Social Networks, Employee Selection and Labor Market Outcomes: Toward an Empirical Analysis*

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WORK IN PROGRESS

Abstract

The Montgomery (1991) model of employee referrals suggests that it is optimal for firms to select new employees through referrals from their most productive workers, as these are likely to know others with high unobserved productivity. In this paper, we use a rich matched employer-employee data with cognitive and non-cognitive test scores to assess the model's ability to explain why firms recruit former coworkers of incumbent employees. Our empirical results support key elements of the model: Incumbent workers of high aptitude are more likely to be linked to entering workers. In addition, firms acquire entrants with better unobserved abilities when hiring linked workers, and entering workers with links to incumbent employees receive higher entry wages than other entrants. Finally, entering workers exhibit wage returns from their linked employees abilities. The results thus support the notion that firms use referrals of productive employees in order to attract workers with better unobserved qualities as well as the notion that firms use the ability-density of social networks when setting entry wages.

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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. Information asymmetries between workers and firms at the time of recruitment motivates fundamental economic concepts such as statistical discrimination, the signaling returns to education, and the matching function which serves as the keystone of current unemployment theory. In addition, the asymmetries motivate large scale public interventions through e.g. 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 builds on the theory outlined by Montgomery (1991) which provides the foundation for much of the existing literature on employee referrals.[2] Montgomery assumes that high ability workers on average are more likely to know other high-ability workers (network inbreeding). Referrals from high ability incumbent 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 referals in equilibrium, despite free entry of firms. In addition, the model present a natural rationale for endogenous skill segregation across firms. But most importantly, the model shows how the intersection between the social structure of society and firms' inability to ex ante observe worker ability can be a source of wage inequality between equally productive workers.

Despite these important implications, and the fact that the model provide a fundamental link between the social network literature and the literature on employee selection under uncertainty (see Oyer and Schaefer (2011)), 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

[1] Data on employers recruitment strategies suggest that a large portion of firms use informal search channels. 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] See section 2 below for a discussion of alternative theories.

[3] An extensive literature however suggests that friends and relatives are important in the job search process (Rees (1966), Granovetter (1973)), which has motivated further research on the role of social networks see Ioannides and Loury (2004) for a survey. For more recent work, see e.g. Dustmann et al. (2011), Galenianos (2011), Brown et al. (2012), Aslund et al. (2009), Bayer et al. (2008), Bentolila et al. (2010), Kramarz and Skans (2011), Cingano and Rosolia (2012), Kramarz and Thesmar (2006). This literature generally suggests that networks are important, but there is less evidence of firm side rationales. The lab experiment by Beaman and Magruder (forthcoming) provide an interesting case however, where subjects refer better workers if provided with economic incentives to do so.

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 relies on insights derived in the literature on employer learning (see Farber and Gibbons (1996), Altonji and Pierret (2001) and Lange (2007)). Following these models we use test scores from armed forces qualifying tests (AFQT) as indicators of elements in 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. Consistent with the logic that test scores indicate elements of productivity that is diffiult to observe at the time of recruitment, we find that the association between wages and test scores increases with tenure, which contrasts to falling or constant returns to schooling. Building on this result, we therefore argue that the test scores can be used as proxies for a wider set of unobserved productivity-enhancing factors that are not easily observed by employers at the time of recruitment, and therefore also not fully priced, as suggested by Montgomery (1991).

Empirically, we focus our analysis on firms who recruit former coworkers of incumbent employees into skill-intensive jobs.[4] Within our 20 years of Swedish population-wide data, about 10 percent of new recruits have a shared working history with an incumbent employee, suggesting that this is a non-trivial recruitment channel. Our data are further linked to AFQT-scores for 32 full cohorts of male workers, allowing us to provide a detailed analysis of the relationship between worker ability, workplace-based social ties and entry wages.

To preview our results, we first document that entrants are more likely to be linked to high ability (defined from test scores) incumbent employees than to low ability incumbents. As a contrast, we only find a low correlation between formal schooling and links. Second, we show that linked entrants are of higher (unobserved) ability. Third, we show that entering workers receive higher 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. Our main analysis focuses on the skilled segments of the labor markets but auxiliary estimates show evidence suggesting that similar mechanisms are at work when firms recruit for low skilled jobs although the selection appear more

[4]See Cingano and Rosolia (2012) and Aslund et al. (2009) for recent empirical papers on coworker networks

focused on non-cognitive skills when jobs are less skill intensive. Qualitatively, our estimates are very robust to variations in the use of control variables, including establishment fixed effects. We also show that the empirical patterns are heavily muted when replacing linked employees with "placebo-linked" workers who worked at the same plants as current incumbents, but not at the same point in time.

In an empirical extension, we analyse jobs with different skill content and introduce measures of non-cognitive ability derived from psycologial assessments that were administered alongside the AFQT tests. Overall, we find smaller effects for the low skilled, but the process is also different. Taken at face value, the results suggest that social ties are used by employers to find workers with good cognitive abilities for skill intensive jobs and to find workers with good non-cognitive abilities for jobs with low skill content, a result which is line with recent evidence of wage returns to different forms of skills, see (Lindqvist and Vestman, 2011). Further results show that network inbreeding is ability specific: incumbent workers' cognitive abilities are correlated with linked entrants' cognitive abilities but not with their non-cognitive abilities, and vice versa.

By highlighting the role of networks for the demand-side of the labor market the analysis deepens our understanding on the mechanisms underlying the well-documented finding that labor market outcomes are correlated within networks.[5] Overall, we interpret our results as being well in line with Montgomery's notion that firms use social networks of productive incumbent employees as a tool to reduce uncertainty and select high ability employees and that this process have real effects on the labor market outcomes of the involved agents, in particular by providing wage returns to workers who are embedded in ability-dense networks. Results from our extended model does however suggest that employers search for abilities differ depending on the nature of the job.

