

Inherited Inequality, Meritocracy, and the Objective of Economic Growth*

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Outline

- 1. Introduction
- 2. Equality of opportunity: a 'canonical model'
- 3. Dispensing with effort: Inherited inequality
- 4. Measurement and the model selection problem
- 5. Public policy and growth / development
- 6. Meritocracy vs. EOp
- 7. Conclusions



Key motivation: Not all inequalities are alike. Some of the dispersion in key outcomes of interest reflect factors beyond individual control or responsibility. This kind of inequality – inequality of opportunity – matters for growth and development <u>in two ways</u>:

- 1. It has considerable normative appeal and should therefore inform the kind of growth we want.
 - Some moral philosophers see it as the modern "currency of egalitarian justice". (John Rawls, 1971; Amartya Sen, 1980; Ronald Dworkin, 1981; Richard Arneson, 1989; Gerald Cohen, 1989)
 - Some evidence that it is a dominant conception of fairness in the population. (e.g., Pew Research Center, 2012; Cappelen et al., 2010)
- 2. There is also evidence that IOp can lead to an inefficient allocation of investments, thereby affecting how much growth we get.
 - E.g., Marrero and Rodriguez (2013), Hsieh et al. (2019)



Figure 2 Opportunities are determined early

Cognitive development for children ages three to five in Ecuador differs markedly across different family backgrounds



Source: Paxson and Schady (2005a).

Note: Median values of the test of vocabulary recognition (TVIP) score (a measure of vocabulary recognition in Spanish, standardized against an international norm) are plotted against the child's age in months. The medians by exact month of age were smoothed by estimating fan regressions of the median score on age (in months), using a bandwidth of 3.

Source: Paxson and Schady, JHR, 2007



Distributions of PISA reading test scores, conditional on father's occupation.



Source: Barros, Ferreira, Molinas & Saavedra (2008)



2. Equality of opportunity

- Two broad approaches to formalizing these ideas in Economics (Ferreira and Peragine, 2016)
 - Direct: Modeling distributions or profiles of opportunity sets
 - e.g., Pattanaik and Xu (1990), Weymark (2003), Savaglio and Vannucci (2007)
 - Indirect: inferring IOp from the association between outcomes, circumstances and efforts
 - e.g., Roemer (1993, 1998); van de Gaer (1993); Fleurbaey (1994, 2008)



• The indirect approach, which has become dominant, rests on one fundamental (if often implicit) assumption:

Classifiability Assumption: a desirable individual outcome $y \in \mathbb{R}$ is a function of two kinds of variables *only*: circumstance variables and effort variables.

 $y = g(\mathcal{C}, e)$

 $C \in \Gamma, e \in E \text{ and } g: \Gamma \times E \rightarrow \mathbb{R}.$

- Some authors have allowed for a third determinant, namely luck (e.g. Lefranc et al. 2009)
- Classifiability does not imply or require separability. Effort levels can be and generally are influenced by circumstances. The only requirement is that they should not be fully determined by them. There must be some individual locus of responsibility ψ , so that $e = h(C, \psi)$.



- Then each and every individual is fully characterized by the triple (y_l, C_l, e_l) .
- Let *e* and all elements of **C** be discrete
- A *type* consist of all individuals with identical circumstances
- A *tranche* consist of all individuals with identical effort levels
- Let there be *n* types and *m* tranches
- Then the population can be represented by the $n \times m$ matrix $[Y_{ij}]$.
- To $[Y_{ij}]$, let there be associated another $n \times m$ matrix $[P_{ij}]$, whose elements p_{ij} denote the proportion of the total population with circumstances C_i and effort level e_j .



	e ₁	e ₂	e ₃	•••	em		
C ₁	X 11	X12	X13	• • •	X _{1m}		
C ₂	X21	X22	X23	•••	X _{2m}		
C ₃	X31	X32	X33	•••	X _{3m}		
•••	•••	•••	•••	•••	•••		
Cn	X _{n1}	X _{n2}	X _n 3	• • •	X _{nm}		

Table 1

Discussion draws on Ferreira and Peragine (2016)





A tranche



- In addition to the classifiability assumption, which allows us to represent society by the matrix [Y_{ij}], the indirect approach posits two explicit normative principles:
 - The *Compensation Principle* states that outcome differences due to circumstances are unfair and should either be eliminated or compensated for.
 - The *Reward Principle* states that outcome differences due to differences in effort levels are fair and should be (at least partly) preserved.



