Journal of Economic Geography (2022) **00**, 1–25 https://doi.org/10.1093/jeg/lbac019

How to enter high-opportunity places? The role of social contacts for residential mobility

Virág Ilyés *,**, *István Boza* ***, *László Lőrincz* *,**
Rikard H. Eriksson ****,*****,†

*Laboratory for Networks, Technology & Innovation, Corvinus University of Budapest, Budapest, Hungary
**Agglomeration and Social Networks Lendület Research Group, Centre for Economic and Regional Studies (KRTK), Budapest, Hungary
***Centre for Economic and Regional Studies (KRTK), Budapest, Hungary
****Department of Geography, Umeå University, Umeå, Sweden
*****Center for Regional Science, Umeå University, Umeå, Sweden
†Correspondence to: *rikard.eriksson@umu.se*

Abstract

The aim of this article is to analyze the contribution of social ties to moving to high-opportunity locations and assess whether their effect is more pronounced for low-income individuals as a compensation for economic resources. This is done by utilizing Swedish administrative data and by focusing on a wide range of relationships (observed directly or inferred from the data): close and distant family ties, former co-workers and university peers. For estimating the effect of social ties, we use linear probability models, where observed migration is regressed on individual-specific and target-specific characteristics. To account for the nonrandom sorting of movers between locations, we apply sending municipality–target municipality–occupation fixed effects. Our results suggest that there is a positive relationship between migration and the presence of links at given targets for all the examined contact types. The effects are even stronger if the targets are hard-to-reach municipalities (located in Stockholm County or a municipality with higher housing prices). We also demonstrate that, when moving to such opportunity-rich areas, ties to former co-workers and university peers are even more essential assets for those with limited resources. Furthermore, we show that direct help with housing through contacts is an existing factor that contributes to the effect of social networks on residential mobility. The results reinforce the idea that social ties may be of great help in reducing barriers to mobility and can be used to compensate for limited economic resources. We demonstrate the validity of our fixed-effect estimation strategy using a placebo contact approach.

JEL classifications: J61, R23, L14
Keywords: Residential mobility, migration, social networks, Sweden, housing
Date submitted: 18 November 2021 **Editorial decision:** 2 June 2022 **Date Accepted:** 15 June 2022

1. Introduction

Increasing regional divergence in wages and labor market participation has been observed throughout the Western world. Although this divergence is rooted in a complex combination of technology-driven structural change, expansion of world trade and spatially selective concentration of new high-skilled and high-paid jobs in urban agglomerations

(Iammarino et al., 2019), different frictions regarding inter-regional mobility are often highlighted as an important factor for this new spatial divergence of economic opportunity. Previous evidence suggests that even skilled workers increasingly face difficulties entering high-opportunity regions (Storper, 2018), despite the perceived benefits of such mobility (De la Roca and Puga, 2017; Autor, 2020). Accordingly, the constrained access to high-opportunity agglomerations has taken center stage in discussions about future regional renewal and growth (cf. Rodríguez-Pose and Storper, 2020).

Although it is widely accepted that social contacts determine human behavior in a variety of contexts (e.g. Ioannides, 2012) as well as structure mobility decisions (e.g. Büchel et al., 2019), there is a lack of systematic evidence on how different types of contacts influence mobility to high-opportunity places (Storper, 2018). For instance, due to the lack of access to place-specific social networks, which may provide help in finding suitable jobs and entering the housing market, workers in more disadvantaged regions may face increasing difficulties moving to high-opportunity and high-cost regions, irrespective of their skill level (Ganong and Shoag, 2017; Hoxie et al., 2019). Such limits on mobility can, in a longer perspective, reinforce intergenerational transmission of place-specific inequalities (e.g. Chetty et al., 2016; Galster and Sharkey, 2017; Van Ham et al., 2018; Gallagher et al., 2019).

To advance our understanding of factors that can improve chances of moving upward in the regional hierarchy to regions typically considered opportunity-rich areas, the aim of the present article is to analyze the influence of social networks on residential mobility. Using matched employer–employee data for Sweden, an economy characterized by increasing inter-regional differences in economic opportunity (Eurofound, 2019), we investigate to what extent the presence of family ties, former co-workers and university peers at possible target destinations influences the migration decisions of a 10% sample of individuals aged 18–35 years. Specifically, we estimate whether the probability of a move increases due to the presence of social contacts at the target destination, while controlling for employment status and occupation, among other factors. In our empirical setting, social ties are either measured directly (e.g. family relations) or are inferred from the data (university contacts and former co-workers). Apart from assessing the general impact of different types of social contacts, we focus on different scenarios: when the target region is less accessible (e.g. due to higher housing prices) or when individuals are less resourceful in that they have a low income or educational attainment, or both.

While a large body of literature has indeed addressed the role of social networks in mobility, we claim to make two distinct contributions. First, rather than either assessing only the role of friends and neighbors (e.g. Belot and Ermisch, 2009; David et al., 2010) or family members (e.g. Hedman, 2013; Spring et al., 2017; Gallagher et al., 2019; Mulder et al., 2020), we analyze the role of various network segments (namely family, former co-workers, university peers) in jointly structuring mobility. Our findings suggest that the importance of different types of ties varies considerably by marital status: Movements of couples are mainly influenced by the presence of close family ties, while for one-person households essentially all kinds of contacts matter.

Second, in addition to showing that people are more likely to move to places where they have contacts compared to any other random destination, we also show that the presence of social ties significantly increases the chances of individuals moving to hard-to-reach regions and may be even more essential for those with lower socioeconomic status (SES). Our results suggest that social connections can essentially compensate for limited economic resources and that the lack of appropriate social networks is associated with lower chances of getting into better regions. Thereby, our article addresses calls to detail how incentives other than strict economic ones may channel migration between regions for different groups of workers (cf., Patacchini and Arduini, 2016). Placebo contacts are used to validate our empirical approach.

2. Literature review

There has been a long discussion in the regional sciences on whether migration is ‘the chicken or egg’ of regional development (Muth, 1971). Although migration is often placed in center stage, this debate has long focused on whether jobs follow people or people follow jobs. Contemporary debates revolve around the amenity-driven argument of urban growth (e.g. Florida, 2002; Glaeser et al., 2003) and a more institutional/evolutionary-driven understanding (Storper and Scott, 2009). Empirical evidence strongly supporting either perspective is scarce, but if anything, it seems as people are following the jobs, although demand and supply shocks also explain a considerable part of migration flows (Partridge and Rickman, 2003). Survey data from Sweden suggest a similar tendency, as (skilled) people tend to motivate their choice of moving to an urban center from a job-seeking perspective rather than with access to a wide supply of amenities (Hansen and Niedomysl, 2009). Hence, finding a job and having access to a thick and diversified labor market tend to be the main motivators for the decision underlying residential mobility.

In more recent studies, the focus has shifted somewhat from various push and pull factors to possession of the resources necessary to move to a high-opportunity region, partially due to the mounting shortage of affordable housing in dense agglomerations. Although the objective of the present article is not to discuss different approaches to housing policy,[1] it is evident that it has become increasingly difficult to enter the so-called escalator regions (Gordon, 2015), as the increased productivity and amenities created by urban density add to the housing costs (Glaeser et al., 2003). The lack of access to affordable housing in opportunity-rich regions (due to the lack of home ownership, booming house prices or longer waiting lists for expensive rentals) can trap people in less-favored regions, and it can also restrict the migration of high-skilled workers, as has been demonstrated for both Spain (De la Roca and Puga, 2017) and Sweden (Bjerke and Mellander, 2019).

Consequently, it is argued that formal skills acquired through education no longer suffice when it comes to succeeding on the labor market (e.g. Storper, 2018). Instead, the role of ‘new economy’ skills, which are often obtained and exercised through social networks, has become more essential. Being at the right place, at the right time, and thereby getting to know the right people, have thus become increasingly important aspects of both finding a job (Patacchini and Zenou, 2012; Barwick et al., 2019) and subsequent career development (De la Roca and Puga, 2017). Accordingly, the presence of former co-workers has been shown to increase the accessible wage of new entrants (Hensvik and Skans, 2016; Boza and Ilyés, 2020; Glitz and Vejlin, 2021), the likelihood of hiring (Saygin et al., 2021) and spatial productivity differences (Eriksson and Lengyel, 2019). The presence of relatives (Kramarz and Skans, 2014), peers from military service (Laschever, 2013), neighbors from the same block (Bayer et al., 2008) and ethnic group membership (Patacchini and Zenou, 2012) is also associated with enhanced hiring

1 See Rodríguez-Pose and Storper (2020) for a detailed discussion.

opportunities and expected wages. Referrals by friends can also facilitate job transitions from rural areas to the city (Barwick et al., 2019). University alumni networks also exert positive labor market effects in relation to gaining access to high-paying jobs (Eliason et al., 2019; Staiger, 2021). Moreover, social networks are influential when making different long-term decisions on, for example, cooperation and the voting behavior of politicians (Battaglini and Patacchini, 2018; Battaglini et al., 2020).

Having network connections in high-opportunity cities[2] may also decrease obstacles to moving there by providing direct and/or indirect assistance with housing. As shown by Büchel et al. (2019), people tend to move to places where they already have many social contacts (based on data on phone calls). Just as in case of international migration (Massey, 1988; Edin et al., 2003; Dekker and Engbersen, 2014), social ties can provide someone with a room in their own apartment, they can utilize their knowledge of the local housing market or they may use their own contacts to present the potential mover with a wider range of options to choose from.

