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Abstract

In the current study, we endeavor to bring a new evidence to the existing literature about the inequality in the Jordanian labor market. Using a nationally representative data set extracted from the Jordanian Labor Market Panel Survey (JLMPS) for the two years 2010 and 2016, we apply both Oaxaca-Blinder decomposition approach and the RIF-based decomposition to provide a detailed examination of the structure and dynamics of the wage inequality between native and non-native workers along the wage distribution in Jordan, and to reveal which part of the wage differentials between the two groups may be explained by differences in productive characteristics (composition effects) and which part may results from differences in returns to such characteristics (discrimination effects). We find an increasing in the average wage gap between the two groups over time, and an intensification of the discrimination against non-natives in Jordan labor market over time. This discrimination increases with the quantiles of the wage distribution in both 2010 and 2016 except for the 90th quantile. The wage differentials are larger in the bottom and median parts of the wage distributions for both 2010 and 2016. The compositional differences in the education attainment between natives and non-natives explain significantly the wage gap only in 2010 but not in 2016. The main drivers of the unexplained component (discrimination effect) of the total wage gap between natives and non-natives appears to stem from the education covariate in both 2010 and 2016.

JEL Classification: E24, J31, J71, O15
Keywords: Wage differentials; non-natives; Oaxaca-Blinder decomposition; Unconditional Quantile Decomposition; Jordan.

1. Introduction

Many of the previous Literature show that both the earnings and the human capital are generally lower for non-native as compared to the native-born (Baker and Benjamin, 1994; Shields and

Wheatly-Price, 1998; Friedberg, 2000;Chiswick and Miller, 2008). This is often justified by the low skills and the imperfect portability of the immigrants' human capital (Sanroma et al., 2015). Empirical research has investigated, for different developed and developing countries, the non-natives/natives pay gap (Friedberg, 2000; Chiswick and Miller, 2008; Accetturo and Infante, 2010 and Dell'Aringa et al. 2015). Most of these studies found a lack of assimilation for non-natives' compared with natives and low return to education over time (Accetturo and Infante, 2010), lower earnings for immigrants as compared to the native-born citizens (Friedberg, 2000; Chiswick and Miller, 2008), and that the human capital characteristics didn't improve the accessibility of immigrants for higher return occupations (Dell'Aringa et al., 2015).

In the last few years, the subject of inequality has shed increasing attention in the Arab countries; The high unemployment and the persistence of deep economic inequality were important factors contributing to the uprisings that have struck many Arab countries since 2011 (Makdisi, 2017). Assaad et al. (2014) investigated the gender gap in labor force participation in Jordan using data from the 2010 Jordanian Labor Market Panel Survey (JLMPS), finding a stagnant female labor force participation, which paradoxically contradicts the rise in women education attainment in Jordan. Also, Wahba (2014) suggested that Jordan exports high skilled workers and imports low skilled labor, and most of the immigrant workers in Jordan are mainly employed in low skilled jobs in the informal sector with very little benefits or security. Said (2012) examined the dynamics of public–private and gender wage inequality in both Egypt and Jordan during the period 1989-2009 finding two distinct phases in Egypt: the first one experienced a wage erosion and narrowing pay differentials, while the second phase experienced a recovery of real wages and decompression of the wage structure.

Jordan didn't escape the consequences of the regional instability; conflicts in the neighboring countries (such as the forced exile of Palestinians after the creation of the State of Israel in 1948 and the occupation of West Bank in 1967, Lebanese civil war from 1975 to 1990, Iraqis wars since the early 1980s, and the Syrian conflict in 2011) have caused a large influx of refugees into Jordan. For example, Jordan has received more than 1.2 millions of Syrian refugees since the Syrian civil war in 2011 (Alshoubaki, W., & Harris, M. (2018). This has triggered serious economic and social repercussions in Jordan and constituted a substantial labor (supply) shock, which is expected to generate both employment and earnings differentials between the native and non-native populations.

Some studies have been developed in the last few years to understand the consequences of refugees and immigration on the Jordanian labor market (Wahba, 2014 and Fallah et al. 2019). To the best of our knowledge, this is the first study that try to understand the dynamic of wage inequality in Jordan between native and non-native workers and decompose the wage gap to reveal any discrimination against non-native workers. In an effort to better understand the impact of refugees on the Jordanian labor market over years, this study uses both Oaxaca–Blinder wage decomposition method (Oaxaca, 1973; Blinder, 1973), and the unconditional quantile regression decomposition approach elaborated by Fortin et al. (2011) to measure the dynamics and backgrounds of the wage inequality between native and non-native workers using the JLMPS carried out in 2010 and 2016. For this reason, we decompose the wage differentials between the two groups along the wage distribution into explained part which displays the differences in the human capital productive characteristics (called composition effect) between the two groups, and unexplained part which reflects any differences in returns to such characteristics (discrimination effect).

The rest of this paper is organized as follows. In the subsequent section we present the data used and a summary of descriptive statistics related to Jordan's labor market. section 3 describe the empirical specification of the study. The empirical results are discussed in section 4, and then we conclude in section 5.

2. Data and descriptive statistics

2.1. Data

We use data drawn from the 2010 and 2016 waves of the JLMPS, a nationally representative dataset with comprehensive information on workers' earning as well as a non-native identifier (i.e., individuals with non-Jordanian citizenship). The two JLMPS waves[1] were conducted through cooperation efforts between the economic research forum (ERF) in Egypt and the

[1]The JLMPSs are part of a series of labor market panel surveys carried out by the Economic Research Forum (ERF) in collaboration with local Statistical Institutes in several Arab countries since 1998.The micro data of these surveys are available for public use through the ERF's Open Access Micro data Initiative (OAMDI). Researchers can access freely these micro data through the ERF Data Portal (www.erfdataportal.com) after completing the required registration procedures. The data from some individual country surveys, such as the JLMPS and the ELPMS (Egypt Labor Market Surveys) can be obtained either as repeated cross section or as panel datasets.

Jordanian Department of Statistics (DoS), which allow for more in-depth analysis of the critical social and economic developments in Jordan (Krafft & Assaad, 2018).

The 2010 sample consisted of 5,102 households and 25,953 individuals distributed among urban and rural areas in the three regions of Jordan: North, Middle, and South. Also, the sample was stratified into 30 strata represented the 12 governorates of Jordan and distributed on five different location classifications: rural area, basic urban, large central city urban in Amman, Zarqa, and Irbid governorates, suburban Amman and Zarqa, and finally exurban Amman. The 2016 sample comes after the Arab spring and was more comprehensive; included large segment of non-Jordanians refugees who inflow to Jordan from Syria and Iraq. In the last two decades, the non-Jordanian individuals (refugees and non-native workers),have played a large and increasing role in the Jordanian labor market. The 2015 Jordanian Population Census of 2015 recorded 9.5 million individuals, amongst, 1.3 million Syrian,636,000 Egyptians as non-native workers, 634,000 non-nationalized Palestinians, and around 131,000 Iraqis and smaller numbers from numerous other countries (see Table 1 below). Therefore, the JLMPS 2016 sample included 3,000 households represented the above non-Jordanian groups. The sampling frame for the 2016 was the Jordan's 2015 Population and Housing Census which surveyed 1.9 million households and 9.5 million individuals as shown in table 1 below.

Table 1: Number of households and individuals in 2015 Census, by nationality

	Jordanian	Syrian	Egyptian	Other Arabs	Other Nationalities	Total
Households	1,412,157	243,972	96,640	159,534	29,600	1,941,903
Individuals	6,613,587	1,265,514	636,270	818,956	197,385	9,531,712

Source: Krafft & Assaad (2018) in Correspondence with DOS

Following some interesting literature in this field (Bishop, et al., 2005; Demurger et al., 2009),we restrict our attention, mainly in decomposition analysis, to individuals aged 15-60, dropped full-time homemakers, self-employed people, full-time students and retirees and only use individuals with positive wage information[2]. Also, any individuals with missing information on core variables summarized in Table8(see Appendix 2) will be excluded from the analysis. The final samples used in the decomposition analysis, which is the main part of the paper, included respectively 4760 and 4630 wage workers (natives and non-natives)in 2010 and 2016.

