2022

ERF Working Papers Series

Social Contacts, Wages, and Turnover: The Case of the Egyptian Labour Market

Omar Mohsen Hussein

Economic Research Forum
منتدى البحوث الاقتصادية

Working Paper No. 1536
February 2022

SOCIAL CONTACTS, WAGES, AND TURNOVER: THE CASE OF THE EGYPTIAN LABOUR MARKET

Omar Mohsen Hussein

Working Paper No. 1536

February 2022

Send correspondence to:
Omar Mohsen Hussein
University of Essex and Institute for Social and Economic Research
om20319@essex.ac.uk

First published in 2022 by
The Economic Research Forum (ERF)
21 Al-Sad Al-Aaly Street
Dokki, Giza
Egypt
www.erf.org.eg

Social Contacts, Wages, and Turnover: The Case of the Egyptian Labour Market

Omar Mohsen Hussein*

Abstract

The objective of this paper is to investigate empirically the role of social networks in the determination of labour match quality in the Egyptian labour market. We study the differentials in wages and turnover between workers who found their jobs through social contacts compared to those who found them through other search methods. Using individual level data from the 2018 round of Egypt Labour Market Panel Survey (ELMPS), we build a worker fixed effect model for wages, and an employment survival model for turnover, and introduce interactions with tenure, skill level, and occupation to assess the possible heterogeneities of network effects. Our findings indicate an overall insignificant effect on initial wages, but there exists a wage penalty that appears on long run for connected workers. The effect on wage is insignificant for low skilled workers and negative for skilled workers. Contacts have a positive and significant effect on job duration for low skilled workers and the effect is insignificant for skilled workers.

JEL classification: J30, J31, J63

Keywords: Wage differentials, Turnover, Match quality, Social contacts, Networks

1 Introduction

Reliance on social networks is ubiquitous in the labour market. Workers often use them to inquire about jobs and receive recommendations, and firms ask workers to refer their connections to fill vacancies (Topa, 2019). In 2018, 43.7% of Egyptian workers reported having found their jobs through

*University of Essex and Institute for Social and Economic Research. Email: `om20319@essex.ac.uk`.

their friends or relatives[1], and similar patterns have been observed in other developing countries such as China (Nie and Yan, 2021) and India (Beaman and Magruder, 2012), as well as developed countries such as the United States (Topa, 2011). Overall, between 25% and 80% of jobs are filled through social contacts depending on the context (Topa, 2019). This suggests that there are some advantages to this method compared to other job search methods in terms of job finding rate, and match quality, i.e., wages and turnover.

While a multitude of theoretical studies on the role of social contacts in the labour market, as facilitators of information transmission, point towards a positive effect of networks on both job finding rates and match quality, the empirical evidence is mixed when it comes to the latter.[2] Regardless of the direction of the effect, social networks explain some of the differentials in labour market outcomes between workers. On one hand, they can lead to segmentation within the labour market as individuals tend to be associated and refer those who have similar characteristics (McPherson et al., 2001). On the other hand, given that low-wage low-skilled workers are their main users [Hellerstein and Neumark (2020), and Fontaine et al. (2020)], if they are beneficial, they could be a factor in reducing labour market outcome differentials. Therefore, exploring the underlying mechanisms to this role is crucial in explaining the evolution and nature of employment, and wage and income gaps.

The objective of this paper is to study the role of social networks in the determination of match quality focusing on the case of the Egyptian labour market. We will investigate empirically whether there is a differential in wages and turnover for workers who found their jobs through social contacts compared to other search methods, and if the differentials are heterogenous across skill and occupation groups.

Literature on subject provides different predictions on the direction of the relationship. Most theoretical studies suggest a positive effect of social networks on match quality because it increases the job arrival rate [Mortensen and Vishwanath (1994) and Galenianos (2014)] and counter information imperfections [Kugler (2003), Galenianos (2013), and Dustmann et al. (2016)]. Others, such as Bentolila et al. (2010), predict a negative effect since they can create a mismatch between skill and occupation. The empirical literature's results are not, however, always consistent with these predictions [see Pellizzari (2010), Glitz (2017), and Nie and Yan (2021)].

Our approach in studying the heterogeneity of the effect follows Galenianos (2014), in positing that since the way social networks function in the labour market is tightly related to search and

[1] Author's calculations using ELMPS 2018, see table 1.

[2] Topa (2011), Topa (2019), and Hellerstein and Neumark (2020) review the theoretical and empirical evidence on the usage and effects of social networks in the labour market.

information frictions, they should matter more to match quality when frictions are higher if we draw an analogy with Rauch (1999). The capacity of the employer to assess the ability of the worker and measure their productivity depends on their skill and task they are performing. Similarly, the capacity of the worker to signal their ability and productivity depends on the nature and complexity of their task and their skill level. Thus, our hypothesis is that the effect of networks on wages and turnover should be heterogenous across labour market segments. We also discuss other hypotheses specific to the Egyptian labour market such as informality, labour mobility, and social risk sharing.

To tackle these hypotheses, this study uses individual level data from the 1998-2018 panel of the 2018 round of Egypt Labour Market Panel Survey (ELMPS) (OAMDI, 2019). Benefiting from the panel structure of the data, we build a wage fixed effect model to control for the workers' unobserved characteristics. We introduce interactions with tenure, skill level, and occupation to assess the possible heterogeneities of network effects on wages. For turnover, we use an employment survival model to estimate the difference of the probability of a person changing the jobs for those who found them through contacts compared to others. Our findings indicate an overall insignificant effect on initial wages, but there exists a wage premium to other methods compared to social contacts that appears with longer tenures. When disaggregating the effect by skill level, the effect is insignificant for low skilled workers and negative as the skill level increases. Furthermore, contacts have a positive effect on tenure for low skilled workers, but the effect becomes insignificant for skilled workers. Generally, there seems to be a premium to the usage of social networks for low skilled workers, and a penalty for high skilled workers.

This paper is situated within the strand of literature that uses large surveys to study the effects of social contacts on labour market outcomes [e.g. Pellizzari (2010), Bentolila et al. (2010) and Dustmann et al. (2016)]. Our results contribute to the debate on the role of the social networks in the labour market; as mentioned, the effects of social networks depend on the study, country, and setting. Second, this work focuses on the heterogeneities of the effects [similar to Antoninis (2006), Cappellari and Tatsiramos (2015), and Brown et al. (2016)] which gives more insights into how social networks affect the differentials of outcomes between and within segments. Third, most of the past studies on this scale addressed labour markets in developed countries; with some more recent exceptions [Bian et al. (2015) and Nie and Yan (2021)]. As the institutions and functioning of the labour market in a developing country, such as Egypt, are different, it allows the investigation of different channels of transmission from social contacts to match quality. This adds another layer to the existing schools of thought on the issue and could be applied to other countries with similar level of development.

This rest of this paper will be organized as follows; the second reviews the theoretical and empirical literature on the subject. The third section describes the data and shows some stylized facts on Egyptian the labour market and the role social contacts play. The fourth section presents the empirical framework for the wage and turnover models. Section 5 shows and discusses the results. Section 6 concludes.

2 Literature review

Social networks[3] operate as a channel of transmission of information in labour markets characterized by search and information frictions. According to Topa (2019), the channels lie on a spectrum between information spill-overs [for example in Calvó-Armengol and Zenou (2005) and Calvó-Armengol and Jackson (2007)], i.e., hearing about a job opportunity from someone in one's circle, to referral[4], where the referee invests some reputational capital to link the referred to the employer [Galenianos (2013) and Dustmann et al. (2016)]. Studies also vary in terms of the motivation behind the usage of social networks, including reducing search costs, monitoring and favouritism.[5] Other studies, like Nie and Yan (2021) and Cappellari and Tatsiramos (2015), distinguish between the type of connection; whether they are weak ties - professional networks – or strong ties – personal relationships like those between friends or family members (Granovetter, 1973). With many factors in play, what is observed empirically, in terms of the effect on wages and turnover, does not always match the main predictions of the prevalent theoretical models. This section reviews the theoretical and empirical literature on the subject.

The theoretical literature on social networks in the labour market overwhelmingly predicts a positive effect on match quality. The main underlying ideas are that they increase the rate with which employers and workers encounter each other and reduce information imperfections. In one of the earliest theoretical formulations, Mortensen and Vishwanath (1994) analysed a labour market with different sources of information yielding various levels of job arrival rates, in an on-the-job search framework. They proposed that wages are higher in the sectors with higher job arrival rates[6]

[3] In this paper, the terms "social networks", "social connections", "referrals" are used interchangeably as in Topa (2019). Some other studies like Bentolila et al. (2010) and Cappellari and Tatsiramos (2015) use the term "contacts".

[4] Nie and Yan (2021) distinguish between using social networks for "information", which is equivalent to spillovers, and influence, equivalent to "referral".

[5] Brown et al. (2016) and Heath (2018) provide a review of the main mechanisms in each of these models, as well as their main predictions.

[6] Wahba and Zenou (2005), in a study on the Egyptian labour market, suggested a non-linear relationship between social networks and the probability of finding a job through contacts. That is, if networks are too large, the job arrival rate actually decreases because of congestion.

– for instance because of larger social networks. Similar propositions were found in Galenianos (2014) model. When information about jobs and wages are transmitted through a worker's network, their wage rate increases when the size of their social network increases, improving their job finding rate, thus increasing the value of their unemployment, thus their reservation wage.

