Journal of Econometrics 233 (2023) 468–506

Contents lists available at ScienceDirect

Journal of Econometrics

journal homepage: www.elsevier.com/locate/jeconom

Social connections and the sorting of workers to firms

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A R T I C L E   I N F O

Article history:
Received 18 May 2020
Received in revised form 15 July 2021
Accepted 5 December 2021
Available online 23 May 2022

JEL classification:
J60
J30
J23

Keywords:
Networks
Job search
Inequality
Job displacement
Hiring

A B S T R A C T

We assess the presumption that social networks reinforce inequality by providing high-wage workers' with preferential access to high-wage establishments. Our results based on very detailed Swedish register data contradict this view. We do show that high-wage job seekers tend to be connected to high-wage workers employed in high-wage establishments. Furthermore, social connections appear to directly cause the allocation of workers to jobs. But the sorting resulting from hires within social networks is *less* unequal than the sorting resulting from market hires, essentially because low-wage firms rely on social connections to hire high-wage workers.

1. Introduction

A very large literature has identified social networks as a key mediator in matching workers and firms. Even though access to useful networks is most often viewed as fundamentally unequal, very few empirical studies analyze the impact of social networks on inequality. This lack of evidence is particularly glaring in the context of *sorting inequality* – defined as inequality arising from the sorting of workers to firms. In this paper, we therefore present the first comprehensive empirical analysis of how social networks affect this aspect of inequality.

Our analysis is motivated by a series of studies showing that sorting between workers and firms affects the wage structure. Using a statistical decomposition of wages into fixed person and firm effects in the spirit of Abowd et al. (1999), AKM hereafter, Card et al. (2013) have shown how the entry of low-paying firms in Germany affected the overall wage distribution and Card et al. (2016) study how sorting of men and women into different firms in Portugal is related to gender wage disparities. These studies show that sorting inequality arises from high-wage workers' disproportional access to jobs in higher paying and more productive firms, a result corroborated using alternative methods and/or data by Barth et al. (2016), Bonhomme et al. (2019), Abowd et al. (2019), Card et al. (2018), and Song et al. (2019) among others.[1] An important contribution, related to ours, is Schmutte (2015) who also uses the AKM-framework to show that neighborhood networks provide workers with access to high-wage firms.

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1 A related set of studies uses structural estimation in the tradition of Postel-Vinay and Robin (2002).

https://doi.org/10.1016/j.jeconom.2021.12.018
0304-4076/

Across the social sciences, researchers often view social networks as an important source of inequality in general. The following quote by an authority in the field illustrates this tendency 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).

The economic literature on job search networks is a case in point. 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 networks (Montgomery, 1991). Furthermore, various job search models imply that strong social ties induce more unequal access to jobs than weaker ties (Ioannides and Datcher Loury, 2004).

Survey evidence consistently shows that a very large share of job matches involve social connections (see, e.g., Ioannides and Datcher Loury, 2004). Connections are likely to alleviate some of the information problems agents face on frictional labor markets. Connections can inform workers about available vacancies (see, e.g., Calvó-Armengol and Jackson, 2004, 2007; Calvó-Armengol et al., 2007) or more generally inform agents on one side of the market (firms/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., 2016; Galenianos, 2013).[2] Social connections may also inform workers about idiosyncratic job amenities which may be important for sorting (Card et al., 2018), or serve as an independent source of amenities if workers prefer to work with people they know as in Heath (2018).

In this paper, we assess the role of social networks in the unequal access and allocation of workers to employers. We rely on three building blocks:

(*i*) workers' social networks as inferred from register data;
(*ii*) estimated person and establishment effects from an AKM decomposition and
(*iii*) establishment closures, forcing groups of workers to search for new jobs under similar conditions.

For the first building block, we use Swedish administrative data to identify family members (siblings, spouses, parents, children), former co-workers, former classmates, and current neighbors with children the same age.[3]

For the second block, we characterize workers and establishments through estimated fixed effects in the AKM tradition. As we are interested in the role of social connections at the time when matches are formed, we focus on the estimates for newly hired workers. Our estimated person effects for these new hires only use *pre-transition* data. We then relate these estimates to the establishment effects of future (potential) employers. This split-sample strategy ensures that the estimation errors of person effects are independent of estimation errors of the relevant establishment effects. Estimated correlations of person and establishment effects will thus not be confounded by biases that arise when person and firm effects are simultaneously estimated in the AKM-setting (the "limited mobility bias").[4] The strategy also insulates us from the threat of reverse causality if post-hire wages are affected by the use of connections. We verify that our main conclusions hold if we instead classify the employers through the clustering procedure of Bonhomme et al. (2019) and/or if we instead rank firms by value-added per worker.

For the third building block, to help identify the impact of connections on hiring patterns, we focus on workers who get displaced after a firm closure. We use the set-up for a different purpose than the standard mass-layoff literature (see e.g. Jacobson et al. (e.g., 1993), Eliason and Storrie (e.g., 2006), Davis and von Wachter (e.g., 2011) where displaced workers are compared to non-displaced workers. We instead let the lay-offs provide us with a set of workers who move under similar (forced out) conditions, because staying in the origin firm is not an option. This allows us to compare multiple workers who must leave the same establishment at the same point in time, but endowed with different social networks.[5]

By contrasting the rehiring patterns of workers from the same closure event, each having different sets of *predetermined* social connections to different employers, we estimate how connections affect the post-displacement allocation of workers. In practice, the baseline model controls for combined displaced-times-connected establishment-pair fixed effects. To ensure that our estimates capture the effect of connections on the allocation of workers, we perform various robustness tests. We use cases of repeated displacements of the same worker to remove worker-specific preferences for

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[2] See Brown et al. (2016), Burks et al. (2015) and Hensvik and Skans (2016) for estimates of connections and information.

[3] Previous studies of social connections in register data have examined each type of network in isolation, see e.g. (e.g., Bayer et al., 2008; Schmutte, 2015) on neighbors (e.g., Cingano and Rosolia, 2012) on former co-workers, (e.g., Dustmann et al., 2016) on immigrants, and (e.g., Kramarz and Skans, 2014) on parents.

[4] See, e.g., Andrews et al. (2008) on the limited mobility bias. We share the split-sample logic with Kline et al. (2020) who shows how leave-out estimation can be used to derive correctly estimated variances and covariances in the AKM setting.

[5] This aspect resemble Cingano and Rosolia (2012), Glitz (2017), and Saygin et al. (2019), who correlate displaced workers' outcomes with the network employment rate of their connections. Our focus on displaced workers differentiate us from Schmutte (2015) who shows that workers employed in high-paying firms connect their neighbors to these jobs and help them climb the job ladder. He relies on the timing of job entry and the neighborhood block structure. In contrast, we study the structure of workers' various social networks, estimate their effects on hiring, and describe the resulting impact on inequality.

each specific establishment (as in the monopsony model of Card et al. (2018)). This alternative approach is identified from variation in each worker's network structure between her displacement events. Furthermore, we use *within worker-and-displacement-event* variation to identify the *relative* importance of connections to high- vs. low-wage employers. This is feasible since workers tend to be connected to multiple establishments (of high- and low-wage types) during the same event.

Our results first show that pre-determined social networks exhibit *baseline 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. Sorting is most pronounced for professional ties, in particular past co-workers and classmates from university, whereas networks of connections within families, neighborhoods, and high schools exhibit much less baseline "homophily" in the AKM-dimensions.

Second, social connections predict hiring patterns. Displaced workers are much more likely to find jobs in the exact establishment where they have a social connection than other workers who were displaced in the same event, but without a connection to that particular employer. Similarly, displaced workers are much more likely to be hired by an employer during a displacement year when she is connected to that employer relative to a displacement year when no such connection – between the same worker and establishment – is observed in our data.

Third, connections that are more likely to be "strong" (e.g. connections of longer duration, more recently established connections, and connections fostered in smaller groups) in the Granovetter (1973) sense, are associated with larger estimated effects than weaker connections.[6] The fact that the estimates are largest in cases where we are most confident that the agents interact with each other lends further support to the network-interpretation of our estimates. Patterns across types of connections also reveal larger estimates in dimensions where it is plausible that interactions are more prevalent: the estimated effects of a family member are the largest, followed by that of a past co-worker, whereas a former classmate or a current neighbor entails a weaker, yet positive, effect.[7]

Fourth, the impact of social connections are much larger for low-wage *employers* than for high-wage employers, *regardless* of whether the connected workers are low- or high-wage. These patterns are unchanged if we instead sort establishments into clusters based on their earnings distribution and rank clusters by their mean wage as in Bonhomme et al. (2019), or if we rank establishments based on firm-level value added per worker. On average, connections have similar effects on hiring for low- and high-wage workers. Our data analyses do not support the notion that social connections are more likely to induce a hire when they link high-wage workers to high-wage employers.

The results show that there are two opposing forces at play when social networks affect sorting inequality. On the one hand, the pre-existing network structure exhibits baseline homophily – high-wage workers are connected to high-wage workers and employers – i.e. "birds of a feather flock together". And, these connections clearly matter for the allocation of workers across establishments. On the other hand, connections cause more hires when employers are of the low-wage/low-productive types, regardless of the type of worker involved — estimates effects are independent of whether the "birds" (workers vs employers) have similar feathers or not. To assess what the net impact of these opposing forces are, we relate the observed (endogenous) sorting patterns of all new hires to indicators of whether the hire involved a social connection or not. The results show that there is less sorting inequality among matches formed through social connections than among unconnected "market" matches. We further show that wage losses from working for a low wage-employer are equally large for connected and non-connected matches. On the positive side, from the workers', and perhaps also firms', perspectives we show that future exit rates are substantially lower among connected matches, regardless of the type of employer.

Our results highlight the large and systematic impact that social networks have on the sorting of workers to jobs. But our results do not support the common presumption that social homophily leads to increased inequality. Instead, they illustrate how social connections may counteract baseline homophily, resulting in more unequal allocations through market mechanisms than through social networks.

The paper is structured as follows: Section 2 describes our empirical strategy. Section 3 presents data and AKM estimates. Section 4 presents the main results, Section 5 analyze post-displacement wages and job-retention, Section 6 presents supporting results. Section 7 concludes.

2. Empirical strategy

2.1. Set-up, definitions and notation

To help collect thoughts, we formulate our empirical strategy as a Rubin-style causal model. Our ("treatment") variable of interest is an indicator $C_{ijk(l)}$, which equals one if there is a social connection between worker i, employed

[6] Few earlier studies have examined the role of ties' strength in linked employer–employee data. Exceptions are Kramarz and Skans (2014) and Gee et al. (2017).

[7] Furthermore, our two first key results jointly imply that the connections that exhibit least baseline homophily (family), also have the largest estimated effects. If the estimates only captured sorting on unobservables, we would instead have found the largest estimates for connections where the homophily was the strongest. This relative ordering is retained when comparing across connections *within a given worker*, ensuring that worker heterogeneity is not driving the results.

in establishment j, and an "intermediary" worker l employed in establishment $k(l)$. Empirically, $C_{ijk(l)}$ measures if i and l belong to the same family, are former coworkers or classmates, or neighbors. In cases where we abstract from the intermediary worker, we use the shorter notation C_{ijk}.

We first describe the distribution of $C_{ijk(l)}$ across combinations of worker and establishment types. We then estimate the treatment effects of social connections on the allocation of workers across establishments following displacements.

Our key outcome is H_{ijk}, which equals one if worker i (from establishment j) is hired by establishment k, and zero otherwise. We use displacement events due to establishment (j) closures to find a set of workers who leave the same firm at the same time under similar exogenous mobility conditions.

Using *potential outcomes notation*, we let H^0_{ijk} equal one if i would be hired by k in absence of connection to k. H^1_{ijk} equals one if i would be hired by k in presence of a connection to k. The *treatment effect* of interest is the difference between the two, i.e. $\gamma_{ijk} = H^1_{ijk} - H^0_{ijk}$ and the observed outcome is

$$H_{ijk} = H^0_{ijk} + \gamma_{ijk} C_{ijk}. \tag{1}$$

Both the treatment effect parameter γ and the non-connected hiring outcome H^0_{ijk} capture factors affecting the probability that worker i (from j) is hired by establishment k:

- The treatment effect γ captures all aspects that require a social connection at the time of displacement. This may include workers' awareness about vacancies or job attributes, of firms' awareness about worker skills (general or specific) as long as this knowledge is transmitted through social connections. It will also include preferences for working together with a connected worker.
- The non-connected hiring outcome H^0_{ijk}, on the other hand, encompasses all aspects that are relevant for whether or not displaced worker i is hired by establishment k even in the absence of a social connection between the two. This includes all combinations of preferences, job attributes, skills and production technologies that are known to the agents even without the connection.

2.2. Identification with constant effects

Eq. (1) defines connections and hiring outcomes for *pairs* of agents (worker i and employer k). We therefore adopt a *dyadic* set-up, where each observation is a combination of a displaced worker and an establishment.[8] For now, assume that the impact of social connections is a constant (i.e., $\gamma_{ijk} = \gamma$). To identify γ, we need to account for any systematic relationship between social connections (C_{ijk}) and the potential that connected employers would have hired the very same (connected) workers through the "market", had the connections not been there (i.e. $H^0_{ijk}|C_{ijk} = 1$).[9] Identification through conditioning on observables is feasible if there exist a set of fixed-effects α and a vector of observable factors X such that $H^0_{ijk} = \alpha + X_{ik}\beta + \varepsilon_{ijk}$ and $\varepsilon_{ijk} \perp C_{ijk}$, i.e. if the presence of a connection is conditionally independent of the potential for a "market" hire. For the remainder of the paper, we maintain this assumption under various fixed effects configurations.

Our main strategy uses a fixed-effect α_{jk} for each *pair of closing establishment (j) and potential hiring establishment (k)*.

Using the dyadic set-up, we estimate the following model:

$$H_{ijk} = \alpha_{jk} + X_{ik}\beta + \gamma C_{ijk} + \varepsilon_{ijk}, \tag{2}$$

where the establishment-pair fixed-effects (α_{jk}) account for all shared aspects that relate the closing establishment (j) and the potential hiring establishment (k) to each other. Because an establishment only shuts down once, these fixed-effects are in practice *year-specific*. X_{ik} is a vector of worker characteristics that may make individual i a more suitable hire for establishment k than other workers from j even in the absence of social connections. The model is easily extended to account for different types of connections (e.g. family, coworkers, classmates and neighbors) by replacing γC_{ijk} with $\sum_{n=1}^{N} \gamma^n c^n_{ijk}$ in equation (2), where $c^1_{ik}, \ldots, c^N_{ik}$ are indicators for N types of social relations (family...) measured in the data.

The dyadic set-up of Eq. (2) resembles Kramarz and Skans (2014), which in turn builds on Kramarz and Thesmar (2013). Following these studies, we estimate the equation using linear probability models and treat each dyad as an independent observation.[10]

Because of the (j, k) fixed-effects, our identifying sample is comprised of all i, k dyads where establishment k is socially connected to at least one (but not all) of the workers in j. Other dyads do not contribute to identification and can therefore be excluded. This is crucial as it makes estimation feasible.

Two remarks are in order. First, the sample-construction relies on the pre-existing network-structure and is *not influenced by any endogenous outcomes*. Second, the sample-construction includes (essentially) all connected dyads since it

8 If workers are displaced multiple times, they form a new set of dyads for each event.

9 For simplicity, we refer to hires without known social connections as "market hires".

10 Kramarz and Skans (2014) study parental connections on labor market entry in Sweden. Saygin et al. (2019) use 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) use the setting of Kramarz and Skans (2014) to analyze the role of summer-job connections over the business cycle.

is extremely rare that all workers in j are connected to k. Thus, the sample-creation is, in practice, akin to the selection of an appropriate control group (those displaced in the same event), and *does not remove any identifying variation of interest*.

The establishment-pair fixed-effects control for the interaction of all aspects related to location, industry, and firm-specific human capital of each *pair* of employers at each point in time. But to identify the model, we need multiple workers to leave the same establishment at the same point in time under similar conditions. The sample of movers from ongoing firms is highly selected as 90 percent of the workforce remains in its original workplace every year.[11] We therefore focus on cases when all workers leave because j closes down. Thus, the *decision to leave the original establishment, and thus entering into our sample, is exogenous from every individual worker's perspective*.

The identifying assumption underlying this model – i.e. that workers from the same displacement event with and without social connections to a specific employer would be equally likely to be hired by that employer through the market, conditional on X – may be challenged *a priori*. However, we provide three sets of corroborating exercises that jointly suggest that the our estimates are reliable.[12]

Specificity: If we replace the actual connected establishment k by other very similar establishment k', the effects shrink toward one-tenth or less of the original effect.[13]

Robustness to time-invariant individual preferences for specific establishments: We exploit time-variation in workers' social networks between displacements for the few workers who are displaced multiple times. This model uses α_{ik} instead of α_{jk}. It thus uses the fact that worker i can be connected to k during one of her displacement events, but not during the other.

The role of social proximity: We construct measures that proxy for social proximity, or "tie strength", of a given social relationship. Estimated effects are consistently larger the closer the social proximity between the connected agents. These patterns suggest that social interactions are crucial.

2.3. Sorting inequality

To analyze sorting inequality in the spirit of Card et al. (2013), we first estimate the AKM model of Abowd et al. (1999):

$$\ln w_{it} = \theta_i + \psi_{k(i,t)} + X_{it}\beta + \varepsilon_{it}, \tag{3}$$

where w_{it} is worker i's wage in year t, θ_i is the person-specific effect, and $\psi_{k(i,t)}$ is an establishment (k) effect. $X_{it}\beta$ contain year dummies and education-specific age controls as in Card et al. (2013).