[2]One limitation of the wage gap decomposition analysis in this study is that we drop those observations with no earnings in 2010 and 2016. This may bias our results if the sample of workers is systematically different from those who are not employed.

2.2. Stylized facts

Table 2 below shows the descriptive statistics (means, standard deviations and normalized differences) for hourly wage, working hours and a group of individual characteristics classified by non-native status for the years 2010 and 2016. Hourly Wage is calculated by adding all forms of earnings received from the main primary and secondary Jobs in Jordan (e.g. all regular wages, bonuses and subsidies received).All wages are measured in 2017 JD by deflating the 2010 and 2016 wages with the Consumer Price Index (CPI) of the basic year 2017 (2017 = 100). Wages are also adjusted for regional variations using the Spatial Consumer Price Index information computed by the World Bank (2009) at the governorate-level.

Table 2 shows that the average wage for native workers in 2010 were higher than that for non-natives although non-native workers were higher educated than natives in regards with university and post-graduate degrees. The natives were found further to work more hours per week compared to their non-natives peers. Unlike 2010, average hourly wage for non-native workers in 2016were higher than that for native workers. Non-native workers in 2016 were better educated than natives, but worked less hours per week compared to non-native workers. In both 2010 and 2016, non-native workers were living in wealthier households compared to natives mainly at the upper end of the household wealth distribution.

Table 2: Summary statistics by group and year

	2010					**2016**				
	Non-natives		Natives		Normalized Difference	Non-natives		Natives		Normalized Difference
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Household wealth										
1st Quintile	0.16	0.37	0.65	0.48	-0.80	0.08	0.27	0.58	0.49	-0.89
2nd Quintile	0.19	0.39	0.09	0.29	0.20	0.15	0.35	0.25	0.43	-0.18
3rd Quintile	0.21	0.41	0.09	0.28	0.25	0.25	0.43	-0.09	0.28	0.32
4th Quintile	0.22	0.42	0.11	0.31	0.22	0.27	0.45	0.04	0.19	0.48
5th Quintile	0.22	0.41	0.07	0.25	0.31	0.26	0.44	0.05	0.22	0.42
Weekly hours	44.32	12.07	53.51	13.61	-0.50	43.33	19.45	48.68	29.31	-0.15
Hourly wage	3.15	6.60	3.62	21.08	-0.02	5.36	32.23	3.18	9.40	0.06
Log hourly wage	0.70	0.76	0.26	0.92	0.37	0.79	0.87	0.36	0.93	0.34
Age	32.83	9.46	31.31	9.75	0.11	33.48	9.38	34.18	9.54	-0.05
Male	0.80	0.40	0.93	0.25	-0.28	0.81	0.40	0.92	0.28	-0.23
Married	0.60	0.49	0.58	0.49	0.03	0.66	0.47	0.69	0.46	-0.05

Education										
Illiterate	0.02	0.13	0.11	0.31	-0.27	0.03	0.18	0.19	0.39	-0.36
Read & Write	0.13	0.33	0.23	0.42	-0.20	0.11	0.31	0.34	0.47	-0.42
Basic Education	0.33	0.47	0.17	0.38	0.27	0.34	0.47	0.17	0.37	0.29
Vocational	0.01	0.11	0.03	0.18	-0.11	0.01	0.09	0.03	0.17	-0.11
Secondary Educ	0.16	0.37	0.26	0.44	-0.17	0.15	0.36	0.11	0.32	0.08
Post-Secondary	0.12	0.33	0.09	0.29	0.06	0.10	0.29	0.08	0.27	0.03
University	0.20	0.40	0.08	0.28	0.24	0.23	0.42	0.08	0.27	0.31
Post-Graduate	0.03	0.18	0.02	0.14	0.06	0.04	0.19	0.01	0.07	0.15
Experience	6.70	6.05	8.66	7.02	0.21	9.95	7.88	8.29	8.27	0.15
Urban	0.72	0.45	0.80	0.40	0.13	0.69	0.46	0.78	0.41	0.14
Region										
Middle	0.49	0.50	0.67	0.47	-0.26	0.45	0.50	0.38	0.49	0.10
North	0.33	0.47	0.24	0.43	0.15	0.37	0.48	0.52	0.50	-0.22
South	0.18	0.38	0.09	0.29	0.18	0.18	0.39	0.10	0.30	0.17

Source: Authors' Calculations based on JLMPSs 2010 and 2016

Table 3 introduces the difference between native and non-native workers regarding their occupations, economic sector, job stability and governorate of residence for the years 2010 and 2016. It was found that 80% of the non-native wage earners worked in formal jobs in both 2010 and 2016, and more than half of them in government jobs and nearby 40% in private sector. In contrast,95% and 74% of the native wage workers worked in private sector in 2010 and 2016 respectively. Only 41% and 31% of native employees were employed in the formal sector in 2010 and 2016 respectively. The high percentage of both native and non-native workers were in service and sales occupations, however, the percentage of non-native workers in professional occupations were much higher than natives in both 2010 and 2016. As expected, the capital Amman encumbered by more than 20% of the total wage earners (natives and non-natives).

Table 3: Labor market characteristics by Migration status and year

	2010					2016				
	Natives		Non-Natives		Normalized Difference	Natives		Non-Natives		Normalized Difference
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Formal	0.80	0.40	0.41	0.49	0.61	0.80	0.40	0.31	0.46	0.80
Economic Sector										
Government	0.53	0.50	0.02	0.15	0.96	0.59	0.49	0.07	0.26	0.94
Public	0.02	0.14	0.00	0.06	0.11	0.01	0.09	0.02	0.13	-0.05
Private	0.44	0.50	0.95	0.22	-0.93	0.39	0.49	0.74	0.44	-0.54
Other	0.00	0.05	0.00	0.00	0.05	0.00	0.07	0.07	0.26	-0.25

International	0.01	0.09	0.02	0.15	-0.10	0.01	0.10	0.10	0.31	-0.29
Job Stability										
Permanent	0.93	0.25	0.92	0.28	0.04	0.88	0.33	0.60	0.49	0.47
Temporary	0.05	0.22	0.07	0.25	-0.04	0.06	0.23	0.18	0.38	-0.27
Seasonal	0.00	0.05	0.00	0.00	0.05	0.01	0.09	0.03	0.17	-0.11
Casual	0.01	0.11	0.02	0.13	-0.02	0.06	0.24	0.20	0.40	-0.30
Occupation										
Managers	0.01	0.12	0.00	0.06	0.08	0.01	0.08	0.00	0.00	0.08
Professionals	0.21	0.41	0.08	0.27	0.28	0.26	0.44	0.07	0.26	0.38
Technicians & Ass. Prof.	0.08	0.27	0.02	0.15	0.18	0.07	0.26	0.02	0.14	0.18
Clerical support workers	0.11	0.31	0.02	0.14	0.25	0.07	0.26	0.03	0.17	0.14
Service and Sales workers	0.28	0.45	0.26	0.44	0.03	0.29	0.45	0.28	0.45	0.02
Skilled Agri., for. and fish	0.01	0.11	0.05	0.22	-0.15	0.02	0.13	0.11	0.32	-0.28
Craft and related trades wor.	0.13	0.34	0.31	0.46	-0.31	0.11	0.32	0.27	0.45	-0.30
Plant and machine oper. and ass.	0.09	0.29	0.07	0.26	0.05	0.09	0.29	0.07	0.25	0.07
Elementary occupations	0.08	0.26	0.18	0.39	-0.23	0.07	0.26	0.15	0.36	-0.17
Governorate										
Amman	0.23	0.42	0.44	0.50	-0.32	0.21	0.40	0.19	0.39	0.02
Balqa	0.08	0.28	0.05	0.22	0.09	0.08	0.27	0.07	0.26	0.02
Zarqa	0.14	0.34	0.17	0.38	-0.07	0.13	0.33	0.10	0.30	0.06
Madaba	0.04	0.20	0.01	0.10	0.13	0.04	0.19	0.02	0.13	0.09
Irbid	0.17	0.37	0.07	0.25	0.22	0.16	0.37	0.11	0.31	0.12
Mafraq	0.08	0.26	0.06	0.24	0.05	0.10	0.30	0.19	0.39	-0.18
Jarash	0.05	0.22	0.09	0.29	-0.11	0.07	0.25	0.23	0.42	-0.33
Ajloun	0.04	0.19	0.02	0.13	0.09	0.04	0.20	0.00	0.00	0.20
Karak	0.08	0.27	0.03	0.16	0.16	0.08	0.27	0.01	0.10	0.24
Tafileh	0.03	0.18	0.01	0.18	0.09	0.03	0.00	0.00	0.18	0.19
Ma'an	0.04	0.19	0.03	0.19	0.04	0.04	0.15	0.02	0.19	0.07
Aqaba	0.03	0.16	0.02	0.16	0.03	0.03	0.25	0.07	0.17	-0.12

