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RESEARCH PAPER

Formal versus Informal Labor Market Segmentation in Iran

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Abstract
This article examines whether there is a wage gap premium in the formal sector versus the informal sector of the Iranian labor market. We used household survey data conducted by the Statistical Centre of Iran for 2001, 2006, 2011, and 2016 to investigate the characteristics of the informal sector as well as differentials in wage structures between sectors. The findings indicate that a significant part of the Iranian labor force is employed in the informal sector, and this sector shows different behavior from the formal sector in determining wages. It has also been concluded that there is a wage gap between the formal and informal sectors, and this gap after a minimal increase in 2006, narrowed over time.
Keywords: Labor Market Segmentation, Informal Sector, Wage Gap, Human Capital, Iran.
JEL Classification: J23, J31, O17, O53.

Introduction

Duality can be traced back to a concern of economic development for many years. According to Lewis (1954), the characteristic of a less developed country rested on "economic dualism" where the "traditional" sector of economics coexists with the "modern" sector. The excess of labor supply in developing countries that exists in the traditional sector eventually flows to the modern sector. In the informality context, this excess will not be absorbed in modern sector jobs; therefore, an informal sector with a low level of productivity, lower wages, and poor working conditions will be formed. A notable feature of less developed countries is the coexistence of large, High-technology, and well-organized firms with small, self-employed businesses that are not under any social securities (Gindling, 1991). The increase in labor supply in this sector results in a decrease in wages and deteriorates the wage gap. According to Baltagi (2013), real hourly wages of informal workers are more sensitive to variations in regional unemployment rates than wages of formal workers in Turkey. This applies to all workers as well as for different gender and age groups.

Measuring the informal sector and its features has always been challenging (See Charmes, 2012). The diversity of experiences and definitions of informality is reflected in the literature. Some studies have found that employment in the informal sector is optional. It means people are working in this sector because of avoiding labor market regulations like taxes and minimum wages law, or simply because they are not interested in working for any employer. Martinez (2017) discussed that only 18% of 527 street vendors wish for a formal job although their wages are low. Moreover, Maloney (1991) analyzes that maybe the informal sector is a more desirable alternative for workers who are inefficient in the formal sector and have a low level of productivity. Nguimkeu (2013) considered employment in the informal sector of Cameroon to be due to both the lack of skills of individuals and the financial constraints that

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this sector faces. As a result, there is heterogeneity within the informal sector that needs to be addressed in policy-making. Nguimkeu argued that this heterogeneity causes households to choose whether to work as subsisters or to start a small business (entrepreneurship/micro-entrepreneurship) using the Maximum Likelihood method. Another group of studies followed the traditional duality hypothesis and considered employment in the informal sector as involuntary. That is due to institutional barriers and the lack of mobility, people work in the informal sector while they are waiting to enter the formal sector (e.g., Gindling, 1991; Marcouiller et al., 1997). However, people in the informal sector can enrich themselves in terms of experience and skills; therefore, the informal sector can be the stepping stone of entering the formal sector (Tumen, 2016). In more recent studies, we can also see that informal sector employment is still high on the agenda. Ayyoub and Gillani (2019) analyzed the determinants of formal and informal sector employment in the urban areas of district Lahore using the multinomial logit model. Their findings indicate that highly educated workers prefer to join the formal sector and show that the likelihood of youth employment in the formal sector is higher. Furthermore, workers with educated mothers are found to be less willing to work as informal workers. El-Haddad and Gadallah (2020) studied the influence of the formalization on the Egyptian economy by running recentered influence function regressions and using Firpo et al. (2007) distributional approach. Then they decomposed wage changes into contributed variables. Their study, however, mainly focused on inequality rather than the formal sector wage premium. The paper concluded that inequality increased the most between the top and bottom deciles and this increasing inequality is primarily driven by the unexplained wage structure effect; moreover, segmented labor markets are foremost responsible for the augmented inequality trend. Tansel et al. (2020) studied the magnitude of the informal sector wage gap in Egypt using the Egyptian Labor Market Panel Survey. They analyzed the wage differential across formal and informal sectors based on estimating Mincer equations both at the mean and at different quantiles of the wage distribution. Finally, they concluded that informal workers have disadvantages in both observable and unobservable characteristics. Studies in Iran began with Renani's efforts in 2004, which is mainly limited to statistically examining the distribution of people between the formal and informal sectors and calculating the likelihood of each sector's membership. However, in this paper, we mostly focused on the structure of wages and the formal sector wage premium.

The labor market in Iran, as a developing country, has been characterized by segmentation into formal and informal sectors. Based on Akbari and Leylaz (2010) this duality is rooted in the land reforms in the agricultural sector in 1961[1], in which the lands of large landowners were purchased by the Ministry of Agriculture and distributed among the farmers of each property. These reforms led to small lands for each farmer. Since not every land is fertile and sometimes on a small scale in Iran, it does not provide the minimum standard of living for rural households. This caused a massive rural-to-urban migration in search of a better life in the cities. But the speed of industrialization was not high enough to provide jobs for all these migrants. Thus, there was no choice for people but to earn their livelihood in the informal sector with significantly lower wages. Consequently, this caused wage differentials between not only rural and urban but also formal and informal. In this paper, we believe that this wage gap has remained until now.

The study measures comprehensively different dimensions of wage inequality as observed in the Iranian labor market while the primary motivation of this paper is to investigate the structure of wage inequality in formal versus informal sectors. To reach this goal, we test the hypothesis that, in developing nations, observably similar workers earn higher wages in the

1. The duality in the Iranian labor market was not necessarily due to the inefficiency of the land reform policy, and according to the literature on development economics, the labor market segmentation inevitably occurs on the path of development; however, the starting point in Iran seems to go back to land reform policies.

formal sector than in the informal sector. We expect a formal premium remains after controlling for individual characteristics. It means that workers with the same level of skills in the relatively same jobs are paid higher only because they are working in the formal sector of the economy.

The rest of the paper is organized as follows. Section II provides the theoretical background of wage determination as well as wage decomposition followed by the paper specification of model and data. Section IV reports the empirical results and we conclude in Section V.

Theoretical Framework

The theoretical model is presented here shows the way people choose to work in a sector and how their wages are determined there. Moreover, we analyze the extent to which the formal-informal wage gap can be accounted by productivity differences as reflected in human capital endowments, and whether they are in rural or urban, versus unexplained differences.

A two-stage estimation similar to Trust and Lee (1984) is adopted in this paper to analyze the wage differentials between formal and informal sectors and in the next step we used Oaxaca decomposition to identify the source of wage differentials between sectors. The underlying idea of two-stage modeling is that the distribution of workers among formal and informal sectors is not random and unobserved characteristics of workers are influencing the sectoral allocation while this sectoral allocation is affecting their wages. According to Heckman and Hotz (1986), to avoid this bias, we employed a selectivity bias correction term in wage equations.

This is assumed that an individual faces M mutually exclusive alternatives to choose from and each option provides him a particular wage level (W_s) that corresponded to a particular level of utility (V). Consider the following equations:

$$W_s = x_s\beta_s + u_s \tag{1}$$

where x_s is a vector of exogenous variables affecting the wage (Table 1) and u_s is a disturbance term. Also:

$$V = z_s\gamma_s + \eta_s \qquad s = 1.2 \ldots . M \tag{2}$$

that z_s is a vector of explanatory variables that captures all the variables affecting utility, including wages.

Let's assume that all variables (x_s and z_s) are exogenous with $E(u_s|x.z) = 0$ and $Var(u_s|x.z) = \sigma_s^2$. The wage level for the sth category is observed only if the individual chooses the sth category. This process is through utility maximization where the individual gain higher utility than any other alternatives:

$$V_s > \max V_j \quad for\ s \neq j \tag{3}$$

If the disturbances in the wage and utility equations are correlated, using Ordinary Least Square in this stage will result in inconsistent $\hat{\beta}$ due to the selectivity bias that occurs in wage regression (Bourguignon and others, 2007).

In this paper, we adopted selection bias correction introduced by Lee (1983). Lee proposed a generalization of the two-step method selection bias correction introduced by Heckman (1979) that allows for any parametrized error distribution instead of simply bi-variate normal. Lee further extended his method to the case where selectivity is modeled as a multinomial logit.

