# Social Norms and Gender Discrimination in the Labor Market: An Agent-Based Exercise

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**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 labor market performance by 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 social networks 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 securing 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 2-income households in favor of single-income households where only the man is employed.

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

**JEL Classification:** C63; J71; D85.

## Introduction

On December 18, 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 CEDAW, the four world conferences on women convened 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 (UN) established as goal number five of the Sustainable Development Goals in the 2030 Agenda for Sustainable Development a goal that seeks to "achieve gender equality and empower all women and girls" (UNDP 2016). Reaching this goal is therefore a major challenge embedded in all the main political and economic agendas of most governments, institutions, and organizations around the world. The European Commission (EC), for instance, recently devised strategies to achieve gender equality (EC 2015).

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). Gender discrimination is thus a major source of inequality and one of the greatest barriers to progress in human development.

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 Organization for

Economic Cooperation and Development (OECD) countries (UNDP 2018). A 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 it was 0.186 for OECD countries. Women were the most disadvantaged in countries with low human development, where the GII value ranged from 0.270 for Europe and Central Asia to 0.531 for the Arab states and 0.569 in sub-Saharan Africa (UNDP 2018).

Likewise, the Global Gender Gap Index (GGGI) examines the gap between men and women in four fundamental categories (0 means imparity, and 1 means parity): economic participation and opportunity, educational attainment, health and survival, and political empowerment. In 2018, the overall Global Gender Gap score stood at 68%, meaning that there was still a 32% gap to close. Regarding each dimension, the scores were as follows: economic participation and opportunity, 59%; educational attainment, 95%; health and survival, 96%; and political empowerment, 22% (World Economic Forum 2018). In other words, global gender parity has almost been achieved in two dimensions, educational attainment (gap to be filled: 5%) and health and survival (gap to be filled: 4%); meanwhile, important gender gaps persist in the other two dimensions. The widest gap is observed in terms of political empowerment (78%), which reflects the lower representation of women in all political roles. The remaining gap in economic participation and opportunity is also large (41%); roughly, this means that women still encounter significant obstacles to entering and remaining in the labor market and, once in the workplace, to assuming managerial or senior official roles (World Economic Forum 2018).

In sum, wide inequalities persist, especially in the political and economic spheres. As previously stated, these inequalities are, to some extent, due to gender discrimination, which can stem from both law (de jure) and practice (de facto).[1] In the first case, legal and political institutions are used to perpetuate gender divisions so that women are denied access to the same legal rights as men. In the second case, culture and tradition play an important role in 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 (UNDP 2015).

To 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 that the problem has several dimensions, this contribution focuses on the impact of social norms that discriminate against women with regard to unemployment, employment, and participation in the labor market. The remainder of this paper is organized as follows. Chapter 2 offers a deeper exploration of gender discrimination in the labor market. Chapter 3 contains current data on gender gaps. Chapter 4 presents the model of labor networks. Chapter 5 presents the simulations and results. Chapter 6 concludes.

## 1. Research background. Gender discrimination and social norms in the labor market

Gender differences in the labor market have been widely studied in recent decades[2] and the empirical evidence so far - based on studies with both national and international scopes, conducted over both short and long time periods - mostly points to the existence of gender gaps against women in terms of key labor market indicators, such as participation, employment, unemployment, and wages (Addabbo, Rodríguez-Modroño and 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 present a brief review of the related literature, focusing on the role of culture, traditions, and social norms in explaining the observed gender differences. We establish in the next section some facts concerning the labor wedge gaps in the OECD countries.

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

The gender wage gap has been widely documented and studied since the work of Sanborn (1964), who documented the existence of this gap. Becker (1965) argues that women face a more complex time allocation problem that men; consequently, 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) observe that an important part of the differences is attributable to cultural aspects. Duval-Hernández and

[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

Orraca Romano (2009) consider differences in human capital and demonstrate how female participation increases to compensate for the lower income when male income and labor possibilities decrease; this points to gender roles inside households, with men playing the role of provider so that female participation is perceived as secondary.

Blau and Khan (2017) surveyed recent literature to identify what has been learned about the explanations for the gender pay gap. They concluded 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 suggests that discrimination cannot be discounted.

