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Inequality of Opportunity and the Probability of Being Very Rich or Very Poor*

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Abstract

Inequality of Opportunity research typically models the effects of background characteristics (such as race, gender, parental socioeconomic status) on average income. However, by focusing only on the means, this research misses one of the most visible forms of inequality—the relative frequency of extreme values. In this paper, we study the links between background characteristics and the tails of the income distribution using some full-distributional regression models. We show that having a father of high socioeconomic status produces a significant increase in average household income, but an even bigger effect on the chance of belonging to the top 1%. Similarly, immigrants are both more likely to be in poverty, and in the top income percentile, than non-immigrants. Since public attention is often focused on these extreme outcomes, our results may partially explain why mean-based Inequality of Opportunity estimates are often lower than intuition would suggest.

Keywords: Inequality of Opportunity, Distributional Differences, Poverty, Top Income, Extreme Values.

JEL Classification Numbers: D31, D63, J3.

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1 Introduction

Economists measure Inequality of Opportunity (henceforward, IOp) as the inequality due to variables beyond individual control such as gender, race or parental socio-economic status (Aaberge *et al.*, 2011; Brunori, 2016; Checchi & Peragine, 2010; F. H. G. Ferreira & Gignoux, 2011; Ramos & Van de gaer, 2012; Roemer & Trannoy, 2016, among others).[1] Most of the empirical research has focused on the effect of these background characteristics on average outcomes such as income, wage or education. However, by focusing predominantly on conditional means, this research neglects important distributional characteristics related to the relative frequency of extreme values. Therefore, traditional methods of measuring IOp do not align with general perceptions of inequality as unequal chances.

In this paper, we apply a full-distributional IOp model in order to analyze the links between background characteristics and the probability of being in the tails of the income and wage distributions. By modeling the conditional mean and conditional variance, we are able to provide a more comprehensive understanding of the complexity of the income-circumstance relationship (Anderson *et al.*, 2020; Davillas & Jones, 2020; Kerm *et al.*, 2016; Kneib *et al.*, 2021; Machado & Mata, 2005; Silbersdorff *et al.*, 2018). To account for the fact that the mean is an insufficient statistic for capturing distributional variance, we look at other features of the distribution providing us additional information that the traditional expected-based approach would have missed. This allows us to explore important differences in the contributions of circumstances across the whole distribution with a special focus on the tails (Silbersdorff *et al.*, 2018).

The relevance of extreme values and heavy tails has been discussed in analyses of the income distribution (Bossert *et al.*, 2021; Ibragimov & Ibragimov, 2018; Schluter, 2012), however, this framework has not been extended to the IOp literature. Our paper is the first, to the limit of our knowledge, to apply this perspective to the measurement of IOp. Emphasizing the tails and their composition is particularly important in providing a more realistic picture of IOp and its implications. The over-representation of minorities among very poor people, for example, is likely to be related to other indicators of disadvantage, including mobility, mortality and crime, that are not immediately evident from mean based statistics. Analogously, the composition of the right tail has important implications for democratic functioning, as high income individuals exerting disproportionate political power in a zero-sum context (Piketty, 2017, 2020). Again, since this influence is a characteristic of very extreme value, IOp models based on conditional expected values will overlook this important aspect of inequality of opportunity.

[1] Roemer (1998) in his seminal contribution distinguished between the effects of circumstances and effort in determining an individual outcome: "circumstances", namely all those factors beyond individual's responsibility, and "effort", all those factors which an individual can be considered as responsible for.

We run a series of simulations to calculate differentials between parametric estimates of unconditional and conditional distributions of household income and weekly wage. We then compute the probabilities of being in the top 1% or below the poverty line as a function of pre-determined characteristics such as gender, race, and social class at birth.[2] We show that there are substantial differences in IOp when modeling the tails of the outcome distribution rather than the mean. We find, for example, that having a father with a university degree has a significant effect on the average household income but an even bigger impact on the probability of being in the top 1%. We also find immigration effects that differ from those found in the more traditional IOp literature. In particular, we find a large variance among immigrants, who are slightly more likely to be in poverty, but also more likely to be in the top percentile than non-immigrants. [3]

Our paper contributes on the one hand to the literature on top incomes (Alvaredo, 2011; Atkinson *et al.*, 2011; Milanovic & Milanovic, 2011; Piketty, 2005; Piketty & Saez, 2006, among others) and poverty measurement (Chen & Ravallion, 2010; Ravallion, 2015; Ravallion & Chen, 2019); and on the other hand, to the growing IOp literature. In addition, our results have implications for the recent literature on inequality and politics (Gethin *et al.*, 2021; Piketty, 2017, 2020; Piketty & Saez, 2006). For instance, the extreme concentration of income and wealth at the very top is accompanied by the concentration of political power (Hacker & Pierson, 2010; Milanovic, 2019), with the rise of a new elite (Milanovic, 2019). Our findings indicate that the access to this exclusive club is strongly dependent on factors outside individual control (e.g., gender, race and class). We further argue that the transmission of educational and financial advantages has enabled the propagation of the power and privilege of these elites across generations (Milanovic, 2019). The systematic exclusion of certain groups from political influence and decision-making power has allowed this self-sustaining upper-class (Milanovic, 2019) to promote their own interests at the expense of others (López & Dubrow, 2020), creating a vicious cycle between economics and politics (Hacker & Pierson, 2010).[4]

Our results also feed into the economic analysis on populism (Bossert *et al.*, 2019; Guiso *et al.*, 2017; Guriev & Papaioannou, 2020; Rodrik, 2021). The persistence of group-based inequalities, racial and gender discrimination have contributed to a growing sense of unfairness and anxiety among those opportunity-deprived sectors of the population (Satz & White, 2021). Stagnating living standards has triggered a sense of insecurity and

[2]Following Bourguignon *et al.* (2007) and F. H. G. Ferreira and Gignoux (2011), we use a parametric ex-ante approach to measure IOp. This approach is usually regarded as more parsimonious than the non-parametric one and allow us to simultaneously consider a large set of circumstances (Brunori, 2016; Niehues & Peichl, 2012).

[3]Effort observability is another relevant problem in the IOp literature, with important implications for the IOp measurements (Brunori, 2016; Luongo, 2011; Pistolesi, 2009).

[4]Particularly, Hacker and Pierson (2010) in their book define the economic system that has generated the hyper-concentration of income at the top and the rise of superstars earners as *winner-take-all* economy and the political system that has supported it through tax cuts, deregulation and government interventions as *winner-take-all* politics.

uncertainty about the future, fueling distrust and resentment towards those elite-lead institutions and their ability to remove social mobility constraints (Guiso *et al.*, 2017; Guriev & Papaioannou, 2020). The resulting anger and the frustration have favored populist parties, spread identity politics and triggered cultural concerns among those who felt left behind (Besley & Persson, 2021; Gennaioli & Tabellini, 2019; Inglehart & Norris, 2017; Norris & Inglehart, 2019).

Lastly, the way people perceive inequality and its fairness has important implications on individual attitudes towards redistributive policies. Different beliefs around equality of opportunity, poverty and social mobility are associated with different degrees of inequality acceptance (Alesina & Angeletos, 2005; Alesina & Giuliano, 2009; Alesina & La Ferrara, 2005; Alesina *et al.*, 2018; Benabou & Ok, 1998; Benabou & Tirole, 2005; Hvidberg *et al.*, 2020; Piketty, 1995) and poltical attitudes (Shayo, 2009, 2020). Our results emphasize the need to reconcile the measurement of IOp with the general perception of the same phenomen (Brunori, 2017; Hufe *et al.*, 2022).

This paper is organized as follows. Section 2 describes the data and construction of our main variables. Section 3 explains our empirical strategy. Our findings are summarized in Section 4. Then, concluding remarks are offered in Section 5. In the Appendix A, we provide additional results.

2 Data

We use the data from the last release (2021) of Household, Income and Labour Dynamics in Australia (HILDA) Survey. HILDA is a panel study that started in 2001, it collects information on different aspects of life from more than 17,000 Australians each year. Our two key variables are: annual household income, which is defined after governmental taxes and transfers, corrected for age and inflation, and standardized using the square-root adult equivalence scale; average weekly wage and salary income (imputed) from all forms of paid employment over the time, defined before taxation and governmental transfers and corrected for age and inflation.[5]

We decided to use these two welfare markers to compare the effects of the circumstances on the different part of the distributions, particularly considering the problem of intra-household inequality. While household income is a good measure of welfare, it does not account for the intra-household distributional variations. Furthermore, we assume perfect distribution of resources when applying equivalence scale. On the other hand, wage is a scant welfare measure, but it is a more representative of the intra-household

[5]We pre-adjust our dependent variables, log household income and log weekly wage, for age to consider changes over time of our inequality measures that are not due to changes in age structure. We first regress log household income and log weekly wage on age and age squared, then we calculate the corrected income/wage as the sum of the average logarithm of income and the residuals from the regression.

resources distribution. The resource sharing inside the household implies also some correlation among the two markers (see Figure 1).

Figure 1: Income and Wage Correlation

Note: The graphs report the scatter plot for our two dependent variables: log household income and log weekly wage.

We consider as circumstances beyond individual control the following socio-demographic variables: gender, immigration and refugee status, parental background information such as parents' immigration status, parents' activity status (employed or not employed, e.g., unemployed, deceased, not living in the household), and parents' educational level (having a university degree or not).[6] Other circumstances include whether English is the first language learned, whether the individual grew up with their biological mother and father or if the parents were divorced/separated and the birth order for being the oldest child.

In Table 1, we report the descriptive statistics for both our samples. Our sample for the household income is composed of more than 242,900 observations, where the sample for the weekly earnings is composed of more than 120,000 observations. In constructing the weekly earnings sample, we remove those individuals who report a weekly wage equal to 0. Although this procedure may generate selectivity issues (Heckman, 1976, 1977), dropping the 0 is important in modelling the conditional income and wage distribution as log-normal. The observations are taken over a period of 20 years from 2001 to 2020.

[6] All information about parents relate to when the respondent was 14 years old.

For the analysis, we consider the logarithm of both our dependent variables. In the Appendix A, we compare the results from two different periods, the first five years (2001-2005) and the last five years (2016-2020) available for our sample, to investigate how IOp has changed in Australia over time.

Table 1: Descriptive Statistics

Variables	Log Household Income Sample		Log Weekly Wage Sample			
	Mean	St Dev	Mean	St Dev	Min	Max
Log Household Income	10.811	0.633			2.105	14.471
Log Weekly Wage			6.860	0.761	0.152	10.431
Circumstances						
Female	0.523	0.499	0.491	0.500	0	1
Refugee	0.017	0.129	0.014	0.117	0	1
Indigenous origin	0.011	0.105	0.008	0.091	0	1
Immigrant	0.204	0.403	0.196	0.397	0	1
Mother immigrant	0.325	0.468	0.323	0.468	0	1
Father immigrant	0.352	0.478	0.350	0.477	0	1
First Language learned: English	0.899	0.301	0.908	0.290	0	1
Parents divorced/separated	0.111	0.314	0.119	0.324	0	1
Oldest child	0.342	0.474	0.350	0.477	0	1
Non-biological father	0.032	0.175	0.031	0.173	0	1
Non-biological mother	0.020	0.140	0.021	0.143	0	1
Father university	0.157	0.364	0.168	0.374	0	1
Mother university	0.126	0.332	0.127	0.333	0	1
Father employed	0.944	0.231	0.949	0.221	0	1
Mother employed	0.534	0.499	0.581	0.493	0	1
Observations	242,994		129,651			

Notes: The table presents means, standard deviations, min and max for all variables used in the paper for the two sample considered in the analysis. Observations are taken over 20 years period. The reference individual is a non-indigenous male from non-immigrant parents.
Source: Authors' own calculations from HILDA database.

