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Help from the past—coworker ties and entry wages after self-employment

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Abstract This paper empirically estimates how referrals mitigate the risk associated with hiring formerly self-employed individuals. We do this by comparing the networks and entry wages for two groups of new hires: those who exit self-employment to become wage-employed and those who change employers as wage employees, i.e., job changers. Referrals are defined as coworker ties through which the new hire and an incumbent worker share a common employment history before their current employment. We use longitudinal Swedish register-based data to evaluate the entry wages of the two groups of new hires for the years between 2010 and 2013. The results show that having coworker ties is associated with 2.9% higher entry wages and that this network premium is uniform across the formerly self-employed and job changers. However, the new hires from self-employment have consistently lower entry wages than the job changers, even if the exiting self-employed have coworker ties.

Plain English Summary Self-employed should use their social ties when they exit and seek employment as it helps to mitigate information asymmetries present in the hiring process. However, even if they do, the self-employed earn less than employees who merely change jobs. Our study provides the first empirical evidence on how the currently self-employed use and gain from their coworker networks. The findings are robust to various definitions of the network as well as sample selection issues. However, the results are driven mainly by the highest skilled individuals and those with high skilled networks. Our results lead to ample future research avenues for both empirical and theoretical contributions in the area.

Keywords Referrals · Network · Self-employment · Entry wages · Labor mobility · Exit

JEL classification J30 · J49 · J62 · L26

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1 Introduction

Scholars have devoted increasing attention to the importance and use of informal networks when finding employment (Bewley, 1999; Fernandez et al., 2000; Hensvik & Skans, 2016; Simon & Warner, 1992).[1] Previous studies suggest that up to 50% of workers are referred to their jobs through their social contacts (Granovetter, 1995; Topa, 2001), and there is growing evidence showing how various types of social ties affect individual labor market outcomes (Bayer et al., 2008; Kramarz & Skans, 2014).[2] Moreover, the previous evidence indicates that self-employed individuals may also use their social contacts when they choose to pursue ordinary employment. This is an underexplored area of research and hence where our paper provides a novel contribution.

Much of the previous research on referrals has focused on social ties via the ethnicity or place of origin of the individuals (Beaman & Magruder, 2012; Dustmann et al., 2016), social ties through family and friends (Cappellari & Tatsiramos, 2015; Kramarz & Skans, 2014), and residence-based networks (Hellerstein et al., 2011; Schmutte, 2015). We, on the other hand, focus on the coworker ties that the individuals have made in their prior careers, similar to Hensvik and Skans (2016), Glitz (2017), and Brown et al. (2016). These job search networks help reduce information deficits in the labor market and lead to productivity gains for both workers and firms (Dustmann et al., 2016; Montgomery, 1991). These gains translate into higher profits for firms and higher earnings for individuals, implying that new hires with existing coworker ties should earn higher entry wages.

Our focus lies in connecting the use of coworker ties when looking at individuals who exit self-employment to become wage employees. Many individuals enter self-employment, but a large share of these individuals eventually exit (Evans & Leighton, 1989) to then return to wage employment (Hessels et al., 2011). Notably, the self-employed have been found to earn significantly less than their wage employee counterparts after returning to employment (Baptista et al., 2012; Hyytinen & Rouvinen, 2008, Lappi et al., 2022), which has been linked to the previously self-employed being seen as riskier hires than those who are already employed (Mahieu et al., 2019). This suggests that self-employed workers might gain significantly from referrals, which decreases the imperfect information employers have regarding their true productivity, especially if they view self-employment experience as particularly risky.

We are the first to explore the extent to which professional networks help the self-employed to gain higher entry wages and how coworker ties factor into their reentry to ordinary employment. This is done by comparing a group of individuals who exit self-employment to employees who change employers and empirically assessing whether the two differ in their use of their coworker ties and entry wages. Our specific interest is in empirically evaluating whether coworker networks work similarly for self-employed and wage employees, which could then at least partly explain the negative earnings difference found in the previous literature between these two groups. We also explore the mitigating role of network characteristics and skills on the use of coworker ties and the difference in entry wages between the two types of new hires.

As much of the usefulness of informal networks in the hiring process is related to the networks providing the employer with information on the recruit's unobserved characteristics, formerly self-employed individuals might need to rely more on their professional networks when seeking employment and negotiating entry wages. Koellinger et al. (2015) show that the self-employed can experience discrimination in the labor market when looking for jobs, which would indicate that the previously self-employed may need to rely particularly heavily on their networks when transitioning back to wage employment. This might result in some firms perceiving those who exit self-employment as failures, which in turn may lead to recruiters stigmatizing these individuals. Therefore, the self-employment experience can send a negative productivity signal to prospective employers, even if it is inaccurate. As Ioannides and Datcher Loury (2004) state, the role of information networks in the job search process is not straightforward, and neither is it clear why some groups rely more on their networks than others or why the earnings payoffs to networks vary across groups. It may also be that the formerly self-employed have gained skills and knowledge that are difficult for prospective employers to

[1] The role of networks and the use of referrals have played an increasing role especially but not exclusively in the job search literature (see, for example, a survey by Ioannides and Datcher Loury (2004); Topa (2011)).

[2] There is evidence of social interactions affecting other outcomes also such as education (Sacerdote, 2001; Zimmerman, 2003), crime (Glaeser et al., 1996), and welfare participation (Bertrand et al., 2000).

observe, and the network is therefore relied upon to provide this valuable information.

We define the network as an individual's existing coworker ties with incumbent workers based on common employment histories. Our empirical strategy uses Swedish employer-employee register data, which covers the population of individuals and establishments throughout the period from 1993 to 2013. Using such data allows us to control a large set of observable individual and establishment-level characteristics. However, the group of individuals who exit self-employment is likely to be significantly different from the group of individuals who change employers. Therefore, we also use matching techniques to make the two groups of new hires comparable to each other. For our empirical estimations, we consider all new self- and wage-employed hires between 2010 and 2013. We empirically evaluate their entry wages and the potential presence of coworker ties in the year of entry.

We estimate the network earnings premium to be approximately 2.9% for both the exiting self-employed workers and the job changers. This network premium is robust to various alternative definitions of coworker ties and several network characteristics. We find consistent and large entry wage differences across both groups, with the formerly self-employed earning approximately 10% less. Additionally, this earnings loss is robust to alternative robustness tests. Taking these two findings and our estimations, we conclude that the self-employed, through coworker networks, can mitigate some of the risks for employers that are associated with hiring new employees. However, these networks cannot fully alleviate the employer's perception of risk associated with hiring someone exiting self-employment, as such workers have no additional associated network premium on top of the estimated 2.9%. We also show that skills play a significant role in this referral process.

The rest of the paper is organized as follows. "Background and previous literature" discusses the previous literature and theoretical background of the study. "Data and empirical strategy" explains the data, how the networks are constructed, and the empirical estimation and provides descriptive statistics of the data. "Results" provides the main results, shows the robustness of the results, and highlights some potential mechanisms. Finally, "Conclusions" concludes and discusses the implications of our findings.

2 Background and previous literature

2.1 The importance of job search networks and referrals for employment outcomes

The literature on job search networks shows that networks are a way for firms to acquire hard-to-observe information about worker characteristics, typically in the form of employee referrals (Casella & Hanaki, 2006; Montgomery, 1991). The traditional Montgomery (1991) model addresses both how workers hired through referrals earn higher wages and the firms that hire referred workers earn higher profits. Importantly, workers are unable to signal their latent ability to employers directly, and referrals function as an information transmission mechanism under imperfect information. Therefore, firms hire workers through productive employee networks, and these new hires have higher unobserved productivity and should theoretically earn more. This stems from the fact that the individual and vacancy are better matched.