Women's generally greater nonmarket responsibilities could impact labor-market outcomes in several ways. The traditional division of labor by gender in the family may, on the one hand, affect the job-searching incentives of women, given their family responsibilities. This affects labor force participation, which is a crucial factor in understanding the development 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). On the other hand, once on the job, as women assume more nonmarket activities, they are less willing to invest in on-the-job training (and thus in human capital), and their expected earnings are thereby affected. In fact, Hersch and Stratton (2002) found that additional hours spent on housework are associated with lower wages.

Burda, Hamermesh, and Weil (2007) studied the use of non-labor time by gender under the social norm whereby it is more difficult for women to find a job because jobs must be offered first to men. Likewise, Bertrand, Kamenica, and Pan (2015) underline that, considering the wide-ranging effects of observance to traditional gender roles on the relative outcomes of men and women, the role of norms and identity must be deepened to explain gender differences in outcomes. In other words, identity, defined as a sense of belonging to a social category, combined with a view about how people belonging to the same category should behave, constitutes a social norm; departures from these norms are perceived as generating costs, hence people seek to avoid them (Akerlof and Kranton 2010).

### 1.2 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). For a variety of occupations, skill levels, and socioeconomic backgrounds, an important proportion of jobs are found through social contacts (Montgomery 1991), and this tendency has been fostered by the prevalence of the Internet and the importance of social media such as Facebook (Gee, Jones and Burke 2017)[3]. Finally, social networks have important implications for labor market outcomes (Myers and Shultz 1951, Rees and Shultz 1970). Loury (1977) argues that job opportunities might differ between individuals, either because they belong to different networks or because not everyone has the same position within the network.

Another channel for inequalities among groups is the transmission of information through the network (Montgomery 1991, 1992, 1994; Arrow and Borzekowski 2004, Topa 2001, Calvó - Armengol and Jakson 2004). Calvó-Armengol and Jakson (2004) were 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 among agents and how that inequality can persist. Following their work, in this contribution, we analyze the effects of network discriminatory transmission of job vacancy information on several labor gender gaps.

### 1.3 The agent-based modeling approach

Given the sociocultural context of gender discrimination and the heterogeneity among agents resulting from it, in this contribution, we build a model under the perspective of agent-based modeling (ABM). The ABM approach is a form of computer simulation that allows for 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 patterns seen in the real world (Hamill and Gilbert 2016). This modeling is increasingly being used in the social sciences because it allows for addressing real-world problems under a wide variety of possible circumstances, in a simplified representation of social reality (Wilensky and Rand 2015). The most significant advantage of ABM is that it enables the realization of social experiments

[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.

while avoiding the difficulties and ethical problems that would arise from conducting them 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 can have a unique set of characteristics and simple rules of behavior that tell 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 and test the validity of assumptions by determining whether they generate the expected patterns. Moreover, agent-based economic models can portray an economic system in which orderly behavior can emerge as a result of interactions between heterogeneous agents, none of whom has any understanding of how the overall system functions, and can be used to simulate, analyze and treat very different problems (Yachou and Aboulaich 2018, Yahyaoui and Tkiouat 2017). By contrast, to solve optimally challenging intertemporal planning problems in a very simple environment using full information, neoclassical economies assume that people understand how the overall system functions.

## 2. Gender gaps in the labor market

In this section, we document some facts related to the complications and limitations that women face in entering and remaining 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; the data refer to aggregate regions grouped both by level of income and by location according to the International Labor Organization (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).

### 2.1. Labor force participation, unemployment, and employment

Table 1 presents the rates of, and gender gaps in, labor force participation, unemployment, and employment 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 - *rates in %*

| Region | Labor force participation rate and gender gap | | | Unemployment rate and gender gap | | | Employment rate and gender gap | | |
|---|---|---|---|---|---|---|---|---|---|
| | *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 |
| North 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 |
| Southeastern 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 Labor Office, Trends Econometric Models (ilo.org/wesodata)

Globally, the labor force participation gap in 2018 was 26.9%, but there were considerable differences between countries at different stages of development in terms of women's access to the labor market. Emerging countries exhibited the largest gaps: 41.7% for lower-middle-income countries and 20.4% for upper-middle-income countries; on average, this equated to almost twice the gap exhibited by developed (15.7%) and developing (14.6%) countries. Gaps were 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 for seeking 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. The participation gap, however, remained wide in many developed countries in European and Asian regions, even in those countries where women and men have near equal educational achievements and working skills; in such cases, explanations must point to other sociocultural factors, such as discrimination. Finally, developing countries showed the smallest gender gap (14.6%) globally; this 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, women are not only less likely than men to participate in the labor market, but they are also more likely to be unemployed: The unemployment rate for women was 0.7% larger than the unemployment rate for men. As for participation, the largest gap was in the lower-middle-income emerging economies (-1.6%) and was only slightly below the 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 fails to distinguish between types of jobs (formal, informal, part-time, *etc*.).

