Inequality of Opportunity and the Probability of Being Very Rich or Very Poor[*,†]

Alessio Rebechi[‡], Nicholas Rohde[§], Gordon Anderson[¶]

December 16, 2022

Abstract

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.

[*]This document uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The unit record data from the HILDA Survey was obtained from the Australian Data Archive, which is hosted by The Australian National University. The HILDA Survey was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views based on the data, however, are those of the authors and should not be attributed to the Australian Government, DSS, the Melbourne Institute, the Australian Data Archive or The Australian National University and none of those entities bear any responsibility for the analysis or interpretation of the unit record data from the HILDA Survey provided by the authors.

[†]We would like to thank Paolo Brunori for all the precious suggestions.

[‡]Department Accounting, Finance and Economics, Griffith University, Australia. **Alessio Rebechi is the corresponding author**. Email: alessio.rebechi@griffithuni.edu.au. Postal address: 170 Kessels Rd, Nathan QLD, 4111, Dept. Accounting, Finance and Economics, Griffith University, Australia.

[§]Department Accounting, Finance and Economics, Griffith University, Australia. Email: n.rohde@griffith.edu.au. Funding: Nicholas Rohde wishes to thank the Australian Research Council, advanced grant ARC DP 1701 00438.

[¶]University of Toronto, Department of Economics, Email: gordonj.anderson@utoronto.ca

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 (Ramos and gaer 2012; Roemer 1998; Roemer and Trannoy 2016, among others).[1] Most of this empirical research has analyzed the effect of these background characteristics on average outcomes such as income, wage or education (*ex-ante* approach). However, by focusing predominantly on conditional means, this approach neglects important distributional characteristics, such as the relative frequency of extreme values.

The *ex-post* approach, on the other hand, overcomes these limitations, satisfying the Roemerian definition of IOp (Roemer 1998). By comparing the effects of circumstances over complete distributions, this approach accounts for possible heterogeneity in the variance. However, it assigns the same relevance to the tails with respect to other parts of the distribution. We argue that more attention should be given to the composition of the left and right tails since they disproportionately influence public perceptions of economic disparity. We therefore propose a complementary approach that reconciles traditional methods of measuring IOp 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. This allows us to explore important differences in the contributions of circumstances across the whole distribution with a special focus on the tails (Anderson, Pittau, and Zelli 2020; Kneib, Silbersdorff, and Säfken 2021; Silbersdorff et al. 2018).

Extreme values and heavy tails have been discussed in analyses of the income distribution (Bossert, D'Ambrosio, and Kamaga 2021). However, this framework has not been applied 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 social 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 exert disproportionate political power in a zero-sum context (Piketty 2017, 2020). Again, since this influence is a characteristic of very extreme values,

[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.

IOp models based on conditional expected values will overlook this important aspect of inequality of opportunity.

We use a panel of high-quality Australian data to run a series of simulations, calculating 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 refers to the literature on top incomes (Piketty 2005; Piketty and Saez 2006; Atkinson, Piketty, and Saez 2011, among others) and poverty/mortality rates among those at the bottom (Case and Deaton 2022), in addition to the growing IOp literature. Further, our results have implications for the recent literature on inequality and politics (Gethin, Martínez-Toledano, and Piketty 2021; Piketty and Saez 2006; Piketty 2017, 2020). In light of this literature, our findings suggest the existence of inequality in opportunities to access political power and influence the democratic process. We further argue that the transmission of educational and financial advantages has enabled the propagation of power and privilege across generations (Milanovic 2019).

Our results also have indirect implications for the economic analysis on populism (Bossert et al. 2022; Rebechi and Rohde 2022; Rodrik 2021). The persistence of group-based inequalities has contributed to a growing sense of unfairness and anxiety among those opportunity-deprived sectors of the population (Satz and White 2021). Stagnating living standards have triggered a sense of insecurity and uncertainty about the future, fueling distrust and resentment towards those elite-led institutions and their ability to remove social mobility constraints.

Last, the composition of the tails also affects individual perceptions of inequality and fairness, with important implications on attitudes towards redistributive policies (Alesina, Stantcheva, and Teso 2018; Piketty 1995; Shayo 2020). Our results emphasize the need to reconcile the measurement of IOp with the general perception of the same phenomenon.

This paper is organized as follows. Section 2 describes the data and construction of our

[2]We use a parametric ex-ante approach to measure IOp. This is usually regarded as more parsimonious than the non-parametric one and allow us to simultaneously consider a large set of circumstances (Brunori 2016).

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

main variables. Section 3 explains our empirical strategy. Our findings are summarized in Section 4, and a discussion of the implications of our findings are provided in Section 5. Then, concluding remarks are offered in Section 6. In the Online Appendix, we provide additional results.

