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Equity, opportunity and health*

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Abstract

This article sets out the foundations for a programme of research that aims to explore equality of opportunity in health by drawing on the statistical tools of causal and mediation analysis, while developing a normative approach to the role of early life circumstances and education as a source of inequality of opportunity in health.

Keywords: equality of opportunity, health equity

JEL codes: I30, I14, I12

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1. Introduction

Following the lead of evidence-based medicine, the social sciences, including economics, have embraced a focus on causal analysis and programme evaluation and this now dominates the academic literature. But this search for causal effects can drive out other important research questions. In contrast, there is a strong tradition in health economics that asserts the importance of a normative approach based on 'empirical ethics' and rooted in political philosophy and social choice theory: using empirical data to quantify the scale of social injustice (e.g., Fleurbaey and Schokkaert 2012). The two perspectives may be brought together by drawing on the statistical tools of causal and mediation analysis, while developing a normative approach to the role of early life circumstances and education as a source of inequality of opportunity in health.

Equality of opportunity is based on an ethic of 'responsibility-sensitive egalitarianism' (Roemer 1998; Roemer and Trannoy 2016). It distinguishes between circumstances, such as which kind of school someone attended, for which people are not held personally responsible, and their personal effort, which may in-part be shaped by those circumstances, for example through the attitudes and behaviours picked up at that school. A normative model draws out the implications of this ethical stance in the data, by disentangling the direct and indirect (through effort) contributions of circumstances and the direct contribution of effort to the distribution of health outcomes.

This article sets out the foundations for a programme of research that aims to explore equality of opportunity in health by:

1) Building a normative model to examine pathways from circumstances to health outcomes. Where circumstances include factors such as date and place of birth, gender, ethnicity, family circumstances as a child, parental occupation, and parental and own education.

2) Taking into account that health is a multidimensional and complex outcome by considering a set of objective health measures (biomarkers) and adopting the best statistical model for each one of these.

3) Evaluating mediating factors, such as cognitive abilities, lifestyles, employment and income, which can affect the pathways between circumstances and health.

4) Extending analysis of the contribution of circumstances to health inequalities by (i)

going “beyond the mean” to assess whether they matter more for people who are at the bottom or top of the pile in terms of their health and (ii) allowing for heterogeneity in the role of circumstances across people who have different characteristics.

2. Equality of opportunity in health

There is a long-established literature in health economics on how to measure inequality and inequity in the financing and delivery of health care and in the health of the population. In defining inequity it is helpful to distinguish norms for horizontal and for vertical inequity. Horizontal equity implies equal treatment of individuals who are equal in relevant respects. While vertical equity implies unequal treatment of individuals who are unequal in relevant respects. In the context of health care financing relevant respects would typically be taken to mean ability to pay and with respect to the use of health care relevant respects would typically be taken to mean need for health care. Health economists have focused mostly on vertical equity in the financing of health care, on how payments vary with ability to pay and whether payments are progressive or regressive, and on horizontal equity in the delivery of health care and whether the norm of equal treatment for equal need is satisfied or whether use of health care varies with other factors such as income after taking account for need. In these cases both ability to pay and need are treated as a legitimate source of variation in the outcomes. In contrast the literature on inequality in population health outcomes has focused on socioeconomic gradients in health, often proxied using household income. In this case income is implied to be an illegitimate or unfair source of inequalities in outcomes. The question of what might be a source of fair inequalities in health – analogous to ability to pay or need – often remains unanswered. The concept of equality of opportunity in health offers one way of plugging this gap in the literature.

When it comes to measurement issues, in health economics, methods based on Gini and concentration indices have typically been used to measure health equity. For example, Van Doorslaer, et al. (2004) present international comparative evidence on the factors driving inequity in the use of health care in EU member states. By using panel data, such as the BHPS and UKHLS, long-run health equity can be measured (Jones and López Nicolás 2004; Hernández Quevedo et al. 2006). These inequality indices can be decomposed to show the contribution of different factors to overall inequalities. Jones and López Nicolás (2006) showed how these decompositions can be extended to allow for individual heterogeneity.

Equality of opportunity (EOp) is a key concept in recent social choice theory and normative economics, based on responsibility-sensitive egalitarianism or 'levelling the playing field'. Many empirical applications have dealt with the assessment of EOp in a variety of outcomes, such as income and educational attainment, and for the evaluation of a wide range of policies in areas such as education and international aid. Applying the concept of equality of opportunity to health outcomes has been advocated by Sen (2002), Rosa Dias and Jones (2007) and Fleurbaey and Schokkaert (2009, 2012).