In terms of reducing information imperfections, there are two classes of models in the literature. First, moral hazard models, where employers cannot perfectly measure the worker's productivity [Kugler (2003) and Heath (2018)]. Because the referee is in a position to monitor the performance of the referred worker, their productivity, thus wage and tenure, will be higher than non-referred workers. The second class of models is symmetric uncertainty, where both workers and firms are uncertain about the match quality before the match is formed [Galenianos (2013) and Dustmann et al. (2016)]. In these models, employers can either ask employees to refer potential candidates or recruit on the external market. Later, firms and workers learn about the match productivity after the match has been formed. The noisy signal for productivity of the match is more accurate for referred workers, implying that they are insured against the realisation of low productivity and thus will have higher reservation wages. On the other hand, for non-connected workers, they can accept a lower initial wage since they are insured against the realisation of low productivity with the possibility of leaving the firm. These models predict that initial wages are higher, and turnover is lower for connected workers. Over time, the wage differential between connected workers and non-connected workers diminishes. As for turnover, the differential decreases with tenure in Dustmann et al. (2016) but flat in Galenianos (2013).

In contrast, there are a few theoretical studies that suggest a negative effect of networks on match quality. Bentolila et al. (2010) proposed a framework where social networks can create a mismatch between skill and occupation. Each group of workers possesses a certain set of skills that is suited to some vacancy but not others. When they choose between a sector in which they are productive and another where they have social connections, they will opt for the latter if the size of their network is large enough. In this case, the value of having a job is higher than the value of unemployment as they wait for an opportunity where they are more productive.[7] Pellizzari (2010) suggested that the direction of the effect depends on the efficiency of the formal channels; if they are effective, firms are more selective when they use referrals for recruitment. The opposite is true when formal channels are not efficient.

Despite the relatively clear-cut conclusions in the theoretical literature, the results are mixed on the empirical front. Some studies found a positive effect, such as Burks et al. (2015), who found

[7] Horváth (2014) countered this argument. He found that mismatch can decrease when homophily is prevalent.

that referred workers are less likely to quit and earn slightly higher wages in a study on several large US firms in different industries. Dustmann et al. (2016) tested their learning model using German data, and their results suggested that referred workers earn higher wages and stay longer at their jobs, and the difference with non-referred workers decreases with tenure. On the other hand, some studies found negative or insignificant effects. For example, Bentolila et al. (2010) found a negative effect on wages using surveys from the US and EU, and Glitz (2017) found no significant effect of co-worker networks on wages in Germany, while Pellizzari (2010) found a wage premium to social networks in some EU countries and negative in others.

Other works analyse the heterogeneity of the effect. In a study on the wage effects of personal contacts in a manufacturing firm in Egypt, Antoninis (2006) found a positive effect only if the referee is familiar with productivity of the worker. The effect of contacts on wages was not significant, but the wage for low skilled workers who used personal contacts to get their job is lower than those who didn't. Brown et al. (2016) examined different hypothesis regarding the effects of referrals, in terms of hiring probability, wages, turnover, and productivity in a US firm. They found that workers who were referred get higher initial wages and enjoy longer tenures, but the effect decreases with tenure, and even reverses after 5 years. Their results also showed a more positive effect for low skilled workers. Nie and Yan (2021) studied the type of ties, kinship or non-kinship, and network resources on match quality in China. They found a wage premium for those who found a job through contacts for both kinship and non-kinship ties. However, the effect on job duration was negative for non-kinship ties. Cappellari and Tatsiramos (2015), using British data, found a positive effect for non-familial ties on the wages of high skilled workers, but the effect is significant for low skilled workers.

To summarize, this review does not provide us with a clear expectation of what and how social networks affect wages and turnover. If the relationship is positive, the explanation could be the reduction of search and information barriers. If it is negative, then social networks could have created a mismatch between skill and occupation, or some other factors more unique to the Egyptian labour market. But we can expect the coefficients to vary by tenure, skill, and occupation, which will be tackled in the following sections.

3 Data and stylized facts

3.1 Data

We use individual level data from the 1998-2018 panel of the 2018 round of Egypt Labour Market Panel Survey (ELMPS). It follows a representative sample interviewed in 1998 onward, with refresher samples in the waves of 2006, 2012, and 2018. It features 86,270 individuals and provides data on their employment and socioeconomic characteristics. We focus on working age (between 15 and 64) wage employees, a sample of 20,965 individuals in all waves.[8] The explanatory variable of interest is a dummy taking a value of 1 if the worker obtained their jobs through their friends or relatives, representing their contacts or networks, and 0 otherwise.

A shortcoming of this dataset is that it does not distinguish between weak and strong ties; Topa (2019) suggested that networks could be more effective for the latter. In addition, it does not provide information on the way the referral or connection was made; whether the worker heard about a job from someone in their circle, they were recommended by a referee, they were introduced to the employer, etc. Using Chinese data, Nie and Yan (2021) were able to distinguish between the types and modalities of connections and found heterogenous effects on match quality. Nevertheless, the variable we are using – friends and relatives – is a standard proxy in the literature where it is not possible to distinguish between the different types of ties [e.g. in Bentolila et al. (2010), Pellizzari (2010), Galenianos (2014), and Dustmann et al. (2016)], and allows us to draw conclusions on the effects of referrals or contacts.

3.2 Stylized facts

The four ELMPS waves are situated in four distinct periods in the Egyptian labour market history. In 1998, the Egyptian economy was going through in a period of transition – structural adjustment – away from a larger role for the State in the economy to a market economy Wahab (2017). The wave of privatisation and reduction of the size of government led to the employment structure shifting towards the private sector away from the government and public enterprise sectors. Between 1998 and 2006, the share of the government in wage employment decreased from 47.6% to 41.1%, with a similar trend in the following years, reaching 29.5% in 2018 (table A.3). Although the year 2006 was amid a period of rapid economic growth, the size of the informal sector increased as the private sector grew. This trend continued with the slowdown of growth after the 2011 revolution and the recovery starting from 2017.

[8] The descriptive statistics on the sample are shown in tables A.1-A.4.

Table 1: Percentage of workers who found their current jobs through social contacts.

	1998	2006	2012	2018
Total	29.9%	23.2%	30%	43.7%
Level of education				
Illiterate	47.9%	28%	37.3%	59.1%
Reads and Writes	42.2%	26.8%	39.1%	56.5%
Less than Intermediate	44.1%	32.7%	41.2%	58.8%
Intermediate	26.2%	23.7%	31.1%	46.4%
Above Intermediate	14.4%	20.4%	20.3%	29.7%
University	14.2%	14.1%	18.2%	20%
Age group				
15 - 19	58.2%	41.8%	44%	72.2%
20 - 29	44.3%	34.2%	37.9%	54.9%
30 - 39	25.1%	19.8%	32.2%	44%
40 - 49	19.4%	13.3%	20.1%	35.6%
50 - 59	17.5%	12.6%	14.5%	24.5%
60 - 64	46.3%	20.8%	35.7%	49.6%
Gender				
Male	33.1%	25%	33.3%	47.4%
Female	18.2%	16.4%	14.7%	24%
Region				
Greater Cairo	41.3%	34%	39.4%	49.4%
Alexandria and Suez Canal	28.2%	26.4%	29.4%	36.3%
Urban Lower Egypt	23.5%	18.8%	28%	40.4%
Urban Upper Egypt	21.7%	15.9%	23%	37.5%
Rural Lower Egypt	31.3%	22%	30.7%	44.8%
Rural Upper Egypt	30.1%	20.5%	29.7%	46.5%
Observations	4598	7377	9999	11739

Notes: Author's calculations using ELMPS 2018.

A second package of structure adjustment was implemented in 2016 that further decreased the size of the government, and liberalized the exchange rate, which led high rates of inflation (Saeed, 2019) and pushing down the real wages in most sectors.[9] Another observation is that unemployment in Egypt is structural and does not fluctuate with conjuncture, instead, the adjustment happens through the change in working conditions; workers become more likely to find employment in the informal sector, or without permanent contracts in the periods of economic stagnation [Assad and Krafft (2013), see Table A.1]. This could suggest an informal or communal form of an unemployment insurance social contract.

Social contacts are the, by far, the most common method for individuals to find employment, and this fact is observed in all years. We see in table 1 that the percentage of workers who reported having obtained their jobs through social contacts changes with the state of the economy; it is highest in 2018 (at 43.7%) in a period of economic instability, and lowest in 2006 (at 23.2%), a period of economic growth.[10]

[9] Real wages fell by 7.2% between 2012 and 2018. Source: Author's calculations using ELMPS 2018.

[10] Related to the mismatch hypothesis (Bentolila et al., 2010), El-Hamidi (2010) found a decrease in education

The method of acquiring employment in the Egyptian labour market is not uniform across groups. The percentage of individuals with low skill having obtained their jobs through social contacts is higher than that for the highest skill group (table 1). Similarly, this rate is higher for blue collar workers (agricultural works, machine operators, etc...) compared to white collar workers (managers, professionals, etc. . .) (table A.6), which is consistent with evidence from other countries (Hellerstein and Neumark, 2020). Reliance on social networks is also more prevalent in the private sector, explaining why it increases in the periods of privatisation and reduction in the size of government. The rate is also higher for young people or workers nearing retirement compared to the groups aged 30-59. It also varies by region; it is highest in major urban areas like Cairo and Alexandria, followed by rural areas and then smaller urban areas (table 1), suggesting a nonlinear relationship between geographical distribution of workers and the size of social networks (Wahba and Zenou, 2005).

Table 2: Baseline OLS regressions for real hourly wages.