Having social contacts at a destination may also make a move more appealing (Hedman, 2013; Costa et al., 2018), as acquaintances living nearby can provide emotional support and help in everyday life (Mulder and van der Meer, 2009). This is particularly true for family contacts and more typically applies during given life-course events, such as childbirth or divorce (Gillespie and Mulder, 2020). Similarly, aging parents and children are also more likely to move closer (Pettersson and Malmberg, 2009; Spring et al., 2017). However, the presence of relatives and other local ties (such as friends and neighbors) at a given location can also hinder residential mobility owing to the noted support exchange reasons and social obligations (Gallagher et al., 2019). It is also well established that people with more extended local contacts tend to be less mobile (Dawkins, 2006; David et al., 2010; Büchel et al., 2019), although these types of networks typically rebuild after moving (Belot and Ermisch, 2009). Therefore, by having contacts solely in low-opportunity places, individuals face not only restricted network access to high-opportunity areas, but also the binding effect of local social networks.

3. Empirical strategy

Social ties can alter an individual's movement decision in two different ways. First, they can affect the decision to migrate versus stay at a given residence (the migration decision) and, second, they can shape the moving individuals' location preferences (location decisions). In the literature, there are various strategies for assessing the role of social ties in facilitating movements. Some papers have focused solely on the network effects on residential location choice conditional on moving (e.g. Schmidheiny, 2006), while others have utilized a two-step approach and investigated the effect of contacts on both the migration and location decisions separately (e.g. Büchel et al., 2019). Unlike these scholars, we follow a strategy aimed at capturing the total effect of contacts in one step.[3] The effect we aim to measure is a composite term covering the effect of having social contacts in a given location on the probability of moving (versus staying) and on the probability of

2 As exemplified by Mulder et al. (2020) on Swedish data, relatives (siblings) can increase the likelihood of return migration to large cities.

3 However, to enhance the comparability of our results, in Supplementary Appendix A we assess the magnitude of contact effects on the migration and location choice separately.

choosing that target as the destination location (versus other options) when the migration decision has been already made.

To model the underlying mobility decision of individuals, we start by assuming that movement probabilities can be modeled using a linear equation of the following form:

$$m_{pij,i\neq j} = \beta_0 X_{pij} + \beta_1 \mathbf{LINK}_{pj} + \beta_{ik}\mathrm{PUSH}_{ik(p)} + \beta_{jk}\mathrm{PULL}_{jk(p)} + \beta_{ijk(p)}\mathrm{PATH}_{ijk(p)} + \varepsilon_{pij} \tag{3.1}$$

That is, we assume that the probability of person p moving from location i to a different location j depends not only on person-specific traits (X_{pij}),[4] but also on target-specific *pull* factors ($\mathrm{PULL}_{jk(p)}$), source-specific push factors ($\mathrm{PUSH}_{ik(p)}$), and factors related to given target–source paths ($\mathrm{PATH}_{ijk(p)}$). The general subscript k stands for some group membership of the given individual and is included to allow for distinct mobility patterns of individuals with different characteristics along the same source–target pairs. For instance, the outflow of medical students from cities with such universities is expected to be high after graduation and is more likely directed into targets with large medical centers, while some other cities may attract a disproportionately large share of IT workers.[5] Finally, we assume that the presence of social ties at given destinations (LINK_{pj}) can also exert an important effect on the mobility decision, either through direct channels (such as the provision of housing opportunities) or indirect channels (transmission of target-related information).

If we could properly control for all the above factors, a model of the form of Equation (3.1) could be estimated, in which β_1 would capture the causal effect of social links on movement probabilites.[6] In this case, the measurement of β_1 would be only affected by the measurement errors inherent in observational data. For instance, while the dataset we use allows for directly locating of even distant family members, we can only proxy real co-worker connections and university peers with overlapping employment spells at the same establishments or shared study periods (respectively). Both assuming that someone—for example, a former co-worker—is a social contact of person i, despite not actually being one, and not being able to capture contacts or friendships formed through other channels lead to the parameters of interest being biased toward zero, so the effect of social links will be underestimated. In addition to the measurement error problem, the inability to properly control for all unobservable factors of mobility could introduce other biases into the estimation of our main variable of interest, β_1, due to the possible correlation between the presence of links and the nonrandom mobility patterns of individuals. For instance, if all doctoral graduates move along a specific path, then observing a high probability of such individuals moving to municipalities with their former university peers may be mistakenly considered a causal role of peers.

4 Including individual characteristics (X_p) and person-specific characteristics relating to either the sending or target municipalities (X_{pj}, X_{pi}).

5 Also, unemployed people are more likely to move into deprived neighborhoods than employed people are (Bergström and van Ham, 2010). Similarly, members of the same ethnic group may tend to choose the same targets when choosing residence due to the knowledge and opportunity hoarding that occurs in specific areas as well as due to tight housing markets in opportunity-rich regions (e.g., Edin et al., 2003).

6 The data required to estimate the above model in a regression form have to contain a row for each individual and potential target destination pair, the outcome variable being an indicator of whether an actual move has been realized along the given path by the given individual. This variable can only take the value of 1 for one row per person in the data, while for stayers all rows contain 0 as the outcome.

To overcome this issue of identification, we propose a fixed-effect approach. Specifically, instead of modeling source- and target-dependent push and pull factors, we include fixed effects for the sending municipality–target municipality pairs to capture the baseline movement probability along any given path. Also, we allow these path-specific effects to vary across groups of different individuals by occupation, assuming for instance a different baseline migration probability for doctors and engineers between the two areas. Therefore, the full set of the included fixed effects will absorb path-specific unobserved factors generally, for each observed groups (k), and for potential push and pull effects, removing the bias that would originate from omission of such (partially unobservable) factors. Hence, identification of contact effects will rely on variation in the availability of (different) social contacts at given targets, across similar individuals of specific groups, k, living in the same sending municipalities. Consequently, our identifying assumption is that having a social contact at a given target is (as good as) random, conditional on personal traits, current residence and group membership. In this way, the covariation between contact availability and the observed moves will capture a total causal effect of social contacts, which could still incorporate both direct and indirect help, but not the systematic sorting to geographical units of contacts, driven by other factors. Accordingly, we propose estimation of the following, simple model.

$$m_{pij,\ i\neq j} = \beta_0 X_{pij} + \beta_1 \mathbf{LINK}_{pj} + \delta_{ijk} + \varepsilon_{pij} \tag{3.2}$$

In our empirical application, δ_{ijk} represents sending municipality–target municipality–occupation fixed effects. Therefore, the parameter β_1 will capture how much more likely a person with contacts will be to move to a given destination compared to persons living in the same municipality and working in the same occupation without such contacts.[7] Although we cannot control for all possible confounding traits, such as ethnicity or immigrant status, we believe that accounting for occupation itself allows for an interpretation that is closer to a causal one, with only small caveats. Moreover, after presenting our main results, we demonstrate that the applied fixed-effect approach does indeed take care of most of the sorting problems related to the use of inferred contact proxies (e.g. university peers and co-workers).

Finally, we note that the cases of return migration may represent fundamentally different life situations, which are often associated with the presence of social contacts (e.g. Patacchini and Arduini, 2016). To avoid overestimating and misinterpreting our parameters, we focus solely on movements to new targets that most probably reflect the help of social ties. Accordingly, we modify Equation (3.2) by including an indicator of return migration, PREV_{pj}, in our model and interact this variable with dummies signaling the presence of different types of social contacts. Therefore, the regression model we will estimate will be:

$$m_{pij,\ i\neq j} = \beta_0 X_{pij} + \beta_1 \mathbf{LINK}_{pj} + \beta_2 \mathrm{PREV}_{pj} + \beta_3 \mathrm{PREV}_{pj} \mathbf{LINK}_{pj} + \delta_{ijk} + \varepsilon_{pij} \tag{3.3}$$

In this setup, the vector of β_1 coefficients will show how much the presence of specific contacts increases the probability that person p will move to municipality j, where she has never lived before, while β_3 will capture the additional effects of contacts for cases of return migration.

7 Those who do not work are treated as a separate category and are compared to each other accordingly.

After estimating the baseline model, we turn to the analysis of scenarios in which either the characteristics of the individuals or of the targets constrain movement possibilities. In both cases, we estimate the model described in Equation (3.4), an extended version of Equation (3.3), where the ontact variables are interacted with the indicators of specific constraints ($\tilde{C}_{pij}$).

$$m_{pij,i\neq j} = \beta_0 X_{pij} + \beta_1 \mathbf{LINK}_{pj} + \beta_2 \tilde{C}_{pij} + \beta_3 \tilde{C}_{pij}\mathbf{LINK}_{pj} + \delta_{ijk} + \varepsilon_{pij} \tag{3.4}$$

In this formulation, $\tilde{C}_{pij}$ can represent either individual-specific (C_p), target municipality-specific constraints (C_j), or source–target relation-specific constraints (C_{ij}). In our estimations, the former set of variables includes indicators marking lower-income (below the median wage at municipality i) and lower-education individuals (below tertiary education). C_j covers specific municipality-level characteristics, such as whether municipality j is part of Stockholm County or the standardized value of the level of housing prices. Relative municipality quality measures include whether the average income or the population at j is higher than i.[8] In these models, the coefficient β_1 captures the network effects in nonconstrained scenarios, while β_3 indicates the additional effect in the constrained situations.[9]

Finally, by interacting the indicators of contacts with both individual characteristics and target-specific features, we try to assess whether the lack of appropriate social contacts hinders low SES people from moving to high-opportunity places. To do so, we estimate the following model:

$$\begin{aligned} m_{pij,\, i\neq j} = \; & \beta_0 X_{pij} + \beta_1 \mathbf{LINK}_{pj} + \beta_2 C_p + \beta_3 C_j + \beta_4 C_p \mathbf{LINK}_{pj} + \beta_5 C_j \mathbf{LINK}_{pj} + \beta_6 C_j C_p \\ & + \beta_7 C_j C_p \mathbf{LINK}_{pj} + \delta_{ijk} + \varepsilon_{pij} \end{aligned} \tag{3.5}$$

In this equation, C_j can stand for any of the already introduced target-related constraints, while C_p will cover the indicator of lower-income individuals. The coefficients of interest, β_7, will show whether or not the (presumably) positive effect of contacts on getting into high-opportunity places is higher for lower-income individuals compared to higher-income ones.

