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# The causal impact of social connections on firms' outcomes[a]

by

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**Abstract**

The paper studies how social connections affect firm-level hiring decisions and performance. We characterize the social connections of firms' employees using register data and for causal identification we use job displacements, which create directed positive shocks towards connected firms by increasing these firms' available supply of connected labor. We ascertain that our results are fully driven by these directed supply shocks. Our results show that firms appear to prefer to hire employed workers to whom they are connected over unconnected or unemployed workers. Employed and connected workers mostly go to high-productivity firms, whereas unemployed and unconnected workers tend to go to low-productivity firms. Strong connections – family, recent, durable, formed in small groups, between socially similar agents – matter the most. A displacement shock causes connected firms, in particular low-productive ones, to hire more of the connected workers, while leaving unconnected hires and separations essentially unaffected. Increases in the supply of connected labor, therefore, cause the creation of additional jobs at the firm level. By using these shocks, we can also show that hiring connected workers has a positive causal impact on firm performance. Our results are consistent with a stylized framework where connections reduce hiring frictions and where the firms' ability to hire connected workers is a function of these workers' outside options.

Keywords: Networks, job search, job displacement, job creation
JEL-codes: J60, J30, J23

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## 1 Introduction

Research has shown that firms recruit intensively using social connections in order to reduce information frictions (see, e.g., Montgomery, 1991; Burks et al., 2015; Dustmann et al., 2016; Hensvik and Skans, 2016). However, we know very little about how firms, endowed with various levels of productivity, differ in their use of these connections. This is likely to be important, since theories of frictional job search and job-to-job mobility show that a firm's ability to attract and recruit workers strongly hinges on its position in the productivity distribution (see, e.g., Postel-Vinay and Robin, 2002; Cahuc et al., 2006; Lise and Robin et al., 2017). Recent empirical studies have also documented the increased role of firms in generating wage inequality, while leaving the role of firms' productivity and social connections relatively unexplored (see, e.g., Card et al., 2013; Card et al., *forthcoming*; Schmutte, 2016; and Song et al., 2016). Because the existing literature has so forcefully shown that both productivity and connections matter for workers' mobility and firms' hiring decisions, this paper examines how they interact. We document that the use of social connections varies with a firm's attractiveness and hiring needs and assess the causal impact of these connections on important firm-level outcomes such as total hires, job separations, and performance measures. Our causal identification strategy uses establishment closures and the fact that (displaced) workers are connected to (other) firms through family members, former coworkers, neighbors, and previous classmates that we can identify using Swedish register data. These connections direct the supply of displaced workers towards connected firms, thereby creating an idiosyncratic labor supply shock, increasing these firms' opportunities to attract connected workers.

When we document how key firm-level characteristics relate to social connections, and the origin of new hires, two important patterns emerge: First, hiring through social connections and recruitments of already employed workers is positively associated with firm-level productivity. The use of more formal hiring strategies (i.e., hiring non-connected and unemployed workers) instead appears more prevalent among low-productive firms. Second, firms rely more on social connections when they hire fewer workers. This suggests that firms exhaust their potential for connected hires before turning to the unconnected market. These findings suggest that social connections are the firms' preferred hiring channel as suggested by, among others, Casella and Hanaki (2006).

As a next step, we outline a theoretical framework that matches the patterns presented just above and that guides our core empirical analyses. In line with much of the previous literature (Montgomery, 1991; Dustmann et al., 2016), we presume that social connections provide firms with better *ex ante* information on the productivity of the employment relationship (see, e.g., Hensvik and Skans [2016] for direct empirical evidence) and consequently reduce the screening costs.[1] However, a firm's ability to reduce hiring costs by hiring connected workers is constrained by three factors: First, not all connected workers will be a good match for the firm. For simplicity, we assume that match quality is binary (productive or not) and revealed before production starts (as in Fujita and Moscarini [2013]). Second, connections are useful only if they transmit information. Following Granovetter (1973), connections that frequently transmit information are labeled "strong". Our empirical work carefully explores this aspect. Third, a worker who is connected to a firm through a strong tie, and who certainly would be a productive match in that firm, may nonetheless not be recruited if already employed in a more attractive firm (cf., Postel-Vinay and Robin, 2002). The latter constraint is clearly binding for low-productive firms in particular. Moreover, each firm has access to a finite (possibly empty) supply of connected labor that can be hired without frictions. Job displacements within the firm's network of social connections will increase the size of this connected supply of labor by reducing the value of the outside options for the connected workers that become displaced. The potential benefits of such displacements are larger for low-productive firms. Because hiring connected workers is costless, and therefore always preferred to costly market search, firms will turn to the market only if their connected supply is exhausted. This is more likely to occur when many workers are hired at the same time. Total hires (and thus job creation) then becomes a positive function of the connected supply of labor, since connections allow firms to circumvent the costs and frictions associated with hiring from the market.

[1] This also parallels Fujita and Moscarini (2015) who contrast recalled workers (i.e., workers who can be put into production without being screened) with workers hired through the market (i.e., workers who need to be pre-screened). Hence, the information conveyed through social connections resembles that contained in recalls.

Our empirical analyses exploit job displacements, due to establishment closures, to study this process in more detail.[2] In the first part of these analyses, we show that establishments are indeed more likely to hire displaced workers who are connected to one of their employees rather than unconnected workers from the same displacement event. Hence, pre-existing social connections, as we measure them, have predictive power. For multi-establishment firms, the effect on the probability that other establishments, within the same firm and local labor market, hire workers is much smaller. This is strong evidence for that the increased probability of hiring connected workers is due to the connections as such, rather than correlated abilities. Moreover, stronger social connections are better predictors of hiring patterns than weaker social connections:[3] Family members (parents, adult children, siblings and spouses) are more important than former coworkers, who in turn are more important than former classmates and present neighbors. In general, the importance of social connections increases with the similarity of the agents,[4] which highlights the social dimension of connections. This is reinforced by the fact that the importance of social connections increases with the duration of interaction, and decreases with both time since interaction and size of the group in which they interaction took place. Our findings also suggest that there is competition for referral information, making social connections less valuable if other searching workers have connections to the very same establishment, and more so if these competing workers have stronger connections.[5]

The second part of our analysis exploits the same displacement events to study the causal impact of social connections on the connected establishments, utilizing the fact that job displacements create shocks to the connected supply of labor in some, but not in other, firms. Our analysis, which uses establishment fixed-effects models that account for local industry-specific displacement rates, shows that job displacements within a firm's network result in a substantial increase in the hiring of connected workers. This increase is the largest among low-productive firms, presumably because less productive

[2] We are not the first to examine networks in the context of displacements, although our approach is very different from that of the previous literature. In particular, Cingano and Rosolia (2012), Glitz (2017), and Saygin et al. (2014), studied the relationship between the employment rate among former coworkers and the speed of reemployment after job displacement. Saygin et al. (2014) also document the importance of former coworkers for matching patterns after displacement.

[3] See also Kramarz and Skans (2014) and Gee et al. (2017) for similar results.

[4] See Bayer et al. (2008) for similar findings.

[5] This is a prevalent idea in the literature on job search networks (see, e.g., Calvo-Armengol and Jacksson, 2004; and Boorman, 1975).

firms struggle to attract (connected) workers as long as these are employed by other firms. Strikingly, we find large (in relative terms) positive effects on the total number of hires. Most of this response is driven by an increase in the number of connected hires, and there is no (statistically significant) crowding-out of unconnected hires. For instance, for each displaced family member, 0.017 are hired in each connected establishment. The corresponding increase in total connected hires (i.e. displaced or not) is 0.012. This implies that the crowding-out of other connected hires is small (only 27%). Instead, most of the response (73%) is because of an increase in the overall number of connected hires. The reduction in unconnected hires is even smaller (and statistically insignificant). Thus, total hires increase by only slightly less than 0.012. Separations are unaffected, which means that firms create jobs in response to the exogenous expansions of the available supply of connected workers.

An emerging question is whether hiring through social connections is good or bad for the firm? We first show that hired workers who has connections to the particular establishment are much more likely to remain in their new job after three years; a finding that is consistent with the previous literature (e.g., Kramarz and Skans, 2014; Dustmann et al., 2016; Burks et al., 2015). Perhaps more importantly, and we believe for the first time, we estimate the causal impact of hiring workers through social connections on firm-level production and productivity.[6] By exploiting job displacements among workers with connections to the firms as identifying variation, we are able to handle reverse causality, i.e. the concern that connected hires increase because of positive productivity shocks. We find that connected hires, in fact, causes an increase in firm-level production and labor productivity, a result which suggests that social connections, indeed, are beneficial to the firms that make use of them.

We note that there are potential threats to our identification strategy, in particular if our directed supply shocks also captured demand shocks or market-level supply shocks (cf., e.g., Gathmann et al., 2017; and Cestone et al., 2017).[7] Further results, however, suggest that our findings are robust to these threats. More precisely, we show that the

[6] The most closely related previous studies have found a positive association between hiring method and individual productivity within specific firms, but without a causal identification strategy (e.g., Yakobovic and Lup, 2006; Burks et al., 2015). Both Bandiera et al. (2007) who uses a field experiment among fruit pickers, and Kramarz and Thesmar (2013) who studies the relationship between CEO connectedness and firm performance, find that connectedness is bad for performance in these settings.

[7] A main difference to Gathmann et al. (2016) is that they focus on very large mass-layoffs (i.e., a workforce reduction of at least 500 employees during a two-year period), whereas most of the events in our data are closures of small to medium sized establishments for which the market effects are likely to be much smaller.

establishments are unaffected by job displacements among workers connected to other establishments within the same industry and location. In addition, our results remain stable when restricting the attention to connected establishments that operate in a different industry than (but the same location as) the closing firm.

Overall, our results are consistent with our stylized framework, where connections reduce frictions and the effective connected supply is a function of outside options within the network.  Strong social connections contribute to a more efficient matching process. Interpreted through the lens of our theoretical framework, the results thus suggest that firm-level hiring and job creation is endogenous to the ability to hire without frictions.

Our study is related to previous studies using register data to investigate the role of various networks in the job search process: neighborhood networks (e.g., Bayer et al., 2008; Hellerstein et al., 2011; Schmutte, 2016), former coworkers (e.g., Cingano and Rosolia, 2012; Saygin et. al., 2014; Hensvik and Skans, 2016; Glitz, 2017), ethnic networks (e.g., Dustmann et al., 2016), and parents (e.g., Kramarz and Skans, 2014). A number of studies have also used detailed personnel records from a small number of larger firms (e.g., Burks et al., 2015; and Brown et al., 2016), but without being able to study the role of firm heterogeneity or the causal impact on firm performance. The studies most closely related to ours are Kramarz and Skans (2014) that documented the matching patterns for young workers while characterizing the agents on both sides of social connections, and Dustmann et al. (2016) that studied matching efficiency as inferred from post-match wage trajectories and tenure. The present study is, however, the first to relate social connections to firms' growth and performance.

Beyond the literature on social networks, there are other studies that have explored how access to (suitable) workers affects firms' employment responses. An interesting example is Horton (*forthcoming*) who uses a field experiment showing that firms with a low expected vacancy yield increase their hiring rates when presented with well-targeted candidates. Similarly, Cahuc et al. (2014) examine the impact of hiring credits on job creation, again finding positive results. Dustmann and Glitz (2015) study hiring responses to changes in the local supply of labor. Moreover, because closures of very large establishments will have an impact on the available market supply, our research is also related to Gathmann et al. (2017) who examine how such closures affect the surrounding region. Cestone et al. (2017) also exploit such shocks, but focus on firm-to-firm mobility within internal labor markets of business groups.

The rest of the paper is structured as follows: Section 2 presents the data. Section 3 provides motivating descriptive results. Section 4 presents our theoretical framework and outlines the empirical set-ups used in the following sections. Section 5 studies to what extent social connections predict who firms hire after displacement events. Section 6 presents our analysis of how job displacements among connected workers affect the firms. Section 7 concludes.

# 2 Data

## 2.1 The administrative registers

The analysis is based on administrative data for the entire Swedish population during the period 1985–2009. The data set links various administrative records through anonymized identification codes at the personal, firm and establishment level. The main source is an employment register (*Registerbaserad arbetsmarknadsstatistik*) with information from the national taxation authorities. The statutory income statements, filed to the taxation authorities by the employers, identify both the employee and the establishment's organization. This allows us to link all employees to their employer. The social connections are identified using information on family trees from population-wide birth records (*Flergenerationsregistret)*, information on household members and neighbors from population registers (*Registret över totalbefolkningen*) and information on graduation classes from high school and college/university from graduation registers. Finally, firm accounts data (*Företagens ekonomi*) is used to measure firm sales and value added.[8]

## 2.2 The closing establishments and displaced workers

We identify establishment closures during the narrower period 1990–2006 to allow for both a pre-closure period when connections could be created and a post-closure follow-up period for the workers and the hiring firms. To identify the establishment closures, we first select establishments with a non-missing identifier in November of year *t*, but whose identifier was no longer in the data in November year *t*+1. We also impose the

[8] These firm data are only available from 1997 onwards.

following restrictions: we only include closures (i) of single-establishments firms, (ii) in the private sector,[9] and (iii) with at least four employees in November year *t*.[10]

To eliminate cases where the establishment identifier was missing for other reasons than that the establishment had ceased to operate (e.g., mergers and dispersals), we follow Hethey-Maier and Schmieder (2013) and define “true” closures (or “atomized deaths”) as those where no cluster of more than 30 percent of the workforce at the exiting establishment in year *t* was found at the same establishment in year *t*+1.

The displaced workers are consequently defined as those, of ages 20–64 years, who in November of year *t* were employed at an establishment that closed down during the following 12 months. For each of these workers we identify their social connections as described in the next section.

### 2.3 Social connections

We consider four broad types of networks: close family members, former classmates, former coworkers, and (a subset of) neighbors. When defining these connections we restrict attention to the cases for which we can be relatively confident that there was an actual interaction between the agents at some point. Hence, we discard less well-identified cases.

*Family members* include parents, children, spouses, and siblings (full or half). We rely on birth records (which are near complete for the Swedish born) to identify parents, children, and siblings. Spouses are defined by household indicators, which capture those who resided together and who either were married or had a joint child.

*Former classmates* are identified at high school and/or at college/ university. High school students are tracked into different occupational programs that usually are offered as one class per school and program combination. Therefore, we identify classmates from high school as those who shared school, program, and graduation year. Students from university are similarly identified as those who graduated at the same college/university, within the same field/major, and during the same year. The graduation records are available from 1985 onwards. This implies that we only have information on former classmates for the younger cohorts. However, our results indicate

[9] In practice, we do this by excluding the public sector defined as all organizations with 2-digit institutional codes of 11–14 or 3-digit institutional codes 151, 152, 501 and 502 before 1999, and all firms with 1-digit institutional codes of 3–5 or 3-digit institutional code 721 thereafter.

[10] Employees are here limited to those having the particular establishment as their main workplace (i.e., the establishment in November from which they receive the largest annual earnings).

that the value of connections from school depreciate fairly rapidly over time (see Section 5.2.3). There are also cases where we fail to identify what could reasonably be defined as a class. When the same schools cater very large cohorts within one field, they are presumably divided into different classes although we cannot separate them. To reduce the influence of pure measurement errors in our measured connections we have, therefore, removed the cases where more than 100 former students are found within the same (constructed) class.[11]

*Former coworkers* comprise workers who were employed at the same workplace in the past. We limit former coworkers to those on the most recent previous workplace, using data going back to 1985.[12] When these workplaces are very large, the measured connections will be very imprecise and noisy. We therefore constrained the data to cases with less than 100 employees at the former workplace (i.e. analogous to the procedure for former classmates).[13]

*Neighbors* are defined as those residing in the same area according to Statistics Sweden's neighborhood indicator SAMS (Small Areas for Market Statistics). There are about 9,200 such areas in Sweden containing on average approximately 1,000 residents. Hence, the identified networks of neighbors will in most cases extend far beyond the group of actual connections. In order to define more appropriate measures of residential networks we include only those who both reside in the same SAMS area and have children in the same ages.[14] The intended logic is that parents with children in the same ages are more likely to meet (or have met) at playgrounds, schools or other local child activities. The notion received strong empirical support in Bayer et al. (2008) that showed that neighbors with same-aged children were substantially more likely to work together than other neighbors. Analogously to former coworkers and classmates we restrict our analyses to groups of neighbors (with children in the same age) with less than 100 people to reduce the impact of measurement errors.[15]

Three additional requirements are imposed on all the social connections defined above: each individual connected to a displaced worker must (i) reside within the same

[11] This excluded 21 and 10 percent of high school and college/university "classmates", respectively.
[12] We only consider each employee's main workplace (i.e., establishment) in the month of November.
[13] This excludes 25 percent of the previous coworkers.
[14] Using Statistics Sweden's child age groups: 0–3, 4–6, 7–10, 11–15, 16–17, or 18+ years.
[15] This excludes 81 percent of others in the same SAMS area.

county;[16] (ii) be of age 20–64 years; and (iii) be employed at an establishment with an associated identifier in the data.[17] All restrictions were imposed after applying the group size constraints of 100 that were described above.