2 Data

We use data from the last release (2021) of the 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 first key variable is 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. Our second key variable is average weekly wage and salary income (imputed) from all forms of paid employment, defined before taxation and governmental transfers and corrected for age and inflation.[4] [5]

We use these two markers to compare the effects of circumstances on different parts of the distributions, accounting for the problem of intra-household inequality. While household income is a good measure of welfare, it does not account for intra-household distributional variations. Furthermore, we assume perfect distribution of resources when applying equivalence scale. On the other hand, wage is a poor welfare measure, but it may be more representative of the intra-household resources distribution. The resource sharing inside the household also implies some correlation among the two markers (see Figure 1). We also consider the different inequality implications of these two variables: while income can be interpreted as a proxy of socio-economic status (low income family vs high income ones), wage can be considered as a proxy for employment status and a measure of influence/power (higher wages are usually associated with higher positions in the organizational chart of a company, CEO vs common employee).

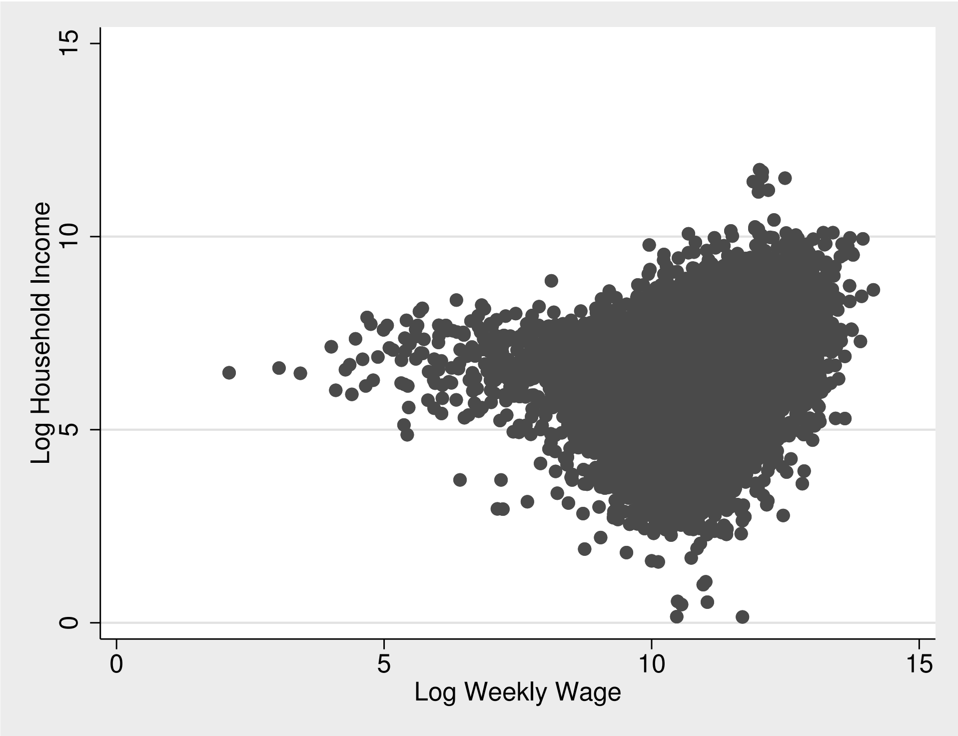
We consider the following socio-demographic variables as circumstances beyond individual control: gender, immigration and refugee status, parental background information such as parents' immigration status, parents' activity status (employed vs unemployed/ deceased/ not living in the household), and parents' educational level (having a university degree or not).[6] Other circumstances include whether English is the first language

[4]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.

[5]We are aware of a possible inconsistency in the comparison of household and individual income at different stages of the redistributive process but, unfortunately, in HILDA the variable for wage is recorded only before taxes.

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

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.

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. Table 1 reports the descriptive statistics for both our samples. Our sample for household income is composed of more than 242,900 observations and our sample for 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; Heckman 1977), dropping the 0 is important in modeling the conditional income and wage distribution as log-normal. The observations are taken over a period of 20 years from 2001 to 2020. For the analysis, we consider the logarithm of both our dependent variables. While pooling the data over such a long period has the advantage of increasing the sample size, and improving statistical power, this approach may ignore possible time trends that can have a significant impact on our IOp estimates. To partially address this problem, 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 (see results in the Appendix).

