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DISCUSSION PAPER SERIES

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ABSTRACT

Do Neighbors Help Finding a Job? Social Networks and Labor Market Outcomes After Plant Closures

Social networks may affect workers' labor market outcomes. Using rich spatial data from administrative records, we analyze whether the employment status of neighbors influences the employment probability of a worker who lost his job due to a plant closure and the channels through which this occurs. Our findings suggest that a ten percentage point higher neighborhood employment rate increases the probability of having a job six months after displacement by 0.9 percentage points. The neighborhood effect seems to be driven not by social norms but by information transmission at the neighborhood level, and additionally by networks of former co-workers who also lost their jobs due to plant closure.

JEL Classification: J63, J64, R23

Keywords: social networks, job search, neighborhood, employment, wages, plant closures

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1 Introduction

The important role of social networks in people's lives raises the question of how these networks influence individual labor market outcomes. Finding a job after being laid off may not only be a function of individual characteristics and vacancies posted by firms but also a result of social networks that influence job search behavior or give job seekers access to information on vacancies. It has been known since the seminal work of Granovetter (1995) that workers use personal networks when searching for jobs. While there has been substantial theoretical work on social networks (see, e.g., the surveys by Ioannides and Loury 2004; Jackson 2010; Topa and Zenou 2015), empirically we know less about how these networks affect labor market outcomes.

In this paper, we try to answer the question of whether the neighborhood in which a job seeker lives affects his probability of finding a job and what the underlying mechanisms are. Our empirical analysis draws on a rich administrative data set that comprises the universe of workers in 23 self-contained labor market regions in Germany. The neighborhoods are constructed by geo-referencing the places of residence of workers within grids of one square kilometer in size. The identification idea for estimating a causal effect of a neighborhood's employment rate on an individual worker's probability of finding a job rests on the assumption that the worker is placed 'randomly' into a grid after a job loss that was beyond his control. Workers having lost their jobs receive 'treatments' of varying degrees by living in neighborhoods that differ in the share of employed workers.

While, as most other studies, we do not directly observe the actual contacts an individual worker has in his social network, our approach is able to address various other difficult issues when it comes to identifying a social network effect. As argued by Manski (1993), common factors affecting the employment status of an individual and her social network may flaw estimates of a social network effect. By focusing on workers who lost their jobs due to firm closures, we can reasonably exclude the possibility that the social network drove the job loss. As long as the displaced worker does not share unobserved characteristics with other individuals in his neighborhood, the employment rate of the neighborhood should be uncorrelated with the residual. We address the issue with a rich set of control variables for the displaced worker.

Nevertheless, it may be that workers chose to live in a specific neighborhood. They may have self-selected into this neighborhood for reasons we cannot observe but that are related to employment-relevant characteristics of the neighborhood. We exploit the exceptional thinness of the German housing market to show that this kind of mis measurement is very unlikely and that our results are robust. Finally, the self-contained labor markets, as we will explain in more detail later on, are defined as labor market regions to which workers can commute. Restricting ourselves to these self-contained labor markets allows us to control for shifts in the relevant labor demand of the job seekers living in a particular neighborhood within a given commuting area. This will help us to avoid falsely attributing a higher likelihood of a worker finding a job to a higher neighborhood employment rate when it is actually driven by a shift of labor demand in the regional labor market.

We expect that higher employment rates in a neighborhood increase the probability of finding a job if all else is equal. The literature suggests three mechanisms that might improve the employment probability of a worker living in a neighborhood where a high share of residents are employed. First, the neighborhood may provide information on job vacancies that workers without these connections may not receive (Topa, 2001; Calvó-Armengol and Jackson, 2007). Second, the network may help potential employers to overcome a problem of asymmetric information. As firms often have difficulties assessing the true productivity of job applicants, referrals may provide valuable information and make it more likely for firms to hire workers who already know someone working in the firm (Montgomery, 1991; Simon and Warner, 1992). Third, one may observe faster transitions back into employment, not because the social network provides information but because it shapes social norms (Akerlof, 1980; Agell, 1999). Workers living in neighborhoods with high employment rates may derive a negative utility from not being employed, as their status is different from the socially prevalent status. Similarly, a neighborhood with relatively high unemployment may provide an environment where being unemployed is the rule and where the unemployed often make relatively low job search efforts. Our empirical analysis tries to shed light on which of these mechanisms are more likely to explain our finding that social networks positively affect the probability of finding a job.

A very early contribution to the empirical literature on neighborhood effects was Datcher (1982), whose findings showed that a substantial fraction of the racial differences in education and earnings can be attributed to the poorer neighborhoods from which blacks come. Subsequently, spatial information was used to show that workers coming from the same residential neighborhood tend to cluster around specific work locations, which is consistent with the idea of local referral networks (see, e.g., Bayer et al. 2008; Hellerstein et al. 2011; Hawranek and Schanne 2014). Schmutte (2015) finds wage premiums of higher quality neighborhoods and Markussen and Røed (2015) show that social insurance take-up is contagious. Hellerstein et al. (2015) report that the effect of residential neighborhoods on workers' re-employment probability varies with the business cycle.

There is also a strand of the literature that studies neighborhood effects among refugees who have been assigned to particular regions according to specific national rules. Beaman (2012) studies, for example, the labor market outcomes of refugees resettled into various U.S. cities. Similar analyses can be found in Edin et al. (2003) for Sweden or in Damm (2009) for Denmark. Social networks, defined not as the neighborhood but as a set of former co-workers, form the starting point for the research of Cingano and Rosolia (2012), Glitz (2013), and Saygin et al. (2014). Here, the idea is that information on vacancies may come from other workers with whom the displaced worker worked for at least a limited period of time at the firm that closed. The study by Cingano and Rosolia (2012) is based on Italian data, Glitz (2013) on German data, and Saygin et al. (2014) on Austrian data. All of these studies find significant effects of the employment rate among former co-workers on the job-finding probability of the displaced worker. Moreover, Hensvik and Nordström Skans (2016) show, based on Swedish data, that employers use networks of former co-workers to overcome the asymmetric information problem when hiring new workers.

Against the background of these previous studies, we are not only able to estimate the effect of the neighborhood's employment rate on an individual's probability of finding a new job: Our data also allow us to look more deeply into the economic mechanisms that are likely to be driving our findings, thus adding to the empirical knowledge of why and how social networks matter. More specifically, we can decompose neighborhood employment rates along socio-demographic lines. This allows us to evaluate whether socio-demographic characteristics of the spatial network influence the transition into employment, and thus whether information is transferred among similar workers. Wage data on displaced workers who found jobs allow us, furthermore, to discriminate between explanations of the neighborhood effect focusing on social norms and explanations of information transmission. Finally, the data allow us to identify whether networks of displaced co-workers have an effect that supports job search on top of the neighborhood effect. In particular, we address the question of whether a plant is more likely to hire a worker from a specific neighborhood if it already employs a worker who was displaced from the same closing plant. To this end, we shed light on the question of whether information not only travels through neighborhoods but is also passed on by displaced co-workers or, in an alternative interpretation, whether the social network helps to overcome the asymmetric information problem of employers when selecting employees.