# 3 Description: Connections, hires and firm characteristics

## 3.1 Firm measures

We use the data described above to characterize the social connections, yearly hiring patterns, and firm-level performance of each establishment. For this description we construct a number of key measures: First, the number of (outside) workers who are socially connected to each establishment through the establishment's present employees. Second, to characterize firms' hiring strategies, we calculate the number of hired workers overall. Within the group of new hires, we calculate the share socially connected workers, the share newly displaced, the share entering from unemployment and other jobs respectively (as measures of the firm's (in)ability to attract job-to-job movers). Finally, firm-level performance is measured by value added per worker.

## 3.2 Descriptive statistics

Table 1 presents descriptive statistics on flows, stocks, and productivity of labor, as well as the fraction of hires through various channels and from various origins. The sample only includes establishments in private sector firms (for which we have measures of productivity), that hires at least one worker in the given year, and with multiple observations during the observation period (because identification comes from within-establishment changes).[18] Most establishments are small (average size is 11 employees) and have been in operation for more than 3 years (83 percent), and have high hiring and separation rates (0.39 and 0.26, respectively). Note that these figures are conditional on hiring at least one worker, the corresponding rates for the full sample are 0.22 (Table A1). For each establishment, we observe, on average, 248 connections; 11 percent of all

[16] The average population in a county is 400,000.

[17] Workers who are employed in establishments without a well specified geographic location (e.g., home care workers) lack the establishment identifier.

[18] Table A1, in Appendix A, shows the corresponding figures for the sample also including non-hiring establishments. A few additional restrictions were imposed on the data: To eliminate the influence of outliers with respect to year-to-year employment changes and changes in the hiring rate, we drop cases where (i) net growth exceeds 100 percent or (ii) the establishment is in the top (bottom) 0.5 percentile in the distribution of total hires (conditional on establishment and year fixed effects) and give the establishment a new unique identifier after that event. If an (original) establishment display a large change according to these criteria more than once during the observation period it is removed altogether. Finally, we remove establishments that are themselves part of the closing-firm sample in order to avoid simultaneity problems.

hires are connected. Because job displacements, as we measure them, are rare events,[19] only 1.6 percent of the hired workers were displaced during the previous year, whereas 31 percent of all hired workers had some unemployment experience during the year.

Table 1 Summary statistics for the establishment-level productivity sample

| | Mean | Std. Dev. | Median | Min | Max |
|---|---|---|---|---|---|
| *Establishment characteristics* | | | | | |
| Size (#employees) | 11.07 | 12.20 | 7 | 2 | 564 |
| Young establishment[a] | 0.166 | 0.372 | 0 | 0 | 1 |
| Log firm VA per worker in *t*-1[b] | 6.000 | 0.562 | 6.0 | -1.9 | 13.4 |
| Hires per worker | 0.390 | 0.350 | 0.3 | 0.005 | 11 |
| Separations per worker | 0.264 | 0.291 | 0.2 | 0 | 21.5 |
| *Number of connections* | | | | | |
| Any connection | 247.7 | 304.5 | 152 | 0 | 14,569 |
| Family | 36.3 | 46.8 | 22 | 0 | 2,148 |
| Coworkers | 59.3 | 83.8 | 27 | 0 | 1,657 |
| Classmates | 78.4 | 127.0 | 37 | 0 | 7,796 |
| Neighbors | 73.7 | 113.9 | 36 | 0 | 5,314 |
| *Fraction of hires that are connected* | | | | | |
| Any connection | 0.107 | 0.257 | 0 | 0 | 1 |
| Family | 0.078 | 0.228 | 0 | 0 | 1 |
| Coworkers | 0.029 | 0.131 | 0 | 0 | 1 |
| Classmates | 0.004 | 0.049 | 0 | 0 | 1 |
| Neighbors | 0.013 | 0.089 | 0 | 0 | 1 |
| *Fraction of hires that are:* | | | | | |
| Unemployed in *t*-1 | 0.308 | 0.371 | 0.143 | 0 | 1 |
| Displaced in *t*-1 | 0.016 | 0.097 | 0 | 0 | 1 |
| # of establishment-year observations | | | 615,373 | | |

*Notes:* The sample includes establishments in private sector firms, for which the productivity measures are available, that hired at least one worker in a given year.
[a] Young establishments are 3 years or less.
[b] Productivity is measured at the firm level.

### 3.3 Descriptive analysis

In this subsection, we show various associations between important firm-side characteristics (size, age, and labor productivity) and hiring patterns. In order to eliminate the influence of regional cycles and cross-industry differentials, all reported associations are conditional on annual local labor market (industry-by-county-by-year) fixed effects. We also control for the number of observed connections throughout.

We start by documenting the conditional associations between firm-side characteristics and the share of hires of workers with observed social connections to the firm's present employees (see Table 2). First, productive firms appear more likely to hire socially connected workers. This finding is potentially interesting, since previous research has been rather silent about the relationship between firms' productivity and their use of social connections in the hiring process. In addition, connected hires are more prevalent in smaller establishments. Furthermore, there is a negative association

[19] Recall that we only identify job-displacements from closures in single establishment firms in the private sector.

between the hiring rate and the share hired through social connections. (i.e., firms rely less on connections when they hire many workers in the same year).[20] This suggests that connected hires is the preferred hiring method and that firms only hire from the (non-connected) market when their demand for labor exceeds the supply of connected workers. At first glance, younger establishments appear to rely less on social connections. However, this effect is essentially due to their larger hiring rate; when conditioning on the frequency of hires, younger establishments are instead found to rely more on social connections (compare Column [1] and [2]). Finally, firms with high separations rates rely less on social connections when hiring (Column ([4]).

The final column of the table repeats the analysis using data averaged across the sample period to reduce the impact of high-frequency simultaneity between the different measures, without changing the results.

Table 2 Explaining connected hires as share of total hires

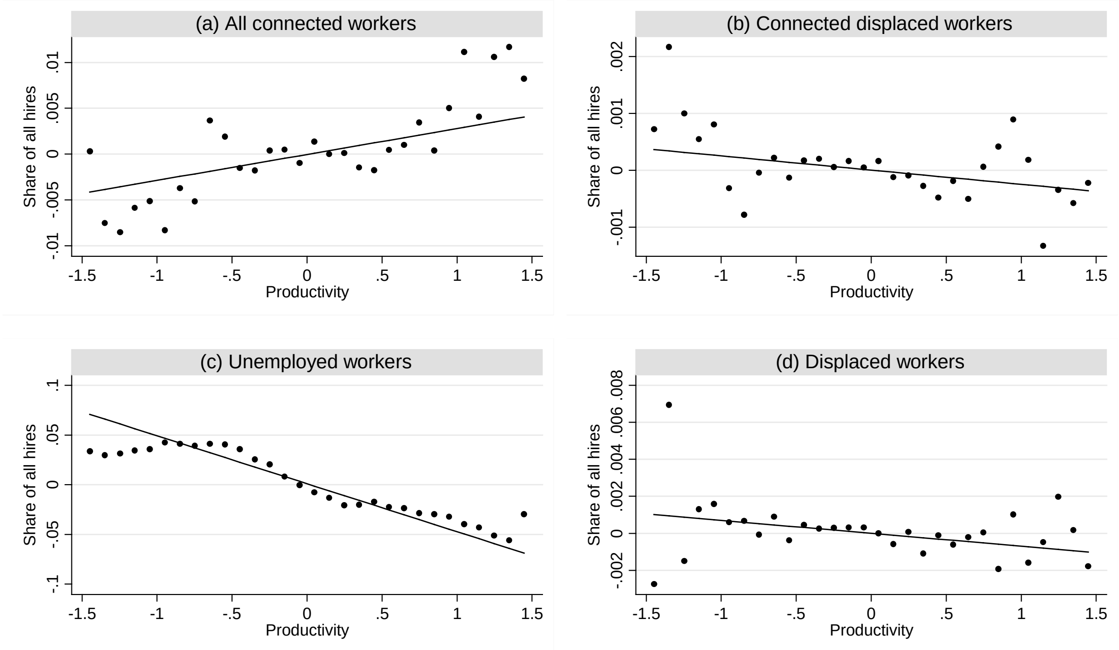
| | Establishments year by year | | | | Establishment average |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Productivity* | | | | | |
| Ln (VA/worker)$_{t-1}$ | 0.0028 | 0.0026 | 0.0026 | 0.0016 | 0.0025 |
| | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0015) |
| *Size* | | | | | |
| Ln (# workers)$_{t-1}$ | -0.0210 | -0.0282 | -0.0282 | -0.0287 | -0.0391 |
| | (0.0014) | (0.0015) | (0.0015) | (0.0015) | (0.0020) |
| *Establishment age* | | | | | |
| < 3 years | -0.0023 | 0.0024 | 0.0024 | 0.0052 | 0.0040 |
| | (0.0012) | (0.0012) | (0.0012) | (0.0011) | (0.0021) |
| *Hiring rate* | | | | | |
| Hires/worker | | -0.0433 | -0.0433 | -0.0285 | -0.0506 |
| | | (0.0012) | (0.0013) | (0.0012) | (0.0025) |
| *Previously displaced* | | | | | |
| Share of hires | | | -0.0038 | -0.0031 | 0.0034 |
| | | | (0.0039) | (0.0040) | (0.0106) |
| *Separation rate* | | | | | |
| Separations (by next year)/worker | | | | -0.0586 | -0.1102 |
| | | | | (0.0021) | (0.0041) |
| # observations | 615,373 | 615,373 | 615,373 | 615,373 | 176,560 |
| R-squared | 0.0351 | 0.0378 | 0.0378 | 0.0413 | 0.0529 |
| Mean dependent variable | 0.107 | 0.107 | 0.107 | 0.107 | 0.124 |
| Network size | Yes | Yes | Yes | Yes | Yes |
| Fixed effect | LLM | LLM | LLM | LLM | LLM |

*Notes*: The dependent variable is the connected hires as share of total hires. The sample includes establishments in private sector firms, for which the productivity measures are available, that hired at least one worker in a given year. The first four columns use yearly observations. The last column instead uses the averages over the sample period. . Hiring and separation rates are calculated as shares of the incumbent work force. All estimations control for the number of observed connections of each type as a share of the present workforce. Fixed effects are at the local labor market (county-industry-year) level. All standard errors are clustered at the industry-county level.

[20] We have verified that the result is robust to the inclusion of establishment fixed effects.

In Figure 1, we further explore how firms' productivity is related to their use of social connections by plotting the non-parametric relationship between productivity and the share of connected hires, displaced hires, connected displaced hires, and unemployed hires, respectively, conditional on the same controls as in Table 2 (i.e. market fixed effects, age, size and connections). The relationship with the share of connected hires is positive and appears to be particularly pronounced in the extreme ends of the productivity distributions (Figure 1a). However, even though productive firms hire more connected workers overall, low-productive firms appear to hire more connected *displaced* workers (Figure 1b). Potentially, this indicates that connected workers' lack of alternative options of offer hiring opportunities to less productive firms. Furthermore, the clear negative association between productivity and the share of hires from unemployment (Figure 1c) supports the notion that productivity is a good measure of firm attractiveness (implicit in Postel-Vinay and Robin [2002], among others).[21].

Figure 1 Productivity and hiring patterns




*Note:* This figure plots correlations between different hiring channels and productivity, conditional on industry-by-county-by-year fixed effects, an indicator for if the establishment is young (≤ 3yrs), lagged size, and the fraction of family members, coworkers, classmates and neighbors that the establishment is connected to. Residual productivity is binned into 30 equally-sized bins. The solid line shows the best linear fit estimated using OLS.

[21] In Appendix C, we also show that more productive firms pay higher firm-specific wages, i.e., the firm fixed effect from an Abowd-Kramarz-Margolis (AKM) decomposition (Figure C1), and have a net (positive) inflow of job-to-job movers (Figure C2). The AKM-effects are, however, estimated with considerable noise in these (often small) establishments.

Overall, these descriptive results suggest that hiring through social connections is positively related to firm-level productivity. Firms that are low-productive (i.e., in a disadvantaged position) are more likely to hire non-connected workers, and firms rely more on social connections when they hire fewer workers, which indicates that firms exhaust their potential for connected hires before turning to the unconnected market. Together, these results suggest that hiring through social connections is the firms' preferred hiring method. However, the estimates presented to this point are merely associations. In order to assess the nature of any causal relationship, between the use of social connections and these key firm-side outcomes, we need some exogenous variation that affects the employers' hiring potential (of connected workers). Hence, we will exploit job displacements, due to establishment closures, as exogenous shocks to each firm's connected supply of labor.

# 4 Theoretical framework and empirical set up

## 4.1 The theoretical framework

In order to structure ideas about how displacement shocks (i.e., job displacements among workers socially connected to a firm's employees) affect firms' hiring patterns, we outline a very stylized framework of firm-level hiring with frictions. The model is designed to be consistent with the descriptive evidence presented above. Most notably, the framework should match the following facts:

1) Only a small share of all social connections results in matches.
2) More attractive firms hire more connected workers.
3) Less attractive firms hire more connected displaced workers.
4) Less attractive firms hire more unemployed workers.
5) Firms rely more on social connections when they hire fewer workers at the same time.

When outlining the framework, we formalize the key elements needed to understand our empirical analysis and ignore all other aspects. In particular, we discuss details regarding the interaction between job search networks, job displacements, and firm heterogeneity, but refrain from modeling the market matching process and let this channel be a residual, black-box, alternative to our object of interest (i.e., the social connections). Moreover, we focus on the firm's hiring decision and do not model any general equilibrium aspects.

### 4.1.1 Heterogeneous firms

Firms are heterogeneous and can be ranked according to their productivity, and workers benefit from being employed at a more productive firm. We denote firms by $k$ and let firm-specific wages ($w_k$) be set according to a function of the market wage $\bar{w}$ and the exogenous firm-level revenue productivity parameter $A_k$ (reflecting the firm-specific surplus).[22] Formally:

$$w_k = aA_k + (1-a)\bar{w}. \tag{1}$$

In Figure C1 (Appendix C), we show that our preferred measure of productivity (value-added per worker) empirically is very closely related to the establishment fixed effects from wage regressions purged of individual heterogeneity as in the Abowd et al. (1999) model. We do not use the establishment fixed effects from the AKM-decomposition in the analysis, since they are likely to be estimated with considerable error in small establishments with few movers.

### 4.1.2 Matching through social connections

Firms' manpower decisions are distorted by frictions. We let a fraction $p$ of all possible matches between workers and firms result in labor input of unity, whereas other matches produce nothing.[23] As in the Fujita and Moscarini (2013) model of recall hires, we let match-specific productivity be revealed before production starts, but assume that acquiring this information through the market is both costly and time consuming.

Following Montgomery (1991), Simon and Warner (1992), and Dustmann et al. (2016), we assume that social connections provide information about the characteristics of the connected agents. To simplify the exposition, we take this to the extreme by assuming that firms and workers, if being socially connected, have full and costless information about the quality of matches. This extreme assumption mimics the Fujita and Moscarini (2013) model of recall hires.

[22] Carlsson et al. (2016) show that Swedish manufacturing wages respond both to firm-level productivity shocks and to changes in the workers' outside options.

[23] This resembles Baydur (2017) who presents a large-firm matching model with Jovanovich (1979) type of learning, and the Fujita and Moscarini (2015) model of recall hires. However, in contrast to these papers, our objective is not to develop a full-fledged general equilibrium search model.

