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Abstract

This paper combines micro-level and macro-level approaches into a unified empirical design to understand the gender gap in Tunisian labor market participation. We use a multilevel propensity score matching analysis in order to reduce selection bias by accounting for the random effects across areas in a hierarchical data structure. Our empirical evidence suggests that despite the admirable progresses in women's rights and human capital in Tunisia, labor force participation rates are still higher for men than for women. This discrepancy between men and women in their labor market force participation generates a per capita income loss of 20 per cent.

Keywords: Female labor force participation, non-linear decomposition, multilevel propensity score matching, Tunisia.

JEL Classifications: J21, J2, J16, J71, J7

ملخص

تجمع هذه الورقة بين مناهج المستوى الجزئي والمستوى الكلي في تصميم تجريبي موحد لفهم الفجوة بين الجنسين في مشاركة سوق العمل التونسي. نحن نستخدم تحليل مطابقة درجة ميل متعددة المستويات من أجل الحد من الانحياز في الاختيار عن طريق حساب التأثيرات العشوائية عبر المناطق في بنية بيانات هرمية. توحي أدلتنا التجريبية أنه على الرغم من التقدم المثير للإعجاب في حقوق المرأة ورأس المال البشري في تونس ، فإن معدلات المشاركة في القوى العاملة لا تزال أعلى بالنسبة للرجال منها بالنسبة للنساء. وهذا التناقض بين الرجال والنساء في المشاركة في قوة سوق العمل يولد خسارة في دخل الفرد تبلغ 20 في المائة.

1. Introduction

Tunisia has made large efforts to provide 'gender equality' in education, employment, as well as political and cultural representation. The enrolment of girls was accelerated and the literacy rate of youth female (ages 15-24) has increased from 63% to 96% between 1984 and 2011. In 2010, 63% of the graduates from higher education institutions were women against only 37% for men.[4] Tunisia was also one of the first Arab countries that ratified the Convention of the Elimination of All forms of Discrimination against Women (CEDAW) in 1985. And in January 2014, the new constitution recognizes officially the equality between men and women in its article 21, which reads "All male and female citizens have the same rights and duties. They are equal before the law without discrimination". These advantages in the area of gender equality and women's rights have made Tunisia a pioneering experiment in the Arab-Muslim world for a long time.

Paradoxically, these admirable progresses in women's rights and human capital have not yet been matched by increases in female's economic participation. Compared to men, women are less likely to be in paid jobs and much more likely to be engaged in precarious and informal employment and paid substantially less than male counterparts. Labor Force Survey data indicate that female labor force participation rates (FLFP) have increased between 2005 and 2011, to reach 27 percent. According to the 2014 National Population and Housing census, the FLFP reached 28.2 percent compared to 65.47 percent for males, but continues to be below the international levels and it would still take about 150 years to attain the current world average (Angel-Urdinola et al 2015). Low participation rates can be explained by both economic and social factors. For instance, the number of babies in the household and the low access to child care coupled with low market wages and low employment quality could be important economic factors that affect a woman's decision to participate in the labor force. Also, women's low educational attainment, social norms and cultural attitudes could influence FLFP (Angel-Urdinola et al 2015). Furthermore, contextual factors such as regional unemployment rate among women and that among men can amplify or weaken the effects of these determinants (Cipollone et al 2014, Elhorst 1996, Ward and Dale 1992).

Female labor market participation rates also differ substantially between urban and rural areas and across regions. Data from the 2014 census reveal that the majority of interior regions (such as Tataouine, Kasserine, and Kairouan) displayed low levels of female labor participation (18.51%, 19.65% and 19.69% respectively), while coastal regions experienced the greatest levels (Sousse (33.99%) and Ariana (37.08%)). An additional salient feature of the Tunisian labor market is the high rate of unemployment among women compared to men. The unemployment rate for women is estimated at 22.5% against 12.4% for men in 2015 and it exceeds 35% for the governorates of Gabes, Kasserine, Jendouba, Kebili, Gafsa and Tataouine (INS). Finding a job becomes more and more difficult for rural women. Less than one in five women in rural Tunisia (18.5 percent) and less than two in five women in urban Tunisia (39.8 percent) have a job (Word Bank 2014).[5] About one out of every four Tunisian

[4] National Institute of Statistics of Tunisia.
[5] Breaking the Barriers to Youth Inclusion, Report No. 89233-TN Tunisia.

females are unemployed (22.45% compared to 11.43 for males), and those with university degrees face a higher rate of unemployment than males (31.72% against 16.42%) and their less educated women as well as. As they face significant constraints to access to formal labor market with good jobs, women are more likely to be in home based employment and also more likely to be in the category of vulnerable, poor and informal employment with decent conditions, low wages and absence of benefits.

While most previous studies focus on the effects of individuals' and households' characteristics on the gender inequality in Tunisian labor market (Angel-Urdinola et al 2015) by using individual data and static model, this study has two main contributions. First, male-female differences in Tunisian labor market (especially in female participation and quality of employment) are examined using the first wave of the Tunisian Labor Market Panel Survey (TLMPS) collected in partnership between the Economic Research Forum (ERF) and the Tunisian National Institute of Statistics in 2014. The TLMPS 2014 includes retrospective information on education trajectories, residential mobility patterns, migration history, and marital and fertility history (Assaad et al 2016), which allows us to capture the change in work preferences and employment dynamics and their impacts on gender discrimination in labor market. Such dynamic model allows the differences in constraints (shocks due to fertility and marital status for example) to reflect possible gender differences in job arrival rates and employment quality (Liu 2016, Eckstein and Lifshitz 2011). Second, we combine the micro-level (individual and household characteristics) and macro-level (regional and institutional factors) approaches into a unified empirical design to understand whether the impact of individual characteristics on market labor participation and employment varies across regions characterized by different institutional structures and cultural attitudes. By considering contextual factors, we try to answer the following questions: Could regional specific factors influence the women's participation in labor force and the quality of women's employment? If so, what would be the implications for thinking through the territorially specific and gendered effects of national employment policies? In terms of modeling framework, we use a multilevel propensity score matching analysis in order to combine micro and macro factors as well as to reduce selection bias by accounting for the random effects across areas in a hierarchical data structure (Thoemmes and West 2011). Additionally, we try to identify factors that shape the informality decision amongst self-employment men and women. As women are particularly active in this sector, and they participate mainly to supplement family income, alleviating gender disparities can potentially boost their ability to improve household income.

In terms of modeling framework, this paper in close to Cipollone et al (2014), Ward and Dale (1992) and Elhorst (1996). Their papers examine the impact of contextual factors on women's employment status by estimating a multilevel analysis. Ward and Dale (1992) estimate a multilevel logit model to assess whether area (Travel-to-Work Area or TTWA) has an effect on women's LFP. Cipollone et al (2014) reveal the important role of contextual factors (such as labor market institutions and family-oriented policies) on the female labor market participation in Europe. They find that those factors explain almost 25% of the increase in

LFP for young women, and more than 30% for highly educated women. With the exception of Cipollone et al (2014), these papers do not study the impact of the changes in the institutional and policy settings on the female labor participation. Although the dynamics of contextual factors have been considered by Cipollone et al (2014), the two measures they used to capture the gaps between women and men in labor market (activity gap index and gap index for those in the labor force) do not consider the selection bias in the estimated models. In this paper, we use, as robustness check, a multilevel propensity score matching analysis that addresses two major advantages: (a) reducing selection bias by matching individuals between the treatment (women) and the control groups (men) on a set of relevant covariates; (b) reducing estimation bias by accounting for the random effects across governorates (Xiang et Tarasawa 2015).

From a public policy perspective, the potential results of this study will help to find which appropriate policies for boosting female participation in labor market, quality of employment and gender equity. Raising female labor participation is not just a matter of fairness, but also an economic objective and a policy priority. Increasing women's participation in the labor market and promoting equal employment opportunities can significantly contribute to achieve inclusive growth and a sustainable social system.[6] Some recent studies agree that a decrease in gender inequality in the labor market can lead to substantial macroeconomic gains. For example, Galor and Weil (1996) explained how gender inequality and economic growth are simultaneously affected. They argue that economic growth generates a feedback on gender inequality by reducing fertility, which leads to a demographic transition and a sustained economic growth thereafter (Cuberes and Teignier 2014).[7] Cuberes and Teignier (2012) show that all women were excluded from the labor market force, the loss in income per capita would be 40 per cent. According to their simulations, the income loss due to the gender gap in labor force is estimated to 20 per cent in Middle East and North Africa. Löfström (2009) shows also that full gender equality in the labor market in the EU could potentially increase GDP by 27 to 29 percent, with a gain of €6,800 per capita. Along the same lines, the evidence from Eurofound shows that the economic loss due to women under-participating in employment in Europe amounted to more than €370 billion in 2013 (about 2.8% of EU GDP).[8] Eckstein and Lifshitz (2011) show that if the labor input of women in the United States has remained at its 1964 level, the 2007 GDP would have been 40 percent lower. Furthermore, a greater balance in employment opportunities not only leads to potential economic gains, it also provides personal power for women in making family decisions and controlling household spending, especially children's health and education (Unicef 1999). Thus reducing such inequalities may imply benefits not only for women but also for men, children and the elderly, and for the poor as well as the rich.

The rest of paper proceeds as follows. Section 2 presents the research background. Section 3 presents the data and descriptive statistics highlighting the gender differential in Tunisian

[6] European Commission: Towards Social Investment for Growth and Cohesion-including implementing the European Social Fund 2014-2020, COM (2013) 83, Brussels 2013.
[7] See Cuberes and Teignier (2014) for a critical review on the link between gender inequality and economic growth.
[8] Eurofound: The gender employment gap: Challenges and solutions, Luxembourg 2016, Publications Office of the European Union.

labor market at both micro and macro levels, followed by empirical models and estimation strategies. Section 4 discuses the estimation results, section 5 provides a robustness test and section 6 offers concluding comments.

2. Theoretical background

2.1. A short literature review

Female labor market participation has always been an important topic in economic theory and policy, and considerable progress has been made in understanding the causes and consequences of women's market participation. Neoclassical theory, feminist theory and social identity theory are the three major lenses through which barriers to women's labor force participation and the occurrence of gender discrimination in the labor market are examined (Kercheval et al 2013). The neoclassical theory assumes that "labor markets are governed by standard microeconomic principles of constrained optimization by individual workers and employers with autonomous tastes and preferences" (Jennings 1999, p. 512). The neoclassical theory is almost considered as a demand-side theory (social and political influences are not considered), where firms seeking to maximize profits hire based on an individual's attributes. Based on this objective, and when physical strength is required for jobs, male is preferred and more highly remunerated than female. The most prominent neoclassical explanation of gender discrimination in the labor market is based on the work of Jacob Mincer and Gary Becker. Mincer, the human capital theorist, stressed women's role in the home and strongly defended the idea that "work at home is still an activity to which women, on the average, devote the larger part of their married life. It is an exclusive occupation of many women and a vast majority when children are present" (Mincer 1962). Becker (1976) argued that women have a comparative advantage in domestic, non-market work and men have a comparative advantage in the more traditional labor market. As a result, women do not invest in human capital (in terms of qualifications, training, education, professional experience, and effort and commitment in general) as much as men, which will subsequently reduce their chances of participation in the labor market and hence the gender pay gap. Given these reasons, gender discrimination in labor market is considered as result of the differences in the skills and knowledge acquired by the workers (Becker 1976 and Hein 1986).

All these arguments have largely criticized by the feminist economists, suggesting that gender discrimination is a multidimensional interaction of economic, social, political and cultural norms in both family and the workplace (Figart 1997). The central idea behind this theory is that the position of women in the labor market is governed by patriarchy or male dominance. If the human capital literature argues that women are less likely to participate in the labor market because they possess capital more relevant to household production, the feminist theory considers other factors that can explain gender discrimination in the labor market such as employer discrimination, sexual harassment and lower levels of training and education given to women (Jacobsen 1999). The social identity theory is based on the fact that individuals define themselves as members of their own social category (in-group) than with members of other categories (out-group). For the case of labor market, and in the workplace more specifically, men would view men more favorably and women less favorably in terms of productivity and vice versa would be true for women (Kercheval et al 2013).

