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THE ROLE OF SOCIAL NETWORKS IN EMPLOYMENT OUTCOMES OF BOLIVIAN WOMEN

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Abstract

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Keywords:

gender, employment, social networks, neighborhood effects.

JEL:

J15, J16, O18, Z13

The role of social networks in employment outcomes of Bolivian women*

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Abstract

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1. Introduction

Female labor market discrimination has important welfare implications in the developing world where labor market earnings are the main component of households' income, especially among poor families. Research on gender gaps in the labor market has traditionally sought explanations on the characteristics and preferences of individual workers or employers. One strand of the literature attributes the associations between workers' sex and their labor market outcomes to differences in training, experience, age, marital status or career commitment. Others focus on employers' preferences for workers of one sex over the other (taste discrimination) or on employers' beliefs that workers of one sex or the other are more costly or less profitable to employ (statistical discrimination).[1]

Even though measuring discrimination is not an easy task, the evidence is that net of human capital characteristics and a variety of other control variables, men out earn women, have better benefits, more on-the-job training and hold more complex jobs with more authority. Moreover, there is no evidence of a decrease in labor market unexplained gender differences, as supporters of market-based theories would expect (Ñopo 2004, 2007; Bernhardt et al. 1995; Arrow 1998).

Recent research in the fields of sociology and economics has shown that in addition to individual characteristics, social networks play an important role in the job matching process since a very important fraction of workers find jobs through friends and relatives.[2] Social interactions have externalities, in which the actions of a reference group affect an individual's

[1] A comprehensive survey of the literature can be found in Altonji and Blank (1999). Moreno et al. (2004), Ñopo (2004), Nuñez and Gutierrez (2004) and, Bravo et al. (2006) are examples of more recent empirical work for Latin America.
[2] Rees (1966) and Granovetter (1973, 1995) suggest that in the United States more than 50 percent of all new jobs were found through friends, relatives, neighbors or occupational contacts rather than through formal means.

preferences.[3] If men and women use their social networks differently and if the networks have different characteristics, then the interactions with their peers would have different effects on their employment patterns and the quality of jobs they can access. This, in turn, could have important welfare effects on families who live in developing countries.

Social network theory differs from traditional studies that assume that only individual characteristics influence individuals' economic decisions and outcomes: personal characteristics as well as their relationships and ties with other actors within the network matter. Hence, in the labor market context, the structure of individuals' social networks turns out to be a key determinant of (i) who gets a job and who gets which job, (ii) how patterns of unemployment relate to gender or ethnicity, and (iii) the incentives that individuals have to educate themselves and to participate in the workforce (Jackson, 2003).

Theoretical models of social networks distinguish two mechanisms through which social contacts impact on the functioning of the labor market. First, employers may reduce uncertainty about prospective worker's productivity through referrals obtained from firms or workers. Second, worker's connections disseminate job information within the supply side of the labor market through word-of-mouth communication. In his seminal work Montgomery (1991) allows workers and firms to choose between formal and informal hiring channels, and concludes that workers who are well connected might fare better than workers with no social ties to high-ability workers, even while holding numerous ties to low-ability workers. More recently, models by Calvó-Armengol and Jackson (2002) and Calvó-Armengol (2004) allow workers to rely both on own search effort and on information exchange with their social circles to find jobs. They conclude that information passed from employed individuals to their unemployed acquaintances makes it more likely that these acquaintances will become employed, and that the duration and

[3] Scheinkman, forthcoming.

persistence of unemployment can be understood as social effects: the longer an individual is unemployed the more likely it is that her social environment is associated with unfavorable unemployment prospects. Calvó-Armengol and Jackson (2004) find that the likelihood of dropping out of the labor force is higher for individuals who have few acquaintances or whose social contacts have poor employment experience.

Empirical studies suggest that social networks do have significant effects on employment outcomes. Case and Katz (1991) find a correlation between youth joblessness and the joblessness of neighbors. Topa (2001) and Conley and Topa (2002) find that social interactions can explain the persistent correlations in patterns of unemployment in US cities. Weinberg et al. (2004) show that one standard deviation improvement in neighborhood social characteristics and in job proximity raises individuals' hours worked by six per cent and four per cent on average, respectively. Similarly, Van Ham and Buchel (2006) find that those willing to work find it easier to do so if they live in regions with low regional unemployment rates.

The empirical literature has also found evidence of differences in the characteristics of men's and women's social networks, which is the result of differences in the social-structural locations of women and men, and which in turn have effects on the access to information about job vacancies. Men are more likely to have wider ranging networks that are work-centered (i.e., colleagues and co-workers) and women are more likely to have kin-centered networks (Brass, 1985; Hanson and Pratt, 1991; McPherson and Smith-Lovin, 1982, 1986). While men are more likely to have higher-status social positions in communities, higher-status jobs and fewer domestic responsibilities, women work in jobs with less socio-economic status and professional responsibilities and have more domestic responsibilities, constraining their possibilities to form networks with people in high-status jobs, creating network disadvantages for women. This has a contemporaneous effect of constraining women's immediate possibilities to form networks with people in high-status jobs, creating network disadvantages for women today. It may also have dynamic effects: the lack of access to better quality networks in the present may limit women's future employment opportunities, as they are excluded from valuable information exchange about employment.

