# Social norms and gender discrimination in the labor market: An agent-based exercise

Quintero Rojas, Coralia Azucena and Viianto, Lari Artur

University of Guanajuato

20 October 2019

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# An agent-based exercise

**Coralia Azucena Quintero Rojas**[a]

**Lari Arthur Viianto**[b]

**Abstract**

The incorporation of women into the labor market remains a challenge for most countries; likewise, gender gaps are observed in indicators such as employment, unemployment and participation. In this paper we study the role of social norms in the labor market performance per gender; that is, how gender gaps arise from conservative gender roles. To this end, we construct an agent-based model where discrimination appears when information on job vacancies is transmitted within a social network with preference to a given gender. Networks are defined by size, closeness and links per family.

Our results show that: Social networks enhance the chance of getting a job. Discrimination deepens gender gaps. Discrimination does not favor the employment situation of households, since the share of non-income households (both members unemployed) is not reduced. Rather, discrimination reduces the number of two-income households in favor of the single-income households where only the man is employed.

[a] University of Guanajuato, Economics and Finance. Fraccionamiento 1, El Establo, Guanajuato, GTO, C.P. 36250. MEXICO. +52 473 7352900 x-2660. e-mail: coralia@ugto.mx

[b] University of Guanajuato, Economics and Finance. Fraccionamiento 1, El Establo, Guanajuato, GTO, C.P. 36250. MEXICO. +52 473 7352900 x-2887. e-mail: lari.viianto@ugto.mx

**SER Keywords**: social networks, social norms, gender inequality, discrimination, labor markets, economic systems.

**JEL classification**: C63 - Computational Techniques; Simulation Modeling, J71 Discrimination, D85 - Network Formation and Analysis: Theory.

## 1. Introduction

On 18 December 1979, the Convention on the Elimination of All Forms of Discrimination against Women (CEDAW) was adopted by the United Nations General Assembly. In its 30 articles, the CEDAW explicitly defined discrimination against women and settled an agenda for national action to end it. However, in spite of the agreements made in the Convention, the four World Conferences on Women carried out so far (Mexico City, 1975; Copenhagen, 1980; Nairobi, 1985; Beijing, 1995), and the creation of the Entity for Gender Equality and the Empowerment of Women in 2010 (UN Women), there is still a long way to go to achieve full equality of rights and opportunities between men and women.

This matters not only because gender equality and women's empowerment are fundamental dimensions of human development, but also because they are of paramount importance for economic growth, employment and social cohesion. Accordingly, the United Nations established as a goal number five in the *Sustainable Development Goals and the 2030 Agenda* to "Achieve gender equality and empower all women and girls" (UNDP, 2016). So, reaching this goal is a major challenge included in all the main political and economic agendas of most governments, institutions and organizations around the world; for instance, the European Commission (EC) has recently designed strategies to achieve gender equality (EC, 2015).

### *1.1 Gender discrimination*

Gender discrimination is defined as: "Any distinction, exclusion or restriction made on the basis of sex which has the effect or purpose of impairing or nullifying the recognition, enjoyment or exercise by women, irrespective of their marital status, on the basis of equality of men and women, of human rights and fundamental freedoms in the political, economic, social, cultural, civil or any other field (CEDAW, 1979)." Owing to this, gender discrimination is a major source of inequality and one of the greatest barriers to human development progress.

As a matter of illustration, in 2017 the average Human Development Index (HDI) worldwide value for women (0.705) was 4.4% lower than that for men; this gap was 5.9% in developing countries and 2.2% in OECD countries (UNDP Statistical Update, 2018). Similar picture is given by the Gender Inequality Index (GII), which is a composite index that captures the inequalities women face in reproductive health, political representation and the labor market (1 indicates absolute inequality and 0 indicates perfect equality). The global GII value in 2017 was 0.441, whereas for OECD countries it was 0.186. Women were the most disadvantaged in low human development countries where the GII value ranged from 0.270

for Europe and Central Asia to 0.531 for the Arab States to 0.569 in Sub-Saharan Africa (UNDP Human Development indices and indicators, 2018).

Likewise, the Global Gender Gap Index (GGGI) examines the gap between men and women in four fundamental categories (0 means imparity and 1 parity): Economic Participation and Opportunity, Educational Attainment, Health and Survival and Political Empowerment. By 2018, the Global Gender Gap score stands at 68%, meaning that there is still a 32% gap to close; regarding each dimension the scores were: Economic Participation and opportunity, 59%; Educational Attainment, 95%; Health and survival, 96%; and Political Empowerment, 22% (Global Gender Gap Index 2018). In other words, global gender parity has almost been achieved on two dimensions: Educational Attainment (gap to be filled: 5%) and Health and survival (gap to be filled: 4%); while important gender gaps persist on the other two dimensions. The widest wedge is observed for Political Empowerment (78%), which reflects the lower representation of women in all political roles. The remaining gap in the Economic Participation and Opportunity is also large (41%), which roughly mean that women still encounter significant obstacles to enter and remain in the labor market and, once in the workplace, in taking on managerial or senior official roles (Global Gender Gap Report, 2018).

Summing up, wide inequalities persist, especially in the political and economic spheres. As said before, in some extent these inequalities are due to gender discrimination. This last can stem from both law (de jure) or from practice (de facto).[1] In the first case, legal and political institutions are used to perpetuate gender divisions, so that women do not have the same legal rights as men. On the other side, culture and tradition play an important role shaping gender roles and family relations through social norms that may affect the livelihood opportunities of women (Arendt, 2005). Norms and traditions that distribute the bulk of unpaid work in the home to women limit women's participation in the labor market and can prevent girls from attending school (Human Development Report, 2015).

At some extent, gender disparities are embedded in social norms and long-standing patterns of exclusion from household and community decision-making that limit women's opportunities and choices. Given the several dimensions of the problem, this contribution focuses on the impact of social norms than discriminate against women on unemployment, employment and participation in the labor market. The rest of this paper is organized as follows. Chapter 2 deepens on gender discrimination in the labor market. Chapter 3 shows current data on gender gaps. Chapter 4 presents the model of labor networks, Chapter 5 shows simulations and results. Chapter 6 concludes.