In our preferred specification, we find that a ten percentage point increase in the neighborhood employment rate increases the probability of being employed after six months by about 0.9 percentage points. We, furthermore, provide evidence that employed neighbors who belong to similar socio-demographic groups make it easier to find new jobs. Regressions of daily earnings on neighborhood employment rates also reveal statistically significantly positive effects. A ten percentage point higher employment rate within a given neighborhood increases the daily wage of neighborhood residents who find a new job within half a year of finding the job by 1.7%.

We interpret the positive effect to suggest that an information transmission channel rather than a social norm effect is driving the results on job finding rates, as this channel would suggest a negative effect of the network employment rate on wages. Regarding the role of co-worker networks, our results suggest that an average firm is much more likely to hire a worker from a particular neighborhood if it already employs a formerly displaced co-worker living in the same neighborhood. This finding can be interpreted in two ways. On the one hand, it could be that displaced co-workers provide information on vacancies that has not been channeled through the residential network. On the other hand, it might be that employers use referrals to overcome the asymmetric information problem that typically makes hiring decisions so difficult.

We proceed by introducing our econometric model and identification strategy in Section 2. Section 3 gives information on our data set. In Section 4 we present our results. The last section concludes.

2 Empirical model and identification

We estimate a linear probability model

$$e_{i,t+1} = \alpha + \delta er_{i,t} + \theta log(n_{i,t}) + \boldsymbol{\beta x}_{i,t} + \epsilon_{i,t} \tag{1}$$

where $e_{i,t+1}$ is an indicator variable for individual i that takes the value of one if the individual found a job six months after job displacement, $er_{i,t}$ is the employment rate of the residential neighborhood at the start of the unemployment spell of individual i, $n_{i,t}$ is the labor force at the place of residence, $\boldsymbol{x}_{i,t}$ is a vector of a large set of controls including worker characteristics, indicator variables for the year of dismissal and the regional labor markets, and $\epsilon_{i,t}$ are unobserved determinants.

We are mainly interested in an estimate of δ. This parameter may be interpreted as causal if there are no common factors affecting the employment probability of an individual and his social network. For various reasons, this is likely to be the case in our analysis. First, we restrict the analysis to workers who have been displaced because of plant closures. By construction, the job loss becomes exogenous to the behavior of the worker, which – as we are interested in determining – could otherwise be a function of his social network. Then displaced workers are 'treated' by the varying employment rates of the neighborhoods in which they live. To the extent that a worker who lost his job does not share unobserved characteristics with other individuals in her neighborhood, the employment rate of the neighborhood should be uncorrelated with the residual. We use a rich set of socio-demographic characteristics for the displaced worker, including education dummies, age, citizenship, occupation, a dummy indicating whether the worker lived and worked in the same labor market region, the real daily wage of the previous job, the employment career over the past five years, plant size at the day of closure, and the sector of the plant. These controls should reduce the likelihood of omitted variables, making it very likely that no sorting is left.

Nevertheless, it may be that our 'treated' workers deliberately chose their places of residence at some time in the past because they wanted to locate close to friends and acquaintances for reasons that our large set of control variables do not cover. They may have selected themselves into particular neighborhoods for reasons that we cannot observe, and those reasons may be related to the probability of finding a new job after displacement. In this case, our estimates would be biased.

We shed light on the issue by providing additional evidence on the thinness of the German housing market that quite likely adds randomness to the housing decision. We may be able to exploit this randomness in our estimations later on. The idea is (see also Bayer et al., 2008) that due to the thinness of the housing market, workers might not have been able to choose a particular neighborhood as there was no appropriate home available there at that time. Descriptive evidence on the German housing market supports such an assumption quite strongly.[1] Average tenancy lasts about 11 years. For those in owner-occupied housing, which applies to about 46% of West German households[2] turnover rates are even smaller. On average, such homes come onto the market only every 40 years. Moreover, as these are

[1]See, e.g., "Wohnungswirtschaftliche Daten und Trends 2015/2016, GdW Bundesverband deutscher Wohnungs- und Immobilienunternehmen", *http : //www.stalys.de/data/mtran.htm* and "Immobilienmarktbericht Deutschland 2015 der Gutachterausschüsse der Bundesrepublik Deutschland".

[2]See Statistisches Bundesamt *www.destatis.de*

average numbers that do not take into account heterogeneity in preferences for housing of a particular size or quality, households may indeed have ended up in a neighborhood close to (but not within) their preferred one. At the time when households were looking for a home, the type of home they were looking for might not have been available within the one square kilometer area where they preferred to live. Thus, the thinness of the German housing market adds randomness to the residential area choice, which we exploit by estimating a specification that includes the average employment rate of surrounding neighborhoods as a further control. In doing so, we essentially restrict the variation to those neighborhood employment rates for which we can reasonably assume that no selection into neighborhoods took place.

Clearly, by definition, we cannot provide direct evidence on whether there is actually randomness in housing decisions based on unobservables. However, we are able to compare the observable individual characteristics of displaced workers with the average characteristics of workers in their neighborhood and the average characteristics of the workers in the surrounding neighborhoods to provide more evidence on the plausibility of the assumption. Of course, this does not prove that there has been no selection on unobservables. However, to the extent that the selection on unobservables is somehow connected to observable characteristics of the workers, it may indicate whether our assumption is plausible.[3] To this end, we ran a regression of the displaced workers' characteristics on the neighborhood characteristics and a regression of the displaced workers' characteristics on the worker characteristics of the surrounding neighborhoods. Then we took the residuals of the two regressions and correlated them. If the actual neighborhoods do not "explain" more of the characteristics of the displaced workers than the surrounding neighborhoods, residuals of the two regressions should be highly correlated. In fact, as shown in Table 3, the correlation coefficients are very close to the coefficient for all socio-demographic characteristics.

Finally, our analysis is based on self-contained labor market regions, which are defined on the basis of workers' residences within commuting dis-

[3]Similarly, Altonji et al. (2005) suggest that the amount of selection on the observed explanatory variables may provide a guide to the amount of selection on the unobservables.

tance of potential employers. With this definition, we are able to control for common shocks to the relevant regional labor market of a displaced worker that influence job-finding rates. For all these reasons, we are confident that we are using a reasonable and robust identification strategy.

3 Data and descriptive statistics

To put this approach into practice, we need detailed data on job and unemployment durations, places of residence, and information on workers' previous employers and potentially on the employers where workers have found a new job. We combine two administrative data sets: the Integrated Employment Biographies (IEB) and the Establishment History Panel (BHP) provided by the Institute for Employment Research (IAB). Both data sets contain longitudinal information on job seekers, workers, and firms for the period 1975 to 2012.

Information on employers comes from the BHP, which consists of data from the German social insurance system aggregated annually on June 30 of every year. The BHP not only contains information on industry and plant size but also, based on a worker flow approach, information on plant closures.[4] The data on workers' job duration and job seekers' unemployment duration (on a daily basis), separations, transitions, wages (deflated by the consumer price index) come from the IEB, which contains the universe of unemployed job seekers and workers who are subject to social security contributions. Since the information contained is used to calculate unemployment benefits and social security contributions, the data set is highly reliable and especially useful for analyses taking wages and labor market transitions into account.[5] Each spell contains a unique worker and establishment identifier and numerous worker characteristics. In addition, the IEB provides information on workers' place of residence and work at the county level.