In certain regions, women even registered lower unemployment rates than men (North America, Eastern Asia, Southeastern Asia and the Pacific, and Eastern Europe). This invites several and even opposite explanations. For instance, a positive unemployment gap might mean that women find work easily because they have higher educational achievement or more skills than men; alternatively, it may mean 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 is the employment rate; nonetheless, the employment gender gap (third block of columns in Table 1) does not provide new information, since its values closely approximate those of the labor force participation gap.

Table 2 presents 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 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 comprises workers who are self-employed in a market-oriented establishment operated by a related person living in the same household but whose degree of involvement in its operation is too limited for them to be considered a partner (ILO 2018). These two categories are considered 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 shares in own-account and contributing family work, 2018 – in %

| Region | Share of own-account workers in total employment and gender gap | | | Share of contributing family workers in total employment and gender gap | | |
|---|---|---|---|---|---|---|
| | *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 |
| North America | 5 | 4 | 1 | 92 | 0 | 92 |
| Arab states | 14 | 8 | 6 | 2 | 5 | -3 |
| Eastern Asia | 33 | 25 | 8 | 5 | 19 | -14 |
| Southeastern 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 Labor Office, Trends Econometric Models (ilo.org/wesodata)

## 3. The model

In this section, we construct a model where the labor force is composed of men and women who are matched to create households formed by traditional man-woman families. Households are randomly grouped into 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 assess this form of discrimination: "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 providers: Giving them preference to be employed is perceived as giving families insurance against the situation of not having any labor income in the family, that is, of being an impoverished family. Even today, 38.8% of respondents worldwide agree with this statement; moreover, countries exhibit 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; thus, firms will send job offers to both men and women and will pay the same wage rate to men and women.

### 3.1. 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, therefore the own partners are the first informed. There is no job hunting while employed; consequently, when the two family members are both already employed and one of them receives a job offer, the information about the vacancy is directly transmitted to their social network's acquaintances. We allow for different levels of discrimination in this process, as follows:

- *Full discrimination:* The information regarding 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 higher probability of receiving the information than unemployed female acquaintances;
- *No discrimination (gender equality):* When men and women have equal weight, there is no discrimination, and unemployed men and women receive the information regarding job vacancies within their network with the same probability.

### 3.2. Networks

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

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

The network is generated in a random way, wherein 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 toward infinity, the binomial distribution tends at the limit toward 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 a probability of $0 \le close \le 1$. 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. In other words,

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

*where:* $F_{i,j} = 0$ 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 ($F_{i,i} = 0$).

### 3.3. 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 also unemployed ($s_j^i = 0$). The intra-family probability, $p^f$, that an unemployed member receives a job offer, then, is:

$$p^f = a + (1-a)as_j^i \tag{3}$$

There is no job hunting while employed; consequently, if the two family members are both already employed and one or both receive a job offer, they pass the information to their network's acquaintances. The probability of having at least one remaining offer is as follows:

$$p_i^1 = (1-(1-a)^2)s_i^M s_i^F \tag{4a}$$

This also might happen if a family with one unemployed member received two offers.

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

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

$$p_i^o = (1-(1-a)^2)s_i^M s_i^F + (a^2)Max\{s_i^M, s_i^F\} \tag{5}$$

### 3.4. Probability of receiving a job offer within the network

An unemployed agent may also receive job vacancy information from his or her 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 follows:

$$e^M_{(nx1)} = FxS^M \tag{6}$$

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

$$e^W_{(nx1)} = FxS^W \tag{7}$$

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

$$l_{(nx1)} = (l_j) = (\textstyle\sum_{i=1}^n F_{i,j}), j = 1,2,\dots,n. \tag{8}$$

The vector with the number of male unemployed acquaintances of each family, then, is given by the difference between (8) and (6):

$$u^M_{(nx1)} = l_{(nx1)} - e^M_{(nx1)} \tag{9}$$

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

$$u^W_{(nx1)} = l_{(nx1)} - e^W_{(nx1)} \tag{10}$$

We consider three possible scenarios. If there is no gender discrimination, all unemployed male and female acquaintances of a family with a remaining job offer will receive the information regarding 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 is partial, the information will be transmitted in a weighted manner in favor of men.