Thereafter, we used the Oaxaca decomposition to identify the sources of wage differentials between sectors.

$$\overline{lnw_f} - \overline{lnw_\iota} = \bar{x}_f'\left(\hat{\beta}_f - \beta^*\right) + \bar{x}_\iota'\left(\beta^* - \hat{\beta}_\iota\right) + (\overline{x_f} - \bar{x}_\iota)'\beta^* \quad (4)$$

Where f, and i, stands for formal, and informal respectively. $\overline{\ln w}$ denotes the mean log wage, vectors of mean values of the explanatory variables of wage regressions are denoted by $\overline{x'}$. $\hat{\beta}$'s are the estimated coefficients, and β^* is the estimated non-discriminatory wage structure for the decomposition. We obtained Neumark's approach (1988) of using a pooled sample which according to Oaxaca and Ransom (1994) yields the smallest estimated standard errors for every estimated differential.

Data and Methodology

Data

The definition of informality is a complex issue and can differ in different countries. However, in the literature, there are two main groups of definitions. The first one defines informality based on job characteristics such as self-employed, unskilled workers, people in marginal jobs, domestic and family workers, and people who work in firms with up to 5 employees (firm-based definition). The second group of definitions is rather "legalistic". In the former context, informality is defined as a part of the labor market that is not under social protection and other external regulations (Lehmann, 2018)[1]. Due to varied data limitations, the first approach has been adopted here. Moreover, only self-employed people (independent of the size of the workplace) are considered as the informal sector regarding the necessity of a country-based definition of informality.

To investigate whether there is a wage gap between formal and informal sectors of the Iranian labor market, this paper defines formal sectors as public formal and private formal wage earners while informal sector is defined as agricultural and non-agricultural self-employment. The study uses cross-section data by using Household surveys belonging to 4 selected years 2001, 2006, 2011, and 2016. The main focus of our study is wage gap analysis; therefore, it is important to provide a precise and comparable measure of earnings as our dependent variable. To achieve this, the log of net wage (for 12 months, net of taxes, and without bonuses) is used. The full definitions of all variables are presented in Table 1.

Table 1. Definition of the Explanatory Variables Used in the Wage and the Sector Assignment Equations

Variables	**Definition**
Sector Assignment Variables	
Sex	1 if female; 0 if male
Head	1 if the head of the family; 0 if not head of the family
Marital (Status)	3 if single; 2 if divorced; 1 if widow/widower; 0 if married
isCity	1 if urban; 0 if rural
Years of Education	Years of schooling
Experience	Age- Years of schooling-6
Experience^2	(Age- Years of schooling-6)^2
Wage Equations	

1. However, some authors assimilated, or restricted informality to self-employment as we did the same in this paper.

Variables	Definition
Sex	1 if female; 0 if male
Years of Education	Years of schooling
Experience	Age- Years of schooling-6
Experience2	(Age- Years of schooling-6)^2

Source: Research's Definitions.

Figure 1 demonstrates the distribution of workers through four sectors for four years. The number of workers in the private sector increased while the public sector after a growth in the first interval started to shrink slowly[1]. Please note that the number of people working in the informal sector is the sum of agricultural and non-agricultural self-employment workers which varied between 39% to more than 51%.

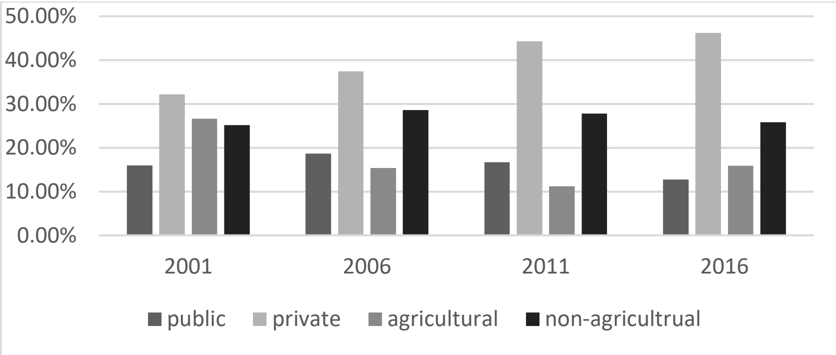

Figure 1. The Distribution of Workers in Sectors
Source: Research finding.

The distribution of real wages in different sectors disaggregated by gender is illustrated in figure 2. The bar charts show that women's wages were lower than men significantly in all four years and among all sectors. Moreover, women working in agricultural self-employment earn the least.

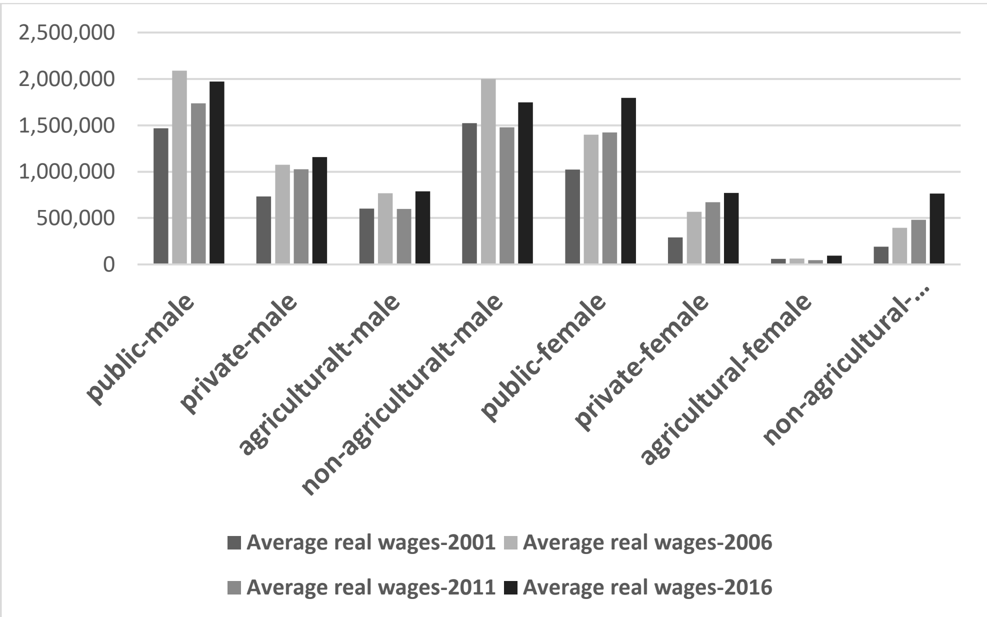

Figure 2. Average Real Wages through Sectors Disaggregated by Gender
Source: Research finding.

1 .This reduction in public sector employment is due to structural adjustment like privatization

Model Specification

As explained in the previous section, we have four main stages in wage gap analysis. In the first step, we will use multinomial logit to calculate the odds of sectors' participation. We assume that there are four mutually exclusive alternatives.

$$M_i = \begin{cases} 1 \text{ if working in the public-formal sector} \\ 2 \text{ if working in the private-formal sector} \\ 3 \text{ if working in the agricultural-informal sector} \\ 4 \text{ if working in the non-agricultural-informal sector} \end{cases}$$

Then in the next step, the results of multinomial logit will be employed in wage regressions of different sectors using Lee's method of selection bias correction. The third stage is merging four sectors into two main sectors called formal and informal to use the Oaxaca decomposition method in the last stage.[1]

Selection bias occurs when the regression error terms correlate with the explanatory variables. In other words, E (x | ε) ≠ 0 that is when the individuals in a given sector do not constitute a random subset of the population (Gindling, 1991). For example, in studying the return of education on the wage rate, the problem will occur when some people despite having higher education, do not want to work because the offered wages are lower than their reservation wages. Now, if education has a positive effect on people's wages, people with a low level of education will be offered lower wages on average and will have lower employment rates than people with higher education. Whereas what a researcher observes is that people with low education have relatively high wages (Puhani, 2000).