The estimates of θ_i and $\psi_{k(i,t)}$ will be treated as data, following, e.g., Card et al. (2013). To ensure that the impact social connections may have on post-hiring wages is not transmitted into the estimates of the person effects of the displaced workers, we estimate these effects using data for the years *preceding* job displacement (i.e., separately for each displacement-year cohort). This also ensures that errors in the estimated person effects of the displaced are unrelated to estimation errors in the establishment effects of potential future employers, as these are estimated in different samples.[14] Thus, the mechanical negative association between estimation errors in simultaneously estimated person and establishment effects discussed by, e.g., Andrews et al. (2008) will not impact our estimates.[15] To further ensure the validity of our strategy, we also present evidence based on (i) estimates where employers are grouped by the clustering algorithm of Bonhomme et al. (2019), (ii) estimates where employers are grouped by the (firm-level) value-added per worker.

To describe the role of social connections for the unequal access of workers to jobs ("sorting inequality"), we start by analyzing the distribution of connections between the various types of agents. We correlate the person-effect of displaced workers (i) with the person-effect of their social connections (i.e., the intermediary workers l). A positive correlation, i.e., $\text{Corr}(\theta_i, \theta_l \mid C_{il} = 1) > 0$, will be interpreted as *baseline homophily*. We also analyze the correlation between the displaced workers' person effects and the types of establishments they are connected to, i.e., $\text{Corr}(\theta_i, \psi_k \mid C_{ik} = 1)$. A positive correlation implies that the structure of social networks contribute to sorting inequality.

We then estimate how the causal effects of connections relate to the person and establishment effects. To do so, we let $\gamma_{ijk} = \gamma(\theta, \psi)$ in Eq. (1) and identify these effects through an extension (described next) of the strategy outlined in Eq. (2).

[11] To use the full sample we would, thus, either have to include a mass of workers who are highly unwilling to move (the majority, stayers) or condition our analysis sample on an endogenous outcome (leaving the original employer).

[12] The establishment-pair fixed-effects identification can be estimated for a large set of combinations of displaced workers and connected establishments, which is necessary if we want to analyze the relationship to sorting inequality. Designing an instrumental variables (IV) identification for this purpose would be extremely difficult since an IV strategy would require social connections to be randomly allocated to specific establishments across the economy. The most useful source of variation would plausibly be mobility of social connections across time. We do exploit such variation and show that it provides estimates that are very similar to our main estimates in models with constant treatment effects.

[13] We use two different types of such "placebo-style" regressions: (i) other, randomly selected, establishment within the same location and industry and (ii) other establishment within the same location and within the same firm.

[14] We use the full sample period when estimating establishment effects in order to maximize precision.

[15] This is potentially important because our measures of sorting concern the relationship between person effects and the establishment effects of new potential employers. In the end, we do, however, show that the sample splitting is in fact not crucial for our qualitative conclusions. Kline et al. (2020), show how variances and covariances can be corrected for estimation errors using cross-sectional split-sample estimation but we are not employing these methods as our purpose is to extract the components, and not to compute the aggregate statistics.

2.3.1. Identification when effects of connections vary with the AKM components

We are interested in how the effects of connections vary with the estimated AKM person and establishment effects of the connected agents (and other sources of effect heterogeneity). Thus, we extend Eq. (2) to:

$$H_{ijk} = \alpha_{jk} + X_{ik}\beta + \gamma(\theta_i, \psi_k)C_{ijk} + \varepsilon_{ijk}. \tag{4}$$

We use different functional forms (e.g. decile dummies) for $\gamma(\theta_i, \psi_k)$, but here it is instructive to focus on the case of a second-order polynomial:

$$\gamma(\theta_i, \psi_k) = \gamma_1\theta_i + \gamma_2\theta_i^2 + \gamma_3\theta_i\psi_k + \gamma_4\psi_k + \gamma_5\psi_k^2, \tag{5}$$

where γ_3 captures how the impact of social connections change when social connections tie high-wage workers to high-wage employers. The parameter thus identifies the contribution of causal effects to sorting inequality. Individual heterogeneity related to θ_i and its interaction with ψ_k will be included in our X_{ik}-vector. Firm-side heterogeneity in the form of ψ_k is fully captured by our fixed effects α_{jk}.

2.3.2. Within-worker identification

As already alluded to, we can estimate a version of the baseline model that relies on repeated displacements using fixed effects for each combination of worker and establishment (α_{ik}):

$$H_{ijk} = \alpha_{ik} + X_{ik}\beta + \gamma C_{ijk} + \varepsilon_{ijk}, \tag{6}$$

where identification comes from changes in the social network structure between displacements. But the sample of repeatedly displaced is small so the strategy's best use is to verify the robustness of our main results. An alternative strategy uses the fact that workers have connections to different establishments at the same point in time. We can thus estimate models that directly assess the *relative* importance of different connections *for this particular worker during a specific displacement event*. This novel "within-worker" identification is well-suited for questions concerning the heterogeneous effects of connections.

In practice, define K_{ij} as the set of k-establishments that displaced worker i (from j), is connected to (i.e., define $K_{ij} : k \in K_{ij}$ iff $C_{ijk} = 1$). To identify the relative importance of the various types of connections or agents within this set, we define a fixed-effect $\phi_{K_{ij}}$ for each K_{ij} set.[16]

Thus, focusing on heterogeneity in terms of agents, we can rewrite Eq. (4) as:

$$H_{ijk} = \phi_{K_{ij}} + X_{ik}\beta + \gamma^I(\theta_i, \psi_k)C_{ijk} + \varepsilon_{ijk}, \tag{7}$$

where γ^I can represent a second-order polynomial and X_{ik} contain the uninteracted components of the same polynomial.[17] Some components of the interacted polynomial are in practice absorbed by the fixed effects and Eq. (5) reduces to:

$$\gamma^I(\theta_i, \psi_k) = \gamma_3^I\theta_i\psi_k + \gamma_4^I\psi_k + \gamma_5^I\psi_k^2, \tag{8}$$

where the parameters are numbered as in Eq. (5) and the estimate of $\gamma_3^{n,I}$ thus identifies the contribution of causal effects to sorting. Eq. (7) allows us to examine the interaction of the AKM effects of the connected establishment or the type of connection *for a given worker* at a specific displacement event. Identification comes from workers with connections to both high- and low-wage establishments. This empirical strategy allows us to handle the fact that the types of workers who are connected to high-wage establishments may be different from those who are connected to low-wage establishments, and that different types of workers have different types of connections.

By extension, we can use a similar model to analyze heterogeneity in other dimensions. But due to the $\phi_{K_{ij}}$ fixed-effects, we always need to leave out one *reference* connection. We will, e.g., use it to estimate the importance of family, co-worker and school connections relative to neighbors by estimating $H_{ijk} = \phi_{K_{ij}} + X_{ik}\beta + \sum_{n=1}^{N-1}\gamma^n c_{ijk}^n + \varepsilon_{ijk}$ to get a separate estimate for each of the N-1 types of connections.

3. Data and definitions

3.1. The administrative registers

We use data on the Swedish population during 1985–2009. The data track individuals, establishments, and firms over time. All employment relationships are documented in a tax based register (*Registerbaserad arbetsmarknadsstatistik*). Family connections are from birth records (*Flergenerationsregistret*) and household identifiers (*LOUISE*). LOUISE also identifies neighbors. Classmates are found in graduation registers (*Skolregistret* and *Universitets- och högskoleregistret*).

[16] As before, identification only comes from the observations (dyads) for which there is variation in c_{ik}^n within the fixed-effect set K_{ij}. 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_{ik}^n.

[17] All person-side heterogeneity is captured by the fixed effect. Comparing $\phi_{K_{ij}}$ to α_{jk}, we note that i is a subset of j, and all k's that are included in K_{ij} are covered by some α_{jk}.

Table 1
Number of connected establishments among displaced workers.

	Type of social connection				
	Family member	Former co-worker	Former classmate	Current neighbor	Any connection
Per displaced worker (i)	1.17	2.59	3.52	1.63	8.82
In total	338,518	749,370	1,019,027	471,032	2,553,066

Note: The Table gives the number of connections for displaced workers within the used sample (1990–2006).

3.2. Employment, closures and displaced workers

Our employment data arise from complete mandatory tax records filed by firms. Raw data include annual earnings for each employer–employee relationship, and indicators for the first and last month of that spell. Throughout, we work with data on the annual frequency. We focus on workers aged 20–64. We use each worker's main job, defined as the job with the highest annual earnings among all job spells that cover November. We make additional restrictions when defining wages for the AKM model as described below.

Establishment j in year t is a *closure event* if the establishment is (i) is a single establishment private firm with at least 4 employees, (ii) has disappeared before November year $t+1$ and (iii) no more than 30 percent of the employees from j are found in any one specific k-establishment in year $t+1$.[18]

Consequently, worker i is *displaced* in t if she is 20–64 years old, work at establishment j in November of year t and if j closes down during the following 12 months. To allow for a pre- and post-period, we use displacements during 1990–2006 covering 31,538 closures and 289,332 displaced workers.

3.3. Defining social connections

We consider four broad types of social connections: family members, former co-workers, classmates, and current neighbors. Throughout, we strive to ensure that the connections we include in our analysis are valid. We therefore focus on cases where it is highly plausible that the workers know each other at a personal level. Consequently, when groups of agents are too large, we do not code them as connections because most agents in the group will not know each other.

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 capturing workers who resided together and who either were married or had common children.

Former co-workers of the displaced are workers who were employed at their last establishment before the closing establishment. To ensure that recorded connections do indeed know each other, we ignore connections formed at establishments with more that 100 employees.[19]

Former classmates are identified at high-school and/or at college/university. Swedish high-school students are enrolled in occupation-specific *programs*. We therefore identify classmates from high-school as graduates that shared school, program, and graduation year. Similarly, classmates from university share school, major, and graduation year. Graduation records are available from 1985 and we therefore only cover classmates for the younger cohorts. However, the value of former classmates appear to depreciate fairly rapidly over time (see Section 6.1). As with coworkers we exclude groups above 100. These cases can arise if schools have large cohorts within one program-type or major.[20] respectively.

Current neighbors are identified using Statistics Sweden's definition *SAMS* (Small Areas for Market Statistics). There are 9200 SAMS-areas with an average of 500 workers, but the distribution is skewed. Hence, SAMS "neighbors" may extend beyond the group of people who actually interact with each other. But, as Bayer et al. (2008) show, neighbors are much more likely to work together if their children are of a similar age. Presumably because these people are more likely to meet, e.g., at playgrounds and schools. To reduce measurement errors, we therefore focus on neighbors with children in the same age-group.[21] Analogously to former co-workers and classmates we constrain these data to those with less than 100 people to further reduce the impact of measurement errors.

Finally, we only keep connections within the age span (20–64) who are consistently employed at a private sector establishment in November of t and $t+1$ (to ensure the direction of causality). Table 1 shows that the average displaced worker is connected to 8.8 potential hiring establishments (k), whereof 1.2 through family, 2.6 through co-workers, 3.5 through classmates, and 1.6 through neighbors.

18 Establishments are physical workplaces. Around 10 percent of workers that do not have a defined physical workplace and can therefore never be displaced through a closure.

19 This excludes co-worker connections of 25 percent of the displaced. Without this restriction, some displaced workers would generate many thousands of dyads arising from recorded social connections, mostly tying the displaced to people they never talked to.

20 This excluded classmates of 21 percent of high school and 10 college/university graduates

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

3.3.1. Incomplete coverage of social networks and measures of tie strength

Just as in every other large-scale empirical study of social networks we aware off, we cannot claim to be observing our subjects' complete set of social relations. But we do not strive to estimate the impact of network size. Instead, our key implicit assumption is that the patterns we unravel from our observed connections are informative about social connections in general. In addition, note that:

- When we study the sorting patterns among connections (searching for "baseline homophily"), we correlate person and establishment effects among the measured connections, thus estimating $\mathrm{Corr}(\theta_i, \psi_k \mid C_{ik} = 1)$. This analysis has general validity as long as our observed connections have the same properties as unrecorded friendships. The analysis would, however, be distorted if we included false connections into the analysis.
- The causal effects are identified by comparing connected dyads to dyads without such connections using $H_{ijk} = \alpha_{jk} + X_{ik}\beta + \gamma C_{ijk} + \varepsilon_{ijk}$. The dyad ($\alpha_{jk}$) fixed-effects identification ensures that estimates can only be biased through random measurement errors if many other workers have unrecorded connections within the set of dyads we analyze, i.e. to an employer where one (or more) co-displaced already has an observed connection. Such unrecorded connections would erroneously attribute some connected dyads to the set of "market matches" (H^0_{ijk}). Thus, the market match frequency would be overestimated and the causal effects γ_{ijk} underestimated. Since the estimated baseline ("market") probability of entering firms to which others have connections empirically turn out to be very low, this does not appear to be an important concern.
- We end our main analysis by studying overall sorting patterns of all realized matches in Section 4.4. Here, 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.
- Not all workers have family members, co-workers, classmates, or neighbors with children the same age, and we lack graduation records for the oldest cohorts. A possible concern is that the difference in coverage across types of connections will generate spurious results. However, our *within-worker identification strategy*, allows us to directly address this issue by explicitly comparing across different types of connections while removing all other aspects of worker heterogeneity.

Part of our analysis uses the concept of tie strength. Since Granovetter (1973), the convention is to label pairs with frequent mutual interactions as "strong ties", in contrast to less active "weak ties". As in Gee et al. (2017), we expect a connection to matter more if it is strong. We therefore restrict the data to cases where it is plausible that agents have some minimal level of interaction. When analyzing the importance of tie strength, we use proxies based on the notion that connections which are more *recent* and/or formed in *durable* and *small* groups should be associated with more interactions (thus, stronger).

3.4. Earnings data and AKM estimates

When estimating the AKM model we use monthly earnings in the main job as the outcome. The measure is constructed by dividing annual earnings by the annual duration of the job spell. We truncate the monthly earnings distribution at 75 percent of the minimum wage. We cannot control for hours worked.

Table 2 shows samples and estimation results. We use the universe of workers and establishments for our full data period 1985–2009 in order to extract establishment effects. The first column shows estimates for this full sample.[22] Note that the dispersion of the estimated effects may be overly wide due to measurement errors since we cannot control for hours worked. The second column includes all job-to-job transitions into private sector establishments. As discussed in Section 2.3, we here use person effects are based on pre-hire data only to avoid the impact of both reverse causality (from connected hiring to wages) and the simultaneity bias arising from correlated estimation errors. Thus, these person effects are from year-specific AKM regressions on samples covering 1985 to $t-1$.[23] The third column uses *connected* job-to-job transitions. The fourth column uses all hires the year after displacements. Finally, the fifth column uses *connected* hires after displacements.

In general, the estimated correlations between person and establishment effects are lower among connected movers than among job changers in general. This is true both for the overall sample of job-to-job movers (0.083 vs. 0.129) and for the displaced (0.049 vs. 0.089). We return to this issue in Section 4.4. The correlations are also lower in the displaced sample (0.089) than in the sample of job-to-job movers in general (0.129).

3.5. Estimation data (dyads)

To create our estimation data, we form pairs between each displaced worker i (from closing establishment j) and each potential hiring establishment k. As outlined in 2.2 we "only" need to include all pairs where *someone* from establishment j has a social connection to establishment k. The procedure generates a data set comprising 41 millions pairs of workers and establishments. Within these data, some workers from establishment j will have an actual connection to establishment k whereas others will not, allowing us to estimate the effects of connections within a model with j, k-pair fixed-effects.

22 See Fig. A.1 for a 3d graph of the joint distribution of person and establishment effects deciles.

23 The correlation between person effects estimated in pre-transition data and the full sample version is 0.89 job-to-job movers.

Table 2
AKM samples and estimates.

	Samples				
	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	7127
Mean of person effects	0.000	−0.104	−0.101	−0.117	−0.111
Mean of establishment effects	4.502	4.525	4.525	4.507	4.503
Std dev. of person effects	0.270	0.269	0.255	0.250	0.245
Std dev. of establishment effects	0.126	0.154	0.152	0.155	0.152
Correlation person/establishment effect	0.038	0.129	0.083	0.089	0.049
Mean of log earnings	9.664	–	–	–	–
Std dev. of log earnings	0.466	–	–	–	–
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. Data in columns (2) and (3) are from Eliason et al. (2019a) that identifies connections for all workers in the economy during 1995–2006. For comparability, we use the same period (1995–2006) in columns (5) and (6). 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 as in Section 3.3.

Table 3
Summary statistics for the main sample.

	Displaced workers (i)		Intermediary workers (l)		Dyads of displaced workers i and potential hiring establishments k	
	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, at closure[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	

Note: The Table gives descriptive statistics of displaced workers (i), intermediary workers (l) and dyads of displaced workers and potential hiring establishments (i, k) within the used sample (1990–2006). The dyads make up the used sample for the causal analysis.
[a]See Section 2.3 for details on the AKM model.

Data are described in Table 3 with separate columns describing 289,000 displaced workers, 2.2 million intermediary workers, and 41 million pairs of displaced workers and potential hiring establishments.[24] Because we focus on private-sector closures, two-thirds of displaced workers are male. Furthermore, we find that 90 percent are Swedish born and

24 Further statistics at the establishment level are provided in Table A.1.

Table 4
Correlations between displaced workers' person effects and connections' person and establishment effects.

	$\mathrm{Corr}(\theta_i, \theta_l \mid C_{il} = 1)$		$\mathrm{Corr}(\theta_i, \psi_k \mid C_{ik(l)} = 1)$		N
	Raw person effects	Residualized person effects	Raw person effects	Residualized person effects	
Panel A:					
Any connection	0.164	0.071	0.061	0.008	1,597,994
Panel B:					
Family member	0.042	0.057	0.027	0.017	195,099
Former co-worker	0.185	0.098	0.097	0.062	501,706
Former classmate	0.201	0.055	0.084	−0.030	587,511
Current neighbor	0.073	0.053	0.026	0.018	304,678
Panel C:					
Family member					
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 classmate					
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 displaced worker (i) and the person effects of the intermediary workers l to whom they are socially connected. In column (2) we show the relationship when both these person effects have been residualized from age at displacement, education level and gender. Column (3) shows the correlation between the AKM person effect of displaced worker i and the AKM establishment effects of connected establishments k. In column (4) we have residualized the AKM person effect of the displaced worker (i) from age at displacement, education level and gender. See also appendix Figs. B.1–B.4.

