Gender gap in Iran: An examination of unemployment duration

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Tables 1 to 3 are available in the Supplementary Files section.
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Abstract

We examine the gender gap in unemployment duration in a large developing economy that is characterised by high gender inequality in social and economic opportunities. Due to sensitivity concerns, such data are often released by authorities in the form of contingency tables, which consist of multiple categories of count data. To overcome this limitation, we estimate a Bayesian log-linear Poisson regression model and develop the Oaxaca-Blinder (O-B) decomposition based on multi-way contingency tables. Using data from the 2019 Iranian Labour Force Survey, our findings indicate that gender gap can be narrowed most substantially if women with university educations face the same labour market opportunities as men.

Keywords: gender gap; unemployment duration; education; Oaxaca-Blinder Decomposition; Bayesian modelling; Count data; Contingency Table

JEL: C11, C25, J16, J64, O53
1. Introduction

The gender gap in unemployment duration (UD) is an important measure of the labour market that has received very little attention by researchers and policymakers. This is in sharp contrast with the voluminous literature on the gender gap in wages. Examining the gender gap in unemployment duration is important not only because unemployment exerts adverse social and economic effects but also because it contributes to broad inequality in human development. Long unemployment spells can expose individuals to prolonged fragile financial situations, and lead to human capital depreciation, poverty, and social delinquency. Quantifying and decomposing the gender gap in unemployment duration can potentially help policymakers to identify segments in the labour market that are most vulnerable to gender bias.

This paper contributes to the literature in two ways. First, it examines and decomposes the gender gap in unemployment duration in a large economy, Iran, which is characterised by high gender inequality in social and economic opportunities. According to the International Monetary Fund (IMF), Iran is ranked as the world’s 18th largest economy in 2019, which is comparable in size to Canada and considerably larger than many advanced economies. Yet it is ranked 144th among 146 countries in terms of gender gap in economic opportunities in 2022. The country’s position is 143rd out of 146 nations in the global gender gap index. Iran’s situation is not unique, and many large economies have similar characteristics.1 Second, we develop a new method that enables the Oaxaca-Blinder (O-B) decomposition to be performed in multi-way contingency tables. Multi-way contingency tables describe the multivariate frequency (count) distribution of variables and they are ubiquitous in business, medical, survey and many other forms of research. Many government agencies regularly

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1 Other examples include Turkey (13th, 130th), Saudi Arabia (16th, 141th), Egypt (21th, 132th), and Pakistan (24th, 143rd). The total population of these five countries is around 500 million.
release economic and demographic data in the form of contingency tables. Unfortunately, it is well-known that contingency tables cannot be readily analysed by linear regression because the count data on multiple variables are generated from a joint distribution of Poisson random variables. In practice, it is particularly difficult to interpret and draw conclusions from high-dimensional contingency tables. Although there exists a huge amount of literature on the O-B decomposition method, to our knowledge, no studies have considered contingency tables -- we are the first to show how this method can be extended to multi-way contingency tables after appropriate regularisation. This is useful because we can then summarise the information in high-dimensional contingency tables in various "explained" and "unexplained" components that are easily interpreted as in the regression framework.

We estimate a Bayesian log-linear Poisson model using a Gibbs sampling algorithm and apply our decomposition method to a contingency table released from the 2019 Iranian Labour Force Survey, which contains the total number of unemployed individuals in various categories of unemployment duration, age, education, and location. Due to sensitivity and political concerns, labour market data in many countries are often released by authorities in the form of contingency tables only – this also illustrates the practical value of our method. As an important contribution to the literature, this study suggests a method for evaluating gender or race gaps in condensed and minimal formats. This approach can be employed for authoritarian countries where sensitive data are mainly presented in a compact form.

Our decomposition method reveals that 53.5 per cent of the gender gap in unemployment duration in Iran can be attributed to differences in the age, education and location distributions between the

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2 Contingency table is also known as a cross tab and it is a table in a minimal format to display the frequency distribution of variables. Specifically, it is an array summarizing the relationship among various categorical factors. The probability of counts in each cell can be modelled by the Poisson distribution, which captures the interrelation among the various categorical factors in the table.

3 The issue of data limitation may be more severe in economies where data release is considered as sensitive. Some data may still be released but they will typically be considered as not useful for policy evaluation. Our count data and decomposition analysis can extract valuable information from these condensed and limited data.

4 Authoritarian countries are listed by Economist Intelligence Unit.
unemployed men and women populations. The calculated gender gap shows that the highest disparity belongs to educated women, especially those experiencing 12+ months of duration. Also, women who live in urban areas are among the most vulnerable groups in the labour market. When our estimates are interpreted in the O-B decomposition sense, approximately 45 per cent of the gender gap is left "unexplained" which is attributable to gender differences in coefficients.

Our paper proceeds as follows. Section 2 provides a literature review on the gender gap in the labour market. Section 3 introduces the model. Section 4 discusses the Iranian gender gap, the data, and estimation results. Section 5 concludes.

2. Literature Review

Although numerous studies have evaluated the effects of age, education and living locations on the gender gap in labour market, few studies have examined unemployment-related outcomes, let alone unemployment duration. We document part of the literature below. The well-known study by Blinder (1973) decomposes the gender and racial gap in the United States. He mentions that age, education and region of residence determine gender gap significantly. Also, a large part of this inequality in the labour market is due to coefficient effects. Barrett and Morgenstern (1974) find that the unemployment probability is higher for blacks, women, and young individuals. Moghadam (1991) examines the Iranian statistical yearbook of 1986 and reveals a severe gender bias against women workers. She indicates that women face a "double-exploitation" situation in the labour market because first, women comprise a small portion of labour participation; second, they are less wage-earner. Meng and Miller (1995) examine the gender gap in China and find that it is mostly related to cultural tradition and scarcity of employment opportunities.

Sabir and Aftab (2007) analyse the earning inequality in Pakistan. They find that age and region affect gender gap significantly. Ortega Masagué (2008) analyses gender gap in unemployment rate in Argentina. He shows that marital status is the major cause of the inequality between men and women.
in the labour market. However, education can narrow the gender unemployment gap. Cudeville and Gurbuzer (2010) examine the gender gap in Turkey mainly depends on socio-economic factors of employees and estimate wage equations for men and women. They indicate that workers' age, education, and region of residence impact the inequality in earning considerably.