Empirical studies on labor market participation can be divided into two groups. The first group seeks the long-term determinants of FLFPs and has been largely led by Ester Boserup's 1970 pioneering work on *Woman's Role in Economic Development* and Claudia Goldin's 1994 article on the U-shaped female labor function. This group states that female labor market participation should be understood in the context of economic development of nations. Goldin (1994) argued that when incomes are extremely low and when certain types of agriculture dominate (rice, cotton, poultry), women are heavily involved in labor force. As incomes raise following technological development and the transition from agricultural to industrial economy, women's labor force participation rates fall. But as economies continue to grow, female education improves and fertility rates decline, women move back into the labor force. Since it was first proposed, the U-shaped hypothesis has found consistent support from empirical studies using cross-countries (Goldin 1995, Mammen and Paxson 2000, Tsani et al. 2013) as well as to time-series and panel data (Goldin 2004, 2006, Olivetti 2013, Tam 2011). Only few recent papers have questioned the U-shaped hypothesis (Gaddis and Klasen 2013, Verme 2015). For MENA countries, over the period covering 1990-2012, Verme (2015) showed that nonparametric estimates confirmed the U-shape hypothesis. However, this relationship disappeared when using parametric estimations. The second group of empirical studies uses cross-section information to analyze the relationship between FRPs and other factors that can vary over the short-term such as marriage, fertility and education. Our paper will focus on the second body of literature.

2.2. The Tunisian labor market

As illustrated in Figure 1, male labor market participation over the period 1990 to 2015 can be characterized by a downward trend until 2005 (from 76.3% to 68.4%) followed by a slight increase thereafter (from 68.8% to 71%). However, female labor market participation showed an increase of 4 percentage points (20.9% in 1990 and 25.2% in 2014).

Figure 2 shows that women continue to face higher risk of unemployment than men during between 1990 and 2015. The unemployment rate in 1991 is estimated at 15.6 percent for men and 20.9 percent for women, resulting in a difference of 5.3 percentage points. This gap fell to 1.7 in 1997, after which it remained above 3 percentage points over the whole period of 1998-2015. The unemployment rates for both male and female reached their maximum levels in 2011 (17.1% and 21.6% respectively), the year of the revolution. Indeed, tourism (the largest source of foreign currency) has fallen by more than 50 percent accompanied by a fall of 20 percent in the foreign direct investment and the closure of more than 80 foreign companies that have left the country.

Unemployment among young people (aged 25-29 years) rose from 12.6% in 1984 to 25.2% in 2008. In addition, unemployment among young graduates exploded, which is an alarming situation: the unemployment rate for graduates of higher education rose from 0.7% in 1984 to

9.4% in 2004 and reached 19% in 2007. Tunisian's unemployment rate is also characterized by important regional disparities between costal and non-coastal areas. It has declined from 12.5% in 1980 to 10.9% in 2010 among coastal area, while it increased in the non-coastal area from 15.2% to 17% during the same period. After the Tunisian's revolution, the gap is even greater between the two areas. The unemployment rate stands at 24.4% for the interior area and 15.5% for the coastal area in 2011. Unemployment for the young university graduates was at alarming levels of around 23% in 2010 reaching 29.2% in 2011, and it increased from 4% to 42.3% in non-coastal area between 1994 and 2011 (Amara and Ayadi 2014).

3. Methodology and data used

3.1. Methodology

Assume that an individual (female) will participate in the labor market if the utility from participation, u_i^p exceeds the utility of non-participation u_i^{np}. Define also the latent variable, y_i^* as $y_i^* = (u_i^p - u_i^{np})$, assumed to be a linear function of the a set of k explanatory socioeconomic variables x_i plus a random term ε_i.

$$y_i^* = \left(u_i^p - u_i^{np}\right) = x_i'\beta + \varepsilon_i \qquad \text{(eq.1)}$$

Clearly, if $y_i^* > 0$ ($u_i^p > u_i^{np}$) then the individual will choose to participate ($y_i = 1$), if the opposite occurs ($y_i = 0$) then the individual will not participate. We went to estimate the probability of participation in the labor market (p_i). Let $F(\square_i|x_i, \beta)$ denote the cumulative distribution function of ε_i conditional on $X_i = x_i$, and the distribution of ε_i depends on β, a vector of parameters.[9] The probability of LFP can be expressed as:

$$p_i = \Pr(y_i = 1|X_i = x_i, \beta) = \Pr(\varepsilon_i \geq -x_i'\beta|X_i = x_i, \beta) = F(x_i'\beta|x_i, \beta) \qquad \text{(eq.2)}$$

Suppose further that the logit of the underlying probability p_i (or the log-odds) is a linear function of the k predictors x_{ki}.

$$\text{logit}(y_i) = \log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \sum_{p=1}^{P} \beta_p x_{pi} \qquad \text{(eq.3)}$$

In order to measure and decompose the Female-Male gap in the labor market participation (F-M gap), we apply the generalized decomposition method suggested by Yun (2004), which provides a detailed decomposition of the effects of each variable or group of variables in the case of non-linear models. Formally, the average estimated probability of LFP is given by:

$$\bar{\hat{p}}_g = \frac{1}{N_g} \sum_{i=1}^{N_G} F(x_{ig}\hat{\beta}_g)\ , (g = \text{Female } (F), \text{ Male } (M)) \qquad \text{(eq. 4)}$$

Where N_g is the number of male (if $g = M$) or female (if $g = F$) in the sample.

The $F - M$ gap in the LFP is given by:

[9] If the distribution function F is assumed to be from a normal with zero mean and constant variance, we will obtain the probit estimates and if F is assumed to be from a logistic distribution we will obtain the logit estimates.

$$\bar{\hat{p}}_F - \bar{\hat{p}}_M = \frac{1}{N_F}\sum_{i=1}^{N_F} F\left(x_{iF}\hat{\beta}_F\right) - \frac{1}{N_M}\sum_{i=1}^{N_M} F(x_{iM}\hat{\beta}_M) \qquad \text{(eq. 5)}$$

The average estimated probability, if there are no differences in response to characteristics between male and female is:

$$\bar{\hat{p}}_0 = \frac{1}{N_M}\sum_{i=1}^{N_M} F(x_{iM}\hat{\beta}_F) \qquad \text{(eq. 6)}$$

Adding and subtracting the term $\bar{\hat{p}}_0$ to Eq. 5, the $F - M$ gap becomes:

$$\bar{\hat{p}}_F - \bar{\hat{p}}_M =$$
$$\left[\frac{1}{N_F}\sum_{i=1}^{N_F} F\left(x_{iF}\hat{\beta}_F\right) - \frac{1}{N_M}\sum_{i=1}^{N_M} F(x_{iM}\hat{\beta}_F)\right] + \left[\frac{1}{N_M}\sum_{i=1}^{N_M} F(x_{iM}\hat{\beta}_F) - \frac{1}{N_M}\sum_{i=1}^{N_M} F(x_{iM}\hat{\beta}_M)\right] \text{(eq. 7)}$$

Where $\left(\frac{1}{N_F}\sum_{i=1}^{N_F} F\left(x_{iF}\hat{\beta}_F\right) - \frac{1}{N_M}\sum_{i=1}^{N_M} F(x_{iM}\hat{\beta}_F)\right)$ represents the proportion of the gap associated with differences in characteristics (the explained component of the gap) and $\left(\frac{1}{N_M}\sum_{i=1}^{N_M} F(x_{iM}\hat{\beta}_F) - \frac{1}{N_M}\sum_{i=1}^{N_M} F(x_{iM}\hat{\beta}_M)\right)$ is associated with differences in response/returns to these characteristics (the unexplained component of the gap due to discrimination) (Yun 2000, 2005).

Individuals from the same governorate j are likely to share the same circumstances (social, institutional and economic contexts that are beyond the individual's control) which may impact their decisions regarding labor force participate. Indeed, the assumption of independence of individual sample within a governorate is problematic. Thus a multilevel logit model with both individual and contextual characteristics reflects the overall level of inequality in the labor market. The share of inequality attributable only to contextual factors can be interpreted as inequality of opportunity. Model in equation (3) can be extended to consider Q $(q = 1, \dots, Q)$ regional or contextual variables (z_{qj}).

Level 1:

$$\log\left(\frac{p_{ij}}{1-p_{ij}}\right) = \text{logit}\left(y_{ij}\right) = \beta_{0j} + \sum_{p=1}^{P} \beta_{\square j} x_{pij} \qquad \text{(eq.8)}$$

Level 2:

$$\beta_{0j} = \beta_{00} + \sum_{q=1}^{Q} \beta_{0q} z_{qj} + \mu_{0j} \qquad \text{(eq. 9)}$$

$$\beta_{pj} = \beta_{p0} + \sum_{q=1}^{Q} \beta_{pq} z_{qj} \qquad \text{(eq. 10)}$$

The compact form of (8)-(9) and (10) is

$$\log\left(\frac{p_{ij}}{1-p_{ij}}\right) = \beta_{00} + \sum_{p=1}^{P} \beta_{p0} x_{pij} + \sum_{q=1}^{Q} \beta_{0q} z_{qj} + \sum_{p=1}^{P}\sum_{q=1}^{Q} \beta_{pq} x_{pij} z_{qj} + \mu_{0j} \text{ (eq. 11)}$$

The double sum in equation (11) captures possible cross-level interactions between variables at different levels. μ_{0j}, called level 2 residuals, specify the relative effectiveness of the governorate j. Equation (11) is estimated for male and female.

3.2. Data and variable definitions

3.2.1. Data

In this paper, we use the Tunisian Labor Market Panel Survey (TLMPS) carried out in 2014 in partnership between the Economic Research Forum (ERF) and the Tunisian National Institute of Statistics.[10] It is the first wave of what will eventually become a longitudinal survey of the Tunisian Labor Market. It is a nationally representative survey that presents information on households and individuals, especially in regards to labor market characteristics. Therefore, for the first time, estimates of discrimination based on real work experience data are presented. Despite the fact that it is a single cross-section, the TLMPS 2014 includes retrospective information on educational trajectories, residential mobility patterns, migration history, marital and fertility history. The initial sample included around 5160 households and done in two stage random sampling: 258 enumeration areas (primary unit of sampling) at the first stage according the principle of probability proportional to size and at the second stage 20 households were randomly selected from each primary unit. From the initial sample, only 4521 were successfully interviewed.

A particularly important focus of the TLMPS 2014 is providing accurate information on individuals' labor force status. Labor force status refers to whether a person was employed, unemployed or not in labor force during the past seven days preceding the enumeration. As in other countries in the MENA region, Tunisia suffers from high unemployment (particularly for university graduates, youth, and women) and from low FLFP (Haouas et al. 2012, World Bank 2014, Assaad et al. 2016). As may be seen from Table 1, more than one out of every four (25.69%) youths aged 15-24 is unemployed. Women aged between 15 and 24 years are the most likely to participate in the labor force (45.86%). The FLFP tends to decrease with the age cohort, reaching 21.33% at the 45-54 years age cohort and 11.89% at the oldest age cohort (55-64 years). Table 2 shows that women with higher education (university level) are more likely to participate in the labor market (70.5%, against 85.2% for men). However, uneducated women have a much lower rate of LFP compared to uneducated men (only 14 percent of them do, against 67 percent of men). As a result, women with university level of education have a higher probability of employment (57 graduates out of one hundred work, versus 12 among non-graduates). Table 3 illustrates the labor force status separately for ever married (currently married, divorced, or widowed) and never married women and men. As one would expect, never-married women have much higher participation rates than married women (54% versus 19.62%), while the participation rates among married men are higher than never married men.

[10] All information concerning the TLMPS 2014 comes from the ERF Working paper of Assaad et al (2016) 'Introducing the Tunisia Labor Market Panel Survey 2014, ERF working paper, n°1040.

3.2.2. Variable definitions

The dependent variable is the labor force participation dummy (LFP) that equal to 1 if the respondent participates in the labor force and 0 otherwise. We thus focus on access to the labor market, rather than women's position in it. Labor force participants refer to persons aged 15-64 years which are defined as unemployed job seekers and those in full-time and part-time employment (including self-employed) during the past seven days preceding the enumeration. Non-participants include those in full-time education, discouraged workers, retired people and those in domestic activities. The summary statistics for LFP by gender are presented in Table 4, which show that labor force participation is at 53 percent. Not surprisingly, men are consistently more likely than women to participate in the labor market (79 percent against 28 percent for women).