Following the empirical literature, to obtain selectivity corrected estimates for β_s, we apply a strictly increasing transformation of standard errors, proposed by Lee (1983), to $\varepsilon_s^* = \Phi^{-1}[F(z_s\gamma_s)]$, where φ is the standard normal cumulative distribution function and $F(z_s\gamma_s)$ is the CDF of ε_s which is given by:

$$F(z_s\,, \gamma_s) = \frac{\exp(\varepsilon_s)}{\exp(\varepsilon_s)+\sum_{j=1.j\neq s}^{M}\exp(z_j\gamma_j)} \tag{5}$$

with this transformation distribution of ε_s^* changes to normal. It is assumed that the random variables u_s and ε_s are jointly normally distributed and:

$$E(u_s|z_s\gamma_s > \varepsilon_s) = -\sigma_s\rho_s\frac{\Gamma(\Phi^{-1}[F(z_s\gamma_s)])}{F(z_s\gamma_s)} \tag{6}$$

where Γ is the standard normal density and ρ_s is the correlation between u_s and ε_s. The wage equation can be rewritten as the following equation:

$$W_s = x_s\beta_s - \sigma_s\rho_s\frac{\Gamma\left(\Phi^{-1}[F(z_s\gamma_s)]\right)}{F(z_s\gamma_s)} + \nu_s \tag{7}$$

In which selectivity bias-corrected wage coefficients and selectivity terms will be estimated.

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1. The practical implementation of the four-step procedure is greatly facilitated by a number of STATA ado-files programmed by different researchers: Below, Oaxaca by Jann (2008) is used for the Oaxaca type decompositions and code based on the one in Selmlog by Bourguignon et al. (2007) for the numerical computation of correction terms.

Estimation Results

As mentioned before, there are four main stages of wage gap analyses in this paper. In this section, these steps will be elaborated.

Multinomial Logit Results

Appendix 1 represents the results of multinomial logit regression (our first step) in which datasets are restricted to individuals aged more than 15 years old. Years of schooling are considered as human capital also we used (age-schooling-6) as a proxy of experience, while experience and experience-squared are indicating productivity. We also used survey weights to obtain a better interpretation of the society. Our base category in this study is the most frequent observation which is the private wage earners. All coefficients are explained in comparison to the base category in multinomial logit regression. For example, if an individual were to increase his years of education by one unit, the multinomial log-odds for preferring the public sector to the private sector would be expected to increase by almost 0.31 units while holding all other variables in the model constant. Moreover, the multinomial logit for females relative to males is 1.18 units higher for preferring the public sector to the private sector, given all other predictor variables in the model are held constant. In other words, females are more likely than males to prefer the public to the private sector. The marginal effects of the model are also calculated and presented in Appendix 2. Using the “years of education” as an example, the findings show that if there was an increase in the years of education, the probability of participating in the formal sector would have elevated by 2.85%, 2.88%, 2.79%, and 2.95% points in 2001, 2006, 2011, and 2016 respectively. On the other hand, the participation rates in all other sectors would have declined. Consider the dummy variable of male (0) and female (1) as another example, the results show that changing the variable from 0 to 1 increases the probability of formal sector and agricultural self-employment participation in comparison to the other two sectors.

Wage Regression Results in 4 Sectors

Following the second stage of the wage gap analyses, the results of wage regressions in four sectors after correcting for selection bias are given in Table 2. The coefficients on years of schooling, experience, and experience-squared are statistically significant at the 1% level. Similarly, the coefficients on most of our dummy variables are statistically significant at the 1% level except for being divorced or widow/er in some cases. As the Human Capital theory would anticipate, the sign on the coefficient of education and experience variable is positive. We also expect to have a negative sign on experience square due to the life-cycle of workers' productivity. The results show that women earn less than men in all sectors while wage discrimination is higher in agricultural self-employment than they earn the least based on table 2. Selection bias terms, represented by _mk k=1, 2, 3, 4, are all significantly different from zero which represents we have selection bias and this correction was necessary. The positive signs for selection terms mean that the workers who are self-selected into sectors had lower wages than those who are randomly assigned. The bigger coefficients indicate higher impact. Since women's participation in the Iranian labor market is less than 20%, the probability of self-selection is very high. Therefore, to consider different aspects in this study, we repeated the same set of estimations for the male and female samples separately, although the purpose of this study was not to compare wage equations between men and women. In the appendix, the results of all regressions are given for men and women separately.

Table 2. Wage Regression Results

	2001				2006				2011				2016			
VARIABLES	**non_agr**	**agr**	**private**	**public**	**non_agr**	**agr**	**private**	**public**	**non_agr**	**agr**	**private**	**public**	**non_agr**	**agr**	**private**	**public**
Sex																
female	-3.7567***	-8.4297***	-0.4847***	-0.3243***	-4.0604***	-10.9736***	-0.7846***	-1.1844***	-3.8152***	-8.5415***	-0.5640***	-0.6730***	-2.8057***	-8.5140***	-0.5274***	-0.3750***
	(0.1404)	(0.0954)	(0.0612)	(0.0477)	(0.2039)	(0.1882)	(0.0602)	(0.1496)	(0.2234)	(0.1931)	(0.0429)	(0.1220)	(0.1984)	(0.2023)	(0.0380)	(0.0945)
Marital																
Widow/er	1.3543***	5.1487***	-0.3543***	-0.7538	1.9073***	6.3004***	-0.1644*	0.8733***	1.8324***	4.2343***	-0.2039**	0.4811**	1.0520***	4.6415***	-0.1289*	-0.2240
	(0.2527)	(0.2164)	(0.0971)	(0.4788)	(0.2857)	(0.3267)	(0.0909)	(0.2585)	(0.2591)	(0.3044)	(0.0928)	(0.1964)	(0.1910)	(0.3217)	(0.0704)	(0.2273)
Divorced	1.3571***	1.8361***	-0.6788*	0.0136	0.1218	-1.9084*	-0.2163	-1.8405*	0.3558	-0.3030	-0.1826**	-0.1976	0.6635***	-1.6819	-0.2395***	0.1004
	(0.4844)	(0.6558)	(0.3531)	(0.0650)	(0.6102)	(0.9870)	(0.1321)	(1.0222)	(0.4172)	(0.9652)	(0.0769)	(0.3169)	(0.2244)	(1.2436)	(0.0688)	(0.1961)
Single	-2.9825***	-3.7880***	-0.3792***	-0.8545***	-3.1805***	-4.2568***	-0.2659***	-2.6291***	-1.9668***	-3.3109***	-0.2672***	-1.4486***	-1.1428***	-2.8443***	-0.2879***	-1.2862***
	(0.1705)	(0.1747)	(0.0386)	(0.0819)	(0.2055)	(0.2283)	(0.0448)	(0.2173)	(0.1706)	(0.2354)	(0.0259)	(0.1485)	(0.1527)	(0.3212)	(0.0267)	(0.1469)
Years of Education	0.1707***	0.1702***	0.1310***	-0.0033	0.1708***	0.2314***	0.1245***	0.4787***	0.1158***	0.1448***	0.1038***	0.3356***	0.1139***	0.1310***	0.0884***	0.1831***
	(0.0080)	(0.0109)	(0.0055)	(0.0156)	(0.0111)	(0.0194)	(0.0048)	(0.0288)	(0.0083)	(0.0151)	(0.0031)	(0.0242)	(0.0083)	(0.0131)	(0.0029)	(0.0224)
Experience	0.2080***	0.3557***	0.0988***	0.0634***	0.1965***	0.4132***	0.0762***	0.1141***	0.1434***	0.3582***	0.0640***	0.0967***	0.0801***	0.3541***	0.0399***	0.0798***
	(0.0101)	(0.0102)	(0.0041)	(0.0068)	(0.0125)	(0.0131)	(0.0039)	(0.0113)	(0.0107)	(0.0126)	(0.0025)	(0.0075)	(0.0088)	(0.0192)	(0.0022)	(0.0065)
Experience2	-0.0023***	-0.0034***	-0.0011***	-0.0008***	-0.0023***	-0.0039***	-0.0008***	-0.0006***	-0.0017***	-0.0030***	-0.0007***	-0.0007***	-0.0009***	-0.0025***	-0.0004***	-0.0008***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
_m4	-1.0050***				-1.5559***				-0.6792***				-0.4864***			
	(0.1204)				(0.1492)				(0.1250)				(0.1466)			
_m3		0.7464***				-0.0393				1.6202***				3.9466***		
		(0.0955)				(0.5349)				(0.4358)				(0.5775)		
_m2			-0.8749***				-0.4655***				-0.6192***				-0.4348***	
			(0.0853)				(0.0713)				(0.0589)				(0.0579)	
_m1				-0.8444***				1.7347***				0.8584***				0.1124
				(0.1355)				(0.1906)				(0.1361)				(0.1523)
Constant	9.9796***	2.5797***	11.7859***	14.0806***	13.8996***	4.7901***	14.9066***	7.4994***	11.1500***	1.1556*	12.3497***	7.1801***	12.1013***	-1.2365	12.6453***	10.2161***
	(0.2624)	(0.2594)	(0.0744)	(0.3918)	(0.3382)	(0.6990)	(0.0708)	(0.6236)	(0.3005)	(0.7012)	(0.0469)	(0.5199)	(0.3169)	(1.0987)	(0.0422)	(0.5433)
Observations	15,271	21,678	20,867	9,711	16,753	21,045	24,959	10,390	16,326	16,658	30,960	10,443	14,580	14,068	31,050	9,411
R-squared	0.3864	0.6216	0.1487	0.2280	0.3134	0.6662	0.1315	0.2367	0.2659	0.6618	0.1542	0.2296	0.1827	0.6216	0.1403	0.1945