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 begin by modeling the conditional distribution of income and earnings as log-normal —one of the most used parametric models for the income distribution (Kleiber and Kotz 2003):

$$y \sim \ln\mathcal{N}(\mu, \sigma^2) \Longleftrightarrow f(y) = \frac{1}{(y\sigma\sqrt{(2\pi)})} \exp(-\frac{(\ln(y) - \mu)^2}{2\sigma^2}) \tag{1}$$

Where y is the income/weekly earnings. We parameterize both the mean and variance (μ and σ^2) as functions of the factors beyond individual control thorough a heteroskedastic linear regression.[7][8] We model the variance as an exponential function of circumstances fitting maximum likelihood estimation (MLE).

$$\hat{\mu_i} = \hat{\beta}_0 + \sum_{j=1}^{k} \hat{\beta}_j x_{ij} \qquad \hat{\sigma_i^2} = \exp{(\hat{\theta}_0 + \sum_{l=1}^{m} \hat{\theta}_l x_{il})} \tag{2}$$

Where 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. $\hat{\beta}_0 ... \hat{\beta}_k$ and $\hat{\theta}_0 ... \hat{\theta}_m$ are the estimated coefficients from the heteroskedastic linear regression.

From the estimated parameters, we 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. For the left tail cut-off, we use the poverty line (z) defined as half of the median income/wage. For the right-tail cut-off, we use the top 1% of overall unconditional income/wage distribution (t). Both the cut-offs are parametrically estimated.[9] For the unconditional distribution, we calculate the following integrals:

$$z_{poor} = \int_0^z f(y)d(y) \qquad z_{rich} = \int_t^\infty f(y)d(y) \tag{3}$$

Instead, for the conditional distribution:

$$z_{poor} = \int_0^z f(y|x)d(x) \qquad z_{rich} = \int_t^\infty f(y|x)d(x) \tag{4}$$

We estimate them as follows:

$$z_{poor} = \frac{z - \hat{\mu}_{x_i}}{\sqrt{\sigma^2_{x_i}}} \qquad z_{rich} = \frac{k - \hat{\mu}_{x_i}}{\sqrt{\sigma^2_{x_i}}} \tag{5}$$

[7] Our approach is very similar to the one proposed by (Jenkins 2007).

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

[9] 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.

Finally, we calculate the cumulative distribution function as follows:

$$\Phi(z) = \int_{-\infty}^{z} \frac{1}{\sqrt[2]{2\pi}} e^{x^2/2} dx \tag{6}$$

$$Pr(y > k) = 1 - \phi(z_{rich}) \qquad Pr(y < z) = \phi(z_{poor}) \tag{7}$$

From these estimated parameters, we compare the effect of different circumstances on the probability of being extremely rich or poor.

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 conditional probabilities of being in the tails calculated for each circumstance (see Table 3).[10] In the Online Appendix, we also report for each of these selected circumstances the graphs of conditional density functions. Additionally, we show the results for all other circumstances used in the analysis but not reported here (see Table A3), the results for the simulations including interactions effects (see Table A10), and the conditional probability results for the two periods considered (see session A.1 in the Online Appendix).

The main idea of the following simulations is to compare the effect of these selected circumstances on the probability of being in the tails. As expected, we find that 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), with a higher variability in terms of log weekly wage. In particular, women are about three times more likely to be poor and have one-third of the probability of being 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).

Together with gender, being an immigrant is usually another source of disparities. While we find that migration status has a small but positive effect on the average log income (3%) and average log wage (8%), its effect is much bigger on the variance of both income and wage. We find that in terms of log income, those born outside Australia are slightly more likely to be poor (8%) but twice as likely to be in the top 1% as 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 percentile.

When looking at the effect of parental education, we find that having parents with a university degree has a much bigger effect on the conditional probabilities than on both

[10] For the sake of completeness, we report in Table A2 the results of the homoskedastic regressions.

the average income and wage. 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. We also find that the father's education effect is different between males and females in terms of log weekly wage (see Table A12). 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. Looking at the effect of parental activity status, we find that growing with an employed father has 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, 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. Instead, growing up with an employed mother has 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. Interestingly, the employment status of both parents negatively impact the variability of log weekly wage.

Finally, we look at the impact of family environment. Growing up with divorced or separated parents has a negative and significant effect on both the average log household income (about -8%) and the average log weekly wage (-3%). However, the effect is much bigger on the variability of outcomes among adult-children of divorced/separated parents. 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.