The paper is structured as follows: In section 2, we introduce the Montgomery model and the testable elements that we take to the data, section 3 describes the empirical strategy and the data. Section 4 contains the results, section 6 extends the analysis, section 5 presents robustness checks and section 7 concludes.

2 The Montgomery model

2.1 Model basics

This paper builds on Montgomery's (1991) formalization of employers' use of referrals. It is a two-period model of the labor market where each worker lives for one period. Workers are observationally equivalent for the employers but can be of two types, either high (H)

[5] See e.g. Munshi (2003), Bayer et al. (2008), Bentolila et al. (2010), Kramarz and Skans (2011), Cingano and Rosolia (2012) and Kramarz and Thesmar (2006).

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 Period 1 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 have higher probability of knowing someone of their own type, Montgomery refer 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 one, 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 equal the productivity of the worker minus the wage, and there is free entry of firms. In period 2, firm's will make a referral offer as long as the expected profits exceeds those from obtaining a worker from the formal market. A key prediction of the model is that firms who, by chance, received a type H worker in period 1 always will want to make a referral offer in period 2, whereas the the firms who received type L workers 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 more than epsilon since the same workers may receive a referral offer from competing firms. The profit levels remain positive for a distribution of wage offers ranging from the market wage to an upper bound which depend 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 a 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 Testable micro-level elements

From the model, we can form testable predictions about the association between referral hires, the selection of new employees, and wages. In our setting, we let incumbent workers j, and entrants, i represent period 1 and period 2 workers respectively.

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.

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. Finally, the model delivers the result that referred period 2 workers receive a wage premium from the abilities of the referring workers. In other words, period 2 workers signal their abilities through the abilities of the period 1 workers within their networks. As a consequence, we expect entry wages of workers that are hired through referrals to be correlated with the abilities of linked incumbent workers.

These predictions present key micro elements in the Montgomery model, but to what extent are they unique to this particular model? The theoretical literature on job search networks 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 tool to acquire information about agent heterogeneity, often in the form of employee referrals. The micro-level elements listed above, with the exception of element 3 which we return to in the empirical section, explicitly concern the role of unobserved worker heterogeneity and therefore diverge from predictions derived from models with workers of homogeneous abilities.

By now the literature contains a number of different referral 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 asymmetries. The Montgomery (1991) model primarily distinguishes itself through its focus on the selection of employees with good unobserved time-constant qualities and by the role played by the productivity of the referring worker.

Both of these aspects differentiate the model from models where referrals are made by random incumbent employees in order to reduce the uncertainty regarding match specific productivity (e.g. Simon and Warner (1992), Dustmann et al. (2011) and Brown et al. (2012)). To the extent that we find evidence for the listed elements in the data, we can therefore show that models which only focus on match specific qualities and homogeneous referees provide an incomplete characterization of the referral process. We would, however, not interpret this as suggesting that match specific productivity is an unimportant element in the referral process.

A recent model, closely related to Montgomery, is Beaman and Magruder (forthcoming) which presumes that high ability workers are more able to identify workers with high ability, and do so if properly incentivized. Hence, if firms provide explicit or implicit incentives for incumbent workers to refer good entrants, the models become observationally equivalent in many dimensions. The models differ in two aspects however: The first is that Beaman and Magruder generate a correlation in abilities by arguing that good workers are better at screening others, whereas Montgomery assumes an inherent inbreeding bias. The second difference is that Montgomery explicitly assumes that entry wages are set under remaining uncertainty about worker quality. The prediction that referred workers receive wage gains from the abilities of referring employees is therefore not inherent to Beaman and Magruder as it is to Montgomery. Thus, the fourth element will present an opportunity to partly discriminate between these two closely related models.

The model by Casella and Hanaki (2006) and Casella and Hanaki (2008), which explicitly builds on Montgomery, emphasizes the signaling role of social networks and explores the resilience of the model to an extension where workers are allowed to provide explicit (but costly) productivity signals. The results show that the usefulness of job search networks is very resilient. 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 the wage premium from being hired through a social network can be reversed (depending on the parameters of the model) if workers are allowed to signal their abilities through other means.

3 Taking the Model to the Data

3.1 Empirical considerations

3.1.1 Measuring observed and unobserved productivity

The Montgomery-model builds on the notion that ability is partly unknown to employers prior to hiring. When taking the model to the data, the model's relevance is therefore confined to the aspects of worker productivity that are difficult for employers to observe. Following the literature on employer learning pioneered by Farber and Gibbons (1996) and Altonji and Pierret (2001) we decompose total worker productivity, (y) into four different components depending on their degrees of visibility. Formally:

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

where employers observe (s_i, q_i) while $(z_i,\ \eta_i)$ are unobserved to the firm. On the other hand, $(s_i,\ z_i)$ is observed by the econometrician. $E(t)$ measures worker experience. To be precise, we can think of s as capturing formal merits such as schooling which is easily observed to all, q indicates parts that are easily observed for firms but are outside of our data, such as letters of recommendation, z captures productive elements that we observe but which are unobserved to the firms, and η captures fundamentally unobserved elements. Importantly, these elements may be correlated with each other so firms may use what they observe to draw inference (although with error) regarding the parts they fail to observe.

A key element is that as workers accumulate experience, firms will gradually become better informed about the true productivity of the workers. This accumulation of information will reduce the loadings on the easily observed signals and instead increase the correlation between wages and the factors that firms are unable to observe directly. Our empirical strategy builds on the notion that firms can acquire additional information about worker productivity through referrals along the lines of Montgomery model. As with employer learning through experience, referrals should therefore reduce the impact of easily observed signals and increase the impact of factors unobserved to the firms.

