Job Search Channels, Neighborhood Effects and Wages Inequality in Developing Countries: The Colombian Case

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Abstract

In this paper we analyze the relationship between social networks and the job search behavior of individuals. Networking is not based just only on friends and relatives. Individuals who are in physical and social proximity share the same sources of information because they share individual characteristics or because they learn from one another' behavior. The geographic proximity is associated to social interactions. Using data from Colombia we explore how the neighborhood has an effect on channel used to search a job. In addition, we study also the inequality due to use a different job search method. We find that the way as the neighbors have found their employment affects the individual's own job search. We find also that the inequality is great at the bottom of wage distribution between people that have found a job through formal channel with to respect people that have used informal channel.

JEL classification: *J11, I18, H55*

Keywords: Job search; Formal and informal networks; Neighborhood effects; Quantile regression

1 Introduction

Networking has increasingly become important not only in gaining friends but also for job searches. Social networks are an important source of information in the labor market and many workers find jobs through their network of friends and relatives. People that search for a job have several options to find it: read newspapers, go to employment agencies, browse in the web and mobilize their local networks of friends and relatives. The empirical evidences indeed suggest that about half of all jobs are founded through contacts. Holzer (1988) shows that among 16-23 years old workers who reported job acceptance, 66% used informal search channels. More evidence also is reported by a recent study by Franzen and Hangartner (2006) around 44% of the workers in the U.S. and 34% of the workers in Germany have found their jobs through social networks.

Given that the social network play an import role in the find a job, the characteristics of that network are likely to influence the intensity and the outcomes of networking. Not only the individual difference determinants of networking are important, but also the effects of networking on employment outcomes. Job seekers with a larger or better composed social network are more likely to use that network in their job search (see Montgomery, 1991). Individuals tend to use several sources of information during job search, particular attention is paid to the choice of search channels and its impact on labor market outcomes (see e.g. Holzer, 1988, van den Berg and van der Klaauw, 2006 and Weber and Mahringer, 2008).

In particular, the literature distinguish between two different search channels: formal and informal search. Formal search is defined as search by newspaper advertisements, internet, public employment office, etc., while informal search refers to search via friends and relatives.

An extensive literature analyzes the effect of networks and informal search on labor market outcomes. One of the most important assumption is that informal job contacts reduce informational asymmetry and this is traduced in terms of labor market outcomes to higher wages and high job duration. However, the empirical evidence is rather mixed it has been found that informal search channel can be associated with a premium as well as with a penalty in terms of wages and employment stability (see Ioannides and Datcher Loury, 2004).

Based on theoretical job search models with differential search channels, this work focus on the search channel choice, network effects, and corresponding labor market outcomes. In particular, with respect to other studies we consider the social interactions that operate at the level of the residential neighborhood as network effect. Methods of job search also vary by location. Elliott (1999) finds that those in high-poverty neighborhoods were substantially more likely to use informal job-search methods than those from low-poverty neighborhoods The geographic proximity is associated to social interactions. Individuals who are in physical and social proximity share the same sources of information because they share individual characteristics or because they learn from one another' behavior (Manski, 2000). Topa (2001) finds geographic correlations in patterns of unemployment across neighborhoods and cites them as evidence of positive correlation between employment and wages of networked individuals. He find that high unemployment rates were concentrated in relatively few areas of Chicago in 1980 and 1990. Conley and Topa (2003a) find that socioeconomic characteristics (and in particular ethnic and occupational distance) explain a substantial component of the spatial dependence in unemployment. The proper identification of such neighborhood effects is complicated, however, by the nonrandom sorting of households into neighborhoods and the likely presence of unobserved individual and neighborhood attributes.

Using data from Colombia we propose a new empirical strategy for identifying neighborhood effects on the job search channel and labour market outcomes. In particular we estimate the probability to find a job trough a informal and informal channel looking at the neighbored effects. In addition, this paper also provide an explanation for the variation in wage differentials between jobs found through formal and informal channels. Using a quantile decomposition we can analyzing the distribution of wage distribution by channel of search.