There have been previous studies on the use of coworker-based networks and their implications for various kinds of labor outcomes (Cingano & Rosolia, 2012; Lindquist et al., 2015). Most of the literature on labor market outcomes looks at employment outcomes and wages. For example, Glitz (2017) finds evidence of an increased employment probability for those with coworker ties but does not obtain any significant effect on wages. On the other hand, Antoninis (2006) finds that there are positive wage effects for recruits when recommended for a job by an individual with direct knowledge of their productivity rather than by family or friends. Similarly, Dustmann et al. (2016) and Hensvik and Skans (2016) find a positive relationship between coworker ties and entry wages. Overall, the current empirical literature indicates the presence of a positive relationship, but this may differ across different groups of individuals based on identifying characteristics such as ethnicity (Ioannides & Datcher Loury, 2004; Aslund et al., 2014).

Much of the previous empirical research on job search networks has relied on employee surveys where individuals are asked from whom they received their current job; see Ioannides and Datcher Loury

(2004) for an overview. Some recent works use data from firms to determine whether the new hires were referred by a current employee (Brown et al., 2016; Burks et al., 2015). Others use more experimental designs to evaluate the use of referrals (Heath, 2018). However, similar to our research design, many also measure referrals through register-based employer-employee datasets and individuals' past common firm experience (Cingano & Rosolia, 2012; Glitz, 2017; Hensvik & Skans, 2016).

2.2 The self-employed and job search

Those who are or have been self-employed are commonly regarded as being more risk-prone because starting a firm entails taking on more risk than being an employee (Kihlstrom & Laffont, 1979). Individuals enter self-employment not only to pursue monetary benefits but also for nonpecuniary reasons such as preferences for being one's own boss and flexible working hours (Moskowitz & Vissing-Jørgensen, 2002). In general, many individual characteristics have been linked to entry decisions, such as age, gender, and education (Berglann et al., 2011; Livanos, 2009).[3] However, many who try self-employment exit after a short period of time (Shane, 2009)[4]; importantly, exit does not uniformly equate with business failure (Gimeno et al., 1997; Taylor, 1999; Wennberg et al., 2010).[5] Based on a traditional model by Jovanovic (1982), exits consist of both low- and high-ability individuals. Andersson Joona and Wadensjö (2013) provide empirical evidence that individuals who exit self-employment (or entrepreneurship) come from both extremes of the ability distribution. Individuals can also leave self-employment voluntarily due to changes in their preferences,[6] and exits do not depend solely on the firm's financial performance but instead on other personal threshold levels of performance (Gimeno et al., 1997). However, among those who do exit, most subsequently transition to paid employment (Hessels et al., 2011).

There has been a growing interest in how individuals fare in the labor market after they exit self-employment. For example, Evans and Leighton (1989), Hamilton (2000), Luzzi and Sasson (2016), and Merida and Rocha (2021) report higher earnings of former entrepreneurs in wage employment, whereas Manso (2016) finds no evidence of former entrepreneurs being either punished or rewarded in the salaried workforce. However, there are some findings supporting negative earnings after self-employment (Bruce & Schuetze, 2004; Hyytinen & Rouvinen, 2008), while others have found that these findings can be explained by industry switching, occupation and industry differences, or the level of education (Daly, 2015; Kaiser & Malchow-Møller, 2011; Lappi et al., 2022). On the other hand, Mahieu et al. (2019) argue that the major mechanism through which the differences between the two groups of employees emerge is that the self-employed have a higher uncertainty associated with their productivity; thus, employers respond to this uncertainty by discounting the wages offered. This can potentially explain the results by Koellinger et al. (2015), who show that self-employed job applicants receive systematically lower response rates despite being equally qualified.

The self-employed who wish to return to wage employment may have to use their professional networks to mitigate information asymmetries regarding their unobserved ability or business success and using these networks should in turn result in higher entry wages. For example, Gimeno et al. (1997) show that firms' survival is dependent on a threshold level of performance rather than any objective level. This may result in asymmetries under which the success of the entrepreneurs' venture might not be fully transparent to the employer. For example, the employer might consider the entrepreneur as a failure even if the entrepreneur closed down their firm for reasons other than financial failure. Information asymmetry can result in the self-employed deriving additional value from referrals, as the difference between their true productivity and the uncertainty with which they are associated is higher.

[3] See Blanchflower (2000) and Parker (2018) for a survey of the literature.

[4] A notion that is confirmed by the industrial organizational literature that many firms exit during the first years of their existence.

[5] For example, Baird and Morrison (2005) show that 10–15% of American businesses that closed filed for bankruptcy, whereas Taylor (1999) estimates that 20% of British male entrepreneurs left self-employment due to bankruptcy whereas one-half quit to take another job.

[6] These could include, for example, the need or willingness to have more stable working hours and income.

On the other hand, the self-employed may be different in multiple inherent characteristics that lead to differences in their use of social networks and their subsequent impact. For example, suppose the employer seeks explicitly to hire someone entrepreneurial, risk-taking, or creative. In that case, they might consider a previously self-employed candidate over others and therefore rely on incumbents to provide information on these candidates. This can result in some employers directly recruiting the self-employed, as Taylor (1999) shows that half of the self-employed exit to take another job. On the other hand, the self-employed are generally more social and extroverted (Burke et al. 2000), among other traits.

It is reasonable to expect that the self-employed might benefit from referrals to a greater extent than their wage employee counterparts. If the self-employed are generally more social and extroverted (Burke et al., 2000), it may follow that they rely naturally more on their social networks when finding a job. On the other hand, if they are more discriminated against by prospective employers (Koellinger et al., 2015), they might find themselves in situations where they are forced to use their social networks more. The self-employed also lose the possibility of gaining coworker ties when they are engaged in self-employment, leading to a potentially smaller professional network. All of this taken together means that the literature does not have a clear theoretical prediction of how the coworker ties of the self-employed operationalize when the self-employed exit and gain employment. We are the first to provide empirical insights on this matter.

3 Data and empirical strategy

3.1 Data

We use register-based employer-employee data provided by Statistics Sweden, where we can match individuals to the respective establishments where they are employed. The data contain information on the labor market status of individuals at a yearly frequency where the employment status is specified in November of each year. Based on this employment status, we can differentiate whether an individual is an employee or self-employed. Self-employment is defined as business ownership, and an individual is reported as self-employed if at least half of her income originates from a business she owns.[7]

Similar to Hensvik and Skans (2016), we exclude establishments with more than 500 employees throughout the period considered in this paper. Using this threshold decreases the computational burden, and the likelihood of mis-specifying links as true coworker ties via common working histories is greater in larger organizations.[8] New hires between any two establishments that exceed 5 employees are excluded from our analysis to avoid including possible mergers and acquisitions following, e.g., Hensvik and Skans (2016). We exclude the agriculture, forestry, and mining industries from our data throughout the period and include only private sector employment. This is done because wages are not comparable across the public and private sectors (Wahlberg, 2010).