The empirical strategy therefore requires access to some information about worker skills that are not directly observed by employers at the initial hiring stage. Following the work of Farber and Gibbons (1996), Altonji and Pierret (2001) and Lange (2007) we assume that cognitive test scores are a valid measure of such skills. If this presumption is true, ability scores should be more closely related to wages the better informed the firms are.[6]

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. In one of our models, we do however follow Farber and Gibbons (1996) and take out the part of z that is orthogonal to observable qualifications, by taking the residuals from a regression of schooling on z. This variable, $\hat{\theta}$ captures the skills presumable unobserved to the firm. It should be noted though that this particular decomposition requires that firms are unable to use other correlates of the test scores when they estimate the worker's true productivity.

In the appendix, we replicate the findings of the employer learning literature using our Swedish data (see below). In line with the previous literature the results suggest that cognitive test scores have a negligible effect on wages during the year of market entry, but become increasingly important with experience. Focusing on workers who stay on their jobs, (in a worker$\times$workplace fixed effects model) we find increasing returns to cognitive skills over time. Hence, in line with the existing literature, we take this as evidence for the notion 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. To support the empirical results of this paper, we also show that the same pattern holds for non-cognitive test scores.

We deviate from the employer learning literature on one important point. The existing literature presupposes that the market learns symmetrically about actual worker productivity when workers accumulate experience. In our setting, we are exploring the potential role played by private information. The Montgomery model argues that firms

[6] Lange (2007) extends the literature by examining the speed at which employers learn about worker productivity. The results suggest that they learn fast.

exploit the private information advantage they have regarding the expected productive ability of workers they can hire through referrals. We therefore analyze firm-specific learning about worker ability through social networks rather than market-general learning through experience as in much of the previous literature.

3.1.2 Measuring social networks

In order to test what we consider to be the key elements of the Montgomery model we need to define workers corresponding to the period 1 and period 2 workers of the model. We use data on incumbent workers and entrants as their empirical counterparts.

We also need to measure social ties between workers. In order to be able to analyze agents on both sides of the market, we rely on register data as has become standard in the empirical literature on labor market networks during the past decade.[7] To define our networks, 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 when agents work together. Thus, it may be particularly useful for employers to let incumbent employees refer their former coworkers (Beaman and Magruder (forthcoming) provide empirical support in this direction).[8] Previous research have also documented the importance of coworker networks for the reemployment probability of laid-off workers (most notably, see Cingano and Rosolia (2012)).

3.2 Data sources and construction of dataset

Our analysis uses a large sample of male workers in the years 2000 through 2005, drawn from administrative employment registers provided by Statistics Sweden. The employment register covers all employed workers aged 16-65 for the period 1985-2007. In addition, we have 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 standardize to mean zero and standard deviation one within each cohort of draftees.

[7] Bayer et al. (2008), Dustmann et al. (2011), Kramarz and Skans (2011), Cingano and Rosolia (2012), Aslund et al. (2009) to mention a few.

[8] 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.

We construct the data for our analysis by generating (yearly) matched pairs of incumbents (j) and entrants (i). For computational convenience, we exclude plants with more than 500 employees. We define incumbents as workers observed in the establishment the current and previous year. Entrants are workers who find employment at an establishment 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. To make sure that we focus on actual hires, we remove entrants previously employed in another establishment within the same firm or organization. Such within firm transitions are fairly common in our data, and the restriction removes 26 percent of the sample. We also 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 establishments side. Wages are collected in October or November each year for a large firm-based sample of private sector workers and the universe of public sector employees. The private sector sample which is stratified by firm size and industry covers 30 percent of the target population.

In the main analysis we restrict the sample to workers entering skill-intensive jobs (40 percent of the total sample).[9] We take this as the starting point since Montgomery (1991) shows that employee referrals should be more relevant when recruiting to skill-sensitive jobs, 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 with models focusing on low-skilled jobs. Here we also exploit variations in worker's non-cognitive test scores which are available for the same sample as the cognitive scores described above. We discuss the non-cognitive test scores in more detail in conjunction with this specific analysis.

Table 1 shows summary statistics for the incumbent workers, entrants, incumbent-entrant pairs and establishments included in our estimating sample of high skilled jobs. For consistency, we focus on pairs with non-missing wages for the entrant throughout our analysis. The average incumbent worker in our data is 38 years of age, has 13.8 years of schooling, 6.9 years tenure with the current employer and ranks 5.6 on the 1-9 scale test score distribution. Entering workers are, as expected, both younger and have higher educational attainment. They also have higher cognitive test scores. 65 percent of the entrants were non-employed the year prior to entry. The employers are equally

[9] Workers entering an occupation with ISCO-88 1-digit codes equal to 2 (Professionals) or 3 (Technicians and associate professionals).

distributed between the private and public sector and 13 percent are single establishment firms. The median establishment has 46 employees, with an upper limit of 499, including both the incumbent and the entering worker. The establishment characteristics in our sample are well in line with the characteristics for the full sample. The main difference is that our sample includes a lower fraction of establishments located in a metropolitan area.[10]

For each incumbent-entrant combination, we then define a variable indicating whether (j) and (i) are former coworkers, which is our measure of (j) and (i) holding a social tie. Pairs are defined as co-workers if employed in the same workplace the same year from 1985 onwards.[11] 9 percent of the entrants have at least one co-worker link in the establishment of entry, which constitutes 1 percent of the entrant-incumbent pairs.

3.2.1 Empirical strategy

We use a separate model for each of the testable elements described in Section 2.2. 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 digit 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 pure 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.

