Social Connections and the Sorting of Workers to Firms*

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Abstract

The literature on social networks often presumes that job search through (strong) social ties leads to increased inequality by providing privileged individuals with access to more attractive labor market opportunities. We assess this presumption in the context of sorting between AKM-style person and establishment fixed effects. Our rich Swedish register data allow us to measure connections between agents – workers to workers and workers to firms – through parents, children, siblings, spouses, former co-workers and classmates from high school/college, and current neighbors. In clear contrast with the above presumption, there is *less* sorting inequality among the workers hired through social networks. This outcome results from opposing factors. *On the one hand, reinforcing positive sorting*, high-wage job seekers are shown to have social connections to high-wage workers, and therefore to high-wage firms (because of sorting of workers over firms). Furthermore, connections have a causal impact on the allocation of workers across workplaces – employers are much more likely to hire displaced workers to whom they are connected through their employees, in particular if their social ties are strong. *On the other hand, attenuating positive sorting*, the (causal) impact is much stronger for low-wage firms than it is for high-wage firms, irrespective of the type of worker involved, even conditional on worker fixed effects. The lower degree of sorting among connected hires thus arises because low-wage firms use their (relatively few) connections to high-wage workers to hire workers of a type that they are unable to attract through market channels.

Keywords: networks; job search; job displacement; hiring

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1 Introduction

A large literature (cited below) has identified social networks as a key mediator in the process of matching workers to firms. However, even though much of the general interest in social networks is motivated by its perceived links to inequality, the links between social networks and *sorting inequality*, defined as inequality arising from systematic sorting of workers to firms, has rarely been investigated. A noteworthy exception is Schmutte (2015) studying the role of neighborhood connections. In this paper, we present the first comprehensive analysis of how different types of social networks relate to sorting inequality. The question is motivated by the fact that systematic sorting in the matching between workers and firms has been shown to be an important mechanism leading to wage inequality in a series of recent and influential papers. Using statistical decomposition of wages into fixed person and firm effects in the spirit of Abowd et al. (1999), these papers have, e.g., shown how entry of low-paying firms in Germany, employing mostly low-wage workers, affects the evolution of the overall wage distribution (Card et al., 2013) and how sorting of men and women into different firms in Portugal is related to gender wage disparities (Card et al., 2016). A salient finding in these studies is the existence of sorting inequality arising from high-wage workers' disproportional access to jobs in higher paying and more productive firms, a finding corroborated using alternative methods and/or data in several recent studies including Barth et al. (2016), Bonhomme et al. (2018), Abowd et al. (2018), Card et al. (2018) and Song et al. (2019).[1]

The extensive literature on social networks, spanning across many social sciences, tends to presume that social networks are an important source of inequality. The following quote by an authority in the field illustrates this very clearly:

> "[...] Social networking, which claims to make connections and bring people together, paradoxically exacerbates social divisions and inequalities. Social networks are inherently unfair and exclusionary. They operate on the principle [...] 'birds of a feather flock together.' [...] If people have lower prestige, socio-economic status, or are the targets of discrimination, then their networks will be composed of people with lower prestige, lower socio-economic status, and who are otherwise disadvantaged." (Kadushin, 2012).

A similar notion is also present in the economic literature on social networks. Widely cited theoretical articles relate social networks and labor market inequality through the preferential dissemination of information about vacancies (Calvó-Armengol and Jackson, 2004) and referral opportunities within social

[1] A related set of studies relies on structural estimation of models with on-the-job search following in the tradition of Postel-Vinay and Robin (2002). In this structural literature, the focus is on the job-to-job mobility process where productive workers receive and accept offers from more productive firms through job ladders. But as in the reduced form literature, the role of social networks is rarely explored.

networks (Montgomery, 1991). In particular, as emphasized by Ioannides and Datcher Loury (2004), *strong* social ties should lead to increased inequality since these ties are assumed to be particularly unequally distributed.

In this paper, we assess the impact of social connections on the sorting of workers to firms. To do so, we examine the distribution of displaced workers' social connections to employed workers and their firms. Our Swedish longitudinal administrative data allow us to measure multiple types of social relations for every individual, of both the strong and the weak sort; we study family members, former co-workers, former classmates, and current neighbors. The data also allow us to match workers to their employers, and to estimate their respective fixed effects using an "AKM"-decomposition following Abowd et al. (1999).

The analysis first shows that birds of a feather indeed flock together in terms of earnings capacity, i.e., we document that social ties, particularly those formed on the labor market, connect high-wage workers to other high-wage workers. Thereafter, we analyze how these connections affect hiring patterns and sorting inequality. In sharp contrast with standard presumptions found in the literature, we show that matching through social networks leads to *less* sorting inequality than "market" matches.

Social networks have been shown to play a quantitatively important role in the process of matching workers to jobs – between one third and one half of all job matches are usually attributed to social connections (see, e.g., Ioannides and Datcher Loury, 2004). Because of their apparent quantitative importance, studying the mechanisms at work when social connections are involved in the matching process is likely to shed light on key aspects of the overall determinants of labor market sorting.[2] Social connections help alleviate some of the information problems that agents face when searching on a frictional labor market. Such connections help inform agents (usually workers) about the presence of available opportunities on the opposite side of the market (see, e.g., Calvó-Armengol and Jackson, 2004, 2007; Calvó-Armengol et al., 2007) or help inform agents on one side of the market (i.e., the firms and/or the workers) about the properties of agents on the opposite side (see, e.g., Montgomery, 1991; Simon and Warner, 1992; Casella and Hanaki, 2006; Dustmann et al., 2015; Galenianos, 2013).[3]

Despite the well-documented role of specific social networks in the allocation of workers to jobs (e.g., former co-workers, ethnic or university/alumni networks, and neighbors), most of the research has examined each type of network in isolation.[4] Because so few studies simultaneously examine multiple

[2] As argued by Galenianos (2013), both information channels are closely related to the use of an aggregate matching function to approximate search frictions. Oyer and Schaefer (2016) make a similar argument from the personnel-economics perspective. They argue that we know too little about the strategies used by firms when filling jobs, explicitly mentioning the use of referrals as a key strategy.

[3] For related empirical studies investigating the information content of connections see, e.g., Brown et al. (2016), Burks et al. (2015) and Hensvik and Skans (2016).

[4] Important related studies have examined, e.g., neighbors (e.g., Bayer et al., 2008), former co-workers (e.g., Cingano and Rosolia, 2012), compatriots (e.g., Dustmann et al., 2016), and parents (e.g., Kramarz and Skans, 2014). The most closely related studies are Bayer et al. (2008) and Kramarz and Skans (2014) that both investigated connections and matching patterns

types of connections, the role of ties' strength, as originally proposed by Granovetter (1973), and the associated "strength of weak ties" hypothesis (i.e., acquaintances matter more than close friends or family members) has rarely been formally tested, and never in the context of sorting inequality.[5]

To explain our empirical set-up, it is useful to relate the probability that a job-seeker is hired by a particular employer (denoted $H = 1$) to her available social connections (denoted $C = 1$). Bayes' rule implies that:

$$\Pr(H=1) = \Pr(H=1 \mid C=0) + \Pr(C=1)[\Pr(H=1 \mid C=1) - \Pr(H=1 \mid C=0)] \tag{1}$$

This formulation makes clear that matches generated through connections add to "market" matches (i.e., unconnected, $C=0$) through a causal effect equal to $\Pr(H=1 \mid C=1) - \Pr(H \mid C=0)$. Thus, the degree to which connections affect sorting depends on the distribution of connections, i.e., "for which types of worker-firm combinations do we observe that $C=1$?", and the distribution of causal effects, i.e., "for which types of worker firm-combinations do we observe that $\Pr(H=1 \mid C=1) > \Pr(H=1 \mid C=0)$?".

To get closer to a causal analysis of the role of social connections in the hiring process, we start by focusing on displaced workers after a firm closure.[6] For these workers, staying in their origin firm is no longer an option. The strategy thus allows us to compare different workers in the same closure event, i.e., who move under similar conditions (without the option of staying) at the same time. To identify the causal effects of social connections, we exploit the fact that workers, displaced in the same event, tend to have social connections to different employers. We provide placebo analyses to support the causal interpretation. We then study how job-finding through social connections interacts with sorting inequality. To this effect, we follow Card et al. (2013), Song et al. (2019), and Schmutte (2015) and decompose wages into a worker and a firm effect, using the AKM approach. Our exceptionally rich data further allow us to complement our baseline analyses with analyses relying on within-worker identification strategies. The latter exploits the fact that most displaced workers are endowed with connections to multiple establishments at the same time to identify the relative importance of connections to high- vs. low-wage employers.

The strategy we adopt thus relies on three building blocks: i) establishment closures as (exogenous) events forcing workers to search for new jobs;[7] ii) the structure of the displaced workers' social networks

by characterizing agents on either side of the connection. None of these studies has looked at sorting and the associated consequences for wage inequality.

[5]The few exceptions that have tried to analyze the respective roles of weak and strong ties (e.g., Kramarz and Skans (2014) and Gee et al. (2017)) have not connected their questions to sorting inequality.

[6]Given the types of connections we are studying, it is not unreasonable to assume that the set of connections is exogenous.

[7]A large number of studies have used firm or establishment closures as quasi-experiments where workers lose their jobs for an exogenous reason. Examples of outcomes of these job displacements that have been studied are earnings (e.g., Eliason and Storrie, 2006; Hijzen et al., 2010), family income (e.g., Eliason, 2011), mortality (e.g., Eliason and Storrie, 2009*a*; Browning and Heinesen, 2012), morbidity (e.g., Eliason and Storrie, 2009*b*, 2010; Browning and Heinesen, 2012), divorce (e.g., Rege et al., 2007; Charles and Stephens, 2004; Eliason, 2012), fertility (e.g., Huttunen and Kellokumpu, 2016; Del Bono et al.,

as inferred from register data on family members, former co-workers, former classmates, and current neighbors; and iii) the varying causal impacts of these social networks across different combinations of person and employer fixed effects.

Finally, to better gauge the role job displacements play for our results, we describe *the sorting patterns of all other job-to-job movers*, i.e., those unaffected by establishment closures, and compare these results to comparable estimates for the displaced sample.

Our results can be summarized as follows: First, we show that our measured social connections exhibit *homophily*, i.e., positive sorting, in terms of earnings capacity. High-wage workers are more likely to be connected to other high-wage workers, and these high-wage workers are more likely to work for high-wage employers. This sorting is most pronounced for professional ties, in particular past co-workers and classmates from university, whereas networks of connections from within families, neighborhoods and high schools exhibit much less baseline homophily in the dimensions described by the estimated AKM effects.

Second, social relationships matter; workers are much more likely to find jobs in the exact establishment where they have a connection than other workers displaced in the same event, but endowed with no such connection to that precise employer. The hiring probability for those with connections, i.e., $\Pr(H=1 \mid C=1)$, increases by at least one order of magnitude relative to the hiring probability for those with no connection, i.e., $\Pr(H=1 \mid C=0)$. The causal effects of family members (in particular parents and spouses) are largest, followed by connections through past co-workers. Former classmates and neighbors have weaker, yet positive, effects. This relative ordering is retained when using an alternative within-worker identification strategy. We interpret family members as ”strong” ties, and show that other indicators of tie strength (connections of longer duration, more recently established, or fostered in smaller groups) also are related to larger causal effects.

Our two first key results jointly imply that the connections that have the largest causal effects (family), also exhibit least homophily, whereas, e.g., university connections link high-wage workers to high-wage firms, but have limited causal effects (in comparison to family ties).

Third, the magnitude of the causal effects of connections is equally large for low-wage and high-wage workers.[8] In contrast, the causal effects are much larger for low-wage *employers* than for high-wage employers, *regardless* of whether the connected workers are low-wage or high-wage. Workers with multiple social connections are more likely to enter a connected low-wage establishment than a connected high-wage establishment if connected to both types. This, again, holds equally for low-wage

2015), alcohol-related morbidity and mortality (e.g., Eliason, 2014), children's school performance (e.g., Oreopoulos et al., 2008; Coelli, 2011; Rege et al., 2011), and criminality (e.g., Rege et al., 2009). In this respect, our approach is similar to that of recent papers by Cingano and Rosolia (2012), Glitz (2017), and Saygin et al. (2014), who all studied the relationship between the displaced workers' network quality (i.e., employment rate) and the speed of reemployment.

[8]This holds for all connections except for spousal ties that are used more by women (who, on average have lower person effects) than by men.

and high-wage workers. Thus, our data do not suggest that social connections have larger effects when they link high-wage workers to high-wage employers.

The resulting outcome is that sorting inequality is lower for those matches that are formed through social connections than for unconnected ”market” matches. This conclusion, which is valid not only for the displaced workers but for all job-to-job movers, is due to a combination of two sets of opposed effects: i) social connections are positively sorted and causally increase the likelihood of being hired; ii) and high-wage workers are more likely to find jobs in low-paying establishments when social connections are involved. The latter force is reinforced by the fact that the types of connections that have the largest causal effects (family) exhibit the lowest levels of homophily (in terms of AKM-components). Hence, the presumption that “birds of a feather flock together” holds; high-wage workers are connected to other high-wage workers who, in turn, work for high-wage employers. However, the causal effects are independent of whether the ”birds” (workers vs employers) have similar feathers or not. As a consequence, the presumption that social homophily necessarily leads to increased sorting inequality is not borne out by our data. Instead, we show that sorting inequality is weaker for connected matches than for “market” matches, despite the prominent role played by strong social ties (typically, family members) in the job-finding process.

The rest of the paper is structured as follows: Section 2 describes the various components of our empirical strategy. Section 3 presents the data sources, including how we define and identify the establishment closures, displaced workers, social connections as well as the AKM-estimates. Section 4 presents the main results in the following order: i) the structure of connections; ii) the average causal effects of social connections together with placebo tests; iii) the causal effects, by person and establishment effects and iv) the overall sorting patterns with and without connections. Section 5 presents extensions where we analyze how connections compete, explore the role of observable characteristics of the agents and show how matching through social connections is related to future labor market outcomes. Section 6 provides concluding remarks.

2 Set-up and empirical strategy

Our goal is to assess how social connections affect the probability that worker i is hired by establishment k and how connected hires in turn affect sorting inequality defined as the tendency for high-wage workers to sort into high-wage establishments and low-wage workers corresponding tendency to sort into low-wage establishments. In this section, we present the overall set-up, the identification strategy, and details of the empirical approach.

2.1 Connections and mobility: modelling and identification

To understand the causal role of social connections in establishments' hiring of workers, a useful starting point is to focus on the probability that worker i moves from establishment j to establishment k (denoted M_{ijk}):

$$\Pr(M_{ijk}=1)=\Pr(C_{ijk(l)}=1)\Pr(M_{ijk}=1\mid C_{ijk(l)}=1)+(1-\Pr(C_{ijk(l)}=1))\Pr(M_{ijk}=1\mid C_{ijk(l)}=0), \quad (2)$$

where $C_{ijk(l)}=1$ denotes the existence of a social connection between worker i (who is employed in establishment j) and a mediating worker $l(i)$ employed in establishment $k(l)$. To go from equation (2) to an analysis of worker-establishment sorting, we must study three elements. First, the structure of worker i's connections across workers $l(i)$ and their establishments $k(l)$. (In the following, we will refrain from referring to the mediating worker l unless necessary, and write $C_{ijk}=1$ for simplicity.) Second, employer k's hiring decisions of various types of workers, conditional on C being equal to either unity or zero. Finally, it also requires that worker$i$ chooses to search for, and accept, a new job in order for her to leave establishment j. The latter component of worker i's decision is particularly significant since remaining in establishment j is the default option adopted by most workers in any year. The determinants of this mobility choice, i.e., if and when a worker separates from her current employer, are multiple and often unobserved. Hence, an analysis of the role of social networks for sorting either has to take the decision of staying vs. leaving very seriously, or condition on the endogenous sample that chooses to relocate. In this paper, we instead focus most of our analysis on cases where this decision is caused by external factors (job displacements due to establishment closures) and return to the more general case at the end of the paper.

To make the focus on forced movers explicit, we define an indicator H_{ijk} equal to one when worker i is hired by k, conditional on having separated from her previous employer j.[9] Establishment closures imply that staying in establishment j is not an option. Hence, we can now directly concentrate on discerning whether establishment k hires worker i or not. It is also useful to re-formulate the problem of equation (2) as:

$$\Pr(H_{ijk}=1)=\Pr(H_{ijk}=1\mid C_{ijk}=0)+\gamma_{ijk}\Pr(C_{ijk}=1), \quad (3)$$

where the *causal effect*

$$\gamma_{ijk}=\Pr(H_{ijk}=1\mid C_{ijk}=1)-\Pr(H_{ijk}=1\mid C_{ijk}=0) \quad (4)$$

[9]Formally, we link H_{ijk} to M_{ijk} by defining indicator S_{ij} equal to one if worker i separates from her previous employer j, and zero otherwise and noting that $M_{ijk}=1$ if $S_{ij}=1\wedge H_{ijk}=1$ and $M_{ijk}=0$ if $S_{ij}=0\vee H_{ijk}=0$. Establishment closures ensure that $S_{ij}=1$ for all workers from j.

isolates the impact of social connections between worker i (from closing establishment j) and employer k on the probability of worker i being hired by employer k. Equation (3) implies that social connections are related to hiring patterns through the combination of $\Pr(C_{ijk(l)} = 1)$ and γ_{ijk}, i.e., the structure of social connections *and* the structure of causal effects.