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	
$\chi 2$ for mean model test	41766.0		20345.5	
$\chi 2$ 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 2. 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 3: Conditional Probabilities of being in the Tails of the distribution

	Probability of being poor	Probability of being in the top 1%	Probability of being poor	Probability of being in the top 1%
	Log Household Income		Log Weekly Wage	
Female	0.126	0.005	0.257	0.004
Male	0.110	0.007	0.092	0.010
Ratio Female/Male	1.150	0.775	2.795	0.363
T-value Female/Male	12.621	4.841	80.031	14.148
P-value	0.000	0.000	0.000	0.000
Immigrant	0.126	0.010	0.132	0.006
Non-Immigrant	0.116	0.005	0.171	0.006
Ratio Immigrant/Non-Immigrant	1.081	2.051	0.773	0.978
T-value Immigrant/Non-Immigrant	5.671	10.996	15.986	0.253
P-value	0.000	0.000	0.000	0.800
Father university	0.086	0.014	0.153	0.010
Father without university degree	0.125	0.005	0.166	0.006
Ratio Father university/non-university	0.689	2.730	0.923	1.732
T-value Father university/ non-university	24.128	14.086	4.753	5.803
P-value	0.000	0.000	0.000	0.000
Mother university	0.089	0.007	0.178	0.010
Mother without university degree	0.123	0.006	0.161	0.006
Ratio mother university/non-university	0.722	1.190	1.105	1.812
T value Mother university/non-university	19.237	2.204	5.347	5.614
P-value	0.000	0.000	0.000	0.000
Father employed	0.115	0.006	0.162	0.006
Father not employed	0.183	0.002	0.180	0.007
Ratio Father employed/not employed	0.627	3.086	0.905	0.883
T value Father employed/not employed	20.277	10.130	3.550	0.773
P-value	0.000	0.000	0.000	0.440
Mother employed	0.096	0.005	0.155	0.006
Mother not employed	0.145	0.007	0.176	0.006
Ratio Mother employed/not employed	0.664	0.715	0.881	0.961
T value Mother employed/not employed	36.619	6.345	9.988	0.549
P-value	0.000	0.000	0.000	0.583
Parents divorced/separated	0.145	0.004	0.173	0.005
Parents non-divorced/separated	0.115	0.115	0.162	0.006
Ratio Parents divorced/Non-divorced	1.257	0.696	1.066	0.887
T value Parents divorced/Non-divorced	13.154	4.336	3.301	1.100
P-value	0.000	0.000	0.001	0.271

Notes: The table presents the conditional probabilities of being in the top 1% or being under the poverty line by all the main circumstances 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.

5 Composition of Right and Left Tails

Our results show the persistent effect of circumstances-based inequalities on two economic outcomes, income and wage. However, their implications extend far beyond individuals' outcomes: the unequal opportunity profiles of those in left and right tails come with important ramifications on social cohesion and the political process. While in the public debate the political salience of IOp has always been emphasized, this aspect has been missing in the academic discussion (Ferreira 2022).

In particular, we argue that the extreme concentration of income and wealth at the very top is accompanied by the extreme concentration of political power (Hacker and Pierson 2010; Milanovic 2019), creating a vicious cycle between economics and politics (Hacker and Pierson 2010).[11] For instance, the overwhelming representation of men among the top 1% is linked to disparity in political representation, with men controlling state legislatures. Male majorities can result in a systematic bias in policy preferences, leading to lower responsiveness and under-representation of women interests. Gender blind-spots around workplace and family environment negatively impact relevant policies (e.g., child-care, maternity leave, wage-gap), stalling the gender convergence.

Differences in political attitudes and policies preferences among genders can also explain the persistence of positional disadvantages among minorities, with women more likely to support welfare programs and progressive policies (Garritzmann and Schwander 2021). Higher female political representation has also a positive impact on institutional quality (Cagé 2022), increasing competence level of politicians (Besley et al. 2017), and improving policy decision-making (Gagliarducci and Paserman 2016). More women among politicians also improve voters' perceptions around female leaders (Beaman et al. 2009) and positively affects parental aspirations and young girls career goals and their educational attainments (Beaman et al. 2012).

Furthermore, gender disparities among leadership positions comes also with significant efficiency costs. Companies with more women among their directory board are more profitable and significantly outperform those with lower gender diversity (Christiansen et al. 2016). In particular, women CEO positively affect firm productivity through a more efficient allocation of female talents, better matching women jobs to their skills but also reducing perceived gender differences between employers and employees. Women executives also positively impact the wage distribution within companies, reducing the gender gap among the top positions and reversing statistical discrimination (Flabbi et al. 2019).