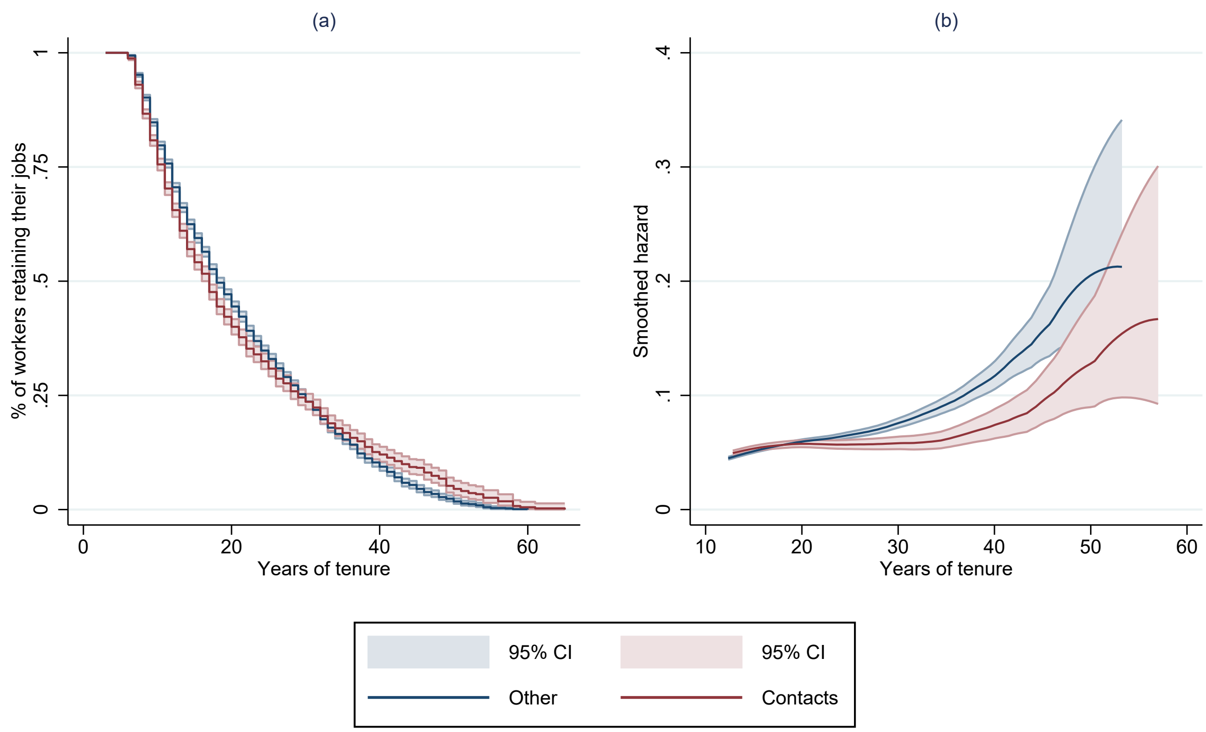
		1998			2006	
	(1)	(2)	(3)	(4)	(5)	(6)
Contacts	-0.185***	-0.004	-0.011	-0.232***	-0.031*	-0.058
	(0.022)	(0.023)	(0.036)	(0.020)	(0.019)	(0.035)
Contacts x tenure			0.005			0.006
			(0.005)			(0.006)
Contacts x tenure squared			-0.000			-0.000
			(0.000)			(0.000)
Controls	No	Yes	Yes	No	Yes	Yes
Observations	4558	4545	4545	7351	7336	7336
R^2	0.017	0.370	0.371	0.020	0.373	0.373
		2012			2018	
	(7)	(8)	(9)	(10)	(11)	(12)
Contacts	-0.249***	-0.075***	-0.039	-0.177***	0.041**	0.022
	(0.015)	(0.016)	(0.030)	(0.014)	(0.016)	(0.030)
Contacts x tenure			-0.004			0.007
			(0.005)			(0.004)
Contacts x tenure square			0.000			-0.000**
			(0.000)			(0.000)
Controls	No	Yes	Yes	No	Yes	Yes
Observations	9995	9913	9913	10247	9412	9412
R^2	0.025	0.246	0.246	0.015	0.171	0.172

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Author's calculations using ELMPS 2018. **Dependent variable:** log real hourly wages. **Controls:** Level of education, age, age squared, gender, tenure, tenure squared, job stability, formality, household size, institutional sector and economic activity.

occupation mismatch between 1998 and 2006 in Egypt. This period also saw a decrease in the reliance on social contacts to find a job.

In terms of wages, on average, the workers who found employment through contacts earn lower wages than those who used other methods (table 2). After controlling for worker characteristics, we see that connected workers earn lower wages 2012, but the difference is insignificant in 2006, 1998 and positive 2018. When we detail the difference in the wages by search method (Table A.9), the difference is entirely due to a premium to finding a job through government offices and government job competitions (mainly in the public sector), which explains why the coefficient for contacts versus others turned positive in 2018 as the size of the public sector decreased.

Figure 1: Survival and hazard estimates by search method.



Notes: Author's calculations using ELMPS 2018. (a) Kaplan-Meier survival estimates. (b) Smoothed hazard estimates.

The difference when tenure increases is generally negative, but its significance is not consistent over the years; it is insignificant in both 2006 and 2012, and only strongly significant in 1998. In 2018, we observe a pattern that could be similar to that in the learning model in Dustmann et al. (2016), i.e. higher initial wages for connected workers but the difference decreases tenure. Similarly, the differences are not consistent over the years when we look at the differential effect by level of education and occupation (Tables A.7 and A.8). On average, contacts are less effective for intermediate and high skilled workers and occupations.

Table (A.10) shows that, overall, workers who obtained their jobs through social contacts work in less stable jobs. Those who found their jobs through social contacts are significantly less likely to get a permanent position, instead they are more likely to get casual, seasonal, or temporary jobs. When we decompose it by informality and level of education, we see that workers employed in the informal sector and those with a low level of education (except for 2018), are more likely to get a permanent job if they obtained it through contacts. For those in the formal sector or are skilled, contacts are less likely to yield them a permanent job.

With this, when it comes to turnover, a preliminary survival analysis in figure 1 shows that connected workers are more likely to have their employment terminated – for any reason – for tenures shorter than 25 years, but the direction is reversed for tenures longer than 25 years. High and intermediate skilled workers who found their jobs through contacts are more likely to change their jobs compared to other workers with the same level of qualifications who use other methods. Conversely, connected low skilled workers are less likely to change their jobs at any time, and the difference with non-connected workers increases with time (Figures A.1 and A.2). Similarly, connected managers and professionals have higher job change hazard, while the rate is lower for blue collar workers (Figures A.3 and A.4). This suggests that the effect of social contacts on turnover is negative for low skilled workers and positive for high skilled workers.

4 Empirical methodology

4.1 Wages

In the previous section, we ran preliminary OLS regressions to study the average wage differentials and patterns across years. Given the endogeneity present in the model, the relationships we observe are correlations, and the estimates do not establish a causal link from networks to wages. This emanates from our inability to capture some of the unobserved individual characteristics correlated with both wage levels and the probability of obtaining a job through social networks.

There are several sources of endogeneity in the model. First, it is possible that a person with high social skills will have a larger social circle, thus more likely to find a job through it. Simultaneously, these skills can help them negotiate a better wage offer or get raises on the long term [Similar to the reasoning in Topa (2019)]. Second, low skilled workers could be more reliant on social networks to find a job to compensate for their inability to use other methods; this group naturally earns less (Nie and Yan, 2021). Another source is that workers with higher separation rates are more likely to use social networks to find a job, as shown by Kuzubas et al. (2009).

We therefore benefit from the panel structure of our dataset and employ a worker fixed effect model to account for unobserved heterogeneities. Following Pellizzari (2010), Dustmann et al. (2016), and other studies, we introduce interaction terms with tenure to observe the change of the effect of contacts. In addition, to capture the heterogeneity of the effect according to level of education and occupation, in the spirit of Galenianos (2013) and Brown et al. (2016), we include interaction terms with both. We estimate the model with the specifications in (1) – (5).

$$\ln(w_{it}) = \alpha k_{it} + \beta X_{it} + \mu_i + \gamma_t + \epsilon_{it} \tag{1}$$

$$\ln(w_{it}) = \alpha_0 k_{it} + \alpha_1 k_{it} T_{it} + \alpha_2 k_{it} T_{it}^2 + \beta X_{it} + \mu_i + \gamma_t + \epsilon_{it} \tag{2}$$

$$\ln(w_{it}) = \alpha_0 k_{it} + \alpha_1 k_{it} Yr_{it} + \alpha_2 k_{it} Yr_{it}^2 + \beta X_{it} + \mu_i + \gamma_t + \epsilon_{it} \tag{3}$$

$$\ln(w_{it}) = \alpha k_{it} + \sum_j \alpha_j k_{it} Educ_{jit} + \beta X_{it} + \mu_i + \gamma_t + \epsilon_{it} \tag{4}$$

$$\ln(w_{it}) = \alpha_0 k_{it} + \alpha_1 k_{it} MP_{it} + \beta X_{it} + \mu_i + \gamma_t + \epsilon_{it} \tag{5}$$

Where k_{it} is a dummy variable taking the value of 1 if the worker i obtained their jobs through friends or relatives in year t, and 0 otherwise. X_{it} is a vector of controls containing Level of education, age, age squared, gender, tenure, tenure squared, job stability, formality, household size, institutional sector and economic activity. μ_i is worker fixed effects, γ_t is year fixed effects[11], and ϵ_{it} is the error term. We introduced an interaction term in (2) with T_{it}, tenure, and both Yr_{it} and $Educ_{itj}$ in (3) and (4), where Yr_{it} is years of education, and $Educ_{jit}$ is a series of dummies indicating the worker's level of education. MP_{it} in (5) indicates whether a person is a manager or professional, as opposed to blue collar workers.