Razavi and Habibi (2014) use the Iranian Household Expenditure and Household Survey (HEIS) dataset from 2002 to 2005 and employ the O-B method to decompose wage disparities between men and women. Their finding reveals that the main portion of gender wage gap is attributable to market discrimination in the Iranian public and private sectors. Hendy (2015) examines why women are consistently discriminated across the different economic sectors in Egypt. She indicates that women's participation in economic activities decreased due to the political instability induced by the Egyptian Revolution. Additionally, she states that rural women are more discriminated group in Egypt because they have fewer opportunities to participate in economic activities. Ahmed and McGillivray (2015) find that improving women's education in Bangladesh can narrow the gender wage gap by 31%.

Dauth (2016) examines the gender gap among the unemployed and finds that women are less likely than men to find jobs, and the likelihood of being unemployed for women is high when they have been married, are less than 35 years, or have young children. Majbouri (2016) analyses labour force participation during the Iranian economic crisis in 1994-95. He shows that there is a labour participation gap between married and never-married women in rural areas. Albanesi and Sahin (2018) examine how cyclical variations in macroeconomy affects gender gaps in economic participation and unemployment. They find that men's unemployment is more sensitive to business cycles compared to women in OECD countries. Also, the employment composition in industrial sectors can explain gender gap in unemployment.

Risse et al. (2018) hypothesise whether personality, geographic remoteness and age can determine gender pay gap. Using Australian data, they find that three main psychological features of men lead them to earn a higher income compared to women. Stevens and Whelan (2018) consider negotiation
overpay as a main factor of the gender wage gap. Their findings reveal that the gap can be partly explained by fewer opportunities among women to negotiate with employers. Bach et al. (2018) use a large-scale dataset and show that an increase in women’s education can reduce the gender wage gap in the US. Faďoš and Bohdalová (2019) indicate that the gender gap in unemployment exists when the unemployment rate for women exceeds the rate for men. Their findings support that the high unemployment rate fuels gender inequality in most European countries.

3. The Model

Modelling count data has a long history in econometrics and statistics. Although lots of valuable methodological attempts have been made, there is no application to empirically identify vulnerable groups in the labour market using count-categorical data. In the framework of count data, estimating coefficients using the ordinary least squares method is biased and it has misleading results (Bauer et al., 2007). Therefore, we consider a Poisson log-linear model consisting of count data in multiple categorical variables. Specifically, we consider a multi-way contingency table in which each cell (denoted by cell-ijkl) represents age category \( i \), education \( j \), living location category \( k \), and unemployment duration category \( l \). We consider two categories of age (25 years and less \((i=0)\); over 25 years \((i=1)\)), three categories of education (primary school \((j=0)\), high school \((j=1)\) and university educations \((j=2)\)), two categories of living location (rural \((k=0)\); urban \((k=1)\)), and three categories of unemployment duration (less than 6 months \((l=0)\); 6-12 months \((l=1)\); over 12 months \((l=2)\)). Therefore, the contingency table contains \(2 \times 3 \times 2 \times 3 = 36\) cells in total for each gender. We have a separate contingency table for each gender \( G \) (G=M for men and G=F for women). In cell-ijkl of contingency table \( G \), the total count of unemployed individuals of gender \( G \) in age \( i \), location \( k \) and

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unemployment duration \( l \) is reported. This count is denoted by \( y_{ijkl}^G \). We assume that \( y_{ijkl}^G \) follows the Poisson distribution in the following manner (implicitly assuming a steady state in the economy):

\[
f(y_{ijkl}^G | \mu_{ijkl}^G) = \frac{e^{-\mu_{ijkl}^G} (\mu_{ijkl}^G)^{y_{ijkl}^G}}{y_{ijkl}^G!}.
\]  

(1)

In equation (1), \( \mu_{ijkl}^G \) is a parameter that denotes the expected number of events/occurrences in the distribution. As discussed below, this parameter is a function of age \( i \), education \( j \), living location \( k \), and the unemployment duration \( l \) for each gender, \( G \).

The likelihood function of the log-linear Poisson model is specified as follows:

\[
L(\mu_{ijkl}^G) = \prod_{i=0}^{1} \prod_{j=0}^{2} \prod_{k=0}^{2} \prod_{l=0}^{2} e^{-\mu_{ijkl}^G} (\mu_{ijkl}^G)^{y_{ijkl}^G} / y_{ijkl}^G!,
\]  

(2)

where the products refer to the cells in the contingency table. In the absence of further restrictions, all the categorical variables in the model are dependent to one other. Indeed, we can construct a saturated log-linear Poisson model with the following saturated representation for \( \mu_{ijkl}^G \):

\[
\log(\mu_{ijkl}^G) = X^G \Lambda^G.
\]  

(3)

where \( \Lambda^G = [\lambda_i, \lambda_j, \lambda_k, \lambda_{ij}, \lambda_{ik}, \lambda_{il}, \lambda_{jk}, \lambda_{jl}, \lambda_{ikl}, \lambda_{ijl}, \lambda_{ijkl}, \lambda_{ijk}, \lambda_{ijl}, \lambda_{ijkl}, \lambda_{ijkl}]^G \) is a vector of parameters corresponding to a full vector of main and interaction effects of each categorical variable \( AGE_i, EDU_j, LOC_k, \) and \( UD_l \): \( X^G = [AGE_i, EDU_j, LOC_k, UD_l, AGE_i \times EDU_j, AGE_i \times LOC_k, AGE_i \times UD_l, EDU_j \times LOC_k, EDU_j \times UD_l, LOC_k \times UD_l, AGE_i \times EDU_j \times LOC_k, AGE_i \times EDU_j \times UD_l, EDU_j \times LOC_k \times UD_l, AGE_i \times EDU_j \times LOC_k \times UD_l]^G \). The parameters \( \lambda_i, \lambda_j, \lambda_k, \) and \( \lambda_l \), stand for the main effects whereas the parameters \( (\lambda_{ij}, \lambda_{ik}, \lambda_{il}, \lambda_{jk}, \lambda_{jl}, \lambda_{ikl}, \lambda_{ijl}, \lambda_{ijkl}, \lambda_{ijk}, \lambda_{ijl}, \lambda_{ijkl}) \), and  