Our results show that search channel is influenced by the way as the neighbors have found their current employment. We find evidence that individuals that live close to other individuals that have found job by formal network have more probability to use the same channel. We also find significantly positive effects of channel used on the wage. Inequality increase across people that have used informal channel in Colombia, especially at the bottom of wage distribution. From a policy point of view to avoid this inequality the government need to take more action in avoid spatial segregation across people.

The remainder of the paper is as follows. Section 2 describes the data used. Section 3 describes the theoretical framework and present the results of the estimation of the probability to use informal or formal channel. Estimation of wage is presented in Section 4. Section 6 is devoted to the discussion and conclusions.

2 Data

The data used in this paper come from the Great Integrated Household Survey (GIHS) for 2009, carried out by the National Administrative Statistics Department (DANE). This cross-section survey has information at micro-data level on labor force of twenty-three major cities with their metropolitan areas in Colombia.[1]

[1]Namely, Medellín, Barranquilla, Bogotá Cartagena, Tunja, Manizales, Florencia, Popayan, Valledupar, Montería, Quibdó, Neiva, Rioacha, Santa Marta, Villavicencio, Pasto, Cúcuta, Armenia, Pereira, Bucaramanga, Sincelejo, Ibagué and Cali.

The sample considered in this work is composed of employees between 16 and 65 years old who have found employment in at least one year. Our final sample is composed by 42179 observations.[2] Turning to the job search channels, in the survey workers are asked to indicate how they have found their current job. There are seven possible job search channels which can be choose only one time:

1. through family, friends or other contacts;
2. by applying to the employer directly;
3. by applying to employment agencies or intermediaries;
4. by inserting or answering adverts in newspapers;
5. by applying to selection processes by convening, it usually government enterprises;
6. through the information system of the SENA[3];
7. other.

These seven alternatives have been regrouped to define two kinds search channels: jobs found through formal and informal channels. In the first channel we regard the alternatives 3, 4, 5 and 6, while in the second channel we include the alternatives 1, 2 and 7. Table 1 depicts some descriptive statistics of all variables used in the analysis for the full sample and for formal channel and informal channel sub-samples.

As Table 1 shows the most workers have found their current job using informal networks (92%). This prevalence of informal channels shows that the Colombian labor market is not sufficiently institutionalized, which could indicate that there are significant deficiencies in the labor intermediation process. With regards to other variables of the labor market, we can see that the average wage among workers who have found job through formal channels is higher than the corresponding average among workers who have found job through formal ones, indeed, the latter earn 30% less than the former. Regarding human capital and personal variables we can see that workers who used formal channels to find their job are on average three younger and more educated than those who used informal networks. Jobs found through formal channels have a higher percentage of individuals with tertiary education (52%), while jobs found through informal channels have a much higher percentage of individuals with primary and secondary education (71%). In the main, there are not differences by gender or marital status between the job search channels: around 50% and 40% of workers have found job using formal or informal channels are men and married, respectively. We also see that individuals who had found out about their current job through a informal contact have more probability of have dependent kids (40%) than those who used formal contacts (35%).

[2]Notice that all employers and self-employed are excluded here.

[3]SENA (*Servicio Nacional de Aprendizaje*) is a national public institution that offers course in technical and vocational training to workers. This institution has an information system which connects the unemployed with the vacancies generated by entrepreneurs. This service is free for both employees and employers.

As regards the characteristics of employment we can see that jobs found through personal contacts or informal networks are concentrated into jobs with less qualification, 61% are blue collar workers, while 56% of those who have found their current job using formal networks are managers or white collar workers. It is also possible to observe that jobs found through formal or informal channels appear to be generally concentrated in the private sector, this is particularly true in the latter channel. The use of informal networks also appears to lead more frequently to jobs in very small sized firms (50%), on the contrary the use of formal networks lead to jobs in firms with more than 51 employees (79%). Finally, data shows that 21% of workers who have found their jobs through formal channels are employed in the industrial sector, similar percentage there is for jobs in the administration public, followed by jobs in the commerce (17%) sector. Meanwhile, the use of informal channels most likely lead to jobs in the service (23%) and commerce sector (21%).