Several studies have been based on the neoclassical theory (Jennings 1999, Becker 1976, 1957), feminist theory (Figart 1997, Jacobsen 1999) and social identity theory (Turner 1987, Haslam 2001) to provide some explanation of the origins of discrimination in the labor market. Following those studies and based on available information from the TLMPS 2014 survey, we estimate the LFP decision as a function of the following individual and household variables: education, age, marital status, number of children in the household (under 6 years old), household size, area of residence, and the number of seniors (aged 65 and over) in the household. Four categories were used to indicate the level of education: no education (used as the reference category), primary level, secondary level and university level. Previous studies indicate that education has a positive effect on the LFP, especially for women. Educational attainment increases a woman's earning capacity, which increases her likelihood to participate (Mincer 1974). The labor force characteristics by gender, shown in Table 4, indicate that among females between 15 and 64 years of age with high level of education, 65.5% are in labor force against only 13.4% of those with no educated. A negative relationship is expected between the number of children in the household and women's LFP. The negative impact of the presence of young child can decrease as the availability of childcare services increases. As indicated by Anderson and Levine (1999) and Joll et al (1993), age has a great impact on female participation, having a positive effect up to a certain point and turning negative. The inverted U-shaped relationship between age and LFP suggest that women who belong to the younger cohorts exhibit greater participation (age squared/100 is added as regressor to test the non-linearity relationship between age and LFP).

To study whether local labor market conditions and contextual factors have an impact on LFP, we consider the following four indicators at the governorate level: labor market efficiency score (between 0 and 1) approximated by the rate at which vacant jobs become billed at regional level (governorate), male unemployment rate, female unemployment rate and the share of economically active population in agriculture (see Table 5 for descriptive statistics). Women may be less likely to participate in the labor market if they feel there are limited employment opportunities and that local markets are unable to provide adequate matching. So we expect a positive relationship between the labor market efficiency score and FLFP. In addition, we expect that women at region with higher female unemployment rate are less likely to be employed, given the discouraged-worker effects. However, when the male unemployment rate increases in those regions, there are more chances for women to participate in the labor market in order to compensate the loss of family income. Regarding the sectoral structure of local employment, it is also expected that agricultural activities in lagging areas generate higher employment opportunities for unskilled women. To see if this relationship exists, we test the effect of the interaction variable between no education (from the individual level) and the share of economically active population in agriculture (from the regional level) on the LFP. We also test the effect of having children and living away from kindergartens on female labor market participation.

4. Empirical results

4.1. Preliminary analyses on gender differences in LFP

Before moving on the formal empirical analysis, figures 3, 4, 5 and 6 plot the marginal effect of the interaction between sex and the main covariates (age groups, education level, number of children and region) on the LFP. Figure 3 displays the life-cycle pattern of LFP for males and females. Labor force participation reaches a peak of 44 percent for women between 15 and 24, and falls steadily thereafter. For men, the predicted probability of being in labor force is low for youth (aged 15-24 years), increasing during prime age, flattering later in life before decreasing as retirement age approaches. Consistent with human capital investment patterns, the probability of participation in labor force is lower for less educated women (13 percent), but reaches higher levels for more educated ones (65.5 percent). By contrast, the probabilities are almost the same (about 80 percent) for men with primary, secondary or university levels of education (Figure 4). With regard to the effects of number of children, the predicted probability of participation in labor force is very low for women compared to men for the same number of children in the household (Figure 5). As compared to men, women from Center West (CE), which is the poorest region with the highest unemployment rates in the country, are less motivated to participate in the labor market (Figure 6).

4.2. Gender differences in LFP: evidence from the logit models

Table 6 shows the coefficients and marginal effects estimated from the logit model on LFP for female (Model 1), male (Model 2) and both men and women (Model 3), without and with regional dummy variables. The marginal effects are computed at the mean of the continuous covariates, and they represent the change in the probability of LFP associated to a discrete change of a dummy variable from 0 to 1. The individual characteristics affected LFP in the expected direction. For instance, being female has a negative and significant impact of 63.4% on the probability of participating in the labor force (Model 3). The negative and significant effect of the age square/100 suggests that there is aninverted-U shaped effect of age on LFP, with the marginal effect being negative on average (-0.025 for female against -0.05 for male (Model 1 and Model 2 respectively)). So participation first increases and then declines with age (starting from 33 years for female and 33.13 years for male, which represent the turning points). The marginal effects of the education indicators are measured with respect to those having no education. In general, having a high education level (specifically, university degree) positively affects the likelihood of female participating in the labor force, with average marginal effects of 41.1%.

Interestingly, obtaining secondary level of education increases a woman's likelihood of being in the labor force by only 15.3 percent (Model 1). Being married decreases a woman's likelihood of participating in the labor force by 20% compared to single woman (Model 1), while the participation tends to be higher (by 14%) among men who are married (Model 2). The presence of children in the household has the expected effects. We clearly see an increasing negative association between women's LFP and the presence of young children under 6 years old in the household. More specifically, having only one child (two children) in the family reduces the likelihood of mother participation by 6.7 percent (8.7 percent). The number of children does not affect the likelihood of male participation. Our results are in line with those of Hilger et al (2014), who used the "Tunisia labor force survey 2010" to show that having one infant in the household decreases female participation by 4 percent, and that having two infants decreases a mother's likelihood of participating by 7.4 percent.

Looking at the regional dummy variables, the great majority of regions (compared to Great Tunis, the reference category) have positive and significant fixed effects on men LFP, with the exception of center west region. Those results confirm the graphs of Figure 6 showing that Great Tunis has the lowest level of men LFP. The North East, North West, and center East regions also have high FLFP compared to Great Tunis. Here, the education level associated with the employment share of agriculture in those regions, are likely to have played a role. Indeed, unskilled women in North region (especially the west part) work mostly in subsistence agriculture, driven more by poverty than by choice.

4.3.Non-linear decomposition

In order to quantify the contribution of different explanatory variables to the observed gap in the predicted LFP rates between female and male, we now turn to a decomposition analysis, using the logit estimates for female and male.[11] Table 7 reports the nonlinear decomposition results (female as the reference) at national level (column 1) and by region (columns 2 to 5). The separate contributions from gender differences in each set of independent variables are also reported. At the national level, the average estimated probabilities of LFP are 0.285 and 0.807 for female and male, respectively. The total predicted LFP gap (differences in expected probabilities of participation) is equals to -0.522. Of this gap, -0.023 (4.6%) is due to variations in observed characteristics, and -0.498 (95.5%) is ascribed to different responses to characteristics across genders. Thus, the increase in the differences in expected probabilities of participation between women and men is almost exclusively explained by differences in effects (discrimination effects). While equalizing commonly observable characteristics would be expected to reduce the female-male participation gap by only 4.6%. For females, there are important regional differences in labor market participation as well. The gender gap in LFP is the smallest in the North West and the largest in the South area, the most socially conservative

[11]We use Yun's (2005) technique to overcome the identification problem associated with the choice of a reference category when dummy variables are included among the predictors. Estimates using probit model are not reported here, but they are very similar to those using logit model.

region of the country. Center East is the least discriminating region in Tunisia (unexplained component explains 89.7% of the female-male gap) while North West and south regions have the highest rates of gender discrimination in Tunisian labor market (unexplained components explain 102.6% and 98.8% of the female-male gap, respectively). There are also significant cohort effects in both groups. Compared to younger cohorts (15-34 years) older cohorts tend to exhibit higher discrimination in the labor force participation (-0.435 versus -0.583).

Panel A and panel B of Table 7 report the explained and unexplained components, respectively. We only focus on panel B, because it explained 95.5% of the total gap at national level and reached 102.6% for south region. The largest component of the unexplained portion of the differences in expected probabilities of participation in labor force is due to differences in age coefficients (age and age square/100), university level coefficient and married coefficient. The coefficient effect of age is negative and quite high in magnitude, showing that women are less likely to participate in the labor market than men of the same age, reflecting an increasing in the female-male gap. The positive and significant effect of university level coefficient suggests that having the same level of education (university degree) as their males colleagues, women are more likely to participate in the labor market. Those findings suggest that education is particularly crucial for women in order to increase their participation rates. Our results are in line with most empirical studies that have long noted a positive correlation between education and FLFP in most developing countries (Verme 2015, Grepin and Bharadwaj 2015). Grepin and Bharadwaj (2015) show for example that each year of education led to 3 percentage point increase in the probability that a Zimbabwean woman works outside the home. However, it is interesting to note that increased education does not universally translate into a higher probability of working. Thus, despite the fact that 70.47 percent of female university graduates are in labor force, 30.19 percent of them are unemployed in 2014 (Table 2). In the case of marital status, the coefficient effect of married dummy was negative, reflecting an increasing in the predicted LFP gap by 47 percent. This result show that compared to married men, women's LFP decreases with marriage (other things being equal).

4.4. Multilevel Analysis

To test if contextual factors have significant effects on labor market participation, we first estimate a two-level empty model (with only random intercept at the second level: governorate), also called the Random intercept-model', the 'null model' or the 'intercept-only' model. The empty model predicts the level 1 (individual) intercept of the dependent variable as a random effect of the level 2 grouping variable, with no other factors at level 1 or 2. The purpose of this step is to test for significant intercept variance, which is a test of the need for mixed modeling.

The results of empty model for the three specifications (female, male and both men and women) indicate that multilevel logit model is more appropriate than simple logit model (the LR tests are significant at the 1% level for all specifications), which allows us to justify the use of this multilevel modeling approach. The between governorate variance is non-zero for the three specifications. This finding is supported by the intraclass correlation coefficients (ICCs) that revealed considerable clustering of individuals within governorates. Indeed, the ICCs indicated that 9.2 and 10.2% of the total variance of female labor force participation and male labor force participation could be, respectively, accounted by governorate-level effects.

The results regarding the impact of individual characteristics (level 1) on labor force participation, for men and women together and separately, with only random intercept at the second level (known as random intercept model) are reported in Table 9. These results are close, both in terms of sign and magnitude of the coefficients, to those reported in Table 6 using regional dummy variables as fixed effects. Education (primary, secondary and university levels) has a highly significant positive effect on labor force participation in all the models, as expected, but women with only primary education remain excluded from the labor market. Our results confirm the importance of increasing human capital investments as mean for increasing the FLFP. Economists have long noted a positive relationship between education and women's LFP in most developing countries and recent natural experiments confirm that this relationship appears to be causal (Bratti 2003, Heath and Jayachandran 2016, Lillydahl and Singell 1985). Human capital theory provides good reasons for this relationship. Education increases a woman's access to more interesting jobs. In addition, education can indirectly affect FLFP by changing woman's desired number of children.

Turning to the contextual variables, we see from Table 10 that market efficiency enters positively and significantly in all three models (for men and women together and separately). A one unit increase in the local labor market efficiency score will produce a 0.17 increase in the probability of participating in the labor market for women and an increase of 0.14 for men.[12] Let's remember that this variable was used to capture the efficiency of job-matching services and transparent labor market information systems controlled by the 'National Employment Agency and Self Employment' (ANETI).[13] The ANETI has a monopoly over the supply of employment services in Tunisia (private intermediation agencies are illegal), which aims to facilitate job-matching by connecting job seekers with available job opportunities through a sophisticated information system that connects the various regional offices and business processes. It also manages a series of programs, including counseling, intermediation, job-search assistance, training, wage subsidies, and programs that help job seekers start a business (Hilger et al 2014). So a positive and significant coefficient of local labor market efficiency score indicates that LFP increases for governorates with higher ANETI's labor intermediation capacity.

Interestingly, the female labor force participation is higher in governorates with large male unemployment rates (but not a significant effect on men's participation), indicating an additional-worker effect. The additional-worker effect occurs when the household income drops to a critically low level due to long-term unemployment of the main breadwinner (who is usually the husband). In this situation, the wife who is not currently in the labor market may

[12] We have also used a stochastic frontier model to estimate the labor market efficiency, the results are almost the same.
[13] *Agence National pour l'emploi et le travail indépendant.*

decide to join the labor force in order to compensate the loss of family income (Congregado et al 2011, Liu et al 2011). The positive sign of the share of economically active population in agriculture variable for women may reflects that women are more likely to participate in the labor force in governorates with larger agricultural sector (the coefficient is not significant for the male equation). There are two possible explanations for this. First, in the lagging areas (North West and Center West regions, specifically) agriculture tends to be a major part of the female labor force. A second explanation is that wives of migrant men (from lagging to leading regions and from rural to urban area) are emerging as the managers of the farm lands. We have also included two cross-level interaction effects between primary education and the share of economically active population in agriculture, and having one or more children and the share of population where the distance from the kindergarten is more than 2 km. We are interested in testing the following two hypotheses: less educated women or men are more likely to work in agriculture and women with one or more children are less likely to participate in the labor market if they do not have access to preschool services. The bottom of Table 10 shows the estimated cross-level interaction effects on LFP for women and men separately and together. The coefficient of the interaction term of (primary) × (Share of economically active population in agriculture) shows that the positive effect of share of economically active population in agriculture is more pronounced for women with less education. While non-agricultural sectors have become more important in the coastal governorates, they still account for only small fraction of female employment in non-coastal governorates (lagging or interior governorates). Consequently, women being mostly illiterate or with low levels of education are more likely to join agricultural sector than industrial or service sectors. These results are supported by Figure 7, showing that less educated female workers are more concentrated in the agricultural sector in lagging regions (North West and Center West) of the country. The coefficient associated to the second interaction variable was also significant and has a negative effect on the female labor participation.