3 Methods

We model the conditional distribution of income and earnings by a log-normal distribution. This is a continuous probability distribution of a random variable, the logarithm of which is normally distributed. The log-normal distribution has the following probability density function:

$$f(y) = \frac{1}{(y\sigma\sqrt{(2\pi)})} exp(-\frac{(log(y) - \mu)^2}{2\sigma^2}) \tag{1}$$

Where y is the income/weekly earnings. We estimate the two parameters of the conditional log normal distribution (μ and σ^2) for each set of circumstances thorough a heteroskedastic linear regression. Our approach is very similar to the one proposed by

Jenkins (2007) with the "LOGNFIT" Stata command. We assume that heteroskedasticity may affect the results of our estimates, with the variance increasing as income grows.[7] We model the variance as an exponential function of circumstances using maximum likelihood estimation (MLE).

$$y_i = x_i\beta + \epsilon_i \tag{2}$$

$$\hat{\mu_i} = \hat{\beta}_0 + \sum_{i=1}^{k} \hat{\beta}_j x_i \tag{3}$$

$$\hat{\sigma_i^2} = \exp{(\hat{\theta}_0 + \sum_{i=1}^{m} \hat{\theta}_j x_i)} \tag{4}$$

Where y is the variable denoting household income or weekly earnings, x_i are the individual circumstances, $\hat{\mu_i}$ and $\hat{\sigma_i^2}$ are the two estimated parameters for each individual, defined as function of the circumstances. $\hat{\beta}$ and $\hat{\theta}$ are the estimated coefficients from the heteroskedastic linear regression.

From the estimated parameters, we are able to calculate the differentials between the probability of being in the tails of the unconditional distribution and the probability of being in the tails of the conditional distribution. We consider as bottom cut-off the poverty line (z), defined as half of the median income/wage and as top cut-off the top 1% of the income/wage distribution (k) of the overall unconditional distribution. Both the cut-offs are parametrically estimated.[8] For the unconditional distribution, we calculate the following integrals:

$$z_{poor} = \int_0^z f(y)d(y) \tag{5}$$

$$z_{rich} = \int_k^\infty f(y)d(y) \tag{6}$$

Instead, for the conditional distribution:

$$z_{poor} = \int_0^z f(y|x)d(x) \tag{7}$$

$$z_{rich} = \int_k^\infty f(y|x)d(x) \tag{8}$$

[7] We verify the validity of this assumption thorough the results of LR tests displayed at the bottom of the regressions output.

[8] We calculate them as following: since the median of the log normal distribution is equal to $\exp(\mu)$, our poverty line z is equal to $\hat{\mu} - \ln(2)$. The top cut-off k instead is equal to $2.33(\sigma) + \mu$, where 2.33 is the value of the z-score that leaves an area equal to 0.99 to the left under a standard normal curve

We estimate them as follows:

$$z_{poor} = \frac{z - \hat{\mu}_{x_i}}{\sqrt{\sigma^2_{x_i}}} \tag{9}$$

$$z_{rich} = \frac{k - \hat{\mu}_{x_i}}{\sqrt{\sigma^2_{x_i}}} \tag{10}$$

We finally calculate the cumulative distribution function in order to estimate the differential in probability of being extremely rich or being extremely poor:

$$\Phi(z) = \int_{-\infty}^{z} \frac{1}{\sqrt[2]{2\pi}} e^{x^2/2} dx \tag{11}$$

$$Pr(y > k) = 1 - \phi(z_{rich}) \tag{12}$$

$$Pr(y < z) = \phi(z_{poor}) \tag{13}$$

4 Results

Here we discuss some of the most relevant circumstances used for the analysis: gender, immigration, parental education, parental activity status and family environment growing up. We compare the coefficients obtained from the heteroskedastic regressions (see Table 2) with the probabilities of being in the tails calculated for each circumstance.[9] We also report for each of these selected circumstances the graphs of the conditional density functions. We report in the Appendix A the results for all the additional circumstances used in the analysis (see Table A2) and the conditional probability results for the two periods considered (see results in Table A5 and A6).

The main idea of the following simulations is to compare the effect of these selected circumstances on inequality. Although separately analyzed, they together contribute to the persistence of divergences in individual outcomes and are behind the systematic exclusions of large groups of the populations, such as women and racial minorities from productive opportunities (F. H. Ferreira, 2022).[10] Understanding the impact of these predetermined characteristics not only on the average outcome but also on poverty and top income inequality has important policy implications in terms of economic efficiency and shared growth (F. H. Ferreira, 2022).

[9] For the sake of completeness, we report in Table 10 the results of the homoskedastic regressions.
[10] In the Appendix A, we report the results for the simulation including interactions effects.

Table 2: Heteroskedastic linear regressions results

	(1)		(2)	
	Log Household Income		Log Weekly Wage	
	$\hat{\mu}$	$\ln(\sigma^2)$	$\hat{\mu}$	$\ln(\sigma^2)$
Female	-0.0501***	-0.00346	-0.415***	0.182***
	(0.00237)	(0.0134)	(0.00394)	(0.0119)
Refugee	-0.0780***	0.0908	-0.0149	0.169**
	(0.0107)	(0.0572)	(0.0180)	(0.0582)
Indigenous origin	-0.255***	-0.105	-0.0233	-0.0602
	(0.0108)	(0.0593)	(0.0211)	(0.0732)
Immigrant	0.0315***	0.170***	0.0800***	-0.0980***
	(0.00510)	(0.0276)	(0.00795)	(0.0242)
Mother immigrant	-0.00491	-0.0421*	-0.00962	-0.0336
	(0.00394)	(0.0214)	(0.00657)	(0.0195)
Father immigrant	0.000132	-0.0121	-0.0137*	0.0107
	(0.00367)	(0.0192)	(0.00614)	(0.0183)
First language learned: English	0.137***	-0.0163	0.101***	0.0110
	(0.00576)	(0.0297)	(0.00870)	(0.0283)
Parents divorced/separated	-0.0797***	0.00790	-0.0300***	0.000133
	(0.00380)	(0.0211)	(0.00609)	(0.0193)
Oldest child	0.0323***	0.0114	0.0447***	0.0402**
	(0.00251)	(0.0139)	(0.00414)	(0.0125)
Non-biological father	-0.136***	-0.0126	-0.178***	0.0351
	(0.00848)	(0.0539)	(0.0153)	(0.0553)
Non-biological mother	0.0179	0.0543	0.0776***	-0.0770
	(0.0107)	(0.0631)	(0.0182)	(0.0571)
Father university	0.159***	0.0821***	0.0680***	0.0879***
	(0.00363)	(0.0204)	(0.00610)	(0.0167)
Mother university	0.0841***	-0.0695**	0.00930	0.171***
	(0.00381)	(0.0219)	(0.00710)	(0.0184)
Father employed	0.186***	0.0421	0.0262**	-0.0649*
	(0.00521)	(0.0271)	(0.00930)	(0.0261)
Mother employed	0.0756***	-0.197***	0.0403***	-0.0566***
	(0.00247)	(0.0137)	(0.00407)	(0.0124)
Constant	10.70***	-0.936***	7.183***	-0.893***
	(0.00960)	(0.0513)	(0.0150)	(0.0462)
Observations	242,994		129,651	
$\chi2$ for mean model test	41766.0		20345.5	
$\chi2$ for heteroskedasticity test	619.2		635.8	
p-value for heteroskedasticity test	0.0000		0.0000	

Notes: The table presents the estimates for the heteroskedastic linear regression models. Model (1) has a dependent variable the log of household income, Model (2) the log of weekly earnings. All the parameters are estimated by MLE with the variance as an exponential function of circumstances as in equation 4. Robust heteroskedasticity consistent standard errors are used. *, **, and *** define significance at 10%, 5%, and 1%, respectively. Observations are taken over 20 years. Dummies are defined relative to a reference individual who is male, non-refugee, non-immigrant, non-indigenous, with English not the first language, with non-immigrant and biological parents, non-divorced, with both parents without a university degree and parents employed when reference individual was 14 years-old.

4.1 Gender

Gender inequality is a well-recognized problem but not much attention has been paid in the inequality literature to gender composition of those at the top and the bottom of the distribution (Bertrand, 2018; Boschini *et al.*, 2020; Guvenen *et al.*, 2014; Yavorsky *et al.*, 2019). Our results show that the gender is a relevant dimension in determining the probability of being in the tails. While being female has a significant and negative effect on the mean of both our dependent variables (-5% for log of household income and -41.5% for log of weekly wage, see results in Table 2), the gender effect on the conditional probabilities is much smaller on household income than log weekly wage. Women are about three times more likely to be poor and have one-third of possibility to be in the top 1% than men in the labor market; while with respect to household income, they are 15% more likely to be poor and 40% less likely to be in top 1% (Table 3). Intra-houshold allocation of resources has been discussed as one of the main reasons behind these differences, as well as convergence in individual characteristics, with top-income women more likely to have a top-income partner (Bobilev *et al.*, 2020; Boschini *et al.*, 2020). The increased relevance of capital income over labor income has also contributed to these striking differences between the household dimension and the labour market one (Boschini *et al.*, 2020).

Despite the significant progress made by women in the "Grand Gender Convergence" (Anderson, 2022; Goldin, 2006, 2014) and a drastic reduction over time in the gender wage gap, the differences in remuneration between men and women are still quite pronounced (Bertrand, 2018; Guvenen *et al.*, 2014). Traditional human capital factors such as education and job experience have been discussed as less relevant in explaining the gender wage gap: women are now more educated than men (Goldin *et al.*, 2006), have increased their labor market participation and narrowed the job experience disparity (Blau & Kahn, 2017; Goldin, 2006, 2014). Instead, difference in occupations and industries have been found still significant factors in unfolding the persistence of gender wage gap (Card *et al.*, 2015): although women are now more likely to be employed in high level jobs (Blau & Kahn, 2017), they continue to be underrepresented at the top ("glass ceiling effect") (Atkinson *et al.*, 2018; Guvenen *et al.*, 2014), and over-represented at the bottom, mainly performing low-paying jobs ("sticky floor effect") (Arulampalam *et al.*, 2007; Booth *et al.*, 2003; Llorens *et al.*, 2005).

It is particularly in those high-skilled jobs that pay differences in the same occupations are more significant and with the gender wage gap has become particularly wider in the upper tail and where also wage convergence has slow down (Albanesi *et al.*, 2015; Albrecht *et al.*, 2003). According to Goldin (2014) this trend can be explained by the differences in rewards for flexibility, workforce interruptions and long work hours in these high level occupations rather than educational or skill levels, with women more likely to have family related interruptions (e.g., motherhood (Guvenen *et al.*, 2014; Juhn & McCue, 2017)), work fewer hours or part-time. Pre-market or specialization choices, and self-selection towards lower wage jobs may also explain these differences in occupational distribution (Sloane *et al.*, 2021).

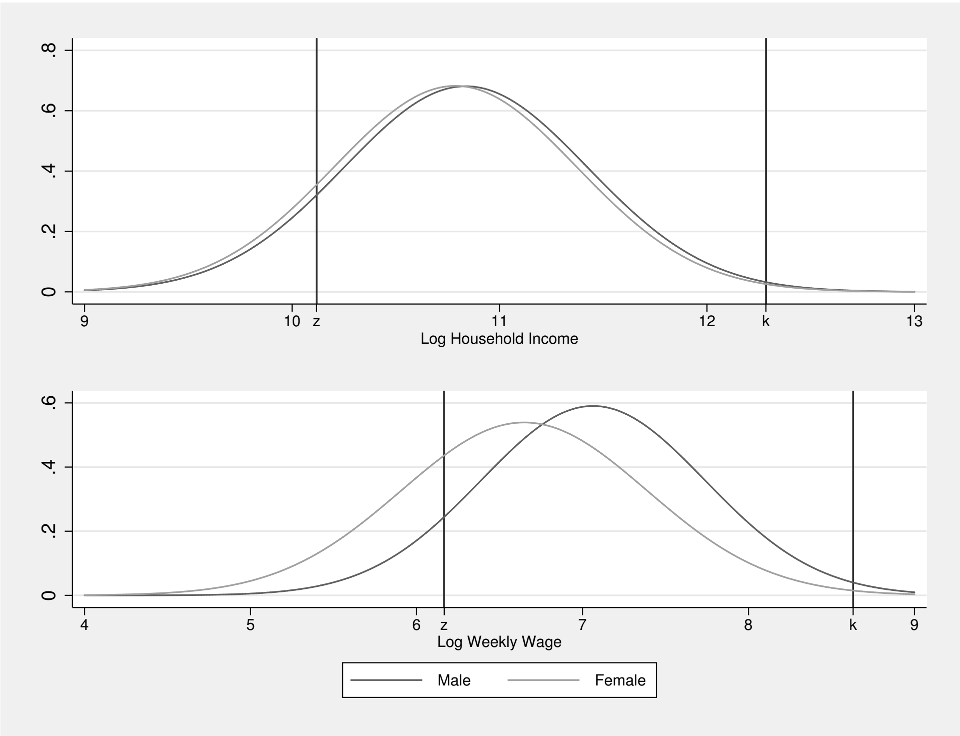
Additionally, gender differences in non-cognitive skills and psychological attributes (e.g., risk-aversion, taste for competition, interpersonal skills) have been recently considered for the unexplained part of the gender wage gap, although it is hard to disentangle the effect of the social context (Cattan, 2014; Fortin, 2008; Manning & Swaffield, 2008; Reuben *et al.*, 2015). Institutional factors such as wage setting and family policies, union coverage, or sociological factors such gender role and gender division of labor are still playing a relevant part in affecting the gap (Barigozzi *et al.*, 2018; Fleche *et al.*, 2018; Olivetti & Petrongolo, 2017).

