Using your ties to get a worse job? The differential effects of social networks on quality of employment: Evidence from Colombia

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Abstract

This article examines the effect of social networks through the use of family, friends or relatives ties on quality of employment (QoE). Drawing from the socioeconomic literature on social networks and labor market, we propose an original and multidimensional measure of QoE, and a fruitful estimation approach of the effect of social networks on QoE that allows to deal with complex inter-groups heterogeneity. Using the Great Integrated Houshold Survey (GIHS) and a sample on Bogota's workers in 2013, we find evidence proving that the use of ties has high negative effects on QoE index for those who are in the lower quality of employment range. Likewise, the use of social networks has very low negative effects on QoE index for individuals who are in the better quality of employment range. Complemented by focus groups interviews, these empirical results raise questions about the difference prevailing in relational practices between *necessity networks* for precarious workers and *opportunity networks* for protected workers.

JEL. J42, L14, O54, Z13

Keywords. Social networks, Quality of employment, Finite Mixture Regression Model, Colombia

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1 Introduction

Jobs and quality of employment are important challenges facing developing countries (DCs) for their structural transformation (World Bank 2013; OECD 2016; McMillan *et al.* 2014). Since the 1980s, the context of increasing globalization, urbanization and political mutations made it difficult to characterize urban labor market dynamics. However, a proper grasp of this social sphere is crucial to efficiently orient public policies of employment.

In a socioeconomic perspective, to understand the dynamics of labor markets it is essential to analyze the social and institutional processes in which individuals and markets are embedded (Smelser and Swedberg 2005). Since Granovetter's seminal study (1974), sociological and economic literatures have emphasized on the importance of social networks in market functioning and in individual behaviors (Rauch and Casella 2001; Jackson 2014). This relational embeddedness of economic actions means that abstracting from social interactions comes with the risk of severely misunderstanding behaviors and their causes (Granovetter 1985). In fact, designing many economic policies requires a deep understanding of social relations and network effects (Jackson *et al.* 2017). In developed labor markets, researches on informal contacts show that a major part of jobs and activities are obtained or developed through family, friends or relatives (Petersen *et al.* 2000; Topa 2011). *A fortiori*, these issues are crucial in DCs which are characterized by formal institutions failing to channel information about market opportunities in which social networks are employed frequently for job search[1] (Fafchamps 2006). Relational embeddedness plays an important but also ambiguous role in determining various labor market outcomes (Ioannides and Datcher Loury 2004; Datcher Loury 2006; Pasquier-Doumer 2013; Bramoullé *et al.* 2016; Nguyen and Nordman 2017).

Some theoretical and empirical studies argue that social networks generate opportunities and are a good channel for the transmission of job information for job-seekers or employees. For unemployed workers, the use of ties may reduce the duration dependence on the exit rates out of unemployment (Calvó-Armengol and Zenou 2005; Bramoullé and Saint-Paul 2010). Kramarz and Skans (2014) indicate that parental ties are an important determinant of how Swedish young workers find and progress in their job. In the United-States, Hispanic men report more frequent use of friends and relatives for job search than non-Hispanic, and found their more recent job through personal networks (Smith 2000). In DCs, Magruder (2010) demonstrates that using the father's networks has a positive effect on the son's employment in South African context. In India, Beaman and Magruder (2012) provide evidence that some workers, those with high skill levels, have useful information about the abilities of members of their social network. In the same way, Nordman and Pasquier-Doumer (2015) indicate that social networks seem to influence the probability to get a job when individuals are unemployed in Burkina Faso. Regarding the positive effect of social networks on earnings, Calvó-Armengol and

[1]For example in Colombia, the National Employment Agency was established in the last trimester of 2013, Law 1636 of 18 June 2013 and the decree 2521 of 15 November 2013.

Jackson (2004) demonstrate theoretically that the higher the wages of contacts, the more information they are willing to give to others. They also show that individuals are more likely to earn higher if their contacts are located in more extensive networks and are employed (Calvó-Armengol and Jackson 2007). Some empirical studies prove these results and show that those who found their job through family, friends and relatives earned more than those using formal methods in the United States (Kugler 2003). Antoninis (2006) observes that new recruits receive a higher starting wage when recommended by an individual with direct experience in the sector. Other authors have documented the positive correlation between the use of ties and the small-business performances in the West African context or the poverty reduction in China (Nguyen and Nordman 2017; Zhang *et al.* 2017).

However, the social networks also produce negative effects for specific types of workers on the labor markets. If social ties are a good channel to receive new informations on the market opportunities, Brady (2015) precises that this effect varies by location, sociodemographic characteristics and types of relations. Some studies argue that those using contacts earned less than those using formal ways or had no persistent wage effects (Bentolila *et al.* 2010). In DCs, Antoninis (2006) also refers the use of referrals from friends and relatives has no effect on the starting wage and may even be negatively related to wages of workers in unskilled jobs in Egyptian context. Marques (2012) shows that relational settings strongly influence individuals access to markets, leading some Brazilian people into worse living conditions and poverty. In Malawi, Beaman *et al.* (2017) also show that men systematically refer few women, despite being able to refer qualified Indian women when explicitly asked for female candidates. Mano *et al.* (2011) show that workers in Ethiopia's cut flower industry who were recruited informally using social ties were paid less than the formally-recruited workers. Moreover, social capital and kinship ties may not be a useful predictor of success for small-scale fisheries and can produce a redistributive pressure (forced solidarity) for small business (Nguyen and Nordman 2017; Crona *et al.* 2016). The risk of over–embeddedness is also developed by Berrou and Combarnous (2012) who demonstrate that informal entrepreneurs have to combine strong and weak ties of social support and business relations to be successful in Burkina Faso. They also indicate that the proportion of network members with a high social status has no significant positive impact on economic outcomes, contrary to more approachable individuals (Berrou and Combarnous 2011).

We identified two main types of networks generating contrasting effects on the labor market. As we saw before, these differential effects are correlated with the heterogeneity and the multi-segmentation of labor markets, particularly in DCs (Fields 2011; Günther and Launov 2012; Radchenko 2016). However, the heterogeneity of labor market outcomes is complex and inevitably comes under a multidimensional process, mixing social institutions and legal regulations. In this way, using the quality of employment concept[2] seems to be crucial (Burchell *et al.* 2014). This multidimensional approach has a considerable interest, allowing precise analysis of employment forms, their further evo-

[2]See Burchell *et al.* (2014) for a specific overview on the quality of employment concept.

lution and abandoning the classical typologies of the labor markets in developing context (Floro and Messier 2011; Ramos *et al.* 2015; Combarnous and Deguilhem 2016). In developed countries, few studies emphasize on the relation between social networks and quality of employment (Granovetter 1974; Montgomery 1992). But, they offer two unidimensional measures of job quality, keeping income and job satisfaction as two fruitless approximations (Sengupta *et al.* 2009; Bustillo *et al.* 2011). In developing countries, Nordman and Pasquier-Doumer (2015) have documented this issue with an approximation of quality of employment levels through a dichotomy between self-employment and wage employment (Bocquier *et al.* 2010). In Colombia, Combarnous and Deguilhem (2016) have shown that this typology is not relevant to deal with the complexity of urban labor markets. Indeed, a clear break does not exist anymore between quality of employment for employees and independents, agreeing with the idea of a continuum.

In the Latin-American context, this paper offers to analyze the determinants of quality of employment for workers on urban labor markets by emphasizing on the role played by the use of social networks. We examine the effects of social ties on quality of employment for two groups of workers by answering the following questions. Do social contacts help to increase the quality of current job for vulnerable and protected workers? Do we observe a similar effect of social networks on quality of employment for the lower and higher quality job workers? What are the differences between social practices of both workers groups?