In the empirical literature on social networks typically define a network according to geographic or cultural proximity of a group of individuals. In this paper we use physical proximity among individuals as a measure of social network. Specifically, we measure the social interactions on job search that operate at the level of the residential neighborhood. The underlying idea is that agents exchange information about job opportunities more frequently with people who live physically close. Figure 1 shows the residence of workers at city block level for Bogotá distinguish between formal and informal job search channel in two different years.[4] For 2009 in the whole sample there are on average approximately 9 workers per city block who have found their current employment using informal networks and approximately 2 workers per city block who found job through formal networks. Hence, the neighborhood effects variable is defined as the ratio of the number of individuals who live in the same block g and have found job through a formal channel in a common economic sector s ($Nformalc_{gs}$) to the total number of individuals in the same block and sector (N_{gs}):

$$\text{Neighborhood effects}_{gs} = \frac{Nformalc_{gs}}{N_{gs}} \tag{1}$$

3 Effects of the social interactions on job search channels

In order to analyze the effects of job search of the neighbors on individual job search, we estimate binary probit models of job search channels. Hence, the probability of using formal networks to find a job can be modeled as

$$Prob(C_i^* > 0) = Prob(N_{gs}\gamma + X_i\beta_i + u_i > 0), \tag{2}$$

[4]The scale of city block in Colombia is comparable to that used in the US Census.

where C_i^* is a latent variable that reflect an underlying benefit - cost calculation of job search through formal channels of individual i; our neighborhood effects variable is contained in N; the individual's observable characteristics are given by X; α and β are set of matrices of parameters to estimate; and u is a component of error which we assume that is distributed (identically and independently) normal with mean zero and variance one. Since we do not observe the latent variable C^*, but we do observe that type of channel has been used (formal, $C = 1$; informal, $C = 0$), formally the probability model can be write as

$$Prob(C_i = 1|N_i, X_i) = \Phi(N_i\gamma + X_i\beta_i + u_i) \;\; iff \;\; C_i^* > 0, \tag{3}$$

where Φ is the standard normal cumulative distribution function.

The results obtained from the estimation of several specifications of the probit model are presented in Table 2. The reported values in the table are marginal effects calculated at the sample mean of the explanatory variables. By and large, the results show that the channel through which the neighbors have found job has an important effect on the individual choice of channel job search, that is, the way as the neighbors have found their employment affects the individual's own job search. It is noted that when we included job characteristics, firm size dummies, city dummies, occupation and industry dummies as additional explanatory variables, a higher proportion of neighbors who have found job by formal channels increases the probability of using formal channels by 8.5 percentage points.

Regarding the personal characteristics variables, the findings display that there are not significant differences in the job search channels between women and men, and married and non-married people. Education has a positive relationship with the use of formal networks to find a job, but only at high education levels. This result suggest two things. On the one hand, it suggest that while the tertiary education gives access to labor market given a higher qualification, the secondary o primary education are levels which only allow individuals to continue in the education system. On the other hand, individuals with high levels qualifications usually do not seek job through informal channels and firms do not use informal channels to fill high-skilled position. We have therefore that a individual with tertiary education increases the likelihood of using an formal job search channel by 3.3 percentage points. As regards age we can see that this variable has a negative and increased effect on the probability of using formal networks. This may reflect the fact that older workers are less likely to search actively a job. Finally, variables related to the type of employment indicate that workers in the private sector are more probable to search jobs through informal channels, while there is a positive relationship between more formal jobs which have any type of contract and formal networks.

4 Empirical Model and Results

4.1 Quantile regression model of wage decomposition

In recent years a new literature has estimated the gender pay gap based on the quantile regression, by looking at the effects of gender and other covariates on different quantiles of log wage distribution and not only at the average of variables.