2.2 Connections and sorting inequality

It is straightforward to adapt this framework, starting with equation (3), to a study of sorting inequality in the spirit of Card et al. (2013). Hence, we use the AKM decomposition of Abowd et al. (1999):

$$\ln w_{it} = \theta_i + \psi_{k(i,t)} + X_{it}\beta + \varepsilon_{it}, \tag{5}$$

where w_{it} is worker i's wage in year t, θ_i is a person fixed effect for worker i, and $\psi_{k(i,t)}$ is an establishment (k) fixed effect in year t. $X_{it}\beta$ is a vector of control variables, which as in Card et al. (2013), includes an unrestricted set of year indicators, and education level interacted with age in quadratic and cubic terms.[10] In what follows, the estimates of θ_i and $\psi_{k(i,t)}$ will be treated as data as in Card et al. (2013) among others. To ensure that the impact that social connections may have on post-hiring wages is not transmitted into the estimates of the worker fixed effects, the person effects are drawn from estimations that only use the years preceding job displacement (i.e., separately for each displacement year cohort).

We let the distribution of connections, and the impact of connections, be functions of the person and establishment effects. Thus, the expected frequency of hires by type-ψ establishments of type-θ workers is:

$$\mathrm{E}[H \mid \theta, \kappa] = \mathrm{E}[H^m \mid \theta, \psi] + \gamma(\theta, \psi)\,\mathrm{E}[C(\theta, \psi)] \tag{6}$$

where we let $H^m = [H \mid C=0]$ denote non-connected "market" hires and where we let market hires, the distribution of connections $\Pr(C_{ijk}=1) = C(\theta_i, \psi_k)$, and the causal effects $\gamma_{ijk} = \gamma(\theta_i, \psi_k)$ be functions of the agents' AKM-components.

Remark: Social connections will increase sorting on the labor market if market hires, i.e., $\mathrm{E}[H^m \mid \theta, \psi]$ in equation (6), are less positively sorted than hires due to connections, i.e., $\gamma(\theta, \psi)\,\mathrm{E}[C(\theta, \psi)]$ in the same equation.

Empirically, we start by analyzing the distribution of connections between different types of agents, $C(\theta, \psi)$. We do this in two steps. First, we correlate the person effects of displaced workers (i) with the person effects of their social connections (i.e., the intermediary workers l). A positive correlation, i.e., $\mathrm{Corr}(\theta_i, \theta_l) > 0$, will be interpreted as *homophily*. Second, we analyze the correlation between the

[10]Education level is categorized in three levels: compulsory school, high school, and college/university. Age is normalized relative to age 40.

displaced workers' person effects and the types of establishments they are connected to, i.e., $\text{Corr}(\theta_i, \psi_k)$. Then, we estimate how the shape of the causal effects of connections, i.e., $\gamma(\theta, \psi)$ relates to the person and establishment effects. We provide separate estimates for different types of (strong and weak) social ties in all these cases.

For identification purposes, we focus the analysis on displaced workers, but towards the end of our main analysis, we provide descriptive regressions comparing the overall sorting patterns for market hires and connected hires. This allows us to describe the overall sorting patterns for connected and non-connected job-to-job transitions and compare them to corresponding estimates for the displaced. To preview the results, these descriptive regressions suggest that the results are similar (at least in a qualitative sense) for the displaced and non-displaced alike.

2.3 Identifying the causal impact of connections: practical details

2.3.1 Identification with constant effects

To illustrate our identification strategy, we assume that the impact of social connections is constant (i.e., $\gamma_{ijk} = \gamma$) – an assumption that we relax below. Because equation (3) defines connections and hiring outcomes for *pairs* of agents (i.e., worker i and employer k), we adopt a "dyadic" data structure, where each observation is a combination of a worker and an establishment.

To identify the causal parameter γ, as defined by equation (4), we use a model that accounts for potential correlations between the social connections and the counterfactual probabilities of market hires ($\Pr(H_{ijk} = 1 \mid C_{ijk} = 0)$) by including fixed effects for each *pair of closing establishment and potential hiring establishment*. These establishment-pair fixed effects account for all shared aspects (e.g., location, industry and year) that may make a displaced worker i from closing establishment j especially likely to be hired by a particular establishment k. Using the dyadic data described above, we estimate the following model:

$$H_{ijk} = \alpha_{jk} + X_{ik}\beta + \gamma C_{ijk} + \varepsilon_{ijk}, \tag{7}$$

where H_{ijk} takes the value one if establishment k hires displaced worker i from closing establishment j and zero otherwise. C_{ijk} is the variable of interest and indicates whether displaced worker i has a social connection to at least one worker (denoted by l when needed) in the existing workforce of establishment k. X_{ik} is a vector of worker characteristics that may affect the probability of being hired by establishment k. The establishment-pair fixed effects (α_{jk}) captures all factors that relate the closing establishments (j) and the potential hiring establishments (k) to each other. Because an establishment only shuts down once, these fixed effects are in practise *year-specific*.

Equation (7) mimics the target equation (i.e., equation 3) if $\alpha_{jk} + X_{ik}\beta$ properly captures $\Pr(H_{ijk} \mid$

$C_{ijk} = 0$), i.e., the probability that a displaced worker i becomes hired by establishment k if there is no social connection between the two (referred to as a market hire for convenience). In the empirical section, we provide alternative models and placebo tests to assess the validity of the causal interpretation of the estimates.

The dyadic (i,k) observations together with establishment-pair (j,k) fixed effects allow us to limit the sample to those dyads where there is variation in C_{ijk} within the corresponding establishment-pair (j,k). Thus, we use data only for pairs of establishments where a potential hiring establishment k is socially connected to some (often one), but not all, of the workers at a closing establishment j. Including also the pairs of establishments that are not socially connected would not affect the identification of the parameter of interest, but make the estimations unfeasible due to the increasingly large sample size.

The formulation resembles Kramarz and Skans (2014), who in turn build on Kramarz and Thesmar (2013). In line with them, we estimate the equation using linear probability models and treat each dyad as an independent observation, conditional on the establishment-pair fixed effects.[11]

2.3.2 Heterogeneous effects

As alluded to above, we are interested in letting the effects of connections be non-constant. Most notably, we allow the effects to vary with functions of the person and establishment fixed effects and/or indicators of connection types reflecting, e.g., different ties' strengths (extensions to other sources of heterogeneity are straightforward). Thus, in the most general form we extend equation (7) to:

$$H_{ijk} = \alpha_{jk} + X_{ik}\beta + \sum_{n=1}^{N} \gamma^n(\theta_i, \psi_k)c^n_{ijk} + \varepsilon_{ijk}, \tag{8}$$

where $c^1_{ik}, \ldots, c^N_{ik}$ are indicators for each type $n = 1, \ldots, N$ of social relations measured in the data (i.e., parents, spouses, adult children, siblings, former co-workers, former classmates from high school, former classmates from college/university, and current neighbors), and where the vector X_{ik} typically includes θ_i, θ_i^2, and $\theta_i\psi_k$, and we assume that $\gamma^n(\theta_i, \psi_k)$ is a second-order polynomial:

$$\gamma^n(\theta_i, \psi_k) = \gamma^n_1\theta_i + \gamma^n_2\theta_i^2 + \gamma^n_3\theta_i\psi_k + \gamma^n_4\psi_k + \gamma^n_5\psi_k^2. \tag{9}$$

Remark 1: The estimate of γ^n_3 identifies the contribution of causal effects to sorting since it governs the role of interactions between person and establishment effects.

Remark 2: The control vector X_{ik} neither includes ψ_k nor ψ_k^2 as these are captured by the establishment-

[11] Kramarz and Skans (2014) study parental connections on labor market entry in Sweden. Saygin et al. (2014) uses a very similar set-up to study the importance of former co-workers for labor market outcomes of displaced workers in Austria. Hensvik et al. (2017) uses the setting of Kramarz and Skans (2014) to analyze the role of summer-job connections over the business cycle.

pair fixed effect α_{jk}.

Remark 3: In some specifications, we instead focus on just one quality dimension at the time (i.e., person or establishment effects). Then, we move away from the polynomial functional form and instead categorize the person/establishment effects into 10 unrestricted decile dummies.

2.3.3 Within-worker identification

Because a worker may be endowed with multiple connections of different types, tying her to different establishments, the model can be modified to assess the strength of these connections *for this particular worker*. This "within-worker" perspective, which is new to the literature, is presented now.

Let us first define K_{ijk} as the set of establishments k that displaced worker i, from closing establishment j, is connected to (i.e., define $K_{ijk} : k \in K_{ijk}$ iff $C_{ijk} = 1$). To identify the relative importance of various types of connections within this set, we define a fixed effect $\phi_{K_{ik}}$ for each K_{ik} set. Comparing $\phi_{K_{ik}}$ to α_{jk}, we note that i is a subset of j, and all k's that are included in K_{ik} are covered by some α_{jk}. As above, we use separate indicators c^n_{ik} for each connection's type n, but here we need to leave out a reference category N because the individual fixed effects will capture one of the types.[12] As above, this model is easily extended to assess how the various types of connections interact with agents' quality, as measured by the estimated worker and establishment effects from the AKM decomposition (see equation 5). Thus, we can rewrite the most general form of equation (8) as:

$$H_{ik} = \phi_{K_{ik}} + X_{ik}\beta + \sum_{n=1}^{N-1} \gamma^{n,I}(\theta_i, \psi_k)c^n_{ik} + \varepsilon_{ik}, \tag{10}$$

where X_{ik} use the non-redundant components of the same polynomial.[13] Although we will, in principle, let γ^{nI} rely on the same functional form as γ^n in equation (9) above, we now have redundant components in this polynomial. The reason is that the fixed effects require the existence of a social connection to the firm for the individual. Thus, we can at most let

$$\gamma^{n,I}(\theta_i, \psi_k) = \gamma_3^{n,I}\theta_i\psi_k + \gamma_4^{n,I}\psi_k + \gamma_5^{n,I}\psi_k^2, \tag{11}$$

where the parameters are numbered as in equation (9) and the estimate of $\gamma_3^{n,I}$ thus identifies the contribution of causal effects to sorting.

Equation (10) allows us to examine the interaction of each type of connection with the AKM effect of the connected establishment *for a given worker*. Identification of the interaction term comes from

[12] As before, identification only comes from the observations (dyads) for which there is variation in c^n_{ik} within the fixed-effect set K_{ik}. Conceptually, there exists a corresponding set of individual fixed effects for dyads without connections but within this set there is by definition no variation in c^n_{ik}.

[13] Since the estimates are derived conditional on the individual's (fixed) set of connections, the model will not capture the direct impact of the worker's quality (i.e., the person effect cannot be included in X_{ik}).

workers with multiple connections of the same type (e.g., two parents) across different establishments endowed with different establishment effects, as if the worker could "choose" between these establishments.

3 Data and definitions

3.1 The administrative registers

The analyses are based on administrative data for the entire Swedish population during the period 1985–2009. The data link various administrative records through anonymized identifiers at the individual, establishment, and firm level. The main source is an employment register (*Registerbaserad arbetsmarknadsstatistik*) with information from the National Tax authority. The statutory income statements, filed to the taxation authorities by the employers, identify both the employee and the establishment's organization, which allowed us to link all employees to their employer. The social connections were identified using information on family trees from population-wide birth records (*Flergenerationsregistret*), information on household members and neighbors from Statistics Sweden's longitudinal database (*LOUISE*), and information on graduation classes from high school and college/university from graduation registers (*Skolregistret* and *Universitets- och högskoleregistret*).

3.2 Defining closing establishments and displaced workers

We only include establishment closures during the period 1990–2006, rather than 1985-2009, to allow both for a pre-closure period when connections are potentially created and for a post-hire period. To identify these closures, we first selected 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 only included closures (i) of single-establishment firms, (ii) in the private sector,[14] and (iii) with at least four employees in November year t.[15] 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 followed Hethey-Maier and Schmieder (2013) and defined "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 were 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 identified their social connections as described

[14]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.

[15]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).

in the next section.

3.3 Defining social connections

We consider four broad types of social connections: family members, former co-workers, former classmates, and current neighbors. Below we give the precise content for each of these groups. Throughout, we restrict the data to those cases where we can be reasonably sure that the measured connections are valid, i.e., that the people involved actually did meet each other. In particular, in cases where groups of agents are very large, we prefer to not code them as social connections in order to not risk including false connections into our data. Details are spelled out below.

Family members include parents, adult children, spouses, and siblings (either full or half). We have relied 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 children in common.

Former co-workers comprise workers who were employed at the same workplace *before the current one i.e., not the closing establishment*. We limited former co-workers to those in the most recent of past workplaces, using data going back to 1985.[16] If a workplace is very large, the measured connections are likely to be very imprecise and noisy. Therefore, we constrained the data to cases with less than 100 employees at the former workplace.[17] [18]

Former classmates were 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 identified former classmates from high-school as those who shared school, program, and graduation year. Students from university were similarly identified as those who graduated at the same college/university, within the same field/major, and during the same year. Because the graduation records are not available prior to 1985, we have information on former classmates only for the younger cohorts. However, our results indicate that the value of former classmates depreciates fairly rapidly over time (see Section 5.2.1). There are also cases where we have failed to identify what could reasonably be defined as a class, because when a school catered large cohorts within one field, it was presumably divided into two (or more) classes, which cannot be observed in that data. To reduce the influence of pure measurement error in our measured connections we have, therefore, removed the cases where more than 100 former students are found within the same (constructed) class (i.e., analogous to the procedure for former co-workers).[19]

[16]We only considered each employee's main workplace (i.e., establishment) in the month of November.

[17]This excluded 25 percent of the former co-workers.

[18]The size requirement, which we also impose on former classmates and current neighbors, is also needed for computational reasons. Otherwise, the number of dyads between all displaced workers and potential hiring establishments would explode.

[19]This excluded 21 and 10 percent of high school and college/university "classmates", respectively.

Current neighbors were 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, and each contain, on average, approximately 1,000 residents. Hence, the identified networks of neighbors would in most cases extend far beyond the group of people who actually interacted with each other. In order to define more appropriate measures of residential networks we have included only those who both resided in the same SAMS area and had children in the same age group.[20] The intended logic is that parents with children in the same age group are more likely to meet (or have met) at playgrounds, schools, or other local child activities. This 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 co-workers and classmates the groups of current neighbors with children of the same age were constrained to those containing less than 100 people to reduce the impact of measurement errors.

Three additional requirements have been imposed on all social connections defined above: each individual connected to a displaced worker must (i) be 20–64 years old, and (ii) be employed at a private sector establishment (with an associated identifier in the data) in November of both years t and $t+1$.[21] [22] All restrictions were imposed after applying the group size constraints of 100 that were described above.

3.3.1 Descriptive statistics for the connections

In Table 1, we summarize how our measured connections link displaced workers (and their establishments) to potential hiring establishments. Overall, the data contain almost 32,000 closing establishments j and somewhat less than 290,000 displaced workers i. Each displaced worker is on average connected to 8.8 potential hiring establishments j: 1.2 establishments through family members (0.30, 1.15, 0.15, and 0.60 through parents, adult children, a spouse, and siblings, respectively); 2.6 establishments through former co-workers; 3.5 establishments through former classmates (3.2 and 0.3 from high school and college/university, respectively); and 1.6 establishments through current neighbors (with same aged children).[23] This results in more than 900,000 connected potential hiring establishments which, on average, are connected to 2.3 closing establishments and 2.8 displaced workers.

[20] Using Statistics Sweden's child age groups: 0–3, 4–6, 7–10, 11–15, 16–17, or 18+ years.

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

[22] This ensures that the connected intermediary worker was employed at the particular establishment at the time of the (potential) hire of the displaced worker.

[23] The number of connections might seem low, but recall that these numbers correspond to the connections that satisfy the restrictions in Section 3.3. These connections should be of working age, be employed in the private sector, and be living in the same county as the closing establishment.

Table 1: The number of social connections by type

Social connection	establ. (k) per displaced worker (i)	establ. (j) per establ. (k)	No of connected displaced workers (i) per establ. (k)	Share of connected displaced workers (i) per pair (i,k)
Any connection	8.824	2.799	2.289	0.062
Family members	1.170	0.371	0.346	0.008
Parent	0.295	0.093	0.090	0.002
Adult child	0.151	0.048	0.046	0.001
Spouse	0.149	0.047	0.045	0.001
Sibling	0.597	0.189	0.182	0.004
Former co-worker	2.590	0.821	0.573	0.018
Former classmates	3.522	1.117	1.025	0.025
High school	3.220	1.021	0.945	0.023
College/university	0.305	0.097	0.085	0.002
Current neighbors	1.628	0.517	0.449	0.011
No of observations	289,332	912,084	912,084	41,111,774

Note: The table shows how displaced workers, (i), connected establishments, (k) and closing establishments (j) are connected through the different types of social connections defined in this section. Column (1) displays the number of establishments (k) that the average displaced worker is connected to; columns (2) and (3) show the number of closing establishments/displaced workers for the average connected establishment and column (4) shows the share of displaced workers with a social connection within the estimation (dyad) data.

3.3.2 Coverage

We do not observe the full set of actual social connections. This limitation is shared with all other studies using data from administrative registers or social media platforms to measure social connections since none of these sources record all kinds of social relations. However, under the assumption that unrecorded friendships have the same properties as the measured types of connections, this should not affect the qualitative conclusions. When studying overall sorting patterns, incomplete coverage should attenuate our estimates since our residual category of ”market” matches will contain a mixture of true market matches and unrecorded social connections.

Furthermore, we cannot observe family members, former co-workers, former classmates and current neighbors for all workers within our sample. This is partly because not all workers have all types of connections, e.g., some workers do not have a spouse. Some workers were never employed before and therefore do not have any former co-workers. Not all workers went to university, and so forth. Furthermore, our data are incomplete in the sense that we lack graduation records for the oldest workers in our samples and because current neighbors with children in the same age can only be identified for workers who actually have children. And, by our restriction, connections formed at very large establishments, neighborhoods or classes are removed because only a few of the agents within them will actually have interacted.