Source: Research finding, using household survey data, 2001,2006,2011,2016.
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Wage Regression Results for Formal and Informal Sectors

Our third stage was the merge of four sectors into two main groups. The public and private wage earners are considered as the “formal” sector, while the agricultural and non-agricultural self-employed are grouped as the “informal” sector. The results are shown in Appendix 3 where coefficients are statistically significant as they were in the previous stage. Return to education in this table is higher in the informal sector unlike the results in table 2. However, this result represents the inherent heterogeneity of the informal sector (Aydin, 2010). Recall that several studies consider the informal sector as a stepping stone for the formal sector. Educated people are waiting for an opportunity to find a job in the formal sector, meanwhile, working informally. Thus, it is not surprising that the return of years of schooling is higher when we merge sectors. We observe that most of the observations we made for the total sample hold for the male sample as well. Yet in the case of the female sample, we note some exceptions. For example, the returns of education are not positive for female samples in the informal sector. Marital status is also more significant for females.

Oaxaca Decomposition Results

In the final part of our analysis, Oaxaca decomposition is used to address the sources of wage differentials between formal and informal sectors. In this method, the regression coefficients obtained in each section are compared with the regression coefficients of the pooled sample. Then, the difference in wage equations is divided into two sections, “explained” by the explanatory and “unexplained” part of the wage differentials. The “unexplained” section is the premium that is expected to be in the formal sector compared to the informal sector and results in the labor market segmentation. In other words, one part of the difference between the formal and informal sectors is associated with human capital endowments of workers such as education, experience, and productivity while the other source of wage differentials so-called “unexplained” portion is due to factors other than the above. Using the Oaxaca decomposition method, it is observed that the unexplained gap is statistically significant and narrowed over time. “Explained” part of “years of education” is negative; this means that the overall difference was even larger if the average years of schooling of people who are in the formal and informal sectors would be the same. Schooling has a positive effect on wages; thus, if we eliminate the schooling advantage of the formal sector, the wage gap would increase. Moreover, using the Oaxaca decomposition method, it is observed that the unexplained gap is statistically significant and after a minimal increase in 2006, narrowed over time. For females, this wage differential is even wider in all years. We observed that the wage differentials narrowed over time for men while for females, we do not see such a decreasing pattern.

Table 3. Oaxaca Decomposition-pooled Sample

		2001			2006			2011			2016	
VARIABLES	**overall**	**explained**	**unexplained**	**overall**	**explained**	**unexplained**	**overall**	**explained**	**unexplained**	**overall**	**explained**	**unexplained**
Sex												
Female		-0.1614***	-0.7201***		-0.1781***	-0.9970***		-0.0468***	-0.7543***		0.0019	-0.5635***
		(0.0120)	(0.0170)		(0.0176)	(0.0260)		(0.0123)	(0.0205)		(0.0090)	(0.0213)
Marital												
Widow/er		0.0198***	0.0548***		0.0172***	0.0513***		0.0171***	0.0543***		0.0097***	0.0371***
		(0.0024)	(0.0037)		(0.0031)	(0.0042)		(0.0027)	(0.0049)		(0.0016)	(0.0037)
Divorced		-0.0028***	0.0147***		-0.0007	0.0122***		-0.0043***	0.0156***		-0.0012	0.0278***
		(0.0010)	(0.0026)		(0.0007)	(0.0044)		(0.0016)	(0.0045)		(0.0012)	(0.0051)
Single		0.1293***	-0.6391***		0.1456***	-0.6489***		0.0787***	-0.3818***		0.0629***	-0.2400***
		(0.0081)	(0.0279)		(0.0097)	(0.0367)		(0.0062)	(0.0262)		(0.0051)	(0.0222)
Years of Education		-0.6200***	1.1814***		-0.6624***	1.7503***		-0.4819***	1.2326***		-0.3888***	1.3285***
		(0.0143)	(0.0460)		(0.0177)	(0.0737)		(0.0135)	(0.0636)		(0.0122)	(0.0826)
Experience		1.4821***	4.3754***		1.3583***	5.1409***		1.0768***	4.2371***		0.6584***	2.0739***
		(0.0452)	(0.2186)		(0.0496)	(0.2738)		(0.0381)	(0.2448)		(0.0282)	(0.2139)
Experience2		-0.9115***	-1.6207***		-0.7590***	-1.7987***		-0.6570***	-1.5245***		-0.3901***	-0.6297***
		(0.0348)	(0.0965)		(0.0360)	(0.1198)		(0.0292)	(0.1073)		(0.0220)	(0.0942)
Informal	10.6304***			13.5484***			11.7193***			12.6254***		
	(0.0325)			(0.0430)			(0.0354)			(0.0324)		
Formal	13.2146***			16.2438***			13.5171***			13.7136***		
	(0.0107)			(0.0180)			(0.0114)			(0.0091)		
difference	-2.5841***			-2.6955***			-1.7978***			-1.0882***		
	(0.0343)			(0.0466)			(0.0372)			(0.0337)		
explained	-0.0645***			-0.0791***			-0.0174			-0.0472***		
	(0.0225)			(0.0278)			(0.0198)			(0.0150)		
unexplained	-2.5196***			-2.6163***			-1.7804***			-1.0410***		
	(0.0330)			(0.0441)			(0.0355)			(0.0322)		
Constant			-5.1661***			-6.1264***			-4.6595***			-3.0750***
			(0.1814)			(0.2354)			(0.2008)			(0.1945)
Observations	67,697	67,697	67,697	73,147	73,147	73,147	74,387	74,387	74,387	69,109	69,109	69,109

Source: Research finding, using household survey data, 2001, 2006, 2011, 2016.
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Conclusion

This study investigates the wage gap in the formal versus informal sector of the Iranian labor market. According to the results obtained (Figure 1), the informal sector of the Iranian labor market is a significant segment in terms of labor force employment (40 to more than 50%). This sector also has varied characteristics from the formal sectors and the return of human capital is different as well. It also seems that the informal sector in our country is heterogeneous in terms of the human capital of the people employed. Another conclusion that has been received is the existence of self-selection in all the sectors studied, which has had different effects on people's wages. Finally, there is a wage gap between the formal and informal sectors despite all characteristic differentials, and this gap appears to narrow over the years studied. Our results are consistent with other studies which have shown that there is a wage premium in the formal sector of developing countries. Understanding informal employment is crucial for understanding how labor markets function as well as the structure of economic activities and talking about labor market segmentation gives us a better perspective of the most efficient allocation of workers. Since the informal sector is not as known as the other parts of the economies of countries and according to this study have different characteristics from the formal sectors, recognizing it politically will have beneficial consequences. It should be noted that one of the characteristics of the informal sector is the weak supervision and the failure of institutions in regulating and taxing these sectors. Therefore, observing, studying, and examining this section can be a necessity for government policies.

Countries have been struggling with the Covid-19 in the past few months and the poor working conditions of individuals in the informal sector make the pandemic worse. Specifically, as most people working in the informal sector rely on daily income, it is almost impossible to quarantine them. It has been observed in April 2020 that many self-employed workers get back to work as usual in Iran. These people are not covered by the social security system/program nor controlled by the government. Even if the government in a less developed country has the financial capacity to support them, all of these people might not be recognized and covered. The high-handed approaches to urban control would negate the sprite of stakeholders' partnership in urban development which would be analyzed the tensions, misconceptions, and confusions associated with the COVID-19 pandemic medical emergency (Onyishi et al., 2020). The failure of the government, in this case, will deteriorate the pandemic. Therefore, it is very important to recognize the vulnerability of the informal sector. We acknowledge the need for further research on the effect of Coronavirus on the informal sector employment and wages.

