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Hatem Jemmali

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Send correspondence to:
Hatem Jemmali
University of Manouba
hatemjemmali79@gmail.com

[1] Higher Institute of Accountancy and Business Administration, University of Manouba & Laboratory for Research on Quantitative Development Economics, University of Tunis El-Manar, Tunisia.

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Abstract

This paper examines the wage differentials between Syrian refugees and native-born and non-refugee migrant workers using a nationally representative data set extracted from the most recent Jordanian Labor Market Panel Survey (JLMPS 2016). On average, Syrian refugees earn 37.2% and 74% less hourly wages than natives and non-refugee workers, respectively. The observed wage differentials are not uniform through the wage distribution, and wage gaps are found to be much higher at the top end than at the bottom and the middle of the wage distribution. By applying newly developed decomposition methods, we decompose the distributional wage differentials between different groups into a composition effect, explained by differences in productivity characteristics, and a discrimination effect attributable to unequal returns to those covariates. We find, on average, that discrimination effect contributes more to the wage gaps than composition effect, while through the first part of wage distribution, endowment effect is found to dominate the wage differentials between native-born and Syrian refugee workers. The compositional differences in education between refugees and non-refugees are found to explain significantly the wage gaps and endowment effects at bottom and middle parts of wage distribution, but when moving up reverse of that is happened by being responsible for a substantial part of discrimination effect.

Keywords: Native-born residents, Syrian refugees, non-refugee migrants, wage differentials, Quantile decomposition.

JEL Classifications: J31, J61

1. Introduction

It is commonly assumed that refugees all over the world are facing discrimination in their jobs, housing, and property rights. They are unable as forced migrants to be employed in host countries due to their refugee status and educational and skills background. Discrimination in earning and work conditions is a continuing issue for all immigrants, but for refugees who have been displaced from their homelands, there can be more barriers to finding work and being well waged and rewarded. A number of explanations have been postulated to understand the origins and causes of such '*refugee gap*'. Forced migrants, on average, are under-skilled, have less employment experience and poorer mental and physical health, and generally reside in more disadvantaged neighborhoods than other immigrants and host communities. Although these factors are well supported by evidence for particular refugee groups, a shortage of representative micro-data for both forced and non-forced migrants has made testing of this refugee gap in access to basic services and labor market outcomes challenging.

The Syrian refugee crisis, which started in March 2011, is considered as one of the major challenges and most pressing disasters faced by the world in this second decade of the twenty-first century. The current Secretary-General of the United Nations (UN), António Guterres, said that "*Syria has become the great tragedy of this century*" and "*a disgraceful humanitarian calamity with suffering and displacement unparalleled in recent history.*" The main effects of such crisis are reverberating around the globe mainly the border neighboring countries. Following the outburst of the civil war, millions of Syrians have been forced to leave their homes toward the Turkish, Lebanese, and Jordanian borders. After nine years of persisting conflict with no clear political resolution of the crisis, there are still huge waves of refugees flowing into the neighboring countries. According to the UN High Commissioner for Refugees (UNHCR) figures, the total number of Syrian refugees has reached about 5.5 million by the beginning of 2020. Around 30% of them are living actually in Lebanon and Jordan while the lion share of Syrians refugees had registered with UNHCR in Turkey (about 64.4%)[2].

Refugee adaptation and integration within the host communities has been an enduring question for international migration research since the work of Portes and Stepick (1985). Most findings of the current literature indicate that refugees all over the world face several obstacles in their economic integration (Kibria 1994; Portes and Stepick 1985; Potocky-Tripodi 2001, 2003, and 2004; Takeda 2000; Waxman 2001; Bakker et al. 2017; Fasani, 2018). The main explanation given is that refugees, considered as forced migrants, do not voluntarily leave their country of origin, they are conceptually different from other migrants (Richmond 1988) and are not selected on a class basis to ensure more successful adaptation (Connor, 2010). In this respect, one may view the large waves of migration occurred from Syria to neighboring countries to escape from the political tensions and repression in their country. Arriving to host communities, refugees often experienced high levels of segregation and discrimination in term of earning and

[2] https://data2.unhcr.org/en/situations/syria

access to workforce and basic services. This may inhibit their career development in host countries (Chiswick et al. 2008; Takeda 2000).

Therefore, the main question remains if a 'refugee gap' in term of economic outcomes and access to basic services actually exists within the receiving society. In other words, we aim in the current study, that focuses specifically on Syrian refugees living in Jordan, to look at what extend the wage earnings of refugees are significantly different from those of non-refugee immigrants and natives-born counterparties. And if so, how can this refugee gaps be decomposed and explained? Do factors such as education, family background, neighborhood, and geographic residence impact refugees differently from other immigrants and natives. Mostly due to the lack of nationally micro representative data in host countries, these questions remained unanswered. Most research on refugee populations within the host communities was conducted to focus on the economic and financial impacts of Syrian crisis on the neighboring countries.

This paper contributes to the current literature by investigating wage determination for native-born, Syrian refugees, and non-refugee migrants and the wage differentials among them. A few previous studies have examined the wages of these particular groups (Jemmali and Morrar, 2020; Fallah et al., 2019; Said, 2012). However, they generally have some limitations. First, they put all migrants in the same basket without distinguishing between non-refugee migrants and Syrian refugees. Second, some of them mainly focus on the impact of the Syrian refugee influx on the Jordanian labor market outcomes. However, it can also be of interest and significance to evaluate the migrants' wage determination at different points of wage distribution to learn more about discrimination based on migration status in Jordan.

The rate of return to factors such as education and working experience may not be uniform through the wage distribution. Furthermore, none of the previous contributions to the existing literature has decomposed natives/refugees and migrants/refugees wage differentials across the wage distribution and examined how individual and labor market characteristics contribute to distributional wage disparities. In this regard, it's worth to note that Jemmali and Morrar, (2020), have focused on the wage differentials between natives-born workers and migrants in Jordan's labor market using the Jordanian Labor Market Panel Survey (JLMPS) for the two years 2010 and 2016 and the same methodology we used in the present paper. The authors have found an increasing average wage gap in favor of resident workers and the wage differentials were found to be larger at the bottom and middle parts of the wage distributions in both 2010 and 2016.

In this paper, using a nationally representative data set from the 2016 JLMPS, we analyze the wage determination for natives-born, Syrian refugees and non-refugee migrants by using OLS estimation and the unconditional quantile regressions developed by Firpo et al. (2009). To decompose the different mean wage gaps, we apply a recently-developed regression-compatible procedure by Fortin (2008). We also combine the mean decomposition method developed by Fortin (2008) with the unconditional quantile regression developed by Firpo et al. (2009) in order to decompose the considered wage differentials at some quantiles (10th, 50th, and 90th percentiles). This computationally outstanding combined method permits us to divide up both the composition effect and the wage structure effect into the contribution of each explanatory covariate.

On average, Syrian refugees are found to earn, respectively, about 74% and 37.2% less wages than natives and non-refugee migrants. We find that these sizable wage gaps are not even across wage distribution. In contrast to the "*sticky floor effect*" found in some others studies focusing on gender wage gaps such as those of Bishop et al., (2005) and Chi and Li (2008), we find that both wage differentials (natives/Syrian refugees and non-refugees/Syrian refugees) are the highest at the top end of wage distribution. As mentioned by Albrecht et al. (2003) in his study dealing with gender wage gap in Sweden, we may interpret this finding as evidence of a "*glass ceiling effect*" in labor market in Jordan.[3] By employing OLS and unconditional quantile regressions, we find that the returns to schooling, working experience and some occupational, industrial, and institutional dummies differ by group of workers and these differences change through wage distribution. Our Oaxaca–Blinder (OB) decompositions findings show that the discrimination effect attributable to unequal returns to labor market characteristics contributes more to the mean wage gap than the composition effect. While the wage differentials between native-born and Syrian refugee workers is significant and largest at the higher end of wage distributions, our quantile decomposition results show that the relative wage discrimination problem is most serious among high wage workers.

The remainder of this paper is constructed as follows. In Section 2 we describe the data and present some stylized facts. Section 3 is a description of the used empirical methodology. Section 4 presents the regression and decomposition results. Section 5 concludes and gives some policy recommendations.

2. Data and descriptive statistics

2.1. Data and variables

The Jordan Labor Market Panel Survey (JLMPS) is the first and only large-scale, nationally representative labor market panel surveys in Jordan (after weighting to account for sample stratification along geographic lines). JLMPS collect comprehensive information on employment, earnings and socio-demographic characteristics of the population containing native-born people and a number of migrants from different neighboring countries (e.g. Syria, Turkey, Lebanon and Egypt). The first wave of the JLMPS was fielded in 2010, just prior to the Arab Spring upheaval and the beginning of the Syrian conflict. A second wave of the JLMPS, which we used in this study, was fielded starting in December 2016 (the large part of

[3] As stated by Albrecht et al. (2003), a "*glass ceiling effect*" may exist when women's wages fall behind men's more at the top of the wage distribution than at the middle or bottom. While a "*sticky floor effect*" means that gender wage gaps are larger among low income workers (through lowest part of wage distribution).

data collection was achieved by April 2017). [4] Both the two waves of the JLMPS were done in collaboration between the Economic Research Forum (ERF) and the Jordanian Department of Statistics (DoS), which was charged to do sampling and fieldwork (Krafft & Assaad 2018).

The second wave tracked sampled households from 2010 survey, including individuals who split to form new households distributed among urban and rural areas in the three regions of Jordan: North, Middle, and South. Giving the Syrian conflict and the great events happened in the Middle East, a refresher sample that over-sampled neighborhoods which were identified in the November 2015 population census as having a high proportion of non-Jordanian households was added to the 2010 sample. Indeed, about 3,000 households, which stratified on governorate and urban/rural/(official) camps, were included with the refresher sample during the 2016 survey. The sampling frame of the JLMPS 2016 was, then, the most recent Population and Housing Census which surveyed 1.9 million households and 9.5 million individuals in 2015 amongst them, 1.3 million are Syrian, 636,000 are Egyptians, 634,000 are non-nationalized Palestinians, and around 131,000 are Iraqis and smaller numbers from numerous other countries (see Table 1). To ensure the representativeness of such population heterogeneity, the sample weights used in the JLMPS 2016, were estimated taking into account the initial wave sampling strategy, the refresher sampling strategy, and the attrition between the two waves on both the household and split household levels (Krafft & Assaad 2018).