4.4. Robustness checks: propensity score weighting with multilevel data

As a robustness check, we extend our results by using propensity score weighting with multilevel data to estimate the differences between women and men in labor force participation. Propensity score methods are widely used with unstructured data to evaluate the gender discrimination in labor market (Heckman et al 1997, Dehejia and Wahba 1999, Manski and Garfinkel 2002).[14] However, labor market surveys are typically clustered in ways that may be relevant to the analysis, for example by Travel-to-Work Area, district, province, or in the example we consider in this paper, governorate. Despite the increasing popularity of propensity score analyses and the vast literature regarding regional variation in labor market participation, the implications of clustered data for propensity score analyses have not been intensively studied. This method is widely used, however, to estimate treatment effects on education outcomes (see for example Xiang and Tarasawa 2015, Arpino and Mealli 2011).

[14] Rosenbaum and Rubin (1983) define the propensity score as "the conditional probability of assignment to a particular treatment given a vector of observed covariates" (p. 41).

Another motivation for using this method is the fact that our groups (male and female) differ greatly in observed characteristics (as shown in table 4). In this case the estimates of differences between groups from standard analytic methods can be biased. In addition, if there are unmeasured confounders that differ between groups but are omitted from the standard propensity score model (that uses unstructured data), the analysis will fail to control for such differences (Li et al 2013). The propensity score weighting with multilevel data is used in our case to overcome these limitations. Since gender is not a "treatment" in the conventional sense of causal inference (because it is not manipulable) our goal is not to establish a causal relationship between gender and labor force participation (causal comparison), but simply to assess the difference in the probability of participating in labor force between males and females with balanced distributions of covariates at both individual and regional levels (descriptive comparison).[15] Two stages are used for this purpose: (1) matching, and (2) outcome analysis. In stage (1), propensity score is used to construct of matched sets with similar distributions of the covariates. Stage (2) estimates the population average controlled difference (ACD), which is none other than the difference in the mean of labor market participation in two groups with balanced covariate distributions. The two stages are presented as follow:

Controlled descriptive comparison (stage 1) : let T_{ij} be a binary variable indicating whether individual i in governorate j is assigned to the treatment ($T = 1$ if female) or the control ($T = 0$ if male).[16] The propensity score e_{ij} ($0 < e_{ij} < 1$) is a function of the observed covariates at individual and regional levels X_{ij} and Z_j, respectively. Three alternative propensity score models are considered in our case: A marginal model, a fixed effects model and a random effect model (see Li et al 2013 for more details).

Marginal model: $\text{logit}(e_{ij}) = \beta_0 + \beta_1 X_{ij}$ (eq. 12)

Fixed effects model: $\text{logit}(e_{ij}) = \beta_j + \beta_1 X_{ij} + \beta_2 Z_j$ (eq. 13)

Random effects model: $\text{logit}(e_{ij}) = \beta_j + \beta_1 X_{ij} + \beta_2 Z_j$ (eq. 14)

Where $\beta_j \sim N(\beta_0, \sigma_\beta^2)$ in equation (eq. 14).

Potential outcomes (stage 2): participation in the labor market (Y_{ij}) = 1 if yes and 0 if not.

Following Li et al (2013), we use two types of propensity score-weighted estimators for the ACD: A nonparametric marginal estimator (the difference of the weighted overall means of the outcome between female and male groups, ignoring clustering) and a nonparametric clustered estimator (the difference of the weighted overall means of the outcome between female and male groups, considering clustering).[17] As for the case of propensity score models,

[15] See Li et al (2013) for more details on the difference between controlled descriptive comparisons and causal comparisons.

[16] We use the terms treatment and control to refer to the groups. The 'ignorability of treatment' assumption of Rosenbaum and Rubin (1983), required for PSM is not satisfied when gender is used as 'treatment'. To overcome this problem, Ñopo (2008) use characteristics and not propensity scores to match individuals. So the objective of this robustness check is a controlled descriptive comparison.

[17] We use the inverse-probability weights $w_{ij} = 1/e_{ij}$ for females ($T_{ij} = 1$) and $w_{ij} = 1/(1 - e_{ij})$ for males ($T_{ij} = 0$). See Li et al (2013) and Li et al (2017), for more details on the weighting strategies for balancing covariates.

we have also hired three outcome models to estimate the ACD: marginal outcome model, fixed-effects outcome model and random-effects outcome model.

Marginal outcome model: $\text{logit}\big(Y_{ij}\big) = \delta_0 + \delta_1 X_{ij} + \delta_2 T_{ij}$ (eq. 15)

Fixed-effects outcome model: $\text{logit}\big(Y_{ij}\big) = \delta_j + \delta_1 X_{ij} + \delta_2 T_{ij} + \delta_3 Z_j$ (eq. 16)

Random-effects outcome model: $\text{logit}\big(Y_{ij}\big) = \delta_j + \delta_1 X_{ij} + \delta_2 T_{ij} + \delta_3 Z_j$ (eq. 17)

Where $\delta_j \sim N(0, \sigma_\delta^2)$ in equation (eq. 17). Under the standard Stable Unit Treatment Value Assumption (SUTVA), the observed outcome (labor force participation) can be expressed as $Y_{ij} = Y_{ij}(1)T_{ij} + Y_{ij}(0)(1 - T_{ij})$ and the descriptive estimand $\pi_{\text{ACD}}$with balanced covariate distributions as:

$$\pi_{\text{ACD}} = E_{X,Z}[E(Y|X,Z,T=1) - E(Y|X,Z,T=0)] \quad \text{(eq. 18)}$$

Figures 8, 9, 10 and 11 report the results of the matching analyses (first stage) and Table 11 displays the point estimates of the outcome models (second stage). Figure 11 shows that distributions are clustered around 50% for the last three models (marginal, fixed and random models) when using inverse probability weighting to balance covariates. Thus, only these models provide balanced covariates associated with cluster assignment. Table 11 reports the results of the ACDs using the three models at the first and second stages, where different rows correspond to different propensity score models and different columns correspond to different outcome models. For all case the F-M gaps in the probability to participate in the labor force are around to -0.51 and they are close to the F-M gap founded in Table 7 (-0.522), which shows that the bias of the non-matching is too small and does not exceed 1.2%. This is also an expected result because the difference in expected probabilities of LFP between women and men before matching is exclusively explained by differences in effects (the variation in observed characteristics between groups explains only 4.6% of the total gender gap in LFP).

Our results are also in accordance with those of Cuberes and Teignier (2012), which show a male-female labor market gap of 0.53 for the Middle East & North Africa countries (Table 12). Cuberes and Teignier (2012) quantify the aggregate effect of gender inequality in the labor market on aggregate income and show that the Middle East & North Africa is the region with larger income losses due to gender gaps (77% as an entrepreneurs' gap and 53% as a labor participation gap). According to their simulation results, these differences between men and women generate a total income loss of 27% (7% due to entrepreneurs' gap and 20% due to labor participation gap). Based on country-by-country Cuberes and Teignier simulation results, presented in Table (12) and our estimated value of M-F gap (51%), we estimate that the total income loss due to both gaps in entrepreneurs and in labor force participation is to be close to 26% (of which almost 20% is due to gender gap in labor market participation).[18]

[18] We use the linear interpolation to estimate the total income loss at the same value of entrepreneurs' gap of Middle East & North Africa (0.77).

5. Conclusion and policy implications

In this paper we have examined the gender labor force participation gap using data from the 2014 Tunisian Labor Market Panel Survey. A logit model of labor force participation was firstly estimated, for males and females, using individual and household characteristics as covariates. The estimated results were used then to evaluate and decompose the gender labor force participation gap into explained and discriminatory or unexplained components. Secondly, we combined both micro and macro variables into a unified empirical design to understand whether the impact of individual characteristics on labor force participation varies across governorates characterized by different institutional structures and cultural attitudes. A propensity score weighting with multilevel data, that assess the difference in the probability of participating in the labor market force between males and females with balanced distributions of covariates at both individual and regional levels, was used to test the robustness of our results.

At the individual level, the empirical evidence presented in this paper suggests that despite the admirable progresses in women's rights and human capital, labor force participation in Tunisia still higher for men than for women. According to our calculation, the male-female labor force gap is about 52%, of which 95 per cent could be significantly attributed to differences in the coefficients, that is, a discrimination effect. This discrimination effect between men and women in the labor market force participation generates a per capita income loss of 20 per cent. Our results show also that having the same level of education (university degree, specifically) as their males colleagues, women are more likely to participate in the labor market. Those findings suggest that education is particularly crucial for women in order to increase their participation rates. In addition, and compared to men, women's TFP decreases with marriage and number of children in the household. The multilevel analysis of the labor force participation reveals that a one unit increase in the local market efficiency score produces a 0.17 increase in the probability of participation in the labor market for women and an increase of 0.14 for men. The results show also that female labor force participation is higher in governorates with large male unemployment rates, indicating an additional-worker effect, and that women are more likely to participate in the labor force in governorates with larger agricultural sector. Providing access to early childhood services increases the female labor force participation.

From a policy perspective, the present paper provides strong and robust evidence that increasing women's education generates a significant increase in FLFP. The difference in the probability of LFP between uneducated women and university education, for instance, amounts to about 41 percentage points. Many policies directed at increasing female education should be putted. One type of policy involves female dropouts at primary school level in Tunisia. Building more schools and making travel to school faster and safer could be a girl-friendly policy if parents are more sensitive to keep their daughters in school than their sons. Another type of policy is conditional cash transfers to poor households that need the labor of their daughters. For example, the *Oportunidades* conditional cash transfer program in Mexico is estimated to transfer 1.1 billion U.S dollars, per year, to 5.8 million families to keep their daughters in school (Debowicz and Golan 2014, Heath and Jayachandran 2016).

There is also need for deliberate policy to less-educated women working in agricultural sector or living in rural area to increase the agricultural sector potential in order to generate additional employment. This will require a new vision for agriculture by providing financial support (facilitation their access to credit, markets and equipment), technical skills and training programs (targeted programs to modernize agriculture and related activities), and ensuring safe transportation systems to and from work for rural women. Promoting agricultural system innovation is an important measure to increase the participation of less-educated women as well as to attract educated women. The minimum wage for agricultural workers should also be revised upwards to increase both women and men participations in the agricultural sector. Moreover, the fact that access to childhood services causes a significant increase in the FLFP suggests that supporting firms to implement family-friendly policies, aiming at reconciliation between family and work, such as maternity benefits and alternative work schedule should encourage the labor force attachment of mothers. Moreover, the government should reform legal institutions and laws to remove discrimination against women working in private sector (for example, women have the right to two months of maternity leave on full pay in public sector, however, only 30 days of paid maternity leave are granted in the private sector). At the same time, increasing the availability and improving the quality of publicly childcare can also affect a mother’s decision to return to work after childbirth.

Our results show also that women may be less motivated to enter the labor force if they feel that employment opportunities provided by formal channels (such as ANETI) are limited. To improve the FLFP, the Tunisian government needs to improve the ANETI’s labor intermediation capacity to ensure transparency and efficiency in the local labor market. Thus, in spite of this positive relationship between LFP and market efficiency, the number of vacancies filled by the ANETI has decreased significantly after the 2011 revolution (Hilger et al 2014). The ANETI faces a number of challenges, which constraints its ability of efficiently insert of job seekers in the labor market. Some of the main challenges are; the limit option in terms of training and the low capacity to provide counseling to job seekers and to follow their progress. In addition, employers do not actively register their vacancies in ANETI and do not clearly define the type of workers they seek (Hilger et al 2014). To overcome these challenges, ANETI should adjust its training programs to meet the employers’ demands for skills. Moreover, ANETI needs to coordinate with the ministry of education and the ministry of higher education in order to reduce the mismatch between the output of the education system and the labor markets needs.