4. Data and definitions

The analysis is based on Swedish matched employer–employee data. The dataset follows the entire Swedish population on a yearly basis using anonymized identifiers, linking information from the employment register and the National Tax Authority. It includes detailed information on the personal characteristics (e.g. gender and year of birth) and work histories of the individuals, and it tracks place of residence on the municipality level. Information on educational attainment from graduation registers, family ties from birth records and data on house/apartment ownership are also linked to the dataset.

8 Although we do not discuss its importance, the distance between two municipalities would fall into this category as well.

9 The β_2 parameters corresponding to the target municipality (C_j) and those of the relative characteristics (C_{ij}) will not be identified in the regressions, as these are absorbed by the δ_{ijk} fixed effects.

Because using the whole population would be too computationally difficult, we reduced the size of the estimation sample by focusing on only one calendar year and by applying random sampling. After obtaining information on contacts from the full sample, we drew a 10% sample of those working age individuals who are observed in the dataset during the years 2015 and 2016.[10] In line with our empirical strategy, it was essential to differentiate between movements directed into new places and residences where the individuals have already lived. Therefore, we kept only individuals whose residence history can be observed since their late childhood, which was possible for persons not older than 13 years in 1994.[11] In this way, we restrict the analysis to those who are 18–35 years in 2015. This younger generation is in fact the group that both tends to be most mobile (Lundholm, 2007) and is most often in the greatest need of support from social contacts (e.g. Mulder et al., 2020).

Residential movers are defined as those who changed their municipality of residence from 2015 to 2016.[12] The obtained sample covers 203,375 individuals, among whom 21,526 (10.6%) have actually moved (see Table 1). Of the movers, 28.8% moved back to municipalities where they had formerly lived, while 71.2% moved to new destinations. The average age and income of the movers are slightly lower than those of nonmovers, while the level of their former movement intensity is higher. The proportion of highly educated individuals is greater among movers. In accordance with the literature (e.g. Ermisch and Mulder, 2019), marital status can be considered as an essential determinant of movement probabilities: 11.6% of the singles and 6.2% of individuals in couples (living either in marriage or cohabitation) have actually moved.

The regional distribution of movement probabilities is presented in Figure 1. The left panel shows the probability that someone living in a given municipality in 2015 will move somewhere else in 2016, while the right panel displays the probability that someone will move to a given target municipality from 2015 to 2016.[13] The attractiveness of cities like Stockholm (East), Gothenburg (West) or Malmo (South) is prominent, but university regions, such as Umea and Luleå along the northern coast or Lund nearby Malmo, tend to be major (intermediate) destinations as well (cf., Eriksson and Rodríguez-Pose, 2017). In the north, we can observe large differences between neighboring municipalities regarding out-flows, while in-flows are consistently low.

Combined, Table 1 and Figure 1 reflect the general regional tendencies of migration and opportunity in Sweden. Although they have relatively low rates of inter-regional migration compared to other European countries (Eriksson and Rodríguez-Pose, 2017), people in Sweden aged 20–30 years are highly mobile and have been since the 1960s (Lundholm, 2007). Regional development over the past few decades is also characterized

10 We also re-estimated our main models on 10 non-overlapping 10% random samples of the dataset and found only minor differences in the estimated parameters.

11 We have data on the individuals' residences since 1991, but municipality codes are consistent only from 1994.

12 Sweden consists of 290 municipalities, which can be considered lower-level local government entities. This is the smallest geographical unit we could utilize for identifying residential movements and for following the individuals' place of residence. As an additional set of estimates, we re-calculated our regressions with a mover definition based on functional labor market areas—72 areas in Sweden nesting the municipalities. Despite the increased probability of misclassification of actual contact presence (due to the use of these larger units), the obtained results are in line with the main results.

13 It is not the ratio of newly arrived residents over all residents of the target municipality, but over all residents who did not live in the target municipality in 2015. Therefore, the map of arrivals is smoother, by definition, as there the denominator is always roughly the same (all Swedes minus the population of the target municipality), while for the leaving probability, the denominator depends on the population of the municipality.

Table 1. Individual characteristics and movements

	Nonmover	Mover	All
No. of individuals	181,849	21,526	203,375
Return migration	–	28.8	–
Individual characteristics (%)			
Single	80.2	89.0	81.2
Female	46.0	49.1	46.3
Age	25.8	24.9	25.7
Education (%)			
Unknown	3.8	3.5	3.7
Elementary	15.8	13.4	15.5
Secondary	46.7	42.7	46.3
Tertiary	33.7	40.4	34.4
Log of yearly work income (in 100 SEK)	7.24	7.05	7.22
Av. no. of previous moves (movement intensity)	1.23	1.67	1.29

Note: Based on the 10% sample of individuals born after 1980.

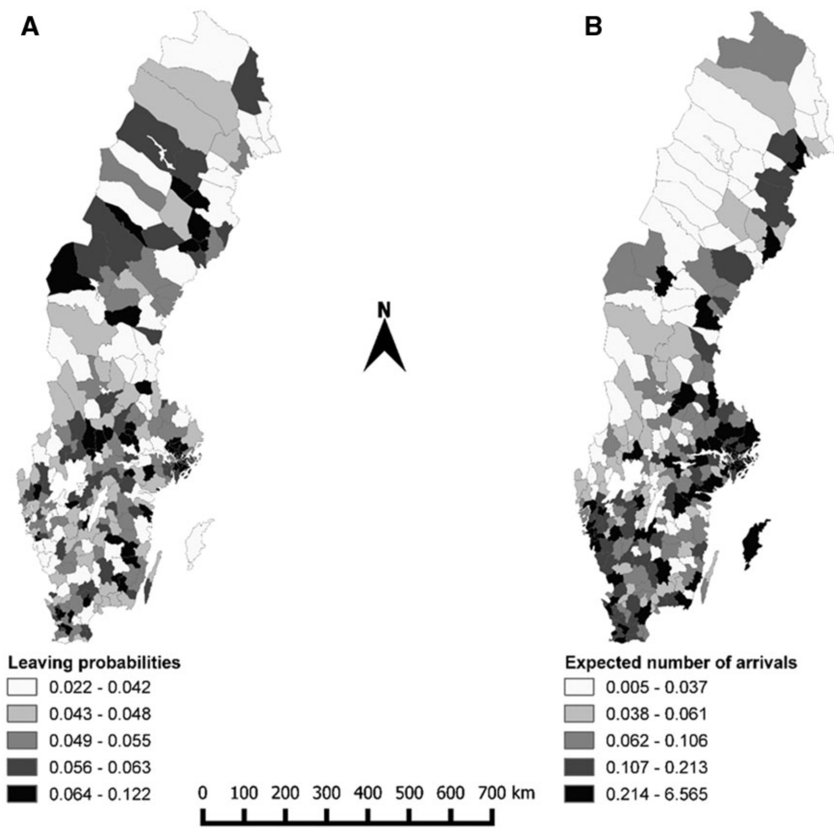

Figure 1. Leaving probabilities (A) and expected arrivals per 1000 inhabitants compared to the population not living there (B) between 2015 and 2016.
Note: Scaled in respective quintiles where white represents the smallest quintile and black the largest.

by mounting regional disparities between prosperous metropolitan regions and larger regional centers, on the one hand, and smaller regions that are lagging behind, on the other. As reported by Eurofound (2019), the widening regional differences in job growth in Sweden are among the fastest in the European Union. These employment differences are also coupled with increasing divergence with respect to migration and access to affordable housing, and it has become increasingly difficult for individuals in less-favored regions to enter the regional growth poles, especially Stockholm, without assistance from family and relatives (Öst, 2011).

4.1. Network definitions

Before sampling 10% of the data, we identified a wide range of contacts from the administrative records: family ties, partners, former co-workers and university peers. Our dataset provides exact information on parent–children triads, allowing us to map both individuals' first- and second-stage relatives (which we refer to as close and distant family, respectively). The first type of contacts covers parents, siblings and adult children,[14] while the second one includes grandparents, half-siblings, uncles, aunts and (first) cousins. As we can only observe any kind of partnership status (legal marriage or cohabitation) if the partners (or any given person) live in the same apartment, we cannot consider partners themselves as possible determinants of moves. However, we can investigate the effect of partners' close and distant relatives.