- Two versions of the Compensation Principle:
 - Ex-ante:
 - Compensates (conceptually) prior to the realization of effort.
 - Equalizes the values of opportunity sets across types.
 - Equality of opportunity attained when: $E(y|C_i) = E(y|C_k), \forall C_i, C_k \in \Gamma$
 - Ex-post:
 - Compensates (conceptually) <u>after the realization of effort.</u>
 - Equalizes incomes at every effort level
 - Must account for the fact that efforts depend on circumstances and are often unobserved
 - Roemer's identification assumption: treat rank in type distribution as relative degree of effort
 - Equality of opportunity attained when $F(y|C_i) = F(y|C_k), \forall C_i, C_k \in \Gamma$



- Many versions of the Reward Principle:
 - Utilitarian
 - Liberal / Natural
 - Inequality averse
 - Agnostic
 - etc.



This framework can be used to: (a) design measures of inequality of opportunities, and/or (b) design policy or allocation rules.

Many such rules have been proposed, depending on the specific versions of compensation and reward principles that are adopted, as well as on the degree of aversion to IOp. Two examples:

• 'Min of means' objective – ex-ante compensation (van de Gaer, 1993)

$$W_V = \min_{T_i} E(y|C_i)$$

• 'Mean of mins' objective – ex-post compensation (Roemer, 1993)

$$W_R = \int_0^1 \min_{T_i} F^{-1}(p|C_i) \, dp$$

When effort is continuous, n=3







This model can be used to: (a) underpin the measurement of inequality of opportunities, and/or (b) design policy or allocation rules.

In essence, the measurement of IOp can be thought of as a two-step procedure:

- First, the actual distribution $[Y_{ij}]$ is transformed into a counterfactual distribution $[\tilde{Y}_{ij}]$ that reflects only and fully the unfair inequality in $[Y_{ij}]$, while all the fair inequality is removed.
 - This first step can be taken in many different ways, depending on the specific form of the compensation (e.g. ex-ante vs. ex-post) and reward principles one adopts.
- Second, a measure of inequality satisfying the usual axioms is applied to $[\widetilde{Y}_{ij}]$.



One example of the first step is the between-types approach (consistent with ex-ante compensation and utilitarian reward):

Between types (\tilde{X}_{BT}): For all $j \in \{1,...,m\}$ and for all $i \in \{1,...,n\}$, $\tilde{x}_{ij} = \mu_i$.

Table 2: Between-types inequality (n=m=3)

	e1	e2	e3
C1	$\mu_{ m l}$	$\mu_{ m l}$	$\mu_{ m l}$
C2	μ_2	μ_2	μ_2
C3	μ_3	μ_3	μ_3



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$$\theta_a = I(\widetilde{x}_{BT})$$

$$\theta_r = \frac{I(\tilde{x}_{BT})}{I(x)} = \frac{I(\mu_i)}{I(x_{ij})}$$

A second example of the first step is the within tranches approach (consistent with ex-post compensation, but not with reward):

Within tranches (\widetilde{X}_{WTR}): For all $j \in \{1,...,m\}$ and for all $i \in \{1,...,n\}$, $\widetilde{x}_{i,j} = g(c_i, e_j)/v_j$.

Table 4: Within tranches inequality (n=m=3)

	e1	e2	e3
C1	x_{11} / v_1	x_{12} / v_2	x_{13}/v_{3}
C2	x21/ V ₁	x_{22}/V_2	X23/ V3
C3	X_{31}/V_1	x _{32/} V ₂	X33/ V ₃

Draws on the mean of mins approach. Satisfies ex-post compensation everywhere, but not the reward principle.



Common concerns and critiques:

- Distinguishing efforts from circumstances is difficult.
- Is there such a thing as free will? (Causal determinism).
- If not, what can people really be held responsible for?
- Do extremely poor people deserve no support if their predicament is "of their own making"?
- Do extremely rich people deserve all the rewards to their effort, regardless of level?
- Some reward principles clash with ex-post compensation (Fleurbaey and Peragine, 2012)



Common problem: The concept of **effort** can be problematic.

"This project turned out to be like peeling away layers of an onion. [...] There is no way to separate a person from the accumulated effects of her interactions with her circumstances, including her opportunities, because the product of those accumulated interactions is the person." (Fishkin, 2014: *Bottleneck: a new theory of equality of opportunity* p. 64.)



Proposed Solution:

(i) Dispense with the *Classifiability* Assumption and the Reward Principle

Classifiability Assumption: a desirable individual outcome $y \in \mathbb{R}$ is a function of two kinds of variables *only*: circumstance variables and effort variables.

The *Reward Principle* states that outcome differences due to differences in effort levels are fair and should be (at least partly) preserved.