## 2. Gender discrimination and social norms in the labor market

Gender differences in the labor market have been widely studied during the last decades[2] and the empirical evidence so far has mostly pointed to the existence of gender gaps against women on key labor market indicators such as participation, employment, unemployment and wage pay; both at national or international scopes and for short or long time periods (Addabbo, Rodríguez-Modroño y Gálvez, 2015; Blau and Kahn, 1995, 1996, 2017; Jaba, Pârtrachi, Chistruga and Balan, 2015; Ngai and Petrongolo, 2017; Olivetti and Petrongolo, 2016; Thévenon, 2013; Peinado and Serrano, 2018).

According to the scope of our contribution, next we shall present a brief review of the related literature focusing on the role of culture, traditions and social norms in explaining the observed gender differences, whereas in next section we establish some facts concerning the labor wedge gaps for the OECD countries.

### *2.1 The labor market gender gaps in wages, participation and unemployment*

The gender wage gap has been widely documented and studied starting from Sanborn (1964), who stated the existence of this gap. Becker (1965) argues that women face a more complex time allocation problem that men, so that their labor market decisions also differ. Blinder (1973) and Oaxaca (1974) decomposed the wage gap to consider differences in education, experience and other relevant variables, showing that most of the gap is purely due to discrimination. Similarly, Fernandez (2007) and Zaiceva and Zimmermann (2014) consider that an important part of the differences is due to cultural aspects. Duval-Hernández and Orraca Romano (2009) take into account differences in human capital and show how women participation increases when male income and labor possibilities decrease to compensate the lower income; this points to gender roles inside households, with men playing the role of provider so that women participation is perceived as secondary.

Blau and Khan (2017) survey recent literature to identify what has been learned about the explanations for the gender pay gap. They conclude that conventional human-capital factors are now relatively unimportant, whereas gender differences in occupations and industries, as well as differences in gender roles and the gender division of labor remain important; moreover, research based on experimental evidence strongly suggest that discrimination cannot be discounted.

Women's generally greater nonmarket responsibilities could impact labor-market outcomes in several ways. On the one side, traditional division of labor by gender in the family may affect the job-searching incentives of women given their family responsibilities. This affects labor-force participation, which is a crucial factor in understanding the developments of women's wages because the receipt of wages is conditional on employment; additionally, women's labor-force attachment is a key factor influencing the gender wage gap (Blau and Kahn, 2017). Furthermore, once on the job, as women assume more nonmarket activities, they are less willing to invest in on-the-job training (and so in human capital) and thereby their expected earnings are affected. In fact, Hersch and Stratton (2002) found that additional hours spent in housework are associated with lower wages.

Burda et al. (2007) study the use of non-labor time per gender under the social norm that jobs must be offered first to men, thereby the job finding is harder for women. Likewise, Bertrand, Kamenica and Pan (2015) underline the wide-ranging effects of observance to traditional gender roles on the relative outcomes of men and women; so that the role of norms and identity must be deepened to explain gender differences in outcomes. That is, identity, defined as a sense of belonging to a social category, combined with a view about how people belonging to a some category should behave, constitute a social norm; and departures from these norms are perceived as generating costs and hence people seek to avoid them (Akerlof and Kranton, 2010).

### *2.2 The role of social networks*

Social networks are another possible source of differences and even of discrimination. Their importance in labor markets is pervasive and well documented (Calvó-Armengol and Jakson, 2004). An important proportion of jobs are found through social contacts for a variety of occupations, skill levels and socioeconomic backgrounds (Montgomery, 1991) and this tendency have been fostered by the prevalence of Internet and the importance of social media like Facebook (Gee, Jones and Burke, 2017).[3] Finally, social networks have important implications on labor market outcomes (Myers and Shultz, 1951; Rees and Shultz, 1970). Loury (1977) argues that job opportunities might differ across individuals, either because they belong to different networks or because not everyone has the same position within the network.

Another channel for inequalities across groups is the transmission of information through the network (Montgomery 1991, 1992, 1994; Arrow and Borzekowski, 2001; Topa, 2001; Calvó- Armengol, 2004). Calvó-Armengol and Jakson (2004) are the first to study an explicit network model to explore the implications for employment of taking the role of social networks as a manner of obtaining information about job opportunities as a given; they show how the network model has important implications for inequality across agents, and how that inequality can persist. Following their work, in this contribution we analyze the effects of network discriminatory transmission of job-vacancies information on several labor gender gaps.

### *2.3 The Agent-Based Modeling approach*

Given the sociocultural context of gender discrimination, and the heterogeneity among agents resulting from it, we built below a model under the perspective of Agent-Based Modeling (ABM thereafter). The ABM approach is a form of computer simulation that lets creating, analyzing and experimenting with artificial worlds of heterogeneous agents; this enables investigation into how interactions between these agents, and between agents and other factors such as time or space add up to form the patters seen in the real world (Hamill and Gilbert, 2016). This modeling is becoming increasingly used in the social sciences since it allows addressing real-world problems under a wide variety of possible circumstances, in a simplified representation of social reality (Wilensky and Rand, 2015). The biggest advantage of ABM is that it makes possible the realization of social experiments, avoiding the difficulties and ethical problems that would arise from carrying them out in the real world (Gilbert, 2008).

Compared to classical representative-agent models, heterogeneity is a key and easily treatable feature in agent-based models: each agent may have a unique set of characteristics and simple rules of behavior that tells them what they can do under different circumstances (Epstein, 2006). The computer model can then be used to generate possible future scenarios and to study the effects of economic policies as well as the testing of the validity of assumptions to see whether they generate the observed patterns. Moreover, agent-based economic models can portray an economic system in which orderly behavior can emerge as a result of interaction between heterogeneous agents, none of whom has any understanding of how the overall system functions. In contrast, neoclassical economies assume that people can to solve optimally challenging intertemporal planning problems, in a very simple environment using full information.

## 3. Gender gaps in the Labor Market

In this section we document some facts related to the complications and limitations that women face to enter and remain in the labor market. To this end, we analyze the gender gaps observed in 2018 for labor force participation, unemployment, employment and two categories of vulnerable employment; data refers to aggregate regions grouped both by level of income and by location according to the ILO classification. As in the recent World Employment and Social Outlook 2018 we find that that “not only are women less likely than men to participate in the labor force, but when they do participate, they are also more likely to be unemployed and more likely to be in jobs that fall outside the scope of labor legislation, social security regulations and relevant collective agreements” (ILO, 2018).