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6 We implicitly assume a steady state in the labour market. Therefore, the counts represent the steady state stock of the unemployed in each category of unemployment duration, age and location. The steady state stock is determined by the reciprocal of the hazard rate. In principle, we can “invert” the empirical distribution of UD to recover the hazard rate. If the hazard rate is homogeneous within each (age, education, location) category, the model is over-identified. If the hazard rate is heterogeneous by discrete types (e.g., easy and difficult job finders), we can recover these rates up to the number of observed categories of UD in the data.
\( \lambda_{ijkl} \) stand for the two, three and four-way interaction effects of the categorical variables. There are 2x3x2x3=36 parameters in this saturated model for each gender. In the space below, we will first discuss the Bayesian estimation method, and then discuss meaningful restrictions to the saturated model.

In contrast to classical methods which estimate the parameters via maximum likelihood, we propose a Bayesian specification for the log-linear Poisson regression, which can incorporate prior beliefs. We assume that the vector of parameters, \( \Lambda^G \), has a prior of a multivariate normal distribution with a mean and variance equal to \( \Lambda_0 \) and \( \Psi_0 \) respectively: \( P(\Lambda) \sim MVN(\Lambda_0, \Psi_0) \). The Bayesian specification of the posterior distribution is given as follows:

\[
P(\Lambda^G \mid y_{ijkl}^G, X^G) \propto \prod_{i=0}^{1} \prod_{j=0}^{2} \prod_{k=0}^{2} \prod_{l=0}^{1} \exp\left[-\exp(X_{ijkl}^G \Lambda^G)\right] \exp\left[-\frac{1}{2}(\Lambda - \Lambda_0)'\Psi_0^{-1}(\Lambda - \Lambda_0)\right]
\]

The above posterior distribution has unknown form and closed forms are unattainable. Therefore, following Christensen et al. (2010), we apply the Markov Chain Monte Carlo (MCMC) simulation method to calculate the marginal posterior distributions of the parameters.

**3.1 Oaxaca-Blinder Decomposition for Multi-way Contingency Tables**

In this section, we first review the standard Oaxaca-Blinder decomposition method, and then discuss how the decomposition can be performed on multi-way contingency tables.

**3.1.1 Review of the Method.**

Based on Oaxaca (1973) and the subsequent literature, the standard decomposition method works under the premise of a linear regression or projection model. We consider the classical example of an O-B decomposition of the gender gap among workers. Let the dependent variable (a labour
market outcome) be Y and the explanatory variables be X. Suppose we regress Y on X separately for the men and women subsamples, and obtain OLS intercept and slope coefficients for men, \((\hat{\alpha}_m, \hat{\beta}_m)\), and OLS coefficients for women, \((\hat{\alpha}_f, \hat{\beta}_f)\). The predicted dependent variable can be written as \(\hat{Y}_{mi} = \hat{\alpha}_m + X_{mi}' \hat{\beta}_m\) and \(\hat{Y}_{fi} = \hat{\alpha}_f + X_{fi}' \hat{\beta}_f\), respectively. Averaging across individuals, we have

\[
\bar{\hat{Y}}_m = \hat{\alpha}_m + \bar{X}_m' \hat{\beta}_m, \quad (5)
\]

\[
\bar{\hat{Y}}_f = \hat{\alpha}_f + \bar{X}_f' \hat{\beta}_f. \quad (6)
\]

Subtracting the second equation from the first, and then rearranging terms, we yield the following equation: \(7\)

\[
\bar{\hat{Y}}_m - \bar{\hat{Y}}_f = [(\bar{X}_m' - \bar{X}_f') \hat{\beta}_m] + [\hat{\alpha}_m - \hat{\alpha}_f] + [\bar{X}_f' (\hat{\beta}_m - \hat{\beta}_f)]. \quad (7)
\]

The left-hand side represents the average gender gap \(\bar{\hat{Y}}_m - \bar{\hat{Y}}_f\), the first term of the right-hand side \((\bar{X}_m' - \bar{X}_f') \hat{\beta}_m\) represents the "explained" component of the gap due to differences in the average observed characteristics between men and women, and the last two terms of the right-hand side, \([\hat{\alpha}_m - \hat{\alpha}_f]\) and \(\bar{X}_f' (\hat{\beta}_m - \hat{\beta}_f)\), represent the "unexplained" component of the gap that is possibly due to gender bias in the labour market, etc. in the O-B decomposition sense.

### 3.1.2 Decomposition for Multi-way Contingency Tables

In this section, we focus on illustrating the main idea behind performing the Oaxaca-Blinder (O-B) decomposition on the four-way contingency table \(G \in \{M,W\}\) with 36 cells: \(\text{AGE} \in \{0,1\}\), \(\text{EDU} \in \{0,1,2\}\), \(\text{LOC} \in \{0,1\}\) and \(\text{UD} \in \{0,1,2\}\). The same idea applies to any multi-way contingency tables with any finite number of cells.

---

7 By the algebraic property of OLS residuals in a linear model, we have \(\bar{\hat{Y}}_m = \bar{\hat{Y}}_m\) and \(\bar{\hat{Y}}_f = \bar{\hat{Y}}_f\).
Without appropriate regularisation, the standard decomposition method cannot be readily applied for several reasons. First, there is no clear distinction between the dependent variable and explanatory variables. Normally we think of a dependent variable as a (linear) function of the explanatory variables plus errors, which are potentially orthogonal to the explanatory variables. However, in a contingency table, it is typical to think of all the data being generated from a *joint* distribution of categorical variables. Second, all the variables in the contingency table are categorical variables. In the standard method, it is typical to assume that $Y$ as continuously distributed, otherwise the relationship between $Y$ and $X$ is potentially nonlinear (e.g., probit) and the standard decomposition does not hold. Third, contingency tables consist of count data exclusively. This implies that the underlying model is nonlinear by construction and the standard decomposition will not apply.