The included new hires are those made between 2010 and 2014. Using these years renders that we have all new hires who exit self-employment or change between two establishments as employees within a window of 4 consecutive years to increase the sample size and the generalizability of the results. The data we use in our empirical estimations are therefore cross-sectional. However, we have information on the employment histories of individuals dating back to 1993, which we use when measuring our coworker networks.

3.2 The network

We are interested in two different types of new hires who at year *t* are both fully employed[9]: those whose

[7] There has been considerable debate regarding the definition and usage of self-employment and entrepreneurship; see Parker (2018) for a review and discussion.

[8] Some alternative cutoff points have been used. For example, Glitz (2017) uses establishments with 5 to 50 employees and Brown et al. (2016) look at a single mid-sized American firm with approx. 2000 to 5000 workers. The threshold value of 500 lies in between these two studies but the results are robust to changing the threshold to a smaller value.

[9] Full-time employment is defined as individuals earning more than 181,200 SEK a year in 2016 price levels, which corresponds to minimum wage agreements between labor unions. We follow the cutoff described in Andersson Joona and Wadensjö (2013). The results are not sensitive to cutoff points around this value, but including all wages severely biases our results because those with links are more likely to gain full-time employment.

employment status at *t-1* was self-employed or those who were wage employed at *t-1*. All the new hires must also change their unique establishment identifiers between years *t-1* and *t*. This restriction, together with excluding labor mobility between two establishments of 5 or more individuals, enables us to exclude all self-employment acquisitions and mergers.[10] As described above, we consider direct transitions for both groups of new hires, meaning that the individual has information on employment status and establishment identifiers at times *t-1* and *t*. We include only new hires with no prior ties to the hiring organization to ensure that we do not capture pure firm selection.

The incumbent workers, i.e., those who refer the new hire, are defined as workers observed at the establishment for at least two consecutive years. Therefore, they are observed at the establishment at least one full year prior to the hiring of the new employee. We construct the network based on similar employment histories between the new hire and the incumbent worker from common previous labor market experience (in terms of establishment and year(s)) before the new hire joins the new workplace. The establishment they are hired into must be different from the establishment where they originally formed the link.

Our data span from 1993 onward, and we allow the coworker ties to be formed at any point between 1993 and 2 years before the individuals are hired. We construct yearly matched pairs of the new hire (*i*) and incumbent worker (*j*). For each new hire-incumbent pair, we define a variable indicating whether (*j*) and (*i*) worked at the same establishment at the same time and are now employed by the same establishment. This leads us to obtain a dichotomous variable indicating whether the new hire has an existing coworker link in the new workplace.

The new hire and the incumbent worker must have worked together at the same establishment for at least 1 year before employment in year *t*. However, it should be noted that we make a significant assumption by concluding that the two employees know each other simply by their prior employment history. We provide various robustness tests to rule out the most likely coworker ties that we misidentify as being referred due to factors such as the large employer effect. The results are also robust when we define the networks within skills levels, i.e., only employees in higher-skilled occupations form links to each other.[11]

3.3 Empirical model and descriptive statistics

Our primary purpose is to examine whether new hires who exit self-employment and have existing coworker ties receive higher entry wages and whether the existence of a coworker tie has similar implications for the self-employed than for those who change employers. The wage equation we estimate for all the new hires is defined as:

$$w_i = \alpha + \tau_1 E_i + \tau_2 Link_i + \tau_3 (Link_i * E_i) + X\gamma + e_f + e_o + e_d + e_m + e_t + \varepsilon_i \quad (1)$$

where w_i is the natural logarithm of entry wages of the new hire (*i*). The entry wages are measured at a yearly level and presented in Swedish Krona using 2016 values. We are specifically interested in the estimated τ coefficients. The variable E_i denotes when the individual is formerly self-employed, i.e., the new hire was self-employed at time *t-1*. The τ_1 term estimates how differently, in general, the individuals who exit self-employment earn relative to job changers. The variable $Link_i$ takes a value of 1 if the new hire has existing coworker ties in the new workplace and 0 if she does not. Therefore, the τ_2 term is the estimated increase in entry wages associated with having coworker ties. We include the interaction term indicating whether the individual comes from self-employment and has coworker ties, denoted as τ_3. This term, therefore, answers the question of whether the ties of exiting self-employed workers differ from those of wage employees. The estimated difference between a formerly self-employed worker with a coworker link and job switchers without a link can be calculated by summating all estimated τ terms.

In the vector of control variables (***X***), we include individual and establishment characteristics that impact wage-setting following the Mincerian wage equation (Mincer 1958, 1974). Specifically, we include the labor market experience of individuals measured separately for the years of employee and self-employment experience (*Experience* and

[10] Changing the establishment is defined as the individual changes between times *t-1* and *t* the unique establishment ID.

[11] These results can be obtained from the authors upon request.

Self-employment Experience). As we measure coworker ties based on previous work history, these experience measures are additionally important as they control for the possibility of having formed ties at the same time while accounting for overall employment experience. These two experience variables are measured in accumulated years of respective experience starting from 1993. We also include the years of schooling, which is based on the highest degree obtained (*Schooling*), the age of the individual (*Age*) and the squared term (*Age*^{2}),[12] the gender of the individual (*Gender)*, whether the individual is married (*Married)*, whether the individual has children living at home (*Children*), and whether the individual was born outside from Sweden (*Foreign-born*). In addition, to control for workplace characteristics in the entry wage determination, we include the size of the establishment based on the total number of employees in logarithmic form (*Establishment size*), the establishment age measured in years since start-up (*Establishment age*), and whether the establishment belongs to a multi-establishment firm (*Multi-establishment*). Table 6 in the Appendix provides a correlation table of the independent variables included in this analysis.

Importantly, in Eq. 1, we control for establishment *f*, occupation *o*, industry *d*, labor market *m*, and year *t* fixed effects. The ε_i term is the error term that is clustered at the establishment level. The occupational data follow the Swedish Standard for Classification of Occupations (SSYK), which corresponds to international standards (ISCO-88). We control for occupations at the 2-digit level. The industry classifications follow the Swedish Standard Industrial Classification codes, which are based on the EU's recommended standards (NACE codes). They are reported at the establishment level, and we control the industry-specific wage determinations at the 2-digit level. The labor markets are based on individual residences and comprise of 60 local labor markets across Sweden. They are constructed based on commuting patterns and existing municipality borders.

We estimate Eq. 1 with an ordinary least squares (OLS) estimation. Our main identification assumption lies in the ability to control for as many observable characteristics of individuals and firms as possible within the detailed register-level data while also controlling for the large set of fixed effects. However, it is well-known that the self-employed and employees are not directly comparable, which has led previous research to apply matching methods to make the two groups of individuals comparable (Kaiser & Malchow-Møller, 2011; Mahieu et al., 2019; Manso, 2016). We use the coarsened exact matching (CEM) matching estimator (Iacus et al., 2012) which allows the balance between the two groups to be chosen ex-ante.[13] We match the exiting self-employed workers and job-switchers the year before they are new hires, i.e., at time *t-1* when they are preparing to leave their prior employment. We match the two groups of individuals based on whether they are foreign-born, their age, gender, labor, and business income, and the firm's productivity defined as value-added. Controlling for the baseline differences, especially the income and performance of the firm, can be important, as these are likely to drive the difference in wage negotiations. Detailed information about the covariate threshold values used in employee matching and the overall matching summary is provided in Appendix Table 7.