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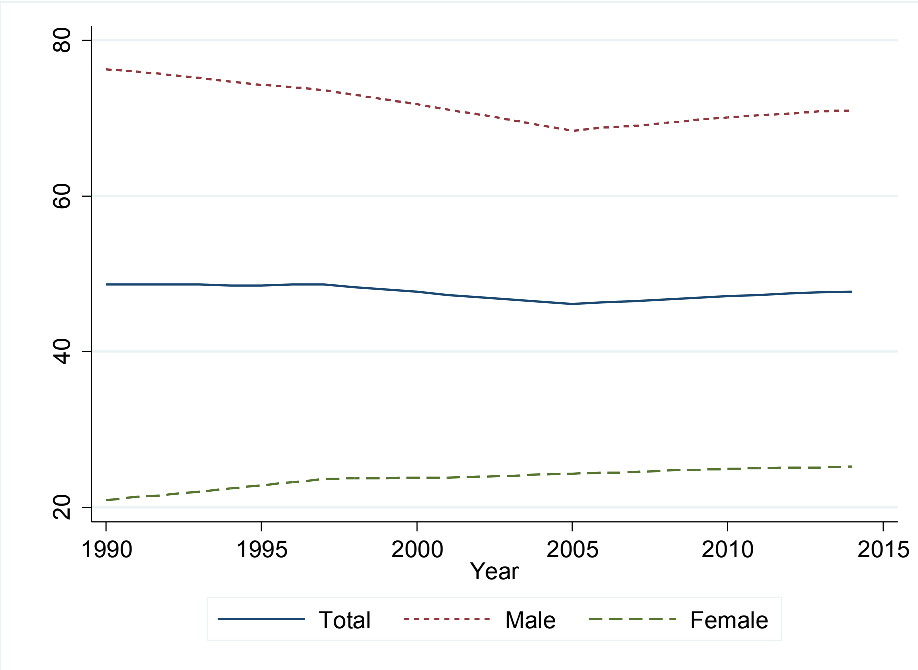
Figure 1: Labor force participation rate by gender (% of population age 15+)



Source: authors' calculations using data from: http://data.worldbank.org.

Figure 2: Unemployment rate by gender

Source: authors' calculations using data from: http://data.worldbank.org.

Figure 3: Male and female labor force participation by age groups (with 95% confidence intervals)

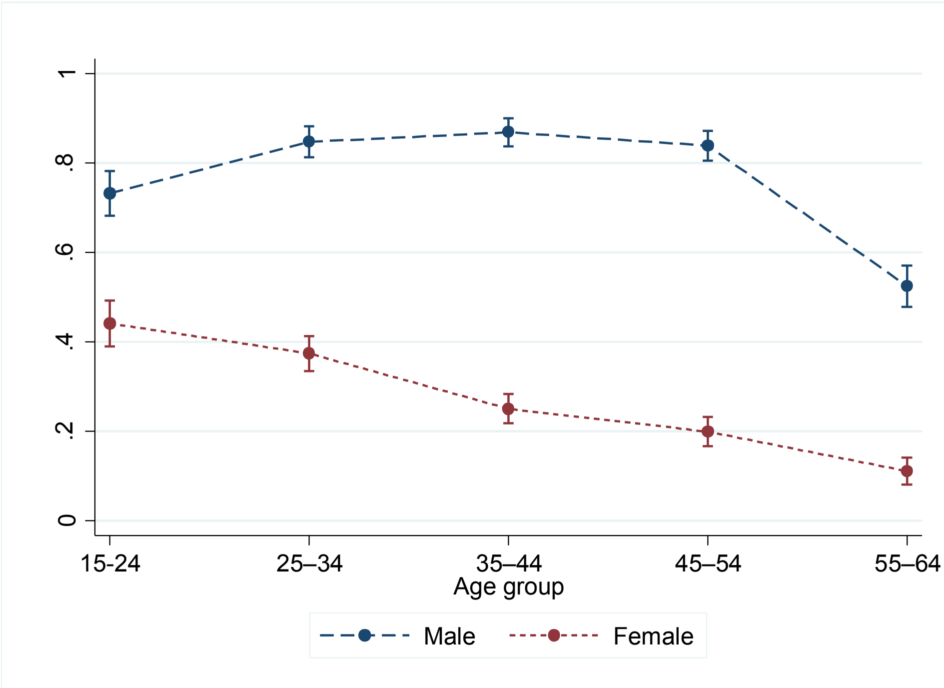


Figure 4: Male and female labor force participation by education (with 95% confidence intervals)

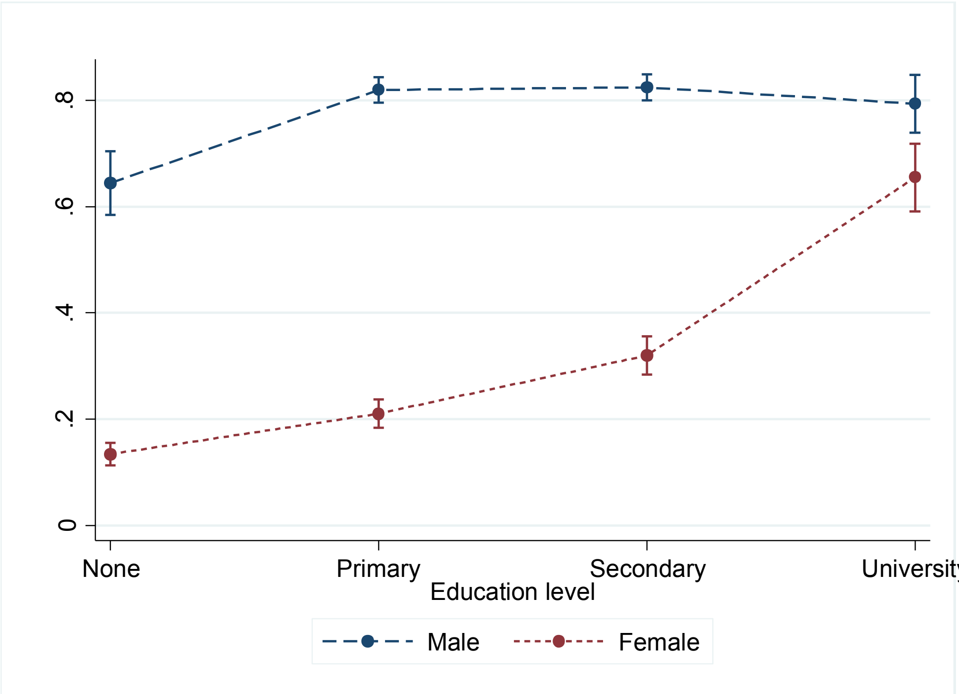


Figure 5: Male and female labor force participation by number of children

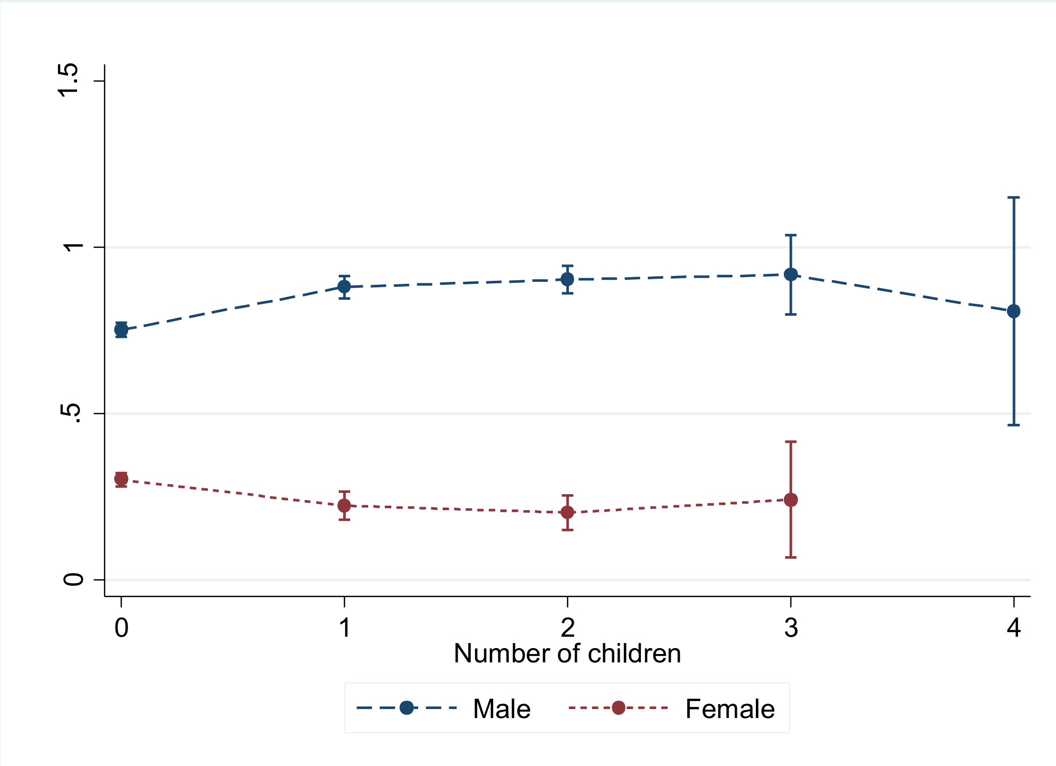


Figure 6: Male and female labor force participation by regions (with 95% confidence intervals)

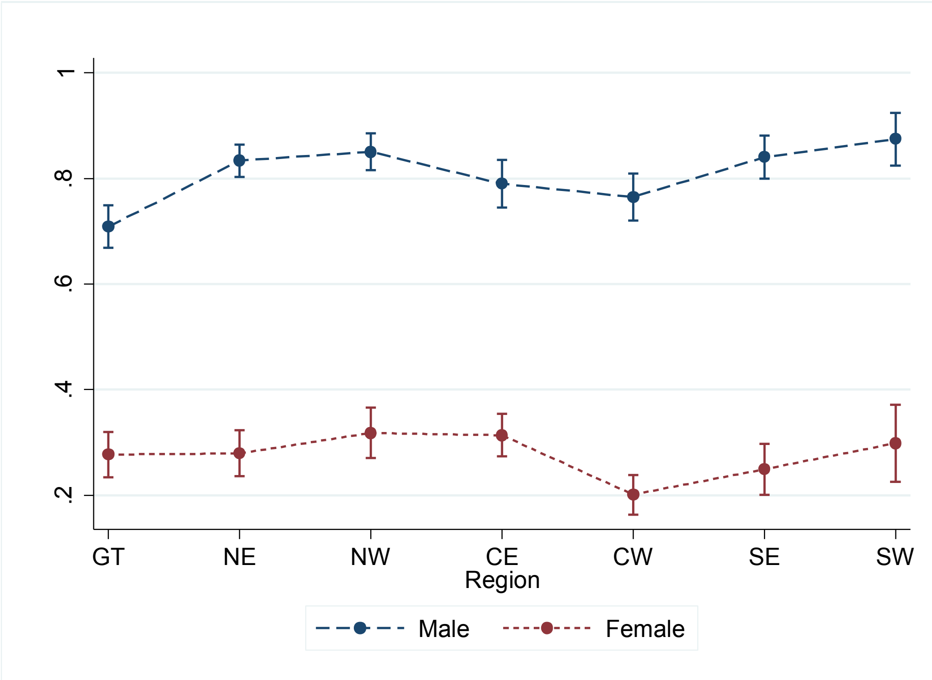


Table 1: Labor force status by age group

Labor force	15-24			25-34			35–44			45–54			55-64		
Status	All sex	Male	Female	All sex	Male	Female	All sex	Male	Female	All sex	Male	Female	All sex	Male	Female
Employed	37.89	49.25	24.39	49.70	73.30	26.91	54.38	86.44	22.85	52.83	84.85	20.66	32.00	52.77	10.60
Unemployed	25.69	29.25	21.47	14.50	15.90	13.15	5.01	6.15	3.90	1.70	2.73	0.67	2.07	2.83	1.29
Out of labor Force	36.41	21.51	54.14	35.80	10.80	59.94	40.61	7.41	73.25	45.47	12.42	78.67	65.92	44.39	88.11

Authors' calculations using TLMPS 2014.

Table 2: Labor force status by education

Labor force	No education			Primary			Secondary			University		
Status	All sex	Male	Female	All sex	Male	Female	All sex	Male	Female	All sex	Male	Female
Employed	25.49	62.82	12.10	49.01	74.30	18.57	53.74	72.40	26.58	55.54	72.33	40.28
Unemployed	2.45	4.02	1.89	7.22	10.32	3.48	10.64	12.75	7.56	21.93	12.85	30.19
Out of labor force	72.06	33.16	86.01	43.78	15.37	77.95	35.62	14.85	65.86	22.53	14.82	29.53

Authors' calculations using TLMPS 2014.