Proposed Solution:

(ii) Weaken the Compensation Principle:

Define a set $H \subset \Gamma$ of characteristics which are inherited at birth, so that:

Weak Principle of Compensation (WPC): In a fair of society, a person's outcome y should be distributed independently of inherited characteristics H. In other words, $y \perp H$.

- Implies: $F(y|H_i) = F(y|H_k), \forall H_i, H_k \in H$
- Which in turn implies: $E(y|H_i) = E(y|H_k), \forall H_i, H_k \in H$



- The selection of $H \subset \Gamma$ is key for the operationalization of the measurement of inherited inequality.
- Whereas the set of circumstances, Γ , is defined by the *classifiability* assumption under IOp, H can be chosen explicitly, in one of two ways:
 - If a society chooses to adopt the WPC as a normative principle to guide policy, then the elements of H should arise as the result of a process of democratic deliberation
 - In the absence of a socially or politically determined specification for the set H, its composition may be left to the discretion of the researcher. In this case, it will likely be jointly determined by the researcher's own normative views and by the data that is available



- Under the orthogonality condition laid out in the WPC $(y \perp H)$ no prediction function f(H) is informative of y
- It is then natural to measure inherited inequality by the extent to which inherited circumstances *H* can predict *y*.
- The concept of unfair inequality that corresponds to the Weak Principle of Compensation is the inequality that can be predicted by the set of inherited circumstances
- A counterfactual matrix $\widetilde{Y'}_{ij}$ can therefore be constructed by letting its typical entry $\widetilde{Y'}_l = \widehat{f}(H_l)$, where f is a prediction function of the form: $y = f(H), f \in \mathcal{F}$



So, an absolute measure of inherited inequality would simply be

$$I(\widetilde{y'}_{ij})$$
 where $\widetilde{y'}_{ij} = \widehat{f}(H_{ij})$

Whereas a relative measure of would take the general form: $I_n = \phi \left(\frac{I(\widetilde{y'}_{ij})}{I(y)} \right)$

Encompassing common measures of mobility and inequality of opportunity:

 $\frac{I(\hat{y}_{EA})}{I(y)}$

For example:
$$y_c = f_M(H, \varepsilon) = \alpha + \beta y_p + \varepsilon$$
Note that: $\rho = \beta \frac{\sigma_p}{\sigma_c}$ Alternatively, $y_c = f_{EAp}(H, \varepsilon) = \alpha + H\beta + \varepsilon$

Encompassing common measures of mobility and inequality of opportunity:

For example:
$$y_c = f_M(H, \varepsilon) = \alpha + \beta y_p + \varepsilon$$
Note that: $\rho = \beta \frac{\sigma_p}{\sigma_c}$ $\rho^2 = R^2$ Alternatively, $y_c = f_{EAp}(H, \varepsilon) = \alpha + H\beta + \varepsilon$ $IOR_{EA} = \frac{I(\hat{y}_{EA})}{I(y)}$

Encompassing common measures of mobility and inequality of opportunity:

For example:
$$y_c = f_M(H, \varepsilon) = \alpha + \beta y_p + \varepsilon$$

Note that:
$$\rho = \beta \frac{\sigma_p}{\sigma_c}$$
 $\hat{\rho} = \sqrt{\frac{I(y_M)}{I(y)}}$ when $I(x) = Var(x)$

Alternatively,
$$y_c = f_{EAp}(H, \varepsilon) = \alpha + H\beta + \varepsilon$$
 $IOR_{EA} = \frac{I(\hat{y}_{EA})}{I(y)}$

- When $H \rightarrow C$, inherited inequality converges to inequality of opportunity
 - But with much lighter normative requirements:
 - No "classifiability" assumption
 - No principle of reward

- When $H \rightarrow y_p$, inherited inequality converges to intergenerational mobility
 - At least for 'origin-independence' measures of IGM (see Fields, 2000)







- Key challenge: model selection
- We observe a join distribution $\{y_i, H_i\}$
- How do we select the "best" prediction function f(H) to predict y from the large set of potential candidates, \mathcal{F} ?
 - Is parental income a sufficient statistic?
 - (Often interpreted that way: IGM capturing "all" transmission of SES across generations)
 - When there are multiple categorical circumstance variables with many categories each, the number of possible interaction terms / partition cells explodes



- How should the population be partitioned / interaction terms selected?
- Consider our UK HLS data set for 2009 :
 - N = 10,987 observations
 - Circumstances:
 - Sex (2 categories)
 - Country of birth (25 categories)
 - Ethnicity (5 categories)
 - Occupation of father and mother (10 categories)
 - Education of father and mother (4 categories each)
 - Number of potential types: 2 x 25 x 5 x 10 X 10 x 4 x 4 = 400,000