Because we do not have direct information on other types of contacts, such as friends from work or school, like other scholars have done we define proxies for the identification of such ties (Eliason et al., 2019). Former *co-workers* are considered as those working-age individuals who have shared a common co-working experience between 2002 and 2014 at the same establishments with a maximum of 100 employees at the time.[15] *University peers* are defined as those who graduated at the same university and in the same field of study with a maximum of one year difference. Naturally, some university fields are more crowded (such as economics and business studies at Stockholm University), which could lead to overestimation of the actual number of acquaintances. Despite the potential measurement errors, in our main estimations, we stick with the more inclusive university peer definition and do not restrict the identification of peer effects to only smaller field-year cohorts.[16] The average number of contacts is reported in Appendix Table A1.

4.2. Covariates

When estimating the models described in Equations (3.3–3.5), we control for a comprehensive set of individual characteristics, including gender, standardized age, education categories (unknown, elementary, secondary or tertiary education), and movement intensity in the past (number of moves before 2015, categorized into 4 values: 0, 1, 2 and 'at least 3').

14 As we cannot observe the residence of individuals under 18, the presence of children is very rare: In our sample approximately 30 persons have any children above that age.

15 Unfortunately, we do not observe the total number of potential former co-workers for those who reached working age before 2002. However, this is not a serious issue, as it affects only the first few employment spells of those born between 1981 and 1984.

16 We re-calculated our estimates with a stricter peer definition as well, where individuals were only considered university peers if they graduated from smaller university fields (below 100 graduates per year) with maximum one-year difference. The use of this definition did not affect the results considerably.

As availability of local contacts influences the likelihood of mobility (Dawkins, 2006; Kan, 2007; Quentin et al., 2010), we also account for the presence of all types of social ties at the individual's sending location. To control for alternative opportunities available to the individuals, we control for the total number of contacts at municipalities other than the target. As proposed in the methodological section, sending municipality–target municipality–occupation fixed effects are included in all regressions to handle the nonrandom sorting of individuals. For occupation, two-digit Swedish Standard Classification of Occupations occupation categories were used, with one extra category corresponding to unemployed workers.[17]

Our covariates of interest are indicators showing whether the individuals have at least one contact of a given type at a specific target municipality. When estimating Equations (3.4 and 3.5), the link variables are interacted with variables related to either individuals or the target municipalities (or both), as discussed earlier.

5. Results

5.1. Baseline results

To understand the role of social contacts in facilitating residential movements, we start by investigating the relationship between movement probabilities and the presence of contacts. First, we estimate the model described in Equation (3.3), where the outcome variable indicates whether a given sending–target municipality movement is realized from 2015 to 2016 (Table 2). Our key variables are dummies indicating whether the individuals' different network segments are present at a given, potential target location.

Akin to previous empirical results (Michielin et al., 2008; Michielin and Mulder, 2008; Ermisch and Mulder, 2019) and life-course models (Coulter et al., 2016; Spring et al., 2017), significant differences can be found between the mobility patterns of singles and couples, because they may have different priorities, goals and aspirations that affect movement decisions. Accordingly, we made separate estimations on the sub-sample of singles and couples only. Regarding couples, we focus on the members of those pairs, where both of the individuals are 18–35 years, as reliable information on previous residences is only available for these individuals.[18] To test for gender-specific, within-couple differences in the contacts' importance, we also estimated the effects separately for the male and female members of the couples. In all specifications, we applied sending municipality–target municipality–occupation fixed effects to account for the typical occupation-related residential movement paths that may emerge due to the geographical dispersion of specific jobs.

Regarding singles, the results suggest that the presence of almost all contact segments can significantly affect the probability that a given sending–target municipality movement will be realized (Table 2). The presence of close family ties increases the probability of a specific movement by 0.0143 for new destinations. This finding is in line with the notion that close kinship ties at other locations may function as pull factors for residential movements and can influence selection of the new destination locations (e.g. Hedman, 2013; Spring et al., 2017; Mulder et al., 2020). We add to this body of literature by also showing that the presence of the individuals' distant family also has a positive, although moderate,

17 In total, there are 47 different occupation categories.

18 As a robustness check, we estimated the regressions without this age restriction and obtained similar results. These estimations are available upon request.

Table 2. The effect of different social contacts on moving to specific locations

	(1) Singles	(2) Couples - Both	(3) Couples - Female	(4) Couples -Male
Close family	0.0143***	0.0038***	0.0053***	0.0023**
	(0.0006)	(0.0006)	(0.0010)	(0.0008)
Distant family	0.0012***	0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Co-workers	0.0004***	−0.0000	−0.0001	−0.0000
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
University peers	0.0004***	0.0000	−0.0001	0.0001
	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Partners' close family	–	0.0031***	0.0022**	0.0041***
		(0.0006)	(0.0007)	(0.0010)
Partners' distant family	–	0.0003*	0.0002	0.0005*
		(0.0001)	(0.0002)	(0.0002)
Partners' co-workers	–	0.0000	0.0001	−0.0000
		(0.0000)	(0.0001)	(0.0001)
Partners' university peers	–	0.0000	0.0001	−0.0001
		(0.0000)	(0.0001)	(0.0001)
Constant	0.0000	0.0002***	0.0001	0.0003***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Observations	47,087,926	10,444,749	5,121,947	4,945,946
R^2	0.063	0.090	0.095	0.123
Baseline movement prob.	0.0003	0.0003	0.0003	0.0003

Note: Estimates of Equation (3.3) separately for singles, couples and the female and male counterparts of couples. Coefficients related to return migration are not reported here but estimated as well. All specifications include sending–target municipality and occupation interaction fixed effects and control for sex, age, education and the categorized no. of residential movements before 2015. We also control for the presence of different contacts at the sending locations and the total no. of contacts at alternative target municipalities. Baseline movement probabilities are estimated as the mean of predicted movement probabilities assuming the lack of any contacts at the given target. Standard errors are in parentheses and clustered at sending and target municipality dyad levels. Statistically significant at the *0.05 level; **0.01 level; ***0.001 level.

effect on the realization of a given sending–target location move. The coefficients for university peers and former co-workers are significant, but even smaller compared to the already introduced ones, and both increase the probability of the realization of given movements by 0.0004. The obtained contact effects can be considered meaningfully large[19] compared to the baseline probability of movements (0.0003 for singles), measured as the average of the predicted movement probabilities on given paths without any contact effects.[20]

19 To make the magnitude of the effects easier to interpret, we re-estimated our model by using fixed effects logit estimates (see Supplementary Appendix C). The presence of contacts multiplies the odds of movements to given municipalities by a factor of 4–9, depending on the investigated contact type. The findings of the logit estimations are consistent with the results of the linear probability models and revealed more substantial differences in contact effects (e.g., for university peers and former co-workers).

20 Effect sizes conditional on individuals already moving are substantially larger. The linear probability models of Supplementary Appendix A present findings corresponding to the mover subsample. Results suggest that while close family members increase the probability of moving to the same municipality by around 0.11, the effects for coworkers or university peers fall below 0.01. The relative importance of different contact types is rather

For individuals living in couples (second column), their own and their partners' close family matter the most, with the former having a higher effect on the probability that a movement will happen. However, women's own close family ties seem to play a more essential role than their partners' close family ties do, but this relation is reversed for men. These findings are in line with the notions that women tend to have stronger relationships with these types of ties (Rossi and Rossi, 1990) and are more likely to engage in care and support exchange with family members (Ikkink et al., 1999; Bell and Rutherford, 2013).

As people usually have only a few contacts in some network segments, like close family, but many contacts in other segments, we assessed the relative importance of different contacts by re-estimating Equation (3.3) with the standardized number of contacts at the target municipalities as our main covariates. The results, presented in Supplementary Appendix B, show similar patterns to the original estimates regarding the relative importance of the different contact types.[21]

5.2. Constrained scenarios

The results of our baseline specification demonstrated that the presence of social ties is associated with an increased probability that given movements will be realized. In this section, we take a step further and investigate whether the estimated network effects change if potential constraints on migration, either individual specific or target related, are present. To do so, we estimate Equation (3.4) where the indicators of links are interacted with either specific individual characteristics or different target municipality features. In the estimations, we analyze potential new targets only (i.e. where the individuals have never lived before) and concentrate on the movement decision of single individuals only.

We start by comparing the network effects among individuals who have more limited income and education resources to those of high-income or highly educated individuals (Table 3). The first column comprises the (previously presented) baseline estimates for all singles without additional interaction terms. In Columns (2 and 3), the bottom panel includes estimates for the benchmark groups, such as high-income or highly educated individuals (β_1 in Equation (3.4)), and the top panel includes the additional effects for the constrained groups (the β_3 interaction terms from Equation (3.4)).

Regarding income, the coefficients in the bottom panel suggest that the presence of any type of tie increases the movement probability for those who earn above the municipality-level median wage. However, the positive interactions in the upper panel indicate that these effects are even stronger for low-income individuals, where the effect of university peers and close family is almost doubled. This latter finding seems reasonable, as low-income individuals and perhaps marginalized groups like inexperienced workers and refugees are more likely to rely on support from family members (Briggs, 1998; Spring et al., 2017).

similar to those presented in Table 2. However, this Appendix also presents an exercise aimed to assess the relative importance of how different contacts affect the migration decision of moving or staying and the location choice between destinations. Under some assumptions, we can infer that the effect on the location decisions is more prominent for most contacts, especially for distant family members, than the effect on the migration decision.