#### *3.4.1. 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 as follows:

$$p_j^{M,n} = \begin{cases} \frac{1}{u_i^M}, & if\ total\ discrimination \\ \frac{1}{u_i^M + u_i^F}, & if\ no\ discrimination \\ \frac{w}{wu_i^M + u_i^F}, w > 1, & if\ partial\ discrimination \end{cases} \tag{11}$$

In the above expression, $w > 1$ represents the higher relative weight of men relative to women. For instance, $w = 2$ means that a man has double the weight of 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 $F_{i,j} p_i^o p_j^n$; consequently, this probability becomes zero if households do not belong to the same network ($F_{i,j} = 0$).

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

$$p_j^{M,any} = \prod_i \left(1 - F_{i,j} p_i^o p_j^n\right) \tag{12}$$

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

$$p_j^{M,one} = 1 - p_j^{M,any} \tag{13}$$

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

$$p_j^{M,job} = p^f + \left(1 - p^f\right) p_j^{M,one} \tag{14}$$

### 3.4.2. 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 as follows:

$$p_j^{W,n} = \begin{cases} \frac{1}{u_i^W} \Leftrightarrow \; u_i^M = 0 \;\; and \; 0 \;\; \Leftrightarrow \;\; u_i^M > 0 & if\ total\ discrimination \\ \frac{1}{u_i^M + u_i^W}, & if\ no\ discrimination \\ \frac{1}{w u_i^M + u_i^W}, w > 1, & if\ partial\ discrimination \end{cases} \tag{15}$$

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

$$p_j^{W,any} = \prod_i \left(1 - F_{i,j} p_i^o p_j^n\right) \tag{16}$$

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

$$p_j^{W,one} = 1 - p_j^{W,any} \tag{17}$$

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

$$p_j^{W,job} = p^f + \left(1 - p^f\right) p_j^{W,one} \tag{18}$$

## 4. 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; the simulations are repeated 10 times for each set of values. This yields up to 57,600 observations, which are used first to evaluate the effects of discrimination on the job-finding probabilities, mean unemployment, and the employment statuses of households and are used subsequently to run several ordinary least squares (OLS) regressions to deepen the analysis.

### 4.1. Baseline parameter values

We assume that the time period taken 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 2,500 days (roughly 10 years). The simulations are dynamic, such that unemployment and the family employment status are computed each period. There are $n = 100, 500, \text{or}\ 1{,}000$ households, and the initial unemployment rate is 5%. The probability of losing a job ($loss, b$) or receiving an offer ($job, a$) both take the same values: 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. The scenarios are total discrimination, partial discrimination (the relative weight of men, w, is higher than that of women, namely, 1.5, 2, 5, and 10), or no discrimination (gender equality, w= 1).

## 4.2. The effects of discrimination

### *4.2.1. The effects of discrimination on the job-finding probabilities*

The mean values of the job-finding probabilities for unemployed men and women under different levels of discrimination (with 9,600 observations in each case) 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 of 1 means gender equality. Weight of ∞ 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.

### *4.2.2. The effects of discrimination on unemployment*

The gap in the job-finding probabilities also affects the 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; thus, 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 | ∞ |
| $\bar{U}^M$ | 0.303 | 0.298 | 0.295 | 0.287 | 0.283 | 0.278 |
| $\bar{U}^W$ | 0.303 | 0.308 | 0.311 | 0.321 | 0.326 | 0.334 |
| $\bar{U}$ | 0.303 | 0.303 | 0.303 | 0.304 | 0.3045 | 0.306 |

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

### *4.2.3. 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 little effect on the number of households with both members unemployed (as can be seen below, this effect is negligible).

Table 5. Households' employment statuses

| 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 of 1 means gender equality. Weight of ∞ means total discrimination. $H^{2e}$: households with both members employed. $H^{1e}$: households with one member employed. $H^{2u}$: households with

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

both members unemployed. $H_M^{1e}$ : households where the man is the provider. $H_W^{1e}$ : households where the woman is the provider.

### 4.3. Least square regressions

To better disentangle the effects that other variables might have, we 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 not 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 ($b$).