Koenker-Basset (1978) proposed a complete new and different method of calculating the quantile regression that can be estimated by minimizing in $\beta(\tau)$ the following expression:

$$\widehat{\beta}(\tau) = min\ n^{-1}\left[\sum_{i}^{n} \rho_\tau(Y_i - X_i\beta)\right],\ (i = 1, ...n),$$

with the check function ρ_τ weighting the residuals μ_i asymmetrically:

$$\rho_\tau(\mu_i) = \begin{cases} \tau\mu_i & if\ \mu_i \geq 0, \\ (\tau - 1)\mu_i & if\ \mu_i < 0. \end{cases}$$

Starting from the study of Koenker-Basset (1978), Machado and Mata (M-M) in 2005 proposed a method to extend the traditional Oaxaca-Blinder decomposition based on the quantile regression. Considering two groups, 0 and 1, whose stochastic characteristics for each group are X_0 and X_1, the regression quantile can be written for each group as:

$$Q_y(Y|X) = X_i\beta(\tau) \qquad \forall\tau, i \in (0, 1) \tag{4}$$

where $Y|X$ is the conditional quantile. M-M propose an estimation of the counterfactual unconditional wage distribution, generate a random sample of size m from a uniform distribution $U[0, 1]$, and then calculate the conditional quantile regression for each group. They simulate the wage distribution of the second group on the basis of the wage distribution and the characteristics of the first group, and repeat these steps m times.

The difference of the unconditional quantiles between the two groups can be decomposed as:

$$\widehat{F}_{Y1}^{-1}(\theta|T = 1) - \widehat{F}_{Y0}^{-1}(\theta|T = 0) = \underbrace{\widehat{F}_{Y1}^{-1}(\theta|T = 1) - \widehat{F}_{Y1}^{-1}(\theta|T = 0)}_{Characteristics} + \underbrace{\widehat{F}_{Y1}^{-1}(\theta|T = 0) - \widehat{F}_{Y0}^{-1}(\theta|T = 0)}_{Coefficients}$$

where $\widehat{F_{Yt}^{-1}}(\theta|T = t)$ denotes the θ^{th} quantile of wage Y for groups t's while $\widehat{F}_{Y1}^{-1}(\theta|T = 0)$ is the counterfactual unconditional wage distribution.

4.2 Results of quantile decomposition

Before to enter in the model estimation of wage decomposition between channel it interesting have some previous analysis on wage. We can see in Figure 2 the Kernel density estimation of logarithm of wage between formal and informal channel. The formal channel present a swift on the left and his distribution, means that people that enter with formal market have better wage at the top of distribution, while at the bottom, both groups are equally. However, the formal channel seems to earn more than informal without any variable control. In Table 3 we present the simple OLS model with 3 specification : M1, M2 and M3. One of explicative variable is the channel. As we can observe, this variable have a positive and significant effect on wage when we do not control for other labour characteristics (M1). However, in specification M2 and M3 become negative and significant. Using formal channel reduce the wage. The rest of variables are in line with the Mincer equation, age, education, marital status and have a contract. Instead, does not have a contract, be female and have dependent kids make to earn less wage. From this first analysis we can conclude that the channel used for search a job has an effect on the wage. In Table 4 the percentile regression by formal or informal channel is presented.

The next step is to check how different is the wage earned by these two groups of people that have used different channels of search. To do that a quantile regression is the most appropriate method. We present the model of Machado and Mata of wage decomposition by channel used for search a job in Figures 3. In this Figure are reported the decomposition of wage in coefficients and characteristics. In addition, we show also the overall and interval of confidence of coefficients. We can observe as the wage gap between formal and informal is positive. Part of this gap is due at difference in the coefficients, especially at the bottom of distribution. One possible explanation of this difference is originated of the segregation that the informal channel is subjected. Instead, looking at the top of wage distribution, the wage gap founded is due at different characteristics between individuals that use formal and informal channel. The returns on formal channel are quite huge with respect to the informal one.

5 Conclusion

In this paper we analyze the relationship between social networks and the job search behavior of individuals. Networking is not based just only on friends and relatives. Individuals who are in physical and social proximity share the same sources of information because they share individual characteristics or because they learn from one another' behavior. The geographic proximity is associated to social interactions. Using data from Colombia we explore how the neighborhood has en effect on channel used to search a job. In addition, we study also the inequality due to use a different job search method.

Our results confirms the theory that the proximity is a social interaction and has an influence on job search method. People use more formal or informal channel if their neighborhood also have used this method. Looking at the wage distribution across people who have used formal or informal channel we find that inequality is present at the bottom of wage distribution. While at the top of wage distribution the difference is due at difference in characteristics, at the bottom of distribution the difference is due at unobservable factors. In particular, part of this inequality that we obverse is due to segregation across neighborhood. Colombia Government need to address policies that avoid to increase more this inequality.