21 However, we must note that we cannot draw strong conclusions from comparing parameters related to different types of contacts, as some of them are more severely affected by measurement error bias than others. While we can observe family contacts almost perfectly, we may misclassify university peers and especially co-worker contacts.

Table 3. Heterogeneity of contact effects by individual characteristics

C_p	(1) –	(2) Lower Income (indicator)	(3) Lower education (indicator)
C_p *x* Link (additional effects)			
Close family	–	0.0103***	0.0010
		(0.0012)	(0.0013)
Distant family	–	0.0014***	−0.0014***
		(0.0002)	(0.0003)
Co-workers	–	0.0002*	−0.0005***
		(0.0001)	(0.0001)
University peers	–	0.0003***	–
		(0.0001)	
Link (benchmark group)			
Close family	0.0143***	0.0067***	0.0140***
	(0.0006)	(0.0009)	(0.0011)
Distant family	0.0012***	0.0005*	0.0023***
	(0.0001)	(0.0002)	(0.0002)
Co-workers	0.0004***	0.0002***	0.0007***
	(0.0000)	(0.0001)	(0.0001)
University peers	0.0004***	0.0001**	0.0003***
	(0.0001)	(0.0001)	(0.0000)
Constant	0.0000	0.0002***	0.0000
	(0.0000)	(0.0000)	(0.0000)
Observations	47,087,926	38,543,380[a]	45,058,461[a]
R^2	0.063	0.060	0.052
Baseline probability	0.0003	0.0002	0.0002

Note: The results are based on Equation (3.4), where $\tilde{C}_{pij}$ represents individual-specific constraints (C_p). The estimation sub-sample covers singles; return migration is excluded. Lower income refers to earnings below the municipality-level median wage, while lower education refers to below tertiary education. For additional controls see Table 2. Baseline movement probabilities are estimated as the mean of predicted movement probabilities assuming the lack of any contacts at the given target. Standard errors are in parentheses and clustered at the level of sending–target municipality dyads. Statistically significant at the *0.05 level; **0.01 level; ***0.001 level.
[a]The number of observations in Columns (2–3) is decreased compared to Column (1), as individuals with either missing income or educational data are excluded from the regressions.

With respect to education, we cannot find meaningful differences between the two education groups as regards the role of close family ties. However, as opposed to income, the effect of distant family members and workplace contacts seems more substantial for highly educated individuals (who are usually more resourceful).

Turning to the investigation of target-specific differences (Table 4), our contact variables are interacted with either specific municipality-level characteristics (e.g. standardized average housing prices, indicator marking whether the target is in Stockholm County) or indicators marking the cases of potential upward mobility in relation to municipality features (the average income level or the overall population is higher at the target municipality than at the sending one). In the latter specifications, we excluded Stockholm from the possible target and sending locations to account for its superiority with respect to the investigated measures as well as to focus on variation among all other municipalities. The bottom panel contains the effect of contacts if a given target municipality does not

Table 4. Heterogeneity of contact effects by target municipality features

C_j	(1) -	(2) Stockholm (indicator)	(3) Av. house prices (standardized)	(4) Target with higher av. income level (indicator)	(5) Target with higher population (indicator)
C_j *x* Link					
Close family	–	0.0027	0.0020***	0.0054***	0.0068***
		(0.0020)	(0.0005)	(0.0015)	(0.0016)
Distant family	–	0.0010*	0.0004***	0.0004	0.0002
		(0.0005)	(0.0001)	(0.0003)	(0.0003)
Co-workers	–	0.0008***	0.0001	−0.0000	0.0001
		(0.0002)	(0.0001)	(0.0001)	(0.0002)
University peers	–	0.0009***	0.0003***	0.0005**	0.0001
		(0.0003)	(0.0001)	(0.0002)	(0.0002)
Link					
Close family	0.0145***	0.0148***	0.0123***	0.0122***	0.0121***
	(0.0006)	(0.0008)	(0.0006)	(0.0010)	(0.0008)
Distant family	0.0013***	0.0013***	0.0010***	0.0011***	0.0012***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Co-workers	0.0004***	0.0004***	0.0003***	0.0004***	0.0003***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
University peers	0.0003***	0.0002***	0.0001	0.0001	0.0002***
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Constant	0.0001**	−0.0000	0.0001**	−0.0000	−0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	46,948,770	35,176,269	46,948,770	32,013,593	32,013,593
R^2	0.051	0.055	0.051	0.057	0.057
Baseline probability	0.0002	0.0002	0.0003	0.0002	0.0002

Note: The results are based on Equation (4), where $\tilde{C}_{pij}$ represents target-specific constraints (C_j). The estimation sub-sample covers singles; return migration is excluded. In specification (2), C_j marks whether the target municipality is in Stockholm County, while in Columns (4) and (5) it indicates whether a given target municipality has a higher av. income level or population compared to the sending municipality of individuals. In specification (3), we interacted the contact dummies with the standardized value of the target municipalities' housing price level. For additional controls, see Table 2. Baseline movement probabilities are estimated as the mean of predicted movement probabilities assuming the lack of any contacts at the given target. Standard errors are in parentheses and clustered at the level of sending–target municipality dyads. Statistically significant at the *0.05 level; **0.01 level; ***0.001 level.

correspond to the destinations indicated in the header, while the upper panel contains the interaction terms corresponding to the additional effects when considering specific subgroups of target municipalities.

In most specifications, the baseline effect of contacts is positive and similar in magnitude to the already presented results. However, if the target destination is Stockholm, the effects are even stronger, except of the individuals' close family. The presence of distant family members in the capital further increases the probability of movements to Stockholm by 0.0010. Moreover, the additional effect of university peers and former co-workers is quite notable as well. Such ties increase the probability of a movement to

Stockholm by approximately 0.0010 on the top of their baseline effect (0.0002 and 0.0004, respectively).

Regarding the other specifications, the role of close family seems to be prominent and most essential compared to other types of ties. Thus, while close family members cannot provide extra aid for those who target Stockholm, they are more helpful in upward mobility aiming at other targets. For instance, while close family members increase movement probability by 0.0123 at municipalities with average housing prices, corresponding probabilities are 0.0110 at the 25th percentile and around 0.0130 around the 75th percentile of the observed distribution of average prices. These differences are not necessarily substantial in this range but can gain great importance when comparing the two tails of the distribution. Former university peers, however, can be quite useful for moves directed to targets with better earning opportunities and more expensive housing prices, while the additional effect of former co-workers is nonsubstantial (virtually zero) in these cases.

5.3. SES and access to high-opportunity places

Social contacts are thus rather important determinants of the movement probabilities of individuals who have limited economic resources. Moreover, they seem to play an essential role in providing access to high-opportunity places, such as Stockholm or municipalities with better earning opportunities or less affordable housing prices. In light of these results, the question is whether social contacts can mitigate the barriers to moving to high-opportunity places experienced by individuals with limited resources.

As a combination of our previous two analyses, we propose a three-way interaction model, as described in Equation (3.5), where the indicators of contacts are interacted with both individual characteristics, specifically income, and target-specific features. The latter set of variables is essentially the same as in the previous estimates, the only difference being that we control for all municipality measures (namely average house prices, population and income level) in a standardized, continuous form—except for the binary indicator of targets in Stockholm County.

The bottom panel (**Link**) of Table 5 presents the effect of social ties for high-income individuals on getting into nonconstrained targets, that is, those that are located outside Stockholm County or that have average house prices, income level or population (Columns 2–5, respectively).[22] According to the results, almost all contact segments, except distant family, greatly increase the movement probabilities in each of these cases. Compared to higher-income individuals, the role of family (including both close and distant relatives) seems more essential for those with lower income level if the movement is directed into the same, nonconstrained targets (***C_p x* Link** panel). Meanwhile, professional ties (university peers and co-workers) may provide them less help. When the target is constrained (***C_j x* Link** panel), the effect of distant family members becomes more prevalent for higher-income individuals. Regarding other types of contacts, we cannot observe such an increase. This suggests that the findings of Table 4 (e.g. the strong role of co-workers in getting into Stockholm) may have been driven by lower-income individuals and their contacts.