#### 4.1.3 The connected supply of labor

We assume that each worker is connected to only one firm. We donate the probability that connections actively transmit information at a given point in time by $\varphi$. Active transmission is related to the frequency of social interactions, mimicking "tie strength" as defined by Granovetter (1973). We explore various indicators of tie strength in the empirical analysis. Tie strength $\varphi$ is a function of the particular relationship between two agents; the first being a worker within firm *k* and the other being an outside worker However, to simplify the notation we treat $\varphi$ as a firm-specific attribute.

As noted above, a fraction $p$ of the connected workers will be productive in the hiring firm. Furthermore, connected workers who are employed would prefer to move from his or her current firm *j* to a connected firm *k* if, and only if, the new wage is higher than the current wage, i.e. if $w_k > w_j$. Because of the wage setting rule, this is equivalent to $A_k > A_j$. The firm is connected to $N$ workers, whereof $pN$ workers constitute productive matches, and information about the subset $p\varphi N$ of these is transmitted to the firm. Hence, the connected supply of labor ($H_{kt}^{Cmax}$), defined as the number of workers willing and able to match with firm *k* through its social connections at time *t*, is equal to

$$H_{kt}^{Cmax} = p\varphi_{kt}N[u_{kt} + (1 - u_{kt})\tilde{G}(A_{kt})], \tag{2}$$

where $u_{kt}$ is the non-employment rate among the workers connected to firm *k* at time *t*, and $\tilde{G}(A_{kt})$ is the employee-weighted fraction of firms that has a lower productivity than firm *k*. This simple set-up results in four intuitive but, nonetheless, important predictions:

1) More productive firms have a larger connected supply of labor.
2) The connected supply of labor increases when connected workers are displaced.
3) The increase in the connected supply of labor, because of job displacements among connected workers, is larger for less productive firms.
4) The increase in the connected supply of labor, because of job displacements among connected workers, is larger when connections transmit information (i.e., when being strong).

The first prediction is clearly in line with the evidence presented in Section 3.3. The second prediction is a straightforward consequence of the reduced value of the connected workers' outside options. The third prediction arise because every worker will accept an offer from the most productive firm, if being connected to this firm, regardless of currently being employed or not. Thus, for the most productive firm it does not matter whether connected workers are displaced or not. For the least productive firm, the situation is the opposite. Only non-employed (displaced) connected workers will accept an offer from this firm. Low-productive firms can, therefore, hire connected workers only in the event of displacements. Due to the inability to "poach" workers through social connections, low-productive firms are also more likely to be engaged in costly market search for unemployed workers (in line with the findings in Section 3.3).

#### 4.1.4 The demand side

Assume that the firm has a well-behaved revenue production function $A_t R(L_t)$ with decreasing returns to scale.[24] The firm inherits a set of workers $L_0$ and lives for one period. For expositional reasons, we let the inherited set of workers ($L_0$) reflect the optimal non-frictional employment level at the start of the period. A fraction $q_t$ of these workers immediately resigns. Revenue productivity $A_t$ can be assumed to evolve according to a Markov process (i.e. it stays at $A_0$ with a positive probability). Based on $L_{0,}\, q_t$, and the new productivity level $A_t$, the firm makes its manpower decisions. It can hire connected workers ($H_t^C$) from its connected supply of labor up to $H_t^{Cmax}$ or post vacancies ( $V_t$) on the market, at a cost of $c^V$ per vacancy, whereof a fraction $m_t$ results in productive matches (employment). The firm can also stay inactive and produce using the $(1 - q_t)L_0$ remaining workers or fire $F_t$ workers at cost of $c^f$per worker. Finally, revenue production occurs, wages and costs are paid, and the firm dies.

The firm strives to maximize profits according to

$$\Pi(A_t, L_0) = max_{H_t^C, V_t, F_t}\{A_t R(L_t) - w_t L_t - c^V V_t - c^f F_t\},$$

subject to the law of motion

$$L_t = (1 - q_t)L_0 + H_t^C + m_t V_t - F_t$$

and

$$V_t \geq 0;\ F_t \geq 0;\ F_t \leq (1 - q_t)L_0;\ H_t^C \leq H_t^{Cmax}$$

[24] Since we do not solve the model for any equilibrium outcomes, we suppress notation for the identity of the firm unless explicitly needed. We use the subscript *t* for variables that exogenously or endogenously shift with shocks.

Notably, all aspects of the firm's social connections can be summarized by its connected supply ($H_t^{Cmax}$). Job displacements among connected workers, which reduces their outside options, affect the firm only by a shift in the constraint $H_t^{Cmax}$ and our focus is thus on the role of this constraint.

Now, consider the case where $A_t = A_0$. The assumption that a firm inherits its non-frictional optimum $L_0$ ensures that $A_t R'(L_0) = w_t$. Since $q_t L_0$ workers quit, two possible cases emerge: First, if $H_t^{Cmax} - q_t L_0 \geq 0$, the firm can replace all resigning workers at a zero cost, and will by definition choose to do so. Second, if $H_t^{Cmax} - q_t L_0 < 0$, the firm will hire $H_t^{Cmax}$ workers at a zero cost, and then there is a trade-off between the benefits from hiring additional workers (moving towards the optimum) and the vacancy costs.[25] Trivially, the cost of posting vacancies implies that the optimal number of employees in this case needs to be lower than $L_0$, since by assumption $R'' < 0$. Thus, firms with unchanged productivity, will on average have more employees if $H_t^{Cmax}$ is larger (i.e., if connected workers become displaced).

The model predictions remain intuitive if $A_t \neq A_0$. If the shock is sufficiently negative, the firm will prefer to shrink (by firing or not hiring) and $H_t^{Cmax}$ will play no role. For positive shocks of limited magnitude the logic of a constant $A_t$ and $H_t^{Cmax} - q_t L_0 < 0$ still applies. For very large positive shocks, the fraction of workers hired through connections will depend on $H_t^{Cmax}$ as in the case of a constant $A_t$ and $H_t^{Cmax} - q_t L_0 > 0$. In Appendix B, we provide some parameter ranges for each of these cases; unsurprisingly the key determinant is the relationship between the curvature of the production function and the yield-corrected vacancy cost ($c^V/m$).

The key takeaway is that the connected supply of labor plays no role for firms who would prefer to shrink, it leads to an increased employment level in firms with smaller hiring needs, and to a shift from hiring through posting vacancies to hiring of connected workers in firms with very large hiring needs. This yields two predictions:

1) *There is a negative relationship between the share of connected hires and the total number of hires.* That is, when the hiring need is very large the firm will exhaust its connected supply of labor and post vacancies. This is one of the features we wanted the model to capture.

[25] The optimal number of vacancies is determined by $A_t R'\left((1 - q_t)L_0 + H_t^{Cmax} + m_t V_t^*\right) = c^V/m_t + w_t$, or equals zero if $V_t^* < 0$.

2) *Firms will, on average, have more employees in t if $H_t^{Cmax}$ is larger, i.e., if $u_{tk}$ is increased through displacements within their network of connections.* We test this prediction in Section 6.3 below.

Note also that a firm's connected supply of labor may exceed its demand for labor. In this case, the firm will hire a (random) subset of the connected workers. Thus, from the worker's point of view, connections to firms with a smaller connected supply are, on average, more valuable. Moreover, firms are less likely to hire connected workers who are displaced if other connected workers are displaced at the same time.[26] We test this last prediction in Section 5.2.5.

#### 4.1.5 Notes on the theoretical framework

Our framework is very stylized, but the intention is neither to explore the full economy-wide consequences of frictionless hires using social connections nor to explore the potential for strategic behavior of the firms (e.g., if the size of the network of connected workers is affected by the hires). Firms are constrained in order not to actively use wages to influence worker decisions, and workers are of a single type, excluding the possibility that firms simultaneously hire and fire workers.[27] We also simplify the exposition by treating all shares as constants and by not accounting for the fact that $q_t$ and $m_t$ should be treated as functions of $A_t$ (implicitly assuming that connected poaching is a marginal phenomenon, and that there is no on-the-job search through the market).

Importantly, however, our simple framework highlights how firms' manpower decisions are affected by job displacements among their employees' social connections, if these connections transmit information about worker qualities. The displacement shocks expand the connected supply of labor by reducing the value of connected workers' alternative options. Although more productive firms will be more prone to use connections in general, connected displacement shocks are more important for less productive firms. These shocks may, actually, create jobs in connected firms, not just reallocate vacancies that otherwise would have been opened. The model also highlights that a key threat to identification is that connected displacement shocks might affect

[26] Intuitively, this would hold even if firms could set wages according to workers outside options since outside options among displaced workers is equal for all.
[27] All of these aspects are interesting areas for future work.

firms' ability either to hire through the market (i.e., by altering $m_t$) or to compete at the output market (i.e., through $A_t$). We return to these issues in Sections 5.2.1 and 6.3.3.

## 4.2 The empirical set-up

In this subsection, we present the basic empirical set-up that we use in all analyses. The framework presented above implicitly incorporates four central agents: the displaced worker *i,* the closing establishment *j,* a worker *l* who is socially connected to the displaced worker *i* and employed at (non-closing) establishment *k*. In what follows, we will focus on agents *j*, *k* and *i*, while we will pay less attention to the intermediary agent *l*.

Throughout our empirical analyses, we exploit establishment closures for identification, using two distinct approaches. The first approach (outlined in Section 4.2.1; results in Section 5) analyzes to what extent our measured connections predict which displaced worker a potential destination firm will hire. This approach validates the use of establishment closures for identification in the following analyses and also allows us to investigate key details of the postulated process with considerable statistical precision. The second approach (outlined in Section 4.2.2; results in Section 6) instead exploits the establishment closures as exogenous shocks to firms' connected supply of labor to study how this supply affects firms' manpower decisions and performance.

### 4.2.1 Set-up for the analysis of hiring patterns

In the first part of our causal analysis (in Section 5), we study to what extent a social connection between worker *i* and establishment *k* (through a worker *l*) affects the probability of a post-displacement match between these two agents in the following year. Using a formulation similar to Kramarz and Thesmar (2013) and Kramarz and Skans (2014),[28] we outline the following model for the probability that establishment *k* hires worker *i* who was displaced from establishment *j*:

$$E_{ijk} = \gamma C_{ik} + \alpha_{jk} + \varepsilon_{ijk}, \tag{3}$$

Here, $E_{ijk}$ takes the value one if there is a match between establishment *k* and displaced worker *i* (from closing establishment *j*) and zero otherwise. $C_{ik}$ is the variable of interest and indicates whether displaced worker *i* has a social connection to at least one worker

[28] Saygin et. al., (2014) also use this set-up to study the importance of former coworkers for reemployment patterns of displaces workers in Austria.

in the existing workforce of establishment $k$. The establishment-pair specific effect $(\alpha_{jk})$ captures the baseline propensity that establishment $k$ hires a worker displaced from establishment $j$. By including this effect, we account for the fact that the $j$–$k$ establishment-pairs, that are connected through their employees, may also be closely related for (any) other reasons. Hence, the key parameter $\gamma$ measures how much more (or less) likely it is that establishment $k$ forms a match with a connected worker relative to a non-connected worker who lost her job within the same establishment closure.

The model is estimated on data with observations in form of dyads, i.e., each combination of a displaced worker $i$ and an establishment $k$ constitute one observation. We include all dyads for which there is variation in $C_{ik}$ within the particular establishment-pair (i.e., all $j$-$k$ pairs of establishments where some, but not all, of the workers displaced from $j$ are connected to establishment $k$). This makes estimation feasible without any endogenous sample selection.

#### 4.2.2 Set-up for the analysis of firm-side responses

In the second part of our analysis (in Section 6), we instead study how increases in an establishment $k$'s connected supply of labor (i.e., job displacements among the workers socially connected to $k$'s current employees), affect establishment $k$'s manpower decisions (i.e., hires, separations, and growth) and performance (i.e., sales and value-added). The basic presumption is that these job displacements provide the firms with less costly opportunities to hire connected workers. The empirical models are estimated on longitudinal establishment-level data and have the following basic structure:[29]

$$Y_{kt} = \theta\overline{DC}_{kt} + \mathbf{X}'_{kt}\boldsymbol{\beta} + \delta_k + u_{kt}, \tag{4}$$

where $Y_{kt}$ is an outcome measure for establishment $k$ in year $t$, $\overline{DC}_{kt}$ is the frequency of displacements within establishment $k$'s employee network in year $t$, $\mathbf{X}_{kt}$ is a vector of control variables capturing, in particular, other labor market factors, and $\delta_k$ is an establishment fixed effect.

## 5 Displacements, connections, and hiring patterns

In this section, we analyze hiring patterns in the wake of displacement shocks in order to demonstrate that our measured social connections capture real social relationships

[29] For convenience, we defer the presentation of the detailed empirical specification to Section 6 and only present the conceptual model here.

that are relevant for firms' hiring decisions. The analysis, which relies on Equation (3) above, allows us to document key aspects of the process with considerable statistical precision. Before presenting the results, we describe the estimation data for this part of the analyses. Thereafter, we present our main results (including test of our identification strategy) followed by analyses of how the importance of social connections vary by (1) the productivity of the potential destination establishment, (2) the strength of the social connection, (3) the characteristics of the displace worker, the intermediary worker, and their similarity, and finally (4) the existence and quality of competing connections.

### 5.1 The estimation data

To generate the necessary data, we start by, in each year, selecting all possible destination establishments *k* with observed social connections to a closing establishment *j* (i.e., a connection between a displaced worker *i* at establishment *j* and an intermediate worker *l* at establishment *k*). This data is expanded to create one observation for each combination of worker *i,* displaced from establishment *j,* and establishment *k* (for which there is any social connection between establishments *k* and *j*, but not necessarily between the particular displaced worker *i* and establishment *k*). This procedure generates a data set containing dyads between displaced workers and potential destination establishments. As noted in Section 4.2.1, the ensuing data set is limited to the observations with variation in the variable of interest, conditional on the establishment-pair specific effects, since potential destination establishments without a connection will not contribute to the identification.

Table 3 presents descriptive statistics for the estimation data. There are almost 32,000 establishment closures (*j*), somewhat less than 300,000 displaced workers (*i*), 900,000 unique connected establishment pairs (*j*-*k*), 41 million dyads (*i*-*k*) whereof 2.5 million are connected dyads. There are on average 66 establishments *k* connected to each closing establishment *j* (Column [1]), and each displaced worker *i* is observed to be socially connected to 9 *k*-establishments (Column [2]).

Table 3 Descriptive statistics of the used data of observed social connections

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Closing establishments (*j*) | Displaced workers (*i*) | Connected establishments (*k*) | Displaced worker and connected establishment dyads (*i*,*k*) |
| # of observations | 31,538 | 289,333 | 912,118 | 41,113,879 |
| # of employees | 11.970 | N/A | 32.905 | N/A |
| | # of establishments *k* connected *to* closing establishment *j* | # of establishments *k* connected to displaced worker *i* | # of closing establishments *j* per connected establishment *k* | Share of dyads with a connection |
| Any connection | 66.199 | 8.825 | 2.289 | 0.062 |
| *By type of connection:* | | | | |
| Family | 9.993 | 1.170 | 0.346 | 0.008 |
| Parent | 2.608 | 0.295 | 0.090 | 0.002 |
| Child | 1.325 | 0.151 | 0.046 | 0.001 |
| Spouse | 1.314 | 0.149 | 0.045 | 0.001 |
| Sibling | 5.254 | 0.597 | 0.182 | 0.004 |
| Coworkers | 16.586 | 2.590 | 0.573 | 0.018 |
| Classmates | 29.660 | 3.523 | 1.026 | 0.025 |
| High school | 27.334 | 3.220 | 0.945 | 0.023 |
| College/university | 2.465 | 0.306 | 0.085 | 0.002 |
| Neighbors | 12.977 | 1.628 | 0.449 | 0.011 |

*Notes:* The table shows the number and connectedness of the closing establishment (Column [1]), the displaced workers (Column [2]), the connected establishments (Column [3]), and the pairs of displaced workers and connected establishment (Column [4]).