The matching aims to control any co-founding differences between the self-employed and the employees. However, the ties are identified only when individuals gain full-time employment, which the matching does not account for. This definition of the ties means that we are unable to measure any choice set individuals have based on potential new employers and their potential referrals in each firm, i.e., we are capturing only ties that are conditional on having gained employment. One possible remedy for overcoming such an issue would be to use surveys, i.e.,

[12] We include the age variable in addition to the labor market experience variables because there could also be age discrimination in the labor market (Johnson & Neumark, 1997), and older individuals tend to have lower rates of mobility (Hutchens, 1988). However, as shown in Table 6 in the Appendix, the experience and age variables are correlated. All results are robust to the exclusion of either the experience or the age variable.

[13] This is an improvement from the PSM-method, in which the balance between the control and treatment groups is chosen through the iterative process of ex post balance checking (see King & Nielsen (2019) for a discussion of the two methods). Another advantage of the CEM is that it reduces model dependence since the matching is conducted before the actual analysis is performed (Ho et al., 2007).

Table 1 Descriptive statistics for new hires

	From self-employment		Job-changers	
	Link	*Without Link*	*Link*	*Without Link*
Individual-level data				
Yearly wages (in SEK)	427,366	366,228	425,631	368,810
Experience (in years)	10.41	7.649	13.75	11.12
Self-employment experience (in years)	4.504	5.463	0.352	0.584
Schooling (in years)	12.69	12.68	12.22	12.32
Age (in years)	44.03	42.83	44.50	42.28
Gender (1 = man, 0 = otherwise)	0.793	0.747	0.684	0.638
Married (1 = married, 0 = otherwise)	0.551	0.497	0.477	0.428
Children (1 = children, 0 = otherwise)	0.651	0.594	0.585	0.550
Foreign-born (1 = foreign-born, 0 = otherwise)	0.217	0.239	0.235	0.281
Establishment size (number of employees)	76.51	44.25	78.50	46.18
Establishment age	12.52	10.77	13.93	11.26
Multi-establishment	0.336	0.268	0.390	0.325
Network characteristics				
Number of Links	3.078		3.177	
Years since the link was established	7.763		5.524	
Individuals	2.718	22,821	84,761	431,327

Mean values presented

obtain more qualitative data on the search process.[14] Using population-wide register data, such as we are using, has the advantage of resulting in large and representative samples where one can track individuals across time. The disadvantage comes from, for example, the inability to trace counterfactuals for individuals' possible choices as one has information on a yearly level only on the registered outcomes. Therefore, we are able only to measure coworker links for individuals who gained employment, and thus the results of having the links should be considered only for a similar type of individuals who also gained full-time employment.[15]

Even if we had access to richer data on coworker ties, the ties are not randomly allocated across individuals, which means that the τ_2 term is endogenous. In the absence of exogenous variations in the coworker ties, our estimations should not be interpreted strictly as causal. Our aim and contribution originate from being the first to map and find a relationship between the usage of coworker ties and the entry wages for the exiting self-employed while controlling for a large set of individuals- and firm-level characteristics.

Table 1 describes the data used for our estimation sample. The mean values for those new hires from self-employment (*From self-employment*) and those changing jobs (*Job changers*) are presented separately. We also show the mean values separately for those with and without coworker links. Table 8 in the Appendix provides a complete set of descriptive statistics.

Overall, approximately 10.6% of exiting self-employed workers and 15.7% of former employees have coworker links. The latter finding is in line with Hensvik and Skans (2016). Those who are hired from employment have coworker links more often, which could be because the self-employed did not have an opportunity to form coworker links in their prior role. This result would descriptively suggest that

[14] For example, Carlsson et al. (2018) conduct their own survey of newly hired employees and Cappellari and Tatsiramos (2015) use British Household Panel Survey.

[15] We are following the literature of, e.g., Hensvik & Skans (2016), Dustmann et al. (2016), Glitz (2017), and Cingano & Rosolia (2012) who face similar identification problems as they use register-based datasets. We model the selection into full-time employment and the potential impact it has for entry wages by a Heckman two-step selection model in "Robustness—earningsand selection into employment".

the formerly self-employed incur an experience cost via the lost opportunity to form coworker ties. This is further supported by the fact that the links are on average around 2 years older for the self-employed compared to the job changers. Otherwise, the number of coworker ties is similar across the two groups of new hires with a mean of 3 coworker links. However, it should be noted that the median value is 1 link per new hire, which implies that the number of coworker ties is likely to be skewed, as seen in Table 8 in the Appendix.

The formerly self-employed and job changers are similar across individual-level characteristics, which indicates that our matching effectively makes the two groups of individuals similar in observable characteristics. However, the self-employed seem to select themselves into slightly smaller and younger single-establishment firms. This highlights the importance of controlling for not only firm-level characteristics but also firm-fixed effects, i.e., all unobservable firm characteristics. Controlling these characteristics accounts for this selection of individuals to firms.

4 Results

4.1 Main results

As previously described, our main purpose is to estimate the entry wages and the potential gains from coworker ties for those who exit self-employment. We estimate Eq. 1 by adding some of the fixed effects stepwise to show the direction of the bias created by their absence. The main and preferred result is presented in Column 4 with the matching weights included. The results are presented in Table 2.

The main results show that the self-employed earn 10.2% lower entry wages than job changers. These results are in line with previous research that reports wage losses for the self-employed when reentering wage employment (Hyytinen & Rouvinen, 2008; Mahieu et al., 2019, Lappi et al., 2022). However, our estimates are of a larger magnitude. Given that we match the two groups of individuals regarding their earnings before changing jobs if wages fully convey productivity, the negative risk associated with self-employment would be exactly the estimated 10.2%. This result implies that employers might consider them to be risky hires and thus offer lower entry wages to compensate for this perceived risk. However, the negative entry wage penalty may include the differences in such factors as reservation wages if their only alternative is unemployment, which might not be fully captured by matching the individuals based on their previous earnings.

On the other hand, the results show that the gains from having an existing link for all new hires are 2.9%. This result means that there are significant gains from having an incumbent worker convey hard-to-observe information about the recruit to the potential employer. The finding is similar to Hensvik and Skans (2016) and Brown et al. (2016), who observe approximately 3 to 3.6% higher wages for referred hires. The result verifies that our estimates are reasonable or even slightly downward biased in comparison. Furthermore, we do not find any evidence that the self-employed rely particularly heavily on these coworker ties, as the interaction term is close to zero and insignificant. These results suggest that the formerly self-employed with existing coworker links can partly overcome the information deficiencies in recruitment, as they earn an estimated 2.9% more than the previously self-employed without a link. When taking the estimated coefficients together, the results imply that the formerly self-employed with coworker ties earn only 7.3% lower entry wages than job changers without ties.

Our main results show that there are significant gains from having professional links, as previously found by Schmutte (2015) and Dustmann et al. (2016). On the other hand, the self-employed earn significantly lower wages (Hyytinen & Rouvinen, 2008; Mahieu et al., 2019). We contribute to the literature by showing that when the self-employed exit and use their self-employment-specific networks, they can overcome some of the wage losses that self-employment experience seems to entail. However, the self-employed receive no additional benefit from having coworker links relative to job changers, which would imply that such individuals cannot fully overcome the potential risk with which potential employers associate them.