However, while we find a persistent gender imbalance at the top, our results also show

[11]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.

that the racial composition of this elite group has become more heterogeneous. While white men are still the most prevalent group, immigrants are now becoming more common among those top positions than they used to do in the past (Advani et al. 2020).[12] The increasing representation of immigrants among top income and wage earners is the results of new trends in the international migration process. Particularly in countries like the UK and the US, selective immigration policies and special migrations schemes (e.g., citizen by investment program (CIP), "golden visas") have not only right skewed the skill level distribution of international migrants (Advani et al. 2020; Card 2009; Kerr et al. 2016), favoring highly-educated individuals, but also attracted rich immigrants from overseas.[13] [14]

Furthermore, this educational advantage may also explain why immigrants are less likely to be in the left tail of the wage distribution, with respect to than the native counterpart. Self-selection, personal and cultural traits, and risk seeking behavior may contribute to the migration of highly educated individuals due to better earning/business prospects (positive sorting) (Grogger and Hanson 2013; Kerr et al. 2017). However, the increasing demand for highly talented individuals in specific sectors has affected stereotypes around some high paid occupations, such as doctors and engineers, where high-skilled immigrants are more likely to be employed. This directly affects the level of acceptance or perceived competition towards the migrant population, where those in high-status positions are viewed as competent and respectful, therefore more likely to be valued. On the other hand, the status attached to this immigrant group may subject them to social envy (Lee and Fiske 2006), and triggering feelings of being 'out of place' or being overtaken by minorities among the native population (Craig and Richeson 2014).

On the other hand, we find that immigrants and women are also more likely to be at the bottom of the income distribution. This tendency has contributed to the perpetuation of stereotypes, reinforced throughout systematic discrimination. In particular, the over-representation of these marginalized sectors of the population among poverty and deprivation indicators affects individual perceptions and beliefs around these groups, consistently excluding them from productive opportunities (Ferreira 2022). Additionally, this disproportion at the bottom comes also with significant costs in terms of social cohesion and welfare support. The sense of deprivation and insecurity experienced by low-income groups has triggered racial anxiety, making in-group membership more salient and boost-

[12]The actual UK cabinet is a good example of this increased heterogeneity, with its first non-white prime minister and most of its members from an immigrant background.

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

[14]These policies, while may have contributed to the 'brain circulation' of those highly talented individuals, have also drained the human capital of the origin countries (usually low and middle income ones), widening the gap between developed and developing ones (Solimano and Avanzini 2010). On the other hand, the international mobility of those already privileged in their own country, have widening the income gap between countries, particularly increasing top income inequality (Milanovic 2016).

ing identity politics (Gennaioli and Tabellini 2019). Particularly, increased competition around social benefits and welfare programs has lead to the perception of immigrants as a threat. This has lowered support for redistributive programs among those sectors of the population that may benefit the most (Shayo 2020), together with a demand for more protectionism (Grossman and Helpman 2020). Furthermore, the frustration and anger towards those elite-led institution has been linked to the political disengagement among those who felt being left behind and has been discussed behind the recent rise of right-wing populist parties (Bossert et al. 2022; Rebechi and Rohde 2022; Rodrik 2021).

Our results also emphasize the relevance of parental background in determining children's future outcomes, with family socio-economic status significantly contributing to disparities between groups and their persistence over time. In particular, the inheritance of occupational and educational advantages throughout the labor market and the education system, allow the social reproduction of those benefits across generations (Chetty et al. 2017; Corak, Piraino, and Ferreira 2016). [15] Family networking, positional rents offer a significant advantage in the labor market, increasing the probability of access to top job positions (Macmillan, Tyler, and Vignoles 2015). The over-representation of individuals from a privileged background among educational or professional elites significantly restrict the access to those high positions (Strømme and Hansen 2017), impacting the job sorting of those from less advantage one (Friedman and Laurison 2020; Toft 2019) and excluding them from those influential groups.

This class ceiling effect (Friedman and Laurison 2020) also affect the composition of the political parties where those educational elites are becoming increasingly common (Bovens and Wille 2017), making harder for those from a working class background and their interests to be represented. Additionally, while parliaments may have become more representative of the demographic changes among the population, the disparities in representation in terms of socio-economic status comes also with significant political costs. Elite politicians tend to discourage the participation and turnout of those from a lower background, further reinforcing the representative gap. This also impact the candidate electoral performance, with those significantly different from their constituents, for example in terms of education, recording a lower consensus (Cagé 2022).

Finally, our results have important implications for democratic functioning. We argue that the heterogeneity in the composition of tails is often followed by similarities in values and attitudes. Especially among those at the top, specific beliefs around economic success and merit tend to emphasize the role of individual responsibility, focusing on individuals rather than external factors in explaining high inequality and low social mobility. While this individualistic approach may comes with a more progressive attitude towards social

[15] 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.

issues, the economic conservationism of those at the top directly impact the support for welfare and redistributive policies, with them often campaign against more social programs or a more progressive taxation system (Page, Bartels, and Seawright 2013; Suhay, Klašnja, and Rivero 2021).

