The Temptation of Social Networks under Labor Search Frictions

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Abstract

While existing theories such as models of screening and peer effects imply that social networks improve job match quality, these theories do not well explain the stylized fact, which we call *negative selection*—workers and employers with lower socio-economic status use social networks more frequently. By proposing an equilibrium search model, we show that social networks create mismatched jobs in the context where negative selection occurs. Our model sheds light on a neglected aspect of social networks: they help to match, but not necessarily with good-match partners. In the presence of search frictions, workers and firms can be tempted by bad-match encounters through social networks. This temptation is stronger for less productive, poorer workers and firms because costly formal channels are less rewarding for them. Using linked employer-employee data in Bangladesh, we find that matching through social networks rather than formal channels results in mismatches. This paper demonstrates that while social networks compensate for search frictions in formal labor markets by matching more workers and jobs, their match quality is low.

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1 Introduction

Despite the existence of formal labor markets, many workers and firms instead use informal social networks to find each other.[1] This widespread use of social networks is the result of labor market imperfections such as search frictions and asymmetric information. Social networks may mitigate labor market imperfections; however social networks may have their own disadvantages as a search channel. Investigation into the use of social networks can identify complementary imperfections of formal labor markets and social networks.

This paper investigates a phenomenon that we call *negative selection*: social networks are used more frequently by workers and employers with lower socio-economic status. This negative selection has been observed in many studies across the world,[2] but existing theories do not explain the mechanism through which negative selection occurs. Thus it remains unknown what type of labor market imperfection drives negative selection.

To uncover the mechanism behind negative selection of workers and employers into network matching, we develop a new equilibrium search model in which negative selection occurs, and derive and empirically test model implications on match quality. Our model has three salient features. First, workers and firms are heterogeneous in liquid assets and occupation-specific productivity. Second, both workers and firms are allowed to search through both social networks and formal channels.[3,4] Third, and most notably, the model sheds lights on a trait of social networks that has been largely overlooked in previous studies: while social networks help workers and firms find each other, they do not necessarily connect good-match workers and firms because social networks are formed for various purposes, not

[1]Examples of the use of social networks include that workers and employers, respectively, receive and spread vacancy information through their social contacts such as friends, relatives, and neighbors and that social contacts make referrals. For the widespread use of social networks, see Ioannides and Loury (2004); Larsen et al. (2011); Topa (2011); Beaman and Magruder (2012).

[2]See Topa (2011) for developed countries, and Wahba and Zenou (2005) and Diaz (2012) for developing countries.

[3]Most studies do not allow for firms choosing search methods.

[4]Formal channels include media advertisement, employment services, job fairs, and online job portals.

only for employment.[5] In other words, social networks are not necessarily helpful in finding a good match. This disadvantageous trait of social networks on match quality contrasts to most of the existing theories, such as models of screening and moral hazard, that show that using social networks can improve match quality. The third feature generates a trade-off between match quality and likelihood of matching. Since whether workers can find good-match jobs through formal channels at a given time is uncertain due to search frictions, workers may be tempted into bad-match encounters through social networks. Similarly, firms make a trade-off between match quality and the probability of finding a worker, and may hire bad-match workers through social networks.

Negative selection occurs in our model: workers with lower occupation-specific skills and liquid assets are more likely to have network-matched jobs, and firms with lower occupation-specific capital and liquid assets are more likely to hire workers through social networks. Negative selection occurs for two reasons. First, since lower occupation-specific productivity implies a smaller increase in production outputs from bad matches to good ones, it implies lower return to a good match. Second, since lack of liquid assets does not allow long or intensive search through formal channels, workers and firms with less liquidity have a lower probability of successfully matching through formal channels. Hence, workers and employers with lower occupation-specific productivity and wealth are more tempted by mismatched encounters through social networks.

Our model predicts that the match quality of network-matched jobs is poorer than that of formally-matched jobs. Network-matched jobs are more likely to be mismatches and pay less than formally-matched jobs. This prediction is a consequence of social network's trait that they are not necessarily connected to good-match occupations. Importantly, this prediction holds conditional on the level of worker's skills, which means that the lower productivity and earnings of network-matched workers result not only from their lower level of skills but also from the fact that they are mismatched.

[5] Only Bentolila et al. (2010) consider this aspect of social networks.

In our empirical analysis, we use nationally representative linked employer-employee survey data of three industries—manufacturing, commerce, and finance—in Bangladesh. Since the data link employers and employees, we can test employee-side predictions by controlling for employers' unobservables. Furthermore, the data include rich information such as cognitive and non-cognitive abilities, job search, employment outcomes, and match quality. In particular, direct measures of match quality in the data are unique and enable us to directly estimate the association between social networks and match quality, while most of the previous studies only indirectly examine it by estimating the association between social networks and wages.

In our empirical context, formal labor markets suffer search frictions and that matching through social networks is quick. More than half of employees and employers use social networks for search. According to our analysis, network-matched workers found their jobs more than 15 percent faster and applied to 15 to 36 percent fewer vacancies than formally-matched workers. We find evidence that employers, too, found workers faster through social networks than formal channels.

Negative selection occurs in our data. Employees with lower education are more likely to have found their current jobs through social networks. Parents' education, as a proxy for employee's wealth, is also negatively associated with the likelihood of having found his job through social networks. Employers with lower education are more likely to use social networks as a main channel of job advertisement. Firm size seems to be negatively associated with this likelihood.

Corroborating the model prediction about match quality, our estimations find that network-matched employees earn 31 percent lower salaries than formally-matched employees. Even among employees who work at the same occupation in the same firm, network-matched employees still receive 15 percent lower salaries than formally-matched ones; if we also control for employee characteristics such as education, cognitive and non-cognitive abilities, and parents' education, still network-matched employees earn 8 percent less than formally-matched employees. Furthermore, we find direct evidence that network-matched employees are poorly matched to their current jobs relative to formally-matched ones. Network-matched employees use skills and knowledge from their education in their jobs less than formally-matched employees. Network-matched employees are approximately 8 percentage points (ppt) less likely to have chosen their jobs for the purpose of career progression than formally-matched employees.

Our theoretical and empirical results demonstrate that search frictions are the market imperfection that underlies the ubiquitous use of social networks, particularly among workers and firms who are poorer and have a smaller amount of occupation-specific skills and capital. This finding about search frictions contrasts with many papers in the literature that emphasize asymmetric information and favoritism as underlying market imperfections. Furthermore, our results demonstrate an overlooked fact: social networks are also imperfect. Although social networks compensate for search frictions in formal labor markets by matching more jobs, those jobs matched through social networks have poorer match quality on average.

Related literature. This paper relates to the literature that seeks to understand why social networks are used in labor markets. Both theoretical and empirical studies have developed many theories about the role of social networks in labor markets (e.g., Ioannides and Loury, 2004; Topa, 2011; Beaman, 2016 for reviews). These theories can be categorized by types of labor market imperfections for which exploiting social networks is hypothesized to compensate: search frictions, screening for mitigating information asymmetry and uncertainty in match quality at the stage of hiring, peer effects and moral hazard, and favoritism.[6] By providing a new theory, our paper contributes to this effort to uncover the reason for the use of social networks.

Our theory is particularly helpful to understand negative selection of workers and firms into matching through social networks. The literature has consistently found this negative

[6]Section 2.5 reviews the theories by these types.

selection as Topa (2011) writes, "There exists a robust consensus in the literature that informal search methods are used more by workers with lower socio-economic status and lower education levels, and for 'lower-status' jobs." Previous studies find this negative selection with respect to different dimensions such as education (Datcher, 1983), wealth (Elliott, 1999), and firm size (Topa, 2011). Furthermore, the negative selection prevails in both developed and developing countries.[7] Despite these consistent findings of the negative selection, none of the existing theories account for the negative selection. Screening theories and peer effect and moral hazard theories imply positive selection of workers into matching through social networks, and favoritism theories do not have clear implications about selection into matching through social networks. A few search frictions theories explain negative selection but only partially. Kuzubas (2010) presents a theoretical model in which heterogeneous workers in terms of job separation rates choose whether to use costly social networks to find jobs. He shows that workers who find jobs through social networks have higher job separation rates and earn less than those who find jobs through formal channels. His model, however, does not allow firms to choose search methods and thus does not explain why firms use social networks even though social networks are dominated by workers with high job separation rates. Loury (2006) suggests the limited choice hypothesis, where workers with limited employment opportunities rely on social networks as a "last resort," but she does not explain why social networks are used as a last resort. Bentolila et al. (2010) and Pellizzari (2010) develop models that imply that compared to workers who find jobs through formal channels, those who find jobs through social networks may earn less depending on the type of social networks used. Although their models explain why the wages of network-matched employees are lower than those of formally-matched employees, the models are silent as to what types of workers choose to use social networks. By contrast, our model fully accounts for what types of workers and firms in terms of skills, capital, and economic status use social networks by explicitly allowing for both workers and firms choosing between social networks

[7] For example, Wahba and Zenou (2005), Mano et al. (2011) and Diaz (2012) for developing countries.

and formal channels for their search.[8]

This paper adds solid empirical evidence concerning wage effects of matching through social networks. The existing evidence about wage effects is mixed. Pistaferri (1999), Bentolila et al. (2010), and Kramarz and Skans (2014) find negative associations between wages and the use of social networks; Simon and Warner (1992), Burks et al. (2015), and Brown et al. (2016) positive associations; Antoninis (2006) and Loury (2006) detect both signs of associations depending on types of social networks used. This mixed evidence is understandable since types of the market failures that underlie the use of social networks differ across contexts.[9] Using Bangladeshi nationally representative linked employer-employee data of formal sectors in manufacturing, commerce, and finance, we add evidence showing a negative association between wages and the use of social networks.

2 Theoretical model

There are two search channels: social networks and formal labor markets. The formal labor markets in the model include all types of search channels and labor markets, other than social networks, such as news paper advertisement, employment services, job fairs, and online job portals.

Social networks of each individual are connected to various occupations because social networks are formed for various reasons. On the other hand, formal labor markets are separated by occupations, and workers and firms enter the formal labor markets of their own types. Since search in formal labor markets is costly, workers are selective about the types of labor markets in which to look for jobs. By contrast, the costs of asking social

[8]Bentolila et al. (2010) inspires our model in respect of how to theorize the role of social networks. We describe the similarities and differences between their model and ours in detail in section 2.5.

[9]Pistaferri (1999) use Italian data collected in 20 regions across the country; Bentolila et al. (2010) data in the U.S. and the European Union; Kramarz and Skans (2014) nationally representative data in Swedish; Simon and Warner (1992) data consisting of scientists and engineers in the U.S.; Burks et al. (2015) data from nine firms in three industries (call centers, trucking, and high-tech); Brown et al. (2016) data from a single large U.S. corporation; Antoninis (2006) data from a single Egyptian manufacturing firm; Loury (2006) youth data in the U.S.

contacts about job opportunities is low, so workers ask their social contacts not selectively but broadly. Thus, conditional on that a worker and firm meet each other, the likelihood of the meeting being a good match is lower when they meet through social networks than formal labor markets.

In the model, efficiency units of worker's and firm's search are exogenously endowed and thus represent wealth, particularly liquid assets. We assume that the efficiency units of search increase worker's probability of finding a vacancy and firm's probability of finding a worker in the case of search through formal labor markets but not search through social networks. Intuitively, since formal labor markets are thick, the probabilities of finding a vacancy and worker can increase with search intensity and duration. On the other hand, individual's social networks are thin, the probabilities does not increase as much. For example, workers can quickly run out of their friends to ask about jobs.

2.1 The model

The model is static, as in Acemoglu (1999) and Bentolila et al. (2010). There are two occupations i $(= 1, 2)$. There is a continuum of measure two risk-neutral workers who gain no utility from leisure. Each worker has occupation-specific skills in exactly one occupation. We refer to workers with type i occupation-specific skills as type i workers. Half of the workers, i.e., measure one of workers, are type 1; the other half are type 2. There are two types of vacancies ($i = 1, 2$): type i vacancies have type i occupation-specific capital. Firms, which maximize expected profits, can create vacancies by paying fixed costs c, which cannot be resold.[10] There is free entry of firms. We first consider that workers and vacancies are homogeneous in the amount of occupation-specific skills and capital. When a vacancy is filled by a worker, production occurs and generates outputs $y = x$, where x indicates match

[10]We use firms and vacancies interchangeably unless distinction between them is necessary.

quality:

$$x = \begin{cases} x_g & \text{if the same type of worker and vacancy match} \\ 1 & \text{if different types match.} \end{cases}$$

We assume $1 < x_g$ and $c < x_g$. Workers and firms meet through two channels: social networks and formal labor markets.

The model proceeds through the following process:

1. Firms decide whether to open vacancies for sunk cost c.

2. Firms and workers may encounter each other through social networks.[11] Social networks encompass both types of vacancies and workers. The total number of meetings through social networks is given by a matching function $m_n(v_1 + v_2, 2)$, where v_i is the measure of type i vacancies, and the second argument is the measure of workers. The function is increasing, concave, and continuously differentiable, has constant returns to scale, and satisfies $m_n(v, u) < \max\{v, u\}$, $\lim_{v\to\infty} m_n(v, u) = u$, and $\lim_{u\to\infty} m_n(v, u) = v$. A worker encounters a vacancy with probability $p_n(\theta_n) \equiv m_n(\theta_n, 1)$, where $\theta_n \equiv (v_1 + v_2)/2$. Note that $p_n(\theta_n)$ is strictly increasing in θ_n. The probability of meeting a type i vacancy is independent of worker's type and hence is given by $v_i p_n(\theta_n)/(v_1 + v_2)$.[12] Similarly, a vacancy meets a worker with probability

[11] Even if this assumption is weakened (i.e., firms and workers search through social networks and formal labor markets simultaneously, and some firms and workers meet first in formal labor markets), the model implications remain unchanged qualitatively. Under this weaker assumption, the firms and workers who meet each other first in formal labor markets always form matches and stop searching. The other firms and workers follow exactly the same process as described here. Obviously, the predictions derived in this section apply to the latter firms and workers. Taking into account the former firms and workers does not change predictions about selection of workers and firms into the use of social networks (propositions 2 and 4). This is because the distributions of occupation-specific skills and capital of the lucky firms and workers are identical to the unconditional distributions of the whole populations, and the distributions of search efficiency of them skew right. Moreover, taking into account the lucky firms and workers does not alter predictions about employment outcomes (propositions 3 and 5) because it simply increases the employment outcomes, across occupation-specific skills and capital and search efficiency, of those who found their jobs through formal labor markets. Calculation of an equilibrium would be more complicated, but their existence is obviously given by proposition 1 since the expected payoff of opening a vacancy continuously decreases and reaches zero as the measure of vacancies increases by lemma 4 and corollary 1.

[12] Modifying the model such that the probability of finding a type i vacancy through social networks is

$q_n(\theta_n) \equiv m_n(1, 1/\theta_n)$, which is strictly decreasing in θ_n.

3. If firms and workers encounter through social networks and agree to form matches, they stop searching and start production. If either of them disagree or if they do not meet anyone, they enter the formal labor markets.

4. The formal labor markets are separated by types: types 1 and 2 labor markets. Type i workers and firms always enter type i labor market, and if they meet partners, the partners are always good fits. The matching function is $m_f(v^e_{fi}, u^e_{fi})$, where v^e_{fi} and u^e_{fi} are the total efficiency units of search by workers and firms in type i labor market. The function $m_f(v, u)$ has the same properties as $m_n(v, u)$. We assume that workers and firms are exogenously endowed with efficiency units of search $s(> 0)$ and $a(> 0)$ that are drawn from the distributions $F(s)$ and $G(a)$. The supports of the distributions $(0, s_M)$ and $(0, a_M)$ are bounded from above, and the distributions have the probability density functions (pdfs) $f(s)$ and $g(a)$. As workers and firms are not allowed to determine how much to invest in their search, the efficient units of search in our model represent wealth, particularly liquid assets. We assume that workers and firms can meet at most one partner and that worker's probability of finding a vacancy is $p_f(s, \theta_{fi}) = \max\{1, s \cdot m_f(\theta_{fi}, 1)\}$, where $\theta_{fi} \equiv v^e_{fi}/u^e_{fi}$. Firm's probability of finding a worker is $q_f(a, \theta_{fi}) = \max\{1, a \cdot m_f(1, 1/\theta_{fi})\}$. Note that $p_f(s, \theta_{fi})$ is weakly increasing in s and θ_{fi} and that $q_f(a, \theta_{fi})$ is weakly increasing in a and decreasing in θ_{fi}. We further assume that firm's efficiency units a are realized only after vacancies are created, so firms ex-ante do not know their efficiency units even though they know the distribution $G(a)$.

5. If workers and firms do not agree to match or do not meet partners, they gain nothing. The worker's final payoff is zero, and the firm's one is $-c$.

higher for type i workers than for type j workers does not change the implications unless the probability of finding the same type conditional on finding is one.

We assume that outputs y are split between workers and firms: workers gain βy, and firms gain $(1-\beta)y$ for some $\beta \in (0,1)$ satisfying $c < (1-\beta)x_g$, regardless of whether they meet in social networks or formal labor markets.[13] We further assume that $c < (1-\beta)(1+x_b)/2$.

To summarize, worker's decision process and payoff are as follows: a type i worker finds a vacancy through social networks with probability $p_n(\theta_n)$. If both the worker and firm agree to match, the worker's final payoff is βx, which is either βx_g or β. If either of them disagrees or if the worker does not find a vacancy through social networks, he enters type i labor market and finds a good-fit vacancy and gains βx_g with probability $p_f(\theta_{fi}, a)$. If he does not find a vacancy, the final payoff is zero. The firm's decision process and payoff are similar: a firm decides whether to open a vacancy of either type, say i, for cost c. Once a vacancy is created, its endowment of efficient unit of search a realizes. The firm meets a worker of either type through social networks with probability $q_n(\theta_n)$. If a match is formed, the firm's final payoff is $(1-\beta)x - c$. If not, the firm looks for a good-fit worker in type i labor market and successfully finds one with probability $q_f(\theta_{fi}, a)$ and has the final payoff $(1-\beta)x_g - c$. If the firm does not meet a worker, the payoff is $-c$.

2.2 Equilibrium characterization

We focus on a symmetric equilibrium between occupations and suppress occupation type subscript i. Since $\theta_n = (v_1 + v_2)/2 = v$ in a symmetric equilibrium, we write v for θ_n. We start by solving worker's and firm's decision problems as to whether to form matches with partners they meet, conditional on a given v and θ_f. We then solve for v and θ_f and prove the existence of an equilibrium.

The decision problem for forming matches conditional on entering formal labor markets is trivial: if workers and firms meet, they always agree to form matches and gain βx_g and $(1-\beta)x_g$, respectively.

[13]When they meet through social networks, negotiations may take into account the endowment of efficiency units of search because the endowments affect the matching probability in the formal labor markets, which affects disagreement payoffs. To make equilibrium analysis simpler, we ignore this sophistication. This simplification can be somewhat justified if the endowments are not common knowledge.