4.2 Sensitivity analysis

4.2.1 Robustness—earnings and selection into employment

Our main dataset does not have information on hourly wages or full-time employment, which

Table 2 Results—baseline

Dependent variable: Ln(Wages)	(1)	(2)	(3)	Matching (4)
SE	−0.089***	−0.105***	−0.111***	−0.102***
	(0.003)	(0.003)	(0.003)	(0.003)
Link	0.037***	0.040***	0.029***	0.029***
	(0.002)	(0.001)	(0.001)	(0.002)
*SE*Link*	0.020**	0.010	0.006	0.003
	(0.008)	(0.008)	(0.008)	(0.008)
Experience	0.014***	0.011***	0.009***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)
Self-employment experience	0.005***	0.002***	0.004***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Schooling	0.050***	0.027***	0.019***	0.018***
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.029***	0.023***	0.023***	0.022***
	(0.000)	(0.000)	(0.000)	(0.001)
Age^2	−0.000***	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Gender	0.132***	0.120***	0.109***	0.124***
	(0.001)	(0.001)	(0.001)	(0.002)
Married	0.056***	0.037***	0.030***	0.026***
	(0.001)	(0.001)	(0.001)	(0.002)
Children	0.002***	−0.004***	−0.008***	0.005***
	(0.001)	(0.001)	(0.001)	(0.002)
Foreign-born	−0.042***	−0.025***	−0.016***	−0.017***
	(0.001)	(0.001)	(0.001)	(0.002)
Establishment size	0.018***	0.015***	−0.016***	−0.016***
	(0.001)	(0.001)	(0.002)	(0.004)
Establishment age	−0.001***	−0.001***	0.006***	0.006***
	(0.000)	(0.000)	(0.000)	(0.001)
Multi-establishment	0.026***	0.007***	0.003	−0.001
	(0.002)	(0.002)	(0.005)	(0.008)
Constant	11.162***	11.706***	11.801***	11.778***
	(0.012)	(0.038)	(0.011)	(0.019)
Observations	614,890	614,890	614,890	541,627
R-squared	0.340	0.438	0.599	0.657
Year FE	Yes	Yes	Yes	Yes
Labor market FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	Yes	Yes
Establishment FE	No	No	Yes	Yes

Standard errors clustered at the establishment level in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

leads us to assume full-time employment through earnings and minimum wages set by the collective bargaining agreements. However, this potentially creates a bias in our sample of individuals. In addition, we have probable self-selection of individuals to full-time employment. Therefore, to understand the underlying robustness of our main findings, we measure our outcome variable with an alternative salary variable and model the selection to full-time employment by a two-step

Table 3 Results—Robustness

	Salaries (1)	Heckman 1st stage (2)	Heckman 2nd stage (3)
SE	−0.108***	−0.015***	−0.115***
	(0.020)	(0.006)	(0.002)
Link	0.040***		0.040***
	(0.007)		(0.001)
*SE*Link*	−0.005		0.010
	(0.050)		(0.006)
Observations	55,447	1,297,921	1,297,921
R-squared	0.663		
Year FE	Yes	Yes	Yes
Labor market FE	Yes	Yes	Yes
Industry FE	Yes	No	Yes
Occupation FE	Yes	No	Yes
Establishment FE	Yes	No	No

Standard errors clustered at the establishment level in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$. Salaries are defined as ln(salaries) taken from employment contracts and adjusted for the working time. The dependent variable in the Hackman selection model in the second stage is the baseline natural logarithm of earnings

Heckman-selection model. The results of both such robustness tests are presented in Table 3.[16]

First, we have access to information from a random sample of private-sector employment contracts that includes information about the percentage of working time and monthly salaries. Therefore, we have a small sample of individuals for whom we can identify full-time employment. We rerun Eq. 1 with our output variable as the natural logarithm of salaries adjusted for working time. Otherwise, all included variables are identical to those in our baseline estimations, with the exception that we now also control for full-time employment. The results are shown in column 1. Using this measure of entry wages also controls the possibility that the difference between the formerly self-employed and job changers is driven by measuring earnings on a yearly level when in truth, the two groups might differ systematically on the timing of their change of employers rather than in actual earnings.

Second, entry wages are subject to, for example, labor supply-related selection, which means that those with entry wages must have employment. Individuals who exit self-employment may not immediately find employment, even if previous literature has found that most do (Hessels et al., 2011). Also, the job changers are likely to show a positive selection of individuals, as some might not find a job and transition to unemployment or inactivity. We estimate a two-step Heckman selection model to control the sample selection to full-time employment (Heckman, 1976, 1979).[17] In the first step, we include all individuals who change out of self-employment or employment between time *t* and *t-1*. Therefore, the selection is modeled using all individuals who change employment status, including those who switch to unemployment, inactivity, or part-time work. The selection model corrects the probable positive selection of changers into our sample. The results of the main variables from both the first and the second step of the estimation are in columns 2 and 3 respectively.[18]

The results for the salaries for which we are able to control and account for full-time work through information provided in employment contracts show similar results to our main estimations. In this scenario, the value of a coworker link is higher than in the baseline results with a point estimate of a 4% coworker premium. The salary estimation shows that our results are not driven by

[16] The full results are shown in Appendix Table 9.

[17] This correction is especially important as our definition of the coworker ties are conditional on finding employment. Thus, this sample selection correction should at least partly correct for some positive selection into employment and thus having coworker ties.

[18] The full results from the first and second step can be found in Appendix Table 9. As exclusion restriction, in the first step we include the natural logarithm of the household income excluding the income of the individual. This is as arguably labor supply decisions are dependent on the income of the spouse.

Table 4 Result—network definition

Dependent variable: Ln(Wages)	Links after 2000 (1)	Links within skill levels (2)	Establishment size (3)
SE	−0.101***	−0.101***	−0.102***
	(0.003)	(0.003)	(0.003)
Link	0.028***	0.029***	0.040***
	(0.002)	(0.002)	(0.003)
*SE*Link*	0.003	0.000	0.004
	(0.009)	(0.011)	(0.012)
$Link{*}Link_{Large}$			−0.020***
			(0.004)
$SE{*}Link{*}Link_{Large}$			−0.005
			(0.016)
Observations	541,627	541,627	541,627
R-squared	0.657	0.657	0.657
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Labor Market FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes
Matching	Yes	Yes	Yes

Standard errors clustered at the establishment level in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$

mismeasuring full-time work or systematic differences in employer changes within the year.

The results corroborate our main findings also for the selection model. Column 2 shows that self-employed workers are less likely to transition to employment than employees. However, the decrease in the probability of employment for self-employed is relatively small at only 1.5%. The overall entry-wage difference between the self-employed and the employees is similar to the 10.2 percentage found in the main estimation. The estimated impact of having links and being formerly self-employed with links is largely unaltered. Our results show that the sample selection of self-employed workers who find full-time employment does not seem to have a large bias for our main results.[19]

[19] Note that we cannot include establishment fixed effects nor the matching weights in the Heckman two-step model which also explains our results being in-line with column 2 in Table 2. We have also estimated all the results from Tables 4 and 5 with the selection model which can be found in Appendix Tables 10 and 11.

4.2.2 Network definition

Our definition of coworker links through common employment histories may lead to us overestimating the number of individuals with coworker ties. Therefore, we need to evaluate the robustness of how we define a network. We provide three different robustness definitions. The results from the alternative coworker ties for the main variables are presented in Table 4. Detailed descriptive statistics for alternative types of links can be found in Appendix Table 8.