- Model selection requires trading off the two competing biases at play:
 - 1. Downward bias from omitted (unobserved) circumstances
 - Ferreira and Gignoux (2011)
 - 2. Upward bias from overfitting
 - Sampling variation around sub-group parameter estimates explodes as cell sizes become too small. (Brunori, Peragine and Serlenga, 2018)



Since
$$I_n = \phi\left(\frac{I(\widetilde{y'}_{ij})}{I(y)}\right)$$
, where $\widetilde{y'}_{ij} = \hat{f}(H_{ij})$

Prediction plays a central role in measuring inherited inequality

- Prediction is precisely the sort of statistical exercise where machine learning techniques from data science excel (Mullanaithan and Spiess, 2017)
- Recent applications have used conditional inference trees (for the ex-ante approach) or transformation trees (for the ex-post)
 - Techniques: Hothorn et al. (2006) and Hothorn and Zeileis (2021)
 - Applications: Brunori, Hufe and Mahler (2023); Brunori, Ferreira and Salas-Rojo (2023)



4. Measurement: ex-ante

Figure 2: Conditional Inference Tree for the UK (HLS), 2009



Source: Own elaboration using data from UKHLS (2009). Note: CIT minimum number of observations per type is set to 200, maximum Bonferroni-adjusted p-value to perform a split is 0.001.



4. Measurement: ex-ante

Figure 2: Conditional Inference Tree for the UK (HLS), 2009



 $I(\tilde{y}) = 0.07$



5.0 7.5 10.0



Parenthesis (using a South Africa example to illustrate specification choice)



Type 27 Pop. Share. % = 5.02% 27 n = 366 y = 4.1111, 12 25 n = 604 Father_Edu p < 0.0010, 2, 4, 5, 6, 7, 8, 9, 10 Type 26 Pop. Share. % = 3.20 y = 2.76 26 n = 238 n = 7297 Ethnicity 1 p < 0.001 Type 24 24 <u>n =</u> 323 Pop. Share. % = 4.43% y = 1.92.3 18 n = 1422 Ethnicity p < 0.001 Type 23 23 n = 225 Pop. Share. % = 3.08% y = 1.24 12 n = 608Father_Edu 1, 2, 3 p = 0.0098, 9, 10, 11 Type 22 Pop. Share. % = 5.25% 22 n = 383y = 0.77 8, 9, 10, 11, 12 Sex 19 n = 1099 p < 0.001 Type 20 Pop. Share. % = 6.73% y = 1.31 20 n = 491 Father Edu Parenthesis 2 n = 6693 p < 0.001 Type 17 Pop. Share. % = 2.85% 17 n = 208 y = 0.65 (using a South Africa 2, 5, 7, 8 11 n = 1596 Mother_ISCO p < 0.001 Type 16 Pop. Share. % = 2.81% 16 n = 205 example to illustrate v = 0.931, 4, 5, 6, 8, 9 14 n = 335 Father_ISCO 0, 1, 2, 3, 4, 5, 6, 7 1, 3, 4, 9 p < 0.001 specification choice) 0, 2, 3, 7, 10 Type 15 Pop. Share. % = 1.78% 15 n = 130 y = 0.751, 2, 3, 4, 5, 7, 8, 9 5, 6, 7, 8, 10, 11 Mother_Edu 12 n = 1388 p < 0.001 0, 1, 2, 3, 4, 9, 12 Type 13 Pop. Share. % = 14.43% 13 n = 1053 y = 0.49Mother ISCO 3 n = 5271 p < 0.001 Type 10 Pop. Share. % = 4.1% 10 n = 299 0, 6, 10 y = 0.642, 3 $x_1 = \mathbf{1}_{race=white} \times \mathbf{1}_{father\ education=11\ or\ 12}.$ Ethnicity 4 n = 3675 p < 0.001 Type 9 Pop. Share. % = 3.3% y = 0.8 9 n = 241 5, 8, 10, 12 Mother_Edu 5 n = 3376 p < 0.001 Type 8 8 <u>n = 20</u>81 Pop. Share. % = 28.52% 0, 1, 2, 3, 4, 6, 7, 9, 11 *x*₁₃ y = 0.39 $= 1_{race=black} \times 1_{father \ education \in \{0-7\}} \times 1_{mother \ occup. \ \in \{0,6,10\}} \times 1_{sex=female}$ Sex 6 n = 3135 p < 0.001 0 Pop. Share. % = 14.44% 7 n = 1054 y = 0.55 $\times 1_{mother \, education \in \{0-4, 6, 7, 9, 11\}}$