The survey covers 7,228 households and 33,450 individuals amongst them 9.06% are from recent forced migrant households from Syria. As our focus is on refugee/native and refugee/migrant wage earnings differentials, we restrict our attention to the refugees, natives born and migrants workers aged between 15 and 64 with positive earnings in 2016, dropped full-time homemakers, full time students, and retirees.[5] The sample size, then, is reduced to 5,191 individuals, of which 4415 are native born workers, 160 are Syrian refugee workers, and 311 are other migrants workers. in Appendix 1, we provide an exhaustive list of variables that we used for the analysis of wage differentials between different groups. To give more insights on the considered sample and wage differentials, we reported separately below in Tables 2, 3 and 4 some summary statistics of used variables by group of wage earners.

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[4] Data collected from the JLMPS survey are publicly available from the ERF Open Access Micro Data Initiative (OAMDI 2018) at: http://www.erfdataportal.com/.

[5] One of the main shortcomings of the current study is that we exclude those observations with no positive earnings from the analysis. This may bias our empirical findings if the sample of wage earners is systematically different from those unemployed ones. However, we cannot use the Heckman's methodology for correcting the selectivity bias due to data limitation and the absence of valid instrumental variable in the data that affects the probability of being employed but exerts no impact on earnings. Furthermore, even if we could find a valid instrument, until now, there's no method that could simultaneously address the selectivity bias and decompose quantile wage differentials into the contribution of each covariate. To the best of our knowledge, the unique method that can address the sample selection issue in a conditional quantile decomposition is developed by Albrecht et al. (2009). But that method is computationally intensive and complicated and will prevent us from estimating the impact of each covariate on endowment effect, while finding these contributions to gender earnings gap is our focal interest. Accordingly, we follow the previous literature (Bishop et al., 2005; Chi and Li, 2008; Magnani and Zhu, 2012; Zhu, 2016) and ignore this empirical issue.

2.2. Descriptive statistics

Table 2 presents the means and standard deviations of earnings and individual characteristics by groups of wage earners (i.e., Syrian refugees, other migrants, and native born). We add in this table, an estimation of the normalized difference for each variable, using the formula shown below, in order to display a first overview of the differences that may exist between Syrian refugees and natives and other migrants. Hourly wage is computed as the sum of reported earnings in all forms received from the primary and secondary jobs in Jordan (counting regular wages and all forms of bonuses and subsidies perceived from the work unit). As commonly computed in labor market surveys, hourly wages are calculated using monthly income and weekly working hours shown further in the table below. In order to take into account, the regional disparities in wellbeing, we further deflate the hourly wages with the governorate poverty lines, shown in the World Bank's (2009) report, in absence of spatial consumer price index.

As expected, when looking at the household wealth quintiles in the first lines of the Table 2, the summary statistics reveal that for the lower quintiles Syrian refugees living in *poor* households are more abundant than native ones while for the upper quintiles, native-born living in relatively rich households are more abundant compared to Syrian refugees. Furthermore, the table show clearly that the hourly wages of native-born and other migrants are much higher than those of Syrian refugees, although Syrian workers work many more hours per week than native born ones. Syrian refugees earn about 80.8% (= 0.862–0.054) and 41.40% less hourly wage than native-born and other migrant workers, respectively.

Among different groups of workers, summary statistics in Table 2 reveal that native-born and other migrants are slightly older and with more years of education than Syrian refugees. The variable *Experience* measures the years of work experience from life history. The mean of *Experience* for both native-born and other migrant workers are considerably greater than their Syrian refugees' counterparts. *Married* is a dichotomous variable that equals one if the wage earner is currently married and zero otherwise. *Urban* is a dummy variable showing whether the respondent is living in urban zones or not. The majority (about 90%) of workers belonging to the three considered groups are living in urban areas.

Additional descriptive statistics of the migration status differences in distributions of economic sectors, job stabilities, occupations and regions of residence are displayed in Table 3. Formal is a binary variable equal to 1 if the respondent is working in formal sector and zero otherwise. As expected, the proportion of native-born workers having a job in formal sector (about 77.40%) is considerably higher than that of Syrian refugees (9.87%) and of others migrants (24.66%). In this respect, Syrian refugees are found to be mainly employed in temporary and seasonal jobs in private firms. In contrast, most native-born and, at less degree, other migrants are working as permanent employees in public sector. Furthermore, the table show that only 6.34% of Syrian refugee workers and 2.19% of other migrant workers hold professional or technical positions, far below the 36.9% for native-born workers. Finally, the bottom part of

Table 3 reveals that the migration status differences in distribution of regions of residence are very small.

From Table 2, we know that on average native-born and other migrant workers earn, respectively, 80.8% and 41.40% higher wages than their Syrian refugees counterparts. To further investigate the Native/Syrian Refugees and Other Migrants/Syrian Refugees wage gaps, we present preliminary statistics of hourly wage for each group by economic sector, job stability, occupation ownership, and governorate of residence in Table 4. Native and other migrant workers are found to earn higher average wages that Syrian refugee workers in every category.

Among the nine occupations, the first part of the table show that Natives/Syrian refugees wage gap is the smallest for plant and machine operators and assistants and the highest for technicians and assistant professionals with Syrian refugees' average wage being 54.89% of that for native ones. While the second part of the table show that other Migrants/Syrian refugees wage gap is the smallest for technicians and assistant professionals and the highest for craft and related trades workers with Syrian refugees' average wage being 81.11% of that for other migrant ones. In terms of job stability, Table 4 show that the Natives/Syrian refugees wage differentials is the largest for seasonal workers, both in absolute (hourly wage difference) and relative terms ($\bar{G}/G$). While for the other migrants/Syrian refugees wage gaps, the highest is for temporary workers and the lowest is for casual ones. We find as well variations in wage differentials across different governorates. The Natives/Syrian refugees and Other Migrants/Syrian refugees wage ratios range, respectively, from 1.90% to 54.84% and 0.87% to 98.78% in these governorates.

Fig. 1a. Kernel density estimates of log wage distributions of natives and Syrian refugees

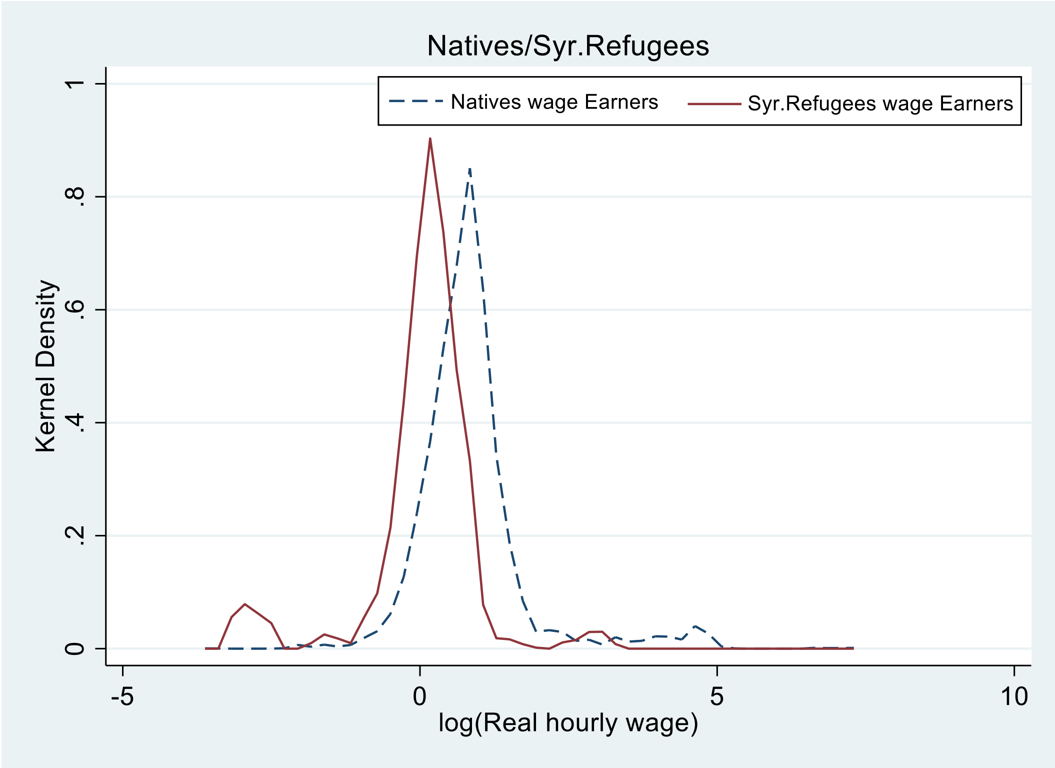
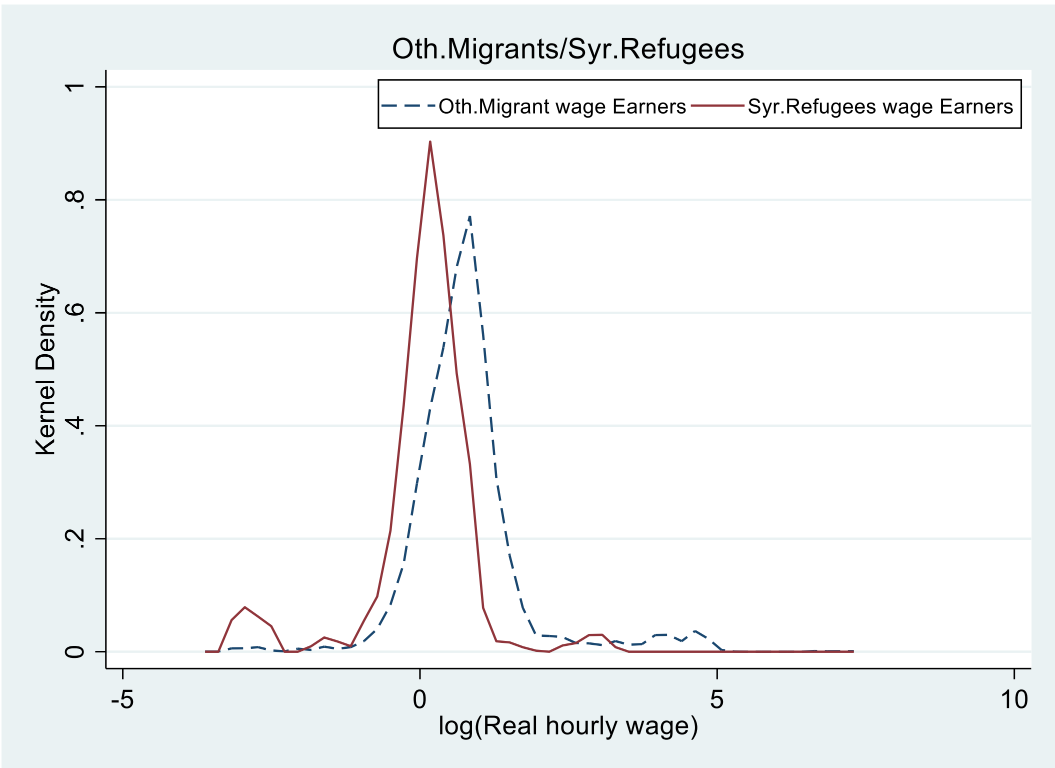


Fig. 1b. Kernel density estimates of log wage distributions of migrants and Syrian refugees



To better describe the wage differentials between the aforementioned groups, we present, below in Figs. 1a and 1b, the kernel density estimates of logarithmic adjusted hourly wages for each group in comparison with the Syrian refugees. From these figures we can see the contrasted wage distributions across different groups of wage earners in Jordan in 2016. In this respect, the two-sample Kolmogorov–Smirnov test rejects the null hypothesis that the logarithmic adjusted hourly wages for each two groups (Natives/Syrian refugees and Other Migrant/Syrian refugees) come from the same distribution (p-value = 0.000) (see Tables 5a and 5b).