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Table 1. **Summary statistics**

	All sample		**Job search channels**			
			Informal		**Formal**	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Hourly wage $	1.49	1.33	1.43	1.28	2.05	1.73
Male	0.49	0.50	0.49	0.50	0.51	0.50
Age	30.88	10.39	31.07	10.51	28.51	8.42
Education:						
Less than primary	0.02	0.13	0.02	0.13	0.001	0.02
Primary	0.34	0.47	0.36	0.48	0.08	0.27
Secondary	0.35	0.48	0.35	0.48	0.40	0.49
Tertiary	0.29	0.45	0.27	0.45	0.52	0.50
Married	0.44	0.50	0.44	0.50	0.40	0.49
Dependent Kids	0.39	0.49	0.40	0.49	0.35	0.48
Region:						
Atlantic	0.24	0.43	0.24	0.43	0.24	0.43
Oriental	0.19	0.39	0.19	0.39	0.16	0.37
Central	0.35	0.48	0.35	0.48	0.35	0.48
Pacific	0.14	0.35	0.14	0.35	0.14	0.35
Bogota	0.08	0.28	0.08	0.27	0.10	0.31
Private sector	0.97	0.18	0.97	0.16	0.84	0.36
Occupation:	6.76	2.47	6.83	2.43	5.84	2.69
Manager	0.07	0.25	0.07	0.25	0.10	0.30
White collar	0.05	0.22	0.05	0.21	0.10	0.30
Low white collar	0.28	0.45	0.28	0.45	0.36	0.48
Blue collar	0.20	0.40	0.20	0.40	0.16	0.37
Low blue collar	0.40	0.49	0.41	0.49	0.27	0.45
Size firm:						
1 - 10 emp	0.52	0.50	0.56	0.50	0.08	0.27
11 - 50 emp	0.16	0.36	0.16	0.37	0.13	0.33
51 or more emp	0.32	0.47	0.28	0.45	0.79	0.41
Sector:						
Agriculture	0.02	0.13	0.02	0.13	0.02	0.14
Industry	0.15	0.35	0.14	0.35	0.21	0.41
Building	0.09	0.29	0.10	0.30	0.01	0.11
Commerce	0.21	0.40	0.21	0.41	0.17	0.38
Hotel	0.08	0.28	0.09	0.28	0.03	0.18
Transport and tel	0.07	0.26	0.07	0.26	0.09	0.28
Financial	0.08	0.28	0.08	0.27	0.12	0.33
Adm. Pub	0.08	0.27	0.07	0.25	0.21	0.41
Service	0.22	0.41	0.23	0.42	0.13	0.34
N	42179		39036		3143	

Figure 1. Location of workers at city block level for Bogotá distinguish between job search channels