However, in order to investigate neighborhood effects, administrative ar-

[4]For details on the BHP, see Spengler (2009) and on the worker flow approach used, Hethey and Schmieder (2010).

[5]For details on the IEB, see Jacobebbinghaus and Seth (2007).

eas such as counties, districts, and postcode areas lack the needed specificity, since their geographic size varies considerably. For this reason, the IEB has been geocoded with the aim of generating small-area regions of one square kilometer in size for the years 2007-2009. To generate neighborhoods, all persons in the IEB were selected on June 30 of each year, and their residential addresses were linked to geocoded data (see Scholz et al., 2012). An individual's neighborhood is thus defined as all workers and job seekers living in the same one square kilometer area on June 30 of the year before the worker was displaced.

From this combined data set, we select the universe of workers and job seekers from 23 local labor markets in West Germany identified by Kosfeld and Werner (2012) based on commuter travel time for the years 2007 to 2009, see Figure 1.[6] In total, we use information on a stock of approximately 5.4 million workers living in one of the 23 selected labor market regions. On average, there were more than 1.1 million workers living in the three metropolitan labor market areas, about 160,000 in the ten urban, and slightly more than 37,000 living in the ten rural labor market areas, see Table 1. The metropolitan labor market areas are split up into more than 4,600 neighborhoods of one square kilometer each. The urban labor market areas contain slightly more than 1,700 neighborhoods and the rural areas contain 623 neighborhoods. For the analysis, we have only considered neighborhoods with a labor force size larger than 50 and where at least one displaced worker lives.

On average over the years 2007, 2008, and 2009, 17,877 plants closed. We retain all workers who were employed full-time on June 30 of the year before plant closure. [7] On average, we have about 30,000 displaced workers

[6] These local labor market regions are computed using factor analyses of commuting distances between German regions, imposing a maximum commuting time of 60 minutes one way. Kosfeld and Werner (2012) define in total 141 self-contained labor markets. From these local labor markets, we selected the three largest, the ten smallest, and ten medium sized regional labor markets in West Germany, which are grouped around the median of the population size across all regions. We focus on West German labor market regions due to structural differences between East and West German regions and regional differences in pay scales.

[7] We are aware that some workers may have anticipated the closure of the plant and left prior to this date, in particular if the actual plant closure took place only a short time after June 30. We therefore also provide results of a robustness test below in which we

per year, meaning that over the course of the three years, we have about 90,000 observations at our disposal. On average, each plant employed five workers before closure. Those displaced workers lived in about 8,000 different neighborhoods at the time of closure. There were four displaced workers per neighborhood at an average labor force per neighborhood of about 550 workers.

Figure 2 shows the histogram of neighborhood sizes. There are a few relatively large neighborhoods in the sample. On average, almost 9 out of ten workers were employed. As shown by the boxplots in Figure 3 there is ample variation with respect to the neighborhood employment rates within the 23 self-contained labor market regions. This is the variation that our analysis draws on. There is, however, hardly any change in neighborhood employment rates over the course of the three years 2007 to 2009. As a result, we refrain from using time variation within neighborhoods for our analysis.

Table 2 presents more information on the 90,000 displaced workers whose job finding probability we are interested in deriving. Of these workers, 59.2% were employed six months after losing a job due to plant closure. We also have a rich set of data on workers' socio-demographic characteristics. We included in our estimations two education dummies, age and the square of it, a dummy for foreign citizenship, four occupation dummies, a dummy indicating whether the worker lived and worked in the same labor market region, the real daily wage in the worker's previous job, plant size on June 30 of the year before closure, and the sector of the plant. Moreover, we included information on the worker's employment history over the past five years, that is, job tenure, number of jobs, and a dummy for being unemployed at least once during the period.

Finally, we are interested in identifying the neighborhoods where displaced workers live. Figure 4 plots the number of neighborhoods where displaced workers from a particular plant resided. Each dot represents the closure of a plant of a particular size. If all displaced workers from that plant lived in different neighborhoods, the dot would lie on the 45-degree

control for workers still employed six months before plant closure.

line. Although not all dots do so, the plot suggests that there is considerable variation in the neighborhoods where displaced workers from a particular plant live. This should allow us to potentially disentangle a neighborhood effect from a former co-worker network effect.

4 Results

4.1 Basic regression

Table 4 presents our main results for four different specifications of the linear probability model described in Equation (1). The dependent variable indicates whether a displaced worker was employed six months after having lost his job. For the regressions that follow, we use a six-month time window, as the average duration of unemployment is about six months in Germany. Later on in the robustness section, we also provide estimates for larger time frames. The parameter estimate we are most interested in is the effect of the neighborhood's employment rate on the employment probability of the displaced worker after controlling for a large set of worker and job-related covariates, year of displacement and labor market region fixed effects. Model (1) is the most parsimonious specification. In Model (2) we add the logarithm of the size of the neighborhood and in Model (3) we additionally include interaction terms of displacement year and labor market region fixed effects to account for potential labor market region specific business cycle effects. Contrary to the three previous specifications, where we used variation among the neighborhoods' employment rates within a labor market region, in Model (4) we also include the average employment rate of the surrounding neighborhoods. Thus Model (4) only uses variation in the employment rates of nearby neighborhoods for which the assumption of random housing choices is likely to hold as we argued before.

For all four models, we find that the neighborhoods' employment rates have a positive effect on the probability of workers being employed again six months after having lost a job. Including the log of the neighborhood's labor force slightly decreases the size of the estimate of the neighborhood employment rate. Adding the interaction of the labor market fixed effects and the year of observation does not alter the estimate of the neighborhood employment rate. Furthermore, the inclusion of the average employment rate of the surrounding neighborhoods hardly changes the effect of the neighborhood employment rate. Given that the probability of having found a job is still driven by the neighborhood in which the displaced worker lives and not on the employment rate of the surrounding neighborhoods, we are fairly confident that we have been estimating a causal effect that is not disturbed by a potential selection of workers into specific neighborhoods based on unobservable characteristics.[8]

Model (3), our preferred specification, implies that a ten percentage point increase in the neighborhood employment rate increases the probability of a worker being employed again six months after losing a job by 0.9 percentage points. Given that roughly every second displaced worker has found a job after six months, the re-employment probability increased by 1.5%. The effect of the neighborhood on the re-employment probability of the displaced workers in our study is within the range of what has been found by others, at least those that are comparable in some respect. In particular, Hellerstein et al. (2015) find for their weighted measure of the Census tract employment rate that an interquartile change raises the re-employment probability in their sample by 1.9% which is the upper bound of their estimates.