Following Albrecht et al. (2003), we plot the raw log wage differentials at some percentiles in Figs. 2a and 2b. The two figures show, commonly, that log wage gap stays at relatively lower levels between the 10th and the 90th percentiles. It becomes increasingly higher at both lower and higher percentiles (under the 10th percentile and upper the 90th percentile, respectively). A sharp acceleration is observed, in the two figures, from the 90th to upper percentiles with the gap is much higher at the top of the wage distribution than the middle. To shed more light on the main drivers of these varied wage differentials across the distributions, we will use thereafter the well-known decomposition method in the empirical analysis of the study.

Fig. 2a. Raw Natives/Syrian refugees log wage gap by some percentiles

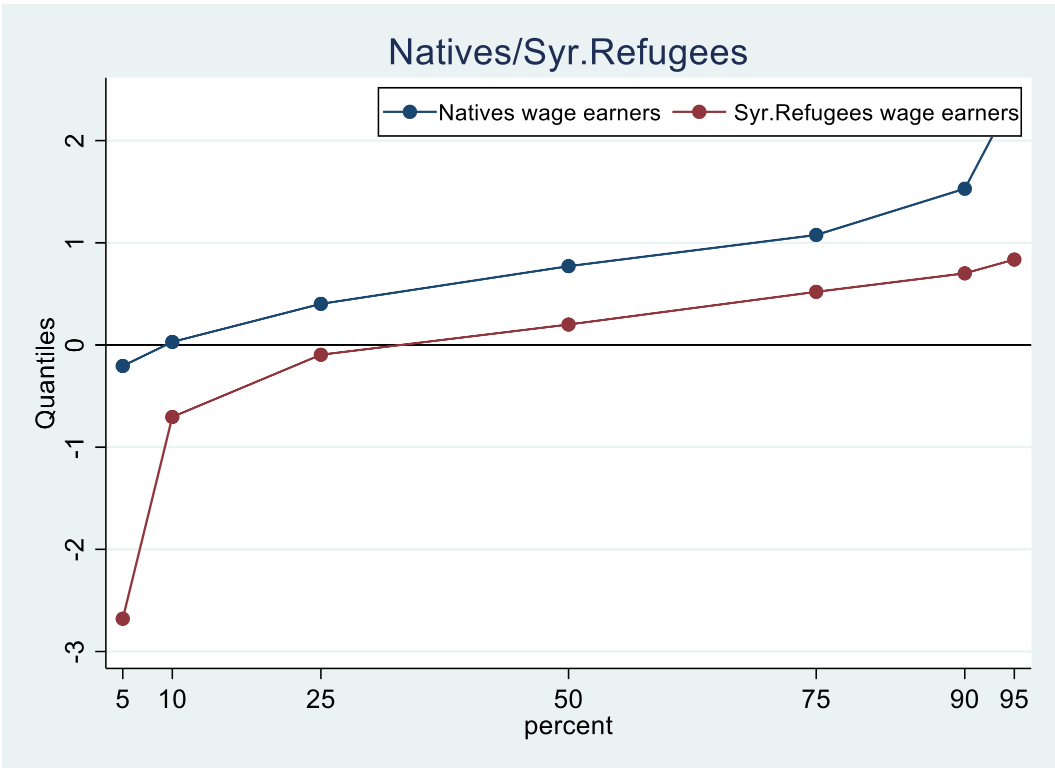
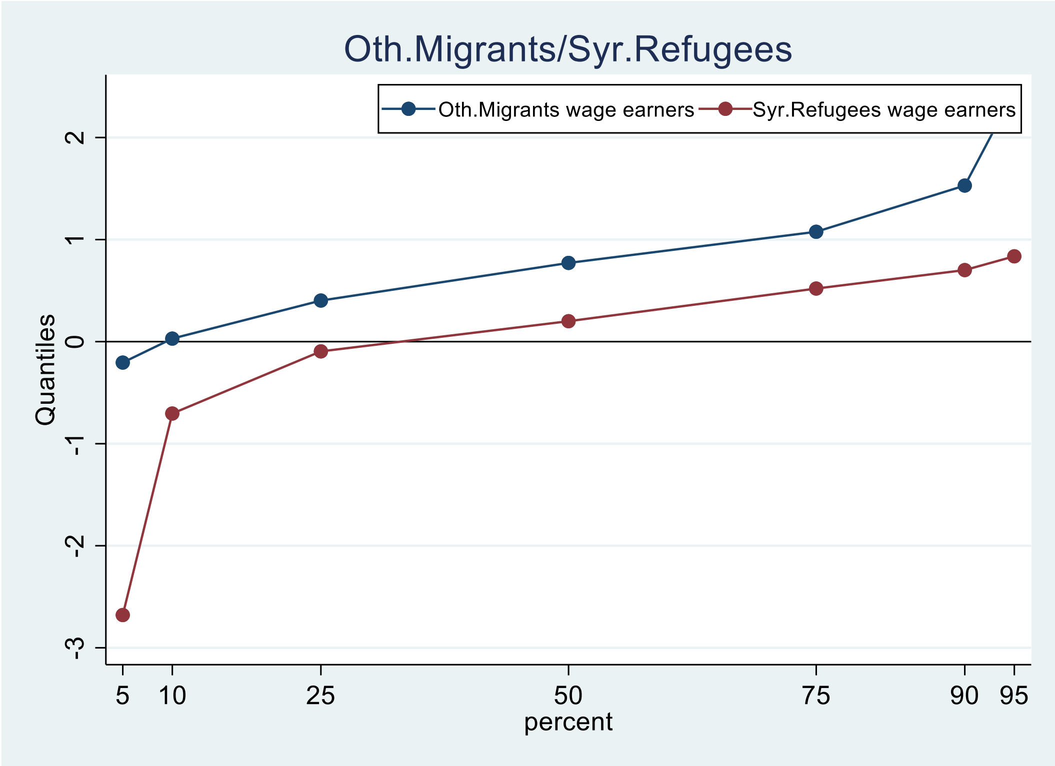


Fig. 2b. Raw Oth. Migrants/Syrian refugees log wage gap by some percentiles



3. Empirical methodology

3.1. OLS regression and mean wage gap decomposition

Following the Jacob Mincer's model of earnings (1974), we apply initially the basic human capital wage equation on micro-data extracted from JLMPS 2016. The basic assumption of such model is that the wage rate should reflect the labor productivity, which also depends on human capital characteristics. The log of real and adjusted hourly wage is considered as the dependent variable, while the covariate matrix including the basic variables of Mincerian equation (schooling and work experience), added to gender, marital status dummy, squared experience, job stability dummy, region of residence, occupations, and economic and institutional sectors. Assume the mean log wage function for different groups i.e. natives-born (*N*), Syrian refugees (*SR*), and other migrants (*M*) is given by the following equation:

$$\mathrm{E}[\mathrm{Y_G}|\mathrm{Y_G}] = \mathrm{X_G}\beta_\mathrm{G} \qquad (1)$$

Where Y denotes the logarithmic real and adjusted hourly wages, X is the vector of some individual and labor market characteristics (including a constant term), β is the vector of coefficients and $G = N$, SR, and M denotes the group of wage earners. Then the OLS estimate of β_G measures the impact of X on the conditional or unconditional mean of Y for each group G.

According to the widely used Oaxaca–Blinder decomposition method (Oaxaca, 1973; Blinder, 1973), the average earnings gap between two different groups could be decomposed into an endowment effect explained by differences in productivity characteristics and an unexplained discrimination effect due to different returns to covariates. Such approach has been criticized in two main points. The first limitation is that when selecting migrant or resident as the base category, the reference wage structure obtained is discriminatory (Oaxaca and Ransom, 1994; Fortin, 2008). The second one is concerned with taking into account only wage decomposition at the mean and ignored others various points in the distribution. To deal with these shortcomings, 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 has been elaborated recently by Fortin et al. (2011).

3.2. Unconditional quantile regression and decomposition

In the current study, we attempt to investigate the range of determinants of wage differentials between refugee and native born and refugee and non-refugee migrant workers in Jordan using a mixed approach of the regression-compatible procedure developed by Fortin (2008) and the unconditional quantile regression-based decomposition approach developed by Firpo et al. (2009) using the JLMPS 2016. We apply such regression-compatible procedure in order to decompose the wage gap at the mean wage for each group, then we combine it with the unconditional quantile regression to decompose each wage differential at some considered quantiles. This mixed approach is also employed to decompose the composition effect and the wage structure effect (discrimination effect) into the contribution of each covariate.

We resort to the unconditional quantile regression instead of the conditional quantile regression developed by Koenker and Bassett (1978) as it can be directly used to assess the economic impact of a change of covariates on the corresponding quantiles of the unconditional distribution of dependent variable, which is usually of real interest in economic applications. The main concept in such kind of regression is the influence function (IF), which is a classified as tool of robust statistics. Explicitly, the influence function represents the influence of an individual observation on a distributional measure of interest such as a quantile or other statistics. The recentered influence function (RIF) is obtained then by adding the influence function back to the statistic we care about.

In details, the approach we follow 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 using the Kernel method. In the second phase, we regress, as follows, the estimated the RIF on X using the OLS regression analysis for each group separately:

$$E(RIF\ (Y, Q_\theta)|X) = X\beta_\theta \qquad (2)$$

Since the RIF (Y, Q_θ) couldn't be observed in practice, we replace all unknown components with their sample estimators as follows [6]:

$$\widehat{\mathrm{RIF}}\ (\mathrm{Y}, \widehat{\mathrm{Q}_\theta}) = \widehat{\mathrm{Q}_\theta} + {(\theta - \mathrm{I}\{\mathrm{Y} \leq \widehat{\mathrm{Q}_\theta}\})}\Big/{\widehat{\mathrm{f}_\mathrm{Y}}(\widehat{\mathrm{Q}_\theta})} \qquad (3)$$

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 and extracting counterfactual distributions that would result if refugees 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 which are: a composition effect, called also productivity effect, explained by differences in productivity characteristics and an unexplained wage structure effect (or discrimination effect) due to different returns to covariates.