We display original results and introduce a four-fold contribution to the line of research that investigates urban labor markets in Latin

America. First, we combine a representative sample of employed persons in Bogota's labor market, produced by the Colombian Great Integrated Household Survey (GIHS) in 2013, with focus groups interviews to capture precisely the diversity of social practices. Second, an original methodology is formulated to construct an index of thirteen variables corresponding to the six interconnected dimensions of the quality of employment concept. Third, dealing with complex inter-groups heterogeneity, we offer an accurate estimation of the differential effects of the use of social networks on the strong and poor quality jobs. Fourth, we found that the use of ties has a general negative impact on the quality of employment, whatever the position of the individual in the labor market. However, this effect is clearly more pronounced for the individuals with low quality of employment and much lower for those with better quality job. From these observations, and thanks to the focus groups, we discuss the distinction between *necessity networks* and *opportunity networks* in the Bogota's labor market.

This paper is organized as follows. Section 2 presents the institutional context of the Bogota's urban labor market, the data and the focus groups scheme. Section 3 introduces the method adopted to construct a relevant QoE index in the Colombian context and summarizes the estimation strategy. Section 4 displays the empirical results and comments qualitatively the differential effects of social networks for different workers groups. Finally, the last Section discusses the findings and the methodological approach.

2 Context and Data

2.1 The Bogota's urban labor market

In 2013, the city of Bogota had nearly 7.6 million inhabitants, compared to 715,000 in 1951. It now represents nearly 17% of the Colombian population, an 87% increase from 1985. Despite a low birth rate, and a downward trend in the average annual urbanization rate – going from 7% between 1950 and 1955 to 1.36% between 2010 and 2015 – the capital district remains marked by urban transition, arising from internal migration. It forms a "hub of the territorial system," hosting populations from forced displacements resulting from the internal conflict (Dureau *et al.* 2015:35). Faced with expanding informal urbanization and growing inequalities, the government implemented a socio-economic space stratification method in order to introduce a mixed subsidy mechanism for municipal services payments. Various homogeneous groups of buildings (6 groups) were established on the basis of the cadastral zones. These "blocks" of homogeneous residences give a good approximation of the social hierarchy: the poorest (1, 2 and 3), representing almost 90% of the population in 2013, receive support for between 40% and 10% of the cost of services, whereas the richest (5 and 6) pay a surcharge of between 40% and 20%. Since the introduction of this policy, Bogota has followed an insular, residentially segregated developmental logic, between a northeastern zone occupied by the wealthiest households, a southern area inhabited by poor households, and a western area occupied by the middle class (Dureau *et al.* 2015:113-114). This social hierarchization directly determines household location decisions, and influences social group identity in access to education, healthcare and employment (SDP 2013). Unlike other Andean metropolis, Bogota has a relatively low rate of poverty, at 17% in 2011; it remains high however in the South of the city and in strata 1 and 2: 40% for strata 1 and 25% for strata 2 (SDP 2013). As an illustration of this heterogeneous situation, the capital city has observed a significant increase in income inequality, with the Gini index for income increasing from 0.51 in 2008 to 0.61 in 2013.[3]

Alongside these socioeconomic elements, we capture important legal factors to present precisely the labor market institutions. In 2013, the monthly minimum wage was 589 500 pesos (Article 145 of the *Codigo Sustantivo de Trabajo*, CST), the unemployment insurance contribution was one month's salary for each year of service and proportionally for fractions of a year (Article 249 of the CST), social protection, pension contribution, occupational risks protection, and family fund contribution are mandatory (Article 10 of the law 1122, Article 7 of the law 797, Article 3 of the law 789 and Article 13 of the decree 1772). However, it is only possible to form a local union in companies with at least 25 employees (Article 359 of the CST, Constitutional Council decision No. C-201-02 of March 19, 2002). In the Colombian socioeconomic context, characterized by the omnipresence of micro-business and small enterprises, this closes the door, for a large number of workers, to the collective defense of their rights. Moreover, article 416 of the Colombian CST, derived from decree 2663 of 1950, excludes public-sector employee unions from the right to collective bargaining

[3] The 2008 Gini index came from Bogota's Department of District Planning (SDP 2013). Authors have calculated the 2013 Gini index on the basis of the 2013 household survey.

and the right to strike. The Constitutional Court did however nuance the scope of this legislation, public-sector employees have access to the right of collective bargaining to some extent, but not the right to strike. In regard to social security, the self-employed do not have, in principle, access to the *Sistema General de Riesgos Laborales* (General System of Occupational Risks Insurance) and an employment contract lasting at least one month is also required for membership to the occupational risk coverage system.

2.2 Data

The data comes from the 2013 Great Integrated Household Survey (GIHS) produced by the National Administrative Department of Statistics. Our analysis covers a representative sample of workers (18-95 years old) who are employed in Bogota's labor market. As such, workers between 15 and 17 years old are excluded because they do not have "normal" rights in their working conditions[4]. Moreover, we excluded workers working more than 120 hours per week[5]. Our final sample consists of 8,855 workers, 5,846 of whom answered the question about the use of social networks. Due to these missing observations in the use of networks (34%), the estimation of the QoE mixture equations is at risk of selection bias. Indeed, some socioeconomic factors can influence the answer probability, therefore we must correct this selection bias (Section 3). Socioeconomic covariates were drawn from number

[4] See, e.g. Delmas *et al.* (2016).

[5] 120 hours per week is equivalent to more than 17 hours on the workplace, and some studies, using Time Use Survey, have documented that the biological time for the reproduction can not be less than 7 hours per day (Hamermesh and Stancanelli 2015).

of domains which are relevant in the Bogota's labor market analysis. Demographic variables include age, education, gender, marital status and household variables. Work-related variables include employment status and firm size.

Moreover, we complement our quantitative approach with focus groups interviews. Following Crossley *et al.* (2015:62), "qualitative methods are useful for investigating unexplored networks; concrete acts, practices and interactions; actors' perceptions and assessment of relationships [...]." In other words, with qualitative methods we explore the content and meaning of relationships, and the meaning of the overall structure of individual social environments. In 2016, we have coordinated three focus groups sessions[6] to get qualitative accounts on different experiences of getting a job through social networks in Bogota. The objective was to understand how individuals choose where to seek or who to ask in their job search effort. The main criteria for structuring the composition of the groups was the balance between the diversity of information that can be extracted from a heterogeneous group, and the incentives to express ideas resulting from being part of a homogeneous group[7] (Madriz 1998). We have selected two types of groups[8]. The dimension used for considering the homogeneity of the group was the segment of the labor market in which the members par-

[6]3 sessions of 2 groups of 5 individuals on average. Every discussion in each group lasted 90 minutes on average. During each discussion, the facilitator coordinates the discussion, the participants provide a narrative of how they got a job. The relator records the conversation, take notes of the observations from the participants and marks the time and key discussion moments.

[7]People are more comfortable talking when they are with their peers.

[8]The group members have been selected at random in different stations of the *Transmilenio* (Bus Rapid Transit System of Bogota) in the center of the city.

ticipate. The reason for this is that the labor market segmentation is pretty strong between low and high quality jobs (Delmas *et al.* 2016). In addition, this dimension is closely with income and strata, which summarizes most of the social differences in Colombia.

3 Empirical strategy

3.1 The differential effects

We start from the idea of heterogeneity between different social groups in terms of *ex post* job quality, so we can distinguish high and low quality of employment in the labor market (Combarnous and Deguilhem 2016; Delmas *et al.* 2016). To obtain a job, a worker may have used different ways with distinct effects depending on his group. In particular, the use of social networks *ex ante* can have two effects for the two heterogeneous groups. Following Rogers and Verhove (1995) and Nordman and Pasquier-Doumer (2015), we can distinguish two basic functions which are specific to the ties:

- Securing and supporting actors with different types of risk in the labor market. In other words, the networks are seen as an instrument of last resort, characterizing a necessary safety net for the vulnerable.