## 5.2 Results

### 5.2.1 Main results on hiring patterns

Table 4 reports the estimates of the parameter of interest (i.e., $\gamma$ in Equation 3) for the various types of social connections.[30] Our baseline specification suggests that displaced workers are 0.27 percentage points more likely to match with a connected establishment *k* compared to other displaced workers from *j* who did not have a connection to *k* (Panel A, Column [1]). [31] This effect may appear small, but is, actually, six times the average match probability of 0.043. This average effect of the connections masks considerable heterogeneity across types of connections: Family members are the most important. Every family member raises the hiring probability by one percentage point (Panel B, Column [1]). The effect varies somewhat also by type of family member: from nearly two percentage points for parents and spouses to just over half a percentage point for children and siblings (Panel C, Column [1]). The second most important type of connection is former coworkers, which increases the hiring probability by 0.25

[30] In Appendix C (Table C1), we provide estimates from models with alternative configurations of the fixed-effects. Although their exact interpretation differ, the estimates are very stable across specifications.
[31] In Appendix C (Table C1), we provide estimates from models with alternative configurations of the fixed-effects. Although their exact interpretation differ, the estimates are very stable across specifications.

percentage points per connection. Both classmates and neighbors are substantially less important (0.07 and 0.09 percentage points).

Table 4 Main results and "placebo" tests based on other non-connected establishments

| | (1) Main model | | (2) Connections across industries only | | (3) Placebo (other establishment in the same firm, location, and industry) | | (4) Placebo (other establishment in the same location and industry) | |
|---|---|---|---|---|---|---|---|---|
| | Est. | (s.e.) | Est. | (s.e.) | Est. | (s.e.) | Est. | (s.e.) |
| *Panel A:* | | | | | | | | |
| Any connection | 0.270 | (0.005) | 0.227 | (0.004) | 0.032 | (0.005) | 0.015 | (0.002) |
| *Panel B:* | | | | | | | | |
| Family | 1.095 | (0.020) | 0.948 | (0.019) | 0.051 | (0.013) | 0.017 | (0.004) |
| Coworkers | 0.253 | (0.010) | 0.182 | (0.008) | 0.076 | (0.015) | 0.023 | (0.003) |
| Classmates | 0.066 | (0.004) | 0.056 | (0.004) | 0.012 | (0.005) | 0.010 | (0.002) |
| Neighbors | 0.086 | (0.008) | 0.070 | (0.008) | 0.005 | (0.008) | 0.017 | (0.006) |
| *Panel C:* | | | | | | | | |
| Family | | | | | | | | |
| Parent | 1.867 | (0.052) | 1.708 | (0.051) | 0.094 | (0.032) | 0.028 | (0.009) |
| Child | 0.670 | (0.052) | 0.560 | (0.048) | 0.010 | (0.032) | -0.007 | (0.009) |
| Spouse | 1.974 | (0.078) | 1.640 | (0.073) | 0.069 | (0.042) | 0.029 | (0.014) |
| Sibling | 0.697 | (0.023) | 0.583 | (0.022) | 0.027 | (0.015) | 0.015 | (0.006) |
| Coworkers | 0.252 | (0.010) | 0.181 | (0.008) | 0.076 | (0.015) | 0.023 | (0.003) |
| Classmates | | | | | | | | |
| High school | 0.064 | (0.004) | 0.054 | (0.004) | 0.010 | (0.005) | 0.011 | (0.002) |
| College/university | 0.084 | (0.018) | 0.074 | (0.018) | 0.033 | (0.019) | 0.006 | (0.006) |
| Neighbors | 0.080 | (0.008) | 0.065 | (0.008) | 0.005 | (0.008) | 0.017 | (0.006) |
| Mean dep. var. | 0.00043 | | 0.00028 | | 0.00010 | | 0.00008 | |
| # of fixed effects | 2,087,791 | | 18,62,235 | | 270,907 | | 1,444,587 | |
| # of observations | 41,113,879 | | 37,853,704 | | 3,620,672 | | 28,248,266 | |

*Notes:* All estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. Estimations include establishment-pair-and-year fixed effects. Standard errors are clustered on establishment-pair-and-year level.

The above results imply that establishments are much more likely to hire displaced workers to whom they have a social connection rather than other workers who were displaced due to the same plant closure. We argue that this should be attributed to causal effects of the social connections. However, one potential concern regarding this causal interpretation is that the closure of a *j*-establishment may affect connected *k*-establishments through reduced product-market competition. Such effects should, in general, affect all workers (with or without a connection) who lost their job due to the same establishment closure, and should, therefore, be captured by the establishment-pair specific effect. Nevertheless, as an additional test of the robustness of our results we have re-estimated the models using only the connections that span across industries, hence limiting the focus to supply shocks with no associated demand shock. As is evident from comparing Columns (1) and (2) of Table 4 the estimates become marginally smaller, but are largely unaffected by this restriction.

We also estimate two sets of "placebo-type" regressions. The first uses the sub-sample of connected *k*-establishments that were part of multi-establishment firms with several establishments within the same location and industry. Each connected establishment is then replaced by another (randomly chosen, if there were several) establishment within the same firm, location and industry. By re-estimating the models using this sample we can assess whether non-connected establishments were more likely to hire workers with connections to other establishments within the same firm (operating within the same location and industry). In a second exercise, the connected establishments are instead replaced by another establishment within a different firm, but within the same location and industry. The estimates presented in Columns (3) and (4) of Table 4 reveal effects that in many cases are statistically significant, but with magnitudes that in most cases are much smaller than the corresponding effect of interest. In our view, these results support our claim that the effects of interest primarily arise because of the actual social connections and not because of correlated abilities (assuming that abilities were equally valued across establishments).

#### 5.2.2 Productivity

A prediction from our theoretical framework is that displacements among connected workers are more important for less productive firms, since more productive firms could have hired the connected workers even if they were employed. In Table 5, we split the sample by firm-level productivity (at thirds of the distribution within each county-industry-year cell). The estimates support the prediction that social connections are more important determinants of the reemployment patterns if they link the displaced workers to low-productive firms, despite the fact that more productive firms use connections more in general (as shown in Section 3.3). In Section 5.2.4, we show that the differences are significant and robust to adding controls for additional differences.

Table 5 Effects of social connections by productivity of the receiving firm

| | | Firm productivity | | |
|---|---|---|---|---|
| | (1) Baseline | (2) Low | (3) Medium | (4) High |
| *Panel A:* | | | | |
| Any connection | 0.270 | 0.320 | 0.253 | 0.212 |
| | (0.005) | (0.016) | (0.010) | (0.010) |
| *Panel B: By type of connection:* | | | | |
| Family | 1.095 | 1.632 | 1.168 | 0.966 |
| | (0.020) | (0.094) | (0.055) | (0.047) |
| Coworkers | 0.253 | 0.271 | 0.230 | 0.183 |
| | (0.010) | (0.029) | (0.020) | (0.020) |
| Classmates | 0.066 | 0.053 | 0.075 | 0.074 |
| | (0.004) | (0.014) | (0.009) | (0.009) |
| Neighbors | 0.086 | 0.114 | 0.088 | 0.118 |
| | (0.008) | (0.032) | (0.021) | (0.022) |
| Mean dep. var. | 0.00043 | 0.00040 | 0.00033 | 0.00032 |
| # of fixed effects | 2,087,791 | 183,510 | 341,280 | 409,877 |
| # of observations | 41,113,879 | 4,458,647 | 8,086,020 | 9,415,717 |

*Notes:* All estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. Estimations include establishment-pair-and-year fixed effects. Standard errors are clustered on establishment-pair-and-year level. The baseline estimates in column (1) correspond to column (1) of Table 4.

### 5.2.3 Tie strength

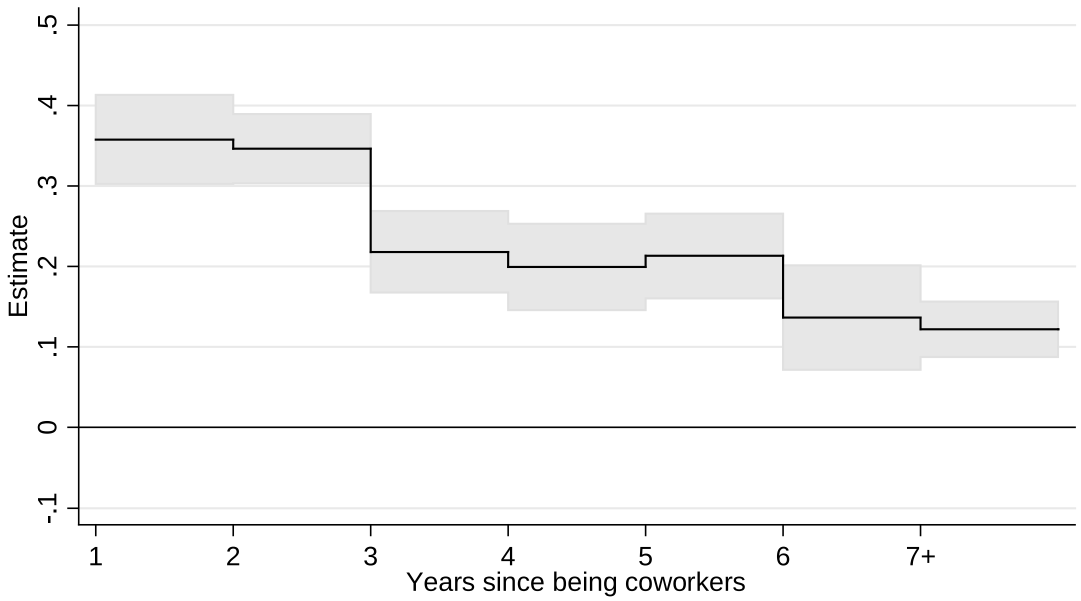
Stronger social connections are assumed to contribute to a more efficient matching process. To test this assumption we have re-estimated the model, but now allowing for further heterogeneity in a number of dimensions: the duration of interaction, the time since interacting, and the size of the group where the interaction took place. These dimensions can be viewed as proxies for tie strength (defined as the frequency of interaction). Assessing the importance of these factors will also shed some light on the data restrictions discussed in Section 2.3. Throughout, we focus on former coworkers for which our proxies for tie strength make most sense.[32]

First, we assess the role of time since interaction in Figure 2. The impact of former coworkers declines with time since they quit working together. The importance of former coworkers seems to halve with every four years since they last worked together. This suggests that our choice to only consider coworkers from the most recent of past workplaces (before *j*) is innocuous.[33]

[32] Similar analyses have been performed also for previous classmates and neighbors. The corresponding results can be found in Appendix C.

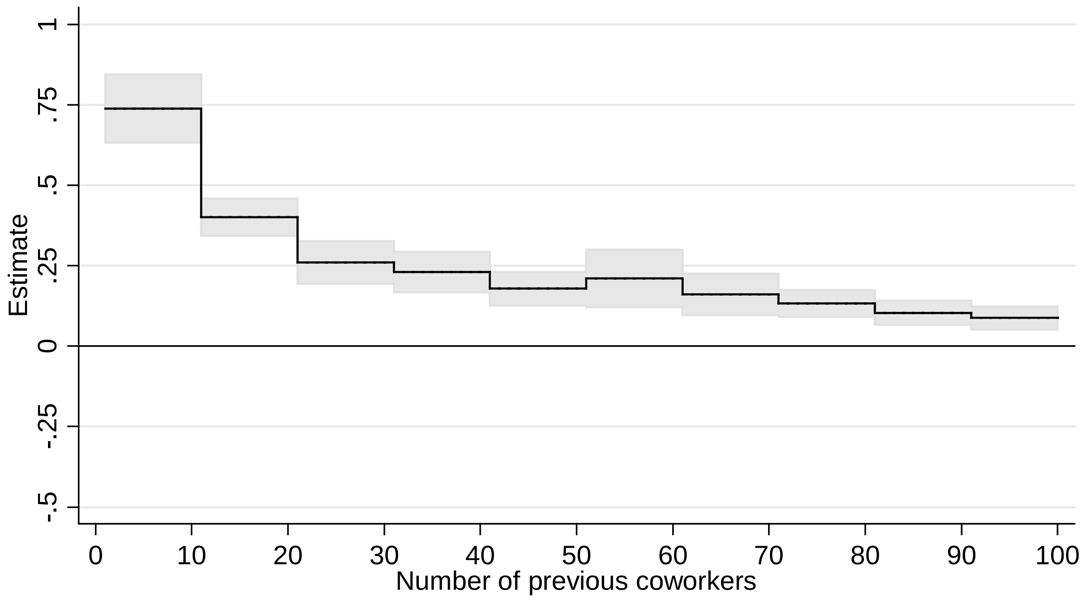
[33] in Appendix C , we show that the effects of classmates from high school depreciate rapidly with age (i.e., with time since graduation). Hence, the connections that are lost, because we observe former classmates only for the relatively young, are likely to be irrelevant

Figure 2 The role of time since working together, with 95% CIs




*Notes:* All estimates are expressed in percentage points. Estimates are interactions between having a former coworker at the establishment and time since working together. In addition, the estimations include the baseline effect of time since working together and establishment-pair-and-year fixed effects. Standard errors are clustered on the establishment-pair-and-year level.

Figure 3 The role of the size of the social context, with 95% CIs

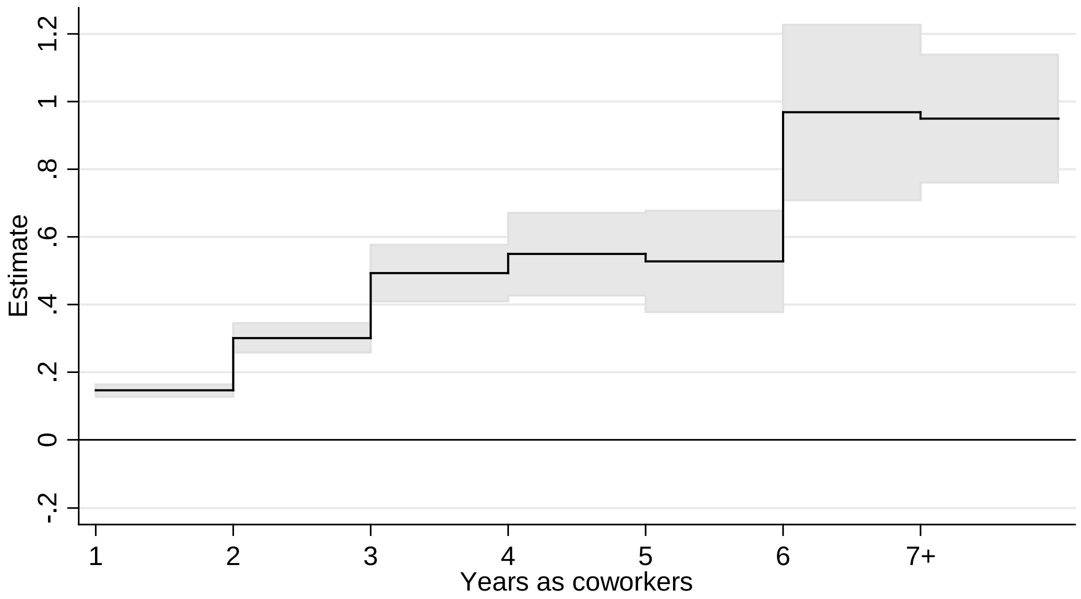



*Notes:* All estimates are expressed in percentage points. Estimates are interactions between having a former coworker at the establishment and the total number of coworkers (10 categories). In addition the estimations include the baseline effect of the total number of coworkers (10 categories) and establishment-pair-and-year fixed effects. Standard errors are clustered on the establishment-pair-and-year level.

Second, Figure 3 shows that connections formed in smaller groups are more useful. The effects of former coworkers depreciate fairly rapidly with the size of the workplace where they used to work together.[34] Already at group sizes of 10–20 coworkers the effect is halved. This suggests that connections, indeed, are more useful if they are formed in smaller social groups. It also supports our standpoint that groups of more than 100 connections are uninformative regarding the true (relevant) connections and can be discarded without any loss of information (see Section 2.3).

Third, in Figure 4 we assess to what extent the importance of social connections varies with the duration of the interaction. As expected there is a strong positive relationship between time spent together as coworkers and how important the connection is: the effect doubles for every three additional years as coworkers.

Figure 4 The role of duration of interaction




*Notes:* All estimates are expressed in percentage points. Estimations include establishment-pair-and-year fixed effects. Standard errors are clustered on establishment-pair-and-year level. In case of a displaced worker having more than one previous co-worker within the same establishment "Years as coworkers" corresponds to the longest respective relation.