Consider encounters through social networks. If workers and firms meet good-fit partners, they always form matches. If they meet bad-fit partners, they may refuse to form matches in the hope that they can find good-fit partners in formal labor markets. On the other hand, for fear of not finding anyone in formal labor markets, they may be willing to work with bad-fit partners to produce less than the maximum possible outputs. To be specific, workers accept bad-fit vacancies if:

$$\beta \geq p_f(s, \theta_f)\beta x_g \Longleftrightarrow p_f(s, \theta_f) \leq 1/x_g,$$

because the payoff of accepting a bad-fit vacancy is β while the expected payoff of refusing them and searching for a vacancy in a formal labor market is $p_f(s, \theta_f)\beta x_g$. Note that $0 < 1/x_g < 1$. Since the probability $p_f(s, \theta_f)$ is strictly increasing in s for any $\theta_f > 0$ until the probability reaches one, there exists a unique value, denoted $s^*(\theta_f)$, that satisfies:

$$s^*(\theta_f) = \frac{1}{x_g \cdot m_f(\theta_f, 1)}. \tag{1}$$

This value $s^*(\theta_f)$, as a function of θ_f, represents the optimum decision rule for workers concerning whether to accept bad-fit vacancies. Similarly, firm's optimum decision rule is:

$$a^*(\theta_f) = \frac{1}{x_g \cdot m_f(1, 1/\theta_f)}. \tag{2}$$

Both $s^*(\theta_f)$ and $a^*(\theta_f)$ are continuous in θ_f; $s^*(\theta_f)$ is decreasing; $a^*(\theta_f)$ is increasing. Lemma 1 summarizes the discussion in this paragraph.

Lemma 1. *For a given tightness in the formal labor markets $\theta_f > 0$, the optimum decision rules for workers and firms on accepting bad-fit partners are uniquely given by equations 1 and 2.*

Intuitively, workers and firms with lower efficiency units of search are more tempted into bad-fit partners since their search in formal labor markets are less likely to be successful.

The greater the output difference between good and bad matches, the less tempted workers and firms are; the tighter the formal labor market is, the less tempted workers are, but the more tempted firms are.

We now derive the measure of workers and firms in the formal labor market of each type for a given v and some decision rules s^* and a^* (i.e. thresholds for accepting bad-fit partners), which may or may not be $s^*(\theta)$ in equation 1 and $a^*(\theta)$ in equation 2. The measure $1-p_n(v)$ of type i workers find no vacancies through social networks and enter type i formal labor market. The measure $p_n(v)/2$ of type i workers find good-fit vacancies through social networks, and all of them form matches. The other $p_n(v)/2$ find bad-fit vacancies and form matches if the efficiency units of search of both workers and firms, s and a, is below or equal to s^* and a^*, which occurs with probability $F(s^*)G(a^*)$ conditional on finding bad-fit vacancies. The total measure of workers in the formal labor market of each type is given by:

$$u_f(v,s^*,a^*) = 1 - p_n(v) + \frac{p_n(v)(1-F(s^*)G(a^*))}{2}.$$

The total measure of vacancies in each formal labor market is:

$$v_f(v,s^*,a^*) = v\Big[1 - q_n(v) + \frac{q_n(v)(1-F(s^*)G(a^*))}{2}\Big].$$

By similar reasoning, the total efficiency units of workers' search are:

$$\begin{aligned} u_f^e(v,s^*,a^*) =&(1-p_n(v))\int_0^{s_M} s\ dF + \frac{p_n(v)(1-G(a^*))}{2}\int_0^{s_M} s\ dF + \frac{p_n(v)G(a^*)}{2}\int_{s^*}^{s_M} s\ dF \\ =&\Big[\frac{(1-p_n(v))1+G(a^*)}{2}\Big]\bar{s} + \frac{p_n(v)G(a^*)}{2}\int_{s^*}^{s_M} s\ dF, \end{aligned} \tag{3}$$

where the first term in the first line is the workers who do not find firms through social networks; the second is the workers who encounter bad-fit firms that are unwilling to form matches; the third is the workers who are unwilling to form matches with bad-fit firms that are willing to form matches. The total efficiency units of firms' search are:

$$v_f^e(v, s^*, a^*) = v\Big[\frac{(1 - q_n(v))1 + F(s^*)}{2}\Big]\bar{a} + \frac{vq_n(v)F(s^*)}{2}\int_{a^*}^{a_M} a\ dG. \tag{4}$$

It is meaningful to view u_f^e and v_f^e as the labor supply and demand in the formal labor market. The tightness θ_f acts as prices because higher tightness reduces search costs for workers and increases the supply, while higher tightness raises costs for firms and decreases the demand. Note that while the labor supply and demand are functions of the tightness, the tightness itself is by definition a function of the supply and demand. Thus, the tightness must converge to an appropriate level at which the market is balanced. We introduce the concept of a partial equilibrium.

Definition 1 (Partial equilibrium)**.** *For a given $v > 0$, tightness θ_f^* and decision rules s^* and a^* constitute a partial equilibrium if the following conditions are satisfied:*

1. *Optimization: Every worker and firm have the optimal decision rules $s^* = s^*(\theta_f^*)$ and $a^* = a^*(\theta_f^*)$.*

2. *Market clearing:*

$$\theta_f^* = \frac{v_f^e(v, s^*, a^*)}{u_f^e(v, s^*, a^*)}.$$

In a partial equilibrium, workers and firms follow the decision rules $s^* = s^*(\theta_f^*)$ and $a^* = a^*(\theta_f^*)$, which determine the labor supply and demand, leading to tightness level θ_f^*, at which the market clears.

The lemma below guarantees the existence of a partial equilibrium.

Lemma 2. *For any $v > 0$, a partial equilibrium exists.*

The proof is in appendix A.1. It is worth noting that θ_f^* depends only a single endogenous variable, v. Multiple partial equilibria may exist. Define the correspondence $\Theta_f^*(v)$ showing the relationship between θ_f^* and v as:

$$\Theta_f^*(v) = \Big\{t \in \mathbb{R} |\ t = \frac{v_f^e(v, s^*(t), a^*(t))}{u_f^e(v, s^*(t), a^*(t))}\Big\}.$$

A partial equilibrium (θ_f^*, $s^*(\theta_f^*)$, $a^*(\theta_f^*)$) where $\theta_f^* \in \Theta_f^*(v)$ is *partial* because firms may want to open more vacancies if the expected profit of opening a vacancy is positive. Let correspondence $\Pi_1(v)$ denote the expected profit in a partial equilibrium for a given v:

$$\Pi_1(v) = \{y \in \mathbb{R} |\ y = \pi_1(v, t) \text{ for some } t \in \Theta_f^*(v)\},$$

where

$$\begin{aligned} \pi_1(v, \theta) &= \int_0^{a_M} \pi_2(v, \theta, a)\ dG, \quad \text{and} \\ \pi_2(v, \theta, a) &= (1 - q_n(v))q_f(a, \theta)(1 - \beta)x + \frac{q_n(v)}{2}(1 - \beta)x \\ &\quad + \frac{q_n(v)}{2} F(s^*(\theta))\mathbb{1}(a \leq a^*(\theta))(1 - \beta) \\ &\quad + \frac{q_n(v)}{2}\Big[1 - F(s^*(\theta))\mathbb{1}(a \leq a^*(\theta))\Big]q_f(a, \theta)(1 - \beta)x - c. \end{aligned} \tag{5}$$

The function $\pi_1(v, \theta)$ is the profit when the tightness is expected to be θ, and $\pi_2(v, \theta, a)$ is the profit conditional on efficiency units of search a. The first term of $\pi_2(v, \theta, a)$ is the profit when firms do not find workers in social networks but find workers in the formal labor market; the second is when they find good-fit workers through social networks; the third is when they find and hire bad-fit workers through social networks; the fourth is when they find but do not hire bad-fit workers and find good-fit workers in the formal labor market; the last is the fixed cost. Adding the condition of zero expected profit leads the economy to an equilibrium.

Definition 2 (Equilibrium)**.** *The measure of vacancies $v^{**} > 0$, tightness θ_f^{**}, and decision rules s^{**} and a^{**} constitute an equilibrium if the following conditions are satisfied:*

1. *Optimization: Every worker and firm have the optimal decision rules* $s^{**} = s^*(\theta_f^{**})$ *and* $a^{**} = a^*(\theta_f^{**})$.

2. *Market clearing:* $\theta_f^{**} = v_f^e(v^{**}, s^{**}, a^{**})/u_f^e(v^{**}, s^{**}, a^{**})$.

3. *Free entry: The expected profit of entry is zero,* $\pi_1^*(v^{**}, \theta_f^{**}) = 0$.

Proposition 1 ensures the existence of an equilibrium. Its proof is in appendix A.2.

Proposition 1. *An equilibrium exists.*

2.3 Model implications

For the sake of brevity, we refer to jobs matched through social networks and formal labor markets as *network-matched jobs* and *formally-matched jobs*, respectively; and workers who found jobs through social networks and formal labor markets to *network-matched workers* and *formally-matched workers*.

Proposition 2 (Self-selection of workers and firms into matching through social networks)**.** *In an equilibrium:*

2-1. *Conditional on being employed, workers with lower efficiency units of search are more likely to have network-matched jobs. Conditional on employing, firms with lower efficiency units of search are more likely to have network-matched workers.*

2-2. *2-1 holds for workers, conditional on being employed at the same occupation in the same firm.*

The proof is in appendix A.3. To have proposition 2-2, we interpret employment at firms with the same amount of efficiency units of search a as employment at the same firm. Since efficiency units of search represent wealth of workers and firms, the proposition implies negative selection of workers and firms in terms of wealth.

Proposition 3 (Predictions about differences in match quality and wages). *In an equilibrium:*

3-1. Match quality and wages are on average lower among network-matched jobs than formally-matched ones.

3-2. 3-1 holds conditional on worker's efficiency units of search and/or on being employed at the same occupation in the same firm.

The proof is in appendix A.3. The intuition of the predictions is that formally-matched jobs are all good matches while network-matched jobs include bad matches as some workers and firms accept bad matches for fear of not finding any.

2.4 Extension: Heterogeneous workers and vacancies in occupation-specific productivity

We now introduce heterogeneity in occupation-specific productivity: workers are heterogeneous in occupation-specific skills; so are vacancies in occupation-specific capital. Occupation-specific skills and capital are useful only when working with good-match partners:

$$y = \begin{cases} hkx_g & \text{if the same type of worker and vacancy match,} \\ 1 & \text{if otherwise,} \end{cases}$$

where h is worker's occupation-specific skills; k is vacancy's occupation-specific capital.

We add the heterogeneity as follows. The amount of occupation-specific skills h is binary, i.e., $h \in \{h_0, h_1\}$, where $1 = h_0 < h_1$. In each type, a half measure of workers have high skills $h = h_1$, and the other half has low skills $h = h_0$. Vacancy's occupation-specific capital k is binary too, i.e., $k \in \{k_0, k_1\}$, where $1 = k_0 < k_1$. The capital costs c are identical between low and high capital vacancies. We assume that the measure v_{k_1} of potential vacancies with high occupation-specific capital is finite, while the measure of potential vacancies with low occupation-specific capital is infinite. The formal labor markets are separated by occupation types but not by the amount of skills or capital. We assume that the distributions of efficiency units of search, F and G, are identical regardless of the levels of occupation-specific skills and capital.[14] We keep assuming that workers and firms split outputs by βy and $(1-\beta)y$.[15]

When workers and vacancies of different types meet through social networks, the production outputs are one regardless of their occupation-specific skills and capital. Higher skills and capital imply higher expected return to entering formal labor markets. Thus, the optimal decision rules differ between skills and capital levels, i.e., $s^{**}_{h_0} > s^{**}_{h_1}$ and $a^{**}_{k_0} > a^{**}_{k_1}$. Note that high capital vacancies may earn positive profit in an equilibrium since their measure is finite. We consider such small v_h that low capital vacancies are created in an equilibrium. While we do not solve for an equilibrium, we consider values of parameters h_1 and k_1 such that an equilibrium exists. Such values obviously exist.[16]

The two propositions below present the main implications of the model. The proof is in appendix A.3.

Proposition 4 (Self-selection of workers and firms into matching through social networks)**.** *In an equilibrium with heterogeneity in worker's skills and vacancy's capital:*

4-1. Conditional on being employed, workers with lower occupation-specific skills and/or lower efficiency units of search are more likely to have network-matched jobs. Conditional on employing, firms with lower occupation-specific capital and/or lower efficiency units of search are more likely to have network-matched workers.

4-2. 4-1 holds for workers conditional on being employed at the same occupation in the same firm.

[14] Allowing high skills workers and high capital vacancies to have distributions that differ from, in particular dominate, the distributions for low skills workers and low capital vacancies does not change our model implications.

[15] This assumption does not take into account the fact that skills and capital levels affect the disagreement payoff as high skills and capital implies high expected return to searching for good-fit vacancies in formal labor markets.

[16] For example, if $h_1 = k_1 = 1 + \epsilon$ for sufficiently small $\epsilon > 0$, an equilibrium exists.

Intuitively, workers and firms with higher returns to working with the right partners are less attracted to the wrong partners encountered through social networks. The proposition implies negative selection of workers and firms in terms of wealth and occupation-specific skills and capital.

Proposition 5 (Predictions about differences in match quality and wages)**.** *In an equilibrium with heterogeneity in worker's skills and vacancy's capital:*

5-1. Match quality and wages are on average lower among network-matched jobs than formally-matched ones.

5-2. 5-1 holds conditional on the level of occupation-specific skills and efficiency units of search and/or on being employed at the same occupation in the same firm.

The proof is in appendix A.3.

2.5 Other theories in the literature

The literature has developed various models that aim to explain why social networks are used in labor markets (Ioannides and Loury, 2004; Topa, 2011; Beaman, 2016 for reviews). These models are categorized into search frictions, screening, peer effects and moral hazard, and favoritism.[17] Our model is a search friction model. We briefly review these models and summarize their predictions.

Search frictions. Search friction models hypothesize that the role of social networks is to help workers and firms find each other. With this hypothesis, many theoretical papers investigate labor market consequences of social networks (e.g., Calvó-Armengol and Jackson, 2004, 2007; Ioannides and Soetevent, 2006). While most of their implications concern employment outcomes at network levels such as neighborhoods and ethnicity, they have an

[17] Beaman (2016), Brown et al. (2016), and Heath (forthcoming) have similar categorizations to ours.

individual-level prediction that network-matched workers, who found their jobs through social networks, have shorter search duration and earn more than formally-matched workers, who did not. The intuition is that since network-matched workers have more contacts on average and thus have more access to vacancy information, they can find jobs faster and have higher reservation wage.[18] Empirically Munshi (2003), Beaman (2012), and Schmutte (2015) find supporting evidence. Importantly, this prediction requires the assumption that the distribution from which social networks draw vacancy information is the same as those from which formal channels do, or the assumption that the distribution of social networks dominates the distribution of formal channels.

A few papers explicitly deviate from this assumption of identical or dominating distributions. Antoninis (2006), Loury (2006), and Pellizzari (2010) argue, and find corroborative evidence, that the types of vacancy information passed on through social networks differ depending on types of social networks and thus that network-matched employees may or may not have better employment outcomes than formally-matched ones.[19] Notable work is Bentolila et al. (2010), who theorize the above argument in a generalized framework. Their way of characterizing how social networks act in labor markets has inspired our model, so their setup is similar to ours: there are two types of jobs, only at one of which each worker has occupation-specific productivity advantage; there are two labor markets that are separated by types of vacancies but *not* by types of workers; social networks of each worker are connected to one of the two labor markets; using social networks increases the probability of finding a vacancy, i.e., the probability of finding a vacancy is higher in the labor market to which worker's social networks are connected than in the other unconnected labor market; workers are homogeneous in search efficiency and skills, and so are firms in search efficiency and capital; workers are heterogeneous in the size of their social networks, i.e., how much their social networks increase the probability of finding a vacancy in a connected labor mar-

[18] Calvó-Armengol (2004) and Calvó-Armengol and Zenou (2005), however, show non-monotonicity of unemployment probability with respect to network size.

[19] The types of social networks examined empirically in these papers are previous colleagues vs friends and relatives (Antoninis, 2006) and older male relatives vs younger relatives and friends (Loury, 2006).

ket; firms do not choose between social networks and formal channels, but rather broadly post vacancies in the labor markets of their types; firms accept whoever they meets irrespective of workers' types and no matter whether workers use social networks or not. Given these settings, the only decision problem arising in the model is for workers as to which labor market, the connected or un-connected one, to enter.[20] Even if the type of the labor market to which a worker's social networks are connected is different from a worker's type, a worker may enter the connected labor market to search for a mismatched job because of the higher probability of finding a job in the connected market. The model predicts that the wages and match quality are lower among network-matched employees than formally-matched ones, which are the same as our predictions 3-1 and 5-1.

Our model is inspired by the model of Bentolila et al. (2010) but substantially different from theirs especially in the following three respects. First, our model has heterogeneity in worker's search efficiency and skills and firm's search efficiency and capital. Adding this heterogeneity is meaningful, especially in search friction models, because the existence of search frictions may have different effects on the choice to use social networks across search efficiency and skills of workers and across efficiency units of search and occupation-specific skills and capital. Besides, without this heterogeneity, a model would be unable to explain negative selection of workers and firms into matching through social networks. On the other hand, Bentolila et al. (2010) consider heterogeneity in the size of social networks.

Second, our model is a two-sided matching model in the sense that both workers and firms choose search methods, while theirs is a one-sided matching model, allowing only workers to choose them. Thus, our model is able to examine why firms use social networks in the labor search.

Third, the role, or the virtue, of formal labor markets is characterized quite differently between the two models. In our model, formal labor markets are separated by types of *both* workers and vacancies, and hence type i formal labor market gathers only type i workers

[20] Firms do not make any choices, except for the choice as to whether to open vacancies or not.

and vacancies and always produces good matches between type i workers and vacancies. By contrast, formal labor markets in their model are separated by types of vacancies but not by types of workers. That is, while type i labor market gathers only type i vacancies, the market includes various types of workers since type j workers can be attracted to type i labor market if their social networks are connected to type i labor market. Hence, in type i labor market, type i workers always meet type i vacancies, but type i vacancies do not always meet type i workers. In other words, in the formal labor markets of our model there exist "right" places for both workers and firms to search for good matches, whereas in labor markets of their model there exist such right places for workers but not for firms.[21,22] The model setting where firms neither choose search methods nor have appropriate places in formal labor markets to search for good-fit workers may be a significant limitation to a model not only because the setting is unrealistic per se but also because (i) the fact that a worker finds his job through social networks may mean that his employer also uses social networks to find him, and (ii) firms can earn positive profits by selecting search methods although such profits are suppressed to zero in an equilibrium.

Screening. Screening models assume that social networks reduce uncertainty about match quality at the stage of hiring by bringing hard-to-observe information of workers and vacancies. In the seminal paper of Montgomery (1991), workers are observationally equivalent, and productivity of workers is ex-ante unknown and revealed only after employment. Wages cannot be contingent on outputs. Social networks are assumed to have the property of inbreeding, or homophily: workers within the same networks are more similar to each other than to those outside their networks. Thus, firms can more accurately infer the productivity of applicants who belong to the social networks of incumbent employees. The model predicts

[21] This third difference between the two models is a direct result of the second difference. In order to allow firms to choose social networks and formal channels for their search, particularly to incentivize firms to turn down bad matches and enter formal labor markets, formal labor markets need to be more likely to offer good-fit workers to firms than social networks.

[22] Because of the second and third differences, solving our model becomes entirely different, as well as more complicated, than solving theirs.

that referred employees have higher unobservable abilities and earn more than non-referred ones conditional on observable abilities. On the other hand, referred employees have lower observable abilities than non-referred ones because non-referred employees have lower unobservable abilities than referred ones and thus needed to have higher observable abilities than referred ones in order to obtain jobs (Hensvik and Skans, 2016). Hensvik and Skans (2016) find empirical evidence for these predictions.

