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Evidence from Iran

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Women’s Waiting Time in Labor Market: Evidence From Iran

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Abstract

The vulnerability of women in the labor market is a well-established fact, but it can be long-lasting when a shock hits them. We examine women’s labor market conditions in a developing country with a substantial set of cultural norms and provide evidence that a job destructive shock persists longer among women. Specifically, probability of remaining unemployed after 20 months is about 50% for women while it is 10% for men. These findings are exacerbated for women who have not worked for more than 5 years and probably have lost their network or are new entrants in the job market. Moreover, women in the private sector, which is a more competitive market in Iran with respect to public jobs, are more prone to these burdens. The COVID-19 does not change this structure. Findings are robust to univariate Kaplan-Meier survival analysis and multivariate Cox models. These findings focus attention on policies that effectively break the vicious cycles causing sticky dynamics in the women’s labor market.

Keywords: Female Labor Force, Labor Market Participation, Kaplan-Meier Survival Analysis, Cox Model.

1. Introduction

Although the literature has gone deep in the context of women’s labor market, many questions remain. Is it the women’s own choice for job flexibility that causes the stylized gender gap in the labor market? Is the higher reservation wage of women simply because they are not expected to be breadwinners for the family, which differentiates their labor market outcomes from men’s? Are there dynamic burdens on women that are transmitting a temporary economic shock to a long-lasting failure in the labor market?

Responses to this concern depend greatly on every cultural and institutional environment. In a developed country, probably, the endogenous desire of women has a higher share in explaining differences Goldin 2006. However, we do not discuss how those desires are rooted in generation-to-generation beliefs or the female instinct here. What we may claim more strongly is the transition of an unemployment shock to a long-lasting unpleasant status for women. Specifically, we focus on the length of job search and the hazard of finding a job or becoming inactive by gender groups in a developing country.[1]

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[1] For literature on the female labor market in developing countries, see Jayachandran 2015, Jayachandran 2021, Bernhardt et al.

To investigate gender differences in labor dynamics, we provide a set of evidence using the labor force survey (LFS) dataset of Iran. Besides a historical cultural set of norms, the country has enjoyed substantial oil revenue for the last 50 years. This has enlarged the state sector, crowding out the private sector and distributing the oil rent in the public sector, where employment is almost permanent and firings are rare. Moreover, stipends are centrally determined, and except for some minor legal differences like paying extra money to married men who are *known as the family breadwinners*, there are no other differences in payments by gender. Indeed, this argument does not rule out the huge gap in position assignments, which is underinvestigated and requires a separate line of study.

Our analysis is based on the panel observations of the LFS, collecting a 2-2-2 rotating panel. We use different observations for an individual to count the spells of job status. Individuals are more than 163,000 in the data, from 2008 to 2022. To avoid losing data on those who are not observed more than once, spells are taken as censored.

Based on findings, when a woman is unemployed, the probability of remaining unemployed is 50% after 20 months of job search. In contrast, the survival statistic is 10% for a man. For a woman and a man who has not worked for more than five years, these survival probabilities become 62% and 28%, respectively. Results are robust to many tests, including using univariate analysis with the Kaplan-Meier model or controlling covariates in a Cox model. All differences are statistically significant. The set of covariates includes marital status, education, age, number of children above and under six, province of residence, and year that the unemployed began.

Many women searching for a job become disappointed and inactive. The survival probability of being actively searching is 19% after 10 months of search for women, while it is 53% for men. If a woman has not worked for the last five years and probably has lost job referrals and networks, the probability of not leaving the labor force is 16 percentage points lower compared to a man who has not worked for five years. Albeit, her probability of finding a job after 10 months is 29% less than a man.

Our findings are consistent with the literature. Disappointment with a differentiated[2] competition is an explanation for why the participation rate is much lower for women in Iran, i.e., 20% for women versus 80% for men Farahzadi and Rahmati 2020; Yousefi et al. 2021. These pieces of evidence are consistent with the literature that claims the looser networks are an explanation for women's lack of success in the job market Brown et al. 2016; Dustmann et al. 2016, especially if they have stayed out of the market for a while Goldin 2006.

Unlike the literature that mainly reports cross-sectional differences among men and women, our analysis is based on dynamic differences between the two groups. We do not focus on a *static* gap; rather, we find evidence of lower success *conditional on participation*. Besides, we indicate that while the diminishing matching likelihood exists for both gender groups, it is exacerbated for women. These findings, to some extent, highlight the exogeneity of the dynamic aspect of the gender gap that is not raised by women's will to stay out of the market.

The rest of the article is as follows. First, we have reviewed the literature on female labor force participation and female unemployment. In section 3, we describe the data along with a brief overview of the labor market in Iran. In section 4, the model and results are presented. The final sections are the discussion and conclusion.

2. Literature

Every community has several informal rules on proper and acceptable behavior, some of them are called institutions that affect everyday life, including the supply and demand of the labor force. **On the supply side**, gender differentiation may be exacerbated by those norms. The belief that a husband should be the family's main provider of income may lead to the idea that, during a recession, men should be given priority for employment over women. Gender roles also give rise to a conflict known as "mother's guilt," which arises from the belief that a working mother is unable to have an intimate bond with her children and cannot spend enough time with them. Women's "purity," a cultural attitude that sees contacting other men outside the family as pollution, could lead to prohibiting them from working outside the home to preserve their purity (Fortin 2015, 2005; Jayachandran

2018, Berniell et al. 2023, Klasen 2019a, Bursztyn et al. 2020, Miller et al. 2019

[2] We reluctantly limit using the words *unfair* or *discriminated*.

2021).

Gender norms are rooted in history. **Many of them are passed down through the generations** and have long-lasting effects on female labor force outcomes. These attitudes are mostly developed at younger ages. For instance, Haaland et al. 2018 showed that in Norway, gender disparities in the labor force are considerably greater for children raised in high gender gap environments than others. High gender gap environments are defined as those with low-educated parents, non-working mothers, or municipalities with higher advocates for conservative parties. Gender norms are passed on to both sons and daughters, influencing the formation of their preferences and attitudes. A study by Fernandez et al. 2004 showed that in the United States, wives of men who were raised by a working mother have a significantly higher probability of being employed. This may be due to differences in preferences in the marriage market between men who had working mothers and men with non-working mothers. Farré and Vella 2013 present evidence of a statistically significant association between a mother's beliefs and her children's inherited beliefs regarding the gender roles in the family and the labor market. Also, a husband's attitude towards gender roles in his youth has a significant impact on his wife's participation in the labor force.