This discrepancy in attitudes and policy preferences around is not optimal in the case of a democracy and may contribute to the dissatisfaction of the general population. The elite bias of public interventions may lead to a sub-optimal allocations of resources away from sectors such as health and education where it may be more needed. This misalignment of interests and incentives between voters, politicians and policy-makers has contributed to a sense of inefficacy in affecting the decision-process and lack of substantive representation among the public, leading to distrust and disapproval towards the government and *la res publica* (Ansell and Gingrich 2022).

6 Summary and Conclusion

In this paper we argue for a novel take on the analysis of IOp. In most prior contributions, IOp is discussed for its detrimental effect on a series of social outcomes. While this approach allows the identification of IOp as one of the harmful form of inequality (Ferreira 2022), it does not fully capture the social and political implications of IOp. We therefore propose a complementary approach, that consider IOp more of a compositional issue, by focusing on the tails and their composition.

In particular, 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 (Ferreira and Gignoux 2011; Brunori, Peragine, and Serlenga 2019).

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; Atkinson and Leigh 2007). 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 (Hacker and 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, Hansen, and Heckman 2003; Heckman 2001).

References

Advani, Arun, Felix Koenig, Lorenzo Pessina, and Andy Summers. 2020. *Importing Inequality: Immigration and the Top 1 Percent.* CESifo Working Paper 8665. Munich.

Alesina, Alberto, Stefanie Stantcheva, and Edoardo Teso. 2018. "Intergenerational Mobility and Preferences for Redistribution." *American Economic Review* 108 (2): 521–54.

Alvaredo, Facundo, Anthony B Atkinson, Thomas Piketty, and Emmanuel Saez. 2013. "The top 1 percent in international and historical perspective." *Journal of Economic perspectives* 27 (3): 3–20.

Anderson, Gordon, Maria Grazia Pittau, and Roberto Zelli. 2020. "Measuring the progress of equality of educational opportunity in absence of cardinal comparability." *METRON* 78 (2): 155–174.

Ansell, Ben, and Jane Gingrich. 2022. "Political inequality." *Institute for Fiscal Studies,* 1–43.

Atkinson, Anthony B, and Andrew Leigh. 2007. "The Distribution of Top Incomes in Australia." *Economic Record* 83 (262): 247–261.

Atkinson, Anthony B., Thomas Piketty, and Emmanuel Saez. 2011. "Top Incomes in the Long Run of History." *Journal of Economic Literature* 49 (1): 3–71.

Beaman, Lori, Raghabendra Chattopadhyay, Esther Duflo, Rohini Pande, and Petia Topalova. 2009. "Powerful Women: Does Exposure Reduce Bias?*." *The Quarterly Journal of Economics* 124, no. 4 (November): 1497–1540. ISSN: 0033-5533.

Beaman, Lori, Esther Duflo, Rohini Pande, and Petia Topalova. 2012. "Female Leadership Raises Aspirations and Educational Attainment for Girls: A Policy Experiment in India." *Science* 335 (6068): 582–586.

Besley, Timothy, Olle Folke, Torsten Persson, and Johanna Rickne. 2017. "Gender Quotas and the Crisis of the Mediocre Man: Theory and Evidence from Sweden." *American Economic Review* 107 (8): 2204–42.

Bossert, Walter, Andrew E Clark, Conchita D'Ambrosio, and Anthony Lepinteur. 2022. "Economic insecurity and political preferences." *Oxford Economic Papers,* ISSN: 0030-7653.

Bossert, Walter, Conchita D'Ambrosio, and Kohei Kamaga. 2021. "Extreme Values, Means, and Inequality Measurement." *Review of Income and Wealth* 67 (3): 564–590.

Bovens, Mark, and Anchrit Wille. 2017. "Political Elites as Educational Elites." In *Diploma Democracy: The Rise of Political Meritocracy.* Oxford University Press, June. ISBN: 9780198790631.

Brunori, Paolo. 2016. *How to measure inequality of opportunity: a hands-on guide.* LCC Working Paper Series 2016-04.

Brunori, Paolo, Vito Peragine, and Laura Serlenga. 2019. "Upward and downward bias when measuring inequality of opportunity." *Social Choice and Welfare* 52:635–661.

Cagé, Julia. 2022. "Political inequality: reasons for optimism?" *Institute for Fiscal Studies,* 1–15.

Card, David. 2009. "Immigration and Inequality." *American Economic Review* 99 (2): 1–21.

Carneiro, Pedro, Karsten T Hansen, and James J Heckman. 2003. *Estimating Distributions of Treatment Effects with an Application to the Returns to Schooling and Measurement of the Effects of Uncertainty on College.* Working Paper, Working Paper Series 9546. National Bureau of Economic Research.

Case, Anne, and Angus Deaton. 2022. "The Great Divide: Education, Despair, and Death." *Annual Review of Economics* 14 (1): 1–21.