Empirical results suggest that female-dominated social networks are associated with lower-quality employment. For instance, Mencken and Winfield (2000) find that women who found their jobs through male informal contacts were less likely to work in female-dominated occupations that offer lower wages, less training, fewer opportunities for advancement, less autonomy, and more limited authority compared to non-female-dominated jobs. Beggs and Hurlbert (1997) find that the gender of the informal contact affects the occupational status: women whose contacts are other women work in occupations with lower socioeconomic index. Finally, Petersen et al. (2000) find that race and gender have a strong impact on the likelihood of having a second interview and on the increase in the salary offer.[4]

The empirical literature on social network effects has almost exclusively relied on data from developed countries. Nonetheless, labor market outcomes in general—and women's outcomes in particular, have important welfare effects in less developed countries.[5] Women are important contributors to total household income and in many cases they carry the burden of raising their family alone: during the 1990-2004 period, between 20 to 50 percent of households were headed by women in developing countries,[6] earning between 25 to 30 percent less than men with similar education and labor market experience. Thus, women's labor choices and outcomes have immediate effects that may make the difference between living in poverty or not. More

[4] However, once they control for the referral method, sex and race effects disappear.
[5] An exception is Wahba and Zenou (2005).
[6] World Bank (2006). Based on available data for the 1990-2004 period; excludes countries with traditional societies where women play minor roles.

generally, in LDCs gender inequality is a widespread phenomenon that enhances poverty and decreases social mobility.

Bolivia is one of the poorest countries of Latin America, with a per capita GDP of less than US$1,000 and with high levels of income inequality. Additionally, serious gender biases are prevalent in its labor market: between 1989 and 2002 women's unemployment rates were consistently higher than men's, and while female labor force participation rates have increased, the entry of more women into the Bolivian job market has not translated into quality jobs. By the end of the period 80 percent of employed women worked in the informal sector, compared to 60 percent of employed men, and 75 percent of employed rural women did not receive any income for their work, limiting their possibilities to escape from poverty.[7] Furthermore, more than 50 percent of Bolivian women supply more than half of their family income, whilst the average hourly wage of women with college education is 40 percent below of their male counterparts (Bravo and Zapata, 2005). Notwithstanding these gender inequities, without the contribution of women to household income poverty rates would have been 11 percentage points higher in 2002.

This paper makes several contributions to the existing empirical literature of social network effects. First, we are among the first to explore the role of social networks in determining employment outcomes in a Latin American context. Second, we contribute an additional piece to the labor market discrimination puzzle by assessing the role of gender in the social interactions that may facilitate employment. Finally, we analyze whether social networks provide access to higher quality employment.

The rest of the paper unfolds as follows. The next section presents our methodological approach and identification strategy, followed by a section that describes the data used and

[7] See www.cepal.cl/mujer

summary statistics. Section 4 contains the estimation results, and the last section concludes with final remarks and policy implications.

2. Empirical framework

2.1 Social network measures

Empirical social network studies typically define a network along geographic or cultural proximity of a group of individuals. The empirical literature has faced the difficult task of explaining if the observed correlation in the behavior of individuals who are physically or socially close is because they share the same sources of information or because they learn from one another's behavior. The difference between the two is that the latter is really a social interaction, while the first simply reflects the fact that the group is affected by similar shocks (a more detailed explanation of the problems that can affect the empirical literature and the potential solutions will be explained in more detail in the following sections).

The literature on social networks acknowledges that a key determinant of the effect of job networks on employment is the strength of social ties. Furthermore, economic studies that define network effects as neighborhood effects recognize that the ties with one's neighbors are weaker than the ties with friends or kin, and it is precisely this kind of ties that is more conductive to generating useful information about jobs. Granovetter (1995) argues that "weak" ties such us colleagues or acquaintances are a richer source of information about job openings than family or friends ("strong" ties), because weak ties link various groups in social space increasing the amount of non-redundant information. In contrast, strong ties connect similar people who are less likely to offer the job searcher information that she does not already have. In a more general context, strong and weak ties have different effects and different benefits. Strong ties are an important source for understanding and support, while weak ties provide access to miscellaneous resources (Hirsh et al., 1990; Cattell, 2001; Granovetter, 1973).

In this paper we use a reference group definition based on physical proximity as a measure of an individual's social network. The underlying idea is that agents exchange information about job openings more frequently with people who live physically close. Let each individual i be a member of a peer group which is indexed by g and is comprised by n_g individuals. We assume that each group is comprised by individuals that live in a common neighborhood, thus $g = \{neighborhood\}$. We observe the (binary) outcome of each individual $y_{i,g} = \{0,1\}$, which represents the labor market outcome under study. We define the social network as the average outcome of the other members in the group:

$$\overline{y}_{i,g} = \sum_{\substack{j=1 \\ j \neq i}}^{n_g} \frac{y_{j,g}}{n_g - 1} \tag{1}$$

Since $y_{j,g}$ is the individual's labor market outcome (e.g., whether she is employed), then $\overline{y}_{i,g}$ is the (left-out) group average outcome.

Social networks need not to be strictly geographic. Networks also develop along other dimensions, such as gender; for instance, Straits (1998) finds that that men and women tend to use same-sex contacts to find employment. In order to obtain an additional measure of social networks we combine the gender social metric with our physical measure of networks. Thus, an individual's sex is considered as an additional indicator of social proximity, so that another measure of social network can be given by:

$$\overline{y}_{i,g} = \sum_{\substack{j=1 \\ j \neq i}}^{n_g} \frac{w_{i,j} \times y_{j,g}}{n_g - 1} \tag{2}$$

where individual i gives a positive weight w equal to 1 to every agent's outcome j who belongs to her same sex, otherwise the outcome is assigned a weight equal to zero. Therefore, if social networks develop along gender lines, the employment outcomes of a female will be affected by the share of women peers with whom she can share information about job offers.