Another seminal paper on screening is Simon and Warner (1992). While their model builds on Jovanovic's (1979) job match model and is different from that of Montgomery (1991), the role of social networks hypothesized is essentially the same: social networks reduce uncertainty about match quality. Since their model is dynamic, they have a prediction of wage growth, which Montgomery (1991) does not have. The settings are as follows: infinitely-lived workers meet firms through either social networks or formal channels; workers are ex-ante homogeneous; when a worker and a firm meet each other, the match quality between them is independently determined by an identical distribution across workers and vacancies; match quality is ex post observable to both workers and firms but is ex-ante observable only partially with noise; wages are renegotiated, and workers can quit jobs; lastly, the noise about match quality is smaller when workers and firms meet through social networks than through formal channels. In an equilibrium, entry wages equal expected productivity, and subsequent wages are adjusted to equal revealed productivity. The model predicts that network-matched employees have higher entry wages than formally-matched ones and that *un*-network-matched workers have higher wage growth.[23] These predictions hold in extended

[23]The intuition is as follows. Since the ex-ante productivity is more uncertain for formally-matched employees than for network-matched ones, the probability that the true productivity turns out to be very high is higher for formally-matched employees than for network-matched ones. The probability that the true productivity turns out very low is also higher for formally-matched employees than for network-matched ones, but formally-matched employees are shielded from this case of very low productivity because they can quit jobs. Thus, compared to network-matched employees, formally-matched ones are more willing to accept bad offers, i.e., vacancies for which noisy signals indicate bad match quality. (On the other hand, employers hire any workers regardless of signal since employers always offer wages that are equal to expected productivity of workers conditional on signal.) Wages in subsequent periods equal revealed productivity. Only when true productivity turns out to be above an identical threshold between network-matched and formally-matched employees, do both types of employees continue working. Therefore, the wages of formally-matched employees grow more because their entry wages are lower than the entry wages of formally-matched

versions such as Dustmann et al. (2016), and Galenianos (2013). Dustmann et al. (2016) formalize the original model slightly and derive the same predictions. Galenianos (2013) adds heterogeneity in firm productivity and allows firm investment in reducing ex-ante uncertainty about match quality, particularly when hiring through formal labor markets.[24] Simon and Warner (1992), Brown et al. (2016) and Dustmann et al. (2016) find corroborative empirical evidence.

Peer effects and moral hazard. Peer effect and moral hazard models hypothesize that social networks are used to exploit peer effects in the workplace. Kugler (2003) develops and empirically tests a model where moral hazard occurs. In her model workers who are referred to their jobs have disutility from shirking due to peer monitoring by their referees. Thus, peer monitoring lowers firms' costs of monitoring.[25] The model predicts that referred employees earn more than non-referred ones. The intuition is that firms pay efficiency wages to referred employees whereas they pay lower wages to non-referred ones and incur shirking since efficiency wages are too high in the absence of the peer monitoring.

Heath (forthcoming) proposes another moral hazard model for a unique setting in which minimum wage restrictions bind firms. Firms want to pay low-ability workers lower entry wages than a minimum wage in order to prevent shirking, but such low wages are prohibited by minimum wage regulations. However, if a low-ability worker has a high-ability worker in his social networks, a firm can get around the minimum wage restriction by bundling up the wages of a low-ability worker and his high-ability companion. This bundling is the main role of social networks in her model. In this particular setting, the model predicts that referred employees have lower observable abilities but higher wage growth than non-referred ones.[26]

ones.

[24] Even in this case, the same predictions about entry wages and wage growth hold conditional on firm productivity. However, the unconditional correlation between the use of social networks and wages can be negative.

[25] To have an equilibrium in which both social networks and formal labor markets are used, she assumes that social networks are less efficient in terms of the meeting probability than formal labor markets.

[26] Different aspects of peer interactions, other than peer monitoring, are empirically investigated in other papers. For example, Bandiera et al. (2013) examine how team productivity differs depending on incentive structures; Bandiera et al. (2005) how individuals respond to potential externalities to their peers; using

Favoritism. In favoritism theories, favoritism by employers and incumbent workers who gain personal returns to referrals motivates the use of social networks. A few papers empirically find the existence of favoritism (Wang, 2013; Fafchamps and Moradi, 2015), but, to our knowledge, no theoretical models exist.[27] Nonetheless, we consider that under favoritism referred employees have shorter job search duration and earn more than non-referred ones conditional on abilities. Observable and unobservable abilities of referred employees may be lower than those of non-referred ones in most cases, but the difference in ability between two types of employees depends on contexts.

Summary of predictions. Table 1 summarizes the predictions of each model. In our model, network-matched employees have shorter job search duration, lower wealth, lower occupation-specific skills, lower match quality, and lower entry wages than formally-matched employees. Wage growth of network-matched employees may or may not be higher than that of formally-matched ones depending on how the difference in match quality between network-matched and formally-matched ones changes with experience at the same occupations. In the search friction models that assume the same or better information through social networks, network-matched employees have shorter search duration, higher match quality, and higher entry wages.[28] In screening models, while network-matched employees may have lower observable abilities than formally-matched ones, network-matched employees have higher unobservable abilities, higher match quality, and higher entry wages than formally-matched ones conditional on observable abilities. As for wage growth, although the model of Simon and Warner (1992) predicts that it is higher for formally-matched employees than for network-matched ones, the opposite case may also be possible based on

experiments, Pallais and Sands (2016) whether referred workers are more productive when working with referrers and whether referred workers exert more effort when they know that their performance is known to referrers and affects referrers' promotion.

[27] Goldberg (1982) builds a favoritism model. However, the model focuses on firm-level implications and does not have employee-level predictions.

[28] Network-matched employees could have lower entry wages than formally-matched ones if network-matched employees tend to originally come from a disadvantaged group, and it would be difficult for them to find jobs without social networks. Even in this case, network-matched employees have higher entry wages than formally-matched ones conditional on employee's characteristics.

the model of Montgomery (1991) if the initial difference in match quality between network-matched and formally-matched employees persists. In peer effect and moral hazard models, network-matched employees have higher observable and unobservable abilities, higher match quality, higher entry wages, and higher wage growth since high-ability peers are more likely to be referred as shown experimentally by Pallais and Sands (2016).[29] In the special case where minimum wage regulations bind employers, network-matched employees have lower observable and unobservable abilities and lower entry wages but higher wage growth (Heath, forthcoming). In favoritism models, network-matched employees have shorter job search duration and higher entry wages conditional on observable and unobservable abilities.

Table 1: Predictions of different theories and the empirical results in this paper

	Search frictions					
Characteristics / outcomes	This paper	Same or better information through networks†	Screening	Peer effect/ Moral hazard	Favoritism	Data
Job search duration	$-$	$-$			$-$	$-$
Selection						
Wealth	$-$					$-$
Observable abilities	$-$		$-/+$	$-^{\ddagger}/+$		$-$
Unobservable abilities	$-$		$+$	$-^{\ddagger}/+$		$-$
Match quality	$-$	$+$	$+$	$-^{\ddagger}/+$		$-$
Entry wage	$-$	$+$	$+$	$-^{\ddagger}/+$	$+$	$-$
Wage growth			$-/+$	$+^{\ddagger}$		$\sim$

Note. This table shows whether network-matched employees, i.e., those who found their jobs through social networks, have higher (+) or lower ($-$) characteristics and outcomes than formally-matched employees according to each theory. A blank cell means no predictions. Sign $-/+$ means that both directions are possible. Sign $\sim$ means there is no difference between network-matched and formally-matched employees. Column *Data* indicates our estimation results. †These search friction models assume that the distribution from which social networks draw vacancy information is the same as, or stochastically dominating, that from which formal labor markets draw. ‡This sign indicates that the predictions apply to the case where minimum wage regulations are binding employers.

[29]Network-matched employees may have lower observable abilities than formally-matched ones since formally-matched ones may compensate the absence of their peers with their high observable abilities.

3 Empirical setting

3.1 Overview of labor markets in Bangladesh

The labor force participation (LFP) rate in Bangladesh is 59% with a large gender difference: the LFP rate of men is 82% while that of women is 36%. As a result of the gender difference in the LFP, the labor force largely consist of men (69%). Rural labor force constitute 72%, and young labor force under age 30 constitute 33%.[30]

The unemployment rate is low at 4% although the youth unemployment is higher, 9%, and increasing. Among the employed population, wage workers are only 39% whereas self-employed workers and family business helpers are, respectively, 43% and 15%. As for sectoral composition, the non-agricultural sectors, i.e., the secondary and tertiary sectors, constitute 57%. Informal employment is dominant (86% of all employment). Since formal employment is concentrated in non-agricultural sectors (94% of all formal employment), formal employment makes up 37% of non-agricultural employment.

In Bangladeshi labor markets, search frictions crucially exist, which aligns with our model. A1 and A2 present employers' perceptions about business-related and labor-related problems in formal sectors. According to table A1, labor is a major concern of employers: 56 percent of employers raise lack of skilled labor as one of the three biggest business-related problems. According to table A2, finding workers is the biggest issue among all labor-related problems: 37 percent of employers raise lack of labor in general as one of the top three labor-related problems; 65 percent report lack of workers with general skills of education; 47 percent list lack of workers with technical skills and education. On the other hand, turnover (30 percent), remuneration costs (26 percent), and minimum wage regulations (13 percent) are not crucial issues. This fact indicates that the biggest labor-related challenge for employers is labor search, not screening, moral hazard, or minimum wage regulations.

[30]The statistics in this and following paragraphs are based on the labor force survey 2015.

3.2 Data

We use Bangladeshi matched employer–employee survey data that were collected in 2012 by the World Bank. The data have rich information, including employees' educational backgrounds, cognitive and non-cognitive abilities, job search experiences, and job match quality. The data are nationally representative of formal-sector employers and employees in manufacturing, commerce, finance, education, and public administration.[31] The survey randomly sampled establishments from the business registry 2009, which was compiled by the government, and then sampled employees within the establishments. The sampling of establishments was stratified by industries (manufacturing, commerce, finance, education, and public administration) and sizes (small, medium, and large).[32] Interviews were conducted separately for employers and employees. Note that while the data represent the employers and employees in the formal sectors, they do not represent all employers or the whole labor force in the country since they do not include other industries or informal sectors or the unemployed.

We restrict the sample as follows. We include only three industries: manufacturing, commerce, and finance, because the other industries, i.e., education and public administration, consist mostly of government or government-aided organizations for public services.[33] Our chosen industries account for 48% of the establishments and 71% of the employees in the formal economy (Nomura et al., 2013). From the establishments in these industries, we exclude those owned by the national and local governments. We only use full-time male employees, excluding female employees, part-time and seasonal employees, day laborers, and contract workers. We further exclude those who were recruited more than five years prior to the survey, because hiring information such as job search experiences and entry salary, which is crucial for our analysis, is retrospective and likely to be less accurate for those employed

[31] See Nomura et al. (2013) for details about the data.

[32] The sizes are based on the number of employees: small establishments have 10 to 20 employees; medium 21 to 70; large 71 and more.

[33] Most schools in Bangladesh are government-aided privately-managed schools. The recruitment of full-time teachers is regulated by the government.

longer ago. Focusing on newer employees also mitigates a potential attrition bias since our data do not include previous employees who already quit. Lastly, we exclude those whose age at recruitment was above 50 years. These older employees constitute only 0.5 percent of either the original sample or the sample after the above restrictions are applied. Our final sample consists of 315 establishments and 2,527 employees while the original sample has 500 establishments and 6,955 employees.[34] We examine robustness of estimation results to these sample restrictions in section 5.5.

The survey asked employees and employers what channels they use for their labor search. Specifically, the survey asked employees, "how did you find this job?" and employers, "what is a common mode of advertising vacancies?" From six pre-prepared answers: social networks, media advertisement, employment services, internet posting, job fairs, and partnership with school, employees chose a single answer while employers chose up to two. If an answer was social networks, the survey further asked employees and employers which type of networks (family and relatives, friends, neighbors, school alumni, or political affiliation) they used.

A main variable in our empirical analysis is the social network dummy indicating that an employee answered that he found his job through social networks. This social network dummy empirically defines employees as network-matched or formally-matched employees.

3.2.1 Descriptive statistics

Table 2 summarizes search channels used by employees and employers. Among employees, the most prevalent channel is social networks (64 percent). In other words, network-matched employees constitute 64 percent. As for the types of networks, families and relatives (23

[34]Our sample restrictions reduce the sample size as follows: 500 establishments and 6,955 employees in the original sample reduce to 350 and 4,833 after the exclusion of the education and public administration industries; to 329 and 4,703 after the exclusion of government owned establishments; to 327 and 4,188 after the exclusion of female employees; to 320 and 3,634 after the exclusion of part-time and seasonal employees, day laborers, and contract workers; to 316 and 2,597 after the exclusion of the employees who were recruited more than five years ago; and to 315 and 2,582 after the exclusion of the employees whose age at recruitment was above 50 years.

percent), friends (28 percent), and neighbors (12 percent) were dominant. Formal channels were dominated by media advertisement (32 percent), and the other formal channels were used by only 4 percent of the employees in total. Among employers, the most prevalent search channels were social networks (72 percent) and media advertisement (70 percent), followed by employment service (23 percent) and internet postings (15 percent). Few employers used the other channels: job fairs (8 percent) and partnership with school (4 percent). As for the types of social networks, family and relatives (26 percent), friends (22 percent), and neighbors (24 percent) are equally used.

Table 2: Search methods of employees and employers

	Mean
Panel 1. How employees found their current jobs	
Social networks, including reference from somebody	0.64
Family and relatives	0.23
Friends	0.28
Same village or town	0.12
School alumni	0.01
Political affiliation	0.00
Media advertisement and posting	0.32
Employment services	0.03
Internet posting	0.01
Job fairs	0.00
Through school	0.00
Observations	2527
Panel 2. How employers advertise job vacancies	
Social networks, including reference from somebody	0.72
Family and relatives	0.26
Friends	0.22
Same village or town	0.24
School alumni	0.01
Political affiliation	0.00
Media advertisement and posting	0.70
Employment service	0.23
Internet postings	0.15
Job fairs	0.08
Through school	0.04
Observations	315

Note. Panel 1 is based on a question to employees, "how did you find this job?" Panel 2 is based on a survey question to employers, "what is a common mode of advertising a vacancy?" Employers were allowed to choose two modes. Since choosing two modes was allowed, the sum of the above means exceeds one. For both employees and employers, if an answer was "social networks," the type of social networks used was asked.

Table 3 shows summary statistics of employees. The mean years of schooling is 9 years, and 30 percent completed high school or tertiary education. On average, employees started their current jobs at age 25, and 30 percent of them changed living locations for their job. 26 percent were recruited as professionals or managers, 60 percent as semi-skilled workers, and 14 percent for elementary positions. The monthly salary, including overtime and the other remunerations, started at 7,472 taka in 2012 value (about 90 USD) and grew to 8,651 taka (105 USD) after 2.78 years. Columns 2 and 3 split the sample into network-matched and formally-matched employees. On the whole, network-matched employees seem to be negatively selected: they are 4.8 years less educated, less likely to have parents who completed primary education, and 1.7 years younger at hire than formally-matched employees. In addition, network-matched employees are less likely to have professional or managerial positions and earn 3,500 to 4,000 taka less throughout their tenures than formally-matched workers.

Table 3 suggests that network-matched employees found their jobs more quickly and easily than formally-matched ones. Average network-matched employees found their jobs in 5.4 weeks after applying to 2.4 openings while formally-matched ones searched for 11.4 weeks and applied to 5.0 openings. The distributions of search duration (figure A4) and the number of openings applied to (figure A5) demonstrate that network-matched employees are more likely to have gotten their jobs in very short duration such as one and two weeks by applying to only one vacancy than formally-matched ones. The differences support our model assumption that workers and firms find each other through social networks first and then formal channels.

Table 3: Summary statistics: Employees

	All	Social networks are used?	
		Yes	No
	(1)	(2)	(3)
Schooling in years	8.86 (4.57)	7.17 (3.79)	11.92 (4.25)
Education level completed			
No school/primary dropout	0.16 (0.37)	0.23 (0.42)	0.04 (0.19)
Primary	0.21 (0.41)	0.28 (0.45)	0.09 (0.29)
JS/SS	0.34 (0.47)	0.36 (0.48)	0.30 (0.46)
HS	0.13 (0.34)	0.09 (0.29)	0.20 (0.40)
Tertiary	0.16 (0.37)	0.04 (0.20)	0.37 (0.48)
Father completed primary education (dummy)	0.69 (0.46)	0.61 (0.49)	0.84 (0.37)
Mother completed primary education (dummy)	0.47 (0.50)	0.37 (0.48)	0.66 (0.47)
Moved before current job (dummy)	0.19 (0.39)	0.17 (0.37)	0.24 (0.43)
Moved for current job (dummy)	0.28 (0.45)	0.29 (0.45)	0.27 (0.44)
Age at hire	25.18 (5.95)	24.57 (6.09)	26.28 (5.53)
Tenure in years	2.78 (1.42)	2.72 (1.43)	2.90 (1.38)
Occupation at hire			
Professional, Manager	0.26 (0.44)	0.22 (0.41)	0.35 (0.48)
Semi-skilled job	0.60 (0.49)	0.62 (0.48)	0.56 (0.50)
Elementary job	0.14 (0.34)	0.16 (0.37)	0.09 (0.29)
Search duration in weeks	7.56 (8.84)	5.44 (5.45)	11.40 (11.97)
No. of applications submitted	3.29 (4.26)	2.35 (2.89)	5.00 (5.60)
Entry salary (monthly, 2012 Taka)	7472 (5110)	6219 (3209)	9740 (6841)
Salary (monthly, 2012 taka)	8651 (5770)	7191 (3729)	11295 (7589)
N	2527	1628	899

Note. *JS*, *SS*, and *HS* stand for junior secondary, secondary, and higher secondary education, respectively. *Moved for current job (dummy)* takes the value of one if an employee moved to his current living place for the purpose of work in the same year as he started his current job. *Semi-skilled job* consists of clerical support workers; service workers; sales workers; skilled agricultural, forestry, and fishery workers; construction, craft, and trade-related workers; plan and machine operators, assemblers, and drivers. The monthly salary includes bonuses, overtime, and other compensations. Standard deviations are in parentheses.

Table 4 presents summary statistics of establishments. Manufacturing, commerce, and finance constitute 60, 22, and 17 percent of the sample respectively; small, medium, and large establishments have 46, 29, and 25 percent respectively. Most of the sample establishments (71 percent) are single-establishment firms. Columns 2 and 3 split the sample into the establishments that use social networks as a common mode of job advertisement and those that do not. Those that commonly use networks are more concentrated in manufacturing and less in finance. They are more likely to be small and a single-establishment firm, and their managements are less educated. These differences indicate that establishments are negatively selected into matching through social networks.

Table 4: Summary statistics: Establishments

	All	Are social networks a main job-ads mode?	
		Yes	No
	(1)	(2)	(3)
Industry			
Manufacturing	0.60	0.74	0.25
Commerce	0.22	0.20	0.27
Finance	0.17	0.06	0.48
Size			
Small (no. employees is 20 and less)	0.46	0.49	0.39
Medium (no. employees is 21-70)	0.29	0.26	0.35
Large (no. employees is 71 and above)	0.25	0.24	0.26
Establishment type			
Single-establishment firm	0.71	0.83	0.40
HQ of multi-establishments firm	0.05	0.03	0.10
Branch of multi-establishments firm	0.24	0.14	0.50
Education of top management			
Primary or less	0.06	0.08	0.01
JS/SS	0.22	0.28	0.05
HS	0.21	0.25	0.11
Tertiary	0.51	0.38	0.83
Employee characteristics			
% employees who found jobs through networks	68.58	79.65	40.04
Observations	315	227	88

Table 4 provides an important implication. Since the social network dummy is based on employee's answers to survey questions, the employers of network-matched employees may not know that the network-matched employees found the jobs through social networks. It could be even possible that employers posted job openings at formal channels and waited for applicants who might or might not use social networks to find the openings. If this was the case, our theoretical model would not apply to the empirical context since network-matched jobs in the model are formed by the employees and employers both of whom use social networks. However, this concern seems not to be the case because the table finds positive correlation between the dummy that an establishment commonly uses social networks for job advertisement and the proportion of network-matched employees within the establishment. The proportion is higher among the establishments that use social networks (80 percent) than those who do not (40 percent). Thus, the social network dummy, that an employee found his job through social networks, seems to imply that an employee and his employer meet each other through social networks as our model assumes. We investigate this further later.