4.2 Turnover

In this subsection, we establish the framework to study turnover. Here, we are interested in studying the likelihood of a job being terminated given worker characteristics. We thus employ a proportional hazard model following Brown et al. (2016) and Nie and Yan (2021), and we use a framework similar to the model found in Meyer (1990). Our failure variable is a dummy in one period indicating that a worker has changed jobs or became unemployed in the next period or the

[11] Galeotti and Merlino (2014) showed that individuals invest in social connections in response to macroeconomic risks, therefore, having year fixed effects controls for some of these feedbacks.

future periods in which were observed. Like many hazard models, our data exhibits right censoring. In the case of an individual did not change or lose their job in the last year they were observed, we cannot measure the true duration of their tenure. Therefore, having a simple model, for example with tenure as a dependent variable, will yield erroneous estimates.

Since we can observe different employment spells for the same individual, this model is in terms of jobs, rather than workers. Suppose N is the continuous duration of a job j for a worker i with a conditional density and cumulative distributions, $f(N/X)$ and $F(N/X)$, respectively. X is a vector of explanatory variables similar to the previous subsection (3.1.). The survivor function $S(N/X)$, hazard functions $\lambda(N/X)$ and the separation hazard are given by (6) – (8).

$$S(N/X) = 1–F(N/X) = Pr(\bar{N} > N/X) \tag{6}$$

$$\lambda(N/X) = \frac{-d\ln[S(N/X)]}{dN} \tag{7}$$

$$\lambda(N/X) = \lambda_0(N/X)\exp(X\beta) \tag{8}$$

$\lambda_0(N/X)$ is the baseline parametric hazard and β is the vector of parameters. Our main estimation uses the exponential specification for parametric hazard. We introduce interactions with the level of tenure, education, and occupation to capture the heterogeneity of the effect. For robustness, we run our model with alternative specifications; Weibull, Gompertz, and the Cox semiparametric estimation (the results of which are found in tables A.11 and A.12). We estimate the model using maximum likelihood with the log likelihood function in (9).[12]

$$\log(L) = \sum_{UC\epsilon j} \log f_j(N_j/X_i) + \sum_{RC\epsilon j} \log S_j(N_j/X_i) \tag{9}$$

Where UC is the is set of uncensored observations, and RC is the set of right censored observations.

The data also exhibits interval censoring due to our inability to observe the exact date job was terminated. For example, an individual observed in 2006 and 2012, who was employed in 2006 and lost their job by 2012, the exact year of termination is within the interval [2006, 2012]. Since 6 years is a significant tenure period, not addressing interval censoring could lead to biased estimates. Therefore, we provide an alternative specification (Reported in the annex, table A.12) that considers both right and interval censoring, and estimate the hazard function using maximum likelihood

[12] Following Nie and Yan (2021).

with the following log likelihood function:[13]

$$\log(L) = \sum_{UC\epsilon j} \log f_j(N_j/X_i) + \sum_{RC\epsilon j} \log S_j(N_j/X_i) + \sum_{IC\epsilon j} \log[S_j(N_{jh}/X_i) - \log S_j(N_{jl}/X_i)] \quad (10)$$

Where IC is the set of interval censored observations. N_{jl} is the lower bound of the time interval and N_{jh} is the upper bound.

5 Results and discussion

5.1 Wages

Table 3: The effect of social contacts on wages, fixed effect model.

	(1)	(2)	(3)	(4)	(5)
Contacts	-0.016	0.009	0.022	0.012	-0.017
	(0.015)	(0.029)	(0.035)	(0.028)	(0.015)
Contacts x tenure		-0.001			
		(0.004)			
Contacts x tenure square		-0.000			
		(0.000)			
Contacts x Years of schooling			0.003		
			(0.010)		
Contacts x Years of schooling squared			-0.001		
			(0.001)		
Contacts x Intermediate				-0.022	
				(0.033)	
Contacts x High				-0.104*	
				(0.054)	
Contacts x Managers and professionals					0.011
					(0.056)
Observations	31206	31206	31200	31206	31206
R^2	0.156	0.156	0.156	0.157	0.156

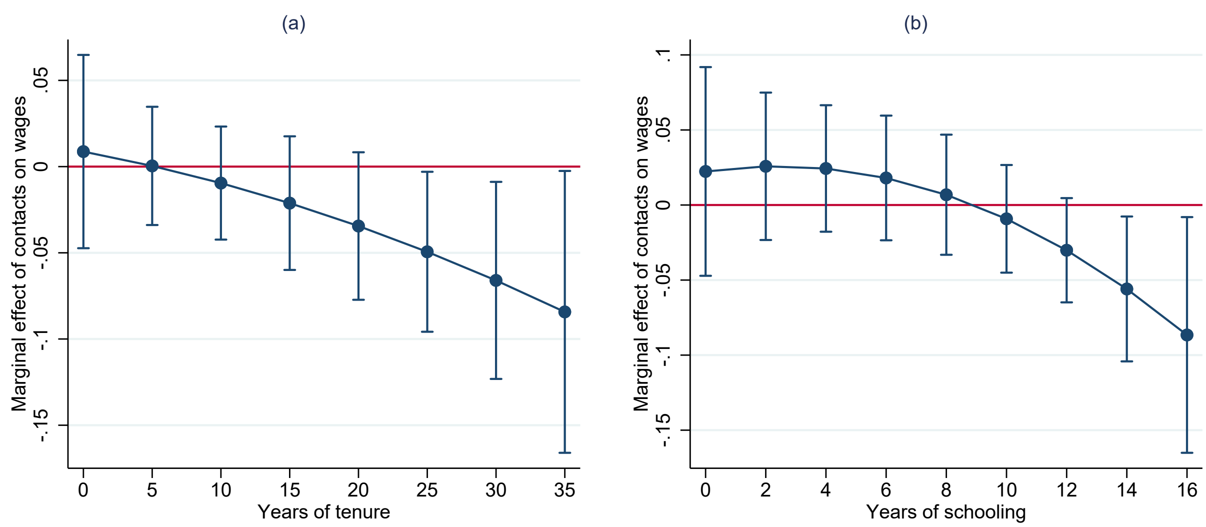
Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Author's calculations using ELMPS 2018. **Dependent variable:** log real hourly wages. **Controls:** Level of education, age, age squared, gender, tenure, tenure squared, job stability, formality, household size, institutional sector and economic activity. **Low:** Illiterate and reads, and writes. **Intermediate:** Less than intermediate, intermediate, and above intermediate. **High:** University.

Table 3 shows the results of the fixed effects regression. The overall effect social contacts on wages is insignificant (column 1). When letting the effect vary according to tenure and level of education,

[13] See Yang et al. (2017).

and occupation, we see that it is heterogenous across groups. Column (2) and figure 2(a) show that, initially, the difference in wages between connected workers and non-connected workers is insignificant, but the difference becomes negative and significant after 25 years of tenure. This implies a long-term penalty to the usage of social networks on wages. When we let the effect vary by level of education in columns (3)-(4), it is insignificant for low levels of education, but turns negative and significant as the level of education increases [figure 2 (b)], specifically, around 16 years of schooling, which is equivalent to a university degree. This is supported by the negative coefficient, with higher magnitude than contacts, of the interaction terms with high level of education (column 3). When it comes to occupation, there is no significant effect for managers and professionals. Provided, there exists some heterogeneity within that group; while professionals overwhelmingly hold a university degree, a significant portion of managers do not.

Figure 2: The effect of social contacts on wages conditional on (a) tenure (b) years of schooling.



Notes: Author's calculations using ELMPS 2018.

5.2 Turnover

Table 4 show the different specifications for the effect of the usage of social contacts on job duration. In all specifications, the effect of networks on job duration is significant and positive; for example, column (1) shows that connected workers are 12.8% less likely to have their employment terminated at any time. With tenure, the probability of changing jobs further decreases. When we decompose that effect by level of education, we see that the effect is only negative for low skilled workers.

For High skilled workers, the difference in coefficient between those who found their jobs through social networks and those who found them through other methods, while positive - i.e. they are more likely to change their jobs, is not statistically significant. These results are robust across methodologies and specifications (Tables A.11 - A.12). It should be noted that, although close in magnitude, we see that the exponential functional form is less precise than its alternatives; the ln(p) and gamma in the Weibull and Gompertz specifications, respectively, are significant.

Table 4: The effect of social contacts on turnover.

	(1)	(2)	(3)	(4)
Contacts	-0.128***	0.318***	-0.218***	-0.141***
	(0.018)	(0.027)	(0.033)	(0.019)
Contacts x tenure		-0.044***		
		(0.002)		
Contacts x Intermediate			0.090**	
			(0.039)	
Contacts x High			0.288***	
			(0.055)	
Contacts x Managers and professionals				0.150**
				(0.059)
Observations	19592	19592	19592	19592
Log pseudolikelihood	-1.4e+04	-1.4e+04	-1.4e+04	-1.4e+04

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Author's calculations using ELMPS 2018. **Dependent variable:** Hazard ratio. The specification for baseline parametric hazard is *exponential*. **Controls:** Level of education, age, age squared, gender, tenure, job stability, formality, household size, institutional sector and economic activity.

