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Social networks, employee selection and labor market outcomes

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Social networks, employee selection and labor market outcomes[a]

by

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Abstract

The paper studies how social job finding networks affect firms' selection of employees and the setting of entry wages. Our point of departure is the Montgomery (1991) model of employee referrals which suggests that it is optimal for firms to hire new workers through referrals from their most productive existing employees, as these employees are more likely to know others with high unobserved productivity. Empirically, we identify the networks through coworker links within a rich matched employer-employee data set with cognitive and non-cognitive test scores serving as predetermined indicators of individual productivity. The results corroborate the Montgomery model's key predictions regarding employee selection patterns and entry wages into skill intensive jobs. Incumbent workers of high aptitude are more likely to be linked to entering workers. Firms also acquire entrants with higher ability scores but lower schooling when hiring linked workers supporting the notion that firms use referrals of productive employees in order to attract workers with better qualities in dimensions that would be difficult to observe at the formal market. Furthermore, the abilities of incumbent workers are reflected in the starting wages of linked entrants, suggesting that firms use the ability-density of social networks when setting entry wages. Overall the results suggest that firms use social networks as a signal of worker productivity, and that workers therefore benefit from the quality of their social ties.

Keywords: Referrals, wage inequality, employer learning, cognitive skills
JEL-codes: M51, J64, J24, J31, Z13

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1 Introduction

The inherent uncertainty about worker productivity that firms face when selecting new employees is at the core of modern labor economics. It motivates fundamental economic concepts such as statistical discrimination, the signaling value of education, and the matching function, which serves as the keystone of current unemployment theory. Ex ante information imperfections between workers and firms also motivate large scale public interventions through job-matching services and short-term employment subsidies. Recent research within personnel economics has drawn the attention to the various strategies employed by firms to overcome this information problem (Oyer and Schaefer, 2011). In this paper we provide an in-depth empirical analysis of the hypothesis that firms use social networks when selecting employees in order to reduce the uncertainty about newly hired workers' abilities.[1]

Our analysis takes its starting point in the theory outlined by Montgomery (1991). This model, which provides the foundation for much of the existing literature on employee referrals, presupposes that the quality of social networks serve as a signal of the productivity of prospective workers.[2] The model assumes that high ability workers on average are more likely to know other high-ability workers (network inbreeding). Referrals from high ability employees therefore serve as a positive signal to employers in search of the most able workers. Firms price these signals by paying referred workers higher wages in order to avoid losing them to competing firms who may have the same information. Since the pass-through from the value of the signal onto wages is partial, the model also allows for positive profits from referrals in equilibrium, despite free entry of firms. In addition, the model presents a natural rationale for endogenous skill segregation across firms. But most importantly, the model shows that firms' inability to ex ante observe

[1] Data on employers recruitment strategies suggest that a large portion of firms use informal search channels even in a country like Sweden with a longstanding tradition of well-developed national databases for (costless) vacancy posting. In a large-scale survey in Sweden, over 60 percent of the surveyed firms stated to have used informal channels when filling the last vacancy as opposed to 38 percent using the public employment office and 26 percent using classified ads (Ekström, 2001).

[2] Other papers in this strain include Simon and Warner (1992), Casella and Hanaki (2006), Casella and Hanaki (2008), Dustmann et al. (2011), Beaman and Magruder (2012) and Brown et al. (2012); see section 2 below for a further discussion.

worker ability can generate wage inequality between workers who are equally productive but embedded in social networks with different ability densities.

Despite these important implications, and the fact that the model provides a fundamental link between the social network literature and the literature on employee selection under uncertainty, this is to our knowledge the first paper to directly test the empirical relevance of the key micro-level arguments.[3] One likely reason for the scarce set of direct evidence on the relevance of the Montgomery model is lack of appropriate data. The model argues that employers use referrals in order to discriminate between high- and low ability workers who are observationally equivalent, and that employers rely on information about the abilities of entrants' social ties when entry wages are set. Hence, key elements of the model can only be analyzed using data on determinants of entrants' individual productivity that are unavailable to employers at the time of recruitment alongside indicators of social networks, referring workers' abilities and entry wages.

Our empirical strategy builds on insights from the literature on employer learning. Following Farber and Gibbons (1996) and Altonji and Pierret (2001) we use test scores from armed forces qualifying tests (AFQT) as indicators for elements of worker productivity that are not directly observable to recruiting employers. Consistent with this notion and the existing literature, we show that our Swedish AFQT scores are not fully priced into wages at the initial hiring stage. However, the association between wages and test scores increases with tenure in contrast to the returns to schooling, which fall or remain constant over time depending on the choice of specification. Building on this result, we therefore argue that the test scores can be used as proxies for a wider set of productivity-enhancing factors that are not easily observed by employers at the time of recruitment, and therefore also not fully priced by the market, along the lines of the unobserved productivity components of the Montgomery (1991) model. To further substantiate the validity

[3]An extensive literature building on Rees (1966) and Granovetter (1973) however suggests that social contacts are important in the job search process (see Ioannides and Loury (2004) for a survey). More recent work include Aslund et al. (2013), Bayer et al. (2008), Beaman and Magruder (2012), Bentolila et al. (2010), Brown et al. (2012), Cingano and Rosolia (2012), Dustmann et al. (2011), Galenianos (2011), Kramarz and Skans, Kramarz and Thesmar (2006), see section 2 for a detailed discussion regarding results therein. It is also well documented that inbreeding (or "‘homophily"’) is a fundamental phenomenon of social networks (McPherson et al., 2001; Currarini et al., 2009).

of this strategy, we throughout compare patterns related to test scores (interpreted as only partially observed by the market) with patterns related to years of schooling (assumed to be readily observed by all agents).

Empirically, we focus our analysis on firms who recruit former co-workers of incumbent employees into skill-intensive jobs in the private sector.[4] Within our 20 years of Swedish population-wide data, 12 percent of new recruits have a shared working history with an incumbent employee, hence co-worker links constitute a non-trivial fraction of new hires. Our data are further linked to AFQT-scores and measures of non-cognitive abilities for 32 full cohorts of male workers, allowing us to provide a detailed analysis of the relationship between worker ability and the use of workplace-based social ties.

Using these data, we analyze key elements of the Montgomery model, focusing on employee selection and entry wages. In particular, we study the relationship between recruitments of former coworkers and the abilities of the incumbent and entering workers, while separating abilities that are are difficult to observe (ability scores) from those that are easy to observe by employers (schooling). We further study the relationship between recruitments of former coworkers and entry wages, and the relationship between incumbent workers' abilities and the starting wages of linked entrants.

To preview our results, we first document that entrants are more likely to be linked to high ability incumbent employees than to low ability incumbents (defined from test scores or wages). We find a much weaker correlation between formal schooling and the frequency of used links. Second, we show that linked entrants have higher test scores given their level of schooling, suggesting that they are of higher (unobserved) ability. In sharp contrast, we find that linked entrants have less formal schooling than other entrants. Third, we show that entering workers receive higher initial wages if they have a link to an existing employee. Fourth, we show that entering workers benefit (through higher wages) from the abilities of linked incumbent workers. Qualitatively, these estimates are very robust to variations in the use of control variables, including establishment fixed effects. Accounting for potential correlations between abilities and network size or quality does

[4]See Cingano and Rosolia (2012), Glitz (2013) and Aslund et al. (2013) for recent empirical papers on co-worker networks.

not affect the results.

Our broad multi-firm data further allows us to test if the empirical regularities are driven by personal interactions, or if other correlated factors are confounding the results. A specific concern is the possibility that the results are driven by alternative mechanisms related to the employment histories of the agents, including, e.g., that employers draw inference from the previous work history rather than from social networks as such. To address this concern, we derive ”placebo-type” estimates by analyzing recruitments of workers who either *(i)* worked at the same establishments as incumbent workers, but not at the same point in time or *(ii)* worked within the same (previous) firm as an incumbent worker, but in a different establishment. Reassuringly, and despite the obvious fact that some of these workers also may be acquainted with incumbent workers due to overlapping networks, we find empirical patterns that are heavily muted when replacing linked employees with either of these two sets of ”placebo-linked” entrants; placebo-linked entrants do not differ from other entrants in terms of cognitive abilities and they do not earn higher wages than other entrants.

In line with the notion of network inbreeding as a key element in the selection process, we also show that entrants and incumbents share similar *types* of skills. We document this by separately exploring the role of our measures of cognitive skills and measures of *non-cognitive* skills derived from psychological assessments administered at the same time as the cognitive tests. We also show that the data, in general, are less in line with the model when studying recruitments to jobs with a lower skill content. The patterns also suggest that non-cognitive abilities are more relevant for jobs with a low skill content which is well in line with the notion that cognitive skills primarily are linked to productivity within high skilled jobs, and that non-cognitive skills are relatively more important within less skill demanding jobs (see also Lindqvist and Vestman (2011) and Brown et al. (2012) for similar conclusions).

Overall, we interpret our results as being consistent with Montgomery’s model suggesting that firms use social networks of productive incumbent employees as a tool to reduce uncertainty and select high ability employees into skill-intensive jobs. Apart from these firm-side benefits, the referral process also appear to have real effects on the labor market outcomes of the individuals by providing wage returns to workers who are embedded in ability-dense networks. Our results thus support the notion that social networks can generate wage inequality between equally productive workers.

The paper is structured as follows: In section 2, we introduce the Montgomery model, Section 3 describes the key components of our empirical analysis and the testable elements of the model that we take to the data, section 4 describes the empirical design and the data in more detail, Section 5 contains the results, section 6 presents robustness checks and section 7 concludes.

2 Theory

2.1 The Montgomery model

This paper builds on Montgomery's (1991) formalization of employers' use of referrals. In this two-period model of the labor market, each worker lives for one period. Workers are observationally equivalent for employers, but can be of two types, either high (H) or low (L) ability. High ability workers produce 1 and low ability workers produce 0, but employers are uncertain of the productivity of any particular worker at the initial hiring stage.

The social structure is characterized by two parameters; the density of the network, τ and the degree of inbreeding bias α. Workers hired in the first period knows (at most) one period 2 worker with probability τ. Conditional on holding a tie, workers in period 1 know someone of his own type with probability $\alpha > 0.5$. This means that workers are more likely to know someone of their own type; Montgomery refers to this as the "'inbreeding bias"'. The links from period 1 workers are randomly distributed over period 2 workers (conditional on α) so that some period 2 workers may have multiple ties and some may have none.

Each firm employs up to one worker per period. In period 1, firms hire workers through the market. As noted above, prospective workers are observationally equivalent, hence employers cannot observe whether any given worker is of high or low ability prior to hiring. Period 1 workers' types are revealed after hiring and prior to the start of the second period. In period 2 employers can choose whether to hire from the formal market, to a wage of w_{M2} or to hire the referrals that current employees provide, to a wage of w_R.