2.2 Empirical framework

Our econometric model follows closely the empirical models presented in the literature studying social interaction effects where the outcome of an individual is not only explained by her personal characteristics, but it is also influenced by the average outcome of her reference group, namely the social network variable (Case and Katz, 2001; Sacerdote, 2001; Bertrand et. al., 2001).

Each individual's labor market outcome depends on a combination of individual-specific and group-specific factors. The individual-specific factors are comprised by observed $\mathbf{x}_i$ (e.g., experience, marital status, number of children). Group-specific factors are partitioned into observed group characteristics $\mathbf{z}_g$ (e.g., poverty rate in the neighborhood) and those that are unobserved, ζ_g (e.g., employment opportunities in the neighborhood), and the average outcome in the group $\overline{y}_{i,g}$. Under these assumptions, the labor market outcome of each individual can be described by the following probability model:

$$\mathbf{P}(y_{i,g} = 1 \,|\, \mathbf{x}_{i,g}, \overline{y}_{i,g}, \mathbf{z}_g) = \mathbf{F}(\mathbf{x}_{i,g}\boldsymbol{\beta} + \gamma \overline{y}_{i,g} + \mathbf{z}_g \boldsymbol{\delta} + \zeta_g) \qquad (3)$$

where social interactions are captured by group characteristics ($\mathbf{z}_g$) and is by the social network variable ($\overline{y}_{i,g}$), measured as the average outcome of other members in the group.

Three alternative hypotheses can explain the correlation in labor market outcomes of individuals who are in physical proximity to one another: endogenous interactions, exogenous or contextual interactions, and correlated effects (Manski 1993, 1999). In the presence of endogenous interactions the probability of an individual of obtaining a job increases with the fraction of her employed peers $\bar{y}_{i,g}$. Consequently, in the presence of endogenous interactions, the coefficient accompanying the group's average choice will be greater than zero ($\gamma > 0$), implying that social contacts have a positive impact on labor market outcomes. This variable captures the idea that social contacts mediate propagation of rich and reliable information among individuals, thereby helping workers to find jobs, and employers to find employees (Calvó-Armengol, 2004). Consequently, the interaction with more individuals that are strongly attached to the labor market (i.e., larger $\bar{y}_{i,g}$) leads to a reduction in the cost of finding information about job availability and/or to an increase the individual's job market referrals, increasing the probability that the individual finds a job.

In addition to the direct impact of social networks, we may expect that an individual's outcome might be also influenced by the average personal characteristics of her reference group. For instance, an individual related to a cluster with a high socioeconomic status might increase her employment opportunities either because a member of the group may employ her, or because the member refers her to another employer. If this is the case, we are in the presence of contextual effects; hence, the effect is through the group characteristics and not through group outcomes.

We may also believe that individuals in the same group tend to behave similarly because they sort into neighborhoods or face similar institutional environments, what Manski calls correlated effects. For example, if the neighborhood where the individual and his group inhabit has better access to jobs, the individual's likelihood of obtaining a job as well as the average employment rate of the group will increase.

In order to draw meaningful public policy implications, these three effects must be disentangled. Both endogenous and contextual effects imply that an individual's outcome is influenced by her group and thus represent real social interactions; nonetheless, endogenous effects imply that the aggregate impact of a policy intervention will be larger than the individual-level impact, giving rise to a social multiplier that will not exist if the social interaction is through contextual effects (Moffitt, 2001 and Soetevent, 2006). In the context of this paper, a social multiplier occurs when an employed person raises the probability of being employed for the rest of the individuals on her group. Correlated effects, on the other hand, do not imply a social multiplier or that social groups matter.

2.3 Identification strategy

Even if we find compelling evidence of correlations in the employment status of individuals who are in physical proximity to one another, we wish to know what explains such correlations. The presence of contextual and endogenous effects makes it difficult to disentangle the true impact of social networks on the employment opportunities of individuals. If these affects are not explicitly accounted for in the estimating procedure, the coefficient on a social network variable will be biased.

The first identification problem that arises in the empirical study of social interactions is the reflection or simultaneity problem. The reflection problem arises due to the fact that social interactions—endogenous and exogenous—not only affect the individual's outcomes but they also impact the outcomes of other agents in the group simultaneously (Sacerdote 2001, Gaviria and Raphael, 2001). Nonetheless, the reflection problem is relevant when the reference group is small, for instance among close friends or classmates, and the simultaneity bias is nearly zero when the size of the group is more than one hundred (Krauth 2004, 2006). When the reference group is large (e.g., neighborhoods) this problem becomes less relevant; thus to attenuate the possibility of this bias, we have limited our sample to neighborhoods with populations above one hundred individuals.

The second major problem in identifying the effect of social interactions is the possibility of unobserved group or neighborhood effects. The presence of the unobservable group effects can, if not accounted for, lead to spurious conclusions concerning the presence of social interactions. For instance, suppose a neighborhood is affected by a positive shock and has more availability of jobs. The correlation between an individual's labor market outcome and the average neighborhood outcome may be positive not because of any influence of social networks, but because average neighborhood employment may be itself correlated with the availability of jobs within the neighborhood. Again, the presence of a non-observable group-specific component that is correlated with the exogenous characteristics of the individuals will generate a non-zero expected value of the error term.