5.3 Discussion

The results in this section summarize as follows; for skilled workers, there is some penalty on wages to the usage of social networks, and none on job duration. For unskilled workers, there is no significant effect on wages, but social networks reduce the probability of job termination on the long run. These results contradict the hypotheses in the models related to the reduction of search costs and information imperfections [e.g., Galenianos (2013), Dustmann et al. (2016)] but could be explained through the lens of the mismatch hypothesis by Bentolila et al. (2010), and other factors specific to the Egyptian labour marker such as labour mobility, informality, and social risk sharing.

For skilled workers, the penalty to social contacts could be explained by several points. First, high skilled workers are more specialized relative to their low skilled counterparts, which leaves more room for skill-occupation mismatch. Therefore, if because of social networks a skilled worker decides to get a job quickly in a sector in which they are not specialised, the distance between their productivity and an equally skilled worker who found a job through formal methods in a sector that suits their qualifications, will increase, thus creating a larger differential in match quality. Second, while this reasoning was applied to low skilled workers in Antoninis (2006), it could be the case that firms use the fact that the method of recruitment is informal to push down the wages of high skilled workers.

Third, skilled workers can choose a low-quality job through their social contacts, but with the intention of leaving it as soon as a better job opportunity presents itself, this is why we observe a higher separation rate compared to non-connected workers. Wahba et al. (2009) found that in the Egyptian labour market employment in the informal sector is a way for workers to move to the formal sector; this mobility is pronounced for male high skilled workers. We observe that most of the jobs that were obtained through friends and relatives are in the informal sector (Table A.6).

For low skilled workers, an opposite reasoning applies. Since low skill occupations are less specialized, the difference in productivity between connected and connected workers will not be as large even in the case of mismatch. They are thus less sensitive to information frictions. Second, the role of social contacts for low skilled workers could be larger than for high skilled workers. While for the latter group, social contacts constitute only a small part of their signal of productivity to the employer, as it also includes formal qualifications and experience that the employer can observe, for the former, social contacts make up almost the entirety of their signal of productivity (Antoninis, 2006). This should yield them a higher initial wage – which is not observed in the results, however, it also could mean that they could be seen as more trustworthy or productive as they are guaranteed by a referee, in line of moral hazard models [Kugler (2003) and Heath (2018)], which could explain their longer tenures.

An explanation to the penalty on match quality for high skilled workers and longer job duration for low skilled workers is social risk sharing. Hellerstein and Neumark (2020) suggest this as a potential factor to the role of social networks in the labour market. Since there is no formal unemployment benefit scheme in Egypt, there could exist an informal social security net against unemployment for high skilled workers and job loss for low skilled workers. A family member or friend can help someone find a temporary job when they go into unemployment until they get back on their feet, given the absence of an alternative source of income. In addition, since there is no outside option, the usage of social contacts could signal to the employer its lack, and a lower reservation wage, thus inducing them to push down their wages. Then, it becomes more likely for high skilled workers to encounter a higher wage offer, which could lead to lower job durations for this group.

For unskilled workers, having a found a job through social contacts could be a guarantee against job loss, even in the case their job is in the informal sector or on a temporary contract. Given the fact that most firms in Egypt are personal enterprises,[14] i.e. small firms where the owners/employers have a large role in recruiting and overseeing workers, the personal connection between the worker or referee on one hand, and the employer on the other, could be a factor preventing the employer from terminating the employment relation.

6 Conclusion

This paper explored the effect of social contacts on wages and turnover in the Egyptian labour market using micro data from the Egyptian labour market panel survey. The results show that finding a job through friends or relatives yields a penalty on match quality for high skilled workers and a premium for low skilled workers. The overall effect on wages was not significant, but on the long run, there appears a differential in wages between connected and non-connected workers in favour of the latter. The effect is insignificant for low skilled workers, but negative and weakly significant for those who hold a university degree. For turnover, high skilled workers who found their jobs through social networks equally likely to have their employment terminated compared to their peers who used other methods. Conversely, low skilled workers who use networks enjoy longer tenure and lower job loss hazard.

This paper motivates future theoretical research in the role of social networks in the labour market in general, and in developing countries in particular. In search and matching models, additional areas in which social networks are included could be explored. First, the fact that a worker is using social networks could be a part of their signal of productivity to the employer. In this case, social networks can simultaneously increase the job arrival rate for a worker, pushing up their wages, and a signal of low productivity due to their reliance of social networks instead of formal channels, lowering their wages. This will yield an ambiguous direction of the relationship, which could explain why in some instances networks yield higher match quality and a lower in others.

Second, a more relevant setting for countries with no unemployment insurance scheme one in which outside option for workers, i.e. the utility flow to unemployment, could be related to the size of their social networks and thus their job arrival rate. A worker with a larger social network can

[14] In 2018, 88% of Egyptian workers are employed in firms with fewer than 100 employees, and 60% work in in firms with 4 or less employees. Author's calculations using ELMPS 2018.

rely on its support during unemployment, increasing their reservation wage and their initial wage. At the same time, a larger network could lead a mismatch between skill and occupation. This also yields an indeterminate direction of the relationship. Following this line of argument, models with social risk sharing between firms and workers could be explored. We can investigate the cases where firms or referees, accept or refer a worker for social reasons, whether they are altruistic, or as an investment in their own social networks that could yield them some benefits in the future.

A final point of this work concerns the notion of match quality. We assume that, for workers, a higher paying job, in which they stay for longer periods is a sign of a good match. However, this does not hold in many cases. Some studies such as Granovetter (1973), Topa (2019), and Nie and Yan (2021) discussed job satisfaction as another dimension of match quality. We observe that in the Egyptian labour market, low skilled low wage workers who find their jobs through social networks stay in their jobs for longer periods - arguably for the entirety of their working lives, which could reflect the absence of an alternative rather the quality of the job. Many in this group stay indefinitely in the informal sector without a job contract, or on a temporary contract. While these jobs are permanent, they lack the job security and stability of a permanent job. Therefore, although this could be measured as a match of quality, this reflects poor job quality.

References

Antoninis, M. (2006). The wage effects from the use of personal contacts as hiring channels. *Journal of Economic Behavior & Organization*, 59(1):133–146.

Assad, R. and Krafft, C. (2013). The structure and evolution of employment in egypt: 1998-2012. Working Paper No.805, Economic Research Forum.

Beaman, L. and Magruder, J. (2012). Who gets the job referral? evidence from a social networks experiment. *American Economic Review*, 102(7):3574–93.

Bentolila, S., Michelacci, C., and Suarez, J. (2010). Social contacts and occupational choice. *Economica*, 77(305):20–45.

Bian, Y., Huang, X., and Zhang, L. (2015). Information and favoritism: The network effect on wage income in china. *Social Networks*, 40:129–138.

Brown, M., Setren, E., and Topa, G. (2016). Do informal referrals lead to better matches? evidence from a firm's employee referral system. *Journal of Labor Economics*, 34(1):161–209.

Burks, S. V., Cowgill, B., Hoffman, M., and Housman, M. (2015). The value of hiring through employee referrals. *The Quarterly Journal of Economics*, 130(2):805–839.

Calvó-Armengol, A. and Jackson, M. O. (2007). Networks in labor markets: Wage and employment dynamics and inequality. *Journal of economic theory*, 132(1):27–46.

Calvó-Armengol, A. and Zenou, Y. (2005). Job matching, social network and word-of-mouth communication. *Journal of urban economics*, 57(3):500–522.

Cappellari, L. and Tatsiramos, K. (2015). With a little help from my friends? quality of social networks, job finding and job match quality. *European Economic Review*, 78:55–75.

Dustmann, C., Glitz, A., Schönberg, U., and Brücker, H. (2016). Referral-based job search networks. *The Review of Economic Studies*, 83(2):514–546.

El-Hamidi, F. (2010). Education-occupation mismatch and the effect on wages of egyptian workers. *Handbook on international studies in education*, pages 123–138.

Fontaine, I., Galvez-Iniesta, I., Gomes, P., and Vila-Martin, D. (2020). Labour market flows: Accounting for the public sector. *Labour Economics*, 62:101770.

Galenianos, M. (2013). Learning about match quality and the use of referrals. *Review of Economic Dynamics*, 16(4):668–690.

Galenianos, M. (2014). Hiring through referrals. *Journal of Economic Theory*, 152:304–323.

Galeotti, A. and Merlino, L. P. (2014). Endogenous job contact networks. *International economic review*, 55(4):1201–1226.

Glitz, A. (2017). Coworker networks in the labour market. *Labour Economics*, 44:218–230.

Granovetter, M. S. (1973). The strength of weak ties. *American journal of sociology*, 78(6):1360–1380.

Heath, R. (2018). Why do firms hire using referrals? evidence from bangladeshi garment factories. *Journal of Political Economy*, 126(4):1691–1746.

Hellerstein, J. K. and Neumark, D. (2020). Social capital, networks, and economic wellbeing. *The Future of Children*, 30(2020):127–152.

Horváth, G. (2014). Occupational mismatch and social networks. *Journal of Economic Behavior & Organization*, 106:442–468.

Kugler, A. D. (2003). Employee referrals and efficiency wages. *Labour economics*, 10(5):531–556.

Kuzubas, T. U. et al. (2009). Endogenous social networks in the labor market. *Unpublished, Unpublished manuscript, University of Minnesota*.