Sometimes, it is not the norms but an **endogenous outcome of the bargaining between spouses** that bans women from working. Perceptions play a role here. Wives' decisions regarding labor supply are influenced by husbands' perceptions of social norms. A study in Saudi Arabia shows that many young married men favor women working outside the home, but they underestimate how many other men share the same view. As a result, they are less inclined to let their spouses work due to the perceived social norm. It is shining to remind that in some Islamic countries, husbands' permission is required for women's job (Bursztyn et al. 2020). Using a rural sample from India, Bernhardt et al. 2018 demonstrate how husbands are less inclined to let their wives work because of the attitude that "spouses of working women are poor providers" since the community will be more critical of the husbands than the wives. An increase in a husband's perception of the percentage of the community opposed to women working is negatively associated with the probability of his wife's participation.

Besides the abstraction of perceptions, there are realities like family work that require a parent to volunteer for it. **The effects of motherhood** on female labor outcomes are empirically assessed in a large body of literature on motherhood and labor. Women with young children may choose to leave the workforce or change their work structure due to gender norms that place the majority of the responsibility of child-rearing on mothers. Working fewer hours may result in human capital depreciation. Women may opt for jobs with more flexibility in working hours or jobs that pay less but are located significantly closer to home (Angelov et al. 2016; Berniell et al. 2021, 2023; de Jong et al. 2017; Goldin 2006; Kleven et al. 2019; Lundborg et al. 2017; Meng et al. 2023; Sieppi and Pehkonen 2019). Numerous studies have been conducted on the positive effect of childcare access on female labor force outcomes. They may reduce job separation for women, less human capital depreciation, and loss of network (Baker et al. 2008; Bauernschuster and Schlotter 2015; Berlinski and Galiani 2007; Carta and Rizzica 2018; Dang et al. 2022; Givord and Marbot 2015; Hojman and Lopez Boo 2022; Wikle and Wilson 2023).

Apart from women's choices to enter the workforce, gender norms may restrict the potential market to search. Social norms may induce women and their families to prefer to work in a same-gender workplace, the so-called gender-segregated labor market, which is associated with a cost to employers and limits women's job choices. These integration costs reduce the aggregate demand for female labor (Miller et al. 2019).

Norms may drive laws and regulations. In particular, there may be more job protection regulations biased towards men (Algan and Cahuc 2006). Even a biased attitude about job protection may cause discrimination. A study by Fortin 2005 using data from 25 OECD countries shows that in countries where there is a greater proportion of men than women who think that *jobs should go to men during a recession*, male employers are more likely to wage-discriminate against female employees.

Social networks may influence labor market outcomes and can be a source of gender gap in labor markets. This effect may be through the hiring process since access to information about job openings can be costly and might be asymmetrically biased towards men in a male-dominated labor market (Ioannides and Loury 2004). To shed light on this channel, one of the important ways of finding employees is through informal channels like referrals. Workers earn higher wages if they obtain their jobs through referral channels (Dustmann et al. 2016, Hensvik and Skans 2016). It is not only in terms of wage differences but in hiring, too. There is evidence that referred candidates have a better chance of getting recruited (Brown et al. 2016). At lower skill levels, the referral effects become more pronounced. Most referrals happen between individuals of the same gender and ethnicity. Notably, men tend to recommend other men for a job even though they have the ability to recommend qualified women (Beaman et al. 2018). The mechanism of social networks may be exacerbated when a crisis like a pandemic destroys a disproportionate share of women's jobs.

Over the past three decades, there has been a surge in female education in developing countries, which has reduced the educational gap between genders and improved women's qualifications for the job market. This was along with a reduction in fertility rates, which enabled women to increase labor supply as their time was freed from child care. Additionally, there has been an improvement in economic growth that is expected to increase the demand for labor. Female labor force participation remained low in many developing countries despite these facts (Klasen 2019b). Since the late 1980s, women's participation in the labor force has been low in India, regardless of the drop in fertility and the increase in educational attainment. According to a study by Klasen and Pieters 2015, the decline in female labor force participation rates between 1987 and 2011 was partly caused by changes in the structure of the economy. The majority of job growth has been in low-skilled services and construction, with manufacturing and white-collar employment growth falling short of meeting the needs of the expanding number of working-age women. According to the International Labor Organization (ILO), in 2017, worldwide labor force participation for women was about 49%, while it was 76% for men. A study by Stephan Klasen and Silva 2021 investigates labor force participation of married or cohabiting women in eight developing countries. The lowest labor force participation of urban women is in Jordan, which is about 20% in 2014, and the highest is in Vietnam and Tanzania, which is above 80%. [3] The paper finds that the returns to participation differ across countries, which leads to different labor force participation. However, in most of the studied countries, there are positive effects of education level and lower number of children on the labor force participation of women.

Tansel and Taşçı 2010 study determinants of unemployment duration in Turkey. Using quarterly data from household and labor force surveys in Turkey, they show that exit rates from unemployment to employment are significantly lower for women than men. Marriage affects men and women differently; married women have lower hazard rates than non-married women. However, the hazard of finding a job is higher for married men than for singles. They demonstrate that searching for a job for the first time has a significant negative effect on hazard rates of leaving unemployment to employment; this effect is worse for first-time job-seeking women. Kupets 2006 study unemployment durations in Ukraine using data from 1998 to 2002, using a *Cox model*. Similar to Turkey, the hazard of finding jobs is higher for married men. That might be due to more intensive job searches or higher opportunity costs for being unemployed.

In Iran, many scholars are studying the differentiation of the female labor market and its roots. Farahzadi and Rahmati 2020 investigate low female labor force participation in Iran through a structural model. Their results show that differentiation in the probability of job finding has a significant impact on lowering married women's participation. However, if all forms of differentiation in the labor market were eliminated, women would still make up a considerably smaller portion of the labor force than men would, which suggests that other variables out of the model, such as culture, may be responsible for Iran's low female participation rate. Esfahani and Shajari 2012 find that the reduction in fertility rate accounts for nearly 60% of the rise in the female participation rate between 1986 and 2006. In contrast, roughly 10% of the increase can be attributed to the expansion of education. To some extent, the rapid pace in the supply of educated women and stagnation in the economy raise competition and deteriorate the return to education. Similar to other countries, being married and having children reduce women's unemployment and participation. Besides the overall trend in Iran, Yousefi et al. 2021 show that COVID-19 had a severe impact on women's participation in the labor force compared to men[4].

[3] The female participation rate in Brazil, Bolivia, and South Africa was about 65-70% in 2014. To add some numbers, similar statistics are about 19% in the Middle Eastern countries and between 15 to 20% in Iran.