4 Estimation strategy

The purpose of estimations is to test the model implications. For proposition 4-1 and 4-2 regarding self-selection of workers into network-matched jobs, we run:[35]

$$Network_i = \alpha + \beta' X_i + \gamma_{cj} + \epsilon_{icj}, \tag{6}$$

where i, c, and j denote employees, occupation levels at the timing of recruitment (i.e., elementary, semi-skilled, and professional/manager), and establishments; $Network_i$ is the dummy indicating that employee i found his job through social networks; X_i is employee's characteristics including skills and wealth; and γ_{cj} is the fixed effect of the interaction between

[35] Since proposition 4 is inclusive of proposition 2, we discuss empirical strategies by referring to proposition 4. Likewise, we refer to only proposition 5, not proposition 3.

establishment and entry occupation. We examine if the coefficients of skills and wealth are negative as prediction 4-1 and 4-2 imply. Recall that efficiency units of search in the model represent wealth. We use employees' education, age at entry, and cognitive and non-cognitive abilities as measures of the level of skills.[36] As a proxy for wealth we use the education of employee's parents: specifically, the dummies indicating whether the father and mother of an employee completed primary education. We clustered standard errors within establishments in all estimations.

We test prediction 4-1 on the employer side by:

$$Network_j = \alpha + \kappa' W_j + \epsilon_j, \tag{7}$$

where W_j is establishment's characteristics. The dependent variable $Network_j$ is either the dummy indicating that establishment j uses social networks as a common mode of job advertisement or the proportion of network-matched employees in establishment j, which is calculated based on the sample. We examine if the coefficients of capital and wealth are negative. As proxies for capital and wealth we use the education of top management, dummies for establishment belonging to single- and multi-establishment firms, and dummies for establishment sizes.

Turning to proposition 5, we estimate differences in monthly salaries and match quality between network-matched and formally-matched jobs by:

$$y_i = \alpha + \theta Network_i + \eta' X_i + \gamma_{cj} + \epsilon_{icj}. \tag{8}$$

As the dependent variable, we mainly use monthly entry salary and two direct measures of match quality: the degree to which employee i currently uses the skills and knowledge from his education in his job,[37] and the dummy indicating that the main reason for having chosen

[36] The cognitive and non-cognitive abilities were measured by short modules in the survey.

[37] The survey asked employees about this degree in the scale of 1 to 10, and we normalize the degree. Since the questions were not asked to employees with no education, non-educated employees are excluded in the

his job is career progression. We examine if the coefficient of $Network_i$ is negative.

Importantly, the social network dummy $Network_i$ may be endogenous, and our estimates may suffer omitted variable biases. We discuss potential bias issues in section 5.5.

5 Results

5.1 Self-selection into matching through social networks

Table 5 shows what kinds of employees are matched through social networks. In line with predictions 4-1 and 4-2, employees with lower human capital and wealth are more likely to have network-matched jobs. Compared to the employees who did not complete primary education, those who completed primary and secondary education are 11 to 14 ppt less likely to have network-matched jobs; those with high school certificates are 47 ppt less likely; those with tertiary diploma and degrees are 66 ppt less likely (column 2). Parents' education, a proxy for employee's wealth, is negatively associated with matching through social networks: employees whose fathers completed primary education are 6 ppt, but insignificantly, less likely to have network-matched jobs than those whose fathers did not; those whose mother completed primary education are 7 ppt significantly less likely to have network-matched jobs.

Among cognitive and non-cognitive abilities, only grit and openness are significant: employees with higher grit by one standard deviation are 5 ppt less likely to have network-matched jobs (column 2); employees with higher openness by one standard deviation are 3.5 ppt more likely to have network-matched jobs unconditional on workplace. Since grit has been found to be a preferable personality trait for education and employment outcomes (Duckworth et al., 2007; Kautz et al., 2014), the negative association between grit and the network dummy aligns with the theoretical prediction. On the other hand, it is unclear whether openness is a preferable trait for productivity. The positive association between openness and the network dummy may mean that workers with higher openness have larger

estimations where the dependent variable is this degree.

social networks and thus are more likely to find jobs through social networks. Math and language scores are positively, but insignificantly, associated with social networks, but their point estimates are economically insignificant: increases in these scores by one standard deviation raise the likelihood of be matched through social networks only by 2.2 and 1.2 ppt. The estimation results are similar whether conditional or unconditional on being employed at the same occupation in the same establishment (columns 1 and 2).

Table 5: Selection of workers into network-matched jobs

	Dep. var.: Social network dummy (= 1 if the job was found through networks)			
	(1)		(2)	
Level of education completed				
Primary	−0.130***	(0.038)	−0.107**	(0.048)
JS/SS	−0.138***	(0.050)	−0.138*	(0.073)
HS	−0.468***	(0.105)	−0.466***	(0.134)
Tertiary	−0.647***	(0.090)	−0.663***	(0.158)
Age at hire	0.000	(0.004)	−0.000	(0.006)
Math z-score	−0.013	(0.018)	0.022	(0.024)
Language z-score	0.020	(0.026)	0.012	(0.038)
Conscientiousness	0.023	(0.029)	−0.001	(0.026)
Emotional stability	0.018	(0.025)	−0.002	(0.023)
Agreeableness	0.015	(0.018)	−0.012	(0.017)
Extraversion	0.005	(0.022)	−0.018	(0.026)
Openness	0.035*	(0.020)	0.035	(0.027)
Grit	−0.032**	(0.016)	−0.053***	(0.019)
Father's primary education	−0.045	(0.039)	−0.062	(0.038)
Mother's primary education	−0.095***	(0.032)	−0.066*	(0.034)
Moved before current job (dummy)	−0.109**	(0.045)	0.010	(0.047)
Moved for current job (dummy)	−0.018	(0.051)	0.021	(0.052)
Firm–occupation fixed effects			*X*	
R-squared	0.256		0.131	
N	2463		2463	

Note. Shown are the regression results of equation 6: $Network_i = \alpha + \beta' X_i + \gamma_{cj} + \epsilon_{icj}$, where the dependent variable is the social network dummy, which indicates that an employee found his current job through social networks. The omitted category for the level of education completed is no education or primary education dropout. The variables of cognitive and non-cognitive abilities are z-scores. All specifications control for recruitment years and geographical divisions fixed effects. *Firm–occupation fixed effects* are fixed effects of interactions between establishment dummies and entry occupation dummies. Standard errors clustered within establishments are in parentheses. Significance levels: ***1%, **5%, *10%.

Turning to the employer side, table 6 presents what kinds of establishments use social networks and have more network-matched jobs. On the whole, the results indicate negative selection of employers into matching through social networks. According to column 1, education of top management, as a proxy for capital and/or economic conditions of establishments, is negatively associated with the use of social networks: establishments with high-school and tertiary educated management are 8 and 17 ppt less likely to use social networks as a main job advertisement channel than those with non or primary educated management. Belonging to a multi-establishments firm is negatively but insignificantly associated with the use of social networks. The size of the establishment is insignificant. This insignificance is understandable given that the estimation controls for whether an establishment is a single-establishment firm or belongs to a multi-establishment firm. As for industrial categories, establishments in commerce and finance are significantly less likely to use social networks than those in manufacturing. Although the particular characteristic that industrial categories share is not quite clear, establishments in commerce and finance may have high capital and wealth. In column 2, we use the proportion of network-matched employees as the dependent variable and find that the proportion is negatively associated with capital and economic conditions.

Column 3 in table 6 addresses a different issue. As discussed in the data section, since our main variable, i.e., the network dummy, is based on employees' answers in the survey, the dummy may not mean that the employers of network-matched employees used social networks. This possibility is a threat to us because our estimations are testing the scenario in which both employees and employers use social networks to match each other. The result in column 3 discredits this possibility. The proportion of network-matched employees, which is based on employee-side information, is strongly correlated with the dummy for an employer using networks as a main job advertisement channel, which is based on employer-side information.

To summarize, all the results discussed here imply negative selection of workers and firms into matching through social networks.

Table 6: Selection of firms into the use of social networks

	Dependent variable		
	Networks being a main mode of job-ads	% employees who used networks	% employees who used networks
	(1)	(2)	(3)
Networks being a main mode of job-ads			12.545***
			(4.576)
Size			
Medium	-0.068	-3.675	-2.820
	(0.046)	(3.306)	(3.336)
Large	-0.001	-0.871	-0.862
	(0.061)	(4.326)	(4.187)
Establishment type			
Headquarters	-0.124	-14.869	-13.312
	(0.164)	(9.350)	(9.178)
Branch	-0.122	-19.259***	-17.726***
	(0.083)	(5.504)	(5.656)
Industry			
Commerce	-0.161**	-8.404**	-6.380
	(0.067)	(4.117)	(4.121)
Finance	-0.557***	-34.485***	-27.503***
	(0.097)	(6.507)	(6.547)
Education of top management			
JS/SS	-0.026	-4.722	-4.400
	(0.036)	(3.460)	(3.571)
HS	-0.081*	-9.975**	-8.959*
	(0.048)	(4.552)	(4.603)
Tertiary	-0.165***	-20.758***	-18.692***
	(0.059)	(4.756)	(4.766)
R-squared	0.393	0.483	0.498
N	315	315	315

Note. Shown are the regression results of equation 7: $Network_j = \alpha + \kappa' W_j + \epsilon_j$. *Size* refers to the establishment size defined by the number of employee. The omitted category for size is small (i.e., the number of employees being 20 or less.) The medium and the large establishments have 21–70 and more than 70 employees. *Establishment type* refers to whether an establishment is a single-establishment firm, the headquarters of a multi-establishments firm, or a branch. The omitted category for establishment type is a single-establishment firm. The omitted category for industry is manufacturing. The omitted category for education of top management is no education/primary school. *JS*, *SS*, and *HS* stand for junior secondary, secondary, and higher secondary education, respectively. Significance levels: ***1%, **5%, *10%.

5.2 Job search duration and intensity

Panel 1 in table 7 demonstrates that network-matched employees found their jobs faster and easier than formally-matched employees. In all columns,[38] network-matched employees had shorter search duration than formally-matched ones by 15 to 34 percent. Furthermore, network-matched employees applied to 15 to 36 percent less vacancies, although this result is insignificant conditional on employee's characteristics in columns 2 and 4. Furthermore, table A3 finds that network-matched employees are more likely to have found their jobs in three weeks than formally-matched ones and that network-matched employees are more likely to have found their jobs by applying to only one to two vacancies.[39]

5.3 Employment outcomes: Salary and match quality

We now test the predictions in proposition 5 regarding differences in wages and match quality between network-matched and formally-matched jobs. Panel 2 of table 7 compares the mean entry salaries and finds corroborative evidence for predictions 5-1 and 5-2. The entry salaries of network-matched employees are lower by 31 percent (column 1), 6 percent, but insignificantly, conditional on employee's characteristics (column 2), and 8 percent conditional on employee's characteristics and working at the same occupation in the same establishment (column 4).

The difference in salary growth between network-matched and formally-matched employees is precisely estimated to be zero (panel 2 of table 7). The estimates of the difference are insignificant in all columns 1–4. According to the 95 percent confidence interval of the estimate in column 4, the annual growth in salary of network-matched employees is at most 2.3 ppt higher than that of formally-matched ones. This implies that it takes 3.5 years at shortest for network-matched employees to catch up their colleagues' salaries.

[38]However, the result in column 2 is insignificant.

[39]Employer-side information also suggests that social networks help employers find workers in short duration. According to table A4, employers who use social networks as a main channel of job advertisement fill vacancies 12 percent faster than those who do not, although this result is statistically insignificantly.

Table 7: Differences in employment outcomes between network-matched and formally-matched employees

	(1)	(2)	(3)	(4)
Panel 1. Job search duration and intensity				
Dep.var.: Log of search duration in weeks				
Social network dummy	-0.34***	-0.15	-0.23*	-0.16*
	(0.08)	(0.09)	(0.12)	(0.09)
Formally-matched mean	1.823	1.823	1.823	1.823
R-squared	0.094	0.171	0.029	0.102
N	2527	2463	2527	2463
Dep.var.: Log of no. applications				
Social network dummy	-0.36***	-0.16	-0.23*	-0.15
	(0.10)	(0.11)	(0.12)	(0.11)
Formally-matched mean	0.990	0.990	0.990	0.990
R-squared	0.082	0.163	0.025	0.101
N	2527	2463	2527	2463
Panel 2. Salary				
Dep.var.: Log of entry salary				
Social network dummy	-0.31***	-0.06	-0.15***	-0.08**
	(0.04)	(0.04)	(0.04)	(0.03)
Formally-matched mean	8.711	8.711	8.711	8.711
R-squared	0.124	0.463	0.059	0.240
N	2527	2463	2527	2463
Dep.var.: Annual salary growth rate				
Social network dummy	0.001	-0.001	0.003	0.001
	(0.011)	(0.013)	(0.011)	(0.011)
Formally-matched mean	1.110	1.110	1.110	1.110
R-squared	0.043	0.074	0.015	0.074
N	2418	2358	2418	2358
Employee's characteristics		X		X
Firm–occupation fixed effects			X	X

Note. Shown is the estimated coefficient of the network dummy in equation 8: $y_i = \alpha + \theta Network_i + \eta' X_i + \gamma_{cj} + \epsilon_{icj}$. The dependent variables are listed in the leftmost column. *Employee's characteristics* include dummies for school levels completed; age at hire; z-scores of math, language, conscientiousness, emotional stability, agreeableness, extraversion, openness, and grit; the dummies for parents having completed primary education; and the dummy for having moved before, but not for, his current job. All specifications control for recruitment years and geographical divisions fixed effects. When the dependent variable is the annual salary growth rate, the employees recruited in the same year as the survey year were excluded. *Formally-matched mean* shows the means of dependent variables among formally-matched employees. Standard errors clustered within establishments are in parentheses. Significance levels: ***1%, **5%, *10%.

Table 8 examines match quality. According to panel 1, the past education of network-matched employees less fit their current jobs than that of formally-matched employees do. Past education was less helpful for network-matched employees to get their jobs than for formally-matched ones.[40] Past education was less useful in the current jobs for network-matched employees than formally-matched employees, although this result is insignificant in columns 2 and 4.

Investigation into the primary reasons why employees chose their jobs also demonstrates that match quality is lower among network-matched jobs than formally-matched jobs (panel 2 of table 8). Network-matched employees are approximately 10 ppt less likely to have chosen their jobs for the purpose of career progression than formally-matched employees. Since career progression probably means career progression in one's specialty, this difference is a direct indication of lower match quality among network-matched jobs. To summarize, both panels 1 and 2 in table 8 support predictions 5-1 and 5-2.

[40] This difference between network-matched and formally-matched employees may simply mean that social networks helped job hunting.

Table 8: Differences in match quality between network-matched and formally-matched employees

	(1)	(2)	(3)	(4)
Panel 1. Match between past education and current job				
Dep.var.: How much education helped to get the job				
Social network dummy	-0.45***	-0.11*	-0.21***	-0.13**
	(0.07)	(0.06)	(0.06)	(0.05)
R-squared	0.130	0.353	0.032	0.154
N	2394	2335	2394	2335
Dep.var.: How much skills/knowledge from education are used				
Social network dummy	-0.41***	-0.08	-0.19***	-0.10
	(0.06)	(0.05)	(0.07)	(0.07)
R-squared	0.107	0.283	0.027	0.108
N	2394	2335	2394	2335
Panel 2. Reason for having chosen current job				
Dep.var.: Career progression				
Social network dummy	-0.13***	-0.10***	-0.10***	-0.08**
	(0.03)	(0.04)	(0.04)	(0.04)
Formally-matched mean	0.206	0.206	0.206	0.206
R-squared	0.058	0.092	0.042	0.067
N	2526	2462	2526	2462
Employee's characteristics		X		X
Firm–occupation fixed effects			X	X

Note. Shown is the estimated coefficient of the social network dummy in equation 8: $y_i = \alpha + \theta Network_i + \eta' X_i + \gamma_{cj} + \epsilon_{icj}$. In panel 1, employees with no education are excluded. The dependent variables are listed in the leftmost column. The dependent variables in panel 1, which are originally in the scale of 1 to 10, are normalized to have one standard deviation. The dependent variables in panel 2 are the binary dummies indicating that a main reason for having chosen the job is the one indicated. *Formally-matched mean* shows means of dependent variables among formally-matched employees. *Employee's characteristics* include dummies for school levels completed; age at hire; z-scores of math, language, conscientiousness, emotional stability, agreeableness, extraversion, openness, and grit; the dummies for parents having completed primary education; and the dummy for having moved before, but not for, his current job. All specifications control for recruitment years and geographical divisions fixed effects. *Formally-matched mean* shows the means of dependent variables among the employees who did not use social networks. Standard errors clustered within establishments are in parentheses. Significance levels: ***1%, **5%, *10%.

5.4 Can other theories explain the empirical results?

The other models reviewed in subsection 2.5 may provide alternative interpretations of the empirical results. Their predictions as well as our estimation results are summarized in table 1. As discussed below, the estimation results clearly reject all the other models.

The estimation results disagree with the search friction models where the social networks pass on the same information as, or better information than, formal channels. The models predict higher match quality and entry wages of network-matched employees than formally-matched ones, which is the opposite of our results.

Screening models do not align with the results either. The models predict that network-matched employees have higher unobservable abilities than formally-matched ones particularly conditional on observable abilities (Hensvik and Skans, 2016). We consider that the cognitive and non-cognitive abilities in our data, which were measured by short tests, are hard-to-observe for employers at the time of recruitment as argued by Altonji and Pierret (2001) and Hensvik and Skans (2016). Using a similar regression specification to that of Hensvik and Skans (2016), who test the screening model of Montgomery (1991), we find that differences in cognitive and non-cognitive abilities are mostly insignificant (table A5). Among all the eight abilities, only openness and grit are significant. Openness is higher among network-matched employees by 0.18 standard deviation than among formally-matched ones (column 13). It is, however, unclear if this higher openness supports the prediction of screening models because openness may not necessarily be a personality trait that raises productivity, and the higher openness of network-matched employees may simply result from more open workers having larger social networks and thus using social networks more. On the other hand, the significant result on grit clearly disagrees with the prediction: network-matched employees have 0.23 standard deviation lower grit (column 16), which is considered to increase productivity. Turning to wages, screening models predict that network-matched employees earn more than formally-matched ones conditional on observable abilities. However, the estimations reported in table A6 find the opposite. Network-matched employees earn less by 5.5 percent insignificantly conditional on observable abilities (column 1) and by 7.2 percent significantly conditional on observable abilities and the firm–occupation fixed effects (column 2).[41]

The estimation results also reject the peer effect and moral hazard model of Heath (forthcoming), where the use of social networks provide employers with a way to get around minimum wage regulations. Her model predicts that network-matched employees have higher wage growth than formally-matched ones, but our estimations find the difference in wage growth to be precisely zero. Besides, according to employer's perception about labor-related problems (table A2), the model does not fit our empirical contexts because only 12 percent of employers raise minimum wage regulations as one of the *three* biggest labor-related problems. The more general type of peer effect and moral hazard models also disagree with our results since the models predict higher observable and unobservable abilities, match quality, and entry wages of network-matched employees than formally-matched ones. Favoritism models contradict the estimation results too, because the results show that network-matched employees earn lower entry wages conditional on abilities, which is the opposite of the prediction of the models.