Firm profits are given by worker productivity minus the wage, and there is free entry of firms. In period 2, firms make referral offers if the expected profits from doing so exceeds expected profits from recruiting workers at the formal market. A key prediction of the model is that firms who, by chance, received workers of type H in period 1 always will prefer to make referral offers in period 2, whereas firms who received workers of type L in period 1 will prefer to hire through the market.

Intuitively, the inbreeding bias generates adverse selection in the open market. More high quality than low quality workers are removed from the formal market since $\alpha > 0.5$. Hence, workers remaining on the period 2 open market will only be of high ability with a probability less than 0.5 whereas workers available through referrals from high ability period 1 workers are high ability workers with a probability larger than 0.5. It is therefore evident that workers hired through referrals (from high ability workers) are more productive on average.

The model results in a partly undetermined wage distribution, but it is shown that (some) firms will find it optimal to offer a wage to referred workers that exceeds the market wage by a non-trivial amount since the same workers may receive a referral offer from competing firms (essentially, the information structure provides an idiosyncratic expected match-specific surplus which is shared between the agents). The profit levels remain positive for a distribution of wage offers ranging from the market wage to an upper bound which depends on the network density and inbreeding bias in the economy.

Importantly, the model proposes a mechanism by which differences in social networks may generate wage differences between equally productive workers. In equilibrium, each worker's wage is determined not by the actual skills but by the number and types of social ties to period 1 workers. Period 2 workers with ties to high ability workers will receive more referrals and hence have higher expected wages, regardless of the individual productivity. All workers who lack social ties to high ability workers are forced to find employment on the open market, even if they actually are of the high ability type. Since the market is afflicted by adverse selection, market wages tend to be lower the more social ties are used in the economy.

2.2 Relationship to alternative network models

There is a long and well-established theoretical literature on job search networks, which dates back to the 1960s. In this section we provide a brief overview of of this literature and relate the Montgomery model to alternative network models. Broadly, the literature is divided into two main strands which differ in the role played by the firm (see e.g. Jackson (2010)). The first part focuses on job search networks as a channel through which workers acquire information about vacancies on a market which is populated by homogeneous agents (see e.g. Calvo-Armengol and Jackson (2004)). The second strand, in which Montgomery (1991) provides the canonical model, stresses the role played by networks as a firm-side tool to acquire information about worker characteristics, often in the form of employee referrals. Since most of the empirical analysis of this paper explicitly concerns the role of individual heterogeneity, our analysis will clearly diverge from any predictions derived from models with homogeneous agents and we therefore focus the discussion below on papers in the second strand of the literature.

By now the referral based literature contains a number of different types of models which partly can be viewed as complementary. The models differ in their focus on the relevant aspects of unobserved qualities, and on the exact nature of the information transmission process. Simon and Warner (1992) provide a theoretical model where referrals are made by random incumbent employees in order to reduce the uncertainty regarding match specific productivity. Dustmann et al. (2011), Galenianos (2011), Brown et al. (2012) and Pinkston (2012) provide recent extensions and applications.

In contrast to these models, the Montgomery (1991) model focuses on the selection of employees with good unobserved predetermined abilities. The key distinguishing aspect of the Montgomery model is, however, the role played by the productivity of the referring worker as a signal used by the employer to form expectations about the productivity of prospective employees. This aspect of the model, which mirrors models of statistical discrimination, also drives the link between the ability density of social networks and wage inequality that persists in equilibrium.

There also exists a set of models which we view as complementary extensions of the Montgomery model. Casella and Hanaki (2006) and Casella and Hanaki (2008) emphasize the signaling role of social networks and explore the resilience of the model predictions to an extension where workers who are not hired through referrals can obtain a costly imperfect signal of true productivity (e.g. through education). The results show that the usefulness of job search networks is very resilient since they provide employers with privileged (and thus not fully priced) information at a low cost.[5] Since the model essentially is an extension of Montgomery (1991), our analysis cannot distinguish between the two, but Casella and Hanakis' emphasis on the signaling aspect of the referral process is very much in line with the structure of our empirical analysis. One particularly relevant result which emerges in the Casella and Hanaki formulation is that workers hired through referrals can forgo the step of obtaining formal productivity signals, which implies that referrals and education are substitutes. Beaman and Magruder (2012) which replaces Montgomery's inbreeding mechanism by the presumption that high ability workers are more able to identify other high ability workers, and that they will do so if properly incentivized.[6] Hence, if firms provide explicit or implicit incentives for incumbent workers to refer good entrants, the models become observationally equivalent in the dimensions related to employee selection.

[5] In order to weaken the resilience of the network, signaling must either be extremely precise or it must be costly in order to separate the high ability from the low ability workers.

[6] The paper also delivers experimental evidence in support of this claim.

3 Taking the model to the data

The key components of the Montgomery model are *(i)* the social ties between period 1 and period 2 workers, *(ii)* the correlation between these workers in terms of inherent productivity, and *(iii)* the setting of (entry) wages according to expected, rather than actual, productivity. In this section we describe how we take these central aspects to the data. We return to more specific details about the data construction in Section 4, where we also discuss the empirical specifications in more detail and provide summary statistics.

3.1 Agents, networks and wages

The Montgomery model defines a matching process involving demand side agents (period 1 workers) and supply side agents (period 2 workers). We let incumbent workers be the empirical counterparts of period 1 workers whereas entrants represent period 2 workers. This implies that entry wages is a straightforward measure of period 2 wages in the model. We return to our measures of worker productivity in section 3.2 below.

To define the ties between incumbent workers and entrants, we use data on links acquired through previous employment relationships (details are in the following subsection). We find this particular type of network to be a useful starting point to test the relevance of the Montgomery model. It seems *a priori* plausible that network inbreeding (in terms of productive capacities) is particularly prominent for social networks that are formed at the labor market. Thus, it may be particularly useful for employers to let incumbent employees refer their former co-workers.[7] Previous research have also documented the importance of co-worker networks for the reemployment probability of laid-off workers (see e.g. Cingano and Rosolia (2012)).

[7] Beaman and Magruder (2012) provide empirical support in this direction: When referral pay is depending on the productivity of the referred worker in a laboratory setting, individuals become more likely to refer coworkers and less likely to refer relatives.

3.2 Observed and unobserved productivity

The model builds on the notion that individual workers' productive abilities are partly unknown at the time of recruitment. To take this key aspect of the model to the data we follow Altonji and Pierret (2001) and decompose prospective workers' individual productivity (y_i) into four different components:

$$y_i = rs_i + \mu q_i + \kappa z_i + \eta_i$$

where all employers can observe (s_i, q_i) while the elements (z_i, η_i) are unobserved. On the other hand, (s_i, z_i) are observed by the econometrician. To be precise, we can think of s as capturing formal merits such as schooling which is easily observed to all, q_i indicates parts that are easily observed for firms but are outside of our data, such as letters of recommendation, z_i captures productive elements that we are able to observe but which are unobserved to the firms, and η_i captures fundamentally unobserved elements. Importantly, these elements may be correlated, although each element is assumed to contain some independent information.

The central feature of the Montgomery model is that firms can mitigate the information problem at the recruitment stage by asking incumbent workers for referrals. More specifically, the inbreeding feature of networks allows firms to form expectations about z_i and η_i by observing the productivity of the referring employee. Assessing the relevance of the model therefore requires access to some information about worker skills that are not directly observed by employers at the initial hiring stage.

Drawing on insights from Farber and Gibbons (1996) and Altonji and Pierret (2001) we assume that cognitive test scores are a valid measure of such skills. In particular, Altonji and Pierret (2001) show that characteristics that are difficult (easy) to observe should be given a growing (diminishing) weight over time if employers learn about worker productivity as they acquire experience. Altonji and Pierret (2001) further show that

AFQT scores have this property.[8]. It is important to emphasize that the scores, in general, may be correlated with factors that are indeed observed by employers (such as schooling); the crucial assumption is that the scores capture skills that are at least partly unobserved.

To strengthen the interpretation of the test scores as valid proxies for abilities that are difficult to observe, we have replicated the analysis of Altonji and Pierret (2001) using our Swedish data (described below). In line with the previous literature, the results shown in *Table A 2* in Appendix A suggest that cognitive test scores have a negligible effect on wages during the year of market entry, but become increasingly important with experience. In contrast to Altonji and Pierret (2001), which emphasizes public learning as workers accumulate experience, the Montgomery model stresses the potential role played by private information about the expected productive ability of workers obtained by firms via referrals. We therefore also show that the patterns look similar when we focus on how the returns to schooling and ability vary within employment spells for workers who remain in their jobs, suggesting that employer learning also affects wages within ongoing employment relationships. We take these results as support for the idea that the test scores known to us capture worker skills that are partly unobserved to employers at the initial hiring stage and therefore not fully priced into workers' entry wages. Since part of the analysis below will incorporate a measures of non-cognitive skills, we also extend the model to account for these measures showing that they exhibit a similar relationship to wages and experience as the cognitive test scores.

3.3 Testable micro-level elements

Relying on our measures of network links, period 2 workers' (entry) wages and unobserved components of individual productivity as defined above, we formulate four testable elements regarding the selection of new employees and the setting of entry wages based on the Montgomery model as outlined in Section 2.

[8]For more recent work on employer learning see e.g. Lange (2007), Schönberg (2007) and Pinkston (2006), Pinkston (2009).

Employee selection:

1. The main proposition stated of the Montgomery model is that firms make referral offers (R) iff they employ type H workers in period 1, i.e $Pr(R=1|Type^1=H)=1$ and $Pr(R=1|Type^1=L)=0$. As an empirical counterpart of this stylized result, we expect that the probability of hiring through social ties will increase in the productivity of the incumbent worker.

2. Because workers (by assumption) are more likely to know someone of their own type ($\alpha>0.5$), the probability that an entrant is of type H is greater for firms who hire through referrals than for firms who hire through the anonymous market, i.e. $Pr(Type^2=H|R=1)>Pr(Type^2=H|R=0)$. Thus, we expect workers hired through referrals to, on average, have more productive unobserved abilities than workers hired through the market.

Entry wages:

3. Montgomery shows that referral wages will be dispersed over an interval ranging from the wage received by period 2 workers hired on the market w_{M2} to an upper bound $w_{Rmax}(\alpha,\tau)$. Thus, we expect entry wages of workers hired through social networks to be higher than entry wages amongst workers that found their jobs through the formal market.

4. The basic presumption of the Montgomery model is that referred period 2 workers signal their abilities through the abilities of referring period 1 workers. As a consequence, we expect entry wages of workers that are hired through referrals to be correlated with the abilities of linked incumbent workers.

The micro elements listed above are all related to fundamental parts of the Montgomery model, but they are also jointly (although not necessarily individually) fairly unique to the distinct class of models related to Montgomery (1991), see Section 2.2. The predictions we are testing, with the exception of the relationship between social ties and average wages (element 3), all explicitly concern the role of individual heterogeneity and the elements therefore clearly diverge from any predictions derived from models with homogeneous agents. In addition, the predictions explicitly tests the role of pre-determined time constant, instead of match-specific, characteristics (element 1, 2 and 4) and emphasize the role of the characteristics of the inside agent both for employee selection (element 1) and for entry wages (element 4).

