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Abstract

This paper quantifies the inequalities of opportunities in monthly wages in the Jordanian labor market, drawing on Roemer (1993)'s distinction between circumstances and other unobserved/unexplained variables (luck, endowed genetics, culture, native ability) which for convenience we call effort. I borrow the parametric approach developed by Bourguignon, Ferreira, and Menéndez (2007) to calculate the shares of "unfair" inequality and analyze the main drivers of inequality of opportunity for the entire population and gender/birth region subgroups, using the nationally representative Jordan labor market panel surveys for 2010 and 2016. Also complementary analyses of inequality of opportunity was conducted; the stochastic dominance test and generalized lorenz curves Lefranc, Pistolesi, and Trannoy (2008), which allowed to visualize the magnitude of the inequality of opportunities. Inequality of opportunity shares are small and decline in the second survey wave. Women and both north and south-born subgroups experience greater unfair inequality. The main drivers across the sample are parental education, father's occupation, and employment sector. Stochastic dominance tests confirm advantages for individuals with publicly employed fathers, white-collar fathers, highly educated parents, and men.

Keywords: Inequality of opportunity, Gini Coefficients, Mean log deviation, Generalized Lorenz curves, Stochastic dominance, Early childhood, Spatial inequality.

JEL Classifications: J1, J2.

ملخص

تحدد هذه الورقة عدم المساواة في الفرص في الأجور الشهرية في سوق العمل الأردني، بالاعتماد على دراسة رومر (1993) بين الظروف والمتغيرات الأخرى غير المرئية/غير المبررة (الحظ، الوراثة الموهوبة، الثقافة، القدرة الأصلية) والتي نسميها للاختصار: الجهد. أستعير النهج البارامتري الذي طوره بورغينيون وفيريرا ومينينديز (2007) لحساب حصص عدم المساواة «غير العادلة» وتحليل الدوافع الرئيسية لعدم المساواة في الفرص لجميع السكان والجنس/المجموعات الفرعية لمنطقة الولادة، باستخدام التمثيل الوطني لمسوح سوق العمل الأردنية لعامي 2010 و 2016. وأجريت أيضا تحليلات تكميلية لعدم المساواة في الفرص ؛ اختبار الهيمنة العشوائي ومنحنيات لورينز المعممة (2008)، والتي سمحت بتصور حجم عدم المساواة في الفرص. يظهر أن عدم المساواة في حصص الفرص تكون صغيرة وتنخفض في موجة المسح الثانية. أيضاً، يظهر أن النساء والمجموعات الفرعية المولودة في الشمال والجنوب تعاني من قدر أكبر من عدم المساواة غير العادلة. الدوافع الرئيسية عبر العينة هي تعليم الوالدين، ومهنة الأب، وقطاع العمل. تؤكد اختبارات الهيمنة العشوائية مزايا الأفراد الذين لديهم آباء عاملون وآباء من أصحاب أعمال الياقات البيضاء وآباء متعلمون تعليماً عالياً.

1. Introduction

Inequality concerns the distribution of resources among various societal groups. Opportunity inequality refers to how an individual's birth circumstances (race, gender, family wealth, class, and parental education) impact their lifetime prospects. Before Rawls (1971), Researchers assessed inequality solely by ranking outcomes, like expenditures or income. Rawl highlighted those circumstances, including social class, parental education, cultural background, inherited traits, and luck, contribute significantly to inequality.

Roemer (1998) viewed inequality of opportunity to be a function of an individual's circumstances and effort. He introduced two principles: the compensation principle, stating that inequalities from circumstances beyond individuals' control should be compensated, and the reward principle, which holds individuals accountable for their choices. Roemer's framework finds effort-based inequality morally justifiable and unworthy of compensation.

The line between circumstances and effort is contentious, as many variables depend on both, with socio-economic background significantly impacting effort levels. A society is more equalitarian when effort, rather than circumstances, mainly determines income distribution. Individuals accept income differences resulting from effort over uncontrollable circumstances. Alesina and Giuliano (2011); Alesina, Stantcheva, and Teso (2018); Cappelen, Hole, Sørensen, and Tungodden (2007).

A child's early years impact lifelong financial, social, emotional, and physical development, influenced by resources from parents or caregivers. Both positive and negative environments shape future adults, leading scholars to argue that children's accomplishments aren't their responsibilities until they reach the appropriate age of consent. Assaad, Krafft, Roemer, and Salehi-Isfahani (2016).

Due to the growing global focus on inequality, many studies examine income or wage inequality based on various factors, but few address inequality of opportunity. Few recent studies on wages and expenditure inequality in Jordan assess the impact of circumstances and efforts. Ramadan (2021) investigated the expenditure inequality between urban/rural and female-headed households in Jordan using HEIS 2017/2018 data. The author found that spatial and gender expenditure gaps favor urban areas and female-headed households. Education and geographical location of household heads drive these expenditure gaps. Krafft and Assaad (2016) found that the functioning of the labor market in Jordan itself is a substantial source of inequality of opportunity (in-market inequality), as its outcomes are driven by background circumstances (pre-market inequality). These results leave more room for further analysis of inequality of opportunity.

Compared to other middle-income countries, Jordan has a relatively low to moderate level of income inequality. Jordan's modern history is characterized by economic and social shifts which makes it a rich inequality case study.

To complement the literature, this paper contributes by applying the parametric approach of Bourguignon, Ferreira, and Menéndez (2007) to the two existing rounds of the Jordan labor market panel surveys, 2010 and 2016. It quantifies the shares of the inequity of opportunity and the main drivers behind it for each subgroup, as well as visually presenting the magnitude of the unfair inequality through the Generalized Lorenz curves and formally detecting any stochastic dominance between the used circumstance variables. These analyses help connect the different aspects of inequality perspectives.

This paper addresses the following questions:

1. What is the level of wage inequality in Jordan by gender and birth region?
2. What are the key drivers behind the inequality of opportunity in monthly wages for each group?
3. What is the magnitude of opportunity inequality among wage earners based on their backgrounds in both waves?

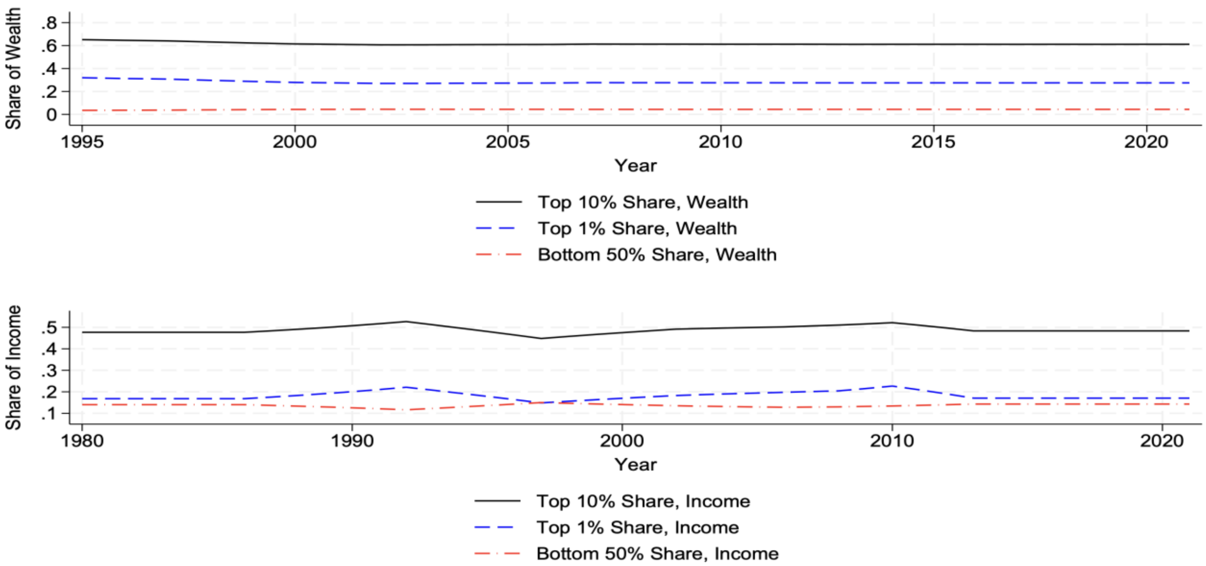
The paper is organized as follows: Section 2 reviews the inequality framework in Jordan. Section 3 describes the data. Section 4 introduces the empirical methods. Section 5 presents the results, and Section 6 concludes, mentioning limitations and suggestions for future research.

2. Frameworks

The inequality present in the Middle East and Northern Africa (MENA) region is primarily attributed to significant income disparities among the countries and the concentration of wealth and income at the upper echelon of the distribution. Alvaredo, Assouad, and Piketty (2019), studying 15 Middle Eastern countries from 1990 to 2016, estimate the top 10% of earners controlled 64% of total income. Hassine (2015) indicates that the Gini index value for the majority of MENA countries is not significantly elevated, signifying low to moderate levels of income inequality. Assaad, Krafft, Roemer, and Salehi-Isfahani (2016) clarify this phenomenon through the potential for significant disparities in opportunities linked to socioeconomic status, which exist beneath the surface of the visible inequality.

Figure 1 shows Jordan's shares of total pre-tax national income and net personal wealth for the top 1%, top 10%, and bottom 50%. In 2010, the top 1% had an all-time high of nearly 23% of pretax national income and close to 32% of net personal wealth in 1995. In 2013, the top 10% held 48.4% of pretax national income and 61.1% of net personal wealth, showing significant income and asset concentration. Finally, the bottom 50% held about 13-15% of pretax national income and roughly 4% of net personal wealth during this period.

Figure 1. Income and wealth inequality in Jordan 1980-2021



Source: World Inequality Database: wid.world/data.

2.1. Four dimensions of inequality in Jordan

This section reviews inequalities in opportunities and outcomes across four key factors: labor market, education, gender, and region.

Inequalities in the labor market include disparities in employment opportunities, wages, hours, job security, safety, and more. Studies show higher inequality reduces participation of vulnerable subgroups in the labor market. According to Krafft and Assaad (2019), Between 2010 and 2016, the mean worker age of Jordanian nationals rose by 25% at an annual rate of 3.7%. In contrast, the working-age population grew by 60%, averaging 8.2% annually, surpassing GDP growth. Following the economic slowdown post-2010, the labor market struggled to accommodate this workforce expansion, resulting in rising unemployment and decreased labor force participation, particularly among women and youth. Furthermore, entrepreneurial opportunities declined, with fewer own-account workers and lower job satisfaction reported among self-employed individuals compared to wage workers.