In our main estimations, we define the network as having been formed any time after 1993 until the individual either exits self-employment or changes employers during the period from 2010 to 2013. To evaluate whether professional links that date back 20 years are appropriate, we truncate the sample such that the networks are formed more recently. We allow the professional link to be formed only from 2000 onwards. By doing so, we exclude 18.3% of the coworker links for the formerly self-employed and 9.6% of the coworker links for the job changers. The results are shown in column 1.

Table 5 Results—network scope and quality

Dependent variable: Ln(Wages)	(1)	(2)	(3)	(4)
SE	−0.102***	−0.101***	−0.101***	−0.056***
	(0.003)	(0.003)	(0.003)	(0.004)
Link	0.029***	0.033***	0.014***	0.005*
	(0.002)	(0.003)	(0.003)	(0.003)
*SE*Link*	0.000	0.003	0.020*	0.019*
	(0.009)	(0.013)	(0.012)	(0.012)
Network size	0.000			
	(0.000)			
*SE*network Size*	0.001			
	(0.001)			
Years worked together		−0.001*		
		(0.001)		
SE years worked together*		−0.000		
		(0.003)		
*Link*high skilled link*			0.026***	
			(0.004)	
*Link*high skilled link*SE*			−0.028*	
			(0.016)	
High skilled				0.227***
				(0.002)
*High skilled *SE*				−0.064***
				(0.005)
*High skilled*link*				0.041***
				(0.004)
High skilled link*SE*				−0.019
				(0.017)
Observations	541,627	541,627	541,627	541,627
R-squared	0.657	0.657	0.657	0.628
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Labor market FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes	Yes
Matching	Yes	Yes	Yes	Yes

Standard errors clustered at the establishment level in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$

We implicitly assume that the incumbent worker and the new hire know each other if they have worked in the same establishment at the same time in the past. However, this may not be the case. To increase the likelihood that the individuals, in fact, know each other, we define that for the two individuals to have a link, they must be within the same broadly defined occupation group. We construct occupational groups to be confined to high- and low-skilled occupations. High-skilled individuals are defined as managers or professionals with university qualifications or the equivalent.[20] When we delimit the coworker ties to be formed within the high- or low-skilled occupations, we exclude 39.1% and 26.8% of the links for formerly self-employed workers and job

[20] In the occupational codes, these include occupations included at the levels 1 to 3 at the first digit level.

changers, respectively. The results are presented in column 2.

The cutoff point of 500 employees might still result in us overestimating true coworker ties if some individuals work in the same large establishment by chance when they, in fact, do not know each other. We, therefore, define two groups of links based on the size of the establishment when the link was formed in (i) workplaces with fewer than 50 employees and (ii) workplaces with 50 or more employees. The likelihood of employees actually knowing each other should be higher in smaller establishments. For the formerly self-employed, 47.8% of the coworker links were formed in large establishments, whereas 58% of the job changers' links were created in large establishments. The results are presented in column 3.

When we trim the time period to be the most recent years in column 1, the results show little difference in the estimated coefficients compared to our main results. This result indicates that although relatively few professional links formed far in the past, they act similarly to the recently formed links. However, this means that coworker links that matter are by and large created in the last decade. The results are also consistent when we define the links within the broad skill groups of workers in column 2. We see a difference from our main results when we consider that the baseline results are driven mainly by coworker ties formed in smaller establishments. There is a positive but smaller network premium of approximately 2% for those with coworker links from larger establishments. The result suggests that our main findings are unlikely to be driven by the firm size selection.

4.2.3 *Network scale and quality*

We have assumed that the size and quality of the network are uniform and independent of the network premium. However, we wish to evaluate to what extent the quality of the coworker ties drives our main results. Therefore, we extend Eq. 1 by adding network quality measures and their interaction with whether they are formerly self-employed. Detailed descriptive statistics on the quality variables can be found in Appendix Table 8.

To evaluate whether there are scale effects of having a larger network, we include a variable that measures how many coworkers links the individuals have. If the network premium is solely driven by having many links, this could entail that we likely measure firm selection rather than any true coworker relationships. However, as described before, the median number of coworker ties is only one. Therefore, we include the number of links and the interaction with being self-employed in Eq. 1, and the results are presented in column 1. Instead of including a continuous variable of network size, we also run estimations where we instead estimate the additional effects of having large networks based on having 2 to 5, 6 to 19, or 20 or more links. The results of this alternative estimation are presented in Appendix Table 12.

If the incumbent and the new hire worked for a longer period of time together, we would expect the referral to have a larger effect. Given the detailed level of our data, we can measure the number of years the new entrant and the incumbent worked together. The expectation is that the longer the individuals work together, the better they know each other and the stronger the tie between them. However, whether the strength of the relationship will directly translate into higher entry wages is not obvious. On average, self-employed workers with coworker ties spent 2.7 years in the same establishment as the incumbent compared to approximately 3 years for job changers. We include the years worked together and the interaction with being formerly self-employed in Eq. 1. The results are presented in column 2.

The theoretical predictions from the Montgomery (1991) model state that entry wages should be higher for entrants who are linked to high-ability incumbents than for workers who are connected to less qualified incumbents. A difference in the quality of the ties differs between self-employed workers and incumbents could potentially explain the earnings difference. Accounting for the tie quality leads us to divide the sample based on the average educational attainment of the linked incumbent workers. A high-skilled link is defined as those whose average coworker ties have more than 12 years of schooling. The formerly self-employed have 63.5% and the job changers 57.9% of their links with highly educated incumbents. We include a variable that indicates whether the link is with a highly educated incumbent and the interaction with whether the individual is previously self-employed in Eq. 1. Results are shown in column 3.

Even if we control for occupation at a detailed level, there might be a systematic difference in how these coworker links operationalize for skilled workers. Therefore, Eq. 1 is modeled to include a variable indicating whether the individual is a high-skilled individual and the interaction terms with our main variables. A high-skilled individual is defined similarly as in "Network Definition". A total of 66.8% of the formerly self-employed workers with links and 49.6% of the job switchers with coworker ties are in high-skilled occupations. In general, descriptive statistics in Appendix Table 8 show that formerly self-employed workers are found more often in these occupations. The results are presented in column 4.

There is no apparent impact of controlling for the size of the network, and the baseline results we obtain for the estimated coefficients are unchanged. This leads us to be confident that we are measuring actual coworker ties rather than another unobserved firm selection. As shown in the distribution of links in Appendix Table 12, we find similar results. There is no evidence that the average years worked together to have a direct impact, as shown in column 2. However, we find that the estimated effect of having links increases slightly to 3.3% when we control for the average strength of the link. The results show that the length of time the new hire and incumbent previously worked together plays a relatively minor role in the earnings of new hires (Table 5).

The findings for network quality in column 3 show more divergent results based on whether the new hires are linked to high- or low-skilled incumbents. The baseline network premium is only 1.4% in this scenario, whereas the premium increases to 4% if the individual has a link to a high skilled incumbent. The evidence points to it being more beneficial to be referred by a high-skilled incumbent, which is in line with Montgomery (1991) and Hensvik and Skans (2016). There is weak evidence that this is not true for self-employed workers with links, but the interaction terms are only significant at the 10% level.

There emerge some apparent differences when we differentiate new hires based on the skill level of the occupations. Low-skilled new hires have a small and weak relationship with having links and entry wages. The difference between the self-employed and job-changers decreases to only 5.6%. The results show that even if the self-employed obtain more high-skilled jobs, they earn 12% less in these occupations. The underlying positive network premium is found only for high-skilled individuals, which we estimate to be 4.1% for both self-employed workers and job changers. We have evidence suggesting that coworker links are particularly important for high-skilled occupations and that there is a systematic difference between previously self-employed individuals and employees at all occupational skill levels.