After estimating the model in Eq. (2) for some quantiles of the wage distribution (the 10th lowest quantile, the median and the 90th highest quantile), we use the unconditional quantile regression to decompose the wage differentials between refugees and others workers into composition and discrimination effects as follows:

$$\widehat{\mathrm{Q}^{i}_\theta} - \widehat{\mathrm{Q}^{j}_\theta} = \left\{\widehat{\mathrm{Q}^{i}_\theta} - \widehat{\mathrm{Q}^{*}_\theta}\right\} + \left\{\widehat{\mathrm{Q}^{*}_\theta} - \widehat{\mathrm{Q}^{j}_\theta}\right\} = (\bar{\mathrm{X}}^{\mathrm{i}} - \bar{\mathrm{X}}^{\mathrm{j}})\widehat{\beta^{i}_\theta} + \bar{\mathrm{X}}^{\mathrm{j}}(\widehat{\beta^{i}_\theta} - \widehat{\beta^{j}_\theta}) \quad (4)$$

where $\widehat{Q_\theta}$ is the unconditional quantile of *log* real and adjusted 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 * represent the natives-born workers (or the non-refugee immigrant workers), Syrian refugees and counterfactual values. The first term on the right-hand side of the Eq. 4, $\left\{\widehat{Q^{i}_\theta} - \widehat{Q^{*}_\theta}\right\}$, measures the composition effect, which denotes the contribution of the differences in distributions of workers' characteristics to the wage differentials at the θ^{th} unconditional quantile. While the second term of the right-hand side of the equation, $\left\{\widehat{Q^{*}_\theta} - \widehat{Q^{j}_\theta}\right\}$, measures the discrimination effect, which denotes the unexplained part of the wage gap due to wage differences (wage discrimination) in returns to the workers' characteristics at the considered unconditional quantile. The set of regressors collects different

[6] The coefficient of parameters $\hat{\beta}_\theta$ estimated as $(X'X)^{-1}X'\widehat{RIF}$ (Y, $\widehat{Q_\theta}$) can be used to recover the average partial effect of a small location shift of covariates X on the unconditional θ-quantile of Y. For more detailed explanation of the RIF-OLS regression, we refer to Firpo et al. (2007) and Firpo et al. (2009).

groups of variables like human capital, economic sectors, and occupational variables (see Appendix 1 for more details about the used variables).

The aforementioned unconditional quantile decomposition of wage gap will be followed by a further detailed decomposition to show how the individual-specific characteristics contributes to each part of the wage differentials (i.e., composition and discrimination effects). Such decompositions are thus carried out as follows:

$$\widehat{Q^{i}_{\theta}} - \widehat{Q^{*}_{\theta}} = \sum_{k}(\overline{X^{i}}_{k} - \overline{X^{j}}_{k})\widehat{\beta^{i}_{\theta,k}} \tag{5a}$$

and

$$\widehat{Q^{*}_{\theta}} - \widehat{Q^{j}_{\theta}} = \sum_{k}\overline{X^{j}}_{k}(\widehat{\beta^{i}_{\theta,k}} - \widehat{\beta^{j}_{\theta,k}}) \tag{5b}$$

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

4. Empirical results

4.1. OLS estimations results

Table 6, below, displays the OLS regression results for different groups of workers (i.e. Native-born, other migrants and Syrian refugees) with Huber–White robust standard errors to correct for the heteroscedasticity. In addition to human capital controls, variables representing occupations, industries, and institutional sectors are also included in the regressions. While these potentially endogenous covariates may be jointly determined with wages, Albrecht, et al (2003) state that they may reflect unmeasured human capital and may help explain wage gaps as an accounting exercise.

Table 6 shows that men earn higher wages than women in both the native and other migrant in Jordanian labor market. On average, the wages of male natives and non refugee migrants are 11.3% and 160.7%, respectively, higher than those of their female counterparts. The returns to schooling are significant only for native workers with value equal to 4.25%, while the rates of experience returns are statistically significant for both natives and Syrian refugees with values equal to 2.93% and 11.9%, respectively. Similarly, the returns to permanent employment are significant only for natives and Syrian refugees with values equal to 18.6% and 53.4%, respectively.

We also find that the magnitudes of coefficient estimate of occupational dummies are generally significant only for non-refugee migrants. Professionals and technicians are found to be among the occupations that reward most in terms of wages for both natives and non-refugee migrants. [7] It's known that this occupation requires relatively more skills and expertise than other occupations. For this reason, it's too difficult to substitute workers holding this job compared to other types of occupations such as service workers. The OLS estimates show that being a

[7] The occupation reference in this regression is the skilled agricultural occupation

professional or technician worker earns 30.09% and 297.7% higher than service agriculture counterparts for both native other migrant workers, respectively.

In terms of industry, native-born workers are found to be highly paid when working in mining, electricity, gas and water distribution, with wages 57.3% highly than the ones in agriculture sector. For Syrian refugees, people working in market services are found to be the highly paid compared to their counterparts in agriculture sector (111%). On contrary, non-refugee migrants are found to be penalized heavily when working in manufacturing sector compared to their counterparts working in agriculture one. Furthermore, we find that self-employed and employer are highly rewarded in terms of wages in comparison with workers in private sector for both Syrian refugees and non-refugee migrants. Private and formal firms pay significantly 109.8% and 73.2% wages higher than wages received by self-employed and employer for non-refugees and Syrian refugees, respectively.

4.2. Unconditional quantile regression results

We report the unconditional quantile regression estimates at the 10th, 50th and 90th percentiles of log real wage distribution separately by group and year in Tables 4 and 5. The coefficient estimates from RIF-OLS regressions are explained as the marginal effects of covariates on the unconditional quantiles of the distributions of log wages for each group.

As expected, we find that the unconditional quantile regressions provide us with a more adequate and accurate description of the wage determination for each one of the considered groups than the aforementioned OLS regression analysis. The RIF-OLS regression results, shown in Table 7, reveal that the estimated returns to workers' characteristics aren't generally the same at different parts of the wage distribution for each group. For instance, Table 6 shows that the average return to one more year of schooling onto wage determination is around 4.25% for native-born workers. However, the RIF-OLS regression results in Table 7 reveal that this mean return has overshadowed the heterogeneity in returns to schooling at different points of natives' wage distribution. Indeed, the marginal return to one year of schooling increases from 2.58% at the 10th percentile to 2.9% at the median and 9.95% at the 90th percentile for natives. For other groups (i.e. non refugees migrants and Syrian refugees), the schooling return is slightly significant only at the median being 2.02% for the first group and -2.26% for the second one. From this, we may conclude that returns to education are found to have driven up the distributional wage gaps between different groups, as RIF-OLS regression results show that native born workers benefit more from education than migrants, including Syrian refugees and non-refugee workers, at the three percentiles of the wage distribution.

To highlight the advantage of the RIF-OLS regressions, we investigate the heterogeneous effects of working in market services on wages. The OLS estimates reported in Table 6 show that among natives-born workers the market services industry pays 31.4% higher wages than the base category of agriculture industry, while this sector pays 111% higher wages than the base category among Syrian refugees. The RIF-OLS results shown in Table 7 reveal that the mean wage premium received by natives working in this sector is mostly attributed to the high payoffs at the top end of wage distribution. At the 90th percentile, they perceived about 67% higher wages than their counterparts working in agriculture base sector. Among Syrian refugees, the wage premium in this industry is primarily driven by the high payoffs at the bottom up of the distribution and above (median). Syrian refugees working in market services industry are found, at the 10th percentile, to earn 164.6% higher than their counterparts in agriculture sector.

Giving all these results, we employ, in the subsequent subsection, the decomposition techniques described in Section 3. based on RIF-OLS estimates in order to identify to degree to which the differences in productivity characteristics and the different returns to those characteristics contribute to the wage differentials between Syrian refugees and other groups (i.e. natives and non-refugees migrants) at different parts of the wage distribution 2016.

4.3. Decomposition results

Subsequently, we decompose each distributional wage differentials $(\widehat{Q_\theta^i} - \widehat{Q_\theta^j})$ (i.e. between natives and Syrian refugees and between non refugee migrants and Syrian refugees) into a composition effect explained by differences in productivity characteristics $(\overline{X^\iota} - \overline{X^J})\widehat{\beta_\theta^{\mathrm{i}}}$ and a discrimination effect (called also wage structure effect) attributed to differential returns to covariates $\overline{X^J}(\widehat{\beta_\theta^{\mathrm{i}}} - \widehat{\beta_\theta^{\mathrm{j}}})$. The decomposition results at the mean and the 10th, 50th, and 90th percentiles of the wage distribution are presented in Table 7a and 7b, respectively.

Before diving on the interpretation of the decomposition results, it's worth to note that the decomposition using linear specification overshadows the overlapping in covariate distributions between native workers and Syrian refugees, for instance. As stated by Nopo (2008), the gap attributable to discrimination effect could be overestimated when the decomposition is conducted without limiting the comparison to workers with comparable characteristics. For this reason, the estimation results reported both in Table 8a and 8b should be considered as the lower bound of the composition effect and the upper bound of the discrimination effect.

The two Table 8a and 8b reveal a range of important findings. First, compared with native-born and non refugees migrants, Syrian refugees are found to earn, respectively, about 74% and 37.2% less wages in 2016, indicating that they are the less paid in Jordan. The Oaxaca–Blinder decomposition results shown in the first columns of the two tables reveal that the discrimination effect explains about 61.43% and 95.16% of the mean wage gaps natives/Syrian refugees and non refugees/Syrian refugees, respectively, so most of the mean wage differentials are due to differential returns to covariates rather than differences in characteristics between the different groups.

Second, the wage differentials (Native/Syrian refugees and Other migrants/Syrian refugees) in Tables 8a and 8b are larger at higher end than at the bottom and middle parts of the wage distributions, which is consistent with the pattern displayed in Fig. 2a and 2b. Quantile decomposition results of wage differentials between natives born and Syrian refugees show that the discrimination effect (unexplained part) contributes more than composition effect (explained part) only at the top end of the wage distribution with value equals to 86.12%. It's easy then to note then that a considerable part of the aforementioned raw wage differentials at the top end of wage distribution are attributable to the differences in returns to individual characteristics (discrimination effect) between native residents and Syrian refugees, while at the bottom up and middle parts, differences in characteristics (composition effect) dominate and explaining more than 102% and about 58.44%, respectively, of the total raw wage differentials.