### *3.1 Labor force participation, unemployment and employment*

Table 1 shows the rates of labor force participation, unemployment and employment as well as the gender gaps for 2018. All gaps are simply computed as the difference between the value for men and the value for women.

Table 1. Gender gaps in labor force participation, unemployment and employment, 2018

| **Region** | **Labor force participation rate (%) and gender gap (percentage points)** | | | **Unemployment rate (%) and gender gap (percentage points)** | | | **Employment rate (%) and gender gap (percentage points)** | | |
|---|---|---|---|---|---|---|---|---|---|
| | *Men* | *Women* | *Gap* | *Men* | *Women* | *Gap* | *Men* | *Women* | *Gap* |
| **World** | **74.9** | **48** | **26.9** | **4.7** | **5.4** | **-0.7** | **71.4** | **45.3** | **26.1** |
| Developing countries | 78.7 | 64.1 | 14.6 | 3.6 | 3.8 | -0.2 | 75.9 | 61.7 | 14.2 |
| Lower-middle income countries | 77.2 | 35.5 | 41.7 | 3.5 | 5.1 | -1.6 | 74.5 | 33.7 | 40.8 |
| Upper-middle income countries | 75 | 54.6 | 20.4 | 6 | 6 | 0 | 70.5 | 51.3 | 19.2 |
| Developed countries | 68.4 | 52.7 | 15.7 | 5 | 5.6 | -0.6 | 65 | 49.8 | 15.2 |
| Northern Africa | 71.2 | 21.6 | 49.6 | 9.1 | 20.8 | -11.7 | 64.8 | 17.1 | 47.7 |
| Sub-Saharan Africa | 73.1 | 63 | 10.1 | 5.6 | 6.2 | -0.6 | 69 | 59.1 | 9.9 |
| Latin America and the Caribbean | 77 | 51.7 | 25.3 | 7 | 9.6 | -2.6 | 71.7 | 46.7 | 25 |
| Northern America | 68.4 | 56.6 | 11.8 | 4.3 | 4 | 0.3 | 65.4 | 54.3 | 11.1 |
| Arab States | 77.2 | 18.4 | 58.8 | 5.8 | 15.6 | -9.8 | 72.8 | 15.5 | 57.3 |
| Eastern Asia | 75.4 | 60.1 | 15.3 | 4.6 | 3.7 | 0.9 | 71.9 | 57.9 | 14 |
| South-Eastern Asia and the Pacific | 78.8 | 55.8 | 23 | 3 | 2.8 | 0.2 | 76.4 | 54.2 | 22.2 |
| Southern Asia | 78.9 | 25.9 | 53 | 2.7 | 4.5 | -1.8 | 76.8 | 24.8 | 52 |
| Northern, Southern and Western Europe | 63.9 | 51.8 | 12.1 | 7.4 | 8 | -0.6 | 59.2 | 47.7 | 11.5 |
| Eastern Europe | 67.3 | 51.7 | 15.6 | 5.5 | 4.9 | 0.6 | 63.6 | 49.2 | 14.4 |
| Central and Western Asia | 73.4 | 63 | 10.4 | 7.8 | 8.8 | -1 | 67.7 | 41 | 26.7 |

*Source:* International Labour Office, Trends Econometric Models (ilo.org/wesodata).

Globally, the labor force participation gap is 26.9%, but there are considerable differences in women's access to the labor market across countries at different stages of development. Emerging countries show the largest gaps: 41.7% for lower-middle countries and 20.4% for upper-middle income countries; in average, this worth to almost twice the gap for developed (15.7%) and developing (14.6%) countries. Gaps are particularly large in the Arab States, Northern Africa and Southern Asia; this may reflect the fact that owing to restrictive gender and cultural norms women are more constrained in terms of their options to seek paid employment in these emerging regions. Conversely, women in developed countries face less restrictive social norms regarding paid work and there exist public policies that play an important role in improving the work–life balance of women (ILO, 2017a). However, the participation gap remains wide in many developed countries in European and Asian regions, even in those countries where women and men have near equal education achievements and working skills; in such cases, explanations must point to other sociocultural factors such as discrimination. Finally, developing countries show globally the smallest gender gap (14.6%), which often mirrors the economic necessity to seek employment, given the prevailing poverty and lack of access to social protection.

Regarding unemployment (second block of columns in table 1), we observe that globally not only women are less likely than men to participate in the labor market, but also they are more likely to be unemployed: the unemployment rate for women is 0.7% percent points larger than for men. As for participation, the largest gap is shown in the lower-middle income emerging economies (-1.6%) and is only slightly below the world average in developed countries (-0.6%). Conversely, in developing and upper-middle income emerging countries women seem close to parity in terms of unemployment rate. Nonetheless, this view can be misleading since the unemployment rate is not a robust test of labor market performance as long as it does not distinguish between types of jobs (formal, informal, part term, etcetera).

In certain regions women even register lower unemployment rates than men (Northern America, Eastern Asia, South- Eastern Asia and the Pacific, and Eastern Europe). This admits several and even opposite explanations. For instance, a positive unemployment gap might mean that women find work easily because they have more education achievements or skills than men; or, at the opposite, that women are more pressed to take up any employment opportunity. To shed more light on the situation we complement the analysis with several employment dimensions. The first one is the employment rate; nonetheless, the employment gender gap (third block of columns in table 1) does not provide newest information since its values are very close to the labor force participation gap.

Table 2 shows the gaps in two other dimensions of employment, namely, the share of own-account workers in total employment and the share of contributing family workers in total employment. The first one comprises workers who, on their own account or with one or more partners, hold the type of job defined as a self-employed job, and have not engaged on a continuous basis any employees to work for them. The second one comprises workers who are self-employed in a market-oriented establishment operated by a related person living in the same household, but with too limited degree of involvement in its operation to be considered a partner (ILO, 2018a). These two categories are considered as vulnerable employment because workers belonging to them are more likely than those in other categories of employment to be in informal employment and to have limited or no access to social protection systems.