Overall, as stipulated in the theory section (Equation [2]), these results show a consistent positive relationship between social proximity and the usefulness of observed social connections in the matching process: the more interaction time, the shorter the time since interaction, and the smaller the size of the group where the interaction took

[34] The same is true for classmates from high school and college/university, as well as for neighbors (although to a somewhat lower extent). See Appendix C for details.

place, the better the social connection predicts where the displaced worker gains new employment.

#### 5.2.4 The displaced and the intermediary worker, and their similarity

So far, we have shown that social connections are important for where displaced workers gain new employment, and also that their importance varies with strength and type. However, the impact of social connections may also vary within the particular type of connection depending on (1) the displaced worker *i*'s own characteristics, (2) the connected intermediary worker *l*'s characteristics, and (3) their social similarity. To investigate this, we re-estimate our model including interactions between the indicator for having any connection and indicators for various characteristics of the two workers constituting each connection (i.e., the displaced worker *i* and the intermediary worker *l*), and their similarity, while controlling for the type of connection (using the most detailed division). The estimates from this analysis are presented in Table 6.

First, in terms of displaced workers' own characteristics, social connections seem to be more important if being male, foreign born, younger, and having less than a university degree. These results support the findings in previous literature (Bentolila et al., 2010; Ioannides and Loury, 2004).

Second, shifting the focus to the characteristics of the intermediary worker, most results are in line with the (in this case, very scarce) previous literature provided by Kramarz and Skans (2014) and Bayer et al. (2008): for the displaced workers it is more useful to be connected to male, foreign born, prime aged, and high wage workers.[35]

Third, there is a long-standing sociological notion (McPherson, et al. 2001) that similarity in all dimensions reinforces the importance of social interactions. Our estimates of how the impact of social connections varies with the similarity, between the displaced and intermediate worker, in terms of sharing the same characteristics support this notion. The estimates are positive and statistically significant for sex, age, immigration status, and education, although having the same sex or immigration status seems to be much more important than having the same education level. This further reinforces the consistent result that social proximity, or tie strength, is crucial for the usefulness of social connections.

[35] Somewhat surprisingly, and in contrast to findings reported in Kramarz and Skans (2014), tenure is negatively related to the usefulness of the connection. Partly, this appears to be driven by connections between former coworkers, and it should be noted that for them tenure is by definition directly related to time since interaction.

Table 6 The estimated importance of social connections by characteristics of the displaced worker (*i*), the intermediary worker (*l*), their similarity, and the recruiting firm/establishment (*k*)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Est. (s.e.) | Est. (s.e.) | Est. (s.e.) | Est. (s.e.) |
| Any connectiontact × characteristics of *i* | | | | |
| Female | -0.050 (0.009) | -0.042 (0.009) | -0.016 (0.009) | -0.033 (0.013) |
| Immigrant | 0.027 (0.016) | 0.020 (0.015) | 0.093 (0.027) | 0.099 (0.039) |
| Age 20–34 yrs | 0.064 (0.013) | 0.069 (0.013) | 0.067 (0.013) | 0.048 (0.019) |
| Age 35–49 yrs | Ref. | Ref. | Ref. | Ref. |
| Age 50–64 yrs | -0.123 (0.019) | -0.099 (0.019) | -0.092 (0.019) | -0.096 (0.030) |
| Education: Compulsory | -0.025 (0.016) | -0.027 (0.016) | -0.019 (0.016) | 0.013 (0.028) |
| Education: High school | Ref. | Ref. | Ref. | Ref. |
| Education: College/university | -0.062 (0.010) | -0.062 (0.010) | -0.052 (0.011) | -0.052 (0.015) |
| Any connection × characteristics of *l* | | | | |
| Female | | -0.030 (0.009) | -0.009 (0.009) | 0.006 (0.014) |
| Immigrant | | 0.045 (0.020) | 0.106 (0.027) | 0.112 (0.040) |
| Age 20–34 yrs | | -0.030 (0.013) | -0.034 (0.013) | -0.041 (0.019) |
| Age 35–49 yrs | | Ref. | Ref. | Ref. |
| Age 50–64 yrs | | -0.158 (0.025) | -0.154 (0.026) | -0.154 (0.037) |
| Education: Compulsory | | 0.045 (0.020) | 0.052 (0.020) | 0.078 (0.032) |
| Education: High school | | Ref. | Ref. | Ref. |
| Education: College/university | | -0.011 (0.010) | -0.002 (0.010) | 0.012 (0.015) |
| Tenure (years) | | -0.011 (0.002) | -0.012 (0.002) | -0.005 (0.002) |
| Wage (percentiles) | | 0.004 (0.000) | 0.004 (0.000) | 0.003 (0.000) |
| Similarity between *i* and *l* | | | | |
| Same sex | | | 0.147 (0.008) | 0.138 (0.012) |
| Same immigration status | | | 0.108 (0.026) | 0.120 (0.038) |
| Same age | | | 0.037 (0.012) | 0.051 (0.018) |
| Same education | | | 0.028 (0.010) | 0.041 (0.015) |
| Any connection × characteristics of *k* | | | | |
| Productivity: High | | | | -0.017 (0.014) |
| Productivity: Medium | | | | Ref. |
| Productivity: Low | | | | 0.050 (0.019) |
| Age ≤ 3 years | | | | 0.085 (0.033) |
| Log Size | | | | -0.034 (0.005) |
| Type of connection | Yes | Yes | Yes | Yes |
| Characteristics of *i* | Yes | Yes | Yes | Yes |
| Mean dep. var. | 0.00043 | 0.00043 | 0.00043 | 0.00034 |
| # of fixed effects | 2,087,791 | 2,087,791 | 2,087,791 | 932,691 |
| # of observations | 41,113,879 | 41,113,879 | 41,113,879 | 21,919,580 |

*Notes:* All estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. Estimations include establishment-pair-and-year fixed effects. Standard errors are clustered on establishment-pair-and-year level. The intermediate worker *l*'s characteristics are within establishment averages. The smaller number of observations in (4) is due to the non-universal coverage of the register containing information on firm productivity. The characteristics of *k*, which are interacted with having any connection, also include sector and county; their coefficients are suppressed for brevity.

Finally, in the descriptive analyses in Section 3.3, we found that low-productive firms were more prone to hire displaced workers to whom they were socially connected through their current employees. From Column (4) it is evident that this finding is robust to accounting for all (observed) aspects of the social connections and the individual agents involved.

### 5.2.5 Competing connections

A prevalent idea in the literature on job search networks (Boorman, 1975; Calvo-Armengol and Jackson, 2004) is that there is competition for referral information between various agents. This is also predicted from the theoretical framework outlined in Section 4.1: if the connected supply of labor exceeds the number of workers needed to reach the non-frictional optimal employment level, the firm will not hire all connected workers that are available. This implies that a social connection should matter less if other displaced workers have connections to the same firm. We have tested two aspects of competition: (1) the existence/number of competing connections and (2) the quality of the competing connections.

First, we test if the fact that other displaced workers are socially connected to the very same establishment affects the usefulness of the own connection. The hypothesis is that other displaced workers having social connections to the same establishment reduces the probability of receiving a referral through each of the own connections (or the usefulness of the connection in general). The results from this first test are presented in Panel A of Table 7 and support this hypothesis, regardless of how we measure competition, i.e., in terms of the total number of competing connections (Column [1]), the existence of any competing connections (Column [2]), or the competing connections as a share of total employment in the potentially hiring establishment (Column [3]).

Table 7 Competing connections

| | (1) | (2) | (3) |
|---|---|---|---|
| Measures of *Competition*: | Total number of competing connections | Any competing connection | Share of competing connections (per incumbent worker) |
| *Panel A:* Any own connection interacted with: | | | |
| *Competition* | -0.0004 | -0.0743 | -0.0021 |
| | (0.0000) | (0.0114) | (0.0004) |
| Measures of *Quality* of the competition: | Sum of predicted quality | Any higher predicted quality | Average predicted quality |
| *Panel B:* Any own connection interacted with: | | | |
| *Competition* | 0.0001 | -0.0396 | -0.0017 |
| | (0.0001) | (0.0130) | (0.0012) |
| *Quality* | -0.1438 | -0.0692 | -0.1057 |
| | (0.0313) | (0.0118) | (0.2880) |
| Type of connection | Yes | Yes | Yes |
| # of fixed effects | 2,087,791 | 2,087,791 | 2,087,791 |
| # of observations | 41,113,879 | 41,113,879 | 41,113,879 |

*Notes:* All estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. Estimations include establishment-pair-and-year fixed effects. Standard errors are clustered on establishment-pair-and-year level.

Second, we test how the quality of competing connections affects the usefulness of own connection. To measure the quality of competing connections, we use predicted match probabilities based on the estimates in Column (3) of Table 6. The estimates, in Panel B of Table 7, suggest that the likelihood that a displaced worker with a social connection to a particular establishment also gets hired by that establishment is negatively affected by the quality of competing connections. This finding is robust to how we define quality, i.e., as the sum of the predicted quality of competing connections, as the existence of competing connections that are of higher quality than the own connection of highest quality, or as the average quality of the competing connections (statistically insignificant).

Overall, these results confirm the notion that social connections do compete, and that they are more useful if no others have stronger connections to the same establishment. More importantly, this reinforces our view that social connections *per se*, rather than any similarity between the establishments, are a crucial link in the matching process.

# 6 Firm-side responses to connected displacements

In this section we present the second part of our analysis in which we solely focus on establishment/firm-side responses, i.e., how an increase in an establishment's connected supply of labor causally affect its manpower decisions and, in the case of single-establishment firms, also production and productivity. Our identification strategy relies on shocks to the available supply of connected labor induced by job displacement within firms' social networks (i.e., the events that we studied in Section 5). The results of the previous section serve as support for the notion, postulated by our theoretical framework, that social connections provide firms with idiosyncratic access to connected workers.

After presenting the estimation data and details about the empirical set-up, we analyze the firms' hiring responses, heterogeneity between high- and low-productive firms, and finally firms' productivity responses.

## 6.1 The estimation data

The data for the establishment-level analyses contain all establishments in the private sector with at least two employees during at least two consecutive years in 1995–2006. For each of the resulting 1,989,278 establishment-year observations (311,817 establishments) we determine the connected supply of labor (according to the definition in Section 2.3), the displacement shocks to the connected supply of labor (according to the definition in Section 2.2), and the manpower and productivity responses (in terms of the constructed measures defined in Section 3.1).[36] Summary statistics are presented in Table A2.[37] Because performance measures only are available at the firm (not establishment) level, our concluding analysis of firm performance will be limited to single-establishment firms for which there is a one-to-one correspondence between the establishment and the firm. Summary statistics for this subsample are presented in Table A1.

### 6.2 Empirical set-up for the causal analysis

The point of departure for the empirical analyses in this section is the reduced-form model of Equation (4). It uses a panel of yearly (*t*) observations of establishments (*k*). We augment the equation and define our set of controls according to the following:

$$Y_{kt} = \theta \overline{DC}_{kt} + \beta^N C_{kt} + \beta^L D_{kt}^{LLM} + \beta^P DC_{kt}^{LLM} + \delta_k + \varphi_t + u_{kt}. \tag{5}$$

The firm-side outcomes ($Y_{kt}$) are explained by socially connected displacements ($\overline{DC}_{kt}$), and establishment ($\delta_k$) fixed effects and year ($\varphi_t$) dummies. The model further controls for the total size of establishment *k*'s measured network ($C_{kt}$) i.e., the sum of its employees' unique social connections of each type, and two measures of local labor market shocks: the first ($D_{kt}^{LLM}$) captures the number of job displacements within the local labor market, while the second ($DC_{kt}^{LLM}$) captures the number of displaced workers with connections to other establishments within the same local labor market.[38]

However, to facilitate interpretation when studying the impact on other hiring margins we also estimate an instrumental variables (IV) model:[39]

$$\begin{aligned} H_{kt}^{DC} &= \theta \overline{DC}_{kt} + \beta^{L1} D_{kt}^{LLM} + \beta^{P1} DC_{kt}^{LLM} + \beta^{N1} C_{kt} + \delta_k^1 + \varphi_t^1 + u_{kt}^1 \\ Y_{kt} &= \mu \widehat{H_{kt}^{DC}} + \beta^{L2} D_{kt}^{LLM} + \beta^{P2} DC_{kt}^{LLM} + \beta^{N2} C_{kt} + \delta_k^2 + \varphi_t^2 + u_{kt}^2. \end{aligned} \tag{6}$$

[36] Because some of the key explanatory variables contain zeros (preventing us from relying on logs), we let all measures be expressed as shares of the mean of the employment in the first and last year that we observe the establishment.
[37] We allocate each connection to the "dominant" type if there are multiple types of connections between one worker and the same establishment using the hierarchy suggested by section 4 above, i.e. family > coworker > neighbor > school.
[38] Local labor markets are, as before captured by year-specific interactions between county and 2-digit industry. We include this control separately by the type of connection.
[39] The superscripts 1 and 2 indicate the first and second stages respectively.

The endogenous instrumented regressor $H_{kt}^{DC}$ is the total number of hired displaced workers with observed connections to establishment *k* in year *t*, and the instrument $\overline{DC}_{kt}$ is, as before, the number of connected displaced workers. Thus, the IV model rescales the reduced form model (Equation [5]), by the fraction of connected displaced workers that the firm hires. We will primarily rely on connections to displaced family members and former coworkers, since the first stage is found to lack the necessary empirical relevance for neighbors and former classmates as shown below.

## 6.3 Results

### 6.3.1 The recruitment of connected displaced workers (first stage)

We begin by estimating the direct impact of job displacements among connected workers on the hiring of the connected displaced workers themselves. These estimates serve as the first stage estimates in Equation (6). In principle, the object we study (i.e., the number of hired connected displaced workers as a function of the number of connected displaced workers) closely resembles the object under study in Section 5.2. However, the estimated model is different, since the present analysis compares establishments over time, whereas the analysis in Section 5.2 compared connected and non-connected workers (who were displaced in the same closure event).

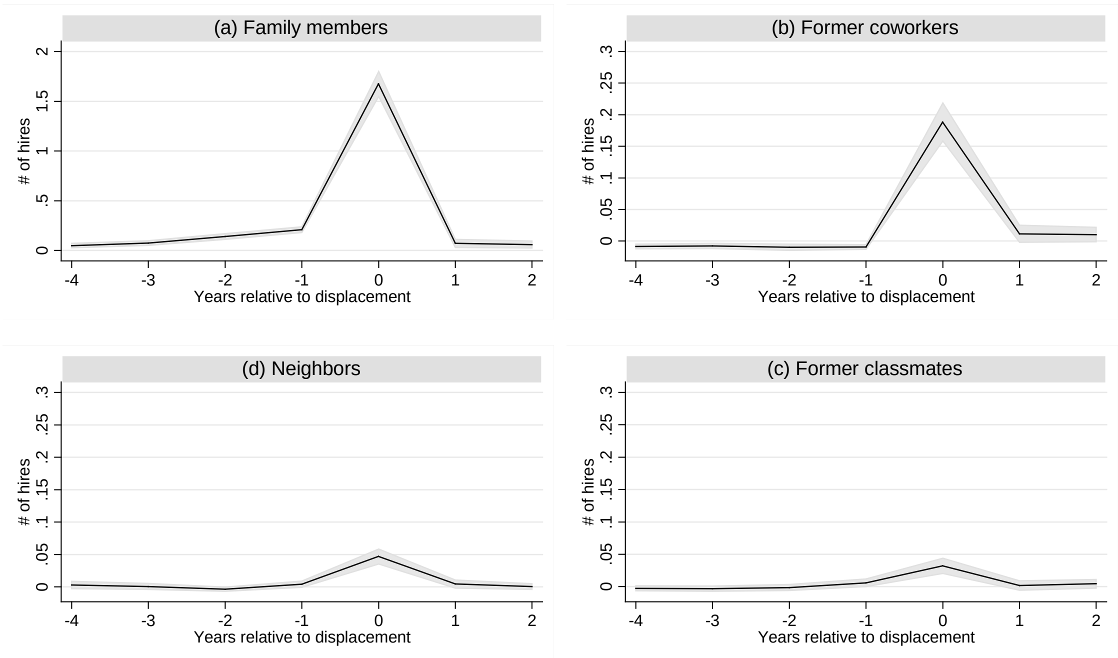
Table 8 The first stage estimates of the effect of the number of connected displaced workers on the number of hires of connected displaced workers

| | Hires of connected displaced workers by type of connection | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Type of connection | Any | Any | Family | Coworker | Neighbor | Classmate |
| Any | 0.225 | | | | | |
| | (0.015) | | | | | |
| Family | | 1.670 | 1.624 | 0.036 | 0.011 | -0.002 |
| | | (0.066) | (0.064) | (0.011) | (0.005) | (0.002) |
| Coworkers | | 0.212 | 0.022 | 0.190 | 0.000 | 0.000 |
| | | (0.018) | (0.006) | (0.017) | (0.000) | (0.000) |
| Neighbors | | 0.064 | 0.009 | 0.007 | 0.046 | 0.001 |
| | | (0.011) | (0.009) | (0.004) | (0.006) | (0.001) |
| Classmates | | 0.016 | -0.010 | -0.004 | -0.002 | 0.032 |
| | | (0.010) | (0.006) | (0.005) | (0.001) | (0.006) |
| # of observations | 1,989,278 | 1,989,278 | 1,989,278 | 1,989,278 | 1,989,278 | 1,989,278 |
| # of establishments | 311,817 | 311,817 | 311,817 | 311,817 | 311,817 | 311,817 |

*Notes:* The standard errors are clustered on the establishment level. We control for the number of displaced workers within the same local labor market and year (i.e., year × industry × county), the number of displaced workers connected through each of the various types to the same local labor market (in the same year), and network size (i.e., number of connections). The outcome is the number of hired connected displaced workers. All variables (right and left side) are scaled by the average size of the establishment. All estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100.