The main idea behind our decomposition method is illustrated below. To fix notations, based on equations (1) and (3), we first write down the following re-parametrisation of the saturated log-linear Poisson model (see Agresti (2013)) that gives $\log(\mu_{ijkl}^G)$ in each of the 36 cells ($AGE=i$, $EDU=j$, $LOC=k$, $UD=l$; $i=0,1; j=0,1,2; k=0,1; l=0,1,2$):

- $(UD = 0, AGE = 0, EDU = 0, LOC = 0): \lambda$
- $(UD = 0, AGE = 1, EDU = 0, LOC = 0): \lambda + \lambda_{A1}$
- $(UD = 0, AGE = 0, EDU = i \in \{1,2\}, LOC = 0): \lambda + \lambda_{Ej}$
- $(UD = 0, AGE = 0, EDU = 0, LOC = 1): \lambda + \lambda_{L1}$
- $(UD = 0, AGE = 1, EDU = \in \{1,2\}, LOC = 1): \lambda + \lambda_{A1} + \lambda_{Ej} + \lambda_{L1} + \lambda_{A1XEj} + \lambda_{A1XL1} + \lambda_{EjXL1}$
- $(UD = l \in \{1,2\}, AGE = 0, EDU = 0, LOC = 0): \lambda + \lambda_{UL}$
- $(UD = l \in \{1,2\}, AGE = 1, EDU = 0, LOC = 0): \lambda + \lambda_{UL} + \lambda_{A1} + \lambda_{ULXA1}$
- $(UD = l \in \{1,2\}, AGE = 0, EDU = j \in \{1,2\}, LOC = 0): \lambda + \lambda_{UL} + \lambda_{Ej} + \lambda_{ULXEj}$
- $(UD = l \in \{1,2\}, AGE = 0, EDU = 0, LOC = 1): \lambda + \lambda_{UL} + \lambda_{L1} + \lambda_{ULXL1}$
- $(UD = l \in \{1,2\}, AGE = 1, EDU = j \in \{1,2\}, LOC = 1): \lambda + \lambda_{UL} + \lambda_{A1} + \lambda_{Ej} + \lambda_{L1} + \lambda_{ULXA1} + \lambda_{ULXEj} + \lambda_{ULXL1} + \lambda_{A1XEj} + \lambda_{A1XL1} + \lambda_{EjXL1} + \lambda_{ULXAXL1} + \lambda_{ULXEXL1} + \lambda_{ULXXL1} + \lambda_{ULXAXXL1} + \lambda_{ULXEXXL1} + \lambda_{ULXXXL1} + \lambda_{A1XEXL1} + \lambda_{A1XXL1} + \lambda_{EjXXL1} + \lambda_{ULXXXL1} + \lambda_{ULXXEXL1} + \lambda_{ULXXXL1} + \lambda_{ULXXXXL1} + \lambda_{ULXXXXL1} + \lambda_{ULXXXXXL1} + \lambda_{ULXXXXXXL1} + \lambda_{ULXXXXXXXL1} + \lambda_{ULXXXXXXXXL1}$
Note that we have 36 parameters in total: 1 for the base category \((\lambda)\), 1 for main effect of age \((\lambda_{A1})\), 2 for main effects of education categories \((\lambda_{Ej})\), 1 for the main effect of living location \((\lambda_{L1})\), 2 for main effects of unemployment duration \((\lambda_{U1})\), 2 for interactions between duration and age \((\lambda_{U1A1})\), 4 for interactions between duration and education \((\lambda_{U1Ej})\), 2 for interaction effects between duration and living location \((\lambda_{U1L1})\), 2 for interaction effects between age and education \((\lambda_{A1Ej})\), 1 for an interaction effect between age and location \((\lambda_{A1L1})\), 2 for interaction effects between education and location \((\lambda_{EjL1})\), 4 for three-way interaction effects among duration, age and education \((\lambda_{U1A1Ej})\), 2 for three-way interaction effects among duration, age and living location \((\lambda_{U1A1L1})\), 4 for three-way interaction effects among age, education and living location \((\lambda_{A1EjL1})\), and, finally, 4 for four-way interaction effects among duration, age, education and living location \((\lambda_{U1A1EjL1})\).

We are interested in describing how the conditional probability of UD \(\in \{0,1,2\}\) depends on AGE and LOC. We invoke a key feature of the log-linear Poisson model: it can be presented by log odd ratios of a multinomial form, and the log ratios are linear functions of \(\lambda\). For instance, the log odd ratios of UD=1 against UD=0, conditional on AGE \(\in \{0,1,2\}\) and LOC \(\in \{0,1\}\), are:

\[
\log \frac{P(UD=1 \mid AGE=0, EDU=0, LOC=0)}{P(UD=0 \mid AGE=0, EDU=0, LOC=0)} = (\lambda + \lambda_{U1}) - \lambda = \lambda_{U1},
\]

\[
\log \frac{P(UD=1 \mid AGE=1, EDU=0, LOC=0)}{P(UD=0 \mid AGE=1, EDU=0, LOC=0)} = (\lambda + \lambda_{U1} + \lambda_{A1} + \lambda_{U1A1}) - (\lambda + \lambda_{A1}) = \lambda_{U1} + \lambda_{U1A1},
\]

\[
\log \frac{P(UD=1 \mid AGE=1, EDU=1, LOC=0)}{P(UD=0 \mid AGE=1, EDU=1, LOC=0)} = (\lambda + \lambda_{U1} + \lambda_{E1} + \lambda_{U1E1}) - (\lambda + \lambda_{E1}) = \lambda_{U1} + \lambda_{U1E1},
\]

\[
\log \frac{P(UD=1 \mid AGE=0, EDU=2, LOC=0)}{P(UD=0 \mid AGE=0, EDU=2, LOC=0)} = (\lambda + \lambda_{U1} + \lambda_{E2} + \lambda_{U1E2}) - (\lambda + \lambda_{E2}) = \lambda_{U1} + \lambda_{U1E2},
\]

\[
\log \frac{P(UD = 1 \mid AGE = 0, EDU = 0, LOC = 1)}{P(UD = 0 \mid AGE = 0, EDU = 0, LOC = 1)} = (\lambda + \lambda_{U1} + \lambda_{L1} + \lambda_{U1L1}) - (\lambda + \lambda_{L1}) = \lambda_{U1} + \lambda_{U1L1},
\]