#### *4.3.1. The effects of the main variables on the probability of receiving a job offer*

In the following 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%). Except for the network size ($n$), all variables are significant at the 1% level.[5]

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

| Partial Discrimination ($W$) | | | Total Discrimination ($D$) | | |
|---|---|---|---|---|---|
| Variable | Coefficien $p_j^{M,job}$ (p-value) | Coefficient $p_j^{W,job}$ (p-value) | Variable | Coefficient $p_j^{M,job}$ (p-value) | Coefficient $p_j^{W,job}$ (p-value) |
| $z$ | 0.009021 (<0.0001) | 0.0652824 (<0.0001) | $z$ | 0.0801065 (<0.0001) | 0.0801065 (<0.0001) |
| $c$ | −4.561e-05 (<0.0001) | −4.657e-05 (<0.0001) | $c$ | −4.9203e-05 (0.0050) | −4.92030e-05 (0.0050) |
| $g$ | 0.0188273 (<0.0001) | 0.0149957 (<0.0001) | $g$ | 0.0142017 (<0.0001) | 0.0142017 (<0.0001) |
| $b$ | −0.0323890 (<0.0001) | −0.0333022 (<0.0001) | $b$ | −0.0335114 (<0.0001) | −0.0335114 (<0.0001) |
| $a$ | 0.0569952 (<0.0001) | 0.0512664 (<0.0001) | $a$ | 0.0502200 (<0.0001) | 0.0502200 (<0.0001) |
| $W$ | 0.00325080 (<0.0001) | −0.00306207 (<0.0001) | $D$ | −0.0387422 (<0.0001) | −0.0387422 (<0.0001) |
| $n$ | 1.20669e-06 (0.2166) | 1.20214e-06 (0.2447) | $n$ | 1.35220e-06 (0.4306) | 1.32643e-06 (0.4306) |
| $R^2$ | 0.891609 | 0.863040 | $R^2$ | 0.891606 | 0.863036 |
| $adj. R^2$ | 0.891595 | 0.863023 | $adj. R^2$ | 0.891594 | 0.891594 |

*Source:* Simulations from the model.

*Note:* $p_j^{M,job}$: 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.

A higher degree of discrimination (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. In both cases, however, we observe that total discrimination has a much greater effect than partial discrimination (more than 12 times greater). The probability of securing a job ($a$) has a positive effect: Larger values of $a$ imply that more people are employed, therefore the probability of having remaining job offers increases for the unemployed (men or women). The job destruction probability ($b$), meanwhile, 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 has a slight negative effect: As the density increases, the probability of finding a job through the network decreases. Conversely, as more households are linked, finding a job becomes easier.

[5] We drop $n$ from the regressions, and the results do not change

#### 4.3.2. The effects of the main variables on average unemployment

Now we explore the impact of the explanative variables on the average unemployment by gender ($\bar{U}^M$and $\bar{U}^W$). Results are displayed in Table 7.

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) |
| $z$ | 0.420515 (<0.0001) | 0.395995 (<0.0001) | $z$ | 0.425876 (<0.0001) | 0.384393 (<0.0001) |
| $c$ | 7.96210e-06 (0.6420) | 8.20412e-06 (0.6036) | $c$ | 8.98294e-06 (0.7438) | 9.83594e-06 (0.6899) |
| $g$ | −0.00594122 (<0.0001) | −0.00450794 (<0.0001) | $g$ | −0.00613600 (<0.0001) | −0.00388501 (<0.0001) |
| $b$ | 0.0493858 (<0.0001) | 0.0519812 (<0.0001) | $b$ | 0.0490175 (<0.0001) | 0.0526540 (<0.0001) |
| $a$ | −0.0640778 (<0.0001) | −0.0632730 (<0.0001) | $a$ | −0.0641139 (<0.0001) | −0.0628769 (<0.0001) |
| $W$ | −0.00202484 (<0.0001) | 0.00235946 (<0.0001) | $D$ | −0.0254597 (<0.0001) | 0.0308206 (<0.0001) |
| $n$ | −4.56675e-07 (0.7813) | −4.66857e-07 (0.7583) | $n$ | −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 |

*Note:* $\bar{U}^M$: 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.

*Source:* Simulations from the model.

In all cases, the determination coefficients are high (80%–83%). Except for the network size ($n$) and the geographic homophily ($c$), all the variables are significant at the 1% level[6]. A higher degree of discrimination 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 employment statuses of households.