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.

One notable pattern in the table is that intermediary workers are much more likely to work in high-wage establishments than displaced workers were. 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. In Section 4.4 we discuss results where we also include "post rehire" data in the estimation of the AKM-effects and results are very similar.

4. Results

This section presents the main results. The allocation of social connections is described in Section 4.1. The average impact of these connections, including robustness tests, is presented in Section 4.2. Interactions with person and establishment effects are estimated in Section 4.3. The role of connections for overall sorting inequality is presented in Section 4.4.

4.1. Sorting of social connections

To document the sorting patterns of connections between establishments and displaced workers we use our data on connections between displaced workers and ongoing (potential hiring) establishments. We first calculate correlations between the person effects of displaced workers (θ_i) and the person effects of the intermediary workers to whom they are socially connected (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.

Results are presented in Table 4. For the average connection in our data, the correlation between person effects of the displaced and intermediary workers is positive at 0.164. Thus, the network structure exhibits positive "baseline homophily" in terms of earnings capacity; "good workers" know other "good workers" as presumed in many standard network models (e.g., Montgomery, 1991). The correlation between person effects of the displaced worker and the establishment effects of the connected employer is also positive, but notably weaker (0.061). These magnitudes 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.[25] Thus, the average within-network sorting between displaced workers and their connected employer (0.061) is nearly as large as the average sorting between workers and re-hiring employers (0.083) for (the rehired portion of) the same sample. By the same metric, the average sorting between persons within networks (0.164) is twice as large as the sorting between person effects and the establishment effects of the new employer.

25 The pre-displacement correlation between estimated person and establishment effects is 0.106.

Panel B shows separate correlations for family members, current neighbors, former co-workers and former classmates. Again, all person-to-person correlations are positive, suggesting that homophily is a general phenomenon, i.e., high-wage workers are connected to other high-wage workers for all our observed connections at this level of aggregation. For all these 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.

In Panel C we disaggregate the types of connections even further and here it is obvious that demographic patterns are strongly associated with some specific types of connections; in the data spouses of men are women and vice versa, and gender wage disparities are clearly reflected in the highly *negative* spousal sorting. To assess the importance of these issues, the table shows separate columns for results based on "residualized" person effects where the impact of age at displacement, 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 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).

To make this description parallel to the analysis of causal effects presented later, we also perform a less parametric analysis of the social networks from an employer-side perspective. We proceed as follows. We calculate the average person effect of the displaced separately by (i) decile of the intermediary workers' person effects and (ii) decile of the connected employers' establishment effect. Results are presented in Fig. 1, where each panel corresponds to one column of Table 4. The relationships mostly appear to be linear, at least after residualizing the data, but there is a tendency for accelerated sorting at the top for the school and co-worker connections when using the non-residualized data.[26]

Overall, this analysis clearly shows that high-wage workers are more likely to be connected to other high-wage workers, in particular when these connections are co-workers or classmates (from university). This baseline homophily within the social network also implies that high-wage workers are more likely to be connected to high-wage establishments. The results thus imply that high-wage workers' social networks contain better employers than low-wage workers' networks do.

4.2. The impact of connections on hiring

Table 5 (left column) reports our main estimates of the average impact of social connections (i.e., γ in Eq. (2)) on hiring 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 may appear small, but recall that we are predicting the very rare event that a given worker is entering into a specific establishment as a function of a connection in that very establishment.[27] Standard errors are clustered at the level of the potential hiring establishment. To put the estimates in perspective, the estimated effect (of an average connection) is 10 times the baseline probability of hiring by the non-connected (i.e., the constant) of 0.026.

The estimated average effect of a connection masks considerable heterogeneity across types of connections. The impact of family members is the largest; a family member within an establishment raises the hiring probability by, on average, 1.1 percentage points (Panel B). The effect varies 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). Former co-workers have the second largest effects. Having a former co-worker within an establishment increases the hiring probability into that establishment by 0.25 percentage points. Even though former classmates or current neighbors also matter, the magnitudes of the effects are substantially lower (0.07 and 0.09 percentage points).

The differences in results between types of connections potentially reflect the frequency of interactions within each 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. In the extreme, if people do not interact at all, the connections should be useless by default. To directly test this presumption, we separate our co-worker connections by size of the establishment where the connection was formed in Panel C. The results show that connections matter more if formed in establishments with less than 20 employees than if formed within larger establishments. We expand on this analysis even further in Section 6.1 where we show further evidence on the importance of the frequency of interactions.

The results just discussed are based on a model with (j, k) establishment-pair fixed-effects (left column of Table 5). Next, we discuss a sequence of robustness tests.

Robustness to time-invariant preferences for specific establishments. The middle column of Table 5 shows estimates from an alternative model estimated on the small sample of workers who are displaced multiple times as outlined in Eq. (6). We restrict the sample to those displaced exactly twice and exploit changes in the employment patterns of their social relations between these events. The model has a fixed effect for each (i, k) combination of displaced person and establishment. The regressions include all dyads to which the worker was connected at least once, and the establishment existed during both displacements. We control for the size of the establishment at the time of displacement. Fixed effects

[26] Results for more detailed types of connections (parents, spouses, …) are found in Figs. B.1 and B.2.

[27] See estimates of individual neighbors in Bayer et al. (2008), or single moved coworkers in Hensvik et al. (2017), which are of similar magnitudes.

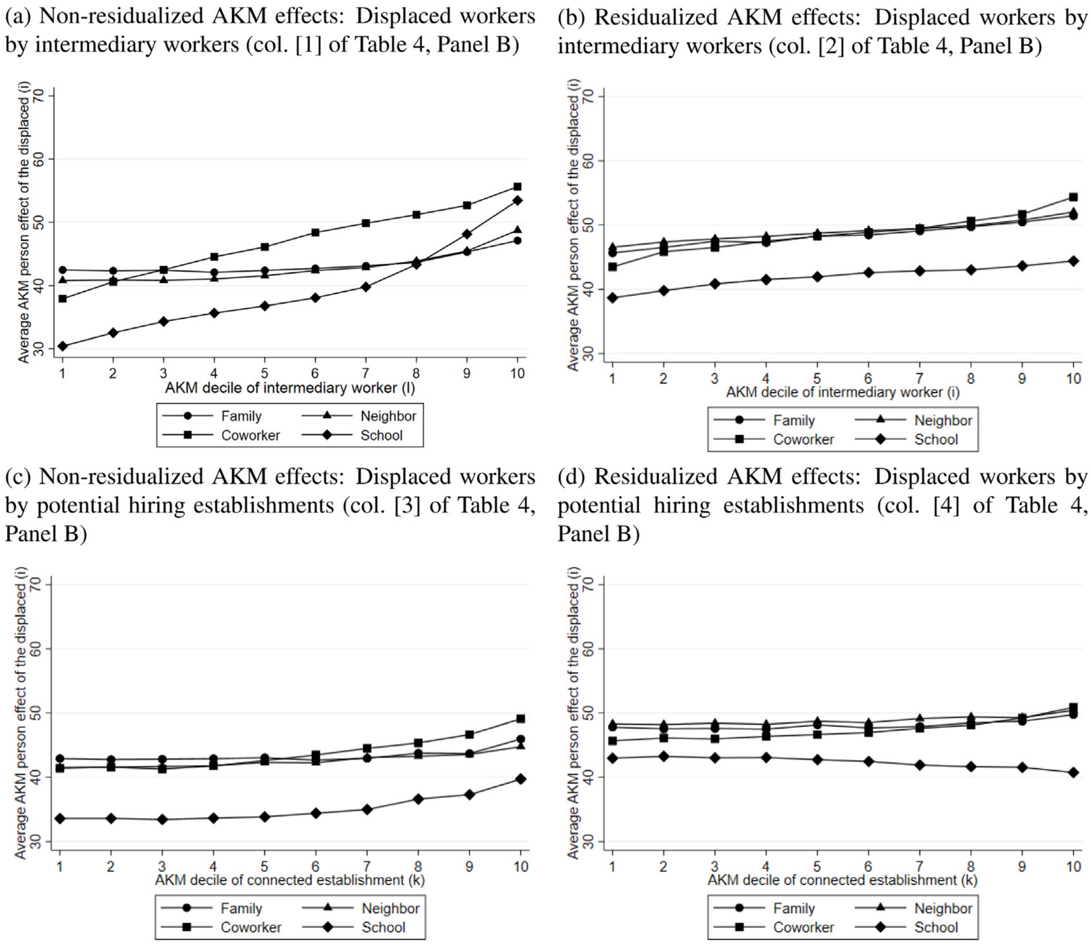


Fig. 1. Average percentile of displaced workers' non-residualized (left hand side) and residualized (right hand side) AKM effects (θ_i and $\hat{\theta}_i$, respectively) by decile of intermediary workers' and the potential hiring establishments' AKM effects ($\theta_l \mid C_{il} = 1$ and $\hat{\theta}_l \mid C_{il} = 1$, respectively) for each type of social connection.

for combinations of displaced workers and connected establishments ensures robustness to all time-invariant individual preferences for specific establishments. The results are slightly less precise than in the baseline, but the estimates are essentially unchanged; the effect of "Any connection" is 0.305 as compared to 0.270 in the baseline.

Robustness to within worker-and-displacement-event identification. The third column of Table 5 shows estimates of the *relative* impact of different types of connections including within worker-and-displacement-event fixed effects. The model has a fixed effect for each worker's set of connected firms (during an event) as outlined in Eq. (7). Thus, these estimates are computed "within" each displaced worker's set of connections. The results mostly concur with the baseline estimates presented in the left-side column. A family member or a former co-worker clearly has a larger effect than a neighbor or a former classmate.

Robustness to variations in controls and samples. Robustness checks where (a) we ignore contacts through self-employed intermediary workers, (b) include more worker characteristics, (c) control for AKM-person effects, (d) focus on small closures, (e) ignore all cases where multiple workers are connected to the same employer or when (f) focusing on connections to small *k*-establishments are found in the Appendix, Tables B.1 and B.2.

Our baseline results should be robust to demand shocks generated by the closure of an establishment since all workers (with or without a connection) at the same closing establishment should be similarly affected by such shocks. But to fully eliminate this "demand-shock" interpretation, we have verified that our patterns are unaffected when focusing on connections to establishments in a different industry from that of the closing establishment, see Table B.2. The estimates are larger when connections span across establishments in the same industry, clearly reflecting that it is easier to transfer skills across similar employers with similar production techniques. It is inevitable that some of the connections we analyze, e.g. in the family dimension, will link workers to jobs that are in completely irrelevant labor market segments

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

	"Baseline" (jk-fixed-effects)		"Multiple displacements" (ik-fixed-effects)		"Within-worker identification" (K_{ij}-fixed-effects)	
	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)
Panel A:						
Any connection	0.270	(0.005)	0.305	(0.025)	N/A	
Constant	0.026	(0.000)	0.085	(0.012)		
Panel B:						
Family member	1.095	(0.020)	1.196	(0.173)	1.464	(0.036)
Former co-worker	0.253	(0.010)	0.477	(0.048)	0.714	(0.030)
Former classmate	0.066	(0.004)	0.101	(0.025)	0.157	(0.026)
Current neighbor	0.086	(0.008)	0.040	(0.033)		
Constant	0.027	(0.000)	0.075	(0.013)	0.014	(0.002)
Panel C:						
Family members						
Parent	1.867	(0.052)	1.692	(0.440)	2.061	(0.058)
Adult child	0.667	(0.051)	0.797	(0.357)	1.388	(0.065)
Spouse	1.971	(0.078)	2.683	(0.741)	2.526	(0.081)
Sibling	0.696	(0.023)	0.832	(0.195)	1.105	(0.042)
Former co-worker						
1–20	0.527	(0.029)	0.960	(0.124)	1.164	(0.045)
21–50	0.217	(0.018)	0.378	(0.073)	0.664	(0.040)
51–100	0.140	(0.014)	0.224	(0.060)	0.545	(0.038)
Former classmate						
High school	0.064	(0.004)	0.094	(0.025)	0.231	(0.027)
College/university	0.088	(0.018)	0.195	(0.117)	0.464	(0.043)
Current neighbor						
1–20	0.072	(0.072)	0.154	(0.428)		
21–50	0.084	(0.021)	0.025	(0.087)		
51–100	0.079	(0.009)	0.037	(0.035)		
Constant	0.026	(0.000)	0.073	(0.013)	0.010	(0.002)
No of fixed-effects	2,087,560		147,996		548,820	
No of observations	41,111,774		295,992		41,111,774	

Note: Data are in dyadic 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. Alternative model for workers with multiple displacements uses fixed-effect for each combination of individual and connected establishment, thus exploiting variation in network structure between displacements. 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 2.3.1 Standard errors are clustered on the potential hiring establishment-and-year level.

(e.g. economists and construction firms). In these cases, workers are very unlikely to transit regardless of whether there is a connection or not. In the context of a linear probability model, this will lead to smaller estimated effects.[28]

Replacing the connected establishment by a non-connected establishment. To verify that the estimates we find in the main analysis are not due to market-level factors, we provide two tests where we replace the connected establishments with other, similar, local establishments as "placebos" in the spirit of Kramarz and Skans (2014) and Hensvik and Skans (2016). In the first exercise, we use potential hiring establishments that are 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) and replace the actual establishment with a randomly selected alternative within this set. Clearly, since connections may also matter at the firm, and not only the establishment, level, this exercise should give us a conservative assessment of any potential bias that may arise because of deviations from the identifying assumptions. In the second analysis, each potential hiring establishment is instead replaced by another establishment within a different firm, but within the same location and 3-digit industry, as a way to simultaneously examine the "common preferences" and the "demand shock" concerns. The estimates from these two regressions, presented in the middle and rightmost column of Table 6, have magnitudes that are an order of magnitude smaller than the corresponding estimates of our baseline analysis. This implies that a worker who is displaced is 10 times more likely to enter an establishment where one of his or her connections are working, than into another establishment within the very same firm and location. The implied bias component (which will be an exaggeration if connections sometimes are used across different establishments within the same firms) is in the order of 0.03 overall, 0.04 for family connections, and 0.08 for former co-workers. We find these small estimates to be reassuring; if unobserved characteristics were driving our baseline results, we should instead find similar estimates for the unconnected establishments within connected firms (assuming that the production function has a large firm-level component). And, if

[28] The same logic applies to ties that link agents that are very distant in terms of locations.

Table 6
Estimated "placebo" effects of similar non-connected potential hiring establishments.

	Baseline reference[a]		Placebo in same firm[b]		Placebo in same industry[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 member	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 neighbor	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)
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 dyadic 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).

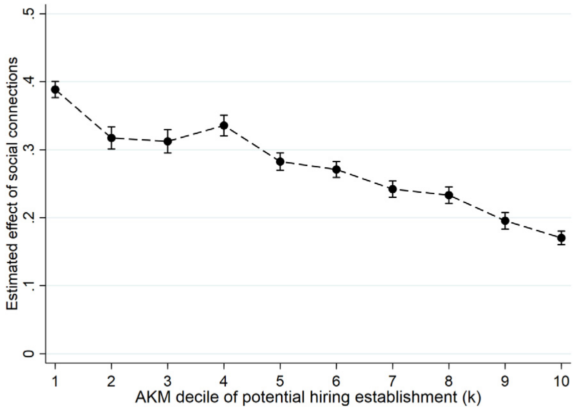


Fig. 2. Estimated effects of any social connection by deciles potential hiring establishments' AKM effects (i.e. ψ_k). *Notes:* The figure shows interactions with AKM deciles of potential hiring establishment (k) using the baseline model with j, k-fixed-effects. All estimates are expressed in percentage points.

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 magnitudes when using unconnected establishments within the same industry, but here the differences are even smaller than in the within-firm exercises.

4.3. The causal impact, by person and establishment effects

In order to estimate if and how the effects of connections affect sorting inequality, we examine the interaction between connections and the estimated (AKM) person and establishment effects as in Eq. (4). 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 using only the observations that precede job displacement to avoid reverse causality (e.g., being hired through connections may lead to higher or lower wages), but also to avoid the "limited mobility bias".

We first focus on the role of establishment and person effects separately before turning to their interplay. Estimates of the effects of social connections across the distribution of demand-side heterogeneity in Fig. 2 show that this dimension is highly relevant. The impact of social connections is more than twice as large for low-wage establishments than for high-wage establishments. The relationship in-between is approximately linear.[29]

[29] Estimates in Fig. 2 and corresponding estimates for persons in Fig. 5 are from separate regressions but results are identical when estimated jointly.

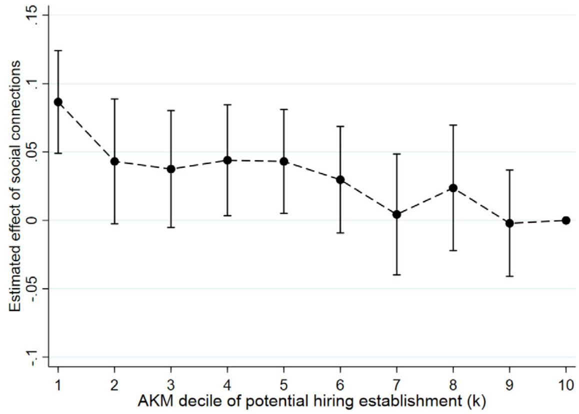


Fig. 3. Within-worker identification estimates by AKM decile of potential hiring establishment (ψ_k). *Notes:* The figure is based on the model of Eq. (7), which includes worker and set of connected establishments and year fixed-effects. It shows the interactions with AKM deciles of potential hiring establishment. Decile 10 is the reference category. All estimates are expressed in percentage points.