3.2.2 Defining placebo links from non-overlapping employment spells

A possible concern may be that the patterns we see in the data are due to unobserved factors associated with their former employer, and not outcomes of social links between former co-workers. We therefore identify a set of "placebo-links" between incumbent workers and entrants. More specifically, we define placebo-linked entrants as workers who have been employed at the same establishment as an incumbent worker, but not

[10] Among the establishments in the full sample 49 percent belong to the private sector, 14 percent to single-establishment firms and the median size is 49 employees. 50 percent of the total number of establishments are located in one of Sweden's three metropolitan areas.

[11] 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 tie could have been established (the median tie was established in 1996).

Table 1: Summary statistics: 2000-2005

	mean	sd	p50	min	max
Incumbent workers:					
Age	38.1	8.3	38	16	57
Schooling	13.8	2.4	14	8	20
Experience					
Tenure	6.9	4.7	5	2	21
Cognitive test score	5.6	1.9	6	0	9
n		601,085 *incumbents*			
Entrants:					
Age	33.3	7.8	32	18	55
Schooling	14.7	2.1	16	8	20
Experience	11.2	4.3	12	0	20
Cognitive test score	5.9	1.7	6	0	9
log(entry wage)	10.1	0.3	9.6	8.9	13.5
From employment	0.65	0.48	1	0	1
No. of previous employers	4.7	2.7	4	0	18
At least one co-worker link in entering plant	0.09	0.28	0	0	1
Number of co-worker links given at least one	3.0	7.07	1	1	137
n		61,937 *entrants*			
Establishments:					
Size	75.3	85.8	46	2	499
Single firm	0.13	0.34	0	0	1
Private sector	0.51	0.49	1	0	1
Fraction in metropolitan area	0.39	0.49	0	0	1
n		16,540 *establishments*			
Pairs:					
Co-worker link	0.009	0.095	0	0	1
Size of plant where link was established	212.7	148.0	190	2	499
Year link was established	1996	4.3	1998	1985	2003
n		1,733,598 *pairs*			

Notes. The table displays summary statistics for the agents, establishments and pairs included in our sample. Establishments are defined to be in a metropolitan area if located in one of Sweden's three largest cities (Stockholm, Gothenburg or Malmö).

at the same time. We further 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.

4 Results

In this section we analyze the testable elements of Montgomery's referral model outlined in Section 2.2 using our data on coworker links. For ease of exposition, we leave robustness checks and the "placebo analysis" to a separate section thereafter.

4.1 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 have productive 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 squared through X_{jt}. W_j represent the various sets of dummy controls in the four specifications, as outlined in Section 3.2.1 above.[12] Based on the prediction derived from the Montgomery model, we expect that $\beta_1 > 0$.

Table 2 shows the results from estimation of equation 1. In line with the predictions of the Montgomery model, able (in terms of test scores) incumbent workers are more likely to be linked to new entrants. The estimated impact of incumbent test score remains positive if we add firm and job characteristics to the model, although the magnitudes diminishes somewhat. As discussed above, the Montgomery model is in essence a model of between-firm differences, but to reduce the potenital impact of alternative explanaions we let our most stringent specification (column 4) compare incumbent workers who are employed at the same establishment. The results from this model still indicate that a one standard deviation higher cognitive test scores for an incumbent worker is associated with a 0.07 percentage points (or three times the average) higher probability of being linked to an entrant. Notably, 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).

[12] 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.

Table 2: Incumbent test score and linked entrants

	(1)	(2)	(3)	(4)
Incumbent cognitive test score	0.0039***	0.0013***	0.0007**	0.0007***
	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Incumbent schooling	0.0001	0.0004***	-0.0001	0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	601,085	601,085	521,557	601,085
R-squared	0.0017	0.0252	0.0290	0.1877
Firm type dummies	no	yes	yes	no
Job Level (incumbent) dummies	no	no	yes	no
Workplace dummies	no	no	no	yes

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. 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 digit in the occupation of the incumbent. All regressions include 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. Mean dependent variable: 0.0210.

4.2 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 weather 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 test scores (z_i) which is orthogonal to s_i as in Farber and Gibbons (1996) since the model-prediction calls for unobserved skills as the outcome variable. It should be noted though that we are unable to rule out that this measure of skills is correlated with other worker characteristics that employers can observe.

Formally, we estimate the following model:[13]

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

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)

[13] We use the full linked 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 the Link indicator, and we wish to keep the same sample for consistency. The standard errors are clustered to handle repeated observations for entering workers.

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.

The estimates are reported in Table 3. They show that linked entrants on average have between 0.10 and 0.16 standard deviations higher (residual) cognitive test scores than entrants without co-worker links. 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 hold both between and within firms and job types.

We also note that 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.[14] Thus, although firms seem to hire links of incumbent employees with lower education level, they are able to find workers with higher (unobserved) ability through high ability referrals.

The results presented to far are therefore consistent with the notion that firms use referrals when they have high-ability employees, and that the outcome of this process is that they acquire new workers with high ability. A straightforward result of this process is that the skill content of firms are likely to be path dependent, resulting in a (partly) technology-independent process of skill segregation between firms.

Table 3: Links and entrant residual cognitive test scores

	(1)	(2)	(3)	(4)
Co-worker link	0.1628***	0.1085***	0.1058***	0.1204***
	(0.0236)	(0.0235)	(0.0235)	(0.0221)
Observations	1,733,598	1,733,598	1,733,598	1,733,598
R-squared	0.0082	0.0589	0.0619	0.2121
Year dummies	yes	yes	yes	yes
Firm type dummies	no	yes	yes	no
Job level (entrant) dummies	no	no	yes	no
Workplace dummies	no	no	no	yes

Notes. *** p<0.01, ** p<0.05, * p<0.1. The level of observation is the incumbent-entrant pair. The dependent variable is the part of the entrant's cognitive skills, z_i which is orthogonal to the level of schooling, s_i. Standard errors robust to heteroscedasticity and accounting for the fact that there are multiple observations for each entrant. The cognitive skills and years of schooling have been mean centered to facilitate interpretation. The job level dummies refer to the first digit in the occupation of the entrant. Firm type refer 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. All regressions include 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.