Galal and Said (2019) pointed that the key institutional change in the Jordanian labor market change from 2010 to 2016 was the maximum wage legislation under civil service law number 82 of 2013 and its 2017 amendments. Capping maximum wages for higher-grade government jobs, especially on temporary contracts, reduced wage inequality by 26% in government and 19% in public enterprises.

Turning to inequality and education, Becker (1962), Bredtmann and Smith (2018); Jensen (2010) argue that children with low standards of living know less about the benefits of education, so they put in less effort for education than children from wealthier backgrounds. Education inequalities are serious issues for MENA countries like Jordan. Rizk and Rostom (2021) point out that boys from disadvantaged backgrounds have a lower transition rate from basic to secondary education due to dropping out to support their families financially.

Jordan has significantly closed the educational gender gap, but it persists in labor markets. The difference between men's and women's labor force participation rates in Jordan is striking; as per the World Development Indicators (2021), the Female Labor Force Participation (FLFP) rate in Jordan is 14.59%, one of the lowest worldwide. According to the World Bank's "Women, Business and the Law 2022" index, Jordan scores 46.9 out of 100, below the regional average, with zero for laws protecting women in the workplace. As of 2021, no laws protect women from hiring discrimination WorldBank (2022). Major conditions inhibit women's participation, including limited economic opportunities and cultural norms that discourage their involvement in the labor force market.

Regional inequality undermines education, health, and economic opportunities. The economic disparities between governorates in Jordan are evident, with a high concentration of activities in the capital, Amman[2]. Moreover, insufficient development programs and public services in other governorates have worsened economic inequality. Assaf (2016) states that despite 28 years of economic growth, Jordan's lack of development programs outside Amman exacerbates the spatial situation inequality.

The Socioeconomic inequality report in Jordan stated that inequality between governorates in Jordan exceeds that between rural and urban areas. Though Jordan has low overall inequality by international standards, it is higher when examining each governate individually. UNDP-UNICEF (2015).

3. Data

The Jordan Labor Market Panel Survey (JLMPS) is part of the LMPS series conducted by the Economic Research Forum (ERF) in various Arab countries since 1998. All surveys and microdata are publicly accessible through ERF data portal[3]. The 2010 wave includes 5,102 households and 25,953 individuals. The JLMPS 2016 follows the existing population and captures a total of 33,450 individuals and 7,229 households. 3,058 households in the 2016 sample are part of the original

[2] Is in the central region.
[3] www.erfdataportal.com

2010 sample; 1,221 are households that split off from the original JLMPS 2010 households, while the remaining 2,950 households are a new refresher sample.

Table 1 displays the real monthly wages by Subgroup, restricted to the observations used in regressions and ages 16-65. Wages are in 2017 Jordanian dinars, adjusted using the CPI. Table 2 lists each variable's number of observations and sample size. Available tables in the Appendix present the Gini coefficients and percentile ratios for the whole sample and subgroups for both survey waves.

Table 1. Real monthly wages by subgroups and circumstances

	Summary Statistics			
	Year			
	2010		2016	
Variable	**Mean**	**Std**	**Mean**	**Std**
Gender				
Men	581.50	1570.32	548.75	3327.83
women	408.24	796.90	402.74	597.74
Region of birth				
North	437.66	693.82	659.83	5033.18
Central	602.58	1698.86	452.70	835.48
South	593.63	1709.67	434.01	422.37
Father's occupation				
White collar	712.20	1716.34	774.49	6474.89
Blue Collar	511.39	1387.54	457.58	845.36
Father's sector				
Public	533.64	1145.78	588.80	4295.21
private wage earner	611.91	2124.02	419.82	644.18
private employer	567.41	941.43	746.79	2094.95
Private self-employed	479.53	976.00	440.28	557.35
Father's Education				
Illiterate	451.67	826.49	435.64	749.31
Read & write	546.00	1594.27	474.74	972.56
Basic Education	475.21	1274.64	506.49	945.22
Secondary Education	499.20	1163.18	930.32	8852.60
Post-Secondary	832.93	1824.41	474.82	419.00
University	955.18	2482.16	481.85	333.85
Mother's Education				
Illiterate	518.05	1519.31	601.57	4532.21
Read & write	512.40	1022.87	403.21	300.82
Basic Education	396.01	862.17	471.79	676.80
Secondary Education	700.14	1592.40	555.91	1121.05
Post-Secondary	1286.23	3058.33	533.99	615.57
University	586.02	640.03	469.98	324.74

Note: Source: Author's calculations from JLMPS (2010 and 2016).

Table 2. Variable's number of observations and sample sizes, 2010 and 2016

	Summary Statistics by Year Year			
	2010		2016	
Variable	Number of Observations	Percentage	Number of Observations	Percentage
Gender				
Men	3,148	80.69%	2,672	81.89%
Women	754	19.31%	618	18.11%
Region of Birth[4]				
North	1,354	32.39%	1,290	34.42%
Central	1,840	55.04%	1,401	56.54%
South	708	12.57%	599	9.04%
Mother's Education				
Illiterate	2,265	54.22%	1,548	43.32%
Read & Write	1,006	26.97%	745	23.77%
Basic Education	277	7.38%	516	16.51%
Secondary Education	202	6.55%	263	9.27%
Post-Secondary	112	3.61%	150	4.55%
University	40	1.27%	68	2.58%
Father's Education				
Illiterate	1,191	27.61%	828	23.71%
Read & Write	1,772	45.39%	1019	30.70%
Basic Education	285	7.44%	718	21.15%
Secondary Education	316	8.99%	324	10.86%
Post-Secondary	152	4.66%	146	4.43%
University	186	5.91%	255	9.15%
Father's Sector				
Public Wage Earner	1,671	40.19%	1,748	47.09%
Private Wage Earner	1,025	28.8%	823	31. 18%
Private Employer	313	9.82%	169	6.02%
Private Self-Employed	893	21.19%	550	15.71%
Father's occupation				
White Collar	643	18.25%	617	20.42%
Blue Collar	3,259	81.75%	2,673	79.58%

Note: Data on region of birth was not distinguished by urban vs. rural.

4. Methods

4.1. Parametric approach

The main task in measuring inequality is quantifying the shape of the distribution of some measure of interest, such as wages Duclos and Araar (2006). To assess total inequality in wages, denoted by y with mean μ, let F(y) be the cumulative distribution function of the wages. Then $\mathrm{F}(y) = p$ is the proportion of the population with wages (y) or less. Let Q(p) for $p \in [0,1]$ be the quantile function, which is the inverse of the distribution function F(y).

It can be interpreted as the wages of individuals whose percentile in the population is p, or the wage level below which we can find p of the population. By definition, F(Q(p)) =p.

Cowell (1985) and Sen (1997) Discuss properties for an index to measure inequality of opportunity: symmetry, principle of transfers, scale invariance, population replication, and additive decomposability.

The mean-log deviation (MLD) or Theil's-L index has been used in the inequality of opportunity literature. Ferreira and Gignoux (2008) argue it is the most suitable index for this purpose as it fulfills all of the above properties. The mean-log deviation is defined as:

$$\mathrm{GE}(0) = \int_0^1 \ln\left(\frac{\mu}{\mathrm{Q(p)}}\right) \mathrm{dp} \tag{1}$$

GE values range from (0, ∞), where 0 indicates perfect income equality in society. It weighs the lower end of the distribution more heavily in measuring inequality.

The goal of the parametric approach of Bourguignon, Ferreira, and Menéndez (2007) is to break down outcome inequality into measurable circumstances and from unobserved factors, choices, luck, and innate ability, which we call effort. To assess inequality of opportunity empirically, we have the choice of estimating it with the synthetic standardized distribution (residual method) or smoothed distribution (direct method).

4.1.1. Residual method

This approach to measuring inequality compares the degree of inequality in a population to a hypothetical standardized distribution if there were no differences in circumstances, only effort. We assume that monthly wages (y) depend on circumstance variables C and effort variables E (along other unobserved circumstances), in an additively separable way which can be implemented using ordinary least squares (OLS):

$$\ln(y_i) = C_i\alpha + E_i\beta + v_i, \tag{2}$$

where α and β are coefficient vectors, v_i represents unobserved factors, and E_i can be defined as

$$E_i = WC_i + n_i \tag{3}$$

where W is a matrix of coefficients capturing circumstances' effect on all other unobserved factors (residuals)[5], and finally, n_i is all other determinants of effort. We do not need to estimate this "full

[5] For example, some people coming from specific backgrounds may find it worth to work harder than others.

specification" model fully as in equation (2); rather it can be estimated as the reduced form expressed as:

$$\ln(y_i) = C_i H + \varepsilon_i \tag{4}$$

where: $H = \alpha + \beta W$ (5) and $\varepsilon_i = \nu_i + n_i\beta$ (5)

If the vector of circumstances that we use in the analysis does not capture all the circumstances that affect the measured variable, then these omitted variables' effect will be captured by ε_i, and our estimation of inequality of opportunity based on the available circumstances will be a lower bound of the true level of inequality of opportunity Ferreira and Gignoux (2011).

We then estimate a counterfactual distribution of wages $\tilde{F}(\tilde{y})$, where all individuals are under the same circumstances, by applying the estimated coefficients $\widehat{H_1}$ to the mean circumstances[6] $\overline{C_1}$ Ferreira and Gignoux (2008):

$$\tilde{y}_l = \exp(\overline{C_1}\widehat{H_1} + \widehat{\varepsilon_1}) \tag{7}$$

The residual method calculates the share of inequality of opportunity from total inequality as:

$$\theta_R = 1 - \frac{GE\left(\tilde{F}(\tilde{y}_l)\right)}{GE\left(F(y_i)\right)} \tag{8}$$

The subscript *r* is used because this measure of inequality of opportunity is estimated from a residual.

I control for age and age squared to prevent omitted variable bias, treating age as a factor that influences within-group, but not between-group, inequality. Omitting age would bias results since it's linked to work experience (impacting wages) and circumstances (like mother's education, which has changed dramatically over time, causing older workers to face different conditions than younger ones).