Table 2. Gender gaps in in shares in own account and contributing family work, 2018

| **Region** | **Share of own-account workers in total employment (%) and gender gap (percentage points)** | | | **Share of contributing family workers in total employment (%) and gender gap (percentage points)** | | |
|---|---|---|---|---|---|---|
| | *Men* | *Women* | *Gap* | *Men* | *Women* | *Gap* |
| **World** | **38** | **28** | **10** | **6** | **18** | **-12** |
| Developing countries | 56 | 44 | 12 | 17 | 43 | -26 |
| Lower-middle income countries | 53 | 42 | 11 | 8 | 25 | -17 |
| Upper-middle income countries | 31 | 24 | 7 | 5 | 15 | -10 |
| Developed countries | 10 | 7 | 3 | 0 | 2 | -2 |
| Northern Africa | 21 | 13 | 8 | 6 | 26 | -20 |
| Sub-Saharan Africa | 53 | 49 | 4 | 15 | 33 | -18 |
| Latin America and the Caribbean | 30 | 26 | 4 | 3 | 7 | -4 |
| Northern America | 5 | 4 | 1 | 92 | 0 | 92 |
| Arab States | 14 | 8 | 6 | 2 | 5 | -3 |
| Eastern Asia | 33 | 25 | 8 | 5 | 19 | -14 |
| South-Eastern Asia and the Pacific | 34 | 30 | 4 | 7 | 21 | -14 |
| Southern Asia | 62 | 46 | 16 | 8 | 1 | 7 |
| Northern, Southern and Western Europe | 12 | 8 | 4 | 1 | 1 | 0 |
| Eastern Europe | 11 | 7 | 4 | 1 | 2 | -1 |
| Central and Western Asia | 26 | 20 | 6 | 5 | 15 | -10 |

*Source:* International Labour Office, Trends Econometric Models (ilo.org/wesodata).

## 4. The Model

In this section we construct a model where the labor force is composed by men and women that are matched to create households formed by traditional man-woman families. Households are randomly grouped in large social networks. Networks are defined by the number of households or nodes in the network, the geographic homophily, and the average number of links per family. We consider a sociocultural source of discrimination that arises when information about job vacancies is transmitted within the network with preference to men. This social norm is congruent with a statement used in the World Value Survey to asses this kind of discrimination, namely: “if jobs are scarce men should have more right to a job than women”. Usually, this discrimination is related to the role of men as provider, so that giving them preference to be employed is perceived as an insurance against the situation of not having any labor income in the family; that is, of being an impoverished family. Still nowadays the 38.8% of respondents agree with that statement worldwide; moreover, countries show strong differences, meaning that discrimination might be stronger in some countries than in others (World Value Survey, 2014).

According to this, the model is simulated under three scenarios: total discrimination, partial discrimination and gender equality; and the effects on the labor gender gaps are analyzed. To clearly assess the effects of discrimination, we assume that there is no other source of discrimination in the model. So, firms will send job offers and pay the same wage rate to both men and women.

### *4.1 Information rules*

The two members of each family belong to the same network and the only form of discrimination is the way in which information is transmitted through the network. Information about a vacancy is shared first within the family, so that the own partners are the first informed. There is no on-the-job search so, when the two family members are employed and one of them receives a job offer, the information about the vacancy is transmitted to their social network’s acquaintances. We allow for different levels of discrimination in this process:

**Full discrimination:** The information of a vacancy is first sent to an unemployed male acquaintance. If no male acquaintances are unemployed, the information is sent to an unemployed female acquaintance.

**Partial discrimination:** Unemployed male acquaintances have a relatively higher probability of receiving the information than unemployed female acquaintances.

**No discrimination (gender equality):** When men and women have the same weight there is no discrimination and unemployed men and women receive the information of job vacancies within the network with the same probability.

### *4.2 Networks*

Networks are formed by $n$ households or nodes. The labor state of any family member is denoted $s_j^i$, for $i = M$ (men), $W$ (women); $j = 1,2,\dots,n$ and takes value 0 if the individual is unemployed and 1 if the individual is employed. Let $S^i$ be the vectors that contains the labor states of men and women in a network:

$$S^M = \left(s_j^M\right),\ S^F = \left(s_j^F\right) \qquad (1)$$

The network is generated in a random way, so that the households to be linked are randomly chosen from a binomial distribution. If the total number of family links within the network is $k$, each family knows on average, $g = \frac{k}{2n}$ other households. As the number of households tends to infinity, the binomial distribution tends at the limit to a Poisson arrival rate, and the probability of forming a link is low and constant. A family will be linked to the closest family with which it is not yet linked with probability $0 \leq close \leq 1$. For high values of $close$, the model generates spatial clustering (friends of my friends are my friends) and a higher local density.

The network is expressed as a squared matrix $F$ where each row and column identify a family. That is,

$$F = \left(F_{i,j}\right)_{nxn}, i, j = 1, \dots, n. \qquad (2)$$

$F_{i,j} = 0$, if households $i$ and $j$ do not know each other. $F_{i,j} = 1$, if households $i$ and $j$ are linked. Since the knowledge is mutual and no family is linked to itself, the matrix is symmetric ($F_{i,j} = F_{j,i}$) and the elements on the diagonal are equal to zero ($F_{i,i} = 0$).

***4.3 Probability of receiving a job offer within the family***

Since firms do not discriminate, each family member may receive a direct job offer with probability $a$ and an indirect offer from their partner with probability $as_j^i$. This probability will be zero if the partner is unemployed too ($s_j^i = 0$). Then, the intra-family probability, $p^f$, that an unemployed member receives a job offer is

$$p^f = a + (1 - a)as_j^i \qquad (3)$$

There is no on-the-job-search. So, if the two family members are employed and one or both receives a job offer, they pass the information to their network's acquaintances. The probability of having at least one remaining offer is:

$$p_i^1 = (1 - (1 - a)^2)s_i^M s_i^F \qquad (4)$$

That also might happen if a family with one unemployed member receives two offers.

$$p_i^2 = (a^2)Max\{s_i^M, s_i^F\} \; (4b)$$

The probability $p_i^o$ that family $i$ has a remaining job offer is equal to $p_i^1 + p_i^2$:

$$p_i^o = (1-(1-a)^2)s_i^M s_i^F + (a^2)Max\{s_i^M, s_i^F\} \text{ (4)}$$

### *4.4 Probability of receiving a job offer within the network*

An unemployed agent may also receive job-offers information from their acquaintances. To compute this probability, we need several previous steps. First, the number of employed men ($e^M$) and women in each network are obtained as,

$$e_{(nx1)}^M = FxS^M \text{ (5)}$$

Similarly, we obtain the vector with the number of employed women in each family network as,

$$e_{(nx1)}^W = FxS^W \text{ (6)}$$

Let $l$ be a $(nx1)$ vector containing the number of linked households in each network, so each entry of this vector corresponds to the sum of the elements in each column of matrix $F$. That is:

$$l_{(nx1)} = (l_j) = \left(\sum_{i=1}^{n} F_{i,j}\right), j = 1,2, \dots, n. \text{ (7)}$$