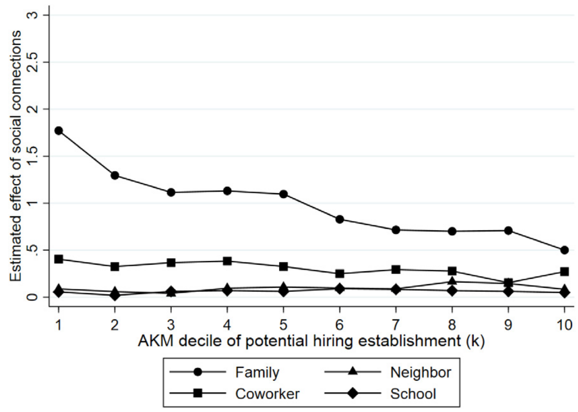


Fig. 4. Estimated effect of each type of social connection by decile of the displaced potential hiring establishments' AKM effects (i.e. deciles of ψ_k). *Note:* The figure shows interactions with AKM deciles of potential hiring establishment (k) using the baseline model with j, k-fixed-effects. For coefficients and standard errors of corresponding estimated linear slopes, see Table B.3 in the Appendix. All estimates are expressed in percentage points.

However, if workers who are more likely to use connections also are more likely to be connected to low-wage employers, our estimates would reflect this unobserved heterogeneity. Fortunately, using within-worker variation allows us to assess this concern. We thus estimate the individual (times connected set) fixed-effects model of Eq. (7) to see if workers with connections to both high- and low-wage establishments are more likely to "use" their connections to low-wage establishments. The reference point here is a connection to an establishment in the highest decile of AKM-effects. Indeed, as shown in Fig. 3, connections to low-wage employers have larger causal effects, even within a given worker. The resulting structure of the estimates from the within-worker model is thus very similar to that of the baseline j, k-fixed-effects model, despite the differences in identifying variation.

Fig. 4 shows estimates of the impact of connections across the distribution of demand-side heterogeneity (AKM decile of potential hiring establishment) separately by type of connection (i.e., family member, former co-worker, former classmate, or current neighbor). The graph clearly shows that the effects of family members are more than twice as large when connecting to low-wage establishments as when connecting to high-wage establishments. This pattern is closely mirrored also for co-workers; the negative slope for these connections is less visible in the graph because the mean effect is much lower, but using a model with a linear slope (see Table B.3) provides a statistically significant estimate of −0.018 which implies that the effect in low-wage establishments is almost twice as large as in high-wage establishments also for co-worker connections.[30] The effects of former classmates and current neighbors are so limited in magnitude that we cannot identify any significant heterogeneity across establishment types.[31]

30 Recall that the mean effect of co-workers is 0.253, and the difference (as implied from the linear model) between lowest and highest decile is 0.18.

31 See Table B.3 for details.

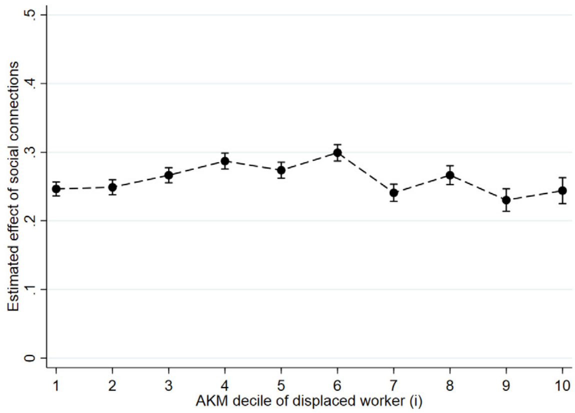


Fig. 5. Estimated effects of any social connection by deciles of the displaced workers' AKM effects (i.e. θ_i). *Notes:* The figure shows interactions with AKM deciles of displaced worker (i) using the baseline model with j, k-fixed-effects. All estimates are expressed in percentage points.

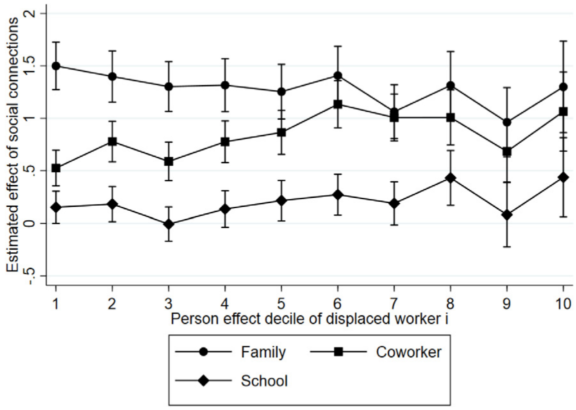


Fig. 6. Individual fixed-effects estimates of the effect of social connections relative to current neighbors by AKM effect (θ_i) decile of displaced worker. *Notes:* The figure is based on the model in column (3) of Table 4, which includes individual and set of connected establishments and year fixed-effects. 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. All estimates are expressed in percentage points.

Estimates of the effects of social connections across the distribution of displaced person-effects (i.e., supply-side heterogeneity) are presented in Fig. 5. The estimates show, in sharp contrast to the demand-side heterogeneity, that connections appear to have equal causal effects for low- and high-wage displaced workers.[32] If anything, the impact appears slightly larger in the middle of the person-effects distribution.

Within-worker identification allows us to assess whether the relative importance of the types of connections for a given worker is stable across the distribution of person effects.[33] In Fig. 6 we show the relative impact of family members, former classmates, former co-workers, and current neighbors across the distribution of person effects. The Figure uses current neighbors as the baseline category across the distribution. The point estimates show that the ranking of effects (i.e., family first then co-workers, classmates, and neighbors [normalized to zero] 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 workers 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. The effects are less dispersed for high-wage workers, because family members are less important for these workers and co-workers instead matter more. The impact of former classmates are only marginally more positive than current neighbors across the distribution of person effects.

Finally, we turn to the interaction between supply- and demand-side heterogeneity. Here, we use a second-order polynomial of both (AKM) worker and establishment effects as outlined in Eq. (5). We illustrate the estimates graphically

32 In Fig. B.5 we show that the relationship is similar if we use person-effects after conditioning on age, gender, and education level.

33 In the Appendix (Table B.3) we show linear relationships with their standard errors from the baseline model with j, k fixed-effects using both raw and residualized person effects.

in Figs. 7(a) to 7(d), which all present different aspects of the same regression. We report the parameter estimates and standard errors in the Table B.4 for completeness.

The effects of a connection vary with the type of worker, separately for different types of connected establishments, are displayed in Fig. 7(a). 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. Slopes are only marginally different across types of workers and the interaction is not statistically significant, see Table B.4.

Next, we show how the effects of a connection vary with the type of worker, separately for different types of connected establishments (using the same underlying estimates). As Fig. 7(b) demonstrates, the effect of connections to establishments with the lowest AKM-effects is twice as large as the effect of connections to establishments with the highest AKM-effects *regardless* of whether the displaced worker is a low-, medium-, or high-wage worker.

It is well-known that the estimated covariance between person and firm effects is, in general, negatively biased as described in detail in, e.g., Andrews et al. (2008) and Kline et al. (2020). The first-order impact of this bias, arising because any over-estimation of establishment effects immediately is transposed into a negative bias in person-effects of that establishment's employees, is removed in this setting because we correlate the person effects (estimated with pre-displacement data only) with the establishment effects of *future* potential employers. But to ensure that our estimates are not affected by the overall noisiness of AKM-estimates for small employers, we have verified that these results are valid also if using other strategies for classifying employers. We first classified all establishments using the clustering-approach of Bonhomme et al. (2019) where we cluster the establishments into 10 groups based on the earnings distribution and then rank the clusters based on mean earnings.[34] We also grouped establishments into 10 groups based on firm-level value-added per worker and proceeded as above. Person effects are in both cases estimated as fixed effects, using pre-displacement data only, in wage regressions that control for cluster-group fixed effects and the same observables as in the AKM-model. We then re-estimated the interacted model and derived Figures corresponding to Figs. 7(a) and 7(b). The ensuing results are presented in Fig. 8. They confirm that connections to low-wage (low-productivity) employers matter the most for all types of workers regardless of the method we use.

Fig. 7(c) shows the full 3D-graph of causal effects as functions of the joint distribution of person and establishment effects (as approximated by the second-order polynomial). Again, the Figure shows that all effects are much larger for low-wage establishments, *regardless* of the person effect. Hence, the distribution of causal effects of connections (i.e., the $\gamma(\theta, \psi)$ in Eq. (4)) does not contribute to sorting inequality. For completeness, we also show in Fig. 7(d) how the person and establishment effects interact with the probability to be hired for non-connected workers; these effects are small throughout.

To ensure that the results are not reflecting underlying individual heterogeneity, we use our within-worker identification, which is immune to such concerns to analyze the relationship between the causal effects of connections and the person and establishment effects of the agents. This model deals directly with, e.g., the first order effect of differences in age, education and gender. When we use this model, the presence of individual fixed-effects limits identification to parts of the interacted second-order polynomial (see Eq. (8)). Results are again illustrated graphically in Fig. 9 with point estimates and standard errors deferred to Table B.4. The results show that a given (displaced) worker is more likely to be hired thanks to connections to a low-wage establishment, regardless of whether she is a low-, medium-, or high-wage worker. The triple interaction between having a connection and the (AKM) person and establishment effects is positive, but tiny in magnitude (as is obvious from the graph) and not statistically significant.[35] Thus, the results using within-worker identification are in full agreement with those of the baseline model; causal effects are always larger for low-wage establishments, independently of the person-effect.

4.4. Social connections and 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 linking a low-wage worker to a low-wage establishment is equal to that connecting a *high*-wage worker to a low-wage establishment. Thus, the structure of social networks adds to sorting inequality, whereas the structure of estimated causal effects does not. Below we assess if the combination of these two forces makes 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 since the sample is selected to include those that actually find employment and since the identification strategy lacks the granular fixed-effects controls of the dyadic model. In addition, this strategy will more clearly suffer from an attenuation bias because we cannot measure all possible friendship relations as discussed in Section 3.3.1 and since our non-connected,

34 We first residualize the data from education, age, gender and year and then cluster the establishments on these residualized data. Following, Bonhomme et al. (2019), we cluster the establishments using the cdfs of log-earnings on a grid of 20 percentiles of the (year-specific) aggregate log-earnings distribution. We optimize over segmented starting values at the center of each of the 20 clustering variables as well as 100 random starting values. Allocations to clusters are fixed across the sample period. Clusters are ordered according to the mean residualized wages in accordance (Bonhomme et al., 2019).

35 See Table B.4.

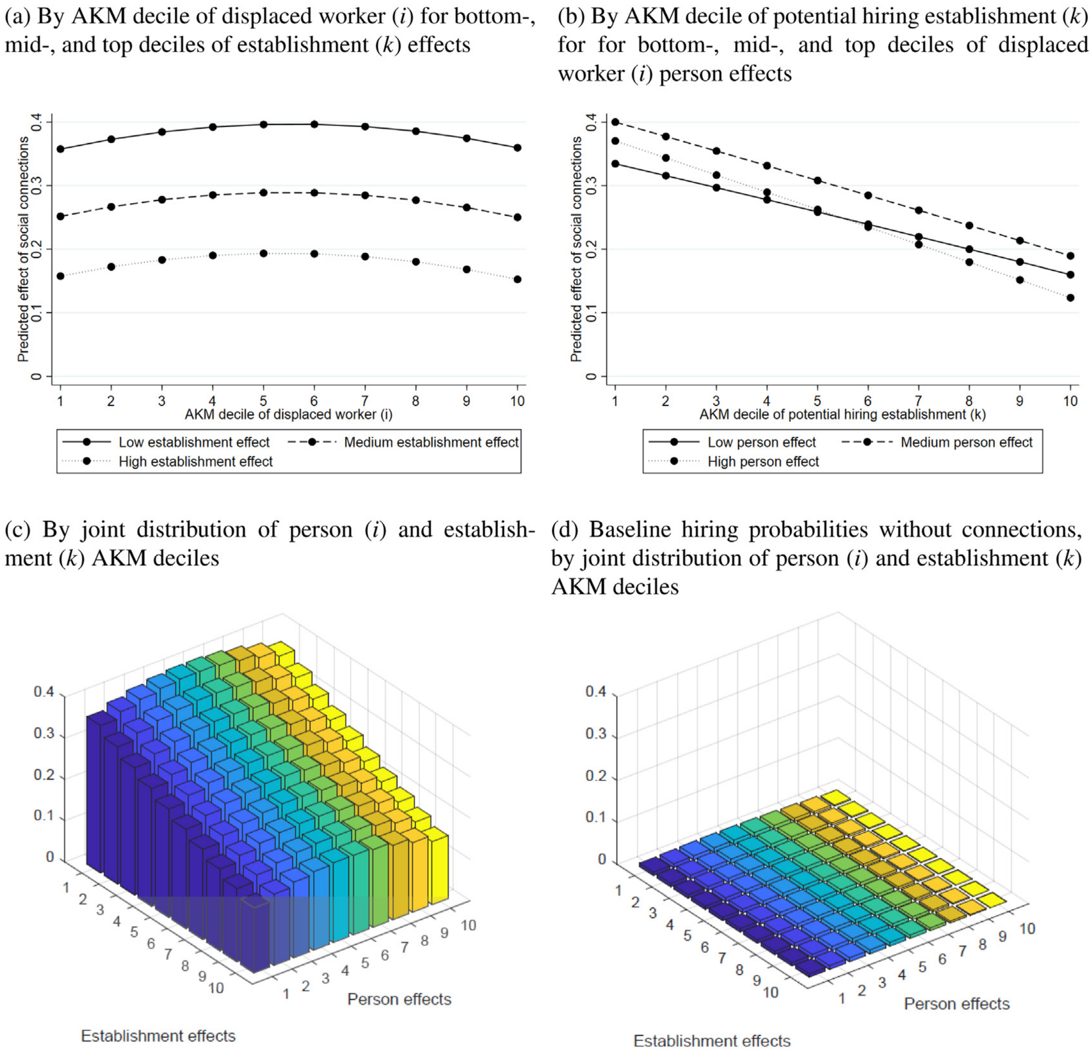


Fig. 7. Effects of social connections on hiring, by joint distribution of person and establishment effects. *Notes:* The figures show the predicted hiring effect of social connections obtained from estimating Eq. (4), i.e., from interacting social connections with a second order polynomial of both the AKM person effect of the displaced and the establishment effect of the potential hiring establishment (in percentiles). All estimates are from the same regression. Panels (a) and (b) show slices of the 3d graph of panel (c). For underlying estimates and standard errors see Table B.4. All estimates are expressed in percentage points.

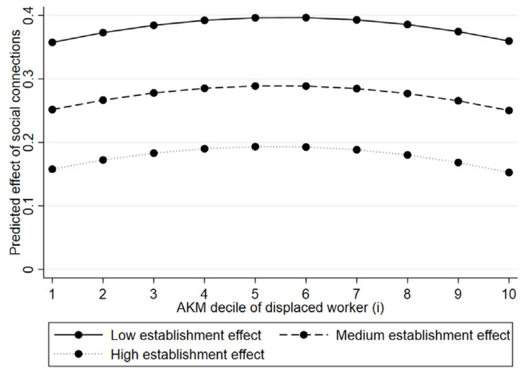
"market", matches therefore almost certainly include cases where unobserved social relations played a role in the process. On the other hand, this analysis also lends itself to an extension to all movers (i.e., also those that are not displaced). These non-displaced movers are analyzed to ensure that the patterns we describe are not limited to the sample of displaced workers.

We estimate the following model on the sample of newly hired workers (an observation is a hired worker):

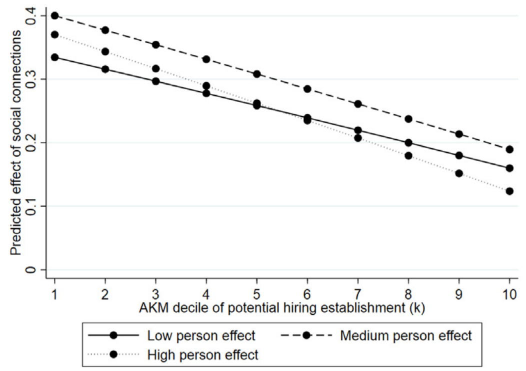
$$\theta_{ik} = \mu + X_i\beta + gC_{ik} + s\psi_k C_{ik} + m\psi_k(1 - C_{ik}) + e_{ik}, \tag{9}$$

where ψ_k indicates the establishment effect of the new employer. As in the rest of our analysis, the person effect θ_{ik} is constructed from an AKM-model using only pre-hire data. The parameter g captures the base "effect" of being hired through a social connection, s captures differences in hiring patterns of socially connected workers between high- and low-wage establishments, and m captures similar differences in hiring patterns for non-connected workers ("market" matches). Differences between estimated s and m indicate differences in sorting between connected and non-connected hires. To reduce the impact of potential differences in observable characteristics, X includes the establishment effect of the previous employer (ψ_j) and the number of connections of each type.