In Section 5 we therefore analyze the role of our imposed restrictions and show that they indeed do help us zoom in on the relevant connections. Furthermore, we can directly address the fact that

we measure different types of connections for different people through our within-worker identification strategy. This strategy precisely compares the role of different types of connections for workers that have multiple types and thus removes all the impact of differences across workers with different types of connections.

3.4 Earnings data and AKM estimates

When estimating the AKM model we use the universe of workers and establishments for our full data period 1985-2009. The sample and estimation results are described in Table 2.[24] The table has five columns. In the first we show estimates for the full sample. In the second, we focus on all job-to-job transitions during our main sample period (1995-2006) and display the person effects (estimated using pre-hire data) and the establishment effects for the sample of private sector hiring establishments. In the third, we focus on job-to-job transitions that are associated with social connections as measured in our data. Fourth, we focus on the sample of new hires after displacements. And in the fifth, we focus on connected hires after displacements. These samples are somewhat smaller than the overall displacement samples since we need the workers to be employed the year before displacement (or earlier) in order to estimate the person effects.

Table 2: Description of the AKM samples

Sample:	AKM estimation sample	All job-to-job hires	Connected job-to-job hires	Displaced hires	Displaced connected hires
Number of person effects	5,785,081	3,315,423	424,789	83,537	10,202
Number of establishment effects	829,111	276,298	119,377	43,469	7,127
Mean of person effects	.000	-.104	-.101	-.117	-.111
Mean of establishment effects	4.502	4.525	4.525	4.507	4.503
Std dev. of person effects	.270	.269	.255	.250	.245
Std dev. of establishment effects	.126	.154	.152	.155	.152
Correlation person/establishment effect	.038	.129	.083	.089	.049
Mean of log wages	9.664	-	-	-	-
Std dev. of log wages	.466	-	-	-	-
No of observations	62,002,038	3,315,521	424,792	83,540	10,202

Note: Column (1) presents summary statistics for AKM person and establishment effects in the full sample of workers and establishments during 1985-2009. In columns (2)–(5) we present statistics for our observation period of interest 1995-2006. When focusing on transitions in columns (2)–(5), we use the AKM person effects estimated in the pre-transition period. Displaced workers are defined in Section 3.2. Connected hires include the four broad types of social connections (family members, former co-workers, former classmates and current neighbors) defined in Section 3.3.

The table shows that the person effects of recent hires are lower than average and that the dispersion of person effects is lower in the samples that were hired through connections both in general and after displacements. Furthermore, estimated correlations between person and establishment effects suggest that connected hires are less sorted than the overall samples of connections, both in general (all hires)

[24] See Appendix Figure A.1 for a 3d graph of the joint distribution of person and establishment effects deciles.

and after displacements. We return to this issue in the final part of the paper.

3.5 Estimation data (dyads)

To create our estimation data, we form pairs between each displaced worker i (from establishment j) with a connection of a particular type (i.e., family member, former co-worker, etc.) and each potential hiring establishment k, for which there is a connection (of the same type) between establishments k and j, but not necessarily between the particular displaced worker i and establishment k. That is, if at least one displaced worker from closing establishment j is connected to a potential hiring establishment k, then each and every displaced worker at establishment j with a connection of the same type to any establishment was paired to the potential hiring establishment k. This strategy allows us to generate a counterfactual set of pairs for each pair i (displaced from j) and k. This procedure generates a data set comprising 41 millions pairs of displaced workers and potential hiring establishments.

Table 3: Summary statistics for the displaced and intermediary workers and for the estimation sample comprised by pairs of potential hiring establishments j and displaced workers i

	Displaced workers (i)		Intermediary workers (l)		Pairs of potential hiring establishments j and displaced workers i	
	N	%	N	%	N	%
Sex						
Female	113,738	39.31	853,104	37.87	24,119,673	58.67
Male	175,594	60.69	1,399,683	62.13	16,992,101	41.33
Nativity						
Swedish born	257,686	89.06	2,095,419	93.01	37,292,005	90.71
Foreign born	31,646	10.94	157,548	6.99	3,819,769	9.29
Age						
20–34 years	149,529	51.68	1,379,492	61.23	25,565,797	62.19
35–49 years	88,075	30.44	629,184	27.93	10,461,203	25.45
50–64 years	51,728	17.88	244,291	10.84	5,084,770	12.37
Attained education						
Compulsory school	69,044	23.86	312,826	13.89	6,538,236	15.90
High school	163,735	56.59	1,374,302	61.00	24,250,767	58.99
College/university	54,829	18.95	561,351	24.92	10,199,868	24.81
Employment in $t+1$						
Any employment	211,282	73.02	2,252,967	100.00	33,921,201	82.51
In connected establishment	9,143	3.16	2,252,967	100.00	17,707	0.04
AKM person effects [a]						
Low	78,098	26.99	1,003,740	44.55	11,711,626	28.49
Medium	65,505	22.64	733,727	32.57	8,495,645	20.66
High	46,444	16.05	445,638	19.78	4,756,028	11.57
N/A	99,285	34.32	69,862	3.10	16,148,479	39.28
AKM establishment effects [a]						
Low	102,714	35.50	509,163	22.60		
Medium	88,522	30.60	795,413	35.31		
High	74,460	25.74	916,296	40.67		
N/A	23,636	8.17	32,095	1.42		
No of observations		289,332		2,252,967		41,111,774

[a] See Section 2.2 for details on the AKM model

Data are described in Table 3 with separate columns describing the 289,000 displaced workers and their 2.2 million intermediary social connections.[25] Because we focus on private-sector closures, two-thirds of displaced workers are male. Furthermore, we find that 90 percent are Swedish born and half of the workers are below age 35, and 74 percent have at least a high school degree. 73 percent find employment within the year after displacement. Since we require a pre-period to estimate the AKM effects of the displaced, we do not have such estimates for about a third of all displaced workers. A much larger share of intermediary workers are employed in high-wage establishments relative to the displaced workers. Notably, the 41 million pairs in our data only make up a small subset of all possible combinations of displaced workers and (non-connected) potential hiring establishments, and matches were obviously formed between displaced workers and establishments not included in this data set. However, given the establishment(-pair) fixed effects included in our models, hiring establishments without any connection to a closing establishment will not contribute to the identification of the parameter of interest, hence are not included.

4 Results

In this section, we present the results from our analyses of (displaced) workers' social connections and how they affect the matching to the potential hiring establishments. In Subsection 4.1, we describe the structure of displaced workers' social connections. We focus on how these connections relate to sorting, in order to answer the following type of questions: Are high-wage *establishments* more likely to be socially connected (through their employees) to high-wage workers? Are high-wage *employees*, more likely to be socially connected to high-wage job-seekers?

Then, we examine the role of connections for hiring in the following subsections. In sequence, we present analyses of the role of (i) the causal impact of connections, including robustness and placebo tests in Section 4.2, (ii) the causal impact of connections, interacted with person and establishment effects in Section 4.3, and (iii) an overall assessment of the role of connections in sorting inequality, both for the displaced and for all hires in Section 4.4.

4.1 Sorting of social connections

In this subsection, we document the sorting patterns of connections between establishments and displaced workers. We use the data on all connections we observe between displaced workers and ongoing (potential hiring) establishments. To describe the underlying sorting patterns we first calculate correlations between the person effects of displaced workers (θ_i) and the person effects of the "intermediary"

[25] Further statistics at the establishment level are provided in Appendix Table A.1.

worker they are connected to (θ_l) and then show the corresponding correlation between θ_i and the establishment effect (ψ_k) of l's employer. Thus, for the sample of displaced workers, we show how their "quality" (in terms of person effects) correlates with both the "quality" of their social connections and the "quality" of these workers' employers.

Table 4: Correlations between the AKM person effect of the displaced worker and the person and establishment of their connections using raw and residualized person effects

	$\text{Corr}(\theta_i, \theta_l \mid C_{il} = 1)$		$\text{Corr}(\theta_i, \psi_k \mid C_{ik(l)} = 1)$		
	Baseline person effects	Residualized person effects	Baseline person effects	Residualized person effects	N
Panel A:					
All connections	0.164	0.071	0.061	0.008	1,597,994
Panel B:					
Family members	0.042	0.057	0.027	0.017	195,099
Former co-worker	0.185	0.098	0.097	0.062	501,706
Former classmates	0.201	0.055	0.084	-0.030	587,511
Current neighbors	0.073	0.053	0.026	0.018	304,678
Panel C:					
Family members					
Parent	0.052	0.031	-0.017	-0.013	37,477
Adult child	0.101	0.046	0.086	0.066	27,265
Spouse	-0.134	0.050	0.032	0.029	25,614
Sibling	0.159	0.072	0.019	0.009	104,743
Former classmates					
High school	0.099	0.047	0.024	-0.033	509,471
College/university	0.289	0.098	0.137	0.013	78,040

Note: Column (1) shows the correlation between the AKM person effect of the displaced (i) and the person effects of their connections (l). In column (2) we show the relationship when the person effects (of both the displaced i and the intermediary l) have been residualized from age, education level and gender. Column (3) shows the correlation between the AKM person effect of the displaced i and the AKM establishment effects of connected establishments k. In column (4) we have residualized the AKM person effect of the displaced (i) from age, education level and gender.

Results are presented in Table 4. For the average connection in our data, the correlation between person effects of the agents (displaced vs. intermediary) is positive at 0.164. Thus, the network structure exhibits fairly strong "homophily" in terms of earnings capacity, as presumed in standard network models (e.g., Montgomery, 1991). The correlation between person effects of the displaced and the establishment effects of the connected employer is also positive, but notably weaker (0.061). This correlation can be compared to the correlation between displaced workers' person effects and the establishment effects of their new employers (thus calculated for the rehired portion of all displaced) which is 0.083 as shown in Table 2 above.

Panel B shows separate correlations for family members, current neighbors, former co-workers and former classmates and Panel C shows results from an analysis where we disaggregate the family members and former classmates. The main take-away from these panels is that all person-to-person correlations are positive (for spouses only after "residualizing" the data, see below), suggesting that homophily, as expected, is a general phenomenon, i.e., high-wage workers are connected to other high-wage work-

ers in all our observed social dimensions. For all broad measures of connections, displaced workers with higher (pre-displacement) person effects are also connected to higher-wage employers.

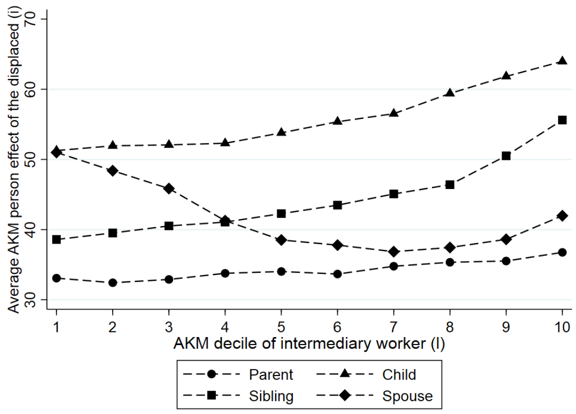
The correlations are clearly largest for the “professional” ties formed at school or in workplaces. The more “socially”-oriented family and neighborhood ties are less sorted. This is, however, partly an artefact of the demographic patterns associated with these connections. Spouses of men are women and vice versa, and gender wage disparities are clearly reflected in the highly *negative* spousal sorting shown in Panel C. In addition, siblings, parents and children have deterministic relative age-relationships. To handle these issues, the table shows separate columns for results based on “residualized” person effects where the impact of age, education and gender have been removed as in Abowd et al. (1999). After this ”residualizing” of the person effects, the correlations for spouses turn positive, reflecting positive assortative mating on the marriage market.

Panel C also shows that much of the positive sorting for former classmates are driven by by very strong homophily within the network of former university classmates (0.289); in contrast, the former high school classmates are much less sorted (0.099). Overall, former co-workers and university classmates do exhibit the strongest levels of homophily in all four columns.

To align the description with the structure of the analysis of causal effects presented later, we have also derived a less parametric description of the social networks from an employer-side perspective. We proceeded as follows: For each decile of (AKM) establishment effects, we calculated the average person effect of all displaced workers connected to these establishments. We then repeat this for each decile of intermediary worker. However, these relationships are all highly linear, at least after residualizing the data. There is somewhat more sorting at the top without residualizing, but the overall impression concur with that of Table 4 (see Figures 1–4, which each correspond to one column of Table 4.

(a) All connections (as 1[st] col. Table 4, Panel A)

(b) Family members



(c) Former classmates

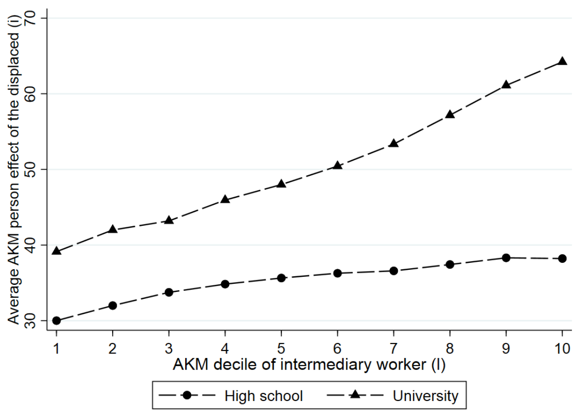
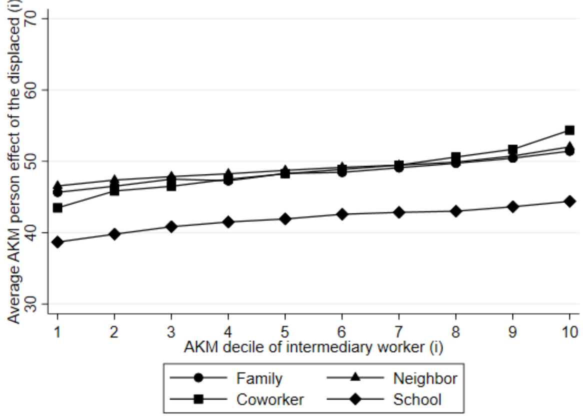
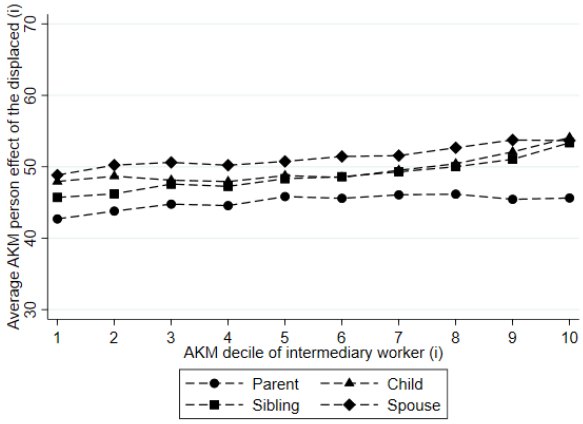


Figure 1: Mean person effects (θ_i) percentile of displaced workers (y-axis) by decile of person effects ($\theta_l \mid C_{il} = 1$) of connected intermediary workers.

(a) All connections (as 2[nd] col. Table 4, Panel A)



(b) Family members



(c) Former classmates

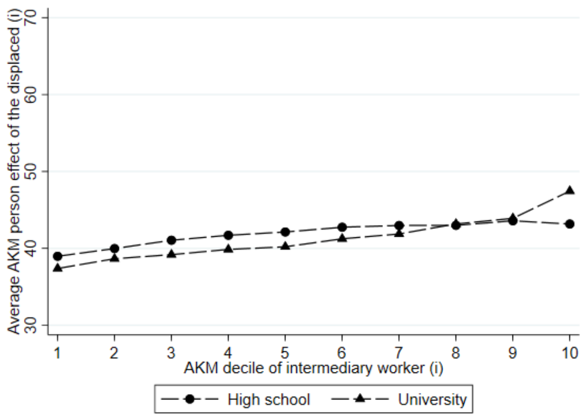


Figure 2: Mean residualized person effects ($\hat{\theta}_i$) percentile of displaced workers (y-axis) by decile of residualized person effects ($\hat{\theta}_l \mid C_{il} = 1$) of connected intermediary workers.

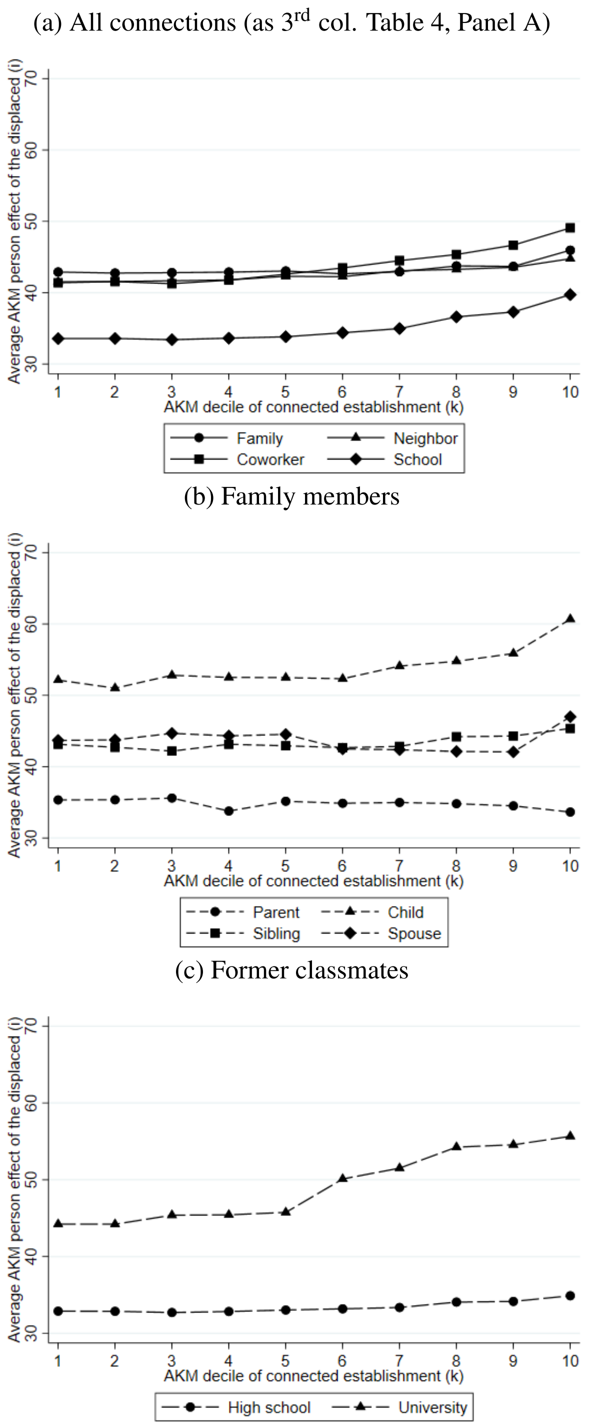


Figure 3: Mean person effects (θ_i) percentile of displaced workers (y-axis) by decile of establishments effects of connected establishments ($\psi_k \mid C_{ik} = 1$).