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Appendix 1. Multinomial Logit Results

	2001			2006			2011			2016		
VARIABLES	**public**	**agr**	**non_agr**	**public**	**agr**	**non_agr**	**public**	**agr**	**non_agr**	**public**	**agr**	**non_agr**
Sex												
Female	1.1797***	0.7133***	0.9144***	0.8942***	1.0497***	0.2845***	0.6732***	1.1298***	-0.0016	0.4118***	0.8033***	0.0477
	(0.0516)	(0.0382)	(0.0438)	(0.0571)	(0.0374)	(0.0479)	(0.0611)	(0.0425)	(0.0545)	(0.0617)	(0.0462)	(0.0570)
Marital												
Widow/er	-0.8647***	-0.6893***	-0.7661***	-0.2007	-0.6284***	-0.3983***	-0.0580	-0.6664***	0.1171	-0.3219*	-0.5845***	-0.0223
	(0.1893)	(0.1027)	(0.1179)	(0.1744)	(0.1241)	(0.1410)	(0.1881)	(0.1322)	(0.1418)	(0.1900)	(0.1311)	(0.1529)
Divorced	-1.2049***	-1.2792***	-0.9137***	-0.6700***	-0.9645***	-0.1481	-1.1825***	-1.0290***	-0.1970	-1.2465***	-0.8354***	-0.0771
	(0.2710)	(0.2204)	(0.2026)	(0.2435)	(0.2361)	(0.1857)	(0.2076)	(0.2265)	(0.1537)	(0.1802)	(0.2068)	(0.1220)
Single	-0.4561***	0.0527	-0.2120***	-0.4385***	0.0965**	-0.1262***	-0.4489***	0.3880***	-0.0337	-0.6165***	0.5178***	-0.2444***
	(0.0559)	(0.0444)	(0.0459)	(0.0590)	(0.0455)	(0.0479)	(0.0648)	(0.0508)	(0.0517)	(0.0651)	(0.0543)	(0.0536)
isCity												
Urban	0.3018***	-2.4046***	0.3659***	0.5877***	-30.4377***	0.3166***	0.6792***	-29.0845***	0.4329***	0.6340***	-28.4296***	0.3929***
	(0.0340)	(0.0362)	(0.0258)	(0.0352)	(0.0284)	(0.0256)	(0.0362)	(0.0291)	(0.0263)	(0.0398)	(0.0285)	(0.0279)
head	0.0262	-0.2053***	-0.0138	-0.0923**	-0.3257***	-0.0512*	-0.0407	-0.3463***	-0.0325	-0.0418	-0.2731***	-0.0205
	(0.0342)	(0.0258)	(0.0264)	(0.0364)	(0.0278)	(0.0283)	(0.0382)	(0.0291)	(0.0292)	(0.0395)	(0.0310)	(0.0303)
Years of Education	0.3135***	0.0511***	0.0989***	0.3034***	0.0320***	0.1167***	0.2878***	0.0189***	0.0811***	0.3003***	0.0364***	0.0727***
	(0.0056)	(0.0046)	(0.0044)	(0.0061)	(0.0047)	(0.0046)	(0.0063)	(0.0049)	(0.0045)	(0.0069)	(0.0048)	(0.0047)
Experience	0.0859***	0.0248***	0.0436***	0.0517***	0.0147***	0.0611***	0.0291***	0.0126***	0.0617***	0.0317***	0.0346***	0.0534***
	(0.0049)	(0.0039)	(0.0039)	(0.0047)	(0.0041)	(0.0041)	(0.0049)	(0.0045)	(0.0042)	(0.0049)	(0.0046)	(0.0042)
Experience2	-0.0008***	0.0005***	-0.0001**	0.0002**	0.0007***	-0.0003***	0.0005***	0.0008***	-0.0003***	0.0005***	0.0006***	-0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant	-4.8065***	-0.9133***	-1.9795***	-5.0252***	-0.9376***	-2.4997***	-5.2935***	-1.3955***	-2.7086***	-6.1079***	-2.1218***	-2.6917***
	(0.0976)	(0.0803)	(0.0802)	(0.1005)	(0.0832)	(0.0839)	(0.1128)	(0.0940)	(0.0893)	(0.1277)	(0.1003)	(0.0951)
Observations	67,697	67,697	67,697	73,147	73,147	73,147	74,387	74,387	74,387	69,109	69,109	69,109

Source: Research finding, using household survey data, 2001, 2006, 2011, 2016.

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix 2. Multinomial Logit- Marginal Effects

		sex	marital status			isCity	head	years of education	experience	experience2
		female	**widow/re**	**divorced**	**single**	**urban**	**head**	**years of education**	**experience**	**experience2**
2001	**Public**	0.0720***	-0.0477***	-0.0682***	-0.0387***	0.0677***	0.00682**	0.0285***	0.00678***	-8.46e-05***
		-0.00497	-0.0161	-0.0195	-0.00499	-0.00348	-0.0034	-0.000412	-0.00047	-7.87E-06
	Private	-0.156***	0.159***	0.230***	0.0348***	0.0982***	0.0128***	-0.0253***	-0.00905***	1.64e-05*
		-0.00539	-0.0219	-0.0379	-0.00733	-0.00435	-0.00421	-0.000624	-0.000623	-8.81E-06
	Agr	0.0190***	-0.0409***	-0.0944***	0.0234***	-0.350***	-0.0252***	-0.00319***	-0.000286	7.52e-05***
		-0.00376	-0.00978	-0.0189	-0.00515	-0.00338	-0.00282	-0.000467	-0.000417	-5.32E-06
	non-agr	0.0653***	-0.0700***	-0.0678**	-0.0195***	0.184***	0.00555	-2.91E-06	0.00255***	-7.03E-06
		-0.00619	-0.0159	-0.0278	-0.00722	-0.00442	-0.00423	-0.00058	-0.000607	-8.51E-06
2006	**Public**	0.0876***	0.00217	-0.0595***	-0.0432***	0.112***	-0.0053	0.0288***	0.00246***	2.94e-05***
		-0.00656	-0.0194	-0.0212	-0.00572	-0.00388	-0.0039	-0.000504	-0.000477	-7.03E-06
	Private	-0.123***	0.0814***	0.0922***	0.0312***	0.109***	0.0252***	-0.0294***	-0.00970***	-1.09E-05
		-0.00695	-0.0253	-0.0352	-0.00797	-0.0046	-0.00481	-0.000678	-0.000669	-9.72E-06
	Agr	0.0705***	-0.0374***	-0.0632***	0.0144***	-0.389***	-0.0242***	-0.00300***	-0.000857***	6.16e-05***
		-0.00263	-0.00766	-0.0146	-0.00344	-0.00289	-0.00203	-0.000334	-0.000296	-3.94E-06
	non-agr	-0.0354***	-0.0463**	0.0305	-0.00238	0.168***	0.0043	0.00360***	0.00809***	-8.01e-05***
		-0.00659	-0.0211	-0.0333	-0.00796	-0.00456	-0.00471	-0.000627	-0.000639	-8.99E-06
2011	**Public**	0.0758***	-0.00954	-0.0952***	-0.0469***	0.0980***	-0.00125	0.0279***	0.000202	6.62e-05***
		-0.00722	-0.019	-0.0125	-0.0058	-0.00351	-0.00394	-0.000546	-0.000488	-7.00E-06
	Private	-0.0915***	0.0114	0.121***	0.0129	0.0765***	0.0199***	-0.0270***	-0.00949***	-3.03e-05***
		-0.00864	-0.0277	-0.0296	-0.00897	-0.00477	-0.00527	-0.000732	-0.000738	-1.05E-05
	Agr	0.0726***	-0.0391***	-0.0487***	0.0274***	-0.336***	-0.0210***	-0.00174***	-0.000487*	5.33e-05***
		-0.00268	-0.00561	-0.0102	-0.00314	-0.00301	-0.0017	-0.000288	-0.000264	-3.48E-06
	non-agr	-0.0569***	0.0372	0.0234	0.00661	0.161***	0.00232	0.000833	0.00977***	-8.92e-05***
		-0.00769	-0.0246	-0.0278	-0.00875	-0.00449	-0.00493	-0.000668	-0.000683	-9.54E-06
2016	**Public**	0.0419***	-0.0320*	-0.103***	-0.0549***	0.0868***	-0.00264	0.0295***	0.00103**	6.38e-05***
		-0.00703	-0.0182	-0.0104	-0.00569	-0.00364	-0.0041	-0.000632	-0.00049	-7.45E-06
	Private	-0.0631***	0.0409	0.0984***	0.0475***	0.0753***	0.0148***	-0.0290***	-0.00980***	-2.72e-05**
		-0.00927	-0.0288	-0.0238	-0.00915	-0.00508	-0.00549	-0.00073	-0.00074	-1.09E-05
	Agr	0.0445***	-0.0268***	-0.0351***	0.0347***	-0.301***	-0.0144***	-0.000272	0.000951***	3.26e-05***
		-0.00268	-0.00504	-0.00822	-0.003	-0.00312	-0.00158	-0.000242	-0.000236	-3.13E-06
	non-agr	-0.0233***	0.0179	0.0395*	-0.0273***	0.139***	0.00223	-0.000233	0.00781***	-6.93e-05***
		-0.00899	-0.0273	-0.0234	-0.00869	-0.00459	-0.00517	-0.000733	-0.000695	-9.74E-06