To compare the impacts of different circumstances, we decompose the inequality of opportunity into partial effects. The partial[7] effect/role of a group of circumstance variables on the inequality

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[6] $\overline{C_1}$ is a set of fixed values of circumstances representing, say, a man with illiterate parents, a blue-collar father in the private sector, born in the north.

[7] Holding a circumstance to its mean could result in spreading out the distribution, possibly causing negative partials, but this usually happens in very small magnitudes.

of opportunity can be obtained by separately holding each circumstance variable to its mean, while controlling for all the other variables, as shown in equation 9 below:

$$\tilde{y}_i^G = \bar{C}_i^G \widehat{H_1}^G + C_i^{G\neq J} H^{G\neq J} + \hat{u}_i \qquad (9)$$

Equation 10 computes the partial effect attributable to circumstance G, which is total inequality – inequality with circumstance G set to its mean, as below:

$$GE\left(\{y_i^T\}\right) - GE\left(\{\hat{y}_i^G\}\right) \qquad (10)$$

Dividing the partial effect by total inequality of opportunity can be interpreted as the percentage share of total inequality due to circumstance G.

4.1.2. Direct method

An alternative to the residual approach is the direct approach. Both the direct and indirect methods of calculating inequality of opportunity generate the same results. The direct approach does not allow for control variables, replacing individuals' outcomes with predictions based on their circumstances:

$$\tilde{u} = \exp\left(C_i H\right) \qquad (11)$$

Individuals with similar circumstances have the same predictions. The share of inequality of opportunity to total inequality can be directly calculated as:

$$\theta_D = \frac{GE\left(\tilde{F}(\tilde{u})\right)}{GE\left(F(y)\right)} \qquad (12)$$

All of the analyses (residual approach and direct approach) incorporate bootstrapped standard errors around the estimated GE(0) statistics.

I have chosen the included circumstances based on data availability and consistency with worldwide empirical research. Monthly wage is the key variable in this paper as it is easily comparable across groups. It encompasses all wage components: salaried income, supplemental wages, bonuses, incentives, overtime pay, and wages from primary and secondary jobs. The main alternative, earned income, involves several non-wage types that require assumptions and various data types to calculate, such as rental income, investment income, capital, and properties.

Equation 13 below displays the wage equation used in the parametric approach:

$$
\begin{aligned}
&ln\ (wage_i) = \alpha_0 + \beta_1(Female_i) + \beta_2(Area\ of\ birth{:}\ center_i) + \beta_3(Area\ of\ birth{:}\ south_i)\ + \\
&\beta_4(father\text{'}s\ employment\ status{:}\ private\ wage\ earner_i) + \beta_5(father\text{'}s\ employment\ status{:}\ private\ employer_i)\ + \\
&\beta_6(father\text{'}s\ employment\ status{:}\ self\ employed_i) + \beta_7(Father\ Occupation{:}\ Blue\ collar_i)\ + \\
&\beta_8(father\text{'}s\ education{:}\ read\ and\ write_i) + \beta_9(father\text{'}s\ education{:}\ Basic_i) + \beta_{10}(father\text{'}s\ education{:}\ Secondary_i) + \\
&\beta_{11}(father\text{'}s\ education{:}\ Post\ Secondary_i) + \beta_{12}(Fathers\text{'}\ educatio{:}\ University_i) \\
&+\beta_{13}(Mother\text{'}s\ education{:}\ Read\ and\ write_i) + \beta_{14}(Mother\text{'}s\ education{:}\ Basic_i) + \beta_{15}(Mother\text{'}s\ education{:}\ Secondary_i) \\
&+ \beta_{16}(\ Mother\text{'}s\ education{:}\ Post\ Secondary_i) + \beta_{17}(Mother\text{'}s\ education{:}\ University_i) + u_i \qquad (13)
\end{aligned}
$$

Table 3 shows the circumstance variables used in the regressions and their categories, with the first row in each circumstance variable being the omitted variable for the OLS regressions. The circumstance variables are as-of when the respondent was 15 years old[8].

Table 3. Used parametric variables and their subcategories

Variable	**Category**
Gender	-Male -Female
Father's Sector	-Public -Private Wage earner -Private employer -Private self-employed
Father's Occupation	-White collar: (managers, professionals, technicians and associate professionals, Clerical support workers) -Blue collar: (Service and sales workers, skilled agricultural, forestry and fishery workers, Craft related trades workers, plant and machine operators, assemblers, elementary occupation)
Father's education	-Illiterate -Read & Write -Basic Education -Secondary Education -Post-Secondary -University
Mother's education	-Illiterate -Read & Write -Basic Education -Secondary Education -Post-Secondary -University
Geographical region of birth	-North (Mafraq, Irbid, Ajloun, Jarash) -Centre (Amman, Balqa, Zarqa ,Balqa'a) -South (Karak, Tafileh, Madaba, Aqaba)

If one of parents died before the individual reached 15, s/he should be asked about the parent's last work, occupation, education…etc.

4.2. Lorenz dominance

I follow the work of Lefranc, Pistolesi, and Trannoy (2008)**,** who argue that equality of opportunity does not exist if opportunity sets are an increasing function of an outcome variable and individuals have the privilege to choose from sets of circumstances, as their choices provide them with more favorable returns of the outcome.

4.2.1. First-order stochastic dominance

Any individual, regardless of risk preferences[9], whose utility function is increasing in an outcome variable x, will prefer an FSD-dominating distribution over a FSD-dominated one. For a random variable G to first-order stochastically dominate another random variable J, G should give a probability at least as high as J for receiving any measured outcome *x*. Lefranc, Pistolesi, and Trannoy (2008) defined FSD as in equation 14 below:

$$F(x \mid G) \leq F(x \mid J) \;\forall x \in \{R\}_{\{+\}} \tag{14}$$

where F(G) and F(J) are the cumulative distribution functions for both variables G and J, while $F(x \mid G)$ and $F(x \mid J)$ are the distribution of outcome x conditional on the vector of circumstances G and J respectively.

4.2.2. Second-order stochastic dominance

First-order stochastic dominance of G over J is a sufficient condition for second-order dominance of G over J. In the expected utility theory (EUT) framework, a risk-averse individual whose concave utility function is increasing in x will prefer a SSD-dominating distribution over a SSD-dominated one. In terms of cumulative distribution functions F_J and F_G, G is second order stochastically dominant over J, $G \geq SSD\, J$, if:

$$\int_0^x F(x \mid G)\, dy \leq \int_0^x F(x \mid J\}\, dy \;\forall x \in \{R\}_{\{+\}} \tag{15}$$

Shorrocks (1983) argued that second-order stochastic dominance is parallel to generalized Lorenz dominance:

$$\forall x \in \{R\}_{\{+\}}\; G \geq SSD\, J \Leftrightarrow \forall p \in [0, 1]\; GL_{\{F(.|G)\}}(p) \geq GL_{\{F(\cdot|J\})}(p) \tag{16}$$

where $GL_{\{F(.|G)\}}(p)$ is the value of the generalized Lorenz curve at p for the distribution $F(. \mid G)$.

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[9] FSD criterion doesn't take the attitudes towards risk (i.e. risk-seeking, risk-averse or risk-neutral) into account, and only rests on the comparison of returns.

The Generalized Lorenz curve captures inequality in graphical form and is an adjusted form of the Lorenz curve, wherein the accumulated fraction of wages up to each fraction of the population is multiplied by the average wages of the distribution.

5. Results and discussion

5.1. Parametric results

5.1.1. Ordinary least squares regression results for the full sample and subgroups

Tables 4 and 5 present the OLS regression results for the whole sample and subgroups for the first and second waves, respectively. Figures in brackets below the coefficients are the standard errors; the first row indicates which category was omitted to act as a reference point in the regression. The log of monthly wages is the dependent variable.

Starting with the demographic variables, being a woman is negatively and significantly associated with higher monthly wages for the whole sample in both waves. Moving to the area of birth, in the first wave individuals who were born in the central and south regions have significantly higher wages than the north-born individuals for the whole sample. For the 2016 wave the area of birth doesn't seem to have any statistically significant impact, the central born have negative signs for the whole sample and both genders, while the south born have positive signs for both women and the whole sample but a negative sign for the men subgroup.

For the father's employment status, most coefficients in this category are not statistically significant for both waves. All sectors have negative signs except for private employers in both waves, which indicates that wage earners whose fathers have public jobs make more than other wage earners but not the individuals whose fathers are private employers.

Moving to the father's occupation, the negative insignificant coefficients in the whole sample and most subgroups in both waves indicate that having a father who is a blue-collar worker has a negative effect on their children's monthly wages when compared to the children of white-collar fathers.

The illiterate variables were omitted for both parents' education variables. The coefficients are almost all positively associated with higher wages for both waves but with varying significances across models. It's important to note that most parental education coefficients increase with higher levels of education, pointing to a non-linear increase in the returns to education associated with higher levels.