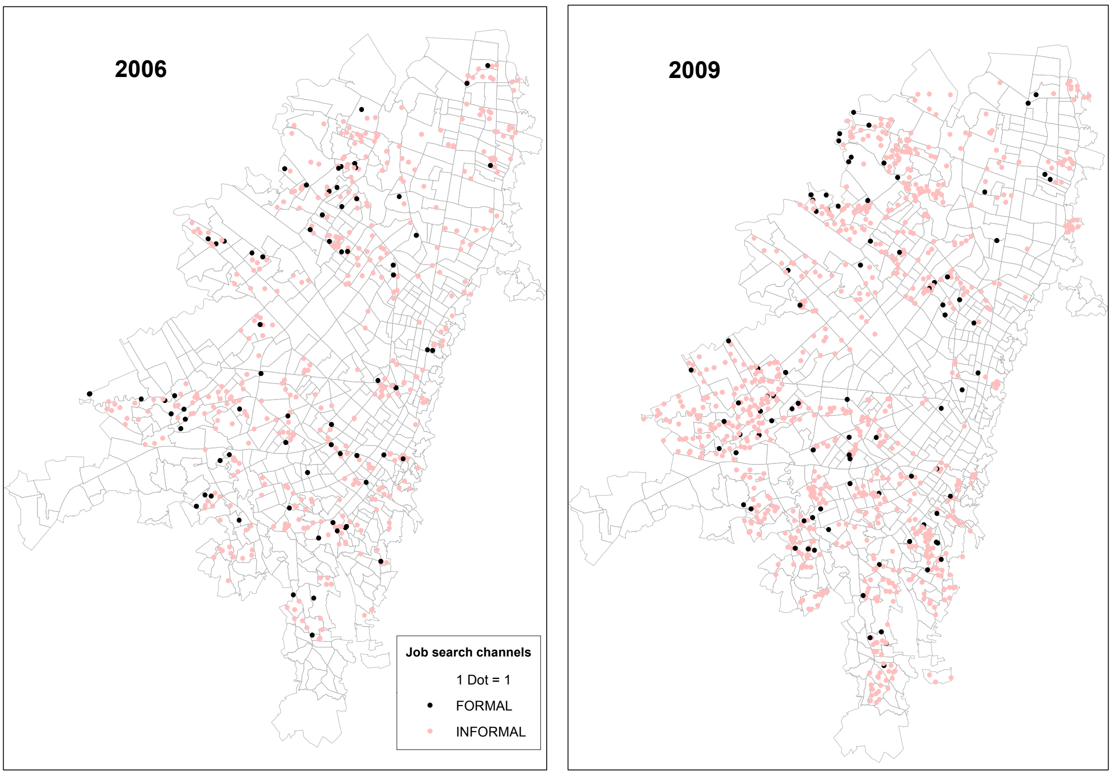

Table 2. **Probability models**

	(1)	(2)	(3)
Neighborhood effects	0.199***	0.093***	0.085***
	(0.010)	(0.011)	(0.011)
Male	0.014***	-0.005*	-0.005*
	(0.003)	(0.003)	(0.003)
Age	0.0003	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)
Age2	-0.00001	0.00003***	0.00002***
	(0.00001)	(0.00001)	(0.00001)
Marital	0.006**	0.0002	0.0001
	(0.003)	(0.003)	(0.003)
Dependent kids	-0.008***	-0.005*	-0.004
	(0.003)	(0.003)	(0.003)
Education:			
Primary	0.005	-0.005	-0.007
	(0.010)	(0.010)	(0.010)
Secondary	0.064***	0.017	0.015
	(0.010)	(0.010)	(0.010)
Tertiary	0.109***	0.034***	0.033***
	(0.010)	(0.010)	(0.010)
Contract		0.017***	0.021***
		(0.003)	(0.004)
Private sector		-0.155***	-0.163***
		(0.008)	(0.008)
Constant	0.007	0.224***	0.238***
	(0.016)	(0.019)	(0.019)
N	42179	42179	42179
Firm size dummies	N	Y	Y
Occupation and industry dummies	N	Y	Y
City dummies	N	N	Y

Robust standard errors in parentheses. Less than primary education as reference for education

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 2. Kernel density of log wage by formal and informal channel