#### 4.3.3. The effects of the main variables on the employment statuses of households

Now we explore the impact of the explanative variables on the labor situations of households: two employed members ($H^{2e}$), two unemployed members ($H^{2u}$), and only the man ($H^{1e,M}$) or the woman ($H^{1e,W}$) is 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 proportion of households with two or one income(s); in the case of no-income households, this impact is non-significant. Thus, as discrimination increases, the number of two-income households decreases in favor of the number of single-income households. It is worth noting that, given that the number of woman-headed households also decreases with discrimination, this increase is biased toward the households headed by men. Thus, discrimination changes the wealth distribution among households; it also changes household composition, as it leads to more single-income man-headed households.

Similar results are obtained in the extreme scenarios of gender equity (see Table 8) and total discrimination (see Table 9), respectively.

[6] We drop $n$ and $c$ from the regressions, and the results do not change.

Table 8. Households' labor statuses 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) |
|---|---|---|---|---|---|
| $z$ | 0.501905 (<0.0001) | 0.318089 (<0.0001) | 0.180005 (<0.0001) | 0.0777477 (<0.0001) | 0.102258 (<0.0001) |
| $c$ | −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) |
| $g$ | 0.0076669 (<0.0001) | −0.00277811 (<0.0001) | −0.00488876 (<0.0001) | −0.00172802 (<0.0001) | −0.00316 (<0.0001) |
| $b$ | −0.0634006 (<0.0001) | 0.0379258 (<0.0001) | 0.0254748 (<0.0001) | 0.0140346 (<0.0001) | 0.0114403 (<0.0001) |
| $a$ | 0.0709325 (<0.0001) | −0.0563674 (<0.0001) | −0.0145651 (<0.0001) | −0.00688030 (<0.0001) | −0.0076848 (<0.0001) |
| $W$ | −0.0004575 (0.0062) | −0.000123 (0.5356) | 0.000580494 (<0.0001) | 0.00248152 (<0.0001) | −0.00190102 (<0.0001) |
| $n$ | 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) |
| $R^2$ | 0.871598 | 0.709664 | 0.550014 | 0.510928 | 0.589391 |
| $adj.R^2$ | 0.871582 | 0.709628 | 0.549958 | 0.510866 | 0.589340 |

*Note:* $H^{2e}$: 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 woman 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.

*Source:* Simulations from the model.

Table 9. Households' labor statuses 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) |
|---|---|---|---|---|---|
| $z$ | 0.508445 (<0.0001) | 0.318389 (<0.0001) | 0.173166 (<0.0001) | 0.06585 (<0.0001) | 0.107316 (<0.0001) |
| $c$ | −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) |
| $g$ | 0.00721521 (<0.0001) | −0.00280178 (<0.0001) | −0.004413 (<0.0001) | −0.001082 (<0.0001) | −0.003332 (<0.0001) |
| $b$ | −0.0637604 (<0.0001) | 0.0378704 (<0.0001) | 0.0258900 (<0.0001) | 0.0147625 (<0.0001) | 0.011127 (<0.0001) |
| $a$ | 0.0705848 (<0.0001) | −0.0563551 (<0.0001) | −0.01423 (<0.0001) | −0.006497 (<0.0001) | −0.007733 (<0.0001) |
| $W$ | −0.00714367 (<0.0001) | −0.00178492 (0.3977) | 0.008929 (<0.0001) | 0.032593 (<0.0001) | −0.023665 (<0.0001) |
| $n$ | 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) |
| $R^2$ | 0.872987 | 0.708385 | 0.545206 | 0.497626 | 0.599797 |
| $adj.R^2$ | 0.872947 | 0.708294 | 0.545064 | 0.497469 | 0.599672 |

*Note:* $H^{2e}$: 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 woman 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.

*Source:* Simulations from the model.

## Conclusions

The results from our 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 toward male employment, such that the information on job vacancies is more likely transferred to men, the job-finding probabilities of men and women are altered. As a consequence, the income and labor statuses of household members are also altered. On the one hand, the employment of men increases, but this is offset by a larger decrease in the employment of women; consequently, general unemployment increases. This pervasive effect on employment becomes more important as discrimination increases, thus reducing the total income generated in the economy.

On the other hand, 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 network size does not affect the 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 an unemployed man or woman receives a job offer, but it does not exert a significant impact on unemployment, nor does it exert a significant impact on households' employment status. For both genders, a higher number of average links per family ($g$) increases the job-finding probability and decreases the mean unemployment, such that employment and the number of two-income households increase. Therefore, provided there are no discriminatory rules in the transmission of information within them, social networks can lead to better job opportunities.

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