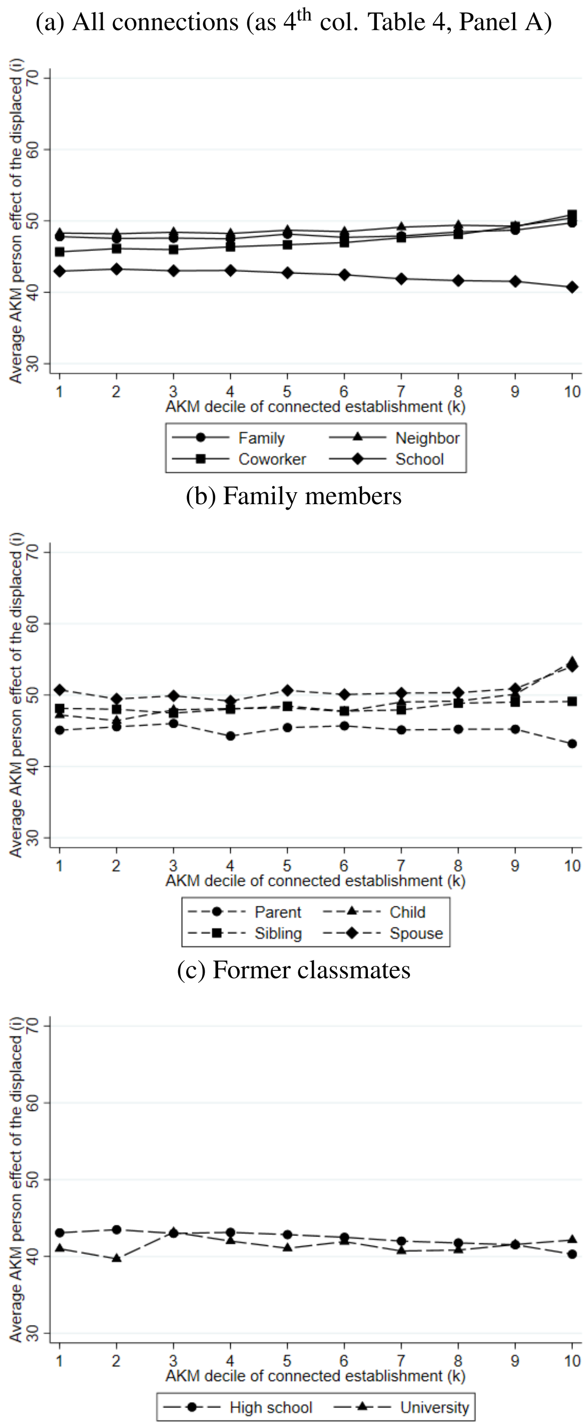


Figure 4: Mean residualized person effects ($\hat{\theta}_i$) percentile of displaced workers (y-axis) by decile of establishments effects ($\psi_k \mid C_{ik} = 1$) of connected establishments.

4.2 Causal impact of connections on hiring

The results above show that the data exhibit substantial homophily within displaced workers' social networks, i.e., better workers have social ties to better workers and (to a lesser extent) to better estab-

lishments. The impact of these connections on sorting inequality does, however, also depends on if, and when, connections affect actual re-hiring patterns. Therefore, we now turn to the analysis of the causal effects of the connections. We start with the average effects of connections before turning to how these effects interact with the (AKM) person and establishment components.

Table 5 (left column) reports the estimates of the average causal effect of social connections (i.e., γ in equation 7) for different subsets of connections. The baseline result suggests that displaced workers are 0.27 percentage points more likely to be hired by each connected establishment k relative to other displaced workers from the same closing establishment j. This effect (of an average connection) is 10 times the baseline probability of hiring by the non-connected (i.e., the constant) of 0.026.

Table 5: Estimated effects of social connections by type of connection, with alternative fixed effects

	Baseline (establishment-pair, and year, fixed effects)		Only closing establishment and year fixed effects		Within-worker identification	
	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)
Panel A:						
Any connection	0.270	(0.005)	0.292	(0.005)		
Constant	0.026	(0.000)	0.025	(0.000)		
Panel B:						
Family members	1.095	(0.020)	1.144	(0.020)	1.464	(0.036)
Former co-worker	0.253	(0.010)	0.337	(0.011)	0.714	(0.030)
Former classmates	0.066	(0.004)	0.081	(0.004)	0.157	(0.026)
Current neighbors	0.086	(0.008)	0.101	(0.007)	0.000	
Constant	0.027	(0.000)	0.024	(0.000)	0.014	(0.002)
Panel C:						
Family members						
Parent	1.867	(0.052)	1.903	(0.050)	2.058	(0.058)
Adult child	0.670	(0.051)	0.708	(0.045)	1.350	(0.065)
Spouse	1.974	(0.078)	2.055	(0.073)	2.502	(0.080)
Sibling	0.697	(0.023)	0.737	(0.023)	1.083	(0.042)
Former co-worker	0.252	(0.010)	0.336	(0.011)	0.788	(0.031)
Former classmates						
High school	0.064	(0.004)	0.076	(0.004)	0.242	(0.027)
College/university	0.088	(0.018)	0.137	(0.019)	0.479	(0.043)
Current neighbors	0.080	(0.008)	0.097	(0.007)	0.000	
Constant	0.026	(0.000)	0.024	(0.000)	0.009	(0.002)
No of fixed effects	2,087,560		912,084		548,820	
No of observations	41,111,774		41,111,774		41,111,774	

Note: Data are in dyad form with one observation per combination of displaced worker and potential hiring establishment. All estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. Baseline model uses a fixed effect for each pair of closing and potential hiring establishments. Since establishments only close once, these fixed effects are year-specific by construction. Within-worker identification uses fixed effect for each combination of individual, set of connected establishments, and displacement year as discussed in Section 2.3.2. Standard errors are clustered on the potential hiring establishment-and-year level.

Furthermore, the estimated average effect of a connection masks considerable heterogeneity across types of connections. The impact of family members is clearly largest; a family member within an establishment raises the hiring probability by, on average, 1.1 percentage points (Panel B). 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 adult children and siblings (Panel C).

Previous co-workers (from another employer) have the second largest effects after family members. Having a former co-worker within an establishment increases the hiring probability of that establishment by 0.25 percentage points. However, both former classmates, and current neighbors, seem to be substantially less important (0.07 and 0.09 percentage points).

Thus, the findings suggest a clear ordering across types of ties where a family member is associated with the largest causal effect, followed by former co-workers, current neighbors, and former classmates. A reasonable explanation for these results is that they measure the frequency of interaction within the relevant network, i.e., tie strength in the terminology of Granovetter (1973), as family members can be presumed to interact more frequently than, e.g., people who went to school together.[26]

The results just presented are based on a model with (j,k) establishment-pair fixed effects (left column of Table 5). In the middle column of Table 5, we, instead, present the estimates from a model with unrestricted fixed effects for the potentially hiring establishment (k). Reassuringly, the results are largely unchanged.[27] In the Appendix, Table B.1, we show further robustness checks, where we vary the control set, focus on small closures and only use cases where a single worker is connected. Further heterogeneity analyses in terms of person and worker characteristics are discussed in Section 5.2 below.

As discussed in Section 2, we are also able to estimate the relative impact of various connections using within-worker identification since the data contain multiple connections of various types for the same displaced worker. Hence, in the right-most column of Table 5, we present the results from estimating a model that compares the *relative* importance of each connection, conditional on fixed effects for the set of establishments that each displaced worker is connected to (i.e., equation 10). Said differently, these estimates are computed "within" each displaced worker's set of connections. The results mostly concur with those in column 1. Family members and former co-workers clearly remain the key connections. However, former classmates (in particular those from college/university) have a somewhat larger coefficient when estimated within person. Since the identifying variation is very different, we find the overall robustness reassuring.[28]

Overall these results show that establishments are much more likely to hire displaced workers to

[26]Note that the longer since the connection was established (e.g., since they went to school together) and the larger the group (i.e., the workplace, the school, or the neighborhood), the lower the expected frequency of interaction. We return to this issue in sub-section 5.2.1.

[27]Note though that we estimate this model using the same sample as in the main model, despite the fact that the sample is constructed to be in accordance with the assumption of the establishment-pair fixed effects.

[28]We may equate the resulting estimates by considering the within-worker identification as providing a measure of a given worker's directed search effort (and amount of information collected) – hence supply – whereas those obtained conditional on (j,k) establishment-pair fixed effects capture the potential hiring establishment's preferences – hence demand – suggesting that a given university educated worker relies more on their university connections (supply side) whereas establishments rely more on other types of connections (demand side).

whom they are connected through social connections rather than other workers who lose their jobs in the same establishment closure. The estimates reflect, we believe, social connections' causal effect on hiring. However, there are potential concerns regarding such a causal interpretation. In particular, it is possible that displaced workers share attributes with their social connections that would make them more likely to enter the same establishment, even without the connection there.

Note, however, that the results in Section 4.1 suggested that displaced workers are more similar to their former co-workers than to their family-members in the AKM-sense. Still, we find that the causal impact of family members is twice as large as the effect of former co-workers, suggesting that the estimates are driven more by social closeness (i.e., family) than by similarity in labor market prospects (i.e., co-workers, at least when measured in terms of person effects).

Another particular concern is that the closure of one establishment may affect (connected) potential hiring establishments through reduced competition on the product market. However, this should, in general, affect all workers (with or without a connection) at the same closing establishment, and should, therefore, be captured by the establishment-pair(-and-year) fixed effect. In addition, we show in Section 5.2.2 that results are identical if we focus on connections spanning across industries.

We have, nevertheless, performed two sets of "placebo" analyses to assert that the causal interpretation is reasonable in the face of the two concerns listed above. In the first analysis, we limited the sample to potential hiring establishments that were part of multi-establishment firms with at least two establishments within the same location and industry (typical cases would be, e.g., retail stores or restaurants). In the data, we replaced each potential hiring establishment by another (randomly chosen, if there were several) establishment within the same firm, location, and industry. If unobserved characteristics were driving our baseline results, we should find similar estimates for these unconnected establishments within connected firms (assuming that the production function is similar across different stores). Similarly, if the baseline results arose because of reduced competition on the product market, rather than the connection per se, we would expect to see estimates of similar magnitude using these unconnected establishments within connected firms. A zero estimated effect would instead suggest that reduced competition on the product market is not a likely explanation but that the social connections have some inherent value.

However, potential transmission of information between establishments within the same firm might imply that the displaced workers were not only more likely to become hired at the establishment to which they had a connection but also at other establishments within the same firm. In that sense, the within-firm placebo is to some extent stacked against our strategy. It is also obviously only possible to estimate for the particular sample of multi-establishment firms.

Table 6: Placebo tests based on other non-connected potential hiring establishments

	Baseline[a]		Placebo I[b]		Placebo II[c]	
	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)
Panel A:						
Any connection	0.270	(0.005)	0.029	(0.004)	0.014	(0.001)
Constant	0.026	(0.000)	0.006	(0.001)	0.006	(0.000)
Panel B:						
Family members	1.095	(0.020)	0.037	(0.011)	0.016	(0.004)
Former co-worker	0.253	(0.010)	0.075	(0.012)	0.016	(0.003)
Former classmate	0.066	(0.004)	0.011	(0.004)	0.010	(0.002)
Current neighbors	0.086	(0.008)	0.015	(0.009)	0.023	(0.006)
Constant	0.027	(0.000)	0.006	(0.001)	0.006	(0.000)
Panel C:						
Family members						
Parent	1.867	(0.052)	0.061	(0.024)	0.017	(0.011)
Adult child	0.670	(0.051)	0.027	(0.040)	-0.011	(0.011)
Spouse	1.974	(0.078)	0.080	(0.043)	0.020	(0.012)
Sibling	0.697	(0.023)	0.018	(0.014)	0.019	(0.006)
Former co-worker	0.252	(0.010)	0.075	(0.012)	0.016	(0.003)
Former classmate						
High school	0.064	(0.004)	0.011	(0.004)	0.010	(0.002)
College/university	0.088	(0.018)	0.006	(0.013)	0.004	(0.005)
Current neighbors	0.080	(0.008)	0.015	(0.009)	0.023	(0.006)
Constant	0.026	(0.000)	0.006	(0.001)	0.006	(0.000)
No of fixed effects	2,087,560		391,438		1,540,941	
No of observations	41,111,774		3,676,175		29,891,982	

Notes: Data are in dyad form with one observation per combination of displaced worker and potential hiring establishment. All estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. All estimations include establishment-pair(-and-year) fixed effects. Standard errors are clustered on the potential hiring establishment-and-year level.

[a] Repeats the first column of Table 5.

[b] Each potential hiring establishment has been replaced by another randomly selected establishment within the same firm, location (i.e., municipality), and industry (i.e., 3-digit code).

[c] Each potential hiring establishment has been replaced by another randomly selected establishment within the same location (i.e., municipality) and industry (i.e., 3-digit code).

Therefore, we have performed a second exercise, where each potential hiring establishment instead is replaced by another establishment within a different firm, but within the same location and industry. The estimates from these two placebo regressions, presented in the middle and rightmost column of Table 6, are in many cases statistically significant, but with magnitudes that are much smaller than the corresponding estimates of our main analysis (cf., leftmost column of Table 6). Overall, we therefore interpret these results as supporting our claim that the effects of interest primarily arise because of the actual social connections and not because of some correlated unobserved factor, such as ability. Next, we turn to the interaction between these causal estimates and estimated person and establishment effects from the AKM model.

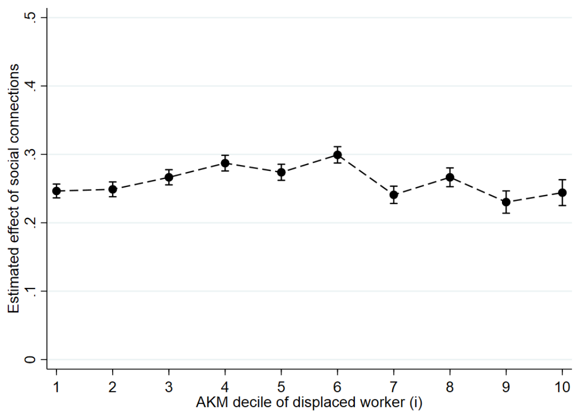
4.3 The causal impact, by person and establishment effects

In order to estimate if and how the causal effects of connections affect sorting inequality, we examine the interaction between connections and the estimated (AKM) person and establishment effects. The analysis thus relies on the model outlined in equation (8). All empirical models control for the (AKM) types of the agents and the types of social connections within their social networks. As noted in Section 2, the person effects are estimated restricting observations to those preceding job displacement to avoid reverse causality, e.g., being hired through connections may lead to higher wages.[29]

First, we focus on the effect of social connections by person and establishment effects, separately. Estimates of interactions with person effects (i.e., supply-side heterogeneity), presented in Figure 5a, show that connections (on average) are equally used by low- and high-wage displaced workers.[30] If anything, workers in the middle of the person-effects distribution rely more on connections.

By contrast, demand-side heterogeneity, as captured by the establishment effects of the potential hiring establishments, is empirically very important as shown in Figure 5b. The impact of connections is more than twice as large for low-wage establishments as for high-wage establishments. The relationship in-between is approximately linear. Thus, the causal effects of social connections are considerably larger for low-wage employers than for high-wage employers.[31]

(a) By (displaced) person effects decile



(b) By potential hiring establishment decile

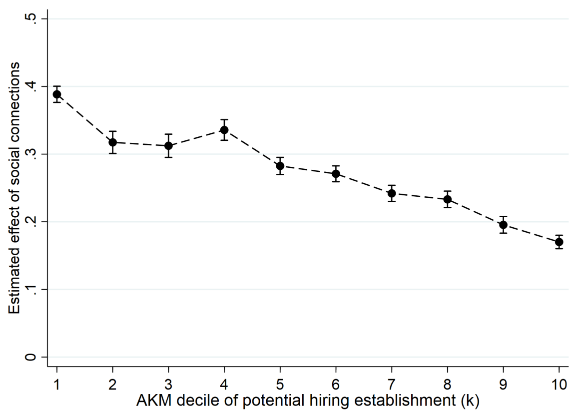


Figure 5: Estimated effects of social connections, by AKM person and establishment effects deciles

Notes: The figure shows interactions with AKM deciles of displaced worker (i) (Figure (a)) and AKM deciles of potential hiring establishment (k) (Figure (b)).

One potential concern would be that workers who, for some reason, are more likely to use connections also are more likely to be connected to low-wage employers. Fortunately, we can use the within-worker variation to assess this concern. We thus estimated the individual (times connected set) fixed-effects

[29] For evidence in this direction, see Appendix Table 9.

[30] In Appendix Figure B.1, we show that the relationship is the same if we use person effects residulized from age, gender and education level.