- Establish a preferred vehicle for dissemination of information about the opportunities offered or created. The networks are then considered as channels facilitating the transmission of information in the social groups with relations between them, especially in the wealthier groups.

Figure 1: *Opportunity networks* effect

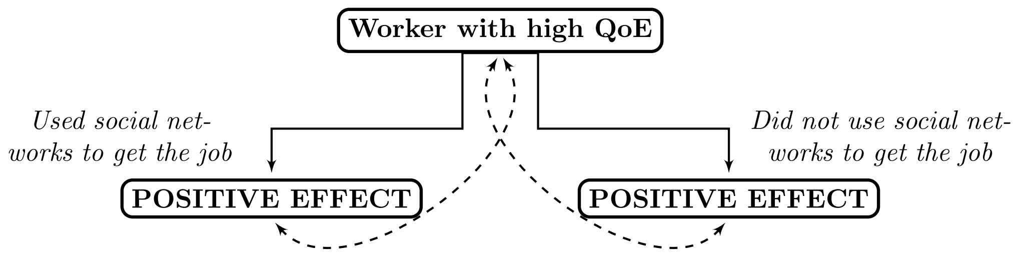
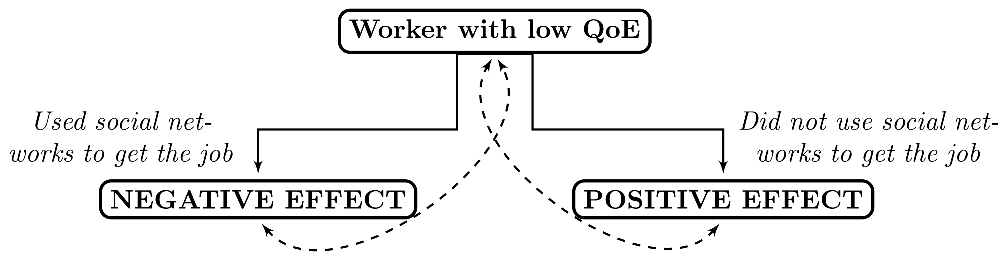


Figure 2: *Necessity networks* effect



In the first group (high QoE), workers have "good" contacts or "good" types of relations, and they use them to get a better job. In this way, using ties do not differ from using formal means on the *ex post* quality of employment. These workers have positive externalities regardless of the way they look for a job. Finally, their *ex post* QoE increases in both cases (Figure 1). In this workers group, using ties is a "good quality job channel" and we call social networks effect: *opportunity networks*.

In the second group (low QoE), workers have a specific type of contacts or relations, equal socioeconomic status or strong ties, for example, and they use them to get a job at all costs. In this way, the use of ties differ from formal means on the *ex post* quality of employment. Inversely than formal procedures, these workers have negative externalities when they use their networks to obtain a job. Finally, their *ex post* QoE decreases (Figure 2). In this workers group, using ties appears as a "bad quality job trap" and we call this social networks effect: *necessity networks.*

3.2 The quality of employment index

Combarnous and Deguilhem (2016) demonstrate that the quality of employment concept must be located in legal and social contexts. Despite this necessity, they show that the following six dimensions mark the "common core" of QoE (Guergoat-Larivière and Marchand 2012; Burchell *et al.* 2014): (i) income level, (ii) working conditions and legal status, (iii) the possibilities of reconciling work and family life, (iv) social securities, (v) collective employment components, (vi) the subjective dimension given to the job. Specifically in Latin America, some studies establish various indicators of quality of employment by raising the type of contract, social security cover, income and working time, multiple activities, workplace, employment security and/or non-wage benefits (Floro and Messier 2011; Farné and Vergara 2015). Following Combarnous and Deguilhem (2016), we opted for a multivariate strategy to formulate the QoE index.[9] Faced with the categorical nature of household survey data, the Multiple Correspondence Analysis (MCA), with its quite robust (stable, invariant) χ^2 metric, is a more appropriate technique to deal with mixed data. This approach constitutes an empirical method adapted to construct a contextualized QoE index based on the factorial scores of each category of some

[9] For a more detailed literature survey on the QoE measurement, see Combarnous and Deguilhem (2016).

indicators of QoE (OECD 2008). In this sense, we assume that the Q indicators are categorical ordinals and the indicator q having j_q categories.

Let us assume that the first factorial axis meets the consistency conditions to be considered as a quality of employment factor, we can then define as an appropriate composite indicator: $QoE = F_1$. In this sense, the QoE index for every worker is calculated from the normalized score of each category of the indicators coming back into the composition of the first factorial axis of the MCA. We can express the quality of employment index for the individual i under the following functional form:

$$QoE_i = \frac{\sum_{q=1}^{q} \sum_{j_{q=1}}^{j_q} W_q^{1,q_j} K_{i,j_q}^q}{Q} \tag{1}$$

Where Q corresponds to the number of categorical indicators, $W_{j_q}^{1,q} = \frac{w_{j_q}^{1,q}}{\sqrt{\kappa_1}}$ is the normalized category-score j_q of the indicator q on the first factorial axis κ_1. K_{i,j_q}^q is a binary variable, taking a value of 1 when the individual i presents the category j_q, 0 otherwise.

The value of the QoE index corresponds well to the normalized category-score average on the first factorial axis of the MCA. We have : $QoE_i \in [-1; 1]$ that we brought back into $[0; 1]$ by linear interpolation, in order to make reading easier. Then, we have a continuous QoE index: $QoE_i \in [0; 1]$, with 0 corresponding to the worst possible job quality, and 1 corresponding to the best possible QoE in this social context.

According to the socioeconomic description of Bogota's labor market, we have therefore selected 13 socioeconomic and legal *ex post* variables to build this QoE index (Appendix A1). Using this selection, we can analyze Bogota's urban labor market in the clearest and most accurate way possible.

3.3 Finite Mixture Regression Model (FMRM)

This approach simultaneously allows to identify heterogeneous groups and to estimate each specific regression model (this econometric strategy is derived from Conway and Deb 2005; Deb and Trivedi 2013; Deb *et al.* 2011). This procedure consists of three successive stages.

Stage 1: Number of components

Before starting the Finite Mixture Regression Model, it is necessary to check that the sample contains a sufficient number of observations to support partitioning, various studies suggest a minimum of $n = 30$ per group (Garver *et al.* 2008). In addition, we must start from the premise that the number of groups is less than the number of observations, which is to capture a "unobserved heterogeneity between groups" rather than between individuals (Salem and Bensidoun 2012; Frühwirth-Schnatter *et al.* 2012).
When applying a FMRM, the number of groups is not known and must therefore be inferred from our data. Choosing the number of components C can then be carried out with different methods, depending on which has placed a greater interest in the quality of the adjustment of density or in the detection of distinct groups (McLachlan and Peel 2000). Thus, if the main interest concerns the estimation of density, proper method is to select the value C which minimizes the

AIC (Akaike 1974) *and* the BIC (Schwarz 1978):

- $AIC = -2\hat{L} + 2K$
- $BIC = -2\hat{L} + (3K - 1)log(n)$

Where $\hat{L}$ is the estimator of the log-likelihood, n is the number of observations and K corresponds to the number of estimated parameters. Ultimately, then we must choose the model that minimizes the absolute values of AIC and BIC.