The detailed decomposition results at the mean and the three selected quantiles are displayed in Table 8a and 8b. Third, starting with the detailed decomposition of wage differentials between native residents and Syrian refugees, we find that the differences in years of schooling can, respectively, explain significantly 28.73 % and 47.94% of the composition effect at the 10th and 50th percentiles of the wage distribution. While they explain significantly about 200% and 73.18% of the total discrimination effect at the middle and top end of distribution, respectively. On average, the schooling differences are found to explain about 72.18% of the mean composition effect and 27.74% of the raw mean wage gap in 2016.

Fourth, we do not find a significant contribution of occupation differences to the mean discrimination effect in Table 8a, while results show significant contribution of the first and last occupations (Professionals/technicians and Craft and related trades works) to the mean composition effect. When considering the different points of wage distribution, we find an evidence of heterogeneity in the contribution of occupational differences at the 50th and 90th percentiles. The first occupation is found to explain about 15.97% of the composition effect at the median, while *Service* occupation contributes with 18.97% in the discrimination effect at the top end of the distribution. Same pattern is observed for industries and institutional sectors. For instance, we find significant and positive contribution of *Agriculture* industry to the discrimination effect at the 10th percentile with coefficient equals to 0.227, while the contribution becomes negative at the top end of the distribution (-0.111). For irregular wage earners, we find that differences has been enlarged between natives-born and Syrian refugees at the 90th percentile compared to the mean of the distribution. In addition, detailed decomposition results show substantial changes in the contribution of *informal and private regular sector* at different points of wage distribution.

Finally, regarding the wage differentials between non-refugee migrants and Syrian refugees, Table 8b does show some different results. For instance, schooling variable is found to contribute significantly only to discrimination effect (at the 50th percentile). The contribution of the other human capital variable, *working experience*, to the wage differentials is found to be significant only at the mean and the median of wage distribution. These significant and negative contributions, -0.891 (at the mean) and -0.595 (at the median) to the wage structure effect, may indicate that experience discrimination penalizes non-refugee migrants rather than Syrian refugees. We do not find significant contribution of this variable on the composition effect of the considered wage differentials. The table shows, further, that *urban* dummy contributes significantly and positively to the discrimination effect of wage differentials at the bottom up and middle of wage distribution, indicating, at these percentiles, the importance of living in urban areas in explaining the wage structure effect between non-refugees and refugee migrants. In addition, no significant contribution of occupation differences to both composition and discrimination effects is shown in Table 8b, except the contribution of *service* occupation at the mean and median of wage distribution. Same pattern is observed for industries and institutional sectors. For example, *Manufacturing* industry is found to be the only *industry* that contributes significantly to both composition and discrimination effects. Regarding the institutional variables, we find that *Formal Private regular sector* is the only variable that have a significant contribution to wage differentials.

5. Discussion of results

We stress a set of important findings: *(i)*. We find sizable mean wage gaps between Syrian refugee workers and both other migrants and natives-born workers, ranging, respectively between 37.2% and 74%. However, these mean wage gaps are overshadowed by an uniformity throughout the wage distribution. We find significant higher wage gaps between considered groups at the top end than at the bottom and the middle of the wage distribution; *(ii)*. OB decomposition shows that discrimination effect dominates composition effects, suggesting that most of the mean wage differentials among the considered sample are not the result of differences in workers' characteristics. However, the composition effect attributable to differences in productivity characteristics contributes more to the wage gap between natives-born and Syrian refugee workers than the wage structure effect through the first half of wage distribution; *(iii)*. While the wage differentials between native-born and Syrian refugee workers is significant and largest at the higher end of wage distributions, our quantile decomposition results show that the relative wage discrimination problem is most serious among high wage workers; *(iv)*. The differences in years of education give higher returns to the composition effect at bottom and middle parts of wage distribution, but when moving up reverse of that is happened by being responsible for a substantial part of discrimination effect. On average, schooling is found to explain the lion share of the mean wage gap; *(v)*. Through wage distribution, we find an evidence of heterogeneity in the contribution of occupational differences to different wage differentials. Same pattern is observed for industries and institutional sectors.

6. Conclusion and policy recommendations

This paper examines the wage differentials between Syrian refugee workers and others migrants and native-born workers in Jordan's labor market, using a nationally representative data set from the 2016 Jordan Labor Market Panel Survey. In the first part of the analysis, we use OLS and unconditional quantile regressions to investigate the determinants of wage differentials between different groups, We find that ordinary least-squares (OLS) regressions cannot provide a reasonably adequate description of wage determination for each group separately, while, the unconditional quantile regression (UQR) results shed a light on substantial differences in the estimated coefficients of different individual and labor-market characteristics at different quantiles of the wage distributions.

In the second part, we perform Oaxaca–Blinder (OB) and quantile decompositions of wage differentials between Syrian refugee workers and their counterparts (i.e., natives-born and non-refugee workers) to discern the endowment effects, explained by differences in productivity characteristics, and discrimination effects, attributable to unequal returns to covariates. We find sizable mean wage gaps mainly between Syrian refugee workers and natives-born workers (74%). However, the wage gaps between different groups are not uniform the wage distribution. We find higher wage differentials between considered groups at the top end than at the bottom and the middle of the wage distribution in 2016. Our OB decomposition shows that refugees/migrant wage gap is mainly attributable to discrimination effect explained by differences in returns to individual workers' characteristics, while the composition effect attributable to differences in productivity characteristics (mainly the *schooling* variable) is found to contributes more to the wage gap between Syrian refugees and natives-born. Using quantile regression decompositions, we find distributional evidence that the relative wage discrimination problem against Syrian refugees is a pressing and serious issue among high-paid workers.

To the best of our knowledge, findings of the current study focusing on the position of Syrian refugees in labor market in Jordan have not been unveiled in previous literature. While migrant workers usually suffer from discrimination when compared to their native-born counterparts (Jemmali and Morrar, 2020), more and specific attention should be paid, too, by policymakers and NGOs to discrimination against Syrian refugees in labor market and their consequences, including powerlessness and lack of access to decent work. Whilst the empirical analysis is restricted to wage earners, the findings which show sizable and significant wage differentials against Syrian refugees compared to other migrants and native-born workers may emphasize that, such groups of forced migrant workers are bearing the double disadvantages of refugee and migrant status.

It's noteworthy in this regard that unlike other migrant workers, most Syrian refugees (as well as all refugees in the world), fleeing conflict in their home country do not migrate to the host countries with the intention to work. Yet most of them arrive to these countries with little to no economic resources and social marginalization risk, and therefore finding a job is the unique chance for them to make ends meet. Giving this situation, they are willing to work outside the Jordan's labor regulations in the informal sector. This may, subsequently, explain, according to a recent International Labor Organization (ILO) study[8], why the majority of them are employed in low-salaries jobs (if employed), which are not subject to national labor legislation, income taxation and social protection. For these arguments, policy-makers in Jordan and all stakeholders should take a set of measures to facilitate the integration of Syrian refugees in formal sector and cope with discrimination against them in terms of wages/salaries, working condition, work security and welfare facilities. They are called, for instance to ease the procedures involved in obtaining valid work permits from the concerned ministry. as differences in *schooling* are found to explain a substantial part of wage differentials through the wage distribution, policy-makers should direct more efforts to increase Syrian refugees' educational attainment.

A few caveats apply to these results. One limitation of this study is that we only rely on very sample of refugees extracted from one data set, the JLMPS 2016, and ignoring the first round of panel surveys, JLMPS 2010, as our main focus is on the Syrian refugee crisis started in March 2011. If other rounds that include a larger sample of refugees will be available in the future, it would certainly be of great interest to provide a moving picture of the wage gap among the considered sample and show its dynamics during the recent decades. Another shortcoming may be related to the limited focus on human capital determinants of wages, instead of extending the set of covariates to include additional worker-specific and firm-specific characteristics (mainly the public/private duality). Finally, particular caution should apply to two main empirical issues: the selectivity bias when dropping observations with no earnings and the choice of basic category when dealing with categorical variables. We leave these caveats for future research and studies.

[8] For more information on the ILO study, entitled "Impact of Syrian Refugees on the Jordanian Labor Market", see the following link: http://www.ilo.org/wcmsp5/groups/public/---arabstates/---robeirut/documents/publication/wcms_242021.pdf

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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

Table 2: Summary statistics by group in 2016

	Natives/Syr.Refugees					Oth. Migrants/Syr.Refugees				
	Natives		Syr. Refugees		Normalized Difference	Oth. Migrants		Syr. Refugees		Normalized Difference
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Household wealth										
1st Quintile	0.07	0.25	0.44	0.50	-0.67	0.75	0.43	0.44	0.50	0.48
2nd Quintile	0.16	0.37	0.37	0.48	-0.34	0.13	0.34	0.37	0.48	-0.40
3rd Quintile	0.23	0.42	0.06	0.24	0.35	0.08	0.27	0.06	0.24	0.05
4th Quintile	0.27	0.45	0.07	0.26	0.39	0.02	0.14	0.07	0.26	-0.18
5th Quintile	0.27	0.44	0.06	0.23	0.42	0.02	0.13	0.06	0.23	-0.15
Weekly hours	43.57	19.58	46.05	22.65	-0.08	53.04	32.24	46.05	22.65	0.18
Hourly wage	6.47	37.93	1.58	2.50	0.13	4.78	13.87	1.58	2.50	0.23
log (Hourly wage)	0.86	0.92	0.05	0.92	0.62	0.47	1.08	0.05	0.92	0.29
Age	34.44	9.95	33.35	8.38	0.08	36.17	8.88	33.35	8.38	0.23
Male	0.81	0.39	0.92	0.28	-0.23	0.97	0.17	0.92	0.28	0.17
Married	0.68	0.47	0.79	0.41	-0.22	0.68	0.47	0.65	0.48	-0.18
Education										
Illiterate	0.03	0.16	0.12	0.33	-0.27	0.33	0.47	0.12	0.33	0.36
Read & Write	0.10	0.30	0.55	0.50	-0.79	0.14	0.35	0.55	0.50	-0.67
Basic Education	0.31	0.46	0.12	0.33	0.34	0.15	0.36	0.12	0.33	0.06
Vocational	0.01	0.11	0.00	0.00	0.11	0.05	0.22	0.00	0.00	0.23
Secondary Education	0.17	0.37	0.09	0.28	0.18	0.18	0.39	0.09	0.28	0.20
Post-Secondary	0.10	0.30	0.04	0.19	0.19	0.09	0.29	0.04	0.19	0.16
University	0.24	0.43	0.08	0.27	0.33	0.05	0.22	0.08	0.27	-0.08
Post-Graduate	0.04	0.19	0.00	0.00	0.20	0.01	0.07	0.00	0.00	0.07
Experience	12.19	9.14	8.57	7.53	0.31	12.02	9.10	8.57	7.53	0.29
Urban	0.87	0.33	0.89	0.31	-0.04	0.89	0.31	0.89	0.31	0.00
Governorates										
Amman	0.34	0.47	0.39	0.49	-0.08	0.47	0.50	0.39	0.49	0.11
Balqa	0.07	0.26	0.08	0.28	-0.04	0.13	0.34	0.08	0.28	0.11
Zarqa	0.13	0.34	0.07	0.25	0.15	0.10	0.31	0.07	0.25	0.09
Madaba	0.03	0.16	0.01	0.10	0.09	0.01	0.12	0.01	0.10	0.03
Irbid	0.22	0.42	0.27	0.45	-0.08	0.16	0.36	0.27	0.45	-0.21
Mafraq	0.06	0.23	0.11	0.32	-0.14	0.06	0.24	0.11	0.32	-0.12
Jarash	0.03	0.17	0.00	0.00	0.18	0.01	0.10	0.00	0.00	0.11
Ajloun	0.03	0.17	0.00	0.00	0.18	0.00	0.00	0.00	0.00	.
Karak	0.05	0.21	0.06	0.24	-0.04	0.01	0.11	0.06	0.24	-0.18
Tafileh	0.01	0.12	0.00	0.00	0.12	0.00	0.00	0.00	0.00	.
Ma'an	0.02	0.14	0.00	0.00	0.14	0.00	0.06	0.00	0.00	0.06
Aqaba	0.02	0.14	0.00	0.00	0.14	0.03	0.17	0.00	0.00	0.18