Table 3: Conditional Probabilities of being in the Tails of the distribution by Gender

	Probability of being poor	Probability of being in the top 1%
	Log Household Income	
Female	0.126	0.005
Male	0.110	0.007
Ratio Female/Male	1.150	0.775
T-value Female/Male	12.621	4.841
P-value	0.000	0.000
	Log Weekly Wage	
Female	0.257	0.004
Male	0.092	0.010
Ratio Female/Male	2.795	0.363
T-value Female/Male	80.031	14.148
P-value	0.000	0.000

Notes: The table presents the conditional probabilities of being in the top 1% or being under the poverty line by gender for the log household income and the log weekly wage. We also report the ratios, the t-statistics, and the p-values for the two sample.

Figure 2: Conditional Density Functions by Gender



Note: The graphs report the probability density functions of the conditional distributions for log household income and log weekly wage by gender.

4.2 Immigration Status

Together with gender, being an immigrant is usually another source of disparities. Immigration has often been analyzed for its distributional impacts, particularly for potential negative effect on wages and employment of native workers. However, the relationship between immigration and inequality is not straightforward (Card, 2009; Kahanec & Zimmermann, 2008; Milanovic, 2016). While immigrants are more likely to be in the bottom of the income distribution, and experience higher poverty rates than natives, they are also more likely to be in the top 1%. In the labor market migrants are usually more concentrated in the top and bottom ends of the wage distribution.[11]

We find that being an immigrant has a small but positive effect on the average log income (3%) and average log wage (8%) (see Table 2). In terms of log income, those born outside Australia are slightly more likely to be poor (8%) but twice more likely to be in the top 1% than those born in Australia. Instead, in terms of log wage, immigrants are less likely to be poor and have the same probability of being in the top first percentile (see Table 4). Over time the effect on the average income has not changed much, while instead, for log weekly wage there has been an improvements over time with immigrants are significantly less likely to be poor and more likely to be in the top 1% in 2016-2020 respect to 2001-2005 (see Table A7 and A8). Additionally, we find that the immigrant effects on poorness are more profound for women (see Table A10).

This variability is related to a higher concentration of immigrants in the low and high ends of skill distribution (Blau & Kahn, 2015; Card, 2009). Different returns of education and occupational mismatch are often the causes of a significant wage gap between migrants and natives, with the low-skilled migrants usually stuck in low-paid occupations and with high skilled immigrants more likely to be over-educated with respect to their occupations (Amo-Agyei, 2020; Borjas, 2015; Dostie, 2022; Hou *et al.*, 2019; Ingwersen & Thomsen, 2021). Imperfect transferability of skills and assimilation issues have contributed to this trend (Chiswick & Miller, 2009; Friedberg, 2000; Kahanec & Zimmermann, 2008). In particular, our results show how women are heavily penalized in the migration process, with female migrants often working in low-skilled jobs (e.g. domestic and caring sectors) (Ehrenreich *et al.*, 2003; Parreñas, 2015), although this tendency is recently started to reverse with a significant increase of highly educated women among immigrants inflows (Dumont *et al.*, 2007; Dumont & Monso, 2007).

The increasing relevance of occupational skills and prevalence of selective immigration policies to attract talent has right skewed the skill level distribution of international migrants, with high-educated individuals more likely to migrate towards those countries with an higher earning variance (positive sorting)(Grogger & Hanson, 2013, 2015; Kerr

[11] According to the latest Forbes list of the richest people in the world, in 2022 13% of US billionaires were immigrants (Durot, 2022).

et al., 2017).[12] Furthermore, firm-specific pay and hiring policies have contributed to wage differential between high skilled and low skilled migrants, increasing the competition within themselves (Ottaviano & Peri, 2012), strongly advantaging those with a university degree (Clarke *et al.*, 2019; Dostie *et al.*, 2021; Hou *et al.*, 2019).

Self-selection may also contribute to the prevalence of migrants in the top of income/earning distribution. Individuals with higher education are more likely to migrate, due to better earnings' prospects in the destination country but also to their higher willingness to take risk (Heitmueller, 2002; Mavletova & Witte, 2017). This risk-seeking behavior has also been link with the higher probability of immigrants becoming entrepreneurs (Batista & Umblijs, 2014; Kahn *et al.*, 2017; Vandor, 2021; Vandor & Franke, 2016) as well as being more innovative (Bernstein *et al.*, 2018). Personal traits and cultural factors, such as a stronger work ethic, may contribute to this trend although it has been found that the migrant work ethic is a temporary phenomenon (Dawson *et al.*, 2018), a signal for productivity to the employers in the new labor market (Vandor, 2021).

This dynamic holds for Australia, where immigrants seem to possess an educational advantage relative to their native counterparts (see figure 8) (Islam & Parasnis, 2014), although some heterogeneity has been found when considering the visa schemes (skills steams vs other steams) (Kahanec & Zimmermann, 2008), and if migrants were from an English-speaking country or not (Breunig *et al.*, 2013).[13]

Special migrations schemes (e.g., citizen by investment program (CIP), "golden visas") that tend to favor the migration of these global elites, particularly towards English-speaking countries, contributing to the rise of top income inequality (Advani *et al.*, 2020; Card, 2009; Kerr *et al.*, 2016; Milanovic, 2016). Immigrants are now over-represented in the upper tail of the income distribution and more likely to be in the top 1% than they used to do in the past (Advani *et al.*, 2020).

[12] Among OECD countries, USA, Canada, Australia and New-Zealand are the main destinations for the majority of high-skilled migrants (Kerr *et al.*, 2016).

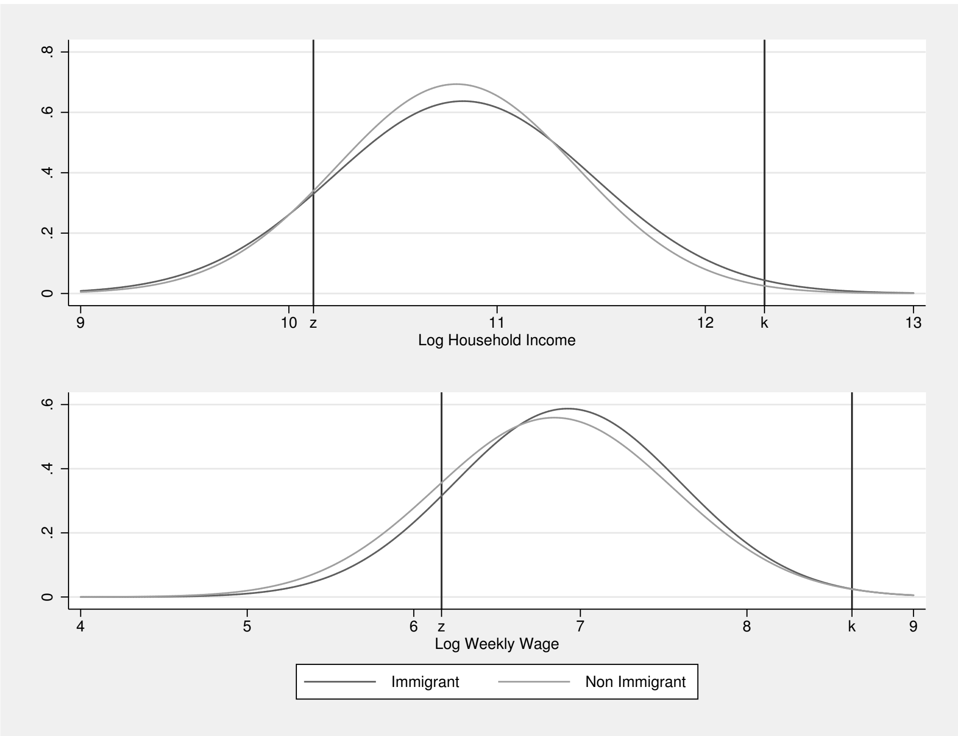
[13] The immigration inflows in Australia is mainly composed by high-skilled individuals. According to the latest release of the Australian Census, in 2016 58% of permanent migrants arrived through a skilled stream; 32% on family stream and only 10% on humanitarian stream. Additionally, 70% of those in the skill stream hold a bachelor degree or a higher qualification.

Table 4: Conditional Probabilities of being in the Tails of the distribution by Immigration status

	Probability of being poor	Probability of being top 1%
	Log Household Income	
Immigrant	0.126	0.010
Non-Immigrant	0.116	0.005
Ratio Immigrant/Non-Immigrant	1.081	2.051
T-value Immigrant/Non-Immigrant	5.671	10.996
P-value	0.000	0.000
	Log Weekly Wage	
Immigrant	0.132	0.006
Non-Immigrant	0.171	0.006
Ratio Immigrant/Non-Immigrant	0.773	0.978
T-value Immigrant/Non-Immigrant	15.986	0.253
P-value	0.000	0.800

Notes: The table presents the conditional probabilities of being in the top 1% or being under the poverty line by immigration status for the log of household income and the log of weekly wage. We also report the ratios, the t-statistics, and the p-values for the two sample.

Figure 3: Conditional Density Functions by Immigration Status



Note: The graphs report the probability density functions of the conditional distributions for log household income by immigration status for the two periods considered.

4.3 Parental Socio-Economic Status (SES)

In the analysis of social inequality, gender, race or immigration status are usually considered together with social class or parental background. The relevance of parental socio-economic status (henceforward SES) in determining individual future outcomes has been extensively discussed not only in the IOp literature (Brunori *et al.*, 2013, 2019; Checchi *et al.*, 2016; F. H. G. Ferreira & Gignoux, 2011), but also in the inter-generational mobility literature (Black & Devereux, 2010; Bowles & Gintis, 2002; Corak, 2013; Jenkins & Siedler, 2007; Raitano & Vona, 2015, among others). Parental education and occupation have been analyzed as main channels of transmission of socio-economic advantage (Maurin, 2002; Suhonen & Karhunen, 2019). While both explain a significant part of the inequality in the average income and wage, our findings confirm how their effect is even stronger in the tails of the distribution (Avram & Cantó-Sánchez, 2017; Brunori *et al.*, 2021; Brunori & Neidhöfer, 2021; Jantti *et al.*, 2006; Raitano & Vona, 2018).

We find that while having parents with a university degree has a positive and significant effect on both the average income and wage (although the effect of father is stronger than of mother with a university degree), the magnitude of this effect is much bigger on the conditional probabilities. In particular, a father with university degree increases the probability in being in the top 1% by about three times for income and about two times for wage (see Table 5). We also find that the father's education effect is different between males and females in terms of log weekly wage (see Table A11). On the other hand, a mother with a university degree increases the probability of being in the top 1% by 19% for income and 81% for wage. Additionally, having parents with a university degree significantly reduces the probability of being poor, with a bigger effect for income.

We also consider the effect of parental activity status. Growing with an employed father has a positive impact on the average household income (about 19%, see Table 2), and a very large effect on the probability of being rich (three times more likely respect to those who grow-up with a father unemployed, deceased or not living in the household, see Table 7), while the effect is much smaller on the average log wage as well as the probabilities of being in the tails of the wage distribution. Growing up with an employed mother has a small and positive impact on both average log household income and weekly wage, with a bigger impact in reducing the probability of being poor for household income and increasing the probability of being in the top 1% for log weekly wage (see Table 8).