The canonical normative model of inequality of opportunity was formulated by John Roemer (1998, 2002). Roemer makes a 'responsibility cut' that partitions all factors influencing individual attainment between a category of *effort factors*, for which individuals should be held partly responsible, and a category of *circumstance factors*, which are judged to be a source of unfair differences in outcomes.

A general health production function can be defined along the lines of Roemer (2002) as $\mathrm{H}(\mathrm{C}, \mathrm{E}(\mathrm{C}))$ where C denotes individual circumstances and E denotes effort, which is itself allowed to be a function of circumstances. To reflect the fact that observed realisations of health outcomes are inherently random and that the equality of opportunity ethic can be expressed in terms of factors associated with the distribution of health, this is written in terms of the distribution function of the realised individual outcomes:

$$H_i \sim H\big(C_i, E_i(C_i)\big)$$

where H_i denotes the observed health outcome for the *i*th individual, and C_i, E_i their circumstances and effort, respectively.

Roemer (1998, 2002) defines social types as groups of people who share identical circumstances. While a group who share the same effort are defined as a tranche. A fundamental feature of this approach is the fact that the distribution of effort within each type is itself a characteristic of that type and, since this is assumed to be beyond individual responsibility, it constitutes a circumstance in itself. This implies that, in addition to assuming a partitioning between C and E, the model assumes that effort is a function of circumstances. To capture the notion that the distribution of effort within a type is itself a circumstance Roemer defines the degree of effort using an individual's rank in the distribution within their type. The model also implies that circumstances are pre-determined and should not be a function of effort.

The concept of equality of opportunity draws on two main ethical principles: compensation and reward (Fleurbaey and Schokkaert 2012). The compensation principle states that differences in outcomes due to circumstances are ethically unacceptable and should be compensated. This can be seen as a principle of horizontal equity with respect to effort. While the reward principle states that differences due to effort are to be considered ethically acceptable and do not justify any intervention. This is a principle of vertical equity with respect to effort and reflects the degree of inequality aversion within types and the extent to which people should be rewarded for different levels of effort. In general it is not possible to fully satisfy both compensation and reward principles, other than in the exceptional circumstances when there is no interaction between circumstances and effort.

These two principles have a parallel with the fairness gap and the direct unfairness approaches proposed by Fleurbaey and Schokkaert (2009). The fairness gap fixes the circumstances at a reference level and focuses on the differences between individual health and the counterfactual health of individuals with the reference circumstances (e.g. best-off type): $\mathrm{FG} = \mathrm{H}(\mathrm{C},\mathrm{E}) - \mathrm{H}(\tilde{\mathrm{C}},\mathrm{E})$. This focuses on the illegitimate inequalities within individuals with the same effort level (the same tranche) and, hence, on horizontal equity with respect to effort. It is therefore compatible with the compensation perspective. Measures of inequality based on the FG will always satisfy the compensation principle but may only satisfy the reward principle at the reference level of C. In contrast, the direct unfairness principle fixes the effort at a reference level for any given type: $\mathrm{DU} = \mathrm{H}(\mathrm{C},\tilde{\mathrm{E}})$. This removes any inequality within type and reflects the reward perspective and vertical equity across levels of effort. Measures of inequality based in DU will satisfy the reward principle but may only satisfy compensation at the reference level of E.

Testing for inequality of opportunity can be done nonparametrically. For example LeFranc et al. (2009) build on the Roemer model and define tests for equality of opportunity in terms of stochastic dominance. These test for differences in the distribution of outcome across types, where these distributions can be interpreted as the set of opportunities available to each type. When it comes to the measurement of inequality of opportunity the benchmark approach is to use a parametric specification. For example Bourguignon et al. (2007) use a formulation of the Roemer model that includes error terms:

$$H_i = H(C_i, E_i, \varepsilon_i) = H(C_i, E(C_i, u_i), \varepsilon_i)$$

From this they define two counterfactual outcomes:

$$\widehat{H}_i = H(\bar{C}, E(\bar{C}, u_i), \varepsilon_i)$$
$$\breve{H}_i = H(\bar{C}, E(C_i, u_i), \varepsilon_i)$$