Then, the vector with the number of male unemployed acquaintances of each family is given by the difference between (7) and (5):

$$u_{(nx1)}^M = l_{(nx1)} - e_{(nx1)}^M \text{ (8)}$$

Similarly, the number of female unemployed acquaintances of each family is given by

$$u_{(nx1)}^W = l_{(nx1)} - e_{(nx1)}^W \text{ (9)}$$

We consider three possible scenarios. If there is no gender discrimination, all unemployed men and women acquaintances of a family with a remaining job offer, will receive the information of the vacancy with the same probability. Conversely, if there is total discrimination against women, the information will be transmitted only to the male acquaintances. Finally, if the gender discrimination if partial, the information will be transmitted in a weighted manner in favor of men.

*4.4.1 Probability for an unemployed man of receiving at least one job offer*

The outer-family probability, $p_j^{M,n}$, that an unemployed man of family $j$, receives a remaining job offer from a family $i$ in their network is:

$$p_j^{M,n} = \begin{cases} \frac{1}{u_i^M}, & if\ total\ discrimination \\ \frac{1}{u_i^M + u_i^F}, & if\ no\ discrimination \\ \frac{w}{wu_i^M + u_i^F}, w > 1, & if\ partial\ discrimination \end{cases} \quad (10)$$

In last expression, $w > 1$ stand for the higher relative weight of men relative to women. For instance, $w = 2$ means that a man counts double than a woman.

In general terms, the probability that an unemployed man of family $j$ will not receive any remaining job offer from a family $i$ is equal to $F_{i,j}p_i^o p_j^n$, so that this probability becomes zero if households do not belong to the same network ($F_{i,j} = 0$).

Then, the probability, $p_j^{M,any}$, that an unemployed man will not receive any information of job vacancies from any other family is then:

$$p_j^{M,any} = \prod_i \left(1 - F_{i,j}p_i^o p_j^n\right) \ (11)$$

Then, the probability of receiving at least one job offer from other households in the network, $p_j^{M,one}$, is equal to:

$$p_j^{M,one} = 1 - p_j^{M,any} \ (12)$$

Therefore, the total probability that an unemployed man in family $j$, receives a direct or indirect job offer is given by:

$$p_j^{M,job} = p^f + (1 - p^f)p_j^{M,one} \ (13)$$

*4.4.2 Probability for an unemployed woman of receiving at least one job offer*

In a similar way, the outer-family probability, $p_j^{W,n}$, that an unemployed woman of family $j$, receives a remaining job offer from a family $i$ in their network is:

$$p_j^{W,n} = \begin{cases} \frac{1}{u_i^W} \Leftrightarrow \ u_i^M = 0 \ \ and\ 0 \ \Leftrightarrow \ u_i^M > 0 & if\ total\ discrimination \\ \frac{1}{u_i^M + u_i^W}, & if\ no\ discrimination \\ \frac{1}{wu_i^M + u_i^W}, w > 1, & if\ partial\ discrimination \end{cases} \qquad (10)$$

And as showed above, the probability, $p_j^{W,any}$, for an unemployed woman in family $j$, of not receiving any information from any other family is then:

$$p_j^{W,any} = \prod\nolimits_i \left(1 - F_{i,j} p_i^o p_j^n\right) \ (14)$$

Then, the probability of receiving at least one job offer from other households in the network, $p_j^{W,one}$, is equal to:

$$p_j^{W,one} = 1 - p_j^{W,any} \ (15)$$

Therefore, the total probability that an unemployed woman in family $j$, receives a direct or indirect job offer is given by:

$$p_j^{W,job} = p^f + (1 - p^f)p_j^{W,one} \ (16)$$

## 5. Results from simulations

The model is simulated using the computer program NetLogo. The model is simulated for the different scenarios, according to the baseline parameter values, simulations are repeated 10 times for each set of values. This yields up to 57600 observations that are firs used to evaluate the effects of discrimination on the job-finding probabilities, mean unemployment, and the labor status of households; and next to run several OLS regressions to deepen the analysis.

### *5.1 Baseline parameter values*

We assume that the time period to receive and accept offers is a day. To ensure the convergence of the mean values we considered a total span of the simulation of 2500 days (roughly 10 years). Simulations are dynamic so that unemployment and the family employment status are computed each period. There are $n = 100, 500 \ or \ 1000$ households and the initial unemployment rate is 5%. The probability of losing job ($loss, b$) or receiving an offer ($job, a$) take both the same values, namely: 1, 4, 7 and 10 %. The average number of links per family ($g$), takes values 3, 5, 8 and 10. The geographic homophily, ($close, c$), is the share of links to close neighbors, and takes values of 0, 0.25, 0.5, 0.75 and 1. Scenarios are total discrimination, partial discrimination (the relative weight of man, w, is higher than women's, namely 1.5, 2, 5 and 10), or there is no discrimination (gender equality, w= 1).

### *5.2 The effects of discrimination*

*5.2.1 The effects of discrimination on the job-finding probabilities*

The mean values for different levels of discrimination (with 9600 observations in each case) of the job-finding probabilities for unemployed men and women are presented in table 3.

Table 3. Mean job-finding probabilities

| Variable | Weight | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 1.5 | 2 | 5 | 10 | ∞ |
| $p_j^{M,job}$ | 0.263 | 0.270 | 0.275 | 0.288 | 0.295 | 0.304 |
| $p_j^{W,job}$ | 0.263 | 0.256 | 0.251 | 0.238 | 0.232 | 0.224 |

*Source:* Simulations from the model. Weight 1 means gender equality. Weight ∞ means total discrimination. $p_j^{M,job}$: total probability that an unemployed man in household $j$ receives a direct or indirect job offer. $p_j^{W,job}$: total probability that an unemployed woman in household $j$ receives a direct or indirect job offer.

When there is no discrimination both genders have the same probability of finding a job, but a gender gap emerges and widens as discrimination increases.