5 Conclusions

This paper provides evidence on whether the self-employed who seek full-time employment can mitigate some of the risk employers associate with hiring them by using their coworker networks. We are the first to link the use of professional networks to self-employed workers reentering the full-time workforce. Similar to previous studies, we find that self-employed workers generally earn lower entry wages upon reentry than those who change employers. Importantly, we identify the difference in information channels between self-employed workers and wage employees.

The results show that the professional networks of those exiting self-employment supply similar information to those of wage employees, which translates to higher entry earnings. There are no findings of self-employed workers relying more on coworker ties than regular job changers. However, we find some caveats to this information transmission and earnings mechanism. The self-employed cannot fully account for their lower entry wages by having employees refer them. The estimated gain for self-employed individuals to have a coworker link is around 2.9%. Considering the benefit of having a coworker link, the results still display a 7.3% lower entry wage than a wage employee who changes their employer without any coworker links. However, the results show that it matters whether the individual is hired in higher- or lower-skilled professions and whether the coworker the individual is linked to is highly skilled.

Approximately 10% of Sweden's labor force is self-employed (Blanchflower, 2000), but Swedish entrepreneurs are more often opportunity- rather than necessity-based compared to US entrepreneurs

(Braunerhjelm & Henrekson, 2013). Additionally, social networks have been found to be different across cultures (Greve & Salaff, 2003). Even if there are institutional differences across countries, there is no evident compelling reason to expect that the results found in this paper would not be replicable in other situations. The compressed wage structure of Sweden might even imply that the wage premiums we find might be a downward bias estimate if extrapolated to other institutional contexts. Future research should further examine whether the results extend to other countries.

Our results show that an imperfect information transmission mechanism cannot explain the earnings gap between the self-employed who exit and employees. If the self-employed had significant and considerable benefits from existing ties, this would have implied that employers utilize some hard-to-observe qualities when hiring them through referrals attached to the self-employment experience. Therefore, we do not show any specific market failures stemming from imperfect information particular to the self-employed. The second finding that corroborates the previous literature is that even if the individual has coworker ties, the previous self-employed earn lower entry wages than those who change employers. Other possible explanations to this finding, besides the one that we tested, could be merely that the former self-employed have lower reservation wages or are not members of employee unions due to their self-employment experience. However, our paper cannot distinguish these possible alternative explanations of the difference in the entry wages and thus urges future research to test such possible mechanisms. Understanding whether the earnings difference stems from a market failure could lead to potential government intervention. On the other hand, if the earnings difference is driven by market forces, for example, purely productivity differences, there would be no need for intervening policy. These reasons are why research in the area is important and warranted.

Appendix

Table 6

Table 6 Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) SE	1.000													
(2) Link	-0.033	1.000												
(3) Experience	-0.102	0.200	1.000											
(4) Self-employment Experience	0.546	-0.040	-0.122	1.000										
(5) Schooling	0.022	-0.020	-0.166	-0.058	1.000									
(6) Age	0.089	0.133	0.558	0.218	-0.098	1.000								
(7) Age^2	0.083	0.122	0.510	0.217	-0.117	0.989	1.000							
(8) Gender	0.044	0.031	0.065	0.065	-0.154	0.021	0.022	1.000						
(9) Married	0.059	0.066	0.259	0.095	0.050	0.371	0.345	0.017	1.000					
(10) Children	0.034	0.043	0.161	0.034	0.010	0.086	0.042	-0.002	0.348	1.000				
(11) Foreign-born	-0.004	-0.023	-0.133	-0.012	-0.004	-0.014	-0.022	-0.009	0.032	0.010	1.000			
(12) Establishment Size	-0.036	0.178	-0.052	-0.065	0.111	-0.064	-0.068	-0.042	-0.007	-0.001	0.035	1.000		
(13) Establishment Age	-0.024	0.094	0.080	-0.021	0.028	0.022	0.018	0.005	0.032	0.025	-0.046	0.423	1.000	
(14) Multi-establishment	-0.053	0.068	0.014	-0.057	0.101	0.033	0.030	-0.096	0.040	0.016	-0.007	0.259	0.125	1.000

Based on a sample with 541,627 observations

Table 7

Table 7 Summary of CEM matching

Before Matching: Multivariate L1 distance 0.556							
Univariate Imbalance:							
	L1	mean	min	25%	50%	75%	max
Foreign-born	0.009	0.009	0	0	0	0	0
Age	0.180	-5.823	-2	-7	-6	-5	1
Gender	0.116	-0.116	0	-1	3	5	0
Income	0.000	12,985	102	42776	2200	-22278	11086258
Value-added	0.010	12,010,610	0	224688	351010	2683859	23840742912
After Matching: Multivariate L1 Distance: 0.411							
	0	1					
All	589128	25762					
Matched	521496	25762					
Unmatched	67632	0					
Univariate Imbalance:							
	L1	mean	min	25%	50%	75%	max
Foreign-born	0.037	-0.037	0	0	0	-1	0
Age	0.038	0.138	2	0	0	0	-1
Gender	0.107	0.107	0	1	0	0	0
Income	0.000	-5817	-102	-1802	-309	6098	16343773
Value added	0.000	1570564	0	-196222	-245768	-906343	-23840742912

The coarsening break values are as follows: foreign-born has two values as the variable is dichotomous, Age has 10 bins with 5-year bin intervals except the youngest values being below 25 years old and the oldest for individuals above 60 years old. Gender has two values as the variable is dichotomous, income has 10 bins with even 50,000 SEK except the lowest bin being between 0 and 100,000 SEK and the highest income bin being above yearly income of 500,000 SEK. The value-added has 8 bins with every 200,000 SEK except for the two highest bins being between 1 million SEK and 3 million SEK and the highest above 3 min SEK

Table 8

Table 9

Table 8 Full descriptive statistics

	From self-employment								From Employment							
	Link				*Without Link*				*Link*				*Without Link*			
	Mean	sd	min	max	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
Individual and Firm characteristics																
Yearly Wages	427,366	239,756	181,278	3.671e+06	366,228	196,278	181,228	7.080e+06	425,631	269,922	181,228	8.934e+06	368,810	228,011	181,228	1.168e+07
Experience	10.41	4.125	2	20	7.649	4.744	1	20	13.75	4.681	3	21	11.12	5.456	2	21
Self-employment Experience	4.504	3.362	1	19	5.463	4.473	1	20	0.352	1.399	0	18	0.584	1.948	0	19
Schooling	12.69	2.021	8	20	12.68	2.078	8	20	12.22	2.029	8	20	12.32	2.035	8	20
Age	44.03	9.123	20	72	42.83	10.13	19	74	44.50	9.588	18	74	42.28	10.35	17	75
Gender	0.793	0.405	0	1	0.747	0.435	0	1	0.684	0.465	0	1	0.638	0.481	0	1
Married	0.551	0.497	0	1	0.497	0.500	0	1	0.477	0.499	0	1	0.428	0.495	0	1
Children	0.651	0.477	0	1	0.594	0.491	0	1	0.585	0.493	0	1	0.550	0.497	0	1
Foreign-born	0.217	0.412	0	1	0.239	0.427	0	1	0.235	0.424	0	1	0.281	0.450	0	1
Establishment Size	76.51	100.6	2	498	44.25	72.31	1	499	78.50	98.23	2	499	46.18	71.77	1	499
Establishment Age	12.52	8.943	1	27	10.77	9.420	0	27	13.93	9.209	1	27	11.26	9.609	0	27
Multi establishment	0.336	0.473	0	1	0.268	0.443	0	1	0.390	0.488	0	1	0.325	0.468	0	1
High-skilled Occupation	0.668	0.471	0	1	0.602	0.490	0	1	0.496	0.500	0	1	0.439	0.496	0	1
Network characteristics																
Number of Links	3.078	7.260	1	149					3.177	7.111	1	390				