Table 3: Labor market characteristics by Migration status

	Natives/Syr.Refugees					Oth. Migrants/Syr.Refugees				
	Natives		Syr. Refugees		Normalized Difference	Oth. Migrants		Syr. Refugees		Normalized Difference
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Formal	0.77	0.42	0.10	0.30	1.31	0.25	0.43	0.10	0.30	0.28
Economic Sector										
Government	0.52	0.50	0.01	0.09	1.00	0.04	0.20	0.01	0.09	0.15
Public	0.01	0.08	0.00	0.03	0.07	0.01	0.09	0.00	0.03	0.08
Private	0.46	0.50	0.90	0.31	-0.75	0.92	0.27	0.90	0.31	0.06
Other	0.00	0.06	0.03	0.17	-0.14	0.03	0.16	0.03	0.17	-0.02
International	0.01	0.11	0.06	0.25	-0.20	0.01	0.08	0.06	0.25	-0.22
Job Stability										
Permanent	0.86	0.34	0.50	0.50	0.60	0.79	0.41	0.50	0.50	0.45
Temporary	0.07	0.25	0.21	0.41	-0.30	0.06	0.23	0.21	0.41	-0.31
Seasonal	0.01	0.08	0.06	0.24	-0.21	0.03	0.17	0.06	0.24	-0.10
Casual	0.07	0.25	0.24	0.43	-0.35	0.12	0.33	0.24	0.43	-0.22
Occupations										
Managers	0.01	0.08	0.00	0.00	0.08	0.00	0.00	0.00	0.00	.
Professionals	0.28	0.45	0.06	0.23	0.45	0.02	0.14	0.06	0.23	-0.14
Technicians & Ass. Prof.	0.09	0.28	0.01	0.08	0.27	0.00	0.05	0.01	0.08	-0.04
Clerical support workers	0.08	0.27	0.01	0.10	0.24	0.01	0.12	0.01	0.10	0.03
Service and Sales workers	0.26	0.44	0.26	0.44	-0.01	0.44	0.50	0.26	0.44	0.26
Skilled Agri., for. and fish	0.01	0.10	0.09	0.28	-0.25	0.22	0.41	0.09	0.28	0.27
Craft and related trades wor.	0.12	0.33	0.38	0.49	-0.44	0.21	0.41	0.38	0.49	-0.27
Plant and machine oper. and ass.	0.09	0.29	0.02	0.15	0.21	0.03	0.16	0.02	0.15	0.01
Elementary occupations	0.06	0.24	0.17	0.38	-0.24	0.07	0.26	0.17	0.38	-0.21
Regions										
Middle	0.56	0.50	0.56	0.50	0.01	0.72	0.45	0.56	0.50	0.25
North	0.34	0.47	0.39	0.49	-0.07	0.23	0.42	0.39	0.49	-0.24
South	0.10	0.30	0.06	0.24	0.11	0.05	0.21	0.06	0.24	-0.04

Table 4: Descriptive average Native/Syr.Refugee and Oth. Migrant/Syr.Refugee earners wage gaps

	Natives/Syr.Refugees						Oth.Migrants/Syr.Refugees					
	Native earners (G)		Syr.Refugee earners ($\bar{G}$)		G-$\bar{G}$	$\bar{G}$/G (%)	Oth.Migrant earners (G)		Syr.Refugee earners ($\bar{G}$)		G-$\bar{G}$	$\bar{G}$/G (%)
	N	Mean	N	Mean			N	Mean	N	Mean		
Economic Sector												
Government	2678	5.11	2	3.94	1.17	77.03	27	17.33	2	3.94	13.39	22.72
Public	36	5.46	1	0.34	5.12	6.21	8	2.24	1	0.34	1.90	15.13
Private	1642	7.96	94	1.58	6.38	19.85	252	4.36	94	1.58	2.78	36.25
Other	18	6.95	22	1.32	5.64	18.95	16	1.53	22	1.32	0.21	86.42
International	41	8.07	41	1.37	6.70	16.94	8	2.30	41	1.37	0.93	59.51
Job Stability												
Permanent	3876	5.43	54	1.24	4.19	22.89	219	5.18	54	1.24	3.93	24.02
Temporary	248	2.60	44	0.86	1.74	33.07	43	1.51	44	0.86	0.65	56.96
Seasonal	37	2.09	9	1.33	0.75	63.95	7	8.29	9	1.33	6.96	16.09
Casual	254	24.51	53	2.95	21.57	12.02	42	2.89	53	2.95	-0.05	101.84
Occupation												
Managers	30	3.58	0	.	.	.	0	.	0	.	.	.
Professionals	1129	8.66	16	2.15	6.51	24.85	10	36.19	16	2.15	34.03	5.94
Technicians & Ass. Prof.	327	4.07	6	2.23	1.84	54.89	3	2.19	6	2.23	-0.04	101.79
Clerical support workers	330	5.67	10	1.26	4.41	22.23	6	1.76	10	1.26	0.49	71.85
Service and Sales workers	1283	5.61	34	1.55	4.06	27.65	104	5.28	34	1.55	3.73	29.38
Skilled Agri., for. and fish	73	1.92	12	0.78	1.14	40.73	48	2.62	12	0.78	1.84	29.84
Craft and related trades wor.	475	5.26	42	1.93	3.33	36.76	75	2.38	42	1.93	0.45	81.11
Plant and machine oper. and ass.	401	8.88	6	1.12	7.76	12.58	23	12.29	6	1.12	11.17	9.09
Elementary occupations	316	4.89	31	1.13	3.76	23.15	39	7.10	31	1.13	5.97	15.94
Governorate												
Amman	877	9.34	14	1.33	8.00	14.29	88	6.70	14	1.33	5.37	19.90
Balqa	333	7.82	3	0.48	7.34	6.20	35	1.97	3	0.48	1.48	24.63

Zarqa	531	6.30	17	1.20	5.10	19.02	27	3.17	17	1.20	1.97	37.82
Madaba	177	10.83	1	0.21	10.63	1.90	9	23.77	1	0.21	23.56	0.87
Irbid	727	4.87	37	2.67	2.20	54.84	18	2.70	37	2.67	0.03	98.78
Mafraq	445	2.54	87	1.39	1.15	54.72	9	1.98	87	1.39	0.59	70.14
Jarash	290	2.85	0	.	.	.	73	3.28	0	.	.	.
Ajloun	186	2.93	0	.	.	.	0	.	0	.	.	.
Karak	371	2.71	1	0.69	2.02	25.48	5	1.62	1	0.69	0.93	42.49
Tafileh	160	2.72	0	.	.	.	0	.	0	.	.	.
Ma'an	178	3.12	0	.	.	.	12	2.33	0	.	.	.
Aqaba	140	2.95	0	.	.	.	35	1.87	0	.	.	.

Table 5a: Test de K-S, Native/Syr.Refugee

Smaller group	D	P-value
Syr.Refugees	0.4721	0
Native	-0.0002	1
Combined K-S	0.4721	0

Table 5b:Test de K-S, Oth.Migrant/Syr.Refugee

Smaller group	D	P-value
Syr. Refugee	0.1576	0.005
Oth. Migrants	-0.0094	0.982
Combined K-S	0.1576	0.01

Table 6: OLS estimation results

VARIABLES	Natives	Oth.Migrant	Syr.Refugee
Male	0.113*	1.607***	0.203
	(0.0638)	(0.428)	(0.260)
Married	0.124**	-0.266	-0.206
	(0.0554)	(0.231)	(0.231)
Work experience	0.0293***	0.0196	0.119**
	(0.00813)	(0.0241)	(0.0464)
Squared Experience divided by 100	-0.0774***	-0.0782	-0.390**
	(0.0224)	(0.0628)	(0.162)
Schooling	0.0425***	-0.00107	0.0125
	(0.00848)	(0.0246)	(0.0289)
Permanent	0.186**	0.304	0.534*
	(0.0752)	(0.225)	(0.285)
Urban	-0.00531	0.0626	-0.273
	(0.0476)	(0.234)	(0.173)
Occupations			
Managers	0.275		
	(0.193)		
Professionals/Technicians	0.309**	2.977***	0.585
	(0.151)	(0.945)	(0.570)
Clerical staff	0.230	1.401**	0.541
	(0.157)	(0.709)	(0.591)
Service workers	0.0829	0.552	0.168
	(0.149)	(0.693)	(0.527)
Craft and related trades workers	-0.0722	1.460**	0.330
	(0.154)	(0.668)	(0.543)
Manufacturing and Elementary occupations	0.132	1.598**	0.268
	(0.150)	(0.623)	(0.548)
Industries			
Manufacturing	0.294**	-1.516**	0.405**
	(0.141)	(0.643)	(0.199)
Construction	0.516***	-1.240*	0.652**
	(0.159)	(0.733)	(0.297)
Mining, Electricity, Gas and Water	0.573***	-0.884	0.695**
	(0.193)	(0.704)	(0.302)
Market services	0.314**	-1.060	1.110***
	(0.128)	(0.681)	(0.156)
Non-Market services	0.191	-0.584	0.321
	(0.129)	(0.683)	(0.221)
Institutional sectors			
Irregular wage	0.0501	-0.506	-0.318
	(0.606)	(0.494)	(0.404)
Private regular	-0.605	-0.798**	-1.147***
	(0.599)	(0.350)	(0.262)
Formal Private regular	-0.647	-1.098***	-0.732**