Source: Research finding, using household survey data, 2001, 2006/Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix 3: Wage Regression Results- Formal vs Informal

	2001		2006		2011		2016	
VARIABLES	**informal**	**formal**	**informal**	**formal**	**informal**	**formal**	**informal**	**formal**
Sex								
Female	-4.8127***	-0.2802***	-7.5374***	-1.4353***	-6.4871***	-0.7810***	-5.1443***	-0.4609***
	(0.1314)	(0.0382)	(0.1743)	(0.0917)	(0.1718)	(0.0673)	(0.2294)	(0.0429)
Marital								
Widow/er	2.2951***	-0.6425***	3.6121***	0.5696***	3.2525***	0.1002	2.7459***	-0.0872
	(0.2297)	(0.1315)	(0.3187)	(0.1283)	(0.3135)	(0.0895)	(0.3115)	(0.0900)
Divorced	0.8425	-0.6671***	0.6578	-0.4763	0.8446	0.0499	1.5961***	-0.1575**
	(0.6798)	(0.2543)	(0.8317)	(0.3532)	(0.6906)	(0.0948)	(0.5130)	(0.0706)
Single	-3.6473***	-0.5372***	-3.9528***	-0.6565***	-2.5223***	-0.4035***	-2.2260***	-0.4245***
	(0.1852)	(0.0381)	(0.1728)	(0.0625)	(0.2148)	(0.0411)	(0.2130)	(0.0359)
Years of Education	0.0621***	0.0781***	0.1742***	0.1407***	0.1066***	0.1004***	0.1253***	0.0813***
	(0.0127)	(0.0029)	(0.0152)	(0.0044)	(0.0139)	(0.0032)	(0.0131)	(0.0023)
Experience	0.2655***	0.0857***	0.3391***	0.0821***	0.3198***	0.0778***	0.2113***	0.0590***
	(0.0100)	(0.0037)	(0.0110)	(0.0050)	(0.0099)	(0.0030)	(0.0116)	(0.0029)
Experience2	-0.0018***	-0.0009***	-0.0027***	-0.0011***	-0.0025***	-0.0010***	-0.0014***	-0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
_m0	7.5643***		7.2481***		7.0571***		6.1828***	
	(0.2320)		(0.2361)		(0.2352)		(0.2486)	
_m1		-1.3523***		0.2801***		-0.4008***		-0.8243***
		(0.0762)		(0.0810)		(0.0626)		(0.0559)
Constant	0.5998**	12.5148***	1.8885***	14.1887***	-0.8431**	11.9809***	1.7200***	12.5855***
	(0.2703)	(0.0887)	(0.2950)	(0.1046)	(0.3336)	(0.0649)	(0.3972)	(0.0651)
R-squared	0.4813	0.2255	0.5092	0.1355	0.4906	0.1476	0.3787	0.1401

Source: Research finding, using household survey data, 2001, 2006, 2011, 2016- Bootstrapped standard errors.
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.

Appendix 4. Wage Regression Results- Four Sectors - Disaggregated by Gender (2001, 2006)

	2001								2006							
	Male				Female				Male				Female			
VARIABLES	**non_agr**	**agr**	**private**	**public**	**non_agr**	**agr**	**private**	**public**	**non_agr**	**agr**	**private**	**public**	**non_agr**	**agr**	**private**	**public**
Marital																
Widow/er	-0.5659	0.0698	-0.5106***	0.2533	2.2692***	9.5224***	0.3217***	-0.8392	-0.4168	-0.7657***	-0.0830	-0.2734	3.3547***	10.8584***	0.3625***	2.5710***
	(0.4220)	(0.2201)	(0.1828)	(0.1768)	(0.3395)	(0.2310)	(0.1207)	(0.6275)	(0.3353)	(0.2588)	(0.1237)	(0.2275)	(0.4883)	(0.5779)	(0.1386)	(0.6110)
Divorced	0.2641	0.1215	-1.1570**	0.1984*	1.5645**	4.9201***	0.3127*	0.2597**	-1.4102*	-5.4466***	-0.2085	-1.1310**	1.8485***	0.0415	0.2524	-0.4954
	(0.4350)	(0.6084)	(0.5753)	(0.1145)	(0.6591)	(1.4607)	(0.1631)	(0.1171)	(0.8279)	(1.3727)	(0.1729)	(0.5611)	(0.6455)	(2.1204)	(0.2173)	(2.1021)
Single	-3.5310***	-4.6999***	-0.4312***	-1.1205***	-0.8049**	-0.0205	0.1782	-0.1235	-3.5372***	-5.0225***	-0.3483***	-2.7597***	-0.4722	-0.4012	0.4429**	-2.1601***
	(0.1974)	(0.2006)	(0.0404)	(0.1059)	(0.3377)	(0.2247)	(0.1220)	(0.1086)	(0.2228)	(0.3143)	(0.0422)	(0.2406)	(0.5048)	(0.4740)	(0.1944)	(0.4418)
Years of Education	0.1168***	0.1771***	0.1334***	-0.0202	0.5651***	-0.0452	0.1385***	0.0326	0.1206***	0.1413***	0.1135***	0.2182***	0.6959***	-0.0531	0.1747***	1.3596***
	(0.0073)	(0.0110)	(0.0068)	(0.0161)	(0.0479)	(0.0289)	(0.0100)	(0.0282)	(0.0101)	(0.0178)	(0.0060)	(0.0199)	(0.0549)	(0.0892)	(0.0095)	(0.1036)
Experience	0.1848***	0.3844***	0.1024***	0.0570***	0.3896***	0.0090	0.0711***	0.0605***	0.1893***	0.5039***	0.0729***	0.1174***	0.4337***	0.1097***	0.0892***	0.1881***
	(0.0105)	(0.0116)	(0.0044)	(0.0073)	(0.0355)	(0.0204)	(0.0115)	(0.0195)	(0.0126)	(0.0163)	(0.0037)	(0.0112)	(0.0474)	(0.0270)	(0.0157)	(0.0293)
Experience^2	-0.0022***	-0.0036***	-0.0011***	-0.0007***	-0.0039***	0.0001	-0.0008***	-0.0008*	-0.0023***	-0.0038***	-0.0008***	-0.0011***	-0.0041***	-0.0006	-0.0010***	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0005)	(0.0003)	(0.0002)	(0.0004)	(0.0002)	(0.0001)	(0.0000)	(0.0001)	(0.0007)	(0.0004)	(0.0002)	(0.0005)
_m5	-0.8347***				-0.8266*				-0.9213***				-2.9254***			
	(0.1037)				(0.4989)				(0.1125)				(0.7129)			
_m4		0.7993***				0.1722				5.6953***				4.1705		
		(0.0923)				(0.2675)				(0.5155)				(2.7920)		
_m3			-1.0017***				-0.0701				-0.4654***				-0.0597	
			(0.0994)				(0.1490)				(0.0791)				(0.1453)	
_m1				-1.0217***				-0.6281***				0.4754***				3.7685***
				(0.1588)				(0.2224)				(0.1671)				(0.6231)
Constant	10.7057***	2.1416***	11.8506***	14.6157***	0.6003	0.7171	10.2094***	12.8912***	13.8469***	-2.8032***	15.0588***	12.1417***	3.4132**	-3.3816*	12.7104***	-7.8270***
	(0.2637)	(0.2890)	(0.0749)	(0.4248)	(0.6346)	(0.5117)	(0.3089)	(0.5995)	(0.3024)	(0.8027)	(0.0656)	(0.5015)	(1.3318)	(1.8321)	(0.3866)	(2.0577)
Observations	12,689	18,162	19,156	8,284	2,648	3,563	1,745	1,450	14,602	16,356	23,028	8,617	2,151	4,689	1,931	1,773
R-squared	0.3087	0.5775	0.1260	0.2522	0.1973	0.4429	0.1254	0.1654	0.2608	0.6113	0.0985	0.2561	0.1861	0.3458	0.1656	0.4314