All the results reported in Table 8 are very similar to those in Section 5.2, but less precisely estimated.[40] The point estimate in Column (1) suggests that, on average, 0.2 percent of each connected displaced worker is hired. From Column (2) it is evident that family members and former coworkers produces the by far largest estimates (1.7 and 0.2 respectively), whereas the estimates for neighbors and former classmates are much smaller (0.06 and 0.01) and in the latter case also statistically insignificant. In Columns (3)–(6) we document, the somewhat tautological fact, that if workers with a particular type of connection are displaced, this has a positive impact on the hiring of displaced workers with the same (but no other) type of connection.

Figure 5 The responses from past, current and future displacements on the number of hires of connected displaced workers, by type of connection




*Notes:* We obtain the coefficients by adding 4 lags and 2 leads of $\bar{D}_{kt}$ in Equation (2). All estimates are expressed in percentage points. The confidence intervals are based on standard errors clustered at the establishment level.

In order to further assert that job displacements among connected workers can be viewed as idiosyncratic shocks to the establishments' connected supply of labor, we first analyze the impact of future and past job displacements on the number of hired connected displaced workers (see Figure 5).[41] Reassuringly, there is no impact from either future or past displacements on current hiring decisions.

[40] In Table C2, Appendix C, we show the corresponding results within and across industries.
[41] We use the same model (Equation [2]), but add 4 lags and 2 leads of $\bar{D}_{kt}$.

The findings above have two implications for the following analyses: (1) job displacements among connected workers can indeed be used as idiosyncratic shocks to the establishments' connected supply of labor; and (2) because the effect on hiring is largely driven by connections between family members and former coworkers we will, henceforth, focus solely on these two types of social connections.

#### 6.3.2 Connected displacements and manpower decisions

In Table 9, we report estimates of the causal impact of connected displacements on hiring decisions. A complete decomposition of all dimensions of connected vs. non-connected hires and of workers who have, and have not, been displaced is reported in Columns (1)–(6), while the final column reports the effect on total hires. Panel A reports the reduced form results based on Equation (5) and Panel B reports the IV results based on Equation (6).

The first column of Panel A reports the first-stage (equivalent to that presented in Table 9, but now without classmates and neighbors) and shows that 1.6 percent of the connected displaced family members, and 0.2 percent of the connected displaced former coworkers, are hired. Consistent with the results on competing connections in Section 5.2.5, the second column shows that displacements lead to a reduction in hires of other (i.e., non-displaced) connected workers in the order of 0.4 percent for family members and 0.03 percent for former coworkers. However, as expected from our theoretical framework, the crowding out is only partial: the total number of hired connected workers increases by 1.2 (family members) and 0.2 (former coworkers) percent for each connected displaced worker. The numbers imply that most of the response (e.g. 73% of the effect for family) is because of an increase in the overall number of connected hires.

The next set of columns shows that the impact on non-connected hires is statistically insignificant, although with a shift towards the displaced. In the final column, we report the ensuing impact on total hires, which is positive and statistically significant. This implies that displacements among connected workers do not only lead to more hires of connected workers, but also to more hires overall. Interpreted within the theoretical framework in Section 4.1, the increase in the connected supply of labor allows firms to circumvent the hiring frictions of the formal market and, therefore, they hire more workers.

The magnitude of our empirical "experiment" is small. Because displacement due to establishment closures is not the primary reason for job separations, the statistical model, and the shocks we use, can only explain a tiny fraction of firms' total hires. Instead, the results should be interpreted as evidence of how firms respond to *marginal* changes in their ability to hire through social connections and the set-up is designed to provide as clean a setting as possible for analyzing such marginal changes. In order to provide an adequate quantification of these marginal responses, we apply the IV model of Equation (6). The metric of the IV estimates scales all (indirect) employment adjustments by the number of connected displaced workers that are hired (the direct effect).

We only present the IV estimates of a compound measure of hires of connected displaced workers (i.e., the sum of displaced former coworkers and family members), but distinguish between the two types of connections in the first stage (i.e. first stages are in Column [1], Panel A). The IV results show that for each connected worker who is hired due to displacements, hires of other connected (non-displaced) workers are reduced by 0.22 percent of a worker (Panel B, Column [2]). As before, total hires of non-connected workers is largely unaffected (Panel B, Column [6]). Hence, for each connected worker who is hired due to the displacements, total hires (including the connected displaced worker) increase by 0.84 workers (Panel B, Column [7]).

Table 9 Impact of network displacements on different type of hires

| | Connected (family/coworkers) hires | | | Non-connected hires | | | Total hires |
|---|---|---|---|---|---|---|---|
| | (1) Displaced | (2) Non-displaced | (3) All | (4) Displaced | (5) Non-displaced | (6) All | (7) All |
| *Panel A: Reduced form* | | | | | | | |
| Family displacements | 1.671 | -0.442 | 1.218 | 0.337 | -0.359 | -0.022 | 1.196 |
| | (0.066) | (0.106) | (0.124) | (0.047) | (0.303) | (0.307) | (0.333) |
| Coworker displacements | 0.212 | -0.029 | 0.183 | 0.057 | -0.008 | 0.049 | 0.232 |
| | (0.018) | (0.023) | (0.030) | (0.012) | (0.070) | (0.071) | (0.078) |
| *Panel B: IV (Family and coworker displacements as instruments, for first stages see Panel A, column 1)* | | | | | | | |
| Hired connected displaced workers | 1 | -0.225 | 0.775 | 0.224 | -0.181 | 0.065 | 0.840 |
| | | (0.056) | (0.056) | (0.027) | (0.167) | (0.164) | (0.174) |
| # of observations | 1,989,278 | 1,989,278 | 1,989,278 | 1,989,278 | 1,989,278 | 1,989,278 | 1,989,278 |
| # of establishments | 311,817 | 311,817 | 311,817 | 311,817 | 311,817 | 311,817 | 311,817 |
| Mean dep.var. | 0.03 | 2.10 | 2.13 | 0.30 | 17.7 | 18.0 | 20.1 |
| Share of total hires | 0.002 | 0.114 | 0.116 | 0.014 | 0.870 | 0.884 | N/A |

*Notes:* The standard errors are clustered on the establishment level. We control for the number of displaced workers within the same local labor market and year (i.e., year × industry × county), the number of displaced workers connected to the same local labor market (and in the same year), and network size (i.e., number of connections). All variables (right and left side) are scaled by the average size of the establishment. The outcomes are expressed in percentage points.

Next, we present the estimates of the impact on job separations and net employment growth (see Table 10). For expositional reasons, we first repeat the impact on total hires in Column (1). The second column shows that job separations are unaffected, which is fully in line with the predictions from the theoretical framework. Access to workers who can be hired at a low screening cost should not affect separations of current employees (as these are already screened). As a consequence of increased hires and unchanged separations, net employment grows at a rate that is identical to the effect on total hires (Column [3]). The impact on net employment growth also appears to be persistent: over a three-year horizon it is only marginally smaller, although the statistical precision precludes us from making any strong statements (Column [4]). Overall, the results imply that firms, as predicted by the theoretical framework, react to positive shocks to their connected supply of labor by creating new jobs. Reassuringly, this job creation response is entirely driven by the increase in hires, whereas separations remain unchanged as predicted from the theory. Notably, if the increases in employment were due to general product market benefits, we would instead have expected reduced separations alongside the increased hiring rate. On the other hand, if the hiring of displaced connections would have had other productive benefits (beyond the hiring stage), then these benefits could have induced the firms to substitute from already employed workers (resulting in *increased* separations). Reassuringly, we see neither of these effects.

Table 10 Impact of network displacements on total hires, separations and net growth

| | (1)<br>Total hires | (2)<br>Separations | (3)<br>Net growth | (4)<br>Net growth<br>in *t* to *t*+3 |
|---|---|---|---|---|
| *Panel A: Reduced form* | | | | |
| Family displacements | 1.196 | 0.251 | 0.880 | 0.826 |
| | (0.333) | (0.336) | (0.485) | (0.739) |
| Coworker displacements | 0.232 | -0.070 | 0.308 | 0.293 |
| | (0.078) | (0.076) | (0.113) | (0.155) |
| *Panel B: IV (Family and coworker displacements as instruments)* | | | | |
| Hired displaced family | 0.840 | -0.003 | 0.827 | 0.755 |
| and coworkers | (0.174) | (0.178) | (0.255) | (0.373) |
| # of observations | 1,989,278 | 1,989,278 | 1,989,278 | 1,323,271 |
| # of establishments | 311,817 | 311,817 | 311,817 | 212,309 |

*Notes:* The standard errors are clustered on the establishment level. We control for the number of displaced workers within the same local labor market and year (i.e., year × industry × county), the number of displaced workers connected to the same year and local labor market, and network size (i.e., the number of connections). All variables (right and left side) are scaled by the average size of the establishment.

### 6.3.3 The validity of the empirical approach

As discussed in Section 5.2.1, a possible threat to our identification strategy is product-market responses to the closing of competing establishments. Put differently, our supply shock might mask a demand shock. As explained above, our main empirical model controls both for the number of displaced workers within the same location and industry and for the number of displaced workers with connections to other firms in the same location and industry, which should alleviate some of these concerns. We also find the lack of responses on the separation margin reassuring. Nevertheless, to gain additional support, we have designed two validation exercises using different, albeit related, approaches.

First, we restrict the identifying variation to connected workers who lost their jobs due to the closures of establishments operating in *other industries* than the connected establishment. If our main results capture product-market responses, rather than responses to actual social connections, we would expect much smaller effects from connections to establishment closures in other industries. In Table 11 we report the results from repeating the estimations of Table 10, but for this restricted sample. Reassuringly, they closely resemble the previously reported estimates.

Table 11 Restricting variation to cross-industry displacements

| | (1) Connected hires | (2) Total hires | (3) Separations | (4) Net growth |
|---|---|---|---|---|
| *Panel A: Reduced form* | | | | |
| Family displacements *across industries* | 1.083 | 1.146 | 0.180 | 0.907 |
| | (0.125) | (0.345) | (0.348) | (0.505) |
| Coworker displacements *across industries* | 0.099 | 0.212 | -0.052 | 0.274 |
| | (0.035) | (0.089) | (0.088) | (0.131) |
| *Panel B: IV (Displacements in other industries as instruments)* | | | | |
| Hired displaced family and coworkers | 0.741 | 0.925 | 0.033 | 0.872 |
| | (0.072) | (0.222) | (0.227) | (0.325) |
| # of observations | 1,989,278 | 1,989,278 | 1,989,278 | 1,323,271 |
| # of establishments | 311,817 | 311,817 | 311,817 | 212,309 |

*Notes:* The standard errors are clustered on the establishment level. We control for the number of displaced workers within the same local labor market and year (i.e., year × industry × county), the number of displaced workers connected to the same year and local labor market, and network size (i.e., number of connections). All variables (right and left side) are scaled by the average size of the establishment

Our second validation exercise is a “placebo-type” analysis, where we directly estimate the impact of displacements of workers who are connected to *other* establishments in the same location and 5-digit industry. The hypothesis is that the estimates should capture any effects of the potential product-market responses, but not the effects of the social connections. Table 12 shows that the effects of these placebo-connections are much smaller than those of real connections. This implies that the main impact of a positive labor supply shock, due to workers being displaced within the local labor market, is confined to those establishments that have actual social connections to these displaced workers.

Table 12 Response to displacements of connections to other firms in the same 5-digit industry and location

| | (1)<br>Hired family and coworkers | (2)<br>Total hires | (3)<br>Separations | (4)<br>Net growth |
|---|---|---|---|---|
| *Panel A: Placebo* | | | | |
| Family displacements of | 0.002 | 0.017 | -0.015 | 0.033 |
| *other* firms in same LLM | (0.002) | (0.008) | (0.008) | (0.009) |
| Coworker displacements | -0.000 | -0.001 | 0.002 | -0.003 |
| of *other* firms in same LLM | (0.000) | (0.001) | (0.001) | (0.002) |
| *Panel B: Baseline reduced form (comparison)* | | | | |
| Family displacements | 1.196 | 0.251 | 0.880 | 0.826 |
| | (0.333) | (0.336) | (0.485) | (0.739) |
| Coworker displacements | 0.232 | -0.070 | 0.308 | 0.293 |
| | (0.078) | (0.076) | (0.113) | (0.155) |
| # of observations | 1,968,518 | 1,968,518 | 1,968,518 | 1,309,019 |
| # of establishments | 308,645 | 308,645 | 308,645 | 209,930 |

*Notes:* The standard errors are clustered on the establishment level. We control for the number of displaced workers within the same year and local labor market (i.e., year × industry × county). All variables (right and left side) are scaled by the average size of the establishment.

#### 6.3.4 Connected displacements and hires in good and bad firms

The descriptive statistics presented in Section 3 suggested that more productive firms are more likely to hire through social connections, except when connected workers are displaced. In Section 4.1, we argued that this should be expected if the mobility of connected workers depends on the attractiveness of connected firms relative to the connected workers' alternative options. In order to take this prediction to the data, we explore how the effect of connected workers becoming displaced on hires of connected workers varies with firm-level productivity. Thus, based on Equation (2) in Section 4.1.3, we use data on realized hires of connected workers to measure movements in the connected supply of labor, and we replicate the analysis presented in Column (3) of Table 9 for samples that are split according to the establishments' rank in the productivity (i.e., value-added per worker) distribution within each local labor market.[42]

The results presented in Table 13 suggest that the impact of the displacement shocks is, indeed, larger among firms in the lower half of the productivity distribution. However, the primary action appears at the extreme ends of the productivity distribution. In particular, the results show that the connected displacement shocks have

[42] To avoid endogeneity and to increase precision, productivity is measured as the average over the sample period.

a more pronounced effect for the least productive firms. To make this more precise, in Panel B we report the estimates from the IV model to show that the volume effect (i.e., that more connected workers are hired) completely dominates the crowding-out effect (i.e., the replacement of other connected hires). There is essentially a one-to-one correspondence (1.05) for the least productive firms, whereas nearly half is crowded out (i.e., the volume effect is 0.58) for the most productive firms. Hence, these results suggest that the least productive firms, to a much larger extent than more productive firms, are prevented from hiring connected workers as long as they remain employed in other firms.

Table 13 Responses within low- and high-productive firms

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | | Firms' position in the productivity distribution | | | |
| | All | <p50 *Low productivity* | ≥p50 *High productivity* | <p20 *Very low productivity* | ≥p80 *Very high productivity* |
| *Panel A: Reduced form, connected hires* | | | | | |
| Family displacements | 1.407 | 1.448 | 1.363 | 1.915 | 0.906 |
| | (0.146) | (0.204) | (0.207) | (0.384) | (0.317) |
| Coworker displacements | 0.214 | 0.227 | 0.202 | 0.199 | 0.148 |
| | (0.0350) | (0.0512) | (0.048) | (0.072) | (0.060) |
| *Panel B: IV: Total connected hires* | | | | | |
| Hired connected | 0.809 | 0.869 | 0.745 | 1.053 | 0.587 |
| displaced workers | (0.059) | (0.088) | (0.078) | (0.157) | (0.136) |
| # of establishments | 238,467 | 113,686 | 125,085 | 39,074 | 49,353 |

*Notes:* The standard errors are clustered on the establishment level. We control for the number of displaced workers within the same local labor market and year (i.e., year × industry × county), the number of displaced workers connected to the same year and local labor market, and network size (i.e., number of connections of each type). All variables (right and left side) are scaled by the average size of the establishment. In columns (2)–(5), we split the establishments according to the firms' position in the distribution of the log average productivity per worker over the years of observation, after accounting for industry-by-county-by-year fixed effects.