\[
\log \frac{P(UD=1 \mid AGE=1, EDU=1, LOC=1)}{P(UD=0 \mid AGE=1, EDU=1, LOC=1)} = (\lambda + \lambda_{U1} + \lambda_{A1} + \lambda_{E1} + \lambda_{L1} + \lambda_{U1A1} + \lambda_{U1E1} + \lambda_{U1L1} + \lambda_{A1E1} + \lambda_{A1L1} + \lambda_{E1L1} + \lambda_{U1A1E1} + \lambda_{U1A1L1} + \lambda_{U1E1L1} + \lambda_{U1A1E1L1}) - (\lambda + \lambda_{A1} + \lambda_{E1} + \lambda_{A1L1} + \lambda_{E1L1} + \lambda_{U1A1E1} + \lambda_{U1A1L1} + \lambda_{U1E1L1} + \lambda_{U1A1E1L1})
\]
\[ \lambda_{L1} + \lambda_{A1\times E1} + \lambda_{A1\times L1} + \lambda_{E1\times L1} + \lambda_{A1\times E1\times L1} = \lambda_{U1} + \lambda_{U1\times A1} + \lambda_{U1\times E1} + \lambda_{U1\times L1} + \lambda_{U1\times A1\times E1} + \lambda_{U1\times A1\times L1} + \lambda_{U1\times E1\times L1} + \lambda_{U1\times A1\times E1\times L1} \]  

(13)

\[
\log \frac{P(UD=1 \mid AGE=1, EDU=2, LOC=1)}{P(UD=0 \mid AGE=1, EDU=2, LOC=1)} = (\lambda + \lambda_{U1} + \lambda_{A1} + \lambda_{E2} + \lambda_{L1} + \lambda_{U1\times A1} + \lambda_{U1\times E2} + \lambda_{U1\times L1} + \lambda_{A1\times E2} + \lambda_{A1\times L1} + \lambda_{E2\times L1} + \lambda_{U1\times A1\times E2} + \lambda_{U1\times A1\times L1}) - (\lambda + \lambda_{A1} + \lambda_{E2} + \lambda_{L1} + \lambda_{A1\times E2} + \lambda_{A1\times L1} + \lambda_{E2\times L1} + \lambda_{U1\times A1\times E2} + \lambda_{U1\times A1\times L1}) = \lambda_{U1} + \lambda_{U1\times A1} + \lambda_{U1\times E2} + \lambda_{U1\times L1} + \lambda_{U1\times A1\times E2} + \lambda_{U1\times A1\times L1} + \lambda_{U1\times E2\times L1} \]  

(14)

The expressions above can be summarised as the following linear function of AGE, EDU, and LOC:

\[
\log \frac{P(UD=1 \mid AGE, EDU, LOC)}{P(UD=0 \mid AGE, EDU, LOC)} = \lambda_{U1} + \lambda_{U1\times A1} \mathbb{1}_{\{AGE = 1\}} + \lambda_{U1\times E1} \mathbb{1}_{\{EDU = 1\}} + \lambda_{U1\times E2} \mathbb{1}_{\{EDU = 2\}} + \lambda_{U1\times L1} \mathbb{1}_{\{LOC = 1\}} + \lambda_{U1\times A1\times E1} \mathbb{1}_{\{AGE = 1\}} \mathbb{1}_{\{EDU = 1\}} + \lambda_{U1\times A1\times E2} \mathbb{1}_{\{AGE = 1\}} \mathbb{1}_{\{EDU = 2\}} + \lambda_{U1\times A1\times L1} \mathbb{1}_{\{AGE = 1\}} \mathbb{1}_{\{LOC = 1\}} + \lambda_{U1\times E1\times L1} \mathbb{1}_{\{EDU = 1\}} \mathbb{1}_{\{LOC = 1\}} + \lambda_{U1\times E2\times L1} \mathbb{1}_{\{EDU = 2\}} \mathbb{1}_{\{LOC = 1\}} \]  

(15)

This forms the basis of O-B decomposition. Note that the saturated model yields interaction terms between AGE, EDU, and LOC in equation (15). While this does not pose problems for our decomposition, the standard decomposition method described in Section 3.1.1 typically does not involve interaction terms in explanatory variables. In addition, the saturated model is also not very meaningful in practice. To draw a parallel comparison with the standard decomposition method, we now clarify the assumption that removes the interaction terms in equation (15). It turns out that conditional independence between AGE, EDU, and LOC given UD is a sufficient condition. Equivalently, the conditional independence assumption imposes 5+12+4=21 restrictions: \(\lambda_{A1\times Ej} = 0\), \(\lambda_{A1\times L1} = 0\), \(\lambda_{Ej\times L1} = 0\), \(\lambda_{U1\times A1\times Ej} = 0\), \(\lambda_{U1\times A1\times L1} = 0\), \(\lambda_{U1\times Ej\times L1} = 0\), \(\lambda_{A1\times Ej\times L1} = 0\), and \(\lambda_{U1\times A\times Ej\times L1} = 0\) for \(j = 1,2\) and \(l = 1,2\). We then have 15 coefficients in the model. Equation (15) is simplified to:

\[
\log \frac{P(UD=1 \mid AGE, EDU, LOC)}{P(UD=0 \mid AGE, EDU, LOC)} = \lambda_{U1} + \lambda_{U1\times A1} \mathbb{1}_{\{AGE = 1\}} + \lambda_{U1\times E1} \mathbb{1}_{\{EDU = 1\}} + \lambda_{U1\times E2} \mathbb{1}_{\{EDU = 2\}} + \lambda_{U1\times L1} \mathbb{1}_{\{LOC = 1\}} \]  

(16)
The O-B decomposition proceeds as follows. Denote the dependent variable as \( Y_{UD=1, UD=0} \equiv \log \frac{p(UD=1 \mid AGE, EDU, LOC)}{p(UD=0 \mid AGE, EDU, LOC)} \), and the explanatory variables are \( 1\{AGE = 1\}, 1\{EDU = 1\}, 1\{EDU = 2\} \) and \( 1\{LOC = 1\} \).