To address this problem econometrically, we account for inter-group differences and exploit geographic variation by including fixed effects for municipalities,[8] which are geographic areas that include several neighborhoods that are homogenous. With this strategy we are implicitly assuming that the most important unobservable effects arise due to characteristics such as economic shocks at the municipal level, which influence the job availability in a group of nearby neighborhoods. We therefore estimate:

$$\mathbf{P}(y_{i,g} = 1 \mid \mathbf{x}_{i,g}, \bar{y}_{i,g}, \mathbf{z}_g) = \mathbf{F}(\mathbf{x}_{i,g}\boldsymbol{\beta} + \gamma\, \bar{y}_{i,g} + \mathbf{z}_g\boldsymbol{\delta} + \zeta_a\boldsymbol{\alpha}) \qquad (4)$$

[8] Similar to the strategy presented in Bertrand et al. (2001).

where $y_{i,g}$ is the individual's labor market outcome, $\mathbf{x}_{i,g}$ is a vector of individual characteristics, $\bar{y}_{i,g}$ is the average outcome observed by the other members of the group, $\mathbf{z}_g$ is a vector containing average characteristics of the group members, and ζ_a are municipality fixed effects. The inclusion of these last two variables allows us to control for the presence of contextual effects and the primary sources of correlated effects, helping to attenuate the bias in the estimated effect the social network variable.

3. Data and variables

This study uses two sources of information. The individual and household-level data are obtained from the 2001 round of Bolivia's national household survey (MECOVI), which was administered by the National Statistical Institute (INE) during the months of November and December. MECOVI is a nationally representative survey that collects detailed data on the characteristics of almost 6,000 households and more than 25,000 individuals. These data allowed us to obtain relevant information on individuals' labor market outcomes, personal characteristics, household composition, and dwellings' characteristics. Additionally, we were able to identify the neighborhood where each individual lives.

We use the Bolivian Census (conducted in August of 2001) to construct our social network measure, as well as all other variables capturing group characteristics. Combining these datasets has two advantages. Firstly, while the Census contains information on the entire population, it provides only basic information on individual characteristics and employment outcomes, and the MECOVI survey contains detailed information on household characteristics and employment outcomes. Secondly, Census data is representative at the neighborhood level, which provides information about the group that surrounds each individual and facilitates the construction of the social network variables and group characteristics, which cannot be obtained from the MECOVI survey because it is not representative for such disaggregated geographic areas.

Bolivia is divided into nine departments that are further divided into 314 municipalities. While the MECOVI covers all nine departments, it was distributed in only 211 municipalities so that our final database contains municipalities covered by both the Census and the MECOVI. The final database contains individuals residing in 526 neighborhoods around Bolivia, all of which have a population above 100 individuals. We restrict our sample to individuals aged 25–60 years so that employment outcomes are not affected by schooling or retirement decisions. Our final sample consists of 3,585 women and 3,315 men.[9]

We explore the role of social networks on two binary employment outcomes: labor market participation and waged employment. The first dependent variable equals 1 if the individual participates in the labor force and 0 otherwise.

In addition to the likelihood of participating in the labor force, we are also interested in the role of social networks in finding better quality employment. In this study, we define a second dependent variable that equals 1 if the individual reports working for a wage (i.e., she is a salaried worker), and equals 0 if she is self-employed. Characterizing the quality of a job is not an easy task. Nonetheless, studies of Latin American labor markets have found that salaried jobs are more stable, pay higher salaries, have access to formal social security programs, and are better protected from adverse health and economic shocks than self-employed jobs.[10] In this sense, our

[9] In our sample, by age 25 male participation rate is over 90 percent, while the female rate is above 65 percent. This remains true for the 25-60 year-old range.

[10] See Inter American Development Bank (2003) and Gasparini and Tornarolli (2007). These studies find that some self-employed workers—those that are entrepreneurs or that are skilled—earn more than salaried workers. Our analysis excludes entrepreneurial business owners, so that our sample includes only low-skilled self-employed workers that on average earn less, have less access to employment benefits and that are more vulnerable to adverse shocks than salaried workers.

study refers to salaried employment as "better" than self employment.

Table 1 presents average participation and employment rates, as well as average labor earnings, by gender and area. As can be observed, earnings from waged labor are almost two times greater than earnings from self-employment; thus, we interpret waged employment as being of higher quality. Labor force participation rates were relatively high among Bolivian workers in 2001—96 and 75 percent among men and women, respectively—relative to other countries with similar income levels. The incidence of salaried employment, on the other hand, was low: only 44 percent of men and 38 percent of women held salaried job positions.

Our variable of interest is the social network variable, which is constructed from Census data according to equation (1). When the dependent variable is labor market participation, the social network is the share of individuals in the neighborhood that are employed. We consider only employed individuals because the unemployed will not provide relevant information about jobs to those who seek employment or who wish to find a new job. Moreover, a larger share of employed individuals may encourage people to participate in the labor market, while high unemployment rates may have the opposite effect. When the dependent variable is waged employment, the social network variable is the share of individuals in the neighborhood who are salaried workers.

We are especially interested in analyzing whether the effect of a social network differs across gender lines. Thus, in order to test the hypothesis that social networks are formed along gender lines, we construct an additional social network variable according to equation (2) that considers the sex of the contacts within the neighborhood. We include the average outcomes of females and males in the neighborhood as separate regressors. If women (men) tend to use same-sex contacts then the average outcome of women (men) will have a significant and positive effect on the same-sex individual's outcome. On the other hand if social networks of women include men and women then both social network variables will have a positive impact.