4.2 Mechanisms

4.2.1 Composition of the neighborhood network

Next, we investigate heterogeneity in the effectiveness of the network. Specifically, we are interested in whether displaced workers benefit more from information transferred between workers who share the same socio-demographic characteristics. The underlying idea is that it is more likely that a displaced worker will receive information if he shares characteristics with his social network. Moreover, the quality of information exchanged might be of greater

[8]The reason for the lower number of observations in Model (4) is that there are few neighborhoods without direct surrounding neighborhoods.

use if shared among similar workers. To investigate whether the similarity of the network has an effect on individuals' employment probability, we split the neighborhood employment rate by key socio-demographic characteristics and investigate whether the employment rate of neighbors who are similar to the displaced worker has a larger effect on the employment probability than the employment rate of dissimilar neighbors. Table 5 presents the results of a set of regressions in which we divide the neighborhood employment rate by gender, citizenship, education, and cohort, where the cohort is a $[-5, +5]-$year window around the displaced worker's age.

Overall, the results confirm earlier evidence on co-worker networks, that network effects are predominantly driven by contacts with workers from the same socio-demographic group (Cingano and Rosolia, 2012; Glitz, 2013). Column (1) of Table 5 shows that a higher neighborhood employment rate of the same gender has a positive effect on the re-employment probability. Thus, for instance, displaced female workers benefit only from employed female neighbors, and information received by male neighbors seems to be irrelevant. Column 2 of Table 5 presents results when breaking down the employment rates into natives and foreigners. Again, it is the employment rate of the workers in the neighborhood who have the same citizenship that drives the job-finding probability of displaced workers, whereas the employment rate of workers with different citizenship seems to be irrelevant (Column 3). This also applies if one splits employment rates by levels of education. Interestingly, the coefficients in Columns (1) to (3) in Table 5 are around the same size as in our baseline specification, which could indicate that information is nearly exclusively transferred within socio-demographic groups. Regarding the age composition of the network, we find that a ten percentage point increase in the neighborhood employment rate of one's cohort increases the probability of having a job half a year after becoming unemployed by 2.1 percentage points. However, a ten percentage point increase in the other age group's employment rate lowers the employment probability after displacement by 1.1 percentage points. The negative sign of the coefficient for the employment rate of workers who belong to other cohorts indicates that the worker's employment chances deteriorate substantially, which could be due to crowding out effects.

4.2.2 Social norms?

The literature on neighborhood networks suggests that neighborhoods may have an effect on an individual's job finding rate by providing information through friends and acquaintances (Topa, 2001; Calvó-Armengol and Jackson, 2007) who possibly also live nearby or by changing the worker's preferences through a social norm effect (Akerlof, 1980; Agell, 1999). One approach that could allow us to rule out one of the two channels is to look into the effect of the neighborhood employment rate on the daily wages of those workers employed six months after losing a job. The underlying idea is as follows: If social norms are at work, higher residential employment will reduce reservation wages and consequently, wages in the new job should be lower. Displaced workers comply with the social norm of having to work for a living and are more inclined to accept jobs, even if they pay less. If, on the other hand, information transmission is at work, reservation wages are likely to increase with the residential neighborhood employment rate as the job seeker can rightly expect to receive more information on vacancies and job offers. Consequently, wages in the new job should be positively correlated with the neighborhood employment rate. In order to discriminate between these two hypotheses, Table 6 displays results of a wage regression with the daily earnings of workers employed (full-time or part-time) six months after becoming unemployed as the dependent variable. [9]

We include in the earnings regressions the same set of controls as in Table 4. In all specifications, we find a statistically positive effect of the neighborhood employment rate on the daily earnings of those displaced workers who found a new job within half a year. This suggests that the provision of information about vacancies by employed neighbors is the driving force rather than social norms. On top of that, our results imply that the job seekers

[9]Note that the data contain no detailed information on the number of hours worked. Also, wages are top-coded at the social security contribution ceiling. In the earnings regressions, we therefore excluded jobs with wages above the ceiling. We obtain almost the same results when imputing wages for top-coded observations.

profit from sizable wage gains. In our preferred specification (3), a ten percentage point increase in the neighborhood employment rate raises the log daily wage by 0.0239 log points. On average this is a 1.7% increase in daily wages.

4.2.3 Co-worker effects

So far, our results point towards information transmission as the predominant effect of the network. It is, however, still an open question whether information travels through the neighborhood only, or if there is also a former co-worker network contributing to a worker's higher re-employment probability. We will shed light on this issue now.

We do not have information on all former co-workers with whom a displaced worker shared a work history before plant closure. However, we know about all workers who lost their job at the time of the plant closure. We define a network based on these co-displaced workers. Then, if there is a co-displaced worker effect in addition to a neighborhood effect, one should observe when comparing two workers living in the same neighborhood that a worker is more likely to end up in a firm that already employs a former co-displaced worker than in another firm that does not employ a former co-displaced worker.

In order to evaluate a potential additional effect arising through information transmission among displaced former co-workers, we adapt an estimation strategy proposed by Kramarz and Nordström Skans (2014). In particular, we estimate a linear model for the probability that individual i starts working in plant j

$$E_{i,n(i),j} = \beta_{n(i),j} + \gamma A_{i,j} + \epsilon_{i,j} \quad (2)$$

where $E_{i,n(i),j}$ is an indicator variable that takes the value of one if an individual i from neighborhood n is working in plant j, $A_{i,j}$ is an indicator variable capturing whether a former co-displaced worker from the closed plant that employed individual i already works in plant j, and $\beta_{n(i),j}$ is a neighborhood plant-specific factor taking into account that an individual i coming from neighborhood n ends up in plant j. The specific factor takes into account our network effect arising from the residential neighborhood, i.e., information transmission through employed workers living in the neighborhood. Then, the estimate on γ tells us how much more likely it is that an average plant will hire an individual from neighborhood n that employs a former co-displaced worker than an individual who has no former co-displaced worker at the plant. If there is no co-displaced worker effect, we expect γ to be zero.

Estimation of Equation (2) would require a data set for every possible combination of a worker and a plant that is hiring workers. In our sample, more than 50,000 workers found a job in one of 40,700 firms that were hiring displaced workers. Combining those two figures would expand our data set to more than two billion lines. Even slicing through the data along the 23 self-contained labor market regions, thereby assuming that workers could only have been hired by one of the firms in the region, yields a data set too large to be estimated with plant-neighborhood fixed effects $\beta_{n(i),j}$. Therefore, in order to estimate Equation (2), we follow Kramarz and Nordström Skans (2014) and Saygin et al. (2014) applying a fixed effect transformation. To this end, all cases are eliminated in which there is no within-plant neighborhood variation in A. Then we calculate the fraction of workers in a plant that also employs former co-displaced workers:

$$R_{nj}^{link} = \frac{\sum_i^{n(i),j} E_{i,n(i),j} A_{i,j}}{\sum_i^{n(i),j} A_{i,j}} = \beta_{n,j} + \gamma + \tilde{u}_{n,j}^{link} \tag{3}$$

Similarly, one determines the fraction of workers hired by a plant from a neighborhood from which it has not previously hired any former co-displaced worker:

$$R_{nj}^{noLink} = \frac{\sum_i^{n(i),j} E_{i,n(i),j}(1 - A_{i,j})}{\sum_i^{n(i),j}(1 - A_{i,j})} = \beta_{n,j} + \tilde{u}_{n,j}^{noLink} \tag{4}$$

Finally, the difference between the two ratios eliminates the plant-neighborhood effect and gives an estimate of γ. It is computed as the fraction of those hired by a plant from a neighborhood among those *with* a former co-displaced worker in the plant minus the fraction of those hired by the plant from the same neighborhood among those *without* a former co-displaced worker in that same plant.