Table 8 (continued)

	From self-employment								From Employment							
	Link				*Without Link*				*Link*				*Without Link*			
	Mean	sd	min	max	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
Years since link was established	7.763	4.378	2	20					5.524	3.981	2	20				
Link after 2000	0.817	0.387	0	1					0.904	0.294	0	1				
Link within occupations	0.609	0.488	0	1					0.732	0.443	0	1				
Link Large Establishment	0.478	0.500	0	1					0.580	0.494	0	1				
Years worked together	2.734	2.193	1	16					2.958	2.482	1	19				
Link with High Educated	0.635	0.482	0	1					0.579	0.494	0	1				
Number of Individuals	2,718				22,821				84,761				431,327			

Variables as described in the text. The values are based on the estimation sample

Table 9 Full results—salaries and Heckman-selection model (based on Table 3 in text)

Dependent variable:	Salaries (1)	Heckman 1st Step (2)	Heckman 2nd Step (3)
SE	-0.108***	-0.015***	-0.115***
	(0.020)	(0.006)	(0.002)
Link	0.040***		0.040***
	(0.007)		(0.001)
*SE*Link*	-0.005		0.010
	(0.050)		(0.006)
Experience	0.006***	0.077***	0.021***
	(0.001)	(0.000)	(0.001)
Self-employment Experience	0.006***	-0.027***	0.009***
	(0.002)	(0.001)	(0.000)
Schooling	-0.013***	0.030***	0.030***
	(0.002)	(0.001)	(0.000)
Age	0.036***	0.104***	0.016***
	(0.002)	(0.001)	(0.001)
Age^2	-0.000***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)
Gender	0.017***	0.343***	-0.111***
	(0.007)	(0.002)	(0.003)
Married	0.006	0.017***	0.037***
	(0.006)	(0.003)	(0.001)
Children	-0.037***	-0.219***	-0.014***
	(0.005)	(0.004)	(0.002)
Foreign-born	-0.001	-0.050***	-0.012***
	(0.006)	(0.003)	(0.001)
Establishment Size	-0.068***		0.016***
	(0.021)		(0.000)
Establishment Age	0.015***		-0.001***
	(0.003)		(0.000)
Multi-establishment	0.142*		0.007***
	(0.080)		(0.001)
Full Time Employment	0.923***		
	(0.013)		
Ln(Household Income)		0.003***	
		(0.000)	
Constant	8.500***	-3.342***	11.878***
	(0.111)	(0.016)	(0.053)
Lambda			0.068***
			(0.013)
Observations	55,447	1,297,921	1,297,921
R-squared	0.663		
Year FE	Yes	Yes	Yes
Labor Market FE	Yes	Yes	Yes
Industry FE	Yes	No	Yes
Occupation FE	Yes	No	Yes
Establishment FE	Yes	No	No

Standard errors clustered at the establishment level in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$

Table 10

Table 10 Replication of Table 4 with Heckman–2.nd step results–network definition

Dependent variable: Ln(Wages)	Links after 2000 (1)	Links within Skill Levels (2)	Establishment Size (3)
SE	-0.115***	-0.115***	-0.115***
	(0.002)	(0.002)	(0.002)
Link	0.039***	0.042***	0.059***
	(0.001)	(0.001)	(0.002)
SE*Link	0.011*	0.013*	-0.018**
	(0.007)	(0.008)	(0.008)
Link*$\text{Link}_{\text{Large}}$			-0.033***
			(0.002)
SE*Link*$\text{Link}_{\text{Large}}$			0.053***
			(0.012)
Observations	1,297,921	1,297,921	1,297,921
Control Variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Labor Market FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes
Establishment FE	No	No	No
Matching	No	No	No

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 11

Table 11 Replication of Table 5 with Heckman–2.nd step results—network scope and quality

Dependent variable: Ln(Wages)	(1)	(2)	(3)	(4)
SE	-0.115***	-0.115***	-0.115***	-0.080***
	(0.002)	(0.002)	(0.002)	(0.003)
Link	0.040***	0.038***	0.011***	0.018***
	(0.001)	(0.002)	(0.002)	(0.002)
SE*Link	0.007	0.007	0.016	0.017
	(0.007)	(0.009)	(0.010)	(0.010)
Network Size	0.000			
	(0.000)			
SE*Network Size	0.001			
	(0.001)			
Years Worked Together		0.001		
		(0.000)		
SE* Years Worked Together		0.001		
		(0.003)		
Link*High Skilled Link			0.048***	
			(0.002)	
Link*High Skilled Link*SE			-0.011	
			(0.012)	
High Skilled				0.165***
				(0.036)
High Skilled *SE				-0.056***
				(0.004)
High Skilled*Link				0.044***
				(0.002)
High Skilled* Link*SE				-0.016
				(0.013)
Observations	1,297,921	1,297,921	1,297,921	1,297,921
Control Variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Labor Market FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Establishment FE	No	No	No	No
Matching	No	No	No	No

***$p<0.01$, **$p<0.05$, *$p<0.1$

Table 12

Table 12 Results—distribution of the network size

Dependent variable: Ln(Wages)	(1)	(2)	(3)	Matching (4)
SE	-0.096***	-0.112***	-0.117***	-0.102***
	(0.003)	(0.003)	(0.003)	(0.003)
Link	0.034***	0.036***	0.026***	0.028***
	(0.002)	(0.002)	(0.002)	(0.003)
*Link*SE*	0.005	-0.007	0.001	-0.002
	(0.010)	(0.010)	(0.010)	(0.011)
*Link*S2*	0.008***	0.009***	0.006**	0.004
	(0.003)	(0.003)	(0.002)	(0.004)
*Link*S3*	0.008	0.011**	0.006	0.004
	(0.005)	(0.005)	(0.004)	(0.007)
*Link*S4*	-0.004	0.002	0.007	0.003
	(0.011)	(0.009)	(0.009)	(0.013)
*Link*SE*S2*	0.032*	0.035**	0.013	0.011
	(0.018)	(0.017)	(0.016)	(0.017)
*Link*SE*S3*	0.031	0.025	0.006	0.003
	(0.028)	(0.027)	(0.026)	(0.029)
*Link*SE*S4*	-0.005	0.020	0.013	0.031
	(0.054)	(0.051)	(0.048)	(0.052)
Observations	541,627	541,627	541,627	541,627
R-squared	0.334	0.437	0.602	0.657
Control Variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Labor Market FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	Yes	Yes
Establishment FE	No	No	Yes	Yes

Standard errors clustered at the establishment level in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. All estimations include the same control variables as in the baseline model. The network size is measured as the number of coworker links. The S2 is defined as the individual having 2 to 5 links, S3 as 6 to 19 links, and S4 above or equal to 20 links

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