[14] The estimates corresponding to column (4) of Table 3 implies that linked entrants have attained 0.18 years less schooling than non-linked entrants.

4.3 Referrals and Entry Wages

In this subsection we turn to an analysis of the relationship between coworker links and wages. Before embarking on the empirical analysis, it is useful to note that there is a massive amount of previous empirical work on this topic. Results from various countries and contexts provide very mixed results regarding the reltionship between social networks and wages. While some studies find a positive wage premium of networks (Brown et al. (2012), Kugler (2003), Loury (2006), Marmaros and Sacerdote (2002), Simon and Warner (1992), Antoninis (2006)) others document no or negative effects (Bentolila et al. (2010), Pellizzari (2009), Kramarz and Skans (2011)). Although several studies report that the wage impact varies with the duration of the employment spell and with the type of contacts, it is difficult to find a clear-cut unifying theme across these studies.[15] An particularly interesting study is Loury (2006), who argues that contacts must be able to convey information to employers about the potential worker in order to generate wage effects. An alternative interpretation, consistent with Montgomery, is that the wage premium depends on employers's expectations about the degree of skill-segregation (or inbreeding) within different types of networks.

In our application, we add to this literature by first examining the third testable element of the Montgomery element outlined in Section 2.2. The prediction states that workers who are hired through social ties earn higher wages than workers hired through the market since the employing firms expect these workers to be more productive. We use data on entering workers and estimate the association between their entry wages and the *Link* indicator using the following straightforward model:

$$log(w_{it_0}) = \phi_0 + \phi_1 Link_{ijt_0} + \phi_2 X_{it_0} + W_{jt_0} + \epsilon_{ijt_0}, \tag{3}$$

where w_{ijt_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 4, 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, nine 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 or

[15] Marmaros and Sacerdote (2002) show that fraternity and sorority members are helpful in obtaining a high-paying job after college. On the other hand, Bentolila et al. (2010) find that workers stating to have obtained their job through friends and relatives receive 8 percent lower wage than workers stating to have used other persons, or methods. Moreover, Kugler (2003) argues, and present cross-country-evidence consistent with, that the wage effect is positively related to the efficiency of the formal labor market intermediaries.

Table 4: Entry wages for linked and non-linked entrants

	(1)	(2)	(3)	(4)
Co-worker link	0.0947***	0.0409***	0.0414***	0.0384***
	(0.0054)	(0.0044)	(0.0043)	(0.0050)
Observations	61,937	61,937	61,937	61,937
R-squared	0.2389	0.4646	0.4801	0.7180
Year dummies	yes	yes	yes	yes
Firm type dummies	no	yes	yes	yes
Job level (entrant) dummies	no	no	yes	no
Workplace dummies	no	no	no	yes

Notes. *** p<0.01, ** p<0.05, * p<0.1. Standard errors robust to heteroscedasticity and clustered at the establishment level reported in parentheses. The job level dummies refer to the first digit in the occupation of the entrant. Firm type refer 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 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.

establishment fixed effects in columns (3) and(4).

It should be noted that, while a positive wage effect of referrals is in line with Montgomery, it is also consistent with other network models of the labor market. A straightforward example is provided by the models of Simon and Warner (1992) and Dustmann et al. (2011) where referred workers earn higher starting salaries than non-referred workers because employers have better information about their match-specific productivity, which in turn increases their wages.

A more unique prediction is that workers should receive a payoff from the skills of their networks, which we listed as the fourth testable element in Section 2.2. 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 the same information. The model therefore suggests that wages of entrants should reflect the signal provided by the skills of the referring worker if employers' perceptions about entering workers' productivity are affected by the skills of referring workers, an argument which is symmetric to the logic of the employer learning model of Altonji and Pierret (2001).

To test the prediction that entry wages are a function of linked 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:

$$log(w_{it_0}) = \gamma_0 + \gamma_1(z_j \times Link_{ij}) + \gamma_2 z_j + \gamma_3 Link_{ij} + \gamma_4 s_i + \gamma_5 X_{it_0} + W_{jt_0} + \epsilon_{it_0} \quad (4)$$

where the dependent variable is the entry wage and, as before, z_j is the skill of incumbent workers, Link is an indicator for having worked together in the past, s_i measures entrant years of schooling, and X_{it_0} measures demographic characteristics of the entering worker at the time of entry.

A positve estimate of γ_1 would imply that entrants receive a wage premium from their incumbent links' abilities, conditional on their own level of schooling and demographic characteristics. By including z_j, which capture the impact of coworker 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_2.

Estimation results are reported in Table 5. The first row of the table shows that entry wages are related to the skills of linked incumbent workers. Entry wages are 1.8 percent higher for each standard deviation of incumbent worker's ability, which correspond 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 suggest a wage impact of about 0.6 percent per standard deviation in test scores, or about one third of the impact of one year of own schooling.[16]

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. As an auxiliary exercise, slightly outside the Montgomery model but enlightening regarding the mechanisms, we have also examined whether the returns to observed and unobserved skills differs depending on whether the entrant is linked or not. If referrals provide information about the true productivity of the worker we expect unobserved skills to be relatively more important for linked entrants. Results (not in the table) suggest that linked entrants have between 3.2 and 1.4 percent larger wage returns from a one standard deviation improvement in test scores than other entrants. Returns to schooling are, in contrast, nearly identical for workers with a coworker link and other workers.