5.5 Potential biases and robustness

A major concern about our estimation results is omitted variable biases as we do not have exogenous variations in the social network dummy. One might think that the social network dummy is correlated with unappealing individual unobservables and hence that network-matched employees have lower salaries.[42] However, as long as these unobservables are about occupation-specific skills and wealth, and the unobservables affect salaries and match quality

[41] The estimation specifications in table A5 are similar to those in table 4 of Hensvik and Skans (2016), who find network-matched employees have lower cognitive abilities than formally-matched ones. The estimation specifications in table A6 is similar to table 7 of Hensvik and Skans (2016), who find higher entry wages of network-matched employees. Following Hensvik and Skans (2016), columns 3 and 4 in table A6 control for years of schooling, instead of dummies of education levels completed, and still find lower entry wages of network-matched employees.

[42] Unobservables of vacancies and employers may not be a concern since we control for firm–occupation fixed effects.

through the mechanism considered in our model, associations between unappealing unobservables and lower salaries are exactly what the model accounts for, and do not threaten our interpretations.[43] For example, a desperate jobless person who recently experienced some negative shocks may tend to take any job his friends pass on regardless of his specialty since he cannot afford to search through formal channels for enough time. Although his negative shocks are omitted in our estimations, they do not invalidate our results.

Unobservable variables of human capital and wealth may be associated with salaries and match quality through the mechanisms implied by the other theories discussed earlier, such as screening models and peer effect models. However, this is unlikely as those theories are all rejected by our estimation results.

Unobservable general skills may be negatively associated with the use of social networks and therefore confound our results. However, this is unlikely for the two reasons. First, the estimation results using direct measures of match quality, i.e., educational fits and career fits, are plausibly robust to unobservable general skills because match quality is all about occupation-specific skills. Second, the estimates of differences in salaries and match quality are actually found insensitive to controls for abilities and wealth. In tables A7–A9, we reestimate the differences in salary and match quality by changing control variables. For all dependent variables, once education is controlled for, the estimates become insensitive to inclusion of cognitive and non-cognitive abilities, parents' education (tables A7–A9). This insensitivity may suggest that potential biases due to unobservable general skills are marginal if any.

Another bias may arise from the endogenous formation of social networks: workers and employers may form social networks through their lives not randomly but for the purpose of finding good production partners. However, this endogeneity does not threaten our results because it would lead the use of social networks to positively correlate with salaries and

[43]Recall that predictions about employment outcomes hold both *unconditionally* and conditionally on employee's occupation-specific skills and search efficiency and vacancy's occupation-specific capital and search efficiency.

match quality.

Lower salaries of network-matched employees may be because network-matched employees had weaker negotiation power against employers than formally-matched employees. Since the model predicts negative selection, in terms of economic status, of workers into matching through social networks, network-matched employees might have lower disagreement payoffs than formally-matched ones. However, this narrative also applies to the employer side. Employers who hired through social networks might have lower negotiation power against workers than employers who hired through formal channels. Thus, this possibility does not well explain the lower salaries of network-matched jobs. Besides, this possibility does not account for the lower match quality of network-matched jobs.

Another interpretation would be that the lower pay and match quality of network-matched jobs reflect compensating wage differentials. Network-matched employees and employers, who met each other through social networks, have lower match quality and productivity but instead enjoy higher non-pecuniary benefits such as the joy of working with close friends. The results in table A10 find suggestive evidence against this possibility. The table shows estimated differences between network-matched and formally-matched employees with respect to the main reasons why they chose their current jobs. These reasons are location, work conditions, salary, having no other offers available, and recommendation from others. Although most of the estimates are insignificant, point estimates suggest that compared to formally-matched employees, network-matched employees are less likely to have chosen the jobs for location and more likely to have chosen them for salary and no other offers. This result suggests that network-matched employees chose their jobs not for non-pecuniary benefits but because of low prospect of finding jobs through formal channels.

There is a data related issue: our data do not include previous employees who had already quit before the survey, and thus our estimates could suffer attrition bias. We run estimations using subsamples of employees who had been recruited recently, in the last year or in the last three years (table A11). Using these newer employee subsamples we find similar results, which suggests that the attrition bias may be marginal.

We examine the robustness of our results to sample restrictions. Using the sample of all male employees, including part-time and seasonal workers who were older than 50 when recruited, we run the estimations and find similar results (table A12). We also find similar results with a female sample (table A13).

6 Conclusions

It has been widely observed that workers and firms with lower socio-economics status are more likely to match through social networks; however, little is understood about why it is so. This paper takes a step toward filling this gap by developing a new model and testing it with novel data from Bangladesh.

The model sheds light on the trait of social networks in that they are less likely to bring good-match partners than formal channels. Analyzing how both workers and firms, who are heterogeneous in occupation-specific productivity and wealth, choose search methods, we derive two predictions. First, negative selection, in terms of occupation-specific productivity and wealth, of workers and firms into network matching occurs. Second, network-matched jobs are poorer matches and pay less than formally-matched jobs. The empirical results corroborate these predictions. Employees with lower education and/or less educated parents are more likely to have matched through social networks. Firms that are smaller and/or have less educated top management are more likely to use social networks as a main channel of job advertisement. Network-matched employees are more likely to be at mismatched occupations and earn lower salaries than formally-matched employees.

This paper demonstrates that search frictions are the market imperfection that underlies the negative selection of workers and firms into matching through social networks. The paper further shows that social networks are also imperfect. Social networks offer an alternative search channel to workers and firms, but this alternative channel tends to lead to mismatches.

This imperfection of social networks highlights the role of formal channels in producing good matches. These findings imply that policies that address search frictions in formal labor markets may improve the social welfare. In particular, given the widespread negative selection, the improvement in social welfare could be substantial. Such policies may include provisions of employment services, job fairs, and online job portals and financial support for job and labor search. Effectiveness of individual policy is a subject of future research.

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A Proof

A.1 Proof of lemma 2

Proof of lemma 2. Define the function $\gamma_1(v,t)$ and $\gamma_2(v,t)$ as:

$$\begin{aligned}\gamma_1(v,t) &= \gamma_2(v,t) - t, \quad \text{and} \\ \gamma_2(v,t) &= \frac{v_f^e(v, s^*(t), a^*(t))}{u_f^e(v, s^*(t), a^*(t))} \\ &= \frac{v\left[1 - q_n(v)\frac{1+F(s^*(t))}{2}\right]\bar{a} + \frac{vq_n(v)}{2}F(s^*(t))\int_{a^*(t)}^{\infty} a\ dG}{\left[1 - p_n(v)\frac{1+G(a^*(t))}{2}\right]\bar{s} + \frac{p_n(v)}{2}G(a^*(t))\int_{s^*(t)}^{\infty} s\ dF},\end{aligned} \tag{9}$$

where $s^*(t)$ and $a^*(t)$ are given by equations 1 and 2. What to show is that there exists $t > 0$ with $\gamma_1(v,t) = 0$. If $\gamma_1(\cdot)$ is continuous, and there exists a closed interval $[a,b]$ with $\gamma_1(a) > 0 > \gamma_1(b)$, such t exists by the intermediate value theorem. The continuity is obvious because $s^*(\cdot)$ and $a^*(\cdot)$ are continuous, and $u_f^e(v, s^*(t), a^*(t)) > 0$ for any t. Since $\lim_{t\to 0} s^*(t) = \lim_{t\to\infty} a^*(t) = \infty$, and $\lim_{t\to\infty} s^*(t) = \lim_{t\to 0} a^*(t) = 0$, it follows that:

$$\begin{aligned}\lim_{t\to 0} u_f^e(v, s^*(t), a^*(t)) &= \lim_{t\to\infty} u_f^e(v, s^*(t), a^*(t)) = \bar{s}(1 - \frac{p_n(v)}{2}), \quad \text{and} \\ \lim_{t\to 0} v_f^e(v, s^*(t), a^*(t)) &= \lim_{t\to\infty} v_f^e(v, s^*(t), a^*(t)) = v\bar{a}(1 - \frac{q_n(v)}{2}).\end{aligned}$$

Hence, $\lim_{t\to 0}\gamma_1(v,t) = v$ and $\lim_{t\to\infty}\gamma_1(v,t) = -\infty$. Since $\gamma_1(v,t)$ is continuous, there exist sufficiently small $w > 0$ and sufficiently large z that satisfy $\gamma_1(w) > 0 > \gamma_1(z)$. □

A.2 Proof of proposition 1

To prove proposition 1, we first prove lemmas 3 and 4 and corollary 1.

Lemma 3. *There exist v_1 and v_2 $(0 < v_1 < v_2)$ such that $\pi_2(v_1, \theta_1^*, a) > 0 > \pi_2(v_2, \theta_2^*, a)$ for all $\theta_1^* \in \Theta_f^*(v_1)$, $\theta_2^* \in \Theta_f^*(v_2)$ and all $a > 0$.*

Proof. We show the existence of v_1. Define $\gamma_3(v)$ and $\pi_2(v, \gamma_3(v), 0)$ as:

$$\gamma_3(v) \equiv \max\{\Theta_f^*(v)\}, \text{ and}$$
$$\pi_2(v, \gamma_3(v), 0) \equiv q_n(v)(1-\beta)\Big[\frac{x + F(s^*(\gamma_3(v)))}{2}\Big] - c.$$

The function $\gamma_3(v)$ is well defined for $v > 0$ since $\Theta_f^*(v)$ is closed and bounded by $2v$. Since $\lim_{v\to 0}\gamma_3(v) = 0$ and $\lim_{t\to 0} s^*(t) = \infty$, we have $\lim_{v\to 0} F(s^*(\gamma_3(v))) = 1$. Since $(1-\beta)(x+1)/2 > c$ by assumption, and $\lim_{v\to 0} q_n(v) = 1$, there exists sufficiently small $v_1 > 0$ satisfying $\pi_2(v_1, \gamma_3(v_1), 0) > 0$. Since $\pi_2(v, \theta, a)$ is decreasing in the second argument, $\pi_2(v_1, \theta_1^*, a) \geq \pi_2(v_1, \gamma_3(v_1), a)$ for all $\theta_1^* \in \Theta_f^*(v_1)$. Now, we have $\pi_2(v_1, \theta_1^*, a) \geq \pi_2(v_1, \gamma_3(v_1), 0) > 0$ for all a since $\pi_2(v_1, \gamma_3(v_1), a) \geq \pi_2(v_1, \gamma_3(v_1), 0)$. The proof of the existence of v_2 is similar, which is to show that the firms with the highest possible efficiency a_M cannot earn positive expected profit if vacancies are too many. □

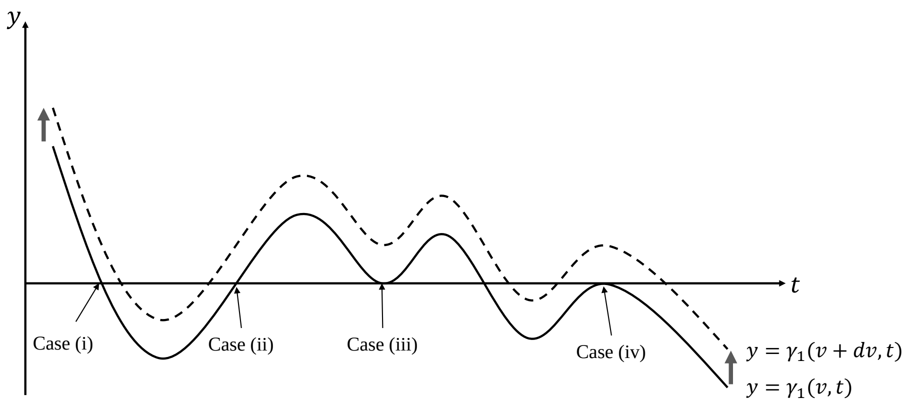
Lemma 4. *There exist v_1 and v_2 ($0 < v_1 < v_2$) that satisfy the following properties: (i) They satisfy the property stated in lemma 3. (ii) There exists a connected set $D \subset \mathbb{R}^2$ such that D is a subset of the graph of $\Theta_f^*(v)$, i.e., $\{(v,t)|t \in \Theta_f^*(v)\}$ and that $(v_1, \theta_{v_1}) \in D$ and $(v_2, \theta_{v_2}) \in D$ with $\theta_{v_1} \in \Theta_f^*(v_1)$ and $\theta_{v_2} \in \Theta_f^*(v_2)$.*

Proof. The labor supply in the formal labor market $u^e(v, s^*, a^*)$ in equation 3 is rewritten as:

$$\begin{aligned} u^e(v, s^*, a^*) &= \Big[1 - p_n(v)\frac{1+G(a^*)}{2}\Big]\bar{s} + \frac{p_n(v)}{2}G(a^*)\int_{s^*}^{s_M} s\ dF \\ &= \frac{p_n(v)}{2}\Big[G(a^*)\int_{s^*}^{s_M} s\ dF - (1+G(a^*))\int_0^{s_M} s\ dF\Big] + \bar{s}, \end{aligned}$$

where $\bar{s} = \int_0^{s^*} s\ dF$. The labor supply $u^e(v, s^*, a^*)$ is strictly decreasing in v for any decision rules s^* and a^* because $p_n(v)$ is strictly increasing and $G(a^*)\int_{s^*}^{s_M} s\ dF - (1+G(a^*))\int_0^{s_M} s\ dF$ is strictly negative. Similarly, the labor demand $v^e(v, s^*, a^*)$ in equation 4 is strictly increasing in v. Hence, $\gamma_1(v, t)$ in equation 9 is strictly increasing in v for all t.

Consider how a solution t^* for $\gamma_1(v, t^*) = 0$ changes with v. Since $\gamma_1(v,t)$ is strictly increasing in v, there are four possible cases regarding how the graph $\{(t, \gamma_1(v,t))$ for a fixed $v\}$ on $\mathbb{R}^2$ intersects with the zero line $\{(x,y)|y=0\}$ at $t = t^*$ (see figure A1 below): (i) the solution increases, i.e., $dt^*/dv > 0$, if the graph crosses the zero line from above; (ii) it decreases with v, i.e., $dt^*/dv < 0$, if the graph crosses from below; (iii) the local solution disappears for $v + dv$ $(dv > 0)$ if the graph is tangent to the zero line from above; (iv) the local solution splits into two, i.e., two solutions emerge, for $v + dv$ if it is tangent from below. In the last case, the two solutions diverge from t^*: one gets smaller than t^*, and the other gets greater.



Note. Shown is the graph of $\gamma_1(v,t)$, i.e., $\{(t, \gamma_1(v,t))$ for a given $v\}$.

Figure A1: Four possible cases as to how solution t for $\gamma_1(v,t) = 0$ changes as v increases

Fix v_1 and v_2 that satisfy the property stated in lemma 3. Since $\gamma_3(v_1) = \max\{\Theta_f^*(v_1)\}$ by definition, the graph $\{(t, \gamma_1(v_1, t))\}$ crosses the zero line from above at $t = \gamma_3(v_1)$. Define function $H^+_{(v_1,\gamma_3(v_1))}(v) : \ [v_1, v_2] \to \mathbb{R}^+$ as:

$$H^+_{(v_1,\gamma_3(v_1))}(v_1) = \gamma_3(v_1), \text{ and}$$
$$\frac{\partial}{\partial v} H^+_{(v_1,\gamma_3(v_1))}(v) = \frac{dt^*}{dv},$$

where dt^* is defined as in the preceding paragraph. Note that $H^+_{(v_1,\gamma_3(v_1))}(v)$ may be the empty value at some $v \in [v_1, v_2]$.

If $H^+_{(v_1,\gamma_3(v_1))}(v)$ does not have the empty value in $[v_1, v_2]$, the graph of $H^+_{(v_1,\gamma_3(v_1))}(v)$

satisfies the conditions for D stated in this lemma since it is continuous in $[v_1, v_2]$. Consider the other case that $H^+_{(v_1,\gamma_3(v_1))}(v)$ has the empty value. The fact that it has the empty value necessarily implies the following (see figures A2 and A3):

1. For some $v_3 \in (v_1, v_2)$, the graph $\{(t, \gamma_1(v_3, t))\}$ touches, or is tangent to, the zero line $\{(x, y)|y = 0\}$ from below at $(t_3, \gamma_1(v_3, t_3)) = (t_3, 0)$. t_3 is greater than $H^+_{(v_1,\gamma_3(v_1))}(v_3)$. In a similar way to $H^+_{(v_1,\gamma_3(v_1))}(v)$, We can define $H^+_{(v_3,t_3)}(v)$ for the dt^* that is positive and increasing with dv and $H^-_{(v_3,t_3)}(v)$ for the dt^* that is negative and decreasing with dv.

2. The graph $\{(t, \gamma_1(v, t))\}$ crosses the zero line from above at point $(H^+_{(v_1,\gamma_3(v_1))}(v), 0)$ and from below at point $(H^-_{(v_3,t_3)}(v), 0)$. Therefore, as v increases and the graph $\{(t, \gamma_1(v, t))\}$ moves upwards, the crossing point $(H^+_{(v_1,\gamma_3(v_1))}(v), 0)$ moves rightwards, i.e., $H^+_{(v_1,\gamma_3(v_1))}(v)$ increases, but the other crossing point $(H^-_{(v_3,t_3)}(v), 0)$ leftwards, i.e., $H^-_{(v_3,t_3)}(v)$ decreases.

3. As v continue rising, the two crossing points eventually join each other for some $v_3' \in (v_3, v_2)$, i.e., $H^+_{(v_1,\gamma_3(v_1))}(v_3') = H^-_{(v_3,t_3)}(v_3')$. Let $t_3' = H^+_{(v_1,\gamma_3(v_1))}(v_3') = H^-_{(v_3,t_3)}(v_3')$.

4. Since the graph $\{(t, \gamma_1(v_3', t))\}$ is tangent to the zero line at $\big(t_3', 0\big)$, for $v_3' + dv$ the graph $\{(t, \gamma_1(v, t))\}$ no longer intersects with the zero line in the neighborhood of $\big(t_3', 0\big)$. That is, $H^+_{(v_1,\gamma_3(v_1))}(v)$ and $H^-_{(v_1,t_3))}(v)$ have the empty value in $(v_3', v_2]$.