Source: Authors' Calculations based on JLMPSs 2010 and 2016

Table 4 describes the distribution of wage gap between native and non-native workers based on economic sector, job stability, occupation, and governorate. Natives employed in the public sector were found to earn higher average wage than non-native workers for both 2010 and 2016. Non-natives who worked in permanent jobs in 2010 earned more than native workers peers, but the figures were reversed in 2016,such as native permanent workers are found to earn more. Wage gap between non-natives and natives in 2010, was the highest for workers in professional occupations, with six times average wage for non-natives compared to native workers. However, in 2016, professional native workers were found to earn more than their migrant workers. In clerical jobs, native workers earned more average wage than non-natives for both 2010 and 2016.Non-native workers Living in principal governorates like Amman and Irbid earned more, on average, than non-native in 2010. However, figures were completely reversed in 2016.

Table 4: Descriptive average Natives/Non-natives earners wage gap.

	2010						**2016**					
	Native earners (G)		Non-Natives earners ($\bar{G}$)		G-($\bar{G}$)	($\bar{G}$)/G (%)	Native earners (G)		Non-Natives earners ($\bar{G}$)		G-($\bar{G}$)	($\bar{G}$)/G (%)
	N	Mean	N	Mean			N	Mean	N	Mean		
Economic Sector												
Government	2398	2.97	7	2.17	0.80	73.01	2722	4.31	39	6.71	-2.40	155.62
Public	93	5.99	1	1.17	4.82	19.53	37	6.28	9	2.02	4.27	32.13
Private	2025	3.11	273	3.69	-0.58	118.60	1778	6.88	406	3.23	3.65	46.92
Other	11	2.64	0	.	.	.	21	2.71	39	1.36	1.35	50.26
International	34	10.67	7	2.69	7.99	25.16	46	9.53	57	1.87	7.66	19.66
Job Stability												
Permanent	4252	3.13	264	3.80	-0.67	121.37	4031	4.66	329	3.38	1.28	72.51
Temporary	237	3.43	19	1.59	1.84	46.31	263	2.11	97	2.19	-0.08	103.99
Seasonal	12	2.68	0	.	.	.	38	2.15	16	2.69	-0.54	125.01
Casual	60	3.98	5	2.21	1.77	55.42	272	19.32	108	3.54	15.78	18.32
Occupation												
Managers	64	4.99	1	2.81	2.17	56.42	30	3.95	0	.	.	.
Professionals	962	4.08	22	23.34	-19.25	571.63	1186	6.70	38	5.42	1.28	80.90
Technicians & Ass. Prof.	361	3.77	7	2.68	1.09	70.97	340	4.28	11	2.40	1.89	55.98
Clerical support workers	482	3.14	6	0.80	2.34	25.49	340	5.05	17	1.47	3.58	29.15
Service and Sales workers	1278	2.68	76	2.64	0.04	98.44	1317	4.46	150	4.10	0.36	91.95
Skilled Agri., for. and fish	53	2.11	14	0.89	1.22	42.05	79	1.80	62	2.10	-0.29	116.28
Craft and related trades wor.	588	2.47	88	1.61	0.85	65.44	511	5.73	149	2.64	3.08	46.13
Plant and machine oper. and ass.	427	2.98	21	4.26	-1.28	142.91	416	7.75	36	4.34	3.40	56.08
Elementary occupations	346	2.89	53	1.12	1.78	38.62	335	3.50	81	2.36	1.14	67.44
Governorate												
Amman	1049	3.55	126	5.70	-2.15	160.62	945	8.80	106	5.90	2.89	67.13
Balqa	382	3.14	15	1.32	1.82	42.07	356	6.32	39	2.76	3.56	43.68
Zarqa	617	2.60	49	1.89	0.71	72.62	584	6.83	54	1.75	5.08	25.66
Madaba	183	2.69	3	1.52	1.17	56.50	179	11.05	10	10.75	0.30	97.33
Irbid	765	2.86	20	4.37	-1.51	152.68	751	4.64	58	2.60	2.04	56.10
Mafraq	343	2.80	17	1.42	1.38	50.78	450	2.45	102	1.34	1.10	54.89

Jarash	237	3.14	27	1.83	1.31	58.34	305	2.61	126	3.41	-0.80	130.59
Ajloun	174	3.79	5	1.99	1.80	52.41	184	3.13	0	.	.	.
Karak	359	3.85	8	0.89	2.96	23.15	367	2.54	6	1.33	1.21	52.18
Tafileh	153	3.29	4	1.43	1.86	43.58	161	2.63	0	.	.	43.58
Ma'an	173	2.80	8	1.53	1.27	54.70	178	2.79	12	2.21	0.58	54.70
Aqaba	126	3.48	6	1.95	1.53	56.13	144	2.45	37	1.68	0.76	56.13

Source: Authors' Calculations based on JLMPSs 2010 and 2016

Graphically, kernel density in figure 1 estimates the logarithmic hourly wages for both native and non-native workers. There were contrasted wage distributions between them in both 2010 and 2016. Also, the p-value (0.000) for the two-sample Kolmogorov-Smirnov test was less than the level of significance (0.05), so we reject the null hypothesis that the logarithmic hourly wages for the two groups came from the same distribution. Figure 2 displays the wage differentials between native and non-native workers at each quantile of the wage distribution. In 2010, the wage gap for native workers expanded until the 50th quantile, diminished until the90th quantile of wage distribution, then it was reversed for non-native workers at the top of wage distribution. The wage gap between the two groups remained relatively low throughout the wage distribution in 2016.

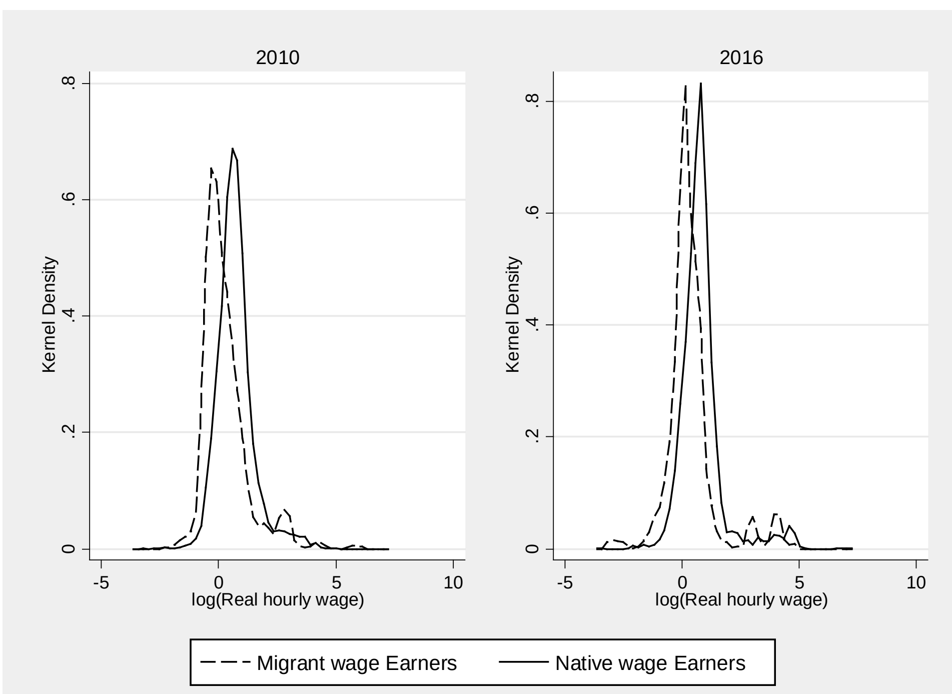

Figure 1. Kernel density estimates of log wage distributions in 2010 and 2016.