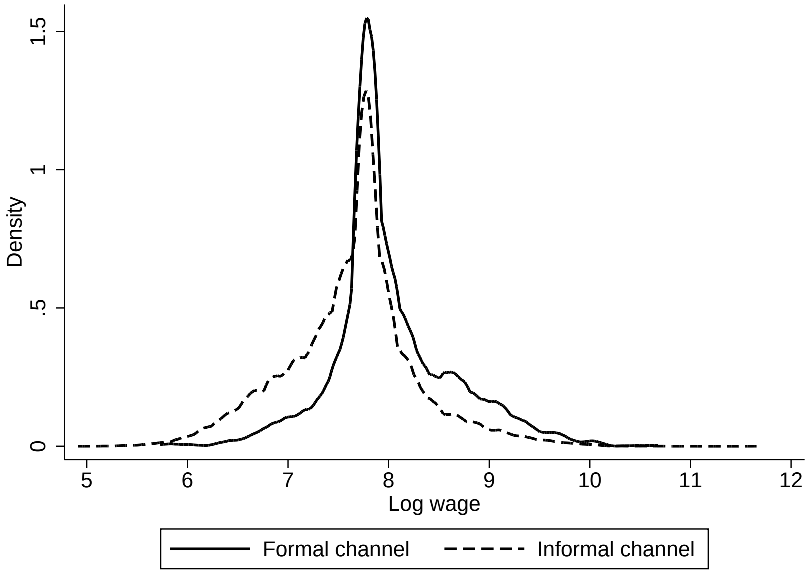

Table 3. **Log Wage, all sample**

	M1	M2	M3
Formal Channel	0.165***	-0.015	-0.031***
	(0.010)	(0.009)	(0.009)
Age	0.050***	0.034***	0.035***
	(0.002)	(0.002)	(0.001)
Age2	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Male	0.240***	0.094***	0.094***
	(0.005)	(0.005)	(0.005)
Marital	0.105***	0.066***	0.068***
	(0.006)	(0.005)	(0.005)
Dependent kids	-0.035***	-0.015***	-0.017***
	(0.006)	(0.005)	(0.005)
Education:			
Primary	0.289***	0.233***	0.202***
	(0.021)	(0.019)	(0.018)
Secondary	0.563***	0.383***	0.354***
	(0.021)	(0.019)	(0.018)
Tertiary	1.094***	0.657***	0.631***
	(0.022)	(0.020)	(0.019)
Have a contract		0.011*	0.108***
		(0.006)	(0.007)
Private sector		-0.261***	-0.293***
		(0.018)	(0.018)
Constant	5.964***	7.039***	7.157***
	(0.034)	(0.038)	(0.038)
N	42179	42179	42179
Firm size dummies	N	Y	Y
Occupation and Industry dummies	N	Y	Y
City dummies	N	N	Y

Robust standard errors in parentheses. Less than primary education as reference for education $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 4. **Log Wage at different percentile**

	Job search channels					
	Formal	Informal	Formal	Informal	Formal	informal
	Q20		Q50		Q80	
Age	0.064***	0.039***	0.028***	0.031***	0.025***	0.024***
	(0.008)	(0.002)	(0.007)	(0.002)	(0.007)	(0.002)
Age2	-0.001***	-0.000***	-0.000***	-0.000***	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.017	0.086***	0.016	0.098***	0.051***	0.099***
	(0.019)	(0.008)	(0.012)	(0.006)	(0.018)	(0.006)
Marital	0.032	0.054***	0.023	0.053***	0.015	0.061***
	(0.020)	(0.007)	(0.016)	(0.006)	(0.021)	(0.006)
Dependent kids	-0.015	-0.015*	-0.015	-0.018***	-0.016	-0.022***
	(0.020)	(0.008)	(0.016)	(0.006)	(0.020)	(0.005)
Education:						
Primary	-0.235	0.161***	0.008	0.190***	0.117	0.161***
	(0.196)	(0.021)	(0.103)	(0.016)	(0.081)	(0.020)
Secondary	-0.107	0.300***	0.091	0.338***	0.223***	0.295***
	(0.200)	(0.022)	(0.107)	(0.017)	(0.081)	(0.021)
Tertiary	-0.008	0.508***	0.193*	0.580***	0.443***	0.591***
	(0.200)	(0.021)	(0.108)	(0.017)	(0.083)	(0.024)
Have a contract	0.251***	0.158***	0.189**	0.108***	0.033	0.062***
	(0.080)	(0.011)	(0.077)	(0.008)	(0.060)	(0.007)
Private sector	-0.007	-0.320***	-0.247***	-0.392***	-0.302***	-0.408***
	(0.063)	(0.019)	(0.061)	(0.017)	(0.056)	(0.025)
Constant	6.468***	6.729***	7.755***	7.379***	8.118***	8.092***
	(0.245)	(0.046)	(0.170)	(0.039)	(0.153)	(0.047)
N	3143	39036	3143	39036	3143	39036
Firm size dummies	Y	Y	Y	Y	Y	Y
Occupation and Industry dummies	Y	Y	Y	Y	Y	Y
City dummies	Y	Y	Y	Y	Y	Y

Robust standard errors in parentheses. Less than primary education as reference for education

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 3. Quantile Decomposition