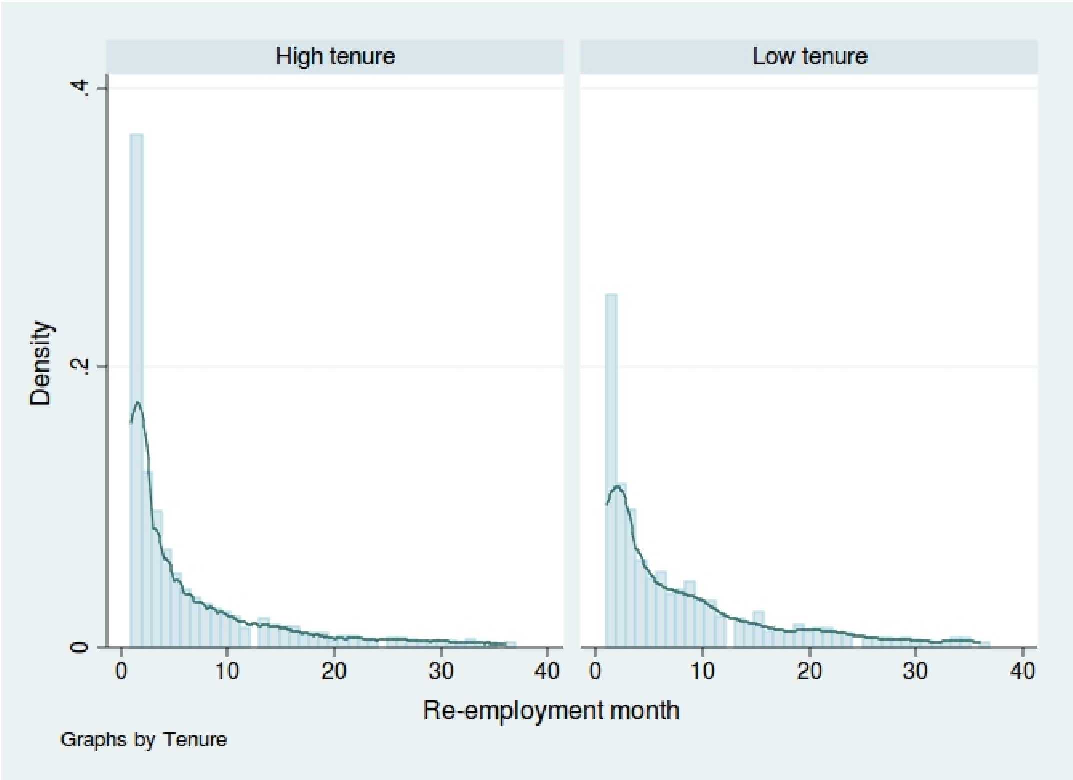
Notes: * p<0.10, ** p<0.05, *** p<0.01; standard errors in brackets clustered by country; age dummies are defined as: 15-24,25-34,35-44, 45-54, 55-64, 65+; the instrumental variable is the share of network members displaced before the pivotal worker's displacement episode.

Table A4: Timing of the social effect - IV Regressions

	All workers		Low Tenured		High Tenured	
	(1)	(2)	(3)	(4)	(5)	(6)
Re-employment in:	Coeff.	S.e.	Coeff.	S.e.	Coeff.	S.e.
1 month	0.465	(0.326)	-0.082	(0.298)	0.630	(0.963)
2 months	0.596	(0.371)	-0.260	(0.270)	2.624	(3.164)
3 months	0.824	(0.563)	0.386	(0.703)	2.673	(4.504)
4 months	0.576	(0.494)	0.532	(0.724)	1.745	(4.208)
5 months	0.600	(0.505)	0.630	(0.818)	1.439	(3.879)
6 months	0.535	(0.491)	0.730	(0.798)	0.706	(3.270)
7 months	0.255	(0.555)	0.262	(0.869)	-0.641	(2.801)
8 months	-0.126	(0.532)	0.602	(0.899)	-3.312	(3.759)
9 months	-0.007	(0.616)	0.840	(0.804)	-3.448	(3.887)
10 months	0.102	(0.476)	1.067	(0.768)	-3.642	(3.997)
11 months	0.124	(0.496)	1.148	(0.807)	-3.666	(3.996)
12 months	0.155	(0.505)	1.154	(0.802)	-3.587	(3.939)
13 months	-0.026	(0.477)	1.118	(0.786)	-4.579	(4.800)
14 months	0.048	(0.427)	1.140	(0.749)	-3.944	(4.296)
15 months	0.300	(0.423)	1.551***	(0.541)	-3.238	(3.728)
16 months	0.324	(0.430)	1.563***	(0.547)	-3.140	(3.562)
17 months	0.297	(0.401)	1.582***	(0.543)	-3.485	(3.813)
18 months	0.252	(0.391)	1.550***	(0.536)	-3.562	(3.960)
19 months	0.151	(0.445)	1.124*	(0.588)	-3.558	(3.941)
20 months	0.170	(0.440)	1.180**	(0.562)	-3.463	(3.829)
21 months	0.126	(0.445)	1.093**	(0.546)	-3.467	(3.910)
22 months	0.556*	(0.315)	1.049**	(0.526)	-0.598	(1.702)
23 months	0.531*	(0.316)	1.046**	(0.524)	-0.606	(1.708)
24 months	0.529*	(0.316)	1.048**	(0.519)	-0.606	(1.708)
25 months	0.548*	(0.320)	1.052**	(0.516)	-0.523	(1.625)
26 months	0.548*	(0.319)	1.052**	(0.516)	-0.556	(1.650)
27 months	0.450*	(0.261)	0.856*	(0.452)	-0.377	(1.609)
28 months	0.441*	(0.258)	0.856*	(0.453)	-0.518	(1.672)
29 months	0.474*	(0.269)	0.912**	(0.448)	-0.349	(1.627)
30 months	0.481*	(0.266)	0.915**	(0.444)	-0.230	(1.618)
31 months	0.515*	(0.286)	0.911**	(0.445)	-0.230	(1.618)
32 months	0.515*	(0.286)	0.911**	(0.445)	-0.230	(1.618)
33 months	0.584**	(0.277)	0.885**	(0.433)	0.258	(1.463)
34 months	0.581**	(0.275)	0.894**	(0.434)	0.258	(1.463)
35 months	0.579**	(0.270)	0.898**	(0.432)	0.258	(1.463)
36 months	0.574**	(0.266)	0.899**	(0.433)	0.258	(1.463)
Observations	10,738		5,457		5,281	