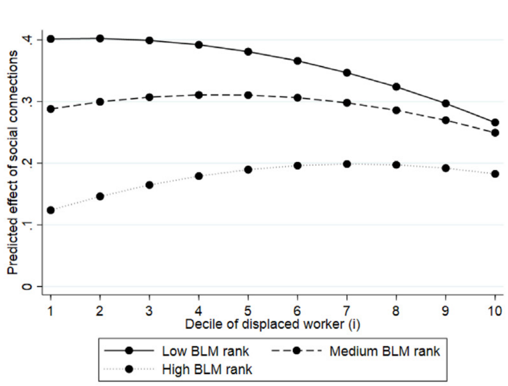
(a) By AKM decile of displaced worker (i) for for bottom-, mid-, and top deciles of establishment (k) effects (as in Figure 7a)



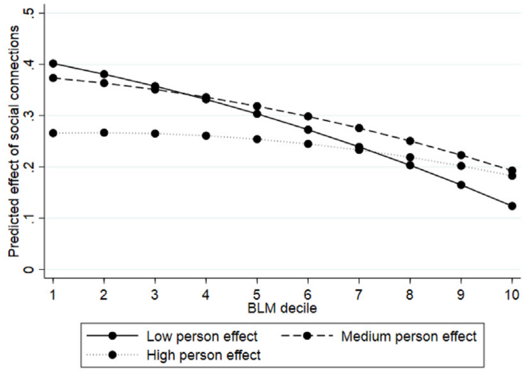
(b) By AKM decile of potential hiring establishment (k) for bottom-, mid-, and top deciles of displaced worker (i) person effects (as in Figure 7b)



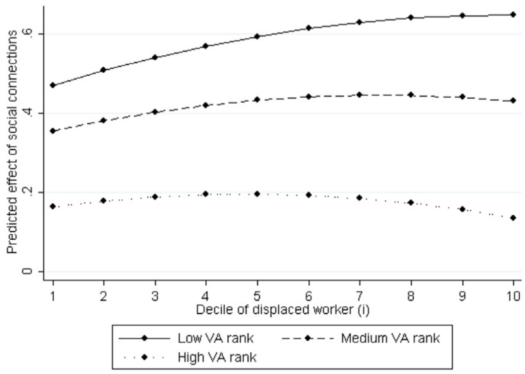
(c) Establishment ranks from BLM clustering



(d) Establishment ranks from BLM clustering



(e) Establishment ranks from VA-distribution



(f) Establishment ranks from VA-distribution

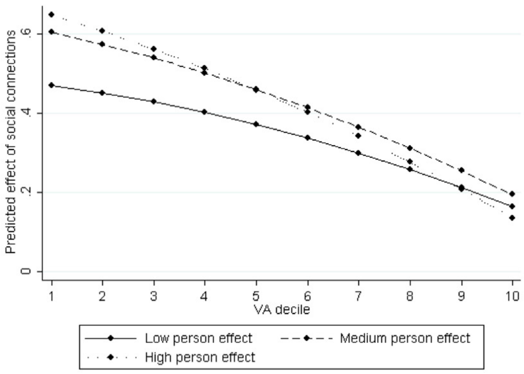


Fig. 8. Alternative measures of establishment deciles. *Notes:* The figures show the predicted hiring effect of social connections obtained from estimating Eq. (4), i.e., from interacting social connections with a second order polynomial of both the person effect of the displaced and the establishment effect of the potential hiring establishment (in percentiles). Panels (a) and (b) are the same as panels (a) and (b) of Fig. 7. Panels (c) and (d) use BLM clustering to rank establishments, while the worker deciles are derived from a wage regression similar to Eq. (3), but replacing the establishment effects with BLM ranks. In panels (e) and (f) we repeat this exercise when ranking establishments based on value added. All estimates are expressed in percentage points.

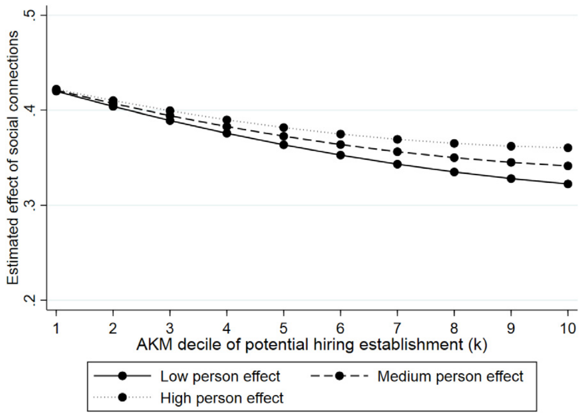


Fig. 9. Within-worker identification estimates by potential hiring establishment deciles, for bottom-, mid-, and top wage displaced workers. *Notes:* The figure is based on the model of Eq. (7), which includes worker and set of connected establishments and year fixed-effects. It shows the interactions 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 Table B.4). All estimates are expressed in percentage points.

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

	Raw AKM person effects		Residualized AKM person effects	
	Coef.	(s.e.)	Coef.	(s.e.)
Panel A: Displaced hires				
Connected hire	1.385	(0.619)	1.463	(0.635)
Hiring establishment AKM-effect				
× Connected hire	0.049	(0.010)	0.013	(0.010)
× Market hire	0.073	(0.005)	0.048	(0.005)
Origin establishment AKM effect	0.079	(0.004)	0.035	(0.004)
F-test: Interactions are equal (p-val.)	0.012		0.0005	
No of observations	83,540		83,540	
R-squared	0.077		0.027	
Panel B: All job-to-job				
Connected hire	2.598	(0.148)	2.554	(0.135)
Hiring establishment AKM-effect				
× Connected hire	0.075	(0.003)	0.035	(0.003)
× Market hire	0.108	(0.002)	0.073	(0.002)
Origin establishment AKM effect	0.107	(0.002)	0.062	(0.001)
F-test: Interactions are equal (p-val.)	0.0000		0.0000	
Observations	3,315,521		3,315,521	
R-squared	0.102		0.037	
Year specific effects	Yes		Yes	
Number of connections	Yes		Yes	

Notes: Data in Panel B are from Eliason et al. (2019a) that identifies connections for all workers in the economy during 1995–2006. For comparability, we use the same period (1995–2006) in Panel A. Controls for the number of connections of the job mover are included separately by type of connection. Standard errors are clustered at the level of the hiring establishment.

Table 7 displays the estimation results. The estimated impact of social connections on the quality of the hired worker is positive. Furthermore, we see evidence of sorting inequality throughout, 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". 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 A) but also in the full sample comprising all job-to-job movers (Panel B). As the table shows, the patterns are similar if we instead use the residualized person effects to characterize worker heterogeneity.

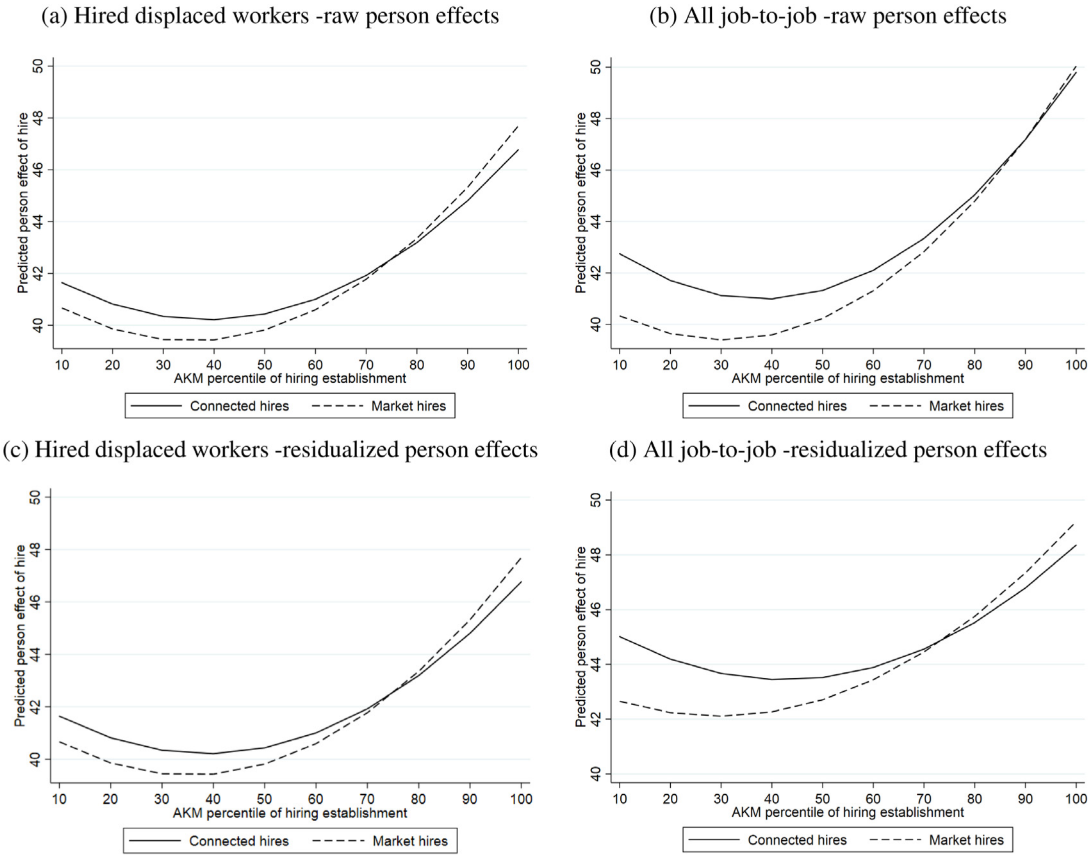


Fig. 10. Predicted person effect of new hire as a function of hiring establishment effects and the use of social connections. *Notes:* The figure shows the predicted relationships between person effects of new hires, the hiring establishment effect and the hiring channel (connection/no connection). For data description, and linear estimates with standard errors, see Table 7. We have added the mean person effect within each sample.

As a further illustration, Fig. 10 shows results from versions of Eq. (9) with more flexible functional forms. Here, we allow the relationship between the AKM establishment effects and the person effects of connected hires and market hires, respectively, to be non-linear. We show separate estimates for displaced and all job-to-job movers, and for raw and residualized person effects. In all panels, low-wage employers clearly hire better workers through connections than through the market. If anything, the converse is true for high-wage employers (the lines converge or cross). These estimates suggest that "bad" employers hire "better" workers when they use connections. In contrast we see small, even reversed, patterns among high-wage firms. This explains why the relationship between person and hiring establishment effects, on average, is flatter among connected hires than among market hires, as shown in Table 7.

In Fig. B.9, we show results from a corresponding analysis where we use person effects estimated from the full sample (instead of the pre-displacement sample) with very similar results.

5. The post-hire outcomes of connected hires

In this Section we show how post-hire outcomes differ between connected hires and "market" hires using a model similar to Eq. (9) that we used to study realized sorting at the end of the previous section. As outcomes, we use (i) monthly earnings the year after displacement (defined as in the AKM-model) and (ii) the probability of staying with the new employer three years after entry.

We thus estimate:

$$Y_{ijk} = \mu + X_i\beta + b\theta_i + gC_{ik} + s\psi_k C_{ik} + m\psi_k(1 - C_{ik}) + e_{ik}, \tag{10}$$

where Y_{ijk} is either log wages or the retention rate in the new job. To facilitate interpretation in the wage regressions, we use the AKM-components as they were estimated (i.e. not in ranks).[36]

[36] Firm-effects of new employer are demeaned after interacting with connections.

Table 8
Log wages and retention rates of new hires as a function of social connections and the ranked AKM establishment effect of the hiring establishment.

	Log(Wages[a])		Log(Wages[a])		Staying at t + 3		Staying at t + 3	
	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)
Panel A: Displaced hires								
Connected hire	−0.027	(0.004)	−0.019	(0.004)	0.097	(0.008)	0.099	(0.008)
Hiring est. AKM-effect								
× Connected hire			0.830	(0.030)			0.261	(0.053)
× Market hire			0.867	(0.015)			0.215	(0.021)
Pre-estimated person effect	0.698	(0.010)	0.663	(0.009)	0.066	(0.011)	0.057	(0.010)
Origin est. AKM-effect	0.490	(0.014)	0.253	(0.011)	0.010	(0.018)	−0.051	(0.018)
Equal interactions (p-val.)			0.2425				0.4072	
Observations	54,134		54,134		54,134		54,134	
R-squared	0.371		0.464		0.014		0.017	
Panel B: All job-to-job								
Connected hire	−0.024	(0.001)	−0.017	(0.001)	0.103	(0.002)	0.106	(0.002)
Hiring est. AKM-effect								
× Connected hire			0.865	(0.010)			0.174	(0.015)
× Market hire			0.922	(0.010)			0.237	(0.010)
Pre-estimated person effect	0.785	(0.004)	0.736	(0.004)	0.084	(0.003)	0.072	(0.003)
Origin est. AKM-effect	0.692	(0.008)	0.327	(0.004)	−0.024	(0.008)	−0.115	(0.007)
Equal interactions (p-val.)			0.0000				0.0000	
Observations	2,181,163		2,181,163		2,181,163		2,181,163	
R-squared	0.438		0.520		0.012		0.015	

Notes :
[a]Log Wages are calculated as annual earnings in the first full year after displacement divided by number of months employed. Data in Panel B are from Eliason et al. (2019a) that identifies connections for all workers in the economy during 1995–2006. For comparability, we use the same period (1995–2006) in Panel A. Controls for the number of connections of the job mover are included separately by type of connection. Standard errors are clustered at the level of hiring establishment.

We start by estimating the model without controlling for the establishment effects of the new employer. Results are presented in Table 8. Connected hires have slightly lower (2.7 percent) monthly earnings but a much higher (9.7 percentage points) probability of remaining with their new employer during the 3 years following entry.[37] The results are very similar between panel A (displaced hires) and panel B (all job-to-job hires). Connected hires appear to benefit in terms of job stability, but not in terms of wages. This is well in line with results presented in Kramarz and Skans (2014).

Next, we present results where we add the interactions between connections use and the establishment-effects of the new employer. The wage impact of being hired through a connection is reduced (to 1.9 percent) once we control for the type of hiring establishment. Hence, the lower earnings among connected hires are partly due to the (lower-wage) establishments at which such workers tend to find their (connected) jobs. This result is fully consistent with our previous finding that low-wage establishments are more likely to use connections to hire. The estimated relationship between the hiring-establishments' plant effects and wages is very similar for market hires and connected hires. Thus, wages vary about with the firm-type but not with the market vs. connected type of hire.

The table also shows that workers stay longer if they are hired by a high-wage employer, or if they are high-wage workers themselves. Furthermore, workers appear to be more "impatient" if their previous employer was of a high-wage type, at least after conditioning on the type of new employer. Importantly for us, and in contrast with the wage estimates, retention rates for connected and non-connected hires are unrelated to the type of the new employer. Hence, workers may benefit in non-pecuniary dimensions from working at connected establishments, see e.g. the discussion in Card et al. (2018) on such idiosyncratic valuations. Alternatively, connections convey information about match quality that are not shared with workers in terms of wages. Either of these explanations should, however, be related to the presence of the intermediate worker, not the establishment as such. Indeed, our analysis of those workers repeatedly displaced showed a strong impact of connections even when accounting for time-invariant worker × employer effects.

Notice that the estimates of the hiring establishment effects should be equal to unity if the assumptions underlying the AKM-decomposition were fully valid and if all components were free of estimation errors, whereas our estimates are in the range of 0.83 to 0.92. Therefore, we have checked that all our conclusions on the role of connections are indeed unaffected if we constrain these estimates (and the impact of the pre-estimated person effect) to unity. Various reasons may account for the non-unity estimates we display. Estimation error is one. Hence, we checked that the estimated effects

[37] In previous versions of the paper, we presented reverse results for regressions where the outcome was *annual* earnings in the displacement year. We believe that the discrepancy arises because connected hires find jobs faster, thus generate higher annual earnings in the year of transition. We therefore use data for the first full year after displacement when calculating starting wages.

do become slightly larger if we instrument gender-specific estimates of the establishment effects with the estimated effect for the other gender. In addition, the establishment effects are estimated over long time periods when we know from the rent sharing literature discussed in, e.g., Card et al. (2018)[38] that firm-effects do change across time in relation with firm profits. Unfortunately, such changes will generate time-varying measurement errors that cannot be instrumented using the above cross-group strategy.

6. The importance of social interactions: Further results

In the coming subsections, we show how connections operate in dimensions that are important, but not directly related to sorting inequality. The exercises lend further support for our claim that the main results are due to social interactions between measured connections, thus validating our overall interpretation.

6.1. Connections' strength and intensity

In this subsection, we examine how strength and intensity of social connections are related to our estimated causal effects. The general presumption is that, if indeed social interactions are important, we should see larger effects in those cases where we expect interactions to be more frequent, i.e. in cases where the social ties are stronger.

Our main results show that connections to a family member are associated with a much larger causal effect than for any other connection type in our data (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 social connections of the strong sort being particularly important on the labor market (see, e.g., Boorman (1975)).

To further assess the robustness of this conclusion, we have re-estimated our model allowing for further heterogeneity in a number of dimensions: the size of the group where the interaction took place (more detailed than in Table 5), 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 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 have frequent social interactions. Hence, we decided to focus on those cases where the connections should be well-measured and most meaningful. In particular, we restricted attention to networks comprising strictly less than 100 individuals.

First, as can be seen in Fig. 11, the size of the group in which the interaction took place matters. We analyze group size for three types of measured connections: former co-workers, former classmates, and current neighbors. More precisely, the estimated effect is decreasing when the size of the group increases; especially so among former co-workers and classmates (from both high-school and college/university). Interestingly, group size matters also for groups that are already very small, co-workers from sites with 10 or less employees matter more than those with 11–20 employees, even though all co-workers at an establishment with 11–20 employees are likely to know each other. This clearly suggests that connections matter and are more useful if they are formed in smaller social groups. It also supports our choice to exclude groups of 100 individuals and above since they appear to be uninformative.

Second, as shown in Fig. 12, time-since-interaction matters. The impact of previous co-workers depreciates rapidly with time since interaction. The estimated effects suggest that the causal impact is decreasing with time since interaction for connections with former co-workers and with former classmates, at least from high school.[39] This also confirms that our choice to restrict attention to former co-workers from the most recent of all past workplaces (before becoming employed at establishment j) is innocuous, and that our lack of data on high-school classmates prior to 1985 is likely to be of minor importance.

Third, as depicted in Fig. 13, the duration of the interaction matters. The estimated effects show that time spent together as co-workers is strongly positively related to the magnitude of the causal estimate. The tendency is similar, but not as marked among those connected through current neighbors.