*5.2.2 The effects of discrimination on unemployment*

The gap in the job finding probabilities also affect gender gap in unemployment (table 4).[4] As discrimination grows, men´s unemployment decreases, since they have better labor opportunities (higher probability of finding a job); conversely, women´s unemployment increases by slightly more as discrimination increases; so, when discrimination is high enough, mean unemployment increases.

Table 4. Mean unemployment for men, women and general unemployment.

| Variable | Weight | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 1.5 | 2 | 5 | 10 | ∞ |
| $\overline{U}^M$ | 0.303 | 0.298 | 0.295 | 0.287 | 0.283 | 0.278 |
| $\overline{U}^W$ | 0.303 | 0.308 | 0.311 | 0.321 | 0.326 | 0.334 |
| $\overline{U}$ | 0.303 | 0.303 | 0.303 | 0.304 | 0.3045 | 0.306 |

*Source:* Simulations from the model. Weight 1 means gender equality. Weight ∞ means total discrimination. $\overline{U}^M$: mean value of unemployment for men. $\overline{U}^W$: mean value of unemployment for women. $\overline{U}$: general mean unemployment.

*5.2.3 The effects of discrimination on the family employment status*

The larger unemployment gap and the increase in the mean unemployment undermine the labor status of the household (table 5). Discrimination reduces the number of two-income households, increases the number of single-income households, and has a little effect on the number of households with both members unemployed (as we will see below this effect is negligible).

Table 5. Households' employment status.

| Variable | Weight | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 1.5 | 2 | 5 | 10 | ∞ |
| $H^{2e}$ | 0.593 | 0.592 | 0.592 | 0.590 | 0.589 | 0.585 |
| $H^{1e}$ | 0.209 | 0.209 | 0.209 | 0.212 | 0.214 | 0.218 |
| $H^{2u}$ | 0.199 | 0.199 | 0.198 | 0.198 | 0.198 | 0.197 |
| $H^{1e,M}$ | 0.104 | 0.109 | 0.113 | 0.123 | 0.129 | 0.137 |
| $H^{1e,W}$ | 0.104 | 0.0997 | 0.0966 | 0.0890 | 0.0854 | 0.0807 |

*Source:* Simulations from the model. Weight 1 means gender equality. Weight ∞ means total discrimination. $H^{2e}$: households with both members employed. $H^{1e}$: households with one member employed. $H^{2u}$: households with both members unemployed. $H_M^{1e}$ : households where the man is the provider. $H_W^{1e}$ : households where the man is the provider.

### ***5.3 Least Square regressions***

To better disentangle the effects that other variables might have, we have run several ordinary least square regressions. All regressions include a constant term ($z$). The explanative variables are the network size ($n$), the geographic homophily ($c$), the average links per family ($g$), the relative weight of men when discrimination is no total ($W$), a dummy variable to compare between total discrimination and gender equality ($D$), the probability of receiving a direct job offer ($a$), and the probability of job destruction ($b$).

*5.3.1 The effects of main variables on the probability of receiving a job offer*

In next regressions, we explore the impact of the explanative variables on the gender probabilities of receiving a job offer ($p_j^{M,job}$ and $p_j^{W,job}$). This is done under partial (weighted) and total discrimination. Results are reported in table 6. In all four regressions the determination coefficients are high (86 – 90%). All variables, except for the network size ($n$), are significant at 1% level.[5]

Table 6. Probability that an unemployed, man or woman, receives a job offer

| **Partial Discrimination ($W$)** | | | **Total Discrimination ($D$)** | | |
|---|---|---|---|---|---|
| **Variable** | **Coefficient** $p_j^{M,job}$ **(p-value)** | **Coefficient** $p_j^{W,job}$ **(p-value)** | **Variable** | **Coefficient** $p_j^{M,job}$ **(p-value)** | **Coefficient** $p_j^{W,job}$ **(p-value)** |
| $\boldsymbol{z}$ | 0.009021 (<0.0001) | 0.0652824 (<0.0001) | $\boldsymbol{z}$ | 0.0801065 (<0.0001) | 0.0801065 (<0.0001) |
| $\boldsymbol{c}$ | −4.561e-05 (<0.0001) | −4.657e-05 (<0.0001) | $\boldsymbol{c}$ | −4.9203e-05 (0.0050) | −4.92030e-05 (0.0050) |
| $\boldsymbol{g}$ | 0.0188273 | 0.0149957 (<0.0001) | $\boldsymbol{g}$ | 0.0142017 (<0.0001) | 0.0142017 (<0.0001) |

| | | | | | |
|---|---|---|---|---|---|
| | (<0.0001) | | | | |
| $\boldsymbol{b}$ | −0.0323890 (<0.0001) | −0.0333022 (<0.0001) | $\boldsymbol{b}$ | −0.0335114 (<0.0001) | −0.0335114 (<0.0001) |
| $\boldsymbol{a}$ | 0.0569952 (<0.0001) | 0.0512664 (<0.0001) | $\boldsymbol{a}$ | 0.0502200 (<0.0001) | 0.0502200 (<0.0001) |
| $\boldsymbol{W}$ | 0.00325080 (<0.0001) | −0.00306207 (<0.0001) | $\boldsymbol{D}$ | −0.0387422 (<0.0001) | −0.0387422 (<0.0001) |
| $\boldsymbol{n}$ | 1.20669e-06 (0.2166) | 1.20214e-06 (0.2447) | $\boldsymbol{n}$ | 1.35220e-06 (0.4306) | 1.32643e-06 (0.4306) |
| $\boldsymbol{R^2}$ | 0.891609 | 0.863040 | $\boldsymbol{R^2}$ | 0.891606 | 0.863036 |
| $\boldsymbol{adj. R^2}$ | 0.891595 | 0.863023 | $\boldsymbol{adj. R^2}$ | 0.891594 | 0.891594 |

*Source:* Simulations from the model. $p_j^{M,job}$: total probability that an unemployed man in household $j$ receives a direct or indirect job offer. $p_j^{W,job}$: total probability that an unemployed woman in household $j$ receives a direct or indirect job offer. $z$: constant term. $c$: geographic homophily. $g$: average links per family. $b$: job destruction probability. $a$: probability of receiving a direct job offer. $W$: relative weight of men. $D$: dummy variable for total discrimination. $n$: network size.