While education may be still a relevant explanation for the persistence of parental background advantage (Bukodi & Goldthorpe, 2011; Goldthorpe & Jackson, 2008), factors other than the transmission of cognitive skills (Black & Devereux, 2010; Blanden *et al.*, 2007; Bolt *et al.*, 2021; Bowles & Gintis, 2002; Heckman *et al.*, 2006; Mogstad, 2017; Raitano & Vona, 2018; Sacerdote, 2000) may explain the heterogeneity of the effect of parental SES on children outcomes. The transmission of non-cognitive skills or soft-skills and personality traits (self-confidence, efficacy) have been discussed as relevant factors in explaining inter-generational mobility (Bowles & Gintis, 2002; Cunha & Heckman, 2007; Heckman *et al.*, 2006; Raitano & Vona, 2018).

However, the strength of the ties between parental background and child's future outcomes can not be entirely explained by the human capital accumulation hypothesis (Raitano & Vona, 2018). Factors such as family networking (nepotism) (Gagliarducci & Manacorda, 2020; Granovetter, 2005; Macmillan *et al.*, 2015; Raitano & Vona, 2018), positional rents (Mocetti, 2016), family social status (Clark & Cummins, 2014; Durante *et al.*, 2011) have been recently discussed as particularly important in explaining the inequality at the top of the earnings distribution (Corak & Piraino, 2011; Raitano & Vona, 2018). The transmission of occupational-specific skills or work experiences (e.g., career following or transmission of employer (Corak & Piraino, 2011; Mocetti, 2016)) offer a significant advantage in the labor market, easing the transition from school to work (Kramarz & Skans, 2014) and increasing the probability of access to top job positions (Macmillan *et al.*, 2015).[14]

Additionally, our results confirm the gender differences in the intergenerational transmission of parental SES, often discussed as consequence of the different educational expectations between daughters and sons, with a stronger relationship for sons (Bowles & Gintis, 2002; Kleinjans, 2010, among others).

Table 5: Conditional Probabilities of being in the Tails of the distribution by Father's Education

	Probability of being poor	Probability of being top 1%
	Log Household Income	
Father university	0.086	0.014
Father without university degree	0.125	0.005
Ratio Father university/non-university	0.689	2.730
T-value Father university/ non-university	24.128	14.086
P-value	0.000	0.000
	Log Weekly Wage	
Father university	0.153	0.010
Father without university degree	0.166	0.006
Ratio Father university/non-university	0.923	1.732
T-value Father university/ non-university	4.753	5.803
P-value	0.000	0.000

Notes: The table presents the conditional probabilities of being in the top 1% or being under the poverty line by father's education for the two periods considered. We also report the ratios, the t-statistics, and the p-values for the two sample.

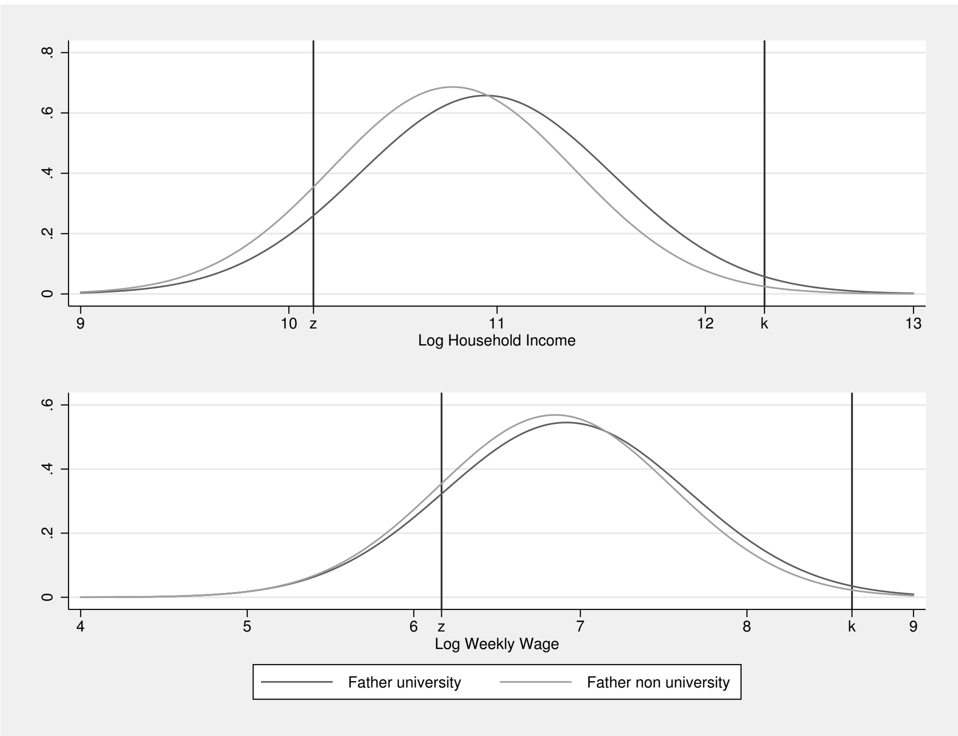
[14] In particular, Raitano and Vona (2018) identify two different ways in which children from a better parental background are advantaged: a "glass-ceiling effect", steeper earning profiles for high educated children of highly educated parents; and "parachute-effect", steeper earnings profiles of low educated children of highly educated parents.

Table 6: Conditional Probabilities of being in the Tails of the distribution by Mother's Education

	Probability of being poor	Probability of being top 1%
	Log Household Income	
Mother university	0.089	0.007
Mother without university	0.123	0.006
Ratio mother university/non-university	0.722	1.190
T value Mother university/non-university	19.237	2.204
P-value	0.000	0.028
	Log Weekly Wage	
Mother university	0.178	0.010
Mother without university	0.161	0.006
Ratio mother university/non-university	1.105	1.812
T value Mother university/non-university	5.347	5.614
P-value	0.000	0.000

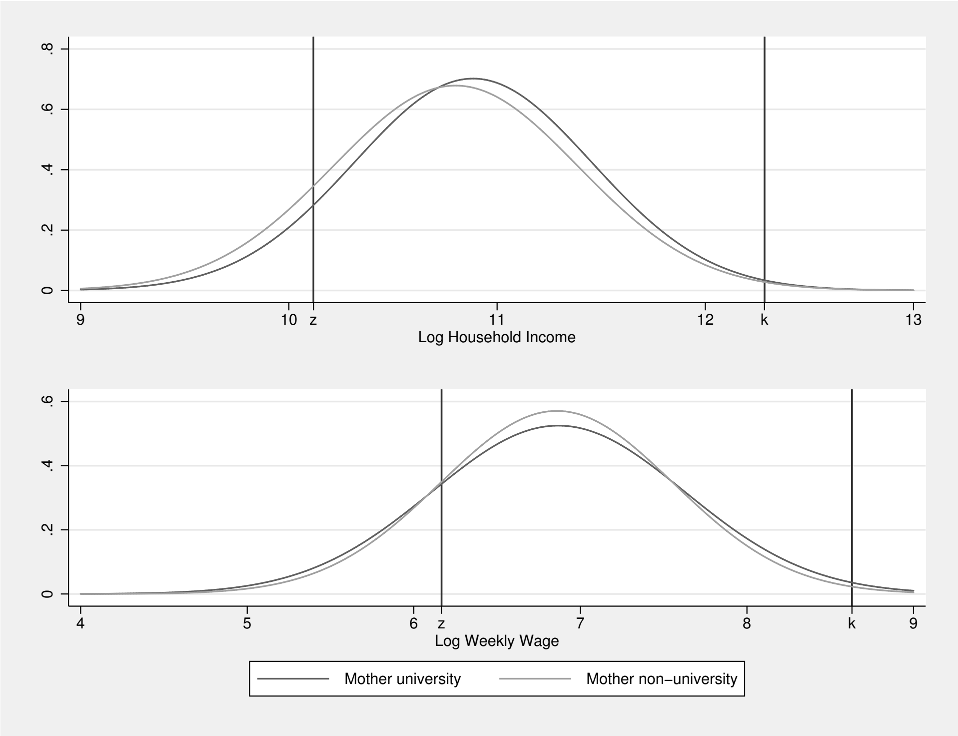
Notes: The table presents the conditional probabilities of being in the top 1% or being under the poverty line by mother's education for the two samples. We also report the ratios, the t-statistics, and the p-values for the two sample.

Figure 4: Log Household Income Conditional Density Functions by Father's Education



Note: The graphs report the probability density functions of the conditional distributions for log of household income and log of weekly wage by father's education.

Figure 5: Log Household Income Conditional Density Functions by Mother's Education



Note: The graphs report the probability density functions of the conditional distributions for log of household income and log of weekly wage by mother's education.

Table 7: Conditional Probabilities of being in the Tails of the distribution by Father's Activity Status

	Probability of being poor	Probability of being top 1%
	Log Household Income	
Father employed	0.115	0.006
Father not employed	0.183	0.002
Ratio Father employed/not employed	0.627	3.086
T value Father employed/not employed	20.277	10.130
P-value	0.000	0.000
	Log Weekly Wage	
Father employed	0.162	0.006
Father not employed	0.180	0.007
Ratio Father employed/not employed	0.905	0.883
T value Father employed/not employed	3.550	0.773
P-value	0.000	0.440

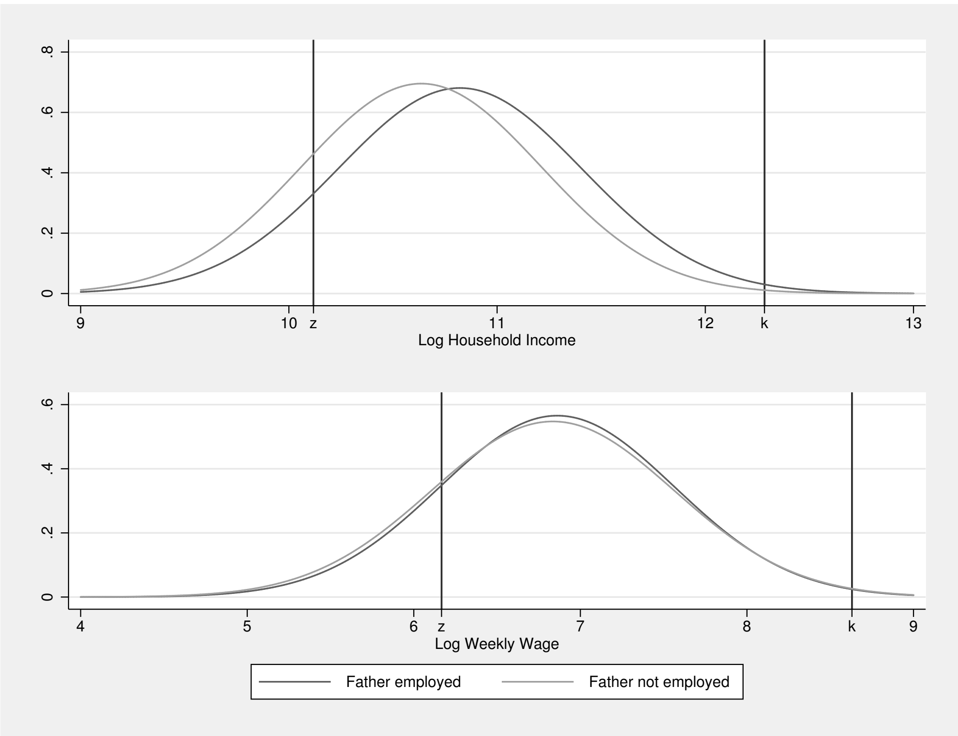
Notes: The table presents the conditional probabilities of being in the top 1% or being under the poverty line by father's activity status. We also report the ratios, the t-statistics, and the p-values for the two samples.