Stage 2: Specification of the FMRM

The linear regression model is to specify the conditional expectation of a dependent variable, the QoE index, as a linear function of the use of ties (SNW) and different explanatory variables.[10] One approach is to specify in a same way the average of the density functions of each of the mixture groups. If we consider a finite mixture of the normal distributions (with the variance values σ_c^2), we can formulate the equation in order to obtain a *finite mixture regression model*:

$$f(QoE|SNW, X; \Theta) = \sum_{c=1}^{C} \pi_c \phi(SNW, \beta_1^c) f_c(QoE|X; \beta_2^c, \mu_c, \sigma_c) \quad (2)$$

Where Θ is the set of parameters, C represents the number of components, π_c is the proportion of the population included in C, $\phi(.)$ corresponds to the density of the Gaussian distribution, β_1^c is the parameter associated with the variable SNW (explaining the proportions within

[10] We use three types of explanatory variables: individual (education, gender, marital status, Age), household (apartment, socioeconomic stata) and employment characteristics (activy sector). For more variable details, see Appendix B1.

the mixture model), β_2^c the set of parameters associated with the set of explanatory variables X, μ_c is the expectation of the distribution and σ_c is the variance in each component.

The average of the densities are no longer estimated parameters, they are now conditional on the values of our variable of interest SNW and other explanatory variables X. They are obtained from the model estimation. Looking at two components ($C = 2$), we consider the following Gaussian mixture model:

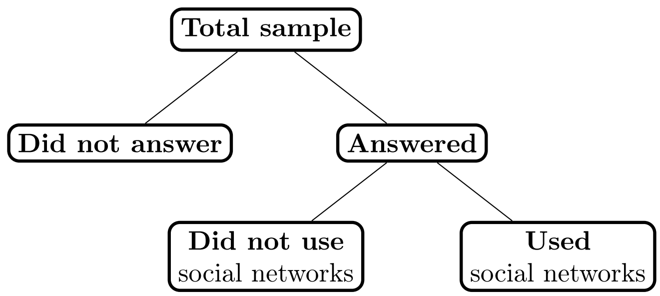
$$\left.\begin{array}{l} \text{C1: } QoE_i^1 = \beta_0^1 + SNW_i^1\beta_1^1 + X_i^1\beta_2^1 + \epsilon_i^1 \\ \text{C2: } QoE_i^2 = \beta_0^2 + SNW_i^2\beta_1^2 + X_i^2\beta_2^2 + \epsilon_i^2 \end{array}\right\} \quad (3)$$

$$\left.\begin{array}{l} \text{C1: } \epsilon_i^1 \sim N(0, {\sigma_i^2}^1) \\ \text{C2: } \epsilon_i^2 \sim N(0, {\sigma_i^2}^2) \end{array}\right\} \quad (4)$$

Where ϵ_i^1 et ϵ_i^2 are independent error terms, identically distributed following a normal distribution with their respective variances ${\sigma_i^2}^1$ and ${\sigma_i^2}^2$.

This analysis would be fine if the missing QoE index data were missing completely at random. However, the decision to answer at the social networks question or not (in the questionnaire), is not randomly distributed (Appendix B1). Thus, those who did not answer constitute a self-selected sample and not a random sample. It is likely that some of the individuals that should be in specific situations choose not to answer and this would account for much of the missing QoE data. Thus, it is likely that we will under estimate the QoE of these individuals in the population. Finally, in the sample we have a first type of decisions that creates selectivity (i.e., individual selection), Figure 3 illustrates the sample selection problem. We resolve that issue by using the Heckman's two-step estimator for estimating selection models (1976, 1979).

Figure 3: Decision Tree for participation in the sample (GIHS, 2013)



Source: Authors.

First, we have determined a dummy variable "Answer" to capture the answering individual decision, that takes the value 1 if the individual answered and 0 otherwise. Indeed, the dependent variable (QoE index) is observed only for those individuals whose variable of answering is superior to 0. Second, we have estimated the probability of response with a Probit model. In this way, we explain the values of "Answer" in terms of explanatory variables to estimate the probability that Answer = 1. Third, after the Probit model estimation we have estimated the Inverse Mills Ratio (λ) for each individual.[11] Finally, we have inserted this correction factor in the Finite Mixture Regression Model.

$$\left.\begin{array}{l} \text{C1: } QoE_i^1 = \beta_0^1 + SNW_i^1\beta_1^1 + X_i^1\beta_2^1 + \lambda_i^1 + \epsilon_i^1 \\ \text{C2: } QoE_i^2 = \beta_0^2 + SNW_i^2\beta_1^2 + X_i^1\beta_2^2 + \lambda_i^2 + \epsilon_i^2 \end{array}\right\} \tag{5}$$

[11]In the selection step, we include an inferior number of explanatory variables than the determination step in each model.

The endogeneity between the QoE index and the use of ties could be another major issue. However, within the GIHS (2013), we capture the use of networks with an *ex ante* variable[12], while the measure of our QoE index is calculated from *ex post* variables (Appendix A1). Thus, SNW captures a retardation behavior before the current occupational status, and finally we do not meet endogeneity problem with our variable of interest.

Stage 3: EM algorithm and maximization of the likelihood function

The EM algorithm, originally developed by Dempster *et al.* (1977), is an iterative algorithm of calculating the maximum likelihood. It is based on the central result that the parameter that maximizes the predicted log-likelihood increases the logarithm of the observed likelihood. In the first step, *expectation-step*, we calculate the expectation of the log-likelihood for the current value of the parameters. In the second step, *maximization-step*, parameters updates are performed by maximizing this new function of these parameters. Finally, the algorithm converges under assumptions of regularity to a stationary point.

4 Results

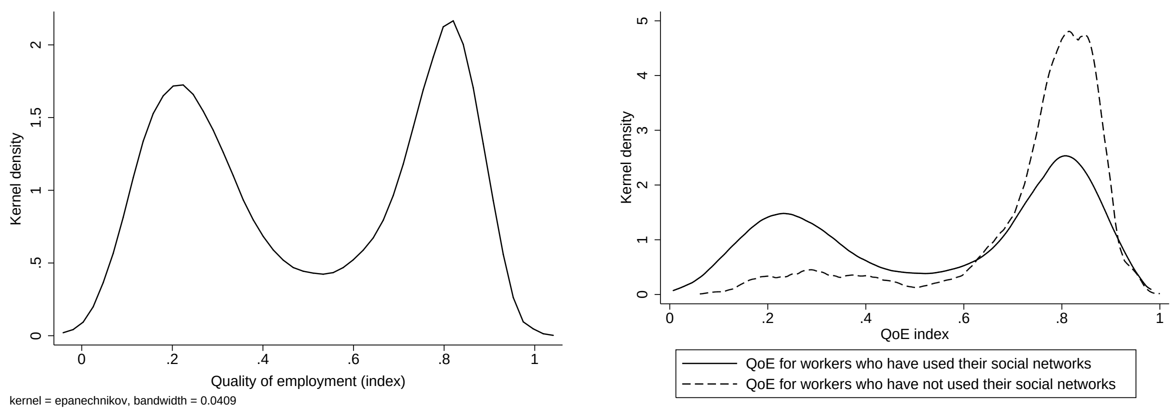
4.1 Summary statistics

The distribution of QoE index clearly shows two different modes (Figure 4), proving a polarization in quality of employment in Bogota and

[12] In the GIHS, the question P6480 is: "How did you find your current job?" the workers answer the means by which they obtained their current job.

structuring two groups of QoE. On the left side, the first mode represents a "poor" quality of employment for precarious and vulnerable workers and on the right side, the second mode shows a "strong" quality of employment group, benefiting from social and lawful protection. Confirming Combarnous and Deguilhem (2016), results demonstrate that it is more relevant to treat the break between good and bad jobs rather than analyzing status typology (Bocquier *et al.* 2010). Indeed, Appendix C1 shows that the distinction between employees and independents is not a relevant proxy of the quality of employment in the specific social context of Bogota's labor market.

Figure 4: QoE index and QoE index by using ties to get a job, GIHS (2013)



Source: Authors.

Furthermore, Appendix B1 shows the averages of all variables used to study Bogota's labor market. Selection bias exists between the total sample and the subsample corresponding to those who answered the social network question. We observe that this selection bias in the dependent variable seems to be correlated with employment status and firm size. Summary statistics show that earnings and QoE index gap between subsamples is considerable: in fact, for the workers who answered the network question and did not use ties, earnings were 37% higher and QoE was 31% better than for the others (Appendix B1).