[31] Estimates in Figure 5a and Figure 5b are from separate regressions but results are identical when estimated jointly.

model of equation (10) to see if workers with connections to both high- and low-wage establishments are more likely to "use" their connections to low-wage establishments. Indeed, as shown in Figure 6, this is the case. Although with a slightly lower magnitude than for the establishment-pair fixed-effects model, the overall results are very similar despite the differences in identification strategies.

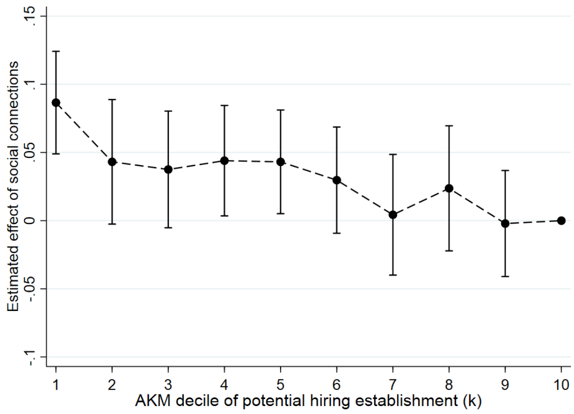
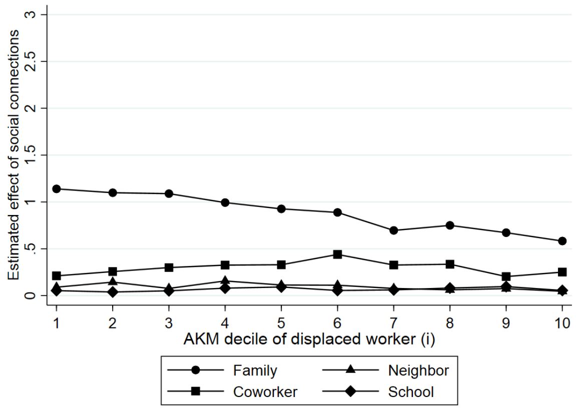


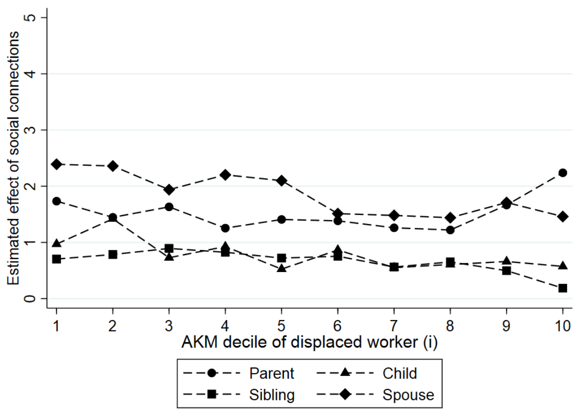
Figure 6: Within-worker identification estimates by AKM decile of potential hiring establishment (ψ_k)
Notes: The figure is based on the model of equation (10), which includes worker and set of connected establishments and year fixed effects. It shows the interactions with AKM deciles of potential hiring establishment. Decile 10 is the reference category.

Next, we disaggregate the effects by type of connection in the parallel Figures 7 and 8. These figures show the point estimates by decile of person and firm, separately by type of connection. In the Appendix (Table B.4) we show corresponding linear relationships with their standard errors. The effects of family members and of co-workers are twice as large when connecting to low-wage establishments as when connecting to high-wage establishments (Figure 8). The figures also show that family members have a larger impact for low-wage workers whereas co-worker connections are somewhat more important for the middle to high-wage workers. The impact of family ties is, however, (as with the sorting of connections discussed in Section 4.1) affected by demographic background characteristics. If we instead use "residualized" person effects purged of observable demographics (see Appendix Figure B.1 and Table B.4), it becomes obvious that most of the negative slope we found for family members is driven by observables, primarily on the spousal side. This is because females (thus, lower-than average person effects) appear to be more likely to be hired through the husbands' employers than the reverse. In all cases, the effects of former classmates and current neighbors are so limited in magnitude that heterogeneity plays little role.

(a) All connections



(b) Family members



(c) Former classmates

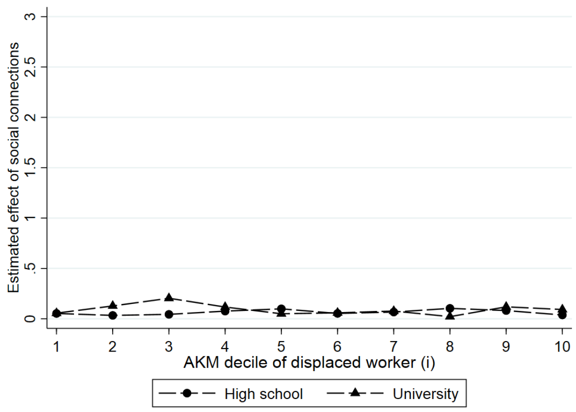
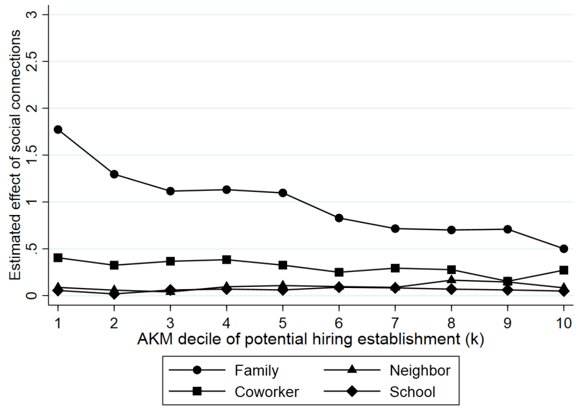


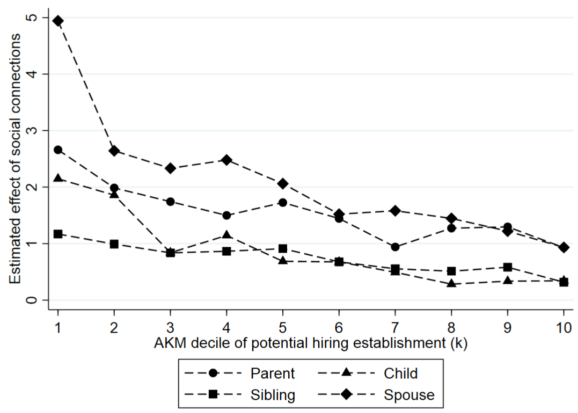
Figure 7: Estimated effect of social connections by AKM effect (θ_i) decile of displaced worker i.

Note: For coefficients and standard errors of the linear slopes, see Table B.4.

(a) All connections



(b) Family members



(c) Former classmates

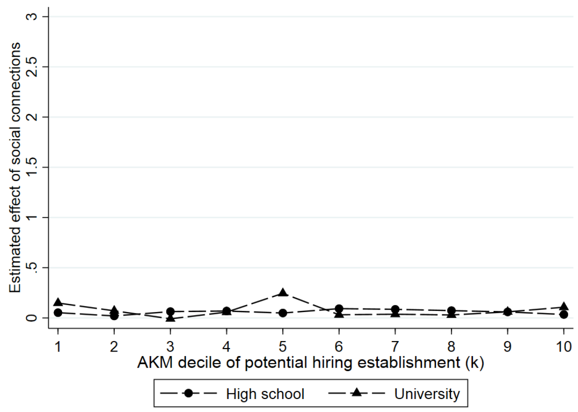


Figure 8: Estimated effect of social connections by AKM effect (ψ_k) deciles of potential hiring establishment k.

Note: For coefficients and standard errors of the linear slopes, see Table B.4.

In Figure 9 we use within-worker identification to assess the relative impact of family members, former classmates, and former co-workers and neighbors across the distribution of person effects. Since the identification compares different connections for the same individual, we need to define a reference

point. The figure therefore uses current neighbors as the baseline. The point estimates show that the ranking of effects (i.e., family first then co-workers, classmates and neighbors last) is the same across the distribution of person effects. The magnitudes of the differences are, however, largest (and statistically significant) for low-wage workers and less pronounced (and not significant) at the very high end. Low-wage individuals are 1.5 percentage points more likely to be hired by establishments where they have family members than where they have neighbors, whereas the corresponding difference for co-workers is 0.5 percentage points for low-wage workers. The effects are more similar for high-wage workers, because family members are less important and co-workers instead matter more. The impacts of former classmates are only marginally positive relative to current neighbors across the distribution of person effects.[32]

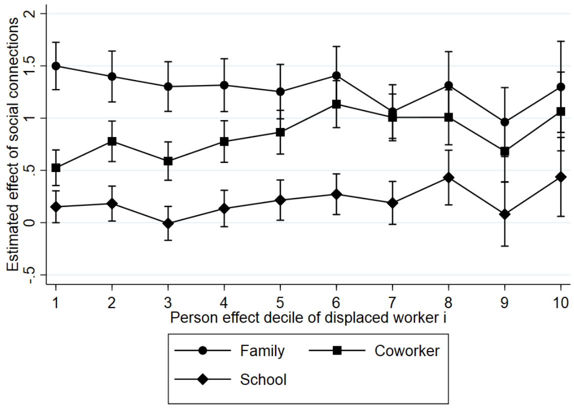


Figure 9: Individual fixed effects estimates of the effect of social connections relative to current neighbors by AKM effect (θ_i) decile of displaced worker

Notes: The figure is based on the model in column (3) of Table 4, which includes individual and set of connected establishments and year fixed effects. It shows the interactions with connection type and the AKM person effect decile. Current neighbors is the reference category. Standard errors are clustered on the potential hiring establishment-and-year level.

Finally, we turn to the interaction between the supply and demand sides by using a second-order polynomial of both (AKM) worker and establishment effects as outlined in equation (9). The parameter estimates and standard errors are presented in the Appendix Table B.5, but here we instead show the estimates graphically in Figures 10a to 10d.

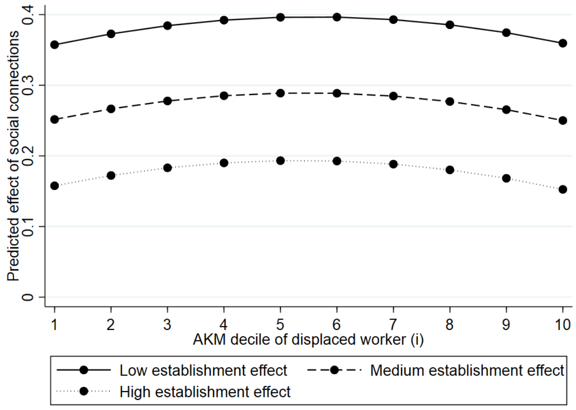
Figure 10a shows that the effect of connections to establishments with AKM-effects belonging to the lowest tercile (solid line) is twice as large as the effect of connections to establishments in the highest tercile (dotted line) regardless of whether the displaced worker is a low-, medium-, or high-wage worker.

Figure 10b shows results from the same analysis but from the worker perspective. These results instead highlight that the effects of connections are larger for low-wage establishments regardless of whether the worker is a high-wage (dotted lined) or a low-wage (solid line) individual (again splitting

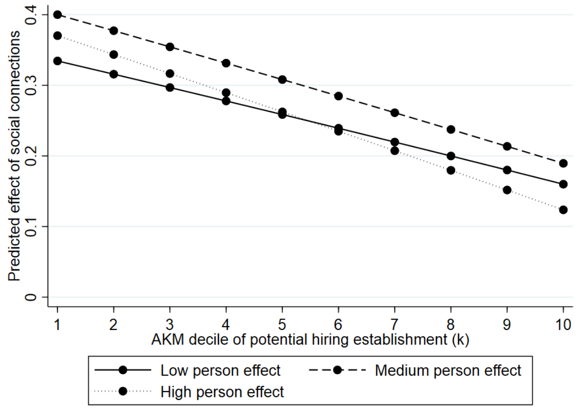
[32]Since the baseline results suggested a larger impact of former classmates from university in the individual fixed-effects model, we explored models separating between classmates from high school and university but the relationships to the person effects were in fact very similar.

the sample by thirds). Slopes are only marginally different across types of workers and the interaction is not statistically significant (see Appendix Table B.5).

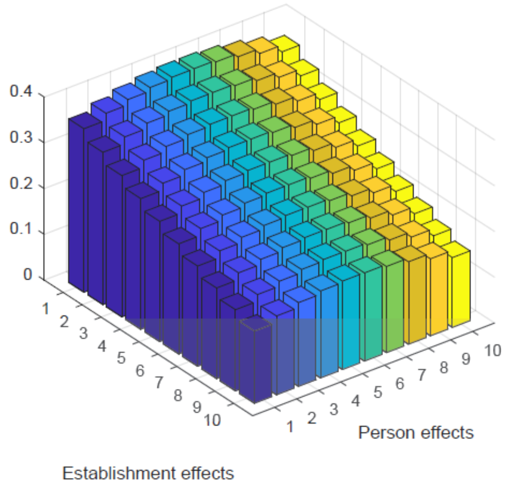
(a) By AKM decile of displaced worker (i) for low, medium and high terciles of establishment (k) effects



(b) By AKM decile of potential hiring establishment (k) for low, medium and high terciles of displaced worker (i) person effects



(c) By joint distribution of person (i) and establishment (k) AKM deciles



(d) Baseline hiring probabilities without connections, by joint distribution of person (i) and establishment (k) AKM deciles

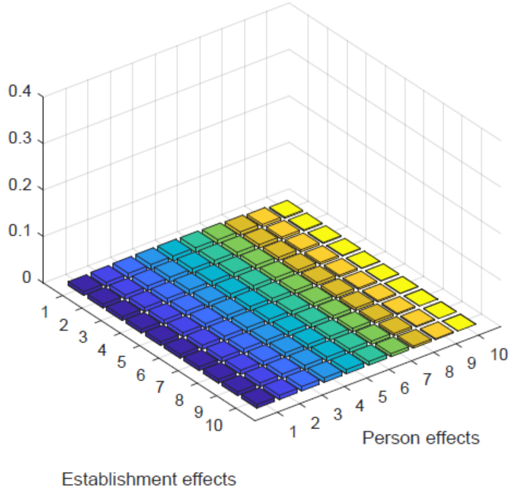


Figure 10: Effects of social connections on hiring, by joint distribution of person and establishment effects

Notes: The figures show the predicted hiring effect of social connections obtained from estimating equation (8), i.e., from interacting social connections with a second order polynomial of both the AKM person effect of the displaced and the establishment effect of the potential hiring establishment (in percentiles). All estimates are from the same regression. Panel a) and b) show slices of the 3d graph of panel c). For underlying estimates and standard errors see the Appendix Table B.5.

Figure 10c shows the full 3D-graph of effects as functions of the different deciles as approximated by the second-order polynomial. Again, the figure clearly shows that all effects are much larger for low-wage establishments, *regardless* of the person effect. This suggests that the distribution of causal effects of connections (i.e., the $\gamma(\theta,\psi)$ in equation (6)) does not contribute to sorting inequality. For completeness, we also show in Figure 10d how the person and establishment effects interact with the probability to be

hired for non-connected workers, but these effects are small throughout.

We next rely on the within-worker identification to analyze the relationship between the causal effects of connections and the person and establishment effects of the agents. But with this model we are limited to the parts of the interacted second-order polynomial that are not soaked up by the individual-fixed effects as highlighted in equation (11). Results are presented graphically in Figure 11 with point estimates and standard errors in Appendix Table B.5. The results show that a given (displaced) worker is more likely to be hired through her connections to low-wage establishment, regardless if she is a low-, medium-, or high-wage worker. The triple interaction between having a connection and the (AKM) person and establishment specific effects is positive but not statistically significant as shown in Appendix Table B.5.

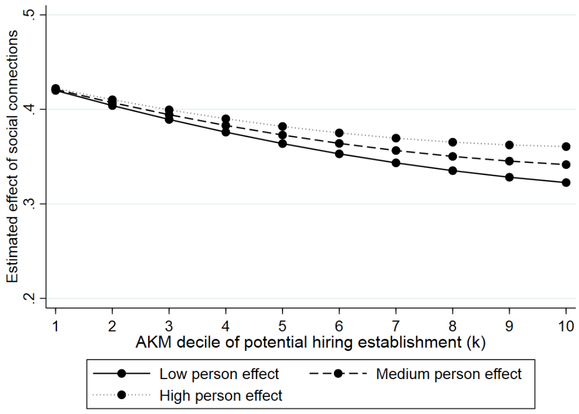


Figure 11: Within-worker identification estimates by potential hiring establishment deciles, for low-, medium-, and high-wage displaced workers.

Notes: The figure is based on the model of equation (10), which includes worker and set of connected establishments and year fixed effects. It shows the interactions with a second order polynomial of the AKM effect of the potential hiring establishment and the interaction between the AKM person effect of the displaced and the establishment effect of the potential hiring establishment. Note that the baseline person effect of the displaced is absorbed by the (worker) fixed effect. The interaction term between person and establishment effect is not significant (see Appendix Table **??**).

4.4 Social connections and overall sorting patterns

As shown in the previous sub-sections, social networks exhibit homophily: high-wage workers are connected to other high-wage workers. But our analysis also demonstrates that the hiring power of a social connection is as large when it connects a high-wage worker to a low-wage establishment as when it connects a *low*-wage worker to a low-wage establishment. Thus, the structure of social networks adds to sorting inequality, but the distribution of the hiring impact of connections does not. However, does the combination of these two forces make connected hires more (or less) sorted than market hires?

To answer this question, we investigate how the person effects of newly hired workers co-vary with the AKM effect of the hiring employer. This analysis presents estimates that require more of a leap of

faith to be interpreted as causal than estimates which we have presented up to now. The reason is that the sample is selected to be those that actually find employment and the identification strategy does not have the granular fixed-effects controls of the dyad model. On the other hand, this analysis also lends itself to an extension to all movers (i.e., also those that are not displaced).