Finally, our three-way interaction terms (presented in the ***C_p x C_j x* Link** panel) indicate whether the positive effect of contacts on getting into high-opportunity places differs

22 These baseline effects are calculated at the mean level of the (standardized) interacting variables.

Table 5. SES and access to high-opportunity places

C_j	(1) -	(2) Stockholm	(3) Av. house prices	(4) Av. income level	(5) Population
C_p	Low Income (indicator)				
C_p x C_j x Link					
Close family	–	0.0054	0.0020^{*}	0.0050	0.0011^{**}
		(0.0043)	(0.0009)	(0.0055)	(0.0004)
Distant family	–	−0.0004	0.0002	0.0018	−0.0000
		(0.0007)	(0.0002)	(0.0012)	(0.0001)
Co-workers	–	0.0014^{**}	0.0002^{*}	0.0005	0.0002^{**}
		(0.0004)	(0.0001)	(0.0004)	(0.0001)
University peers	–	0.0013^{**}	0.0004^{***}	0.0002	0.0004^{**}
		(0.0005)	(0.0001)	(0.0003)	(0.0001)
C_j x Link					
Close family	–	0.0001	0.0009	−0.0081	0.0001
		(0.0031)	(0.0008)	(0.0055)	(0.0004)
Distant family	–	0.0016^{*}	0.0004^{*}	−0.0018	0.0004^{***}
		(0.0006)	(0.0002)	(0.0012)	(0.0001)
Co-workers	–	−0.0001	−0.0000	-0.0008^{*}	0.0001^{*}
		(0.0002)	(0.0001)	(0.0004)	(0.0001)
University peers	–	0.0003	0.0001	-0.0006^{*}	0.0003^{*}
		(0.0003)	(0.0001)	(0.0003)	(0.0001)
C_p x Link					
Close family	0.0103^{***}	0.0092^{***}	0.0079^{***}	0.0025	0.0072^{***}
	(0.0012)	(0.0015)	(0.0013)	(0.0050)	(0.0012)
Distant family	0.0014^{***}	0.0018^{***}	0.0011^{***}	−0.0002	0.0011^{***}
	(0.0002)	(0.0003)	(0.0002)	(0.0011)	(0.0002)
Co-workers	0.0002^{*}	0.0000	0.0000	−0.0004	−0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0004)	(0.0001)
University peers	0.0003^{***}	0.0001	−0.0001	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0001)
Link					
Close family	0.0067^{***}	0.0073^{***}	0.0058^{***}	0.0138^{**}	0.0066^{***}
	(0.0009)	(0.0011)	(0.0009)	(0.0049)	(0.0009)
Distant family	0.0005^{*}	0.0001	0.0002	0.0021	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0011)	(0.0002)
Co-workers	0.0002^{***}	0.0003^{***}	0.0003^{***}	0.0009^{*}	0.0003^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0004)	(0.0001)
University peers	0.0001^{**}	0.0002^{**}	0.0001^{*}	0.0007^{**}	0.0001
	(0.0001)	(0.0001)	(0.0000)	(0.0002)	(0.0001)
Constant	0.0002^{***}	0.0000	0.0002^{***}	0.0001^{**}	0.0001^{***}
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	38,543,380	28,558,928	38,543,380	38,543,380	38,543,380
R^2	0.060	0.065	0.060	0.060	0.060
Baseline probability	0.0002	0.0002	0.0003	0.0002	0.0003

Note: The results are based on Equation (3.5), where individual-specific (C_p) and target-specific constraints (C_j) are jointly interacted with the contact indicators. The estimation sample covers singles; return migration is excluded. For additional controls see Table 2. Baseline movement probabilities are estimated as the mean of predicted movement probabilities assuming the lack of any contacts at the given target. Standard errors are in parentheses and clustered at sending–target municipality level. Statistically significant at the *0.05 level; **0.01 level; ***0.001 level.

between lower- and higher-income individuals. As the positive, and significant, coefficients suggest, the effect of former co-workers and university peers is more substantial for lower-income individuals if the target is Stockholm. The same applies to those targets where the average house prices and population are higher. In such targets, the effect of close family is also prominent. Column (4), on income level, shows clearly different patterns compared to the other specifications, as most of the additional effects are insignificant or even negative. One explanation for such results could be that the average income level is calculated based on the residents' earnings instead of on the wages of those who work in a given municipality—especially in the case of small municipalities. This also explains some of the differences between the coefficients in Columns (3) and (4), as in some smaller municipalities (specialized in, e.g. mining and manufacturing) housing costs and earnings may vary greatly.

Taken together, the presented results indicate that social ties may be essential assets for people with lower SES in gaining access to opportunity-rich places and may compensate for their limited economic resources. The utilization of personal networks, thus, may contribute to the equalization of the economic opportunities of individuals and may provide an escape from becoming trapped in places with limited possibilities.

5.4. Robustness checks

The validity of our findings depends on the argument that the fixed-effect approach properly deals with the nonrandom sorting of individuals into given municipalities. We therefore generated a set of placebo contacts with similar characteristics as the true ones, the only exception being that the chance of having an actual relationship with such individuals is considerably lower. Placebo co-workers are defined as employees of the individual's firm, who work at the same municipality as the individual (in the same time window), but in a different workplace (establishment). Placebo university peers cover individuals who graduated from the same university and field of study, but with a difference of 3–5 years. Then, we re-estimated Equation (3.3) on the sub-sample of singles by extending the set of already used control variables with an indicator marking the presence of either one of the introduced placebo contacts at given targets in cases when true contacts were not present.[23]

Three model specifications are introduced for both estimates: one without any fixed effects, one with sending municipality–target municipality and one with sending municipality–target municipality–occupation fixed effects (Table 6). We observe positive coefficients for both true and placebo contacts in the specification without any fixed effects. Although the latter are considerably lower, their presence indicates that the nonrandom sorting of individuals is indeed a relevant issue. However, after the inclusion of fixed effects, the coefficients of true contacts remain significant while the placebo contacts lose their significance. This suggests that the proposed fixed-effects approach does indeed eliminate a substantial part of the potential selection problems.

Although the exercise with placebo contacts indicates that the measured effects probably do not result from the nonrandom sorting of individuals, there may still be a chance that individuals end up at the same municipalities, independently of one another, without providing any

23 In the set of estimates when the indicator of placebo university contacts was used, we restricted the estimation sample to individuals born before 1989 and after 1980 to ensure the possibility of having all types of upper and lower cohorts. The original university peer definition was also extended in these equations to account for the somewhat likely relationships between the closer upper and lower cohorts.

Table 6. Robustness test on co-workers and university peers

	(1) Without FE	(2) Sending–target municipality FE	(3) Sending–target municipality and occupation FE
Panel A: Robustness test on co-workers			
Former co-workers	0.0021***	0.0005***	0.0004***
	(0.0001)	(0.0001)	(0.0000)
Placebo co-workers	0.0007***	−0.0000	−0.0000
	(0.0001)	(0.0000)	(0.0001)
Constant	0.0000	0.0001*	0.0001**
	(0.0000)	(0.0000)	(0.0000)
Observations	47,569,078	47,569,078	46,948,770
R^2	0.003	0.013	0.051
Panel B: Robustness test on peers			
Peers, who graduated with 0–2 years difference	0.0007***	0.0003***	0.0002***
	(0.0001)	(0.0000)	(0.0000)
Peers, who graduated with 3–5 years difference	0.0002***	0.0001*	0.0001
	(0.0000)	(0.0000)	(0.0000)
Constant	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)
Observations	16,756,806	16,756,806	16,129,824
R^2	0.002	0.015	0.078

Note: Table includes a re-estimation of Equation (3.3) on the sub-sample of singles and excluding cases of potential return migration, using an extended set of contact variables. Placebo co-workers refer to individuals who worked at the same firms at the same time, but in different establishments of the firm in the same municipality. The dummies for placebo presence take the value of one only if no true contacts (true co-workers or peers from same or closer cohorts) were present at the target municipality. For additional controls see Table 2. Standard errors are in parentheses and clustered at the level of sending–target municipality dyads. Statistically significant at the *0.05 level; **0.01 level; ***0.001 level.

help or support for each other. Table 7 shows the conditional probabilities that individuals will move to the same block[24] or apartment as their contacts, if their movement is directed into their ties' municipalities. When moving to new areas, the probability of having a parent there is around 8.2%. However, conditional on moving into the same municipality where a parent lives, ending up in the same apartment is quite probable, as indicated by the 73% rate in the third column. The second column represents a category a bit broader than moving into the same apartment. For many contacts (e.g. close family or grandparents), moving very close and moving in together is strongly correlated. For university peers, co-workers and more distant family members, however, it is more likely that they will move close, but not too close, to contacts. This may indicate the presence of indirect help.[25]

24 Data on 100 m*100 m blocks using the geographical coordinates of individuals' (main) properties.

25 On the other hand, these weaker contacts may provide help in other ways. In an analog to Table 7, instead of focusing on getting into the same house, we check whether people who move to the same municipality as their contacts also tend to end up in the same firm/establishment, conditional on having a job (Supplementary Appendix D). Not surprisingly, there is a strong correlation concerning co-workers and university peers, suggesting that one main driving factor of moving to contacts comes from getting job opportunities at the same

Table 7. Probabilities of ending up in same apartment or block

	P(municipality)	P(block | municipality)	P(apartment | municipality)	P(apartment | block)
Parents	0.082	0.745	0.727	0.977
Children	0.001	0.914	0.914	1.000
Siblings	0.098	0.358	0.316	0.884
Grandparents	0.038	0.090	0.076	0.842
Aunts and Uncles	0.078	0.041	0.032	0.794
Cousins	0.111	0.028	0.016	0.558
Half-siblings	0.017	0.169	0.149	0.884
Co-workers	0.356	0.089	0.067	0.745
University peers	0.105	0.103	0.053	0.517
University peers—only same class	0.089	0.084	0.052	0.623

Note: Based on the full population of singles, born after 1977. The number of movements to new locations is 142,554. Block refers to a 100 m × 100 m area based on geographical coordinates.

Although these results show that moving in together is common, it does not imply that having more opportunities (provided by contacts) would definitely increase an individuals' propensity to move. To capture whether this channel leads to migration, we augmented our regression models with the total number of extra rooms at the apartments of social links (of the given types). As the number of available rooms can reflect opportunities for moving to the contacts' place, the inclusion of such variables may capture the contacts' direct help.[26] Our results, presented in Supplementary Appendix D, suggest that this channel is mostly relevant for former co-workers.