Generally, people who have used ties to get their current job are less educated, less likely to be in upper strata (3, 4, 5 and 6), less likely to have a personal car or to have a formal employment compared with people who did not used social networks (Appendix B1). Following Rogers and Verhove (1995:268), these observations illustrate that a worker "[...] does not live directly in the total society, or even, in the local community. The effective social environment of [the worker] is its network of friends, neighbors, relatives and particular social institutions. This is the primary social world." In other words, the different classes of workers in the labor market are constructed reference groups affecting relational practices, social behaviors and labor market outcomes.

However, Figure 4 and Appendix C1 show that the distribution of the use of ties for all workers, employees and independents is more complex. Indeed, among those who mobilized ties, we can observe a clear distinction between two populations: (i) poor job quality workers who have used ties to obtain a job and (ii) high job quality workers. This inter-group heterogeneity illustrated by Figure 4 and Appendix C1 justifies the use of FMRM in our estimation stage. We confirm the relevance of our empirical strategy with the Quantile Regressions (QR). Indeed, we take into account different percentiles in the QoE index distribution, to test the stability of the FMRM estimations, as robustness tests. In this way, we switch between a semi-parametric to a non-parametric model with bootstrapped standard errors to compare with a robust standard deviation in the models of interest (Appendix E3).

4.2 The differential effects of using ties

The first step in the estimation of FMRM is to determine the most suitable number of components. Table 1 shows that the breakdown of quality of employment into two segments is preferable than other options across information criteria (smallest value). Unlike Salem and Bensidoun (2012), the parameters can be clearly identified and we do not experience the over-parametrized problem. Finally, the division between low quality job workers and high quality job workers is relevant for modeling the heterogeneity of the QoE index in Bogota's labor market.

Table 1: Model selection and number of components

	AIC	**BIC***
2 Components	5724.04	5573.72
3 Components	6074.54	5847.32
4 Components	6180.30	5876.17
5 Components	6284.71	5903.67

Note: *We have used the sample size adjusted BIC.
Source: Authors.

Table 2, Appendix E1 and Appendix E2 present the estimation results (FMRM and OLS) of the QoE index for the total sample, for employees and independents separately. The first piece of information to be gleaned from this results refers to the potential bias in the QoE equation resulting from answering the question or not. Indeed, the significance of the correction term (λ) for all specifications actually suggests that unobserved characteristics of the populations in and out of the sample are fairly different in Bogota's labor market, and thus that the estimation of a FMRM without selection term would have led to biased estimated coefficients. In the Probit estimations, we observe a higher response probabilty for formal employees, formal independents, informal employees, workers in large firms rather than for informal independents and self-employed workers (Appendix D1). Finally, these results show that the λ correction is necessary to capture these differential probabilities of answering.

The estimated mixture model with two segments produced a distribution of 44% of the total sample in low quality job situations and 56% in high quality job positions (Table 2). In Appendix E1 and Appendix E2, we found that the estimated separate FMRM for employees and independents produced the same distributions, 44% of individuals in low quality job situations and 56% in high quality job positions. Each group has enough observations and the groups are clearly enough separated to avoid the degeneration problem in our results[13]. In the first place, we provide results which compare estimates generated by FMRM models with estimates derived from traditional statistical analysis (OLS) (Table 2, Appendix E1 and Appendix E2). To complete this comparison, we then provide results of the QR for the same specification (Appendix E3).

In Table 2, OLS estimates show that the use of social networks lowers the QoE index (–9% in the total sample, –11.5% for independents and –8% for employees) suggesting high significant difference between workers who used ties and those who did not. However, these results

[13] With these specifications, our models did not converge in the local and instable maximum.

contrast with the FMRM estimations.

Table 2: FMRM and OLS for QoE index (total sample), GIHS (2013)

	FMRM		**OLS**[‡]
Variable	Component 1	Component 2	
Social networks	-0.138***	-0.008***	-0.091***
	(0.016)	(0.002)	(0.005)
Age	0.001	0.001	0.002*
	(0.001)	(0.000)	(0.001)
Age^2	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Education	0.010***	0.003***	0.011***
	(0.001)	(0.000)	(0.001)
Gender	-0.008	-0.002	-0.008
	(0.008)	(0.003)	(0.006)
Strata 2	0.018*	0.020***	0.041***
	(0.010)	(0.005)	(0.009)
Strata 3	0.034***	0.026***	0.055***
	(0.012)	(0.005)	(0.010)
Strata 4	0.098***	0.030***	0.081***
	(0.020)	(0.006)	(0.013)
Married	0.030***	0.009***	0.023***
	(0.010)	(0.003)	(0.007)
Apartment	0.010	0.007***	0.011*
	(0.008)	(0.003)	(0.006)
λ	-0.132***	-0.070***	-0.265***
	(0.011)	(0.007)	(0.010)
σ_c	0.154	0.058	
	(0.005)	(0.001)	
π_c[†]	0.440	0.560	
	(0.014)	(0.014)	
Constant	0.365***	0.742***	0.517***
	(0.035)	(0.012)	(0.027)
Log likelihood	2905.02		
Wald χ^2	2252.19***		
Adjusted R^2			0.385
N	5846		5846

Note: For the FMRM, robust standard errors are in parentheses and the model converges in 11 iterations. Regressions also include activity sector dummies. The first component is the low quality of employment range and inversely for the second component.
[†] π_c is the probability that an observation is in component c.
[‡] For the OLS estimation, robust standard errors are in parentheses. Each predictor was uncorrelated with the other predictors.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
Source: Authors.

Looking at the Table 2, Appendix E1 and Appendix E2, we clearly observe the differential effects of the use of ties for low and high quality job workers, between the QoE semi-parametric groups.[14] Workers, employees or independents in the first Component (low quality jobs) experiment large statistically significant decreases in QoE index when using ties. In a markedly different manner, participants in the second Component (high quality jobs) had small statistically significant decreases in QoE index following the use of ties.

As shown previously, we found that using contacts to get a job has a high negative effect (respectively –14% for all workers, –13% for employees and –8% for independents) on quality of employment of the lower group, when comparing with formal means. This interesting result, qualitatively explained in the next subsections, appears to be robust. Indeed, with the same specification in QR, we observe that the high negative effects in the first percentiles of the QoE index distribution (q10, q20 and q30, Appendix E3) are very consistent with the first component results. In the same group, we observe that being a woman has significant negative effect on QoE index for employees, confirming studies on gender gap in the Colombian labor market (Hoyos *et al.* 2010). However, the same coefficient is non-significant for independent women. This observation shows that potential discrimination does not appear statistically in employment status, but this does not mean that the discrimination does not occur. Indeed, the discriminations suffered by independent women seem to be held upstream from their participation in the labor market, particularly in

[14] To test the robustness of our results, we generated the bootstrapped standard errors in the case of Quantile Regressions. We show that the negative effects decrease and are robust along the QoE distribution (Appendix E3).

the distribution of unpaid work in households (Alaniz and Gindling 2013). Also, Farné and Vergara (2015) show that, between 2002 and 2011 in Colombia, there has been an improvement in the quality of employment for women. They explain this progress by the low decrease of domestic work duration, predominantly a female occupation. Moreover, like in the spatiality of social capital approaches (Ioannides and Loury 2004), we have shown a positive effect of upper socioeconomic area and married status on quality of employment for all workers in the first component.