Thus, we estimate the following model:

$$\theta_{ijk} = \mu + \lambda \tilde{\psi}_j + X_i\beta + \phi C_{ijk} + p\tilde{\psi}_k C_{ijk} + q\tilde{\psi}_k(1 - C_{ijk}) + e_{ijk}, \tag{12}$$

where $\tilde{\psi}$ indicates (for ease of exposition) deviations from within-sample means of the ψ variable. The parameter ϕ captures the mean "effect" of being hired through a social connection, p captures differences in hiring patterns of socially connected workers between high- and low-wage establishments, and q captures similar differences in hiring patterns for non-connected workers. Differences between estimated p and q indicate differences in sorting between connected and non-connected hires. To reduce the impact of potential differences in observable characteristics, we control both for the establishment effect of the previous employer and for observable worker characteristics (see table notes for details). As mentioned above, the model can only be estimated for the restricted sample of realized hires.

Table 7: AKM person effect of new hire as a function of the AKM establishment effect of the hiring establishment and social connections

	(1)		(2)		(3)		(4)	
	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)
Panel A: All hires								
Connected hire	2.301	(0.084)	2.524	(0.084)	2.481	(0.084)	1.479	(0.094)
Hiring establishment effect – connected hire	0.081	(0.001)	0.051	(0.001)	-0.009	(0.001)	-0.020	(0.002)
Hiring establishment effect – market hire	0.116	(0.000)	0.088	(0.001)	0.029	(0.001)	-	-
Test: Connected hire = Market hire (Prob > F)		0.0000		0.0000		0.0000		-
Observations		3,315,521		3,315,521		3,315,521		3,315,521
R-squared		0.302		0.306		0.309		0.408
Panel B: Hired displaced workers								
Connected hire	1.467	(0.500)	1.573	(0.499)	1.612	(0.499)		
Hiring establishment effect – connected hire	0.048	(0.008)	0.032	(0.008)	-0.027	(0.009)		
Hiring establishment effect – market hire	0.079	(0.003)	0.064	(0.003)	0.008	(0.005)		
Test: Connected hire = Market hire (Prob > F)		0.0002		0.0001		0.0000		
No of observations		83,540		83,540		83,540		
R-squared		0.264		0.267		0.269		
Year specific effects		Yes		Yes		Yes		Yes
Sending establishment AKM effects		No		Yes		Yes		Yes
Sending×Hiring establishment AKM effects		No		No		Yes		Yes
Hiring establishment FE:s		No		No		No		Yes

Notes: We account for the age, gender, education level and the number of connections of the job mover.

Table 7 displays the estimation results, both for the sample of hired displaced workers and the full sample of job-to-job movers in the economy. The estimates show that the average "impact" of social connections is positive, which implies that employers, on average, hire more high-wage workers through social

connections (as postulated by Montgomery (1991)). Furthermore, we see that job-to-job transitions contribute to sorting inequality, i.e., high-wage employers are more likely to hire high-wage workers regardless of whether they hire through social connections or through the "market". Thus, hired workers are positively sorted in terms of wage potential. However, this sorting is (statistically) significantly *less* pronounced among workers hired through connections than among workers hired through the market. These patterns arise not only in the sample of hired displaced workers (Panel B) but also in the full sample comprising all job-to-job movers (Panel A).

To illustrate the role of connections for different types of establishments, Figure 12 uses the estimates of Table 7 to trace out the person effects as a function of the AKM establishment effects for connected hires and market hires. The top Figure (a) "All hires" clearly shows that low-wage employers hire better workers through connections than through the market, whereas the converse is true for high-wage employers. Interestingly, comparing Figures 12 (a) and (b), sorting is steeper for the former (All hires) than for the latter (Hired displaced workers) showing that our identification strategy helps us attenuate the component of sorting due to the option to stay in one's origin establishment.

(a) All hires (b) Hired displaced workers

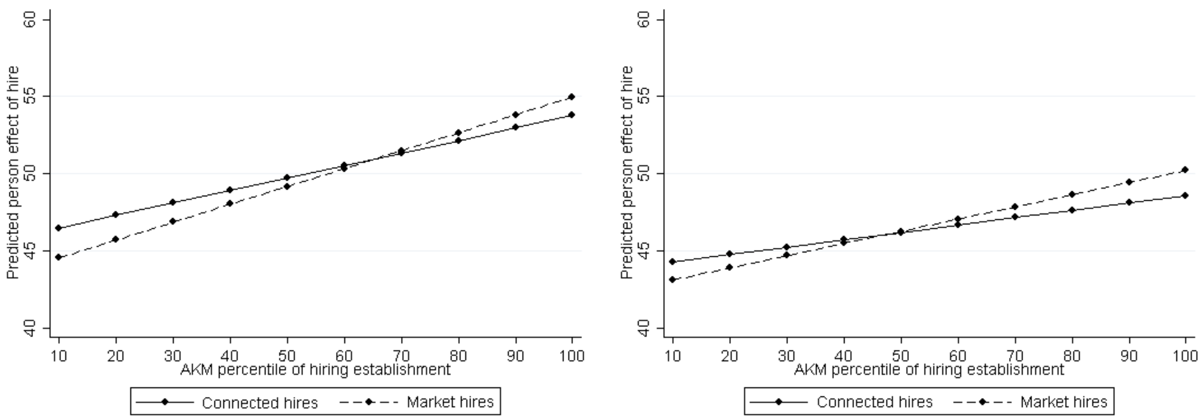


Figure 12: Predicted person effect of new hire as a function of hiring establishment effects and the use of social connections

Notes: The figure shows the predicted relationships between person effects of new hires, the hiring establishment effect and the hiring channel (connection/no connection). For estimates and standard errors see Table 7. We have added the mean person effect within each sample.

5 Extensions

5.1 Competing connections and their quality

The results so far demonstrate that connections are useful for establishments in their hiring process. But establishments may face a "choice" between multiple connected workers and therefore have to select the connected worker that fits them best. This idea, that connections are competing, has a long tradition

in the literature on job search networks (see, e.g., Boorman, 1975; Calvó-Armengol and Jackson, 2004). To study how competition operates, we focus on cases where multiple displaced workers are connected to the same establishment. We test two aspects of competition effects: (i) the existence of competing connections, and (ii) the relative quality of these competing connections.

The first hypothesis is that if an establishment is connected to several displaced workers through its employees, it will reduce the probability that a "referral" from a given intermediary worker will result in a hire. The results from our test of this hypothesis are presented in Panel A of Table 8. The resulting estimate indeed shows that the causal effect of a connection is much lower if other displaced workers are connected to the same establishment. We present estimates where we measure competition through the existence of any competing connections, but results are similar if we instead use as our competition measure the number of competitors or the number of competitors as a share of all incumbent employees. The three columns show estimates separately depending on the quality of the connected (k) establishment and it is clear that the usefulness of connections is largest for low-ψ_k establishments, whereas the negative role of competitors is growing in ψ_k, thus competition is more important at more attractive employers.

The second hypothesis is that the quality of competing connections affects the likelihood that a particular connected displaced worker is hired. Previous studies that have investigated the role of network quality for the reemployment of displaced workers have measured quality in terms of the employment rate in the particular network. In contrast to this literature, we try to predict the precise destination of displaced workers and the role played by the nature and the quality of their network. Here, these intermediary workers constitute these workers' network; its quality is measured using the estimated person effects of these intermediaries. Hence, in Panel B, we present results where we use an indicator for cases where the displaced worker faces competition from another displaced worker endowed with a "better" (in terms of person effects) connecting intermediary worker. The results, consistent across the high-wage/low-wage status of the establishment, imply that competition of better-connected workers reduces the predictive hiring power of a worker's social connection.[33] We have also explored the role of the relative quality of the displaced workers (in terms of person effects), but the results show that this aspect plays no consistent role. This is fully in line with the results shown above in which the usefulness of connections is independent of the displaced worker's own person effect.

[33] We find similar results if we instead measure competing quality based on the observable (combined) characteristics of the displaced worker, the type of connection and the intermediary worker.

Table 8: The role of competing connections (of higher quality), by potential hiring establishment effects

	Estimated AKM effects of (potential) hiring establishment					
	Low ψ_k		Medium ψ_k		High ψ_k	
	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)
Panel A						
Any connection	0.2513	(0.0093)	0.2127	(0.0069)	0.1628	(0.0059)
Any connection × Competing Connection	-0.0691	(0.0185)	-0.1022	(0.0182)	-0.1301	(0.0191)
Constant	0.0164	(0.0005)	0.0210	(0.0004)	0.0149	(0.0003)
No of fixed effects		478,128		684,111		734,016
No of observations		9,496,877		13,182,356		13,747,457
Panel B						
Any connection	0.2604	(0.0098)	0.2112	(0.0069)	0.1562	(0.0059)
Any connection × Competing Connection	-0.0196	(0.0220)	-0.0568	(0.0213)	-0.0573	(0.0229)
Any connection × Competing Connection Quality (θ_l)	-0.1038	(0.0225)	-0.0699	(0.0162)	-0.0964	(0.0151)
Constant	0.0163	(0.0005)	0.0210	(0.0004)	0.0149	(0.0003)
No of fixed effects		478,128		684,111		734,016
No of observations		9,496,877		13,182,356		13,747,457

Notes: The OLS regressions are restricted to potential hiring establishments where no two (or more) employees had connections to the same displaced worker. Observations with missing quality measures are accounted for missing variable indicators. All estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. All estimations include establishment-pair(-and-year) fixed effects. Competition and quality measures are demeaned (using the mean among those with a connection). Standard errors are clustered on the potential hiring establishment-and-year level. "Competing Connection" is an indicator taking the value one if some other displaced worker (in the same year) has a connection to the same establishment. "Competing Connection Quality" (CCQ) is an indicator variable taking the value one if (some) Competing Connection is mediated by an intermediary worker with a higher estimated person effect than subject i's intermediary worker (i.e., $CCQ_{ik} = I[\theta_{l(\tilde{i},k)} > \theta_{l(k,i)}$ for some $\tilde{i}$ who is displaced in the same year as i with a connection to k.).

5.2 Heterogeneity in observable dimensions

To provide a context to our main results, we here present results where we interact the estimates with a number of observable characteristics.

5.2.1 Social connections and tie strength

Our main results show that family members are associated with much larger causal effects than other connections, even though the networks provided by family members exhibit less homophily in the AKM-dimension than professional connections. We interpret this as evidence in favor of strong social connections being particularly important at the labor market. This notion is important because it relates to the theoretical notion that matching through strong social ties may increase labor market efficiency, see e.g., the seminal work by Boorman (1975).

To further test the robustness of this conclusion, we have re-estimated our model, but now allowing for further heterogeneity in a number of dimensions: the size of the group where the interaction took place, the duration of interaction, and the time since interacting. These dimensions can be viewed as proxies for ties' strength, and in particular the intensity of the interaction. Assessing the importance

of these factors will also shed some additional light on the data restrictions discussed in Section 3.3 where we imposed a set of boundaries on the observed connections. For example, former high-school classmates are (for data availability reasons) not observed for those who graduated before 1985. Moreover, as is apparent from Section 3.3, our measures of social connections are comprehensive and largely error-free in a statistical sense (co-workers were paid by the same employer), but they do not necessarily capture agents that frequently interact on a social level. Hence, we decided to focus on those cases where the connections should be well-measured and most meaningful. Most notably, we excluded networks with 100 or more individuals.

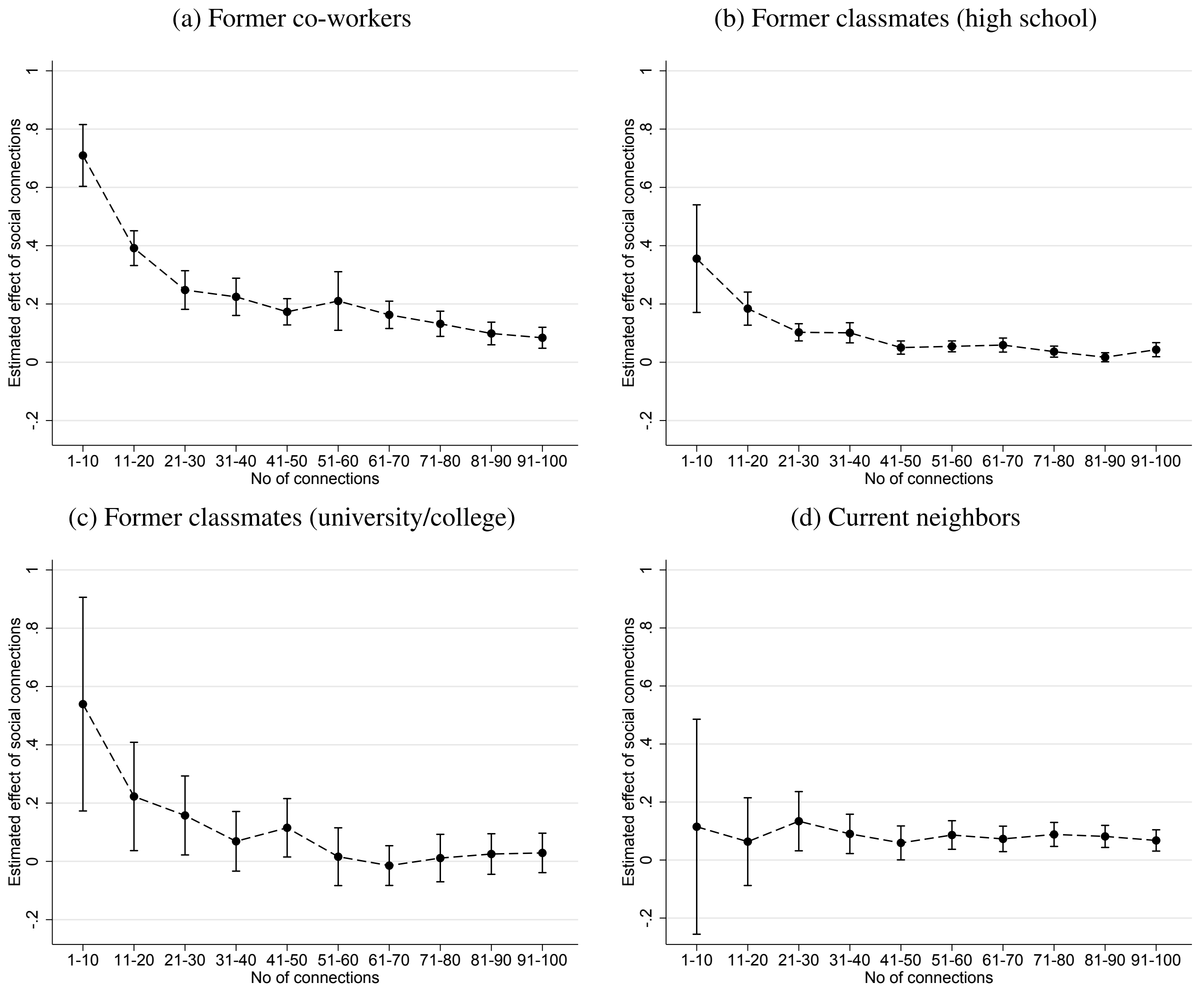
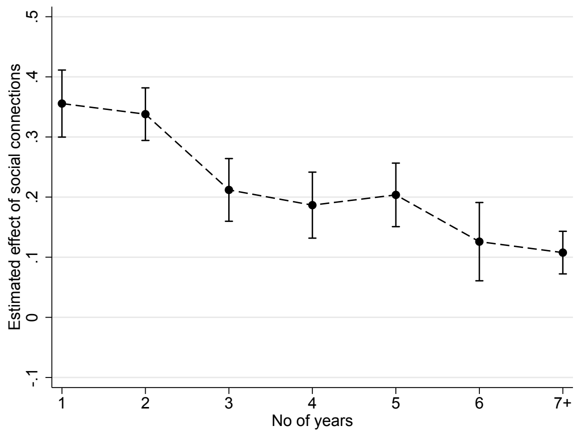


Figure 13: The estimated impact of a connection on the hiring probability, by the size of the particular network (i.e., the workplace, class, or neighborhood), with 95 percent confidence intervals, for former co-workers, former classmates (high school and college/university), and current neighbors

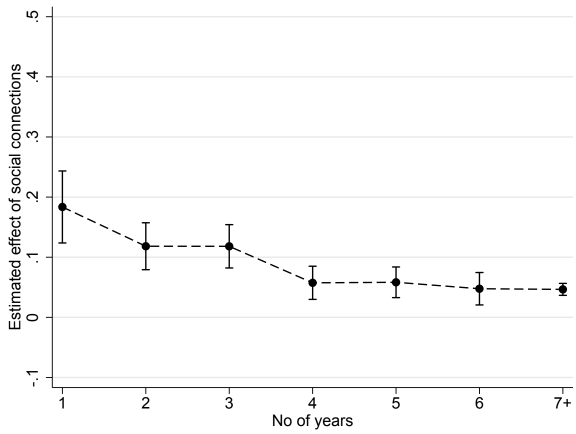
Notes: All estimates are obtained from the same estimation, where the indicator for the particular connection has been replaced by its interactions with the size of the particular network (10 categories). The estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. All estimations include establishment-pair(-and-year) fixed effects. Standard errors are clustered on the potential hiring establishment-and-year level.

First, explore the role of the size of the group in which the interaction occurred. This matters for three types of measured connections: former co-workers, former classmates (here, to a very small extent), and current neighbors. As can be seen in Figure 13, among all the connected displaced workers the hiring probability is decreasing with the size of the group, but especially so among former co-workers and classmates (from both high-school and college/university). Importantly, group size matters also for groups that are already very small, co-workers from sites with less than 10 employees matter more than those with 10–20 employees. This thus strongly suggests that connections, indeed, are more useful if they are formed in smaller social groups. It also supports our choice to exclude groups of more than 100 individuals since they appear to be uninformative regarding the *relevant* connections.