McPherson, M., Smith-Lovin, L., and Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual review of sociology*, 27(1):415–444.

Meyer, B. D. (1990). Unemployment insurance and unemployment spells. *Econometrica*, pages 757–782.

Mortensen, D. T. and Vishwanath, T. (1994). Personal contacts and earnings: It is who you know! *Labour economics*, 1(2):187–201.

Nie, P. and Yan, W. (2021). Effects of social networks on job attainment and match quality: Evidence from the china labor-force dynamics survey. Working Paper No. 14504, IZA.

OAMDI (2019). Labor market panel surveys (LMPS), version 2.0 of licensed data files; ELMPS 2018. Egypt: Economic Research Forum (ERF). Available at: http://erf.org.eg/data-portal/.

Pellizzari, M. (2010). Do friends and relatives really help in getting a good job? *ILR Review*, 63(3):494–510.

Rauch, J. E. (1999). Networks versus markets in international trade. *Journal of international Economics*, 48(1):7–35.

Saeed, M. (2019). Impact of the imf loan program on macroeconomic performance and social protection in egypt 2016/2019. *Management & Economics Research Journal*, 1(3):54–61.

Topa, G. (2011). Labor markets and referrals. In *Handbook of social economics*, volume 1, pages 1193–1221. Elsevier.

Topa, G. (2019). Social and spatial networks in labour markets. *Oxford Review of Economic Policy*, 35(4):722–745.

Wahab, M. A. (2017). Economic reform and structural adjustment program (ersap), & privatization. *Middle East Review of Public Administration (MERPA)*, 3(3):2760.

Wahba, J. et al. (2009). Informality in egypt: a stepping stone or a dead end? In *Cairo, Egypt: Economic Research Forum (ERF), Working Paper*, number 456.

Wahba, J. and Zenou, Y. (2005). Density, social networks and job search methods: Theory and application to egypt. *Journal of Development Economics*, 78(2):443–473.

Yang, X. et al. (2017). Analyzing interval-censored survival-time data in stata. In *2017 Stata Conference*, number 10. Stata Users Group.

Appendix

Table A.1: Labour force charateristics.

	1998	2006	2012	2018
Labour force				
Unemployed	11.6%	8.6%	8.8%	8.4%
Employed				
Wage employee	73.5%	65.3%	71.9%	74.7%
Employer	9.7%	13.1%	10.4%	7.2%
Self-employed	9%	10%	9.6%	10.9%
Level of education				
Illiterate	19.6%	21.9%	19%	17.5%
Reads and Writes	9.6%	6.6%	4.2%	6.3%
Less than Intermediate	17.2%	15.4%	16.1%	14.7%
Intermediate	27%	32.8%	36%	38.6%
Above Intermediate	7.6%	4.7%	3.9%	3.2%
University	18.7%	18.5%	20.8%	19.7%
Age group				
15 - 19	7.4%	6.2%	4.1%	4.6%
20 - 29	24.1%	30.5%	31.2%	24.7%
30 - 39	28.3%	26.2%	29.6%	33.9%
40 - 49	23.1%	20.8%	18.8%	20.1%
50 - 59	14.3%	14.1%	13.9%	14.3%
60 - 64	2.8%	2.2%	2.5%	2.4%
Gender				
Male	78.5%	76.5%	80.4%	81.5%
Female	21.5%	23.5%	19.6%	18.5%
Region				
Greater Cairo	19.7%	15%	11%	7.9%
Alexandria and Suez Canal	11.9%	10.3%	8.6%	5.9%
Urban Lower Egypt	16.6%	12.7%	11.5%	10.4%
Urban Upper Egypt	18.6%	15.6%	14.3%	13.5%
Rural Lower Egypt	20.2%	24.7%	29.3%	30.3%
Rural Upper Egypt	13%	21.6%	25.3%	32%
Observations	6343	11344	13990	15956

Notes: Author's calculations using ELMPS 2018.

Table A.2: Characteristics of wage workers.

	1998	2006	2012	2018
Wage workers				
Level of education				
Illiterate	14.3%	12.7%	12.9%	13.5%
Reads and Writes	8.7%	5.7%	3.7%	5.7%
Less than Intermediate	16.4%	14.6%	15.3%	13.7%
Intermediate	28.8%	36.5%	38.3%	40.3%
Above Intermediate	9%	6%	4.5%	3.7%
University	22.7%	24.4%	25.2%	23.1%
Age group				
15 - 19	6.6%	5.3%	3.6%	4.1%
20 - 29	24.4%	31.8%	33.3%	26.1%
30 - 39	29.8%	27.2%	30.8%	35%
40 - 49	23.6%	21.6%	18.3%	19.4%
50 - 59	14.2%	13.3%	13.3%	14.2%
60 - 64	1.5%	0.7%	0.8%	1.2%
Gender				
Male	77.9%	79.1%	82.2%	84.2%
Female	22.1%	20.9%	17.8%	15.8%
Region				
Greater Cairo	22.1%	19%	12.9%	9.3%
Alexandria and Suez Canal	13.3%	12.7%	10.1%	6.9%
Urban Lower Egypt	16.6%	13.3%	11.8%	10.6%
Urban Upper Egypt	18.8%	16.2%	15%	13.9%
Rural Lower Egypt	18.3%	23.4%	28%	29.3%
Rural Upper Egypt	10.9%	15.4%	22.1%	30%
Observations	4598	7377	9999	11739

Notes: Author's calculations using ELMPS 2018.

Table A.3: Employment characteristics of wage workers.

	1998	2006	2012	2018
Wage workers				
Work conditions				
Temporary	6.6%	10%	10.7%	14.6%
Seasonal	1%	0.4%	0.5%	2.1%
Casual	11.6%	10.3%	24.1%	20%
Institutional sector				
Government	47.6%	41.1%	36.1%	29.5%
Public entreprise	10.6%	7.6%	4.8%	2.6%
Private sector	39.9%	49%	56.5%	63.3%
Other	1.8%	2.2%	2.4%	1.3%
Occupation				
Managers	5.9%	5.1%	3.6%	2.9%
Professionals	24.4%	21%	20%	16.2%
Technicians	8.1%	13.8%	12.3%	5.9%
Clerical support	11.3%	6.4%	3.8%	8.2%
Service and sales workers	14.1%	16.3%	11.4%	15.6%
Agricultural workers	6.1%	6.4%	9.5%	12.3%
Crafts and related trades	20.8%	19.2%	20.1%	20.8%
Plant and machine operators	6.7%	8.8%	11.2%	10.2%
Economic Activity				
Agriculture	7.3%	7.6%	9.7%	12.9%
Manufacturing	18.4%	16.2%	14.1%	11.8%
Mining	0.4%	0.4%	0.3%	0.3%
Electricity, water, etc..	2.1%	2%	2.3%	1.7%
Construction	7.8%	9.8%	13.7%	16.2%
Services	46.3%	49.5%	47.2%	47.6%
Public administration	17.7%	14.6%	12.6%	9.5%

Notes: Author's calculations using ELMPS 2018.

Table A.4: Summary statistics.

	mean	sd	count	min	max
ln(hourly real wages)	2.296239	.7100595	32151	-3.7281	9.029748
Contacts (dummy)	.3325127	.4711206	33713	0	1
Years of schooling	10.36149	4.927327	33691	0	24
Tenure	11.62318	9.76113	33109	0	53
Age	35.80622	11.06153	33713	15	64
Household size	4.800374	2.126826	33713	1	26
Observations	33713				

Table A.5: Method for obtaining job for wage workers.

	1998	2006	2012	2018
Method of obtaining job				
Friends or relatives	29.9%	23.2%	30%	43.7%
Governmental office	30.5%	18.7%	12.5%	11.2%
Private office	0.3%	0.8%	1.3%	1.5%
Government job competition	15.8%	15.4%	14.4%	13.2%
Job application	5.3%	11.5%	11%	6.4%
Inquired at work location	2.3%	4.8%	2.3%	10.9%
Placed an ad.	0.6%	0.5%	0.4%	0.2%
Newspapers ad.	2.4%	1.9%	1.3%	1.8%
Gathering place	0.5%	0.9%	1.7%	5.4%
Other	11.9%	22.2%	25.1%	5.8%
Observations	4598	7377	9999	11739

Notes: Author's calculations using ELMPS 2018.

Table A.6: Percentage of workers who found their current jobs through social contacts (friends or relatives), continued.

	1998	2006	2012	2018
Work conditions				
Temporary	58.9%	42.5%	42.8%	57.1%
Seasonal	53.2%	46.2%	52%	65.9%
Casual	39%	22.3%	35.5%	59%
Institutional sector				
Government	7.3%	6.3%	6.9%	10.2%
Public entreprise	28.2%	23.4%	28.6%	23.1%
Private sector	56.7%	37.4%	44.7%	60.1%
Other	41%	24.2%	32.6%	29%
Occupation				
Managers	11.4%	5.1%	12%	17%
Professionals	9.1%	10.1%	11%	10.9%
Technicians	16.4%	16.1%	14.8%	27%
Clerical support	15.6%	15.6%	19.4%	19.3%
Service and sales workers	44.5%	35.5%	45.9%	52.6%
Agricultural workers	48.2%	28.8%	41.8%	60.1%
Crafts and related trades	46.3%	29.5%	35.1%	58.2%
Plant and machine operators	52.3%	35.7%	49.1%	62.9%
Economic Activity				
Agriculture	42.3%	25.5%	42%	58.6%
Manufacturing	49.1%	36.6%	42.6%	56.3%
Mining	40%	31%	29%	37.5%
Electricity, water, etc..	14.6%	11.5%	20.3%	21.2%
Construction	33.6%	20.6%	30%	52.4%
Services	28.5%	23.9%	29.4%	40.2%
Public administration	8.4%	8.2%	10.7%	14.1%

Notes: Author's calculations using ELMPS 2018.