Table 4: Regression results, full sample and subgroups, 2010 wave

	Whole Sample		Women	North	Center	South
Gender/ Men Omitted						
Women	-0.290***			-0.326***	-0.316***	-0.111
	-0.034			-0.055	-0.047	-0.078
Region of Birth / North-born Omitted						
Central-born	0.078**	0.075*	0.116			
	-0.03	-0.034	-0.062			
South-born	0.138***	0.074	0.353***			
	-0.039	-0.042	-0.087			
Father's Sector/ Public Wage Worker Omitted						
Private Wage Earner	-0.057	-0.053	-0.08	-0.134*	-0.046	0.035
	-0.038	-0.042	-0.074	-0.054	-0.054	-0.088
Private Employer	0.098	0.048	0.258*	0.069	0.099	0.304
	-0.055	-0.063	-0.101	-0.086	-0.074	-0.324
Private Self-Employed	-0.071	-0.066	-0.098	-0.091	-0.052	-0.069
	-0.037	-0.042	-0.073	-0.057	-0.056	-0.075
Father's Occupation / White Collar Omitted						
Blue Collar	-0.071	-0.063	-0.078	0.068	-0.114	-0.149
	-0.041	-0.049	-0.066	-0.063	-0.059	-0.096
Father's Education / Illiterate Omitted						
Read & write	0.094**	0.101**	0.072	0.071	0.111*	0.051
	-0.031	-0.035	-0.072	-0.054	-0.047	-0.058
Basic Education	0.072	0.088	-0.003	0.091	0.08	-0.087
	-0.068	-0.077	-0.143	-0.08	-0.107	-0.208
Secondary Education	0.131*	0.113	0.188	0.262***	0.079	0.044
	-0.057	-0.067	-0.104	-0.072	-0.085	-0.111
Post-Secondary	0.192	0.218	0.182	0.227	0.157	0.473
	-0.101	-0.122	-0.142	-0.146	-0.135	-0.335
University	0.356***	0.371***	0.336*	0.386**	0.315**	0.535*
	-0.089	-0.11	-0.148	-0.145	-0.121	-0.243
Mother's Education / Illiterate Omitted						
Read & Write	0.058	0.029	0.160*	0.002	0.102*	-0.002
	-0.033	-0.037	-0.067	-0.048	-0.047	-0.074
Basic Education	-0.013	-0.02	0.006	-0.106	0.029	0.039
	-0.065	-0.071	-0.121	-0.088	-0.097	-0.139
Secondary Education	0.282***	0.279**	0.259*	0.201*	0.332***	0.191
	-0.071	-0.088	-0.108	-0.085	-0.096	-0.157
Post-Secondary	0.538***	0.551*	0.527***	0.121	0.710***	0.583
	-0.14	-0.226	-0.151	-0.151	-0.192	-0.394
University	0.235	0.013	0.457*	0.328	0.254	0.428
	-0.148	-0.199	-0.204	-0.426	-0.177	-0.27
Age	0.071***	0.078***	0.026	0.047*	0.081***	0.070*
	-0.012	-0.012	-0.033	-0.018	-0.017	-0.03
Age ^ Age	-0.001***	-0.001***	0	0	-0.001***	-0.001
	0	0	0	0	0	0
Intercept	4.038***	3.927***	4.475***	4.431***	3.912***	4.306***
	-0.207	-0.222	-0.542	-0.316	-0.297	-0.491
Number of Observations	3902	3148	754	1354	1840	708
Adjusted R-squared	0.13	0.11	0.18	0.1	0.14	0.13

*Note: *** p<.001, ** p<.01, * p<.05.*

Age is positive in the whole sample and all subgroups, whereas the coefficient for age squared is negative and significant for the whole sample and subgroups except for women, north and south-born subgroups in the second wave, and women subgroup in the first wave only, indicating decreasing return to monthly wages for older cohorts.

The adjusted R-squared for the whole sample in 2010 is 13%, and for the subgroups are men 11%, women 18%, areas of birth: north 10%, center 14%, and south 13%. The differences across women and men subgroups could point to the fact that these circumstances can explain more of the inequality of opportunity in the monthly wages that women face. The adjusted R-squared declines in 2016 for all groups, indicating that the share of the variation in monthly wages of the used circumstances is higher in the first wave.

Table 5: Regression results, full sample, and all subgroups, 2016 wave

	Whole Sample	Men	Women	North	Center	South
Gender/ Men Omitted						
Women	-0.220***			-0.295***	-0.184***	-0.164***
	-0.042			-0.087	-0.05	-0.045
Region of Birth / North-born Omitted						
Central-born	-0.061	-0.071	-0.009			
	-0.038	-0.041	-0.086			
South-born	0.017	-0.009	0.126			
	-0.042	-0.047	-0.093			
Father's Sector/ Public Wage Worker Omitted						
Private Wage Earner	-0.076	-0.081	-0.056	-0.149	-0.041	-0.113
	-0.039	-0.044	-0.086	-0.08	-0.047	-0.091
Private Employer	0.111	0.109	0.084	-0.015	0.187	0.079
	-0.092	-0.111	-0.113	-0.082	-0.151	-0.092
Private Self-Employed	-0.024	-0.046	0.084	-0.091	0.033	-0.067
	-0.049	-0.056	-0.111	-0.088	-0.07	-0.072
Father's Occupation / White Collar Omitted						
Blue Collar	-0.106	-0.076	-0.275*	-0.182	-0.086	-0.096
	-0.055	-0.057	-0.137	-0.111	-0.07	-0.059
Father's Education / Illiterate omitted						
Read & Write	0.068	0.08	0.027	0	0.121	-0.023
	-0.053	-0.06	-0.11	-0.079	-0.079	-0.099
Basic Education	0.111*	0.128*	0.025	0.025	0.156*	0.08
	-0.052	-0.06	-0.097	-0.092	-0.073	-0.08
Secondary Education	0.058	0.046	0.1	0.008	0.076	0.025
	-0.079	-0.09	-0.143	-0.128	-0.109	-0.1
Post-Secondary	0.114	0.143	-0.009	0.014	0.171	0.001
	-0.085	-0.097	-0.173	-0.127	-0.112	-0.12
University	0.086	0.125	-0.103	-0.087	0.148	-0.002
	-0.08	-0.089	-0.183	-0.165	-0.101	-0.111
Mother's Education / Illiterate Omitted						
Read & Write	0.04	0.04	0.025	-0.041	0.061	0.127*
	-0.045	-0.05	-0.103	-0.075	-0.067	-0.06
Basic Education	0.081	0.088	0.039	0.054	0.078	0.132
	-0.053	-0.058	-0.126	-0.095	-0.078	-0.095
Secondary Education	0.210**	0.150*	0.367*	0.416*	0.139	0.122
	-0.071	-0.073	-0.176	-0.181	-0.077	-0.078
Post-Secondary	0.225**	0.222*	0.262	-0.072	0.334**	0.289**
	-0.08	-0.092	-0.156	-0.163	-0.107	-0.11
University	0.194	0.183	0.223	-0.303	0.306**	0.146
	-0.108	-0.129	-0.186	-0.278	-0.112	-0.133
Age	0.061***	0.06	0.057	0.082***	0.051**	0.043*
	-0.012	-0.013	-0.039	-0.019	-0.017	-0.021
Age ^ Age	-0.001***	-0.001***	-0.001	-0.001***	-0.001*	0
	0	0	-0.001	0	0	0
Intercept	4.701***	4.703***	4.572***	4.573***	4.712***	5.022***
	-0.23	-0.247	-0.717	-0.351	-0.318	-0.358
Number of Observations	3290	2672	618	1290	1401	599
Adjusted R-squared	0.07	0.06	0.09	0.08	0.07	0.07

*Note: *** p<.001, ** p<.01, * p<.05.*

5.1.2. Inequality of opportunity share

The results for the shares of inequality of opportunity estimates for the full sample and the subgroups for both survey waves are presented in tables A.1-A.6 in the Appendix. The total inequality column in each table displays the total inequality value measured through the GE(0) index, which is simply the sum of the latter two columns: within and between group inequalities, which are the inequalities due to individual efforts or unobserved circumstances and the used circumstances in the regressions.

Inequality due to effort or within-group inequality is calculated using the residual method (which controls for age), while between-group inequality is measured through the direct method. The final three columns display the opportunity shares of total inequality that can be attributed to circumstances using both the residual and direct calculations, while the last column displays the number of observations in each subgroup.

For all groups, total inequality as measured by the GE(0) index has declined in the second wave, except for the north subgroup. It happens that the results based on the direct and the residual approaches show different levels of inequality, as the estimates of the inequality of opportunity are sensitive to the method employed. Yet most subgroups have notable consistencies over the two periods in both approaches.

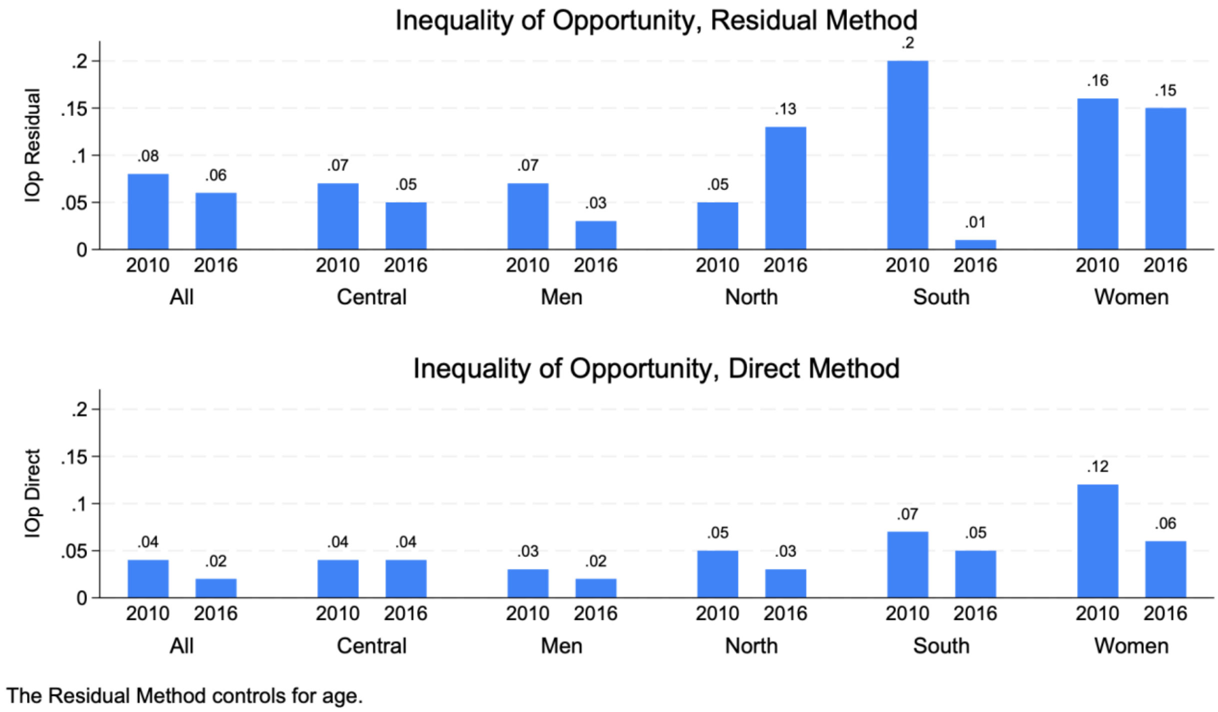
According to the direct approach in Table A.1, circumstances approximately accounted for a modest share of between 4% and 2% (in 2010 and 2016 respectively) of total monthly wage inequality for the whole sample. The residual approach suggested that there is a decline in the share of inequality of opportunity from the previous wave (from 8.2% to 5.5%).