(a) Former co-workers



(b) Former classmates (high school)



(c) Former classmates (university/college)

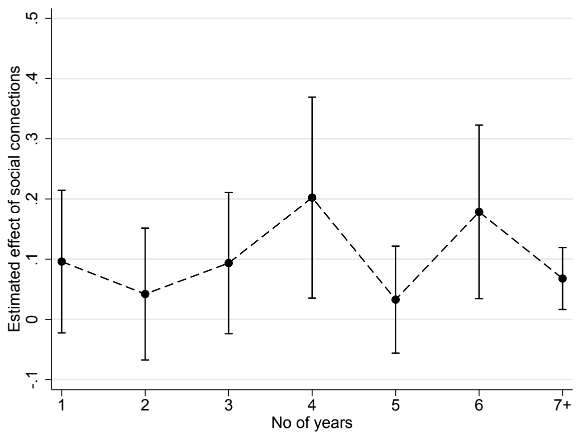


Figure 14: The estimated impact of a connection on the hiring probability, by time since interaction, with 95 percent confidence intervals, for former co-workers and former classmates (high school and college/university)

Notes: All estimates are obtained from the same estimation, where the indicator for the particular connection has been replaced by its interactions with time since interaction (7 categories). The estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. All estimations include establishment-pair(-and-year) fixed effects. Standard errors are clustered on the potential hiring establishment-and-year level.

Second, the role of time since interaction matters for former co-workers and former classmates. The impact of previous co-workers depreciates rapidly with time since interaction. The estimates as presented in Figure 14 suggest that the causal impact is decreasing with this time since interaction for connections with former co-workers and with former classmates, at least from high school. Estimates for former college/university classmates are very imprecise, and no clear result arises. This also suggests that our choice to consider only former co-workers from the most recent of all past workplaces (before becoming employed at *j*) is innocuous, and that our lack of data on high-school classmates prior to 1985 is likely to be of minor importance.

Third, the duration of the interaction is relevant for former co-workers as well as current neigbors. The estimates depicted in Figure 15 show that there is a strong positive relationship between time spent together as co-workers and the magnitude of the causal estimate. There is a similar tendency among those connected through current neighbors, even though it is not as marked since all estimates in this category are small.

(a) Former co-workers (b) Current neighbors

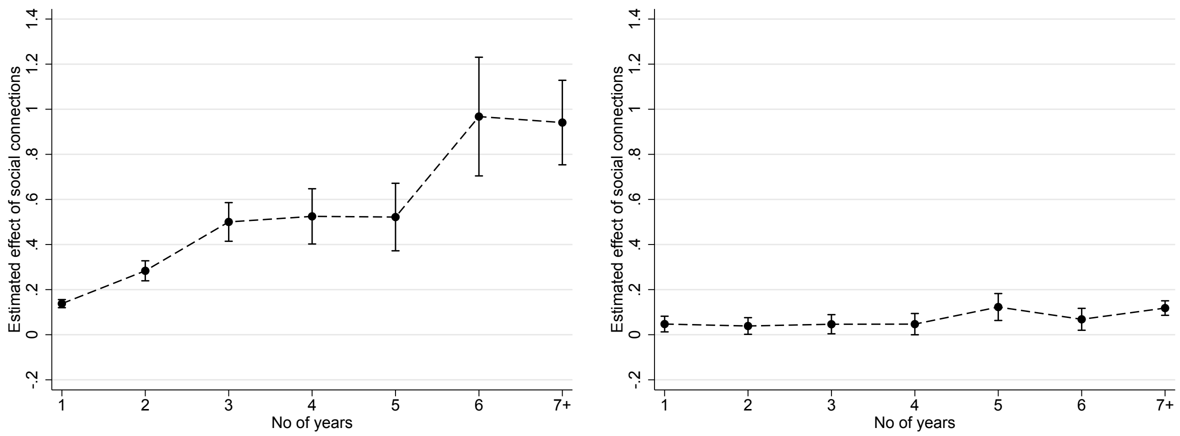


Figure 15: The estimated impact of a connection on the hiring probability, by interaction time, with 95 percent confidence intervals, for former co-workers and current neighbors

Notes: All estimates are obtained from the same estimation, where the indicator for the particular connection has been replaced by its interactions with interaction time (7 categories). The estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. All estimations include establishment-pair(-and-year) fixed effects. Standard errors are clustered on the potential hiring establishment-and-year level.

Overall, these results show a consistent positive relationship between social proximity and the resulting hiring probability. Effects are decreasing with the size of the group where the interaction took place and with time since interaction but growing with the duration of interaction between the agents. We have estimated the role of similarity in terms of demographic characteristics along the lines of Bayer et al. (2008) and the results presented in Appendix Table B.3 show that similarity in gender, age and immigration status is more important than similarity in terms of education, again supporting the notion

that social proximity is crucial.

5.2.2 Establishment-level characteristics

One of our main findings is that the causal impact of social connections varies dramatically with the wage-level of the connected establishment. Therefore, we have also repeated the main analysis for various subsamples based on other characteristics of the potential hiring establishment. In Figure 16, we present estimates for an average across all connections and relegate the analysis for each specific type of connection to the Appendix Table B.2.

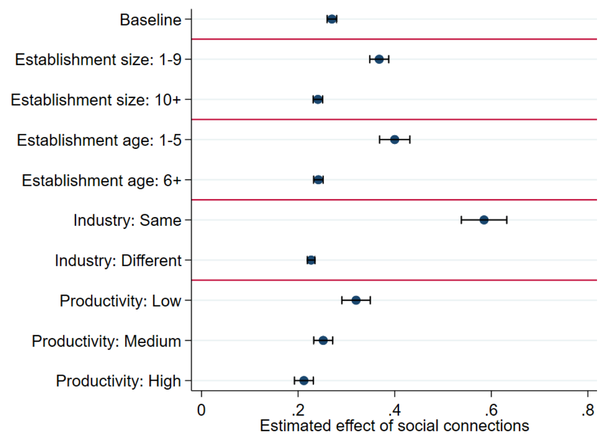


Figure 16: The estimated importance of social connections by characteristics of the potential hiring establishment (k)

Notes: All estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. All estimations include establishment-pair(-and-year) fixed effects. Standard errors are clustered on the potential hiring establishment-and-year level. See the Appendix for results disaggregated by connection type.

The figure first shows that the effects are more potent for small establishments and for comparably young establishments. A reason may well be that there are establishments where hiring frictions are more pronounced.

Next, we split the sample into cases where closing establishment j and potential hiring establishment k are in the same industry, vs when they operate in different industries. This sample-split is clearly related to the potential fear that the closure of an establishment may affect product market competition in the industry and location as discussed in Section 4 above. Separating between inter- and intra-industry connections serves as an additional test on top of the placebos: if competition effects were indeed a major force, our results should mostly come from within-industry connections. However, when the closing and potential hiring establishment operate within the same industry, the displaced workers' skill sets obviously satisfy the requirements of the potential hiring establishment.[34] Results in Figure 16 show that

[34]Not surprisingly, the baseline probability of intra-industry hiring (0.162) of non-connected displaced workers is more than 10 times the equivalent probability of inter-industry hiring (0.015).

the estimated importance of connections is much larger (0.58) for within-industry connections than for between-industry connections (0.23). However, the impact of between-industry connections is clearly significant and, even more important, the between-industry estimate is very close to the baseline impact. The reason is that most connections span across industries.

Finally, we show how the use of connections in the hiring process varies with firm's productivity.[35] It is well-known that productivity measures tend to correlate heavily with firm or establishment effects from AKM-decompositions. Thus, we expect the effects to be larger in cases where the productivity of firm k is lower than average. This conjecture is confirmed in Figure 16 which shows that the causal impact of connections is negatively related to the productivity of the connected firm.

5.3 Post-hire outcomes

Even though the focus of the paper has been to document sorting patterns, we believe it useful to also examine if and how post-hire outcomes differ between connected hires and market hires. In Table 9, we compare the earnings and employment outcomes between those with and without a connection to their new employer. The sample includes displaced workers who found a job directly after displacement. The regressions include closing-establishment fixed effects, as well as controls for pre-displacement earnings and employment histories. The estimates should thus be interpreted as comparisons between similar displaced workers who found jobs with vs. without social connections.

Results show that earnings and job stability are higher for workers who were rehired through social connections. The results are near universal. The one key exception is that workers who found their next job through family members receive lower earnings early on, but positive earnings in the longer run, a result which closely mimics the results for parental contacts in Kramarz and Skans (2014). The results for earnings 3 years after university connections are very close to zero, but all other remain solidly positive in both the short and medium run. As is prevalent in the previous literature, we find positive estimates from all connections on the probability of remaining in the post-hire establishments three years after the displacement.

[35] The productivity measure is only available for a sub-sample of our firms. It is measured at the firm-level rather than the establishment-level. Productivity is then categorized (i.e., low, medium, and high productivity) based on the firm's position in the distribution of value-added per worker within the local labor market and industry.

Table 9: Post-hire outcomes

	Outcomes after 1 year		Outcomes after 3 years					
	Log(Earnings) [a]		Log(Earnings) [a]		Employed [b]		Job stability [c]	
	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)
Panel A								
Any connection	0.083	(0.013)	0.175	(0.019)	0.029	(0.004)	0.128	(0.007)
Constant	11.043	(0.026)	10.805	(0.027)	0.747	(0.005)	0.249	(0.005)
Panel B								
Family members	0.002	(0.018)	0.152	(0.027)	0.028	(0.006)	0.136	(0.008)
Former co-worker	0.137	(0.019)	0.148	(0.031)	0.020	(0.006)	0.076	(0.011)
Former classmates	0.179	(0.029)	0.201	(0.049)	0.021	(0.010)	0.158	(0.017)
Current neighbors	0.126	(0.037)	0.197	(0.059)	0.036	(0.013)	0.152	(0.023)
Constant	11.043	(0.026)	10.805	(0.027)	0.747	(0.005)	0.249	(0.005)
Panel C								
Family members								
Parent	-0.123	(0.030)	0.073	(0.043)	0.020	(0.009)	0.101	(0.014)
Adult child	0.055	(0.059)	0.177	(0.096)	0.029	(0.019)	0.109	(0.029)
Spouse	0.086	(0.034)	0.104	(0.058)	0.031	(0.011)	0.117	(0.018)
Sibling	0.042	(0.027)	0.161	(0.045)	0.025	(0.009)	0.135	(0.015)
Former co-worker	0.135	(0.019)	0.149	(0.031)	0.020	(0.006)	0.077	(0.011)
Former classmates								
High school	0.180	(0.030)	0.217	(0.053)	0.022	(0.011)	0.158	(0.018)
College/university	0.156	(0.092)	-0.020	(0.124)	-0.008	(0.019)	0.137	(0.044)
Current neighbors	0.132	(0.037)	0.208	(0.058)	0.037	(0.013)	0.159	(0.023)
Constant	11.043	(0.026)	10.806	(0.027)	0.747	(0.005)	0.250	(0.005)
No of fixed effects	29,554		29,554		29,554		29,554	
No of observations	208,738		208,738		208,738		208,738	

Notes: The estimation sample is all displaced workers who were employed in in November of year $t+1$. All estimations include closing establishment (-and-year) fixed effects and controls for the workers' age, sex, education, and three years of pre-displacement employment, earnings, and employer history. Standard errors are clustered on the closing establishment (-and-year) level.

[a] Earnings is defined as annual labor income and has been left censored at SEK 1,000.

[b] Employed is defined as being employed in November of year $t+3$.

[c] Job stability is defined as being employed at the same establishment in November of both year $t+1$ and $t+3$.

6 Conclusions

A vast number of studies have shown that social connections play a quantitatively important role in the process of matching workers to jobs. And, because social relations tend to be homophilous – with persons of similar social status being connected – the literature has presumed that social networks exacerbate labor market inequality.

In this paper, we assess this presumption. To do so, we document the causal role of a wide set of social connections (i.e., family members, former co-workers, former classmates, and current neighbors) in the matching of displaced workers and establishments within a unified empirical framework. Our analyses rely on establishment closures as exogenous events forcing workers to search for new jobs, allowing us to compare the reemployment outcomes of workers who lost their jobs in the same closure event, and to document to what extent social connections causally affect where these workers are rehired.

Focusing on the hiring impact of social connections, family members are the most important of all measured social connections. Former co-workers also matter, and in particular if they worked together relatively recently (i.e., the value of the connection seems to depreciate fairly rapidly). Former classmates and current neighbors seem to be surprisingly unimportant overall. More generally, we show a consistent positive relationship between social proximity and the hiring probability: the more interaction time, the shorter the time since interaction, and the smaller the size of the group where the interaction took place, the more likely that the connected displaced worker is hired. These findings clearly favor the hypothesis that a "strong" tie makes a connecting agent more useful than a "weak" tie.

Focusing on sorting inequality, we show that social connections – in particular those formed at school and at work – connect high-wage workers to other high-wage workers. This also holds when using the residualized person effects, which only capture the "unobservable" dimensions of the person effects. The strong person-to-person "homophily" translates into a (weaker) pattern where high-wage workers have social connections within high-wage establishments. In turn, these social connections have a large causal impact on hiring when the demand side is a low-productivity/low-wage establishment, regardless of the type of worker. Displaced workers with multiple social connections are more likely to enter a low-wage establishment than a high-wage establishment if connected to both types of establishments, both for low-wage and high-wage workers. As a consequence, low-wage establishments are able to attract high-wage workers through social connections. Thus, hiring through social connections is associated with less sorting than market matches, despite of the strong homophily within our social networks and the prevalence of connections between high-wage workers and high-wage establishments. This conclusion – hiring through social connections being less sorted than market matches – holds for hired displaced workers as well as for all hires. As highlighted in the introduction, these novel empirical regularities stand in sharp contrast to a standard presumption shared between the theoretical literature in economics and sociology.

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Appendix A Further descriptive statistics

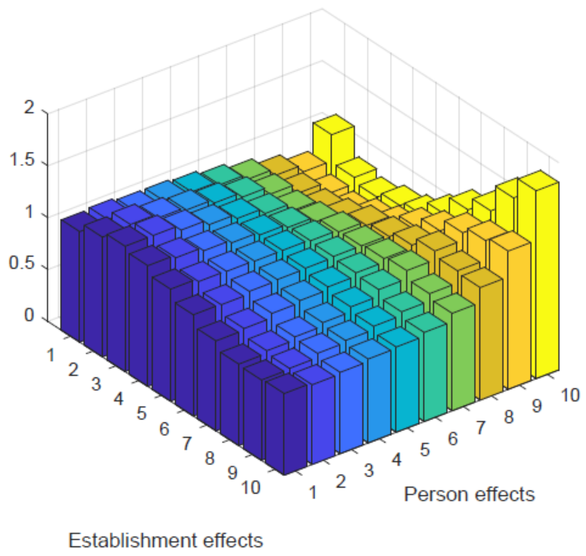


Figure A.1: Joint distribution of AKM person and establishment effects in the sample of all new hires

Table A.1: Summary statistics by closing and potential hiring establishments and for the estimation sample comprised by pairs of potential hiring establishments and displaced workers

	Closing establishments (j)		Potential hiring establishments (k)		Pairs of potential hiring establishments j and displaced workers i	
	N	%	N	%	N	%
Size						
1–9 employees	22,047	69.91	395,587	43.37	10,161,663	24.72
10+ employees	9,491	30.09	516,497	56.63	30,950,111	75.28
Age						
1–5 years	17,602	55.81	195,361	21.42	7,384,653	17.96
6+ years	13,936	44.19	716,723	78.58	33,727,121	82.04
Productivity *						
Low			98,408	10.79	4,750,955	11.56
Medium			151,629	16.62	7,793,214	18.96
High			153,217	16.80	9,414,202	22.90
N/A			508,83	55.79	19,153,400	46.59
AKM establishment effects						
Low	12,929	40.99	321,440	35.24	10,270,584	24.98
Medium	7,414	23.51	316,960	34.75	14,639,048	35.61
High	6,093	19.32	247,058	27.09	15,575,697	37.89
N/A	5,102	16.18	26,626	2.92	626,441	1.52
No of observations		31,538		912,084		41,111,774

* Productivity is only available for a subsample of all establishments.