Table 3: Labor force status by marital status

Labor force	Single			Maried			Divorced/widowed		
Status	All sex	Male	Female	All sex	Male	Female	All sex	Male	Female
Employed	49.04	60.25	34.13	47.90	81.00	16.70	31.16	56.27	26.86
Unemployed	21.49	22.78	19.77	3.21	3.52	2.92	5.46	10.79	4.55
Out of labor force	29.47	16.97	46.10	48.89	15.48	80.38	63.38	32.94	68.59

Authors' calculations using TLMPS 201

Table 4: Labor force characteristics by gender

	Female labor force participation rate, %	Male labor force participation rate, %	Total labor force participation rate, %
All	27.81	78.78	53.34
Area			
Urban	29.74	77.76	54.14
Rural	23.87	81.06	51.62
Age group			
15-24	44.09	73.28	60.16
25-34	37.37	84.74	60.42
35-44	25.00	86.91	55.63
45-54	19.87	83.91	51.50
55-64	11.04	52.47	31.89
Marital status			
Single	51.04	77.61	66.29
Married	18.38	80.72	48.32
Divorced/widowed	28.80	53.88	32.90
Education			
None	13.40	64.43	26.81
Primary	21.02	81.96	54.06
Secondary	31.98	82.45	61.49
University	65.47	79.39	72.09
Number of children (<6years) in household (for married female and male)			
0 child	30.05	75.13	43.60
1 child	22.24	88.04	55.44
2 children	20.16	90.31	55.52
More than 2 children	22.93	90.79	57.85
Wealth (quintile)			
First quintile (poorest)	25.99	76.75	49.94
Second quintile	25.90	83.26	53.95
Third quintile	28.37	79.83	54.65
Fourth quintile	28.41	78.34	53.78
Fifth quintile (richest)	30.29	75.58	53.80
Region			
Greater Tunis (GT)	27.69	70.90	50.20
North East (NE)	27.92	83.38	55.88
North West (NW)	31.79	85.06	58.09
Center East (CE)	31.36	78.99	55.12
Center West (CW)	20.11	76.47	46.93
South East (SE)	24.93	84.03	53.97
South West (SW)	29.84	87.45	58.60
Number of observations	4966	4416	9382

Authors' calculations using TLMPS 2014.

Table 5: Regional labor market characteristics (contextual variables)

	Mean	Standard deviation	Min	Max
Labor market efficiency score	0.62	0.16	0.17	0.93
Male unemployment rate (%)	12.02	5.06	7.22	43.67
Female unemployment rate (%)	24.18	9.13	12.29	48.19
Share of economically active population in agriculture (%)	11.19	8.31	0.61	28.58
Share of population where the distance from the kindergarten is more than 2 km (%)	24.14	17.36	3.51	56.58
Number of governorates		24		

For the labor market efficiency score, we use data from the 'National Employment Agency and Self Employment', and the 2014 census data for the three other variables.

Table 6: Logit estimation results for labor force participation by gender

	Female (Model 1)				Male (Model 2)				All (Model 3)			
Variables	Logit coefficients	Marginal Effects	Logit coefficients with regional dummies	Marginal Effects with regional dummies	Logit coefficients	Marginal Effects	Logit coefficients with regional dummies	Marginal Effects with regional dummies	Logit coefficients	Marginal Effects	Logit coefficients with regional dummies	Marginal Effects with regional dummies
Gender									-2.579***	-0.634***	-2.601***	-0.639***
									(0.086)	(0.020)	(0.087)	(0.021)
Age	0.089***	0.016***	0.089***	0.016***	0.241***	0.033***	0.240***	0.032***	0.190***	0.047***	0.190***	0.047***
	(0.028)	(0.005)	(0.028)	(0.005)	(0.031)	(0.004)	(0.031)	(0.004)	(0.024)	(0.006)	(0.024)	(0.006)
Age square/100	-0.135***	-0.025***	-0.136***	-0.025***	-0.363***	-0.050***	-0.363***	-0.049***	-0.265***	-0.065***	-0.264***	-0.065***
	(0.034)	(0.006)	(0.035)	(0.006)	(0.036)	(0.005)	(0.036)	(0.005)	(0.027)	(0.007)	(0.026)	(0.007)
Education (None as reference)												
Primary	0.297**	0.055**	0.302**	0.056**	0.531***	0.072***	0.571***	0.076***	0.480***	0.118***	0.496***	0.122***
	(0.125)	(0.023)	(0.129)	(0.024)	(0.190)	(0.025)	(0.195)	(0.026)	(0.096)	(0.024)	(0.099)	(0.024)
Secondary	0.823***	0.153***	0.835***	0.154***	0.532***	0.073***	0.617***	0.083***	0.726***	0.178***	0.771***	0.190***
	(0.140)	(0.026)	(0.146)	(0.027)	(0.204)	(0.026)	(0.211)	(0.029)	(0.109)	(0.027)	(0.113)	(0.028)
University	2.217***	0.411***	2.233***	0.411***	0.227	0.031	0.349	0.047	1.638***	0.403***	1.688***	0.415***
	(0.193)	(0.037)	(0.198)	(0.038)	(0.263)	(0.032)	(0.268)	(0.036)	(0.169)	(0.041)	(0.170)	(0.042)
Marital status (single as reference)												
Married	-1.070***	-0.198***	-1.112***	-0.205***	1.020***	0.139***	1.031***	0.138***	-0.476***	-0.117***	-0.489***	-0.120***
	(0.155)	(0.029)	(0.153)	(0.028)	(0.255)	(0.041)	(0.254)	(0.033)	(0.139)	(0.034)	(0.138)	(0.034)
Divorced/widowed	0.028	0.005	0.005	0.001	0.002	0.001	-0.038	-0.005	0.231	0.057	0.205	0.050
	(0.243)	(0.045)	(0.248)	(0.046)	(0.568)	(0.077)	(0.570)	(0.076)	(0.251)	(0.062)	(0.255)	(0.063)
Number of children in the household												
One child	-0.360**	-0.067**	-0.375**	-0.069**	0.019	0.003	0.047	0.006	-0.108	-0.027	-0.105	-0.026
	(0.161)	(0.030)	(0.162)	(0.030)	(0.202)	(0.027)	(0.202)	(0.027)	(0.105)	(0.026)	(0.106)	(0.026)
Two childen	-0.459**	-0.085**	-0.456**	-0.084**	0.069	0.009	0.067	0.009	-0.146	-0.036	-0.148	-0.036
	(0.200)	(.0371)	(0.202)	(0.037)	(0.274)	(0.036)	(0.272)	(0.036)	(0.127)	(0.031)	(0.127)	(0.031)
More than two chidren	-0.315	-0.058	-0.281	-0.052	-0.181	-0.025	-0.218	-0.029	-0.124	-0.030	-0.127	-0.031
	(0.549)	(0.102)	(0.580)	(0.107)	(0.731)	(0.112)	(0.730)	(0.098)	(0.323)	(0.079)	(0.341)	(0.084)
Urban (1 if urban)	-0.017	-0.003	0.057	0.010	-0.148	-0.020	-0.039	-0.005	-0.097	-0.024	-0.013	-0.003
	(0.098)	(0.018)	(0.101)	(0.019)	(0.110)	(0.015)	(0.123)	(0.017)	(0.069)	(0.017)	(0.075)	(0.018)
Log of household size	0.086	0.016	0.133	0.024	0.091	0.012	0.113	0.015	0.132	0.032	0.164	0.040
	(0.126)	(0.023)	(0.132)	(0.024)	(0.158)	(0.022)	(0.158)	(0.021)	(0.106)	(0.026)	(0.108)	(0.027)
Old men/women in the household (65 or more)	0.050	0.009	0.055	0.010	-0.095	-0.013	-0.100	-0.013	-0.013	-0.003	-0.007	-0.002
	(0.104)	(0.019)	(0.105)	(0.019)	(0.130)	(0.018)	(0.130)	(0.017)	(0.089)	(0.023)	(0.090)	(0.022)
Region												
North East			0.319*	0.057*			0.634***	0.085***			0.428***	0.105***
			(0.191)	(0.035)			(0.168)	(0.023)			(0.123)	(0.030)
North West			0.719***	0.136***			0.908***	0.121***			0.776***	0.191***
			(0.178)	(0.032)			(0.215)	(0.029)			(0.131)	(0.032)

Center East		0.457***	0.084***		0.403**	0.054**		0.459***	0.113***
		(0.174)	(0.032)		(0.187)	(0.025)		(0.127)	(0.031)
Center West		-0.124	-0.023		0.078	0.010		0.061	0.015
		(0.203)	(0.037)		(0.204)	(0.027)		(0.138)	(0.034)
South East		-0.094	-0.014		0.611***	0.082***		0.280**	0.069**
		(0.212)	(0.039)		(0.213)	(0.029)		(0.135)	(0.033)
South West		0.240	0.050		0.807***	0.108***		0.498***	0.122
		(0.219)	(0.040)		(0.282)	(0.037)		(0.163)	(0.040)
Constant	-2.248***	-2.546***		-2.740***	-3.274***		-1.839***	-2.259***	
	(0.537)	(0.574)		(0.630)	(0.660)		(0.431)	(0.446)	
Pseudo R2	0.172	0.182		0.119	0.132		0.286	0.293	
Observations	4,490	4,490		3,903	3,903		8,393	8393	

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 7: Decomposition of the gap in labor force participation between female and male by region

	All regions	North East (including Greater Tunis)	North West	Center East	Center West	South (East and West)
Panel A: Overall decomposition						
Pr(LFP = 1 | gender = Female)	0.285	0.286	0.319	0.319	0.200	0.275
Pr(LFP = 1 | gender = Male)	0.807	0.777	0.852	0.825	0.772	0.856
Gap = Pr(LFP = 1 | gender = Female) – Pr(LFP = 1 | gender = Male)	-0.522***	-0.491***	-0.533***	-0.506***	-0.572***	-0.581***
Characteristics	-0.023***	-0.025***	0.014	-0.053***	-0.034***	-0.008
Contribution (%)	4.60	5.09	-2.60	10.30	5.94	1.20
Coefficients	-0.498***	-0.466***	-0.547***	-0.454***	-0.538***	-0.574***
Contribution (%)	95.50	94.90	102.60	89.70	94.06	98.80
Panel B(1): explained component						
Age	0.003***	-2.00e-04**	n.s	0.009***	n.s	n.s
Age square/100	-0.002***	0.009**	n.s	-0.017***	n.s	n.s
Primary	-0.004***	-0.002***	n.s	-0.013***	n.s	n.s
Secondary	-0.017***	-0.015***	-0.006*	-0.027***	-0.025***	n.s
University	0.004***	0.004***	0.013*	0.009***	-0.006***	n.s
Married	-0.009***	-0.018***	n.s	-0.009***	-0.003***	n.s
Divorced/widowed	n.s	n.s	n.s	n.s	n.s	n.s
One Child	5.96e-05**	n.s	n.s	n.s	n.s	n.s
Two Children	1.11e-05**	n.s	n.s	-2.35e-04*	n.s	n.s
More than two children	n.s	5.13e-04*	n.s	n.s	n.s	n.s
Urban	n.s	n.s	n.s	n.s	n.s	n.s
Log of household size	n.s	n.s	n.s	n.s	n.s	n.s
Number of seniors (aged 65 and over)	n.s	n.s	n.s	-0.006*	n.s	n.s
Panel B(2): unexplained component						
Age	-1.125***	-1.196**	-1.617**	n.s	n.s	-2.146***
Age square/100	0.730***	0.741**	0.880**	n.s	0.777**	1.251***
Primary	n.s	n.s	-0.123***	n.s	n.s	-0.103**
Secondary	n.s	n.s	n.s	n.s	n.s	n.s
University	0.046***	0.064***	0.040**	n.s	0.042***	0.061***
Married	-0.245***	-0.262***	n.s	-0.354***	-0.290***	-0.181**
Divorced/widowed	n.s	n.s	n.s	n.s	n.s	n.s
One child	n.s	n.s	-0.031*	n.s	n.s	n.s
Two children	n.s	n.s	-0.036*	-0.024*	n.s	-0.041**
More than two children	n.s	0.005*	n.s	n.s	n.s	-0.013*
Urban	n.s	n.s	n.s	n.s	n.s	n.s
Log of household size	n.s	n.s	n.s	n.s	n.s	n.s
Number of seniors (aged 65 and over)	n.s	n.s	0.033*	n.s	n.s	n.s
Constant	n.s	n.s	n.s	n.s	n.s	n.s

*** p<0.01, ** p<0.05, * p<0.1; n.s: coefficient not significant.

Table 8: Empty multilevel logistic models

	Female	Male	All
Constant (β_{00})	-1.184***	1.102***	-0.095
	(0.125)	(0.132)	(0.089)
Variance of the random effect ($\sigma^2_{\mu_0}$)	0.334***	0.374***	0.177***
	(0.109)	(0.120)	(0.056)
Odds ratio = exp(β_{00})	0.306	3.010	0.909
Probability (p_{ij})	0.234	0.751	0.476
Intraclass Correlation Coefficient (ICC)	0.092	0.102	0.051
LR test vs. logistic Regression	187.28***	237.05***	259.03***
Observations	4,966	4,416	9,382
Number of groups	24	24	24

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The ICC is the proportion of the variance of the governorate-level random effect out of the total variance. Given that the unobserved individual latent variable follows a logistic distribution with individual level variance equal to ($\pi^2/3$), the ICC is calculated as: $(\sigma^2_{\mu_0})/(\sigma^2_{\mu_0} + \pi^2/3)$.