To capture contextual effects, we control for several observable group characteristics such as the poverty incidence in the neighborhood, the share of indigenous inhabitants in the neighborhood and the share of high educated individuals that live in each neighborhood.[11] Finally, to control for unobservable group characteristics we include municipality fixed effects in all our estimations. In our sample, municipalities in urban areas contain an average of four neighborhoods, while in the rural area they have two neighborhoods. Table 2 presents selected neighborhood characteristics.

The vector of individual characteristics includes labor market experience (proxied by age),[12] education of the individual measured as years of schooling, and dummy variables equal to 1 if the individual is: head of the household, married, and if she belongs to an indigenous group. Household demographic composition is captured by including variables for the number of pre-school aged children (less than 6 years), school-aged children (between 6 and 18 years), adults (between 19 and 60 years) and elderly (60 years or older) in the household. Summary statistics for individual and household characteristics are found in Table 3.

4. Empirical results

In this section we present and discuss the results of estimating equations (3) and (4) using a normal probability model for the two employment outcomes under study. We perform all the estimations separately for women and men, and by area of location. In all regression tables, columns 1 and 3 present the results for the average social network measure that includes men and

[11] We measure poverty using the unsatisfied basic needs method, which measures poverty based on the extent to which the population is deprived of one or more of the basic needs in shelter, water and sewerage services, and education and health services.

[12] As is standard in the empirical labor market literature, we test whether the effect of experience has diminishing returns by including a term for age-squared.

women as potential employment contacts (equation (1) above), and columns 2 and 4 present results the social network variable separated along gender lines (equation 2).

4.1 Women

Social Networks

Table 4 reports the results of estimating women's labor force participation probability. We find that, controlling for municipality fixed-effects and contextual characteristics, the coefficient of the social network variable (measured as the fraction of employed inhabitants in the neighborhood) is not statistically significant in either urban or rural areas (columns 1 and 3 respectively), which would suggest that social networks do not have an effect on women's decision to participate in the labor market.

However, once we divide the social network measure along gender lines, we find that a higher share of employed women in the neighborhood is positively correlated with the probability that a woman participates in the labor market, both in urban and rural areas. This suggests that among women, the availability of same-sex contacts is positively correlated with their decision to enter the labor market.

Additionally, we find that in Bolivia's rural areas as the share of employed men in the neighborhood increases, the probability that a woman participates in the labor market decreases. This finding suggests that in rural areas there is a substitution effect between men and women's work. When there are high unemployment rates among men, women enter the labor market to substitute the income loss of the unemployed husband. In urban areas, men's employment rates do not affect women's participation.

Table 5 presents results of estimating the probability that women have a salaried job. We find that a larger social network (measured as the fraction of salaried workers in the neighborhood) does have a positive and statistically significant effect on the probability that women hold salaried employment, both in urban and rural areas (columns 1 and 3, respectively). This finding suggests that having a higher share of neighbors employed as waged workers—regardless of their sex—is positively correlated with the likelihood that women find a salaried job, providing empirical support to social network theories that propose that information channels have positive effects on individual employment outcomes. Furthermore, in Bolivia these information channels seem to provide access to better quality jobs.

When we consider gender in the definition of the social network variable, we find that urban women are more likely to hold salaried jobs if a higher share of other women in their neighborhood hold salaried employment (column 2). In contrast, rural women are more likely to have a salaried job if the share of her male neighbors with waged work is higher, while her waged-work likelihood is unaffected by her female social network (column 4). This finding suggests that social or cultural differences exist between urban and rural Bolivia: while urban women benefit from same-sex contacts, in rural areas women benefit more from their male contacts.

Neighborhood Characteristics

Table 4 reveals that women are more likely to be active in the labor force if they live in neighborhoods with a higher share of indigenous population. A possible explanation is that the concentration of indigenous population may itself function as a type of network, and therefore a larger share of indigenous neighbors may imply a larger network in which to obtain information about possible job prospects (see Contreras et al., 2006). The strength of this correlation is higher—both in magnitude and statistical significance—in rural areas.

As Table 5 reveals, a higher share of indigenous population in the neighborhood is negatively correlated to the likelihood that a woman works as a salaried worker in rural areas (columns 3 and 4). Expressed differently, women living in neighborhoods with higher indigenous populations are more likely to be self-employed, which is consistent with results in Contreras et al. (2006) where the authors find that social networks are an effective channel in finding employment among indigenous heads of households—particularly self-employment. In other words, access to a social network that is indigenous is correlated to lower-quality self employment, since jobs in this sector have lower earnings and are more unstable than salaried jobs.

Individual and Household Characteristics

When analyzing the probability that a woman participates in the labor market (Table 4), the variables that control for individual characteristics display the expected signs. Women who are heads of their households are more likely to work or seek work than women who are not the head of the household, and the effect is significant in both urban and rural areas. Experience (proxied by age) has a positive but decreasing effect on the likelihood of participating in the labor force. Women with more education are more likely to be in the labor market, while married women are less likely, yet these effects are only significant in urban areas of Bolivia. Family composition does not appear to affect the likelihood that a woman participates in the labor force.

Being the head of the household and labor market experience do not affect the likelihood that a woman holds salaried employment, in either urban or rural areas (Table 5). Education, on the other hand, has a positive and significant effect on the likelihood of waged employment in both urban and rural areas. Among urban women, being married and the presence of pre-school aged children are negatively correlated with the probability that they hold salaried employment.