3.4 Previous empirical evidence

A growing body of empirical studies document various aspects of the usage and consequences of labor market networks. A stylized fact emerging from the existing literature is that labor market outcomes are correlated within networks.[9] For the purpose of this paper we are however primarily interested in the relationship between networks and demand side characteristics, agent heterogeneity and the setting of entry wages.

Considering the amount of papers that have analyzed the usage of networks using supply side data, we know surprisingly little from the demand side. Most of what we do know is based on single firm studies such as Fernandez et al. (2000), Castilla (2005) and Yakubovich and Lup (2006) for call centers, Brown et al. (2012) for a retail firm as well as Burks et al. (2013) for seven call centers, a trucking firm and a "‘high-tech"’ firm. These studies all explore detailed and accurate data from referral systems that are well-documented by the firms' human resource departments. Although the data analyzed in these studies are intriguing, a natural limitation arising from the study design is that the results pertain to firms with well-structured internal documentation of formalized referral processes. With the exception of minor parts of both Brown et al. (2012) and Burks et al. (2013), the focus is also on jobs with a low skill content, which, as our results will indicate, may be an important factor.

The paper which most closely investigates the role of the productivity of the inside agent is Yakubovich and Lup (2006), who show that the productivities of the referring employees within virtual call centers are correlated with the probability that referred applicants are being recruited. Somewhat related, both Fernandez et al. (2000) and Burks

[9] See e.g. Munshi (2003), Bayer et al. (2008), Bentolila et al. (2010), Kramarz and Skans, Cingano and Rosolia (2012) and Kramarz and Thesmar (2006). Ioannides and Loury (2004) present a survey of older studies.

et al. (2013) show that the characteristics of referrals and referrers tend to be correlated. Kramarz and Skans use economy-wide data to study family ties and youth labor market entry. Consistent with the notion that firms use employee productivity as a signal of the productivity of linked prospective workers, parents are found to be more relevant in the job finding process if they have longer tenure and higher wages, even conditional on firm fixed effects and observable characteristics of the youths. Kramarz and Skans also find a positive association between the use of family networks and firm profitability as suggested by the Montgomery model.

The evidence is also scarce when it comes to differences in individual productivity between workers who enter through social ties and workers who enter through other means. In general, conclusions regarding this issue is either inferred from the wage impact, which we return to below, or derived from readily observed indicators of productivity (i.e. schooling).[10] However, by relying on easily observable indicators of productivity such as schooling, these results are by definition uninformative regarding the role played by social networks for overcoming information asymmetries at the time of recruitment.[11]

The existing evidence on the relationship between social networks and wages provides very mixed results in general. Since the focus of our paper is on uncertainty and asymmetric information during recruitment, we are primarily interested in studies documenting the association between networks and entry wages. Here, Bentolila et al. (2010) using survey data on youths for various European countries and the US find a negative association and Kramarz and Skans find negative associations between entry wages the use of family ties, in particular when conditioning on firm fixed effects. In contrast Dustmann et al. (2011) find positive effects from ethnic networks conditional on worker and firm fixed

[10] A frequent finding is that networks in general are used more prevalently among the lesser educated, see e.g. Pellizzari (2009).

[11] Castilla (2005) uses direct measures of productivity from a call center and finds that referrals are initially more productive in the new job than other entrants whereas Burks et al. (2013) fail to find any such differences, although they find lower accident rates amongst truckers and a higher innovation rate amongst referrals within their high-tech firm. Similar to us, Burks et al. (2013) also study cognitive skills among call center staff and truckers, but do not find any differences between referrals and other entrants.

effects. In general, it is not clear why the wage estimates differ so much between studies, but one possible explanation is that the role of networks differ depending on the type of information they can convey regarding workers abilities, see e.g. Loury (2006). An alternative interpretation, consistent with Montgomery, is that the wage premium depends on employers's expectations regarding the degree of skill-segregation (or inbreeding) within different types of networks. An interesting recent contribution is Brown et al. (2012), who study explicit data on referrals (within a single firm) and find a positive impact on entry wages for most (but not all) types of jobs.[12] They also show that employees who receive referrals from older workers, more tenured workers or workers in higher ranks have the highest initial starting salaries. Importantly, we have not found any studies directly exploring the relationship between incumbent worker abilities and the abilities and wages of linked entrants.

4 Data

Our analysis uses a large Swedish sample of entering and incumbent male workers during the years 2000-2005, drawn from administrative employment registers provided by Statistics Sweden. The data cover the work histories of all employed workers aged 16-65 for the period 1985-2007. In addition, we use detailed individual demographics (e.g. age, gender and education level) along with military draft scores for males born between 1951 and 1979. In these cohorts almost all males went through the draft procedure at age 18 or 19 (they took the draft in 1969-2000). The cognitive test scores provide an evaluation of cognitive ability based on several subtests of logical, verbal and spatial abilities and are similar to the AFQT in the US. Individuals are graded on a 1-9 scale, which we standard-

[12] Kugler (2003) and Simon and Warner (1992) find support for a referral entry wage premium using the 1982 NLSY and the 1972 Survey of Natural and Social Scientists and Engineers. In the same vein, Pinkston (2012) documents a higher correlation between initial wages and subjective productivity measures for referrals using the 1982 Employment Opportunity Pilot Project (EOPP), which covers around 3,000 establishments. In addition, Marmaros and Sacerdote (2002) show that fraternity and sorority members are helpful in obtaining jobs with high starting salaries after college.

ize to mean zero and standard deviation one within each cohort of draftees. In addition, the data contain non-cognitive scores based on assessments by a trained psychologist. We return to a discussion of these data in section 5.2.3.

We construct the data for our analysis by generating (yearly) matched pairs (dyads) of incumbent workers (j) and entrants (i). For computational convenience, we exclude plants with more than 500 employees. We define incumbents as workers observed at the establishment in the current and in the previous year. Entrants are workers entering from outside the firm into establishments where they have never worked before (at least since 1985). For entrants with multiple jobs during the year, we keep the work spell generating the highest annual income. We exclude entrants who arrive in large groups (more than 5) from the same establishment. We do this to avoid classifying entrants through mergers as new hires. This restriction excludes 2.9 percent of the entrants.

We characterize the entry jobs using full-time adjusted monthly entry wages as well as occupational classifications using an additional register (Strukturlönestatistiken), which is fully linked to the employment register on both the worker and the establishment side. Wages are collected in September or October each year for a large firm-based sample of private sector workers.[13] The private sector sample which is stratified by firm size and industry covers about 30 percent of the target population.

In the main analysis we restrict the sample to workers entering skill-intensive jobs in the private sector. More specifically, we select all entry jobs in occupations with ISCO-88 1-digit codes equal to 2 (Professionals) or 3 (Technicians and associate professionals). About 1/3 of all entry jobs in the private sector are high-skilled according to this definition. We take this as the starting point since Montgomery-type referral processes are likely to be more relevant for skill intensive jobs (Montgomery (1991)), and since the correlations between productivity and different skill dimensions may depend on job complexity (Lindqvist and Vestman, 2011). We complement these results in Section 6.3 with

[13]Data also contain the universe of public sector employees; we include these in a robustness check.

models focusing on low-skilled jobs, exploiting also variations in worker's non-cognitive test scores.

For each incumbent-entrant dyad, we define a variable indicating whether (j) and (i) are former co-workers, which is our measure of (j) and (i) being linked to one another. Pairs are defined as linked if they were (previously and simultaneously) employed at the same establishment anytime since 1985.[14]

4.1 "Placebo" links: non-overlapping employment spells, and other plants within the same firm

To assess the importance of the actual personal interaction between former co-workers, we will contrast our empirical results to two sets of "placebo-links" between incumbent workers and entrants.

Our first approach is to define placebo-linked entrants as workers who have been employed at the same establishment as an incumbent worker, but not at the same time. We refer to these links as *Placebo links of Type I*. We require that the placebo-linked entrant was employed at the (old) establishment within 3 years after the incumbent worker left, or within 3-years before the incumbent joined that employer. Since placebo-linked workers have a non-overlapping, but otherwise similar, work history as incumbent workers, they provide a measure of the impact of (indirect) factors related to former workplaces, other than those related to personal interactions at the workplace.

Our second definition of placebo-linked entrants (*Placebo links of Type II*) are workers that were employed in the same firm at the same time as an incumbent worker, but in a different establishment.[15] The strategy can only be used for firms with at least two establishments, which implies that we for this analysis will restrict the set of former workplaces where valid "interactions" can take place to multi-establishment firms. To generate a plausible comparison to the true links we furthermore require that the two establish-

[14]Because we focus on workers hired in 2000 through 2005, and require that incumbent workers have at least 2 years tenure, 2003 is the last year that a link could have been established.
[15]See e.g. Kramarz and Skans for a similar strategy.

ments defining the placebo-link must operate within the same 5-digit industry. Since the necessary restrictions change the identifying sample, we will also present results of the actual links for an overlapping sample.

4.2 Summary statistics

Table 1 shows summary statistics for the establishments, incumbent workers, entrants and incumbent-entrant pairs included in our estimating sample of high skilled jobs. The median establishment has 37 employees, with an upper limit of 499, including both the incumbent and the entering worker. For consistency, we focus on pairs with non-missing wages for the entrant and test-scores for both agents throughout our analysis. The average incumbent worker in our data is 37 years of age, has 13 years of schooling, 7 years of tenure and a mean cognitive (non-cognitive) test score of 5.5 (5.3) on the 1-9 scale.[16] Entering workers are four years younger on average, have one additional year of schooling and higher mean cognitive and non-cognitive test scores. 72 percent of the entrants were employed the year prior to entry.

The table also reports the frequency of true and placebo links among incumbents and entrants described in the previous section. About 3 percent of the incumbent workers share a link with an entrant in a given year; 12 percent of the entrants are former co-workers with someone in the entry establishment; and 1 percent of the entrant-incumbent dyads share a link with each other.

The numbers are similar for the placebo-links although we do see a somewhat lower frequency of placebo links defined from non-overlapping employment spells in the same previous establishment (Placebo co-workers of *Type I*). This is not surprising as the definition of this placebo-link requires that the two agents joined/left the previous plant during a time window of 3 years.

[16]For simplicity, we focus on years of schooling in the main analysis, extracted from a discrete variable indicating the highest completed education level attained by the individuals in the following way: Less than compulsory school: s=8; Compulsory school: s=9; High school: s=12; College short: s=14; College long: s=16; PhD: s=20.