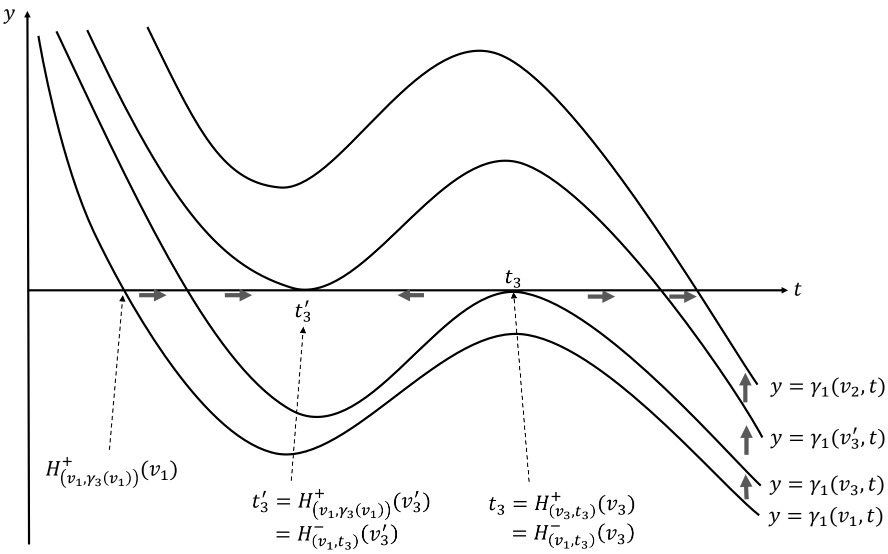


Figure A2: How $H^+_{(v_1,\gamma_3(v_1))}(v)$, $H^-_{(v_3,t_3)}(v)$, and $H^+_{(v_3,t_3)}(v)$ move as v increases from v_1 to v_2

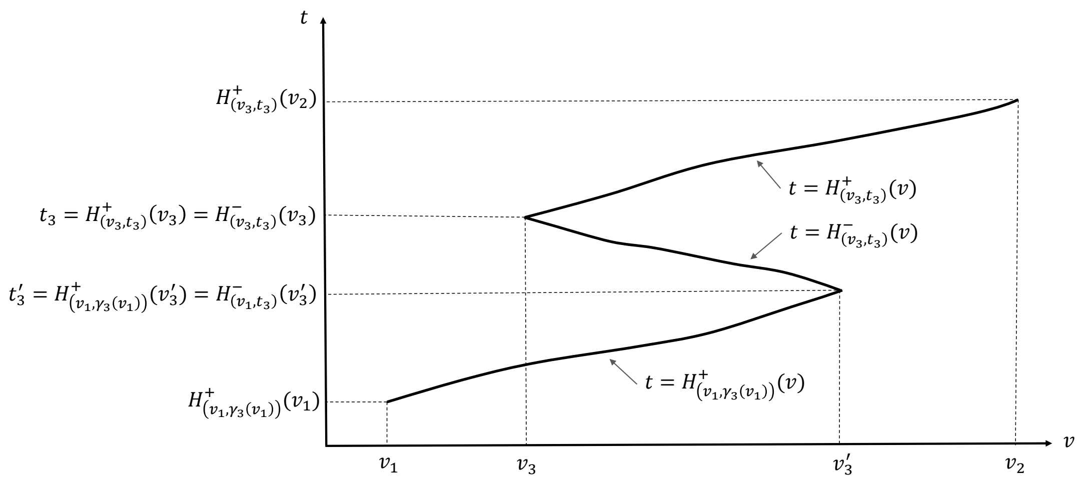


Figure A3: Graphs of $H^+_{(v_1,\gamma_3(v_1))}(v)$, $H^-_{(v_3,t_3)}(v)$, and $H^+_{(v_3,t_3)}(v)$

Importantly, the graph of $H^+_{(v_1,\gamma_3(v_1))}(v)$ connects with the graph of $H^-_{(v_3,t_3)}(v)$ at $\left(v_3', t_3'\right)$. Since the graph of $H^-_{(v_3,t_3))}(v)$ connects with that of $H^+_{(v_3,t_3)}(v)$ at $\left(v_3, t_3\right)$, that of $H^+_{(v_1,\gamma_3(v_1))}(v)$ connects with that of $H^+_{(v_3,t_3)}(v)$. Hence, if $H^+_{(v_3,t_3)}(v)$ does not have the empty value in $[v_3, v_2]$, the union of the graphs of $H^+_{(v_1,\gamma_3(v_1))}(v)$, $H^-_{(v_3,t_3)}(v)$, and $H^+_{(v_3,t_3)}(v)$ satisfies the conditions for the set D stated in this lemma. If $H^+_{(v_3,t_3)}(v)$ has the empty value, then the same process above repeats, and we have $H^-_{(v_i,t_i)}(v)$ and $H^+_{(v_i,t_i)}(v)$ for $i = 4, \ldots$ until we have $j \geq 4$ such that $H^+_{(v_j,t_j)}(v)$ is well defined at v_2. Since $H^+_{(v_i,t_i)}(v)$ is bounded by v, such j exists. Then, the union of the graphs of $H^+_{(v_1,\gamma_3(v_1))}(v)$, $H^-_{(v_i,t_i)}(v)$, $\ldots$, $H^-_{(v_j,t_j)}(v)$, $H^+_{(v_i,t_i)}(v)$, $\ldots$, $H^+_{(v_j,t_j)}(v)$ is the required D. The θ_{v_1} and θ_{v_2} in the statement of lemma are $\theta_{v_1} = H^+_{(v_1,\gamma_3(v_1))}(v_1) = \gamma_3(v_1)$ and $\theta_{v_2} = H^+_{(v_j,t_j)}(v_2)$. □

Define the correspondence $\Pi_2(v,a) : \mathbb{R}^{++} \times \mathbb{R}^+ \to \mathbb{R}$ as:

$$\Pi_2(v,a) = \{y|\ y = \pi_2(v,t,a) \text{ for some } t \in \Theta^*_f(v)\}.$$

Corollary 1. *There exist v_1 and v_2 $(0 < v_1 < v_2)$ that satisfy the following conditions: (i) They have the property stated in lemma 3. (ii) There exists a connected set $D' \subset \mathbb{R}^2$ such that D' is a subset of the graph of $\Pi_2(v,a)$, i.e., $\{(v,y)|y = \pi_2(v_1,t,a)$ with $t \in \Theta^*_f(v)\}$ and that $(v_1, \pi_2(v_1, \theta_{v_1}, a)) \in D'$ and $(v_2, \pi_2(v_2, \theta_{v_2}, a)) \in D'$ for $\theta_{v_1} \in \Theta^*_f(v_1)$ and $\theta_{v_2} \in \Theta^*_f(v_2)$.*

Proof. $\pi_2(v_1,t,a)$ in equation 5 is obviously continuous in t for every a. (Although $\pi_2(v_1,t,a)$ includes the indicator function $\mathbb{1}(a \le a^*(\theta))$, which is discontinuous at $a = a^*(\theta)$, its discontinuity is not carried over to $\pi_2(v_1,t,a)$. Intuitively, the fact that the firms with $a = a^*(\theta)$ are indifferent between forming a bad-match or searching for a good-fit worker in the formal labor market implies that firms' profits are continuous with respect to a at $a = a^*(\theta)$.) $\pi_2(v_1,t,a)$ is bounded. Hence, with lemma 4, it follows that the required subset D' exists. □

Now we prove proposition 1.

Proof of proposition 1. Note that $\pi_2(v,t,a)$ is continuous in v and t and that $|\pi_2(v,t,a)|$ is bounded by $\max\{x_g, c\}$, which is integrable with respect to G. By the bounded convergence theorem, $\pi_1(v_1,t)$ is continuous. Hence, with corollary 1, there exists a connected set $D'' \subset \mathbb{R}^2$ such that D'' is a subset of the graph of $\Pi_1(v)$, i.e., $\{(v,y)|y = \pi_1(v_1,t)$ for $t \in \Theta^*_f(v)\}$, and that $(v_1, \pi_1(v_1,\theta_{v_1})) \in D''$ and $(v_2, \pi_1(v_2, \theta_{v_2})) \in D''$ with $\pi_1(v_1,\theta_{v_1}) > 0$ and $\pi_1(v_2,\theta_{v_2}) < 0$. Since D'' is connected, it intersects with the zero line at some v^{**}, where $\pi_1(v^{**}) = 0$. v^{**} constitutes an equilibrium. □

A.3 Proofs of propositions 2–4

Notations. Let e, e_n, e_f, e_b, and e_g be indicator functions denoting that a worker or a firm has a job; has a network-matched job; has a formally-matched job; has a bad-fit job; and has a good-fit job. Let $e(a)$ be a indicator function denoting that a worker is employed at a firm with a. Similarly, $e(s)$ indicates that a firm employs a worker with s. Let $Pr[\cdot]$ and $pr(\cdot)$ denote a probability measure and a pdf. In the proof, we write p_n and p_f instead of $p_n(v)$ and $p_f(\theta)$ (and likewise for other similar notations), and suppress the asterisks (**) denoting an equilibrium except that we use s^{**} and a^{**} to denote optimal decisions.

Note 1. In this proof, we do not explicitly state that the results hold conditional on job types. This is because they obviously hold given that an equilibrium we consider is symmetric between job types.

Note 2. In this proof, we assume that a firm has at most one vacancy.

Proof of proposition 2. Conditional probability of having a network-matched job: The probability for a worker having a network-matched job conditional on being employed at a firm with a and his search efficiency s is the following:

$$
\begin{aligned}
Pr[e_n = 1|e(a) = 1, s] &= \frac{pr(e_n = 1, e(a) = 1|s)}{pr(e(a) = 1|s)} \\
&= \frac{\frac{p_n}{2} g(a) + \frac{p_n}{2} g(a)\mathbb{1}(a \leq a^{**})\mathbb{1}(s \leq s^{**})}{\frac{p_n}{2} g(a) + \frac{p_n}{2} g(a)\mathbb{1}(a \leq a^{**})\mathbb{1}(s \leq s^{**}) + \left(1 - \frac{p_n}{2} - \frac{p_n}{2}\mathbb{1}(s \leq s^{**})G(a^{**})\right)\frac{p_f(s)q_f(a)g_f(a)}{\int q_f(a)g_f(a)da}} \\
&= \frac{1 + \mathbb{1}(a \leq a^{**})\mathbb{1}(s \leq s^{**})}{1 + \mathbb{1}(a \leq a^{**})\mathbb{1}(s \leq s^{**}) + \left(\frac{2}{p_n} - 1 - \mathbb{1}(s \leq s^{**})G(a^{**})\right)\frac{2p_f(s)q_f(a)}{p_n \int q_f(a)g_f(a)da}\frac{g_f(a)}{g(a)}} \\
&= \frac{1 + \mathbb{1}(a \leq a^{**})\mathbb{1}(s \leq s^{**})}{1 + \mathbb{1}(a \leq a^{**})\mathbb{1}(s \leq s^{**}) + \left(\frac{2}{p_n} - 1 - \mathbb{1}(s \leq s^{**})G(a^{**})\right)\frac{2p_f(s)q_f(a)}{p_n \int q_f(a)g_f(a)da}\frac{Pr[entry|a]}{Pr[entry]}},
\end{aligned}
$$

where $g_f(a)$ is the pdf conditional on firms entering formal labor markets; $Pr[entry]$ is the probability for a firm entering a formal labor market; and $Pr[entry|a]$ is the probability for a firm with a entering a formal labor market. For any a, $Pr[e_n = 1|e(a) = 1, s]$ given above is decreasing with s.

It also follows that the probability for a worker having a network-matched job conditional on s and being employed, $Pr[e_n = 1|e = 1, s]$, is decreasing with s. Since the circumstances are symmetric between workers and firms, we have that the probability for a firm employing a network-matched worker conditional on a and employing a worker, $Pr[e_n = 1|e = 1, a]$, is decreasing with a. These probabilities can be specified as below:

$$Pr[e_n = 1|e = 1, s] = \frac{Pr[e_n = 1|s]}{Pr[e_n = 1|s] + Pr[e_f = 1|s]},$$

where

$$\begin{aligned}
Pr[e_n = 1|s] &= \frac{p_n}{2} + \frac{p_n}{2}G(a^{**})\mathbb{1}(s \leq s^{**}) \\
Pr[e_f = 1|s] &= \Big(1 - p_n + \frac{p_n}{2}\mathbb{1}(s > s^{**}) + \frac{p_n}{2}\mathbb{1}(s \leq s^{**})(1 - G(a^{**}))\Big)p_f(s) \\
&= \Big(1 - \frac{p_n}{2} - \frac{p_n}{2}\mathbb{1}(s \leq s^{**})G(a^{**})\Big)p_f(s),
\end{aligned}$$

and

$$Pr[e_n = 1|e = 1, a] = \frac{Pr[e_n = 1|a]}{Pr[e_n = 1|a] + Pr[e_f = 1|a]},$$

where

$$\begin{aligned}
Pr[e_n = 1|a] &= \frac{q_n}{2} + \frac{q_n}{2}F(s^{**})\mathbb{1}(a \leq a^{**}) \\
Pr[e_f = 1|a] &= 1 - q_n + \frac{q_n}{2}\mathbb{1}(a > a^{**}) + \frac{q_n}{2}\mathbb{1}(a \leq a^{**})(1 - F(s^{**}))q_f(a) \\
&= \Big(1 - \frac{q_n}{2} - \frac{q_n}{2}\mathbb{1}(a \leq a^{**})F(s^{**})\Big)q_f(a).
\end{aligned}$$

Conditional probability $Pr[e_n = 1|s]$ decreases in s while $Pr[e_f = 1|s]$ increases. Hence, $Pr[e_n = 1|e = 1, s]$ decreases with s.

$$
\begin{aligned}
Pr[e_n = 1] &= \int Pr[e_n = 1|s]dF \\
&= \int \frac{p_n}{2} + \frac{p_n}{2} G(a^{**}) \mathbb{1}(s \leq s^{**}) dF \\
&= \frac{p_n}{2} + \frac{p_n}{2} G(a^{**}) F(s^{**}) \\
Pr[e_f = 1] &= \int Pr[e_f = 1|s]dF \\
&= \int \Big(1 - \frac{p_n}{2} - \frac{p_n}{2} \mathbb{1}(s \leq s^{**}) G(a^{**})\Big) p_f(s) dF
\end{aligned}
$$

□

Proof of proposition 3. Since the means of outputs and wages are proportional to the proportion of good matches, it suffices to show the result on match quality. Since the proportion of bad matches among formally-matched jobs is always zero, the conditional proportions of bad matches among network-matched jobs, given below, complete the proof.

$$
\begin{aligned}
Pr[e_b = 1|e_n = 1, s, a] &= \frac{\frac{p_N}{2} g(a)\mathbb{1}(s \le s^{**})\mathbb{1}(a \le a^{**})}{\frac{p_N}{2} g(a) + \frac{p_N}{2} g(a)\mathbb{1}(s \le s^{**})\mathbb{1}(a \le a^{**})} \\
&= \frac{\mathbb{1}(s \le s^{**})\mathbb{1}(a \le a^{**})}{1 + \mathbb{1}(s \le s^{**})\mathbb{1}(a \le a^{**})} \\
&= \begin{cases} \frac{1}{2} & \text{if } s \le s^{**} \text{ and } a \le a^{**} \\ \\ 0 & \text{if otherwise.} \end{cases} \\
Pr[e_b = 1|e_n = 1, s] &= \frac{Pr[e_b = 1, e_n = 1|s]}{Pr[e_n = 1|s]} = \frac{\frac{p_n}{2} G(a^{**})\mathbb{1}(s \le s^{**})}{\frac{p_n}{2} + \frac{p_n}{2} G(a^{**})\mathbb{1}(s \le s^{**})} \\
&= \frac{G(a^{**})\mathbb{1}(s \le s^{**})}{1 + G(a^{**})\mathbb{1}(s \le s^{**})} \\
&= \begin{cases} \frac{G(a^{**})}{1+G(a^{**})} & \text{if } s \le s^{**} \\ \\ 0 & \text{if otherwise.} \end{cases} \\
Pr[e_b = 1|e_n = 1] &= \frac{Pr[e_b = 1, e_n = 1]}{Pr[e_n = 1]} = \frac{\frac{p_n}{2} G(a^{**})F(s^{**})}{\frac{p_n}{2} + \frac{p_n}{2} G(a^{**})F(s^{**})} \\
&= \frac{G(a^{**})F(s^{**})}{1 + G(a^{**})F(s^{**})} \\
Pr[e_b = 1|e_f = 1] &= Pr[e_b = 1|e_f = 1, s] = Pr[e_b = 1|e_f = 1, s, a] = 0
\end{aligned}
$$

□

Proof of proposition 4. Conditional probability of having a network-matched job: The probability of a worker and firm having a network-matched job conditional on vacancy's search efficiency a and capital k and worker's search efficiency s and human capital h is given below:

$$
\begin{aligned}
&Pr[e_n = 1|e(a,k) = 1, s, h] = \frac{pr(e_n = 1, e(a,k) = 1|s,h)}{pr(e(a,k) = 1|s,h)} \\
&= \frac{\frac{p_n}{2} g(a,k) + \frac{p_n}{2} g(a,k)\mathbb{1}(a \le a_k^{**})\mathbb{1}(s \le s_h^{**})}{\frac{p_n}{2} g(a,k) + \frac{p_n}{2} g(a,k)\mathbb{1}(a \le a_k^{**})\mathbb{1}(s \le s_h^{**}) + \left(1 - \frac{p_n}{2} - \frac{p_n}{2}\mathbb{1}(s \le s_h^{**})G(a_k^{**})\right)\frac{p_f(s)q_f(a)g_f(a,k)}{\int q_f(a)(g_f(a,k)+g_f(a,k'))da}} \\
&= \frac{1 + \mathbb{1}(a \le a_k^{**})\mathbb{1}(s \le s_h^{**})}{1 + \mathbb{1}(a \le a_k^{**})\mathbb{1}(s \le s_h^{**}) + \left(\frac{2}{p_n} - 1 - \mathbb{1}(s \le s_h^{**})G(a_k^{**})\right)\frac{2p_f(s)q_f(a,k)}{p_n \int q_f(a)g_f(a,k)da}\frac{Pr[entry|a,k]}{Pr[entry]}},
\end{aligned}
$$

where $g(a,k)$ is the pdf of all vacancies that are opened; $g_f(a,k)$ is the pdf conditional on vacancies entering formal labor markets. Conditional probability $Pr[e_n = 1|e(a,k) = 1, s, h]$ increases with h and s. So does the probability $Pr[e_n = 1|s, h]$.

□

Proof of proposition 5. The conditional proportions of bad matches: The proportion of bad matches conditional on being employed through social networks, given below, is weakly greater than the conditional proportions on being employed through formal labor markets, which is always zero.

$$\begin{aligned}
Pr[e_b = 1|e_n = 1] &= \frac{Pr[e_b = 1, e_n = 1]}{Pr[e_n = 1]} = \frac{\frac{p_n}{2}G(\tilde{a}^{**})F(\tilde{s}^{**})}{\frac{p_n}{2} + \frac{p_n}{2}G(\tilde{a}^{**})F(\tilde{s}^{**})} \\
&= \frac{G(\tilde{a}^{**})F(\tilde{s}^{**})}{1 + G(\tilde{a}^{**})F(\tilde{s}^{**})},
\end{aligned}$$

where $\tilde{s}^{**}$ and $\tilde{a}^{**}$ are such that:

$$\begin{aligned}
G(\tilde{s}^{**}) &= \frac{G(s^{**}_{h_0}) + G(s^{**}_{h_1})}{2}, \quad \text{and} \\
G(\tilde{a}^{**}) &= \frac{v_{k_0}G(a^{**}_{k_0}) + v_{k_1}G(a^{**}_{k_1})}{v_{k_0} + v_{k_1}}.
\end{aligned}$$

$$\begin{aligned}
Pr[e_b = 1|e_n = 1, s, h] &= \frac{Pr[e_b = 1, e_n = 1|s, h]}{Pr[e_n = 1|s, h]} = \frac{\frac{p_n}{2}G(\tilde{a}^{**})\mathbb{1}(s \le s^{**}_h)}{\frac{p_n}{2} + \frac{p_n}{2}G(\tilde{a}^{**})\mathbb{1}(s \le s^{**})} \\
&= \frac{G(\tilde{a}^{**})\mathbb{1}(s \le s^{**}_h)}{1 + G(\tilde{a}^{**})\mathbb{1}(s \le s^{**}_h)} \\
&= \begin{cases} \frac{G(\tilde{a}^{**})}{1+G(\tilde{a}^{**})} & \text{if } s \le s^{**}_h \\ 0 & \text{if otherwise,} \end{cases}
\end{aligned}$$

where

$$G(\tilde{a}^{**}) = \frac{v_{k_0}G(a^{**}_{k_0}) + v_{k_1}G(a^{**}_{k_1})}{v_{k_0} + v_{k_1}}.$$

$$
\begin{aligned}
Pr[e_b = 1 | e_n = 1, s, h, a, k] &= \frac{\frac{p_N}{2} f(s,h) g(a,k) \mathbb{1}(s \leq s_h^{**}) \mathbb{1}(a \leq a_k^{**})}{\frac{p_N}{2} f(s,h) g(a,k) + \frac{p_N}{2} f(s,h) g(a,k) \mathbb{1}(s \leq s_h^{**}) \mathbb{1}(a \leq a_k^{**})} \\
&= \frac{\mathbb{1}(s \leq s_h^{**}) \mathbb{1}(a \leq a_k^{**})}{1 + \mathbb{1}(s \leq s_h^{**}) \mathbb{1}(a \leq a_k^{**})} \\
&= \begin{cases} \frac{1}{2} & \text{if } s \leq s_h^{**} \text{ and } a \leq a_k^{**} \\ 0 & \text{if otherwise.} \end{cases}
\end{aligned}
$$