[16] Note that the low returns to schooling is partly due to the restriction to high-skilled jobs requiring at least college education.

Table 5: Entry wages as a function of links and incumbent skills

	(1)	(2)	(3)	(4)
Incumbent skills:				
Cognitive test score × co-worker link	0.0177***	0.0118***	0.0105***	0.0064**
	(0.0042)	(0.0039)	(0.0038)	(0.0030)
Cognitive test score	0.0428***	0.0143***	0.0125***	-0.0002
	(0.0007)	(0.0004)	(0.0004)	(0.0001)
Co-worker link	0.0653***	0.0277***	0.0265***	0.0325***
	(0.0082)	(0.0078)	(0.0077)	(0.0068)
Entrant skills:				
Schooling	0.0177***	0.0260***	0.0206***	0.0199***
	(0.0010)	(0.0009)	(0.0009)	(0.0009)
Observations	1,733,598	1,733,598	1,733,598	1,733,598
R-squared	0.2658	0.4643	0.4790	0.6622
Year dummies	yes	yes	yes	yes
Firm type dummies	no	yes	yes	yes
Job level (entrant) dummies	no	no	yes	no
Workplace dummies	no	no	no	yes

Notes. *** p<0.01, ** p<0.05, * p<0.1. The level of observation is the incumbent-entrant pair. Standard errors robust to heteroscedasticity and accounting for the fact that there may be multiple observations for each entrant. The cognitive skills and years of schooling have been mean centered to facilitate interpretation. The job level dummies refer to the first digit in the occupation of the entrant. Firm type refer 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 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, and the log size of the hiring plant.

5 Robustness and placebo

5.1 Robustness

In our main specifications we tried to keep a uniform set of covariates for ease of exposition. But in Table B.1 we include various additional controls capturing characterisitcs of incumbent and entrant characteristics to equations 1-4. To concerve space we rely on the establishment fixed effects specification throughout.

Panel A reestimates the model of 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 attachement, which could explain why they more often are linked to entrants. To investigate whether the effects are driven by the charactersistics of the networks, we add controls for the size of the incumbent worker's total network (defined from past coworkers) as well as the employment rate within this network.[17] As is evident from Table B.1 in Appendix B, the estimated effect of interest is unaffected

[17]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 $t-1$.

by the inclusion of these controls. Both network size and network employment rate are significantly and positively associated with the probability of hiring a co-worker link (not reported in the table).[18]

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 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.[19] 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 regrding entry wages corresponding to equations 3 and 4 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).[20] 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 differences in network characteristics between workers.

5.2 Placebo

In order to furher test the robustness of our results to possible alternative explanations, we use the set of "placebo-linked" workers defined in Section 3.2.2. Placebo-linked workers are entrants who previously worked for the same employer as an incumbent, but at a different point in time (but less than three years apart). The point of this excercise is to assess whether the associations we mesure are driven by other, non-network, aspects related the the joint work histories of the employees. This includes the possibility that employers draw inference from 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 the placebo-linked workers in some cases since they almost by definition have overlapping networks through intermediaries. If this is the case, we should see part of the Montgomery type effects also in the placebo analysis. We therefore interpret the placebo excercise as providing a very

[18]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.

[19]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.

[20]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.

strikt baseline for our main analysis.

The third column of Table B.1 in Appendix B presents the results. As in the robustness analysis above, 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. The one exception is the impact of incumbent ability on the probability of hiring a linked (in this case placebo-linked) worker (see Panel A). Here we find a significant effect which is less than half as large as when analyzing actual links. We interpret this estimate as suggesting 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 is an important element in this process.

In contrast, the estimates related to equations 2-4 are all small in magnitude and statistically insignificant: Placebo linked entrants are not more skilled than other entrant to the same firms. Placebo linked entrants do not earn higher wages than other entrants to the same firms. And placebo linked entrants do not earn high wages if they have a placebo link to a high skilled incumbent worker. Overall, we interpret therefore interpret the evidence from this exercise as reassuring. It apperas that the regularities we document in the baseline analysis require a history of direct interactions between the involved agents. Indirect effects caused by, or transmitted through, the work history as such appear to be confined to the the first of our four testable elements, and even in this case with a heavily muted impact compared to that of the actual links.

6 Extension: Non-cognitive test scores and low skilled jobs

Our analysis so far have focused on recruitments to skill-intensive jobs and the role of cognitive skills. When replicating the analysis presented above for low skilled jobs (not in the paper), we find a similar but less pronounced pattern.

One reason for why the difference may be that private information about worker productivity could be relatively more important in skill-sensitive jobs (see the discussion in Montgomery (1991)). Lindqvist and Vestman (2011) do however show that wage returns to cognitive skills are less important for low-skilled workers in general which suggest that cognitive test scores may be less informative regarding how productive workers are in less skill demanding job.

In this section we therefore extend the analysis to low-skilled workers and simultaneuously introduce measures of workers' non-cognitive skills. Our non-cognitive test scores are based on standardized, mandatory, interviews with certified psychologists during the draft process. The results are graded on a similar 1-9 scale as the cognitive skills. The evaluation is based on 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.[21]

The analysis, presented in Table 6 provide three important insights. The first is that there is notable heterogeneity in the importance of the different skills; cognitive skills are clearly a better predictor of referral hires and sorting in high-skilled jobs, whereas non-cognitive skills are a better predictor for low skilled jobs. To be more specific, Panel A shows that incumbent workers with high cognitive test scores are more likely to be linked to entrants in high-skilled jobs, while their non-cognitive skills have no significant impact. Similarly, recruitments of former co-workers are associated with better sorting in terms of cognitive skills (panel *B.1*) whereas linked entrants are no better in terms of non-cognitive traits (panel *B.2*). As a contrast, the pattern is reversed when we focus our attention to less skill-intensive jobs in the second column. Here, entrants are less likely to be linked to incumbent workers with high cognitive skills but more likely to be linked to workers with non-cognitive skills (Panel A). Linked entrants to these jobs are of higher average (residual) non-cognitive ability (panel *B.2*), but not more able in terms of cognitive skills (panel *B.1*).