#### 6.3.5 Are connections good or bad?

Our theoretical framework suggested that social connections help firms overcome hiring frictions. However, an alternative interpretation would be that firms hire connected workers for nepotistic reasons. This would suggest that hires of connected workers are detrimental to firm performance. It could also be noted that our stylized framework, if interpreted literally, suggests that firm performance should be affected only through the trade-off between the reduced resources spent on hiring and the negative impact through the scale effect, since we assume that all uncertainty about match productivity is revealed before production starts. However, if, as suggested by Dustmann et al. (2016) and Fredriksson et al. (2015), there is remaining uncertainty when production starts, we would expect hired connected workers to stay longer and also that the firms who hired them perform better.

Table 14 Post-matching outcomes with closing establishment fixed effects

| | | | Outcomes after three years | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) Ln(Starting wage) | | (2) Employed | | (3) In same establishment | | (4) Ln(Earnings) | | (5) Ln(Wage) | |
| | Est. | (s.e.) | Est. | (s.e.) | Est. | (s.e.) | Est. | (s.e.) | Est. | (s.e.) |
| *Panel A* | | | | | | | | | | |
| Any connection | 0.016 | (0.009) | 0.007 | (0.003) | 0.133 | (0.007) | 0.094 | (0.012) | 0.015 | (0.007 |
| *Panel B* | | | | | | | | | | |
| Family | 0.019 | (0.009) | 0.005 | (0.004) | 0.136 | (0.010) | 0.079 | (0.018) | 0.015 | (0.008) |
| Coworkers | 0.007 | (0.010) | 0.007 | (0.003) | 0.068 | (0.009) | 0.061 | (0.016) | 0.004 | (0.007) |
| Classmates | 0.016 | (0.010) | -0.007 | (0.006) | 0.121 | (0.014) | 0.073 | (0.023) | 0.029 | (0.011) |
| Neighbors | -0.002 | (0.017) | 0.010 | (0.007) | 0.120 | (0.020) | 0.068 | (0.037) | -0.007 | (0.015) |
| Mean dep. var. | 9.913 | | 0.911 | | 0.319 | | 11.802 | | 9.973 | |
| # of fixed effects | 6,840 | | 27,778 | | 27,778 | | 27,764 | | 9,748 | |
| # of observations | 16,583 | | 168,029 | | 168,029 | | 167,508 | | 28,578 | |

*Notes:* All estimates are expressed in percent/percentage points, i.e., the coefficients are multiplied by 100. The estimated models include closing-establishment fixed effects. Standard errors are clustered on the level of the fixed effects. All estimations include year fixed effects, sex, being foreign born, age, education, county of residence, tenure at closing establishment, employment status and earnings during three years preceding displacement.

To document the impact on workers' post-matching outcomes (i.e., job stability, employment, wages, and earnings), we use individual level data on the sub-sample of displaced workers that regained employment and estimate linear regression models conditioning on closing-establishment fixed effects and worker characteristics (i.e., sex, age, education, immigration status, county of residence, tenure in the closing firm, and earnings during the last three years).[43] We focus our discussion on job stability (i.e., the probability of remaining in the same job three years later), but for completeness we also present the results for wages, earnings, and employment (see Table 14).[44] As in many previous studies, workers who gain employment through their social connections have a much higher probability (13 percentage points relative to a mean of 32 percent) of remain employed in the new job after three years (Column [3]). This effect is quite similar across the various types of social connections, although somewhat smaller in magnitude for coworkers. Hence, to the extent that we are willing to use job stability as

[43] We do not include worker fixed effects, because the sample of workers with repeat incidences of displacements due to closures is small and, possibly, selected. For the same reason, we do not include hiring-firm fixed effects.

[44] The previous literature (most notably Dustmann et al. [2016] on ethnicity-based networks, Kramarz and Skans, [2014] on family ties of youths, and Brown et al. [2016] and Burks et al. [2015] on referral hires within single-firms) have documented how starting wages, wage growth, ensuing tenure, and employment differ between matches that are, and are not, formed through documented social connections. The most conclusive result from these studies is that the likelihood of remaining in the new job is a positive function of the use of social networks. The standard interpretation is that this indicates a successful match if quality is only partially observed before production commences (as in Jovanovic, 1979).

a measure of match quality, all connections appear to generate match quality that on average supersedes the quality of market matches.[45]

Finally, we turn to the impact on firm productivity (i.e., total value-added, total sales, value-added per worker, and sales per worker). Our theoretical framework suggests that firm production should grow with the positive shocks to its connected supply of labor. Productivity per worker may, however, either decrease because of diminishing returns to scale or increase because fewer resources have to be spent on the hiring process. Alternatively, although not part of the model set-up, productivity can increase because the quality of matches formed through social connections is superior.

As before, we use the network displacement shocks as instruments for hires of connected displaced workers to explain these outcomes using the models outlined in Equations (5) and (6). Since the performance measures are available only at the firm (not establishment) level, we limit this analysis to single-establishment firms.[46] It is important to note the causal nature of this analysis, which makes it very different from the descriptive analysis provided in Section 3.3. Because we use displacement shocks to generate variations in the connected supply of labor, we are relying on variations in the connected hiring opportunities that are unrelated to other aspects of the productivity evolution of the firm. Thus, as long as this identification strategy is valid (as we believe the results above indicate), we capture the causal impact of changes in the connected supply of labor (and with the IV model, of connected hires) on firm performance.

The results are presented in Table 15 and suggest that firms grow in terms of sales and value-added when connected workers are displaced. The positive effect on the number of employees is essentially a corroboration of the notion that firms grow when they have access to workers who may be hired at lower screening costs. Reassuringly, the positive results are particularly pronounced for family members. This result is to some extent expected since the hiring responses are by far the largest for these connections, but at the same time these are also the connections where nepotism may be the most likely alternative candidate explanation (see, e.g., Beaman and Magruder,

[45] Our results show that workers who find new jobs through connections (of some kind) have higher than average starting wages as in Dustmann et al. (2016) and Hensvik and Skans (2016), but in contrast to Kramarz and Skans (2014) who focused on young workers. A possible interpretation of the differences in effects is that gaining a job through social connections induces a negative wage effects for young market entrants (see also Bentolila et al. [2010] for results in that direction), whereas the effects are positive for experienced workers, potentially because the information problem is different for market entrants (see Fredriksson et al., 2015). Notably, displaced workers are, by definition, not market entrants.

[46] In Appendix C, Table C3, we present the hiring results for the same sample of firms.

2012). The IV model displays a positive overall response on sales and value-added of 0.5 and 0.8 percent, respectively, for each hire of a connected displaced worker.

Table 15 The impact on firm and worker productivity

| | (1) log(VA) | (2) log(sales) | (3) log(VA/ worker) | (4) log(sales/ worker) |
|---|---|---|---|---|
| *Panel A: Reduced form* | | | | |
| Family displacements | 0.017 | 0.016 | 0.010 | 0.010 |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| Coworker displacements | 0.002 | -0.001 | 0.001 | -0.002 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| *Panel B: IV (using family and coworker displacements as instruments)* | | | | |
| Hired displaced family and coworkers | 0.008 | 0.005 | 0.005 | 0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| # of observations | 948,195 | 948,195 | 948,195 | 948,195 |
| # of establishments | 164,860 | 164,860 | 164,860 | 164,860 |

*Notes:* The standard errors are clustered on the establishment level. Sample only include single establishment firms. We control for the number of displaced workers within the same local labor market and year (i.e., year × industry × county), the number of displaced workers connected to the same year and local labor market, and network size (i.e., number of connections). All variables (right and left side) are scaled by the average size of the establishment.

Although the production responses are important as they corroborate the finding that firms size is endogenous to the supply of connected workers, the results are not necessarily implying that firms are becoming more efficient. A worst-case scenario would be that firms are becoming inefficiently large because of nepotistic recruitments. This, however, does not seem to be the case as the results for value-added and sales per worker do not suggest that productivity is declining. In fact, the results for family members are consistently positive and marginally significant for both performance outcomes. The results for coworkers are again less conclusive and less precise. The IV model, with its compound measure for the two types of connections, shows positive impact on both performance measures (although not statistically significant for sales per worker). The fact that value-added per worker grows faster, than sales per worker, is not surprising given that the capital/labor ratio should be attenuated when the number of employees increases due to the increase in the connected supply of labor.

Overall, from this novel analysis of the causal impact of social connections on firm performance, we conclude that the results do support the notion that access to connected labor allows firms to expand, in terms of both employment and production, with increasing or (a very conservative interpretation) at least constant labor productivity. The fact that the productivity responses are positive throughout for family members are particularly noteworthy, since these are the connections for which nepotism should, *a priori,* be the most likely alternative explanation.

## 7 Conclusions

Our analysis has provided a number of results on firms' hiring through social connections, whereof most are new to the literature. First, firms appear to prefer to use social connections when hiring. Attractive firms use connections more, and firms use connections more when hiring relatively few workers. Second, the social aspect of connections is crucial for their usefulness. Social connections are better predictors of reemployment destination the closer the social proximity (as indicated by family ties, demographic similarity, duration of interaction, time since interaction, size of the context). Third, idiosyncratic changes in the firms' connected supply of labor, induced by job displacements among their employees' social connections, affect the hiring patterns of the firms, while leaving the separation rate unaffected. The process leads to increased establishment-level job creation and a growth in production with unaffected or increasing labor productivity. This response is strongest for the very least productive firms. Fourth, the impact on firm performance is positive.

Our results are largely consistent with a stylized theoretical framework that assumes that social interactions between (strongly) connected workers convey information that can reduce the hiring frictions and vacancy costs of connected firms. If strong social connections allow firms to hire workers with less frictions or screening costs, then firms will hire more workers when connected workers are being displaced (and hence have worse alternative options). This model shows that reductions in the available options (through displacements) of connected workers who can be hired without frictions can generate more hires among firms that, otherwise, are constrained by hiring frictions. As long as these benefits are purely on the hiring side, separations should remain unaffected. The results thus suggest that strong social connections reduce matching frictions to the benefit of productive firms, but that low-productive firms take advantage of situations when connected workers are laid off.

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## Appendix A: Descriptive statistics for the firm-level analysis

Table A1 Summary statistics for the establishment-level productivity sample, including non-hiring establishments

| | (1) Mean | (2) Std. Dev. | (3) Median | (4) Min | (5) Max |
|---|---|---|---|---|---|
| *Establishment characteristics* | | | | | |
| Size (#employees) | 8.04 | 10.06 | 5 | 2 | 564 |
| Young establishment[a] | 0.157 | 0.363 | 0 | 0 | 1 |
| Log firm VA/worker in *t*-1[b] | 6.00 | 0.595 | 5.99 | -2.12 | 13.41 |
| Hires per worker | 0.218 | 0.326 | 0.111 | 0 | 11 |
| Separations per worker | 0.217 | 0.273 | 0.143 | 0 | 21.5 |
| *Number of connections* | | | | | |
| Any contact | 177.3 | 252.5 | 97 | 0 | 14,569 |
| Family | 26.92 | 38.04 | 15 | 0 | 2,148 |
| Coworkers | 41.32 | 69.81 | 11 | 0 | 1,657 |
| Classmates | 54.65 | 103.88 | 13 | 0 | 7,796 |
| Neighbors | 54.44 | 94.82 | 0 | 0 | 5,314 |
| *Fraction of hires that are connected:* | | | | | |
| Any contact | 0.107 | 0.257 | 0 | 0 | 1 |
| Family | 0.078 | 0.228 | 0 | 0 | 1 |
| Coworkers | 0.029 | 0.131 | 0 | 0 | 1 |
| Classmates | 0.004 | 0.049 | 0 | 0 | 1 |
| Neighbors | 0.013 | 0.089 | 0 | 0 | 1 |
| *Fraction of hires that are:* | | | | | |
| Unemployed in *t*-1 | 0.308 | 0.371 | 0.143 | 0 | 1 |
| Displaced in *t*-1 | 0.016 | 0.097 | 0 | 0 | 1 |
| # of establishment-year observations | | | 1,118,075 | | |

[a] Young establishments are less than 3 years old.
[b] Productivity is measured at the firm level.

Table A2 Summary statistics for the establishment-level sample

| | (1) Mean | (2) Std. Dev. | (3) Median | (4) Min | (5) Max |
|---|---|---|---|---|---|
| Size (initial) | 6.76 | 10.37 | 4 | 2 | 820 |
| Number of connected workers: | | | | | |
| Any type of connection | 152 | 234 | 79 | 0 | 14,944 |
| Family | | | | | |
| Parent | 3.57 | 6.39 | 2 | 0 | 413 |
| Child | 9.65 | 14.58 | 5 | 0 | 1,111 |
| Spouse | 2.59 | 4.54 | 1 | 0 | 316 |
| Sibling | 8.36 | 13.35 | 5 | 0 | 933 |
| Coworker | 35.73 | 64.55 | 7 | 0 | 1,973 |
| Classmate | | | | | |
| High school | 37.74 | 78.25 | 0 | 0 | 6,171 |
| University | 6.45 | 30.30 | 0 | 0 | 2,151 |
| Neighbor | 47.76 | 90.15 | 0 | 0 | 5,586 |
| Number of connected displaced workers | | | | | |
| Any type of connection | 0.88 | 2.48 | 0 | 0 | 152 |
| Any type of connection within same industry | 0.12 | 1.04 | 0 | 0 | 127 |
| Any type of connection within different industry | 0.76 | 2.16 | 0 | 0 | 114 |
| By type: | | | | | |
| Family | | | | | |
| Parent | 0.02 | 0.16 | 0 | 0 | 6 |
| Child | 0.01 | 0.11 | 0 | 0 | 22 |
| Spouse | 0.04 | 0.21 | 0 | 0 | 13 |
| Sibling | 0.27 | 1.86 | 0 | 0 | 113 |
| Coworker | | | | | |
| Classmate | 0.25 | 0.76 | 0 | 0 | 47 |
| High school | 0.03 | 0.23 | 0 | 0 | 28 |
| University | 0.25 | 0.78 | 0 | 0 | 80 |
| Outcome variables: | | | | | |
| Number of hires in total | 1.52 | 2.68 | 1 | 0 | 180 |
| Net growth of employment | -1.79 | 33.96 | 0 | -629 | 486 |
| Number of separations | 1.53 | 2.69 | 1 | 0 | 396 |
| # of establishment-year observations | | | 1,989,278 | | |
| # of establishments | | | 311,817 | | |

*Notes:* Summary statistics for the establishments in our sample.

## Appendix B: Details on the interpretative framework

Ignoring the case of firm closure where all workers are fired, we have four possible cases:

**Case 1**) Workers are fired ($F > 0$) if $A_t < \frac{w-c^f}{R'\left((1-q)L_{t-1}\right)}$ .

**Case 2**) Firms stay inactive, thus producing with $(1-q)L_{t-1}$ workers, if

a) $\frac{w-c^f}{R'\left((1-q)L_{t-1}\right)} \leq A_t \leq \frac{w}{R'\left((1-q)L_{t-1}\right)}$ or

b) $\frac{w-c^f}{R'\left((1-q)L_{t-1}\right)} \leq A_t \leq \frac{c^V/m_t + \mathrm{w}}{R'\left((1-q)L_{t-1}\right)}$ and $H_t^{Cmax} = 0$ .

**Case 3**) Workers are hired though social connections ($H^C > 0, V = 0$) if $A_t > \frac{w}{R'\left((1-q)L_{t-1}\right)}$ and $H_t^{Cmax} > 0$.