- In light of this IOp / Inherited Inequality perspective, to what end should a benevolent policymaker design rules and policies using the resources at their disposal?
 - Priority to inequalities you inherit
 - Leveling down objection





Two standard static approaches, corresponding once again to ex-ante and ex-post perspectives:





• Shortcomings / limitations:

- Completely static missing important dynamic trade-offs?
- No room for any absolute aversion to absolute poverty
- Ignores non-income dimensions, including the hierarchic superiority of certain freedoms
- Ignores planetary and feasibility constraints
- Ignores process fairness considerations



$$\max_{\phi \in \Phi} \int_{t}^{\infty} e^{\delta(t-s)} \int_{0}^{1} \min_{T_{i}} F_{is}^{-1}(p,\phi|H_{i}) dp ds$$
$$s.t. \ x_{ls} \ge z_{s}, \forall l, s$$

Modified from Bourguignon, Ferreira and Walton (2007)





"Growth matters"

Modified from Bourguignon, Ferreira and Walton (2007)



• Implications

- Ensuring that no one is left in extreme deprivation at any time
- Organize incentives and resources so that growth benefits the most disadvantaged
 - Likely the children of the poor, with some more specific targeting in horizontally unequal societies
 - Objective is lexicographic, so that as poorer types are brought upwards, more groups are included in the target group
 - Dynamics emphasize the need to account for equity-efficiency trade offs where those occur. Incentives matter and designing mechanisms that harness them remains key.



- Implications: $\phi \in \Phi$ incorporates
 - Feasibility constraints (budget, technology, environment, etc.)
 - Respect for essential personal freedoms (Rawls's Liberty Principle)
 - Process considerations (nod to Nozick)
 - Including with regard to merit considerations in some realms



- Meritocracy is a normative allocation principle, alternative to and distinct from - equality of opportunity.
 - Suppose there is an (intermediate) "productivity" variable π , so that (1) becomes:

$$y = h(\pi(C, e)) = g(C, e)$$

- Recall that **EOp** is attained when $F(y|C_i) = F(y|C_k), \forall C_i, C_k \in \Gamma$
- Meritocracy requires that $y_l = y_m \Leftrightarrow \pi_l = \pi_m, \forall l, m \in N$
- Consider the problem of allocating a scarce number of 'goods' across a population of two types, Advantaged (A) and Disadvantaged (D)
 - E.g., places or positions in kindergarten, school, university, government jobs



• With an EOp criterion, on the margin, one equalizes Roemer's relative degree of effort.



Solve for p^* , given L_I

$$L_J^{EOp} = (L_A + L_D)(1 - p^*)$$

Expected productivity (merit) in J is on the margin lower in the D group, but effort levels are equalized



• Allocating a limited number of vacancies for J according to a meritocratic criterion: on the margin, equalize expected productivity.



Solve for π^* , given L_J

$$L_{J}^{M} = L_{A} (1 - G_{A}(\pi^{*})) + L_{D} (1 - G_{D}(\pi^{*}))$$

Expected productivity (merit) in J is equal on the margin, but D group members must exert more effort to qualify.



• Which contrasts with a discriminatory criterion (e.g., taste-based discrimination), where members of the Advantaged group may be selected, despite having a lower expected productivity:



Expected productivity (merit) in J is on the margin lower in the A group, and D group members must exert an even greater level of effort to qualify.



• The meritocratic and the EOp criteria might apply differently to different allocation problems (e.g., kindergarten vs. medical school). One might even conceive of convex combinations of the two, with different weights on effort versus merit.



As in Meritocracy, a greater proportion of A group members is selected, and D group members must exert a greater effort to qualify. As is EOp, the marginal A group member selected has a higher productivity than the marginal D group member.

E.g. Affirmative action programmes in some US universities until recently



7. Conclusions

- In a world where advantage and disadvantage are inherited, adopting an EOp lens to public policy means a priority for reducing those inequalities
- Re-stating the key normative principle in terms of outcomes being orthogonal to inherited circumstances (WPC) reduces both the cognitive and the normative burdens associated with the *classifiability* assumption and the principle of reward.
- This framework also highlights an inherent similarity between mobility, IOp, and inherited inequality: the "weight of the past"
- Public policy objectives can be augmented to include concerns with freedoms and rights, environmental constraints, process fairness and poverty aversion.



7. Conclusions

- EOp is about equalizing advantage at a given relative level of effort
- Meritocracy is about equalizing advantage at a given level of merit / productivity
- Within an overarching EOp programme, meritocratic criteria may bear on selections in different realms
 - Because of efficiency considerations that raise final outcomes for the disadvantaged
 - Because of socially agreed fairness-in-process considerations



Thank you for your attention.