6. Conclusions

Considering recent discussions on the increasing geographical divergence of opportunity coupled with the constrained access of people in less-favored regions to entering opportunity-rich regions (Storper, 2018; Autor, 2020), the aim of the present article was to investigate to what extent social networks structure access to high-opportunity places.

Our results, based on a random 10% sample of all individuals aged 18–35 years in Sweden, suggest that there is a positive correlation between a specific movement to a destination and the presence of contacts. These results correspond to findings from previous studies using phone data (e.g. Büchel et al., 2019), but we also find significant differences between the movements of singles and those of couples. Movements of couples are mostly affected by the presence of family contacts, and in accordance with other studies (Ikkink et al., 1999; Bell and Rutherford, 2013), our results indicate that mobility decisions are influenced by the family of women to a higher extent than the relatives of men. For singles, we document that all the examined contact segments (close and distant family,

employers. Also, even in the rare case of working individuals moving to new locations where their parents live, they will start working in the same firm in 84.5% of observed cases, and in 57.5% of cases in the same establishment as well.

26 We note that moving to someone's apartment is influenced by many factors, but as Table 7 showed, it is not uncommon.

university peers, former co-workers) significantly affect the probability that a given sending–target municipality movement will be realized. The results reinforce the notion that, besides the traditionally considered economical aspects, social ties are also, or even more, essential factors in our understanding of the geographical mobility of workers (Michaelides, 2011), as they may pave the way for future migration flows (Mulder et al., 2020).

However, the most novel contribution of the present article is that we can show that the effects are generally stronger if we focus on several constrained scenarios that typically could hinder migration. That is, when the target municipality is hardly accessible or when the individuals are less privileged. We show that the presence of contacts may increase the chance of getting into (in absolute terms) opportunity-rich target municipalities, and they can also facilitate movements to targets that are better (more populated or wealthier) than the individuals' previous location. Moreover, we demonstrate that the contacts' presence (especially the role of family ties) is more essential for lower-income individuals compared to those with more abundant resources, especially if the targets are hardly accessible. The presence of contacts increased to a meaningful extent the movement probabilities of people with lower SES to get into Stockholm County, or municipalities with above average housing prices, population and income level. On the one hand, such patterns may suggest that individuals with limited economic capital are more reliant on their social contacts than their more affluent counterparts are. This is exemplified in studies on the internal migration of refugees from small to large cities in Sweden, which is often characterized by cohabitation due to limited housing opportunities (Edin et al., 2003). On the other hand, it may also imply that network connections (social capital) can be utilized to counteract the scarcity of economic capital, which is a form of transformation of social capital into economic capital (Bourdieu, 1986).

Taken together, our results demonstrate that for gaining access to high-opportunity places, having many network connections is not enough. The location of these contacts is also crucial. Networks in high-opportunity regions are associated with migration advantages, so lacking such resources obviously increase the risk of people becoming trapped in their current location. This implies that, because inequality in social capital can be an important factor in sustaining or deepening the intergenerational transmission of regional inequalities (Van Ham et al., 2014; Chetty et al., 2016; Hedman et al., 2021), removing barriers to migration and increasing access to education are crucial policy challenges (OECD, 2018; Connor and Storper, 2020).

Before making this conclusion, however, it must be noted that movement to metropolitan regions is not the only opportunity for those in less-favored areas, as social mobility is also possible without moving. In fact, for low-income youth in the USA, opportunities for social mobility were found to be better in more rural, distant or non-metropolitan counties than in big cities (Chetty et al., 2014; Weber et al., 2018). Given that the social mobility potential of places varies over time (Connor and Storper, 2020), matching skills and jobs also plays a fundamental role together with access to education. Nevertheless, social network structures can still shape opportunities for social mobility, as they can be quite different in urban and rural areas depending on the local supply of and demand for skills. Assessing possibilities for social mobility among different groups in different geographies thus remains an important question for further research.

Data availability statement

The micro-data analyzed in this study are compiled by Statistics Sweden and made available to researchers by permission from Statistics Sweden only. A fee applies. By law, the authors of the present study cannot share the data; interested researchers must approach Statistics Sweden directly.

Funding

This research was funded by the Swedish Research Council (grant number 2016-01803) and the Marianne and Marcus Wallenberg Foundation (grant number 2017.0042).

Conflicts of interest statement

The authors declare no conflict of interest.

Supplementary material

Supplementary data for this paper are available at *Journal of Economic Geography* online.

Acknowledgments

The authors would like to thank the editor and two anonymous referees for insightful comments that significantly improved the paper.

References

Autor, D. (2020) *The Faltering Escalator of Urban Opportunity*. Cambridge, MA: MIT Program on Work of the Future.

Barwick, P. J., Liu, Y., Patacchini, E., Wu, Q. (2019) *Information, Mobile Communication, and Referral Effects*. National Bureau of Economic Research working paper no. w25873. Available online at: https://doi.org/10.3386/w25873.

Battaglini, M., Patacchini E. (2018) Influencing connected legislators. *Journal of Political Economy*, 126: 2277–2322.

Battaglini, M., Leone Sciabolazza V., Patacchini E. (2020) Effectiveness of connected legislators. *American Journal of Political Science*, 64: 739–756. Available at:

Bayer, P., Ross, S. L., Topa, G. (2008) Place of work and place of residence: informal hiring networks and labor market outcomes. *Journal of Political Economy*, 116: 1150–1194.

Bell, D., Rutherford, A. C. (2013) Individual and geographic factors in the formation of care networks in the UK. *Population, Space and Place*, 19: 727–737.

Belot, M., Ermisch, J. (2009) Friendship ties and geographical mobility: evidence from Great Britain. *Journal of the Royal Statistical Society Series A*, 172: 427–442.

Bergström, L., van Ham, M. (2010) Understanding neighbourhood effects: selection bias and residential mobility. IZA Discussion Paper No. 5193, SSRN. Available online at: https://ssrn.com/abstract=1682714 [Accessed 22 June 2022].

Bjerke, L, Mellander, C. (2019) Mover stayer winner loser – A study of income effects from rural migration. The Royal Institute of technology Centre of Excellence for Science and Innovation Studies (CESIS). CESIS Electronic Working Paper Series, no. 476.

Bourdieu, P. (1986) The forms of capital. In J. Richardson (ed) *Handbook of Theory and Research for the Sociology of Education*, pp. 241–58. Westport, CT: Greenwood.

Boza, I., Ilyés, V. (2020) Decomposition of co-worker wage gains. *IZA Journal of Labor Economics*, 9(1). https://doi.org/10.2478/izajole-2020-0008

Briggs, X. D. S. (1998) Brown kids in white suburbs: housing mobility and the many faces of social capital. *Housing Policy Debate*, 9: 177–221.
Büchel, K., Ehrlich, M. V., Puga, D., Viladecans-Marsal, E. (2019) Calling from the outside: the role of networks in residential mobility. *Journal of Urban Economics*, 119: 103277.
Chetty, R., Hendren, N., Katz, L. F. (2016) The effects of exposure to better neighborhoods on children: new evidence from the Moving to Opportunity experiment. *American Economic Review*, 106: 855–902.
Chetty, R., Hendren, N., Kline, P., Saez, E. (2014) Where is the land of opportunity? The geography of intergenerational mobility in the United States. *Quarterly Journal of Economics*, 129: 1553–1623.
Connor D. S., Storper, M. (2020) The changing geography of social mobility in the United States. *Proceedings of the National Academy of Sciences*, 117: 30309–30317.
Costa, D. L., Kahn, M. E., Roudiez, C., Wilson, S. (2018) Persistent social networks: civil war veterans who fought together co-locate in later life. *Regional Science and Urban Economics*, 70: 289–299.
Coulter, R., van Ham, M., Findlay, A. M. (2016) Re-thinking residential mobility: linking lives through time and space. *Progress in Human Geography*, 40: 352–374.
David, Q., Janiak, A., Wasmer, E. (2010) Local social capital and geographical mobility. *Journal of Urban Economics*, 68: 191–204.
Dawkins, C. J. (2006) Are social networks the ties that bind families to neighborhoods? *Housing Studies*, 21: 867–881.
De la Roca, J., Puga, D. (2017) Learning by working in big cities. *Review of Economic Studies*, 84: 106–142.
Dekker, R., Engbersen, G. (2014) How social media transform migrant networks and facilitate migration. *Global Networks*, 14: 401–418.
Edin, P. A., Fredriksson, P., Åslund, O. (2003). Ethnic enclaves and the economic success of immigrants—Evidence from a natural experiment. *The Quarterly Journal of Economics*, 118: 329–357.
Eliason, M., Hensvik, L., Kramarz, F., Skans, O. N. (2019) Social connections and the sorting of workers to firms. CEPR Discussion Papers 13672, CEPR.
Eriksson, R. H., Rodríguez-Pose, A. (2017) Job- related mobility and plant performance in Sweden. *Geoforum*, 83: 39–49.
Eriksson, R.H., Lengyel, B. (2019) Co-worker networks and agglomeration externalities. *Economic Geography*, 95: 65–89.
Ermisch, J., Mulder, C. H. (2019) Migration versus immobility, and ties to parents. *European Journal of Population*, 35: 587–608.
Eurofound. (2019) *European Jobs Monitor 2019: Shifts in the Employment Structure at Regional Level*. Luxembourg: Publications Office of the European Union.
Florida, R. (2002) *The Rise of the Creative Class*. New York, NY: Basic Books.
Gallagher, R., Keastner, J., Persky, J. (2019) The geography of family differences and intergenerational mobility. *Journal of Economic Geography*, 19: 589–618.
Galster, G., Sharkey, P. (2017) Spatial foundations of inequality: a conceptual model and empirical overview. *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 3: 1–33.
Ganong, P., Shoag, D. (2017) Why has regional income convergence in the US declined? *Journal of Urban Economics*, 102: 76–90.
Gillespie, B. J., Mulder, C. H. (2020) Nonresident family as a motive for migration. *Demographic Research*, 42: 399–410.
Glaeser, E. L., Kolko, J., Saiz, A. (2003) Consumers and cities. *Research in Urban Policy*, 9: 177–183.
Glitz, A., Vejlin, R. (2021) Learning through coworker referrals. *Review of Economic Dynamics*, 42: 37–71.
Gordon, I. R. (2015) Ambition, human capital acquisition and the metropolitan escalator. *Regional Studies*, 49: 1042–1055.
Hansen, H. K., Niedomysl, T. (2009) Migration of the creative class: evidence from Sweden. *Journal of Economic Geography*, 9: 191–206.
Hedman, L. (2013) Moving near family: the influence of extended family on neighbourhood choice in an intra-urban context. *Population Space and Place*, 19: 32–45. Available at: https://doi.org/10.1002/psp.1703