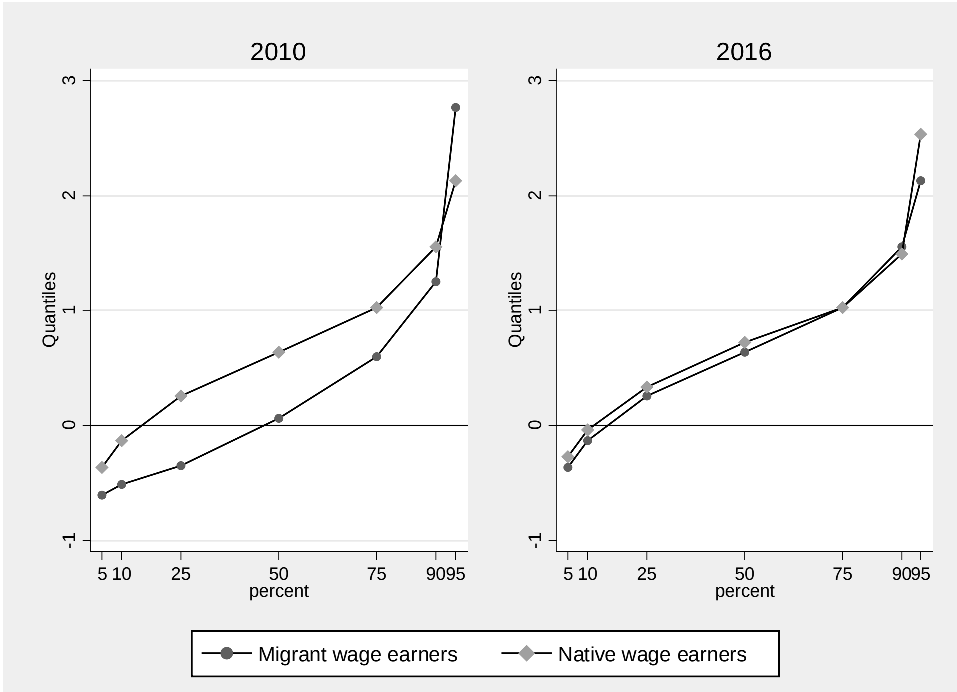

Figure 2.Raw log hourly wage gaps between non-native and natives workers by quantile in 2010/2016.
Note: Authors' Calculations based on JLMPSs 2010 and 2016.

3. Empirical Methodology

We apply the well-known Mincer's (1974) human capital wage equation on a pooled cross-section data constructed independently from the two random sample surveys of the same population for the two periods 2010 and 2016. Human capital theory provides a more flexible approach to examine the earnings differentials between two groups (Mincer, 1958, 1974; Becker, 1964). The basic assumption is that the wage rate should reflect the potential of worker productivity, which also based on different human capital characteristics. Using pooled cross-sectional data gives more precise estimates, because of the increased sample size, and has only minor statistical complications (Wooldridge, 2003). In this regard, we use a year dummy variable in order to consider the differences in the population distribution between the two different time periods and to allow for aggregate changes over time. The log of real hourly wage is used as the dependent variable, while the covariate matrix included the basic variables of Mincer equation: education and experience, in addition to squared experience, gender, occupation and job sector dummies; migration dummy which distinguishes workers on the basis of non-native status (non-native vs. native workers); urban and region dummies. We add an interaction variable between the year and non-native dummies to test if the wage differentials between non-native and native workers will vary between 2010 and 2016 (See appendix 1 for the detailed wage equation and appendix 2 for the definition of variables).

According to the standard Oaxaca–Blinder wage decomposition method (Oaxaca, 1973; Blinder, 1973), any wage gap between two groups of workers can be decomposed into an explained and unexplained parts. The explained part displays the differences in the human capital productive characteristics (called composition effect) between the two groups, while the unexplained part reflects any differences in returns to such characteristics (discrimination effect).

Oaxaca-Blinder decomposition approach has been criticized in two main points. First, the dissymmetry in wage discrimination refer to which group (i.e. male or female) is the reference group. The second point is concerned with the inclusion of only wage decomposition at the mean and ignorance of wage differentials over the wage distribution. To deal with the shortcomings of Oaxaca–Blinder decomposition method, Dinardo et al. (1996) proposed a reweighting procedure; Machado and Mata (2005) introduced a quantile-based decomposition approach; while Firpo et al. (2009) suggested the unconditional quantile regression-based decomposition approach which then elaborated by Fortin et al. (2011).

In this study, we attempt to analyze the determinants of wage differentials between native and non-native workers in Jordan using a mixed approach of the regression-compatible procedure by Fortin (2008) and the unconditional quantile regression-based decomposition approach developed by Firpo et al. (2009) using the two JLMPSs 2010 and 2016.We apply the regression-compatible procedure in order to decompose the gap in the mean wage among each group, then we combine it with the unconditional quantile regression to decompose each wage differentials at different quantiles. This mixed approach is also used to decompose the composition effect and the wage structure effect (discrimination effect) into the contribution of each covariate.

In details, we use the following estimation wage equation using log-linear formula:

$$\ln Y^J = X^J \beta^J + \varepsilon^J ; \; J = (Native, non\ native) \tag{1}$$

Where $\ln Y^J$ is the real logarithmic hourly wage, X^J is the vector of the set of the Mincerian explanatory variables augmented with job attributes and labor market and regional characteristics (see appendix 1 for more detailed information about the explanatory variables), and ε is assumed as an i.i.d. idiosyncratic error term with mean zero and constant variance σ_ε^2.

The self-selected of wage earners from a large population can sometimes create differences between the true and the observed wage differentials for native and non-native workers. The ignorance of this selectivity bias may create an overestimation of the discrimination (Reimers, 1983; Kee, 1995; de Coulon, 2001). To overcome this bias; at least in the ordinary least square (OLS) regression analysis, the two-step Heckman selection model will be used (Heckman, 1979). It is worth to mention that we will follow Bishop et al. (2005) and Chi and Li (2008) who didn't not deal with the selectivity bias in the quantile regression and wage gap decomposition analysis. Although Albrecht et al. (2009) developed a new technique to address this issue but it remains computationally intensive and has many complexities.

Thus, the Heckman correction term λ (or the inverse of Mill's ratio) will be included in the wage equation as follows:

$$\ln Y^J = X^J \beta^J + \lambda^J \beta_\lambda^J + \varepsilon^J \qquad (2)$$

The sign of the Heckman's correction term (λ) determines whether the observed wage for each group of workers is above or below the offered wage if self-employed workers, unemployed or out of work force individuals were wage earners (Michael and Stelios, 2012). A negative λmeans thatthe offered wage is greater than the observed wage.

The aforementioned unconditional quantile regression is also used to investigate the wage differentials between native and non-native workers along the wage distribution. It consists of two phases. In the first phase, we estimate the RIF by replacing all unknown quantities (Q_θ) by their observable counterparts (θ^{th}) and deriving the density of Y at that point by Kernel method. In the second phase, we regress the estimated RIF on X using the OLS regression analysis for each group (natives and non-natives) separately:

$$\mathrm{E}(\mathrm{RIF}\ (Y, Q_\theta)|X) = X\beta_\theta \qquad (3)$$

X represents the set of covariates. Since the RIF (Y, Q_θ) couldn't be observed in practice, we replace all unknown components with their sample estimators in our empirical application as follows:

$$\mathrm{RIF}\ (Y, Q_\theta) = Q_\theta + {}^{(\theta - I\{Y \leq Q_\theta\})}\Big/_{f_Y(Q_\theta)} \qquad (4)$$

where f_Y is the marginal density function of Y and I is an indicator function.