4.2 Men

Social Networks

Tables 6 and 7 present results for the likelihood that men participate in the labor market and that they hold salaried employment, respectively. Our results indicate that social networks have a positive and significant effect on the probability that urban men participate on the labor market (Table 6, column 1). Furthermore, when we consider gender in the social network variable, we find that urban men benefit from same-sex contacts, i.e., in neighborhoods with a larger male employment rate, men have a higher likelihood of participating in the labor market (column 2). Social networks do not play a role in men's participation in Bolivia's rural areas.

Social networks play an even greater role—in magnitude of the effect and in its statistical significance—in determining the probability that men have salaried jobs (Table 7). We find that a higher share of neighbors employed as salaried workers is positively correlated with the probability that rural men hold salaried employment (column 3). The analysis across gender lines reveals that both urban and rural men benefit if their male neighbors are employed in waged work (columns 2 and 4, respectively), whereas higher fraction of female neighbors working as salaried workers is negatively correlated with the likelihood that urban men are hold better quality jobs (column 2). This finding suggests that substitution effects exist between male and female salaried employment in rural areas.[13]

[13] Neighborhood, individual and household characteristics had similar effects on the probabilities of male labor force participation and salaried employment, so for brevity of exposition they will not be discussed. Nonetheless, full results are presented in Tables 6 and 7.

5. Final Remarks and Policy Implications

Traditional studies of labor market outcomes consider only individual characteristics, ignoring the fact that individuals are also influenced by their social interactions. Gender differences exist in access to and characteristics of social networks, so that they may explain, at least in part, the observed differences in employment outcomes of women vis-à-vis men.

This paper provides evidence on the variables that determine female labor market participation in Bolivia, focusing on the role of social networks. It is one of the first studies to analyze social network effects in Latin America, and to explore whether men and women use different types of networks and whether networks affect their employment outcomes differently.

Our empirical results reveal that the likelihood that women participate in the labor market is greater in neighborhoods with higher share of employed women, both in urban and rural areas. Furthermore, we find that social networks (measured as the share of neighbors employed in waged work) have a positive effect on the probability that men and women have salaried jobs, and furthermore that men and urban women tend to use same sex contacts to find salaried employment. This finding suggests that social contacts have positive externality effects that can potentially increase the welfare of Bolivian workers, as these contacts are useful in finding better quality jobs.

Our findings regarding individual and family variables are in line with the international evidence. We find that marriage and the presence of pre-school aged children are negatively correlated with the probability that women participate in the labor market, whereas we find weak evidence that marriage and the presence of young children increase the probability that men participate in the labor market, suggesting that families in Bolivia distribute responsibilities along traditional gender roles. Women are mainly responsible for domestic and child care activities, while men are mainly responsible for market activities. Therefore, in order to increase female labor participation, policies need to facilitate women's entry into labor markets by alleviating at least part of the burden of traditionally "female" activities, through publicly-funded pre-school and/or day care services.

The role of education is strong and robust: education is positively correlated with female labor force participation (at least in urban areas), and with the probabilities of finding better (salaried) employment for both men and women, in urban and rural areas. This result highlights the importance of public programs that seek to increase educational attainments, which is particularly important for Bolivian women who have much less education than their male counterparts.

The implications of these findings are threefold. First, analysis of discrimination in the labor market should consider the effects of social networks. Ignoring this variable may lead to incorrect interpretation of outcomes such as labor market segregation and wage differentials as discrimination, while these might in fact be the result, at least to some extent, of the mechanisms that men and women use to find jobs.

Second, social networks in Bolivia are useful in finding salaried employment vs. self-employment, which suggests that networks are, to some extent, used by employers to eliminate part of the asymmetry of information they have about prospective employees, and future employees use networks to obtain information about job openings. Policies oriented to reduce these asymmetries of information in the labor market, such us referral or employment agencies, may make the job search process more swift and efficient. Finally, if policy makers are interested in eliminating or at least reducing the gender inequities found in the Bolivian labor market, policies need to be sensitive to gender disparities and oriented to reduce them.

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Table 1

Employment rates and earnings, by gender and area

	Men	Women	Total
Labor force participation rate (%)			
Urban	94.7	73.3	83.4
Rural	98.9	78.4	88.6
Total	96.2	75.0	85.2
Salaried employment (%) [1]			
Urban	59.4	41.9	51.8
Rural	18.5	20.7	19.1
Total	44.1	37.8	41.7
Self-employment (%) [1]			
Urban	40.6	58.1	48.2
Rural	81.5	79.3	80.9
Total	55.9	62.2	58.3
Average Labor Earnings (US$/month)			
Salaried employment			
Urban	210	171	196
Rural	122	84	112
Average	196	162	184
Self-employment			
Urban	163	85	120
Rural	81	84	82
Average	117	85	103
Salaried/Self-employment ratio (average)	**1.7**	**1.9**	**1.8**

Source: Authors calculations based on MECOVI 2001. Includes individuals aged 25–60 years.

[1] As a percentage of paid workers.

Table 2
Selected neighborhood characteristics

Variable	Urban				Rural			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Percent-indigenous	29.2	22.9	0.7	90.4	58.5	36.3	0	100
Percent-poverty	48.6	33.8	0.4	100	82.7	20.5	6.8	100
Share population with high-school educ. or more (%)	39.3	20.0	5.5	86.9	13.5	12.1	0	70.1
Share of employed workers in neighborhood (%)	66.2	4.9	51.0	82.1	67.5	15.4	23.5	100
Share of employed women in neighborhood (%)	52.7	7.4	29.8	71.5	47.9	24.2	0	100
Share of employed men in the neighborhood (%)	81.4	4.7	58.1	98.6	86.6	11.3	44.4	100
Share of salaried workers in neighborhood (%)	31.3	7.4	10.2	52.6	15.4	11.8	0	50.7
Share of salaried women in neighborhood (%)	21.6	9.3	3.8	48.1	7.8	8.0	0	34.1
Share of salaried men in the neighborhood (%)	42.1	7.4	13.2	68.6	22.7	17.5	0	90.3
Total Population	3,699	901	291	8,002	611	603	103	3,912

Authors' own calculations based on 2001 Census.