	(0.601)	(0.324)	(0.297)
Public and Government	-0.416		
	(0.604)		
Constant	-0.114	-0.517	-0.540
	(0.596)	(0.706)	(0.699)
Observations	3,978	268	150
R-squared	0.102	0.244	0.521

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

Table 7: Unconditional quantile regression results

	Native workers			Oth.Migrant workers			Syr.Refugee workers		
VARIABLES	10th	50th	90th	10th	50th	90th	10th	50th	90th
Male	0.127**	0.121***	0.151	2.426***	0.848***	1.107	-0.0859	0.0841	0.0898
	(0.0566)	(0.0336)	(0.122)	(0.929)	(0.243)	(0.883)	(0.210)	(0.129)	(0.147)
Married	0.0565	0.100***	0.172*	-0.517*	-0.323***	-0.322	-0.376**	0.0372	-0.000389
	(0.0587)	(0.0316)	(0.0969)	(0.308)	(0.123)	(0.492)	(0.162)	(0.101)	(0.155)
Work experience	0.0290***	0.0234***	0.0265*	0.0518	0.0175	0.0597	0.0524	0.0536***	0.0257
	(0.00991)	(0.00464)	(0.0136)	(0.0394)	(0.0203)	(0.0511)	(0.0397)	(0.0169)	(0.0218)
Squared Experience divided by 100	-0.0713**	-0.0593***	-0.0467	-0.103	-0.0585	-0.216*	-0.113	-0.162***	-0.0696
	(0.0298)	(0.0129)	(0.0386)	(0.0949)	(0.0683)	(0.125)	(0.132)	(0.0567)	(0.0877)
Schooling	0.0258**	0.0290***	0.0995***	-0.0100	0.0202*	-0.0242	-0.00104	-0.0226*	0.0266
	(0.0106)	(0.00485)	(0.0186)	(0.0262)	(0.0107)	(0.0471)	(0.0206)	(0.0128)	(0.0199)
Permanent	0.0668	0.132***	0.213	-0.177	0.120	0.222	0.274	0.156	0.0620
	(0.116)	(0.0494)	(0.139)	(0.719)	(0.216)	(0.449)	(0.244)	(0.100)	(0.182)
Urban	-0.00772	-0.0131	-0.0449	1.195**	0.293	-0.523	-0.168	-0.216**	-0.102
	(0.0491)	(0.0286)	(0.0891)	(0.582)	(0.188)	(0.571)	(0.215)	(0.0874)	(0.125)
Occupations									
Managers	0.360	0.347	-0.0780	0	0	0	0	0	0
	(0.297)	(0.218)	(0.442)	(0)	(0)	(0)	(0)	(0)	(0)
Professionals/Technicians	0.326	0.292**	0.0247	0.0659	0.437	6.764***	-0.511	0.459*	0.186
	(0.293)	(0.135)	(0.218)	(1.256)	(0.347)	(2.040)	(0.655)	(0.242)	(0.360)
Clerical staff	0.332	0.158	0.119	-0.330	-0.113	3.966***	-0.330	0.0528	0.196
	(0.292)	(0.139)	(0.238)	(1.087)	(0.466)	(1.511)	(0.671)	(0.281)	(0.296)
Service workers	-0.00274	0.145	0.0806	-1.219	-0.926***	3.270**	-0.778	-0.190	-0.324
	(0.292)	(0.132)	(0.206)	(1.127)	(0.239)	(1.532)	(0.669)	(0.127)	(0.224)
Craft and related trades workers	0.103	0.0934	-0.152	-0.234	-0.0106	4.346***	-0.625	-0.125	0.316
	(0.297)	(0.136)	(0.234)	(1.058)	(0.364)	(1.472)	(0.638)	(0.181)	(0.296)

Manufacturing and Elementary occupations	0.174	0.109	0.100	-0.744	-0.00145	4.771***	-0.505	-0.161	0.243
	(0.289)	(0.133)	(0.205)	(0.918)	(0.218)	(1.418)	(0.631)	(0.157)	(0.231)
Industries									
Manufacturing	-0.308	0.0231	0.539**	0.617	-0.113	-4.623***	1.308***	0.287**	-0.402
	(0.211)	(0.130)	(0.243)	(0.993)	(0.333)	(1.462)	(0.500)	(0.135)	(0.263)
Construction	-0.150	0.133	0.988***	-0.0760	-0.0886	-2.990*	1.564***	0.390**	-0.389
	(0.241)	(0.136)	(0.317)	(1.171)	(0.366)	(1.737)	(0.502)	(0.152)	(0.272)
Mining, Electricity, Gas and Water	-0.204	0.362**	1.402***	1.842*	0.592*	-3.429*	1.378***	0.186	-0.0485
	(0.243)	(0.147)	(0.397)	(1.084)	(0.307)	(2.002)	(0.485)	(0.197)	(0.287)
Market services	-0.224	-0.0193	0.670***	0.718	-0.108	-3.515**	1.646***	0.461***	0.360*
	(0.203)	(0.125)	(0.221)	(1.048)	(0.216)	(1.527)	(0.507)	(0.0990)	(0.201)
Non-Market services	-0.351*	0.00105	0.518**	0.596	0.124	-2.582*	1.075*	0.0336	-0.205
	(0.210)	(0.127)	(0.228)	(1.083)	(0.214)	(1.520)	(0.545)	(0.130)	(0.252)
Institutional sectors									
Irregular wage	-0.428*	-0.252	1.088**	-0.321	0.0327	-3.102**	-0.0754	0.251	0.0393
	(0.245)	(0.568)	(0.538)	(0.772)	(0.334)	(1.357)	(0.261)	(0.192)	(0.207)
Informal Private regular	-0.674***	-0.567	0.187	-0.736*	-0.150	-2.416***	-0.308*	0.0263	-0.00687
	(0.244)	(0.569)	(0.521)	(0.422)	(0.223)	(0.874)	(0.176)	(0.194)	(0.132)
Formal Private regular	-0.319	-0.563	-0.133	-0.373	-0.278	-3.254***	0	0	0
	(0.245)	(0.569)	(0.525)	(0.404)	(0.216)	(0.854)	(0)	(0)	(0)
Public and Government	-0.117	-0.293	-0.231	0	0	0	-0.436	0.325**	1.160***
	(0.259)	(0.570)	(0.534)	(0)	(0)	(0)	(0.366)	(0.160)	(0.359)
Constant	-0.280	0.195	-0.867	-2.806***	-0.361	2.622	-0.780	-0.136	0.339
	(0.211)	(0.563)	(0.553)	(1.080)	(0.413)	(1.816)	(0.590)	(0.224)	(0.276)
Observations	3,978	3,978	3,978	268	268	268	150	150	150
R-squared	0.095	0.195	0.064	0.186	0.347	0.252	0.436	0.443	0.318

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

Table 8a: Decomposition at the mean and selected percentiles between Natives and Syrian Refugees

	Mean			10th percentile			50th percentile			90th percentile		
VARIABLES	overall	explained	unexplained	overall	explained	unexplained	overall	explained	unexplained	overall	explained	unexplained
Male		-0.00997	-0.0833		-0.0107	0.202		-0.0110	0.0239		-0.0134	0.0475
		(0.00908)	(0.243)		(0.00916)	(0.235)		(0.00841)	(0.138)		(0.0143)	(0.181)
Married		-0.0172	0.274		-0.00783	0.422**		-0.0145*	0.0517		-0.0229	0.138
		(0.0111)	(0.198)		(0.00895)	(0.172)		(0.00820)	(0.0995)		(0.0169)	(0.160)
Work experience		0.0958**	-0.804*		0.0965**	-0.301		0.0793***	-0.334*		0.0846	-0.0175
		(0.0415)	(0.433)		(0.0459)	(0.440)		(0.0307)	(0.183)		(0.0518)	(0.244)
Squared Experience divided by 100		-0.0737**	0.430*		-0.0686*	0.0889		-0.0584***	0.172*		-0.0436	0.0410
		(0.0306)	(0.241)		(0.0352)	(0.224)		(0.0215)	(0.0976)		(0.0382)	(0.141)
Schooling		0.205***	0.240		0.133***	0.227		0.151***	0.445***		0.450***	0.513**
		(0.0463)	(0.231)		(0.0503)	(0.206)		(0.0304)	(0.124)		(0.101)	(0.217)
Permanent		0.0637**	-0.186		0.0309	-0.128		0.0471**	-0.0233		0.0715	0.0731
		(0.0294)	(0.158)		(0.0413)	(0.168)		(0.0205)	(0.0668)		(0.0494)	(0.127)
Urban		6.27e-05	0.237		-5.38e-05	0.183		0.000151	0.208**		0.000547	0.0578
		(0.000591)	(0.159)		(0.000611)	(0.233)		(0.000501)	(0.0927)		(0.00165)	(0.142)
Occupations												
Professionals/Technicians		0.0499**	-0.0104		0.0381	0.00900		0.0503***	-0.0371		-0.0172	0.000385
		(0.0237)	(0.0216)		(0.0249)	(0.0230)		(0.0161)	(0.0230)		(0.0404)	(0.0223)
Clerical staff		0.00635	-0.00169		0.00999*	-0.000642		0.00252	-0.00193		0.00212	0.000749
		(0.00605)	(0.00299)		(0.00582)	(0.00280)		(0.00418)	(0.00272)		(0.0113)	(0.00268)
Service workers		-0.00225	0.00958		-0.00762	0.0304		0.000978	0.0126		-0.000404	0.133*
		(0.00433)	(0.0422)		(0.0112)	(0.0649)		(0.00219)	(0.0294)		(0.00472)	(0.0724)
Skilled agricultural workers		0.0102	0.0133		0.0147	-0.0715		0.00917	-0.0268		0.00702	0.0164
		(0.0137)	(0.0521)		(0.0251)	(0.0817)		(0.0126)	(0.0245)		(0.0169)	(0.0302)
Craft and related trades workers		0.0594**	-0.111		0.0223	0.0270		0.00760	-0.0281		0.0673	-0.130
		(0.0275)	(0.0945)		(0.0286)	(0.105)		(0.0138)	(0.0633)		(0.0470)	(0.108)