The discrimination degree (measured by the relative weight of men, $W$) increases the probability that an unemployed man receives a job offer. Conversely, discrimination decreases the probability that an unemployed woman receives a job offer; but in both cases we observe that total discrimination has a much greater effect than partial discrimination (more than 12 times bigger). The probability of getting a job ($a$) has positive effect since bigger values of $a$ imply that more people is employed, so their probability of having remaining job offers increase for the unemployed (men or women). By the way, the job destruction probability ($b$) has the opposite effect. The network structure affects the probability that an unemployed man or woman receives a job offer through two channels: the geographic homophily (measured by $c$) and the average links per family ($g$); the first one has a slight negative effect since as the density increases, the probability of finding a job through the network decreases; conversely, as more households are linked, finding a job is easier.

### *5.3.2 The effects of main variables on average unemployment*

Now, we explore the impact of the explanative variables on the average unemployment per gender ($\bar{U}^M$and $\bar{U}^W$). In all cases, the determination coefficients are high (80 – 83%). All variables, except for the network size ($n$) and the geographic homophily ($c$), are significant at 1% level.[6] The discrimination degree reduces the mean unemployment for men but increases the mean unemployment for women by slightly more than the reduction in the mean unemployment for men; this has a slight positive effect on general unemployment. Finally, total discrimination still has a positive effect more than 12 times larger than partial discrimination. This effect on unemployment will influence the labor status of households.

Table 7. Average unemployment of men ($\bar{U}^M$) and women ($\bar{U}^W$)

| **Partial Discrimination** ($W$) | | | **Total Discrimination** ($D$) | | |
|---|---|---|---|---|---|
| **Variable** | **Coefficient** $\bar{U}^M$ **(p-value)** | **Coefficient** $\bar{U}^W$ **(p-value)** | **Variable** | **Coefficient** $\bar{U}^M$ **(p-value)** | **Coefficient** $\bar{U}^W$ **(p-value)** |
| $\boldsymbol{z}$ | 0.420515 (<0.0001) | 0.395995 (<0.0001) | $\boldsymbol{z}$ | 0.425876 (<0.0001) | 0.384393 (<0.0001) |
| $\boldsymbol{c}$ | 7.96210e-06 (0.6420) | 8.20412e-06 (0.6036) | $\boldsymbol{c}$ | 8.98294e-06 (0.7438) | 9.83594e-06 (0.6899) |
| $\boldsymbol{g}$ | −0.00594122 (<0.0001) | −0.00450794 (<0.0001) | $\boldsymbol{g}$ | −0.00613600 (<0.0001) | −0.00388501 (<0.0001) |
| $\boldsymbol{b}$ | 0.0493858 (<0.0001) | 0.0519812 (<0.0001) | $\boldsymbol{b}$ | 0.0490175 (<0.0001) | 0.0526540 (<0.0001) |
| $\boldsymbol{a}$ | −0.0640778 (<0.0001) | −0.0632730 (<0.0001) | $\boldsymbol{a}$ | −0.0641139 (<0.0001) | −0.0628769 (<0.0001) |
| $\boldsymbol{W}$ | −0.00202484 (<0.0001) | 0.00235946 (<0.0001) | $\boldsymbol{D}$ | −0.0254597 (<0.0001) | 0.0308206 (<0.0001) |
| $\boldsymbol{n}$ | −4.56675e-07 (0.7813) | −4.66857e-07 (0.7583) | $\boldsymbol{n}$ | −5.15651e-07 (0.8451) | −5.25330e-07 (0.8244) |

| | | | | | |
|---|---|---|---|---|---|
| $R^2$ | 0.807753 | 0.834751 | $R^2$ | 0.802684 | 0.839079 |
| $adj. R^2$ | 0.807729 | 0.834731 | $adj. R^2$ | 0.802622 | 0.839029 |

*Source:* Simulations from the model. $\bar{U}^M$: mean value of unemployment for men. $\bar{U}^W$: mean value of unemployment for women. $\bar{U}$: general mean unemployment. $z$: constant term. $c$: geographic homophily. $g$: average links per family. $b$: job destruction probability. $a$: probability of receiving a direct job offer. $W$: relative weight of men. $D$: dummy variable for total discrimination. $n$: network size.

*5.3.3 The effects of main variables on the labor status of households*

Now, we explore the impact of the explanative variables on the labor situation of households: two employed members ($H^{2e}$), both unemployed ($H^{2u}$), and only the man ($H^{1e,M}$) or the woman ($H^{1e,W}$) are employed. The coefficient of determination is over 87% for the two-income households, and around 70% for the no-income households (both members unemployed). However, in all three cases of single-income households, only around 50% of the variation in the dependent variable is explained by the model. In all cases, both the geographic homophily ($c$) and the network size ($n$) are non-significant. The relative weight of men ($W$) has a negative and significant impact on the portion of households with two or one income; in the case of no-income households this impact is non-significant. So, as discrimination increases, the number of two-income households decreases in favor of the number of single-income households. Notice that this increase is biased towards the households headed by men, given that the number oh women-headed households also decreases with discrimination. Thus, discrimination changes the wealth distribution among households as well as the household's composition, since it leads to more single-income men-headed households.

Similar results are obtained in the extreme scenario of gender equity versus total discrimination (see table 9).