Table 1: Summary statistics: 2000-2005

	mean	sd	p50	min	max
Incumbent workers:					
Age	37.3	8.3	37	16	57
Schooling	13.2	2.3	12	8	20
Experience	12.4	4.6	13	0	20
Tenure	7.2	5.2	5	2	21
Cognitive test score	5.6	1.9	6	1	9
Non-cognitive test score	5.3	1.7	5	1	9
At least one co-worker link to entrant in a given year	0.03	0.16	0	0	1
At least one placebo link of *Type I* to entrant in a given year	0.01	0.10	0	0	1
At least one placebo link of *Type II* to entrant in a given year	0.04	0.20	0	0	1
Number of true links given at least one in a given year	1.22	0.70	1	1	14
			$n = 359,462$		
Entrants:					
Age	33.3	7.6	32	18	55
Schooling	14.3	2.1	16	8	20
Experience	12.0	4.6	12	0	20
Cognitive test score	6.1	1.7	6	1	9
Non-cognitive test score	5.7	1.6	6	1	9
log(entry wage)	10.1	0.33	10.1	8.9	13.5
From employment	0.72	0.45	1	0	1
No. of previous employers	5.1	2.8	5	0	19
At least one co-worker link in entering establishment	0.12	0.32	0	0	1
At least one placebo link of *Type I* in entering establishment	0.07	0.26	0	0	1
At least one placebo link of *Type II* in entering establishment	0.09	0.29	0	0	1
Number of true links given at least one:	3.34	7.47	1	1	136
			$n = 28,414$		
Establishments:					
Size	75.7	94.5	37	2	499
Single plant firm	0.25	0.43	0	0	1
Private sector	1	0	1	1	1
Fraction in metropolitan area	0.39	0.49	0	0	1
			$n = 8,264$		
Incumbent-entrant dyads:					
Co-worker link	0.01	0.10	0	0	1
Placebo link *Type I*	0.004	0.06	0	0	1
Placebo link *Type II*	0.02	0.13	0	0	1
Size of plant where link was established	212.0	147.0	190	2	499
Years since link was established	5.8	4.0	4	2	20
			$n = 1,065,480$		

Notes. The table displays summary statistics for the incumbents, entrants, establishments and incumbent-entrant dyads included in our sample. Placebo links of *Type I* are defined from non-overlapping employment spells in the same establishment; placebo links of *Type II* are defined from overlapping employment spells in the same firm but at different establishments (within industries). Establishments are defined to be in a metropolitan area if located in one of Sweden's three largest cities (Stockholm, Gothenburg or Malmö).

5 Empirical analysis

5.1 Empirical specifications

In this section we analyze the testable elements of Montgomery's referral model outlined in Section 3.3 using our data on co-worker links. We use a separate model for each of the four elements. For each of these models, we provide estimates from four empirical specifications: Specification (1) controls for individual (incumbent and/or entrant) background characteristics, an indicator for whether the establishment is located in a metropolitan area, log size of the establishment, and year effects. Specification (2) adds firm-type dummies obtained from the interaction between establishment size in six brackets (1-9, 10-19, 20-49, 50-99, 100-199, 200-499) and 3-digit industry. Specification (3) adds job-type dummies referring to the first two digits of the ISCO-88 occupation code of either the incumbent or entrant depending on the specification. Finally, specification (4) adds establishment fixed effects.

Because the Montgomery model in its purest form is a model of differences in referral hiring patterns between firms, specification (2) is most closely related to the theory. However, by adding additional controls, we reduce the risk that the results are driven by differences between firms that are outside the scope of the stylized model.

To assess the robustness of the estimates, we also estimate models accounting for additional controls such as network size and quality and/or the labor market history of the relevant agent. In the interest of streamlining the presentation, we have however deferred models using these controls to a robustness section since the set of additional covariates will differ depending on the estimated model. In the robustness section, we also present our two sets of ”placebo tests”.

5.2 Results on Employee selection

5.2.1 Testable element 1: Incumbent ability and the use of referrals

The first prediction of the Montgomery model suggests that firms hire through employee referrals if, and only if, they employ already productive incumbent employees. To test this prediction, we define a model which allows us to associate the incidence of recruitments through social links (former colleagues) with the abilities of the incumbent workers. Using data on incumbent workers, we estimate a model of the following form:

$$Pr(Link_{jt} = 1) = \beta_0 + \beta_1 z_j + \beta_2 s_j + \beta_3 X_{jt} + W_j, \tag{1}$$

where $Link_{jt}$ takes the value one if incumbent worker j is linked (through the employment history) to any worker entering the establishment in year t, and where z_j is the standardized cognitive test score of the incumbent worker. We also control for the incumbent workers' years of schooling s_j, as well as age and age^2 through X_{jt}. W_j represent the various sets of dummy controls in the four specifications, as outlined in Section 5.1 above.[17] As mentioned, we return to specifications with additional controls, variations in the measured skills and "placebo"-type tests in section 6.

Based on the prediction derived from the Montgomery model, we expect that $\beta_1 > 0$. In line with this prediction, the results in *Table 2* show that able (in terms of test scores) incumbent workers are more likely to be linked to new entrants. The estimated impact of the incumbent's test score remains positive if we add firm and job characteristics to the model, although the magnitudes diminish quite substantially when we control for "'firm type"' (i.e. size-bracket specific industry dummies). Thus, high-skilled firm types are more likely to employ former coworkers of incumbent employees. As discussed above, the Montgomery model is in essence a model of between-firm differences, but to reduce the potential impact of alternative explanations we let our most stringent specification (column 4) compare incumbent workers who are employed at the same establishment. The results from this specification still indicate that a one standard deviation higher cognitive test scores for an incumbent worker is associated with a 0.1 percentage points higher probability of being linked to an entrant. Notably however, the schooling of the incumbent worker does not have a robust relationship to the incidence of being linked to an entrant (conditional on the cognitive test scores).

In the second panel (b) of *Table A 4* in Appendix B, we replace the cognitive test score of the incumbent employee with the wage as an alternative measure of incumbent skills. In line with the results of *Table 2* we find that high-wage workers are more likely to be

[17] The controls are (by specification): (1) the log size of the workplace and a dummy indicating whether the workplace is located in any of Sweden's three metropolitan areas, (2) adding firm type dummies, defined from the interaction between workplace size in 5 bins and 3-digit industry, (3) adding job level dummies for the job held by the incumbent worker and (4) establishment fixed effects.

linked to entrants, conditional on their level of schooling.[18] We provide further robustness checks and analyse our placebo links in Section 6.

Table 2: Incumbent test score and linked entrants

	(1)	(2)	(3)	(4)
Incumbent cognitive test score	0.0042***	0.0017***	0.0011***	0.0011***
	(0.0003)	(0.0003)	(0.0004)	(0.0003)
Incumbent schooling	0.0016***	0.0006***	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Fixed effects	-	Firm Type	Firm Type + Job Level	Establishment
Observations	359,462	359,462	308,136	359,462
R-squared	0.0041	0.0322	0.0377	0.2086

Notes. *** p<0.01, ** p<0.05, * p<0.1. The level of observation is the incumbent worker and the dependent variable takes the value one if any of the entrants is a former colleague of incumbent worker j in year t. Standard errors are robust to heteroscedasticity and accounting for the fact that there are multiple observations for each incumbent worker due to the panel structure of the data. Firm type is the interaction between workplace size (1-9, 10-19, 20-49, 50-99, 100-199 and 200-499) and 3-digit industry. The job level dummies refer to the first 2 digits in the occupation of the incumbent worker, observed for 85 percent of the total sample. All regressions include year dummies, incumbent characteristics (age and age^2), a dummy indicating if the employer is located in one of Sweden's three metropolitan areas and log size of the establishment. The mean of the dependent variable is 0.025.

5.2.2 Testable element 2: Referrals and entrant ability

The second element of the Montgomery model which we take to the data is the prediction that employers obtain workers with better unobserved abilities when they hire workers with social links to incumbent employees. We test this prediction by measuring if the cognitive skills of entrants with links to incumbent employees are higher than the cognitive skills of entrants without such links. In this particular model, we rely on the part of the entrant test scores (z_i) which is orthogonal to schooling (s_i) as in Farber and Gibbons (1996) since the model-prediction calls for unobserved skills as the outcome variable.[19] Formally, we estimate the following model:

$$\hat{\theta}_i = \delta_0 + \delta_1 Link_{ij} + \delta_2 z_j + \delta_3 X_j + W_{ijt_0} + \varepsilon_{ij}, \quad (2)$$

[18] A one percent wage increase is associated with a 0.01 percentage point (or 0.5 percent) increase in the probability of hiring a linked worker.

[19] We extract the residual test scores from a regression of test scores on years of schooling, but we have also tried using indicators for the highest completed level of education and the detailed field of education, which did not alter the conclusions. As expected, using the cognitive test scores as dependent variable while conditioning on schooling in equation 2 also gave very similar results.

where $\hat{\theta}_i$ is the orthogonal part of the cognitive skills, $Link_{ij}$ is a dummy indicating whether worker i and j have a social link (they worked together in the past); z_j is the standardized cognitive test score of the incumbent worker; X_j includes the incumbent's age and years of schooling; W_{ijt_0} is the same vector of dummy controls as in equation (1) measured at the time of entry (t_0) and ε_{ij} is the error term. We should expect to find $\delta_1 > 0$, if firms use referrals of former co-workers in the Montgomery-sense.

We use the dyad-level data in this specification (i.e. with one observation for each combination of entrants and incumbent workers) since we, in variations presented below, interact incumbent workers' abilities with $Link_{ij}$, and we wish to keep the same sample for consistency, but collapsing the data to the entrant level provide very similar results. The standard errors are clustered to handle the dyad structure of the data by accounting for repeated observations of both entering and incumbent workers Cameron et al. (2011).

The estimates are reported in Panel A of *Table 3*. They show that linked entrants on average have between 0.13 and 0.16 standard deviations higher (residual) cognitive test scores than entrants without co-worker links. Here, we find estimates that are very stable across specifications. The estimates are only marginally affected by covariates that account for establishment type (column 2), job type (column 3), or establishment fixed effects (column 4). The results thus suggest that employers receive workers with higher (unobserved) ability, when recruiting through co-worker based networks, and that this pattern holds both between and within firms and job types.

It should be noted that we are unable to rule out that the residual test scores are correlated with other worker characteristics that employers can observe. But, if we replace the residual test scores as the outcome variable with an easier-to-observe skill of the entrant (years of schooling) we find a robust and significant *negative* relationship. The estimates, reported in Panel B suggest that linked entrants have attained 0.3 years less schooling than non-linked entrants. Thus, firms appear able to find workers with higher (unobserved) ability through high ability referrals although they hire entrants of lower education level.

Notably, the negative results on years of schooling are well in line with the substitutability between referrals and education implied by Casella and Hanaki's extension of the Montgomery model, as well as earlier studies showing a negative correlation between the use of social ties and educational attainment (Pellizzari, 2009).