Economic sectors												
Agriculture		0.0398*	0.0308		-0.0282	0.227**		0.0105	0.0249		0.0861**	-0.111**
		(0.0213)	(0.0258)		(0.0251)	(0.111)		(0.0144)	(0.0224)		(0.0424)	(0.0545)
Manufacturing		0.00439	0.0329		0.0209	-0.0870		0.0132	-0.0419		0.0299	0.0533
		(0.0148)	(0.0490)		(0.0189)	(0.0698)		(0.0105)	(0.0376)		(0.0291)	(0.0693)
Construction		-0.0279	0.0145		-0.00858	-0.0778		-0.00711	-0.0252		-0.0411	0.109*
		(0.0174)	(0.0475)		(0.0180)	(0.0566)		(0.00844)	(0.0254)		(0.0332)	(0.0616)
Mining, Electricity, Gas and Water		0.00278	0.000686		-0.000234	-0.00212		0.00309**	0.00249		0.00762*	0.00473
		(0.00175)	(0.00203)		(0.00134)	(0.00211)		(0.00141)	(0.00176)		(0.00419)	(0.00328)
Market services		-1.08e-06	-0.145***		-4.12e-05	-0.150**		-0.000273	-0.0935***		-4.19e-05	-0.133*
		(0.000160)	(0.0533)		(0.000952)	(0.0677)		(0.00623)	(0.0317)		(0.00100)	(0.0696)
Non-Market services		-0.0577**	0.00881		-0.0666**	-0.00406		-0.0396**	0.0141		-0.0767	-0.00694
		(0.0276)	(0.0186)		(0.0337)	(0.0315)		(0.0182)	(0.0122)		(0.0562)	(0.0210)
Institutional sectors												
Irregular wage		-0.110**	0.236*		0.0712	-0.222		-0.00881	0.0370		-0.309***	0.760***
		(0.0487)	(0.141)		(0.0469)	(0.185)		(0.0195)	(0.0709)		(0.104)	(0.218)
Informal Private regular		0.0873*	0.561***		0.260***	-0.425*		0.130***	0.0336		-0.186**	0.984***
		(0.0523)	(0.180)		(0.0676)	(0.256)		(0.0300)	(0.124)		(0.0848)	(0.269)
Formal Private regular		-0.0414***	0.0499		-0.0358**	-0.0723		-0.0499***	0.00938		0.0167	0.135*
		(0.0157)	(0.0375)		(0.0151)	(0.0547)		(0.0146)	(0.0192)		(0.0253)	(0.0725)
Natives	0.870***			0.0457*			0.773***			1.526***		
	(0.0226)			(0.0237)			(0.0138)			(0.0403)		
Syr. Refugees	0.132			-0.408***			0.234***			0.712***		
	(0.120)			(0.123)			(0.0565)			(0.0671)		
difference	0.739***			0.453***			0.539***			0.814***		
	(0.122)			(0.125)			(0.0582)			(0.0782)		
explained	0.284***			0.463***			0.315***			0.113		
	(0.0855)			(0.0785)			(0.0498)			(0.151)		

unexplained	0.454***			-0.00986			0.223***			0.701***		
	(0.112)			(0.145)			(0.0591)			(0.152)		
Constant			-0.343			0.116			-0.199			-1.968***
			(0.459)			(0.680)			(0.257)			(0.557)
Observations	4,128	4,128	4,128	.	.	.	.	.	.	.	.	.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8b: Decomposition at the mean and selected percentiles between Other Migrants and Syrian Refugees

	Mean			10th percentile			50th percentile			90th percentile		
VARIABLES	overall	explained	unexplained	overall	explained	unexplained	overall	explained	unexplained	overall	explained	unexplained
Male		0.107	1.273***		0.129	1.860**		0.0537	0.612**		0.0907	1.129
		(0.107)	(0.463)		(0.133)	(0.732)		(0.0538)	(0.280)		(0.113)	(1.000)
Married		0.0449	-0.0503		0.0696	0.0883		0.0518*	-0.302*		0.0667	-0.327
		(0.0443)	(0.271)		(0.0526)	(0.275)		(0.0311)	(0.163)		(0.107)	(0.529)
Work experience		0.0594	-0.891*		0.125	-0.279		0.0503	-0.595**		0.208	0.317
		(0.0778)	(0.480)		(0.111)	(0.568)		(0.0627)	(0.299)		(0.212)	(0.618)
Squared Experience divided by 100		-0.0721	0.429*		-0.0754	0.103		-0.0513	0.269*		-0.234	-0.224
		(0.0665)	(0.254)		(0.0777)	(0.273)		(0.0643)	(0.159)		(0.177)	(0.267)
Schooling		-6.66e-05	-0.104		-0.000497	-0.0501		0.00119	0.415**		-0.00182	-0.490
		(0.00175)	(0.291)		(0.00640)	(0.271)		(0.0151)	(0.174)		(0.0233)	(0.487)
Permanent		0.0781	-0.122		-0.0362	-0.275		0.0294	-0.0674		0.0748	0.111
		(0.0631)	(0.193)		(0.148)	(0.354)		(0.0537)	(0.137)		(0.144)	(0.317)
Urban		0.000639	0.297		0.00972	1.047**		0.00284	0.541***		-0.00657	-0.452
		(0.00337)	(0.257)		(0.0366)	(0.488)		(0.0108)	(0.199)		(0.0255)	(0.639)
Occupations												
Professionals/Technicians		-0.0643	0.0720		-0.0301	0.0443		-0.0195	-0.0368		-0.114	0.171
		(0.0592)	(0.0643)		(0.0379)	(0.0553)		(0.0193)	(0.0316)		(0.123)	(0.156)
Clerical staff		-0.000729	-0.00432		0.00122	0.000815		-0.000393	-0.00402		-0.00369	-0.00862
		(0.00218)	(0.00489)		(0.00290)	(0.00410)		(0.00172)	(0.00528)		(0.00897)	(0.0103)
Service workers		-0.224**	-0.207**		-0.0811	-0.000392		-0.188***	-0.182***		-0.396	-0.243
		(0.109)	(0.103)		(0.0711)	(0.0977)		(0.0725)	(0.0693)		(0.258)	(0.244)
Skilled agricultural workers		-0.195	-0.121		0.0721	-0.00956		0.000167	-0.0226		-0.713	-0.504*
		(0.129)	(0.0958)		(0.0970)	(0.104)		(0.0252)	(0.0310)		(0.435)	(0.293)

Craft and related trades workers		0.0264	-0.0820		-0.0776	0.234		0.00166	-0.0266		0.103	-0.260
		(0.0618)	(0.157)		(0.0682)	(0.173)		(0.0537)	(0.141)		(0.166)	(0.359)
Economic sectors												
Agriculture		0.0878	0.198*		-0.0490	0.156		-0.00641	0.0401		0.350	0.471*
		(0.0825)	(0.107)		(0.0748)	(0.134)		(0.0174)	(0.0335)		(0.292)	(0.278)
Manufacturing		0.147**	-0.160*		-9.80e-05	-0.0635		0.0399	-0.0839		0.500**	-0.559**
		(0.0683)	(0.0838)		(0.0479)	(0.0968)		(0.0509)	(0.0828)		(0.225)	(0.244)
Construction		0.0187	-0.0887		0.0287	-0.204*		0.00772	-0.0740		0.0101	0.0303
		(0.0283)	(0.0761)		(0.0420)	(0.112)		(0.0161)	(0.0587)		(0.0540)	(0.191)
Mining, Electricity, Gas and Water		2.07e-05	-0.00127		-0.00562	0.00509		-0.00287	0.00421		0.00408	-0.00596
		(0.00207)	(0.00327)		(0.00417)	(0.00463)		(0.00203)	(0.00300)		(0.00934)	(0.0122)
Market services		0.00331	-0.189**		-0.00151	-0.147		0.00308	-0.132**		0.0148	-0.354*
		(0.0135)	(0.0838)		(0.00754)	(0.0974)		(0.0121)	(0.0541)		(0.0582)	(0.197)
Non-Market services		0.0619	0.0525		-0.00335	0.0108		0.0111	0.0365		0.0717	0.0480
		(0.0515)	(0.0348)		(0.0634)	(0.0473)		(0.0284)	(0.0235)		(0.129)	(0.0686)
Institutional sectors												
Irregular wage		0.0698	-0.0568		0.0353	-0.229		-0.00429	0.0443		0.527	-0.713
		(0.0769)	(0.194)		(0.0868)	(0.274)		(0.0438)	(0.132)		(0.354)	(0.548)
Informal Private regular		0.0125	0.205		0.00921	-0.449		0.00223	0.188		0.0464	-0.842
		(0.0679)	(0.258)		(0.0500)	(0.344)		(0.0125)	(0.206)		(0.251)	(0.690)
Formal Private regular		-0.144*	-0.0365		-0.0391	-0.0897		-0.0347	0.0238		-0.525**	-0.247
		(0.0757)	(0.0467)		(0.0456)	(0.0717)		(0.0309)	(0.0338)		(0.266)	(0.158)
Oth. Migrants	0.504***			-0.380***			0.293***			1.256***		
	(0.107)			(0.0972)			(0.0735)			(0.264)		
Syr. Refugees	0.132			-0.407***			0.246***			0.712***		
	(0.120)			(0.141)			(0.0762)			(0.0806)		
difference	0.372**			0.0269			0.0465			0.544**		

	(0.160)			(0.171)			(0.106)			(0.276)		
explained	0.0179			0.0801			-0.0521			0.0736		
	(0.155)			(0.162)			(0.110)			(0.345)		
unexplained	0.354*			-0.0532			0.0986			0.470		
	(0.192)			(0.220)			(0.126)			(0.397)		
Constant			-0.0580			-1.808			-0.550			3.422*
			(0.736)			(1.127)			(0.475)			(1.971)
Observations	418	418	418	.	.	.	.	.	.	.	.	.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix 1

The wage equation is specified as follows:

$$log(w) = \beta_0 + \beta_1 D_{Male} + \beta_2 D_{Married} + \beta_3 Exp + \beta_4 SqrExp + \beta_5 Sch + \beta_6 D_{Permanent} + \beta_7 D_{Urban} + \sum_{i=1}^{6} \beta_{8i} Occ_i + \sum_{i=1}^{5} \beta_{9i} Ind_i + \sum_{i=1}^{4} \beta_{10i} Ins_i + \varepsilon$$

The variable D_{Male} is a gender dummy equals 1 if male and 0 otherwise, and $D_{Married}$ equals 1 if married and 0 otherwise. The variable *Exp* and its square reflect the non-linear relationship of experience with wage earnings if β_4 is statistically significant. *Sch* is the schooling years variable and $D_{Permanent}$ if working in permanent job and 0 otherwise. D_{Urban} equals 1 if living in urban areas and 0 otherwise. The variables Occ represent the 6 broad occupation dummies, *Ind* represent the 5 industry dummies, and *Ins* represent the 4 institutional sectors. Finally ε represents an i.i.d. idiosyncratic error term.