Table 8: Conditional Probabilities of being in the Tails of the distribution by Mother's Activity Status

	Probability of being poor	Probability of being top 1%
	Log Household Income	
Mother employed	0.096	0.005
Mother not employed	0.145	0.007
Ratio Mother employed/not employed	0.664	0.715
T value Mother employed/not employed	36.619	6.345
P-value	0.000	0.000
	Log Weekly Wage	
Mother employed	0.155	0.006
Mother not employed	0.176	0.006
Ratio Mother employed/not employed	0.881	0.961
T value Mother employed/not employed	9.988	0.549
P-value	0.000	0.583

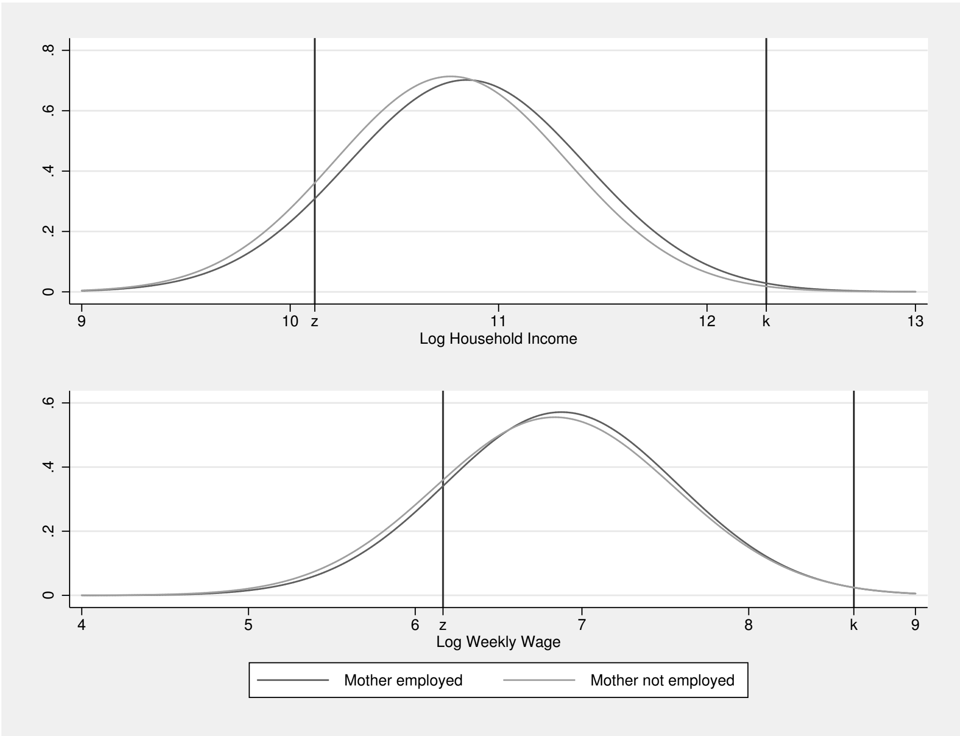
Notes: The table presents the conditional probabilities of being in the top 1% or being under the poverty line by father's activity status. We also report the ratios, the t-statistics, and the p-values for the two samples.

Figure 6: Conditional Density Functions by Father's Activity Status



Note: The graphs report the probability density functions of the conditional distributions for log of household income and log of weekly wage by father's activity status.

Figure 7: Conditional Density Functions by Mother's Activity Status



Note: The graphs report the probability density functions of the conditional distributions for log of household income and log of weekly wage by mother's activity status.

4.4 Family Environment

The impact of family environment on individual outcomes has often been overlooked in the inequality literature, although early experiences such as a difficult childhood can have a huge impact in terms of adult prospects and well-being (Amato & Anthony, 2014; Lopoo & DeLeire, 2014; McLanahan & Percheski, 2008; McLanahan *et al.*, 2013, among others). In particular, the effects of parental divorce or separation on long-term achievements of the children have been heavily debated. While there is no consensus on the causal effect of a divorce (Björklund *et al.*, 2007; Björklund & Sundström, 2006; Corak, 2001; Francesconi *et al.*, 2010; Ginther & Pollak, 2004), our regression results confirm the limited relevance of parental divorce on average individual outcomes (Amato & Anthony, 2014; Corak, 2001): we find that the effect of growing up with divorced or separated parents is negative and significant on both the average log household income (about -8%) and the average log weekly wage (-3%) (see Table 2).

However, while the negative effect of a divorce has been discussed as reflecting of a selection issue, other factors have been proposed to explain the heterogeneity of performances of adult-children (Amato & Anthony, 2014; Demo & Fine, 2010): the timing of the divorce, with a stronger impact on early-childhood outcomes (Ermisch & Francesconi, 2001; Fronstin *et al.*, 2001; Furstenberg & Kiernan, 2001), the background characteristics of the parents before the divorce, with economically poor family more likely to divorce, and unobservable differences between children, with possible benefits from the end of the parents' relationship. We find confirmation of this variability of outcomes among adult children of divorced/separated parents in our results when considering the household income: growing up with divorced or separated parents also increases the probability of being poor by 25% for income, while reduces the probability of being rich by one-third. Instead, these differences are much smaller on the labor market: 6% more likely to be poor and a tenth less likely to be rich on the log weekly wage distribution(see Table 9).

Additionally, our results are in line with previous research that show how the impact of divorce is different with respect to the position on the income distribution: single parent children usually record worse educational outcomes and lower collage attendance (Björklund & Sundström, 2006; Ermisch & Francesconi, 2001; Francesconi *et al.*, 2010; Lopoo & DeLeire, 2014; McLanahan *et al.*, 2013; Piketty, 2003; Sun & Li, 2001), if their parents tend to less resources ("resource-deprivation perspective" (Sun & Li, 2011)). Single parented individuals tend to have higher poverty rates and lower income than dual parented individuals, and this effect is stronger among those from highly educated parents (Bernardi & Boertien, 2016). Children from lower income families are more impacted since fewer resources are available to compensate for the loss of a parent (Corak, 2001). This is especially true when the children grow up in female-headed household, since they are more likely to experience significant income drops after divorced, being more at risk of poverty (Frimmel *et al.*, 2016).

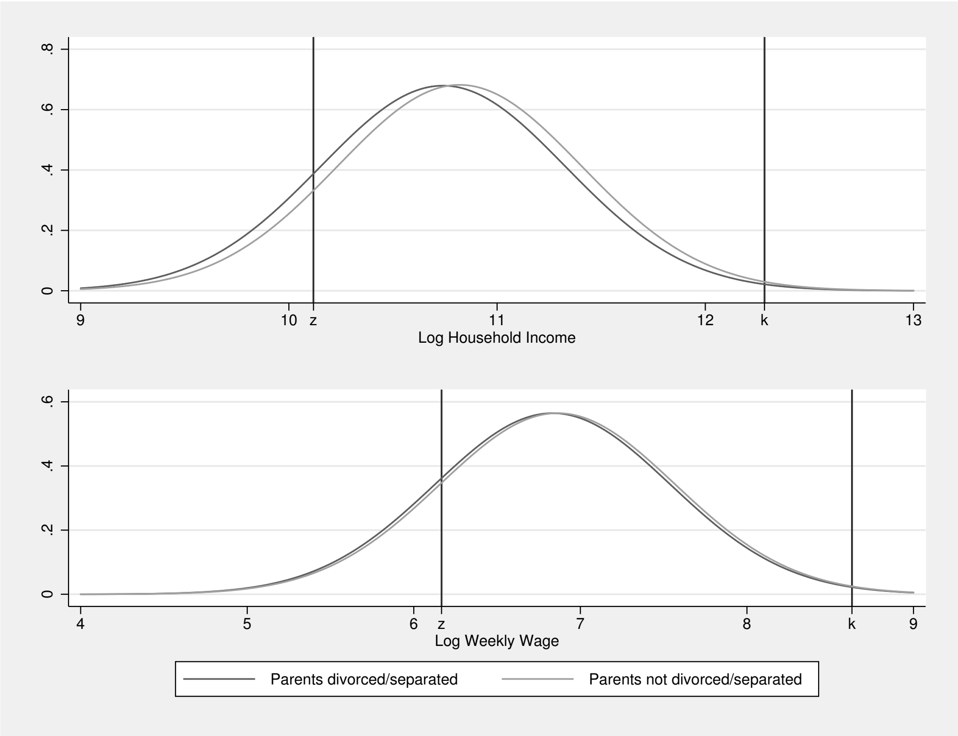
Finally, the higher probability of children from divorced/separated parents of being in the bottom of the income/wage distribution may be also related higher experience of behavioral problems (smoking or use drugs), anxiety and depression (Amato, 2010; Ermisch & Francesconi, 2001), and unstable relationships (Amato & Patterson, 2017; Cavanagh *et al.*, 2008; Wolfinger, 1999) with important implications on their early life choices. Girls for example are more likely to enter the labor market earlier due to a higher likelihood of teenage motherhood, while boys are more likely to die early or enter the labor market quite late (Frimmel *et al.*, 2016).

Table 9: Conditional Probabilities of being in the Tails of the distribution by Parents' marital status

	Probability of being poor	Probability of being top 1%
	Log Household Income	
Parents divorced/separated	0.145	0.004
Parents non-divorced/separated	0.115	0.006
Ratio Parents divorced/Non-divorced	1.257	0.696
T value Parents divorced/Non-divorced	13.154	4.336
P-value	0.000	0.000
	Log Weekly Wage	
Parents divorced/separated	0.173	0.005
Parents non-divorced/separated	0.162	0.006
Ratio Parents divorced/Non-divorced	1.066	0.887
T value Parents divorced/Non-divorced	3.301	1.100
P-value	0.001	0.271

Notes: The table presents the conditional probabilities of being in the top 1% or being under the poverty line by father's activity status. We also report the ratios, the t-statistics, and the p-values for the two samples.

Figure 8: Conditional Density Functions by Parents' Marital Status



Note: The graphs report the probability density functions of the conditional distributions for log of household income and log of weekly wage by mother's activity status.

5 Summary and Conclusion

In this paper we show how the measurement of IOp based on the average outcome provides a limited view of the effects of circumstances compared to measurement based on the entire outcome distribution. We model outcome variance as a function of circumstances, which allows us to detect heterogeneity among individuals from the same type. This is particularly important when we are trying to capture the effects on the extremes.

We find that women are consistently penalized in the labor market, experiencing a significant gender wage gap, which diminishes when considering allocated household incomes due to the intra-household resource re-allocation. Immigrants instead while experiencing higher poverty rates than natives, are more also more likely to be in the top 1% percentile. We also find that having a father with a university degree significantly increases the probability of being in the top percentile, making it even more relevant in terms of social mobility than it is usually emphasized. Additionally, family environment characteristics such as growing up with divorced parents seems particularly relevant in determining the probability of being poor.

The utility of our approach in providing a more comprehensive picture of IOp is confirmed by our results, especially those regarding immigration status and parental background. Additionally, our findings have important implications for the IOp measurement:

focusing more on the variance rather than the mean, we are able to provide a possible additional explanation of why mean-based IOp estimates are often lower than intuition would suggest (Brunori *et al.*, 2019; F. H. G. Ferreira & Gignoux, 2011; Hufe *et al.*, 2022).

The composition of the tails is particularly relevant to debates around the widening gap between the top 1% and the bottom 99%. Such debates often focus on the size and income/wealth share of the two groups (Alvaredo *et al.*, 2013; Biddle *et al.*, 2019; Hérault *et al.*, 2021). Meanwhile, scant attention has been paid to each group's composition and the factors behind the probability of being a CEO versus being unemployed. The implications of our results go far beyond the income domain: unequal distribution of resources implies also unequal distribution of political power. Those most privileged in terms of income and wealth have disproportionate access to and influence on the political process, with the potential to perpetuate inequalities (Atkinson & Leigh, 2007; Hacker & Pierson, 2010; Milanovic, 2019; Piketty, 2017, 2020). In a society with increasing social conflicts and political polarization, addressing the problem of extreme inequality is crucial for revitalizing the state of our democracy.

Our paper has also important implications for public policy design. Going beyond a mean-based approach is relevant to provide a more comprehensive picture of the distributional impact of public policies. Focusing on the entire distribution allows researchers to capture heterogeneous effects of those policies and properly identify those who gain and those who lose from their implementation (Carneiro *et al.*, 2003; Heckman, 2001).