Table A.2 shows that inequality of opportunity shares for the men subgroup has declined from 6.8% to 2.6% between 2010 and 2016 using the residual approach, while the direct approach shows a 1.3% decline (from 2.9% to 1.6%). In Table A.3, both approaches confirm that inequality of opportunity for the women subgroup goes down between 2010 and 2016. It declines from 16.4% to 14.7% using the residual approach, while the direct approach shows a decline from 12.2% to 6.1%.

For the north-born subgroup, the residual approach shows that inequality of opportunity based on the used circumstances has increased, ranging from a lower end of 4.8% in 2010 to 12.7% in 2016, while the direct approach shows a decline from 4.6% to 3%, as seen in table A.4.

Moving to the center-born wage earners in Table A.5, the residual approach shows a decline from a lower end of 7.3% to 4.8%. The direct approach shows a decline in the inequality share from almost 4.3% to 3.5%. Finally, for the south-born wage earners subgroup in Table A.6, both methods show a decline in the share of the inequality of opportunity ranging from a lower end of 6.7% in 2010, to 4.6% in 2016 through the direct method, while the residual approach shares declined from 19.7% to 0.59%. Figure 2 shows the inequality of opportunity shares for the residual and direct methods.[10]

Figure 2. Inequality of opportunity shares, residual and direct methods, 2010 and 2016



5.1.3 Parametric decomposition

Although the overall level of inequality of opportunity in the whole sample isn't high, each subgroup's experience is differently marked from other subgroups and stems from different origins. The parametric decomposition asks how much each circumstance contributes to the levels of inequality of opportunity. Tables A7-A9 in the Appendix present the parametric decomposition

[10] ESCWA (2019) noted that regional inequalities are expected to be much higher when taken into consideration the large flow of Syrian refugees, as it could affect Jordanians wage workers especially at the lower tail of the wage distribution. This was a major event between the two waves. I run a simple correlation test between the differentiated Gini index between the two waves in each governorate, looking at everyone who has a monthly wage in the kingdom and the percentage of Syrian refugees who reside in it. The correlation coefficient between the refugees' share in 2016 and the differentiated Gini coefficient for the twelve governorates indicated no strong direct relationship between the Syrian crisis and inequality. Results can be provided on request.
The key drivers of deep-rooted inequality would be unlikely to be affected by short-term trends, especially at the higher end of the social ladder. Inequality in different governorates could decline for many reasons, which could be or could not be related directly to the Syrian crisis, such as technological change, globalization, increasing the wages of the poorest, and capping the ratio of top executive pay to worker pay.

results. The coefficients are presented for each circumstance variable for both survey rounds; numbers below the coefficients are the standard errors.

The whole sample decomposition in Table A.7 shows that the main drivers of inequality of opportunity in 2010 are the mother's education with about 39% share, followed by the father's education by 27%. Gender and birth region come later with 17% and 10% shares respectively, and the father's occupation comes last with a contribution of around 7%. The second wave is different. Father's occupation and sector account for more than half of the circumstances' shares that drove inequality of opportunity with a share of 61% combined, gender contributes with a share of 23%, while birth region plays a role of 14%; parental education contributes the smallest portions.

Moving to the men subgroup in Table A.8, mothers' and fathers' education are the major drivers for inequality of opportunity in the 2010 wave with 49% and 34% respectively, followed by birth region at 10% and father's occupation at 7%. For the later wave father's occupation and employment sector are the main drivers with shares close to 75% jointly. The region of birth contributes 25%. For the women subgroup in the year 2010, parental education is the main driver for inequality of opportunity (41% combined), followed by the region of birth 29%, and finally, the father's occupation and sector drive inequality of opportunity with a share of 30%. In the later wave, the mother's education comes first with a contribution of 57%, followed by the father's occupation at 37% and the father's sector at 6%.

The decomposition for the area of birth subgroups as shown in Table A.9 shows that for the north-born subgroup in the year 2010, gender comes first with a 51% share, and parental education comes in second place with a contribution of 45%. In the next wave, the father's sector and occupation are the main drivers of inequality of opportunity with around 66% share jointly, followed by parental education at 20%, and lastly gender at 14%.

In the first wave, the center-born subgroup has parental education as the main driver for the unfair inequality 59%, followed by gender 32% and the father's occupation 9%. For the second wave, the father's sector is the key driver with a 67% share, followed by gender 21% and father's education 12%. The south-born subgroup has parental education as the key driver in the first wave 76% followed by the father's sector and occupation with 24% combined. For the later wave, gender comes first with a 66% share of inequality followed by the father's sector of employment at 34%.

Gender fluctuations are likely to be due more to measurement errors owing to smaller women's sample sizes[11] than actual reflections of the contributor circumstances to the unfair inequality.

[11] Women make up less than 20% of the whole sample and they present 17% of the north subgroup, 22% and 19% in the south and the center subgroups respectively.

Most variables come out as insignificant, presumably because of the limited power to distinguish which variable is driving the partials since the number of wage earners is a limited sample.

The decomposition results for all subgroups and the whole sample for both waves are graphed in Figure 3 below. The partial shares per circumstance for the whole sample and subgroups for both waves are listed in Table 6.

Figure 3. Partial shares decomposition for the whole sample and Subgroups, 2010 and 2016

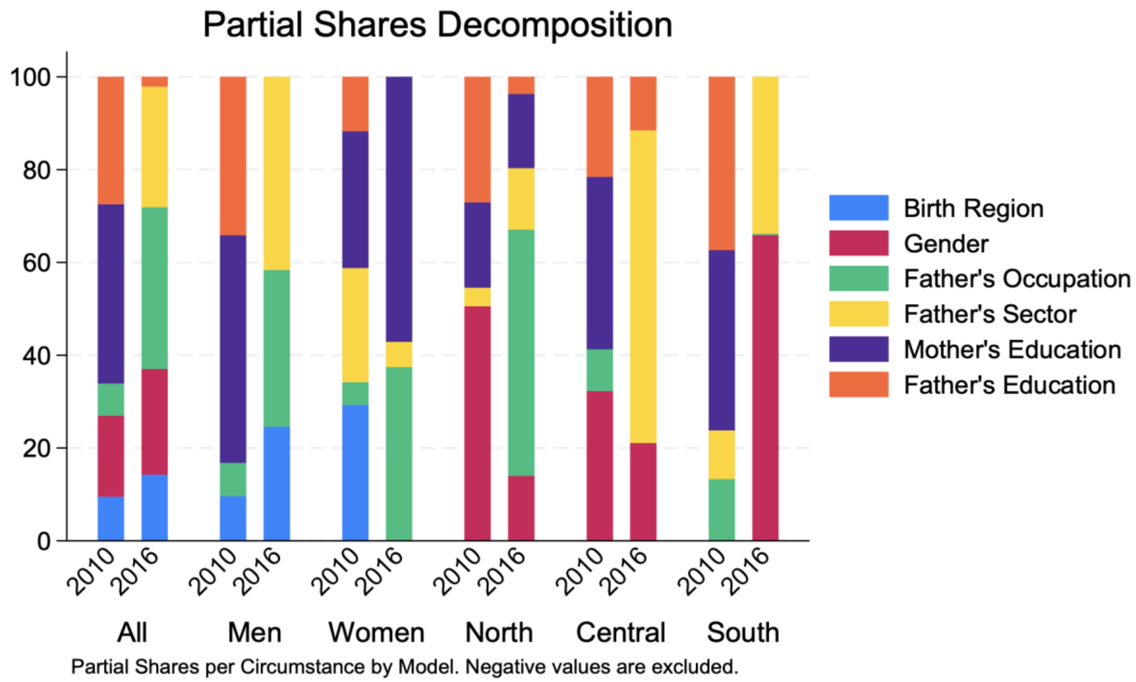


Table 6. Partial shares per circumstance for the whole sample and subgroups, 2010 and 2016

Model	Birth Region	Gender	Family Background
Whole- 2010	9.53%	17.47%	72.98%
Whole-2016	14.26%	22.76%	62.98%
Men-2010	9.65%	-	90.35%
Men-2016	24.58%	-	75.42%
Women-2010	29.30%	-	70.70%
Women-2016	0.00%	-	100%
North-2010	-	50.56%	49.44%
North-2016	-	14.03%	85.97%
Central- 2010	-	32.29%	67.71%
Central-2016	-	21.09%	78.91%
South-2010	-	0.00%	100%
South-2016	-	65.98%	34.02%

5.2. Stochastic dominance tests

5.2.1. Lorenz curves

Lorenz curves for monthly wages by background circumstances are presented in graph A.1 in the Appendix**.** Comparing two GL curves results in three scenarios: one curve is above the other, the curves intersect, or they are identical. The first case violates equality of opportunity, the second is indeterminate, while the third indicates strong equality opportunity. Most Lorenz curves cross, suggesting that detecting inequality of opportunity visually is a little challenging. The further apart the Lorenz curves are from each other (i.e., the gap or the vertical distance between curves) the more the magnitudes of inequality of opportunity based on the specified characteristics.

Starting with the father's employment sector, individuals whose fathers are in the public sector dominated the wages of individuals who have self-employed and private-wage fathers. The dominance is quite observable based on the father's occupation, as having white-collar fathers grants better opportunities regarding wages than blue-collar fathers across the two survey rounds. The magnitude of inequality of opportunity is higher at the higher end of the distribution, as revealed by the gaps between the curves. The gender variable exhibits wide gaps, which indicates constant dominance by the male wage earners.

The higher educated parents' curves lie above the low and no-education curves; hence, individuals with higher educated parents have the advantage of higher wages than those with lower or uneducated parents. Moving to the region of birth[12], the south-born subgroup's wages dominate the other regions only in the first wave. No dominance is detected based on the region of birth in the second wave, since all curves intersect most of the time, confirming the parametric decompositions result that the area of birth has a minor role in all subgroups.

The decline in the magnitude of the inequality of opportunity, as suggested by the GE(0) index, is consistent with the narrowing gaps between higher parental education and the rest of the educational levels, as well as the gaps between father's occupation categories and the different regions of birth over the second wave of the survey, indicating more social mobility as these circumstances are becoming less deterministic of the monthly wages.

In Figure A.2 in the appendix, I show the quintile distribution of wages conditional on the used circumstances. These distributions reproduce closely to the observations made from the generalized Lorenz curves. Social mobility based on the wage quintile's distribution conditioned on the family background characteristic confirmed that there is a higher percentage of wage earners in the top quantities who are men and individuals with more advantaged backgrounds, such as higher educated parents, white collar fathers, and public or private employer fathers. Nevertheless, a significant proportion of individuals originating from less privileged backgrounds has ascended

[12] No data exists on whether individuals have moved from their birthplace to another governorate or between the two waves, which could obscure the true impact of regions on wage opportunity inequality.

to the upper echelon of the wage distribution, indicating a society characterized by flexibility or fluidity in which the inequality of opportunities remains moderate.