Appendix B Further results

B.1 Further robustness

Table B.1: Sensitivity analysis

	Main model [a]		Incl. worker characteristics [b]		Incl. worker char. and AKM controls[c]		Closure size <10		At most one connection per worker and potential hiring establishment [d]	
	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)
Panel A:										
Any connection	0.270	(0.005)	0.270	(0.005)	0.272	(0.005)	0.360	(0.011)	0.202	(0.004)
Constant	0.026	(0.000)	0.028	(0.001)	0.029	(0.001)	0.065	(0.005)	0.017	(0.000)
Panel B:										
Family members	1.095	(0.020)	1.095	(0.020)	1.070	(0.038)	1.376	(0.049)	0.908	(0.019)
Former co-workers	0.253	(0.010)	0.253	(0.010)	0.252	(0.028)	0.304	(0.020)	0.149	(0.007)
Former classmates	0.066	(0.004)	0.066	(0.004)	0.068	(0.002)	0.064	(0.010)	0.038	(0.003)
Current neighbors	0.086	(0.008)	0.085	(0.008)	0.086	(0.004)	0.111	(0.028)	0.041	(0.006)
Constant	0.027	(0.000)	0.028	(0.001)	0.029	(0.001)	0.081	(0.005)	0.018	(0.000)
Panel C:										
Family members										
Parent	1.867	(0.052)	1.866	(0.052)	1.810	(0.077)	2.414	(0.125)	1.513	(0.050)
Adult child	0.670	(0.051)	0.672	(0.051)	0.655	(0.011)	0.760	(0.135)	0.528	(0.046)
Spouse	1.974	(0.078)	1.974	(0.078)	1.925	(0.011)	2.612	(0.210)	1.828	(0.080)
Sibling	0.697	(0.023)	0.697	(0.023)	0.693	(0.005)	0.881	(0.054)	0.524	(0.020)
Former co-workers	0.252	(0.010)	0.252	(0.010)	0.251	(0.003)	0.302	(0.020)	0.149	(0.007)
Former classmates										
High school	0.064	(0.004)	0.064	(0.004)	0.066	(0.003)	0.062	(0.010)	0.038	(0.003)
College/university	0.088	(0.018)	0.088	(0.018)	0.086	(0.009)	0.096	(0.065)	0.042	(0.012)
Current neighbors	0.080	(0.008)	0.080	(0.008)	0.081	(0.004)	0.100	(0.028)	0.040	(0.006)
Constant	0.026	(0.000)	0.028	(0.001)	0.029	(0.001)	0.077	(0.005)	0.018	(0.000)
No of fixed effects	2,087,560		2,087,560		2,087,560		852,619		1,923,085	
No of observations	41,111,774		41,111,774		41,111,774		2,328,984		36,990,336	

Notes: All estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. All estimations include establishment-pair(-and-year) fixed effects. Standard errors are clustered on the potential hiring establishment-and-year level.
[a] Repeats the estimates of the left column of Table 5.
[b] In the main estimation no (displaced) worker characteristics were included in X_{it}, while here we have included age (3 categories), sex, nativity, and attained education level (3 categories).
[c] Here we add the person effect and the interaction between the person and the establishment effect (note that the baseline establishment effect is accounted for by the fixed effect). We dummy out the cases where there is no estimated person effect.
[d] This restriction has been imposed in the analyses in Appendix B.2.

Table B.2: The estimated importance of social connections by characteristics of the potential hiring establishment (j)

	Establishment size (employees)				Establishment age (years)				Industry (2 digits)				Productivity					
	1–9		10+		1–5		6+		Same		Different		Low		Medium		High	
	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)
Panel A																		
Any connection	0.368	(0.010)	0.241	(0.005)	0.400	(0.016)	0.242	(0.005)	0.585	(0.024)	0.227	(0.004)	0.320	(0.015)	0.252	(0.010)	0.212	(0.010)
Constant	0.013	(0.001)	0.031	(0.000)	0.045	(0.001)	0.022	(0.000)	0.162	(0.002)	0.015	(0.000)	0.023	(0.001)	0.020	(0.001)	0.020	(0.001)
Panel B																		
Family members	1.814	(0.054)	0.896	(0.021)	1.675	(0.071)	1.008	(0.021)	3.034	(0.132)	0.948	(0.020)	1.570	(0.089)	1.182	(0.057)	0.966	(0.047)
Former co-workers	0.284	(0.018)	0.242	(0.012)	0.501	(0.032)	0.178	(0.009)	0.545	(0.040)	0.182	(0.008)	0.279	(0.029)	0.223	(0.021)	0.183	(0.020)
Former classmates	0.033	(0.005)	0.074	(0.005)	0.064	(0.011)	0.067	(0.004)	0.153	(0.023)	0.056	(0.004)	0.055	(0.013)	0.074	(0.009)	0.074	(0.009)
Current neighbors	0.060	(0.013)	0.094	(0.010)	0.100	(0.028)	0.084	(0.009)	0.358	(0.079)	0.070	(0.008)	0.117	(0.032)	0.085	(0.021)	0.118	(0.022)
Constant	0.014	(0.001)	0.031	(0.000)	0.045	(0.001)	0.023	(0.000)	0.161	(0.002)	0.015	(0.000)	0.024	(0.001)	0.020	(0.001)	0.021	(0.001)
Panel C																		
Family members																		
Parent	2.840	(0.127)	1.560	(0.055)	2.781	(0.194)	1.754	(0.053)	4.137	(0.313)	1.708	(0.051)	2.401	(0.203)	1.957	(0.140)	1.618	(0.121)
Adult child	1.594	(0.168)	0.452	(0.050)	1.332	(0.178)	0.555	(0.052)	2.148	(0.366)	0.560	(0.048)	1.119	(0.226)	0.583	(0.134)	0.544	(0.122)
Spouse	4.558	(0.252)	1.347	(0.075)	3.909	(0.307)	1.704	(0.078)	6.167	(0.521)	1.640	(0.073)	2.813	(0.338)	2.525	(0.243)	1.344	(0.163)
Sibling	0.972	(0.056)	0.618	(0.025)	0.986	(0.074)	0.652	(0.024)	2.146	(0.154)	0.583	(0.022)	1.077	(0.103)	0.771	(0.066)	0.717	(0.058)
Former co-workers	0.280	(0.018)	0.242	(0.012)	0.498	(0.032)	0.177	(0.009)	0.544	(0.040)	0.181	(0.008)	0.278	(0.029)	0.223	(0.021)	0.183	(0.020)
Former classmates																		
High school	0.035	(0.006)	0.072	(0.005)	0.059	(0.011)	0.065	(0.005)	0.154	(0.024)	0.054	(0.004)	0.056	(0.013)	0.073	(0.009)	0.070	(0.010)
College/university	0.006	(0.012)	0.099	(0.021)	0.122	(0.046)	0.079	(0.020)	0.146	(0.066)	0.078	(0.018)	0.090	(0.091)	0.098	(0.041)	0.099	(0.033)
Current neighbors	0.053	(0.013)	0.089	(0.010)	0.094	(0.028)	0.078	(0.009)	0.346	(0.079)	0.065	(0.008)	0.111	(0.032)	0.078	(0.021)	0.113	(0.022)
Constant	0.013	(0.001)	0.031	(0.000)	0.044	(0.001)	0.022	(0.000)	0.160	(0.002)	0.015	(0.000)	0.023	(0.001)	0.020	(0.001)	0.020	(0.001)
No of fixed effects		501117		1,586,443		362,995		1,724,565		225,541		1,862,019		196,128		328,600		409,768
No of observations		10,161,663		30,950,111		7,384,653		33,727,121		3,260,438		37,851,336		4,750,956		7,793,215		9,414,202

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

B.2 The displaced and the intermediary worker's characteristics and their similarity

Here we study the extent to which the impact of social connections varies with observable characteristics in the following dimensions: (i) the connected displaced worker i's own characteristics, (ii) the intermediary worker l's characteristics, and (iii) their similarity in terms of these characteristics. We re-estimate our model including interactions between the indicator for having a connection (of any kind) and indicators for various characteristics (i.e., sex, age, nativity, and attained education level) of the two workers constituting the connection (i.e., the displaced worker i and the intermediary worker l), and their similarity in terms of these characteristics.

For simplicity, we drop establishment-pairs where the potential recruiting establishment is connected to a displaced worker through multiple intermediary workers. We focus on connections through former co-workers since this is the only type of connection that does not impose strong boundaries on the characteristics of the two workers and their similarity. For example, a parent-child connection has strong implications for the ages of the two, and formerly being classmates has strong implications for both the age and level of attained education. We present the results of the analyses of the mediating role of the displaced and intermediary workers' characteristics (and their similarity) in Table B.3.

Before turning to the mediating role of displaced and intermediary workers' characteristics, it may be useful to note that the inclusion of worker characteristics has no impact at all on our estimates of interest. This supports our choice to rely only on establishment-pair(-and-year) fixed effects in previous estimations.

Turning to the mediating role of the displaced workers' characteristics, the impact of a co-worker connection seems to be mediated the most by being female (negatively) and being aged 50–64 years (negatively). These results support the findings in previous literature (Bentolila et al., 2010; Ioannides and Datcher Loury, 2004).

Shifting the focus to the intermediary workers' characteristics, we find that if the intermediary worker is a man, prime aged, or has no more than compulsory schooling the connected displaced worker seems to be more likely to get hired. These results are in line with the (in this case, very scarce) previous literature provided by Kramarz and Skans (2014) and Bayer et al. (2008).

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 similarity, between the displaced and the intermediary worker, in terms of sharing the same characteristics support this notion. The estimates are positive and statistically significant for all characteristics, in particular in the immigration, gender, and age dimensions (more than education). This further reinforces the consistent result that social proximity, or tie strength, is crucial for the usefulness of social connections.

Table B.3: The estimated importance of social connections by characteristics of the displaced worker (i), the intermediary worker (l), and their similarity

	Model I		Model II		Model III	
	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)
Type of connection						
Former co-worker	0.214	(0.017)	0.247	(0.023)	0.077	(0.042)
Former co-worker × characteristics of *i*:						
Female	-0.060	(0.014)	-0.050	(0.014)	-0.042	(0.014)
Immigrant	0.002	(0.020)	-0.001	(0.020)	0.063	(0.032)
Age 20–34 yrs	-0.038	(0.017)	-0.027	(0.016)	-0.040	(0.018)
Age 35–49 yrs (ref.)	0.000		0.000		0.000	
Age 50–64 yrs	-0.062	(0.022)	-0.065	(0.022)	-0.055	(0.022)
Compulsory school	-0.011	(0.017)	-0.016	(0.017)	-0.006	(0.018)
High school (ref.)	0.000		0.000		0.000	
College/university	-0.039	(0.017)	-0.028	(0.017)	-0.022	(0.017)
Former co-worker × characteristics of *l*:						
Female			-0.025	(0.015)	-0.017	(0.015)
Immigrant			0.030	(0.025)	0.080	(0.032)
Age 20–34 yrs			-0.060	(0.017)	-0.070	(0.018)
Age 35–49 yrs (ref.)			0.000		0.000	
Age 50–64 yrs			-0.010	(0.027)	-0.004	(0.027)
Compulsory school			0.048	(0.024)	0.056	(0.024)
High school (ref.)			0.000		0.000	
College/university			-0.039	(0.015)	-0.030	(0.016)
Former co-worker × similarity of *i* and *l*:						
Same sex					0.049	(0.014)
Same immigration status					0.096	(0.032)
Same age					0.058	(0.017)
Same education					0.030	(0.015)
Constant	0.033	(0.001)	0.033	(0.001)	0.033	(0.001)
Characteristics of *i*		✓		✓		✓
No of fixed effects		465,743		465,743		465,743
No of observations		13,069,429		13,069,429		13,069,429

Notes: The analyses are restricted to the potential hiring establishments where no two (or more) employees had connections to the same displaced worker. All estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. All estimations include establishment-pair(-and-year) fixed effects. Standard errors are clustered on the potential hiring establishment-and-year level.

B.3 Causal effects by type and person effect (as in Figures 5a and 7, but after residualizing from demographics).

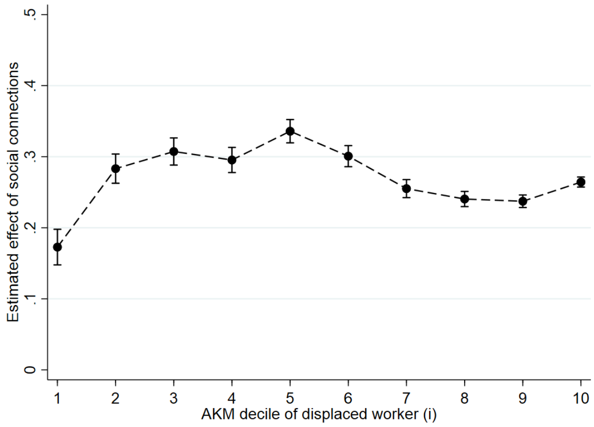
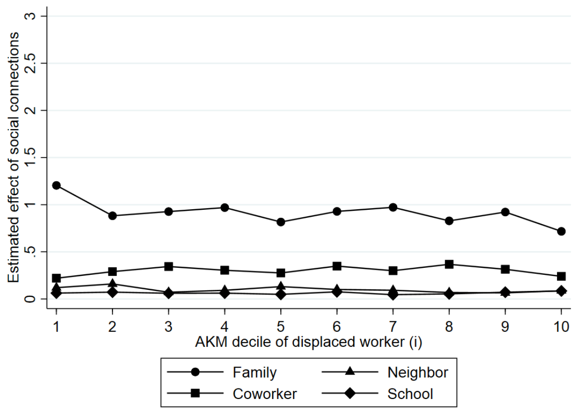


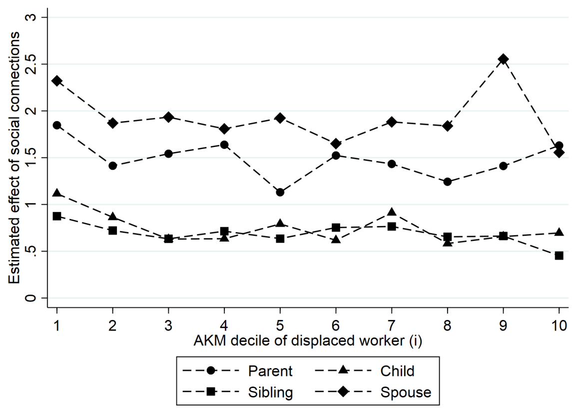
Figure B.1: Estimated effects of social connections, by residualized AKM person effects deciles

Notes: The figure repeats Figure 5a with the one difference that the AKM person effects of the displaced worker (*i*) have been residualized from age, education level and gender.

(a) All connections



(b) Family members



(c) Former classmates

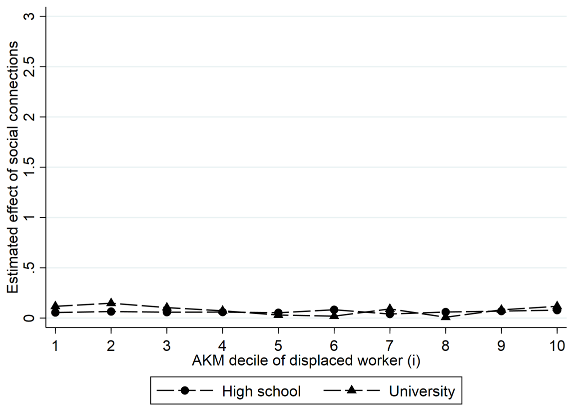


Figure B.2: Estimated effect of social connections by residualized AKM effect ($\hat{\theta}_i$) decile of displaced worker (i)

Notes: The figure repeats Figure 7 with the one difference that the AKM person effects of the displaced worker (*i*) have been residualized from age, education level and gender. For coefficients and standard errors of the linear slopes, see Table B.4.

B.4 Estimates underlying Figures 7, 8, 10, 11, and B.2

Table B.4: Linear slope coefficients for Figures 7, 8 and B.2

	Figure 7		Figure B.2		Figure 8	
	Coef.	(s.e)	Coef.	(s.e)	Coef.	(s.e)
Panel A: All connections:						
Family members	-0.065	(0.008)	-0.020	(0.008)	-0.131	(0.008)
Former co-worker	0.006	(0.004)	0.004	(0.004)	-0.018	(0.003)
Former classmates	0.004	(0.002)	-0.000	(0.002)	0.002	(0.001)
Current neighbors	-0.006	(0.004)	-0.004	(0.003)	-0.000	(0.003)
Panel B: Family members:						
Parent	-0.042	(0.028)	-0.038	(0.025)	-0.182	(0.020)
Adult child	-0.057	(0.022)	-0.006	(0.021)	-0.173	(0.022)
Spouse	-0.116	(0.031)	-0.008	(0.033)	-0.366	(0.033)
Sibling	-0.044	(0.009)	-0.017	(0.010)	-0.083	(0.009)
Panel C: Former classmates:						
High school	0.006	(0.002)	-0.000	(0.002)	0.002	(0.001)
College/university	-0.006	(0.008)	-0.002	(0.006)	-0.003	(0.007)

Notes: Columns (1) and (2) display the estimates for the linear interaction between social connections and AKM person effect deciles. Columns (3) and (4) display the same estimates when the AKM person effects of the displaced worker (i) have been residualized from age, sex, and education level. Columns (5) and (6) display the estimates for the linear interaction between social connections and AKM establishment effect deciles. Graphical representations of the results (from more flexible specifications using interactions with decile dummies) are shown in Figures 7, B.2, and 8. All estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. Standard errors are clustered on the potential hiring establishment-and-year level.

Table B.5: Estimates underlying Figures 10 and 11

	Figure 10 [a]		Figure 11 [b]	
	Coef.	(s.e.)	Coef.	(s.e.)
Any connection	0.361	(0.029)		
Any connection × (Person effect/100)	0.194	(0.087)		
Any connection × (Person effect/100)^2	-0.189	(0.083)		
Any connection × (Person effect/100) × (Establishment effect/100)	-0.009	(0.077)	0.044	(0.066)
Any connection × (Establishment effect/100)	-0.251	(0.088)	-0.176	(0.079)
Any connection × (Establishment effect/100)^2	-0.029	(0.076)	0.065	(0.071)
(Person effect/100)	0.021	(0.007)		
(Person effect/100)^2	-0.026	(0.008)		
(Person effect/100) × (Establishment effect/100)	-0.004	(0.006)		
Constant	0.032	(0.001)	0.429	(0.017)
No of observations		24,600,167		1,682,201
R-squared		0.228		0.203

Notes: All estimates are expressed in percentage points, i.e., the coefficients are multiplied by 100. Standard errors are clustered on the potential hiring establishment-and-year level.

[a] The column displays the estimates from equation (8), where an indicator for social connection is interacted with a second order polynomial of both AKM person effects of the displaced and establishment effects of potential hiring establishments (in percentiles). Graphical representation of the results are shown in Figure 10 in the main text.

[b] The column displays the estimates from equation (10), which include worker and set of connected establishments and year fixed effects. It shows the interactions with a second order polynomial of the AKM effect of the potential hiring establishment and the interaction between the AKM person effect of the displaced and the establishment effect of the potential hiring establishment (in percentiles). Note that the baseline person effect of the displaced is absorbed by the (worker) fixed effect.