Second, the wage results suggest that referrals produce a much smaller entry wage premium for low-skilled jobs compared to high-skilled jobs (Panel C). For both types of jobs we do still however find that the entry wage of linked entrants is associated with the (cognitive and non-cognitive) skills of their incumbent link with similar magnitudes (Panel D).

The third insight is that referral inbreeding is 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 measures of the linked worker's ability. In a world with continuous skill-inbreeding we can think of this interaction term as measuring the strength of the inbreeding bias (are better incumbents linked to better entrants?). The results, for both high-skilled and low-skilled jobs, show a a clear pattern where incumbent cognitive skills predict entrant (residual) cognitive skills (panel *B.1*) and incumbent non-cognitive skills predict entrant (residual) non-cognitive skills (panel *B.2*), whereas three out of four cross-effects are insignificant.[22][23]

[21] The motivation for doing the military service should not be taken into account when grading. Lindqvist and Vestman (2011) provide a detailed account of the data.

[22] The exception is incumbent non-cognitive skills which predict cognitive skills of entrants into low-skilled jobs.

[23] The results provide insights that are closely in line with recent findings by Brown et al. (2012). They have a very different methodological approach, but relying on an intruiging single-firm data set, they derive results suggesting that corporations use of referrals have different rationales in different parts of the corporate hiararchy. They suggest that simple traits such as punctuality may be valued at positions with lower educational requirements, whereas strategic thinking may be valued higher up in the hiararchy.

Table 6: 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	0.0006***	-0.0009***
	(0.0002)	(0.0003)
Incumbent non-cognitive test score	0.0003	0.0005**
	(0.0002)	(0.0002)
Incumbent Schooling	0.0002**	-0.0005***
	(0.0001)	(0.0001)
Observations	587,627	763,182
B: Dep. var: Entrant residual skills (eq. 2)		
1. *Cognitive test scores*		
Co-worker link	0.1181***	0.0087
	(0.0062)	(0.0053)
Co-worker link × Incumbent cognitive test score	0.0337***	0.0309***
	(0.0069)	(0.0060)
Co-worker link × Incumbent non-cognitive test score	-0.0014	0.0233***
	(0.0064)	(0.0057)
Observations	1,697,092	2,484,156
2. *Non-cognitive test scores*		
Co-worker link	0.0108	0.0206***
	(0.0071)	(0.0057)
Co-worker link × Incumbent cognitive test score	0.0052	0.0013
	(0.0080)	(0.0064)
Co-worker link × Incumbent non-cognitive test score	0.0166**	0.0369***
	(0.0074)	(0.0061)
Observations	1,638,284	2,314,695
C: Dep. var: log(Entry wage) (eq. 3)		
Co-worker link	0.0384***	0.0058*
	(0.0050)	(0.0035)
Observations	61,937	81,778
D: Dep. var: log(Entry wage) (eq. 4)		
Incumbent skills:		
Cognitive test score × co-worker link	0.0062*	0.0060***
	(0.0033)	(0.0021)
Non-cognitive test score × co-worker link	0.0121***	0.0071***
	(0.0024)	(0.0016)
Cognitive test score	-0.0001	-0.0001
	(0.0001)	(0.0001)
Non-cognitive test score	-0.0001*	0.0001
	(0.0001)	(0.0001)
Entrant skills:		
Schooling	0.0199***	0.0274***
	(0.0009)	(0.0010)
Observations	1,697,092	2,484,156
Workplace dummies	yes	yes

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 1-4 respectively. The dependent variable for each model is given by the table. See equations 2-4 for the exact empirical specifications and controls included. To facilitate interpretation, we have mean-centered the cognitive and non-cognitive test scores in the regressions reported in panel B and D.

7 Conclusions - in progress

This paper has provided an empirical assessment of the notion that firms use referrals in order to attract new employees with better unobserved abilities. The analysis builds on the theory outlined by Montgomery (1991) and applies an empirical strategy building 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 coworker networks, wages and AFQT scores, we show several pieces of evidence suggesting that key elements of the Montgomery model of referrals are well aligned with the data.

In particular we 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. In addition, we show that entering workers receive higher wages if they have a link to an existing employee and that entering workers benefit (through higher wages) from the abilities of linked incumbent workers.

In an extended model, we allow for both cognitive and non-cognitive skills while separating between jobs of different complexity. We show that referral sorting mainly appear to be related to cognitive skills for the more skill demanding jobs, whereas referrals are closely linked to non-congitive skills when jobs are less skill intensive. This analysis also shows that the inbreeding caused by referral recruitments is ability specific in the sense that incumbent cognitive abilties only predict entrants' cognitive abilities, whereas incumbent non-cognitive abilities predict entrants' non-cognitive abilities.

Overall, the paper highlights the role of networks for the demand-side of the labor market. The results suggest that mechanisms related to uncertainty in the employee-selection process is a key mechanisms underlying the well-documented finding that labor market outcomes are correlated within networks. The results imply that networks and referral recruitments foster skill sorting between firms as well as wage inequality between equally productive workers.