Table 9: Multilevel logit with random intercept and individual characteristics (by gender)

	Female		Male		All	
Variables	**Logit coefficients**	**Marginal Effects**	**Logit coefficients**	**Marginal Effects**	**Logit coefficients**	**Marginal Effects**
Gender					-2.713***	-0.424***
					(0.063)	(0.005)
Age	0.082***	0.013***	0.269***	0.036***	0.208***	0.033***
	(0.021)	(0.003)	(0.023)	(0.003)	(0.016)	(0.002)
Age square/100	-0.123***	-0.019***	-0.394***	-0.053***	-0.285***	-0.045***
	(0.026)	(0.004)	(0.027)	(0.004)	(0.019)	(0.003)
Primary	0.097	0.015	0.498***	0.066***	0.333***	0.052***
	(0.108)	(0.017)	(0.136)	(0.018)	(0.079)	(0.012)
Secondary	0.706***	0.109***	0.507***	0.068***	0.654***	0.102***
	(0.123)	(0.019)	(0.147)	(0.020)	(0.089)	(0.014)
University	2.404***	0.370***	0.441**	0.059**	1.848***	0.289***
	(0.161)	(0.029)	(0.201)	(0.027)	(0.125)	(0.019)
Married	-0.774***	-0.119***	0.940***	0.126***	-0.359***	-0.056***
	(0.122)	(0.019)	(0.189)	(0.026)	(0.100)	(0.016)
Divorced/Widowed	-0.079	-0.012	0.204	0.027	0.134	0.021
	(0.197)	(0.030)	(0.415)	(0.055)	(0.178)	(0.028)
One child	-0.457***	-0.070***	0.043	0.006	-0.191**	-0.030**
	(0.123)	(0.019)	(0.156)	(0.021)	(0.087)	(0.014)
Two children	-0.656***	-0.101***	0.073	0.010	-0.277**	-0.043**
	(0.168)	(0.026)	(0.225)	(0.030)	(0.113)	(0.018)
More than two chidren	-0.954**	-0.147**	0.680	0.091	-0.227	-0.035
	(0.408)	(0.063)	(0.648)	(0.087)	(0.245)	(0.038)
Urban	-0.064	-0.010	-0.190*	-0.025*	-0.130**	-0.020**
	(0.093)	(0.014)	(0.102)	(0.014)	(0.066)	(0.010)
Log of household size	0.183*	0.028*	0.160	0.021	0.196***	0.031***
	(0.099)	(0.015)	(0.113)	(0.015)	(0.072)	(0.011)
Number of seniors (aged 65 and over)	0.011	0.002	-0.194*	-0.026*	-0.074	-0.011
	(0.079)	(0.012)	(0.106)	(0.014)	(0.065)	(0.010)
Constant	-2.340***		-3.284***		-2.133***	
	(0.440)		(0.489)		(0.328)	
LR test vs. logistic regression	153.12***		61.13***		168.16***	
ICC	0.096		0.062		0.061	
Observations	4,490		3,903		8,393	
Number of groups	24		24		24	

Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Multilevel logit with random intercept, individual and governorate characteristics, and interaction effects (by gender)

Variables	Female		Male		All	
	Multilevel logit coefficient	Marginal effects	Multilevel logit coefficient	Marginal effects	Multilevel logit coefficient	Marginal effects
Individual factors						
Gender					-2.711***	-0.422***
					(0.063)	(0.005)
Age	0.081***	0.012***	0.268***	0.036***	0.207***	0.032***
	(0.021)	(0.003)	(0.023)	(0.003)	(0.016)	(0.002)
Age square/100	-0.121***	-0.018***	-0.392***	-0.053***	-0.283***	-0.044***
	(0.026)	(0.004)	(0.027)	(0.004)	(0.019)	(0.003)
Primary	0.443**	0.067**	0.764***	0.104***	0.643***	0.100***
	(0.210)	(0.032)	(0.278)	(0.038)	(0.160)	(0.025)
Secondary	1.037***	0.157***	0.775***	0.105***	0.958***	0.149***
	(0.216)	(0.033)	(0.282)	(0.038)	(0.165)	(0.026)
University	2.720***	0.412***	0.714**	0.097**	2.144***	0.334***
	(0.236)	(0.038)	(0.312)	(0.042)	(0.185)	(0.028)
Married	-0.783***	-0.119***	0.954***	0.129***	-0.363***	-0.056***
	(0.122)	(0.019)	(0.189)	(0.026)	(0.100)	(0.015)
Divorced/Widowed	-0.089	-0.013	0.234	0.032	0.135	0.021
	(0.198)	(0.030)	(0.416)	(0.056)	(0.178)	(0.028)
One child	-0.148	-0.022	-0.021	-0.003	0.036	0.006
	(0.199)	(0.030)	(0.236)	(0.032)	(0.136)	(0.021)
Two children	-0.336	-0.051	0.002	0.001	-0.038	-0.006
	(0.232)	(0.035)	(0.293)	(0.040)	(0.157)	(0.024)
More than two children	-0.673	-0.102	0.645	0.087	0.002	0.001
	(0.435)	(0.066)	(0.668)	(0.091)	(0.264)	(0.041)
Urban	-0.042	-0.006	-0.170*	-0.023*	-0.117*	-0.018*
	(0.093)	(0.014)	(0.103)	(0.014)	(0.066)	(0.010)
Log of household size	0.189*	0.027*	0.141	0.019	0.197***	0.031***
	(0.099)	(0.015)	(0.114)	(0.015)	(0.073)	(0.011)
Number of seniors (aged 65 and over)	0.003	0.001	-0.200*	-0.027*	-0.080	-0.012
	(0.079)	(0.012)	(0.106)	(0.014)	(0.065)	(0.010)
Regional factors						
Local labor market efficiency score	1.103*	0.167*	1.028*	0.139*	0.947*	0.147*
	(0.674)	(0.102)	(0.582)	(0.079)	(0.504)	(0.078)
Unemployment rate (male)	0.033*	0.005*	0.026	0.004	0.026*	0.004*
	(0.019)	(0.003)	(0.019)	(0.003)	(0.015)	(0.002)
Unemployment rate (female)	-0.015	-0.002	0.008	0.001	-0.002	-0.001
	(0.013)	(0.002)	(0.012)	(0.002)	(0.010)	(0.002)
Share of economically active population in agriculture	0.025*	0.004*	0.011	0.001	0.021*	0.003*
	(0.014)	(0.002)	(0.012)	(0.002)	(0.011)	(0.002)
Interaction factors						
One or more children in the household × Share of population where the distance from the kindergarten is more than 2 km	-0.012* (0.006)	-0.002* (0.001)	0.002 (0.007)	0.001 (0.001)	-0.009** (0.004)	-0.001** (0.001)
primary × Share of economically active population in agriculture	0.022* (0.012)	0.003* (0.002)	0.016 (0.015)	0.002 (0.002)	0.019** (0.009)	0.003** (0.001)
Constant	-3.742***		-4.841***		-3.594***	
	(0.730)		(0.731)		(0.547)	
LR test vs. logistic regression	121.99***		41.28***		133.79***	
ICC	0.062		0.042		0.038	
Observations	4,490		3,903		8,393	
Number of groups	24		24		24	

Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 11: Propensity score weighting with multilevel data results

	Weighted method		Doubly-robust method (DR)		
PS model	**Marginal**	**Clustered**	**Marginal**	**Fixed**	**Random**
Marginal	-0.5064***	-0.5095***	-0.5112***	-0.5130***	-0.5129***
	(0.0124)	(0.0118)	(0.0104)	(0.0103)	(0.0103)
Fixed	-0.5092***	-0.5106***	-0.5113***	-0.5132***	-0.5130***
	(0.0124)	(0.0118)	(0.0104)	(0.0103)	(0.0103)
Random	-0.5065***	-0.5095***	-0.5113***	-0.5130***	-0.5129***
	(0.0124)	(0.0118)	(0.0104)	(0.0103)	(0.0103)

Note: Standard error in parenthesis, *** p<0.01. Doubly-robust method (DR) refers to the large sample property that the estimated π_{ACD} is a consistent estimator if either the propensity score model (stage 1) or the potential outcome model (stage 2) is correctly specified, but not necessary both (Li et al 2013).

Table 12: Income loss due to gender gap

Regional groups	**Number of countries**	**Entrepreneur gender gap**	**LFP gender gap**	**Income Loss**	**Loss due to entrepreneur gender gap**	**loss due to LFP gender gap**
Middle East & North Africa	8	0.77	0.53	0.27	0.07	0.20
Sub-Saharan Africa	9	0.44	0.24	0.13	0.04	0.09
East Asia & Pacific	12	0.53	0.28	0.15	0.05	0.10
Europe & Central Asia	33	0.63	0.23	0.14	0.06	0.08
Latin America & Caribbean	20	0.54	0.33	0.17	0.05	0.12
South Asia	5	0.60	0.47	0.23	0.05	0.17

Country-by-country results

Country	Year	Entrepreneur gender gap	LFP gender gap	Income Loss	Loss due to entrepreneur gender gap	loss due to LFP gender gap
Algeria	2004	0.7769	0.5603	0.2732	0.0677	0.2055
Bhutan	2005	0.5790	0.5383	0.2452	0.0481	0.1971
Guatemala	2002	0.6571	0.5890	0.2711	0.0544	0.2167
Malta	2007	0.7733	0.5206	0.2589	0.0686	0.1903
Morocco	2007	0.8065	0.6912	0.3232	0.0663	0.2568
Qatar	2004	0.8796	0.5582	0.2840	0.0793	0.2047
Turkey	2007	0.8230	0.6514	0.3106	0.0695	0.2411
United Arab Emirates	2005	0.5443	0.5796	0.2569	0.0439	0.2130

Source: Cuberes and Teignier (2012).