[4] There are more studies carried on women's labor force in Iran. Moeeni 2021 shows that women's participation follows an inverse U-shaped function for their bargaining power. The power increases by the extra education of women compared to their husbands. keshavarz haddad 2014 shows that a woman's labor supply has a negative elasticity for the husband's wage. A study by Egel and Salehi-Isfahani 2010 determines the factors affecting the duration of unemployment and job-finding probability in Iranian

Regarding the length of unemployment for women in Iran, there are few studies (in Persian) that employ the survival methodology to analyze unemployment spells in Iran. Isazadeh et al. 2021 and Jahadi and Elmi 2022 use the 2-2-2 panel of observations in the LFS data, restricted to 2018, and report a lower probability of finding a job for unemployed women and youth. Also, they report evidence of a higher chance of employment for women with previous job experience. Although the findings of these studies are consistent with ours, they have limited data to only one year in 2018, which coincides with the US unilateral withdrawal from the Joint Comprehensive Plan of Actions. The withdrawal exacerbated sanctions in Iran and caused a recession in the country. Besides the issues on the macro shocks, those studies employ a very limited sample of observations (about 2000) that appeared in the 2-2-2 panel. A study by Jafari Seresht and Naeini 2023 investigates the hazard of finding a job matched to academic education and reports a higher probability for women.

3. Iran Labor Force Data and Background

We use the labor force survey (LFS), which is a household-based survey conducted by the Statistical Center of Iran (SCI). The survey is conducted in the middle month of each quarter, and about 180,000 individuals are interviewed. Our sample is from quarter-2 2008 to quarter-4 of 2022. We consider quarter-1 of 2020 to quarter-4 of 2021 as the periods affected by COVID-19. The survey collects information on the labor market characteristics of individuals in Iran on the national level and changes in the labor market. LFS contains data on household structure, household members' demographic characteristics, labor market activities, and labor market histories[5]. We limit our study to unemployed individuals living in urban areas and of working age, i.e., 15- to 65-year-olds.

LFS has a rotating panel structure. It has a 2-2-2 rotating format in which a household is surveyed at most four times. A household is in the sample for two consecutive quarters, excluded from the sample for the next two quarters, and included again for the next two quarters, which will then be out of the sample. The rotating panel makes it possible to conduct longitudinal analysis by using panel elements as well as cross-sectional analysis. In this paper, we create an unbalanced panel from LFS data, in which we follow each individual until the individual is out of the sample.

The dataset contains information about demographic characteristics, including marital status, education level, and age. The survey includes labor market activities, information on current job status, working hours, job type like public or private sector, current and past work experiences for employed individuals and unemployeds[6]. We use the employment status of people who are sampled more than once in the 2-2-2 panel, besides answers of other individuals about the duration of job search and whether they have worked for two consecutive weeks in the last 5 years. These two indicators are our benchmark for unemployment duration and work experience, respectively.[7]

Figure 1a shows the participation rate in Iran. There is a significant gap between the participation rate of women and men. Women's labor force participation is below 20%, which is extremely low compared to many developing countries. Figure 1b shows the unemployment rate, which is higher for women than men. Table 1 presents summary statistics of data.

Table 2 provides dynamic statistics of the data. Among unemployed women, 73.2% have no work experience

youth. They find that family backgrounds do not affect women's unemployment duration and probability of employment. To see other aspects of the labor market in Iran and corresponding datasets, check Yousefi and Farajnia 2022 and Birjandi-Feriz and Yousefi 2017 for labor productivity among manufacturing plants, and Yousefi and Taiebnia 2023 for vulnerable groups using administrative data from the Social Security Organization of Iran.

[5] For examples of studies using the LFS of Iran, see Farahzadi and Rahmati 2020, Yousefi et al. 2021, Moeeni and Tanaka 2023.

[6] There are also sampling weights associated with each individual-quarter, from which we consider the first weights observed for an individual.

[7] If a respondent is observed in one of the previous quarters of data and her previous job status is not consistent with her current response about the length of unemployment, we consider the minimum one. Thus, we ensure that our analysis is the lower boundary of the length of unemployment. In line with this concern, we consider the shortest length of unemployment for those with an unemployed status in one quarter and an employed status in the next one. The time between the two interviews is either 1 or 2 quarters.

Table 1: Summary Statistics for the Individuals with Unemployed Status

	Women	**Men**	**Difference (Men-Women)**
Unemployment rate	0.19	0.10	-0.09
	(0.021)	(0.014)	(0.003)
Participation rate	0.16	0.73	0.57
	(0.019)	(0.017)	(0.003)
Employment rate	0.13	0.65	0.53
	(0.016)	(0.020)	(0.003)
Observations	4,851,016	4,891,975	9,742,991
Mean age	28.15	30.95	2.65
	(6.489)	(10.07)	(0.035)
Married Share	0.296	0.375	0.07
	(0.457)	(0.484)	(0.002)
Primary school share	0.0301	0.146	0.12
	(0.171)	(0.354)	(0.001)
High school share	0.259	0.540	0.29
	(0.438)	(0.498)	(0.002)
Higher education share	0.705	0.286	-0.43
	(0.456)	(0.452)	(0.002)
Observations	67,089	143,862	210,951

Source: Authors' calculation, based on the LFS.
Note: Standard Deviations are in the parantheses. Data is from 2008 to 2022, with ages between 15- to 65- years old.

in the last 5 years, while this is 25.7% for men. The average length of job search is about 14.5 months for women versus about 10.8 for men. Moreover, a high fraction of unemployed women have been inactive before, i.e., 76.7% inactive versus 23.3% employed.

Table 2: Labor Market Dynamics, 2008-2022

	Women	**Men**
Entire sample		
Not worked in last 5 years (%)	73.21	25.68
Last job private (%)	23.64	58.03
Last job public (%)	3.15	16.29
	100	100
Job search length (months) *	14.51	10.80
Was employed (%)	23.34	74.17
Was inactive (%)	76.66	25.83
	100	100
Observations	67,089	143,862
Sample limited to observations in the 2-2-2 panel		
Unemployed last quarter (%)	46.98	45.93
Inactive last quarter (%)	43.48	18.81
Observations	26,675	56,160
Unemployed last year (%)	23.27	22.97
Inactive last year (%)	61.55	27.16
Observations	17,691	35,787

Source: Authors' calculations, based on LFS data of Iran.
Note: * The Length of unemployment is limited to the last observation for individuals who appeared in the 2-2-2 rotating panel

4. Model and Results

We apply a duration model to obtain the hazard of leaving unemployment status (see Meyer 1990 and Cox 1972). Let the random variable T denote the survival time. The distribution function of T is defined by the equation $F(t) = P(T < t)$ and measures the probability of survival up to time t. The survival function $S(t)$ is the probability of survival until time t or longer and is given by:

$$S(t) = P(T \geq t) = 1 - F(t) \tag{1}$$

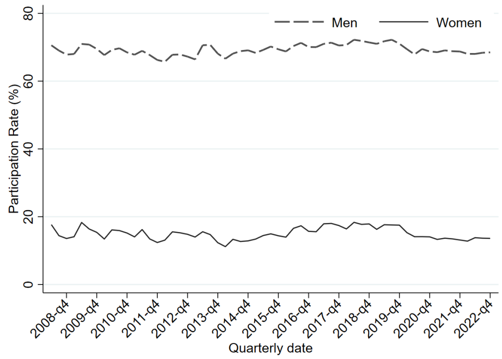
The hazard function $\lambda(t)$ measures the instantaneous failure rate given the survival until time t.