We have also examined the magnitude of the effects for agents with similar observable characteristics, along the lines of Bayer et al. (2008). Indeed, in line with what is found in the above, we find that similarity matters. The results, displayed in our working paper version (Eliason et al., 2019b), showed that similarity in terms of gender, age, and immigration status is more important than similarity in terms of education, providing additional support for the importance of social proximity.

38 See Carlsson et al. (2016) for Swedish evidence.

39 Estimates for former college/university classmates are very imprecise, and no clear result arises.

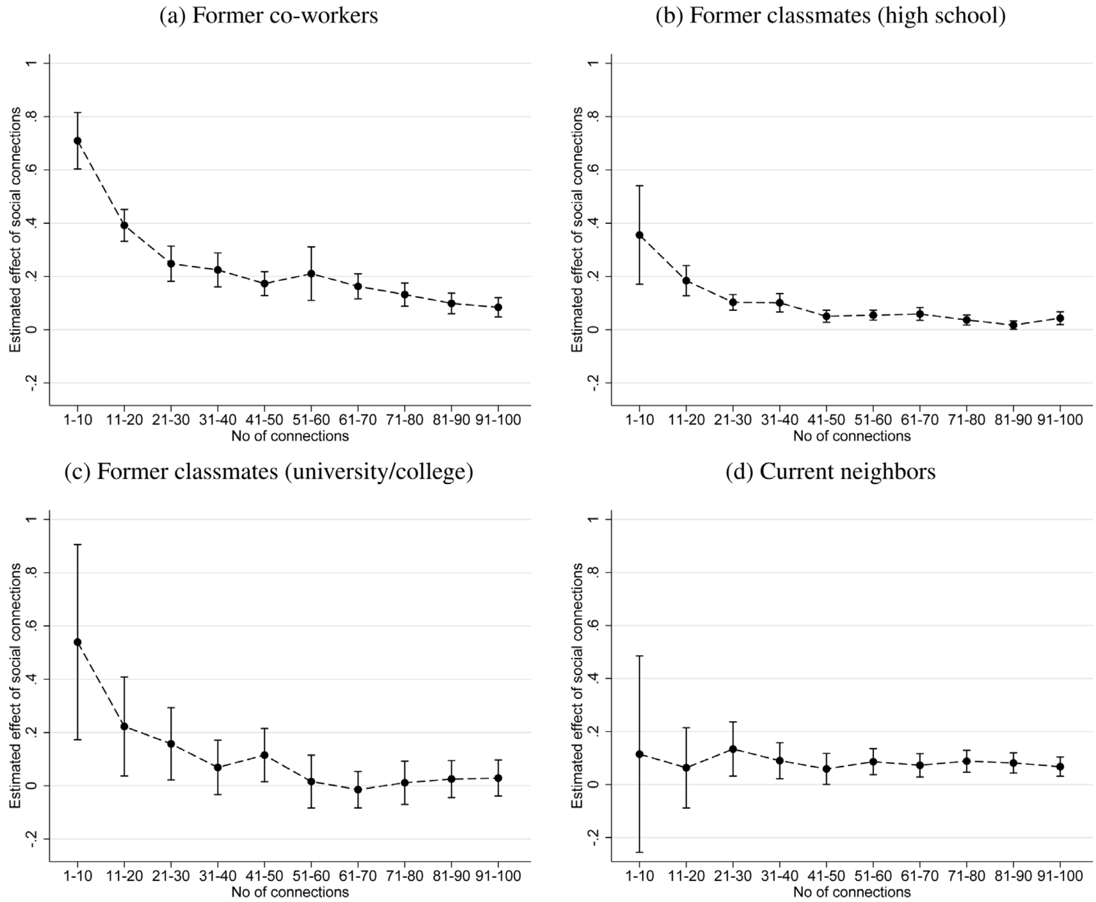


Fig. 11. The estimated impact of a connection on the hiring probability, by the size of the particular network (i.e., the workplace, class, or neighborhood), with 95 percent confidence intervals, for former co-workers, former classmates (high school and college/university), and current neighbors. *Notes:* 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.

Overall, our results show a consistent positive relationship between social proximity and the magnitude of our estimated causal effects. 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 as well as with the similarity of the connected agents.

6.2. Competing connections and their quality

The results from the previous Section demonstrate that connections are useful for establishments in their hiring process. If connections indeed matter, then a "better" connection should be more useful than a worse one. In addition, if connections matter and multiple connections coexist, they may affect each other.

Indeed, establishments may face a "choice" between multiple connected workers and therefore may 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 analyze what happens when multiple displaced workers are connected to the same establishment. We test two aspects of these competition effects: (i) when competing connections co-exist, and (ii) when the relative quality of these competing connections differ.

If an establishment is connected to several displaced workers through its employees, competition should reduce the probability that a given connection results in a hire. To test this hypothesis, we estimate the following extension of our

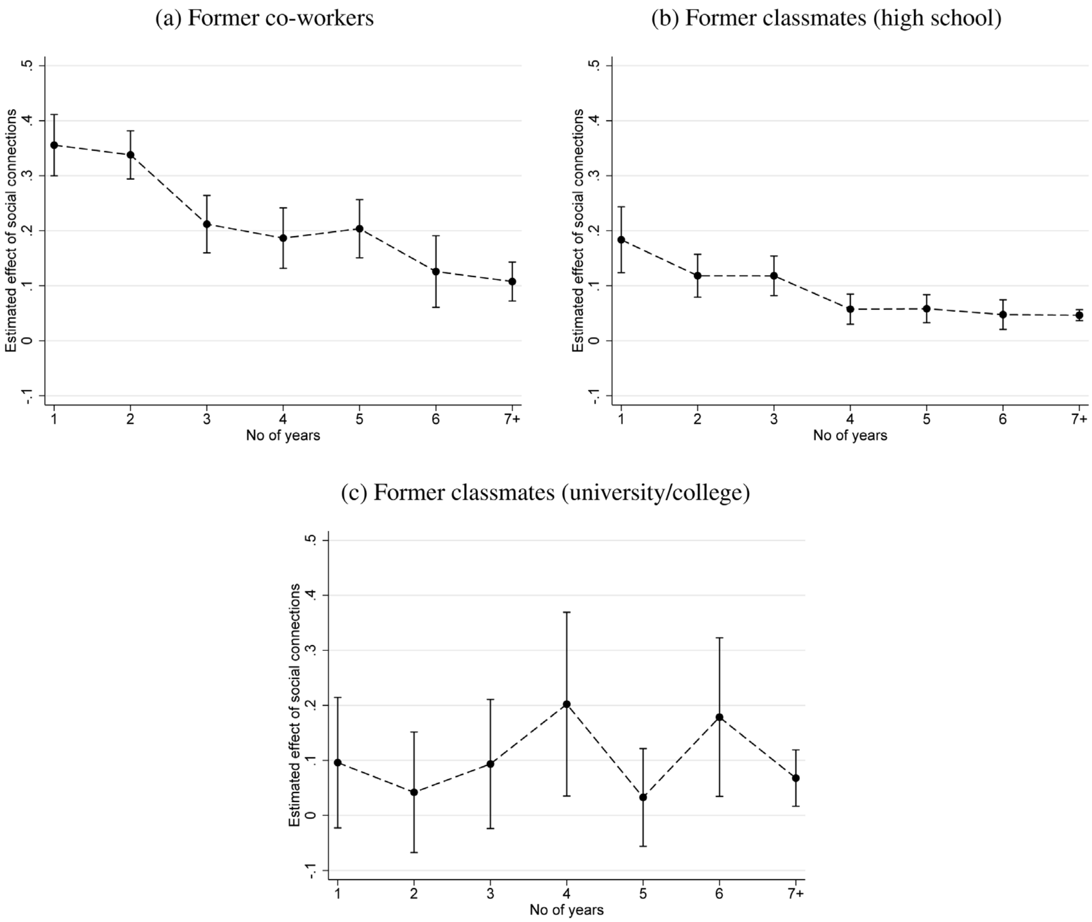


Fig. 12. The estimated impact of a connection on the hiring probability, by time since interaction, with 95 percent confidence intervals, for former co-workers and former classmates (high school and college/university). *Notes:* All estimates are obtained from the same estimation, where the indicator 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.

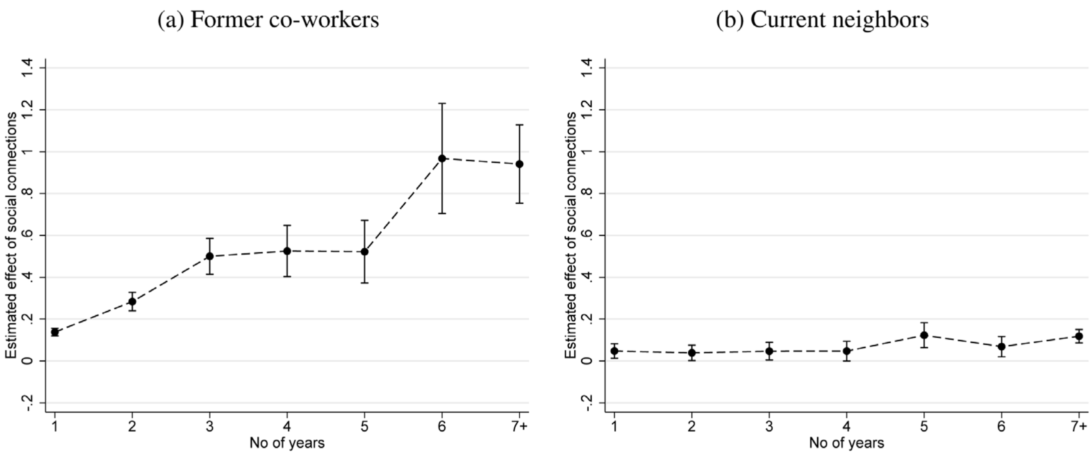


Fig. 13. The estimated impact of a connection on the hiring probability, by interaction time, with 95 percent confidence intervals, for former co-workers and current neighbors. *Notes:* All estimates are obtained from the same estimation, where the indicator for the particular connection has been replaced 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.

Table 9
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 (C)	0.2513	(0.0093)	0.2127	(0.0069)	0.1628	(0.0059)
C × Competing Connection (CC)	−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 (C)	0.2604	(0.0098)	0.2112	(0.0069)	0.1562	(0.0059)
C × CC	−0.0196	(0.0220)	−0.0568	(0.0213)	−0.0573	(0.0229)
C × Higher CC Quality	−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 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. "Higher Competing Connection Quality" (HCCQ) 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., $HCCQ_{ik} = I[\theta_{l(\tilde{i},k)}] > \theta_{l(k,i)}$ for some $\tilde{i}$ who is displaced in the same year as i with a connection to k).

main model:

$$H_{ijk} = \alpha_{jk} + X_{ik}\beta + \gamma C_{ijk} + \lambda C_{ijk}B_k + \varepsilon_{ijk}, \tag{11}$$

where B_k is an indicator for multiple connections of displaced workers to k in the same year.[40] The results are presented in Panel A of Table 9. 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. Results are similar if we instead use the number of competitors or the number of competitors as a share of all incumbent employees as our competition measure. We show separate estimates depending on whether the connected establishment (k) is low, middle, or high ψ_k. 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.

If an establishment is connected to several displaced workers through different employees, the relative quality of these competing connections should affect who will be hired. Previous studies that have investigated the role of network quality for the re-employment 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 using a direct measure of the quality of the network as provided by the estimated person effects of these intermediary workers (θ_l). Hence, Panel B presents results from an extended version of Eq. (11) that includes 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 coming from better-connected workers reduces the predictive hiring power of a worker's social connection.[41] 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.[42]

7. 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.

40 The year aspect does not matter in other parts of our analysis as displacements jk by definition are year-specific.

41 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.

42 Thus, connected workers are not crowded out (more) if competing connected workers are of "better" quality. This result is reasonable in light of our main analysis which suggested that "better" and "worse" workers are equally likely to be hired by the connected establishment, see Fig. 3.

In this paper, we assess this presumption in the context of sorting inequality. To do so, we document the 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 setting. Our analyses rely on establishment closures as exogenous events forcing workers to search for new jobs, allowing us to compare the re-employment outcomes of workers who lost their jobs in the same closure event, and to document to what extent social connections affect where these workers are rehired.

We use estimates from an AKM-decomposition to characterize workers and employers quality in terms of earnings capacities and discern to what extent connections affect the sorting between workers and employers. We first show that connections exhibit baseline homophily, i.e. high-wage workers are connected to other high-wage workers, and (to a lesser extent) also to high-wage employers. This is particularly true for professional networks such as past co-workers or classmates from university, but less so for family connections.

Next, we show that all our measured social connections predict post-displacement hiring patterns. To assess the causal interpretation of this finding, we perform various robustness checks. In particular, we use variation in network structure between events for the sample of repeatedly displaced workers to show that our results are unlikely to arise because the job searcher and her "friend" have shared preferences for the same employer.

The impact is largest if the social connection to an establishment is made through a family member, followed by connections through a past co-worker. Co-worker contacts are particularly useful if both worked together relatively recently (i.e., the value of the connection seems to depreciate fairly rapidly). Each former classmate and current neighbor (with children the same age) matter as well, but less than a family member or a co-worker. More generally, we show a consistent positive relationship between social proximity and intensity of the connection on one part and the magnitudes of the estimated causal effects on the other: 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 support the presumption that measured social connections only affect hiring probabilities if social interactions are strong.

We also consistently show that social connections have a larger causal impact on hiring when the demand side is a 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. This is true both for low-wage and high-wage workers. As a consequence, low-wage establishments are able to attract high-wage workers through social connections.

We find negative effects of connections on entry wages, partly because connections are used more intensively by low-wage employers. We also show that connected workers' wages vary as much with the type of employer as does the wages of market hires. Benefits of connections on the worker side arise mostly through increased job stability.

Overall, we find that hiring through social connections is associated with *less* sorting than market matches, despite of the clear baseline 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 job-to-job hires.

These novel empirical regularities stand in sharp contrast to a standard presumption shared between the theoretical literature on social networks in economics and sociology discussed in the introduction. Although social networks may generate inequality of opportunities, in particular because of their strong homophily, our results clearly show that such inequality does not imply that allocations through social networks lead to more inequality than allocations through market mechanisms.

Acknowledgments

We are grateful for very helpful comments from two anonymous referees, from David Card, the invited editor, as well as from Pierre Cahuc, François Fontaine, Giuseppe Moscarini, Rafael Lalive, Xavier D'Haultfoeuille, Magne Mogstad, and seminar audiences at Yale, LSE, Lausanne, Mainz, Oslo, IFN, CREST, SOLE 2014, ESSLE 2013, SOFI, EEG-NIPE, Århus, Uppsala University, SSE, 9th Nordic Workshop on Register Data and Economic Modelling, Annual Symposium in LE (Rome 2019), the Warwick Labour Workshop, and the Models of Linked employer–employee Data conference (NY, 2019).

Funding

Kramarz and Skans acknowledge funding from the ERC advanced grant FIRMNET (project ID 741467). Hensvik and Skans acknowledge funding from the Ragnar Söderberg foundation, Sweden.

Appendix A. Further descriptive statistics

See Fig. A.1 and Table A.1.

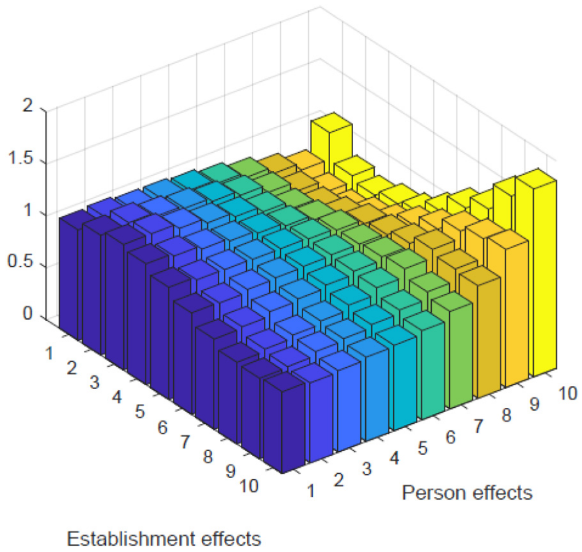


Fig. A.1. Joint distribution of AKM person and establishment effects in the sample of all new hires.

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)		Dyads of displaced workers (i) and potential hiring establishments (k)	
	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[a]						
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	

[a]Productivity is only available for a subsample of all establishments.

Appendix B. Further results

See Figs. B.1–B.8, Tables B.1 and B.2.

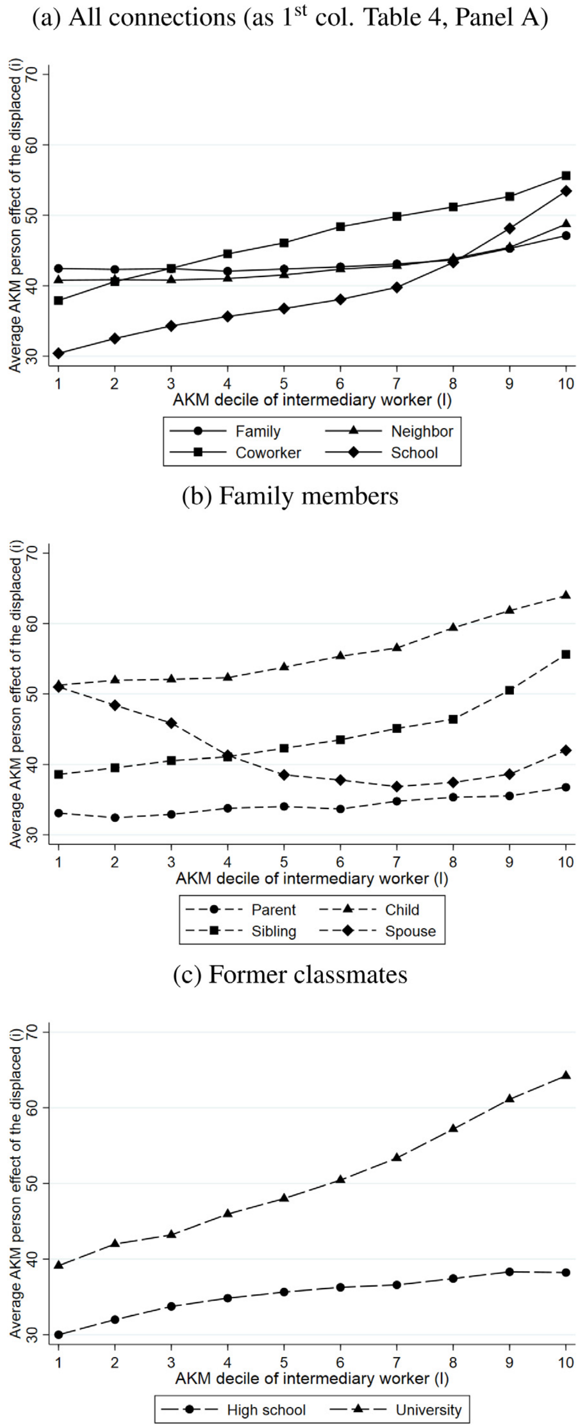


Fig. B.1. Mean residualized person effects ($\hat{\theta}_i$) percentile of displaced workers (y-axis) by decile of residualized person effects ($\hat{\theta}_l \mid C_{il} = 1$) of connected intermediary workers.