Table 3: Links and entrant skills

	(1)	(2)	(3)	(4)
		Dep. var: "unobservable skills" ($\hat{\theta}_i$)		
Co-worker link	0.1537***	0.1289***	0.1219***	0.1418***
	(0.0283)	(0.0295)	(0.0291)	(0.0258)
		Dep. var: "observable skills" (s_i)		
Co-worker link	-0.4559***	-0.4088***	-0.4235***	-0.3108***
	(0.0853)	(0.0825)	(0.0793)	(0.0735)
Fixed effects	-	Firm Type	Firm Type + Job Level	Establishment
Observations	1,065,480	1,065,480	1,065,480	1,065,480

Notes. *** p<0.01, ** p<0.05, * p<0.1. The level of observation is the incumbent-entrant pair. The dependent variable in the first panel is the part of the entrant's cognitive skills, z_i which is orthogonal to years of schooling, s_i. Standard errors are corrected to account for the dyad structure of the data by clustering on both entrants and incumbents as suggested by Cameron et al. (2011). Firm type is the interaction between firm size in 6 bins (1-9, 10-19, 20-49, 50-99, 100-199 and 200-499) interacted with 3-digit industry. The job level dummies refer to the first 2 digits in the occupation of the entrant. All regressions include year dummies, the age, schooling and standardized cognitive test score of the incumbent worker, a dummy indicating if the employer is located in one of Sweden's three metropolitan areas and the log size of the hiring plant.

Before turning to the analysis of wages it is worth noting that the results presented so far are consistent with the notion that firms use referrals when they have high-ability employees and that an outcome of this process a further acquisition of high ability workers. A natural interpretation of this result is that the skill content of firms is likely to be path dependent.

5.2.3 Employee selection, network inbreeding and multidimensional skills

Our baseline model relies on measures of cognitive abilities for worker productivity but our data also contain information about non-cognitive skills, which are based on standardized, mandatory, interviews with certified psychologists during the draft process. The psychologist evaluates non-cognitive traits that are deemed important in order to succeed in the military, such as responsibility, independence, outgoing character, persistence, emotional stability, power of initiative and social skills. The non-cognitive skills are graded on a similar 1-9 scale as the cognitive skills. The motivation for doing the military service is not taken into account when grading.[20] In *Table 4* we utilize this information and introduce the non-cognitive test score alongside the cognitive skills in equations 1 and 2.

The point of this exercise is twofold; first it serves as a validation check for the use of the cognitive skills as the preferred measure of worker productivity in the high-skilled segments of the labor market. In this respect, the results clearly support that it is the cognitive skills that matter. More specifically, Panel A shows that only the cognitive skills of incumbent workers predict the hiring of linked to entrants, while their non-cognitive skills have no significant impact. Moreover, firms hiring linked entrants obtain entrants with higher average residual cognitive skills but there is no significant difference in terms of (residual) non-cognitive skills (suggested by the main effect captured by the ”co-worker link” estimates in Panel B).

Characterizing incumbents and entrants in two dimensions also allows us to provide a deeper investigation of the concept of network inbreeding, the key assumption in the Montgomery model. More specifically, we test whether realized matches occur between linked workers that have similar *types* of qualities, as would be expected if the driving force is networks formed between agents that are fundamentally similar. In our view, the results seem more open to alternative explanations if incumbents with better cognitive (non-cognitive) abilities also ”refer” entrants with better non-cognitive (cognitive) abilities.

We find that the sorting indeed appear to be ability-specific. We derive this result by enriching the analysis of equation 2, interacting the main effect of being linked to an incumbent worker with the vector z_j, now including both the incumbent link's cognitive and non-cognitive ability:

[20]See Mood et al. (2012) for a more detailed description of the non-cognitive test scores.

$$\hat{\theta}_{i,cog.} = \delta_0 + \delta_1 Link_{ij} + \delta_2 Link_{ij} \times z_j + \delta_3 z_j + \delta_4 X_j + W_{ijt_0} + \varepsilon_{ij} \tag{3}$$

$$\hat{\theta}_{i,non-cog.} = \delta_0 + \delta_1 Link_{ij} + \delta_2 Link_{ij} \times z_j + \delta_3 z_j + \delta_4 X_j + W_{ijt_0} + \varepsilon_{ij} \tag{4}$$

In a world with continuous skill-inbreeding we can think of this interaction as measuring the strength of the inbreeding bias (are better incumbents linked to better entrants?). The results clearly shows that incumbent cognitive skills predict entrant residual cognitive skills, while incumbent non-cognitive skills have no relationship to the entrants' cognitive abilities (panel *B*). Similarly, incumbent cognitive abilities are unrelated to entrants non-cognitive skills, whereas incumbent non-cognitive skills appear related to entrant non-cognitive skills although the estimates are not statistically significant.

Table 4: Employee selection and inbreeding, by type of skills

	(1)	(2)	(3)	(4)
A: Dep. var: Co-worker link (eq. 1)				
Incumbent cog. test score	0.0040***	0.0017***	0.0010**	0.0010***
	(0.0003)	(0.0003)	(0.0004)	(0.0003)
Incumbent non-cog. test score	0.0007**	-0.0000	0.0001	-0.0002
	(0.0003)	(0.0003)	(0.0004)	(0.0003)
Observations	359,462	359,462	308,137	359,462
Fixed effects	-	Firm Type	Firm Type + Job Level	Establishment
B: Dep. var: Entrant residual skills (eq. 2), Inbreeding highlighted in **bold**				
		Dep.var: Cognitive test scores		
Co-worker link	0.1561***	0.1268***	0.1202***	0.1363***
	(0.0283)	(0.0295)	(0.0291)	(0.0252)
Co-worker link × Incumbent cog.	**0.0208**	**0.0222***	**0.0208**	**0.0205****
test score	**(0.0135)**	**(0.0132)**	**(0.0130)**	**(0.0102)**
Co-worker link × Incumbent non-cog.	-0.0022	-0.0035	-0.0009	-0.0004
test score	(0.0103)	(0.0105)	(0.0105)	(0.0087)
Observations	1,065,480	1,065,480	1,065,480	1,065,480
		Dep.var: Non-cognitive test scores		
Co-worker link	0.0368	0.0315	0.0400	0.0171
	(0.0401)	(0.0375)	(0.0368)	(0.0291)
Co-worker link × Incumbent cog.	0.0123	0.0061	0.0059	0.0019
test score	(0.0140)	(0.0137)	(0.0137)	(0.0116)
Co-worker link × Incumbent non-cog.	**0.0200**	**0.0166**	**0.0143**	**0.0104**
test score	**(0.0141)**	**(0.0128)**	**(0.0126)**	**(0.0102)**
Observations	1,065,480	1,065,480	1,065,480	1,065,480
Fixed effects	-	Firm Type	Firm Type + Job Level	Establishment

Notes. *** p<0.01, ** p<0.05, * p<0.1. The estimates in Panel A are obtained from adding incumbent non-cognitive test-scores to equation 1 (*Table 2* gives the controls included). For the estimates in Panel B we added interactions between link and incumbent cognitive and non-cognitive skills to equation 2. The main effect of incumbent cognitive and non-cognitive test scores are included in the regression but not reported in the table (see *Table 3* for all the controls included).

5.3 Results on entry wages

5.3.1 Testable element 3: Average entry wages

In this subsection we turn to an analysis of the relationship between co-worker links and wages. As noted in Section 3.4 results from various countries and contexts provide very mixed results regarding the relationship between social networks and entry wages. In our application, we add to this literature by first examining the third testable element of the Montgomery element outlined in Section 3.3 (i.e. higher entry wages): Employing firms should, according to the model, expect referred workers to be more productive and therefore share parts of the expected surplus with the workers to avoid losing them to other linked firms. We use data on entering workers and capture the association between their entry wages and the *Link* indicator through a straightforward wage equation:

$$log(w_{it_0}) = \phi_0 + \phi_1 Link_{it_0} + \phi_2 X_{it_0} + W_{t_0} + \varepsilon_{ijt_0}, \tag{5}$$

where w_{it_0} is the entry wage of worker i starting employment in year t_0; $Link_{it_0} = 1$ if the entrant has at least one former co-worker in the new establishment and zero otherwise. X_{it_0} includes schooling, age and experience of the entrant. As before, W_{t_0} denote the control variables by specification.

The results, reported in *Table 5*, suggest a sizable positive wage premium for entering workers with links to existing employees consistent with the notion of Montgomery type referrals. Linked entrants have, on average, four percent higher wages than non-linked entrants. About half of this association remains when we control for firm-type in Column (2), and the estimates change very little when adding controls for job type in column (3), and even increase somewhat when we include establishment fixed effects in column (4). Notably, our within-establishment estimate of 3.6 percent is almost identical to that of

Brown et al. (2012) who analyze referred workers within a single U.S corporation.[21]

Although a positive wage effect of referrals is in line with Montgomery, it should be noted that it also is consistent with other types of network models, including the supply-side model of Calvo-Armengol and Jackson (2004), where well-connected workers earn higher wages because they have better outside options, as well as matched based models such as Simon and Warner (1992), Dustmann et al. (2011) and Brown et al. (2012) where referred workers earn higher starting salaries than non-referred workers because employers have better ex ante information about their match-specific productivity.

Table 5: Entry wages for linked and non-linked entrants

	(1)	(2)	(3)	(4)
Co-worker link	0.0461***	0.0299***	0.0297***	0.0360***
	(0.0068)	(0.0061)	(0.0059)	(0.0071)
Fixed effects	-	Firm Type	Firm Type + Job Level	Establ.
Observations	28,414	28,414	28,414	28,414
R-squared	0.2871	0.4026	0.4325	0.6820

Notes. *** p<0.01, ** p<0.05, * p<0.1. The level of observation is the entrant worker and the dependent variable is the (log) entry wage. Standard errors robust to heteroscedasticity and clustered at the establishment level reported in parentheses. The job level dummies refer to the first 2 digits in the occupation of the entrant. Firm type is the interaction between firm size in 6 bins (1-9, 10-19, 20-49, 50-99, 100-199 and 200-499) interacted with 3-digit industry. The regressions also include year dummies, entrant background characteristics (years of schooling, a full set of age and experience dummies), a dummy indicating whether the workplace is located in one of Sweden's three metropolitan areas (Stockholm) and the log size of the hiring plant.

5.3.2 Testable element 4: Entry wages and incumbent skills

A more unique prediction following the fundamental logic of the Montgomery model is that entering workers signal their productivity through the abilities of linked incumbent employees. Thus, we expect workers to receive a payoff from the skills of other members of their networks, which we listed as the fourth testable element in Section 3.3. Networks convey a signal of the entrants true productivity due to the inbreeding bias. This signal feeds into entry wages if firms fear that some competing recruiters may have access to

[21] Note that the wage effect may seem overly large if contrasted with the impact on entrant skills displayed in *Table 3*. But, importantly, our indicators of worker skills are not complete and we expect entrants to also have better abilities in dimensions which we as econometricians (also) are unable to observe, i.e. the part denoted by η in the wage decomposition of Section 3.2.

the same information. The logic of the model therefore suggests that entry wages should be higher for entrants that are linked to high ability incumbents than they are for workers who are linked to less able incumbents.