Inversely and surprisingly, we found that using contacts to get a job has a very small but significant negative effect (between 0.5% and 1.5%) on the quality of employment of high quality job workers, in comparison with the use of mediating resources to obtain a job. This unexpected negative effect for this type of workers (Granovetter 1974, Montgomery 1992, Jackson *et al.* 2017), seems to be robust with the QR estimates. Indeed, Appendix E3 shows a relative stability in the small negative effects for the last percentiles selected in the QoE index distribution (q70, q80 and q90). In this group, we also saw that being a woman has no effect. Conversely to other studies in DCs (Nordman and Wolff 2009), this interesting result shows that women are close to break the glass-celling on this specific segment in the Bogota's labor market, because they live in highest socioeconomic area and they are better educated. We also found that upper socioeconomic strata residency, married status and living in an apartment have a smaller significant positive effect for workers in the second component than in the first component.

4.3 *Necessity networks* and bad quality job trap

The high negative significant and robust effects of using ties has an interesting interpretation in this context of low quality job workers. Two reasons appeared relevant during the focus groups interviews with them.

First, past research has differentiated between strong ties–people that we know well and with whom we interact frequently–and weak ties–people that we know less well and with whom we interact less frequently. The advantages of weak ties lie in their abilities to provide timely access to non-redundant information and to influence employers directly. In contrast, strong ties are associated with indirect influence on employers through well-connected intermediaries (Yakubovitch 2005). Finally, weak ties have been found to be more beneficial in accessing new information and to be instrumental in finding new jobs (Granovetter 1974; Montgomery 1992). The three focus groups of low quality job workers highlights that these workers have used strong ties to obtain their actual job and this can explain the large negative effect of using contacts, which challenges Kramarz and Skans' results (2014). In this way, Gloria, a 47 year old woman living in strata 2, highlights her expectations to improve her quality of life. She explains that she contacted directly her strong friends in her neighborhood to find a better job. They recommended her at their jobs, she finally obtained a job but it was not better than the previous one. Harold, a 26 year old man living in strata 3, found his last job through his father's contacts, but he had long working hours in a large firm. They created a local union to negotiate better working conditions, but two months after the beginning of the negotiations, Harold was fired without unemployment allocations.

Second, we can explain the large negative effect through the homophily in the social network of the low quality job workers. Homophily isolates workers who present the same social characteristics from workers with other social characteristics, which then limits the extent to which individuals in one group hear about openings and opportunities known to the other group (Jackson *et al.* 2017). In other words, workers appealing to contacts who are in a same social position, have a lower probability to get high labor market outcomes than workers appealing to contacts who are in better social positions. In the focus groups of low quality job workers we find that they have rarely contacted parents or strong friends in better positions than themselves because of trust issues. Patricia, a 30 year old woman living in strata 2, has searched a job through specialized web pages and professional contacts who were in better social and occupational position. However, these means were not fruitful: the lack of information from her relatives about her preferences and background as well as the "inadaptation" of these websites to her profile, made the job search difficult. She found a job through close friends and family contacts in the same social position. Vanesa, a woman who lives in strata 3, was fourth month unemployed making it difficult to keep her living standards. She found her job through her mother's contacts with approximately the same social position than herself. Finally, she found a job with lower responsibilities and the same salary than the one before.

Finally, these qualitative results tend to confirm the model presented in the Section 3 for the "poor" quality job workers. More generally, we found that strong and homophilic ties are simultaneously a unique instrument of last resort and a negative resource to increase quality of employment for these workers (Rogers and Verhove 1995). The focus groups interviews display that for these type of workers ties are strong, homophilic and also a necessary safety.

4.4 Are *opportunity networks* really appropriate to access high quality jobs?

We observe quantitatively that the use of networks does almost not affect the QoE index comparing with the use of formal means for the high quality job workers. However, this effect is negative and always statistically significant for this group of workers as for the low quality group. We can formulate some hypothesis to explain these observations and we use the focus group interviews to conclude and complement these results. First, to clarify this small effect we can assume that protected workers could use different types of networks (weak, professional and heterophilic ties) to obtain a job unlike vulnerable workers. Second, the negative effect of networks on the QoE index in this group could be explained by two reasons: a social acceptation of worst working conditions in the short run (over-loyalty and over-subordination effects), and because using ties over formal means could send a bad signal on the labor market. Protected workers have all the information and skills to obtain a job through intermediation means but by choosing ties, they miss out on better opportunities.
Some studies show that the advantages of weak ties (low emotional intensity and low frequency) is clear for high skilled workers (Gra-

novetter 1974; Yakubovitch 2005). In contrast with what is said about bad job workers, good job workers use weak ties more frequently because the latter are more beneficial in accessing novel information and are instrumental in finding new jobs. In this way, the three focus groups of high quality job workers highlight that a major part of them have used weak ties to obtain their actual job and this can explain the small negative effects comparing with formal means. Paula, a 26 year old woman living in strata 3, highlights that she found her last job through a second degree contact. Indeed, she received information from an uncle of a scholar friend who worked at the firm. She was unsatisfied with this activity and decided to search for a new job. During this period, she received a lot of job offers sent by her scholar and professional contacts. Finally, she found her current job through a scholar relative recommendation, where she has better responsibilities, a higher salary and lower working time than in her last job. Camilo, a 28 year old man living in strata 4, explains that family members and strong friends could not help him in the job search process. However, a scholar friend recommended him to his contacts, but Camilo did not know them. He explains that for him this network process appeared "murky." There seems to be a signal effect: people did not know each other, but everyone in the network was trustworthy because they had the same scholar background.

Conversely to what we said previously, we can explain the low negative effect through the heterophily in the social network of high quality job workers. In other words, workers appealing to contacts who are in a better social position, have a higher probability to get better labor market outcomes (Lin 2002). In the focus groups of good quality job workers, we find that they have always contacted friends or relatives in a better position than themselves because their recommendations have greater impact than those of others. Odys, a 55 year old woman living in the strata 4, found clients through contacts with her managing directors. She has an efficient professional network with people in a better social position than her because of their influence and offer of opportunities (Lin 2002). However, she sometimes accepted lower working conditions in order to maintain this professional network. Carlos, a 23 year old man who lives in strata 4, found his last job in the Central Bank of Colombia. In this occupational position, he had a strong professional network who sent him new job opportunities by mail. Using this means, Carlos found a job opportunity at the University. However, he did not apply directly, a professional contact recommended him to a professor, who was the department director, allowing him to obtain the job. However, in this new job, he accepted worse working conditions than in the first one. He explained that he needed to show his skills and his loyalty in the new occupational position, pending to transition towards better professional projections. The over-subordination effect in the short run appears clearly in some cases of this group.

We do not confirm the model offered in Section 3 for the good quality job workers. Our results show a low negative and significant effect of networks compared to formal means to obtain a job. During the focus groups, we found that weak, professional and heterophilic ties clearly constitute a better job channel, but they also generate over-loyalty and subordination effect, explaining the negative effect (Rogers and Verhove 1995).

5 Conclusions

In this paper, we studied the role of ties in the quality of the employment for workers in the Bogota's labor market. Confirming Combarnous and Deguilhem (2016), results demonstrate the relevance of treating the break between good and bad jobs rather than analyzing status typology (Bocquier *et al.* 2010). We have shown that employees and independents can be found both in the high and low QoE group. Thanks to our focus group-based qualitative approach, we observe some different types of social networks in terms of the strength of ties and social resources embedded in the contacts.The focus groups interviews confirm that for the low quality workers, the ties are strong, homophilic and also a necessary safety. For high quality job workers, our results precise the low negative and statistically significant effect comparing with formal means to get a job. Confirming a part of the sociological and economic literature, we demonstrate that weak, professional and heterophilic ties constitute a good job channel for the "good job" workers. However, these type of ties also generate over-loyalty and over-subordination effect, explaining why social networks also have a negative effect on the QoE index for these workers (Rogers and Verhove 1995).