$$\lambda(t) = \lim_{\delta \to +\infty} \frac{P(t \leq T < t + \delta | T \geq t)}{\delta} = \frac{f(t)}{S(t)} \tag{2}$$

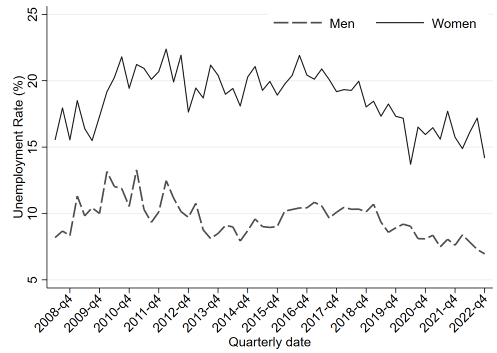
Therefore, one can obtain the relationship between the survival function and hazard function, which is as follows:

$$\Lambda(t) = \int_0^t \frac{f(u)}{S(u)} du = -\ln S(t) \tag{3}$$

The Kaplan-Meier survival rate is defined as the probability of an individual being unemployed for at least t. The Kaplan-Meier estimator is a non-parametric analysis method that does not impose any functional assumption on the baseline hazard; instead, it calculates the probabilities by simply taking the ratio of the number of units



(a) Participation Rate



(b) Unemployment Rate

Source: Authors' calculations based on LFS data from Iran.
Note: Participation and unemployment rates are calculated for individuals aged from 15- to 65-year-olds in the LFS data.

survived till time t divided by the total number of units. It is univariate, too, and doesn't account for covariates. It helps compare survival curves by groups. We advance analysis using the Cox duration model, enabling us to control for multiple covariates. The Cox proportional hazard model is semi-parametric and defines the hazard function as:

$$\lambda(t) = \lambda_0(t)\exp(X\beta) \tag{4}$$

in which X is the vector of k explanatory variables, β is the vector of regression coefficients, $\lambda(t)$ if the hazard function and $\lambda_0(t)$ is the baseline hazard. The model estimates a baseline hazards function, $\lambda_0(t)$, as a function of time that can take any form. The parametric assumption of the model is that covariates have a proportional effect on the baseline hazard function, which itself is constant for all individuals.

Figure 2a presents the results of the univariate Kaplan-Meier analysis without covariates. The survivor function shows the proportion of people who are still unemployed at each point in time before finding a job. The graphs show that women endure a longer period of unemployment compared to men. The probability of staying unemployed beyond 10 months is approximately 60% for women and 20% for men. It is shown that women with at least two weeks of work experience within the previous five years have slightly higher survival probability compared to men without more than 2 weeks of job experience in the last 5 years.

Figure 2b shows survival probabilities from unemployment status to inactivity. Diagram 1b indicates that women leave unemployment sooner and stop searching for jobs compared to men, with the probability of staying active equal to 46% and 13% after a year, respectively for men and women. Diagram 2b shows that individuals with job experience in the last 5 years stay longer in an active job search status before leaving the labor force.

The remaining KM diagrams in Figures **??** and **??** indicate that COVID-19 has not changed the gender-related structure of the labor market (diagrams 3a and 3b), and the private sectors are tougher for women (diagrams 4a and 4b)[8]. Notably, being tough is a gender-related issue. While the private sector is very tough for women (diagrams 4a and 4b of Figures **??** and **??**), the overall lookout of the private sector is not that much different from the public sector (diagrams 3a and 3b of Figures 3a and 3b).

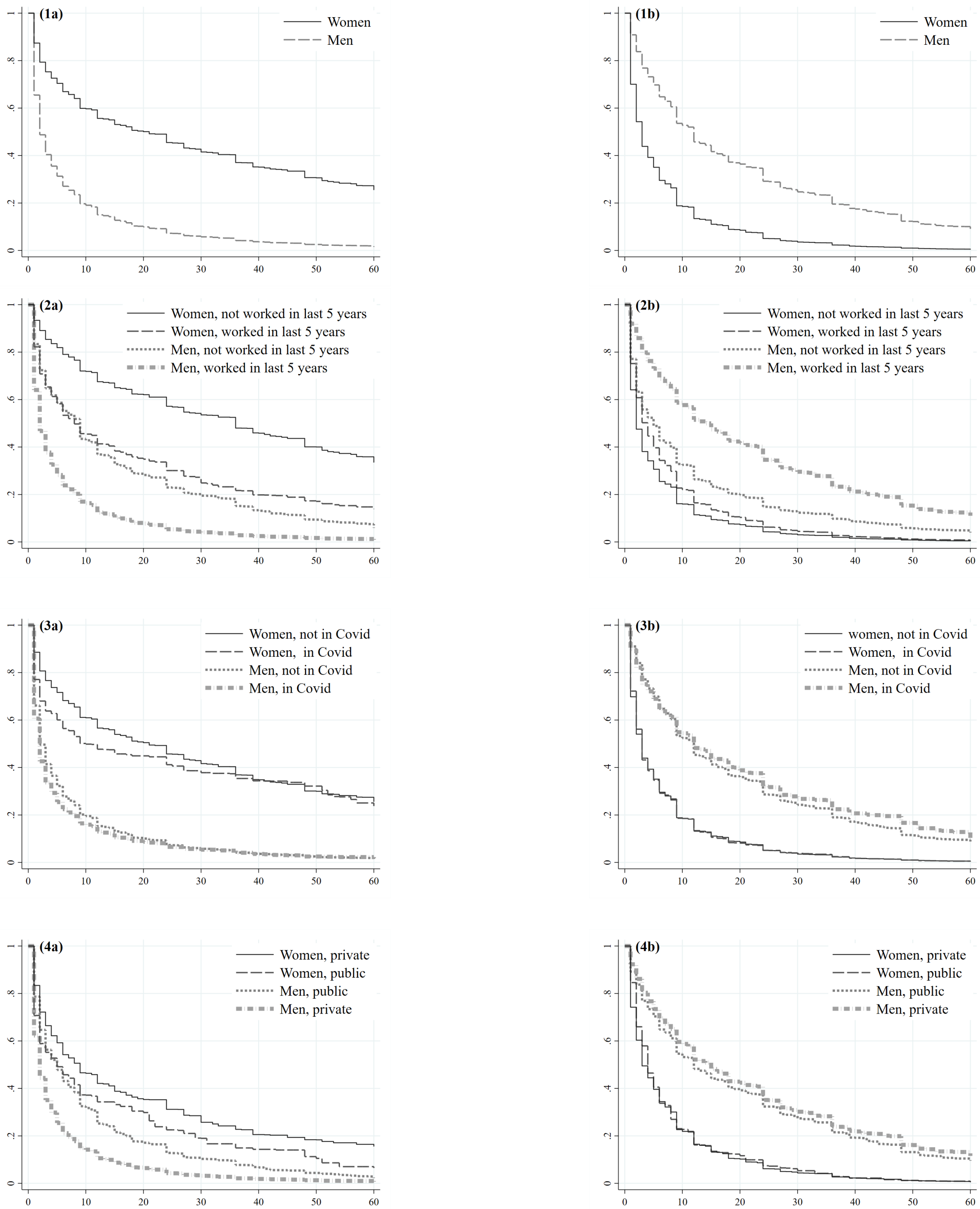
Table 3 presents the estimation results of the Cox model for transition from **unemployment to employment**. In all specifications, we control for age, marital status, number of children, education, place of residence, and