To test the prediction that entry wages are a function of the linked incumbent worker's ability, we use the full data, including all combinations of entrants and incumbents, in order to relate the wages of entrants to the measured skills of the linked incumbents. Formally, we estimate :

$$log(w_{it_0}) = \gamma_0 + \gamma_1(Link_{ij} \times z_j) + \gamma_2 Link_{ij} + \gamma_3 z_j + \gamma_4 s_i + X_{ijt_0} + W_{jt_0} + \varepsilon_{it_0} \qquad (6)$$

where the dependent variable is the entry wage and, as before, $Link_{ij}$ is an indicator for having worked together in the past, z_j is the skill of incumbent workers, s_i measures entrant observable skills (years of schooling), X_{it_0} measures demographic characteristics of the entering worker at the time of entry and W_{t_0} denote the control variables by specification. As before, we cluster standard errors for repeated observations of both entering and incumbent workers using the procedure suggested by Cameron et al. (2011).

By including z_j, which capture the impact of co-worker skills in general, we parametrically control for many of the unobserved differences between establishments that could motivate differences in pay between workers depending on the skill structure of the firm. Hence, if there are general returns from entering a firm with a skilled labor force, this will be captured by γ_3.

Estimation results are reported in *Table 6*. The first row of the table shows that entry wages are related to the skills of linked incumbent workers. Entry wages are 1.3 percent higher for each standard deviation of incumbent worker's ability, which corresponds to the impact of one year of own schooling in this sample. The association drops somewhat when accounting for differences related to the type of establishment and job, but remains statistically significant also in the establishment fixed effects specification. The latter suggests a wage impact of about 0.84 percent per standard deviation in test scores, or about one third of the impact of one year of own schooling.[22] We interpret the association between entry wages and the ability of the linked worker as strong support for a signaling value of networks along the lines of the Montgomery-model.

Note that the model does not account for entrant test scores. The reason is that we expect a wage premium from the incumbent worker's skills precisely because these help firms to make inference about the entrant's unobserved skills. However, the estimate is only slightly reduced if we do account for the entrants' own test score (it changes from 0.0084 (s.e. 0.0035) to 0.0078 (s.e. 0.0035)). The fact that the wage premia from incumbent workers remains even after controlling for the skills of the entrant is in line with Montgomery's notion that employers discriminate on the basis of expected rather than actual productivity, which in turn generates wage differences between entrants with identical skills.

[22] Note that the low returns to schooling partly is driven by the restriction to high-skilled jobs. Note also that the baseline effect of coworker links is somewhat different from in *Table 5* since these data are dyad weighted.

Table 6: Entry wages as a function of links and incumbent skills

	(1)	(2)	(3)	(4)
Incumbent skills:				
Co-worker link × Cognitive test score	0.0137***	0.0129***	0.0114**	0.0084**
	(0.0053)	(0.0049)	(0.0049)	(0.0035)
Co-worker link	0.0184*	0.0075	0.0085	0.0207***
	(0.0105)	(0.0101)	(0.0099)	(0.0083)
Cognitive test score	0.0263***	0.0127***	0.0113***	-0.0001***
	(0.0013)	(0.0010)	(0.0009)	(0.0000)
Entrant skills:				
Schooling	0.0267***	0.0279***	0.0215***	0.0185***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Fixed effects	-	Firm Type	Firm Type + Job Level	Establishment
Observations	1,065,480	1,065,480	1,065,480	1,065,480
R-squared	0.3191	0.0519	0.0307	0.0127

Notes. *** p<0.01, ** p<0.05, * p<0.1. The level of observation is the incumbent-entrant pair. Standard errors are corrected to account for the dyad structure of the data by clustering on both entrants and incumbents as suggested by Cameron et al. (2011). The cognitive skills have been mean centered to facilitate interpretation. The job level dummies refer to the first 2 digits in the occupation of the entrant. Firm type refers to the interaction between firm size in 6 bins (1-9, 10-19, 20-49, 50-99, 100-199 and 200-499) interacted with 3-digit industry. The regressions also include year dummies, incumbent years of schooling, and incumbent years of schooling interacted with the "'co-worker link"' dummy, entrant background characteristics (a full set of age and experience dummies), a dummy indicating whether the workplace is located in one of Sweden's three metropolitan areas, and the log size of the hiring plant.

6 Placebo and robustness

6.1 Evidence from placebo links

A key advantage of our broad data set is that we are able to present an empirical test assessing to what extent the patterns we derive are due to the personal interactions (networks) we are interested in or if it stems from alternative factors related to the labor market history. To this end we use the two sets of ”placebo-linked” workers defined in Section 4.1 to see if the empirical patterns are similar for entrants who are not linked, but who still share employment patterns with incumbent workers in a similar fashion as the linked entrants. Our first test defines entrants as placebo-linked of *Type I* if they previously worked for the same employer as an incumbent employee, but at a different point in time (but less than three years apart). Our second test, defines entrants as placebo-linked of *Type II* if they simultaneously worked within the same firm (and establishment-level industry), but within a different establishment, as an incumbent worker. The point of these exercises is to assess whether the associations we measure are driven by other, non-network, aspects related to the joint work histories of the employees. This includes the possibility that employers draw inference from the firms or the actual establishments, rather than from referrals as such, which may convey a similar type of information as the referrals we have in mind.

It is clear however that incumbent workers are likely to know some of the placebo-links if they have overlapping networks through intermediaries. If this is the case, and such overlapping networks also result in referrals, we should see evidence of Montgomery-type effects also in the placebo analysis. We therefore interpret the placebo exercises as providing a very conservative baseline for our main analysis (see also Kramarz and Skans for similar tests).

Table A 5 in Appendix B contrasts the baseline results to the results for the placebo-links. To conserve space we rely on the establishment fixed effects specification throughout. The results, with one exception, do not suggest that key elements of the Montgomery model are present for placebo-linked workers of either type. The one exception is the impact of incumbent ability on the probability of hiring a placebo-linked worker of Type I (see Panel A). Here we find a significant effect which is less than half as large as when analyzing actual links. The estimate thus suggests that employers are more likely to recruit workers from the establishments where their high ability workers used to work in the past. The difference in magnitude between actual links and placebo links does however suggest that the direct personal interaction at the workplace between the incumbent worker and prospective employees reinforces this process. The estimates for placebo linked workers of Type II are positive, but insignificant, in this specification.

The results related to equations 2-6 are all small in magnitude and statistically insignificant for both types of placebo links: Placebo linked entrants are not more skilled than other entrants to the same firms (Panel B). Placebo linked entrants do not earn higher wages than other entrants to the same firms (Panel C). And placebo linked entrants do not earn higher wages if they have a placebo link to a high skilled incumbent worker (Panel D).

In order to assess if the samples used for the placebo-links are comparable to those of the actual links, we also present models where we introduce placebo-links alongside actual links into the same model.[23] Here we restrict the sample to employers hiring both true and placebo links over the sample period. This exercise is however not possible to execute for equation 1 where the links serve as the dependent variable. For all other models we do however find a very similar pattern as in the main analysis, although with dwindling precision in some cases.

Overall, we interpret the evidence from this exercise as reassuring. The regularities we document in the baseline analysis appear to require a history of direct interactions

[23] We harmonize the samples by using identical receiving firms since confounders related to the firms is our main concern. Selection on the worker side for a given set of firms is, on the other hand, endogenous to the model.

between the involved agents. Indirect effects caused by, or transmitted through, the work history, or the firm as such appear to be confined to the first of our four testable elements (if at all present), and even in this case with a heavily muted impact compared to that of the actual links.

6.2 Covariates and samples

In our main specifications we tried to keep a uniform set of covariates for ease of exposition. But in *Table A 6* we include various additional controls capturing incumbent and entrant characteristics to equations 1-6. As in the placebo analysis above, we rely on the establishment fixed effects specification throughout.

Panel A repeats the estimates from equation 1. To recap, this model estimates the association between the skills of incumbent workers and the probability of having at least one former co-worker among the set of new hires. A potential concern with the baseline specifications of this model is that high-ability workers may have a larger network or contacts with a stronger labor force attachment, which could explain why they more often are linked to entrants. To investigate whether the effects are driven by the characteristics of the networks, we add controls for the size of the incumbent worker's total network (defined from past co-workers) as well as the quality of this network as indicated by the employment rate within the network.[24] As is evident from the results in column (2) of *Table A 6*, the estimated effect of interest is unaffected by the inclusion of these controls. Both network size and network employment rate are however significantly and positively associated with the probability of hiring a co-worker link (not reported in the table).[25]

Panel B reports the association between a co-worker link and the entrant's residual cognitive skills as specified in equation 2. In order to reduce the potential for a spurious correlation, we include the same controls for the incumbent worker's network as in

[24] Network size is the total number of former co-workers of the incumbent between 1985 and $t-2$. The employment rate within the network is the fraction of all former co-workers employed in $t-1$.

[25] The average total network size is 359, and the network employment rate is 79 percent. The probability of hiring a link increase by 0.07 percentage points from 10 additional network members, and 0.004 percentage points from a one percent increase in the fraction of employed in the network.

Panel A, but also add the controls for the entrant's total number of former employers, as well as monthly earnings on the previous job.[26] The point of adding these two additional sets of controls is to account for aspects of the networks of both incumbent and the entering workers which may be correlated with the ability measures of the agents on both sides. The estimated effect of interest is, again, very similar to the effect in our baseline specification.

Panel C and D report results regarding entry wages corresponding to equations 5 and 6 respectively. Here we add variables capturing the entering worker's total number of former employers and monthly earnings in the previous job (as in Panel B).[27] As in panels A and B, these variables do not affect the estimates of interest. We interpret this as suggesting that the entry wage impact of referrals, and of linked workers' skills, are not due to omitted variables that are correlated with network characteristics.

We also evaluated the sensitivity of our estimates to variations of the type of controls for observable skills, modelled as a linear function of the entrant's years of schooling in our main analysis. More specifically, we ran specifications replacing the years of schooling with indicators for the highest completed level of education of the entrant as well as for the detailed (4-digit) field of education. Overall these results were similar to the ones reported in our main analysis, which supports the idea that the test scores, given the number of years of schooling, capture correlates of productivity that are difficult to observe for employers at the time of the hire.

Our main sample consist of private sector employees. But we have also reestimated the model using the full sample which also include the universe of public sector employees. The results, which are presented in the final column of *Table A 6* in Appendix B are very similar (although in most cases somewhat muted) as when focusing on the private

[26] We use the monthly earnings to avoid restricting our sample to individuals that are sampled twice in the wage register. We calculate the monthly earnings from the annual earnings divided by the months of employment. Previously non-employed workers are separated through a dummy variable.