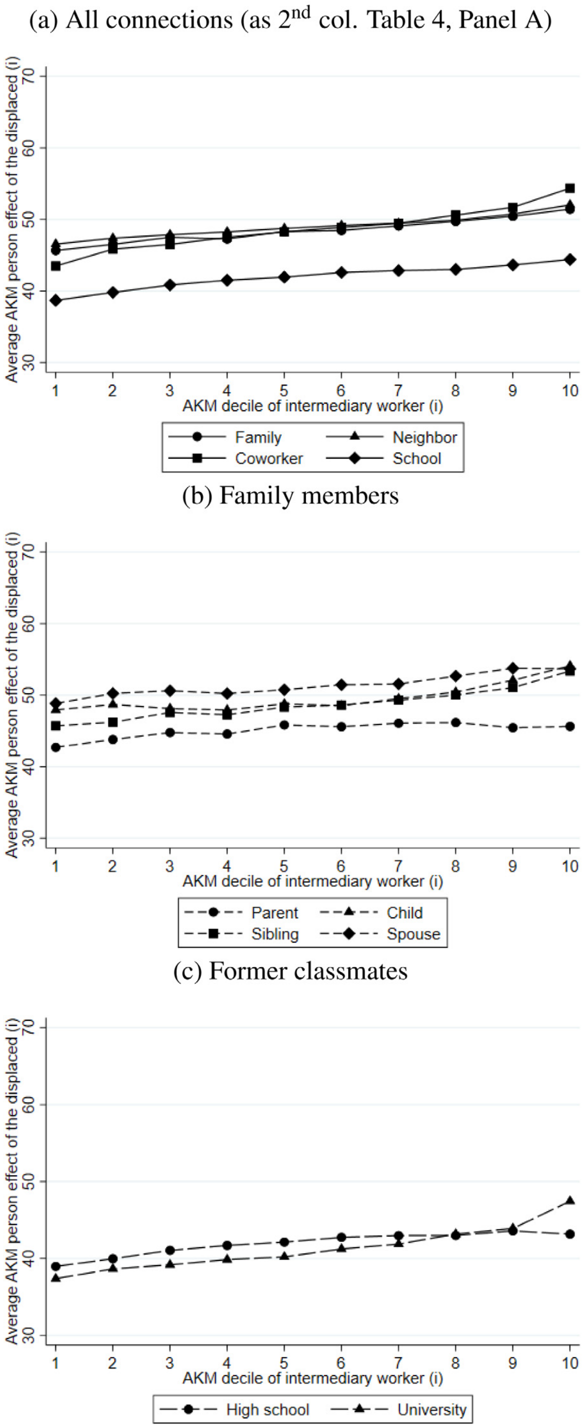


Fig. B.2. Mean residualized person effects ($\hat{\theta}_i$) percentile of displaced workers (y-axis) by decile of residualized person effects ($\hat{\theta}_l \mid C_{il} = 1$) of connected intermediary workers.

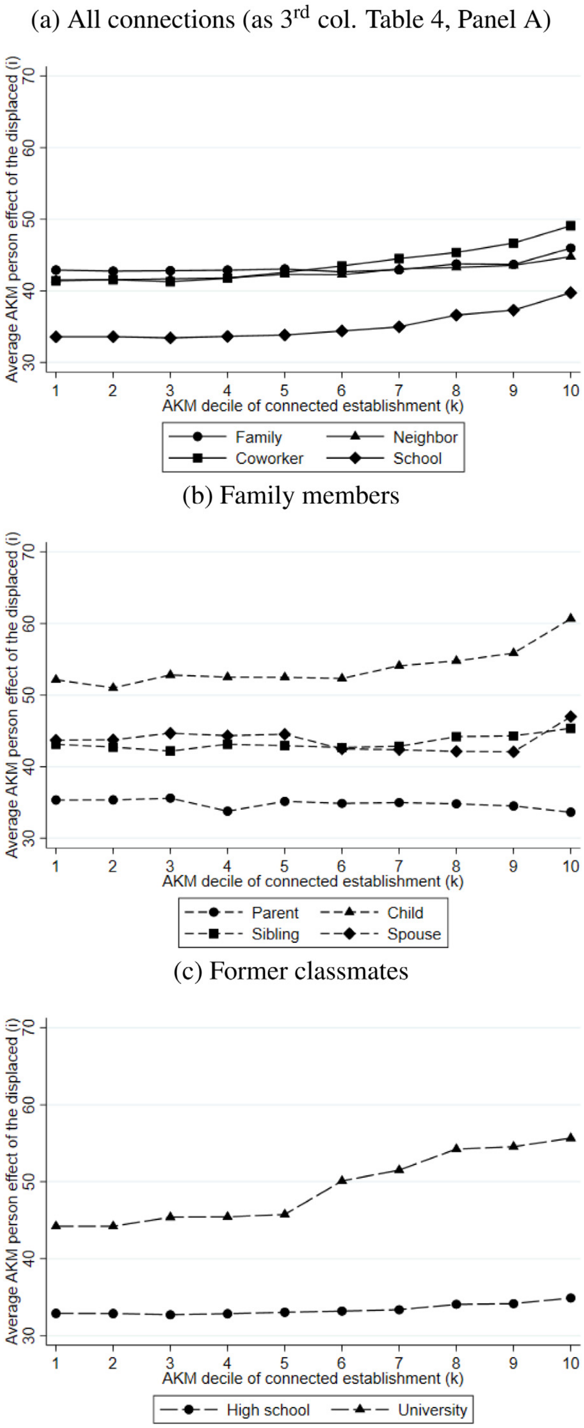


Fig. B.3. Mean person effects (θ_i) percentile of displaced workers (y-axis) by decile of establishments effects of connected establishments ($\psi_k \mid C_{ik} = 1$).

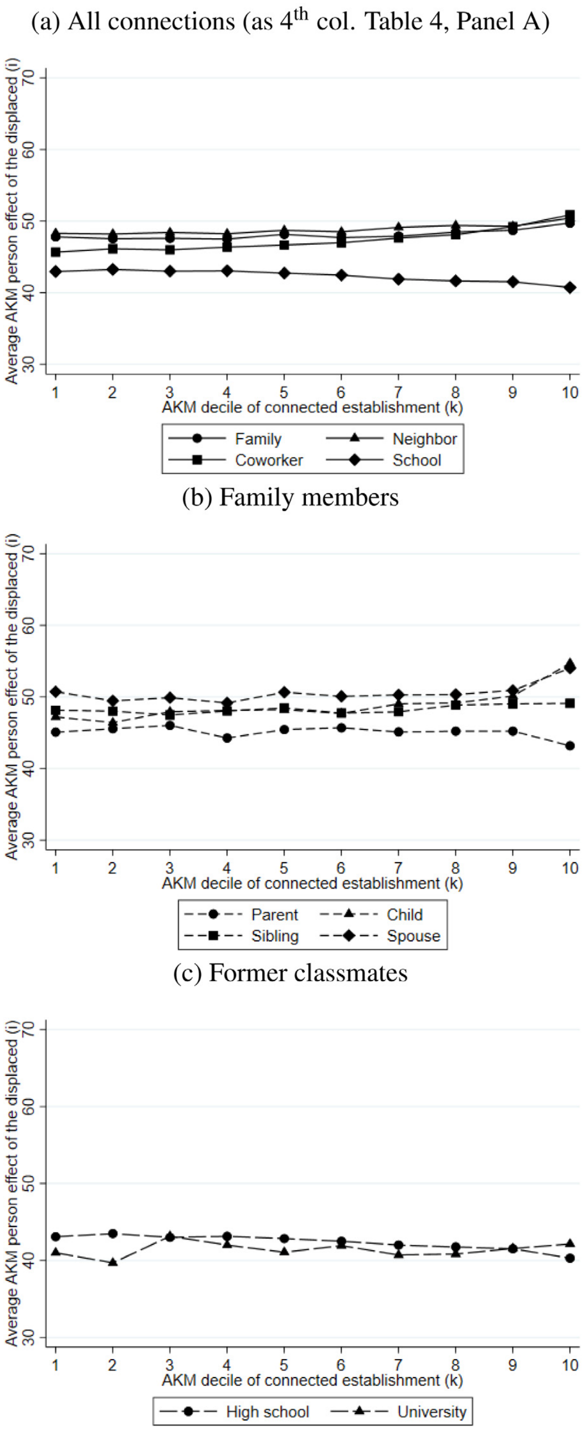


Fig. B.4. Mean residualized person effects ($\hat{\theta}_i$) percentile of displaced workers (y-axis) by decile of establishments effects ($\psi_k \mid C_{ik} = 1$) of connected establishments.

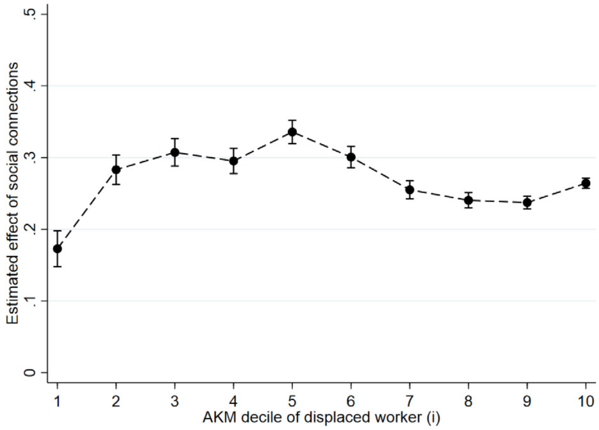


Fig. B.5. Estimated effects of social connections, by residualized AKM person effects deciles. *Notes:* The figure repeats Fig. 5 with the one difference that the AKM person effects of the displaced worker (i) have been residualized from age at displacement, education level and gender.

Table B.1
Sensitivity analysis; controls and samples.

	Main model[a]		Excl. self-employed intermediary workers[b]		Incl. worker characteristics[c]		Incl. worker char. and AKM controls[d]		Closure size < 10		At most one connection per worker and potential hiring establishment	
	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)	Coef.	(s.e.)
Panel A:												
Any connection	0.270	(0.005)	0.265	(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	(0.000)	0.028	(0.001)	0.029	(0.001)	0.065	(0.005)	0.017	(0.000)
Panel B:												
Family member	1.095	(0.020)	1.111	(0.021)	1.095	(0.020)	1.070	(0.038)	1.376	(0.049)	0.908	(0.019)
Former co-worker	0.253	(0.010)	0.256	(0.010)	0.253	(0.010)	0.252	(0.028)	0.304	(0.020)	0.149	(0.007)
Former classmate	0.066	(0.004)	0.066	(0.004)	0.066	(0.004)	0.068	(0.002)	0.064	(0.010)	0.038	(0.003)
Current neighbor	0.086	(0.008)	0.086	(0.009)	0.085	(0.008)	0.086	(0.004)	0.111	(0.028)	0.041	(0.006)
Constant	0.027	(0.000)	0.028	(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)	1.835	(0.053)	1.866	(0.052)	1.810	(0.077)	2.414	(0.125)	1.513	(0.050)
Adult child	0.670	(0.051)	0.675	(0.053)	0.672	(0.051)	0.655	(0.011)	0.760	(0.135)	0.528	(0.046)
Spouse	1.974	(0.078)	2.188	(0.086)	1.974	(0.078)	1.925	(0.011)	2.612	(0.210)	1.828	(0.080)
Sibling	0.697	(0.023)	0.702	(0.024)	0.697	(0.023)	0.693	(0.005)	0.881	(0.054)	0.524	(0.020)
Former co-worker	0.252	(0.010)	0.255	(0.010)	0.252	(0.010)	0.251	(0.003)	0.302	(0.020)	0.149	(0.007)
Former classmate												
High school	0.064	(0.004)	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)	0.080	(0.018)	0.088	(0.018)	0.086	(0.009)	0.096	(0.065)	0.042	(0.012)
Current neighbor	0.080	(0.008)	0.081	(0.009)	0.080	(0.008)	0.081	(0.004)	0.100	(0.028)	0.040	(0.006)
Constant	0.026	(0.000)	0.027	(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		2,067,009		2,087,560		2,087,560		852,619		1,923,085	
No of observations	41,111,774		37,838,199		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]Excludes the possibility that the intermediary worker is the firm-owner.

[c]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).

[d]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.

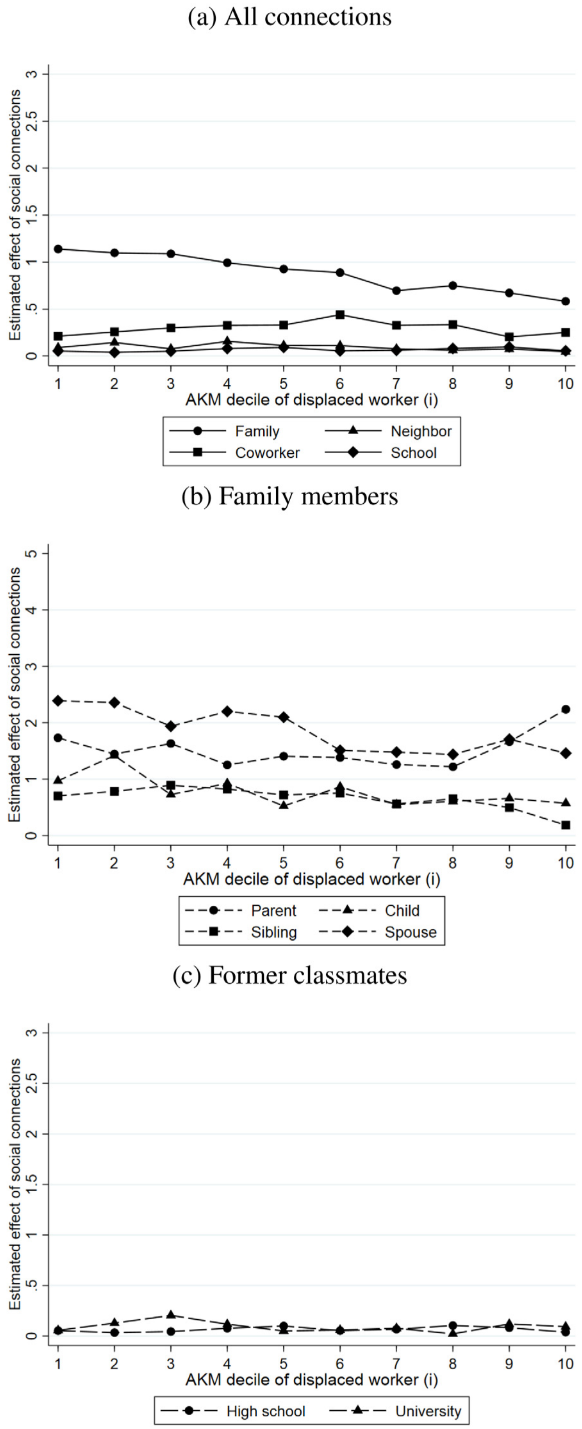


Fig. B.6. Estimated effect of social connections by AKM effect (θ_i) decile of displaced worker i. *Note:* For coefficients and standard errors of the linear slopes, see Table B.3.

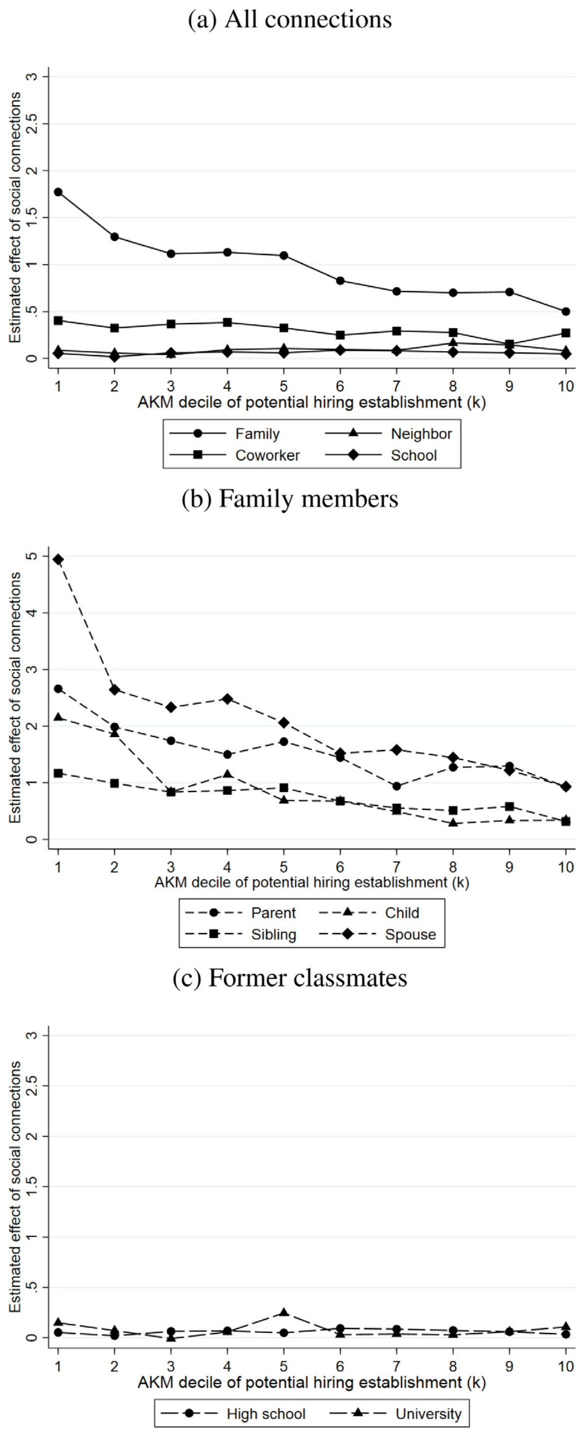


Fig. B.7. Estimated effect of social connections by AKM effect (ψ_k) deciles of potential hiring establishment k. *Note:* For coefficients and standard errors of the linear slopes, see Table B.3.