Table A.7: Baseline OLS regressions for real hourly wages, by level of education.

	(1) 1998	(2) 2006	(3) 2012	(4) 2018
Contacts	0.057	0.056	-0.041	0.140***
	(0.046)	(0.043)	(0.034)	(0.036)
Contacts x Reads and writes	-0.020	-0.143*	0.046	-0.003
	(0.071)	(0.075)	(0.075)	(0.072)
Contacts x Less than intermediate	-0.051	-0.010	0.029	-0.029
	(0.061)	(0.056)	(0.047)	(0.053)
Contacts x Intermediate	-0.108*	-0.130**	-0.077*	-0.106**
	(0.058)	(0.051)	(0.040)	(0.042)
Contacts x Above intermediate	-0.299***	-0.140*	-0.068	-0.201**
	(0.093)	(0.075)	(0.087)	(0.093)
Contacts x University and Higher	-0.035	-0.130**	-0.056	-0.308***
	(0.073)	(0.063)	(0.051)	(0.053)
Controls	Yes	Yes	Yes	Yes
Observations	4545	7336	9913	9412
R^2	0.372	0.374	0.247	0.175

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Author's calculations using ELMPS 2018. **Dependent variable:** log real hourly wages. **Controls:** Level of education, age, age squared, gender, tenure, tenure squared, job stability, formality, household size, institutional sector and economic activity.

Table A.8: Baseline OLS regressions for real hourly wages, by occupation.

	(1) 1998	(2) 2006	(3) 2012	(4) 2018
Contacts	0.024	-0.273***	0.004	0.124
	(0.105)	(0.083)	(0.048)	(0.076)
Interaction with contacts				
Managers	0.047	0.165	-0.139	-0.240*
	(0.150)	(0.243)	(0.140)	(0.139)
Professionals	0.011	0.161	-0.098	-0.278***
	(0.131)	(0.103)	(0.069)	(0.097)
Technicians	-0.150	0.266***	-0.201***	-0.332***
	(0.130)	(0.102)	(0.072)	(0.100)
Clerical support	-0.157	0.010	-0.294***	-0.294***
	(0.122)	(0.115)	(0.088)	(0.101)
Service and sales workers	-0.079	0.293***	-0.115*	-0.067
	(0.116)	(0.092)	(0.063)	(0.085)
Agricultural workers	0.172	0.324***	-0.103*	0.026
	(0.122)	(0.097)	(0.059)	(0.084)
Crafts and related trades	-0.074	0.262***	-0.060	-0.043
	(0.111)	(0.090)	(0.056)	(0.079)
Plant and machine operators	0.104	0.281***	0.012	-0.066
	(0.122)	(0.093)	(0.062)	(0.088)
Controls	Yes	Yes	Yes	Yes
Observations	4545	7336	9913	9412
R^2	0.374	0.375	0.248	0.176

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Author's calculations using ELMPS 2018. **Dependent variable:** log real hourly wages. **Controls:** Level of education, age, age squared, gender, tenure, tenure squared, job stability, formality, household size, institutional sector and economic activity.

Table A.9: Wage differential by search method, compared to social contacts.

	(1) 1998	(2) 2006	(3) 2012	(4) 2018
Governmental office	0.046	0.100***	0.134***	0.048
	(0.035)	(0.030)	(0.031)	(0.037)
Private office	-0.015	-0.089	0.108	0.060
	(0.097)	(0.068)	(0.081)	(0.072)
Government job competition	0.077**	0.062**	0.111***	0.056
	(0.034)	(0.029)	(0.029)	(0.036)
Job application	-0.084*	-0.044	0.032	0.007
	(0.044)	(0.029)	(0.028)	(0.033)
Inquired at work location	0.003	-0.044	0.079*	-0.076***
	(0.055)	(0.034)	(0.043)	(0.022)
Placed an ad.	-0.082	-0.130	-0.031	-0.232
	(0.109)	(0.082)	(0.146)	(0.216)
Newspapers ad.	-0.012	-0.003	0.138*	0.016
	(0.054)	(0.045)	(0.072)	(0.058)
Gathering place	-0.017	0.039	0.093**	-0.092***
	(0.091)	(0.062)	(0.037)	(0.028)
Other	-0.018	0.067***	0.071***	-0.049
	(0.034)	(0.022)	(0.018)	(0.034)
Observations	4521	7324	9913	9412
R^2	0.373	0.377	0.247	0.173

Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Author's calculations using ELMPS 2018. **Dependent variable:** log real hourly wages. **Controls:** Level of education, age, age squared, gender, tenure, tenure squared, job stability, formality, household size, institutional sector and economic activity.

Table A.10: Job stability by formality and level of education.

	1998		2006		2012		2018	
Method of finding the current job	Other	Contacts	Other	Contacts	Other	Contacts	Other	Contacts
Percentage of workers with permanent jobs								
Total	85.4%	70.1%	81.9%	71.2%	68.7%	55.1%	70.3%	47.1%
Formality								
Informal	34.4%	54.2%	53%	61.5%	28.8%	42%	39%	41%
Formal	97.4%	91.5%	94.4%	84.4%	91.4%	82%	92.2%	79.2%
Level of education								
Low	63.6%	69.5%	68.2%	75%	42.2%	51.1%	46.8%	42.8%
Intermediate	86.4%	68.3%	81.4%	69.9%	65.9%	52.1%	67.8%	46.3%
High	97%	77.6%	91.4%	71.1%	87.1%	73.3%	84.4%	62.2%

Notes: Author's calculations using ELMPS 2018. **Low:** Illiterate and reads, and writes. **Intermediate:** Less than intermediate, intermediate, and above intermediate. **High:** University.

Table A.11: The effect of social contacts on turnover, alternative specifications.

	Weibull			Gompertz		
	(1)	(2)	(3)	(4)	(5)	(6)
Contacts	-0.051*	-0.203***	-0.066**	-0.087***	-0.253***	-0.097***
	(0.028)	(0.047)	(0.029)	(0.027)	(0.057)	(0.028)
Contacts x Intermediate		0.187***			0.223***	
		(0.059)			(0.065)	
Contacts x High		0.328***			0.268***	
		(0.086)			(0.085)	
Contacts x Managers and professionals			0.173			0.119
			(0.106)			(0.098)
ln_p	1.180***	1.181***	1.180***			
	(0.008)	(0.008)	(0.008)			
gamma				0.146***	0.146***	0.146***
				(0.002)	(0.002)	(0.002)
Observations	19592	19592	19592	19592	19592	19592
Log pseudolikelihood	-6.8e+03	-6.8e+03	-6.8e+03	-8.4e+03	-8.4e+03	-8.4e+03

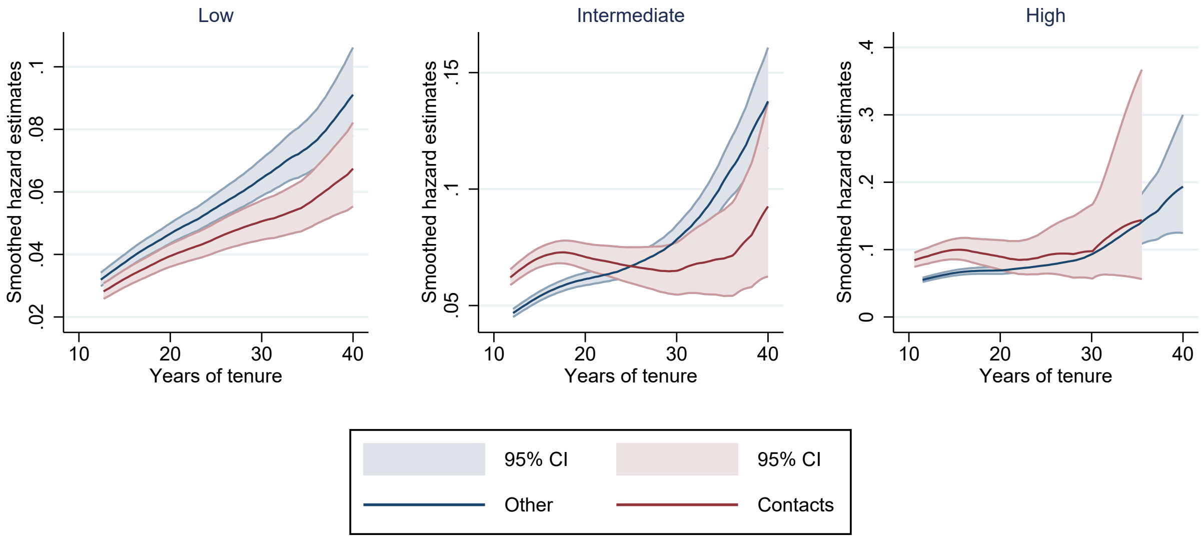
Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Author's calculations using ELMPS 2018. **Dependent variable:** Hazard ratio. **Controls:** Level of education, age, age squared, gender, job stability, formality, household size, institutional sector and economic activity.

Table A.12: The effect of social contacts on turnover, (1)-(3) Cox proportional hazard model, (4)-(6) interval censoring model (equation 10).