[27] The impact of lagged monthly earnings is positive as expected, the impact of number of employers is small, negative and statistically significant in both models.

sector sample.

6.3 Extending the analysis to low-skilled jobs

We have so far tested the elements of the Montgomery model when firms hire workers to fill high-skilled jobs. In this section we turn our focus to the low-skilled jobs in order to assess the model's ability to explain the sorting and wage patterns in the low-skilled segments of the labor market. We utilize the information on both cognitive and non-cognitive test scores, as previous research suggests that non-cognitive skills may be more relevant for individual productivity in the low-skilled labor market (see e.g. Lindqvist and Vestman (2011)). On a similar note Brown et al. (2012) argue that different traits may be valued at different positions within the firm (e.g. simpler traits such as punctuality in positions with lower educational requirements, and strategic thinking higher up in the hierarchy) and that firms may use referrals to detect different types of worker skills needed at different levels of the within-firm hierarchy.

Two indications consistent with this notion are found in Appendix B. First, the difference in cognitive ability between workers in high-skilled and low-skilled jobs is almost twice as large as the difference in non-cognitive skills (see *Table A 3*). Second, although the probability of hiring a linked entrant has a positive relationship to the *wages* of incumbents at high-skilled and low-skilled jobs, the impact of cognitive abilities have opposing signs (see *Table A 4*). This contrast is a clear indication that the cognitive skills fail to capture the relevant aspects of the referral process in low-skilled jobs.

Table 7 contrasts all our results (element by element) for the high-skilled jobs with those obtained for low-skilled jobs. Although some elements appear to be present also for the low skilled jobs, our general impression is that the data are less in line with the model for these jobs. As when Burks et al. (2013) analyze call centers and truckers, links do not result in entrants with better cognitive or non-cognitive skills in our broad sample of low skilled jobs, although network inbreeding is still present. The results further suggest a notable heterogeneity in the importance of different types of skills along the lines suggested by Lindqvist and Vestman (2011). In particular, while cognitive skills are a better predictor of linked hires in high-skilled jobs, it is the non-cognitive skills of the incumbent worker that predict the recruitments of linked entrants into low skilled jobs. On a similar note, the incumbent's non-cognitive skills appear to predict both cognitive and non-cognitive scores among the linked entrants for the low-skilled jobs (panel *B.2*). For both types of jobs, the linked incumbent's cognitive score only predict the entrant's cognitive score.

The wage results show an insignificant wage return for low-skilled jobs (Panel C). For both types of jobs we do however find that the entry wage of linked entrants is associated with the (cognitive and non-cognitive) skills of their incumbent link, although precision is an issue and the estimate appear smaller for the low-skilled (Panel D).

Table 7: Extension to non-cognitive test scores and low skilled jobs

	(1) High-skilled jobs	(2) Low-skilled jobs
A: Dep. var: Co-worker link (eq. 1)		
Incumbent cognitive test score	0.0010***	-0.0009***
	(0.0003)	(0.0003)
Incumbent non-cognitive test score	-0.0002	0.0007**
	(0.0003)	(0.0003)
Observations	359,462	509,972
B: Dep. var: Entrant residual skills (eq. 3 and 4)		
	1. *Dep.var: Cognitive test scores*	
Co-worker link	0.1363***	0.0046
	(0.0256)	(0.0184)
Co-worker link × Incumbent cognitive test score	0.0205**	0.0356***
	(0.0102)	(0.0088)
Co-worker link × Incumbent non-cognitive test score	-0.0004	0.0266***
	(0.0087)	(0.0068)
Observations	1,065,480	1,958,576
	2. *Dep.var: Non-cognitive test scores*	
Co-worker link	0.0171	0.0056
	(0.0291)	(0.0193)
Co-worker link × Incumbent cognitive test score	-0.0019	-0.0027
	(0.0116)	(0.0084)
Co-worker link × Incumbent non-cognitive test score	0.0104	0.0186***
	(0.0102)	(0.0068)
Observations	1,065,480	1,958,576
C: Dep. var: log(Entry wage) (eq. 5)		
Co-worker link	0.0360***	0.0048
	(0.0071)	(0.0039)
Observations	28,414	56,598
D: Dep. var: log(Entry wage) (eq. 6)		
Incumbent skills:		
Co-worker link × Incumbent cognitive test score	0.0056	0.0066
	(0.0059)	(0.0048)
Co-worker link × Incumbent non-cognitive test score	0.0126**	0.0055*
	(0.0052)	(0.0036)
Cognitive test score	-0.0001	-0.0002
	(0.0014)	(0.0005)
Non-cognitive test score	-0.0001	0.0001
	(0.0012)	(0.0003)
Entrant skills:		
Schooling	0.0185***	0.0279***
	(0.0020)	(0.0016)
Observations	1,065,480	1,958,576
Fixed effects	Establishment	Establishment

Notes. *** p<0.01, ** p<0.05, * p<0.1. Panels A-D report the establishment fixed effect specification corresponding to column (4) of Tables *Table 1-Table 5* respectively. The dependent variable for each model is given by the table. See equations 2-6 for the exact empirical specifications and controls included. All specifications include year dummies. To facilitate interpretation, we have mean-centered the cognitive and non-cognitive test scores in the regressions reported in panel B and D. The mean of the dependent variables in Panel A is 0.025 (column 1) and 0.034 (column 2).

7 Conclusions

The theory of referral recruitments outlined by Montgomery (1991) builds on the notion that abilities are correlated within networks, which allows employers to extract private information about prospective worker's productivity by observing the productivity of their employed social links. This paper has provided an empirical assessment of the key aspects of this model, using an empirical strategy which builds on the literature on employer learning as formulated by, in particular, Altonji and Pierret (2001). Using a very large Swedish register data set with information on co-worker networks, wages, AFQT scores, and indicators of non-cognitive abilities, we show several pieces of evidence suggesting that key elements of the Montgomery model of referrals are well aligned with the data in the high-skilled segment of the labor market.

In particular we first find that high ability workers are more likely to be linked to entering workers and that the test scores of entrants and linked incumbents are correlated. Previous research suggests that cognitive abilities are closely related to individual productivity among the high skilled, whereas non-cognitive abilities are more important for the low skilled (Lindqvist and Vestman, 2011). Consistent with this notion, we show that recruitments of previous coworkers mainly appear to be related to cognitive scores for the more skill demanding jobs, whereas recruitments of previous coworkers appear more closely linked to the non-cognitive scores of the incumbent worker when jobs are less skill intensive. In line with models of network inbreeding between similar individuals, the analysis also suggests that referral recruitments are ability specific: incumbent cognitive abilities only predict linked entrants' cognitive abilities, whereas incumbent non-cognitive abilities primarily predict linked entrants' non-cognitive abilities.

Second, we show that entering workers receive higher entry wages if they have links with an existing employee and that this wage premium is increasing in the abilities of the linked incumbent worker. This result is in line with the model suggesting that employers discriminate between observably equivalent workers based on the ability of their social links when setting entry wages.

Overall, the paper provides one of the first large-sample documentations of the role played by networks for the behavior on the demand-side of the labor market. The results suggest that mechanisms related to uncertainty about worker qualities in the employee-selection process is a key explanation for why firms rely on employee networks when searching for new workers. As a result, referrals foster endogenous skill sorting between firms. In addition, the results support the notion that workers who are embedded in low ability social networks will be profiled as low productive since they remain in the pool of adversely selected workers who use formal search channels. The results therefore imply that the use of networks is a source of wage inequality, and that changes in the social structure can affect the wage distribution.

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Test scores and employer learning

Our estimating strategy requires that we have access to information about worker skills that are not readily observed by employers at the initial hiring stage. Following the work of Farber and Gibbons (1996), Altonji and Pierret (2001) and Lange (2007) on employer learning we assume that cognitive test scores are a valid measure of such skills. Altonji and Pierret (2001) specify the productivity of individual i in time t as:

$$y_{i,t} = rs_i + \mu q_i + \kappa z_i + \eta_i + E(t_i)$$

where employers observe (s_i,q_i) while (z_i, η_i) are unobserved. (s_i, z_i) observed by econometrician and $E(t_i)$ is the experience profile of productivity. Observed and unobserved skill components are assumed to be correlated. Firms cannot observe z_i, but draw inference about z_i by observing s_i, q_i and the productivity tracks workers accumulate with experience. As employers learn by experience, wages should become increasingly aligned with true productivity, hence also ability scores, and less aligned with the easily observed characteristics such as schooling in a competitive labor market.

We replicate the analysis in Altonji and Pierret (2001) using male workers in 1997 to 2007. We use the same administrative data as for the main analysis to create a dataset containing individual demographics (age, education level and field) and the full-time equivalent monthly wage. In addition we construct measures of potential experience, counted from when the person leaves school (i.e. negative values are excluded). The wages are measured once a year (in September or October) and available for all public sector employees and a sample of private sector employees. The sampling is stratified by firm size and industry covering 30 percent of all private sector employees in total.

We focus on the cohorts of males who went through the mandatory draft procedure at age 18 in 1969-1997.[28] The cognitive tests provide an evaluation of cognitive ability based on several subtests of logical, verbal and spatial abilities and are similar to the

[28] For these cohorts almost all males went through the draft.

AFQT in the US. Individuals are graded on a 1-9 scale, which we standardize within each cohort of draftees.

We regress log wages on schooling, s_i and ability z_i, interacted with experience replicating the same specification as Altonji and Pierret (2001). Thus, the estimating equation controls for calender year dummies, a cubic in experience, as well as education and cognitive standardized test scores interacted with a cubic time trend (base year 2007). We perform the analysis on the stock of male employees with non-missing wages during the period 1997-2007.

Table A 1 displays descriptive statistics for both samples and *Table A 2* reports the returns to schooling and test scores by experience. Overall, the picture concur with the conclusions of Altonji and Pierret (2001). First, cognitive test scores have a strong relationship with wages after controlling for education; a one standard deviation increase is associated with an increase in the log wage of 0.04. Second, the effects of education on wages is estimated to increase with experience if we assume that the impact of cognitive abilities is constant. Third, the relationship changes dramatically when we also let the returns to cognitive test scores change with experience (Column 2). Here, we find a sharp contrast between the two skill measures: The returns to schooling is close to flat from a non-trivial initial level (0.04). But the initial impact of cognitive test scores is essentially zero (0.004) and instead grows sharply with experience (0.02 per year).[29]

We proceed by extend the analysis from Altonji and Pierret (2001) in a couple of ways which we find illustrative for the purpose of this paper. First, we included worker fixed effects in the regressions to account for selection in and out of employment. Obviously, this precludes us from estimating the direct impact of the skill measures, but the interactions with experience are still identified. As shown in Column (3) these interactions clearly diverge, with a positive interaction estimate for ability scores and a negative interaction estimate for schooling. Next, we examine how the returns to schooling and test scores change along the duration of an employment spell. Here, we account for a fixed effect for each interaction between a worker and a workplace identifier. The results displayed

[29]The pattern is similar, but less pronounced if we use the sample of labor market entrants. As Altonji and Pierret (2001), we have also tried using actual experience instrumented by potential experience as our experience measure, finding similar results as in *Table A 2*.

in Columns (4) are very similar to those of Column (3), suggesting that employer learning affect worker's wages also within ongoing employment spells. This part is important since our main analysis rests on the presumption that recruiting employers, in general, are partially uninformed about entrant abilities at the time of recruitment.[30]

Finally, in Column (5), we add non-cognitive test scores from the enlistment procedure as an additional measure of skills that are difficult to observe for employers at the time of recruitment. The non-cognitive test scores are based on standardized, mandatory, interviews with certified psychologists during the draft process aimed to evaluate traits to succeed in the military, such as responsibility, independence, outgoing character, persistence, emotional stability, power of initiative and social skills. The schooling coefficient remains negative when we include the non-cognitive skills, and the interaction between non-cognitive skills and experience is 0.0213, suggesting a positive increase in the returns to both cognitive and non-cognitive traits with labor market experience (the correlation between the cognitive and non-cognitive test score is 0.36).