Table 8: Household's labor status under partial discrimination

| Variable | Coefficient $H^{2e}$ (p-value) | Coefficient $H^{2u}$ (p-value) | Coefficient $H^{1e}$ (p-value) | Coefficient $H^{1e,M}$ (p-value) | Coefficient $H^{1e,W}$ (p-value) |
|---|---|---|---|---|---|
| $\boldsymbol{z}$ | 0.501905 (<0.0001) | 0.318089 (<0.0001) | 0.180005 (<0.0001) | 0.0777477 (<0.0001) | 0.102258 (<0.0001) |
| $\boldsymbol{c}$ | −1.15562e-05 (0.4658) | 4.60360e-06 (0.8068) | 6.95256e-06 (0.5489) | 3.59724e-06 (0.5930) | 3.35532e-06 (0.5115) |
| $\boldsymbol{g}$ | 0.0076669 (<0.0001) | −0.00277811 (<0.0001) | −0.00488876 (<0.0001) | −0.00172802 (<0.0001) | −0.00316 (<0.0001) |
| $\boldsymbol{b}$ | −0.0634006 (<0.0001) | 0.0379258 (<0.0001) | 0.0254748 (<0.0001) | 0.0140346 (<0.0001) | 0.0114403 (<0.0001) |
| $\boldsymbol{a}$ | 0.0709325 (<0.0001) | −0.0563674 (<0.0001) | −0.0145651 (<0.0001) | −0.00688030 (<0.0001) | −0.0076848 (<0.0001) |
| $\boldsymbol{W}$ | −0.0004575 (0.0062) | −0.000123 (0.5356) | 0.000580494 (<0.0001) | 0.00248152 (<0.0001) | −0.00190102 (<0.0001) |
| $\boldsymbol{n}$ | 6.59703e-07 (0.6646) | −2.63460e-07 (0.8841) | −3.9624e-07 (0.7220) | −2.0321e-07 (0.7532) | −1.93e-07 (0.6941) |
| $\boldsymbol{R^2}$ | 0.871598 | 0.709664 | 0.550014 | 0.510928 | 0.589391 |
| $\boldsymbol{adj.R^2}$ | 0.871582 | 0.709628 | 0.549958 | 0.510866 | 0.589340 |

*Source:* Simulations from the model. $H^{2e}$: households with both members employed. $H^{1e}$: households with one member employed. $H^{2u}$: households with both members unemployed. $H_M^{1e}$ : households where the man is the provider. $H_W^{1e}$ : households where the man is the provider.$z$: constant term. $c$: geographic homophily. $g$: average links per family. $b$: job destruction probability. $a$: probability of receiving a direct job offer. $W$: relative weight of men. $n$: network size.

Table 9: Household's labor status under total discrimination

| Variable | Coefficient $H^{2e}$ (p-value) | Coefficient $H^{2u}$ (p-value) | Coefficient $H^{1e}$ (p-value) | Coefficient $H^{1e,M}$ (p-value) | Coefficient $H^{1e,W}$ (p-value) |
|---|---|---|---|---|---|
| $\boldsymbol{z}$ | 0.508445 (<0.0001) | 0.318389 (<0.0001) | 0.173166 (<0.0001) | 0.06585 (<0.0001) | 0.107316 (<0.0001) |
| $\boldsymbol{c}$ | −1.35305e-05 (0.5868) | 5.28091e-06 (0.8596) | 8.2496e-06 (0.5868) | 4.5511e-06 (0.6949) | 3.69845e-06 (0.6428) |
| $\boldsymbol{g}$ | 0.00721521 (<0.0001) | −0.00280178 (<0.0001) | −0.004413 (<0.0001) | −0.001082 (<0.0001) | −0.003332 (<0.0001) |
| $\boldsymbol{b}$ | −0.0637604 (<0.0001) | 0.0378704 (<0.0001) | 0.0258900 (<0.0001) | 0.0147625 (<0.0001) | 0.011127 (<0.0001) |
| $\boldsymbol{a}$ | 0.0705848 (<0.0001) | −0.0563551 (<0.0001) | −0.01423 (<0.0001) | −0.006497 (<0.0001) | −0.007733 (<0.0001) |

| | | | | | |
|---|---|---|---|---|---|
| $\boldsymbol{W}$ | −0.00714367 (<0.0001) | −0.00178492 (0.3977) | 0.008929 (<0.0001) | 0.032593 (<0.0001) | −0.023665 (<0.0001) |
| $\boldsymbol{n}$ | 7.43054e-07 (0.7559) | −2.97512e-07 (0.9173) | −4.45543e-07 (0.7559) | −2.27609e-07 (0.8382) | −2.179e-07 (0.7759) |
| $\boldsymbol{R^2}$ | 0.872987 | 0.708385 | 0.545206 | 0.497626 | 0.599797 |
| $\boldsymbol{adj.R^2}$ | 0.872947 | 0.708294 | 0.545064 | 0.497469 | 0.599672 |

*Source:* Simulations from the model. $H^{2e}$: households with both members employed. $H^{1e}$: households with one member employed. $H^{2u}$: households with both members unemployed. $H_M^{1e}$ : households where the man is the provider. $H_W^{1e}$ : households where the man is the provider.$z$: constant term. $c$: geographic homophily. $g$: average links per family. $b$: job destruction probability. $a$: probability of receiving a direct job offer. $D$: dummy variable for total discrimination. $n$: network size. $n$: network size.

## 6. Conclusions

Our results from simulations show that gender roles, expressed as the way in which the information on job vacancies is transmitted through a social network, negatively affect the gender gaps in the labor market. When there is a social bias towards male employment, so that the information on job vacancies is more likely transferred to men, the job-finding probabilities of men and women are altered. By consequence, the income and labor status of the households' members is also altered. On the one side, the employment of men increases, but this is offset by a larger decrease in the employment of women, so that general unemployment increases. This pervasive effect on employment becomes more important as discrimination increases, reducing thus the whole income generated in the economy.

On the other side, discrimination reduces the number of two-income households; however, this does not imply a lower risk of having both family members unemployed, that is no-income households. Instead, the number of single-income households headed by men grows, thereby increasing the economic dependence of women.

Regarding the social network effects, we find that the size does not affect results when the number of nodes is larger than 100. The geographic homophily (measured by $c$) seems to be a short-term effect that reduces the probability that unemployed, men or women, receives a job offer, but it does not have significant impact on unemployment nor on the households' employment status. For both genders, the average links per family ($g$) increases the job finding probability and decreases the mean unemployment, so that employment and the number of two-income households increase. Therefore, social networks could lead to better job opportunities, as long as there are no discriminatory rules in the transmission of information within the network.

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[1] The CEDAW Convention recognizes and addresses both forms of discrimination, whether contained in laws, policies, procedures or practice.

[2] See Peinado and Serrano (2018) for a recent literature review.

[3] Indeed, the increasing use of digital social media has popularized the concept of networking, which refers to the ability (of an individual or enterprise) to create a network of contacts with the purpose of generating job or business opportunities.

[4] Unemployment values are high in mean since the gap between the probability of losing a job and getting a job offer might have great differences, as between a probability of 10% of losing a job and 1% to get a job offer.

[5] We have dropped $n$ from the regressions and the results do not changed.

[6] We have dropped $n$ and $c$ from the regressions and the results do not changed.