	Cox			Interval censoring model		
	(1)	(2)	(3)	(4)	(5)	(6)
Contacts	-0.063**	-0.215***	-0.077***	-0.183***	-0.348***	-0.189***
	(0.025)	(0.044)	(0.025)	(0.017)	(0.038)	(0.018)
Contacts x Intermediate		0.186***			0.166***	
		(0.054)			(0.043)	
Contacts x High		0.326***			0.375***	
		(0.078)			(0.056)	
Contacts x Managers and professionals			0.161*			0.056
			(0.093)			(0.063)
ln_p				1.629***	1.631***	1.629***
				(0.008)	(0.008)	(0.008)
Observations	19592	19592	19592	21871	21871	21871
Log pseudolikelihood	-7.5e+04	-7.5e+04	-7.5e+04	-1.8e+04	-1.8e+04	-1.8e+04

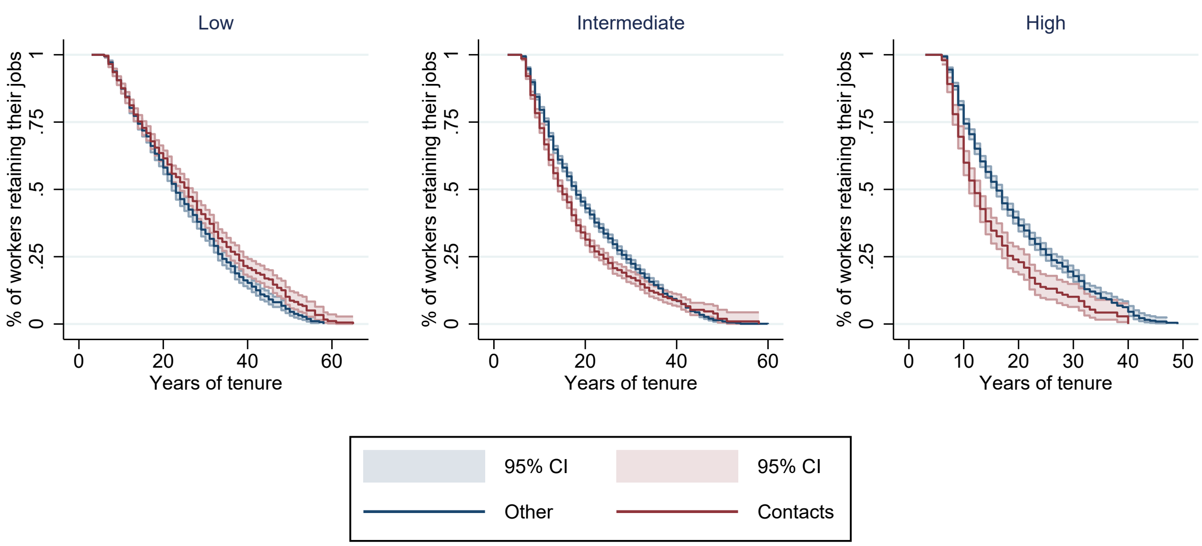
Notes: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Author's calculations using ELMPS 2018. **Dependent variable:** Hazard ratio. For (4)-(6) we followed a Weibull specification for the baseline parametric hazard. **Controls:** Level of education, age, age squared, gender, job stability, formality, household size, institutional sector and economic activity.

Figure A.1: Smoothed hazard estimates by search method and level of education.



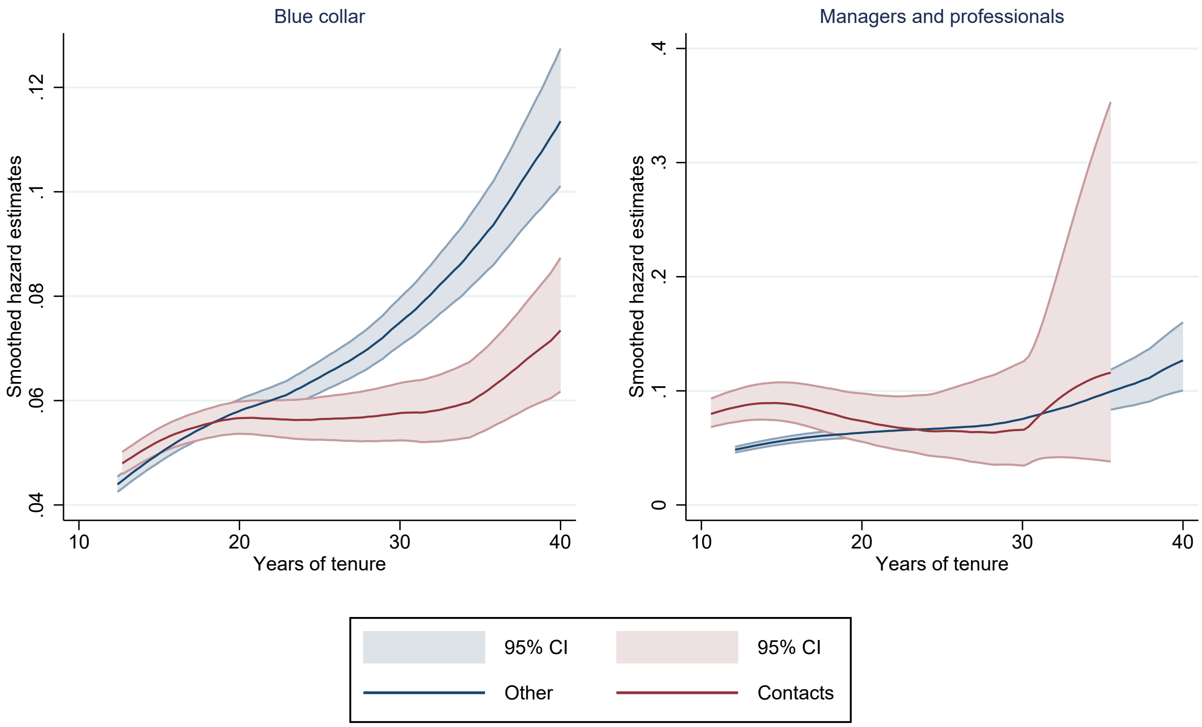
Notes: Author's calculations using ELMPS 2018. **Low:** Illiterate and reads, and writes. **Intermediate:** Less than intermediate, intermediate, and above intermediate. **High:** University.

Figure A.2: Kaplan-Meier survival estimates by search method and level of education.



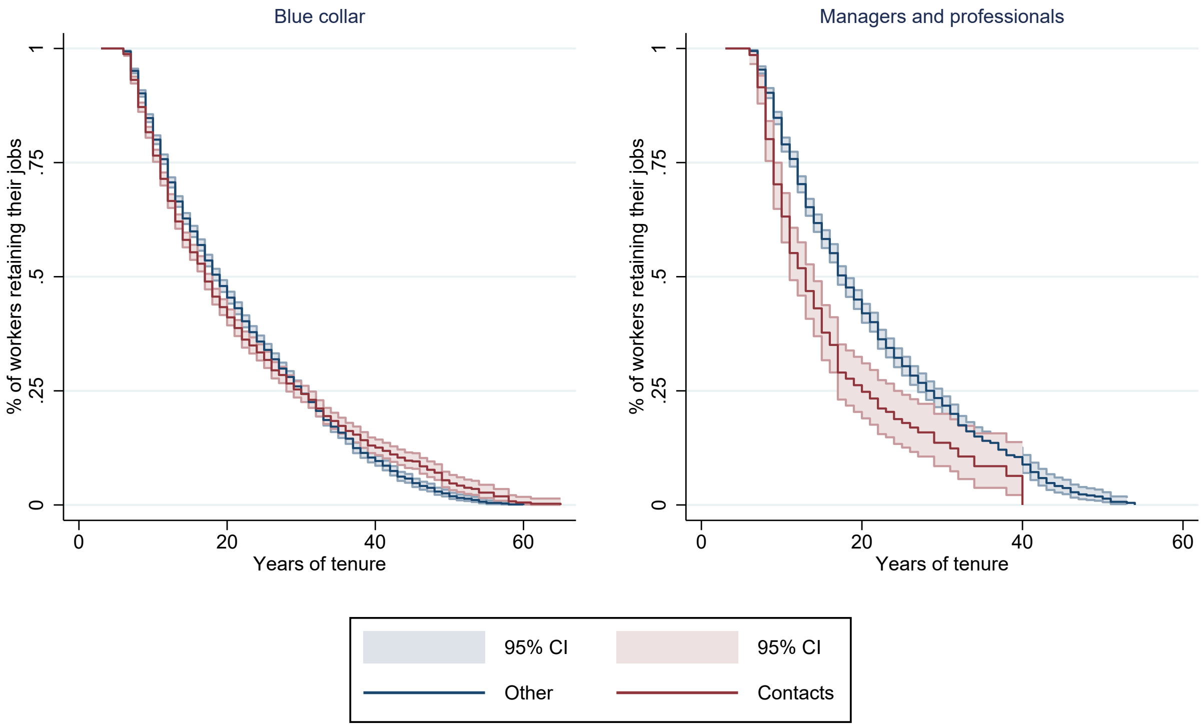
Notes: Author's calculations using ELMPS 2018. **Low:** Illiterate and reads, and writes. **Intermediate:** Less than intermediate, intermediate, and above intermediate. **High:** University.

Figure A.3: Smoothed hazard estimates by search method and occupation.



Notes: Author's calculations using ELMPS 2018.

Figure A.4: Kaplan-Meier survival estimates by occupation.



Notes: Author's calculations using ELMPS 2018.