In this paper, given the limited number of variables in the GIHS, we had no opportunity to control precisely the cognitive and non-cognitive skills of workers (it is just proxied by years of schooling). Indeed, we could think that the differential negative effects of relational factor on the QoE index is influenced also by cognitive abilities and by non-cognitive skills (Heckman *et al.* 2006) of workers. Furthermore, we think that geography impacts the use of the social networks to get a job (Ioannides and Datcher Loury 2004; Jackson *et al.* 2017). However, we only use the socioeconomic strata of each worker since no other geographical factor could be identified in the survey. Finally, we are limited by the fact that answering the question about social networks is incomplete in the GIHS. This question allows us to distinguish between formal and informal means or mediating resources, but we have been unable to explore statistically the strength of ties, the structural dimensions of networks and the contacts' attributes. Indeed, the main questions remains: how can we explain these differential negative effects between workers? can this difference come from distinct kinds of ties? In our case, we must develop a more systematical approach than focus groups interviews to explore precisely the information about social ties. In this way, we are presently workin on a Bogota's workers survey to produce quantitative data on the following four crucial elements (contents embedded in the ties, structures of social networks, contact attributes or resources and accessible social capital) and develop a networks analysis (Berrou and Combarnous 2011, 2012; Nordman and Pasquier-Doumer 2015).

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Appendix

Appendix A1

Table 3: Indicators of the QoE index (GIHS, 2013)

Indicators	**Characterizations**
Income	1 if individual earns less than the minimum wage (MW); 2 if individual earns less than 2 MW; 3 if individual earns less than 4 MW; 4 if individual earns more than 4 MW
Stability	1 if more than 1 year; 2 if not
Contract completeness	*See the note under the table*
Other activity	1 if yes; 2 if not
Workplace	1 if individual works in hard local; 2 if household work; 3 if other
Transport	1 if individual has transport benefits; 2 if not
Time	1 if individual works less than 24 hours per week; 2 if he works between 24 and 48 hours per week (legal employment); 3 if he works more than 48 hours per week
Social security	1 if individual contributes to social security; 2 if he has special social security (*Army, Ecopetrol, Public University*); 3 if he has subsidized social security; 4 if not
Occupation risk	1 if individual has an occupation protection; 2 if not
Pension	1 if individual has a pension; 2 if not
Family fund	1 if individual has a family protection system; 2 if not
Union	1 if he is in a union; 2 if not
Subjectivity	*See the note under the table*

Note: The *Contract completeness indicator* is a scoring variable constructed from seven variables of contract composition. Category 0 illustrates the situation of workers without any forms of contract; category 1 identifies the primary elements of formal contract. Category 2 marks the passage to a written contract, but contents of which remain rather weak. Category 3 marks the appearance of social contents in contracts, 4 and 5 are complete contracts. We do not presume the importance of every category, of this fact weighting method is not necessary. The *Subjectivity indicator* constitutes an objective indicator of the subjective representations. Like the QoE index, this variable is a synthesis constructed across MCA from eight variables expressing the necessity of change and the satisfaction of workers. The first factorial axis explaining more than 88% of the corrected eigenvalues (Greenacre 1993), it can be defined as the factor of workers? satisfaction. After analysis of distribution, we have discretized this quantitative variable in three groups: 1 is a good satisfaction level and a will to stay in current job, 2 is an intermediate satisfaction level and 3 a dissatisfaction level.

Appendix B1

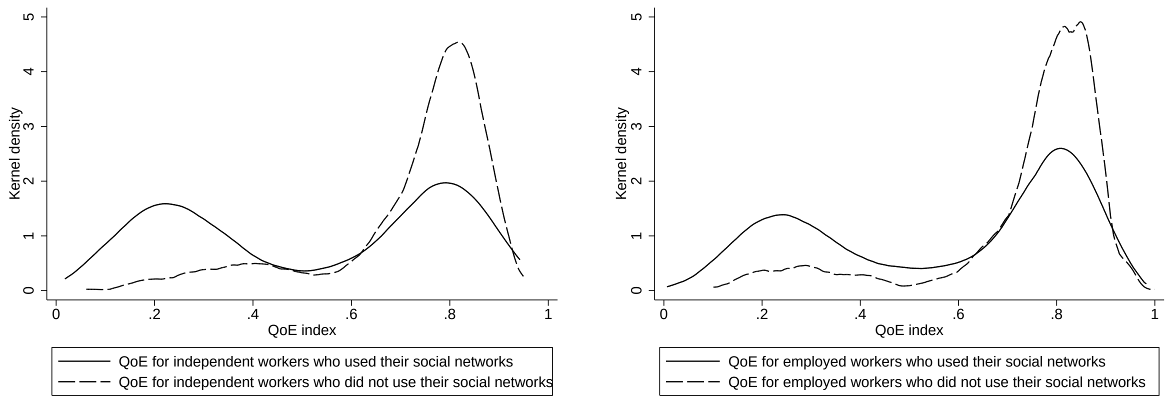
Table 4: Descriptive statistics, GIHS (2013)

	Total Sample	Answer		Social Networks	
Variable		Yes	No	Yes	No
QoE index*	0.508	0.6214	0.2879	0.5592	0.7365
Sd.	(0.280)	(0.258)	(0.169)	(0.273)	(0.178)
Income* (per hour)	6117.51	5926.31	6488.98	5243.93	7187.99
Sd.	(9433.73)	(7918.46)	(11828.26)	(6943.69)	(9331.15)
Age (years)	45.75	44.78	47.63	44.75	44.84
Sd.	(14.67)	(14.55)	(14.73)	(14.50)	(14.64)
Education* (years)	9.997	10.09	9.82	9.60	10.98
Sd.	(4.90)	(4.82)	(5.04)	(4.73)	(4.85)
Gender (%)	35.20	36.08	33.50	35.66	36.84
Strata 1 (%)	11.78	11.60	12.13	11.89	11.06
Strata 2 (%)	43.22	44.44	40.84	45.97	41.62
Strata 3 (%)	34.40	33.73	35.69	32.50	36.01
Strata 4†(%)	10.60	10.23	11.33	9.65	11.31
Married (%)	28.20	28.02	28.55	27.28	29.39
Personal car (%)	21.76	20.87	23.50	19.74	22.95
Formal employee (%)	47.76	68.30	7.84	65.26	73.93
Formal independent (%)	16.65	18.59	12.86	16.84	21.83
Informal employee (%)	9.73	5.42	18.11	6.59	3.27
Informal independent (%)	25.86	7.68	61.18	11.31	0.97
Self-employed (%)	23.88	5.80	59.02	8.59	0.63
2-5 employees (%)	19.41	18.66	20.87	25.88	5.31
6-10 employees (%)	7.19	8.40	4.85	10.25	4.97
11-50 employees (%)	11.97	15.45	5.22	17.32	11.99
51-100 employees (%)	3.77	5.20	1.00	4.69	6.14
More than 100 (%)	33.77	46.49	9.04	33.26	70.96
Manufacturing (%)	15.39	16.63	12.99	16.70	16.47
Commercial services (%)	20.84	17.19	27.92	18.90	14.04
Transport (%)	8.24	8.18	8.37	8.17	8.19
Finance (%)	17.56	18.73	15.29	16.39	23.05
Household (%)	9.73	9.80	9.60	13.31	3.31
Hotels and rest (%)	6.47	7.63	4.22	8.80	5.46
Public (%)	3.94	4.53	2.79	2.21	8.82
Education (%)	5.33	6.11	3.82	3.82	10.33
Social and medical (%)	6.38	5.23	8.61	4.35	6.87
Apartment (%)	67.24	67.98	65.80	66.50	70.71
Property owner (%)	31.58	30.36	33.93	29.44	32.07
Toilet user‡(%)	89.65	89.65	89.66	88.16	92.40
Cable or satellite TV (%)	80.68	81.70	78.70	80.97	83.04
People per household (average)	3.36	3.45	3.19	3.50	3.37
Sd.	(1.57)	(1.56)	(1.59)	(1.57)	(1.52)
Obs.	8855	5846	3009	3794	2052

Note: *Means are statically different at 1% level. †*Strata 4* aggregates the stratas 4, 5 and 6. ‡*Toilet user* is a binary variable coded "Yes" if people from the household are exclusive users of the toilets. *Source:* Authors.