Then, take expectations over the distribution of AGE, EDU, and LOC on both sides of equation (16). Due to the conditional independence assumption, we yield the following equation:

\[
E[Y_{UD=1, UD=0}] = \lambda_{U1} + \lambda_{U1 \times A1}P{AGE = 1} + \lambda_{U1 \times E1}P{EDU = 1} + \lambda_{U1 \times E2}P{EDU = 2} + \lambda_{U1 \times L1}P{LOC = 1}
\]

(17)

This equation is analogous to equations (5) and (6), as can be seen by replacing the expectations/probabilities with sample counterparts and replacing the parameters with numerical estimates. We perform the analysis separately for men data and women data, and obtain two equations:

\[
\begin{align*}
E[Y^M_{UD=1, UD=0}] = \lambda^M_{U1} + \lambda^M_{U1 \times A1}P^M{AGE = 1} + \lambda^M_{U1 \times E1}P^M{EDU = 1} + \lambda^M_{U1 \times E2}P^M{EDU = 2} + \lambda^M_{U1 \times L1}P^M{LOC = 1}, \\
E[Y^F_{UD=1, UD=0}] = \lambda^F_{U1} + \lambda^F_{U1 \times A1}P^F{AGE = 1} + \lambda^F_{U1 \times E1}P^F{EDU = 1} + \lambda^F_{U1 \times E2}P^F{EDU = 2} + \lambda^F_{U1 \times L1}P^F{LOC = 1},
\end{align*}
\]

(18), (18')

Taking the difference, we obtain the O-B decomposition as follows:

\[
E[Y^M_{UD=1, UD=0}] - E[Y^F_{UD=1, UD=0}] = \lambda^M_{U1 \times A1}[P^M{AGE = 1} - P^F{AGE = 1}] + \lambda^M_{U1 \times E1}[P^M{EDU = 1} - P^F{EDU = 1}]
\]

\[
+ \lambda^M_{U1 \times E2}[P^M{EDU = 2} - P^F{EDU = 2}] + \lambda^M_{U1 \times L1}[P^M{LOC = 1} - P^F{LOC = 1}]
\]

\[
+ [\lambda^M_{U1} - \lambda^F_{U1}] + [\lambda^M_{U1 \times A1} - \lambda^F_{U1 \times A1}]P^F{AGE = 1} + [\lambda^M_{U1 \times E1} - \lambda^F_{U1 \times E1}]P^F{EDU = 1}
\]

\[
+ [\lambda^M_{U1 \times E2} - \lambda^F_{U1 \times E2}]P^F{EDU = 2} + [\lambda^M_{U1 \times L1} - \lambda^F_{U1 \times L1}]P^F{LOC = 1}.
\]

(19)

The left-hand side represents the average gender gap in "long" unemployment duration (UD=1 (or 6 to 12 months)) relative to the base category of "short" unemployment duration (UD=0 (or less than 6 months)). A positive gap implies that the relative proportion of individuals having UD=1 relative to UD=0 is higher among men than women. A negative gap implies that the relative proportion of individuals having UD=1 relative to UD=0 is lower among men than women. We expect this gap to be negative because, in our data, women tend to have longer unemployment duration than males.
The second and third lines in equation (19) capture the "explained" component of the gender gap due to differences in the average observed characteristics between men and women. The fourth and fifth lines in equation (19) capture the "unexplained" component of the gender gap represented by differences in coefficient estimates between men and women.

Finally, note that we can define multiple gender UD gaps because UD ∈ {0,1,2} is a categorical variable. Specifically, we are interested in two different gap measures, which all use UD=0 as the base category. The gender UD gap defined over UD=l (l=1,2) relative to UD=0 is decomposed as follows:

\[
E[Y_{UD=l,UD=0}^M] - E[Y_{UD=l,UD=0}^F] = \lambda_{UlxA1}^M (P_{AGE = 1}^M - P_{AGE = 1}^F) + \lambda_{UlxE1}^M (P_{EDU = 1}^M - P_{EDU = 1}^F) \\
+ \lambda_{UlxE2}^M (P_{EDU = 2}^M - P_{EDU = 2}^F) + \lambda_{UlxL1}^M (P_{LOC = 1}^M - P_{LOC = 1}^F)
\]

\[
+ [\lambda_{UlxA1}^M - \lambda_{UlxA1}^F] P_{AGE = 1}^F + [\lambda_{UlxE1}^M - \lambda_{UlxE1}^F] P_{EDU = 1}^F \\
+ [\lambda_{UlxE2}^M - \lambda_{UlxE2}^F] P_{EDU = 2}^F + [\lambda_{UlxL1}^M - \lambda_{UlxL1}^F] P_{LOC = 1}^F. \tag{20}
\]

As can be seen above, different gap measures yield different O-B decompositions because the coefficients are different.

4. Data and Estimation

Our empirical analysis is based on data from the Iranian economy, which we briefly describe below. According to the world economic outlook report (2019) by the International Monetary Fund (IMF), Iran is ranked as the world’s 18th largest economy in 2019. The size of this economy is almost equal to Canada and the total size of Australia and New Zealand, and it is much larger than many advanced economies such as the Netherlands, Norway, Sweden, and Denmark. However, based on the World Economic Forum (2022) and the Heritage Foundation (2022), the other indices are much lower ranked. For instance, Iran is ranked as the 142nd (out of 146) and 170th (out of 177) country in the world regarding gender equality in political empowerment and economic freedom, and these ranks are lower
than that of Canada and Australia. Compared to other big economies, the Iranian economy is also relatively centralised in terms of the government's involvement in main industries, for instance, monopolistic production and export of certain profitable industries such as oil and gas. Imposing quotas on resource allocations such as energy – especially on gasoline—and foreign currencies has made Iran a relatively planned economy.