Appendix

Table A1: Decomposition of the female-male gap in labor force participation by age cohorts

	15/64 years	15-34 years	35-64 Years
Panel A: Overall decomposition			
Pr(LFP = 1 | gender = Female)	0.285	0.391	0.171
Pr(LFP = 1 | gender = Male)	0.807	0.826	0.754
Gap = Pr(LFP = 1 | gender = Female) – Pr(LFP = 1 | gender = Male)	-0.522***	-0.435***	-0.583***
Characteristics	-0.023***	-0.061***	-0.015**
Coefficients	-0.498***	-0.374***	-0.568***
Panel B(1): explained component			
Age	0.003***	n.s	-0.020**
Age square/100	-0.002***	n.s	0.016**
Primary	-0.004***	-0.008***	-0.004*
Secondary	-0.017***	-0.022***	-0.023***
University	0.004***	0.037***	-0.028***
Married	-0.009***	-0.044***	0.019***
Divorced/ widowed	n.s	-	n.s
One Child	5.96e-05**	-0.013**	n.s
Two Children	1.11e-05**	-0.015**	n.s
More than two children	n.s	-	n.s
Urban	n.s	-0.001**	0.002**
Log of household size	n.s	0.001*	n.s
Number of seniors (aged 65 and over)	n.s	n.s	n.s
Panel B(2): unexplained component			
Age	-1.125***	n.s	n.s
Age square/100	0.730***	n.s	n.s
Primary	n.s	n.s	n.s
Secondary	n.s	n.s	n.s
University	0.046***	0.037**	0.050***
Married	-0.245***	-0.078***	-0.317***
Divorced	n.s	n.s	n.s
One child	n.s	n.s	n.s
Two children	n.s	-0.013*	n.s
More than two children	n.s	n.s	n.s
Urban	n.s	n.s	n.s
Log of household size	n.s	n.s	n.s
Number of seniors (aged 65 and over)	n.s	n.s	n.s
Constant	n.s	n.s	n.s

*** p<0.01, ** p<0.05, * p<0.1; n.s: coefficient not significant.

Table A2: Gender gap by governorate using cluster weighted estimator

governorate	marginal model	Fixed effects model	Random effects model
Tunis	-0.390	-0.392	-0.390
Ariana	-0.599	-0.598	-0.599
Ben Arous	-0.310	-0.311	-0.310
Manouba	-0.540	-0.540	-0.540
Nabeul	-0.518	-0.519	-0.518
Zaghouan	-0.599	-0.599	-0.599
Bizerte	-0.524	-0.524	-0.524
Beja	-0.471	-0.470	-0.471
Jendouba	-0.609	-0.610	-0.609
Le Kef	-0.403	-0.404	-0.403
Siliana	-0.498	-0.501	-0.498
Sousse	-0.533	-0.535	-0.533
Monastir	-0.537	-0.536	-0.537
Mahdia	-0.423	-0.425	-0.423
Sfax	-0.464	-0.465	-0.464
Kairouan	-0.688	-0.689	-0.688
Kasserine	-0.528	-0.528	-0.528
Sidi Bouzide	-0.458	-0.461	-0.458
Gabes	-0.554	-0.555	-0.554
Medenine	-0.637	-0.638	-0.637
Tataouine	-0.537	-0.539	-0.537
Gafsa	-0.590	-0.593	-0.590
Tozeur	-0.370	-0.375	-0.370
Kebili	-0.330	-0.329	-0.330

Figure 7: Less educated females versus share of female workers in agriculture

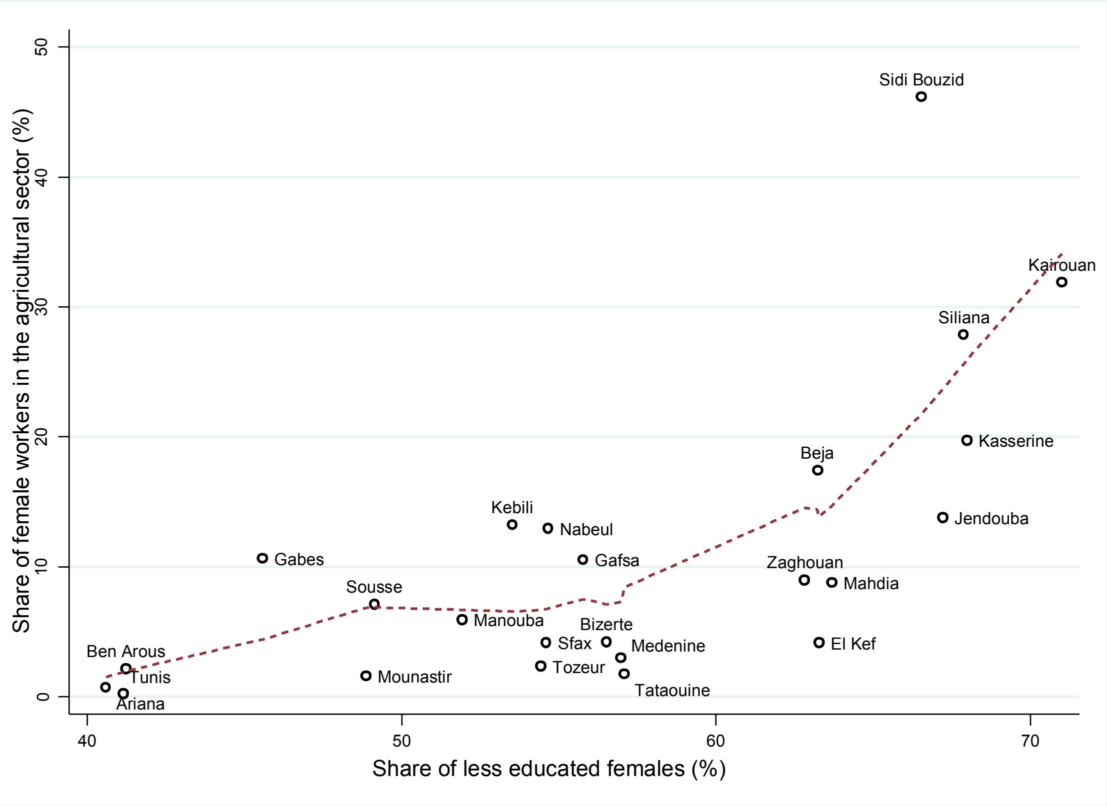


Figure 8: Propensity scores using marginal model

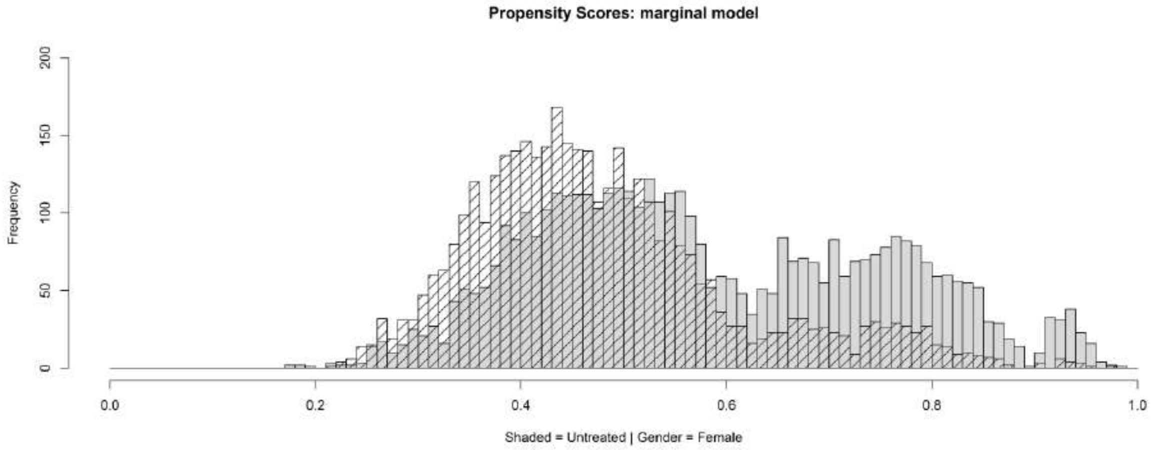


Figure 9: Propensity scores using fixed effects model

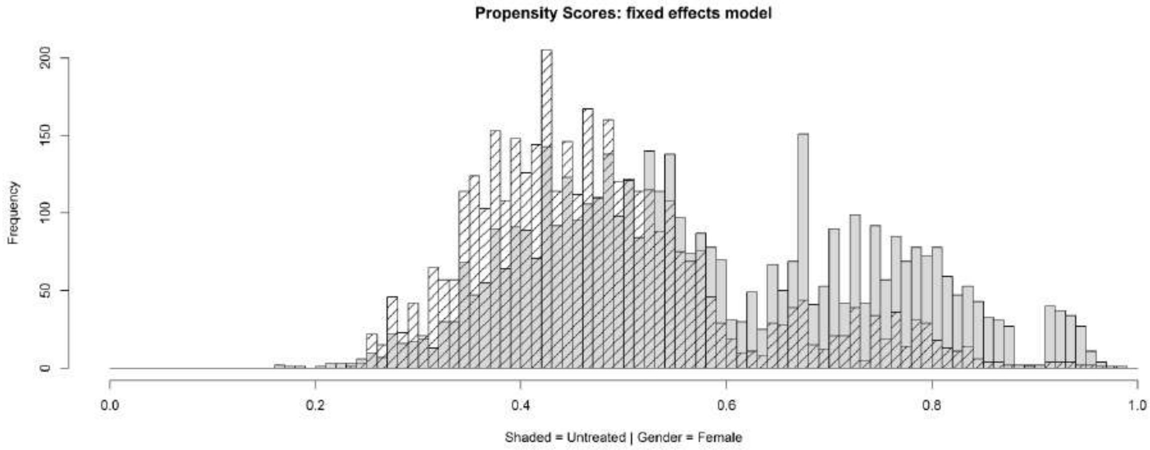


Figure 10: Propensity scores using random effects model

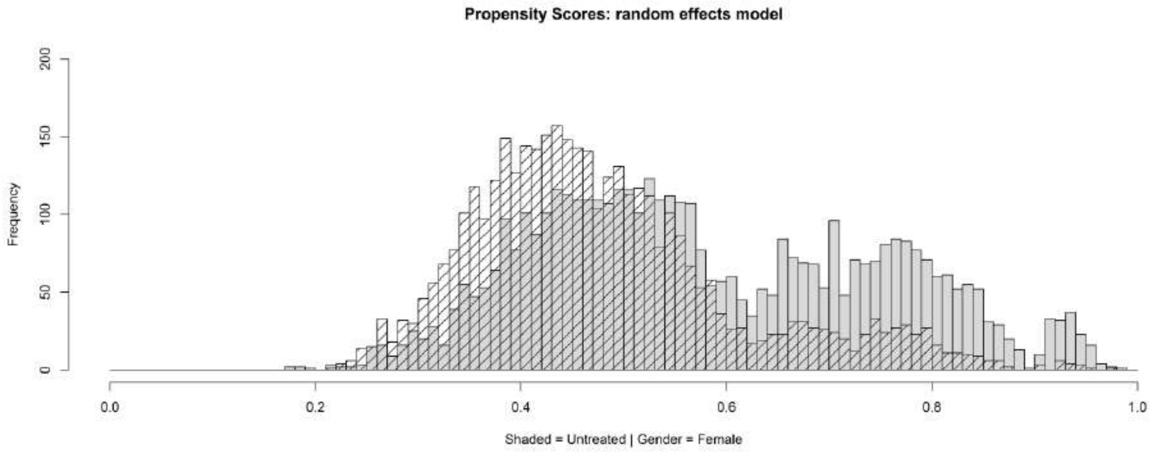
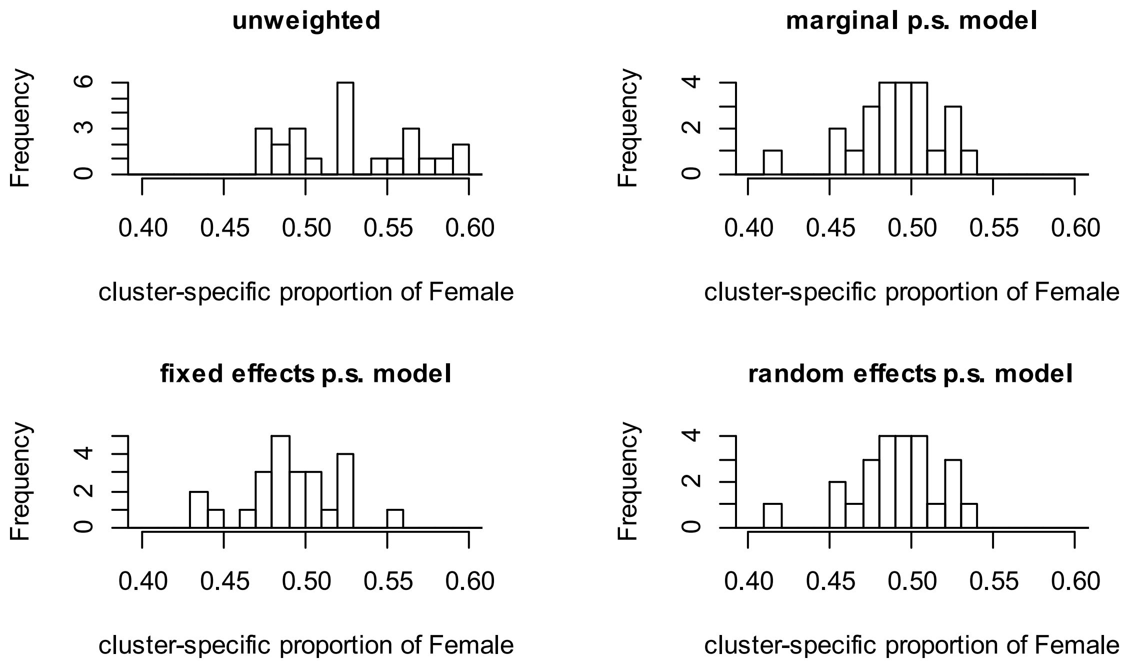


Figure 11: Histogram of cluster (governorate)-specific proportions of the weighted numbers of women using propensity scores estimated from different models



Values close to 0.5 indicate good balance in governorate membership between genders