Table A 1: Summary statistics

	mean	sd	p50	min	max
Log of annual wage	10.05	.345	9.99	8.66	14.03
Age	37.98	8.48	38	18	63
Potential experience	22.92	12.03	23	0	50
Tenure at workplace	6.44	4.35	6	1	17
Years of schooling	12.89	2.64	12	8	20
Cognitive test score	5.35	1.92	5	1	9
Non-cognitive test score	5.21	1.70	6	1	9
Standardized test score	.0	1.0	-.11	-2.69	2.75
Standardized non-cog. test score	.0	1.0	-.11	-2.87	3.76
Correlation cog. and non-c. test scores			0.36		

[30] Note that the falling returns to education is inconsistent with the alternative explanation that initial skills and human capital accumulation (caused by e.g. on-the-job training) are complements.

Table A 2: Returns to skills by experience

	Panel A - Full sample				
	(1)	(2)	(3)	(4)	(5)
Schooling	0.0334***	0.0400***			
	(0.0002)	(0.0002)			
Cognitive test score	0.0424***	0.0044***			
	(0.0001)	(0.0005)			
Schooling × experience	0.0121***	0.0078***	-0.0120***	-0.0111***	-0.0114***
	(0.0000)	(0.0000)	(0.0002)	(0.0002)	(0.0002)
Cognitive test score × experience		0.0225***	0.0031***	0.0144***	0.0072***
		(0.0001)	(0.0011)	(0.0012)	(0.0012)
Non-cognitive test score × experience					0.0213***
					(0.0003)
R-squared	0.492	0.496	0.918	0.949	0.949
Education field	yes	yes	yes	yes	yes
Worker fixed effects	no	no	no	yes	yes
Worker*Workplace fixed effects	no	no	no	no	yes

Notes. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. The test scores have been standardized to mean zero and standard deviation one. Experience is modeled with a cubic polynomial. Regressions in columns (1) and (2) control for year effects, education interacted with a cubic time trend and test scores interacted with a cubic time trend. In the fixed effects specifications in columns (3) and (4) we control for education and test scores interacted with the square and the cube of time. The base year for the time trends is 2007. The sample size is 5,137,349 observations from 912,044 individuals in Panel A, and 106,509 from 33,452 in Panel B.

Additional tables

Table A 3: Incumbent worker's skills, by job skill-type

	High-skilled jobs (H)	Low-skilled jobs (L)	Difference ($H-L$)
Cognitive test score	5.6	4.7	0.9
Non-cognitive test score	5.3	4.9	0.4
Schooling	13.2	12.1	1.1
Age	37.3	36.7	0.6
Experience	12.4	10.2	2.2
Tenure	7.3	8.0	-0.7
Observations	359,462	509,972	

*Notes.*The table reports mean characteristics of male incumbent workers in the sample of high-skilled (column 1) and low-skilled jobs (column 2) respectively. Column 3 reports the relative difference.

Table A 4: Wage as alternative measure of incumbent worker's skills

	(1)	(2)	(3)	(4)
		I. High-skilled jobs		
a. Incumbent skills measure: cognitive test score (baseline)				
Incumbent cognitive test score	0.0042***	0.0017***	0.0011***	0.0011***
	(0.0003)	(0.0003)	(0.0004)	(0.0003)
Incumbent schooling	0.0016***	0.0006***	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Observations	359,462	359,462	308,136	359,462
b. Incumbent skills measure: ln(wage)				
ln(wage)	0.0177***	0.0091***	0.0097***	0.0109***
	(0.0011)	(0.0012)	(0.0013)	(0.0011)
Incumbent schooling	0.0015***	0.0005***	0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Observations	308,136	308,136	308,136	308,136
		II. Low-skilled jobs		
c. Incumbent skills measure: cognitive test score				
Incumbent cognitive test score	-0.0007**	-0.0008***	-0.0006*	-0.0006**
	(0.0003)	(0.0003)	(0.0004)	(0.0003)
Incumbent schooling	-0.0001	-0.0002	0.0001	-0.0005***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Observations	509,972	509,972	426,965	509,972
d. Incumbent skills measure: ln(wage)				
ln(wage)	0.0033***	0.0011	0.0029**	0.0045***
	(0.0012)	(0.0013)	(0.0015)	(0.0013)
Incumbent schooling	-0.0003*	-0.0004***	-0.0002	-0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	426,965	426,965	426,965	426,965
Fixed effects	-	Firm Type	Firm Type + Job Level	Establishment

Notes. *** p<0.01, ** p<0.05, * p<0.1. The level of observation is the incumbent worker and the dependent variable takes the value one if any of the entrants is a former colleague of incumbent worker j in year t. Standard errors robust to heteroscedasticity and accounting for the fact that there are multiple observations for each incumbent worker due to the panel structure of the data. The job level dummies refer to the first digit in the occupation of the incumbent. Firm type is the interaction between workplace size (1-9, 10-19, 20-49, 50-99, 100-199 and 200-499) and 3-digit industry. All regressions include year dummies, incumbent characteristics (age and age^2), a dummy indicating if the employer is located in one of Sweden's three metropolitan areas and log size of the employer. The mean of the dependent variable is 0.025 for the high-skilled jobs and 0.034 for the low-skilled jobs.

Table A 5: Robustness checks: True links vs. placebo links (4)

	(1)	(2)	(3)	(4)	(5)
	Baseline	Placebo *Type I*:		Placebo *Type II*:	
	True links:	Non-overlapping in network plant		Same network firm-different plant	
A: Dep. var: Co-worker link (eq. 1)					
Incumbent cognitive test score	0.0010***	0.0005**		0.0005	
	(0.0003)	(0.0002)		(0.0003)	
Incumbent schooling	0.0002	0.0003**		-0.0008***	
	(0.0001)	(0.0001)		(0.0001)	
Observations	359,467	359,467		359,462	
B: Dep. var: Entrant residual skills (eq. 2)					
Co-worker link (True)	0.1418***		0.1662***		0.1575***
	(0.0258)		(0.0352)		(0.0356)
Co-worker link (Placebo)		-0.0246	-0.0093	0.0343	0.0621*
		(0.0253)	(0.0286)	(0.0321)	(0.0351)
Observations	1,065,480	1,065,480	604,961	1,065,480	589,590
C: Dep. var: log(Entry wage) (eq. 5)					
Co-worker link (True)	0.0360***		0.0315***		0.0523***
	(0.0071)		(0.0073)		(0.0082)
Co-worker link (Placebo)		-0.0014	0.0057	0.0102	0.0120*
		(0.0098)	(0.0088)	(0.0100)	(0.0090)
Observations	28,414	28,414	9,348	28,414	9,066
D: Dep. var: log(Entry wage) (eq. 6)					
Incumbent skills:					
Co-worker link (True)	0.0084**		0.0096**		0.0041
× Incumbent cognitive test score	(0.0035)		(0.0038)		(0.0038)
Co-worker link (Placebo)		0.0006	-0.0001	-0.0084**	-0.0040
× Incumbent cognitive test score		(0.0033)	(0.0044)	(0.0038)	(0.0034)
Incumbent cognitive test score	-0.0001	-0.0000	-0.0001**	0.0001**	-0.0002*
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Entrant skills:					
Schooling	0.0185***	0.0185***	0.0198***	0.0185***	0.0197***
	(0.0013)	(0.0013)	(0.0018)	(0.0013)	(0.0018)
Observations	1,065,480	1,065,480	607,354	1,065,480	589,590
hline Fixed effects	Est.	Est.	Est.	Est.	Est.

Notes. Panel A-D report the establishment fixed effect specification corresponding to column (4) of Tables *Table 2-Table 5* respectively. Columns (3) and (5) restrict the sample to firms that hired at least one true co-worker link and one placebo link during the observation period. The construction of the placebo-links is described in section 4.1.

Table A 6: Robustness checks

	(1) More controls†	(2) Baseline	(3) Including public sector
A: Dep. var: Co-worker link (eq. 1)			
Incumbent cognitive test score	0.0011***	0.0010***	0.0006*
	(0.0003)	(0.0003)	(0.0002)
Incumbent schooling	-0.0006*	0.0002***	0.0002*
	(0.0002)	(0.0001)	(0.0001)
Observations	311,566	359,462	594,591
B: Dep. var: Entrant residual skills (eq. 2)			
Co-worker link	0.1409***	0.1418***	0.1204***
	(0.0260)	(0.0258)	(0.0220)
Observations	958,276	1,065,486	1,715,262
C: Dep. var: log(Entry wage) (eq. 5)			
Co-worker link	0.0312***	0.0360***	0.0359***
	(0.0068)	(0.0071)	(0.0049)
Observations	28,414	28,414	61,623
D: Dep. var: log(Entry wage) (eq. 6)			
Incumbent skills:			
Co-worker link × Incumbent cognitive test score	0.0088**	0.0084**	0.0072**
	(0.0038)	(0.0035)	(0.0032)
Incumbent cognitive test score	-0.0001***	-0.0001***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)
Entrant skills:			
Schooling	0.0209***	0.0206***	0.0202***
	(0.0013)	(0.0084)	(0.0010)
Observations	803,567	1,065,480	1,621,086
Fixed effects	Est.	Est.	Est.

Notes. Panel A-D report the establishment fixed effect specification corresponding to column (4) of Tables *Table 2-Table 5* respectively. The middle column (2) reviews the baseline estimates. The left hand column (1) compares the results when more controls are added to each model. The right hand column (3) reports the estimates based on the same sample including entrants in public sector establishments. †The controls included in each specification varies with the level of observation. In panel A (incumbent level) we include the size of the incumbent's network of former co-workers and the network employment rate; in panel B and D (incumbent-entrant level) we in addition include the entrant's wage in $t-1$ as well as the number of previous employers, and in panel C (entrant level) we include the former wage of the entrant and the number of previous employers.

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