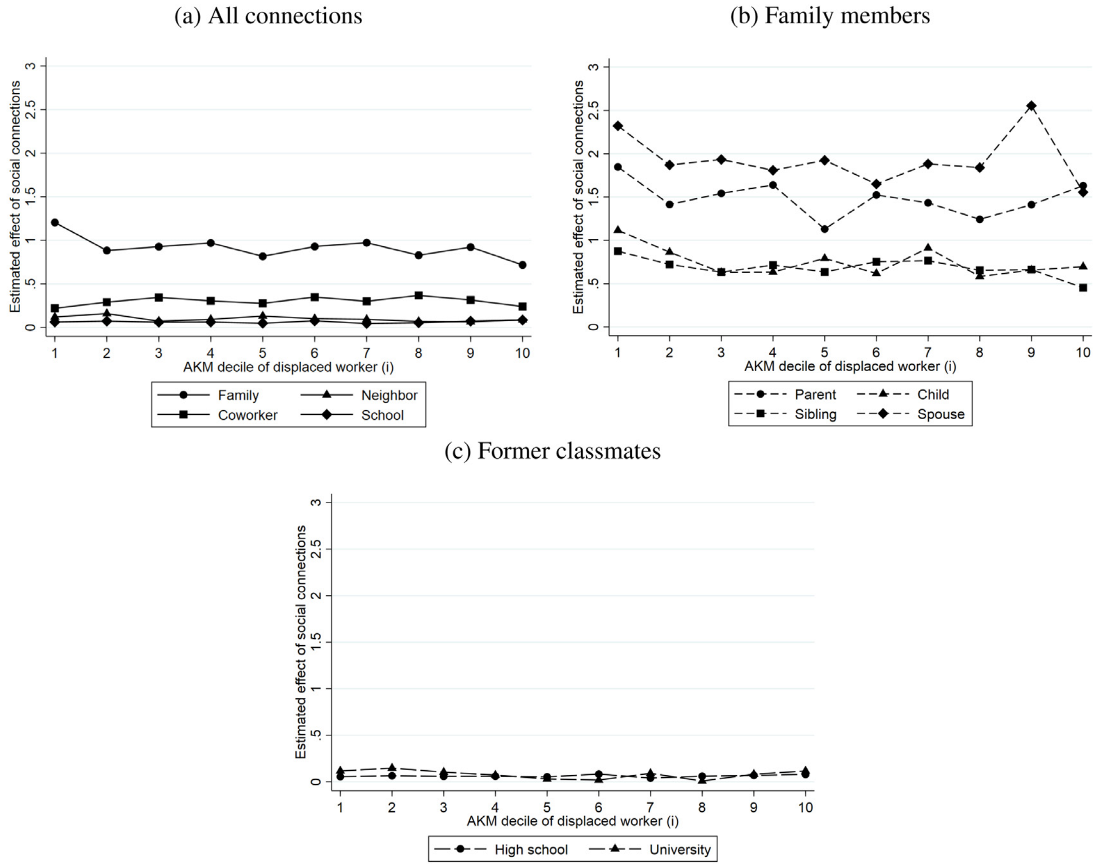


Fig. B.8. Estimated effect of social connections by residualized AKM effect ($\hat{\theta}_i$) decile of displaced worker (i). *Notes:* The figure repeats Fig. B.6 with the one difference that the AKM person effects of the displaced worker (i) have been residualized from age at displacement, education level and gender. For coefficients and standard errors of the linear slopes, see Table B.3.

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

	k-establishment size (employees)				Industry (2 digits)				Productivity					
	1–9		10+		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.)
Panel A														
Any connection	0.368	(0.010)	0.241	(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)	0.162	(0.002)	0.015	(0.000)	0.023	(0.001)	0.020	(0.001)	0.020	(0.001)
Panel B														
Family member	1.814	(0.054)	0.896	(0.021)	3.034	(0.132)	0.948	(0.020)	1.570	(0.089)	1.182	(0.057)	0.966	(0.047)
Former co-worker	0.284	(0.018)	0.242	(0.012)	0.545	(0.040)	0.182	(0.008)	0.279	(0.029)	0.223	(0.021)	0.183	(0.020)
Former classmate	0.033	(0.005)	0.074	(0.005)	0.153	(0.023)	0.056	(0.004)	0.055	(0.013)	0.074	(0.009)	0.074	(0.009)
Current neighbor	0.060	(0.013)	0.094	(0.010)	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)	0.161	(0.002)	0.015	(0.000)	0.024	(0.001)	0.020	(0.001)	0.021	(0.001)
Panel C														
Family member														
Parent	2.840	(0.127)	1.560	(0.055)	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)	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)	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)	2.146	(0.154)	0.583	(0.022)	1.077	(0.103)	0.771	(0.066)	0.717	(0.058)
Former co-worker	0.280	(0.018)	0.242	(0.012)	0.544	(0.040)	0.181	(0.008)	0.278	(0.029)	0.223	(0.021)	0.183	(0.020)
Former classmate														
High school	0.035	(0.006)	0.072	(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)	0.146	(0.066)	0.078	(0.018)	0.090	(0.091)	0.098	(0.041)	0.099	(0.033)

(*continued on next page*)

Table B.2 (*continued*).

	k-establishment size (employees)				Industry (2 digits)				Productivity					
	1–9		10+		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.)
Current neighbor	0.053	(0.013)	0.089	(0.010)	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)	0.160	(0.002)	0.015	(0.000)	0.023	(0.001)	0.020	(0.001)	0.020	(0.001)
No of fixed-effects	501,117		1,586,443		225,541		1,862,019		196,128		328,600		409,768	
No of observations	10,161,663		30,950,111		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.1. Estimates related to results presented in graphs

See Tables B.3 and B.4.

Table B.3
Linear slope coefficients for Figs. B.6, B.8, 4 and B.7.

	Fig. B.6		Fig. B.8		Fig. 4/B.7	
	Coef.	(s.e)	Coef.	(s.e)	Coef.	(s.e)
Panel A: All connections:						
Family member	−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 classmate	0.004	(0.002)	−0.000	(0.002)	0.002	(0.001)
Current neighbor	−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 at displacement, 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 Figs. B.6, B.8, and B.7. 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.4
Estimates underlying Figs. 7 and 9.

	Fig. 7[a]		Fig. 9[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)		

(*continued on next page*)

Table B.4 (*continued*).

	Fig. 7[a]		Fig. 9[b]	
	Coef.	(s.e.)	Coef.	(s.e.)
(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 Eq. (4), 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 is shown in Fig. 7 in the main text.

[b]The column displays the estimates from Eq. (7), 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.

B.2. Sorting patterns when including post-hire data in the estimation of AKM person effects (related to Fig. 10)

See Fig. B.9.

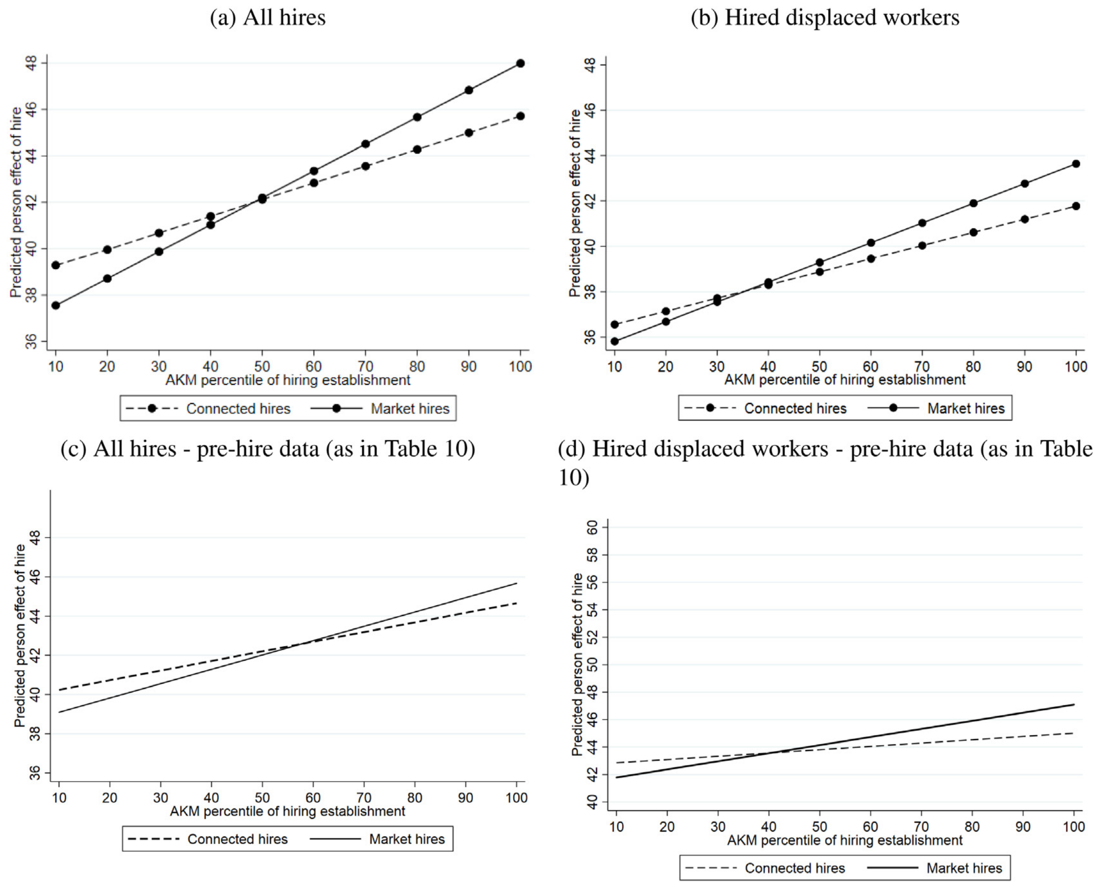


Fig. B.9. Predicted person effect of new hire as a function of hiring establishment effects and the use of social connections. *Notes:* Figures a and b are the same as linear versions of Fig. 10 with the only difference that the person effects estimated in the pre-displacement period have been replaced with person effects using the entire data. Figures c and d show the linear versions of Fig. 10 for comparison. We have added the mean person effect within each sample.

References

Abowd, J.M., Kramarz, F., Margolis, D.N., 1999. High wage workers and high wage firms. Econometrica 67 (2), 251–333.

Abowd, J.M., McKinney, K.L., Schmutte, I.M., 2019. Modeling endogenous mobility in earnings determination. J. Bus. Econom. Statist. (3), 405–418.

Andrews, M.J., Gill, L., Schank, T., R., U., 2008. High wage workers and low wage firms: Negative assortative matching or limited mobility bias? J. Roy. Statist. Soc. Ser. A 171 (3), 673–697.

Barth, E., Bryson, A., Davis, J., Freeman, R., 2016. It's where you work: Increases in the dispersion of earnings across establishments and individuals in the United States. J. Labor Econ. 34, S67–S97.

Bayer, P., Ross, S.L., Topa, G., 2008. Place of work and place of residence: Informal hiring networks and labor market outcomes. J. Polit. Econ. 116 (6), 1150–1196.

Bonhomme, S., Lamadon, T., Manresa, E., 2019. A distributional framework for matched employer-employee data. Econometrica 81, 699–739.

Boorman, S.A., 1975. A combinatiorial optimization model for transmission of job information through contact networks. Bell J. Econ. 6 (1), 216–249.

Brown, M., Setren, E., Topa, G., 2016. Do informal referrals lead to better matches? Evidence from a firm's employee referral system. J. Labor Econ. 34 (1), 161–209.

Burks, S.V., Cowgill, B., Hoffman, M., Housman, M., 2015. The value of hiring through employee referrals. Q. J. Econ. 130 (2), 805–839.

Calvó-Armengol, A., Jackson, M.O., 2004. The effects of social networks on employment and inequality. Am. Econ. Rev. 94 (3), 426–454.

Calvó-Armengol, A., Jackson, M.O., 2007. Networks in labor markets: Wage and employment dynamics and inequality. J. Econom. Theory 132 (1), 27–46.

Calvó-Armengol, A., Verdier, T., Zenou, Y., 2007. Strong and weak ties in employment and crime. J. Public Econ. 91 (1), 203–233.

Card, D., Cardoso, A.R., Kline, P., 2016. Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women. Q. J. Econ. 131 (2), 633–686.

Card, D., Cardoso, A.R., Heining, J., Kline, P., 2018. Firms and labor market inequality: Evidence and some theory. J. Labor Econ. 36 (S1), S13–S70.

Card, D., Heining, J., Kline, P., 2013. Workplace heterogeneity and the rise of West German wage inequality. Q. J. Econ. 128 (3), 967–1015.

Carlsson, M., Messina, J., Skans, O.N., 2016. Wage adjustment and productivity shocks. Econ. J. 126 (595), 1739–1773.

Casella, A., Hanaki, N., 2006. Why personal ties cannot be bought. Am. Econ. Rev. 96 (2), 261–264.

Cingano, F., Rosolia, A., 2012. People I know: Job search and social networks. J. Labor Econ. 30 (2), 291–332.

Davis, S.J., von Wachter, T., 2011. Recessions and the costs of job loss. Brook. Pap. Econ. Act..

Dustmann, C., Glitz, A., Schönberg, U., Brücker, H., 2016. Referral-based job search networks. Rev. Econom. Stud. 83 (2), 514–546.

Eliason, M., Hensvik, L., Kramarz, F., Skans, O.N., 2019a. The Causal Effects of Social Connections of Firms' Performance. Mimeo, Uppsala Universitet.

Eliason, M., Hensvik, L., Kramarz, F., Skans, O.N., 2019b. Social Connections and the Sorting of Workers to Firms. Discussion Paper 12323, IZA.

Eliason, M., Storrie, D., 2006. Lasting or latent scars? Swedish evidence on the long-term effects of job displacement. J. Labor Econ. 24 (4), 831–856.

Galenianos, M., 2013. Learning about match quality and the use of referrals. Rev. Econ. Dyn. 16 (4), 668–690.

Gee, L., Jones, J., Burke, M., 2017. Social networks and labor markets: How strong ties relate to job finding on facebook's social network. J. Labor Econ. 35, 485–518.

Glitz, A., 2017. Coworker networks in the labour market. Labour Econ. 44, 218–230.

Granovetter, M.S., 1973. The strength of weak ties. Am. J. Sociol. 78 (6), 1360–1380.

Heath, R., 2018. Why do firms hire using referrals? Evidence from Bangladeshi garment factories. J. Polit. Econ. 126 (4), 1691–1746.

Hensvik, L., Muller, D., Skans, O.N., 2017. Connecting The Young: High School Graduates' Matching to First Jobs in Booms and Great Recessions. Working Paper 2017:2, IFAU.

Hensvik, L., Skans, O.N., 2016. Social networks, employee selection, and labor market outcomes. J. Labor Econ. 34 (4), 825–867.

Ioannides, Y.M., Datcher Loury, L., 2004. Job information networks, neighborhood effects, and inequality. J. Econ. Lit. 42 (4), 1056–1093.

Jacobson, L.S., LaLonde, R., Sullivan, D., 1993. Earnings losses of displaced workers. Amer. Econ. Rev. 83 (4), 685–709.

Kline, P., Saggio, R., Solvsten, M., 2020. Leave-out estimation of variance components. Econometrica 88, 1859–1898.

Kramarz, F., Skans, O.N., 2014. When strong ties are strong: Networks and youth labour market entry. Rev. Econom. Stud. 81 (3), 1164–1200.

Kramarz, F., Thesmar, D., 2013. Social networks in the boardroom. J. Eur. Econom. Assoc. 11 (4), 780–807.

Montgomery, J.D., 1991. Social networks and labor-market outcomes: Toward an economic analysis. Am. Econ. Rev. 81 (5), 1408–1418.

Postel-Vinay, F., Robin, J.-M., 2002. Equilibrium wage dispersion with worker and employer heterogeneity. Econometrica 70 (6), 2295–2350.

Saygin, P., Weber, A., Weynandt, M., 2019. Coworkers, networks, and job search outcomes among displaced workers. Ind. Labor Relat. Rev..

Schmutte, I.M., 2015. Job referral networks and the determination of earnings in local labor markets. J. Labor Econ. 33 (1), 1–32.

Simon, C.J., Warner, J.T., 1992. Matchmaker, matchmaker: The effect of old boy networks on job match quality, earnings, and tenure. J. Labor Econ. 10 (3), 306–330.

Song, J., Price, D.J., Guvenen, F., Bloom, N., Von Wachter, T., 2019. Firming up inequality. Q. J. Econ. 134 (1), 1–50.