Appendix C1

Figure 5: QoE index for independents and employees, GIHS (2013)



Source: Authors.

Appendix D1

Table 5: Marginal effects on the probability of answering, GIHS (2013)

Variable	**Probit**(1)		**Probit**(2)		**Probit**(3)	
Education	-0.010***	(0.001)	-0.005***	(0.002)	-0.006***	(0.001)
Age	-0.001	(0.001)	0.002**	(0.001)	-0.001**	(0.000)
Gender	-0.000	(0.013)	-0.066***	(0.019)	0.028***	(0.009)
Formal employee	0.544***	(0.015)			0.392***	(0.024)
Formal independent	0.189***	(0.018)	0.999***	(0.000)		
Informal employee	0.125***	(0.016)				
2-5 employees	0.290***	(0.011)	0.512***	(0.023)	0.085***	(0.008)
6-10 employees	0.250***	(0.011)	-0.437***	(0.012)	0.091***	(0.006)
11-50 employees	0.289***	(0.010)	-0.485***	(0.013)	0.103***	(0.007)
51-100 employees	0.277***	(0.008)	-0.356***	(0.011)	0.0092***	(0.006)
More than 100	0.422***	(0.015)	-0.707***	(0.015)	0.197***	(0.013)
TV	-0.024	(0.015)	0.005	(0.024)	-0.030***	(0.010)
People	0.024***	(0.004)	0.087***	(0.006)	-0.023***	(0.003)
Car	-0.008	(0.016)	0.032	(0.023)	-0.033**	(0.014)
Owner	-0.015	(0.015)	0.042*	(0.022)	0.005	(0.011)
Log likelihood	-3035.71		-1573.17		-1246.31	
χ^2	5279.06***		1943.73***		1871.12***	
Pseudo R^2	0.465		0.382		0.429	
N	8855		3764		5091	

Note: The first model treats all sample, the second treats only the independents and the third only the employees. Standard errors are in parentheses. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.
Source: Authors.

Appendix E1

Table 6: FMRM and OLS for QoE index (independents), GIHS (2013)

Variable	FMRM Component 1	FMRM Component 2	OLS[‡]
Social networks	-0.081***	-0.016***	-0.114***
	(0.026)	(0.005)	(0.011)
Age	-0.006**	0.001	-0.004
	(0.003)	(0.001)	(0.002)
Age^2	0.000***	-0.000	0.000*
	(0.000)	(0.000)	(0.000)
Education	0.005***	0.003***	0.009***
	(0.001)	(0.001)	(0.001)
Gender	0.017	-0.003	0.034**
	(0.012)	(0.006)	(0.013)
Strata 2	0.037**	0.027***	0.051***
	(0.010)	(0.010)	(0.021)
Strata 3	0.039**	0.038***	0.060***
	(0.016)	(0.010)	(0.010)
Strata 4	0.118***	0.050***	0.140***
	(0.039)	(0.012)	(0.026)
Married	0.027**	0.010*	0.020
	(0.012)	(0.003)	(0.013)
Apartment	0.007	0.006	0.017
	(0.011)	(0.005)	(0.011)
λ	-0.093***	-0.061***	-0.287***
	(0.019)	(0.014)	(0.018)
σ_c	0.108	0.069	
	(0.009)	(0.003)	
π_c[†]	0.404	0.596	
	(0.018)	(0.018)	
Constant	0.458***	0.725***	0.727***
	(0.073)	(0.033)	(0.067)
Log likelihood	680.96		
Wald χ^2	341.16***		
Adjusted R^2			0.408
N	1536		1536

Note: For the FMRM, robust standard errors are in parentheses and the model converges in 17 iterations. Regressions also include activity sector dummies. The first component is the low quality of employment range and inversely for the second component.
[†] π_c is the probability that an observation is in component c.
[‡] For the OLS estimation, robust standard errors are in parentheses. Each predictor was uncorrelated with the other predictors.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.
Source: Authors.

Appendix E2

Table 7: FMRM and OLS for QoE index (employees), GIHS (2013)

	FMRM		OLS‡
Variable	Component 1	Component 2	
Social networks	-0.132***	-0.005***	-0.079***
	(0.015)	(0.003)	(0.006)
Age	0.003*	0.001*	0.003**
	(0.001)	(0.000)	(0.001)
Age^2	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Education	0.012***	0.003***	0.012***
	(0.001)	(0.000)	(0.001)
Gender	-0.024***	-0.005*	-0.023***
	(0.009)	(0.003)	(0.007)
Strata 2	0.003	0.015**	0.037***
	(0.013)	(0.006)	(0.011)
Strata 3	0.026*	0.020***	0.049***
	(0.014)	(0.006)	(0.011)
Strata 4	0.081***	0.023***	0.061***
	(0.022)	(0.007)	(0.014)
Married	0.027**	0.010***	0.028***
	(0.012)	(0.003)	(0.008)
Apartment	0.012	0.007**	0.013*
	(0.009)	(0.003)	(0.007)
λ	-0.224***	-0.152***	-0.462***
	(0.020)	(0.012)	(0.019)
σ_c	0.159	0.055	
	(0.004)	(0.001)	
π_c †	0.438	0.562	
	(0.014)	(0.014)	
Constant	0.350***	0.741***	0.504***
	(0.040)	(0.012)	(0.030)
Log likelihood	2317.21		
Wald χ^2	2274.36***		
Adjusted R^2			0.405
N	4310		4310

Note: For the FMRM, robust standard errors are in parentheses and the model converges in 11 iterations. Regressions also include activity sector dummies. The first component is the low quality of employment range and inversely for the second component.

† π_c is the probability that an observation is in component c.

‡ For the OLS estimation, robust standard errors are in parentheses. Each predictor was uncorrelated with the other predictors.

$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Source: Authors.

Appendix E3

Table 8: Quantile Regressions (total sample), GIHS (2013)

	QR					
Variable	q10	q20	q30	q70	q80	q90
Social networks	-0.136***	-0.163***	-0.119***	-0.026***	-0.018***	-0.012***
	(0.014)	(0.019)	(0.013)	(0.004)	(0.003)	(0.003)
Adjusted R^2	0.206	0.283	0.327	0.134	0.100	0.066
N	5846	5846	5846	5846	5846	5846

Note: Bootstrapped standard errors are in parentheses (500 rep.).
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
Source: Authors.

Table 9: Quantile Regressions (independents), GIHS (2013)

	QR					
Variable	q10	q20	q30	q70	q80	q90
Social networks	-0.148***	-0.207***	-0.181***	-0.055***	-0.032***	-0.029***
	(0.029)	(0.035)	(0.026)	(0.010)	(0.008)	(0.007)
Adjusted R^2	0.187	0.270	0.332	0.160	0.116	0.082
N	1536	1536	1536	1536	1536	1536

Note: Bootstrapped standard errors are in parentheses (500 rep.).
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
Source: Authors.

Table 10: Quantile Regressions (employees), GIHS (2013)

	QR					
Variable	q10	q20	q30	q70	q80	q90
Social networks	-0.134***	-0.152***	-0.093***	-0.020***	-0.012***	-0.008***
	(0.019)	(0.021)	(0.015)	(0.004)	(0.003)	(0.003)
Adjusted R^2	0.224	0.306	0.341	0.155	0.122	0.086
N	4310	4310	4310	4310	4310	4310

Note: Bootstrapped standard errors are in parentheses (500 rep.).
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
Source: Authors.