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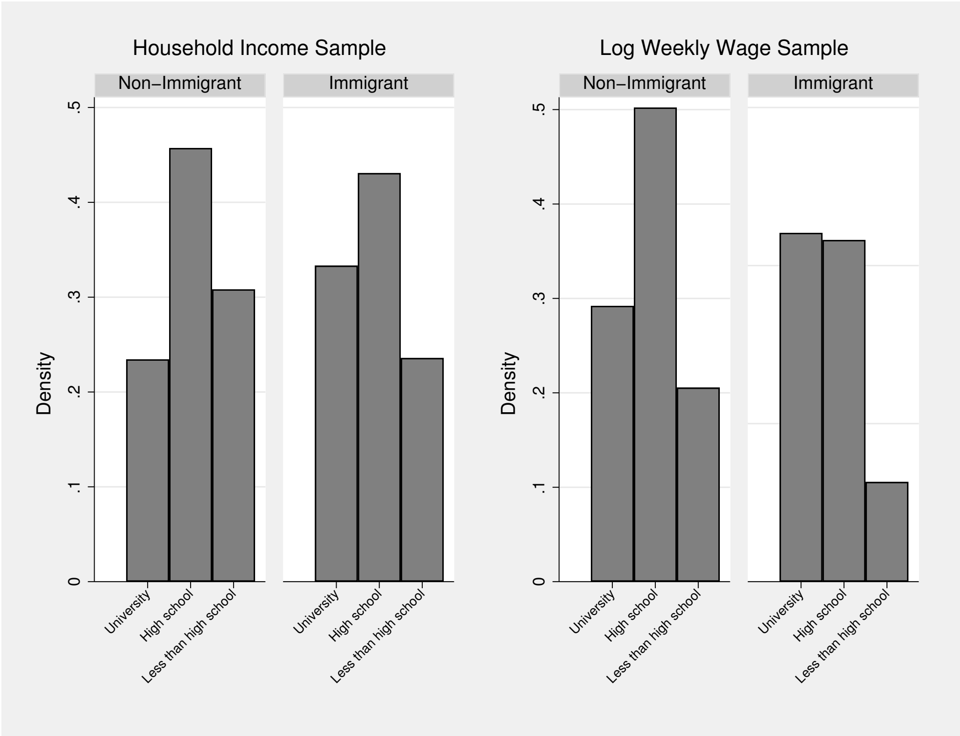
Table 10: Homoskedastic linear regressions results

	(1)	(2)
	Log Household Income	Log Weekly Wage
Female	-0.0515***	-0.415***
	(0.00239)	(0.00396)
Refugee	-0.0804***	-0.0184
	(0.0108)	(0.0183)
Indigenous origin	-0.268***	-0.0214
	(0.0109)	(0.0210)
Immigrant	0.0312***	0.0793***
	(0.00513)	(0.00801)
Mother immigrant	-0.00724	-0.00707
	(0.00392)	(0.00667)
Father immigrant	0.000197	-0.0156*
	(0.00364)	(0.00628)
First language learned: English	0.137***	0.0937***
	(0.00573)	(0.00877)
Parents divorced/separeted	-0.0774***	-0.0258***
	(0.00382)	(0.00610)
Oldest child	0.0335***	0.0453***
	(0.00254)	(0.00418)
Non-biological father	-0.140***	-0.173***
	(0.00898)	(0.0158)
Non-biological mother	0.0259*	0.0646***
	(0.0114)	(0.0187)
Father university	0.159***	0.0689***
	(0.00366)	(0.00599)
Mother university	0.0806***	0.0117
	(0.00387)	(0.00693)
Father employed	0.188***	0.0166
	(0.00524)	(0.00935)
Mother employed	0.0752***	0.0405***
	(0.00247)	(0.00408)
Constant	10.700***	7.204***
	(0.00957)	(0.01511)
Log sigma2		
Constant	-1.060***	-0.684***
	(0.00687)	(0.00594)
Observations	242,994	129,651
$\chi 2$ for mean model test	40032.2	18865.7

Notes: The table presents the estimates for the homoskedastic linear regression models. Model (1) has a dependent variable the log of household income, Model (2) the log of weekly wage. All the parameters are estimated by MLE. Robust heteroskedasticity consistent standard errors are used. *, **, and *** define significance at 10%, 5%, and 1%, respectively. Observations are taken over 20 years. Dummies are defined relative to a reference individual who is male, non refugee, non immigrant, non-indigenous, with English not the first language, with non immigrant and biological parents, non divorced, with both parents without a university degree and parents employed when reference individual was 14 years-old.

Figure 9: Educational levels by immigration status



Notes: The graphs reports the distribution of educational level by immigration status for both our samples.

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A Appendix

In this section we report some additional results. We perform a log-normality test of our two main variables and report the results in Table A1.

Table A1: Skewness\Kurtosis tests for Normality

				—— joint ——	
Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
Log Household Income	242,994	0.0000	0.0000	.	.
Log Weekly Wage	129,651	0.0000	0.0000	.	.

Note: The table reports the resutls of skewness and kurtosis test for normality on the two main variables log of household income and log of weekly wage.

In Table A2, we report the unconditional and conditional probabilities of being in the tails of the distribution considering the effects of the additional circumstances used for the analysis.

Table A2: Unconditional and Conditional Probabilities of being in the tails of the distribution: Additional Circumstances

	Probability of being poor	Porbability of being top 1%	Probability of being poor	Porbability of being top 1%
	Log Household Income		Log Weekly Wage	
Unconditional	0.137	0.010	0.181	0.010
Conditional				
Refugee	0.157	0.006	0.188	0.010
Non Refugee	0.118	0.006	0.163	0.006
Ratio Refugee/Non Refugee	1.335	0.956	1.157	1.659
T-value Refugee/Non Refugee	6.887	0.220	2.752	1.687
P-value	0.000	0.826	0.006	0.092
Indigenous origin	0.214	0.001	0.164	0.004
Non Indigenous origin	0.117	0.006	0.163	0.006
Ratio Indigenous/Non Indigenous	1.823	0.157	1.006	0.727
T-value Indigenous/Non Indigenous	12.234	8.314	0.088	0.815
P-value	0.000	0.000	0.930	0.415
First language learned: English	0.113	0.006	0.160	0.006
First language learned: non English	0.167	0.003	0.196	0.004
Ratio Non English/English	1.472	0.538	1.226	0.634
T-value Non English Speaking/ English	21.600	7.112	9.552	3.737
P-value	0.000	0.000	0.000	0.000
Mother Immigrant	0.116	0.005	0.163	0.005
Mother Non Immigrant	0.119	0.006	0.164	0.006
Ratio Mother Immigrant/Non immigrant	0.973	0.839	0.996	0.853
T-value Mother Immi/Non Immi	2.344	3.120	0.317	2.091
P-value	0.019	0.002	0.751	0.037
Father Immigrant	0.117	0.006	0.167	0.006
Father Non Immigrant	0.119	0.006	0.164	0.006
Ratio Father Immigrant/Non Immigrant	0.983	0.958	1.023	0.983
T-value Father Immi/Non Immi	1.467	0.775	1.730	0.226
P-value	0.142	0.438	0.084	0.821
Oldest child	0.112	0.007	0.157	0.007
Non Oldest child	0.121	0.006	0.167	0.005
Ratio Oldest/Non Oldest	0.922	1.217	0.937	1.374
T-value Oldest/Non Oldest	6.945	3.539	4.954	4.267
P-value	0.000	0.000	0.000	0.000
Non-biological father	0.167	0.003	0.234	0.003
Biological father	0.117	0.006	0.161	0.006
Ratio Non Bio/Bio Father	1.432	0.480	1.452	0.552
T-value Non Bio/Bio father	11.691	4.957	10.763	2.923
P-value	0.000	0.000	0.000	0.003
Non-biological mother	0.118	0.008	0.129	0.006
Biological mother	0.118	0.006	0.164	0.006
Ratio Non Bio/Bio Mother	1.003	1.313	0.787	1.045
T-value Non Bio/Bio mother	0.080	1.454	5.354	0.180
P-value	0.936	0.146	0.000	0.857

Note: The table presents the unconditional and conditional probabilities of being in the top 1% or being under the poverty line considering all the other circumstances used in the analysis. We also report the ratios, the t-statistics and the p-values for the two sample.

A.1 Additional Analysis

A.1.1 IOp over time

In this subsection, we analyze the evolution of IOp in Australia comparing the results between two different periods: 2001-2005 and 2016-2020.

Table A3: Heteroskedastic linear regressions results: Log Household Income

	2001-2005		2016-2020	
	Log Household Income		Log Household Income	
	$\hat{\mu}$	$\ln(\sigma^2)$	$\hat{\mu}$	$\ln(\sigma^2)$
Female	-0.0567***	-0.00339	-0.0404***	-0.0587*
	(0.00485)	(0.0267)	(0.00466)	(0.0253)
Refugee	-0.0643**	-0.206**	-0.120***	0.237*
	(0.0198)	(0.0719)	(0.0227)	(0.113)
Indigenous origin	-0.155***	-0.957***	-0.274***	-0.143
	(0.0185)	(0.122)	(0.0188)	(0.0842)
Immigrant	0.0395***	0.181***	0.0214*	0.164**
	(0.0106)	(0.0511)	(0.0100)	(0.0562)
Mother immigrant	-0.00973	-0.0456	-0.00155	-0.0409
	(0.00797)	(0.0400)	(0.00761)	(0.0382)
Father immigrant	0.00596	-0.00483	0.00585	-0.0343
	(0.00739)	(0.0356)	(0.00705)	(0.0333)
First language learned: English	0.171***	-0.142**	0.0877***	0.0912
	(0.0127)	(0.0541)	(0.0106)	(0.0606)
Parents divorced/separeted	-0.0924***	0.0192	-0.0607***	-0.0510
	(0.00790)	(0.0500)	(0.00708)	(0.0372)
Oldest child	0.0422***	0.0259	0.0216***	0.0428
	(0.00514)	(0.0276)	(0.00491)	(0.0281)
Non-biological father	-0.0939***	-0.137	-0.143***	0.138
	(0.0183)	(0.0736)	(0.0161)	(0.110)
Non-biological mother	0.0108	-0.119	0.00341	-0.0424
	(0.0218)	(0.0926)	(0.0201)	(0.125)
Father university	0.178***	0.00260	0.135***	0.125***
	(0.00734)	(0.0390)	(0.00703)	(0.0367)
Mother university	0.119***	-0.140***	0.0602***	-0.0706
	(0.00778)	(0.0425)	(0.00730)	(0.0390)
Father employed	0.178***	-0.0215	0.204***	0.0398
	(0.0105)	(0.0466)	(0.0104)	(0.0532)
Mother employed	0.0757***	-0.199***	0.0704***	-0.218***
	(0.00502)	(0.0277)	(0.00488)	(0.0256)
Constant	10.21***	-0.947***	10.73***	-0.997***
	(0.0176)	(0.0818)	(0.0159)	(0.0831)
Observations	50930		66092	
$\chi 2$ for mean model test	4344.2		2867.3	
$\chi 2$ for heteroskedastic test	230.7		147.7	
p-value for heteroskedastic test	0.000		0.000	

Notes: The table presents the estimates for the heteroskedastic linear regression model with log household income as dependent variable. The first specification considers the period from 2001 to 2005, the second specification from 2016 to 2020. All the paramters are estimated by MLE with the variance as an exponential function of circumstances as in equation 4. Robust heteroskedasticity consistent standard errors are used. *, **, and *** define significance at 10%, 5%, and 1%, respectively. Observations are taken over 5 years period. Dummies are defined relative to a reference individual who is male, non refugee, non immigrant, non-indigenous, with English not the first language, with non immigrant and biological parents, non divorced, with both parents with a university degree and parents employed when reference individual was 14 years-old.