Hedman, L., Van Ham, M., Tammaru, T. (2021) Three generations of intergenerational transmission of neighbourhood context. *Social Inclusion*, 9(2), 129–141.
Hensvik, L., Skans, O. N. (2016) Social networks, employee selection and labor market outcomes. *Journal of Labor Economics*, 34: 825–867.
Hoxie, P., Shoag, D., Veuger, S. (2019) Moving to density: half a century of housing costs and wage premia from queens to King Salmon. Working Paper No. 2019–24, AEI Paper & Studies.
Iammarino, S., Rodriguez-Pose, A., Storper, M. (2019) Regional inequality in Europe: evidence, theory and policy implications. *Journal of Economic Geography*, 19: 273–298.
Ikkink, K. K., van Tilburg, T., Knipscheer, K. C. P. M. (1999) Perceived instrumental support exchanges in relationships between elderly parents and their adult children: normative and structural explanations. *Journal of Marriage and the Family*, 61: 831–844.
Ioannides, Y. M. (2012) *From Neighborhoods to Nations*. Princeton, NJ: Princeton University Press.
Kan, K. (2007) Residential mobility and social capital. *Journal of Urban Economics*, 61: 436–457.
Kramarz, F., Skans O. N. (2014) When strong ties are strong-networks and youth labor market entry. *Review of Economic Studies*, 81: 1164–1200.
Laschever, R. A. (2013) The doughboys network: social interactions and the employment of world war I veterans. *SSRN Electronic Journal*, 1–54. http://dx.doi.org/10.2139/ssrn.1205543
Lundholm, E. (2007) Are Movers still the Same? Characteristics of Interregional Migrants in Sweden 1970–2001. *Tijdschrift voor Economische en Sociale Geografie*, 98(3): 336–348.
Massey, D. S. (1988) Economic development and international migration in comparative perspective. *Population and Development Review*, 14: 383–413.
Michaelides, M. (2011) The effect of local ties, wages, and housing costs on migration decisions. *The Journal of Socio-Economics*, 40: 132–140.
Michielin, F., Mulder, C. H. (2008) Family events and the residential mobility of couples. *Environment and Planning A: Economy and Space*, 40: 2770–2790.
Michielin, F., Mulder, C. H., Zorlu, A. (2008) Distance to parents and geographical mobility. *Population, Space and Place*, 14: 327–345.
Mulder, C. H., van der Meer, M. (2009) Geographical distances and support from family members. *Population, Space and Place*, 15: 381–399.
Mulder, C. H., Lundholm, E., Malmberg, G. (2020) Young adults' migration to cities in Sweden: do siblings pave the way? *Demography*, 57: 2221–2244.
Muth, R. F. (1971) Migration: chicken or egg? *Southern Economic Journal*, 37: 295–306.
OECD. (2018) A broken social elevator? *How to Promote Social Mobility*. Paris, France: OECD Publishing.
Öst, C. E. (2011) Parental wealth and first-time homeownership: a cohort study of family background and young adults' housing situation in Sweden. *Urban Studies*, 49: 2137–2152.
Patacchini, E., Zenou, Y. (2012) Ethnic networks and employment outcomes. *Regional Science and Urban Economics*, 42: 938–949.
Patacchini, E., Arduini, T. (2016) Residential choices of young Americans. *Journal of Housing Economics*, 34: 69–81.
Partridge, M. D., Rickman, D. S. (2003) The waxing and waning of regional economies: the chicken–egg question of jobs versus people. *Journal of Urban Economics*, 53: 76–97.
Pettersson, A., Malmberg, G. (2009) Adult children and elderly parents as mobility attractions in Sweden. *Population, Space and Place*, 15: 343–357. Available at: https://doi.org/10.1002/psp.558
Quentin, D., Janiak, A., Wasmer, E. (2010) Local social capital and geographical mobility. *Journal of Urban Economics*, 68: 191–204.
Rodríguez-Pose, A., Storper, M. (2020) Housing, urban growth and inequalities: the limits to deregulation and upzoning in reducing economic and spatial inequality. *Urban Studies*, 57: 223–248.
Rossi, A. S., Rossi, P. H. (1990) *Social Institutions and Social Change of Human Bonding: Parent-Child Relations across the Life Course*. New York, NY: Aldine de Gruyter.
Saygin, P., Weber, A., Weynandt, M. A. (2021) Co-workers, networks, and job-search outcomes. *Industrial and Labor Relations Review*, 74: 95–130.
Schmidheiny, K. (2006) Income segregation and local progressive taxation: empirical evidence from switzerland. *Journal of Public Economics*, 90: 429–458.
Spring, A., Ackert, E., Crowder, K., South, S. J. (2017) Influence of proximity to kin on residential mobility and destination choice: examining local movers in metropolitan areas. *Demography*, 54: 1277–1304.

Staiger, M. (2021) The intergenerational transmission of employers and the earnings of young workers. Washington Center for Equitable Growth Working Paper. https://equitablegrowth.org/working-papers/the-intergenerational-transmission-of-employers-and-the-earnings-of-young-workers/ [Accessed 22 June 2022].

Storper, M. (2018) Separate Worlds? Explaining the current wave of regional economic polarization. *Journal of Economic Geography*, 18: 247–270.

Storper, M., Scott, A. J. (2009) Rethinking human capital, creativity and urban growth. *Journal of economic geography*, 9: 147–167.

Van Ham, M., Hedman, L., Manley, D., Coulter, R., Östh, J. (2014) Intergenerational transmission of neighbourhood poverty: an analysis of neighbourhood histories of individuals. *Transactions of the Institute of British Geographers*, 39: 402–417.

Van Ham, M., Tammaru, T., Janssen, H. J. (2018) A multi-level model of vicious circles of socio-economic segregation. *Divided Cities: Understanding Intra-Urban Disparities*, pp. 19–51. Paris: OECD Publishing.

Weber, B., Fannin, J. M., Miller, K., Goetz, S. (2018) Intergenerational mobility of low-income youth in metropolitan and non-metropolitan America: a spatial analysis. *Regional Science Policy & Practice*, 10: 87–101.

Appendix

Table A1. Network connections of individuals by relationship status and mobility

	Relationship status		Mobility		All
	Single	Couple	Nonmover	Mover	
Average number of contacts					
Close family	2.75	2.68	2.74	2.69	2.74
Parent	1.67	1.49	1.63	1.62	1.63
Sibling	1.08	1.19	1.11	1.07	1.10
Children	0.00	0.00	0.00	0.00	0.00
Distant family	7.62	7.82	7.67	7.57	7.66
Grandparent	1.34	0.92	1.25	1.35	1.26
Aunts and uncles	2.21	2.20	2.21	2.19	2.21
Cousins	3.72	4.31	3.85	3.71	3.84
Half-sibling	0.35	0.39	0.36	0.33	0.36
Co-workers	45.14	72.20	50.56	47.48	50.24
Peers	30.47	64.33	37.04	35.22	36.85
Peers (from fields<100)	22.51	50.90	28.01	26.58	27.85
Partner	–	1.00	0.20	0.11	0.19
Partners' close family	–	2.69	0.54	0.26	0.51
Partners' parents	–	1.48	0.30	0.15	0.28
Partners' siblings	–	1.20	0.24	0.12	0.23
Partners' children	–	0.00	0.00	0.00	0.00
Partners' distant family	–	7.84	1.56	0.75	1.48
Partners' grandparents	–	0.93	0.18	0.10	0.18
Partners' aunts and uncles	–	2.20	0.44	0.21	0.41
Partners' cousins	–	4.31	0.86	0.40	0.81
Partners' half-siblings	–	0.40	0.08	0.04	0.08
Partners' co-workers	–	71.67	14.19	7.61	13.49
Partners' peers	–	65.34	12.70	8.97	12.30
Partners' peers (from fields<100)	–	51.54	10.07	6.62	9.71

Note: Based on the 10% sample of individuals born after 1980.