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A Unobservable skills and employer learning

Our estimating strategy requires that we have access to information about worker skills that are unobserved 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. They specify the productivity of individual i as:

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

Employers observe (s_i,q_i) while (z_i, η_i) are unobserved. (s_i, z_i) observed by econometrician. 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. As employers learn by experience, ability scores should become increasingly correlated with wages. [24]

We base the analysis on male workers in 1997 to 2007. The data come from administrative registers provided by Statistics Sweden, which includes wage information for a large sample of Sweden's working age population along with with unique individual, firm and workplace identifiers. We create a dataset containing individual demographics (age, education level and field) and wages. In addition construct measures of potential experience, counted from when the person leaves school (i.e. negative values are excluded). Monthly wages are measured once a year (in November) 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.

Draft scores available for all males born between 1951 and 1979. Almost all males went through the draft procedure at age 18 or 19 in these cohorts (i.e. they were tested in 1969-2000). The cognitive tests 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 use to construct a percentile ranking

[24] Lange extends the literature by examining the speed at which employers learn about worker productivity. The results suggest that they learn fast.

within each cohort of draftees.

Following Altonji and Pierret (A&P), we regress log wages on schooling, s and ability z, interacted with experience. The estimating equation controls for calender year dummies 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 as well as on a flow sample of males entering the labor market in 1997-2007. Table A.1 report descriptive statistics for both samples.

Table A.1: Summary statistics

	mean	sd	p50	min	max
			Stock sample		
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
			Flow sample		
Log of annual wage	9.87	.24	9.86	8.80	13.10
Age	24.39	3.39	24	18	57
Potential experience	4.69	3.24	4	0	40
Education	12.69	2.07	12	8	20
Cognitive skills	4.94	1.91	5	1	9
Non-cognitive skills	4.64	1.73	5	1	9
Entry year	1997	1.21	1998	1997	2007

Table A.2 report the returns to schooling and test scores by experience. Overall, they are very similar to the results found in Altonji and Pierret. 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 0.0424. The effect of education on wages increase slightly with experience, but this effect diminish as we include the linear interaction between experience and test scores and the coefficients on the returns to cognitive test scores with experience is about ten times as large as the coefficient on the returns to schooling with experience. The pattern is similar, but less pronounced if we use the sample of labor market entrants (Panel B).[25]

[25] As A&P we have also tried using actual experience instrumented by potential experience as our experience measure,

In columns (3)-(5) we extend the analysis from A&P in two ways. First, we include worker and worker× workplace fixed effects in the regressions. Thus, we examine how the returns to schooling and ability vary within employment spells for those who stay in their jobs. The results look similar (Columns (3) and (4)) indicating that employer learning happens within, and not solely between firms.

Second, in the final column we add non-cognitive test scores from the enlistment procedure as an additional measure of hard-to-observe skills. 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 coefficient between non-cognitive skills and experience is 0.0213, suggesting a positive increase in the returns to non-cognitive traits with labor market experience.

finding similar results as in Table A.2.

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***	0.00718***
		(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
	Panel B - Flow sample (entrants)				
Schooling	0.0203***	0.0251***			
	(0.0022)	(0.0025)			
Cognitive test score	0.0092***	-0.0148***			
	(0.0007)	(0.0049)			
Schooling × experience	0.0156***	0.0056**	-0.0005	-0.0039	-0.0040
	(0.0022)	(0.0025)	(0.0028)	(0.0035)	(0.0070)
Cognitive test score × experience		0.0468***	0.0096	0.0155	0.0070
		(0.0048)	(0.0093)	(0.0014)	(0.0137)
Non-cognitive test score × experience					0.0260***
					(0.0040)
R-squared	0.420	0.423	0.821	0.900	0.900
Education field	yes	yes	yes	yes	yes
Worker fixed effects	no	no	yes	yes	yes
Worker*Workplace fixed effects	no	no	yes	yes	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.

B Robustness checks

Table B.1: Robustness checks

	(1)	(2)	(3)
	MORE CONTROLS†	BASELINE True links	PLACEBO: Placebo links
A: Dep. var: Co-worker link (eq. 1)			
Incumbent cognitive test score	0.0006**	0.0007***	0.0003*
	(0.0002)	(0.0002)	(0.0002)
Incumbent schooling	-0.0004*	0.0002***	0.0002*
	(0.0001)	(0.0001)	(0.0001)
Observations	531,398	601,085	531,395
B: Dep. var: Entrant residual skills (eq. 2)			
Co-worker link	0.0980***	0.1204***	0.0015
	(0.0063)	(0.0061)	(0.0088)
Observations	1,564,829	1,733,598	1,733,598
C: Dep. var: log(Entry wage) (eq. 3)			
Co-worker link	0.0388***	0.0384***	-0.0009
	(0.0059)	(0.0050)	(0.0063)
Observations	50,547	61,937	61,937
D: Dep. var: log(Entry wage) (eq. 4)			
Incumbent skills:			
Cognitive test score*co-worker link	0.0086***	0.0064**	0.0023
	(0.0021)	(0.0030)	(0.0029)
Cognitive test score	-0.0001	-0.0002	-0.0001***
	(0.0002)	(0.0001)	(0.0001)
Entrant skills:			
Schooling	0.0206***	0.0199***	0.0200***
	(0.0001)	(0.0009)	(0.0009)
Observations	1,565,007	1,733,598	1,733,598
Year dummies	yes	yes	yes
Workplace dummies	yes	yes	yes

Notes: Panel A-D report the establishment fixed effect specification corresponding to column (4) of Tables 1-4 respectively. The middle column (II) reviews the baseline estimates. The left hand column (I) compares the results when more controls are added to each model. The right hand column (III) reports the placebo-estimates based on the same sample as the main analysis. The construction of the placebo-links is described in section 3.2.2. †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 and E (entrant level) we include the former wage of the entrant and the number of previous employers.