Table A4: Heteroskedastic linear regressions results: Log Weekly Wage

	2001-2005		2016-2020	
	Log Weekly Wage		Log Weekly Wage	
	$\hat{\mu}$	$\ln(\sigma^2)$	$\hat{\mu}$	$\ln(\sigma^2)$
Female	-0.483***	0.266***	-0.349***	0.127***
	(0.00938)	(0.0261)	(0.00696)	(0.0221)
Refugee	-0.00940	0.161	-0.0763*	0.157*
	(0.0369)	(0.125)	(0.0361)	(0.0783)
Indigenous origin	-0.0109	-0.709**	-0.0536	0.000639
	(0.0770)	(0.234)	(0.0319)	(0.0979)
Immigrant	0.0141	-0.127*	0.0979***	-0.118**
	(0.0191)	(0.0546)	(0.0143)	(0.0427)
Mother immigrant	-0.00878	0.0608	-0.0151	-0.00817
	(0.0165)	(0.0452)	(0.0112)	(0.0345)
Father immigrant	0.0376*	-0.0648	-0.0128	0.0260
	(0.0150)	(0.0458)	(0.0105)	(0.0333)
First language learned: English	0.0845***	-0.0161	0.108***	0.0148
	(0.0202)	(0.0601)	(0.0159)	(0.0509)
Parents divorced/separeted	0.00762	-0.0396	-0.0399***	-0.00233
	(0.0144)	(0.0415)	(0.0106)	(0.0341)
Oldest child	0.0539***	-0.00698	0.0319***	0.0658**
	(0.00976)	(0.0273)	(0.00737)	(0.0233)
Non-biological father	-0.0931**	-0.284	-0.177***	0.0314
	(0.0342)	(0.156)	(0.0259)	(0.103)
Non-biological mother	0.0152	0.152	0.0291	-0.0742
	(0.0418)	(0.155)	(0.0321)	(0.109)
Father university	0.0691***	0.186***	0.0498***	0.139***
	(0.0163)	(0.0386)	(0.0103)	(0.0309)
Mother university	0.0258	0.242***	0.0223*	0.0600
	(0.0212)	(0.0494)	(0.0110)	(0.0325)
Father employed	0.0240	-0.214***	0.0361*	0.0778
	(0.0233)	(0.0621)	(0.0156)	(0.0451)
Mother employed	0.0488***	-0.0627*	0.0282***	-0.0386
	(0.00938)	(0.0266)	(0.00739)	(0.0227)
Constant	6.709***	-0.515***	7.153***	-1.032***
	(0.0330)	(0.0905)	(0.0239)	(0.0722)
Observations	24332		37789	
$\chi 2$ for mean model test	2865.9		3321.4	
$\chi 2$ for heteroskedastic test	213.7		117.6	
p-value for heteroskedastic test	0.000		0.000	

Notes: The table presents the estimates for the heteroskedastic linear regression model with log weekly wage as dependent variable. The first specification considers the period from 2001 to 2005, the second specification from 2016 to 2020. All the paramters are estimated by MLE with the variance as an exponential function of circumstances as in equation 4. Robust heteroskedasticity consistent standard errors are used. *, **, and *** define significance at 10%, 5%, and 1%, respectively. Observations are taken over 5 years period. Dummies are defined relative to a reference individual who is male, non refugee, non immigrant, non-indigenous, with English not the first language, with non immigrant and biological parents, non divorced, with both parents with a university degree and parents employed when reference individual was 14 years-old.

Table A5: Two sample T-test: Log Household Income 2001-2005 vs 2016-2020

	Δ		DF	T-test		P-value	
	$\hat{\mu}$	$\ln(\sigma^2)$		$\hat{\mu}$	$\ln(\sigma^2)$	$\hat{\mu}$	$\ln(\sigma^2)$
Female	0.0163	-0.055	61265	2.423	-1.504	0.015	0.133
Refugee	-0.0557	0.443	1937	-1.849	3.308	0.065	0.001
Indigenous Origin	-0.119	0.814	1271	-4.512	5.491	0.000	0.000
Immigrant	-0.0181	-0.017	23690	-1.242	-0.224	0.214	0.823
Mother immigrant	0.00818	0.005	37774	0.742	0.085	0.458	0.932
Father immigrant	-0.00011	-0.029	41071	-0.011	-0.605	0.991	0.545
First language learned: English	-0.0833	0.233	105334	-5.036	2.871	0.000	0.004
Parents divorced/separated	0.0317	-0.070	12963	2.988	-1.126	0.003	0.260
Oldest child	-0.0206	0.017	40106	-2.898	0.429	0.004	0.668
Non-biological father	-0.0491	0.275	3667	-2.014	2.078	0.044	0.038
Non-biological mother	-0.00739	0.077	2332	-0.249	0.492	0.803	0.622
Father Univerisity	-0.043	0.122	18614	-4.231	2.286	0.000	0.022
Mother university	-0.0588	0.069	14951	-5.512	1.203	0.000	0.229
Father Employed	0.026	0.061	110443	1.759	0.867	0.079	0.386
Mother employed	-0.0053	-0.019	62751	-0.757	-0.504	0.449	0.614

Notes: The table presents the results for two sample t-tests of the parametric changes from Table A3.

Table A6: Two sample T-test: Log Weekly Wage 2001-2005 vs 2016-2020

	Δ		DF	T-test		P-value	
	$\hat{\mu}$	$\ln(\sigma^2)$		$\hat{\mu}$	$\ln(\sigma^2)$	$\hat{\mu}$	$\ln(\sigma^2)$
Female	0.134	-0.139	30518	11.472	-4.064	0.000	0.000
Refugee	-0.067	-0.004	842	-0.513	-0.027	0.608	0.978
Indigenous Origin	-0.043	0.710	501	-0.512	2.798	0.609	0.005
Immigrant	0.084	0.009	12142	3.512	0.130	0.000	0.897
Mother immigrant	-0.006	-0.069	20023	-0.317	-1.213	0.751	0.225
Father immigrant	-0.050	0.091	21742	-2.753	1.603	0.006	0.109
First language learned: English	0.024	0.031	56375	0.914	0.392	0.361	0.695
Parents divorced/separated	-0.048	0.037	7459	-2.658	0.694	0.008	0.488
Oldest child	-0.022	0.073	21843	-1.799	2.028	0.072	0.043
Non-biological father	-0.084	0.315	1890	-1.956	1.687	0.051	0.092
Non-biological mother	0.014	-0.226	1255	0.264	-1.194	0.792	0.233
Father Univerisity	-0.019	-0.047	10807	-1.001	-0.951	0.317	0.342
Mother university	-0.004	-0.182	8268	-0.147	-3.078	0.883	0.002
Father Employed	0.012	0.292	58973	0.432	3.802	0.666	0.000
Mother employed	-0.021	0.024	36415	-1.725	0.689	0.085	0.491

Notes: The table presents the results for two sample t-tests of the parametric changes from Table A4.

Table A7: Conditional Probabilities of being in the tails of the distribution: Log Household Income 2001-2005 vs 2016-2020

	2001-2005		2016-2020		T -test 2001-2005 vs 2016-2020		P-value Poor	P-value Top 1%
	Poor	Top 1%	Poor	Top 1%	Poor	Top 1%		
Female	0.111	0.007	0.127	0.007	5.981	0.854	0.000	0.393
Male	0.093	0.009	0.120	0.010	10.327	1.837	0.000	0.066
Ratio Female/Male	1.194	0.742	1.057	0.688				
T value Female/Male	6.748	2.919	2.659	4.423				
P-value	0.000	0.004	0.008	0.000				
Refugee	0.101	0.002	0.196	0.011	5.981	2.299	0.000	0.022
Non Refugee	0.102	0.008	0.122	0.008	10.813	1.529	0.000	0.126
Ratio Refugee/Non Refugee	0.988	0.316	1.603	1.268				
T value Refugee/Non Refugee	0.128	3.170	5.868	0.697				
P-value	0.898	0.002	0.000	0.486				
Indigenous origin	0.056	0.000	0.224	0.001	9.098	1.028	0.000	0.304
Non Indigenous origin	0.102	0.008	0.122	0.009	10.642	1.840	0.000	0.066
Ratio Indigenous/Non Indigenous	0.547	0.001	1.830	0.133				
T value Indigenous/Non Indigenous	3.730	18.748	7.393	6.426				
P-value	0.000	0.000	0.000	0.000				
First language learned: English	0.096	0.008	0.121	0.009	13.376	2.402	0.000	0.016
First language learned: non English	0.178	0.005	0.142	0.004	5.099	0.801	0.000	0.423
Ratio Non English/English	1.859	0.698	1.172	0.478				
T value Non English Speaking/ English	14.190	2.035	4.794	5.459				
P-value	0.000	0.042	0.000	0.000				
Immigrant	0.109	0.014	0.133	0.014	5.664	0.123	0.000	0.902
Non Immigrant	0.101	0.006	0.121	0.007	9.768	1.780	0.000	0.075
Ratio immigrant/Non Immigrant	1.078	2.134	1.099	1.830				
T value Immigrant/Non Immigrant	2.241	5.834	3.749	5.901				
P-Value	0.025	0.000	0.000	0.000				
Mother Immigrant	0.101	0.007	0.121	0.008	6.080	1.394	0.000	0.163
Mother Non Immigrant	0.103	0.008	0.125	0.009	9.789	1.390	0.000	0.165
Ratio Mother Immigrant/Non Immigrant	0.981	0.815	0.966	0.869				
T value Mother Immi/Non Immi	0.679	1.849	1.592	1.580				
P-value	0.497	0.064	0.111	0.114				
Father Immigrant	0.100	0.008	0.120	0.008	6.134	0.524	0.000	0.600
Father Non Immigrant	0.103	0.008	0.125	0.009	9.584	1.961	0.000	0.050
Ratio Father Immigrant/Non Immigrant	0.978	1.014	0.958	0.919				
T value Father Immi/Non Immi	0.798	0.129	1.998	0.972				
P-value	0.425	0.897	0.046	0.331				
Parents divorced/separated	0.134	0.005	0.137	0.006	0.528	0.341	0.598	0.733
Parents non divorced/separated	0.099	0.008	0.122	0.009	11.728	1.973	0.000	0.048
Ratio Parents Divorce/Non Divorced	1.355	0.666	1.128	0.632				
T value Parents Divorced/Non Divorced	7.104	2.421	3.764	3.524				
P-value	0.000	0.015	0.000	0.000				
Oldest child	0.095	0.009	0.124	0.010	9.290	0.778	0.000	0.437
Non Oldest child	0.106	0.007	0.122	0.008	6.990	1.685	0.000	0.092
Ratio Oldest/Non Oldest	0.899	1.346	1.019	1.265				
T value Oldest/Non Oldest	3.817	2.763	0.847	2.659				
P-value	0.000	0.006	0.397	0.008				
Non-biological father	0.119	0.003	0.190	0.007	5.930	2.043	0.000	0.041
Biological father	0.102	0.008	0.119	0.009	9.212	2.054	0.000	0.040
Ratio Non Bio/Bio Father	1.173	0.355	1.595	0.837				
T value Non-Bio/Bio Father	2.079	3.555	8.310	0.770				
P-value	0.038	0.000	0.000	0.441				
Non-biological mother	0.086	0.005	0.117	0.008	2.517	0.685	0.012	0.493
Biological mother	0.102	0.008	0.123	0.009	11.246	1.798	0.000	0.072
Ratio Non-Bio/Bio Mother	0.838	0.696	0.950	0.884				
T value Non Bio/Bio mother	1.820	0.974	0.698	0.421				
P-value	0.069	0.330	0.485	0.674				
Father university	0.061	0.016	0.101	0.019	10.068	1.474	0.000	0.140
Father without university degree	0.111	0.007	0.129	0.007	8.617	1.074	0.000	0.283
Ratio Father University/non-university	0.549	2.392	0.783	2.599				
T value Father university/ non-university	15.924	6.158	8.760	8.595				
P-value	0.000	0.000	0.000	0.000				
Mother university	0.060	0.009	0.100	0.009	9.067	0.233	0.000	0.816
Mother without university	0.109	0.007	0.127	0.008	9.277	1.869	0.000	0.062
Ratio mother university/non-university	0.552	1.157	0.784	1.057				
T value Mother university/non-university	14.274	0.920	7.960	0.455				
P-value	0.000	0.357	0.000	0.649				
Father employed	0.099	0.008	0.120	0.009	11.316	2.001	0.000	0.045
Father not employed	0.170	0.003	0.197	0.003	2.801	0.338	0.005	0.736
Ratio Father Employed/not employed	0.579	2.349	0.609	3.110				
T value Father employed/not employed	10.210	4.003	11.395	5.695				
P-value	0.000	0.000	0.000	0.000				
Mother employed	0.080	0.007	0.102	0.007	9.261	0.865	0.000	0.387
Mother not employed	0.128	0.009	0.152	0.011	8.062	2.111	0.000	0.035
Ratio Mother employed/not employed	0.630	0.752	0.671	0.680				
T value Mother employed/not employed	17.446	2.800	19.067	4.042				
P-value	0.000	0.005	0.000	0.000				

Note: The table presents the conditional probabilities of being in the top 1% or being under the poverty line for log household income by the two periods of analysis. We also report the ratios, the t-statistics and the p-values for the two sample.