Table 7 summarizes the estimates of γ for all 23 labor market regions. We assumed that displaced workers only search for jobs within one of the local labor market areas. There are 57,883 plant-neighborhood pairs with variation in A left in total. Comparing the likelihoods of an average plant hiring from an average neighborhood with and without a former co-displaced worker already employed in that plant reveals that it is more likely for a worker from a specific neighborhood to be hired if the plant hiring already employs a worker from the same former employer. The estimates of γ are significantly larger than zero and indicate a two percentage point higher likelihood that an average firm will hire from a particular neighborhood if it already employs at least one former co-displaced worker. The result is also robust to estimates of the effect for the sub-samples of rural, urban, and metropolitan labor market areas.

However, while the fixed effect transformation eliminated plant-neighborhood specific effects, it may still overestimate a co-worker effect in cases where former co-displaced workers live in the same neighborhood. In order to check whether our results are sensitive to this hypothesis, we applied an alternative specification of the indicator variable A defined such that a former co-displaced worker already working in a new plant does not live in the same neighborhood. Results did not substantiate the hypothesis.

Overall, our estimates using co-displaced workers confirm earlier results by Saygin et al. (2014), Cingano and Rosolia (2012), and Glitz (2013) that co-worker networks play an important role in a worker's re-employment probability. In the context of our approach, we can interpret this finding in two ways. First, it may be that the co-displaced workers who already found a job provide information on vacancies that the neighborhood network does not provide. Second, our findings may be seen as evidence that a co-displaced worker already working for a particular plant helps that plant to overcome the inherent asymmetric information problem when hiring new employees. While all displaced workers in a given neighborhood have the same information on vacancies, those who know someone already working in a plant could have better chances of actually being hired.

4.3 Robustness

Table 8 presents the results of various robustness checks. First of all, one may be concerned about the linear probability model estimated so far given that the dependent variable is an indicator variable. Model (1) replicates the baseline regression using a probit model, which yields essentially the same results as the linear probability model. In this case, the marginal effect is 0.085.

Second, we also ran a placebo experiment by randomizing the assigned employment rates among neighborhoods. Column (2) of Table 8 shows that the estimated coefficient of the neighborhood employment rate is not statistically significant. However, the log of the labor force of the neighborhood becomes significantly different from zero in this case. The negative and significant coefficients for labor force size may be due to the fact that the neighborhood size is correlated with the neighborhood employment rate. We therefore also ran a regression where we included an interaction term of the employment rate and the log of the neighborhood size in our preferred specification (Model (3) from Table 4). It turned out that this did not change our main results.

Third, we changed the definition of being employed part-time or full-time to being employed full-time six months after plant closure, but did not arrive at different results. Fourth, we wanted to investigate whether workers at the closed plants who change jobs more frequently have an effect on our results. We included an indicator variable that takes on the value of one for all displaced workers with tenure of more than two years at their last job, and the interaction of the indicator variable with the neighborhood employment rate. As shown in Model (4), the effect of the neighborhood employment rate increases slightly, and workers with longer tenure are more likely to find a job within the six months after dismissal. However, the interaction term is not significant.

Fifth, Model (5) includes a fixed effect for each of the closed plants, thereby substituting the worker-plant-specific variables we used earlier. Again, the estimated parameter stays robust. This is also comforting in the sense that a selection of workers from specific neighborhoods into particular firms, where the workers might have chosen their neighborhoods for unobserved reasons, seems not to distort our results. Sixth, we estimated a Model (6) where we included indicator variables for different firm sizes and their interaction with the neighborhood employment rate to check whether the size of the former firm affects the likelihood of finding a new job. It does not.

Seventh, in Model (7), we included indicator variables for the type of labor market region and interactions with the neighborhood employment rate, using the urban labor market regions as the reference. It turns out that the effect of the neighborhood employment rate in urban areas is about twice as high as for the overall sample. While the effect of the neighborhood employment rate of the rural labor market regions seems not to differ from that for the urban regions, the estimates for metropolitan areas are smaller. In Model (8), we substituted the linear specification of the neighborhood employment rate with a more flexible specification where we included indicator variables for the size of the neighborhood employment rates. Again, we find that higher neighborhood employment rates increase a worker's re-employment probability. Ninth, we defined the neighborhood employment rate as the time average, which also leaves our results unaffected, as shown in Model (9). Given that most of the variation that we draw upon comes from differences in employment rates between neighborhoods, this result is, however, not surprising.

Tenth, one may be concerned that workers leave plants in advance of plant closure, somehow foreseeing the event. This could distort our sample of displaced workers. Therefore, we constructed an additional variable that indicates whether a worker of a closing plant was employed at that plant half a year before closure. We included this indicator variable and its interaction with the neighborhood employment rate in Model (10). As one might have expected, workers leaving earlier have a higher chance of finding a job within the following half a year. Evaluating the marginal effect of the neighborhood employment rate at its average yields an only slightly lower effect if compared to our basic specification. Finally, for Models (11) and (12), we changed the dependent variable looking into the employment status after 12 and 18 months. Results show that the effects of the neighborhood employment rate on being reemployed 12 and 18 months after closure are somewhat smaller than the effect after six months.

5 Conclusion

Social networks may affect individual workers' labor market outcomes. This paper investigates the extent to which the employment rate among the neighbors of a worker who lost his job with plant closure affects the worker's employment status six months after the displacement. We find that a ten percentage point higher employment rate in the neighborhood increases the probability of having a job six months after the displacement by 0.9 percentage points. Moreover, not only do higher employment rates in the neighborhood help workers to find jobs; workers also profit from higher earnings. On average, a worker's daily earnings increase by 1.7% with a ten percentage point increase in the neighborhood employment rate.

We attempted to unravel the mechanisms that are potentially behind these findings. The positive effect of the neighborhood employment rate on daily earnings suggests that the neighborhood effect is driven by information provision through the worker's social network rather than by a social norm effect. Moreover, there is strong evidence that the neighborhood effect is driven by the employment rate of the socio-demographic group in the neighborhood where the job seeker lives. Further analyses suggest that information that travels through former co-displaced worker networks has an additional effect on a worker's re-employment probability. Our results show that it is more likely that an average firm will hire a worker from a particular neighborhood if that firm already employs a former co-displaced worker. This finding may be interpreted as evidence that plants use the social networks of co-displaced worker who were hired after being displaced due to plant closures to overcome the asymmetric information problem when hiring, or that co-displaced workers who already found a job provide information on vacancies over and above the information provided through neighborhood networks.

The findings have theoretical as well as potential policy implications.