[8] More figures are in Appendix 7.. According to the diagram 1a in Figure 3a, the likelihood of staying in the pool of unemployments before becoming employed is about 57% in the 10^{th} month for a person who had not a job in the last five years, while it is about 19% for others. Moreover, a person who has not worked in the last five years is more likely to stop searching for a job (diagram 1a in Figure 3b). The structures are not changing during COVID-19 (diagrams 2a and 2b).

Figure 2: Survival Probability by Months of Unemployment, by Kaplan-Meier Estimates

(a) Probability of Staying Unemployed Before Becoming **Employed**

(b) Probability of Staying Unemployed Before Becoming **Inactive**



Source: Authors' analysis based on LFS data from Iran.

Note: Survivor function for the transition from unemployment to employment and inactivity are depicted on panels a and b, respectively. Horizontal axis is months of unemployment. Diagrams $4a$ and $4b$ are limited to individuals who report having a previous job. *Public* jobs are defined as state-related jobs categorized as public and cooperative. *Private* jobs are categorized as employers, self-employed, and non-wage family workers.

year of unemployment. The findings are consistent with the KM figures. Column (1) illustrates that a woman's likelihood of transitioning from unemployment to employment is 0.4 of the similar statistics for a man. Coefficients in column (2) indicate that those who have not worked for longer than two weeks in the last five years have a far lower chance of getting employment than those who have had a job; their job-finding hazard is 0.56 of someone with work experience. This conclusion may be related to the impacts of losing one's network or entering the workforce.

In column (3), we see the minor effects of COVID-19 on the overall hazard of finding a job. However, in column (5), no heterogeneity is found regarding the impacts of COVID-19 on gender-differentiations. However, as shown in column (6), during the COVID-19, the hazard of finding a job for a person with no job experience in the last 5 years was 0.85 of the hazard when not in COVID-19.

In column (4), the coefficient on interaction of women and work history shows that women who have not had a job in the last 5 years have lower rates of finding a job than their male counterparts. This result may be due to the greater impact of losing networks or fewer opportunities for female entrants in the job market compared to men.

In column (7), the coefficient of the interaction of COVID-19 and work history and gender shows a significantly lower hazard of finding jobs for women. For a woman with no job experience in the last 5 years who is in search of a job during COVID-19, the hazard of finding a job is on average 0.66 of hazard of finding a job compared to a similar man. That is, a destructive shock to the labor market heterogeneously affects men and women, with a pronounced effect on women without job experience in the last five years.

Column (9) shows that for women whose previous jobs were in the private sector, the hazard of leaving unemployment to employment is significantly lower compared to women who worked in the public sector.

As a robustness check, we run separate analyses for the two groups of men and women in columns $(12 - 15)$. For both groups, work experience in the last 5 years is a predictor of finding a job. It is also shown that COVID-19 had no significant effect on either men or women.

Considering other covariates like marital status, we find a reverse effect for men and women. Married men have a higher hazard rate of finding a job than single men. In contrast, the likelihood of finding a job is lower for a married woman. Family responsibilities may bias employers to avoid recruiting women, or those women may have higher reservation wages; either way, fewer job opportunities are for married women compared to singles.

Table 4 studies the transition from **unemployment to inactivity**. Estimates for females in column (1) show a significantly higher hazard rate, almost 2.4 times higher, of leaving the labor force compared to men. Also, there is evidence that people without job experience in the last 5 years have about 1.83 higher hazard of leaving the labor force than others. Despite such a large effect, women are more resilient, and their hazard of becoming inactive is about 0.65 of men. This might be because they are aware of their lower matching probability.

Marriage affects women differently than men; married men have a lower rate of leaving unemployment to inactivity when compared to singles (column 12); this may be due to family responsibilities that force men to stay in the labor force. However, married women approximately have 1.46 times higher hazard of leaving the labor force compared to single women(column 13). In COVID-19, we see a higher hazard of leaving the labor force to inactivity for women (column 15).

Table 3: Hazard Rate of Employment from Unemployment, Cox Model

	All Individuals							With work experience in last 5 years				Men	Women	Men	Women
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Female	0.40^{***}			0.51^{***}	0.41^{***}		0.50^{***}		0.67^{**}		0.65^{**}				
	(0.01)			(0.02)	(0.01)		(0.02)		(0.09)		(0.09)				
Not worked in last 5 years		0.56^{***}		0.75^{***}		0.57^{***}	0.75^{***}					0.76^{***}	0.60^{***}		
		(0.01)		(0.02)		(0.01)	(0.02)					(0.02)	(0.03)		
In COVID-19			1.07^{*}		1.05	1.10^{**}	1.07^{*}			1.04	1.00			1.06	0.96
			(0.03)		(0.03)	(0.03)	(0.03)			(0.07)	(0.07)			(0.03)	(0.07)
Female × not worked in last 5 years				0.80^{***}			0.85^{**}								
				(0.05)			(0.05)								
Female × in COVID-19					0.96		1.22^{*}				1.45				
					(0.06)		(0.12)				(0.46)				
In COVID-19 × not worked in last 5 years						0.85^{**}	0.92								
						(0.04)	(0.05)								
Female × in COVID-19 × not worked in last 5 years							0.66^{**}								
							(0.09)								
Private								1.10^{**}	1.20^{***}	1.09^{**}	1.19^{***}				
								(0.03)	(0.04)	(0.04)	(0.04)				
Female × private									0.73^{*}		0.73^{*}				
									(0.10)		(0.11)				
In COVID-19 × private										1.05	1.07				
										(0.07)	(0.08)				
Female × private × in COVID-19											0.85				
											(0.28)				
Married	1.33^{***}	1.25^{***}	1.28^{***}	1.30^{***}	1.33^{***}	1.25^{***}	1.30^{***}	1.37^{***}	1.36^{***}	1.37^{***}	1.36^{***}	1.48^{***}	0.74^{***}	1.51^{***}	0.75^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.06)
Number of children under/equal 6	1.07^{***}	1.08^{***}	1.09^{***}	1.07^{***}	1.07^{***}	1.08^{***}	1.07^{***}	1.07^{***}	1.05^{**}	1.07^{***}	1.05^{**}	1.06^{**}	0.94	1.06^{**}	0.93
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.07)	(0.02)	(0.06)
Number of children above 6	1.05^{***}	1.05^{***}	1.04^{**}	1.05^{***}	1.05^{***}	1.05^{***}	1.05^{***}	1.05^{**}	1.05^{**}	1.05^{**}	1.05^{**}	1.04^{**}	1.11^{*}	1.04^{**}	1.08
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.02)	(0.05)
Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age group	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of unemployment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	210,951	210,951	210,951	210,951	210,951	210,951	210,951	118,056	118,056	118,056	118,056	143,862	67,089	143,862	67,089

Source: Authors' calculations, based on LFS data of Iran.