Source: Research finding, using household survey data, 2001, 2006. / Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

Appendix 5. Wage Regression Results- Four Sectors- Disaggregated by Gender (2011, 2016)

	2011								2016							
	Male				Female				Male				Female			
VARIABLES	**non_agr**	**agr**	**private**	**public**	**non_agr**	**agr**	**private**	**public**	**non_agr**	**agr**	**private**	**public**	**non_agr**	**agr**	**private**	**public**
Marital																
Widow/er	-0.1756	-0.4020*	-0.1213	0.1328	4.6708***	7.7324***	0.0121	3.1850***	-0.1433	0.2124	-0.1518*	-1.0520*	2.4681***	6.9261***	0.0937	1.6889***
	(0.1984)	(0.2297)	(0.0866)	(0.1681)	(0.4831)	(0.5254)	(0.1644)	(0.5974)	(0.1394)	(0.1917)	(0.0801)	(0.6180)	(0.3518)	(0.6738)	(0.1079)	(0.4382)
Divorced	-1.3950***	-2.5372**	-0.2278***	-1.7399**	3.5083***	0.7156	0.1426	0.3073	-0.4218*	-2.6872**	-0.4521***	0.0903	2.5467***	-2.1740	0.1470	1.8967**
	(0.5175)	(1.2293)	(0.0622)	(0.8819)	(0.3277)	(1.6807)	(0.1445)	(0.4341)	(0.2364)	(1.0614)	(0.0897)	(0.2451)	(0.3327)	(2.3666)	(0.1282)	(0.7912)
Single	-2.2089***	-3.6370***	-0.3068***	-2.0417***	-0.1666	-0.2032	0.0779	-0.4637*	-1.3357***	-3.2210***	-0.3087***	-1.7549***	-0.2243	0.5095	-0.0600	1.0330**
	(0.1768)	(0.3196)	(0.0276)	(0.1908)	(0.5735)	(0.2815)	(0.0982)	(0.2459)	(0.1548)	(0.4007)	(0.0284)	(0.1880)	(0.4666)	(0.4278)	(0.1072)	(0.4525)
Years of Education	0.0749***	0.1512***	0.0889***	0.2077***	0.4812***	-0.1507**	0.1570***	0.7286***	0.0741***	0.1384***	0.0800***	0.1261***	0.3538***	-0.1944**	0.1020***	0.0529
	(0.0069)	(0.0141)	(0.0036)	(0.0181)	(0.0489)	(0.0719)	(0.0086)	(0.0952)	(0.0065)	(0.0114)	(0.0036)	(0.0192)	(0.0470)	(0.0842)	(0.0083)	(0.1402)
Experience	0.1329***	0.4188***	0.0608***	0.0922***	0.2740***	0.0536**	0.0739***	0.1519***	0.0767***	0.3873***	0.0392***	0.0729***	0.0915**	0.0803***	0.0298***	0.0860
	(0.0107)	(0.0161)	(0.0025)	(0.0076)	(0.0421)	(0.0237)	(0.0102)	(0.0342)	(0.0081)	(0.0225)	(0.0024)	(0.0071)	(0.0405)	(0.0300)	(0.0073)	(0.0533)
Experience^2	-0.0016***	-0.0031***	-0.0007***	-0.0009***	-0.0028***	0.0000	-0.0006***	-0.0020***	-0.0010***	-0.0026***	-0.0004***	-0.0008***	-0.0005	0.0006*	-0.0002*	-0.0034***
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0006)	(0.0003)	(0.0001)	(0.0006)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0007)	(0.0004)	(0.0001)	(0.0008)
_m5	-0.5417***				-0.5395				-0.3872***				-0.0139			
	(0.0853)				(0.5988)				(0.0931)				(0.5466)			
_m4		3.7552***				3.4857**				4.5206***				7.6392***		
		(0.4292)				(1.4086)				(0.5762)				(1.9152)		
_m3			-0.5008***				-0.3837***				-0.3090***				-0.4358***	
			(0.0639)				(0.1180)				(0.0673)				(0.1302)	
_m1				0.4779***				1.2754**				0.0094				-2.3189**
				(0.1239)				(0.5675)				(0.1490)				(1.0460)
Constant	11.5930***	-2.8360***	12.4578***	9.4565***	1.3766	-2.1209**	10.6198***	0.1458	12.5350***	-2.6447**	12.6763***	11.3442***	5.3630***	-6.3351***	11.8446***	14.3876***
	(0.2644)	(0.8268)	(0.0445)	(0.4295)	(1.1040)	(0.9048)	(0.2167)	(2.0729)	(0.2356)	(1.2235)	(0.0436)	(0.4899)	(0.8746)	(1.5991)	(0.1905)	(3.6239)
Observations	14,900	13,407	28,862	8,750	1,426	3,251	2,098	1,693	13,109	11,715	28,852	7,926	1,471	2,353	2,198	1,485
R-squared	0.2066	0.5851	0.1228	0.2715	0.1803	0.3504	0.2180	0.4721	0.1116	0.4862	0.1209	0.2314	0.1318	0.3744	0.1349	0.4103

Source: Research finding, using household survey data 2011, 2016. / Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix 6. Wage Regression Results- Formal vs Informal- Disaggregated by Gender

	2001				2006				2011				2016			
	Male		Female		Male		Female		Male		Female		Male		Female	
VARIABLES	informal	formal	informal	formal	informal	formal	informal	formal	informal	formal	informal	formal	informal	formal	informal	formal
Marital																
Widow/er	-0.8389**	-0.4507**	5.8297***	-0.2611	-0.6453*	-0.1420	7.7192***	3.0648***	-0.3532	0.0093	6.5445***	1.7247***	0.8417**	-0.3012	4.8134***	0.8759***
	(0.3945)	(0.2135)	(0.3971)	(0.2396)	(0.3844)	(0.1159)	(0.4912)	(0.3575)	(0.3216)	(0.0781)	(0.4569)	(0.2586)	(0.3569)	(0.2416)	(0.5258)	(0.1719)
Divorced	-2.0678***	-1.0590**	3.7595***	-0.0123	-1.7850*	-0.3799**	2.8459**	0.6278	-0.0150	-0.3107**	2.2309***	1.0767***	0.3647	-0.2647**	2.2495**	0.4098***
	(0.6911)	(0.4526)	(1.1356)	(0.1137)	(1.0438)	(0.1794)	(1.2391)	(0.8776)	(0.7551)	(0.1558)	(0.8578)	(0.1686)	(0.4597)	(0.1110)	(0.9050)	(0.1258)
Single	-4.4661***	-0.5882***	-1.4304***	-0.1835**	-4.5660***	-0.7083***	-2.0686***	0.1830	-2.6913***	-0.5208***	-1.4791***	0.4546***	-2.4915***	-0.4939***	-1.4126**	0.0373
	(0.2114)	(0.0406)	(0.3753)	(0.0717)	(0.2591)	(0.0541)	(0.5044)	(0.2414)	(0.2340)	(0.0439)	(0.4221)	(0.1040)	(0.2002)	(0.0424)	(0.6566)	(0.0771)
Years of Education	0.1272***	0.0805***	-0.5078***	0.1272***	0.1908***	0.0973***	-0.2468***	0.5529***	0.1223***	0.0763***	-0.0803	0.3356***	0.1138***	0.0742***	-0.1656*	0.1843***
	(0.0122)	(0.0028)	(0.0920)	(0.0214)	(0.0130)	(0.0030)	(0.0730)	(0.0435)	(0.0109)	(0.0022)	(0.0739)	(0.0311)	(0.0098)	(0.0021)	(0.0978)	(0.0181)
Experience	0.3129***	0.0882***	-0.1090***	0.0700***	0.3702***	0.0893***	0.1142***	0.1053***	0.3275***	0.0794***	0.1691***	0.0973***	0.2076***	0.0593***	0.0832**	0.0654***
	(0.0118)	(0.0039)	(0.0394)	(0.0106)	(0.0124)	(0.0046)	(0.0427)	(0.0267)	(0.0114)	(0.0026)	(0.0410)	(0.0131)	(0.0101)	(0.0030)	(0.0418)	(0.0109)
Experience^2	-0.0021***	-0.0009***	0.0012**	-0.0007***	-0.0030***	-0.0011***	-0.0018***	-0.0015***	-0.0025***	-0.0010***	-0.0019***	-0.0017***	-0.0014***	-0.0006***	-0.0010**	-0.0011***
	(0.0001)	(0.0001)	(0.0005)	(0.0002)	(0.0001)	(0.0001)	(0.0005)	(0.0006)	(0.0001)	(0.0000)	(0.0005)	(0.0003)	(0.0001)	(0.0000)	(0.0005)	(0.0003)
_m0	7.8398***		10.2289***		6.9997***		11.3864***		6.8746***		8.9979***		5.3938***		9.7773***	
	(0.2653)		(0.8771)		(0.2503)		(0.6309)		(0.2362)		(0.6087)		(0.2406)		(0.8833)	
_m1		-1.4238***		-0.6421***		-0.1940***		3.2137***		-0.6801***		1.5738***		-0.9947***		0.2359
		(0.0783)		(0.1966)		(0.0662)		(0.3577)		(0.0679)		(0.2950)		(0.0664)		(0.2212)
Constant	-0.8834***	12.5217***	3.2851***	11.1619***	1.4669***	14.7289***	-0.7597	6.3042***	-1.0088***	12.3295***	-3.4104***	7.0955***	2.7869***	12.7404***	-0.3378	10.0305***
	(0.3378)	(0.0925)	(0.6817)	(0.4674)	(0.3594)	(0.0897)	(0.8884)	(0.8038)	(0.3745)	(0.0648)	(0.8794)	(0.5681)	(0.3640)	(0.0621)	(1.0465)	(0.4052)