5.2.2. Stochastic dominance tests

The stochastic dominance test complements and formalizes the visual inspections offered by the Generalized Lorenz curves (GLC). If one circumstance variable dominates another, it means that inequality of opportunity exists (have higher wages along the wage distribution), although this test does not indicate the magnitude of the inequality.

Table 4 shows that men and wage earners whose fathers are white-collar second-order stochastic dominate women and wage earners whose fathers are blue-collar, respectively, and consistently in both waves. In the first wave, individuals with educated parents dominate those whose parents had low or no education. In the later wave, the father's education still provides advantages, while there is no SSD by the mother's education. The wages of the children whose fathers are in the public sector dominate the wages of the children whose fathers are self-employed in the first wave, while in the second wave, they dominate both wage earners whose fathers are in the private sector as well the self-employed. Finally, south-born individuals SSD north and the center-born individuals in the first wave, while there is no second-order dominance detected based on the region of birth in the second wave of the survey.

Table 7. Stochastic dominance tests, 2010 and 2016

		2010				**2016**		
Circumstance		**High**	**Low**	**None**		**High**	**Low**	**None**
Father's Education	High	-	-	-	High	-	-	-
	Low	<	-	-	Low	<	-	-
	None	<	?	-	None	<	<	-
		High	Low	None		High	Low	None
Mother's Education	High	-	-	-	High	-	-	-
	Low	<	-	-	Low	?	-	-
	None	<	?	-	None	?	?	-
		Men	Women			Men	Women	
Gender	Men	-	-		Men	-	-	
	Women	<	-		Women	<	-	
		White Collar	Blue Collar			White Collar	Blue Collar	
Father's Occupation	White Collar	-	-		White Collar	-	-	
	Blue Collar	<	-		Blue Collar	<	-	
		Public Employee	Private Employee	Self Employed		Public Employee	Private Employee	Self Employed
Father's Employment	Public Employee	-	-	-	Public Employee	-	-	-
	Private Employee	?	-	-	Private Employee	<	-	-
	Self Employed	<	?	-	Self Employed	<	?	-
		North	Central	South		North	Central	South
Region of birth	North	-	-	-	North	-	-	-
	Central	?	-	-	Central	?	-	-
	South	>	>	-	South	?	?	-

Note: The symbols read as follows: > The row dominates the column, < The row is dominated by the column, ? Lorenz curves cross or CDFs are not comparable at the second order, -is placed in cells where the comparator is the same group or cells are in no use.

6. Conclusion

Many believe that hard work, punctuality, and self-reliance are essential for achieving success. However, family background significantly influences adult labor market outcomes and determines an individual's social position. Often, these backgrounds are persistent and require multiple generations to change.

The findings document a decline from 2010 to 2016 in total inequality measured by the GE(0) index and the shares of the inequality of opportunity (increase in social mobility). In the 2010 wave, according to the residual method, women and south-born subgroups experienced the highest inequality of opportunity shares: 16.4% and 19.7% respectively. In the second wave, north-born groups and women had the highest inequality of opportunity: 12.7% and 14.7%, respectively. These shares are lower bounds as adding more background circumstances will help explain more of the unfair inequality shares. Groups that are regularly deprived compared to others limit their economic and social opportunities participation.

The decomposition reveals that family background significantly drives opportunity inequality, while gender and birthplace have lesser impacts. The magnitude of the inequality of opportunity as suggested by the horizontal gap between the generalized curves for parental education and father's occupation has shrunk in 2016. Some circumstances such as the mother's education and region of birth have lost dominance over the second survey wave, suggesting other more deterministic factors have come into play, e.g., one's effort or other unobserved circumstances. Without significant policy changes, opportunity inequality will continue transferring from one generation to the next, repeating the same patterns, particularly affecting the most disadvantaged and vulnerable groups.

Policy implications require significant commitment, support, resources, leadership, accountability, incentives, training, and capacity to implement successfully. Additionally, challenges like administrative and financial hurdles may delay the implementation and visible results of reforms.

Women face the highest share of inequality of opportunity in monthly wages because of their circumstances along with their low labor market participation rates. This suggests that outcomes based on gender are likely to be biased regardless of how much effort a woman puts into her work. This should signal policymakers to address labor market dilemmas and barriers for women's entry. Enacting laws against workplace gender discrimination is essential, as Jordan currently lacks protections for women. Additionally, addressing promotion disparities and providing flexible work options in both sectors is necessary women.

The results of this paper require cautious interpretation due to several limitations. First, the data restricts family background variables used, failing to capture all circumstances affecting inequality of opportunity. The limited six-year period is insufficient to observe shifts in circumstance variables. Furthermore, the shares from the parametric approach serve as a lower bound, likely underestimating other significant unobserved family background variables.

This analysis excludes fractional or cyclical unemployment, unpaid family work, and individuals with no positive wages—significant segments of the workforce, especially among women, Bedouins, and those in agriculture and construction. Additionally, high-income individuals may receive less payment as wages or salaries, influencing the sample observed each year.

Future research initiatives may aspire to utilize more comprehensive and detailed panel datasets, akin to those available in more advanced nations. This should encompass a broader spectrum of deterministic familial background factors, including the quality and quantity of time dedicated to children's development during their preschool and early schooling years, skin color, family wealth, and land ownership, among others. Moreover, employing a diverse array of outcome variables beyond mere monthly wages—such as earnings and consumption expenditures—would yield more precise estimates concerning the proportional shares and primary determinants of opportunity inequality, particularly for women, whose labor force participation remains notably low.

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Appendix

A.1. Parametric results on inequality of opportunity in monthly wages, 2010 and 2016

Table A.1. Parametric results on inequality of opportunity in monthly wages, whole sample, 2010 and 2016. The results ll and ul are the lower and upper bounds of the 95% confidence interval

Year	Result type	Total Inequality	Within Group Inequality	Between Group Inequality	Opp. Share (Residual)	Opp. Share (Direct)	N
2010	Point Estimates	0.486858***	0.446553***	0.019834***	0.082786	0.040740***	3902
	se	(0.049733)	(0.041458)	(0.005138)	(0.044278)	(0.008525)	
	p	(p<0.000000)	(p<0.000000)	(p<0.000113)	(p<0.061527)	(p<0.000002)	
	ll	(0.389382	(0.365296	(0.009763	(-0.003997	(0.024030	
	ul	0.584333)	0.527810)	0.029906)	0.169570)	0.057449)	
2016	Point Estimates	0.375204***	0.354551***	0.008132***	0.055045*	0.021673*	3290
	se	(0.085117)	(0.075408)	(0.002366)	(0.026167)	(0.009310)	
	p	(p<0.000010)	(p<0.000003)	(p<0.000588)	(p<0.035413)	(p<0.019919)	
	ll	(0.208378	(0.206755	(0.003495	(0.003759	(0.003425	
	ul	0.542030)	0.502348)	0.012769)	0.106331)	0.039920)	

Table A.2. Parametric results on inequality of opportunity in monthly wages, men subgroup, 2010 and 2016. The results ll and ul are the lower and upper bounds of the 95% confidence interval

Year	Result Type	Total Inequality	Within Group Inequality	Between Group Inequality	Opp. Share (Residual)	Opp. Share (Direct)	N
2010	Point Estimates	0.512111***	0.477171***	0.014906*	0.068226	0.029107*	3148
	se	(0.042385)	(0.033805)	(0.006369)	(0.050632)	(0.011701)	
	P	(p<0.000000)	(p<0.000000)	(p<0.019258)	(p<0.177822)	(p<0.012867)	
	Ll	(0.429038	(0.410915	(0.002424	(-0.031011	(0.006172	
	Ul	0.595183)	0.543428)	0.027388)	0.167462)	0.052041)	
2016	Point Estimates	0.396536***	0.385928***	0.006356***	0.026751	0.016028	2672
	se	(0.110436)	(0.103440)	(0.002045)	(0.028496)	(0.008657)	
	P	(p<0.000330)	(p<0.000191)	(p<0.001881)	(p<0.347850)	(p<0.064109)	
	Ll	(0.180084	(0.183189	(0.002348	(-0.029100	(-0.000940	
	Ul	0.612987)	0.588667)	0.010363)	0.082602)	0.032996)	

Table A.3. Parametric results on inequality of opportunity in monthly wages, women subgroup, 2010 and 2016. The results ll and ul are the lower and upper bounds of the 95% confidence interval

Year	Result Type	Total Inequality	Within Group Inequality	Between Group Inequality	Opp. Share (Residual)	Opp. Share (Direct)	N
2010	Point Estimates	0.334473***	0.279602***	0.041115***	0.164052*	0.122925***	754
	se	(0.035458)	(0.022811)	(0.009740)	(0.066223)	(0.022876)	
	P	(p<0.000000)	(p<0.000000)	(p<0.000024)	(p<0.013239)	(p<0.000000)	
	Ll	(0.264976	(0.234894	(0.022025	(0.034258	(0.078089	
	Ul	0.403969)	0.324310)	0.060205)	0.293846)	0.167761)	
2016	Point Estimates	0.242131**	0.206469***	0.014826	0.147284	0.061232*	618
	Se	(0.079585)	(0.030557)	(0.016631)	(0.133109)	(0.031290)	
	P	(p<0.002347)	(p<0.000000)	(p<0.372678)	(p<0.268513)	(p<0.050359)	
	Ll	(0.086147	(0.146578	(-0.017770	(-0.113604	(-0.000096	
	Ul	0.398114)	0.266360)	0.047423)	0.408172)	0.122560)	

Table A.4. Parametric results on inequality of opportunity in monthly wages, born in the north subgroup, 2010 and 2016. The results ll and ul are the lower and upper bounds of the 95% confidence interval