From a theoretical point of view, spill-over effects like those reported here may aggravate small shocks to labor markets, thereby increasing initially minor differences between regions or socio-economic groups. Given that the returns of finding a job are larger for society as a whole than for the individual, policies such as subsidizing job search efforts that internalize externalities may be called for.

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Figure 1: Local labor market regions

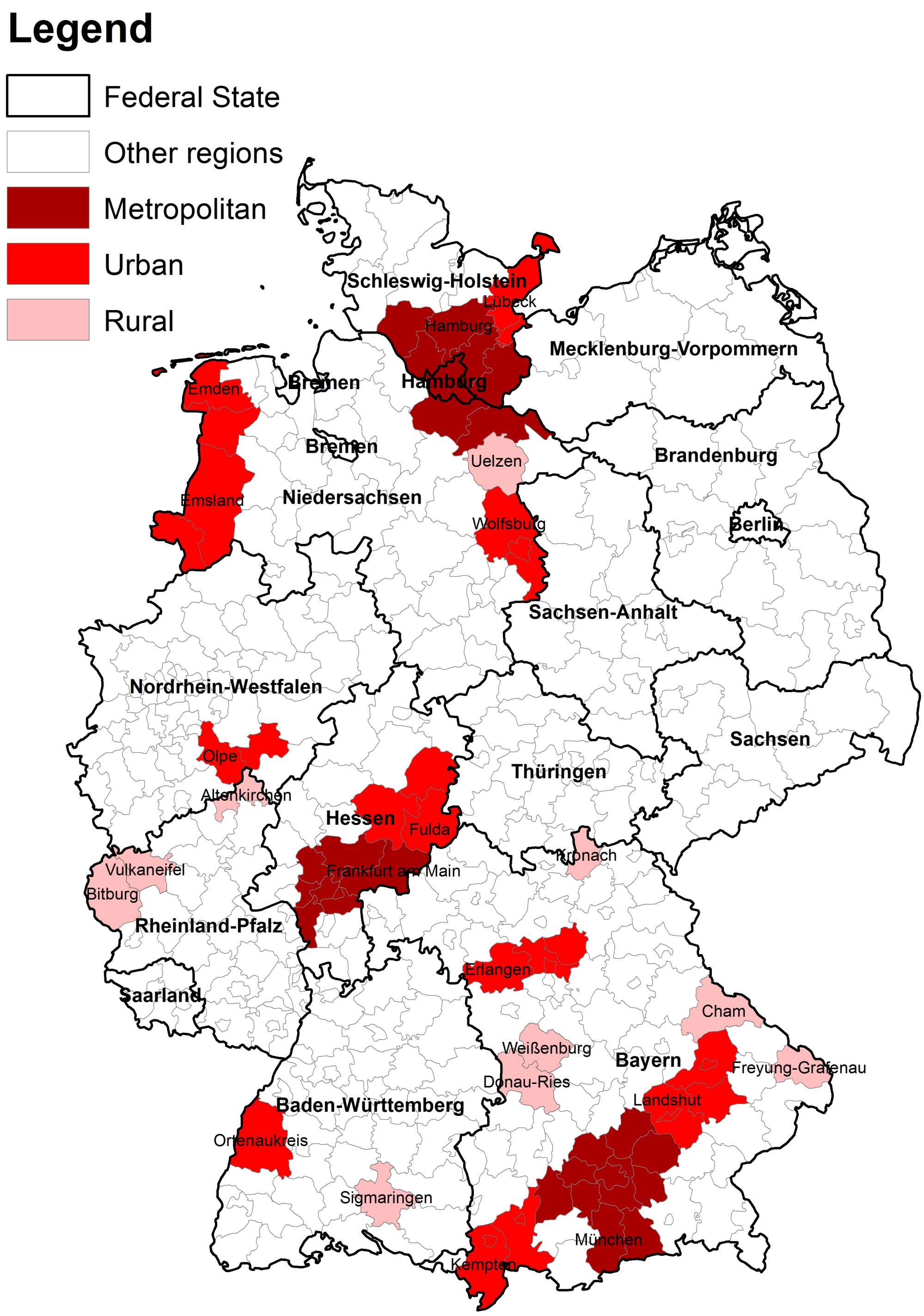

Figure 2: Neighborhood sizes

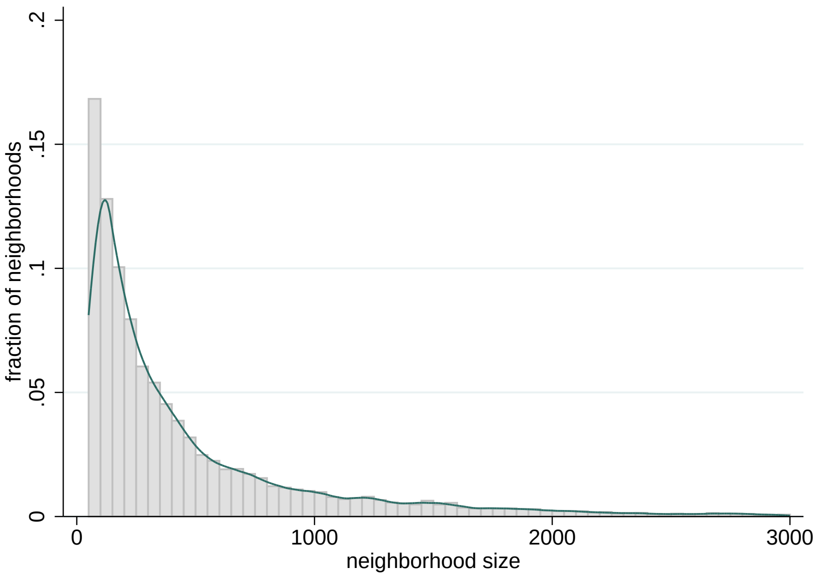

Figure 3: Variation of neighborhood employment rates within labor market regions

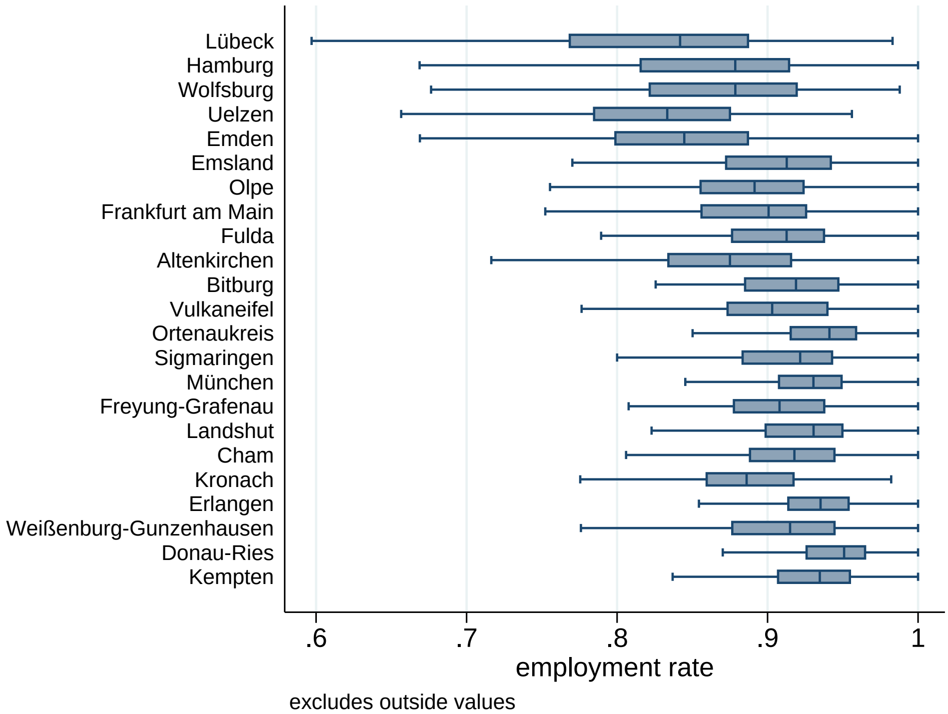

Figure 4: Number of different neighborhoods displaced workers live in by size of closing plant

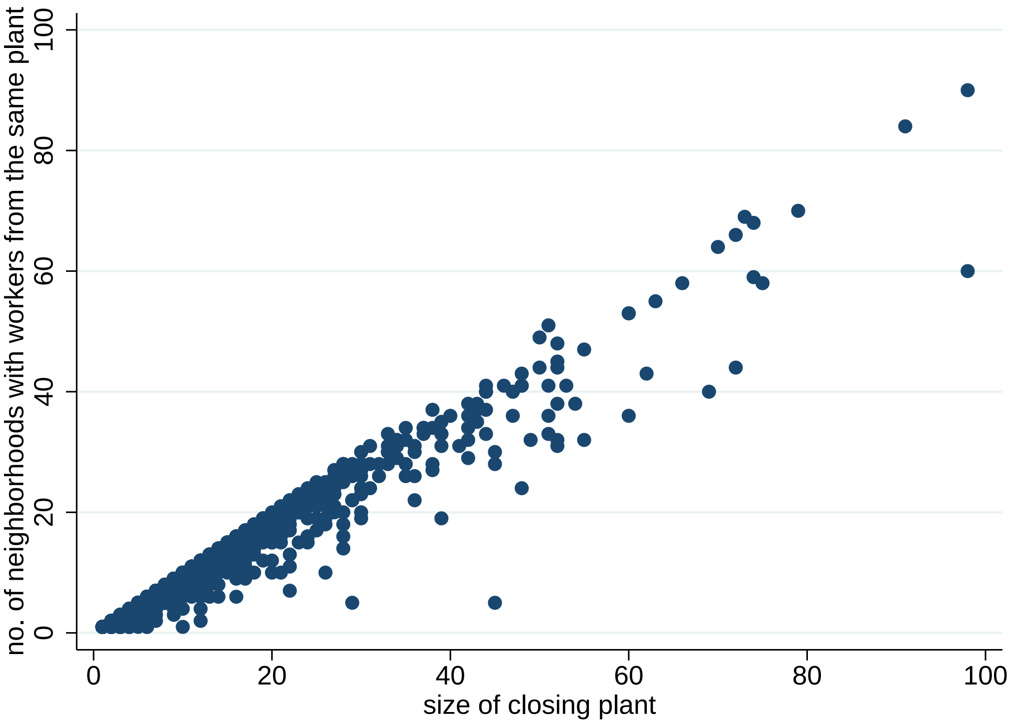

Table 1: Sample statistics - neighborhoods and labor market region

	Mean	St. dev.
Displacements and closing plants		
Number of closing plants	17,877	810
Size of closing plants	5	19
Number of displacements (previously full-time)	30,142	2,174
Neighborhood characteristics		
Number of neighborhoods	8,020	155
Number of full-time displacements in neighborhood	4	6
Share of displacements in neighborhood	0.015	0.009
Labor force in neighborhood	553	808
Employment rate in neighborhood	0.889	0.071
Labor market region (LMR)		
Number of labor market regions	23	
Metropolitan	3	
Urban	10	
Rural	10	
Labor force in labor market region		
Metropolitan	1,137,427	161,925
Urban	161,991	10,028
Rural	37,547	10,527
Number of neighborhoods in labor market region		
Metropolitan	4,680	1,974
Urban	1,722	592
Rural	623	235
Share of all workers displaced in a labor market region		
Metropolitan	0.012	0.001
Urban	0.011	0.002
Rural	0.011	0.002

Notes: The data sets used are the universe of the IEB and the BHP for 23 labor market regions, 2002-2011. Geo-referenced data are available for the years 2007, 2008, and 2009. Averages over unit year are displayed.