Table 3
Summary Statistics

Variable	Women Mean	Women Std. Dev.	Women Min	Women Max	Men Mean	Men Std. Dev.	Men Min	Men Max
Urban								
Labor force participation	0.713	0.452	0	1	0.948	0.222	0	1
Salaried employment	0.428	0.495	0	1	0.611	0.488	0	1
Head of household	0.199	0.399	0	1	0.839	0.367	0	1
Age	39.0	9.7	25	60	38.8	9.6	25	60
Age^2	161,281	79,949	62,500	360,000	159,594	78,919	62,500	360,000
Yrs. Education	8.1	5.4	0	17	9.9	4.8	0	17
Married	0.753	0.431	0	1	0.826	0.379	0	1
HH members aged under 6 yrs.	0.7	0.9	0	7	0.7	0.9	0	7
HH members aged 6 to 18 yrs.	1.6	1.4	0	7	1.5	1.4	0	7
HH members aged 60 or older	0.2	0.4	0	3	0.1	0.4	0	3
Rural								
Labor force participation	0.768	0.422	0	1	0.988	0.111	0	1
Salaried employment	0.246	0.431	0	1	0.249	0.432	0	1
Head of household	0.150	0.357	0	1	0.889	0.314	0	1
Age	40.0	10.0	25	60	40.0	9.9	25	60
Age^2	170,048	83,522	62,500	360,000	169,816	82,610	62,500	360,000
Education	3.7	4.0	0	17	5.9	4.0	0	17
Married	0.831	0.375	0	1	0.855	0.353	0	1
HH members aged under 6 yrs.	0.9	1.0	0	5	0.9	1.0	0	5
HH members aged 6 to 18 yrs.	1.9	1.6	0	11	1.7	1.6	0	11
HH members aged 60 or older	0.1	0.4	0	2	0.1	0.4	0	2

Source: Authors' calculations based on MECOVI 2001.

Table 4
Probability of participating in the labor market - Women
Probit regressions (Marginal probabilities)

Explanatory Variable	**Urban** (1)	(2)	**Rural** (3)	(4)
Social Networks				
Ave. employed workers in neighborhood	-0.0016		0.0010	
	(0.0032)		(0.0015)	
Ave. employed women in neighborhood		0.0040*		0.0027***
		(0.0024)		(0.0010)
Ave. employed men in the neighborhood		-0.0051		-0.0040**
		(0.0041)		(0.0019)
Group characteristics				
Percent-indigenous	0.0019**	0.0009	0.0023***	0.0018***
	(0.0008)	(0.0009)	(0.0006)	(0.0006)
Percent-poverty	-0.0018**	-0.0016*	0.0009	0.0004
	(0.0008)	(0.0008)	(0.0015)	(0.0015)
Share of people with high-school education or more	-0.0020	-0.0037**	0.0013	-0.0006
	(0.0016)	(0.0016)	(0.0029)	(0.0030)
Individual and Family Characteristics				
Head of household	0.0843***	0.0840***	0.1574***	0.1566***
	(0.0293)	(0.0291)	(0.0281)	(0.0279)
Age	0.0629***	0.0630***	0.0395***	0.0401***
	(0.0096)	(0.0096)	(0.0129)	(0.0126)
Age^2	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Education	0.0064***	0.0062***	0.0044	0.0041
	(0.0024)	(0.0024)	(0.0043)	(0.0043)
Married	-0.1107***	-0.1106***	-0.0355	-0.0211
	(0.0254)	(0.0253)	(0.0406)	(0.0403)
HH members under 6 years of age	-0.0103	-0.0098	-0.0342**	-0.0344**
	(0.0119)	(0.0118)	(0.0169)	(0.0160)
HH members aged between 6 to 18	-0.0148*	-0.0137	-0.0081	-0.0078
	(0.0088)	(0.0088)	(0.0092)	(0.0093)
HH members 60 years old or older	0.0065	0.0051	0.0540	0.0453
	(0.0255)	(0.0254)	(0.0507)	(0.0493)
Observations	2292	2292	1293	1293

Note: Robust standard errors are reported in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5
Probability of salaried employed - Women
Probit regressions (Marginal probabilities)