**Case 4)** Vacancies are posted ($V > 0$) if $A_t > \frac{c^V/m_t + \mathrm{w}}{R'\left((1-q)L_{t-1} + H_t^C\right)}$ and $H_t^C = H_t^{Cmax}$. These are posted until $A_t = \frac{c^V/m_t + \mathrm{w}}{R'\left((1-q)L_{t-1} + H_t^C + m_t V_t\right)}$.

These results imply that job displacements among workers socially connected to the firm, which are expanding the largest possible number of connected hires $H^{Cmax}$, has a set of fairly intuitive consequences for firm-level manpower decisions. First, firm-level firings are not affected by these job displacements. Second, the inactivity range is reduced since the cost of recruiting is lower. Third, the threshold for when market vacancies are posted is raised when connected workers are displaced because of the cheaper alternative hiring option they provide. As a consequence, displacements among the set of workers that a firm is connected to will, on average, lead to unchanged firing patterns, but increased net hires and, consequently, also net employment growth. The impact on total hires depends on the crowding out of market (vacancy) hires.

At intermediate values of $A_t$, there is a positive impact on hires, with no crowding out. The range of values on $A_t$, for which the inactivity is reduced by strictly positive values on $H_t^{Cmax}$ (hence the range at which $H_t^{Cmax}$ affect hiring without crowding out), equals the difference in threshold values for hires when $H_t^{Cmax} = 0$ or $H_t^{Cmax} > 0$:

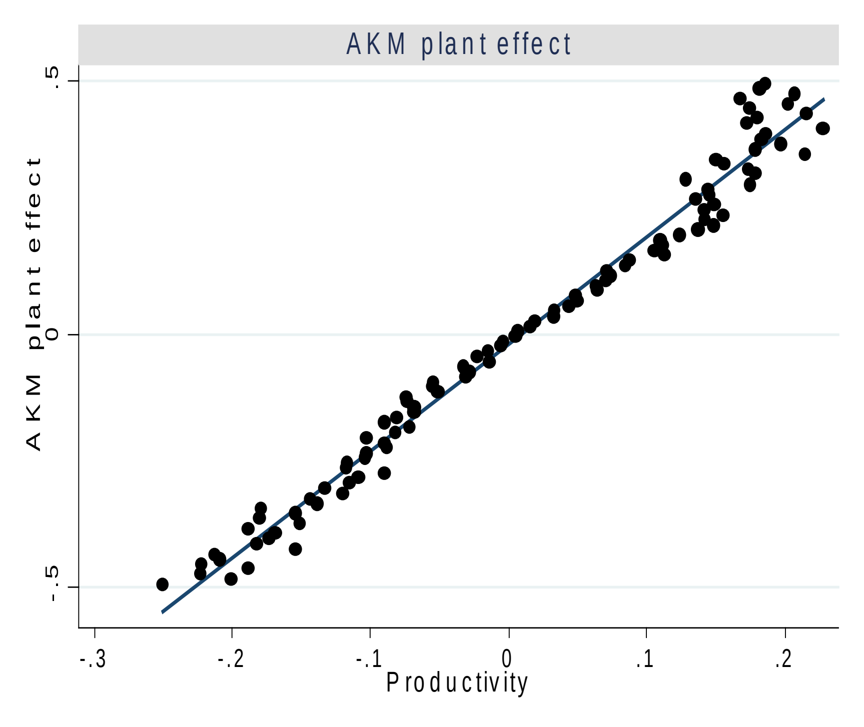
$$\frac{c^V/m_t + \mathrm{w}}{R'\big((1-q)L_{t-1}\big)} - \frac{w}{R'\big((1-q)L_{t-1}\big)} = \frac{c^V/m_t}{R'\big((1-q)L_{t-1}\big)}$$

Notable, the threshold values crucially hinges on the ratio of the effective vacancy cost ($c^V/m_t$) to the marginal product. It is also evident that the range at which displacement of connected workers lead to increased hiring depends on the quit rate ($q$) and the curvature of the production function. A higher exit rate reduces the role of $H_t^{Cmax}$, since it forces more firms to hire even at low levels of $A_t$. This effect is more pronounced if production losses from the quits are relatively large, i.e., when the production function is less curved.[47]

[47] For a closed form solution, evaluated at the point where the sum of inherited workers correspond to the frictionless optimum at the expected value of $A_t$ (i.e., when $L_{t-1}$ satisfies $E(A_t)R'(L_{t-1}) = w$), use $E(A_t)R'(L_{t-1}) = w$, assume $R(L) = L^\alpha$ and normalize $E(A_t) = 1$, to get the size of the zero crowding out range: $\frac{c^V/m_t}{R'\left((1-q)L_{t-1}\right)} = \frac{c^V/m_t}{w(1-q)^{\alpha-1}}$ which is decreasing in $q$ and increasing in $\alpha$.

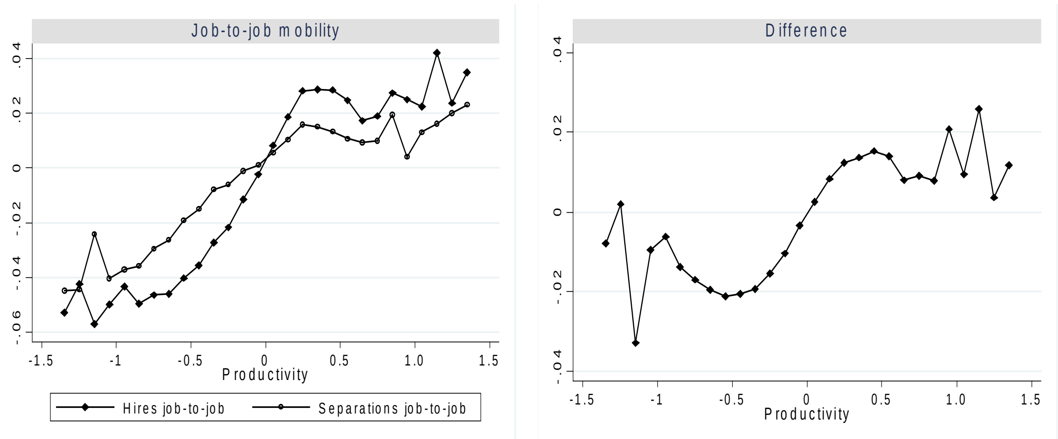
## Appendix C: Additional results

Figure C1 Productivity and estimated plant effects from AKM-models



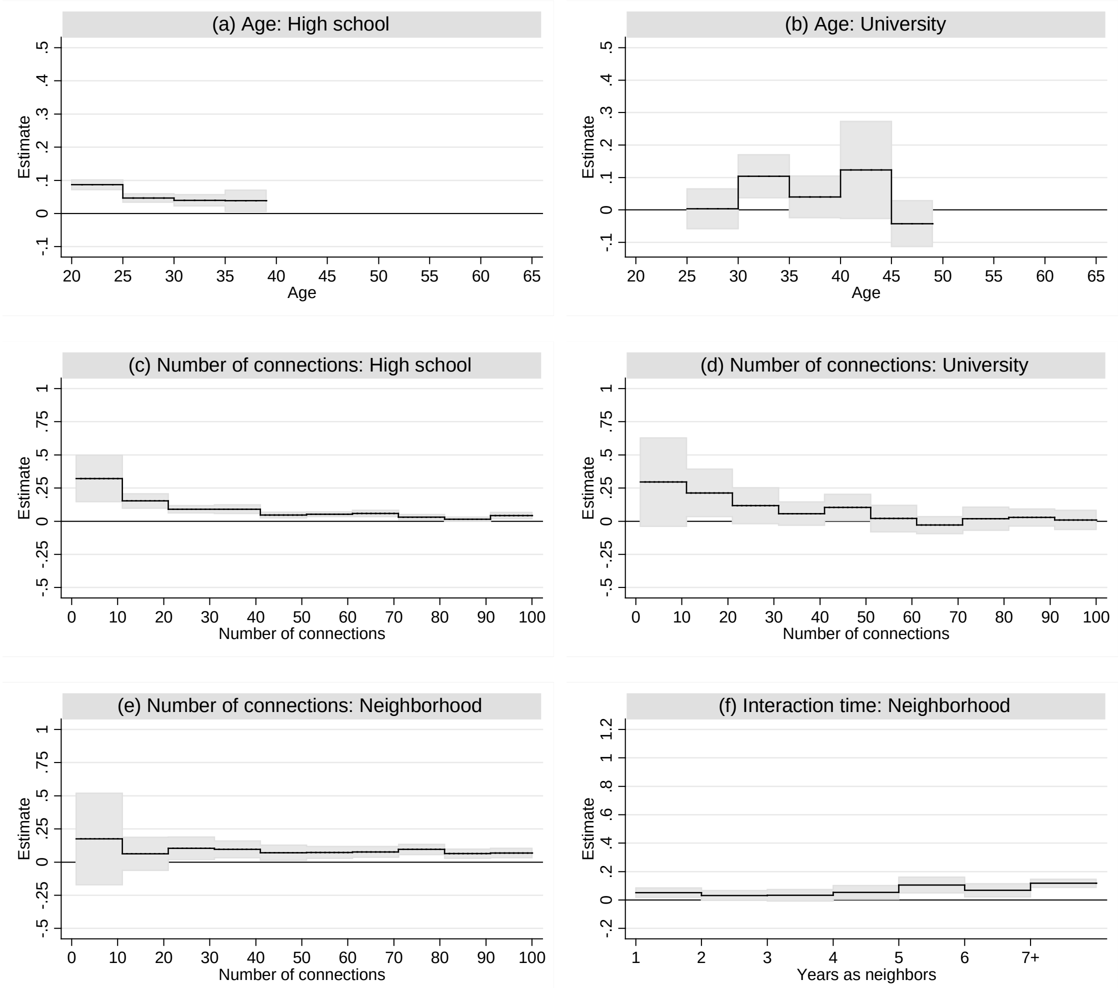

*Notes:* The figure plots the correlation between the estimated AKM (see Abowd et al. 1999) establishment effect and productivity, after controlling for industry-municipality-and-year fixed effects, an indicator for if the plant is young (≤3yrs), lagged size, and the fraction of family members, coworkers, classmates and neighbors that the establishment is connected to. Residual productivity is binned into 100 equally sized bins. The solid line shows the best linear fit estimated using OLS. The sample has been trimmed to remove the bottom and top 1 percentile of the productivity distribution.

Figure C2 Productivity and job-to-job movers among hires and separated workers




*Note:* The left figure shows the relationship between the fraction hired from job-to-job and productivity, as well as the fraction of separations from job-to-job, after controlling for industry-municipality-and-year fixed effects, an indicator for if the plant is young (≤3yrs), lagged size, and the fraction of family members, coworkers, classmates, and neighbors that the establishment is connected to. Residual productivity is binned into 30 equally-sized bins, and the left figure shows the net difference between job-to-job hires and separations. The sample has been trimmed to remove the bottom and top 1 percentile of the productivity distribution.

Figure C3 The role of time since interaction (i.e., age), size of the social context (i.e., number of connections), and interaction time, with 95% CIs




*Notes:* All estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. Estimates are interactions between having the particular type of connection (i.e., a classmate from high school or college/university) and different measures of tie strength. Age (5-year categories) captures time since going to high school/university. The number of connections is divided into 10 categories. In case of a displaced worker having more than one previous neighbor within the same establishment "Years as neighbors" corresponds to the longest relation. All estimations include establishment-pair-and-year fixed effects. Standard errors are clustered on the establishment-pair-and-year level.

Table C1 Estimated effects of social connections by type of contact from models with alternative fixed effects

| | (1) Closing-and connected-establishment-pair-and-year (*j,k,t*) fixed effects | | (2) Displaced-worker-and-year (*i,t*) fixed effects | | (3) Closing-establishment-and-year (*j,t*) fixed effects | | (4) Connected-establishment-and-year (*k,t*) fixed effects | |
|---|---|---|---|---|---|---|---|---|
| | Est. | (s.e.) | Est. | (s.e.) | Est. | (s.e.) | Est. | (s.e.) |
| *Panel A:* | | | | | | | | |
| Any contact | 0.270 | (0.005) | 0.314 | (0.006) | 0.289 | (0.006) | 0.292 | (0.004) |
| *Panel B:* | | | | | | | | |
| Family | 1.095 | (0.020) | 1.194 | (0.021) | 1.204 | (0.021) | 1.144 | (0.019)) |
| Coworkers | 0.253 | (0.010) | 0.414 | (0.014) | 0.397 | (0.013) | 0.337 | (0.010) |
| Classmates | 0.066 | (0.004) | 0.058 | (0.005) | 0.050 | (0.005) | 0.081 | (0.004) |
| Neighbors | 0.086 | (0.008) | 0.086 | (0.009) | 0.070 | (0.008) | 0.101 | (0.007) |
| *Panel C:* | | | | | | | | |
| Family | | | | | | | | |
| Parent | 1.867 | (0.052) | 1.911 | (0.048) | 1.943 | (0.049) | 1.903 | (0.049) |
| Child | 0.670 | (0.052) | 0.834 | (0.045) | 0.780 | (0.046) | 0.708 | (0.044) |
| Spouse | 1.974 | (0.078) | 2.214 | (0.072) | 2.300 | (0.074) | 2.055 | (0.071) |
| Sibling | 0.697 | (0.023) | 0.746 | (0.023) | 0.749 | (0.023) | 0.737 | (0.022) |
| Coworkers | 0.252 | (0.010) | 0.414 | (0.014) | 0.397 | (0.013) | 0.336 | (0.010) |
| Classmates | | | | | | | | |
| High school | 0.064 | (0.004) | 0.057 | (0.005) | 0.048 | (0.005) | 0.076 | (0.004) |
| College/university | 0.084 | (0.018) | 0.130 | (0.021) | 0.108 | (0.018) | 0.135 | (0.018) |
| Neighbors | 0.080 | (0.008) | 0.083 | (0.009) | 0.066 | (0.008) | 0.097 | (0.007) |
| Mean dep. var. | 0.00043 | | 0.00043 | | 0.00043 | | 0.00043 | |
| # of fixed effects | 2,087,791 | | 289,333 | | 31,538 | | 912,118 | |
| # of observations | 41,113,879 | | 41,113,879 | | 41,113,879 | | 41,113,879 | |

*Notes:* All estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. Standard errors are clustered on the level of the fixed effects.

Table C2 First stage estimates using only cross-industry displacements

| | (1) Displaced connections: *All industries* | (2) Displaced connections: *Other industries* |
|---|---|---|
| Any contact | 0.225 | 0.165 |
| | (0.015) | (0.015) |
| *By type of contact:* | | |
| Family | 1.670 | 1.455 |
| | (0.066) | (0.061) |
| Coworkers | 0.212 | 0.140 |
| | (0.018) | (0.019) |
| Neighbors | 0.064 | 0.064 |
| | (0.011) | (0.012) |
| Classmates | 0.016 | 0.000 |
| | (0.010) | (0.010) |
| # of observations | 1,989,278 | 1,989,278 |
| # of fixed effects | 311,817 | 311,817 |
| R-squared | 0.187 | 0.009 |

*Notes:* Column (1) shows the estimates from columns (1) and (2) of Table 8 for comparison. Column (2) shows the estimates when we restrict variation to displacements in other industries than the receiving firm.

Table C3 Hiring effects for the profit sample

| | (1) Connected hires | (2) Total hires | (3) Separations | (4) Net growth |
|---|---|---|---|---|
| *Panel A: Reduced form* | | | | |
| Family displacements | 1.404 | 1.171 | 0.008 | 1.164 |
| | (0.196) | (0.478) | (0.507) | (0.715) |
| Coworker displacements | 0.229 | 0.166 | 0.056 | 0.110 |
| | (0.046) | (0.109) | (0.113) | (0.165) |
| *Panel B: IV (Family and coworker displacements as instruments)* | | | | |
| Hired displaced family | 0.761 | 0.605 | 0.070 | 0.535 |
| and coworkers | (0.062) | (0.185) | (0.195) | (0.268) |
| # of observations | 948,195 | 948,195 | 948,195 | 948,195 |
| # of establishments | 164,860 | 164,860 | 164,860 | 164,860 |

*Notes:* The table shows the main hiring results for the sample of single-establishment private firms where firm-level productivity is available. The standard errors are clustered on the establishment level. We control for the number of displaced workers within the same year and local labor market (i.e., year × industry × county), the number of displaced workers connected to the same year and local labor market, and network size (i.e., number of connections). All variables (right and left side) are scaled by the average size of the establishment.