Note: Table shows coefficient estimates and standard errors for the hazard of leaving unemployment to inactivity in a given month, conditional on remaining unemployed up to the previous month. All specifications include age group, education level, marital status, number of children above six years old, number of children equal to or below six years old, province of residence, and year that the unemployment begins. In columns (12-15) analysis is done separately for men and women.

The exponentiated coefficients are displayed. *, **, and ***, respectively, show significance at 5, 1, and 0.1 percent levels.

Table 4: Hazard Rate of Inactivity from Unemployment, Cox Model

	All individuals							With work experience in last 5 years				Men	Women	Men	Women
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Female	2.38***			2.76***	2.34***		2.72***		2.11***		2.07***				
	(0.05)			(0.09)	(0.05)		(0.10)		(0.19)		(0.19)				
Not worked in last 5 years		1.83***		1.72***		1.83***	1.73***					1.38***	1.23***		
		(0.04)		(0.05)		(0.04)	(0.05)					(0.04)	(0.04)		
In COVID-19			1.09**		1.05	1.09*	1.09			0.86	0.91			1.08	1.21***
			(0.03)		(0.04)	(0.05)	(0.05)			(0.08)	(0.09)			(0.05)	(0.05)
Female $\times$ not worked in last 5 years				0.65***			0.64***								
				(0.03)			(0.03)								
Female $\times$ in COVID-19					1.14**		1.12				1.17				
					(0.05)		(0.08)				(0.35)				
In COVID-19 $\times$ not worked in last 5 years						1.01	0.93								
						(0.05)	(0.06)								
Female $\times$ in COVID-19 $\times$ not worked in last 5 years							1.04								
							(0.10)								
Private								1.10*	0.87**	1.07	0.85***				
								(0.05)	(0.04)	(0.05)	(0.04)				
Female $\times$ private									1.31**		1.33**				
									(0.13)		(0.13)				
In COVID-19 $\times$ private										1.35**	1.27*				
										(0.13)	(0.13)				
Female $\times$ private $\times$ in COVID-19											0.90				
											(0.27)				
Married	1.11***	1.21***	1.17***	1.15***	1.11***	1.21***	1.15***	1.00	1.04	1.00	1.04	0.71***	1.46***	0.69***	1.45***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
Number of children under/equal 6	1.00	0.99	0.97	1.01	1.00	0.99	1.01	0.87***	0.90**	0.87***	0.90**	0.87**	1.19***	0.86**	1.19***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Number of children above 6	0.98	0.97	0.98	0.98	0.98	0.97	0.98	0.93**	0.94*	0.93**	0.94*	0.94	1.03	0.94	1.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age group	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of unemployment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	210,951	210,951	210,951	210,951	210,951	210,951	210,951	118,056	118,056	118,056	118,056	143,862	67,089	143,862	67,089

Source: Authors' calculations, based on LFS data of Iran.

Note: Table shows coefficient estimates and standard errors for the hazard of leaving unemployment to employment in a given month, conditional on remaining unemployed up to the previous month. All specifications include age group, education level, marital status, number of children above six years old, number of children equal to or below six years old, province of residence, and year that the unemployment begins. In columns (12-15) analysis is done separately for men and women.

The exponentiated coefficients are displayed. *, **, and ***, respectively, show significance at 5, 1, and 0.1 percent levels.

5. Discussion

Iran is one of the countries with a considerable gender differentiation in the labor market. Participation rate and employment rates are substantially lower for women, i.e., 16% and 81% respectively. Though, similar statistics are about 73% and 90% for men. Like many other countries, COVID-19 and its mechanisms (e.g., childcaring and vulnerability of gender-segregated sectors) have worsened the gap. In our study, we don't find evidence that COVID-19 affects the hazard of finding a job for women compared to men. (columns 5 and 15 of Table 3) However, regarding the transition from unemployment to inactivity, results confirm an increase during COVID-19, reported in columns 5 and 15 of Table 4, consistent with other studies about Iran (Yousefi et al. 2021). However, the length of unemployment spells that end to employment are not differentiated among men and women. This might be due to at least two mechanisms. First, the pandemic did not last too long to affect the market structure. Second, many women exited the market, and more room was left for the remaining. Although it is important to know the share of each of the above-mentioned mechanisms, we have not gone that route here.

Job segregation is an important factor in developing countries like Iran. Some of these segregated jobs are designed by employers who explicitly announce their gender preferences in hiring advertisements, while it is an undocumented cultural norm in others. Segregation should not be seen as a negative factor in every circumstance. It might also be as a transition path from a non-participation status towards participation. In many cultures, participation in a gender-mixed environment is not mentally accepted by the person, even if there is no external ban. Therefore, without any option for segregated jobs, many women may exit the market.

Our study lacks many other differentiated factors like wages, job formality, and promotions. The LFS doesn't document wages, assets, or other incomes of either the family or individuals. This may significantly influence reservation wages, particularly in Iran, where gender norms do not place the burden on women to provide for the family. This might be pronounced when a person is not working for a long period, and his/her human capital and referral networks diminish. We also don't explore the distinctions between the formal and informal sectors. More vulnerable groups may be concentrated in the informal sector, which is typically associated with lower earnings, a lack of health insurance, a lack of labor force regulations, and lower job security. Future studies may inform us more about gender-driven dynamics in the informal sector.

Finally, job promotions are not studied here, while those can be a shining course of evidence for gender differentiation. The glass ceiling is certainly an existing mechanism in many developing countries, like Iran, that bans women from reaching positions. This can be explored in future studies.

6. Conclusions

The dynamics of gender differentiation is an under-investigated concern. We use Iran's labor force data and implement Kaplan-Meier analysis and multi-variate Cox models to investigate the probabilities of movements from unemployment to either employment or inactivity by gender groups. Findings indicate that women's waiting time in the search for jobs is much longer, and their disappointment towards inactivity is much higher. These gender differences are pronounced in private jobs that are more competitive and cruel to women. Moreover, it consists of many micro-sized firms in Iran, with no possibilities for gender segregation. There are cultural bans for many women to be present regularly in a male-dominated small environment. Mechanisms for such avoidance are well discussed in the literature, including norms on *women purity*.