$\square$

B Additional figures and tables

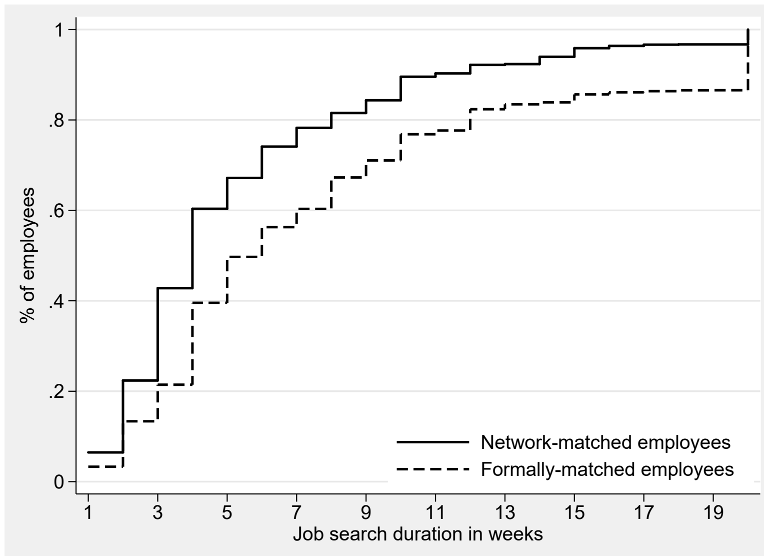


Figure A4: Duration in weeks to have found current jobs

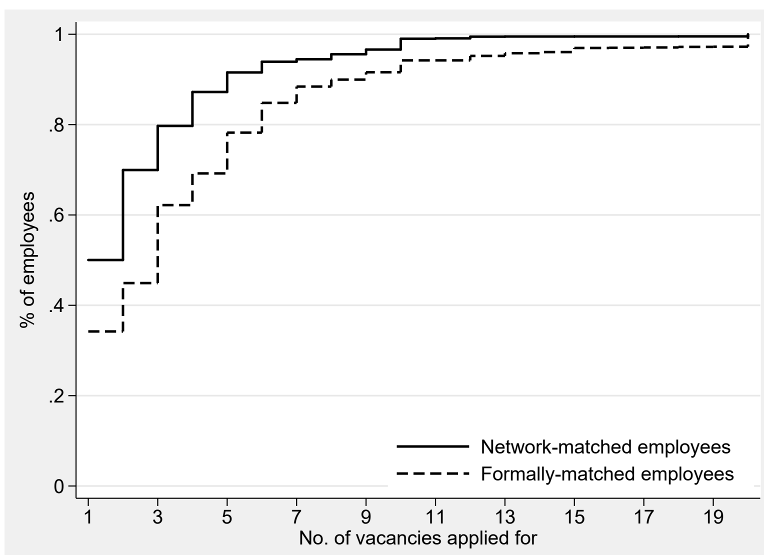


Figure A5: No. of applications submitted until current jobs were found

Table A1: Problematic business environments

	All	Social networks are a main job advertisement channel	
		Yes	No
Lack of skilled workers	0.56	0.59	0.47
Financial access and cost	0.26	0.29	0.18
Electricity	0.75	0.74	0.77
Telecommunication/transportation	0.19	0.16	0.28
Land availability	0.19	0.19	0.19
Tax	0.10	0.05	0.20
Business licensing/permits	0.07	0.05	0.13
Regulations on customs/trade	0.18	0.20	0.15
Political uncertainty/ economic instability	0.44	0.44	0.43
Corruption	0.16	0.18	0.10
Observations	315	227	88

Note. Shown is the proportion of the employers who answered that a problem listed was one of the three biggest problems for their business operation and growth. The survey asked employers the question, "Can you please indicate top three most problematic business environment factors in operations and growth of your business?" Employers were allowed to choose up to three problems from the choices listed. For example, 55 percent of employers chose *lack of skills* as one of the three biggest problems.

Table A2: Labor-related problems

	All	Social networks are a main job advertisement channel	
		Yes	No
Lack of labor in general	0.37	0.42	0.26
Lack of workers with general skills and education	0.65	0.67	0.59
Lack of workers with technical skills and education	0.47	0.44	0.52
Lack of workers with job experiences	0.50	0.48	0.55
High turnover	0.30	0.31	0.26
High remuneration costs	0.26	0.25	0.28
Minimum wage regulation	0.13	0.15	0.09
Employment protection legislation	0.30	0.25	0.43
Observations	315	227	88

Note. Shown is the proportion of the employers who answered that a problem listed was one of the three biggest labor-related problems for their business operation and growth. The survey asked employers the question, "Can you please indicate top three most problematic labor factors in operations and growth of your business?" Employers were allowed to choose up to three problems from the choices listed. For example, 37 percent of employers chose *lack of labor in general* as one of the top three problems.

Table A3: Did network-matched employees find jobs very quickly and easily?

	(1)	(2)	(3)	(4)
Dep.var.: Duration = 1 week (dummy)	0.02	-0.00	0.01	0.01
	(0.02)	(0.03)	(0.03)	(0.03)
Formally-matched mean	0.033	0.033	0.033	0.033
R-squared	0.032	0.054	0.015	0.055
N	2527	2463	2527	2463
Dep.var.: Duration $\leq$ 2 week (dummy)	0.07*	0.01	0.03	0.03
	(0.04)	(0.05)	(0.05)	(0.05)
Formally-matched mean	0.134	0.134	0.134	0.134
R-squared	0.048	0.081	0.005	0.046
N	2527	2463	2527	2463
Dep.var.: Duration $\leq$ 3 week (dummy)	0.20***	0.14**	0.17**	0.16**
	(0.06)	(0.07)	(0.07)	(0.06)
Formally-matched mean	0.214	0.214	0.214	0.214
R-squared	0.059	0.104	0.040	0.106
N	2527	2463	2527	2463
Dep.var.: No. application = 1 (dummy)	0.14**	0.07	0.11	0.09
	(0.06)	(0.07)	(0.07)	(0.06)
Formally-matched mean	0.342	0.342	0.342	0.342
R-squared	0.051	0.104	0.025	0.074
N	2527	2463	2527	2463
Dep.var.: No. application $\leq$ 2 (dummy)	0.23***	0.12*	0.18***	0.12*
	(0.06)	(0.06)	(0.07)	(0.06)
Formally-matched mean	0.449	0.449	0.449	0.449
R-squared	0.092	0.173	0.040	0.104
N	2527	2463	2527	2463
Employee's characteristics		X		X
Firm–occupation fixed effects			X	X

Note. The estimates of the coefficient of the social network dummy are shown. The same note of table 7 applies. Significance levels: ***1%, **5%, *10%.

Table A4: Employer's search duration

	Dependent variable
	Log of weeks to fill vacancies
	(1)
Networks being a main mode of job-ads	-0.127
	(0.080)
Size	
Medium	-0.027
	(0.072)
Large	0.036
	(0.097)
Establishment type	
Headquarters	0.310**
	(0.129)
Branch	0.278***
	(0.099)
Industry	
Commerce	-0.113
	(0.080)
Finance	0.331***
	(0.123)
Education of top management	
JS/SS	-0.111
	(0.106)
HS	-0.111
	(0.102)
Tertiary	-0.115
	(0.115)
R-squared	0.358
N	313

Note. Shown is the regression result by equation: $SearchDuration_j = \alpha + \kappa W_j + \epsilon_j$. *Size* refers to the establishment size defined by number of employees. The dependent variable is based on employer's answers to the question, "How many weeks does it usually take to fill your vacancy?" The omitted category for size is small (i.e., 20 or less employees). The medium and the large establishments have 21–70 and more than 70 employees. *Establishment type* refers to whether an establishment is a single-establishment firm, the headquarters of a multi-establishments firm, or a branch. The omitted category for establishment type is a single-establishment firm. The omitted category for industry is manufacturing. The omitted category for education of top management is no education/primary school. *JS*, *SS*, and *HS* stand for junior secondary, secondary, and higher secondary education, respectively. Geographical divisions fixed effects are controlled for. Significance levels: ***1%, **5%, *10%.

Table A5: Robustness check: Differences in hard-to-observe abilities between network-matched and formally-matched employees

	Years of schooling		Age at hire		Math z-score	
	(1)	(2)	(3)	(4)	(5)	(6)
Social networks	-2.605***	-1.098***	-1.370**	-0.699	-0.200**	-0.009
	(0.328)	(0.340)	(0.660)	(1.073)	(0.085)	(0.079)
Firm–occ fixed effects		X		X		X
R-squared	0.296	0.086	0.036	0.011	0.159	0.019
N	2527	2527	2527	2527	2527	2527
	Language z-score		Conscientiousness		Emotional stability	
	(7)	(8)	(9)	(10)	(11)	(12)
Social networks	-0.197**	-0.080	0.127	0.002	0.003	-0.064
	(0.098)	(0.111)	(0.133)	(0.093)	(0.090)	(0.079)
Firm–occ fixed effects		X		X		X
R-squared	0.229	0.065	0.155	0.021	0.112	0.014
N	2527	2527	2520	2520	2494	2494
	Agreeableness		Extraversion		Openness	
	(13)	(14)	(15)	(16)	(17)	(18)
Social networks	0.040	-0.040	0.024	-0.080	0.074	0.114
	(0.072)	(0.076)	(0.103)	(0.130)	(0.066)	(0.070)
Firm–occ fixed effects		X		X		X
R-squared	0.055	0.014	0.048	0.026	0.081	0.023
N	2489	2489	2514	2514	2519	2519
	Grit					
	(19)	(20)				
Social networks	-0.038	-0.218***				
	(0.078)	(0.067)				
Firm–occ fixed effects		X				
R-squared	0.140	0.020				
N	2499	2499				

Note. Shown are differences in hard-to-observe abilities between network-matched and formally-matched employees conditional on observable characteristics. The regression equation is $x_i = \alpha + \delta Network_i + \beta' X_i + \gamma_{cj} + \epsilon_{icj}$, where X_i are dummies for school levels completed; age at hire; the dummies for parents having completed primary education; the dummy for having moved before, but not for, the current job; recruitment year dummies; and geographical division dummies. The column titles indicate dependent variables. All dependent variables are normalized to be z-scores. *Firm-occ fixed effects* are fixed effects of interactions between establishments and entry occupations. Standard errors clustered within establishments are in parentheses. Significance levels: ***1%, **5%, *10%.

Table A6: Robustness check: Difference in entry salary conditional only on observable characteristics

	Dep.var.: Log of entry salary			
	(1)	(2)	(3)	(4)
Social network dummy	-0.055	-0.072**	-0.096**	-0.083***
	(0.037)	(0.031)	(0.040)	(0.031)
Level of education completed				
Primary	0.044	0.053		
	(0.036)	(0.046)		
JS/SS	0.119**	0.151***		
	(0.046)	(0.057)		
HS	0.384***	0.286***		
	(0.072)	(0.095)		
Tertiary	0.800***	0.616***		
	(0.088)	(0.103)		
Age at hire	0.017***	0.011***	0.021***	0.012***
	(0.003)	(0.003)	(0.003)	(0.002)
Father's primary education dummy	0.025	0.039	-0.015	0.028
	(0.038)	(0.024)	(0.044)	(0.024)
Mother's primary education dummy	0.010	0.002	0.020	-0.004
	(0.031)	(0.036)	(0.032)	(0.035)
Moved before current job (dummy)	-0.083	-0.076*	-0.107**	-0.083**
	(0.051)	(0.039)	(0.054)	(0.035)
Firm–occupation fixed effects		X		X
R-squared	0.443	0.202	0.409	0.202
N	2527	2527	2527	2527

Note. Shown are results of regressions of log of entry salary on observable characteristics. The omitted category for the level of education completed is no education or primary education dropout. All specifications control for recruitment years and geographical divisions fixed effects. *Firm–occupation fixed effects* are fixed effects of interactions between firm dummies and entry occupation dummies. Standard errors clustered within establishments are in parentheses. Significance levels: ***1%, **5%, *10%.

Table A7: Robustness to unobservable human capital: Difference in entry salaries

	Dep.var.: Log of entry salary						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Social network dummy	-0.307***	-0.266***	-0.050	-0.051	-0.052	-0.049	-0.057
	(0.043)	(0.038)	(0.037)	(0.037)	(0.039)	(0.039)	(0.038)
Entry age		X	X	X	X	X	X
Education			X	X	X	X	X
Cognitive skills				X	X	X	X
Non-cognitive skills					X	X	X
Parents' education						X	X
Migration							X
Firm–occ fixed effects							
R-squared	0.124	0.222	0.438	0.450	0.458	0.458	0.463
N	2527	2527	2527	2527	2463	2463	2463
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Social network dummy	-0.146***	-0.136***	-0.074**	-0.079**	-0.080**	-0.078**	-0.078**
	(0.036)	(0.037)	(0.031)	(0.033)	(0.034)	(0.035)	(0.034)
Entry age		X	X	X	X	X	X
Education			X	X	X	X	X
Cognitive skills				X	X	X	X
Non-cognitive skills					X	X	X
Parents' education						X	X
Migration							X
Firm–occ fixed effects	X	X	X	X	X	X	X
R-squared	0.059	0.101	0.193	0.211	0.233	0.234	0.240
N	2527	2527	2527	2527	2463	2463	2463

Note. Shown are results of regressions of log of entry salary. *Entry age* indicates that entry age is included. *Education* indicates that dummies for education levels completed and the entry age variable are included. *Parents' education* indicates that dummies for parents' primary education are included. *cognitive abilities* indicates that the z-scores of math and language skills are included. *Non-cognitive abilities* indicates that the z-scores of non-cognitive abilities are included. *Migration* indicates that the dummy for having moved before, but not for, the current job is included. *Firm–occupation fixed effects* indicates that fixed effects of interactions between firm dummies and entry occupation dummies are included. Standard errors clustered within establishments are in parentheses. All specifications control for recruitment years and geographical divisions fixed effects. Significance levels: ***1%, **5%, *10%.

Table A8: Robustness to omitted variable biases: Difference in match quality measured by the use of skills and knowledge from education

	Dep.var.: Degree to which skills/knowledge from education are currently used						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Social network dummy	-0.413***	-0.375***	-0.109	-0.111*	-0.117*	-0.083	-0.076
	(0.056)	(0.060)	(0.067)	(0.064)	(0.060)	(0.054)	(0.052)
Entry age		X	X	X	X	X	X
Education			X	X	X	X	X
Cognitive skills				X	X	X	X
Non-cognitive skills					X	X	X
Parents' education						X	X
Migration							X
Firm–occ fixed effects							
R-squared	0.107	0.125	0.238	0.257	0.269	0.282	0.283
N	2394	2394	2394	2394	2335	2335	2335
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Social network dummy	-0.190***	-0.186***	-0.101	-0.107	-0.113	-0.101	-0.101
	(0.071)	(0.068)	(0.081)	(0.075)	(0.072)	(0.070)	(0.070)
Entry age		X	X	X	X	X	X
Education			X	X	X	X	X
Cognitive skills				X	X	X	X
Non-cognitive skills					X	X	X
Parents' education						X	X
Migration							X
Firm–occ fixed effects	X	X	X	X	X	X	X
R-squared	0.027	0.029	0.071	0.090	0.103	0.108	0.108
N	2394	2394	2394	2394	2335	2335	2335

Note. Shown are results of regressions of the degree to which an employee currently uses skills and knowledges from his education. *Entry age* indicates that entry age is included. *Education* indicates that dummies for education levels completed and the entry age variable are included. *Parents' education* indicates that dummies for parents' primary education are included. *cognitive abilities* indicates that the z-scores of math and language skills are included. *Non-cognitive abilities* indicates that the z-scores of non-cognitive abilities are included. *Migration* indicates that the dummy for having moved before, but not for, the current job is included. *Firm–occupation fixed effects* indicates that fixed effects of interactions between firm dummies and entry occupation dummies are included. Standard errors clustered within establishments are in parentheses. All specifications control for recruitment years and geographical divisions fixed effects. Significance levels: ***1%, **5%, *10%.

Table A9: Robustness to omitted variable biases: Difference in match quality measured by career progression

	Dep.var.: Reason for having chosen a current job = Career progression						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Social network dummy	-0.127***	-0.128***	-0.104***	-0.104***	-0.106***	-0.102***	-0.100***
	(0.033)	(0.035)	(0.040)	(0.039)	(0.039)	(0.038)	(0.038)
Entry age		X	X	X	X	X	X
Education			X	X	X	X	X
Cognitive skills				X	X	X	X
Non-cognitive skills					X	X	X
Parents' education						X	X
Migration							X
Firm–occ fixed effects							
R-squared	0.058	0.058	0.074	0.077	0.090	0.091	0.092
N	2526	2526	2526	2526	2462	2462	2462
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Social network dummy	-0.098***	-0.099**	-0.094**	-0.093**	-0.084**	-0.078**	-0.078**
	(0.037)	(0.039)	(0.041)	(0.040)	(0.039)	(0.039)	(0.038)
Entry age		X	X	X	X	X	X
Education			X	X	X	X	X
Cognitive skills				X	X	X	X
Non-cognitive skills					X	X	X
Parents' education						X	X
Migration							X
Firm–occ fixed effects	X	X	X	X	X	X	X
R-squared	0.042	0.043	0.049	0.052	0.054	0.059	0.067
N	2526	2526	2526	2526	2462	2462	2462

Note. Shown are results of regressions of the dummy for having chosen a current job for career progression. *Entry age* indicates that entry age is included. *Education* indicates that dummies for education levels completed and the entry age variable are included. *Parents' education* indicates that dummies for parents' primary education are included. *cognitive abilities* indicates that the z-scores of math and language skills are included. *Non-cognitive abilities* indicates that the z-scores of non-cognitive abilities are included. *Migration* indicates that the dummy for having moved before, but not for, the current job is included. *Firm–occupation fixed effects* indicates that fixed effects of interactions between firm dummies and entry occupation dummies are included. Standard errors clustered within establishments are in parentheses. All specifications control for recruitment years and geographical divisions fixed effects. Significance levels: ***1%, **5%, *10%.

Table A10: Main reason for having chosen a current job

	(1)	(2)	(3)	(4)
Dep.var.: Reason = Location				
Social network dummy	-0.00	-0.01	-0.02	-0.03
	(0.05)	(0.04)	(0.08)	(0.05)
Formally-matched mean	0.122	0.122	0.122	0.122
R-squared	0.014	0.047	0.006	0.059
N	2526	2462	2526	2462
Dep.var.: Reason = Work conditions				
Social network dummy	-0.02	-0.01	-0.01	0.01
	(0.04)	(0.05)	(0.08)	(0.06)
Formally-matched mean	0.304	0.304	0.304	0.304
R-squared	0.014	0.065	0.005	0.053
N	2526	2462	2526	2462
Dep.var.: Reason = Salary				
Social network dummy	0.04*	0.06**	0.03	0.03
	(0.03)	(0.03)	(0.04)	(0.03)
Formally-matched mean	0.207	0.207	0.207	0.207
R-squared	0.051	0.095	0.028	0.067
N	2526	2462	2526	2462
Dep.var.: Reason = No other offers				
Social network dummy	0.07***	0.03	0.03	0.01
	(0.02)	(0.02)	(0.03)	(0.03)
Formally-matched mean	0.087	0.087	0.087	0.087
R-squared	0.026	0.056	0.015	0.042
N	2526	2462	2526	2462
Dep.var.: Reason = Recommendation from others				
Social network dummy	0.07***	0.06***	0.08***	0.09***
	(0.02)	(0.02)	(0.03)	(0.03)
Formally-matched mean	0.009	0.009	0.009	0.009
R-squared	0.038	0.071	0.031	0.056
N	2526	2462	2526	2462
Employee's characteristics		X		X
Firm–occupation fixed effects			X	X

Note. Shown is the estimated coefficient of the social network dummy in the regression by equation 8: $y_i = \alpha + \theta Network_i + \eta' X_i + \gamma_{cj} + \epsilon_{icj}$. The dependent variables are binary dummies indicating main reasons for having chosen current jobs. *Formally-matched mean* shows means of dependent variables among formally-matched employees. *Employee's characteristics* include dummies for school levels completed; age at hire; z-scores of cognitive and non-cognitive abilities; the dummies for parents' primary education; and the dummy for having moved before, but not for, the current job. All specifications control for recruitment years and geographical divisions fixed effects. *Formally-matched mean* shows the means of dependent variables among the employees who did not use social networks. Standard errors clustered within establishments are in parentheses. Significance levels: ***1%, **5%, *10%.