We chose the Iranian labour market for two reasons. Firstly, the data limitation employed by the government. Iran, as a planned economy, does not provide sufficient micro-level data on unemployment. Instead, it often only releases key labour market variables in the form of contingency tables. Secondly, we chose Iran for its low level of gender equality when compared globally. According to the World Economic Forum report in 2022, Iran is ranked as the 143rd country among 146 countries across the world in terms of the gender gap. In this sense, Iran is among those countries characterised by high rates of gender inequality in social and political opportunities as well as access to health-related and educational facilities. The "gender gap index" in Iran is equal to 57.6 per cent, which implies that women are only able to access less than 58 per cent of economic and political opportunities in society as well as health-related and educational facilities relative to men. The gender ratio of labour force participation is equal to 21.5 per cent and ranked the 146th in the world, indicating that the ratio between women and men in labour force is less than a quarter; however, based on the Iranian National Population and Housing Census in 2016, men and women have almost equal shares in population. In addition, the sub-index of "wage equality" between women and men equals 54.2 per cent, placing Iran in the 121st global rank.

4.1. Data Description

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8 Based on Iranian census in 2016, the shares of males and women of population are 50.66 and 49.34 per cent, respectively.
Our data on contingency tables are constructed from released information by the Iranian Labour Force Survey in 2019, which contains 2,897,621 unemployed individuals, of which 30.62% are youth with 25 years or less and 69.38% have more than 25 years old\(^9\). The number of unemployed with primary, high school, and university educations includes 377027, 1214263, and 1306331 individuals, containing 13.01%, 41.91% and 45.08% of the unemployed population, respectively. The number of unemployed living in rural and urban areas is 511796 and 2385825 individuals, representing 17.66% and 82.34% of total unemployment, respectively. Figure 1 depicts the proportion of unemployed individuals based on gender, age, education, and living location.

*Figure 1 should be here*

As seen in the figure, young men and women aged 25 years and less have the same share of the distribution of unemployment, roughly 30%. Among unemployed men, most unemployment belongs to individuals with high school educations, 50.37%. The unemployment distribution for women reflects that most unemployed people have university educations, 72.46%. However, only 3.86% of women with primary education are unemployed. It implies that there is a greater challenge for women with university educations to find jobs than for those with primary or secondary educations. Among the unemployed urban residents, 79.60% are men and 88.23% are women; note that within the overall Iranian population, 73.88% are urban residents. The ratio of urban to rural unemployed men equals 3.9, whereas this urban-rural ratio for women is equal to 7.5. Merely 4% of the total unemployed are rural women. Note that the low proportion of unemployed rural women does not necessarily imply that rural women face a better labour market. First, it is important to examine their distribution of unemployment duration compared to other subgroups. If rural women are subject to long unemployment duration, it is indicative of difficult circumstances in the labour market. Second, some rural women may be discouraged from entering the rural labour market, resulting in fewer women

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\(^9\) Heckman and Hotz (1986), Maasoumi and Wang (2017), and Risse et al. (2018) mention that age can be considered as a measure of experience. They show that labour market disparities can be quantified by this factor.
being unemployed. Both can contribute to compositional differences between the women and men unemployed.

Figure 2 reports the empirical distribution of unemployment duration among unemployed men and women.

*Figure 2 should be here*

Overall, the shapes of the unemployment duration distribution differ substantially between men and women. Men tend to experience unemployment for shorter spells. In this regard, 38.54% of unemployed men are categorised with less than 6 months of unemployment duration. By contrast, the unemployment duration distribution for women is heavily skewed to the left, with merely 19.58% of individuals with less than 6 months of unemployment duration and the highest proportion of individuals (~48%) with more than 12 months of unemployment duration. It shows that the average unemployment duration among women is much higher than men's. The difference suggests that unemployment among women may be structural because most of them experience a very long unemployment duration.

Table 1 reports the number of unemployed individuals by gender, age, education and living location, given different levels of unemployment duration.

*Table 1 should be here.*

As can be seen, the age, education and location composition differ considerably between the men and women unemployed. For example, consider the ratio between urban and rural unemployed individuals who are unemployed between 6 to 12 months and over is 4.88 (=469,414/96,089) for men and 9.90 (=272,101/27,484) for women. In addition, the overall ratio of older (over 25 years) to younger (25 years and less) unemployed for less than 6 months of unemployment duration is 2.50 (=545,003/217,726) for men, and 1.78 (=115,147/64,780) for women. Therefore, policymakers need to consider these compositional differences in age, education and living location when assessing the gender differences in the labour market.
4.2. Estimation Results

We estimate the Bayesian log-linear Poisson model in Section 3 using data from a contingency table consisting of the counts of unemployed men and women in each of the 36 categories, which are combinations from 3 categories of unemployment duration, 2 categories of age, 3 categories of education and 2 categories of living location. In the space below, we report results from the restricted model in Section 3, in which there are 15 parameters in total and all parameters are normalised with respect to the base category of <6 months of UD (UD=0), <=25 years old (AGE=0), primary education (EDU=0), and rural residents (LOC=0). We estimate two separate models, one for men and one for women.

The Open BUGS software is used for the Bayesian estimation of the log-linear Poisson regression model. The Gibbs sampling method with 10,000 iterations is used. The initial 1000 iterations are burnt out and discarded; the remaining 9,000 are used to compute the posterior marginal distributions. To show the validity of the estimation results, we report results from some diagnostic tests, such as the history of simulation and posterior distributions of coefficients. The results of these tests confirm the validity of the estimation procedure and they are reported in the Appendix.

The estimation results for the restricted male and women models are provided in Table 2, which consists of the mean and standard deviation of the posterior marginal distribution of each parameter:

*Table 2 should be here.*

The estimates from the restricted models are able to capture the main features of the data. For example, the coefficient $\lambda_{A1}$ is positive, reflecting the predicted counts are higher in relative terms among those who are aged 25+, compared to those who are aged <=25 years old (keeping AGE=0, EDU=0, and LOC=0). The negative value of $\lambda_{E1}$ for men indicates that the predicted counts are lesser for unemployed men with a university education than men with primary education (keeping AGE=0, EDU=0, LOC=0). For women, the coefficient $\lambda_{E1}$ is also negative, indicating that the predicted counts are lesser for unemployed women with a university education than women with primary education (keeping AGE=0, EDU=0, LOC=0).
EDU=0, and LOC=0). Similarly, the positive $\lambda_{u1}$ coefficient reflects the higher predicted counts of unemployed in urban relative to rural areas (keeping AGE=0, EDU=0, and LOC=0). The relative sizes of the coefficients $\lambda_{u1}, \lambda_{u2}$ also reflect the gender difference in the general shape of the UD distribution, e.g., $\lambda_{u1}$ is positive for women, indicating lesser predicted counts of those with 6 to 12 months of UD relative to <6 months of UD (keeping AGE=0, EDU=0, and LOC=0). The interaction coefficients are quite different in magnitude across genders, although they have the same sign across genders except for $\lambda_{u2A1}$ and $\lambda_{u4A2}$. In particular, the interaction coefficients between UD and location ($\lambda_{u1L1}, \lambda_{u2L1}$) are all more positive among males than women. This suggests that the predicted UD tends to be higher among urban men relative to rural men (keeping AGE=0) but the distinction is smaller between urban women and rural women (keeping AGE=0).