Another mechanism that is well traced among our findings is the depreciation of human capital and referral networks among those who last worked a while ago. Not having job experience in the last five years significantly reduces the likelihood of finding jobs for everyone, but the effect is pronounced for women. Interestingly, women with no job experience stay longer in the job search before becoming disappointed and inactive compared to similar men.

While this study sheds light on dynamic aspects of the labor market, wage investigation is missed because our data source does not include income information. Those can be determinants in explaining market differentiations. Also, we leave the questions on informality, sectoral heterogeneities, and promotions to future studies.

Finally, while all this literature is lightening, it becomes abstract if it doesn't lead to changing the reality. The most light needed today is to move towards a less gender-oriented environment where everyone could equally benefit based on his/her efforts and talents, regardless of gender and any other birth-inherited categorizations.

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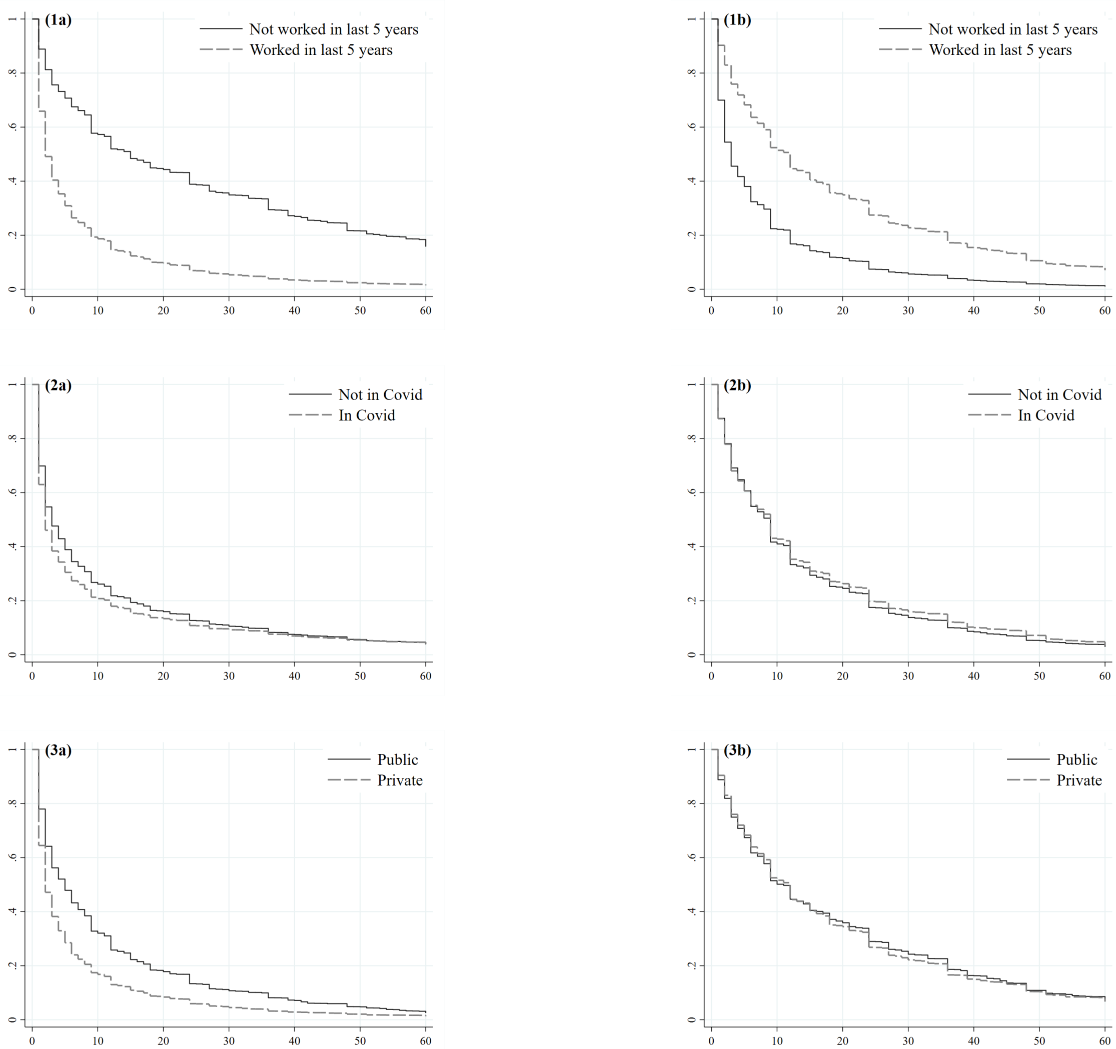
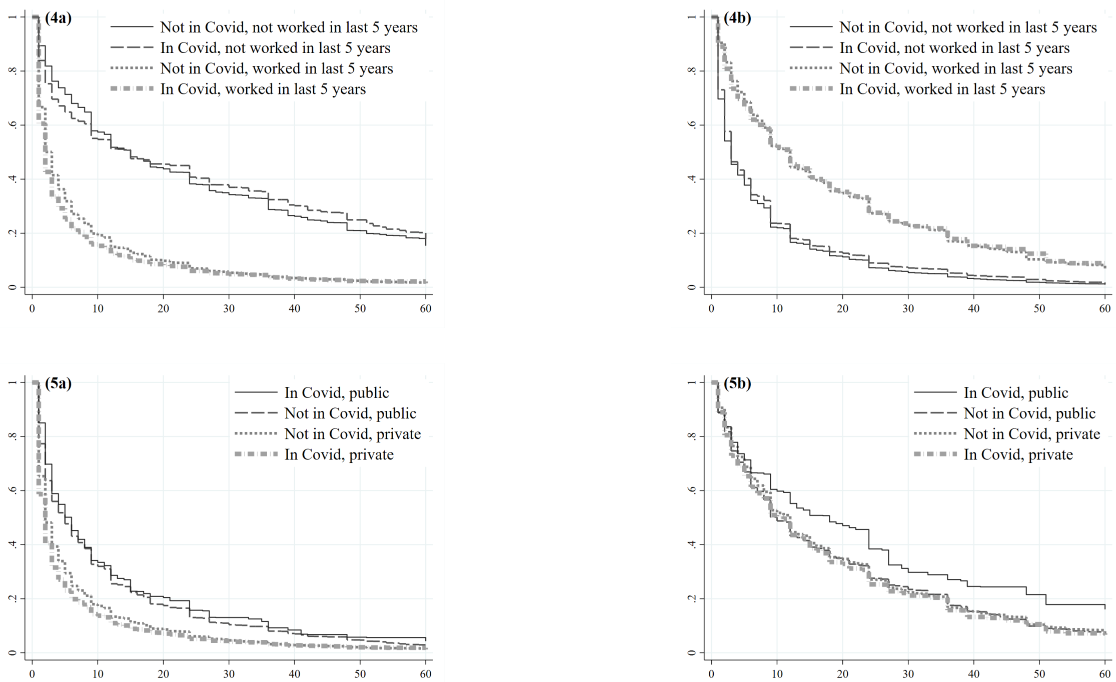
7. Appendix

Figure 3: Survival Probability by Months of Unemployment, by Kaplan-Meier Estimates

(a) Probability of Staying Unemployed Before Becoming **Employed**

(b) Probability of Staying Unemployed Before Becoming **Inactive**





Source: Authors' analysis based on LFS data from Iran.
Note: Survivor function for the transition from unemployment to employment and incativity are depicted on panel (a) and (b), respectively. Horizental axis is months of unemployment.