Table A11: Robustness checks on attrition bias

	(1)	(2)	(3)	(4)
Panel 1. Sample = Employees who were recruited in last 1 year				
Dep.var.: Log of entry salary	-0.40***	-0.13*	-0.07	-0.03
	(0.10)	(0.08)	(0.05)	(0.05)
R-squared	0.209	0.445	0.011	0.371
N	437	427	437	427
Dep.var.: How much skills/knowledge from education are used	-0.58***	-0.04	-0.14	-0.09
	(0.19)	(0.15)	(0.20)	(0.20)
R-squared	0.082	0.363	0.014	0.217
N	403	394	403	394
Dep.var.: Career progression	-0.23***	-0.17**	-0.04	-0.03
	(0.08)	(0.08)	(0.09)	(0.10)
R-squared	0.113	0.165	0.012	0.118
N	437	427	437	427
Panel 2. Sample = Employees who were recruited in last 3 years				
Dep.var.: Log of entry salary	-0.34***	-0.07**	-0.14***	-0.06*
	(0.05)	(0.04)	(0.05)	(0.04)
R-squared	0.150	0.508	0.049	0.297
N	1718	1681	1718	1681
Dep.var.: How much skills/knowledge from education are used	-0.50***	-0.08	-0.14**	0.01
	(0.07)	(0.07)	(0.06)	(0.07)
R-squared	0.114	0.324	0.008	0.154
N	1629	1593	1629	1593
Dep.var.: Career progression	-0.10***	-0.08**	-0.09*	-0.06
	(0.03)	(0.04)	(0.05)	(0.05)
R-squared	0.047	0.076	0.038	0.072
N	1717	1680	1717	1680
Employee's characteristics		X		X
Firm–occupation fixed effects			X	X

Note. The estimates of the coefficient of the social network dummy are shown. Panel 1 uses the sample of employees who were recruited in the last one year while panel 2 uses those who were recruited in the last three years. For other details, refer to the notes of tables 7 and 8. Significance levels: ***1%, **5%, *10%.

Table A12: Robustness checks on sample restrictions: All male employees

	(1)	(2)	(3)	(4)
	Sample: All types of male employees			
Dep.var.: Log of entry salary				
Social network dummy	-0.28***	-0.05	-0.13***	-0.08***
	(0.05)	(0.04)	(0.03)	(0.03)
Formally-matched mean	8.609	8.609	8.609	8.609
R-squared	0.185	0.417	0.204	0.355
N	4102	3979	4102	3979
Dep.var.: How much skills/knowledge from education are used				
Social network dummy	-0.46***	-0.06	-0.14**	-0.05
	(0.06)	(0.05)	(0.06)	(0.04)
Formally-matched mean	2.585	2.585	2.585	2.585
R-squared	0.134	0.308	0.085	0.177
N	3796	3681	3796	3681
Dep.var.: Career progression is the reason for having chosen current job				
Social network dummy	-0.14***	-0.11**	-0.10**	-0.09**
	(0.04)	(0.04)	(0.05)	(0.04)
Formally-matched mean	0.217	0.217	0.217	0.217
R-squared	0.076	0.113	0.065	0.082
N	4100	3977	4100	3977
Employee's characteristics		X		X
Firm–occupation fixed effects			X	X

Note. The sample is all male employees, including part-time and seasonal employees who were recruited more than five years prior to the survey at age above 50 years, in the manufacturing, commerce, and finance establishments that were not owned by governments. For other details, refer to the notes of tables 7 and 8. Significance levels: ***1%, **5%, *10%.

Table A13: Robustness checks on sample restrictions: Female employees

	(1)	(2)	(3)	(4)
Sample: Female employees				
Dep.var.: Log of entry salary				
Social network dummy	-0.23**	-0.06	-0.06	-0.01
	(0.10)	(0.05)	(0.06)	(0.05)
Formally-matched mean	8.525	8.525	8.525	8.525
R-squared	0.268	0.685	0.216	0.435
N	340	334	340	334
Dep.var.: How much skills/knowledge from education are used				
Social network dummy	-0.53***	-0.17**	-0.43**	-0.23***
	(0.13)	(0.09)	(0.17)	(0.08)
Formally-matched mean	2.724	2.724	2.724	2.724
R-squared	0.145	0.464	0.160	0.409
N	311	306	311	306
Dep.var.: Career progression is the reason for having chosen current job				
Social network dummy	-0.16*	-0.18**	-0.21	-0.20**
	(0.09)	(0.07)	(0.13)	(0.08)
Formally-matched mean	0.151	0.151	0.151	0.151
R-squared	0.128	0.300	0.168	0.418
N	340	334	340	334
Employee's characteristics		X		X
Firm–occupation fixed effects			X	X

Note. The sample is full-time female employees who were recruited in the five years before the survey and whose age at recruitment was equal to or less than 50 years old. For other details, refer to the notes of tables 7 and 8. Significance levels: ***1%, **5%, *10%.

Table A14: Difference in job search duration

	Dep.var.: Log of search duration in weeks			
	(1)	(2)	(3)	(4)
Social network dummy	-0.343***	-0.148	-0.225*	-0.161*
	(0.082)	(0.094)	(0.121)	(0.088)
Level of education completed				
Primary		0.211**		0.163
		(0.082)		(0.103)
JS/SS		0.301***		0.074
		(0.108)		(0.121)
HS		0.504***		0.275
		(0.152)		(0.195)
Tertiary		0.798***		0.459**
		(0.185)		(0.194)
Age at hire		-0.009		-0.009
		(0.006)		(0.006)
Math z-score		0.009		-0.037
		(0.046)		(0.071)
Language z-score		-0.027		0.027
		(0.038)		(0.052)
Conscientiousness		-0.095***		-0.077*
		(0.032)		(0.045)
Emotional stability		-0.003		-0.040
		(0.040)		(0.033)
Agreeableness		0.026		0.078
		(0.040)		(0.078)
Extraversion		0.017		0.002
		(0.026)		(0.040)
Openness		0.079***		0.064*
		(0.024)		(0.036)
Grit		0.022		0.013
		(0.055)		(0.054)
Father's primary education dummy		0.018		0.127*
		(0.090)		(0.074)
Mother's primary education dummy		0.040		0.096
		(0.075)		(0.061)
Moved before current job (dummy)		-0.027		0.206***
		(0.070)		(0.050)
Firm–occupation fixed effects			X	X
R-squared	0.094	0.171	0.029	0.102
N	2527	2463	2527	2463

Note. Shown are the full results of table 7 for the regressions of job search duration. The omitted category for the level of education completed is no education or primary education dropout. The variables of non-cognitive abilities are z-scores. All specifications control for recruitment years and geographical divisions fixed effects. *Firm–occupation fixed effects* are fixed effects of interactions between firm dummies and entry occupation dummies. Standard errors clustered within establishments are in parentheses. Significance levels: ***1%, **5%, *10%.

Table A15: Difference in the number of applications submitted

	Dep.var.: Log of no. applications			
	(1)	(2)	(3)	(4)
Social network dummy	-0.359***	-0.165	-0.227*	-0.146
	(0.102)	(0.112)	(0.121)	(0.109)
Level of education completed				
Primary		-0.027		0.041
		(0.089)		(0.102)
JS/SS		0.117		0.043
		(0.092)		(0.091)
HS		0.263*		0.193
		(0.143)		(0.136)
Tertiary		0.528***		0.655***
		(0.190)		(0.191)
Age at hire		0.007		0.009
		(0.005)		(0.006)
Math z-score		0.057		0.033
		(0.040)		(0.036)
Language z-score		0.037		0.013
		(0.045)		(0.057)
Conscientiousness		-0.055*		-0.131**
		(0.031)		(0.052)
Emotional stability		-0.077**		-0.073*
		(0.035)		(0.043)
Agreeableness		-0.026		-0.024
		(0.040)		(0.062)
Extraversion		0.055*		-0.003
		(0.033)		(0.027)
Openness		-0.037		0.037
		(0.043)		(0.050)
Grit		0.068*		-0.007
		(0.040)		(0.035)
Father's primary education dummy		0.024		0.050
		(0.089)		(0.105)
Mother's primary education dummy		0.002		0.110
		(0.067)		(0.068)
Moved before current job (dummy)		-0.019		0.038
		(0.057)		(0.058)
Firm–occupation fixed effects			X	X
R-squared	0.082	0.163	0.025	0.101
N	2527	2463	2527	2463

Note. Shown are the full results of table 7 for the regressions of the number of applications submitted until the current job was found. The omitted category for the level of education completed is no education or primary education dropout. The variables of non-cognitive abilities are z-scores. All specifications control for recruitment years and geographical divisions fixed effects. *Firm–occupation fixed effects* are fixed effects of interactions between firm dummies and entry occupation dummies. Standard errors clustered within establishments are in parentheses. Significance levels: ***1%, **5%, *10%.

Table A16: Difference in entry salaries

	Dep.var.: Log of entry salary			
	(1)	(2)	(3)	(4)
Social network dummy	-0.307***	-0.057	-0.146***	-0.078**
	(0.043)	(0.038)	(0.036)	(0.034)
Level of education completed				
Primary		0.037		0.022
		(0.035)		(0.036)
JS/SS		0.103***		0.081**
		(0.034)		(0.039)
HS		0.351***		0.228***
		(0.066)		(0.065)
Tertiary		0.750***		0.514***
		(0.081)		(0.087)
Age at hire		0.018***		0.012***
		(0.003)		(0.003)
Math z-score		0.066**		0.069***
		(0.028)		(0.027)
Language z-score		-0.025		-0.013
		(0.026)		(0.031)
Conscientiousness		-0.038**		-0.022*
		(0.015)		(0.013)
Emotional stability		0.015		0.040**
		(0.014)		(0.018)
Agreeableness		-0.000		-0.021
		(0.020)		(0.018)
Extraversion		0.019		0.002
		(0.013)		(0.016)
Openness		0.022		-0.029**
		(0.016)		(0.012)
Grit		0.018		-0.014
		(0.015)		(0.019)
Father's primary education dummy		0.026		0.026
		(0.036)		(0.024)
Mother's primary education dummy		0.013		0.008
		(0.032)		(0.034)
Moved before current job (dummy)		-0.080*		-0.071**
		(0.042)		(0.033)
Firm–occupation fixed effects			X	X
R-squared	0.124	0.463	0.059	0.240
N	2527	2463	2527	2463

Note. Shown are the full results of table 7 for the regressions of entry salaries. The omitted category for the level of education completed is no education or primary education dropout. The variables of non-cognitive abilities are z-scores. All specifications control for recruitment years and geographical divisions fixed effects. *Firm–occupation fixed effects* are fixed effects of interactions between firm dummies and entry occupation dummies. Standard errors clustered within establishments are in parentheses. Significance levels: ***1%, **5%, *10%.

Table A17: Difference in salary growth

	Dep.var.: Annual salary growth rate			
	(1)	(2)	(3)	(4)
Social network dummy	0.001	-0.001	0.003	0.001
	(0.011)	(0.013)	(0.011)	(0.011)
Level of education completed				
Primary		-0.008		-0.002
		(0.012)		(0.015)
JS/SS		-0.013		-0.013
		(0.013)		(0.016)
HS		-0.016		-0.018
		(0.015)		(0.020)
Tertiary		-0.015		-0.034
		(0.016)		(0.023)
Age at hire		-0.000		-0.000
		(0.000)		(0.001)
Math z-score		-0.009		-0.013**
		(0.007)		(0.006)
Language z-score		0.007		0.002
		(0.007)		(0.007)
Conscientiousness		0.002		0.003
		(0.005)		(0.004)
Emotional stability		-0.007		-0.012**
		(0.004)		(0.005)
Agreeableness		0.002		0.005
		(0.005)		(0.004)
Extraversion		-0.004		-0.003
		(0.004)		(0.005)
Openness		0.003		0.006*
		(0.003)		(0.003)
Grit		-0.002		0.005
		(0.004)		(0.005)
Father's primary education dummy		0.002		-0.004
		(0.009)		(0.007)
Mother's primary education dummy		-0.009		0.009
		(0.014)		(0.009)
Moved before current job (dummy)		0.016***		0.016**
		(0.006)		(0.007)
Firm–occupation fixed effects			X	X
R-squared	0.043	0.074	0.015	0.074
N	2418	2358	2418	2358

Note. Shown are the full results of table 7 for the regressions of annualized salary growth. The workers who were recruited in the same year as the survey year are excluded. The omitted category for the level of education completed is no education or primary education dropout. The variables of non-cognitive abilities are z-scores. All specifications control for recruitment years and geographical divisions fixed effects. *Firm–occupation fixed effects* are fixed effects of interactions between firm dummies and entry occupation dummies. Standard errors clustered within establishments are in parentheses. Significance levels: ***1%, **5%, *10%.

Table A18: Difference in the degree to which employee's education helped get his current job

	Dep.var.: How much education helped to get the job			
	(1)	(2)	(3)	(4)
Social network dummy	-0.450***	-0.108*	-0.210***	-0.126**
	(0.070)	(0.064)	(0.056)	(0.051)
Level of education completed				
Primary		0.030		-0.065
		(0.117)		(0.100)
JS/SS		0.592***		0.319**
		(0.129)		(0.131)
HS		0.946***		0.678***
		(0.183)		(0.167)
Tertiary		1.074***		0.588***
		(0.198)		(0.200)
Age at hire		0.009		0.004
		(0.006)		(0.006)
Math z-score		-0.058		0.018
		(0.061)		(0.055)
Language z-score		0.112**		0.059
		(0.047)		(0.040)
Conscientiousness		-0.001		-0.001
		(0.042)		(0.042)
Emotional stability		-0.087***		-0.050*
		(0.024)		(0.027)
Agreeableness		0.030		-0.095***
		(0.026)		(0.030)
Extraversion		0.006		-0.042*
		(0.025)		(0.025)
Openness		0.060*		0.007
		(0.034)		(0.033)
Grit		0.041		0.024
		(0.035)		(0.026)
Father's primary education dummy		0.110		0.014
		(0.082)		(0.096)
Mother's primary education dummy		0.051		-0.013
		(0.047)		(0.042)
Moved before current job (dummy)		-0.013		-0.090
		(0.093)		(0.066)
Firm–occupation fixed effects			X	X
R-squared	0.130	0.353	0.032	0.154
N	2394	2335	2394	2335

Note. Shown are the full results of table 8 for the regressions of the degree to which employee's education helped him to get his current job. The dependent variable is normalized to have one standard deviation. Workers who do not have any formal education are excluded from the sample. The omitted category for the level of education completed is no education or primary education dropout. The variables of non-cognitive abilities are z-scores. All specifications control for recruitment years and geographical divisions fixed effects. *Firm–occupation fixed effects* are fixed effects of interactions between firm dummies and entry occupation dummies. Standard errors clustered within establishments are in parentheses. Significance levels: ***1%, **5%, *10%.

Table A19: Difference in the degree to which an employee currently uses skills and knowledge from his education

	Dep.var.: How much skills/knowledge from education are used			
	(1)	(2)	(3)	(4)
Social network dummy	-0.413***	-0.076	-0.190***	-0.101
	(0.056)	(0.052)	(0.071)	(0.070)
Level of education completed				
Primary		-0.025		-0.096
		(0.113)		(0.104)
JS/SS		0.349**		0.050
		(0.158)		(0.124)
HS		0.540***		0.291*
		(0.173)		(0.161)
Tertiary		0.829***		0.523**
		(0.213)		(0.211)
Age at hire		0.010*		0.000
		(0.006)		(0.006)
Math z-score		-0.032		0.070
		(0.061)		(0.043)
Language z-score		0.144**		0.090**
		(0.059)		(0.035)
Conscientiousness		-0.025		-0.013
		(0.043)		(0.058)
Emotional stability		-0.015		0.041
		(0.038)		(0.042)
Agreeableness		0.043		-0.072
		(0.033)		(0.054)
Extraversion		0.055		0.014
		(0.039)		(0.035)
Openness		-0.012		-0.017
		(0.041)		(0.036)
Grit		0.025		-0.009
		(0.043)		(0.030)
Father's primary education dummy		0.123		0.026
		(0.091)		(0.083)
Mother's primary education dummy		0.178***		0.111*
		(0.062)		(0.060)
Moved before current job (dummy)		0.075		0.024
		(0.127)		(0.075)
Firm–occupation fixed effects			X	X
R-squared	0.107	0.283	0.027	0.108
N	2394	2335	2394	2335

Note. Shown are the full results of table 8 for the regressions of the degree to which an employee currently uses skills and knowledge from his education. The dependent variable is normalized to have a standard deviation of one. The workers who do not have any formal education are excluded from the sample. The omitted category for the level of education completed is no education or primary education dropout. The variables of non-cognitive abilities are z-scores. All specifications control for recruitment years and geographical divisions fixed effects. *Firm–occupation fixed effects* are fixed effects of interactions between firm dummies and entry occupation dummies. Standard errors clustered within establishments are in parentheses. Significance levels: ***1%, **5%, *10%.

Table A20: The reason for having chosen a current job: Career progression

	Dep.var.: Career progression			
	(1)	(2)	(3)	(4)
Social network dummy	-0.127***	-0.100***	-0.098***	-0.078**
	(0.033)	(0.038)	(0.037)	(0.038)
Level of education completed				
Primary		0.057**		0.056*
		(0.027)		(0.029)
JS/SS		-0.018		0.005
		(0.033)		(0.049)
HS		-0.027		-0.011
		(0.050)		(0.068)
Tertiary		0.092		0.087
		(0.058)		(0.076)
Age at hire		-0.003*		-0.003
		(0.002)		(0.002)
Math z-score		0.013		-0.007
		(0.010)		(0.014)
Language z-score		-0.002		0.011
		(0.018)		(0.024)
Conscientiousness		0.020		0.006
		(0.013)		(0.017)
Emotional stability		0.006		-0.008
		(0.010)		(0.012)
Agreeableness		-0.002		0.016
		(0.013)		(0.016)
Extraversion		-0.016		0.006
		(0.012)		(0.015)
Openness		0.003		-0.015
		(0.012)		(0.014)
Grit		0.014		0.010
		(0.012)		(0.013)
Father's primary education dummy		0.004		0.024
		(0.028)		(0.034)
Mother's primary education dummy		0.025		0.045
		(0.027)		(0.032)
Moved before current job (dummy)		0.027		0.081*
		(0.039)		(0.045)
Firm–occupation fixed effects			X	X
R-squared	0.058	0.092	0.042	0.067
N	2526	2462	2526	2462

Note. Shown are the full results of table 8 for the regressions of the dummy that an employee chose his job for career progression. The omitted category for the level of education completed is no education or primary education dropout. The variables of non-cognitive abilities are z-scores. All specifications control for recruitment years and geographical divisions fixed effects. *Firm–occupation fixed effects* are fixed effects of interactions between firm dummies and entry occupation dummies. Standard errors clustered within establishments are in parentheses. Significance levels: ***1%, **5%, *10%.