Chetty, Raj, John N Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan. 2017. *Mobility Report Cards: The Role of Colleges in Intergenerational Mobility.* Working Paper, Working Paper Series 23618. National Bureau of Economic Research.

Christiansen, Lone Engbo, Huidan Huidan Lin, Joana Pereira, Petia Topalova, and Rima Turk. 2016. "Gender Diversity in Senior Positions and Firm Performance: Evidence from Europe." *IMF Working Papers* (USA) 2016 (050): A001.

Corak, Miles, Patrizio Piraino, and Francisco HG Ferreira. 2016. "The inheritance of employers and nonlinearities in intergenerational earnings mobility." In *Inequality and Growth: Patterns and Policy,* 1–34. Springer.

Craig, Maureen A., and Jennifer A. Richeson. 2014. "More Diverse Yet Less Tolerant? How the Increasingly Diverse Racial Landscape Affects White Americans' Racial Attitudes." PMID: 24625658, *Personality and Social Psychology Bulletin* 40 (6): 750–761.

Durot, Matt. 2022. *A Record Number Of Immigrants Have Become Billionaires In The U.S.* Accessed: 13/05/2022, April. https://www.forbes.com/sites/mattdurot/2022/04/18/a-record-elon-musk-eric-yuan-peter-thiel-number-of-immigrants-have-become-billionaires-in-the-us/?sh=65da53cd2f4b.

Ferreira, Francisco H. G., and Jérémie Gignoux. 2011. "The Measurement of Inequality of Opportunity: Theory and an Application to Latin America." *Review of Income and Wealth* 57 (4): 622–657.

Ferreira, Francisco HG. 2022. "Not all inequalities are alike." *Nature* 606 (7915): 646–649.

Flabbi, Luca, Mario Macis, Andrea Moro, and Fabiano Schivardi. 2019. "Do Female Executives Make a Difference? The Impact of Female Leadership on Gender Gaps and Firm Performance." *The Economic Journal* 129, no. 622 (August): 2390–2423. ISSN: 0013-0133.

Friedman, Sam, and Daniel Laurison. 2020. *The class ceiling: Why it pays to be privileged.* Oxford University Press.

Gagliarducci, Stefano, and M. Daniele Paserman. 2016. *Gender Differences in Cooperative Environments? Evidence from the U.S. Congress.* Working Paper, Working Paper Series 22488. National Bureau of Economic Research. https://doi.org/10.3386/w22488. http://www.nber.org/papers/w22488.

Garritzmann, Julian L., and Hanna Schwander. 2021. "Gender and attitudes toward welfare state reform: Are women really social investment promoters?" *Journal of European Social Policy* 31 (3): 253–266.

Gennaioli, Nicola, and Guido Tabellini. 2019. *Identity, Beliefs, and Political Conflict.* CESifo Working Paper Series 7707. CESifo.

Gethin, Amory, Clara Martínez-Toledano, and Thomas Piketty. 2021. "Brahmin Left Versus Merchant Right: Changing Political Cleavages in 21 Western Democracies, 1948–2020." *The Quarterly Journal of Economics* 137 (1): 1–48. ISSN: 0033-5533.

Grogger, Jeffrey, and Gordon Hanson. 2013. "The Scale and Selectivity of Foreign-Born PhD Recipients in the US." *The American Economic Review* 103 (3): 189–192. ISSN: 00028282, accessed May 4, 2022.

Grossman, Gene M, and Elhanan Helpman. 2020. "Identity Politics and Trade Policy." *The Review of Economic Studies* 88 (3): 1101–1126. ISSN: 0034-6527.

Hacker, Jacob S, and Paul Pierson. 2010. *Winner-take-all politics: How Washington made the rich richer–and turned its back on the middle class.* Simon / Schuster.

Heckman, James J. 2001. "Micro Data, Heterogeneity, and the Evaluation of Public Policy: Nobel Lecture." *Journal of Political Economy* 109 (4): 673–748. ISSN: 00223808, 1537534X.

Heckman, James J. 1977. *Sample Selection Bias As a Specification Error (with an Application to the Estimation of Labor Supply Functions).* Working Paper, Working Paper Series 172. National Bureau of Economic Research.

Heckman, James J. 1976. "The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models." In *Annals of Economic and Social Measurement, Volume 5, number 4,* 475–492. NBER Chapters. National Bureau of Economic Research, Inc.

Jenkins, Stephen P. 2007. *LOGNFIT: Stata module to fit lognormal distribution by maximum likelihood.* Statistical Software Components, Boston College Department of Economics.