Table 5: Hazard Rate of Employment from Unemployment, Cox Model

	All Individuals							**With work experience in last 5 years**				**Men**	**Women**	**Men**	**Women**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Female	0.38^{***} (0.01)			0.48^{***} (0.02)	0.38^{***} (0.01)		0.47^{***} (0.02)		0.64^{***} (0.08)		0.63^{***} (0.08)				
Not worked in last 5 years		0.52^{***} (0.01)		0.71^{***} (0.02)		0.53^{***} (0.01)	0.72^{***} (0.02)					0.73^{***} (0.02)	0.58^{***} (0.03)		
In COVID-19			1.13^{***} (0.03)		1.12^{***} (0.03)	1.19^{***} (0.03)	1.16^{***} (0.03)			1.17^{*} (0.07)	1.12 (0.07)			1.13^{***} (0.03)	1.01 (0.08)
Female × not worked in last 5 years				0.82^{***} (0.04)			0.85^{**} (0.05)								
Female × in COVID-19					0.95 (0.06)		1.14 (0.10)				1.39 (0.41)				
In COVID-19 × not worked in last 5 years						0.86^{**} (0.04)	0.92 (0.05)								
Female × in COVID-19 × not worked in last 5 years							0.71^{**} (0.09)								
Private								1.11^{***} (0.03)	1.22^{***} (0.03)	1.12^{***} (0.03)	1.22^{***} (0.04)				
Female × private									0.71^{**} (0.09)		0.71^{*} (0.10)				
In COVID-19 × private										0.99 (0.06)	1.02 (0.06)				
Female × private × in COVID-19											0.84 (0.26)				
married	1.26^{***} (0.03)	1.17^{***} (0.02)	1.22^{***} (0.02)	1.23^{***} (0.03)	1.26^{***} (0.03)	1.17^{***} (0.02)	1.23^{***} (0.03)	1.29^{***} (0.03)	1.28^{***} (0.03)	1.29^{***} (0.03)	1.28^{***} (0.03)	1.40^{***} (0.03)	0.68^{***} (0.05)	1.45^{***} (0.03)	0.70^{***} (0.05)
Number of children under/equal 6	1.09^{***} (0.02)	1.10^{***} (0.02)	1.11^{***} (0.02)	1.08^{***} (0.02)	1.09^{***} (0.02)	1.10^{***} (0.02)	1.08^{***} (0.02)	1.09^{***} (0.02)	1.07^{***} (0.02)	1.09^{***} (0.02)	1.07^{***} (0.02)	1.08^{***} (0.02)	0.92 (0.06)	1.08^{***} (0.02)	0.92 (0.06)
Number of children above 6	1.06^{***} (0.01)	1.06^{***} (0.01)	1.05^{***} (0.01)	1.06^{***} (0.01)	1.06^{***} (0.01)	1.06^{***} (0.01)	1.06^{***} (0.01)	1.06^{***} (0.01)	1.06^{***} (0.01)	1.06^{***} (0.01)	1.06^{***} (0.01)	1.05^{***} (0.01)	1.11^{*} (0.05)	1.05^{***} (0.01)	1.09 (0.05)
Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age group	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of unemployment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	210,951	210,951	210,951	210,951	210,951	210,951	210,951	118,056	118,056	118,056	118,056	143,862	67,089	143,862	67,089

Source: Authors' calculations, based on LFS data of Iran.

Note: The exponentiated coefficients are displayed. *, **, and ***, respectively, show significance at 5, 1, and 0.1 percent levels.

Table 6: Hazard Rate of Inactivity from Unemployment, Cox Model

	All individuals							**With work experience in last 5 years**				**Men**	**Women**	**Men**	**Women**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Female	2.29***			2.60***	2.26***		2.60***		1.95***		1.94***				
	(0.04)			(0.08)	(0.04)		(0.09)		(0.16)		(0.16)				
Not worked in last 5 years		1.82***		1.71***		1.82***	1.72***					1.38***	1.23***		
		(0.04)		(0.05)		(0.04)	(0.05)					(0.04)	(0.04)		
In COVID-19			1.30***		1.25***	1.26***	1.27***			1.08	1.15			1.26***	1.40***
			(0.04)		(0.05)	(0.05)	(0.06)			(0.10)	(0.11)			(0.06)	(0.05)
Female $\times$ not worked in last 5 years				0.66***			0.65***								
				(0.02)			(0.03)								
Female $\times$ in COVID-19					1.11**		1.03				1.10				
					(0.05)		(0.07)				(0.30)				
In COVID-19 $\times$ not worked in last 5 years						1.02	0.93								
						(0.04)	(0.06)								
Female $\times$ in COVID-19 $\times$ not worked in last 5 years							1.14								
							(0.10)								
Private								1.08	0.85***	1.05	0.84***				
								(0.04)	(0.04)	(0.04)	(0.04)				
Female $\times$ private									1.35***		1.36***				
									(0.12)		(0.13)				
In COVID-19 $\times$ private										1.24*	1.19				
										(0.11)	(0.12)				
Female $\times$ private $\times$ in COVID-19											0.88				
											(0.25)				
Married	1.02	1.11***	1.07**	1.06**	1.02	1.11***	1.06**	0.90**	0.93*	0.90**	0.93	0.66***	1.34***	0.63***	1.33***
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)
Number of children under/equal 6	0.97	0.97	0.95*	0.99	0.97	0.97	0.99	0.87***	0.90**	0.87***	0.90**	0.86***	1.14***	0.85***	1.15***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Number of children above 6	0.97	0.96*	0.97	0.97	0.97	0.96*	0.97	0.92***	0.93**	0.92***	0.92**	0.93*	1.02	0.94*	1.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)
Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age group	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of unemployment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	210,951	210,951	210,951	210,951	210,951	210,951	210,951	118,056	118,056	118,056	118,056	143,862	67,089	143,862	67,089

Source: Authors' calculations, based on LFS data of Iran.

Note: The exponentiated coefficients are displayed. *, **, and ***, respectively, show significance at 5, 1, and 0.1 percent levels.