A counterfactual distribution will be used (see Machado and Mata, 2005; Grandner and Gstach, 2014) to extend the Oaxaca-Blinder decomposition of mean wage differentials to the full distribution. The idea is to estimate conditional quantile regressions for each group (natives and non-natives) and extracting counterfactual distributions that would result if non-natives would achieve similar return on their productivity-relevant characteristics as natives. Then we compare the conditional quantile regressions for each group with the counterfactual distribution in order to find the main contributors for each part of the wage gap: the explained part attributes to the workers features differentials (*composition effects*), and the part explained by differences in returns to those features (*discrimination effects*).

After estimating the model in Eq (2) for different quantiles of the population (the 10th lowest quantile, the median and the highest quantile 90th), we use the unconditional quantile regression to decompose the wage gap between native and non-native workers into a component refers to the differences in the distribution of characteristics (productivity effect) and a component refers to the differences in the distribution of returns (discrimination effect) as follows:

$$\widehat{Q_\theta^i} - \widehat{Q_\theta^j} = \left\{\widehat{Q_\theta^i} - \widehat{Q_\theta^*}\right\} + \left\{\widehat{Q_\theta^*} - \widehat{Q_\theta^j}\right\} = (\overline{X^i} - \overline{X^j})\widehat{\beta_\theta^{\mathrm{i}}} + \overline{X^j}(\widehat{\beta_\theta^{\mathrm{i}}} - \widehat{\beta_\theta^{\mathrm{j}}}) \qquad (5)$$

where$\widehat{Q_\theta}$ is the unconditional quantile of *log*real hourly wage, $\bar{X}$ is the vector of covariate averages, and $\widehat{\beta_\theta}$ represents the estimate of the unconditional quantile partial effect. Superscripts i, j, and * are the natives, non-natives and counterfactual values. The first term on the right-hand side of Eq. 4, $\left\{\widehat{Q_\theta^i} - \widehat{Q_\theta^*}\right\}$, is the composition effect, which denotes the contribution of the differences in distributions of workers features to inequality at the θ^{th} unconditional quantile. The second term of the right-hand side of the equation, $\left\{\widehat{Q_\theta^*} - \widehat{Q_\theta^j}\right\}$, is the discrimination effect, which denotes the unexplained part of inequality due to wage differences (wage discrimination) in returns to the workers' characteristics at the θ^{th} unconditional quantile. The set of regressors collects different groups of variables like human capital, demographics, and occupational variables.

The unconditional quantile decomposition of wage gap will be followed by further decomposition to show how the individual-specific household characteristics contributes to each part of wage differentials (explained and unexplained parts) as follows:

$$\widehat{Q_\theta^i} - \widehat{Q_\theta^*} = \sum_k (\overline{X^i}_k - \overline{X^j}_k)\widehat{\beta_{\theta,k}^i} \quad (6a)$$

and

$$\widehat{Q_\theta^*} - \widehat{Q_\theta^j} = \sum_k \overline{X^j}_k (\widehat{\beta_{\theta,k}^i} - \widehat{\beta_{\theta,k}^j}) \quad (6b)$$

for*k: 1...K* the total number of covariates

It is important to note that when we have a categorical covariate, then the decomposition results is determined by the choice of omitted category (left-out category). In other words, the changing of the left-out category will change the decomposition result for the dummy or categorical covariate and the contribution of this covariate to the wage structure (Oaxaca & Ransom, 1994, Fortin, 2008; Jann, 2008). To deal with this identification problem we normalize the contribution of the categorical covariate to wage structure effect (Yun, 2005). However, Fortin et al. (2010) think that there is no definitive solution to this specification problem, which means that the wage structure results still arbitrary for the categorical covariate in the decomposition methods.

4. EmpiricalResults

As argued earlier, we start our analysis by the OLS estimation of the Mincerian earning function using Heckman correction for selection bias. Then we discuss the results of decomposition method based on RIF-OLS regressions.

4.1. OLS estimation results

Table 5compares between the pooled OLS estimates which does not correct for the selection problem (Model I) and the selectivity corrected pooled OLS estimates using the Heckman two-step procedure (Model II). Results show that controlling for selection bias change considerably the magnitude of the estimation coefficients. Some coefficients are underestimated and others overestimated. Given the significant Mill's ratio in Model II, we rely on it to estimate the Mincerian earning function.

As expected, Model II shows that the estimated coefficient of the human capital variables (experience, experience squared and schooling) are all significant and have the expected signs.

For example, one year of schooling increase the wage by 0.0269 log points. The negative sign for the squared experience coefficient exhibits the widespread inverted U-shape relationship between hourly wages and experience. The positive coefficient for the year dummy indicates an increase in the base wage rate in the year 2016 compared with2010. On average, native workers earn significantly 0.792 higher hourly log wage than non-native workers, but no significant variation in the wage differentials depicted by the considered OLS corrected model between the two years. The log gender wage gap between male and female 0.168. This finding is consistent with the existing studies on gender wage differentials in neighboring countries (Galal and Said, 2018; Assaad, et al, 2014, Ilkkaracan and Selim,2007). Workers in urban regions are found to earn 0.0424 log hourly higher wages than their counterparts in rural regions. Also, workers living in the North regions of Jordan earn 0.052 hourly log wage less hourly wage than workers in South. However, no significant differences is wage was found between the central and south regions of Jordan.

Albrecht et al. (2003) point out that occupation and sector of employment dummies are important determinants of wage differentials, which is also consistent with the results in Table 5. Compared with the elementary occupations, managers and professionals are amongst the occupations with most reward in terms of wages. It's well known that these two occupations relatively require more skills and competences, so the substitution cost of workers in these jobs is higher than that for other types of occupations such as service workers. For example, manager workers earn 0.567 more hourly log wage than workers employed in elementary occupations, professionals and technicians are found to earn 0.456 and 0.22 more hourly log wage than workers in elementary occupations respectively. In terms of wage variation across the economic sector, results in Table 5 (model II) display that workers are penalized heavily when working in private firms in comparison with international firms (offshore), while the wage earning in the government sector is found to be higher than that in the private firms.

Table 5: OLS estimation results Vs Heckman two-stage analysis

	Pooled OLS without Selection correction (Model I)	Pooled Heckman two-stage result (Model II)		
VARIABLES	*log(w)*	*log(w)*	Labor Force Participation	mills
Year2016	0.0638**	0.0484***		
	(0.0254)	(0.0171)		
Non-native	-0.153**	-0.180***		
	(0.0749)	(0.0492)		

MigYr	0.0711	0.0633	
	(0.125)	(0.0618)	
Male	0.220***	0.168***	
	(0.0378)	(0.0231)	
Experience	0.0286***	0.0247***	
	(0.00768)	(0.00337)	
SqrExperience/100	-0.0566**	-0.0351***	
	(0.0240)	(0.0113)	
Schooling	0.0269***	0.0284***	
	(0.0102)	(0.00318)	
Occupation			
Managers	0.649***	0.567***	
	(0.119)	(0.0907)	
Professionals	0.511***	0.456***	
	(0.0949)	(0.0404)	
Technicians & Ass. Prof.	0.259***	0.220***	
	(0.0824)	(0.0435)	
Clerical Suupport Workers	0.191**	0.179***	
	(0.0792)	(0.0408)	
Service and sales workers	-0.00261	0.0634*	
	(0.0812)	(0.0332)	
Skilled Agri. Foresty and Fish.	-0.104	-0.0905	
	(0.183)	(0.0650)	
Craft and related trades Workers	0.0228	0.0743**	
	(0.0814)	(0.0365)	
Machine operators and Assemblers	0.195**	0.192***	
	(0.0908)	(0.0395)	
Elementary occupations	-	-	
Economic Sector			
Government	-0.112	-0.139**	
	(0.117)	(0.0706)	
Public	0.0367	0.0667	
	(0.138)	(0.0965)	
Private	-0.292**	-0.304***	
	(0.117)	(0.0704)	
Other	-0.246	-0.331***	
	(0.200)	(0.120)	
International	-	-	
Urban	0.0211	0.0425**	
	(0.0385)	(0.0196)	
Region			
Middle	-0.00856	-0.0245	
	(0.0337)	(0.0242)	
North	-0.0272	-0.0502**	
	(0.0349)	(0.0244)	
South	-	-	
Married			0.216***
			(0.0187)
Number of siblings			0.0110***
			(0.00208)