Table 2: Sample statistics - displaced workers

	Mean	S.D.
Employment status		
Employed after 6 months	0.592	0.491
Employed after 12 months	0.639	0.480
Employed after 18 months	0.654	0.476
Male	0.620	0.485
Non German	0.177	0.382
Mean age	38.78	11.76
Share of skill group		
Low skilled	0.178	0.382
Medium skilled	0.591	0.492
High skilled	0.231	0.421
Worked and lived in same LMR	0.838	0.369
Real daily wage before dismissal	61.52	36.97
Tenure in years, past 5 years	2.229	1.717
Unemployed, past 5 years (dummy)	0.476	0.499
Number of jobs, past 5 years	2.421	3.245
Share of occupational group		
Occ: Manufacturing	0.269	0.443
Occ: Gastronomy, health, and social services	0.197	0.398
Occ: Commercial and business-related services	0.358	0.480
Occ: IT and natural sciences	0.025	0.155
Occ: Protecting, logistic, and cleaning services	0.151	0.358
Sectoral shares		
Construction sector	0.110	0.313
Manufacturing sector, general	0.059	0.236
Manufacturing sector, metal	0.039	0.193
Manufacturing sector, transport	0.004	0.063
Service sector	0.774	0.418
Agricultural sector	0.014	0.117
Observations	90,426	

Notes: The data sets used are the universe of the IEB and the BHP for 23 labor market regions, 2002-2011.

Table 3: Correlation coefficients on residuals of displaced worker characteristics and average characteristics of neighbors, and surrounding neighbors

Male	German	Low skilled	Med. skilled	High skilled	Age 16-30	Age 31-45	Age 46-65
0.994	0.954	0.996	0.983	0.984	0.988	0.992	0.990

Notes: The data sets used are the universe of the IEB and the BHP for 23 labor market regions, 2002-2011. Correlation coefficients for residuals are reported after regressing first the mean characteristics of displaced workers on average characteristics of the own neighborhood and second, the mean characteristics of displaced workers on average characteristics of the surrounding neighborhoods.