The first of these, which fixes both the direct and the indirect (through effort) contribution of C, is used to define the overall opportunity share based on an inequality index *I(.)* such as Theil, Gini, variance or mean log deviations:

$$\theta = \frac{I(H) - I(\widehat{H})}{I(H)}$$

The second counterfactual is used to distinguish a direct effect:

$$\theta^D = \frac{I(H) - I(\breve{H})}{I(H)}$$

and hence an indirect effect:

$$\theta^I = \theta - \theta^D$$

Assuming a linear specification the model can be written in structural form:

$$H_i = \beta_0 + \beta_1 C_i + \beta_2 E_i + \varepsilon_i$$

$$E_i = \gamma_0 + \gamma_1 C_i + u_i$$

This can be rearranged to give the reduced form:

$$H_i = (\beta_0 + \beta_2\gamma_0) + (\beta_1 + \beta_2\gamma_1)C_i + (\varepsilon_i + \beta_2 u_i) \quad = \pi_0 + \pi_1 C_i + v_i$$

Then the counterfactuals are given by:

$$\widehat{H}_i = \hat{\pi}_0 + \hat{\pi}_1\bar{C} + \hat{v}_i$$

$$\breve{H}_i = \hat{\beta}_0 + \hat{\beta}_1\bar{C} + \hat{\beta}_2 E_i + \hat{\varepsilon}_i$$

Note that the first counterfactual only requires that the reduced form be estimated, regressing the outcome on circumstances alone, while the second draws on estimates of the structural form to distinguish direct and indirect contributions.

There is a growing empirical literature on the measurement of inequality of opportunity in health and studies have shown evidence of inequality of opportunity in health in the UK (Rosa Dias 2009,2010; Balia and Jones 2011; Li Donni et al. 2014), France (Trannoy et al. 2010; Jusot, et al. 2013) and the Netherlands (Garcia-Gomez et al. 2015).

3. Building a normative framework for empirical analysis

Despite the growing prominence of theoretical analysis of inequality of opportunity over the past twenty years, empirical evaluation of real-world policies has been rare. Jones, Roemer & Rosa Dias (2014) address this by proposing a normative framework to model the influence of educational policy on health outcomes grounded in Roemer's model of equality of opportunity. This uses a comparison of the distribution functions for outcomes split by type under different policy regimes as the basis for policy evaluation.

Carrieri and Jones (2018) present new decomposition-based approaches to measure inequality of opportunity in health that captures Roemer's distinction between circumstances and effort. The approach is fully nonparametric in the way that it handles differences in circumstances and provides decompositions of both a rank-dependent relative (the Gini coefficient) and a rank-independent absolute inequality index (the variance). This relies on three normative assumptions:

(i) the partitioning of circumstances and effort ("responsibility cut");

(ii) that effort is a function of circumstances and not *vice versa* ("control");

(iii) that, conditional on circumstances (type), there is a linear relationship between effort and outcomes (linearity).

The decompositions distinguish the contribution of effort from the direct and indirect (through effort) contribution of circumstances to the total inequality. The methods are illustrated by an empirical application which uses objectively measured biomarkers as health outcomes and as proxies for relevant effort variables. Using data from the Health Survey for England from 2003 to 2012, shows that circumstances are the leading determinant of inequality in cholesterol, glycated haemoglobin and in a combined ill-health index while effort plays a substantial role in explaining inequality in fibrinogen only.

Recent work has explored the role of different types of schooling as a source of inequality of opportunity in health. Members of the UK 1958 birth cohort, the National Child Development Study (NCDS), attended different types of secondary school, as their schooling lay within the transition period of the comprehensive education reform in England and Wales. This provides a natural setting to explore the impact of educational attainment and of school quality on health and health-related behaviour later in life (Jones, Rice & Rosa Dias 2011). Basu, Jones & Rosa Dias (2018) have extended the evaluation of comprehensive schooling by estimating person-centred treatment effects (PeT) that allow the estimated impact of the policy to differ according to both observed and unobserved characteristics of those affected.

Bijwaard & Jones (2018) have developed a method for mediation analysis applied to Dutch register data on schooling, intelligence and mortality rates. Large differences in mortality rates across those with different levels of education are a well-established fact. Cognitive ability may be affected by education so that it becomes a mediating factor in the causal chain. The paper estimates the impact of education on mortality using inverse probability weighted (IPW) estimators. It develops an IPW estimator to analyse the mediating effect in the context of survival models. The estimates are based on administrative data, on men born between 1944-1947 who were examined for military service in the Netherlands between 1961-1965, linked to national death records. The results show that levels of education have hardly any impact on the mortality rate. Using the mediation method they only find a significant effect of education on mortality running through cognitive ability, for the lowest education group that amounts to a 15% reduction in the mortality rate. For the highest education group they find a significant effect of education on mortality through other pathways of 12%.