Age			0.00479***	
			(0.000782)	
Attended school			0.693***	
			(0.0404)	
Lambda				-0.132*
				(0.0721)
Constant	0.0316	0.225*	-1.603***	
	(0.190)	(0.129)	(0.0490)	
Observations	9,344	33,041	33,041	33,041

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

4.2. Unconditional quantile regression results

As we have mentioned above, the decomposition method based on RIF-OLS regression allows for more depth information about the average return of covariates along the wage distribution (quantile) (Zhu, 2016), which helps to identify the degree to which the returns of specific workers' characteristics contribute to the wage differentials between native and non-native workers at different parts of the wage distribution. In other words, we focus our attention here to the wage penalty that non-native workers face, as compared to native workers, in the overall return to some individual characteristics (gender, experience, years of schooling, etc.) at different quantiles of the wage distribution.

Table 6 below summarizes the estimation results of the unconditional quantile regression at the 10th, 50th and 90th quantiles of the wage distribution. The RIF-OLS regression results reveal that non-native workers earn 0.79 point (log wage) less than native workers in the first quantile, however the gap was dissipated in the 10th and 90thquantile. The base wage rate was increased for non-native workers in the year 2016 compared with 2010 (0.583 point) at the 10th quantile, but no significant wage gap was found in the second and third quantile. The gender wage premium is much higher at the bottom (0.279 log point) and top (0.30 log point) than the middle (0.141 log point) of the wage distribution.

The returns to one additional year of experience exhibit an inverted U-shaped pattern in the 10th and 50th quantile, while this effect is disappearing at the 90th quantile. Unconditional quantile regression result in Table 6 reveals that the mean returns in table 5 may concealed the heterogeneity in returns to schooling at different points of wage distribution. The quantile returns to one additional year of schooling exhibit insignificant result in the 10th quantile, then follow an increasing pattern between the 50th and 90th quantile. This means that returns to education have driven up wages at only the median and the top end quantiles of the wage distribution, or those in the high quantiles benefit more from the acquisition of more years for schooling.

In lower and median quantiles (10th and 50th), workers in the occupations of managers and professionals explain about the same amount of the variance in earnings as the managers and professionals in table 5 (standard Mincerian specification). Also, the returns by quantile for managers occupations exhibit a sharp and strictly increasing pattern between the first and third quantiles. However, the 90th-10th inter-quantile difference is much higher for managers (0.876) than professionals (0.195). The returns by quantile for technicians and associated professionals, clerical support workers, craft, and machine operators and assemblers exhibit are only significant in the bottom and median of the age distribution but not in the top of the wage distribution.

Similarly, the quantile returns of working in different economic sectors show heterogeneous results. The marginal effect of working in the public sector shows insignificant results across quantiles, while the wage penalty of working in the government sector becomes negative and very large in the 90th quantile. The wage penalty is the private sector is the lowest at the 90th quantile. In addition, working in the private sector earns less hourly wages than working in public, government and international sectors. Concerning the regional covariates, there is no variation in returns between different regions (north, middle and south) in in the 10th and 90th quantiles, but workers in the middle region earn lower wage penalty in the 50th quantile compared to their counterparts in the north and south region.

Table 6: Unconditional quantile regression results (RIF-OLS regression)

VARIABLES	10th	50th	90th
Year2016	0.0394	0.036**	-0.0823
	(0.0290)	(0.0168)	(0.0504)
Non-native	-0.792***	-0.0373	-0.0202
	(0.123)	(0.0404)	(0.139)
MigYr	0.583***	-0.0155	0.152
	(0.167)	(0.0613)	(0.199)
Male	0.279***	0.141***	0.300***
	(0.0612)	(0.0217)	(0.0733)
Experience	0.0297***	0.0238***	0.0129
	(0.00853)	(0.00424)	(0.0119)
SqrExperience/100	-0.0641**	-0.0477***	0.0126
	(0.0270)	(0.0138)	(0.0396)

Schooling	0.0147	0.0175***	0.0366**
	(0.0108)	(0.00497)	(0.0148)
Occupation			
Managers	0.459***	0.599***	1.335***
	(0.115)	(0.0764)	(0.380)
Professionals	0.412***	0.481***	0.607***
	(0.108)	(0.0528)	(0.147)
Technicians & Ass. Prof.	0.441***	0.319***	0.0540
	(0.0913)	(0.0518)	(0.143)
Clerical Suupport Workers	0.308***	0.179***	0.0561
	(0.0947)	(0.0491)	(0.135)
Service and sales workers	-0.0987	0.0357	0.000465
	(0.0952)	(0.0426)	(0.133)
Skilled Agri. Foresty and Fish.	0.0317	0.120	-0.200
	(0.269)	(0.136)	(0.244)
Craft and related trades Workers	0.220**	0.105**	-0.163
	(0.104)	(0.0504)	(0.137)
Machine operators and Assemblers	0.233**	0.148***	0.0748
	(0.0904)	(0.0483)	(0.151)
Elementary occupations			
Economic Sector			
Government	0.00717	0.0331	-1.026***
	(0.0594)	(0.0760)	(0.323)
Public	-0.00150	0.0496	-0.430
	(0.0719)	(0.0986)	(0.383)
Private	-0.392***	-0.269***	-0.809**
	(0.0614)	(0.0776)	(0.322)
Other	-0.474*	-0.190	-0.845**
	(0.281)	(0.158)	(0.426)
International			
Urban	0.0138	0.0485*	0.0766
	(0.0561)	(0.0262)	(0.0631)
Region			
Middle	-0.000264	-0.100***	-0.0320
	(0.0826)	(0.0242)	(0.0653)
North	-0.00542	0.00534	-0.0751
	(0.0796)	(0.0271)	(0.0683)
South	-	-	-
Constant	-0.715***	0.103	1.434***

	(0.176)	(0.103)	(0.389)
Observations	9,344	9,344	9,344
R-squared	0.138	0.249	0.054

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

4.3. Decomposition results

In this section, we use the decomposition technique to further explore any possible wage gap between native and non-native. Particularly, the distributional wage differentials $\widehat{Q_\theta^N} - \widehat{Q_\theta^M}$ between natives and non-natives is decomposed into either composition effect (explained component) which explains any differences in the productivity characteristics $\left(\overline{X^N} - \overline{X^M}\right)\widehat{\beta_\theta^N}$, and thee discrimination effects (unexplained component) which attributed to differential returns to covariates $\overline{X^M}(\widehat{\beta_\theta^N} - \widehat{\beta_\theta^M})$. Before analyzing the decomposition result, it is important to note that using linear specification to decompose the wage differentials between native and non-native workers may ignore the overlapping in their covariate distributions. The discrimination effects could be overestimated due to the inability to assign the decomposition for only workers with comparable attributes, (Nopo, 2008). For this reason, results reported in tables 7a and 7b represent the lower bound of the composition effects and the upper bound of the discrimination effect.

The two Tables 7a and 7b report the detailed wage decomposition results of the wage gap between natives and non-natives for the years 2010 and 2016, respectively. The log-average hourly wage gap will be decomposed at both the mean using Oaxaca-Blinder decomposition (see the first three columns in the two tables), and across the wage distribution at 10th, 50th and 90th quantiles using the estimates of the unconditional quantile regression approach developed by Firpo et al. (2009).