Table 4: Employment probability after six months

	(1)	(2)	(3)	(4)
Employment rate	0.110**	0.087**	0.087**	0.101*
	(0.022)	(0.028)	(0.028)	(0.037)
Employment rate surrounding neighborhood				0.034
				(0.043)
(Log) neighborhood size		-0.003	-0.003	-0.004*
		(0.002)	(0.002)	(0.002)
Dissyear FE	Y	Y	Y	Y
Lmr FE	Y	Y	Y	Y
Lmr*Dissyear FE	N	N	Y	Y
Observations	90,426	90,426	90,426	90,395
R-squared	0.045	0.045	0.046	0.046

Notes: The data sets used are the IEB and the BHP covering the universe of the labor force for 23 labor market regions, 2002-2011. Standard errors clustered at the labor market region level in parentheses, ** $p<0.01$, * $p<0.05$. Covariates included in the estimations are two education dummies, age and the square of it, a dummy for foreign citizenship, four occupation dummies, a dummy indicating whether the worker lived and worked in same labor market region, real daily wage of the previous job, job tenure (past five years), number of jobs (past five years), dummy for being unemployed (past five years) before dismissal, plant size at day of closure, and sector of closing plant.

Table 5: Composition of neighborhood

	(1)	(2)	(3)	(4)
Different gender	-0.0045			
	(0.030)			
Same gender	0.095**			
	(0.032)			
Different citizenship		-0.013		
		(0.010)		
Same citizenship		0.080**		
		(0.018)		
Different education			-0.010	
			(0.026)	
Same education			0.080**	
			(0.019)	
Different cohort				-0.110**
				(0.034)
Same cohort				0.213**
				(0.032)
Observations	90,426	87,788	90,426	90,426
R-squared	0.046	0.046	0.046	0.047

Notes: The data sets used are the IEB and the BHP covering the universe of the labor force for 23 labor market regions, 2002-2011. Standard errors clustered at the labor market region level in parentheses, ** p<0.01, * p<0.05. The cohort is a [-5, +5]-year window around the displaced worker's age. Covariates included in the estimations are two education dummies, age and the square of it, a dummy for foreign citizenship, four occupation dummies, a dummy indicating whether the worker lived and worked in same labor market region, real daily wage of the previous job, job tenure (past five years), number of jobs (past five years), dummy for being unemployed (past five years) before dismissal, plant size at day of closure, and sector of closing plant. In addition we include the log of the labor force in the neighborhood, labor market region fixed-effects, displacement year fixed-effects, and the interaction of latter two fixed-effects.

Table 6: Earnings effect

	(1)	(2)	(3)	(4)
Employment rate	0.183**	0.239**	0.239**	0.246**
	(0.032)	(0.047)	(0.047)	(0.068)
Employment rate surrounding neighborhood				-0.019
				(0.072)
(Log) neighborhood size		0.009*	0.009*	0.008*
		(0.004)	(0.004)	(0.003)
Dissyear FE	Y	Y	Y	Y
Lmr FE	Y	Y	Y	Y
Lmr*Dissyear FE	N	N	Y	Y
Observations	52,225	52,225	52,225	52,207
R-squared	0.418	0.418	0.419	0.419

Notes: The data sets used are the IEB and the BHP covering the universe of the labor force for 23 labor market regions, 2002-2011. Standard errors clustered at the labor market region level in parentheses, ** $p<0.01$, * $p<0.05$. Covariates included in the estimations are two education dummies, age and the square of it, a dummy for foreign citizenship, four occupation dummies, a dummy indicating whether the worker lived and worked in same labor market region, real daily wage of the previous job, job tenure (past five years), number of jobs (past five years), dummy for being unemployed (past five years) before dismissal, plant size at day of closure, and sector of closing plant.

Table 7: Co-worker effect

	Rural	Urban	Metropolitan	All
γ	0.012**	0.025**	0.019**	0.020**
	(0.005)	(0.002)	(0.001)	(0.001)
R_{nj}^{noLink}	0.018**	0.010**	0.001**	0.003**
	(0.003)	(0.001)	(0.000)	(0.000)
R_{nj}^{Link}	0.030**	0.035**	0.021**	0.023**
	(0.005)	(0.002)	(0.001)	(0.001)
Observations	1,202	9,362	47,319	57,883

Notes: The data sets used are the IEB and the BHP covering the universe of the labor force for 23 labor market regions, 2002-2011. Standard errors clustered at the labor market region level in parentheses, ** $p<0.01$, * $p<0.05$.

Table 8: Robustness

VARIABLES	(1) Probit	(2) Placebo	(3) Full time	(4) Tenure	(5) Plant FE	(6) Plant size	(7) Region	(8) Quintile Er	(9) Mean Er	(10) 6 months before	(11) 12 months	(12) 18 months
Employment rate (Er)	0.085**		0.087**	0.110*	0.088*	0.093**	0.184**			0.185**	0.064**	0.075**
	(0.027)		(0.025)	(0.042)	(0.041)	(0.032)	(0.031)			(0.053)	(0.021)	(0.024)
(Log) neighborhood size	-0.003+	-0.006**	-0.002	-0.003+	-0.004	-0.003+	-0.003+	-0.003	-0.003	-0.004+	-0.007**	-0.007*
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Random employment rate		0.022										
		(0.019)										
Tenure above two years				0.081*								
				(0.038)								
Er * tenure above two years				-0.061								
				(0.045)								
Plant size 11-100						0.008						
						(0.043)						
Plant size 101-500						0.117						
						(0.177)						
Plant size above 501						0.356						
						(0.351)						
Er * Plant size 11-100						0.029						
						(0.051)						
Er * Plant size 101-500						-0.059						
						(0.196)						
Er * Plant size above 501						-0.507						
						(0.396)						
Rural LMR							-0.154					
							(0.133)					
Metroplitan LMR							0.104**					
							(0.036)					
Er * Rural LMR							0.008					
							(0.152)					
Er * Metropolitan LMR							-0.135**					
							(0.044)					
Er 2nd quintile								0.015*				
								(0.007)				
Er 3rd quintile								0.014*				
								(0.005)				
Er 4th quintile								0.026**				
								(0.006)				
Er 5th quintile								0.020*				
								(0.008)				
Mean employment rate									0.099**			
									(0.028)			
Employed 6 months before plant closure										0.165**		
										(0.038)		
Er * Employed 6 months before plant closure										-0.135**		
										(0.041)		
Observations	90,426	90,426	90,426	90,426	90,426	90,426	90,426	90,426	90,426	90,426	90,426	90,426
R-squared	0.035 (a)	0.046	0.068	0.046	0.029	0.048	0.046	0.046	0.046	0.048	0.044	0.045
Number of plants					53,630							

Notes: The data sets used are the IEB and the BHP covering the universe of the labor force for 23 labor market regions, 2002-2011. (a) Pseudo R-squared. Standard errors clustered at the labor market region level in parentheses, ** p<0.01, * p<0.05. Covariates included in the estimations are two education dummies, age and the square of it, a dummy for foreign citizenship, four occupation dummies, a dummy indicating whether the worker lived and worked in same labor market region, real daily wage of the previous job, job tenure (past five years), number of jobs (past five years), dummy for being unemployed (past five years) before dismissal, plant size at day of closure, and sector of closing firm. In addition, we include the log of the labor force in the neighborhood, labor market region fixed effects, displacement year fixed effects, and the interaction of latter two fixed effects.