Year	Result Type	Total Inequality	Within Group Inequality	Between Group Inequality	Opp. Share (Residual)	Opp. Share (Direct)	N
2010	Point Estimates	0.325202***	0.309467***	0.015051***	0.048385*	0.046283***	1354
	se	(0.028146)	(0.027221)	(0.002804)	(0.022748)	(0.006852)	
	P	(p<0.000000)	(p<0.000000)	(p<0.000000)	(p<0.033420)	(p<0.000000)	
	Ll	(0.270036	(0.256114	(0.009555	(0.003800	(0.032854	
	Ul	0.380367)	0.362820)	0.020547)	0.092970)	0.059713)	
2016	Point Estimates	0.560842*	0.489242**	0.017021*	0.127665	0.030348	1290
	se	(0.233582)	(0.159103)	(0.006952)	(0.068804)	(0.028798)	
	P	(p<0.016348)	(p<0.002105)	(p<0.014356)	(p<0.063527)	(p<0.291959)	
	ll	(0.103030	(0.177406	(0.003395	(-0.007189	(-0.026095	
	ul	1.018653)	0.801078)	0.030647)	0.262518)	0.086792)	

Table A.5. Parametric results on inequality of opportunity in monthly wages, born in the center subgroup, 2010 and 2016. The results ll and ul are the lower and upper bounds of the 95% confidence interval

Year	Result type	Total Inequality	Within Group Inequality	Between Group Inequality	Opp. Share (Residual)	Opp. Share (Direct)	N
2010	Point Estimates	0.559106***	0.517895***	0.024492*	0.073709	0.043805*	1840
	se	(0.049011)	(0.047925)	(0.011928)	(0.040038)	(0.019784)	
	P	(p<0.000000)	(p<0.000000)	(p<0.040040)	(p<0.065625)	(p<0.026815)	
	ll	(0.463046	(0.423964	(0.001114	(-0.004764	(0.005030	
	ul	0.655166)	0.611826)	0.047870)	0.152183)	0.082581)	
2016	Point Estimates	0.268492***	0.255407***	0.009593	0.048734	0.035728	1401
	se	(0.078012)	(0.059541)	(0.005450)	(0.055333)	(0.018387)	
	p	(p<0.000578)	(p<0.000018)	(p<0.078366)	(p<0.378452)	(p<0.051996)	
	ll	(0.115591	(0.138709	(-0.001088	(-0.059716	(-0.000309	
	ul	0.421393)	0.372105)	0.020274)	0.157185)	0.071765)	

Table A.6. Parametric results on inequality of opportunity in monthly wages, born in the south subgroup, 2010 and 2016. The results ll and ul are the lower and upper bounds of the 95% confidence interval

Year	Result Type	Total Inequality	Within Group Inequality	Between Group Inequality	Opp. Share (Residual)	Opp. Share (Direct)	N
2010	Point Estimates	0.502910***	0.403542***	0.033976**	0.197587*	0.067559**	708
	Se	(0.087297)	(0.062035)	(0.012830)	(0.097964)	(0.022953)	
	P	(p<0.000000)	(p<0.000000)	(p<0.008093)	(p<0.043704)	(p<0.003246)	
	Ll	(0.331811	(0.281955	(0.008830	(0.005580	(0.022572	
	Ul	0.674010)	0.525129)	0.059123)	0.389593)	0.112546)	
2016	Point Estimates	0.146114***	0.145241***	0.006861*	0.005971	0.046959*	599
	se	(0.034618)	(0.033755)	(0.003321)	(0.040596)	(0.022430)	
	p	(p<0.000024)	(p<0.000017)	(p<0.038804)	(p<0.883057)	(p<0.036294)	
	ll	(0.078264	(0.079083	(0.000353	(-0.073595	(0.002998	
	ul	0.213963)	0.211400)	0.013370)	0.085537)	0.090921)	

*Note: *** p<.001, ** p<.01, * p<.05*

A.2. The parametric decomposition results

Table A.7. Whole sample partials, 2010 and 2016

Year	Region of Birth	Father’s Employment Sector	Mother's Education	Father's Education	Gender	Father's Occupation
2010	0.009800	-0.001848	0.039719	0.028207	0.017957*	0.007082
	(0.005527)	-0.005042	(0.025983)	(0.016178)	(0.007507)	(0.006520)
2016	0.010105	0.018416	-0.014043	0.001486	0.016131	0.024720
	(0.010985)	-0.020147	(0.016708)	(0.015043)	(0.010793)	(0.021154)

*Note:*** p<.001, ** p<.01, * p<.05*

Table A.8. Men and women partials, 2010 and 2016

Year	Region of Birth	Father’s Employment Sector	Mother's Education	Father's Education	Father's Occupation
			Men		
2010	0.008985	-0.002974	0.045674	0.031739	0.006657
	(0.005762)	(0.004909)	(0.033612)	(0.019396)	(0.008043)
2016	0.013354	0.022596	-0.017268	-0.006370	0.018363
	(0.012801)	(0.022662)	(0.015355)	(0.019896)	(0.020136)
			Women		
2010	0.061463	0.051609	0.061841	0.024537	0.010275
	(0.033081)	(0.033633)	(0.039607)	(0.032395)	(0.014914)
2016	-0.007329	0.009196	0.096942	-0.003165	0.063601
	(0.019830)	(0.023691)	(0.071755)	(0.030307)	(0.049442)

*Note:*** p<.001, ** p<.01, * p<.05*

Table A.9. Region of birth partials, 2010 and 2016

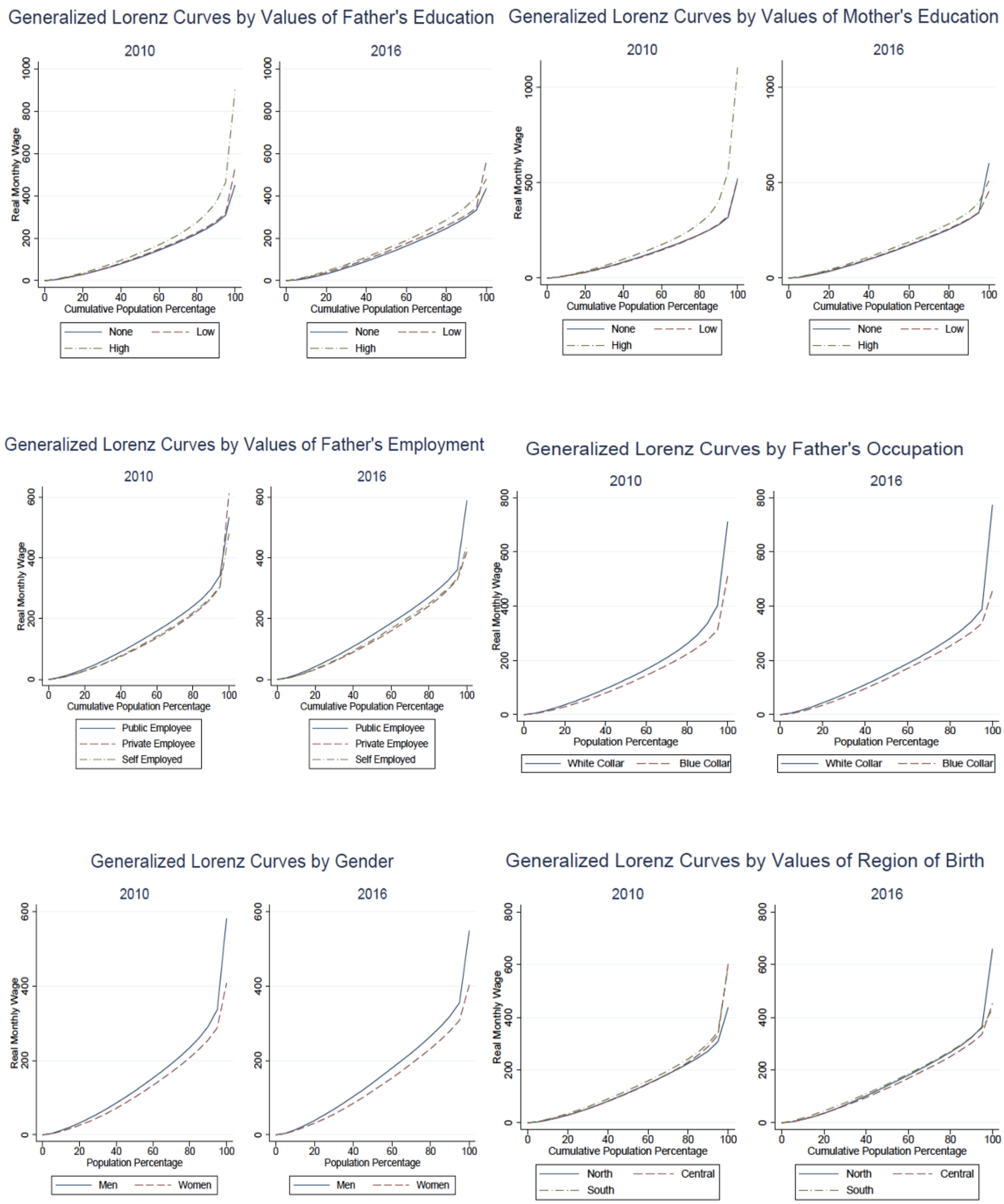
Year	Gender	Father's Employment Sector	Mother's Education	Father's Education	Father's Occupation
			North		
2010	0.022769*	0.001807	0.008280	0.012176	-0.002391
	(0.009999)	(0.008726)	(0.011284)	(0.023538)	(0.005065)
2016	0.017366	0.016435	0.019784	0.004532	0.065633
	(0.025242)	(0.014160)	(0.043743)	(0.037144)	(0.048101)
			Centre		
2010	0.029789***	-0.002781	0.034302	0.019868	0.008291
	(0.007745)	(0.007015)	(0.033641)	(0.014776)	(0.009745)
2016	0.013806	0.044082	-0.008447	0.007551	-0.001033
	(0.009409)	(0.056014)	(0.020712)	(0.013836)	(0.007338)
			South		
2010	-0.007999	0.030873	0.114065	0.109616	0.039047
	(0.013843)	(0.039628)	(0.114711)	(0.094484)	(0.033483)
2016	0.027109*	0.013893	-0.023815	-0.007198	0.000079
	(0.012654)	(0.018082)	(0.024500)	(0.016231)	(0.006777)