Explanatory Variable	**Urban**		**Rural**	
	(1)	(2)	(3)	(4)
Social Networks				
Ave. salaried workers in neighborhood	0.0280***		0.0121**	
	(0.0052)		(0.0047)	
Ave. salaried women in neighborhood		0.0221***		-0.0013
		(0.0047)		(0.0049)
Ave. salaried men in the neighborhood		0.0033		0.0092***
		(0.0042)		(0.0027)
Group characteristics				
Percent-indigenous	-0.0000	0.0025	-0.0023***	-0.0028***
	(0.0018)	(0.0016)	(0.0008)	(0.0006)
Percent-poverty	-0.0004	0.0002	0.0009	0.0011
	(0.0012)	(0.0013)	(0.0017)	(0.0015)
Share of people with high-school education or more	-0.0061**	-0.0053*	-0.0073*	-0.0075*
	(0.0025)	(0.0027)	(0.0040)	(0.0040)
Individual and Family Characteristics				
Head of household	-0.0314	-0.0344	0.0020	0.0167
	(0.0602)	(0.0589)	(0.0683)	(0.0680)
Age	-0.0228	-0.0223	0.0043	0.0042
	(0.0185)	(0.0189)	(0.0224)	(0.0212)
Age^2	0.0000	0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Education	0.0397***	0.0397***	0.0334***	0.0321***
	(0.0040)	(0.0040)	(0.0062)	(0.0055)
Married	-0.2020***	-0.1897***	0.0197	0.0252
	(0.0588)	(0.0582)	(0.0595)	(0.0580)
HH members under 6 years of age	-0.0325*	-0.0350*	0.0059	0.0010
	(0.0196)	(0.0198)	(0.0276)	(0.0283)
HH members aged between 6 to 18	0.0119	0.0169	-0.0278*	-0.0303**
	(0.0152)	(0.0152)	(0.0156)	(0.0153)
HH members 60 years old or older	0.0228	0.0357	-0.0870*	-0.0842*
	(0.0427)	(0.0430)	(0.0522)	(0.0507)
Observations	1325	1325	423	423

Note: Robust standard errors are reported in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6
Probability of participating in the labor market - Men
Probit regressions (Marginal probabilities)

Explanatory Variable	**Urban** (1)	(2)	**Rural** (3)	(4)
Social Networks				
Ave. employed workers in neighborhood	0.0027*		0.0000	
	(0.0016)		(0.0000)	
Ave. employed women in neighborhood		-0.0002		-0.0000
		(0.0008)		(0.0000)
Ave. employed men in the neighborhood		0.0034**		0.0000
		(0.0014)		(0.0000)
Group characteristics				
Percent-indigenous	0.0008*	0.0007	0.0000	0.0000
	(0.0005)	(0.0005)	(0.0000)	(0.0000)
Percent-poverty	-0.0001	-0.0001	0.0000	-0.0000
	(0.0003)	(0.0003)	(0.0000)	(0.0000)
Share of people with high-school education or more	0.0003	0.0004	0.0000	0.0000
	(0.0004)	(0.0004)	(0.0000)	(0.0000)
Individual and Family Characteristics				
Head of household	0.0498**	0.0519**	0.0000	0.0000
	(0.0208)	(0.0211)	(0.0000)	(0.0000)
Age	0.0083***	0.0084***	0.0000	0.0000
	(0.0031)	(0.0030)	(0.0000)	(0.0000)
Age^2	-0.0000***	-0.0000***	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Education	-0.0007	-0.0007	-0.0000	-0.0000
	(0.0007)	(0.0007)	(0.0000)	(0.0000)
Married	0.0290**	0.0277**	0.0000	-0.0000
	(0.0115)	(0.0114)	(0.0000)	(0.0000)
HH members under 6 years of age	0.0111**	0.0108***	-0.0000	-0.0000
	(0.0044)	(0.0042)	(0.0000)	(0.0000)
HH members aged between 6 to 18	0.0031	0.0024	0.0000	0.0000
	(0.0026)	(0.0025)	(0.0000)	(0.0000)
HH members 60 years old or older	0.0018	0.0018	-0.0000	-0.0000
	(0.0068)	(0.0067)	(0.0000)	(0.0000)
Observations	2034	2034	1281	1281

Note: Robust standard errors are reported in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7
Probability of salaried employment - Men
Probit regressions (Marginal probabilities)

Explanatory Variable	**Urban** (1)	(2)	**Rural** (3)	(4)
Social Networks				
Ave. salaried workers in neighborhood	0.0018		0.0110***	
	(0.0040)		(0.0029)	
Ave. salaried women in neighborhood		-0.0094*		0.0016
		(0.0049)		(0.0047)
Ave. salaried men in the neighborhood		0.0068**		0.0063***
		(0.0034)		(0.0018)
Group characteristics				
Percent-indigenous	0.0003	0.0001	-0.0007	-0.0009
	(0.0012)	(0.0012)	(0.0007)	(0.0007)
Percent-poverty	-0.0002	-0.0002	-0.0010	-0.0008
	(0.0011)	(0.0011)	(0.0013)	(0.0013)
Share of people with high-school education or more	0.0012	0.0047*	-0.0032	-0.0023
	(0.0023)	(0.0027)	(0.0023)	(0.0028)
Individual and Family Characteristics				
Head of household	-0.0283	-0.0224	-0.1452*	-0.1429*
	(0.0535)	(0.0540)	(0.0810)	(0.0832)
Age	-0.0417***	-0.0417***	-0.0221*	-0.0220*
	(0.0155)	(0.0156)	(0.0130)	(0.0129)
Age^2	0.0000**	0.0000**	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Education	0.0121***	0.0121***	0.0233***	0.0227***
	(0.0035)	(0.0036)	(0.0044)	(0.0043)
Married	0.0048	0.0083	-0.0823	-0.0853
	(0.0497)	(0.0497)	(0.0603)	(0.0617)
HH members under 6 years of age	0.0201	0.0222	0.0040	0.0033
	(0.0179)	(0.0180)	(0.0150)	(0.0149)
HH members aged between 6 to 18	0.0096	0.0089	-0.0059	-0.0065
	(0.0115)	(0.0115)	(0.0102)	(0.0103)
HH members 60 years old or older	-0.0246	-0.0117	-0.0698	-0.0716
	(0.0467)	(0.0468)	(0.0585)	(0.0586)
Observations	1692	1692	1167	1167

Note: Robust standard errors are reported in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%.