4. Biomarkers and the Understanding Society Panel Study

Panel data models have been used to unpick the relationship between health and socioeconomic status (SES). For example, Contoyannis *et al.* (2004), Jones and Schurer (2011) and Jones, Koolman and Rice (2006) explore the dynamics of self-reported health in the British (BHPS), German (GSOEP) and European (ECHP) panels. These kinds of models have been used in analyses of health inequalities to distinguish pathways associated with the *social causation hypothesis* (SES has an impact on health), the *health selection hypothesis* (health has an impact on SES) and the *indirect selection hypothesis* (health and SES are influenced by common confounding factors) that are used in economics (e.g. Adams *et al.,* 2003), epidemiology (e.g. Foverskov and Holm, 2016) and statistics (e.g., Kröger *et al.*, 2016).

Understanding Society, the UK Household Longitudinal Study (UKHLS), began in 2009 and is one of the largest household panel studies in the world. UKHLS incorporates a sample of respondents from the *British Household Panel Study* (BHPS), which had been running since 1991, along with an expanded general population sample (GPS). The UKHLS included nurse health assessment interviews, at wave 2 for the GPS and wave 3 for the BHPS, where blood samples were collected for 13,571 respondents. As a result, comprehensive longitudinal socioeconomic data, that includes suitable measures of circumstances and effort, has been linked to biomarkers that include physical measurements and blood analytes (Benzeval *et al.*, 2014). UKHLS includes cognitive scores for respondents (McFall, 2013) and in future it may be further enhanced by linkage to mortality and cancer registers and to the Hospital Episode Statistics (HES).

The availability of such objectively measured data allows researchers to investigate biological factors that contribute to and interact with health, education, and social conditions. When combined with the longitudinal data, biomarkers can shed light on the complex interplay between biology, behaviour, and environment over the life course. The UKHLS biomarkers allow a focus on chronic conditions and psycho-social stress: they span coronary heart disease (blood pressure, body fat, cholesterol and triglycerides); diabetes (HbA1c); liver disease (LFTs); kidney function (creatinine, urea); anaemia and poor nutrition (Hb, ferritin); inflammatory markers (CRP, fibrinogen, CMV); and hormones (testosterone, IGF-1, DHEAs).

By linking the 18 waves of BHPS to the new data being collected for UKHLS panel data models for the dynamics of self-reported health and socioeconomic status (SES) can be used as inputs into distributional analysis of the health assessments and biomarkers collected in UKHLS. Davillas, Jones and Benzeval (2018) focus on preparing the combined BHPS-UKHLS data, including the biomarker data, for analysis. In addition they set the scene for the distributional regression methods. Rather than addressing inequality of opportunity per se, this article adds to the literature on the income-health gradient by exploring the association of short- and long-term income with a wide set of self-reported health measures and objective nurse-administered and blood-based biomarkers as well as employing estimation techniques that allow for analysis "beyond the mean". Unconditional quantile regressions reveal that the differences between the long-run and the short-run income gradients are more evident towards the right tails of the distributions, where both higher risk of illnesses and steeper income gradients are observed. Carrieri & Jones (2017) have explored the impact of income across the full distribution of the biomarkers measured in the Health Survey for England.

Davillas and Jones (2018) address the issue of selecting which model to use for each biomarker. Using data from the UK Household Panel Survey (UKHLS), they illustrate the comparative performance of a set of flexible parametric distributions, which allow for a wide range of skewness and kurtosis: the four-parameter generalized beta of the second kind (GB2), the three-parameter generalized gamma (GG) and their three-, two- or one-parameter nested and limiting cases. Commonly used blood-based biomarkers for inflammation, diabetes, cholesterol and stress-related hormones are modelled. Although some of the three-parameter distributions nested within the GB2 outperform the latter for most of the biomarkers considered, the GB2 can be used as a guide for choosing among competing parametric distributions for biomarkers. Going "beyond the mean" to estimate tail probabilities shows that GB2 performs fairly well with some disparities at the very high levels of HbA1c and Fibrinogen. Commonly used OLS models are shown to perform worse than almost all the flexible distributions.

The challenge for the future is to build a normative model for the full conditional distributional of health outcomes, proxied by biomarkers, that conditions on circumstances and effort, treating the latter as mediators. This could be estimated using distributional regressions, along the lines of Carrieri & Jones (2017) and Davillas, Jones and Benzeval (2018). The estimated distributions could then be decomposed into direct and indirect contributions, along the lines of Carrieri and Jones (2018).

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