The two tables below display several consistent and important findings. Oaxaca-Blinder decomposition results show that native workers earn 42.1% wage in 2010 and 46.2% in 2016 compared with non-native workers, which implies an increasing in the average wage gap between the two groups over time. Results also display that the ratio of the composition effect from the total mean wage gap between natives and non-natives has decreased from 50.6% in

2010 to 43.94%, indicating an intensification of the discrimination against non-natives in Jordan labor market over time. The ratio of discrimination effects to its corresponding overall wage differential is used as an index of relative discrimination against non-natives at that specific point of wage distribution (Bishop et al., 2005; Gardeazabal and Ugidos, 2005; Zhu, 2016).

The estimated penalty for non-native workers increases between the 25th and 50th percentiles in both 2010 and 2016. In other words, the wage differentials are larger in the bottom and median parts of the wage distributions in both 2010 and 2016, which aligns with the pattern shown in the Figure 2 above. However, no significant wage gap is find in 2010, while small (0.252) and weak (only significant at 10% level of significance) wage gap in 2016. This confirms the importance of quantile regressions to explore better the patterns of wage differentials from native and non-native workers along the entire wage distribution (Buchinsky, 1998).

The ratio of composition effect and discrimination effect to the wage differentials at each quantile is also detailed for both years in tables 7a and 7b. It is clear that the wage discrimination problem against non-native workers is more severe at the median of wage distribution, i.e. discrimination effects contribute more to the wage differential only at the median of the wage distribution for both 2010 (61.5%) and 2016 (52.3%). The composition effects dominate in the lower part of the wage distribution in both 2010 and 2016. In figures, 61.66% and 64.48% of the overall wage differentials at the 10th quantile in 2010 and 2016 respectively are attributed to the differences in the productivity characteristics between natives and non-natives(see Column 4 in Tables 7a and 7b).

Tables below also present the detailed decomposition results of the contribution of Mincerian covariates (gender, experience, and age) and other individual characteristics like occupation, industry and region to the mean and considered quantile of the wage distribution. Looking across the results, it is clear that the differences in the Mincerian covariates between native and non-native workers significantly explain 27.87%, 29.58%, and 104.28%of the composition effects at the 10th, 50th and 90th quantiles of the wage distribution in 2010, respectively. In 2016, the standard Mincerian covariates explain significantly 36.14% of the mean composition effects at only the median part of the wage distribution; no significant effect is observed at the lower and the higher parts of the wage distribution. On average, the general characteristics can significantly explain 30.09% of the mean composition effects and by 15.22% (0.0641/0.241) of the raw overall wage gap in 2010, and 94.09% of the mean composition effect and 41.34% (0.191/0.462) of the raw mean wage gap in 2016.

Oaxaca and Blinder decomposition results in columns 2 and 3 reveal that, on average, educational differences between natives and non-natives explain around 20.23% of the composition effects and 10.24% of the raw mean wage gap in 2010, but have no significant contribution to the mean composition effects in 2016. Educational differences between the two groups contribute negatively to the discrimination effect in 2010.In 2010, the contribution of the differences in educational level between natives and non-natives workers to the overall composition effects shows little variation between the lower and median quantiles of the wage distribution with 21.65% and 20.65% respectively. No significant contributions of these educational differences is shown over the wage distribution in 2016.

Occupation differences between native and non-native workers yield the largest contribution (41.08%) to the composition effect at the mean and the 25th (37.4%), 50th (37.7%) and 75th (47%) quantiles of the wage distribution in 2010. Thus, we conclude that occupation differences, in 2010, enlarge the wage gap between native and non-native workers, in term of composition effects, at different points of the wage distribution. Similarity, in 2016, occupation differences contribute respectively to 37.58% and 35.65% of the composition effect at the bottom and middle parts of the wage distribution. However, at the 90th quantile, the occupational differences exhibit a negative contribution to the composition component (coefficient of returns = -0.176).

We do not find any significant contribution of regional differences between natives and non-natives to the composition effect of the wage differentials at the higher part of wage distribution in both 2010 and 2016. However, the it contributes to 8.4% of the composition effect at the mean and to 13% and 12% of the composition effect at the lower and median parts of the wage distribution. This pattern has been changed in 2016. We find that the regional differences contribute negatively (-4.6%) to the composition effect at the mean and positively only at the median part (7.08%). Concerning the wage gap due to employment in different economic sectors, the Oaxaca and Blinder decomposition results in 2016 (see Column 2 in Table 7b) show that on average the economic sector differences explain 23.20% of the mean composition effects and 10.19% of the raw mean wage gap in 2010. in 2010, this covariate is not included in the quantile decomposition analysis due to lack of data.

In summary, the main drivers of the unexplained component (discrimination effect) of the wage gap between natives and non-natives at the mean appears to stem from the education covariate in both 2010 and 2016, while the compositional differences in occupation between natives and non-natives explain a significant portion of the average wage differentials in 2010, and the compositional differences in Mancerian covariates explain the largest portion of the wage gap in 2016. The compositional differences in education between natives and non-natives explain significantly the wage gap only in 2010 but not in 2016. Furthermore, the sorting into different economic sectors and regions is partly responsible for the compositional wage differentials between the two groups in both years.

Using a more detailed analysis, tables 7a and 7bdisplaythat the wage structure effects in 2010 attributed to the differences in general characteristics, occupation and education level between native and non-native workers are different to those observed in 2016, and the human capital of non-nativesare not similarly rewarded as that of native workers between the two years. For instance, no significant discrimination effects attributed to the occupation covariates is revealed in 2010, while in 2016, the positive contribution of occupation covariate to the discrimination effect only found at the 10th quantile (significant only at 10% level of significance). The contribution of educational differences to the discrimination effect between natives and non-natives exhibits different signs between 2010 and 2016; i.e. it contributes negatively to the discrimination effect in 2010 and positively in 2016. We conclude that that the discrimination effects attributed to different education returns increase over time.

Similarly, the contribution of the general characteristics (Mincerian covariates) to the composition effect displays positive and increasing patterns between 2006 and 2016. No significant contribution to the discrimination effect is find in both 2010 and 2016. The coefficient estimates of the regional dummy negatively contribute to the discrimination effect only in the lower part of the wage distribution in both 2010 and 2016.

Table 7a: Decompsition at the mean and selected percentiles in 2010

	Mean			10th percentile			50th percentile			90th percentile		
VARIABLES	overall	explained	unexplained	overall	explained	unexplained	overall	explained	unexplained	overall	explained	Unexpla
Natives	0.703***			-0.126***			0.636***			1.528***		
	(0.0118)			(0.0153)			(0.0108)			(0.0295)		
Non-natives	0.282***			-0.499***			0.0741			1.269***		
	(0.0600)			(0.0263)			(0.0580)			(0.250)		
difference	0.421***			0.373***			0.562***			0.259		
	(0.0612)			(0.0305)			(0.0590)			(0.251)		
explained	0.213***			0.230***			0.216***			0.187***		
	(0.0235)			(0.0278)			(0.0226)			(0.0485)		
unexplained	0.209***			0.143***			0.346***			0.0722		
	(0.0605)			(0.0402)			(0.0594)			(0.252)		
General Characteristics		0.0641***	0.551		0.0641**	0.840***		0.0639***	1.603***		0.195***	1.88
		(0.0240)	(0.544)		(0.0324)	(0.289)		(0.0213)	(0.523)		(0.0663)	(2.29
Education		0.0431**	-0.176**		0.0498*	0.00819		0.0446**	0.0765		-0.0776	-0.34
		(0.0216)	(0.0806)		(0.0287)	(0.0435)		(0.0200)	(0.0779)		(0.0569)	(0.33
Occupation		0.0875***	0.0633		0.0860***	-0.0516		0.0815***	0.0910		0.0881***	-0.41
		(0.0123)	(0.142)		(0.0158)	(0.0691)		(0.0117)	(0.136)		(0.0296)	(0.59
Region		0.0179***	-0.246		0.0299***	-0.301***		0.0260***	-0.169		-0.0184	0.13
		(0.00517)	(0.180)		(0.00741)	(0.0907)		(0.00511)	(0.173)		(0.0131)	(0.76
Constant			0.0164			-0.353			-1.255**			-1.18
			(0.624)			(0.333)			(0.600)			(2.62
Observations	4,760	4,760	4,760	4,760	4,760	4,760	4,760	4,760	4,760	4,760	4,760	4,76