Table A8: Conditional Probabilities of being in the tails of the distribution: Log Weekly Wage 2001-2005 vs 2016-2020

	2001-2005		2016-2020		T -test 2001-2005 vs 2016-2020		P-value Poor	P-value Top 1%
	Poor	Top 1%	Poor	Top 1%	Poor	Top 1%		
Female	0.2849	0.0042	0.2291	0.0046	10.792	0.527	0.000	0.598
Male	0.0874	0.0107	0.0930	0.0125	1.708	1.458	0.088	0.145
Ratio Female/Male	3.261	0.394	2.463	0.371				
T value Female/Male	40.550	5.926	36.593	8.302				
P-value	0.000	0.000	0.000	0.000				
Refugee	0.1923	0.0107	0.1991	0.0094	0.251	0.193	0.802	0.847
Non Refugee	0.1697	0.0065	0.1523	0.0076	5.676	1.469	0.000	0.142
Ratio Refugee/Non Refugee	1.133	1.634	1.308	1.241				
T value Refugee/Non Refugee	1.205	0.850	2.330	0.375				
P-value	0.228	0.396	0.020	0.708				
Indigenous origin	0.0905	0.0002	0.1721	0.0061	1.695	1.403	0.091	0.161
Non Indigenous origin	0.1702	0.0066	0.1526	0.0076	5.799	1.389	0.000	0.165
Ratio Indigenous/Non Indigenous	0.5317	0.0289	1.1279	0.8033				
T value Indigenous/Non Indigenous	1.776	2.900	1.108	0.410				
P-value	0.076	0.004	0.268	0.682				
First language learned: English	0.1673	0.0068	0.1494	0.0079	5.642	1.585	0.000	0.113
First language learned: non English	0.2000	0.0052	0.1877	0.0048	1.133	0.192	0.257	0.848
Ratio Non English/English	0.8366	1.3120	0.7960	1.6544				
T value Non English Speaking/ English	3.661	0.988	5.616	2.504				
P-value	0.000	0.323	0.000	0.012				
Immigrant	0.1539	0.0048	0.1151	0.0077	6.107	2.042	0.000	0.041
Non Immigrant	0.1742	0.0072	0.1621	0.0076	3.526	0.539	0.000	0.590
Ratio immigrant/Non Immigrant	0.8836	0.6702	0.7103	1.0164				
T value Immigrant/Non Immigrant	3.497	2.048	10.876	0.109				
P-Value	0.000	0.041	0.000	0.913				
Mother Immigrant	0.1772	0.007451	0.1557	0.0071	3.951	0.255	0.000	0.798
Mother Non Immigrant	0.1668	0.0063	0.151395	0.0078	4.211	1.881	0.000	0.060
Ratio Mother Immigrant/Non Immigrant	1.0623	1.1920	1.0283	0.9148				
T value Mother Immi/Non Immi	1.987	1.037	1.082	0.709				
P-value	0.047	0.300	0.279	0.478				
Father Immigrant	0.1565	0.0063	0.1577	0.007749	0.247	1.282	0.805	0.200
Father Non Immigrant	0.1668	0.0068	0.1514	0.0075	4.125	0.805	0.000	0.421
Ratio Father Immigrant/Non Immigrant	0.9380	0.9233	1.0417	1.0355				
T value Father Immi/Non Immi	2.090	0.482	1.620	0.284				
P-value	0.037	0.630	0.105	0.777				
Parents divorced/separated	0.1635	0.0060	0.1650	0.0065	0.176	0.274	0.861	0.784
Parents non divorced/separated	0.1709	0.0067	0.1511	0.0077	6.137	1.423	0.000	0.155
Ratio Parents Divorce/Non Divorced	0.9565	0.8964	1.0924	0.8420				
T value Parents Divorced/Non Divorced	0.989	0.440	2.428	0.965				
P-value	0.322	0.660	0.015	0.334				
Oldest child	0.1770	0.0074	0.150843	0.0094	5.059	1.593	0.000	0.111
Non Oldest child	0.1576	0.0062	0.1539	0.0067	0.989	0.590	0.323	0.555
Ratio Oldest/Non Oldest	1.1231	1.2009	0.9799	1.4135				
T value Oldest/Non Oldest	3.841	1.110	0.800	2.802				
P-value	0.000	0.267	0.423	0.005				
Non-biological father	0.1705	0.0014	0.2195	0.0043	2.671	1.215	0.008	0.224
Biological father	0.1701	0.0069	0.147389	0.0080	7.413	1.595	0.000	0.111
Ratio Non Bio/Bio Father	1.0022	0.2053	1.4889	0.5359				
T value Non-Bio/Bio Father	0.028	3.772	5.758	1.853				
P-value	0.978	0.000	0.000	0.064				
Non-biological mother	0.1828	0.0113	0.1343	0.0067	2.323	0.844	0.020	0.399
Biological mother	0.1698	0.0065	0.1531	0.0076	5.421	1.549	0.000	0.121
Ratio Non-Bio/Bio Mother	1.0768	1.7259	0.8768	0.8773				
T value Non Bio/Bio mother	0.780	1.042	1.387	0.284				
P-value	0.435	0.297	0.166	0.776				
Father university	0.168235	0.0132	0.1532	0.0126	1.932	0.230	0.053	0.818
Father without university degree	0.1703	0.0059	0.1529	0.0066	5.246	1.075	0.000	0.283
Ratio Father University/non-university	0.9878	2.2514	1.0016	1.9112				
T value Father university/ non-university	0.293	3.518	0.055	2.937				
P-value	0.770	0.000	0.956	0.003				
Mother university	0.1874	0.0139	0.1529	0.0097	3.484	1.442	0.000	0.149
Mother without university	0.1684	0.0061	0.1529	0.0072	4.835	1.539	0.000	0.124
Ratio mother university/non-university	1.1127	2.2724	1.0003	1.3460				
T value Mother university/non-university	2.072	2.891	0.008	1.886				
P-value	0.038	0.004	0.993	0.059				
Father employed	0.1683	0.0064	0.1526	0.0077	5.054	1.911	0.000	0.056
Father not employed	0.2023	0.0117	0.1561	0.0050	3.268	1.922	0.001	0.055
Ratio Father Employed/not employed	0.8323	0.5471	0.9776	1.5330				
T value Father employed/not employed	2.907	1.709	0.410	1.593				
P-value	0.004	0.087	0.682	0.111				
Mother employed	0.1583	0.0065	0.1475	0.0075	2.724	1.114	0.006	0.265
Mother not employed	0.1829	0.0067	0.1620	0.0076	4.406	0.881	0.000	0.378
Ratio Mother employed/not employed	0.8656	0.9708	0.9101	0.9855				
T value Mother employed/not employed	5.092	0.188	3.758	0.119				
P-value	0.000	0.851	0.000	0.905				

Note: The table presents the conditional probabilities of being in the top 1% or being under the poverty line for log weekly wage by the two periods of analysis. We also report the ratios, the t-statistics and the p-values for the two sample.

A.1.2 Heterogeneity Analysis

We run a series of additional specifications in order to capture the differences between genders of background characteristics such as immigration and father education.

Table A9: Heteroskedastic linear regressions results with interaction effects

	(1)		(2)	
	Log Household Income		Log Weekly Wage	
	$\hat{\mu}$	$\ln(\sigma^2)$	$\hat{\mu}$	$\ln(\sigma^2)$
Female	-0.0595***	0.00844	-0.438***	0.204***
	(0.00276)	(0.0162)	(0.00465)	(0.0142)
Refugee	-0.0777***	0.0893	-0.0138	0.173**
	(0.0107)	(0.0570)	(0.0181)	(0.0585)
Indigenous origin	-0.254***	-0.103	-0.0189	-0.0735
	(0.0108)	(0.0591)	(0.0210)	(0.0727)
Immigrant	0.0279***	0.144***	0.0922***	-0.0967***
	(0.00599)	(0.0299)	(0.00971)	(0.0282)
Mother immigrant	-0.00554	-0.0414	-0.00994	-0.0360
	(0.00394)	(0.0213)	(0.00657)	(0.0194)
Father immigrant	0.000933	-0.0107	-0.0131*	0.0130
	(0.00367)	(0.0192)	(0.00614)	(0.0183)
First language learned: English	0.137***	-0.0215	0.103***	0.0126
	(0.00578)	(0.0295)	(0.00872)	(0.0283)
Parents divorced/separated	-0.0801***	0.00863	-0.0297***	-0.000988
	(0.00380)	(0.0211)	(0.00608)	(0.0193)
Oldest child	0.0324***	0.0115	0.0437***	0.0409**
	(0.00251)	(0.0139)	(0.00414)	(0.0125)
Non-biological father	-0.136***	-0.0124	-0.178***	0.0367
	(0.00849)	(0.0537)	(0.0154)	(0.0555)
Non-biological mother	0.0168	0.0536	0.0752***	-0.0761
	(0.0107)	(0.0628)	(0.0182)	(0.0569)
Father university	0.192***	0.0704**	0.134***	0.0156
	(0.00478)	(0.0246)	(0.00832)	(0.0215)
Mother university	0.0841***	-0.0695**	0.00945	0.169***
	(0.00381)	(0.0218)	(0.00709)	(0.0184)
Father employed	0.185***	0.0416	0.0251**	-0.0652*
	(0.00521)	(0.0270)	(0.00932)	(0.0262)
Mother employed	0.0755***	-0.197***	0.0408***	-0.0596***
	(0.00248)	(0.0137)	(0.00408)	(0.0124)
female=0 # father university=1	-0.0700***	0.0184	-0.121***	0.135***
	(0.00660)	(0.0361)	(0.0110)	(0.0301)
female=0 # immigrant =1	0.00719	0.0441	-0.0190	-0.00566
	(0.00624)	(0.0330)	(0.00975)	(0.0305)
Constant	10.70***	-0.937***	7.192***	-0.901***
	(0.00960)	(0.0514)	(0.0150)	(0.0465)
Observations	242,994		129,651	
$\chi 2$ for mean model test	41758.6		20300.2	
$\chi 2$ for heteroskedasticity test	623.2		641.1	
p-value for heteroskedasticity test	0.0000		0.0000	

Notes: The table presents the additional estimates for the heteroskedastic linear regression models with the inclusion of interaction effect between gender, father's education and immigration status. Model (1) has a dependent variable the log of household income, Model (2) the log of weekly earnings. All the parameters are estimated by MLE with the variance as an exponential function of circumstances as in equation 4. Robust heteroskedasticity consistent standard errors are used. *, **, and *** define significance at 10%, 5%, and 1%, respectively. Observations are taken over 20 years. Dummies are defined relative to a reference individual who is male, non-refugee, non-immigrant, non-indigenous, with English not the first language, with non-immigrant and biological parents, non-divorced, with both parents without a university degree and parents employed when reference individual was 14 years-old.

Table A10: Conditional Probabilities of being in the Tails of the distribution by Gender and Immigration Status

	Probability of being poor	Probability of being in the top 1%
	Log Household Income	
Female immigrant	0.132	0.009
Male immigrant	0.119	0.012
Ratio Female/Male	1.108	0.703
T-value Female/Male	4.308	3.972
P-value	0.000	0.000
	Log Weekly Wage	
Female immigrant	0.258	0.004
Male immigrant	0.089	0.010
Ratio Female/Male	2.890	0.393
T-value Female/Male	36.723	5.731
P-value	0.000	0.000

Notes: The table presents the conditional probabilities of being in the top 1% or being under the poverty line by gender and immigration status for the log household income and the log weekly wage. We also report the ratios, the t-statistics, and the p-values for the two sample.

Table A11: Conditional Probabilities of being in the Tails of the distribution by Gender and Father's Education

	Probability of being poor	Probability of being in the top 1%
	Log Household Income	
Female with father with university degree	0.088	0.014
Male with father with university degree	0.084	0.013
Ratio Female/Male	1.154	1.019
T-value Female/Male	1.1583	0.218
P-value	0.113	0.828
	Log Weekly Wage	
Female with father with university degree	0.213	0.006
Male with father with university degree	0.103	0.015
Ratio Female/Male	2.065	0.390
T-value Female/Male	22.519	6.728
P-value	0.000	0.000

Notes: The table presents the conditional probabilities of being in the top 1% or being under the poverty line by gender and father's education for the log household income and the log weekly wage. We also report the ratios, the t-statistics, and the p-values for the two sample.