*Note:*** p<.001, ** p<.01, * p<.05*

A.3. Lorenz curves for monthly wages by background circumstances 2010, 2016

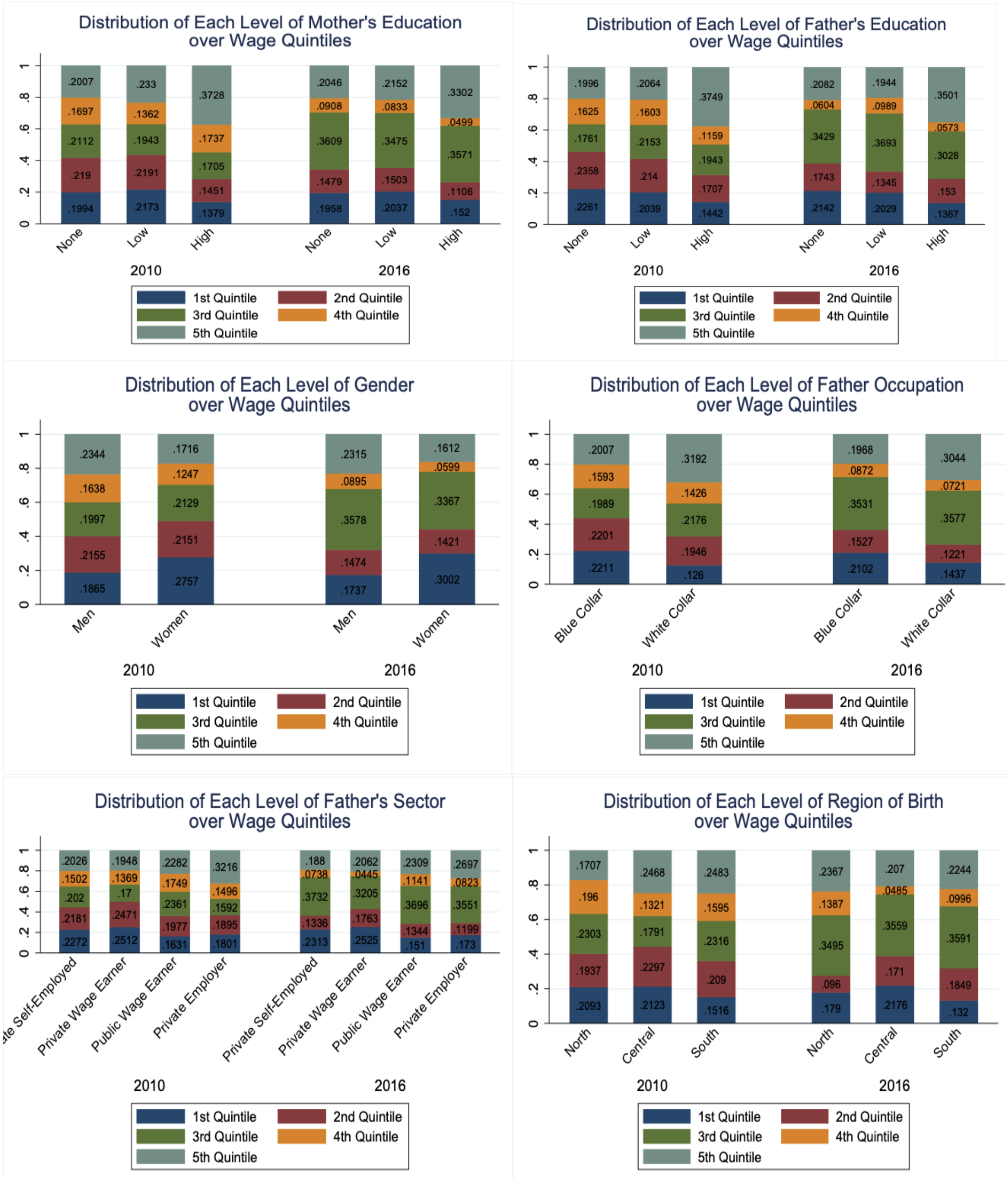
Figure A.1 shows Generalized Lorenz curves for monthly wages by background circumstances, with the Y-axis representing CPI-adjusted real monthly wages in 2017 JOD and the X-axis indicating cumulative population percentage. For better visualization, I subdivided the categories for parental education levels as follows: (“None: no education/ illiterate”, “Low: read and write, basic education and secondary”, and “High: post-secondary and university.

Figure A.1. Lorenz curves for monthly wages by background circumstances 2010, 2016



A.4. Mobility by circumstances: share of each circumstance by wage quintile

Figure A.2. Mobility by gender and social background circumstances 2010 and 2016

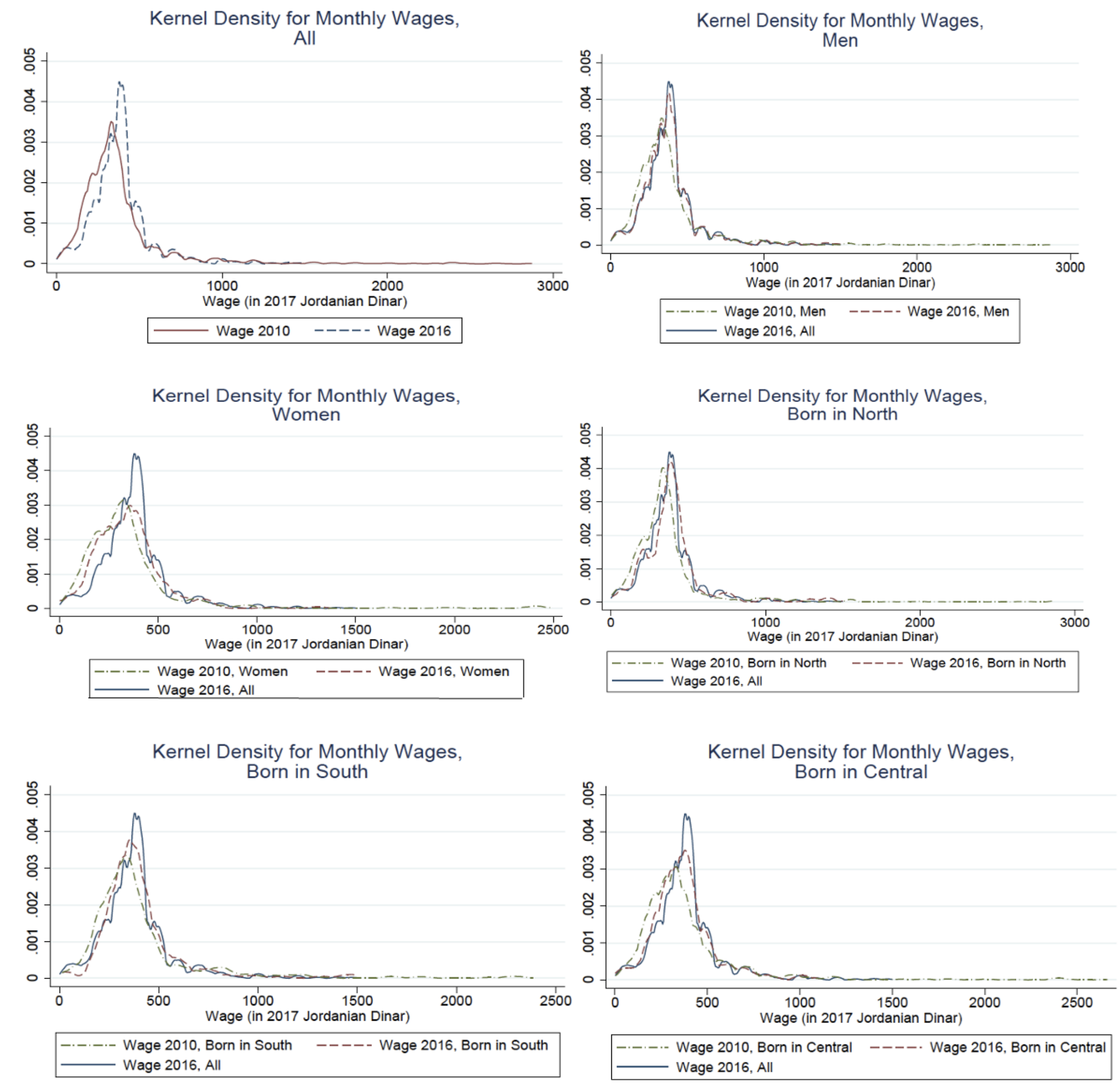


Note: The first quintile represents the poorest, while the fifth quintile represents the top 20%.

A.4.1. Kernel density functions

Figure A.3 shows the kernel density[13] functions for the whole sample and the five subgroups for both survey waves. The distribution of monthly wages for the full sample in the 2016 wave is represented on all the subgroups' graphs as a reference point. All distributions are strongly skewed to the right with long tails, which means that higher monthly wage earners i.e., upper percentiles of the distributions earn a remarkable amount of the total wages.

Figure A.3. Kernel density function for the whole sample and the five subgroups, both waves



[13] The top 2% of observations in the sample and subgroups have been trimmed to improve graph legibility due to significant outliers.

A.5. Gini coefficients and percentile ratios

A.6.1. Gini coefficient

Table A.10. The Gini coefficient for the whole sample and subgroups, 2010 and 2016

Population	Gini-2010	Gini-2016
All	0.512519	0.425625
Men	0.526317	0.437380
Women	0.421657	0.342950
North	0.408661	0.527722
Central	0.553140	0.357078
South	0.520342	0.264517

A.6.2. 90/10, 50/10 and the 90/50 Ratios

Table A.11: Percentile ratios for the whole sample and subgroups, 2010 and 2016

Population	90/10-2010	90/10-2016	50/10-2010	50/10-2016	90/50-2010	90/50-2016
All	4.285714	3	2	1.9	2.142857	1.578947
Men	4	3.060898	1.866667	1.875	2.142857	1.632479
Women	3.825	2.898148	2.133333	1.944444	1.792969	1.490476
North	3.45	3.684211	2.09375	2.105263	1.647761	1.75
Central	4.285714	3	1.961905	1.75	2.184466	1.714286
South	4.355556	2.4	1.92	1.52	2.268519	1.578947

Table A.12. P10, p50, and p90 for the whole sample and subgroups, both waves

Population	p10-2010	p10-2016	p50-2010	p50-2016	p90-2010	p90-2016
All	167.06	200	334.12	380.00	715.98	600.00
Men	178.99	208	334.12	390.00	715.98	636.67
Women	143.20	180.00	305.48	350.00	547.72	521.67
North	159.11	190.00	333.13	400.00	548.92	700.00
Central	167.06	200.00	327.76	350.00	715.98	600.00
South	178.99	250.00	343.67	380.00	779.62	600.00