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

Table 7b: Decompsition at the mean and selected percentiles in 2016

	Mean			10th percentile			50th percentile		
VARIABLES	overall	explained	unexplained	overall	explained	unexplained	overall	explained	unexpla
Native	0.811***			-0.0381**			0.706***		
	(0.0150)			(0.0160)			(0.00957)		
Non-Natives	0.349***			-0.525***			0.146***		
	(0.0517)			(0.0665)			(0.0256)		
difference	0.462***			0.487***			0.560***		
	(0.0538)			(0.0684)			(0.0273)		
explained	0.203***			0.314***			0.267***		
	(0.0358)			(0.0391)			(0.0230)		
unexplained	0.259***			0.172**			0.293***		
	(0.0625)			(0.0779)			(0.0342)		
General Characteristics		0.191***	-0.0294		0.112	-0.605		0.0965**	0.346
		(0.0729)	(0.367)		(0.0781)	(0.491)		(0.0435)	(0.195
Education		-0.0254	0.343**		0.0897	0.0895		0.0559	0.098
		(0.0609)	(0.155)		(0.0657)	(0.206)		(0.0362)	(0.081
Sector		0.0471***	0.0892						
		(0.0157)	(0.166)						
Region		-0.00951**	-0.0270		-0.00574	-0.414**		0.0189***	0.0001
		(0.00427)	(0.149)		(0.00487)	(0.201)		(0.00425)	(0.078
Occupation					0.118***	0.370*		0.0952***	-0.064
					(0.0170)	(0.222)		(0.00983)	(0.088
Constant			-0.116			0.733			-0.087
			(0.483)			(0.641)			(0.258
Observations	4,630	4,630	4,630	4,630	4,630	4,630	4,630	4,630	4,630

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

5. Conclusion

Using a nationally representative cross-sectional data from 2010 and 2016 Jordan Labor Market Panel Surveys, we investigate the determinants of the wage differentials between native and non-native workers in the Jordanian labor market using a mixed approach of OLS, Oaxaca-Blinder decomposition and unconditional quantile regressions. The pooled Heckman two stage analysis found that the human capital variables (experience, experience squared and schooling) are all significant and have the expected signs. On average, native workers earn significantly 0.792 higher hourly log wage than non-native workers, and male workers earn 0.168 higher hourly log wage than female. However, the OLS regression is not adequate description of the wage determination for each group at different parts of the wage distribution. Therefore, the RIF-OLS regression show the estimated returns to characteristics at different parts of the wage distribution for each group, and decompose the distributional native/non-native wage differentials into composition effects, explained by differences in productivity characteristics, and discrimination effects, attributable to unequal returns to covariates.

The RIF-OLS regression results reveal that non-native workers earn 0.79 hourly log wage less than native workers in the first quantile, however the gap was dissipated in the 10th and 90th quantile. The base wage rate was increased for non-native workers in the year 2016 compared with 2010 at the 10th quantile, but no significant wage gap was found in the second and third quantile. The gender wage premium is much higher at the bottom and top than the middle of the wage distribution. Returns to education have driven up wages at only the median and the top end quantiles of the wage distribution, or those in the high quantiles benefit more from the acquisition of more years for schooling. The returns by quantile for managers occupations exhibit a sharp and strictly increasing pattern between the first and third quantiles, but the 90th-10th inter-quantile difference is much higher for managers than professionals. The marginal effect of working in the public sector shows insignificant results across quantiles, while the wage penalty of working in the government sector becomes negative and very large in the 90th quantile. The wage penalty is the private sector is the lowest at the 90th quantile.

Oaxaca-Blinder decomposition results show increasing in the average wage gap between the two native and non-native workers over time (42.1% higher wage in 2010 and 46.2% in 2016 for native workers). The ratio of discrimination effects to its corresponding overall wage differential is used as an index of relative discrimination against non-natives at that specific point of wage distribution. We find an intensification of the discrimination against non-natives in Jordan labor market over years. It is clear that the wage discrimination problem against non-native workers is more severe at the median of wage distribution. We also find that the main drivers of the unexplained component (discrimination effect) of the wage gap between natives and non-natives at the mean appears to stem from the education covariate in both 2010 and 2016. The coefficient estimates of the regional dummy negatively contribute to the discrimination effect only in the lower part of the wage distribution in both 2010 and 2016.

The composition effects dominate in the lower part of the wage distribution in both 2010 and 2016. The compositional differences in occupation between natives and non-natives explain a significant portion of the average wage differentials in 2010, and the compositional differences in The sorting into different economic sectors and regions is partly responsible for the compositional wage differentials between the two groups in both years. Also, the contribution of the general characteristics (Mincerian covariates) to the composition effect displays positive and increasing patterns between 2006 and 2016.

APPENDIX 1

The wage equation is specified as follows:

$$log(w) = \alpha_0 + \beta_1 D_{Yr} + \beta_2 D_{Mig} + \beta_3 D_{Mig\times Yr} + \beta_4 D_{Male} + \beta_5 Exp + \beta_6 SqrExp + \beta_7 Sch + \sum_{i=1}^{9} \beta_{8i} Occ_i + \sum_{i=1}^{5} \beta_{9i} Sec_i + \beta_{10} D_{Urb} + \sum_{i=1}^{3} \beta_{11i} Reg_i + \beta_{12} Mill + \varepsilon$$

The variable D_{Yr} is a year dummy equal to 0 if a person comes from the first round (2010) and 1 if a person comes from the second round (2016-2017).The intercept for 2010 is α_0 and the intercept for 2016 is $(\alpha_0 + \beta_1)$ .D_{Mig} represents the workersmigration status, 1 if a worker is non-native and 0 as native. The coefficient β_2 represents non-native workers in 2010 and $\beta_2 + \beta_3$ in 2016. The variable D_{Male} is a gender dummy equals 1 if male and 0 otherwise. The variable *Exp* and its square reflect the non-linear relationship of experience with the wage earnings if β_6 is statistically significant. *Sch* is the schooling years variable. The variables Occ represents the 9 broad occupation dummies and *Sec* represents the 5 job sector dummies. D_{Urb} is the urban dummy equals 1 if a worker belongs to urban area and 0 for rural areas. *Reg* represents the three broad regional dummies. The variable Mill represents the inverted Mills ratio if the selection bias is taken into account and finally ε represents an i.i.d. idiosyncratic error term.

APPENDIX 2

See Table 8

Table 8: Variables used in wage equation

Variable	Variable description
Dependant Variable	
Log of hourly wage	Log real hourly wage: Natural logarithm of real hourly wages at 2017 prices and based on spatial price index of each governorate. Quantile regression at main quantiles 10th, 50thand 90th quantiles.
Explanatory variables	
Yr	Time dummy variable, equal to 1 if the person comes from the first round (2010) and 0 if he/she comes from the 2nd round (2016-2017)
Mig	Non-native dummy, equal to 1 if the person is a non-native and 0 otherwise.
MigYr	Non-native year dummy interaction, indicating the change of non-native earnings from 2010 and 2016.
Male	Gender dummy, 1 if male and 0 if female.
Exp	Experience in years
SqrExp	Square of Experience divided par 100
Sch	Schooling years
Occ	Occupation categories: Occ1 as Managers, Occ2 as Professionals, Occ3 as Technicians and associate professionals, Occ4 as Clerical support workers, Occ5 as Service and sales workers, Occ6 as Skilled agricultural, forestry and fishery workers, Occ7 as Craft and related trades workers, Occ8 as plant and machine operators, and assemblers, Occ9 as Elementary occupations (reference group).
Sec	Job sector categories:Sec1 as government, Sec2 as Public (reference group), Sec3

	as Private, Sec4 as Other and Sec5 as international (reference group).
Urb	Urban dummy, 1 if a person living in urban area and 0 if he/she living in rural areas
Reg	Regional dummies: Reg1 as Middle, Reg2 as North, and Reg3 as South (reference group).

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