Source: Research finding, using household survey data, 2001, 2006, 2011, 2016- Bootstrapped standard errors
Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0$

Appendix 6. Oaxaca Decomposition-pooled sample_ Male

	2001			2006			2011			2016		
VARIABLES	**overall**	**explained**	**unexplained**	**overall**	**explained**	**unexplained**	**overall**	**explained**	**unexplained**	**overall**	**explained**	**unexplained**
Marital												
Widower		-0.0012	0.0019		-0.0011*	-0.0004		-0.0002	-0.0001		-0.0004	0.0022*
		(0.0007)	(0.0013)		(0.0006)	(0.0010)		(0.0004)	(0.0011)		(0.0006)	(0.0011)
Divorced		0.0013	0.0010		0.0002	-0.0041		-0.0008	-0.0033		-0.0006	-0.0004
		(0.0008)	(0.0014)		(0.0007)	(0.0030)		(0.0007)	(0.0030)		(0.0005)	(0.0025)
Single		0.1675***	-0.7638***		0.1742***	-0.7723***		0.0985***	-0.4341***		0.0785***	-0.2887***
		(0.0100)	(0.0296)		(0.0113)	(0.0387)		(0.0073)	(0.0274)		(0.0058)	(0.0214)
Years of Education		-0.3310***	0.9651***		-0.2682***	1.2568***		-0.1908***	0.7768***		-0.1800***	0.6381***
		(0.0104)	(0.0452)		(0.0106)	(0.0666)		(0.0077)	(0.0530)		(0.0075)	(0.0626)
Experience		1.5803***	5.0477***		1.3744***	5.4216***		0.9891***	4.1917***		0.5940***	2.0885***
		(0.0475)	(0.2330)		(0.0487)	(0.2733)		(0.0352)	(0.2436)		(0.0259)	(0.1987)
Experience^2		-1.0850***	-1.8202***		-0.9031***	-1.9067***		-0.6955***	-1.4686***		-0.4124***	-0.6966***
		(0.0366)	(0.1027)		(0.0357)	(0.1160)		(0.0271)	(0.1052)		(0.0200)	(0.0872)
Informal	11.7106***			15.0380***			12.6415***			13.2588***		
	(0.0304)			(0.0387)			(0.0303)			(0.0252)		
Formal	13.2676***			16.4052***			13.5887***			13.7535***		
	(0.0112)			(0.0161)			(0.0106)			(0.0091)		
difference	-1.5570***			-1.3672***			-0.9472***			-0.4947***		
	(0.0324)			(0.0419)			(0.0321)			(0.0268)		
explained	0.3319***			0.3763***			0.2003***			0.0791***		
	(0.0190)			(0.0205)			(0.0143)			(0.0106)		
unexplained	-1.8890***			-1.7436***			-1.1475***			-0.5737***		
	(0.0331)			(0.0421)			(0.0328)			(0.0277)		
Constant			-5.3208***			-5.7384***			-4.2100***			-2.3168***
			(0.1908)			(0.2310)			(0.1914)			(0.1674)
Observations	58,291	58,291	58,291	62,603	62,603	62,603	65,919	65,919	65,919	61,602	61,602	61,602

Source: Research finding, using household survey data, 2001, 2006, 2011, 2016.
Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

Appendix 7. Oaxaca Decomposition-pooled Sample Female

	2001			**2006**			**2011**			**2016**		
VARIABLES	**overall**	**explained**	**unexplained**	**overall**	**explained**	**unexplained**	**overall**	**explained**	**unexplained**	**overall**	**explained**	**unexplained**
Marital												
Widower		0.1159***	0.5714***		0.0557	0.4370***		0.2178***	0.4694***		0.1358***	0.3982***
		(0.0333)	(0.0365)		(0.0401)	(0.0356)		(0.0452)	(0.0400)		(0.0325)	(0.0357)
Divorced		-0.0330***	0.1012***		-0.0254**	0.0937***		-0.0914***	0.1659***		-0.0551**	0.2666***
		(0.0110)	(0.0163)		(0.0126)	(0.0220)		(0.0188)	(0.0225)		(0.0219)	(0.0340)
Single		0.0248**	-0.1138		0.0362	-0.0526		-0.0506*	-0.0749		-0.0447*	0.0709
		(0.0110)	(0.0787)		(0.0257)	(0.1083)		(0.0264)	(0.0822)		(0.0247)	(0.0890)
Years of Education		-1.8699***	1.4948***		-3.0810***	3.3293***		-2.8005***	3.2640***		-2.3399***	4.2160***
		(0.0875)	(0.1779)		(0.1331)	(0.2816)		(0.1274)	(0.2548)		(0.1283)	(0.2893)
Experience		0.8817***	1.8604***		1.5300***	6.3182***		1.4838***	4.4814***		0.7946***	0.8050
		(0.1252)	(0.5904)		(0.1774)	(0.9333)		(0.1820)	(0.8192)		(0.1447)	(0.8125)
Experience^2		-0.6895***	-0.9645***		-1.0351***	-2.1289***		-0.9859***	-1.1947***		-0.5222***	0.2921
		(0.1081)	(0.2488)		(0.1385)	(0.4660)		(0.1626)	(0.4053)		(0.1406)	(0.3932)
Informal	4.8346***			5.5995***			5.1075***			7.4962***		
	(0.0883)			(0.1204)			(0.1294)			(0.1734)		
Formal	12.8047***			15.1004***			12.9357***			13.3933***		
	(0.0341)			(0.0874)			(0.0560)			(0.0382)		
difference	-7.9701***			-9.5009***			-7.8282***			-5.8971***		
	(0.0946)			(0.1488)			(0.1410)			(0.1776)		
explained	-1.5701***			-2.5197***			-2.2268***			-2.0315***		
	(0.0817)			(0.1166)			(0.1154)			(0.1128)		
unexplained	-6.4000***			-6.9812***			-5.6014***			-3.8656***		
	(0.1188)			(0.1883)			(0.1773)			(0.1686)		
Constant			-9.3495***			-14.9780***			-12.7125***			-9.9143***
			(0.5093)			(0.7710)			(0.6452)			(0.7023)
Observations	9,406	9,406	9,406	10,544	10,544	10,544	8,468	8,468	8,468	7,507	7,507	7,507

Source: Research finding, using household survey data, 2001, 2006, 2011, 2016.
Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1