Although the coefficients have condensed the information from the contingency table, it is still difficult to assess the extent of the gender gap. We now apply our O-B decomposition method in equation (20). To perform the O-B decomposition, we first need to calculate the age and location compositions, i.e., $P(AGE=1)$, $P(EDU=1)$, $P(EDU=2)$ and $P(LOC=1)$ for each gender. From the contingency table, $P_M(AGE=1)=0.693$ among men. The value is $P_F(AGE=1)=0.696$ among women. The probabilities of having secondary and university educations are $P_M(EDU=1)=0.504$ and $P_M(EDU=2)=0.324$ among men. These likelihoods are $P_F(EDU=1)=0.237$ and $P_F(EDU=2)=0.725$ among women with high school and university educations. The probabilities of residing in an urban area are $P_M(LOC=1)=0.796$ among men and $P_F(LOC=1)=0.882$ among women. The results from the O-B decomposition are reported in Table 3 below.

Table 3 should be here.

Our measures reveal a uniformly negative gender UD gap, which implies that women are more likely to be subject to long unemployment duration relative to men. In addition, the gender UD gap is much wider when we consider categories of long unemployment duration. For example, consider the expected log odd ratio between 6-12 months of UD versus <6 months of UD. The gender difference in
this measure is -0.80. By contrast, when we consider the expected log odd ratio between 12+ months of UD versus <6 months of UD, the gender difference is -1.056, which is almost 30% larger.

Interestingly, despite the different magnitudes of the gender UD gap, consistently more than 50% of the gap (i.e., "explained" gap) can be attributed to gender differences in the age, education and location composition of the unemployed. For example, in the second column, 55% of the gender UD gap (-0.577 out of -1.056) is attributable to gender differences in age, education and location. The cumulative composition effects, the third column, reveal that there is a gender gap in favour of women with secondary school educations (0.462). However, the negative value of this decomposition for EDU=2 indicates a severe gender UD gap against women with university educations (-1.353). The results also show no gender differences attributable to age (0.001), whereas 10% (-0.102/-0.992) of the explained gender gap is due to geographical location.

Somewhat surprisingly, despite the sizable gender differences in the composition of the unemployed, approximately 45% of the gender UD gap is left "unexplained" by these characteristics and are attributable to gender differences in coefficients instead. In the O-B decomposition sense, this is the "black-box" component that is possibly due to gender differences in labour market conditions. In this context, enacting pro-women labour market policies may enhance gender equality.

5. Conclusions and Remarks

This paper filled a gap in the empirical literature by estimating and decomposing the gender unemployment duration gap in a large economy characterised by high gender inequality in socio-economic activities. Few studies have examined this outcome to date. We estimated a Bayesian log-linear Poisson model which was suitable for count and categorical data analysis. We also provided a methodological contribution by extending the Oaxaca-Blinder decomposition method to multi-way contingency tables, which consist of count data and are very common in various research fields. This
overcomes the limitation that the standard approach does not apply to contingency tables and opens up opportunities for future research.

The information summarised by our O-B decomposition on a contingency table was easily interpretable. By providing a like-for-like comparison between groups, our analysis facilitated a better understanding of which groups of unemployed people are more vulnerable in the labour market. We found that women with university educations were most vulnerable in the Iranian labour market, and a large gender UD gap exists overall, characterised by a high proportion of unemployed women with very long unemployment duration. If the labour market opportunities were made equal to that for educated women (in the O-B decomposition sense that the gender-specific coefficients were equalised), the overall gender unemployment duration gap would significantly be narrowed. The narrowing of the gender UD gap can also be achieved by equalising labour market opportunities between urban women and men, although the magnitude is smaller because the urban market appears to be less uneven across gender (in the O-B decomposition sense).

On this basis, although more analysis is needed, implementing "long-term" labour market policies in favour of women (especially women with university educations) can potentially improve gender equality. By targeting women with long unemployment spells, these policies can play a significant role in decreasing structural gender differences in the labour market. To eliminate the gender UD gap among different groups in the labour market, stronger interventions may potentially be considered, such as establishing a specific gender ratio in future recruitment. Gender-based or vulnerability-based selections of labour force can potentially be performed in the labour market. Empowerment of women or vulnerable groups according to the needs of society, building a culture and confronting beliefs that oppose women's participation, and codification of certain laws in support of employment of women and vulnerable groups are some of the measures that can be beneficial in this regard.
For future work, our log-linear Poisson model with multi-way interaction effects can be applied to other issues and data in economics, such as immigration, health, transportation, or the evaluation of ethnic and racial gaps in labour market outcomes. It can be used to evaluate gender or race disparities in authoritarian countries where sensitive data are mainly provided in condensed and minimal formats. Furthermore, one can apply a cross-sectional or panel count data method with multi-way interaction effects across states or countries. These approaches will help identify various vulnerable groups based on gender, minority, or race in different regions.

Compliance with Ethical Standards

**Funding:** There was no funding received for this study.

**Conflict of Interest:** The authors declare that they have no conflict of interest.

**Ethical approval:** Not applicable.

Data Availability

The following link provides access to the data used in this research: [http://www.amar.org.ir](http://www.amar.org.ir)

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Figures

Figure 1

The distribution of unemployment by age, education and living location for men and women

Source: Iranian labour force survey, 2019
Figure 2

The distribution of unemployment by unemployment duration for men and women


Supplementary Files

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- Appendices.docx
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