Kerr, Sari Pekkala, William Kerr, Çağlar Özden, and Christopher Parsons. 2016. "Global talent flows." *Journal of Economic Perspectives* 30 (4): 83–106.

———. 2017. "High-Skilled Migration and Agglomeration." *Annual Review of Economics* 9 (1): 201–234.

Kleiber, Christian, and Samuel Kotz. 2003. *Statistical size distributions in economics and actuarial sciences.* John Wiley & Sons.

Kneib, Thomas, Alexander Silbersdorff, and Benjamin Säfken. 2021. "Rage Against the Mean – A Review of Distributional Regression Approaches." *Econometrics and Statistics,* ISSN: 2452-3062.

Lee, Tiane L., and Susan T. Fiske. 2006. "Not an outgroup, not yet an ingroup: Immigrants in the Stereotype Content Model." Special Issue: Attitudes towards Immigrants and Immigration, *International Journal of Intercultural Relations* 30 (6): 751–768. ISSN: 0147-1767.

Macmillan, Lindsey, Claire Tyler, and Anna Vignoles. 2015. "Who Gets the Top Jobs? The Role of Family Background and Networks in Recent Graduates' Access to High-status Professions." *Journal of Social Policy* 44 (3): 487–515.

Milanovic, B. 2019. *Capitalism, Alone: The Future of the System That Rules the World.* Harvard University Press. ISBN: 9780674987593.

———. 2016. *Global inequality.* Harvard University Press.

Page, Benjamin I., Larry M. Bartels, and Jason Seawright. 2013. "Democracy and the Policy Preferences of Wealthy Americans." *Perspectives on Politics* 11 (1): 51–73.

Piketty, Thomas. 2020. *Capital and Ideology.* Harvard University Press. ISBN: 9780674980822.

Piketty, Thomas. 2017. *Capital in the Twenty-First Century.* Harvard University Press. ISBN: 9780674979857.

———. 1995. "Social Mobility and Redistributive Politics*." *The Quarterly Journal of Economics* 110 (3): 551–584. ISSN: 0033-5533.

———. 2005. "Top income shares in the long run: An overview." *Journal of the European economic association* 3 (2-3): 382–392.

Piketty, Thomas, and Emmanuel Saez. 2006. "The evolution of top incomes: a historical and international perspective." *American economic review* 96 (2): 200–205.

Raitano, Michele, and Francesco Vona. 2018. "From the cradle to the grave: The influence of family background on the career path of Italian Men." *Oxford Bulletin of Economics and Statistics* 80 (6): 1062–1088.

Ramos, Xavier, and Dirk Van de gaer. 2012. *Empirical Approaches to Inequality of Opportunity: Principles, Measures, and Evidence.* IZA Discussion Papers 6672. Institute of Labor Economics (IZA), June.

Rebechi, Alessio, and Nicholas Rohde. 2022. "Economic insecurity, racial anxiety, and right-wing populism." *Review of Income and Wealth,* https://doi.org/https://doi.org/10.1111/roiw.12599.

Rodrik, Dani. 2021. "Why Does Globalization Fuel Populism? Economics, Culture, and the Rise of Right-Wing Populism." *Annual Review of Economics* 13 (1): 133–170.

Roemer, J.E. 1998. *Equality of Opportunity.* Harvard University Press. ISBN: 9780674259911.

Roemer, John, and Alain Trannoy. 2016. "Equality of Opportunity: Theory and Measurement." *Journal of Economic Literature* 54 (4): 1288–1332. ISSN: 00220515, accessed April 10, 2022.

Satz, Debra, and Stuart White. 2021. "What is Wrong with Inequality?" *Inequality: The IFS Deaton Review.*

Shayo, Moses. 2020. "Social Identity and Economic Policy." *Annual Review of Economics* 12 (1): 355–389.

Silbersdorff, Alexander, Julia Lynch, Stephan Klasen, and Thomas Kneib. 2018. "Reconsidering the income-health relationship using distributional regression." *Health Economics* 27 (7): 1074–1088.

Solimano, Andrés, and Diego Bernardo Avanzini. 2010. *The International Circulation of Elites.* Technical report 30. Helsinki, Finland.

Strømme, Thea Bertnes, and Marianne Nordli Hansen. 2017. "Closure in the elite professions: the field of law and medicine in an egalitarian context." *Journal of Education and Work* 30 (2): 168–185.

Suhay, Elizabeth, Marko Klašnja, and Gonzalo Rivero. 2021. "Ideology of Affluence: Explanations for Inequality and Economic Policy Preferences among Rich Americans." *The Journal of Politics* 83 (1): 367–380.

Toft, Maren. 2019. "Mobility closure in the upper class: assessing time and forms of capital." *The British Journal of Sociology* 70 (1): 109–137.