Notes: * p<0.10, ** p<0.05, *** p<0.01; standard errors in brackets clustered by country of origin. The coefficients are estimated using equations (1) and (2), where the dependent variable is the probability of finding a job by each of the 36 months following job loss. Standard errors are clustered by country of origin; controls include age and gender dummies, nationality, time of displacement and the interaction between the first city of work, nationality and time of displacement. *Low Tenured* workers are individuals that have a number of months in employment below the median.

Figure A1: Re-employment probabilities by month (up to 36 months) and by tenure



Notes: author's calculations on INPS data for the period 1980- 2001. Closures occurring after December 1998 and before January 1980 are excluded from the analysis. The percentage of the sample individuals censored is about 27%. The blue line plots the Kernel density function. A worker is defined as *low tenured* if he has a number of months in employment below the median.

Appendix B: Immigration Policies in Italy

Between 1970 and 1980 Italy changed from being an emigration country into an immigration country; in 1985 the number of foreign residents was almost 500,000, accounting for about 0.8% of the total population. Only in 1986, the first law recognizing the legal status to foreigners working and living in Italy was introduced. Few years later, 1990, the Italian government issued a law regulating immigration policy and implementing a quota system; based on the demand for labor of Italian firms, the Italian government had to set every year a maximum number of immigrants that can enter the country.

The main effect of these two first immigration laws was to grant amnesties that conferred legal status to more than 300,000 migrants already working in Italy. The low level of quotas, which were insufficient to satisfy the demand for foreign workforce, and the expectations of future amnesties increased the illegal entry of immigrants. In 1996 and 1998 two other amnesties were granted, regularizing respectively 250,000 and 218,000 undocumented foreign workers.

Since 1998, an immigrant who wants to reside and work legally in Italy is required to hold a permit of stay (before this law, legalization was acquired primarily via amnesties). The permit of stay however does not apply to all migrants: immigrants from countries that signed the Schengen Agreements do not need any permits to live and work in Italy and they can freely enter the country.[29]

The 1998 reform established a maximum period of non-employment following job loss for immigrants to be set equal to one year. In 2001 a new restrictive law passed and the maximum time without working was reduced to six months, past this period, the immigrant becomes unauthorized and he/she has to leave Italy. In the same year the biggest amnesty took place regularizing almost 650,000 undocumented foreign residents.

Overall Italian immigration amnesties involved almost 1.5 million individuals: it is clear that amnesties represented the main gateway into the country. In order to be eligible for regularization a migrant has to show a regular job offer.

The estimates on illegal migrants are based on the number of applications to amnesties, these measures are very noisy and range from 10 to 40 per cent of the legal workers, i.e. in 2001 1.4 million of migrants were present in Italy meaning that the estimates of illegal migrants are around 140,000 to 500,000 unauthorized migrant. (Venturini and Villosio,2008, Fasani 2010). Several institutions, such as *Caritas* of the national statistics office, ISTAT, also provide estimates of illegal migrants operating in the black economy.

[29]Moreover countries belonging to the European Union are excluded. In the observation period (i.e. up to 2001), migrants from the following countries were exempted from the permit of stay regulation: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom.