Unfair inequality: the definition of merit, the role of country of birth and the cumulative disadvantage

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Fairness views shape individuals' acceptance of inequality, thus their preferences for redistribution and individual incentives, which, in turn, affect policy intervention and economic growth. Since the 1970s *equality of what* debate (Sen, 1980), unbalances in the distribution of resources are assessed as fair or not depending on the sources of the observed inequality. A society in which worse life outcomes are strongly correlated with the characteristics people is born with, like sex or ethnicity, rather than individual effort and preferences, is commonly considered as undesirable. Equality of opportunities turns out to the be a principle of justice that enjoys widespread approval both in the debate about the egalitarian paradigm involving political philosophers and theoretical economists (Rawls, 1971; Arneson, 1989; Cohen, 1989; Dworkin, 1981a,b; Roemer, 1998; Fleurbaey and Schokkaert, 2009) and in the general public alike. Social surveys and experiments eliciting preferences for redistribution provide indeed evidence that individuals are more willing to accept differences in income which are due to effort rather than exogenous circumstances (Fong, 2001; Cappelen et al., 2010; Alesina and Giuliano, 2009).

> Equal opportunities expand the range of paths open to us – educationally, professionally and in other spheres – thereby giving us the freedom to pursue lives whose contours are at a greater degree chosen by us, rather than dictated by limited opportunities.[...] Opportunities shape not only the paths we pursue but also the skills and talents we develop and the goal we formulate. (Fishkin, 2014, p. 2-3)

In this thesis I embrace the aversion to inequality due to circumstances at birth together with the idea, inspired by Fishkin and enclosed in the previous quote, that we care about opening up opportunities, especially to the individuals who have limited ones, also because opportunities matter for human flourishing and well-being. I contribute to the discourse on distributive justice by considering diverse facets and perspectives. Firstly, exploring the adverse effects on

social welfare resulting from the misleading commitment to meritocracy as a system supposed to ensure equitable distribution of opportunities and rewards. Secondly, assessing the role of the region of birth, among other circumstances, in predicting income inequality over the European continent. Lastly, incorporating a multidimensional notion of well-being, which takes into account the issue of clustering of multiple disadvantages, in the estimation of inequality of opportunity in Australia.

Political discussions about inequality widely rely on the call for the equalization of opportunities which usually end up with the call for meritocracy as an 'effective' way to assign social roles and positions delivering social justice and legitimising inequality. However, merit has been widely questioned both as a normative basis for resource allocation and for the consequences of systems based on it, on social cohesion and on its promises of social mobility (Rawls, 1971; Frank, 2016; Markovits, 2019; Sandel, 2020). More importantly, judgements of fairness invokes a combination of multiple principles ruling the access to opportunities for the development of skills, the factors that matter to compete for roles and positions (where meritocracy can play a role), and the rewards attached to different positions; appealing to a single principle is reductive and misleading. It is exactly on the issues linked to this inaccurate use of meritocracy that the first project of this Ph.D thesis has developed. It builds on Joseph Fishkin's novel perspective on the challenges associated with achieving equal opportunities. Specifically, he claims that the practice of approaching the problem of giving equal opportunity by focusing on single scale of outcomes, with the consequent framing of the system of allocation of rewards with single scale metrics to assess merit, has detrimental impacts on well-being (Fishkin, 2014). Chapter 1, entitled "**Mind the bottlenecks: the social cost of narrow definitions of merit**", is dedicated to the exploration of the consequences on social welfare of a specific definition of meritocracy: a system relying on sorting mechanisms, based on narrow definitions of merit, for the distribution of rewards, which are always opportunities, inputs, for the next competition for resource allocation. The narrow definition of merit is identified as the mechanism driving the failure of meritocracy as an efficient and equitable allocation system. The intuition is that such a narrow reward system would affect individual incentives shaping their aspirations and directions of effort making them converge on the unique goal of obtaining that uniquely defined merit, eventually constraining their freedom and ability to experiment and pursue their

personal form of flourishing, not dictated by limited contextual opportunities (circumstances), which is one of the reasons why opportunities matter in the first place. A theoretical model simulates extreme reward systems in a world with heterogeneous individuals, revealing that monodimensional criteria, affecting preferences, lead to higher inequality, reduced well- being, and skill homogenization, unlike multidimensional criteria. Given that the merit acts as a gate in the opportunity structure, the final call for social justice would imply, therefore, to mind the bottlenecks, meaning to identify which are the narrow definitions of success acting as gates for many opportunities and reducing their unintended impacts by making them more plural (Fishkin, 2014).

Chapter 2 (coauthored with Paolo Brunori[1], Pedro Salas-Rojo[2] and Francisco Ferreira[3]), entitled "**Playing the birth lottery in Europe**", presents an analysis of inequality of opportunity à la Roemer (1998) at a continental level in Europe. The concept of inequality of opportunity refers to the share of inequality that can be predicted by circumstances beyond individual control, such as sex, socioeconomic background and ethnicity. Previous studies have estimated inequality of opportunity at the country level and have often neglected the role of the country of birth. However, as suggested by Milanovic (2015), country of birth may be a key factor in global inequality of opportunity. This is why we turn our attention to supranational inequalities of opportunities, notably, considering the European continent as an entity and assessing the relationship between the continental income distribution and country of origin, along with other circumstances related to familiar background. The research employs three different household surveys to cover as many European countries as possible to analyze inequality of opportunity in the continent: the European Union Statistics on Income and Living Conditions, the German Socio-Economic Panel and The UK Household Londitudinal Survey. Following Brunori et al. (2023c), inequality of opportunity is estimated adopting a data-driven approach based on the Conditional Inference Trees, a Machine Learning algorithm introduced by Hothorn et al. (2006). However, Conditional Inference Trees bear a technical shortcoming: unordered categorical variables with more than 30 categories pose an unsolvable computational limit. Given that the key circumstance of this paper is the individual's country of birth, which can take up to

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179 possible values, we introduce a shortcut in the algorithm to solve this issue. Findings reveal that more than half of the total income inequality in the European continent can be attributed to circumstances and the country in which one is born appears to have the most relevant role in shaping inequality of opportunity in the continent.

Chapter 3 (coauthored with Paolo Brunori[1] and Antonio Consolo[2]), entitled "**Born to struggle: inequality of opportunity in income, health and education**", is dedicated to inequality of opportunity in income, health and education. The focus moves to such definition of the valuable life outcome because well-being is inherently a multidimensional notion (Stiglitz et al., 2009), people care about multiple aspects of life. Moreover, one-dimensional analysis fails to account for the clustering of multiple disadvantages, thus, the dependence between dimensions, which is the key feature of multidimensionality (Decancq, 2014; Ferreira and Lugo, 2013; Kobus et al., 2020). Imagine a fictitious unfair society in which as female and migrant, one can expect a lower income than males who are born within the country. If female migrants are also the group which is more likely to be deprived jointly in terms of level of education and health status, the society is definitely even more unfair. The exploration of interdependence is not only relevant as a fine description of multidimensional well-being, but it holds a pivotal position within the framework of pluralistic distributive justice theory. As theorized by the political philosopher Michael Walzer (1983), while simple equality deals with the distribution of one dimension of well-being, like income, in a multidimensional perspective, complex equality requires that the dimensions of well-being are autonomous or independent. The presence of cumulative deprivation, thus, of individuals who occupy a low position on all well-being dimensions at the same time, would be a indicator of complex inequality in the society. We introduce this perspective into the framework of equality of opportunity given also that as Fishkin (2014) claims, structuring the system with the aim of giving equal opportunities for a single scale outcome, say income, in the end may restrict individuals' freedom to choose what they care about affecting the role that opportunities have in the personal development of skills, talents and goals.

Following Decancq (2023), we adopt a position-based indicator as a proxy of multidimensional well-being. Inequality of opportunity is estimated adopting a data-driven approach based on the Soft Regression Trees, a Machine Learning algorithm introduced by Consolo et al. (2024).

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Birth circumstances such as sex, area of birth, Aboriginal status, and parental socioeconomic background are used as predictors. Drawing on two decades of data from the Household, Income, and Labour Dynamics in Australia survey, the research observes the evolution of multidimensional inequality of opportunity, and of the dependence among its defining dimensions, across cohorts of people living in Australia and born between 1951 and 1996. The findings suggest a stable trend in the level of association among income, health and education, together with an increase in relative inequality of opportunity. Additional insights on the importance of the single circumstances on the well-being predictions are extracted by employing the SHAP (SHapley Additive exPlanation) method. Across the birth cohorts, there is an increase in the relative importance of maternal occupation in predicting well-being compared to paternal occupation. Additionally, across the various birth cohorts, Aboriginal status has a significant negative impact on multidimensional well-being, although its low frequency in the population results in a relatively lower overall influence compared to other circumstances.

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If one asked a slum youth why he did not take steps to pursue a middle-class path to success... the answer might well be not «I don't want that life», but instead, «Who, me?».

Ann Swidler, 1986

1

Mind the bottlenecks: the social cost of narrow definitions of merit

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Abstract

Nowadays the discussion on distributive fairness mainly lies on the sphere of opportunities rather than on outcomes. Inequalities in rewards are perceived as acceptable as long as they reflect differences in effort, ability, or performance across individuals, rather than inherited privilege. At the same time, meritocracy is widely sustained and called for as the system delivering an efficient and fair final allocation of opportunities and rewards. Its appeal is plain to see: assigning roles on the basis of individual achievements rather than ascription seems crucial to move towards a fair distribution of unequal outcomes. Recently, a vast literature in the social sciences has documented its unfulfilled and unfulfillable promise and its side effects on the society overall. This paper identifies in the key element of a meritocratic system, the definition and measure of merit, the mechanism driving its failure as an efficient and equitable allocation system. In a world with heterogeneous individuals, the reliance on sorting mechanisms based on necessarily narrow definitions of merit for the distribution of rewards can produce undesirable consequences. A theoretical model is built as to simulate the dynamics of individuals' choices under two extreme reward systems, to explore how they differently shape aggregate social outcomes. Under a mono dimensional, narrow, evaluation rule, the society suffers as a result in terms of inequality, social welfare and diversification, compared to a world in which the evaluation rule is pluridimensional. Given that the merit acts as a gate in the opportunity structure, the final call for social justice would imply, therefore, to *mind the bottlenecks*, meaning to identify which are the narrow definitions of success acting as gates for many opportunities and reducing their unintended impacts by making them more plural (Fishkin, 2014).

Keywords: social justice, pluralism, inequality, merit, opportunities
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1.1 Introduction

Nowadays the discussion on distributive fairness mainly lies on the sphere of opportunities rather than on outcomes. Inequalities in rewards are perceived as acceptable as long as they reflect differences in effort, ability, or performance across individuals, rather than inherited privilege, implying a call for interventions to guarantee equal opportunities, a leveled playing field at the *starting gate* of the competition for jobs and social roles. At the same time, meritocracy is widely sustained and called for as the system delivering an efficient and fair final allocation of rewards. Its appeal is plain to see: assigning roles on the basis of individual achievements rather than ascription seems to lead towards a fair distribution of unequal outcomes.[1] But what is the exact meaning of meritocracy and equal opportunity and how do the two concepts relate to each others? As the famous quote by Sen says: *the idea of meritocracy may have many virtues, but clarity is not one of them* (Arrow et al. (2000), pg.5). Tracing back the concepts to their origin may be helpful for the following discussion with no claim of being exhaustive.

Meritocracy represents the vision of a hierarchical form of social organization in which the group of people who have power over the rest of the population are chosen according to individual merit, not by social origins as in a caste-like system. Although it is believed to be part of the *Western thought* developed during the Enlightenment, it had actually formed the basis of the Chinese model of statecraft for centuries (Graeber and Wengrow, 2021). Despite the long history of this form of social stratification, the term itself was relatively recently coined by Young in 1959 in his dystopian novel *The rise of the meritocracy, 1870-2033: The new elite of our social revolution*. It was used to describe a world that, transitioning from an hereditary to a new class system based on merit, identified by intelligence tests and education in the name of growth, ends up with worsen social outcomes in terms of social divisions and inequality, due to the moral claim of personal worth implied in the concept of merit. Despite its pejorative origins, starting with Bell (1972), a positive interpretation took hold. The concept, especially the education-based meritocracy, attracted considerable support and it has been widely used as an expedient tool of policy-making and political propaganda since the post-war years. Raising the school-leaving age and the mass secondary school education, among other *welfare state* reforms,

[1] In this chapter merit, achievement, success, performance, evaluation rule are used interchangeably, as well as opportunities and rewards, since I assume there does not exist a final reward which is not an opportunity for something else.

like public housing, national health service and social security, contributed to the improvement of the working classes' living conditions and the upward mobility of their offspring in the hierarchy of occupations, income and, to some degree, status. Meanwhile, the booming idea of a personal and national prosperity driven by knowledge, the human capital theory (Mincer, 1958; Becker, 1960; Schultz, 1971) and the resulting need for governments to stimulate individuals' effort, fuelled the support for a selection system based on talent, proxied by educational achievement. In today's economy, it is indeed believed that the more skills and credentials one has, the more productive one becomes, the higher one's income reflecting the higher contribution to national production (Becker, 2006). Notwithstanding the widespread support and adoption of the education-based meritocracy in the name of efficiency, the critiques and debates in philosophy and sociology were not lacking, especially on the issue of the relation between meritocracy, equality and social justice. The shortcomings of such system of allocation were indeed already evident: the positive effect on social mobility dissipated soon with the establishment of a new enclaved class, a cognitive elite, able to pass on their offspring their achieved status. Moreover, during the same decades, a new vision of social justice as equality of opportunity was emerging: theories in both political philosophy and normative economics burgeoned starting with Rawls (1971). He challenged the dominant *welfarist* paradigm by disputing whether equity and social justice could be defined only with reference to the distribution of individual preference satisfaction, arguing that a mere equality of outcomes is not ethically desirable because it does not hold individuals responsible for their choices. An equitable society is rather one that equalizes, for all its members, the opportunity to attain the outcomes they care about (Ferreira and Peragine, 2016). In political philosophy it became the debate "equality of what?" as termed by (Sen, 1980), which generated several non-welfarist theories from the right to the left ends of the political spectrum (Nozick, 1974; Dworkin, 1981a; Arneson, 1989; Cohen, 1989; Sen, 1980). Common to these views is the idea of the individual responsibility for life outcomes, whether successful or not; however the choice of the boundary between what lies within and beyond individual control, thus, when to socially intervene to compensate for disadvantages is vague. As a result, views concerning what is required for equal opportunity cover a large spectrum, from the nondiscrimination principle ensuring equality as *career open to talent* (Rawls, 1971) to the social intervention to correct and compensate as early as possible the disadvantages due to birth circumstances (Roemer, 1993; Arrow et al., 2000). Thinking about meritocracy, the

merit-based social stratification, and the basic version of equality of opportunity as *career open to talent*, it immediately emerges a similarity between the two. This could be one of the reasons why discourses about efficiency and equity started to overlap and mixing in a ambiguous idea of social justice guaranteed by a meritocratic rule for social advancement combined with interventions aimed at compensating initial disadvantages potentially affecting individual merit. With this framework in mind, we can think of the boom in the use of standardized tests and rankings, used to objectively assess and compare individuals' educational achievement that, considered a proxy of their productive traits, should be incentivised for the social welfare. Besides, in line with the reasoning above, the introduction of social policies like positive discrimination (affirmative actions), compensatory education, school integration and so on, were thought to help undo the effects of previous disadvantages (historical, familiar, geographical, etc.).

Despite social scientists and philosophers have been expressing worries about the flaws of such system and especially the risks of the misuse of the concept of responsibility (and merit) with its blurred distinction from the moral claim of individual deserviness since the developments of the two concepts (Young, 1959; Rawls, 1971; Sen, 1980; Fleurbaey, 1995), meritocracy and/or equal opportunity turn up everywhere, advocated by politicians of any color, in the narratives of the movies and media but also of ordinary people's stories about their lives. The belief in it seems to be as strong as it ever was, paradoxically, since within society inequalities has grown and social mobility has not. Mijs and Savage (2020) explain this inconsistency exactly pointing to the aforementioned reason of concern of the main exponents of the ideas themselves: the focus on individual responsibility which legitimizes the inequalities probably more than any other form of social organization, and relative allocation of rewards, no matter how arbitrary. As concerns those who succeed, the elites, the belief in meritocracy[1] gives them a sense of entitlement which make them forget the role of luck in their achievements, which is not limited to the birth lottery - involving family wealth, genetic traits, upbringing - but it keeps playing a crucial role throughout one's life, as Frank (2016) has thoroughly explained.[2] This sense of entitlement carries a worrying blame of the *undeserving poors* for their failure and the inherent disregard and reduced support for redistribution (Alesina and Angeletos, 2005; Krawczyk,

[1] Whatever definition of meritocracy we have in mind, being it a *shallow* one, the general non-discrimination principle in recruitment, or a *sound* one, which would involve interventions aimed at compensating for the inequalities due to birth circumstances.

[2] He contributed in a major way to a growing literature which quantifies the impact of luck on individual social and economic success.(Pluchino et al., 2018; Sobkowicz et al., 2020).

2010; Hecht, 2021). Poor people, on their side, are convinced they have themselves to blame for their inability to overcome the barriers of social mobility. This narrative leaves the individuals alone with their good or bad choices, impairing class consciousness and solidarity, thus, the social class conflict. Sandel (2020) brings this argument further claiming that the current system of winners and losers contributed to the triggering of the anger and social resentment explaining the raise of populism. To make it even worse, it still remains to recognize that the emphasis on responsibility and the adoption of a meritocratic (knowledge-based) system of allocation to assess and sustain progression towards individual prosperity in life rather than to specific institutional roles entails an overlap between what should have been *institutional desert* and personal worthiness. This ideology, thus, makes all the possible forms of individual flourishing converge to the dominant knowledge-based definition of merit, shaping life itself as a zero-sum competition. Questions arise regarding the opportunities left, if any, in this form of social organization to those who do not conform to the prevalent definition of merit, think of the mentally disabled and, more in general, to people with abilities not envisioned as productive skills. Is this good enough for social justice? Is it better than the old caste-like system of social hierarchy in terms of efficiency? Does it allocate status and power to the most qualified individuals, no matter their social origins and connections? As Young (1959) foresaw and as it has been observed, although increased access to higher education was introduced and seen as a great equaliser, a couple of generations later, it revealed to be a great *stratifier*: just a system that enables the emergence of new privileged classes on the basis of the prevalent merit concept, educational achievements, which are then able to consolidate their power exactly by managing the definition of merit itself. As Mijs (2016) exhaustively argues, education-based meritocracy is not only an unfulfilled promise, but an unfulfillable one. Indeed, three aspects he identifies as responsible of its failure are the following:

1. uneven playing field, since important factors for success, natural endowments such as natural ability, IQ, physical condition, attractiveness etc, are unequally distributed by the birth lottery;

2. biased assessment, driven by teacher bias, stereotype threat and the design of examinations and selection procedures;

3. no neutral definition of merit, since what constitutes merit is historically shaped and

institutionally specific.[1]

In response to its failure, many calls for a better meritocracy (Wooldridge, 2021) and the issue of the uneven playing field mainly motivates the well known ongoing efforts by scholars and policy makers for the equalization of opportunities and the closing of achievement gaps. Although persuasive, it is ontologically and practically impossible to fully compensate individuals for the disadvantages due to factors beyond one's control, if we embrace a theory of human development seen as a process of iterative interaction between the individuals, with their genetic heritage and traits, their ambitions and effort, and the environment. As Fishkin argues, the attempt to distinguish between the person and her counterfactual, *what would have been her outcome under different circumstances*, to assess and reward her own contribution to the achievement, is an endless work "like peeling away the layers of an onion" (Fishkin, 2014, p. 64), separating the person from herself, which, taken to the extreme, could even lead to the creepy idea of gene engineering.[2]

1.2 Bottlenecks of the opportunity structure

Inspired by the works by Fishkin (2014) and Mijs (2016), among others, this paper claims that a meritocratic system of allocation of opportunities is an illusion and it is undesirable. Firstly, it is an illusion because, given the impossibility to fully equalise opportunities and its reliance on a single, context-dependent definition and measure of merit, it will end up reproducing existing inequalities failing in its efficiency and equity purpose. Secondly, it is undesirable as an ideology because it worsen social welfare not only through to the increased polarization and stigma of the losers, but through its narrow definition of what matters for human flourishing which increases competition, reduces the possibility to experiment different life paths, makes

[1] Mijs (2016) reports many interesting studies describing important traits rewarded with social status in different historical period and societies; for instance, manliness, aggression, asceticism and (bi)sexuality in Sparta,400 B.C. or pacifism, vegetarianism and asexuality in Western Europe anno 479 and so on.

[2] This argument is indeed backed up by the works in behavioral and experimental economics which provide evidence supporting the theory of endogenous preference formation process (Akerlof and Kranton, 2000; Hoff and Stiglitz, 2010; Sheehy-Skeffington, 2021; Guyon and Huillery, 2021; Falk et al., 2021; Delavande et al., 2020) as well as the fast developing literature that quantify and estimate the importance of genes, environments and their interaction on socioeconomic outcomes (thanks to the recent advances in genetic discovery and the availability of genetic data in many social science datasets (Pereira et al., 2022; Biroli et al., 2022; Harden, 2021), besides the above mentioned literature on the role of luck over the life course.

the society much more homogeneous in terms of preferences and skills and makes positional the value of the measure used as proxy. The latter point brings to mind what Strathern defines Goodhart's law: "when a measure becomes a target, it ceases to be a good measure" (Strathern, 1997, p. 308): educational credential indeed have acquired much more value as status signal and the educational system itself appears to be increasingly focused on serving the purpose of training ground for the labor market, disregarding the role of education in building character and citizenship (Mijs, 2016). In the present paper I argue that it it the case because the mechanism behind these unintended side effects on social welfare is exactly the defining feature of meritocracy: the reliance on one, narrow definition of merit, thought as a way to make more objective the comparison of individuals' abilities and the framing of opportunity-equalizing policies. Fishkin (2014) offers the example of an hypothetical unitary modern society, the big test society, in which individuals can pursue several different careers and professions depending on their performance on a test, taken at age sixteen. The test is what he defines a bottleneck of the opportunity structure, meaning a narrow gate through which one must pass in order to pursue a wide range of paths. Allocating opportunities according to a single crucial criterion, like the test, eventually drifts the society apart from the original purpose of ensuring fairness together with maximizing efficiency. The intuition is the following: such a narrow reward system would affect individual incentives shaping their aspirations and directions of effort making them converge on the unique goal, for instance, of passing the test, eventually constraining their freedom and ability to experiment and pursue their personal form of flourishing, not dictated by limited contextual opportunities (circumstances), which is one of the reasons why opportunities matter in the first place. Moreover, the measure of merit, being narrow, will inevitably reduce human complexity and favor some skills more than others, then reproducing initial inequalities relative to those chosen skills. Lastly, given that such an evaluation tends to mirror preexisting advantages, allocating the pie according to a ranking of individual's merit will inevitably lead to higher inequality because those who happen to have high ability in the field referred to as a proxy for merit will get the highest share of the pie reducing the other's opportunities.

Similarly, the allocation of academic positions to researchers and public funds to universities increasingly relies on rankings mainly based on the use of citation-based bibliometric indicators to quantify the impact of published research. Emerging undesirable incentive dynamics

can explain the observed increase in self-citation rates and exchange of citations between co-authors (Fire and Guestrin, 2019). The latter is among many papers about the effect on science of environmental contexts where governance by indicators is practiced; among the effects of such a narrow research evaluation system there is the reduction of intellectual diversity and pluralism, the suppression of interdisciplinary research, herd behavior in selection of topics but even bad practice that corrupts science, making it a dogma guaranteed by the label of the top publication, rather than a battle of ideas (Baccini, 2018).

Eventually, Fishkin calls for *Opportunity Pluralism*, the removal or reduction of the bottlenecks in the opportunity structure, as the direction to follow to guarantee an open range of opportunities to everyone at every stages of life. It could reduce the constraints on individual and families investment choices and the competition for single valued life path. It might also reduce the association between personal worthiness and productive skills, the resulting social polarization and it may increase diversification of skills. If national growth and competitiveness is what societies aims for with incentives for hard work, pluralism and diversification of skills, as in biological systems, achieve long-term stability in a changing environment such as the current globalized world.

1.3 Objective

The main goal of the paper is to study how the rules according to which society allocates opportunities affect social welfare, through individuals' choices. To this end, I develop a model of a simple economy of heterogeneous agents who choose how to invest their effort across several fields to develop skills from which they get rewards according to an evaluation rule of their total skill level, a measure of the individual's merit. The aim is to show that if this rule is narrow, monodimensional, meaning that it weighs only the skills at one activities, the society suffers as a result in terms of social welfare, inequality, consolidation of initial advantages and lack of diversity, compared to a world in which the evaluation rule is pluridimensional.

The current prevalent definition of merit is knowledge-based, proxied by educational achievements, but, as previously mentioned, the tendency to allocate rewards, resources sorting on the basis of one meaning of merit proxying productivity has not only interested the individual but

also organizations such as schools, universities and hospitals, with cascading effect on the employees' incentives and the beneficiaries of the services. That is the reason why I suggest that the image of bottlenecks in the opportunities structure emblematically represent real world trends: they directly bring to mind the heavy reliance on standardized screening and assessment tests for decisions related to many valuable individual outcomes like university admission, internships, occupational licensing and entrance into prestigious occupations but also used to allocate resources to schools and universities.

1.4 Methodology

The awareness of the pervasiveness of this system of allocation drives the choice to develop an abstract model that can ideally encompass many different settings and illustrate the stylized mechanisms driving the undesirable consequences in the final allocations. Therefore, this work adopts a computational technique, a preliminary theoretical agent-based model with little empirical ambition, as a way to study large-scale outcomes deriving from the behavior and interaction among heterogeneous individuals and the environment. This approach appears useful because it allows to consider a greater level of complexity incorporating more realistic models of human heterogeneity in abilities and behavior, not limited to the rational maximizing one, but also on the sources of information which the agents make their decisions on.

1.4.1 Model description

Agents and parameters

The economy is populated by N individuals $i = 1, ..., N$ who select, over multiple periods, how to invest effort $e_i \in \mathbb{R}^M$ across M possible activities or fields, getting final skills $s_i \in \mathbb{R}^M$ as a function of their initial abilities $a_i \in \mathbb{R}^M$. We assume heterogeneity in the individuals' level of initial abilities at the different fields, but no inequality in the total amount of resources, the total effort they can invest across the activities, $\sum_j e_i = 1 \quad (j = 1, ..., M)$. The agents' utility depends on the reward they get from their skill score and the cost of effort exerted. The amount available in the society for the allocation of the individual rewards is endogenous to the economy, being equal to the total yearly production. Each field contributes to the total value production Ω according to a coefficient of production $\beta \in \mathbb{R}^M$.

The society distributes the value produced Ω allocating rewards to the agents on the basis of their skill score $\lambda_i \in \mathbb{R}$, which is what we called the ***measure of merit***, a metric used to assess, compare and reward, indeed, individuals. The design of the just mentioned metric, meaning the way in which the skill score is constructed on the basis of the skills at the different fields is our main feature of interest. In this basic model we simply assume a linear combination of the skills at the different fields weighted by the coefficient γ, which stands for a sort of notional contribution of each activity to social value. By varying the number of dimensions along which the skill score is computed, we define two extreme cases: the *pluridimensional* score which uniformly combines all the fields' skill levels and the *monodimensional* one that takes as input the skill level at only one field.

The functions used for this basic model are listed below:

- Skills: $S_{ij} = (A \circ E)_{ij}$ for $i = 1..., N$ and $j = 1, ..., M$
- Skill scores: $\lambda = \gamma \cdot (S)_{ij}$ with $\gamma \in \mathbb{R}^M$
- Rewards: $r = \Omega \frac{\lambda}{\sum_i^N \lambda_i}$

  with total production: $\Omega = \sum_{i=1}^N \beta \cdot (S)_{ij}$ with $\beta \in \mathbb{R}^M$
- Cost of effort: $c = \sum_{j=1}^M (E)_{ij}^2$[1]
- Utility: $u = r - c$

Individual behavior and social dynamics over time

We now introduce time periods and different individual behaviors in the population in order to explore what happens over time in the two *worlds* defined by the extreme definition of *measure of merit*: pluridimensional and monodimensional.

In the first period of time ($t = 0$) each agent starts out by investing a randomly selected effort strategy $e \in \mathbb{R}^M$, but at any later time step ($t = 1, , T$), they individually choose how to allocate effort among the M activities.
We assume three possible behaviors:

[1] The function chosen suggests individual's preference for diversification of effort.

- the individual acts rationally, with a probability α;
  Rational agents choose to allocate their effort e_t^* maximizing their current utility ($u_{i,t}$), based on last year total production (Ω_{t-1}) and total skill score in the population ($\sum_{i=1}^{N} \beta \cdot (S)_{ij}$), naively ignoring the contribution of theirs and others' choices to the current period's total production and total skill score.

- the individual acts randomly, with a probability δ; or

- as a conformist.
  The conformist agent imitates the effort investment strategy of the top-ranked individual in terms of utility, the individual who got the maximum utility in the previous period. The imitation attitude can be thought as due to the interaction of uncertainty about own abilities, risk aversion and myopia.

Over time, agents' abilities at each activity evolve according to the effort invested according to the following rule:

$$(A)_{ij,t+1} = (A)_{ij,t} \times \left(\frac{(E)_{ij,t}}{0.06} \right)^{1/30}$$

which leads to no ability growth with minimum effort level, defined as effort uniformly distributed among the activities, and slow increase/decrease in case of effort higher/lower than the minimum level.

Outcomes of interest

The model is built as to simulate the dynamics of individual agents' choices under two different extreme institutional settings, to observe how they differently affect social welfare. As stated above, the parameter of interest is $\gamma \in \mathbb{R}^M$. The two extreme cases considered are one in which it is concentrated, meaning that it gives weight to only one field (γ_m, *monodimensional*) and the other in which it is uniformly spread among the M fields γ_p, *pluridimensional*). On the other hand, we assume that the real contribution to value production $\beta \in \mathbb{R}^M$ is the same for all the M activities.

We are interested in observing the dynamics of the following macroscopic variables, under the two different settings:

- welfare, defined in standard way as the sum of individual utilities;

- diversification of skills in the population;
- inequality in the final utility distribution;
- role of effort and luck.

Simulating the model

The model has been coded and the simulation run in Python with the following inputs:

- Niter - number of iterations: 100
- N - number of agents: 1000
- M - number of fields/actions: 15
- T - number of time steps: 10
- α - probability of behaving as utility maximizer: 0.5
- δ - probability of choosing effort randomly: 0.05
- $(1 - \alpha - \delta)$ - probability of behaving as conformist: 0.45

1.5 Results and discussion

The simulation of individual choices over 10 periods in the two extreme institutional settings delivers the following preliminary aggregate results:

- as figure 1.1 shows, social welfare in the world characterized by a pluridimensional measure of merit is almost always higher that in the monodimensional case;
- figure 1.2 shows the utility distributions in the two institutional settings at the last period T: in the world defined by a monodimensional measure of merit, the dispersion of utility is higher compared to what emerges under a pluridimensional rule. The Gini coefficient indicates indeed a lower level of inequality in the latter;

- as regards the diversification or specialization of skills in the society overall, the heatmap in figure 1.3 illustrates the skill level achieved by each individual for each activity, under the two reward systems. It is evident that in the *monocultural* world the society ends up being highly specialized in the only field considered by the evaluation rule whereas, under a pluridimensional measure, the societal skills are way more diversified.

The mechanism envisioned behind the result is the incentive inherent in the narrow definition of what is to be rewarded: individuals' efforts converge towards that rewarded field, disregarding initial abilities. This will not increase the size of the pie since we assume a production function to which all fields uniformly contributes. However, it affects individual utility since concentration is assumed to be costly for the individuals. It leads to higher inequality because the focus on relative performance and the access to everyone to the same competition, create a winner-takes-all market, where small differences in performance turns into large differences in rewards (Frank and Cook, 2013).

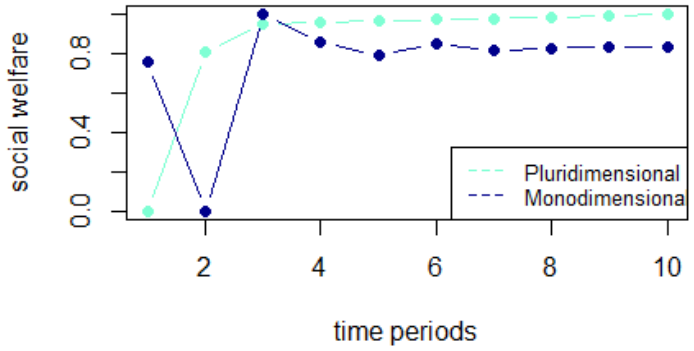


Figure 1.1: Simulation's result: social welfare over time under monodimensional and pluridimensional measure of merit

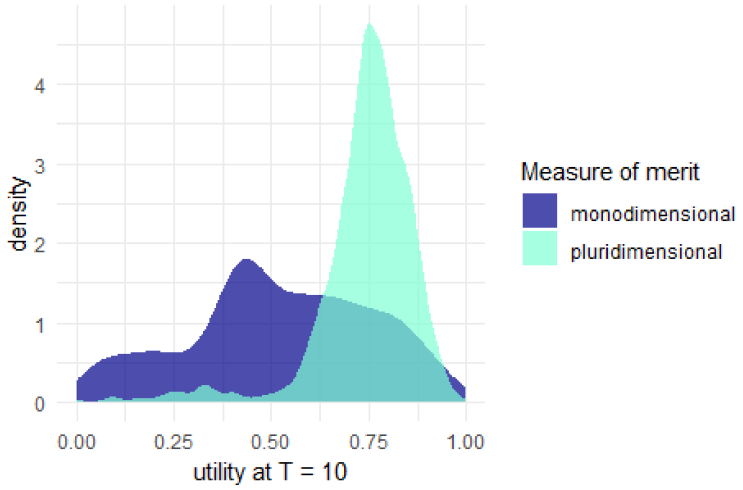
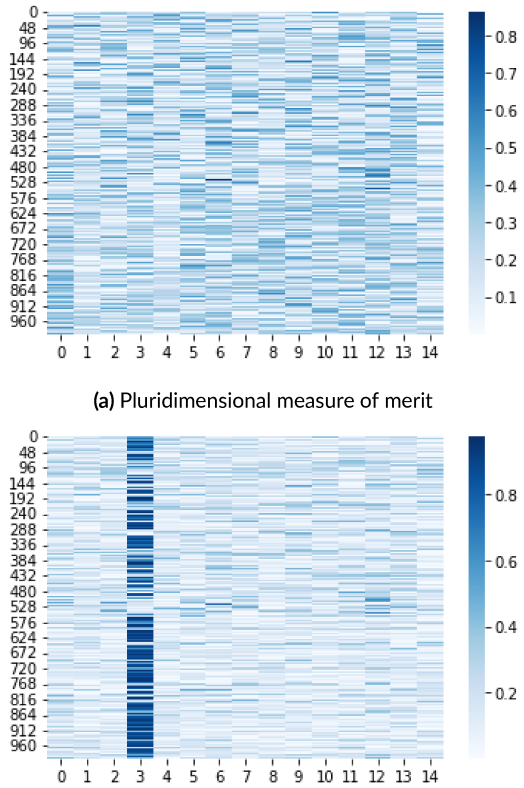


Figure 1.2: Simulation's result: utility distribution at time T under monodimensional and pluridimensional measure of merit



(a) Pluridimensional measure of merit

(b) Monodimensional measure of merit

Figure 1.3: Simulation's result: skill levels across individuals and activities at time T under monodimensional and pluridimensional measure of merit

1.6 Conclusions

The idea inspiring this chapter is to show that the system through which we currently allocates opportunities, although thought as more efficient and fair than any other arbitrary rule of hierarchical social organization, has actually undesirable consequences on the overall well-being of the society. The need to compare individuals' outcomes on the same scale is inherent in a meritocratic system of allocation of jobs and social roles and in the framing of the unfair inequalities issue and the consequent policies aiming at equalizing opportunities. The main claim, inspired by Fishkin (2014)'s concept of *bottlenecks* of the opportunity structure, is that the definition of a unique, easy to measure, scale and the sorting themselves lead to undesirable outcomes in terms of convergence of preferences, with the consequent lower skills diversification, increased competition and higher inequality in rewards. The incentives to compete induce strategic behaviors which may not be desirable when the good used as measure of merit has other purposes beyond serving as scale of comparison. The tasks of educational institutions is not limited to sorting efficiently for the labor market but preparing for active citizenship and opening the range of paths that one can envision for his future too, for instance; however, the focus on its use to sort individuals and signal their productive potential in the labor market (their merit) crowd out its other purposes and makes its value positional. Moreover, a narrow definition of merit implies a dimensionality reduction of human identities, since it narrowly organize social structures around one salient dimension of identity, the productive traits we are able to perceive and measure, with all other dimensions switched off. Such a system inevitably excludes groups of people that for genetic, historical or environmental reasons, and the interaction of those, happen to have lower scores in that measure. The issue arises when the gatekeepers defining and assessing merit are exactly the *deserving* ones according to the dominant definition of merit; this will lead to a reproduction and consolidation of existing inequalities, historical biases and under representation.

Given the complexity of the debate on efficiency and social justice and the pervasiveness of the belief in a meritocratic system of allocation in different settings, an abstract stylized model of interaction of individual choices and the institutional environment has been developed and tested, employing a computational method which provides more flexibility in the representation of the heterogeneity of the individuals and their behavioral rules. The world with the bottleneck in the opportunity structure, thus characterized by a monodimensional definition of

merit, has been contrasted to a pluralistic world where many dimensions inform the merit score. A pluralistic world where a larger variety of contributions to social value is contemplated seems to be a society where people can experience and follow different paths to a flourishing life, leading to a higher diversification in skills and lower inequality in rewards. Moreover, the resulting social organization is expected to be less susceptible to the mentioned undesirable consequences of meritocracy like the polarization and blaming of the unsuccessful, the high competition and the reproduction of existing inequalities. It it not easy to propose an alternative allocation system, to concretely frame pluralism; as Fishkin (2014) conceives it, it is more a direction of effort: identifying the narrow definitions of merit that give access to broad range of opportunities and social roles and working with the objective to open them, potentially empowering diverse institutions as gatekeepers and so reducing the bias towards one dominant standard.

As a society we should probably try to come up with creative solutions to the fair social organization issue and, to this end, as Graeber and Wengrow (2021) argue, we may first try to approach the human past with fresh eyes, acknowledging that the actual archaeological evidence is inconsistent with the dominant narratives of humans as either innately hierarchical or egalitarian[1]. That view constrains our sense of human possibility since it leads to a conception of the the current social organization as the inevitable form of social arrangement guaranteeing overall prosperity, even though requiring compromises in terms freedom and equality. Graeber and Wengrow (2021) provide evidence from archaeology and anthropology suggesting that peoples of prehistoric times had their specific rules of social allocation of labor and power and those varied considerably across the societies, refusing the narrative of a primordial inferior human soup that evolved with economic progress.

[1] Hobbesian hawks and Rousseauian doves (Graeber and Wengrow, 2021).

No, but where are you 'really' from?

Ball et al.,2022;CNN, 2017

2

Playing the birth lottery in Europe

Thesis advisor: Professor Paolo Brunori Annaelena Valentini

Playing the birth lottery in Europe

Abstract

We have no choice over the geographic area where we are born and raised and the stakes of this lottery of birth are very high, considering that nowadays, despite a decreasing trend, between-country inequality still contributes to half of the global income inequality. The paper explores the role that the country of birth plays in explaining income inequality across European citizens. Being a factor beyond individual control, region of birth is a circumstance as sex, socioeconomic background and ethnicity, the ones traditionally considered as unfair sources of inequality in the Inequality of Opportunity literature. Employing a data-driven methodology we estimate inequality of opportunity in household income at a continental level in Europe in 2019 and we assess the specific contribution of the country of birth, among other circumstances. The study gather data from three different household surveys - EUSILC, GSOEP and UKHLS - and from EUROSTAT, to cover as many European countries as possible and to obtain a dataset representative of European citizens, including migrants. The findings reveal a level of inequality of opportunity ascending to 0.22 Gini points, suggesting that more than half of the total income inequality in Europe can be attributed to circumstances at birth. The country in which one is born appears to have the most relevant role in shaping unfair inequality, accounting for 62% of the estimated I.Op, followed by another factor beyond individuals' control, the father's occupation, which contribute to 18%.

Keywords: inequality of opportunity, place of birth, migration, income distribution, Europe.

JEL codes: D31,J60,O52,O54

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2.1 Introduction

We generally do not think of birth as a type of lottery but this is an analogy that works well when we consider how significantly factors beyond individual control, like race, sex, parental background and location of birth may affect the life chances of the newborn. Since the 1970s *equality of what* debate (Sen, 1980), unbalances in the distribution of outcomes are assessed as fair or not depending on the sources of the observed inequality. A society in which worse life outcomes are strongly correlated with the characteristics people is born with, the lottery of birth, rather than individual effort and preferences, is commonly considered as undesirable. The pioneering work of Roemer (1993) and Fleurbaey (1995) paved the way for the development of an empirical literature aimed at measuring how far a society is from a fair distribution of outcomes, in which there is equality of opportunity (EOp), when inequalities is not predicted by factors beyond individual control[1].

Empirical applications of this idea have traditionally focused on a specific country (Lefranc et al., 2009; Checchi and Peragine, 2010) and cross-country comparisons (Ferreira and Gignoux, 2011; Marrero and Rodríguez, 2012). However, nowadays, the country in which one happens to be born is a key factor of the lottery of birth. Indeed, despite a decreasing trend observed over the last 30 years, between-country inequality still contributes to half of the global income inequality (Milanovic, 2024). As Milanovic (2012) shows, if you are lucky enough to be born in Italy or in Germany, in the worst case scenario of ending up in the poorest 5% of the national distribution of income, you will have an income equal or higher than, respectively, the 60% and 80% of the the world population. Conversely, if you "lose" the country of birth lottery and you are born in Mozambique, your life chances will be more limited: even if you are among the richest 20% of the population, you will be at the 65th percentile of the world income distribution.[2] As the world has become more integrated, people's awareness of the different standards of living has increased as well as individual incentives to migrate. Consequently, the relevance and the interest in the estimation of world inequality and the share of it explained by country differences has increased.

On a smaller scale but at a greater intensity, the process of economic and political integra-

[1] For a survey of the theoretical framework, see Roemer and Trannoy (2015) and Ferreira and Peragine (2013)

[2] Distributions based on global data derived from nationally-representative household surveys conducted around 2005 (Milanovic, 2012).

tion of European countries, guaranteeing the free movement of goods and people, has strongly increased life opportunities for many people as well as their perception of social inequalities.

In this paper we turn our attention to supranational inequalities of opportunities, notably, we consider the European continent as an entity and we assess the relationship between the continental income distribution and country of origin, along with other circumstances related to familiar background.

One of the reasons that makes relevant focusing on inequalities between European citizens is what has been termed the *Europeanization* of social inequalities (Heidenreich, 2016), which suggests both that the supra-national developments objectively affect the national distribution of income and opportunities of people and that, from a subjective perspective, the reference group for Europeans has changed: they compare their living situation not only with their compatriots, but also with other Europeans. A second key reason is that the principles of non-discrimination and equal opportunities for all individuals, regardless of their nationality, are integral to the European project. The community of nations has often expressed two lofty aims: first, already in the 1957 Treaty of Rome establishing the European Economic Community (EEC), that the life chances available to European citizens should not be overly determined by their nationality or their sex.[1] Second, that disparities across European regions should be gradually eliminated.[2] While the latter has been constantly monitored leading to abundant evidence of the process of catching up of poorer countries with the rest of the continent observed between 1980 and 2008, there is less evidence on the evolution of the integration process in terms of fairness. The evaluation of the level of inequality of opportunity in income in Europe has always been conducted relying on cross-country comparisons, thus, not including the country of birth among the circumstance variables. (Marrero and Rodríguez, 2012; Checchi et al., 2016; Brunori et al., 2023c).[3]

[1] Article 7 of the Treaty of Rome of 1957 states: "Within the scope of application of this Treaty, and without prejudice to any special provisions contained therein, any discrimination on grounds of nationality shall be prohibited."; Article 119 of the Treaty of Rome of 1957 states: "Each Member State shall during the first stage ensure and subsequently maintain the application of the principle that men and women should receive equal pay for equal work."

[2] As stated in Article 158 of the Treaty establishing the European Community: "In order to promote its overall harmonious development, the Community shall develop and pursue its actions leading to the strengthening of its economic and social cohesion. In particular, the Community shall aim at reducing disparities between the levels of development of the various regions and the backwardness of the least favored regions or islands, including rural areas."

[3] Similarly, the evaluation of poverty and inequality is measured as population-weighted average of national

Using unique data on the national origin of parents, this paper sheds light on the following questions. First, how important is the lottery of birth in contemporary Europe: what share of the continent's overall income inequality is accounted for by circumstances at birth, such as parental education, occupation, and country of birth? Second, we ask which is the most relevant factor, between parental background and country of birth, in shaping inequality of opportunity in Europe. Third, focusing on migrants, we explore the heterogeneity in income opportunities among various origin countries.

This work builds on and provides a contribution both to the literature on inequality of opportunity and to the one concerned with the estimation of income inequality in supranational entities. Estimating inequality of opportunities among world citizens, as well among European citizens, is a challenging task since it requires comparable individual incomes to derive a supranational distribution[1] and detailed individual information on countries of birth and parental background. There are indeed few previous works aimed at estimating supranational inequality of opportunities.

In 2015, Milanovic estimates global inequality of opportunity employing a two-pronged approach: first, he assumes migration as a negligible factor, and second, he limits the number of controlled variables. Although this allowed for satisfactory coverage of the global population, as he recognizes, using country of residence as a controlled variable may not be entirely accurate, as individuals can migrate. Furthermore, Milanovic's study did not take into account key variables, such as sex, ethnicity, and socioeconomic background, which are commonly used in the measurement of inequality of opportunity, being widely recognized as factors that should not affect life outcomes. Even though the analysis was based on only two circumstances, mean income of the country of residence and its level of inequality, approximately half of the total inequality in global income appears to be due to inequality of opportunity. This finding is noteworthy as it suggests that a significant proportion of income disparities can be attributed to factors such as access to education, healthcare, and other opportunities linked to the coun-

results, ignoring the between-country component of European inequality. For instance, the EU-28 at-risk-of-poverty rate (the share of people with an equivalised disposable income below the at-risk-of-poverty threshold expressed in purchasing power standards and set at 60% of the national median) is calculated as a population-weighted average of the national rates.

[1] As concerns the difficulties with the estimation of global inequality and European inequality as inequality between the citizens and not between mean country incomes, see, respectively, Milanovic (2011) and Brandolini and Rosolia (2019).

try in which one happens to be born and raised rather than inherent differences in ability or productivity.

Inspired by Milanovic's paper, in this work we estimate inequality of opportunity in income at the European level. Up to now, at least to our knowledge, the working paper by Filauro et al. (2023) has taken a Pan-European perspective in the estimation of inequality of opportunity in individual labor earnings. By using three waves of the EU Statistics on Income and Living Conditions (2005, 2011, 2019) they assess the evolution in cross-country inequality of opportunity in EU as a whole, when the country of residence is used as additional birth circumstance. The findings suggest that about 60% of total earnings inequality is explained by circumstances and it is higher than the average of the national indices.

Two key aspects of our approach are the following. Firstly, we expand the set of circumstances considered in the analysis to include typical ascriptive characteristics such as sex and parental background. Additionally, by considering the country of birth rather than the country of residence as a proxy for the former, we introduce a circumstance that more closely correspond to the notion of pre-determined circumstances. People can choose to migrate, but the country of origin bears much more information that may significantly affect individual trajectories, linked both to cultural aspects and factors related to history and relationships between countries. It is relevant to understand whether the economic inequalities between countries affect individual life outcomes even after migration, thus exploring the persistence of *the curse or the blessing* of the lottery of the country of birth, both from an ethical point of view and for policy reasons. Indeed, the share of individuals living in a country different from the country of birth in Europe is significant and rising (Dossche et al., 2022).

We depart from previous approaches also in terms of estimation methodology. Following Brunori et al. (2023c) we adopt a data-driven approach based on the Conditional Inference Trees (CITs), a Machine Learning algorithm introduced by Hothorn et al. (2006). CITs divide the population into non-overlapping subgroups by partitioning the regressors' space. Then, individuals' prediction is obtained by taking the average of the subgroup they belong to. CITs are particularly suitable to deal with highly non-linear data-generating processes and, in our specific case, they exactly implement the partition in types postulated by the theory of equality of opportunity (Van De Gaer, 1995; Roemer, 1998). Moreover, CITs search for all possible combinations of regressors that can best explain the dependent variable's variability without

overfitting the data. This translates into the minimization of the risk of upward and downward bias when estimating inequality of opportunity (Ferreira and Gignoux, 2011; Brunori et al., 2019). However, Conditional Inference Trees bear a technical shortcoming: unordered categorical variables with more than 30 categories pose an unsolvable computational limit. Given that the key circumstance of this paper is the individual's country of birth, which can take up many more possible values, we introduce a shortcut in the algorithm to solve this issue. Finally, in order to improve the robustness of our conclusions, we bag regression trees drawing a large number of samples from the observed distribution. This allows us to make inferences about our estimates by taking into account two sources of uncertainty: the fact that we do not observe the entire population, and the fact that each tree represents only one possible partition. We recognize that the "true" partition of types is inherently unknowable.

For the analysis of inequality of opportunity in Europe the data comes from three different national household surveys: the European Union Statistics on Income and Living Conditions (Europe-SILC), the German Socio-Economic Panel (GSOEP) and Understanding Society - the UK Household Longitudinal Study (UKHLS). Most of the countries are covered using the Europe-SILC, a widely-used survey run in the European Union that gathers information about several income sources and socioeconomic factors related to living conditions. The survey is delivered on an annual basis, but only three waves (2005, 2011, 2019) have specific modules collecting information about circumstances. Still, we use the 2019 wave because it is the one providing exact information on parents' countries of birth, which can be used to infer the country of birth of the respondent when born outside the country of residence. We turn to the GSOEP as a resource because the information on parental country of birth is not reported by Germany in the 2019 Europe-SILC. In a similar vein, we utilize Understanding Society as a data source, given that the European Union Statistics on Income and Living Conditions does not encompass the United Kingdom starting from 2018. This allows us to get a dataset of around 300, 000 observations, covering 29 European countries and up to 179 countries of origin. We use census data to extract, from this dataset, a sample representative of European citizens, including migrants, obtaining a final sample of 138, 268 observations.Besides the country of birth, the circumstances we use in our analysis are sex, parental education and occupation. After accounting for differences in purchasing power, equivalences of scales and the age of the respondent, we estimate the share of overall income inequality in Europe that can

be predicted with the above-mentioned circumstances.

According to our estimates, the portion of total income inequality in the European continent that can be attributed to circumstances amounts to 56%. The country of birth appears to have the most relevant role in shaping inequality of opportunity in the continent, accounting for about 62% of the estimated income IOp.

2.2 Theory and Methods

2.2.1 Inequality of Opportunity

Consider a population of individuals indexed by $i \in (1, , N)$ and a variable y characterizing an economic outcome of interest, like income, whose distribution is a function of the set of circumstances faced by the individual, c_i, and the amount of effort exerted, e_i, such that

$$y_i = f(c_i, e_i).$$

Circumstances are defined as a finite vector of J elements and are, by definition, exogenous to individual choices. Following Roemer (1998), any population can be divided into a set Π of exhaustive and mutually exclusive groups, called types, such that all individuals belonging to the same type T_j share the same circumstances.

A salient approximation to the measurement of equality of opportunity (EOp) follows the so-called ex-ante approach Van De Gaer (1995). EOp is achieved when circumstances are not associated with differences in the expected outcome of interest, this is when the mean outcome is statistically the same across all types.

$$\bar{y}_j = \bar{y}_s \quad \forall j, s \text{ such that } T_j, T_s \in \Pi \tag{2.1}$$

Consequently, outcome disparities across types violate the equal opportunity principle. A measure of the extent of this violation delivers an estimate of the level of inequality of opportunity (IOp), which in this setting consists of estimating between-type inequality. In practice, IOp is measured by constructing a counterfactual smoothed distribution $\hat{y}_i$, where each observation receives the average outcome of the type she belongs to. Applying a suitable dispersion measure I(·) - such as the Gini index, the mean logarithmic deviation (MLD), or the variance -

to $\hat{y}_i$ delivers a measure of the inequality attributed to the set of observed circumstances.

$$\text{IOp: } I(\hat{y}_i) \tag{2.2}$$

2.2.2 IOp Estimation

According to Equation (2.2), the problem of estimating ex-ante IOp reduces to obtaining the smooth vector $\hat{y}_i$. Until quite recently, most ex-ante IOp analyses followed the so-called parametric approach (Bourguignon et al., 2007; Ferreira and Gignoux, 2011), that proposed running an OLS regression to approximate the function $y = f(c)$. This regression-based approach is equivalent to the estimation of all types' mean under the assumption that the covariance between circumstances and outcome is linear and additive (Brunori et al., 2023c).

Recent contributions have shown that estimates based on this approach could be unreliable (Brunori et al., 2019). First, the traditional interpretation of the parametric IOp estimation as a lower bound has been questioned. If two types have the same average outcome in the population but different average outcomes in the sample observed, the income dispersion across types will be spuriously attributed to IOp, introducing an upward bias. Second, the assumption of a linear and additive relationship between circumstances and outcomes limits the ability of the model to fit the data, potentially introducing biases with the opposite sign. Overall, the uncertainty regarding the type partition leading to $\hat{y}$ has compromised the trust in parametric IOp estimates. IOp estimates based on this 'fine partition' may be plagued by an upward 'overfitting' bias that arises when there are 'too many' types, so that sampling error becomes large within each type (see Brunori et al. (2019) and Salas-Rojo and Rodríguez (2022)).

As a solution, novel contributions have proposed data-driven approaches that take information on the data to generate statistically meaningful and non-arbitrary type partitions (see Li Donni et al. (2015), Brunori et al. (2023c), Moramarco et al. (2023) and Brunori et al. (2023a)). The remainder of the section explains how one specific regression tree algorithm, the Conditional Inference Trees, is perfectly suited to estimate ex-ante IOp.

Conditional Inference Regression Trees

Regression tree algorithms are trained to predict an output variable by splitting the observed sample into non-overlapping subgroups, based on a partition of the regressors' space. The bi-

nary splitting used to grow trees makes them particularly suitable to fit non-linear data-generating processes. From the wide variety of available regression trees, Conditional Inference Trees (CIT, Hothorn et al. (2006)), have recently been proposed by Brunori et al. (2023d) to estimate ex-ante IOp, and are schemed as follows:

1. First, select an α value.

2. CIT test on the global null hypothesis of independence between the outcome (y) and all circumstances (c). For each circumstance, the algorithm stores the Bonferroni-adjusted p-statistic.[1]

3. The algorithm selects the circumstance with the lowest Bonferroni adjusted p-value, i.e., that with the strongest association with y. If $p_{adj} > \alpha$, the algorithm stops. Otherwise, it continues by setting the selected circumstance as a splitting variable.

4. The final step consists of choosing the splitting value that divides the sample into two sub-samples. When the variable is categorical, the algorithm checks all potential binary splits. For each possible partition, the algorithm performs a difference-in-means t-test and obtains a p-value. The partition -group of categories in the previously selected circumstance-, producing the smallest p-value is selected to split the sample.

5. Steps 2 to 4 are repeated for each resulting sub-sample until the null hypothesis of independence cannot be rejected for the critical $(1 - \alpha)$.

Once the algorithm stops, each observation gets its expected income, equivalent to the average income of the sub-sample it belongs to (*type* in the IOp framework). Notably, this prediction produces the counterfactual distribution $\hat{y}_i$ that allows the IOp estimation as in Equation (2.2).

CITs bear a technical shortcoming. As explained, in step 4, when non-ordered categorical circumstances are used as regressors, the tree tests across all possible groupings of categories. This implies a factorial number of combinations, that grows exponentially with the number of categories in the selected regressor. To make the problem computationally finite, CITs limit

[1] The Bonferroni correction corrects the p-value to avoid type I error in multiple test settings: $p_{adj} = 1 - (1 - p)^C$, where C is the number of tests run.

the number of possible unordered categories to 30, which already delivers $2.65 * 10^{32}$ different combinations. As further explained in the data section, the key circumstance in this paper is the individual's country of birth, which can take up to 179 possible values. Including this variable as an unordered categorical poses an unsolvable limit for the computation of CIT.

We implement a shortcut in the CIT algorithm to solve this issue. Before every testing for possible splits, we order the values of the categorical variable (country of birth) according to the category-specific mean outcome. This allows us to treat the unordered variable as an ordinal categorical variable. The recursive reordering of the values in the regressors makes the original limitation computationally trivial, while not affecting the type of partition we get: binary splits in CITs are based on differences in means in the resulting subgroups. By construction, categories in two nodes born from the same split may be ordered according to their mean outcome.[1]

Random Forest and Shapley value decomposition

Regression trees are often characterized by low bias but high variance, implying that the tree structure is quite sensitive to the specific sample observed (Hastie et al., 2009). CITs are no exception, so it is a common practice to mitigate this aspect by obtaining predictions with *random forests*. First, several sub-samples are drawn from the original data, growing trees from each one of them.[2] The individual prediction $\hat{y}_i$ is obtained after averaging all predictions from individual trees. We follow the random forest methodology proposed by Hothorn et al. (2006) and Hothorn and Zeileis (2008), including the modification that deals with a high number of unordered categories.

Besides exploring the ability of circumstances to predict incomes and obtain $\hat{y}$, a complementary yet meaningful step consists of estimating the specific contribution of circumstances to IOp.[3] Among the many possible approaches, we follow the literature and apply a Shapley value decomposition (Shapley et al., 1953; Shorrocks, 2013).

[1] We have confirmed this shortcut idea with Torsten Hothorn and Achim Zeileis and we are grateful for their support.

[2] This process, similar to bootstrapping, is actually called *bagging*, as sub-samples are drawn without replacement. The size of each sub-sample is set to 0.632 as a convention (see Hothorn and Zeileis (2015))

[3] Our data only allows us to provide a descriptive analysis of circumstances' influence on IOp, so our results should not be interpreted as causal effects.

Intuitively, a Shapley value decomposition estimates the overall contribution of a variable x to some outcome y as the average decrease in the variability of y across all possible combinations that exclude x as a factor in explaining the variability of y. To address the sensitivity of estimates based on a single tree, we follow a random forest approach and consider multiple samples. Our Shapley value decomposition estimation follows Brunori et al. (2023a) and can be schemed as:

1. Draw a sub-sample sized 62.3% of the full sample;
2. Estimate a deep CIT on the sub-sample lowering the confidence level $(1 - \tilde{\alpha})$ close to 0, so the tree is allowed to explore many possible partitions;
3. Measure IOp as between-terminal nodes inequality;
4. Repeat by systematically generating all possible sequences in which each circumstance c_j can be eliminated from the model;
5. After each elimination sequence, estimate IOp. Store its difference with respect to overall IOp;
6. The stored values across all elimination sequences for each circumstance c_j are averaged and stored;
7. Repeat steps 1-6 n times;

In our case, the contribution of c_j to IOp is the average contribution across 100 bagged iterations.

2.3 Data

While most inequality, mobility, and IOp analyses lie on within and between-countries comparisons, in this paper we explore, for the first time, a measure of continental IOp. This implies that our estimates of European IOp are based on a pool of European countries treated as coming from the very same region.[1] We combine data from three distinct national household surveys, using data from 2019: the European Union Statistics on Income and Living Conditions

[1] Throughout the remaining sections of the paper, with 'Europe' we are specifically referring to the 29 countries covered in our data set.

(EU-SILC), the German Socio-Economic Panel (GSOEP), and Understanding Society - the UK Household Longitudinal Study (UKHLS). These three surveys allow us to cover 29 European countries: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Serbia, Slovakia, Spain, Sweden, Switzerland, United Kingdom.[1]

The EU-SILC is a widely employed survey conducted in a group of countries conforming the European Union plus some others. It collects data on various sources of income and socioeconomic factors relevant to living conditions. While the survey is administered annually, specific modules capturing information about circumstances are available only for three specific waves: 2005, 2011, and 2019. We use the 2019 wave that, for the working-age population, collects information on factors related to childhood and adolescence, as well as the country of origin of the parents, which is used to proxy the individual's country of origin as explained below. However, in 2019 it does not include the United Kingdom, so we rely on the Understanding Society survey (UKHLS, waves 10 and 11) as an alternative data source. The UKHLS provides the necessary information on household income and other relevant factors specific to the United Kingdom for our analysis. We also employ an alternative data source for Germany, the German Socio Economic Panel (GSOEP), as in the Europe-SILC 2019 the information on the parents' country of origin is not provided in detail.

The outcome of interest is the annual disposable household income, adjusted by Purchasing Power Parity conversion factors to US 2019 dollars.[2] We account for equivalences of scales by dividing incomes over the squared root of the household size. Finally, accounting for life-cycle income dynamics, we adjust the dependent variable erasing the age effect on income.[3]

The EU-SILC data does not provide detailed information on the respondent's country of birth. However, it includes a variable stating whether she was born in the country of residence, in another European country, or outside the EU. If the individual was born in the country of residence, no additional adjustments are made. However, to get a closer idea about the country

[1] Although the Brexit referendum was held in 2016, the United Kingdom formally belonged to the European Union until January 2020. Slovenia and Romania are excluded because the data is incomplete.

[2] World Bank, PPP Conversion Factor, Private Consumption (LCU per International$). https://databank.worldbank.org/metadataglossary/world-development-indicators/series/PA.NUS.PRVT.PP

[3] We run a regression of incomes against age and age squared. Our outcome of interest is the sum of the constant and the residuals of the regression.

of origin of those born abroad, we use the information on parents' country of birth, included in the 2019 wave. For those who report to be born outside the country of residence we assign the country of birth of their mother. As a result, we are left with 179 different places of birth. Exploiting GSOEP and UKHLS, which contains both the information, we have checked that the share of individuals born in a country different from the one of the mother is relatively small, around 10%. Moreover, the country of origin of the mother bears much information for the children given that relevant cultural aspects such as religion, language and social norms are transmitted from mothers to children (Caneva and Pozzi, 2014).

Polling together different data sources bears some shortcomings. First, the dataset does not proportionally represent the population structure in Europe. For instance, Germany has a population about 16 times larger than Norway, but only twice the sample size in the dataset. Furthermore, the survey weighting variable is constructed nationally to make each sample representative of the population of the country, so the weights assigned to individuals ensure the representativeness of the population in terms of demographic characteristics (such as age, sex, and geographical location), household composition, and socioeconomic factors (European Commission, 2003). However, country of birth, our key variable of interest, is not included as a factor in the weight assignment process.

To address these issues, we design a stratified sampling procedure that draws a sub-sample from the original data set while taking into account two key factors: the proportion of European residents for each country covered in our data set, and the proportion of first-generation immigrants within each country. This procedure can be schemed as follows:

- We use census data[1] to get information on the population living in each European country in 2019, as well as the number of individuals by countries of birth, within each country;
- we divide the population into distinct strata based on the country of residence and, within each stratum, we divide the individuals based on their countries of birth;

[1] Specifically, for most of the countries we rely on 2011 census data reported in the Eurostat database about country population shares by country of birth. For Germany, Ireland, Greece, Croatia, Poland, Portugal, data are based on on 2011 census data about resident by their citizenship rather than country of birth. For Serbia and Malta the available data are, respectively, the 2022 and 2021 census.

- we set a threshold to avoid potential issues caused by very small population sizes: we consider only countries of birth that represent up to 0.1% of the population resident in Europe in the 29 countries in the data set. For countries of birth falling below this threshold, we aggregate their frequencies into broader regions based on the United Nations geoscheme.[1] We end up with 60 countries and 17 macro regions of birth;[2]

- we draw a random sample of the original dataset respecting the proportions of the population living in each of the 29 European countries as well as the proportions of individuals by place of birth within each country.

As a result of the sampling, and keeping individuals of working age (between 25 and 65 years old) our final sample representing Europe is composed of $138,268$ observations. Table 2.1 shows the composition of our final sample and few statistics for each country. Considerable heterogeneity across the European countries included in our sample in 2019 emerges in terms of average household incomes, which exceed PPP \$ $40,000$ for people living in Switzerland (CH), Norway (NO) and Luxembourg (LU)[3], while it does not reach PPP \$ $10,000$ on average for individuals living in Serbia (RS) (PPP \$ $3,821$), Bulgaria (BG), Hungary (HU), Poland (PL), Croatia (HR), Latvia (LV), Slovakia (SK), Greece (EL) and Lithuania (LT), representing together almost 17% of the sample. In terms of inequality, the range goes from the lowest value of the Gini coefficient of 0.22, observed in Denmark (DK), up to 0.38 Gini points of Bulgaria (BG). Aimed at keeping the European representativeness in all our results, the bagged sub-samples are drawn taking into account this procedure. For robustness, we have checked the distribution of individuals within the original sample and in the sub-sample in terms of sex,

[1] For instance, individuals born in Curaçao or Jamaica represent less than $0,1\%$ of the population living in the original sample of countries, so we include them in the macro region "Other Caribbean". See the table with the definition of the aggregates in Table 2 in Appendix Section 3.5

[2] Afghanistan, Albania, Argentina, Austria, Bosnia and Herzegovina, Bangladesh, Belgium, Bulgaria, Brazil, Switzerland, China -including Hong Kong-, Colombia, Cyprus, Czechia, Germany, Denmark, Dominican Republic, Algeria, Ecuador, Estonia, Egypt, Greece, Spain, Finland, France, Croatia, Hungary, Ireland, India, Iraq, Iran, Italy, Sri Lanka, Lithuania, Luxembourg, Latvia, Morocco, Nigeria, Netherlands, Norway, Peru, Philippines, Pakistan, Poland, Portugal, Romania, Serbia, Russia, Sweden, Slovakia, Senegal, Syria, Tunisia, Turkey, Ukraine, United Kingdom, United States, Venezuela, Vietnam, South Africa.
The macro regions we define are: Other Caribbean, Other Central Africa, Other Central American, Other Central Asia, Other East Africa, Other East Asia, Other Europe, Other Middle East, Other North Africa, Other North American, Other Oceania, Other South American, Other South Asia, Other South East Asia, Other West Africa, and Others.

[3] Three countries that represent together less that 3% of the total population.

parental education and occupation to verify that the sampling process does not create other demographic imbalances.

Although we focus our analysis on the country of origin, the IOp framework allows us to take into consideration other circumstances. In particular, we make use of the respondents' sex, their parents' education level (based on the International Standard Classification of Education 2011 (ISCED-11)) and their parents' occupation when they were 14 years old (based on the 1-digit International Standard Classification of Occupations ISCO-08). The complete list of circumstances and respective categories used in the analysis can be found in Appendix Section 3.5 Table 1. All remaining descriptive statistics are available upon request.

Table 2.1: Composition and summary statistics of the representative European sample

Country	N	N(%)	Foreign Born (%)	Avg Eq Income	St.Dev.	Gini
AT	2,411	1.74	0.19	29,356	17,954	0.28
BE	3,135	2.27	0.17	27,823	14,214	0.25
BG	1,928	1.39	0.03	5,855	6,730	0.38
CH	2,310	1.67	0.29	52,348	47,446	0.29
CY	232	0.17	0.22	20,704	13,640	0.30
CZ	2,893	2.09	0.04	11,350	5,635	0.23
DE	22,672	16.40	0.12	24,995	33,251	0.37
DK	1,561	1.13	0.11	36,895	16,830	0.22
EE	369	0.27	0.15	13,291	6,917	0.29
EL	2,786	2.01	0.03	9,470	8,162	0.32
ES	12,713	9.19	0.13	17,768	11,345	0.32
FI	1,485	1.07	0.06	32,837	20,269	0.26
FR	17,535	12.68	0.13	26,559	86,216	0.31
HR	1,108	0.80	0.01	8,410	4,996	0.29
HU	2,654	1.92	0.03	6,278	4,482	0.28
IE	1,352	0.98	0.13	30,653	20,239	0.29
IT	16,592	12.00	0.12	21,130	13,676	0.32
LT	760	0.55	0.04	9,748	6,768	0.34
LU	161	0.12	0.45	43,490	27,593	0.31
LV	528	0.38	0.12	9,023	5,883	0.33
MT	131	0.09	0.15	19,921	11,545	0.28
NL	4,691	3.39	0.13	28,336	18,568	0.27
NO	1,461	1.06	0.16	46,429	25,661	0.24
PL	10,304	7.45	0.00	7,832	4,898	0.30
PT	2,808	2.03	0.05	11,308	8,329	0.34
RS	1,583	1.14	0.06	3,821	2,615	0.34
SE	2,776	2.01	0.19	29,231	13,218	0.23
SK	1,482	1.07	0.03	9,359	4,011	0.23
UK	17,847	12.91	0.08	19,539	13,848	0.30

Source: Own elaboration, data from EU-SILC, UKHLS, GSOEP and shares from census data.

2.4 Continental Inequality of Opportunity

In this section, we present the key findings obtained from our estimation of ex-ante European IOp. First, we focus on the European IOp estimates from both, the tree and the random forest, and on describing the results of the Shapley value decomposition. Later, we explain the opportunity structure of the specific tree reported, and we finish by focusing on the opportunities of migrants in Europe.

2.4.1 European IOp estimates

We run the algorithm on the representative sample of 138, 268 individuals, with information on the following circumstances (with the respective number of categories in parenthesis): sex (2), countries of birth (77), parental education (3 categories available for each parent), parental occupation (11 categories available for each parent).[1] The algorithm yields a final partition of the population in 124 types, where the smallest type comprises only 0.08% of the sample, while the largest type represents 7% of the sample. We use the obtained CIT type partition to estimate IOp at the European level. Table 2.2 shows the main results employing the Gini index as dispersion measure. While income inequality among European citizens amounts to 0.39 Gini points[2], absolute IOp, estimated on the smoothed distribution $\hat{y}$ (see Equation (2.2)), rises to 0.24 points. Note that this implies that the six circumstances, combined on simply 124 types, generate an inequality as high as 62% of total income inequality. The corresponding metric obtained with the random forest, which takes into account the different plausible data realization, mildly decreases the Gini coefficient to 0.22, reaching a value equivalent to 56% of the overall income inequality.

[1] We run the CIT with an $alpha = 0.01$, and set the minimum number of observations at each terminal node (minbucket) to 100. The remaining parameters in the algorithm are set to the default values proposed in Hothorn and Zeileis (2015).

[2] Which compares to 0.29 Gini points obtained with the unweighted average of the within-country coeffients reported in Table 2.1.

Table 2.2: European income inequality and inequality of opportunity

Overall Gini	Absolute IOp Gini (tree)	Rel. IOp Gini (tree)	Absolute IOp Gini (forest)	Rel. IOp Gini (forest)
0.39	0.24	0.62	0.22	0.56

Source: Own elaboration, data from EU-SILC, UKHLS, GSOEP. The tree is estimated with $\alpha = 0.01$, and $minbucket = 100$. The random forest is estimated with $\alpha = 0$, $minbucket = 50$, and 200 bagging subsamples of 0.1 the original sample size.

This result alings with Milanovic (2015)'s, who finds that more than half of the variability of individual percentile incomes across world citizens in 2015 are explained by two characteristics of the country of residence (beyond individual control), GDP per capita and Gini coefficient. The European context, although characterized by greater cohesion and integration, shows a comparable estimate in this study. This alignment is likely due to our use of the entire income distribution derived from the household surveys, rather than focusing on percentile mean income inequality. Additionally, our analysis takes into account countries of birth rather than residence and other circumstance factors, potentially providing more variability.

Taking a Europe-as-a-whole perspective, rather than a cross-country approach, appears to be key if we are interested in assessing fairness and inclusiveness over the continent. An unweighted average estimate over all the 29 countries indices would suggest a different picture: the absolute index of IOp between European citizens (0.22 Gini points) is indeed more than double than the simple average (0.07 Gini points).[1] This ratio is in line with the findings by Filauro et al. (2023) concerning IOp in labor earnings as an average across countries vs a pan-European estimate. The lottery of birth in the European continent appears to be a high stake lottery, given that more than half of the variability in household income is predicted at birth. The picture of the continent that emerges in terms of opportunities is similar to the one observed in Latin American countries like Brazil, Panama or Colombia by Brunori et al. in 2023b.[2]

Table 2.3 presents the results of the Shapley value decomposition. The country of birth of the respondent accounts for 62.4% of IOp, and it is followed by the occupation of the father (18.2%) and of the mother (8.8%). Parental education accounts for 14.5% of the overall in-

[1] Unweighted average of the random forest estimates relative to each of the 29 countries using all the circumstances but country of birth and reported in Appendix Section 3.5 Table 4.

[2] Using the same methodological approach as this paper (*conditional inference forests*), Brunori et al. observes IOp of around 0.22 Gini points in Brazil in 2014, in Panama in 2008 and in Colombia 2010.

equality of opportunity. The contribution of sex is rather small, barely reaching 1.3% of total IOp, but it is important to keep in mind that our outcome variable is the equivalised household income, such that our measure ignores intra-household inequality. Thus, the contribution of sex to IOp reflects inequality associated with single-sex households.[1]

Table 2.3: Shapley value decomposition

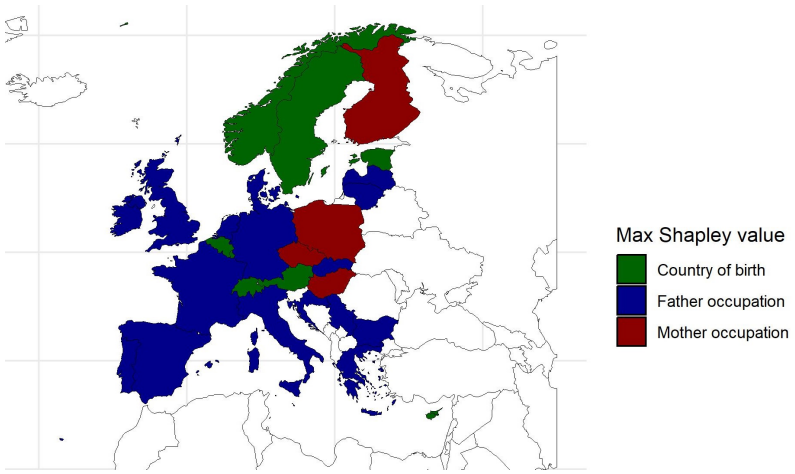
Circumstance	Contribution to I.Op.
Country of birth	62.4
Father's occupation	18.2
Mother's occupation	8.8
Father's education	5.7
Mother's education	3.8
Sex	1.3

Source: Own elaboration, data from EU-SILC, UKUS, GSOEP. The Shapley value decomposition is estimated with a random forest procedure, with $\alpha = 0.1$, $minbucket = 50$ and 100 bagged repetitions sized 0.1 the original sample size.

The Shapley value decomposition estimated for each single country and reported in detail in Appendix Section 3.5 Table 5 confirms the need to resort to a Europe-wide perspective rather than to rely on cross-country analysis. As the illustrative map in Figure 2.1 shows, relying on the analysis of the opportunity structure within country would suggest a prevalence of inequality persistence associated to the occupation of the father, while, as we have seen, as citizens of the continent, the strongest predictor of unfair inequality is the country in which one happens to be born.

[1] We have repeated the whole exercise excluding Sex, and the results remained essentially the same. Still, we prefer to keep this circumstance to account for the potential disparity of single-parent and same-sex households.

Figure 2.1: Shapley value decomposition by country



Source: Own elaboration, data from EU-SILC, UKUS, GSOEP.
The map shows the circumstance factor that contributes the most to the inequality of opportunity estimated using conditional random forest for each country included in the sample.

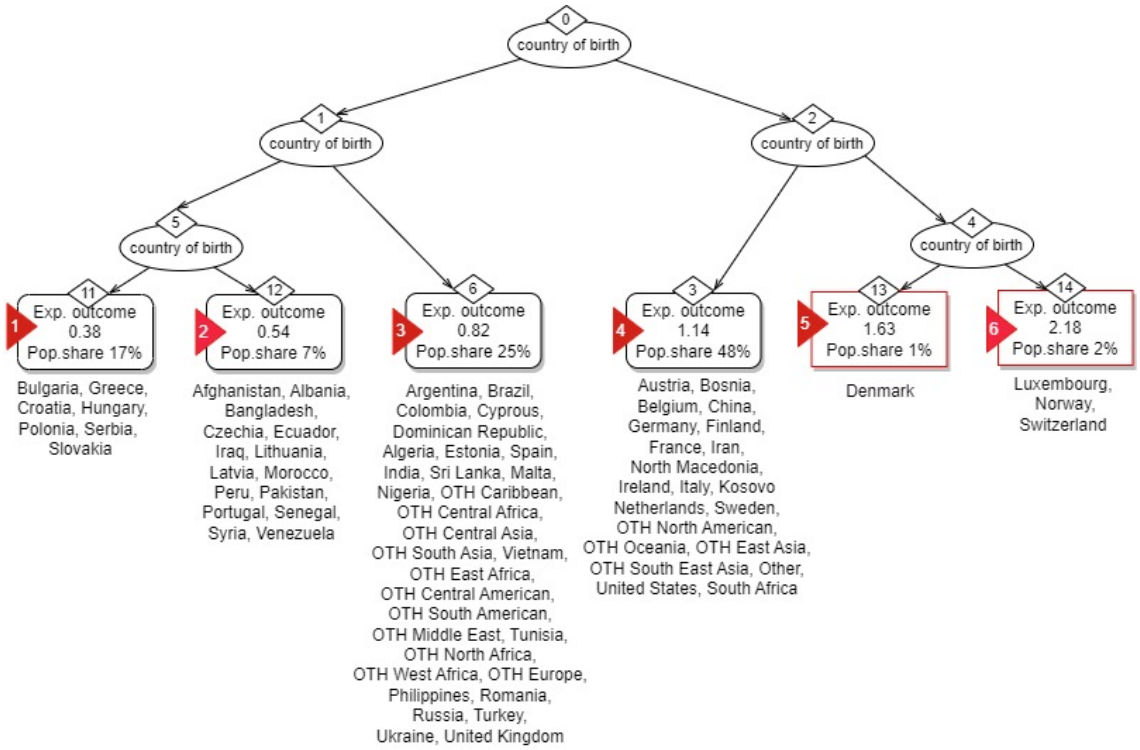
2.4.2 European Tree Structure

As mentioned above, the CIT generates 124 different types. This very large structure hinders its graphical exposition. Besides, we are fully aware of the limitations inherent to CITs (Moramarco et al., 2023): the deterministic binary splitting structure impedes the finding of many types and may generate terminal nodes with the same expected outcome. In any case, with all due caution, we believe that a graphical representation of some features of the obtained CIT allows highlighting some interesting results.

We focus on the upper part of the *root* tree (Figure 2.2), which shows the splits up to the nodes defined only by *country of birth*.

The fundamental importance of the country of birth, which has been highlighted by the Shapley value decomposition, is rather apparent: this key variable identifies, on the first steps of the CIT algorithm, six clusters that group the population living in Europe according to statistically significantly different expected mean income. All bottom nodes in Figure 2.2 report the expected income in that node, scaled with the continental mean (21, 166) equals to 1, and the share of the population represented by that sub-sample. It is striking to notice that the only fact of being born in Denmark, Luxembourg, Norway or Switzerland is associated with an income advantage that goes from 163% to 218% of the average European citizen. Indeed, if we stopped

Figure 2.2: European Opportunity Tree: upper structure



Source: Own elaboration, data from EU-SILC, UKUS, GSOEP.
The tree is shown up to the nodes in which the circumstance *country of birth* is used as a splitting variable. The first number in the bottom nodes indicates the share of the population belonging to that sub-sample while the second number is the predicted income of the group.

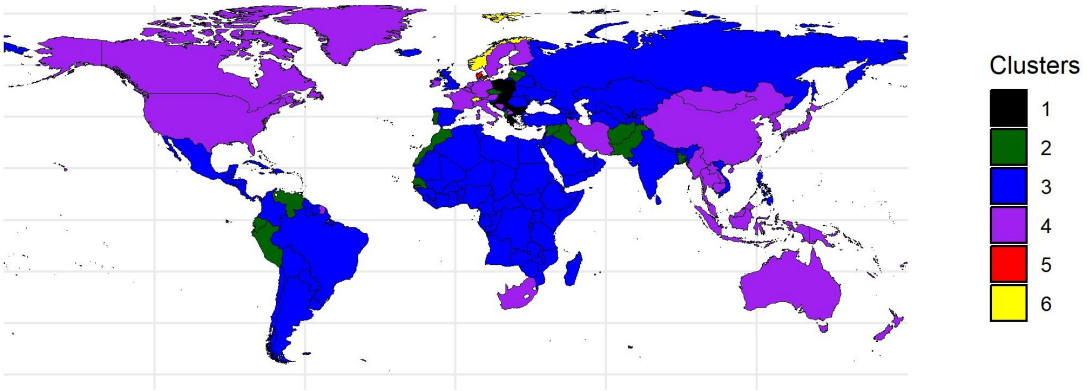
the algorithm here and we used these six nodes as types, we would get an IOp rising to 0.20 Gini points, only 4 Gini points less than what we get letting the tree grow up to the 124 final types.[1]

Each of the first four clusters (nodes 11, 12, 6, 3) gives rise to a sub-tree of varying depth and splitting variables, a complex structure of opportunities. The two red boxes on the right-hand side of Figure 2.2 (clusters 5 and 6) are terminal nodes, meaning that in the sub-samples of the population in nodes 13 and 14, the algorithm could not reject the null hypothesis of no correlation between each circumstance and the outcome variable.

To enhance the readability of the tree presented in Figure 2.2, the map illustrated in Figure 2.3 groups the countries of birth of the individuals living in the 29 European countries

[1] Running the CIT using only *country of birth* as predictive circumstance we get an Gini coefficient of 0.22.

Figure 2.3: European Opportunity Tree: upper structure (clusters map)



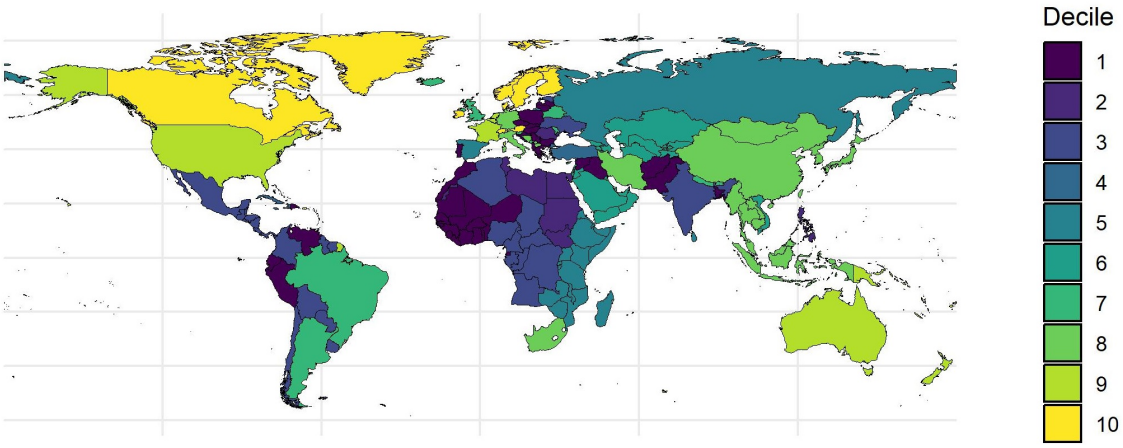
Source: Own elaboration, data from EU-SILC, UKUS, GSOEP.
The map illustrates the countries of birth as grouped in the six clusters obtained from the tree shown up to the splits that use *country of birth* as splitting variable.

included in our sample, based of the six clusters identified by the CIT. Although the clusters identified by the tree have statistically significantly different expected mean income, we should keep in mind that there is further variability within each cluster. Moreover, we are aware of the sensitivity of the tree structure to the sample observed. Therefore, we supplement the analysis of the picture provided by the tree with the map in Figure 2.4 which shows the average income by country of birth predicted by the conditional random forest.

Cluster 1 (in *black* on the map in Figure 2.3) represent 17% of the total sample. It identifies individuals born in Bulgaria, Croatia, Greece, Hungary, Poland, Serbia and Slovakia as the most disadvantage (as a group) among European citizens, with an expected outcome reaching merely 38% of the European average. They are individuals born in European countries that, as we have already observed looking at the summary statistics in Table 2.1, show average equivalised household income which are way lower than the average on the continent. However, the story is likely not only about convergence. Indeed, the countries of birth in cluster 1 show high shares of migrants over the continent, from the 5% of Greeks, to the 13% and 12% of Croatian and Bulgarians, respectively. Although migrants from these countries can expect higher incomes than those who have not moved, their average outcomes are systematically below the country of residence's mean. Of course, this is only speculation, since studying immigration presents the well-known issues linked to selection. Individuals grouped in Cluster 2 have an expected outcome reaching 54% of the European average and represent 7% of the total sample.

They are born in middle-income European countries, specifically Czechia, Portugal, Latvia and Lithuania, and in developing countries of the world, among which, countries afflicted by war, civil conflict and economic crisis, from which countries in Europe have received high shares of asylum applications, such as Afghanistan, Iraq, Pakistan, Syria and Venezuela. The third cluster have an expected income of 82% of the European average income and it represents 25% of our sample. As we can see in Figure 2.3 the *blue* countries cover a big area of the developing world, Central and Latin America, Africa, South Asia, Russia, plus others which are apparently surprisingly like UK and Spain. However, if we look at the same area in the map in Figure 2.4, we can notice a high variability of colors: individuals born in Tunisia, Nigeria, India, Philippines or Ukraine can expect to be at most in the third decile of the income distribution of the continent, while people from UK, Spain, Cyprous have an expected household income at least above the fifth decile. Lastly, almost half of our sample (48%) creates a cluster with an average expected income around the overall average, 114% of the European average. Most countries are the developed and upper middle-income Western and Central European economies, although it is surprising to find Kosovo and Bosnia among them, plus US, South Africa, Oceania, South East Asia.

Figure 2.4: Average Predicted Income by Country of Birth



Source: own elaboration with data from EU-SILC, UKHLS and GSOEP.

Table 6 in Appendix Section 3.5 reports the exact values of average predicted income by country of birth.

2.4.3 Migrants in Europe

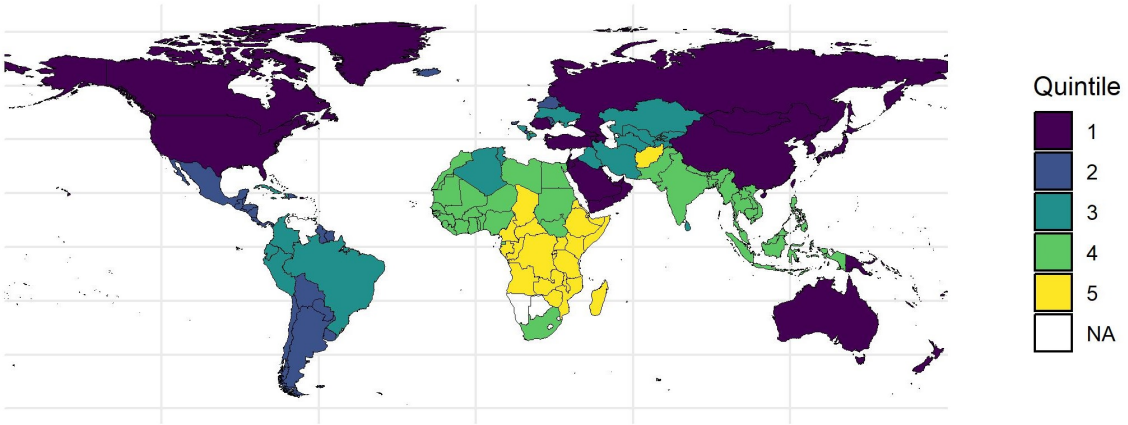
Given the remarkable importance of country of birth, now we focus specifically on the opportunities of migrants, this is, individuals born in a country different from the one of residence. We consider, separately, migrants born in countries outside our region of analysis - the 29 European countries included in our sample -, and those born inside but living in another country within the continent (e.g. individuals born in Italy and living in Germany). First, we compare their expected income, as European citizens, in relation to the GDP per capita in their countries of origin. This provides us with a proxy measure of the increase in opportunities (or decrease) unlocked by the decision to move. Then, we inspect whether there are important differences of this ratio across destination countries.[1]

The map in Figure 2.5 shows the ratio between the average predicted income and the GDP per capita for individuals born outside our region of analysis, in relative terms. Specifically, each country of birth has a color corresponding to the quintile to which it belongs in the distribution of the values of the ratio at study. Among all migrants born outside Europe, individuals born in East and Central Africa and Afghanistan, in *yellow* in the map, appears to experience, through migration, the biggest improvement of their opportunities (in terms of expected income).

Moreover, it is revealing to observe the ratio of internal migrants in Figure 2.6. In relative terms, individuals born in rich countries like Denmark, Finland, France Norway gain more than the other European migrants from the choice to settle in another country over the continent.

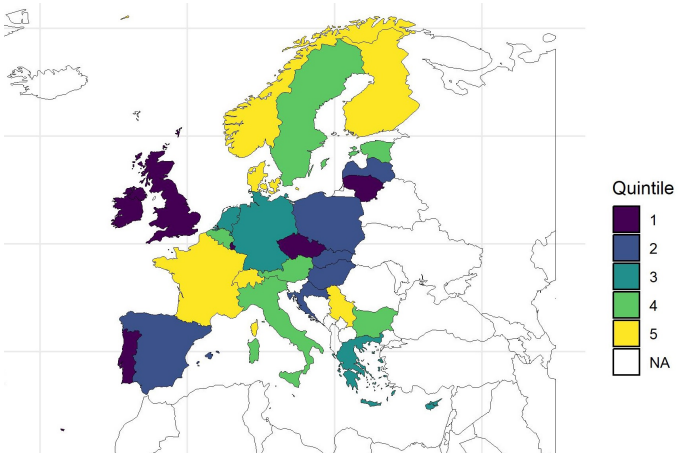
[1] We recognize that the following analysis of migration results is speculative, as the examination of immigration involves acknowledged specificities associated with selection.

Figure 2.5: Migrants born outside Europe



Source: own elaboration with data from EU-SILC, UKHLS and GSOEP.
The map shows the ratio, by quintiles, between the average predicted income in Europe and GDP per capita for each country of birth of individuals born outside Europe. Table 7 in Appendix Section 3.5 reports the exact values of the ratio.

Figure 2.6: Migrants born in Europe

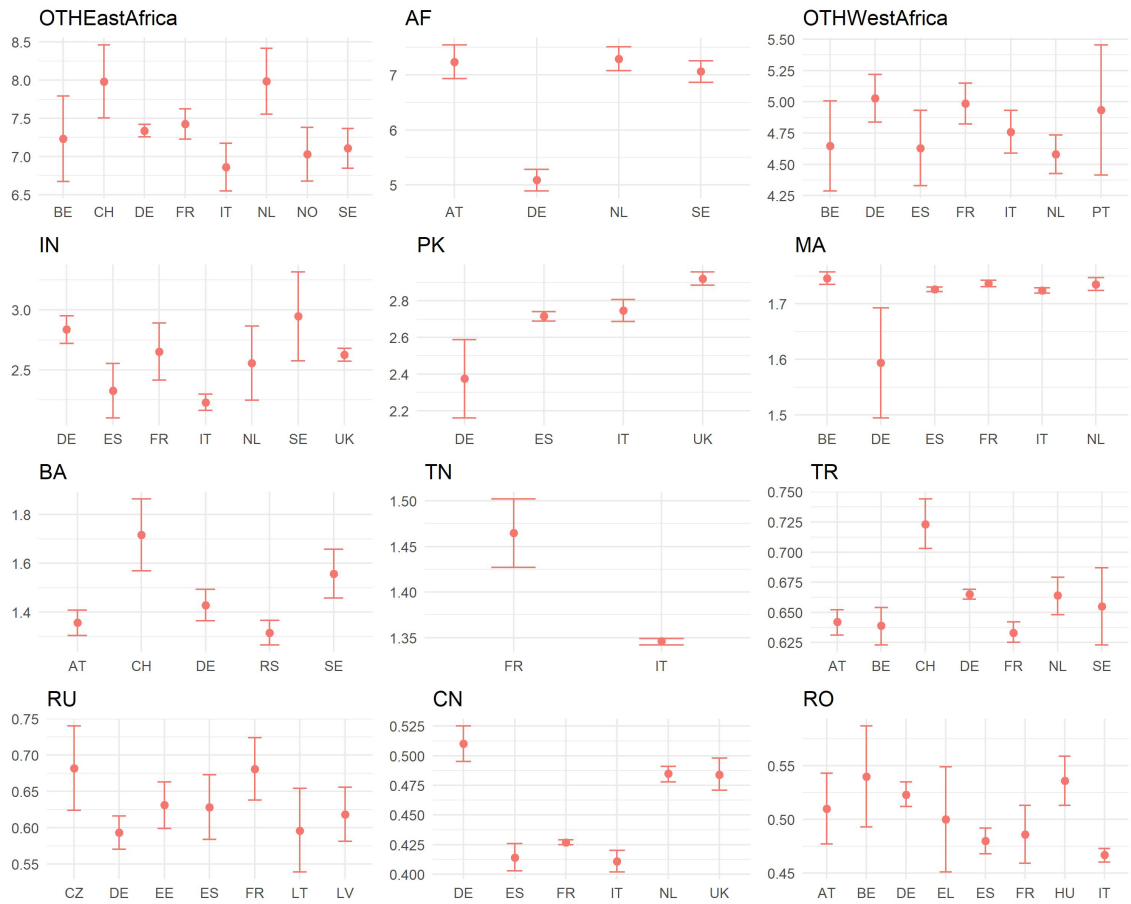


Source: own elaboration with data from EU-SILC, UKHLS and GSOEP.
The map shows the ratio, by quintiles, between the average predicted income in Europe and GDP per capita for each country of birth of individuals born in our region of of analysis. Table 7 in Appendix Section 3.5 reports the exact values of the ratio.

Moreover, we wonder whether the country of destination matters for migrants in terms of increase or decrease of opportunities. Figure 2.7 shows the heterogeneity of the average ratio of the predicted income to GDP per capita in the country of birth across the main residence coun-

tries of 12 groups of migrants born outside the region of analysis and representing at least 0.1% of the European population. Each plot refers to a single country of birth. The x-axis reports the main countries of residence for the specific origin country and for each of them the plot shows the average ratio with its 95% confidence intervals. On average, the ratios are quite homogeneous, the variability across countries of residence, in terms of magnitude, lies mostly within the decile order. One exception is Afghanistan that is among the countries who benefits most from migration in relative terms (as shown in Figure 2.5): An Afghan moving to Germany can still expect an income that multiplies by five his country of birth's GDP per capita but she can expect this dividend to be around seven if moving to Austria, Netherlands or Sweden. Although with lower magnitude, we can infer statistically significant differences between Indians living in Sweden, Germany, France or UK and those living in Italy, who experience a smaller improvements in their opportunity set compared to the former. Similarly for people born in Pakistan: moving to the UK yields in expectation a greater jump with respect to moving to Germany, Spain or Italy. Additional interesting findings concerns individuals born in Tunisia who appears to have higher dividends by settling in France rather than in Italy. The specific immigration and asylum policies of the country of residence, language barriers and historical relationships with the origin countries are some of the factors that may play a role in explaining the variability in the average advantage that a specific community can expect from the investment of migration to the different host countries.

Figure 2.7: Heterogeneity by country of destination



Source: own elaboration with data from EU-SILC, UKHLS and GSOEP.
For each country of birth, the table shows the ratio, between the individual predicted income and the GDP per capita of the relative country of birth, averaged for the main countries of residence. The table with the exact values is available upon request.

2.5 Conclusions

The literature on inequality of opportunity has traditionally focused on within-country and cross-country estimates, and research on Europe-wide inequality has been limited. However, analyzing inequality of opportunity at a continental level in Europe is relevant for policymakers, particularly in monitoring income convergence among European countries and promoting social cohesion. In this paper, we present an analysis of inequality of opportunity in the continent, which refers to the share of inequality among European citizens that can be attributed

to circumstances beyond individual control. We use data from three household surveys covering as many European countries as possible - the EUSILC, the GSOEP, and the UKHLS - and census data, obtaining a sample representative of European citizens, including migrants. Our analysis reveals a substantial impact of the lottery of birth on income inequality in contemporary Europe. The share of overall income inequality in the European continent that can be attributed to circumstances, such as parental education, occupation, and country of birth, amounts to 56%, with the country of birth being the most significant factor in shaping inequality of opportunity. Overall, our study contributes to the ongoing discourse on inequality of opportunity and calls for a comprehensive and inclusive approach to address the sources of disparity within the European continent.

The consequences for quality of life of having multiple disadvantages far exceed the sum of their individual effects.

Stiglitz et al.,2009

3

Born to struggle: inequality of opportunity in income, health and education

Thesis advisor: Professor Paolo Brunori Annaelena Valentini

Born to struggle: inequality of opportunity in income, health and education

Abstract

The study estimates inequality of opportunity in income, health and education, adopting a position-based index as a measure of multidimensional well-being and a data-driven technique to predict it. Birth circumstances such as sex, country of birth, Aboriginal status, and parental socioeconomic background are used as predictors. Drawing on two decades of data from the Household, Income, and Labour Dynamics in Australia survey, the research observes the evolution of multidimensional inequality of opportunity, and of the dependence among its defining dimensions, across cohorts of people living in Australia and born between 1951 and 1996. The findings suggest a stable trend in the level of association among income, health and education, together with an increase in inequality of opportunity. Additional insights on the importance of the single circumstances on the well-being predictions are extracted by employing the Shapley additive explanation framework. Across the birth cohorts, there is an increase in the relative importance of maternal occupation in predicting well-being compared to paternal occupation. Additionally, across the various birth cohorts, the Aboriginal status negatively impacts multidimensional well-being, although its low frequency in the population results in a relatively lower overall influence compared to other circumstances.

Keywords: multidimensional well-being, inequality of opportunity, diagonal dependence index, machine learning, Australia.

JEL codes: D63,I31

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3.1 Introduction

The academic and public debate on socioeconomic inequalities usually implies underlying fairness considerations. Imagine a society where individuals' life trajectories are strongly predicted by the characteristics they are born with, like sex or ethnicity. Most theories of distributive justice deem the arising inequality in well-being as *unfair*. The 70s' *equality of what* debate (Sen, 1980) introduced the concept that when assessing a distribution as just or not, the source of inequality matters. Whether worse life outcomes are due to disadvantaged backgrounds, rather than to individual effort and preferences, appears to be a crucial information for both justice considerations and policy intervention. This is the essence of the theory of equality of opportunity: in a fair society, individuals should compete on a levelled playing field to acquire resources; in such a way, disparities in life outcomes would mirror disparities in individual preferences and choices, rather than in factors outside of individual control, commonly referred to as circumstances. This concept has found widespread support among political philosophers (Rawls, 1971; Cohen, 1989; Arneson, 1989; Sen, 1980), economists (Roemer, 1998; Fleurbaey, 1995; Ferreira and Gignoux, 2010), and the general public alike. Beyond the relevant normative considerations, indeed, there are at least two other key reasons for advocating for equality of opportunity. First, experimental evidences have shown that individuals distinguish between factors within individual responsibility and beyond, when assessing outcome distributions (Cappelen et al., 2010) and that their fairness concerns and perceptions affect preferences for redistribution (Alesina and La Ferrara, 2005). Additionally, inequality stemming from circumstances might have an adverse impact on economic growth by reducing individual incentives to invest in human capital (Ferreira et al., 2014). Consistent with this, Marrero and Rodríguez (2013) have found a clear negative relationship between inequality of opportunity and growth in the U.S. As a consequence, the theoretical and empirical literature on equality of opportunity has grown enormously in the last decades.

Most of the empirical studies estimating inequality of opportunity, across countries and over time, originate from the framework introduced by Roemer (1998) and typically focus on one-dimensional outcomes of interest such as income, or other monetary variables like earnings and wealth, but also education or health. By considering one valuable life outcome at a time, these studies neglect the importance of embracing a broader perspective of a fulfilling life when defining and measuring well-being (Stiglitz et al., 2009), concept that has a solid ground in the

field of poverty measurement.[1] Furthermore, even though some empirical studies simultaneously investigate inequality of opportunity across multiple outcomes (Bourguignon et al., 2007; Ferreira and Gignoux, 2011), they often treat these outcomes as distinct entities, neglecting the importance of transcending the dimension-by-dimension approach. This fails to account for the clustering of multiple disadvantages (cumulative deprivation) or advantages (cumulative affluence), thus, the dependence between dimensions, which is the key feature of multidimensionality (Decancq, 2014; Ferreira and Lugo, 2013; Kobus et al., 2020). To get an intuition of the consequences, imagine an unfair society in which as female and migrant, one can expect a lower income than males who are born within the country. If female migrants are also the group which is more likely to be deprived jointly in terms of level of education and health status, the society is definitely even more unfair. The exploration of interdependence is not only relevant as a fine description of multidimensional well-being, but it holds a pivotal position within the framework of pluralistic distributive justice theory. As theorized by the political philosopher Michael Walzer (1983), while simple equality deals with the distribution of one dimension of well-being, like income, in a multidimensional perspective, complex equality requires that the dimensions of well-being are autonomous or independent. The presence of cumulative deprivation, thus, of individuals who occupy a low position on all well-being dimensions at the same time, would be an indicator of complex inequality in the society.

Some recent works have moved in the direction of the measurement of inequality of opportunity in a multidimensional setting, both theoretically and empirically. In a relevant contribution, Kobus et al. (2020) develop a normative approach to measure ex-ante Inequality of Opportunity (IOp) in a multidimensional framework. The authors characterize three classes of social welfare functions, endorsing ex-ante compensation and reflecting three different reward principles. They subsequently develop the corresponding normative inequality indices that adhere to the fundamental principles for equal-opportunity measures, along with satisfying standard properties of inequality indices.[2] Essentially, inequality of opportunity is assessed based on the individual utilities derived from the aggregation of the multiple outcomes. In the

[1] Indeed, inspired by the capability approach proposed by Sen (1985) and Nussbaum (2000) and with the early contribution of Atkinson and Bourguignon (1982) and Bourguignon and Chakravarty (2003), among others, several multidimensional measures of well-being have been developed and introduced in policy circles (think of the Human Development Index and the Multidimensional Poverty Index).

[2] These properties include inequality aversion between types, within-type transfer insensitivity for the former, and monotonicity, utilitarian aggregation, and ratio-scale invariance for the latter.

mentioned contribution, Kobus et al. apply the indices to estimate inequality of opportunity across education, health, and income dimensions in the U.S. in 2008. Hufe et al. employ Kobus et al.'s approach to compare multidimensional inequality of opportunity in income, education and health across 29 European countries in 2019 (2022b) and to study the unequal distribution of opportunities for the acquisition of both income and wealth in the U.S. over the time period 1983-2016 (2022a).

We contribute to this literature by exploring the association between birth circumstances and the joint distribution of income, health and education in Australia across birth cohorts. This paper differ from the existing works in two key aspects: first, we adopt an intuitive indicator of multidimensional well-being, obtained through a position-based approach based on Decancq's work on the measurement of cumulative deprivation and affluence through copula functions (Decancq, 2023, 2020). Moreover, following the recent methodological advancements brought about by Brunori et al. (2023c), we adopt an innovative data-driven approach to obtain the partition of the population and estimate between-type inequality, the Soft Regression Tree model by Consolo et al. (2024). Finally, we extract insights on the importance of the single birth circumstances on the well-being predictions by employing the SHAP (SHapley Additive exPlanation), a framework developed by Lundberg and Lee (2017a) to enhance the interpretability of complex machine learning models, understanding how the predictor variables contributes to the generation of the individual well-being prediction.

By exploiting the rich information contained in 20 annual waves (covering 2001-2021) of the Household, Income and Labour Dynamics in Australia survey, we provide a longitudinal analysis of inequality of opportunity in income, health and education, and of their interdependence, by comparing birth cohorts of people born between 1951 and 1996.

The findings suggest a stable trend in the level of association among income, health and education, together with an increase of the share of inequality in well-being predicted by circumstances at birth from 15% for individuals born in the 50s to 21% for those born in the 90s. Across the birth cohorts, there is an increase in the relative importance of maternal occupation in predicting well-being compared to paternal occupation. Additionally, across the various birth cohorts, Aboriginal status significantly negatively affects multidimensional well-being, although its low frequency in the population results in a relatively lower overall influence compared to other circumstances.

The paper is structured as follows. Section 2 explains the methodology employed and the theoretical frameworks behind. Section 3 describes the source survey and the variables used. Section 4 elaborates on the findings and Section 5 concludes.

3.2 Theory and Methods

The paper contributes to the developing literature on multidimensional inequality of opportunity and builds on two main methodological frameworks. First, the copula function and the downward diagonal dependence curve that we use to measure the dependence between multiple dimensions of well-being and to get a position-based indicator of multidimensional well-being. Second, the tree-based model used to estimate to what extent multidimensional well-being is predicted by ascriptive characteristics, a measure of unfair inequality according to the theory of equality of opportunity.

3.2.1 Dependence in multivariate distributions

Copula function

The copula is a mathematical concept used to model the dependence structure between random variables, particularly in multivariate distributions. It provides a way to separate the marginal distributions from the joint distribution of all the variables. In the context of this paper, following the work of Decancq (2014, 2020) and Pérez and Prieto-Alaiz (2016), the copula is employed to capture the dependence between different dimensions of well-being.

Considering m dimensions of well-being such as income, health, education, etc., the random vector $\mathbf{Y} = (Y_1, \ldots, Y_m)$ describes the distributions of the m outcomes across the individuals in the society. For each realization of the random sample $\mathbf{Y}, y = y_1, \ldots, y_m$, the cumulative distribution function $F_y(y_1, \ldots, y_m)$ gives the proportion of the population who have a less or equal value in each dimension.

$$F_Y(y_1, \ldots, y_m) = \Pr\left[Y_1 \leq y_1 \text{ and } \ldots \text{ and } Y_m \leq y_m\right]$$

Being F_j the marginal distribution function of one dimension, where $j = 1, \ldots, m$, we can denote the position of the individual having value y in dimension j, as $p_j = F_j(y_j)$, which can

be interpreted as the rank the individual has in the distribution of dimension j.

For each individual, a position vector $p = (p_1, \ldots, p_m)$ denotes the list of their positions in all dimensions of well-being. A position vector equal to $(1, \ldots, 1)$, suggests that the individual sits at the top of the ranking of the population in each dimension of well-being. Similarly, an individual with a position vector $(0, \ldots, 0)$ is bottom-ranked in every dimension. Considering the whole population, the random variable $P_j = F_j(Y_j)$ describes the distribution of the positions of the individuals in dimension j and the random vector $P(Y) = (F_1(Y_1), \ldots, F_m(Y_m))$ returns the distribution and the alignment of the positions in the society across the dimensions. A *copula function* C_Y is the cumulative distribution function of the positions, thus $F_P(Y)$. For each position vector $p = (p_1, \ldots, p_m)$, the copula C_Y gives the proportion of individuals in the society who are outranked by the position vector, meaning the proportion of individuals who occupy an equal or lower position than p_j in each dimension $j = 1, \ldots, m$.

$$C_Y(p_1, \ldots, p_m) = \Pr\left[F_1(Y_1) \leq p_1 \text{ and } \ldots \text{ and } F_m(Y_m) \leq p_m\right]$$

A higher value of the copula function for any given position vector, meaning a higher proportion of outranked individuals, would suggest a higher alignment of the position vectors.

The Sklar's theorem 1959 shows that it is possible to describe any multivariate distribution function F_Y as a function of its marginal distribution functions F_j and its copula function C_Y:

$$F_Y(y_1, \ldots, y_m) = C_Y(F_1(y_1), \ldots, F_m(y_m))$$

In a situation in which the dimensions of well-being are independent, the independence copula will be: $C^{\perp}(p_1, \ldots, p_m) = p_1 \times \ldots \times p_m$ suggesting the simple definition of a joint distribution function as the product of its marginal distribution functions. Any copula function is bounded between the Fréchet-Hoeffding bounds (Nelsen, 2006):

$$C_-(p_1, \ldots, p_m) \leq C_Y(p_1, \ldots, p_m) \leq C_+(p_1, \ldots, p_m)$$

The lower bound, the countermonotonic C_-, describes a situation in which there is no position vector which outranks or is outranked by another position vector since there are high

rankings in certain dimensions which correspond to low rankings in others. The upper bound or comonotonic C_+ copula, on the contrary, describes a situation in which there is clear ranking hierarchy across the position vectors, since there is one individual holding the top rank in all dimensions of well-being, another individual second-ranked across all dimensions, and so on.

Downward Diagonal Dependence Curve

The copula function enables the measurement of the dependence between the dimensions of well-being. Specifically, we are interested in one specific aspect of dependence: the alignment of the positions across all the dimensions, with a particular focus on the alignment of bottom positions. The main diagonal of a copula function connects the position vector that consists of the bottom position in all dimensions with the position vector that consists of the top position in all dimensions. Following Decancq (2020), we study the downward dependence by by deriving the downward diagonal dependence curve $D_Y(p)$ which is the diagonal section of a copula function along the main diagonal. For each position p, it quantifies the proportion of individuals with a position lower or equal to p in all the considered dimensions:

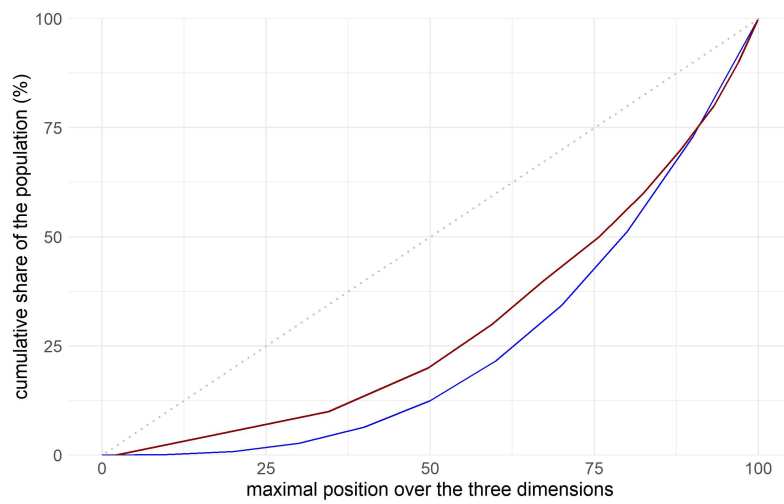
$$D_Y(p) = C_Y(p, \ldots, p)$$

Based on Decancq (2020) and Decancq (2023) we can summarize the level of dependence with an approach similar to the Gini approach to inequality measurement with the downward diagonal dependence curve playing a role comparable to the Lorenz curve. As shown by Decancq it is possible to approximate the downward diagonal dependence curve with the cumulative distribution function of the maximal positions. The vector of maximal positions is a n-dimensional vector, with n the total number of individuals in the population, reporting for each individual their highest position among their positions in the m rankings. figure Figure 3.1 shows the diagonal dependence diagram for one of the Australian birth cohorts analyzed in the paper but in this context it only serves an illustrative purpose. For each position between 0 and 100[1] on the horizontal axis, the downward diagonal dependence curve (the red curve) gives, on the vertical axis, the share of the population that obtains a lower maximal position than the position in question. In other words, the y-axis of the diagonal dependence diagram coincides

[1] Positions, between 0 and 1, multiplied by 100.

with the copula density. The dashed grey line represents the diagonal dependence curve of the co-monotonic case, C_+, characterizing a situation of maximal dependence, in which every individual occupies the same position in each dimension ranking. In the case of no dependence between dimensions, the downward diagonal dependence curve is given by $(p)^m$ (the curve represented in blue in figure 3.1). In a society with $m = 3$ independent dimensions of well-being, 12.5% of the population would sit in the first half of the ranking in all dimensions of well-being. In case of maximal dependence, when the maximal position is equal to the other positions, 50% of the population would be below the median in all dimensions.

Figure 3.1: Downward Diagonal Dependence Curve



Source: own elaboration with data from HILDA.

This is an illustration of a downward diagonal dependence curve obtained using the data of the Australian birth cohort 1957-1966

The diagonal dependence index is intuitively derived by measuring the area between the cumulative deprivation curve (represented in red) and the blue arched curve that represents independence, multiplied by 100. It equals 0 when there is no dependence between the well-being dimensions and 100 when there is maximal dependence. As Decancq (2020) has demonstrated, the diagonal dependence index turns out to be equal to the multidimensional generalisation of the Spearman's Footrule.[1]

[1] The sample version of Spearman's footrule with $m = 3$ is equal to the average of the three pairwise sample

Maximal position

In the present paper, the maximal position serves not only the purpose of measuring dependence between positions, but it is adopted as an indicator of individual well-being in relative terms. It can be interpreted as an upper bound of multidimensional well-being, since we know for sure that the individual does not occupy higher positions than that one in any dimension. Moreover, it can be understood as a proxy for multidimensional well-being with a particular sensitivity to the correlation between bottom positions: the lower the maximal position, the stronger the clustering of relative disadvantages.

3.2.2 Inequality of Opportunity

Inspired by the philosophical literature introducing the idea that the source of inequality matters when discussing about egalitarianism (Rawls, 1971; Cohen, 1989; Arneson, 1989; Sen, 1980; Dworkin, 1981a), economists have developed opportunity egalitarian frameworks to distinguish fair from unfair inequality (Roemer, 1998; Van De Gaer, 1993; Fleurbaey and Schokkaert, 2009). This is possible under the key assumption that the distribution of a unidimensional outcome variable y, like income, within a population of n discrete individuals indexed by $i = 1, \ldots, n$, is a function of the set of circumstances faced by the individual, $\mathbf{c}_i$, factors beyond individuals' control like sex and the family background, and of the amount of effort exerted e_i.

$$y_i = f(c_i, e_i) \tag{3.1}$$

Within such framework, any finite population can be partitioned in a set of exhaustive and mutually exclusive groups of individuals sharing the same circumstances, $\Pi = \{T_1, \ldots, T_k\}$, the so-called *types* (Roemer, 1998). Adopting Van De Gaer's *ex-ante utilitarian* approach, the value of a type's opportunity set can be described by the expected value of its outcomes, $E[y|c]$. Equality of opportunity (EOp) holds when different birth circumstances are not associated with differences in the outcome of interest, thus, when the expected outcome does not vary

Spearman's footrule coefficients:

$$\hat{\varphi}^{(1)} = 1 - \frac{3}{n^2 - 1} \sum_{i=1}^{n} |p_{i1} - p_{i2}|$$

See Pérez and Prieto-Alaiz (2016) for an extensive discussion on the multivariate Spearman's footrule.

between types.[1]

$$\bar{y}_k = \bar{y}_s \ \forall \ k, s \mid T_k, T_s \in \Pi \tag{3.2}$$

As a consequence, measures of inequality of opportunity (IOp) quantify the extent to which individual outcomes are predicted by circumstance characteristics, the *between-type* inequality. These measures are frequently constructed in two steps. Firstly, by obtaining a counterfactual smoothed distribution $\hat{y}_i$, where each observation is assigned with the average outcome of the type she belongs to. Secondly, by applying a suitable dispersion measure I(.) to the smoothed distribution $\hat{y}_i$. This reveals the absolute level of IOp, while relative measures of IOp (3.3) are simply expressed as the share of the total inequality in the population predicted by the between-type inequality:

$$\text{Relative IOp.: } \frac{I(\hat{y}_i)}{I(y_i)} \tag{3.3}$$

In most empirical applications I() represents an inequality index like the variance, the Gini index or the mean logarithmic deviation (MLD). The choice of I() has a normative meaning since it specifies the extent of inequality aversion at different points of the distribution. In this work the outcome variable Y is given by the *maximal position* among the positions each individual occupies in the three population rankings related to income, education and health. Differently from the traditional outcome variable the IOp literature deals with, this is an ordinal outcome. We are agnostic about the normatively correct choice of I(), we present our results in relative terms, as the share of the variance in the maximal positions predicted by the circumstances.

The counterfactual distribution has been traditionally estimated in the empirical works through both non-parametric and parametric approaches. The former involves partitioning the population into types defined by all the possible combination of the categories of the available circumstances. The latter consists in running a regression model, thus, assuming a log-linear and additive relationship between the circumstances and the outcome variable (Bourguignon et al., 2007; Ferreira and Gignoux, 2011). In the first contributions to the empirical literature, a specif model was assumed, without acknowledging the need to select the most appropriate specification by trading-off upward and downward biases depending on the arbitrary choices

[1] See Fleurbaey and Peragine (2013) for an analysis of the theoretical distinctions between the ex-ante and ex-post approaches to equality of opportunity.

of the researchers as regards the number of types partitions or the functional form of the regression (Brunori et al., 2019). The recent advancements in the empirical literature aims at mitigating the bias-variance trade-off by introducing machine-learning algorithms, specifically regression trees and forests, which provide the most relevant partition given the available data set and circumstances (Brunori et al., 2023c,a).

Regression Trees

A way to trade-off the two biases consists in partitioning the ample by estimating a tree or a collection of trees (forests). Regression trees and forests fall under the category of supervised learning techniques designed to predict an outcome variable out-of-sample using various observable predictors. In general, these algorithms partition the data set into mutually exclusive subsets on the basis of the values of the regressors and statistically meaningful splitting rules, imposing minimal assumptions on the functional form. These models belong to the decision tree family, and their structure resembles a tree with a root, intermediate nodes (branch nodes), and leaves (leaf nodes). The final prediction is typically calculated as the mean, or another suitable statistic, of the response variable values associated with the subsample that fall into that leaf node. These two basic general aspects of regression trees make the connection with the estimation of inequality of opportunity quite straightforward. If the predictors represents birth circumstances, the resulting subsamples falling in the leaf nodes can be seen as corresponding to the *Roemerian* types and the predicted outcome aligns with the estimation of the counterfactual distribution. Moreover, as with other machine learning models, regression trees are constructed using techniques like cross-validation with the goal to minimize the overall prediction error by managing the bias-variance trade-off, thus creating a model that generalizes well to new data while also capturing the underlying patterns in the data. This turns out to fit the challenge of mitigating the downward/upward biases induced by the researchers arbitrary choices both when imposing a functional form and choosing the relevant types partition of the population (Brunori et al., 2023c).

The recent contributions to the literature of IOp estimation adopting regression trees have employed the Conditional Inference Trees developed by Hothorn et al. (2006) (Plassot et al., 2022; Escanciano and Terschuur, 2022).

This study makes a novel contribution to existing research by implementing a fresh regres-

sion tree algorithm developed by Consolo et al. (2024), the *Soft Regression Tree* (SRT hereafter). The use of SRT represents an improvement with respect to other tree-based algorithms proposed in the literature for two main reasons. First, compared to greedy tree based model, such as CART and Conditional Inference Tree, where an impurity criteria or a local statistical test are considered, the SRT is based on an effective method for constructing globally optimized decision trees that directly consider the actual error measure. This allows to obtain a shallow tree that is both easily interpretable and competitive in terms of accuracy with the classical ensemble random forest methods. Second, by including linear predictions at each leaf node cluster, SRT performs better than the CIT when the data generating process is linear.

Soft Regression Trees

In regression tasks, we handle a dataset consisting of pairs of input vectors $(\mathbf{c}_i, y_i)$ that represent an individual i, with i ranging from 1 to n. In this context, the vectors of predictors variables $\mathbf{c}_i$ are k-dimensional and represent the birth circumstances, while the corresponding response values y_i, the multidimensional well-being index.

Regression trees are used to partition the population into distinct, non-overlapping groups. Each of these groups exhibits homogeneity with respect to the input variables. These groups are commonly referred to as terminal or leaf nodes $t \in \tau_L$. In traditional regression trees, a constant prediction value $\hat{y}_{it}$ is assigned to each individual. This prediction value is identical to the mean of the response values of the group (leaf node) to which the individual is assigned based on their $\mathbf{c}_i$ values. In contrast, the prediction at each leaf node $t \in \tau_L$ of an SRT model is determined by considering a linear combination of the k input features. This combination involves the use of coefficients and an intercept specific to that particular leaf node.

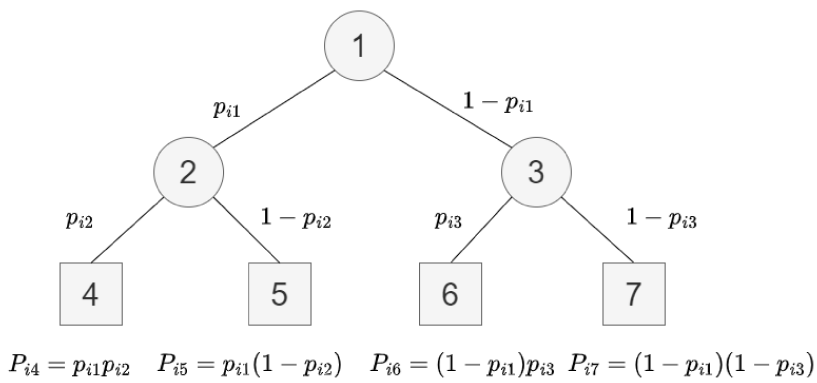
For a given depth D, the SRT constructs a maximal decision tree, exploiting the full depth without excluding any potential branches. This implies an *a priori* number of branch nodes τ_B and leaf nodes τ_L. The sample is split into two distinct groups at each branch node $t \in \tau_B$ according to a probabilistic decision rule. Indeed, at each branch node $t \in \tau_B$, the choice to assign any observation i to the left branch depends on the value p_{it} obtained through the

following logistic regression:

$$p_{it} = F(\mathbf{w}_t^T \mathbf{c}_i) = F(w_{0t} + \frac{1}{p}\sum_{j=1}^{p} w_{jt} c_{ij}), \tag{3.4}$$

where $F(\cdot;\mu) = \frac{1}{1+e^{-\mu(\cdot)}}$[1] and $\mathbf{w}_t$ denotes the $(k+1)$-dimensional vector containing the k coefficients and the intercept of branch node t. The right branch is taken with probability $1 - p_{it}$. Figure 3.2 provides an example of an SRT of depth $D = 2$.

Figure 3.2: Soft regression Tree - Example of depth $D = 2$.



Using the logistic function to split the sample in two sub-samples implies a soft split at branch nodes, since every input vector falls into the branch nodes and the leaf node with a probability rather than with a yes/no rough rule. Therefore, every observation has a nonzero probability to be assigned into every leaf node $t \in \tau_L$.

For any given leaf node t within τ_L, we can define two sets of ancestor nodes. One set, denoted as $A_L(t)$, includes the ancestor nodes whose left branches are part of the path from the root to leaf node t. The other set, $A_R(t)$, includes the ancestor nodes for the right branches along this path. The overall probability that any input vector $\mathbf{c_i}$ falls into any leaf node $t \in \tau_L$ is given by the product of the two set of ancestors probabilities:

$$P_{it} = \prod_{t_l \in A_{L(t)}} p_{it_l} \prod_{t_r \in A_{R(t)}} (1 - p_{it_r}) \tag{3.5}$$

[1] The parameter $\mu > 0$ controls the slope of the function.

Eventually, the prediction $\hat{y}_{it}$ in each leaf node $t \in \tau_L$ is determined as a linear combination of the p input features:

$$\hat{y}_{it} = \boldsymbol{\beta}_t^T \mathbf{c}_i = \beta_{0t} + \beta_{1t} c_{i1} + \cdots + \beta_{pt} c_{ip} \tag{3.6}$$

where the $(k+1) \times |\tau_L|$ matrix $\boldsymbol{\beta} = (\beta_{jt})$ with $j = 0, 1, \ldots, k, t \in \tau_L$ contains all the parameters of the leaf nodes. For $t \in \tau_L$ the variable $\beta_{0t} \in \mathbb{R}$ represents the intercept of the linear prediction in the leaf node t.

The training process involves obtaining the SRT model's parameters (coefficients and intercepts) by minimizing the following weighted mean squared error loss function:

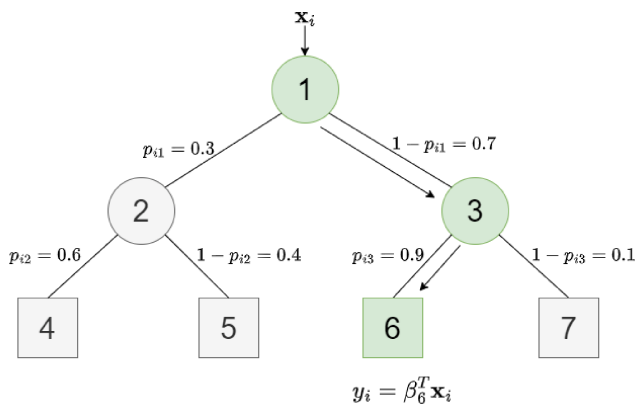
$$\min_{\mathbf{w},\boldsymbol{\beta}} E(\mathbf{w}, \boldsymbol{\beta}) := \frac{1}{N} \sum_{i \in I} \sum_{t \in \tau_L} \prod_{\ell \in A_{L(t)}} p_{i\ell}(\mathbf{w}_\ell) \prod_{r \in A_{R(t)}} (1 - p_{ir}(\mathbf{w}_r)) \cdot (\hat{y}_{it}(\boldsymbol{\beta}_t) - y_i)^2 \tag{3.7}$$

$$\min_{\mathbf{w},\boldsymbol{\beta}} \frac{1}{N} \sum_{i \in I} \sum_{t \in \tau_L} P_{it}(\mathbf{w}) \cdot (\hat{y}_{it}(\boldsymbol{\beta}_t) - y_i)^2. \tag{3.8}$$

where weight P_{it} are the probabilities of reaching leaf node t for each input vector i.

Training such model is a challenging task, due to both the nonconvexity of function (3.7) and the computational load when the size of the problem increases (number of features, number of samples and layers of the tree). Consolo et al. (2024) propose a specific training algorithms where the original problem is splitted in a sequence of subproblems (corresponding to subset of nodes) that are sequentially optimized, keeping fixed the others. Once the model is trained, the final output of the SRT for any input vector $\mathbf{x} \in \mathbb{R}^k$ is computed in a deterministic way. For any individual i the actual prediction is taken as the linear regression associated with the (single) leaf node reached by following the branches with highest probability, starting from the root. Figure 3.3 shows an example of the prediction procedure for a SRT of depth $D = 2$.

Figure 3.3: Soft Regression Tree - Example of prediction procedure for a single data point.



Example of prediction procedure for a data point $\mathbf{c}$. Following the branches with the highest probability (indicated by the arrows) leads to a single leaf node for making predictions. $\beta_6^T \cdot \mathbf{c}_i$ represents i's final prediction.

3.2.3 Model interpretation

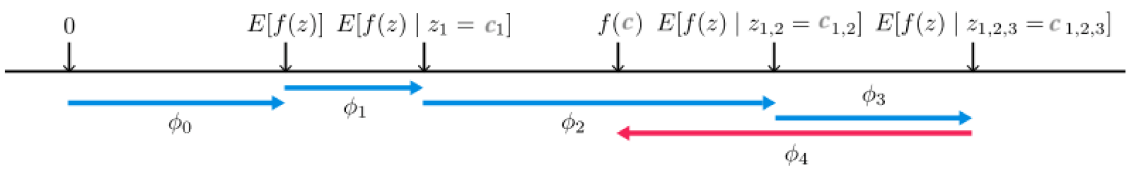
To enhance the understanding of how the predictor variables contributes to the generation of the individual model's prediction, this paper leverages the SHapley Additive exPlanations framework (SHAP), introduced by Lundberg and Lee (2017a). SHAP is founded on the concept of Shapley values, which has its roots in collaborative game theory as a method for assigning payouts to players depending on their contribution to the total payout (Shapley et al., 1953). In this context, the "game" is the prediction task for a single input vector of the dataset. The "total payout" is the difference between the prediction for that specific input vector and the average prediction for all observations in the dataset. The "players" are the predictor variables that contribute to predict the final value for the specific input vector. The Shapley value is the average marginal contribution of a predictor variable to the "total payout" across all possible combinations of the predictor variables.

Figure 3.4 presents an illustrative example from Lundberg and Lee (2017b). For each input vector $\mathbf{c}_i$ (the vector of birth circumstances in this case), the SHAP value φ_j attributes to each predictor c_j, where $j = 1, \ldots, k$[1], the difference between the individual prediction $f(\mathbf{c})$ and the expected model prediction $E[f(\mathbf{z})]$ (where $\mathbf{z}$ is the set of variables used for the prediction) when

[1] Where k is the total number of predictors.

conditioning on that feature. Given the presence of non-linearity and correlations between the input features, it is crucial to consider the order in which the variables are added to the set of predictors **z**. Therefore, the SHAP values stem from the averaging of φ_j values across all possible orderings. In a nutshell, φ_j tells how much the prediction changes when feature c_j is included, considering all possible combinations of variables.

Figure 3.4: Shapley Additive ExPlanation framework



Source: illustration adapted from Lundberg and Lee (2017b)

The Python library *shap* provides a comprehensive framework for computing Shapley values efficiently, even for complex machine learning models. These values can be visualized to understand the importance of single predictors on the model predictions, making the interpretation of the model more transparent.

3.3 Data and context

The analysis is based on the micro data from 20 annual waves (2001 – 2021, Release 21) of the Household, Income and Labour Dynamics in Australia survey (HILDA). HILDA is a longitudinal household based survey collecting information on a wide range of topics related to income, socio-economic status, education and health on all members of sample households aged 15 and over. It includes a remarkable amount of retrospective information on individual characteristics widely considered in the socio-economic literature, as factors over which individuals have no control. For instance, questions on the education and occupation of parents and country of origin are included in the questionnaire. The retrospective information and the wide range of topics covered make HILDA a valuable resource for estimating both multidimensional well-being and inequality of opportunity in Australia, as recently done, respectively, by Rohde and Guest (2018), and Martinez Jr et al. (2017) and Wu et al. (2021).

Despite Australia's position among the growing economies of the developed world, evi-

dence suggests, that the benefits from economic growth have not been evenly distributed. As shown by Azpitarte (2014), on average low-income people benefited from the growth of the first decade of the XXI century more than those who were poor in multiple dimensions. Interestingly, Australians have consistently shown less concern about inequality compared to the OECD average over the past few decades. They also express higher levels of confidence in the belief that hard work leads to success in life, coupled with a lower-than-average demand for redistribution. (OECD, 2021). It is therefore interesting to explore the relevance of factors beyond individual control in the inequality observed. Specifically, we believe that Australia is a context in which it is particularly meaningful to look at multidimensional inequality of opportunity. Historically, indeed, there have been groups that have experienced discrimination such as the Aboriginal and Torres Strait Islander and the first generation of immigrants after the war (Argy, 2006). Aboriginal and Torres Strait Islander individuals (hereafter Aboriginal), represent 3.2% of the total Australian population as the Census 2021 reports (ABS, 2022). They have endured historical displacement and discrimination since the British colonization in 1788. Pervasive policies contribute to intergenerational trauma, resulting in disparities in health, education, employment, and criminal justice. The period known as the 'Stolen Generation', spanning from 1910 to 1970, witnessed the forced removal of Aboriginal children from their families with the aim of assimilating them into mainstream society. In 2008, the Australian government committed to "close the gap", enhancing the health and well-being outcomes of Aboriginal communities (Davis, 2015). Despite some improvements, the gaps in the rates of child mortality, school attendance, employment and life expectancy have not been reduced (Agency, 2020). Indigenous communities experience considerable hardships across many domains, with distinctive disparities compared to non-indigenous Australians, such as an average life expectancy at birth lagging by 8 years, employment rates standing approximately 30% below the average of non-indigenous and imprisonment rates soaring seventeen times higher (ABS, 2022).

Our unit of analysis is the individual in the working age range 25-55. Well-being is assessed considering simultaneously income, health and education. These variables stems from the intersection of the set of key dimensions suggested by Stiglitz et al. (2009) for the definition of multidimensional well-being[1] and the ones typically regarded as valuable outcomes against

[1] The remaining key dimensions recommended by Stiglitz et al. (2009) are: (iv) personal activities, (v) political

which equalizing opportunities in the equality of opportunity literature (Kobus et al., 2020; Hufe et al., 2022b; Rosa Dias, 2009; Fleurbaey and Schokkaert, 2009; Davillas and Jones, 2020; Brunori et al., 2023c; Ferreira and Gignoux, 2010; Palmisano et al., 2022).

As regards income, the proxy for material living conditions, we consider the equivalised household disposable income, adjusted for inflation, using the Australian Bureau of Statistics (ABS) Consumer Price Index, so that income in all waves is expressed at March 2023 prices. It is derived by dividing household disposable incomes over the square-root of the household size. This approach ensures the inclusion of unemployed, inactive, or unable to work individuals in the analysis, and it considers economies of scale within the household. However, it is acknowledged that this may result in negligible variation with respect to sex. Moreover, following Brunori and Neidhöfer (2021), we address the issue of income variations linked with the life-cycle, by regressing the equivalised household income for each individual on their age and age-squared, eventually employing as our outcome variable the sum of the constant and resulting residuals from this regression.

We measure education in years of formal schooling and, following Leigh et al. (2005), we use two variables to construct it. The first is highest year of schooling completed or currently attended which covers from 5 up to 12 years. The other education variable is the highest educational level achieved; when the respondent holds a post-school qualification, the years of schooling are coded as: 17, if it is a postgraduate degree, 16 for graduate diploma/certificate, 15 when it is a bachelor's degree, 14 if it is an advanced diploma/diploma and 13 for certificate III or IV.

We measure health by the SF-6D health state classification provided by HILDA, which is a standardized multidimensional health state classification constructed from variables related to the several health dimensions - social functioning, physical functioning, role limitations, bodily pain, mental health, vitality - and Australian preference or utility weights elicited from a sample of the population (Brazier et al., 2002; Norman et al., 2014). Following Brunori et al. (2022), we account for the age-specific variations in health by regressing the individual health score on 5-year age classes and employing the sum of the constant and the residuals as our indicator of health status.

voice and governance, (vi) social connections and relationships, (vii) environment (present and future conditions), (viii) insecurity (of an economic as well as a physical nature).

Based on the factors commonly considered beyond individual's control in the literature on inequality of opportunity and the context-specific high relevant factors, the birth circumstances introduced in the analysis are the following: sex, area of birth, aboriginal status, parental occupation, education and area of birth, the number of siblings and whether the respondent was living with the parents when 14 years old. The list of circumstances with their respective categories is reported in Appendix Section 3.5 in Appendix .2.

Given the longitudinal nature of the HILDA survey, there are individuals who are observed across multiple waves, representing different life stages within the specified working age range of 25 to 55 years. However, this paper studies how the dependence between income, health and education and the multidimensional IOp evolve across birth cohorts compared in the same age range. Therefore, for the individuals interviewed more than ones across the 20 waves, a single observation is retained. This choice is not problematic for the values of the circumstance variables since, by definition, they are stable over time. Meanwhile, the outcome variables might exhibit changes, although the analysis is confined to an age span during which income, attained educational levels, and overall health tend to remain relatively steady. To handle this issue and track one representative observation of the individual's well-being during his or her working age period of life, for each outcome variable we consider the median value of the various individual's observations.

Finally, observations presenting missing values in one of the three outcome variables are dropped while we run a nonparametric method to impute the missing values in the predictors, specifically a method based on random forest from the R package *missForest* developed by Stekhoven (2022).[1]

The final sample consists of 20.161 individuals born between 1945 and 1996. To discern gradual patterns, we divide the dataset into cohorts using 10-year rolling periods based on birth years. It is important to note that the birth year denotes the middle year of the respective 10-year interval (for example, the interval 1962 includes the years 1958–1967). In order to mitigate any potential distortion due to varying and limited sample sizes, we only include cohorts with a minimum of 3000 observations, obtaining a set of 38 cohorts.[2]

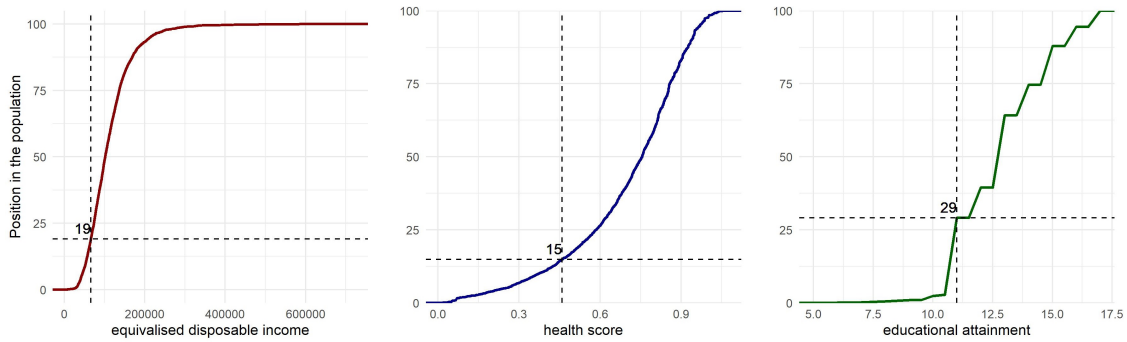
[1] https://CRAN.R-project.org/package=missForest

[2] Essentially, the initial and final cohorts, which have limited observations, are excluded from consideration.

3.3.1 Deriving the maximal position

In each birth cohort we follow Decancq's position-based approach (2023), firstly by ranking the individuals in each well-being dimension.[1] The individual's position is then expressed in (0,100), indicating the percentile rank, thus, the percentage of the population which is below the subject's position in that specific outcome variable. For illustrative purposes, we report in Figure 3.5 the cumulative distribution functions for the three dimensions for one birth cohort 1957-1966. From the individual's position vector summarising the positions in the three dimensions (e.g. for individual j, (y_{ji}, y_{je}, y_{jh})) we extract the maximal position which equals the highest value of the position vector.

Figure 3.5: Cumulative distribution functions for income, education and health



Source: own elaboration with data from HILDA.

The maximal position for the random individual shown in this figure with position vector $(19, 15, 29)$ is 29.

3.4 Results

Our analysis proceeds in three steps. First, we describe the evolution of the dependence between the three dimensions of well-being in Australia. This involves plotting the downward diagonal dependence curve and computing the diagonal dependence index for each birth cohort. Second, using the maximal position across the three outcomes' rankings, as a measure of multidimensional well-being, we estimate the inequality in the counterfactual distribution $\hat{y}$, obtained by predicting the maximal position using as predictors factors beyond individual

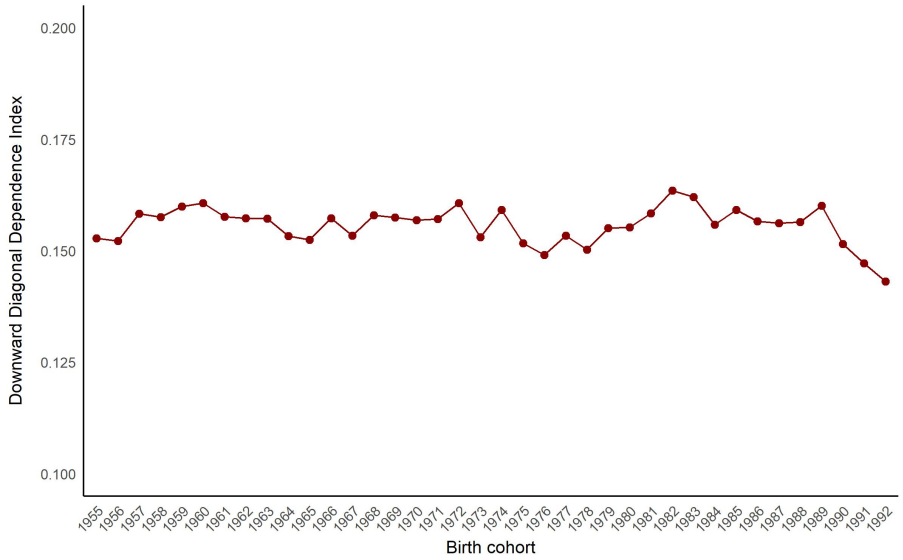
[1] In case of ties, the individuals are sorted randomly.

control. Third, we assess the relative contribution of each birth circumstance in predicting the individual's maximal position across the population rankings for income, education and health.

3.4.1 The Diagonal Dependence Index

As introduced in the methodological section, we follow Decancq (2023)'s approach to study the evolution of dependence between the three well-being dimensions. The proposed downward dependence index is a measure of how clustered the disadvantages in income, health and education are. Estimating the value of the index for each birth cohort and plotting the trend, as in Figure 3.6, we observe a relatively stable pattern.

Figure 3.6: Evolution of the Downward Diagonal Dependence Index



Source: own elaboration with data from HILDA.

3.4.2 Multidimensional Inequality of Opportunity

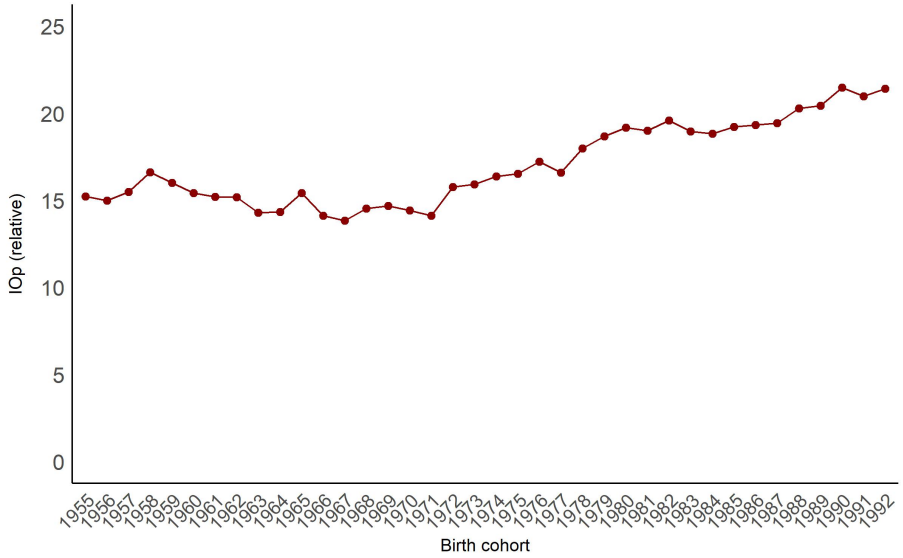
We now turn to the analysis of the evolution, across birth cohorts, of inequality of opportunity for multidimensional well-being, proxied by the *maximal position*.

We opt to utilize the Soft Regression Tree algorithm by evaluating its performance against Conditional Inference Trees, Random Forest and linear regression through a 10-fold cross-validation approach. This assessment involves comparing out-of-sample performance metrics,

specifically Mean Squared Error and R-squared.[1]

Inequality of opportunity, as measured by the variance of the maximal positions predicted only using birth circumstances, accounts for between 15% and 21% of the total inequality. This measure exhibits a rising pattern across consecutive birth cohorts, as illustrated in figure 3.7.

Figure 3.7: Multidimensional Inequality of Opportunity (relative)



Source: own elaboration with data from HILDA.

The plot shows the estimated relative IOp by birth cohort.

Model interpretation

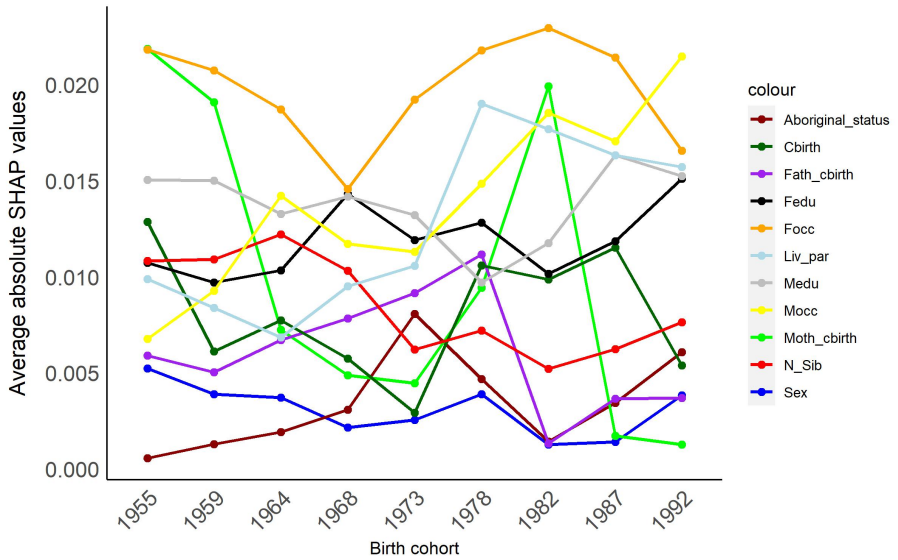
To get an overview of the relative importance of the different circumstances at birth to the well-being prediction and to explore how the pattern changes over time, we employ the Shapley Additive Explanation framework, as introduced in the methodological section. In this section we summarize the findings by plotting the averages across the cohorts.

Firstly, we look at the relative contribution of each birth circumstance to the well-being prediction. The plot in Figure 3.8 provide insights into the global impact of each predictor variable on the model's predictions across the birth cohorts. For each circumstance and birth cohort the dot represents the absolute SHAP values averaged across all the individuals, expressed in relative terms to the total across all birth cohorts. For each cohort we observe the circumstances

[1] For insights into the process and outcomes of this comparison, please feel free to request further details.

arranged in descending order of their influence on the predictions. Overall, we clearly observe a stable high relative importance of the occupation of the father (the *orange* line) and an increasing trend for the occupation of the mother (the *yellow* line).

Figure 3.8: SHAP values average trend



Source: own elaboration with data from HILDA

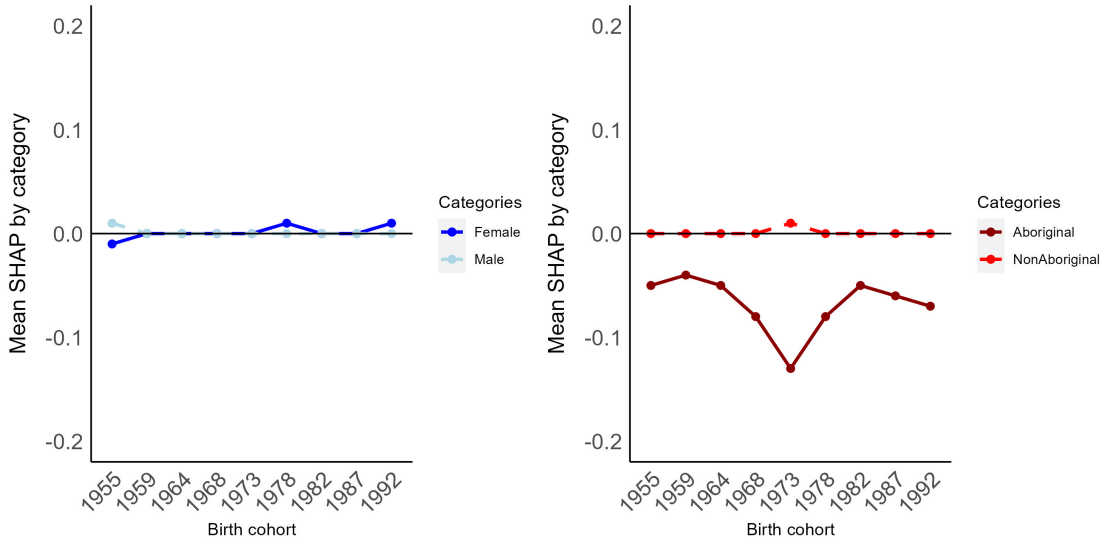
Each dot is obtained averaging the individual SHAP values of each predictor over the whole population of the specific birth cohort.

By considering only the sum of the magnitudes of the SHAP values over all observations, we might lose interesting insights on the phenomenon at study. Firstly, impacts averaged over the whole population may hide substantial impacts of circumstances that are not highly frequent in the data. Secondly, by referring to average absolute values, we do not discern positive and negative impacts. Therefore, we complement the analysis of the absolute relative contribution to the well-being prediction by looking at the sign and magnitude of the impacts averaged on the population of reference, meaning on the observations who present the specific feature's value. The plots in Figure 3.9 and 3.10 show, indeed, the impacts on the prediction for some of the circumstances, averaged on the population who assume a certain feature's value.[1] To make it clear, the dots in the left plot in Figure 3.9 represent the average of the individual SHAP values

[1] The plots displaying the remaining birth circumstances are shown in Appendix Section 3.5 in Figure 11,12,13, 14, 15 and 16.

of the circumstance *sex* computed, the blue, over females and the light blue, over males. This allows to discern positive and negative impacts but also marginal effects of low frequent circumstances. For instance, as is clear from the plot on the right in Figure 3.9, the status of aboriginal has an average impact on the well-being prediction which is high and negative for all the birth cohorts. However, in terms of overall importance, as seen in Figure 3.8, the Aboriginal status ranks among the least influential birth circumstances affecting well-being, primarily because the share of Aboriginal individuals in the sample is very small. The tiny impact of the respondent's sex on individual well-being predictions should be observed keeping in mind that one of the tree dimensions of well-being is the equivalised household income, that, by definition, masks intra-household variation. The country of birth gives a relatively small contribution to the predictions (as in Figure 3.8) but it interesting to notice in Figure 3.10 that being a migrant both from English speaking countries and from non English-speaking countries has a positive impact on the predicted well-being.

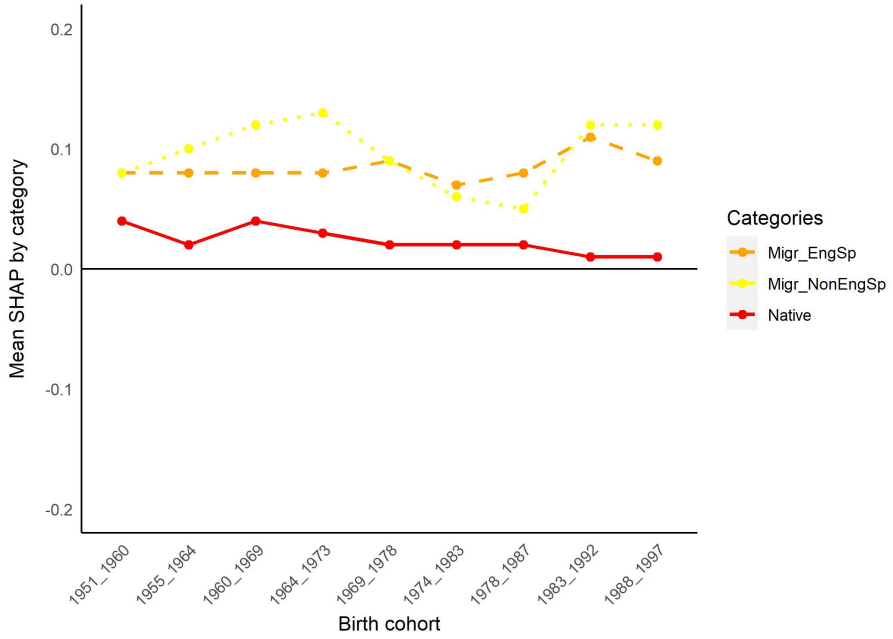
Figure 3.9: SHAP values - Sex and Aborigenal status



Source: own elaboration with data from HILDA

Each dot is obtained averaging the individual SHAP values of the predictors *sex* (on the left) and *aboriginal status* (on the right) over the individuals who show a specif category of that circumstance (for instance, the *dark red* dot on the right plot is given by the average of the SHAP values of *aboriginal status* across the individuals who belong to indigenous people).

Figure 3.10: SHAP values - Country of birth



Source: own elaboration with data from HILDA

Each dot is obtained averaging the individual SHAP values of the predictors *country of birth* over the individuals who show a specif category of that circumstance (for instance, the *yellow* dot is given by the average of the SHAP values of *country of birth* across the individuals born in non-English speaking countries).

3.5 Conclusions

In this paper, we study inequality of opportunity in income, health and education in Australia across birth cohorts born over the time period 1951-1996. The key novelty is that we study the association between birth circumstances and the three dimensions altogether, considering the multidimensionality of well-being as well as the key issue of interdependence, the clustering of disadvantages. Our findings document a stable pattern in terms of correlation between income, health and education. As regards unfairness, we observe an increasing trend in the share of inequality in well-being predicted by factors beyond individual's control. Lastly, while the occupation of the father has been constantly highly relevant for the prediction of individual well-being, we notice an increasing pattern in the relative predictive importance of the occupation of the mother. Although not substantial in overall relative terms, across all birth cohorts, the status of Aboriginal highly and negatively affects individual well-being predictions.

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.1 Appendix Chapter 2

Table 1: List of circumstances - EUSILC-GSOEP-UKHLS

Circumstance	Categories
Respondent's country of birth:	179 values (classification of Countries using SCL Geo codes)
Respondent's sex:	• (1) Male • (2) Female
Father/mother education (based on international Standard Classification of Education 2011 (ISCED-11):	• (1) Low level (less than primary, primary education, or lower secondary education) • (2) Medium level (upper secondary education and post-secondary non-tertiary education) • (3) High level (short-cycle tertiary education, bachelor's or equivalent level, master's or equivalent level, doctoral or equivalent level)
Father/mother's main occupation (based on International Standard Classification of Occupations, published by the International Labour Office ISCO-08):	• (0) Armed Forces Occupations • (1) Managers • (2) Professionals • (3) Technicians and Associate Professionals • (4) Clerical Support Workers • (5) Services and Sales Workers • (6) Skilled Agricultural, Forestry and Fishery Workers • (7) Craft and Related Trades Workers • (8) Plant and Machine Operators and Assemblers • (9) Elementary occupations • (10) Unemployed, deceased or not living with the respondent

Table 2: Definition of countries of birth aggregates

Macro area of birth	Countries
OTHCaribbean:	Anguilla, Antigua and Barbuda, Aruba, Bahamas, Barbados, Bonaire Saint Eustatius and Saba, British Virgin Islands, Caribbean, Cayman Islands, Cuba, Curaçao, Dominica, Former Netherlands Antilles, Grenada, Haiti, Jamaica, Montserrat, Sint Maarten, St. Kitts and Nevis, St. Vincent and the Grenadines, St-Barthélemy, St-Martin, Trinidad and Tobago, Turks and Caicos Islands, U.S. Virgin Islands
OTHSouthAmerican:	Bolivia, Chile, Falkland Islands, French Guyane, Guyana, Paraguay, Suriname, Uruguay
OTHcentralAmerican:	Belize, Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, Mexico, Panama
OTHNorthAmerican:	Canada, Greenland, Saint Pierre and Miquelon, Puerto Rico, Bermuda
OTHWestAfrica:	Burkina Faso, Benin, Togo, Ghana, Côte d'Ivoire, Liberia, Sierra Leone, Guinea-Bissau, Guinea, Niger, Cape Verde, Gambia, Mauritania, Saint Helena, Mali
OTHNorthAfrica:	Egypt, Libya, Sudan, South Sudan, Western Sahara
OTHCentralAfrica:	Angola, Cameroon, Central African Republic, Chad, Congo, Gabon, Democratic Republic of the Congo, Equatorial Guinea, São Tomé and Principe
OTHEastAfrica:	Burundi, Comoros, Djibouti,Eritrea, Ethiopia, Kenya, Madagascar, Malawi, Mayotte, Mauritius, Mozambique, Rwanda, Seychelles, South Sudan, Somalia, Somaliland, Tanzania, Uganda, Zambia, Zimbabwe

Continued on the following page.

Table 3: Definition of countries of birth aggregates

Macro area of birth	Countries
OTHSouthAfrica:	Lesotho, Eswatini, Namibia, Swaziland, Botswana
OTHMiddleEast:	Arab Emirates, Armenia, Azerbaijan, Bahrain, Georgia, Israel, Jordan, Kuwait, Lebanon, Oman, Palestine, Qatar, Saudi Arabia, Yemen
OTHCentralAsia:	Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, Uzbekistan
OTHEastAsia:	Japan, North Korea, South Korea, Mongolia, Taiwan
OTHSouthEastAsia:	Brunei, Cambodia, Indonesia, Lao PDR, Malaysia, Myanmar Burma, Myanmar, Singapore, Thailand, Timor-Leste
OTHSouthAsia:	Bhutan, Maldives, Nepal
OTHOceania:	American Samoa, Ashmore and Cartier Island, Australia, Australia and New Zealand, Cook Island, Federated States of Micronesia, Fiji, French Polynesia, Guam, Kiribati, Marshall Island, Melanesia, Micronesia, Nauru, New Caledonia, New Zealand, Niue, Norfolk Island, Palau, Papua New Guinea, Pitcairn Island, Polynesia, Samoa, Solomon Island, Tonga, Tuvalu, Vanuatu, Wallis and Futuna Island
OTHEurope:	Aland, Andorra, Belarus, Faeroe Island, Gibraltar (UK), Guernsey, Iceland, Isle of Man, Jersey, Liechtenstein, Monaco, Montenegro, Moldova, San Marino, Slovenia, Vatican

The table reports the definition of the macro regions in which we aggregate the frequencies of the countries of birth that represent less than 0.1% of the population living in Europe. It is based on the United Nations geoscheme.

Table 4: Inequality of Opportunity by Country

Country	Overall Gini	Rel. IOp (forest)
AT	0.2756511	0.0647285
BE	0.2516459	0.0940977
BG	0.3793774	0.1316450
CH	0.2873452	0.0812846
CY	0.2921413	0.1083639
CZ	0.2309446	0.0521827
DE	0.3600380	0.1059701
DK	0.2195579	0.0400998
EE	0.2898580	0.0979086
EL	0.3190488	0.0600319
ES	0.3193829	0.0935350
FI	0.2613834	0.0257396
FR	0.3076551	0.0852062
HR	0.2895027	0.0809313
HU	0.2793296	0.0474816
IE	0.2934348	0.0877829
IT	0.3149416	0.0819349
LT	0.3379890	0.0799054
LU	0.3112877	0.1970717
LV	0.3265333	0.0887172
MT	0.2745955	0.0845104
NL	0.2689108	0.0468317
NO	0.2300268	0.0545547
PL	0.2975762	0.0591884
PT	0.3375003	0.0775457
RS	0.3374104	0.0886270
SE	0.2261984	0.0586158
SK	0.2319304	0.0528050
UK	0.2986735	0.0508644

Source: Own elaboration with data from EUSILC, GSOEP and UKHLS.
The table reports the overall income inequality and relative inequality of opportunity in income estimated, through conditional random forest, within country. The estimates are based on the original data set relative to each country (not the one we get after the re-sampling to get the sample representative of European citizens).

Table 5: Shapley Value Decomposition by Country

Country	Sex	Cbirth	Fedu	Medu	Focc	Mocc
AT	19.84	100.00	35.58	46.67	60.88	45.33
BE	14.53	100.00	45.04	43.78	56.00	35.15
BG	4.26	-0.92	81.81	83.44	100.00	99.40
CH	26.63	100.00	70.50	52.94	37.41	26.08
CY	10.46	100.00	66.79	50.77	98.93	87.55
CZ	24.78	-1.73	65.99	58.93	67.58	100.00
DE	19.87	42.89	88.52	98.34	100.00	73.53
DK	30.43	23.19	21.10	18.75	100.00	72.83
EE	9.69	11.50	72.24	74.34	80.33	100.00
EL	8.48	21.71	69.38	42.32	100.00	50.37
ES	5.03	67.00	54.24	33.78	100.00	41.75
FI	8.14	20.05	47.92	50.80	100.00	86.30
FR	15.60	39.47	63.96	28.05	100.00	31.75
HR	6.57	7.94	60.07	55.94	100.00	77.58
HU	6.66	-2.85	65.34	62.57	68.71	100.00
IE	11.19	63.80	59.75	80.34	100.00	47.97
IT	13.81	56.90	61.95	40.40	100.00	63.55
LT	16.41	-2.47	87.12	79.09	88.94	100.00
LU	7.38	100.00	32.10	27.28	38.75	23.92
LV	10.09	13.72	62.66	49.07	100.00	99.20
MT	3.74	32.92	73.59	57.76	100.00	26.79
NL	7.73	13.96	42.87	23.44	100.00	17.48
NO	8.49	100.00	19.74	33.17	8.54	64.58
PL	7.76	-1.66	51.87	55.39	91.52	100.00
PT	3.45	-4.24	19.74	16.94	100.00	58.16
RS	4.77	10.44	81.21	70.54	100.00	86.42
SE	8.49	53.54	8.14	18.89	15.63	100.00
SK	18.37	-1.95	50.80	59.30	88.48	100.00
UK	22.68	72.42	45.87	54.78	100.00	74.81

Source: Own elaboration with data from EUSILC, GSOEP and UKHLS.
The table reports the Shapley value decomposition of the inequality of opportunity in income estimated within each country and reported in Table 4.

Table 6: Average Predicted Income by Country of Birth

Country of Birth	Avg Predicted Income	Country of Birth	Avg Predicted Income
Switzerland	220.13	OTHCaribbean	86.87
Norway	218.23	Turkey	86.49
Luxembourg	217.18	OTHCentralAfrica	85.13
Denmark	207.74	India	84.80
OTHNorthAmerican	169.62	Algeria	82.78
OTH	146.45	Estonia	82.69
Finland	145.36	OTHCentralAmerican	82.56
Austria	143.61	Ukraine	81.36
Sweden	143.60	Colombia	80.89
Ireland	139.36	Nigeria	80.26
OTHOceania	138.68	OTHSouthAmerican	80.25
Netherlands	138.07	Tunisia	79.49
Belgium	135.71	Philippines	79.41
France	130.02	OTHNorthAfrica	78.81
United States	130.02	Romania	77.43
OTHSouthEastAsia	129.10	OTHWestAfrica	76.91
Germany	121.11	Dominican Republic	76.45
South Africa	116.88	Venezuela	75.96
North Macedonia	116.56	Peru	75.26
OTHEastAsia	115.64	Pakistan	72.47
Kosovo	114.82	Albania	71.27
China	112.82	Senegal	70.41
Iran	111.73	Ecuador	70.29
Italy	108.02	Bangladesh	70.22
Bosnia and Herzegovina	107.46	Morocco	70.01
OTHSouthAsia	100.09	Afghanistan	63.45
Malta	99.83	Iraq	60.32
Brazil	98.34	Syria	55.40
Argentina	97.87	Portugal	54.88
Cyprus	95.66	Czechia	53.63

Continued on the following page.

Country of Birth	Avg Predicted Income	Country of Birth	Avg Predicted Income
United Kingdom	92.91	Latvia	52.77
OTHEurope	91.95	Lithuania	51.41
OTHCentralAsia	91.32	Slovakia	50.02
OTHMiddleEast	91.08	Greece	49.20
Vietnam	90.40	Croatia	43.29
OTHEastAfrica	89.17	Poland	41.62
Russia	88.98	Serbia	33.46
Spain	87.02	Bulgaria	32.73
Sri Lanka	86.90	Hungary	32.08

Source: Own elaboration with data from EUSILC, GSOEP and UKHLS.
The table reports the income predicted through conditional random forest averaged by country of birth and expressed as % of the European average income.

Table 7: Average Predicted Income to GDP per capita by Country of Birth

Country of Birth	Avg Pred Income/GDPpc	Country of Birth	Avg Pred Income/GDPpc
OTHEastAfrica	7.37	Denmark	0.73
Afghanistan	6.19	Serbia	0.72
OTHCentralAfrica	6.01	Norway	0.67
OTHWestAfrica	4.91	Turkey	0.66
OTHSouthAsia	4.62	Russia	0.63
Senegal	4.17	Switzerland	0.62
Nigeria	3.21	Finland	0.60
Pakistan	2.85	France	0.59
Bangladesh	2.61	OTHEastAsia	0.58
India	2.61	Bulgaria	0.57
Kosovo	2.06	Sweden	0.54
OTHSouthEastAsia	1.88	Austria	0.53
Philippines	1.85	Italy	0.52
Vietnam	1.79	Belgium	0.52
Morocco	1.73	Estonia	0.50
South Africa	1.71	Romania	0.50
OTHNorthAfrica	1.65	OTHMiddleEast	0.49
OTHCaribbean	1.63	Netherlands	0.49
Iran	1.61	Cyprus	0.47
OTHCentralAsia	1.54	Greece	0.47
Tunisia	1.46	Germany	0.47
Algeria	1.45	Croatia	0.46
Bosnia and Herzegovina	1.43	Latvia	0.46
North Macedonia	1.37	China	0.46
Brazil	1.36	Slovakia	0.45
Sri Lanka	1.29	Spain	0.44
Ukraine	1.29	Hungary	0.44
Ecuador	1.25	Poland	0.43
Peru	1.20	United States	0.42
Iraq	1.19	Portugal	0.41

Continued on the following page.

Country of Birth	Avg Pred Income/GDPpc	Country of Birth	Avg Pred Income/GDPpc
Colombia	1.08	United Kingdom	0.41
Albania	1.05	Luxembourg	0.38
OTHCentralAmerican	0.98	Lithuania	0.38
OTHSouthAmerican	0.91	Czechia	0.35
Argentina	0.90	Ireland	0.33
Dominican Republic	0.85	OTH	NA
OTHEurope	0.83	Syria	NA
OTHOceania	0.78	Venezuela	NA
OTHNorthAmerican	0.74		

Source: Own elaboration with data from EUSILC, GSOEP and UKHLS.
The table reports, for each country of birth, the ratio between the average predicted income and the country's GDP per capita.

.2 Appendix Chapter 3

Table 8: List of circumstances - HILDA

Circumstance	Categories
Respondent's sex:	• (1) Male • (2) Female
Country of birth:	• (1) Australia • (2) Main English-speaking country • (3) Other
Aboriginal status:	• (1) Not of indigenous origin • (2) Aboriginal or Torres Strait Islander or Both Aboriginal and Torres Strait Islander
Number of siblings :	discrete
Living with parents :	• (1) With both own mother and father at age 14 • (2) Father and stepmother • (3) Mother and stepfather • (4) Father only - no mother or stepmother • (5) Mother only - no father or stepfather • (8) Other

Continued on the following page.

Circumstance	Categories
Father/mother education:	• (1) None • (2) Primary school only • (3) Secondary school, no more than Year 10 • (4) Year 11 or equivalent((eg 5th form, Leaving Certificate) • (5) Year 12 or equivalent (eg 6th form, Matriculation)
Father/mother's main occupation (based on International Standard Classification of Occupations, published by the International Labour Office ISCO-08):	• (0) Armed Forces Occupations • (1) Managers • (2) Professionals • (3) Technicians and Associate Professionals • (4) Clerical Support Workers • (5) Services and Sales Workers • (6) Skilled Agricultural, Forestry and Fishery Workers • (7) Craft and Related Trades Workers • (8) Plant and Machine Operators and Assemblers • (9) Elementary occupations • (10) Unemployed, deceased or not living with the respondent
Father/mother's country of birth:	• (1) Australia • (2) Other

Table 9: Descriptive Statistics by birth cohort - HILDA

Cohort	N	Income	Health	Edu	Fem	Aborig	N Sibl	Liv Par
1951_1960	3,028	108,224.2	0.71	12.98	52.34	1.55	3.43	86.26
1952_1961	3,197	109,029.6	0.71	12.98	52.30	1.91	3.40	86.05
1953_1962	3,393	109,644.9	0.70	13.00	52.52	1.95	3.39	86.03
1954_1963	3,581	110,859.6	0.70	13.02	52.30	2.07	3.38	85.42
1955_1964	3,776	111,384.0	0.70	13.04	52.28	2.22	3.35	84.77
1956_1965	3,930	112,399.9	0.70	13.05	51.96	2.32	3.32	83.61
1957_1966	3,973	111,986.4	0.70	13.06	51.93	2.52	3.27	82.93
1958_1967	4,013	112,430.1	0.70	13.06	51.96	2.62	3.24	82.43
1959_1968	4,030	112,651.8	0.70	13.05	52.38	2.53	3.18	81.49
1960_1969	4,064	112,752.5	0.70	13.06	52.36	2.71	3.11	81.03
1961_1970	4,102	113,005.1	0.70	13.08	52.44	2.83	3.06	80.45
1962_1971	4,121	113,501.8	0.70	13.11	52.34	2.94	2.98	79.06
1963_1972	4,135	113,290.6	0.70	13.13	52.58	3.12	2.89	78.69
1964_1973	4,139	113,835.0	0.70	13.16	52.62	3.04	2.82	78.21
1965_1974	4,099	113,330.2	0.70	13.19	52.33	3.03	2.77	77.73
1966_1975	4,144	114,082.2	0.70	13.24	52.24	2.97	2.72	77.61
1967_1976	4,198	113,908.4	0.70	13.29	52.29	3.10	2.66	77.37
1968_1977	4,179	114,385.8	0.70	13.33	51.93	3.37	2.61	76.88
1969_1978	4,080	114,548.6	0.70	13.37	51.54	3.33	2.56	76.25
1970_1979	4,043	115,125.7	0.70	13.40	51.15	3.14	2.52	75.61
1971_1980	3,965	115,108.2	0.70	13.44	50.90	3.15	2.47	75.59
1972_1981	3,901	115,845.5	0.70	13.47	50.70	3.08	2.48	75.26
1973_1982	3,850	116,379.8	0.70	13.49	50.47	3.32	2.46	74.75
1974_1983	3,804	118,323.5	0.70	13.53	50.84	3.39	2.44	74.79

Continued on the following page.

Cohort	N	Income	Health	Edu	Fem	Aborig	N Sibl	Liv Par
1975_1984	3,790	118,796.6	0.70	13.55	50.47	3.59	2.43	74.59
1976_1985	3,779	119,700.9	0.70	13.57	50.38	3.49	2.41	73.46
1977_1986	3,845	120,168.1	0.70	13.58	50.53	3.36	2.40	72.98
1978_1987	3,940	120,374.8	0.70	13.58	50.71	3.27	2.40	72.64
1979_1988	3,999	121,092.5	0.70	13.59	51.04	3.53	2.40	72.04
1980_1989	4,068	121,717.0	0.70	13.58	51.30	3.74	2.41	71.80
1981_1990	4,121	121,539.9	0.70	13.55	51.27	4.08	2.41	70.57
1982_1991	4,148	121,175.8	0.70	13.55	50.99	4.22	2.43	69.67
1983_1992	4,176	120,565.9	0.69	13.53	51.41	4.45	2.42	68.63
1984_1993	4,153	120,989.4	0.69	13.52	51.75	4.70	2.42	67.85
1985_1994	4,053	121,812.9	0.69	13.52	51.76	4.89	2.42	67.65
1986_1995	3,905	121,674.2	0.69	13.51	51.78	5.10	2.43	67.55
1987_1996	3,698	122,046.8	0.69	13.50	51.97	5.54	2.43	67.14
1988_1997	3,354	121,361.9	0.68	13.50	52.03	5.58	2.42	66.91

Data: HILDA Release 21.

Note: This table displays descriptive statistics by birth cohort. N displays the number of observations in each cohort. Income is defined as the average equivalised household income. Health shows the average health score (defined between 0 and 1). Edu reports the average number of years of schooling with the maximum being 17. Fem and Aborig displays the share of Female and Aboriginal, respectively, in the population. N Sibl reports the average number of siblings. Liv Par shows the share of individuals who lived with both parents when 14.

Table 10: Descriptive Statistics by birth cohort

Cohort	N	Cbirth	MothCbirth	FathCbirth	Medu	Fedu	Mocc	Focc
1951_1960	3,028	26.65	34.81	37.15	3.13	3.11	7.77	5.49
1952_1961	3,197	26.43	34.91	37.22	3.15	3.13	7.73	5.50
1953_1962	3,393	27.03	35.90	38.34	3.17	3.15	7.64	5.48
1954_1963	3,581	26.84	36.30	38.68	3.20	3.18	7.55	5.48
1955_1964	3,776	27.07	37.08	39.33	3.21	3.20	7.49	5.45
1956_1965	3,930	27.02	37.46	39.59	3.23	3.21	7.45	5.44
1957_1966	3,973	27.36	37.96	40.37	3.26	3.23	7.33	5.44
1958_1967	4,013	26.89	38.20	40.67	3.27	3.24	7.26	5.42
1959_1968	4,030	26.90	38.11	40.87	3.29	3.26	7.23	5.42
1960_1969	4,064	26.55	38.26	41.17	3.32	3.28	7.15	5.41
1961_1970	4,102	26.47	38.88	41.96	3.35	3.30	7.03	5.39
1962_1971	4,121	25.75	38.87	41.91	3.37	3.31	7.02	5.40
1963_1972	4,135	24.96	38.45	42.01	3.40	3.34	6.95	5.36
1964_1973	4,139	24.55	38.46	42.23	3.43	3.37	6.86	5.37
1965_1974	4,099	24.01	38.35	42.55	3.48	3.43	6.78	5.35
1966_1975	4,144	23.67	38.27	42.45	3.52	3.47	6.72	5.29
1967_1976	4,198	23.49	38.07	42.09	3.56	3.51	6.61	5.27
1968_1977	4,179	22.78	37.69	41.23	3.60	3.54	6.55	5.24
1969_1978	4,080	22.72	37.48	40.98	3.64	3.58	6.47	5.19
1970_1979	4,043	22.48	36.88	40.27	3.68	3.62	6.42	5.18
1971_1980	3,965	22.27	36.52	40.08	3.74	3.67	6.29	5.13
1972_1981	3,901	22.51	36.61	39.71	3.77	3.70	6.21	5.15
1973_1982	3,850	21.95	35.97	38.78	3.83	3.74	6.10	5.10
1974_1983	3,804	21.77	35.41	37.93	3.87	3.78	6.01	5.09
1975_1984	3,790	21.58	34.88	37.26	3.90	3.82	5.96	5.06
1976_1985	3,779	21.43	35.06	37.18	3.95	3.86	5.88	5.09
1977_1986	3,845	21.14	35.16	37.14	3.99	3.90	5.83	5.11
1978_1987	3,940	20.84	34.67	36.27	4.01	3.92	5.80	5.14

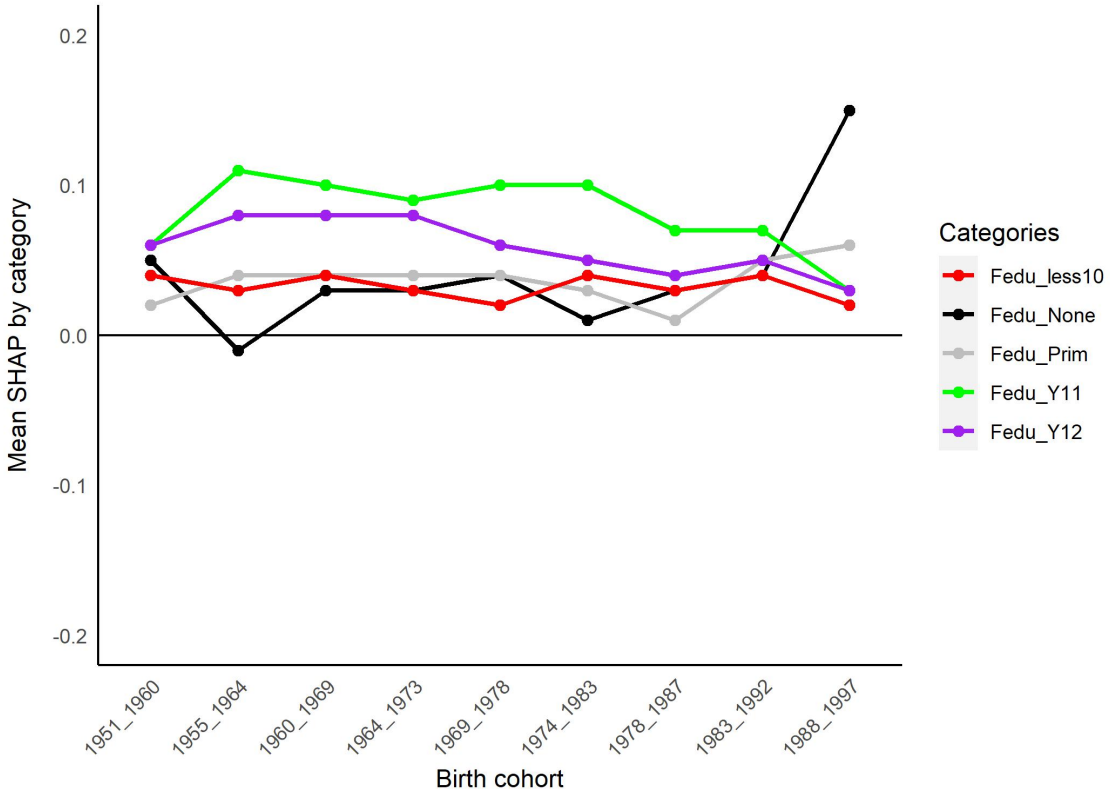
Continued on the following page.

Cohort	N	Cbirth	MothCbirth	FathCbirth	Medu	Fedu	Mocc	Focc
1979_1988	3,999	20.08	34.01	35.23	4.04	3.95	5.75	5.14
1980_1989	4,068	19.54	33.70	34.51	4.06	3.97	5.71	5.18
1981_1990	4,121	18.83	32.76	33.32	4.07	3.98	5.67	5.22
1982_1991	4,148	18.35	32.11	32.91	4.09	3.99	5.67	5.25
1983_1992	4,176	17.39	31.54	32.09	4.10	3.98	5.64	5.28
1984_1993	4,153	16.11	30.51	31.42	4.12	3.97	5.64	5.34
1985_1994	4,053	14.88	29.51	30.55	4.13	3.97	5.62	5.30
1986_1995	3,905	13.93	28.45	29.99	4.13	3.96	5.58	5.32
1987_1996	3,698	13.01	27.72	29.69	4.16	3.97	5.52	5.31
1988_1997	3,354	12.52	27.43	29.58	4.17	3.98	5.50	5.33

Data: HILDA Release 21.

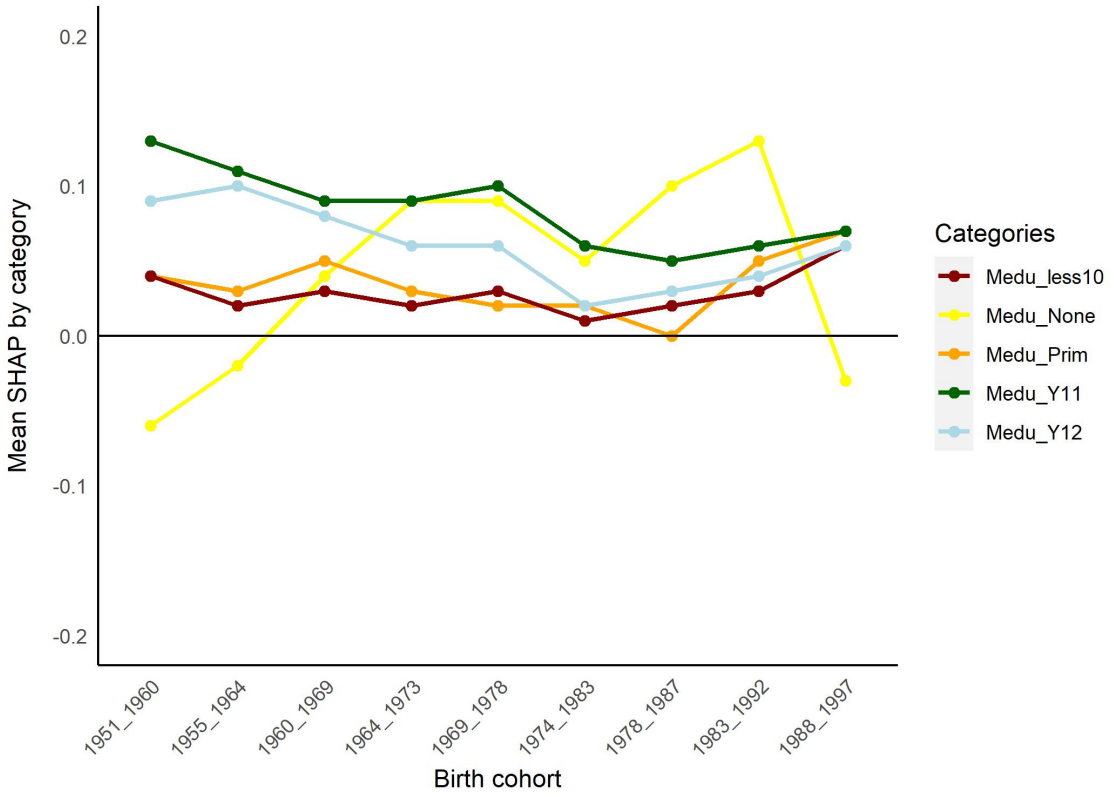
Note: This table displays descriptive statistics by birth cohort. N displays the number of observations in each cohort. Cbirth shows the share of the population born outside Australia (in both English and non-English speaking countries). MothCbirth (FathCbirth) reports the share of the population whose mother (father) was born abroad. Fedu (Medu) reports the average level of educaiton of the father (Mother) with 5 being the maximum. Mocc (Focc) displays the average occupation level of the mother (father) with higher values associated to lower-paid jobs.

Figure 11: SHAP values - Father education



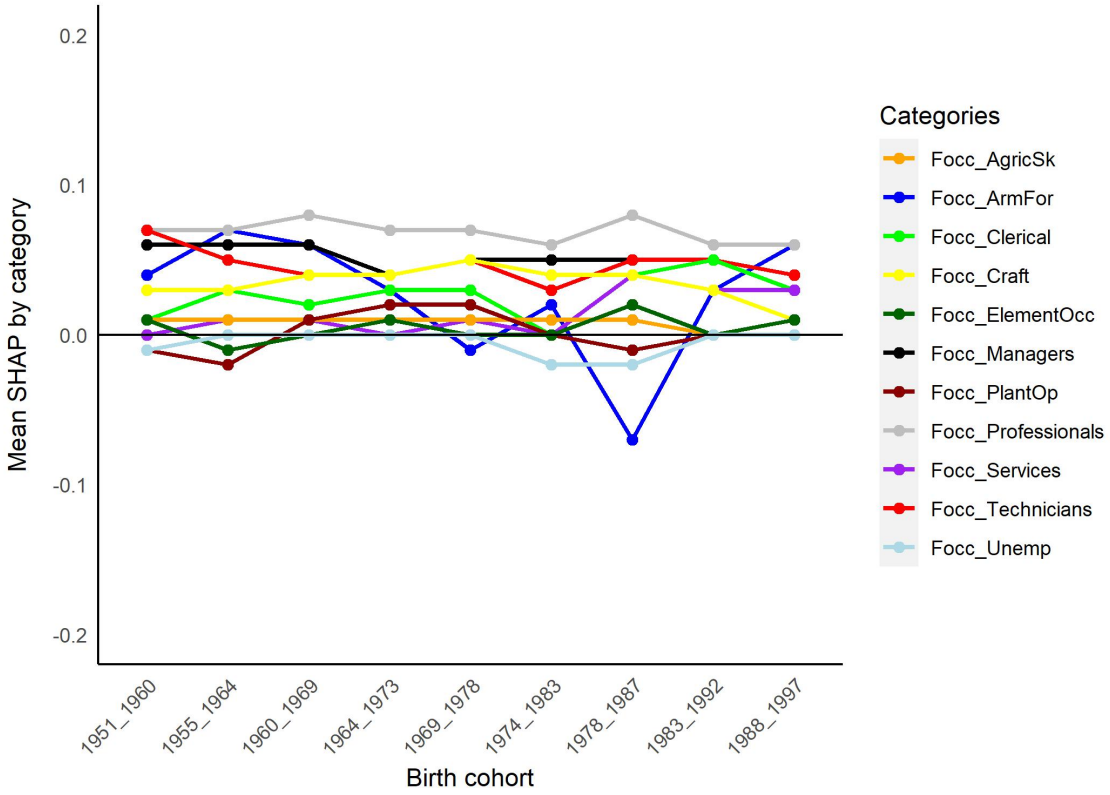
Source: own elaboration with data from HILDA
Each dot is obtained averaging the individual SHAP values of the predictor *father education* over the individuals who show a specif category of that circumstance (for instance, the *green* dot is given by the average of the SHAP values of *father education* across the individuals whose father had a level of education lower than Y10).

Figure 12: SHAP values - Mother education



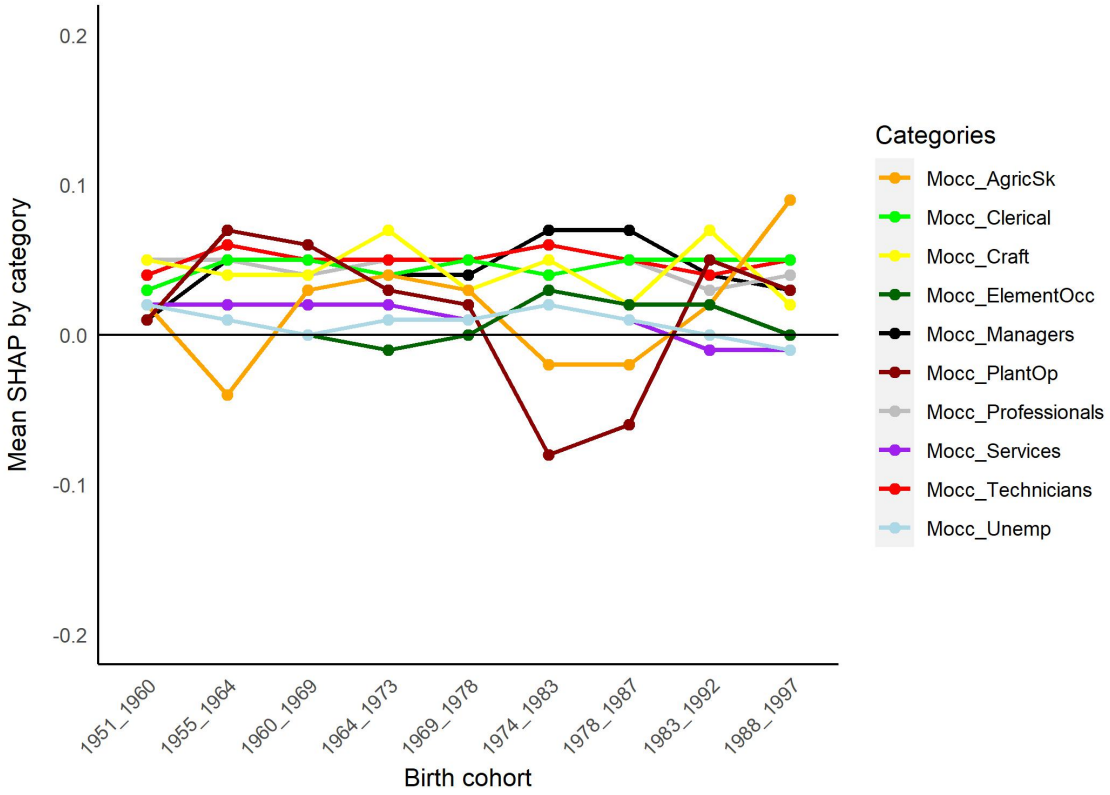
Source: own elaboration with data from HILDA
Each dot is obtained averaging the individual SHAP values of the predictor *mother education* over the individuals who show a specif category of that circumstance (for instance, the *yellow* dot is given by the average of the SHAP values of *mother education* across the individuals whose mother had the primary education).

Figure 13: SHAP values - Father occupation



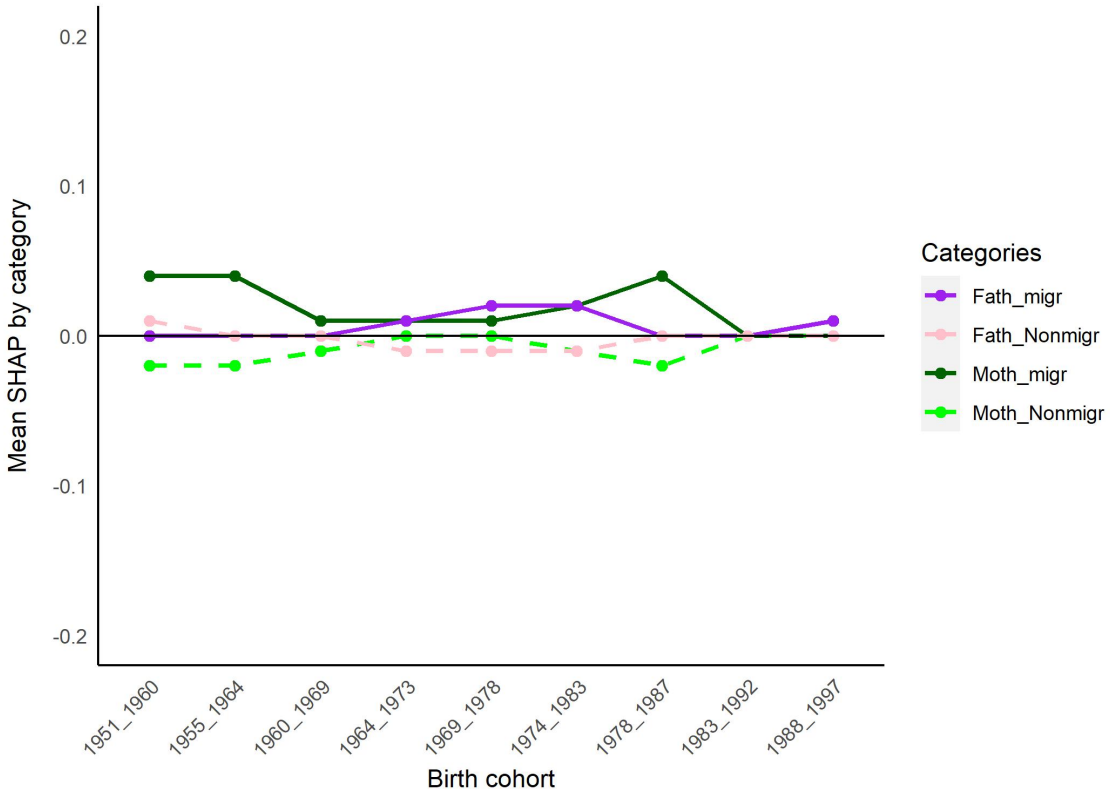
Source: own elaboration with data from HILDA
Each dot is obtained averaging the individual SHAP values of the predictor *father occupation* over the individuals who show a specif category of that circumstance (for instance, the *grey* dot is given by the average of the SHAP values of *father occupation* across the individuals whose father had an occupation as "professional").

Figure 14: SHAP values - Mother occupation



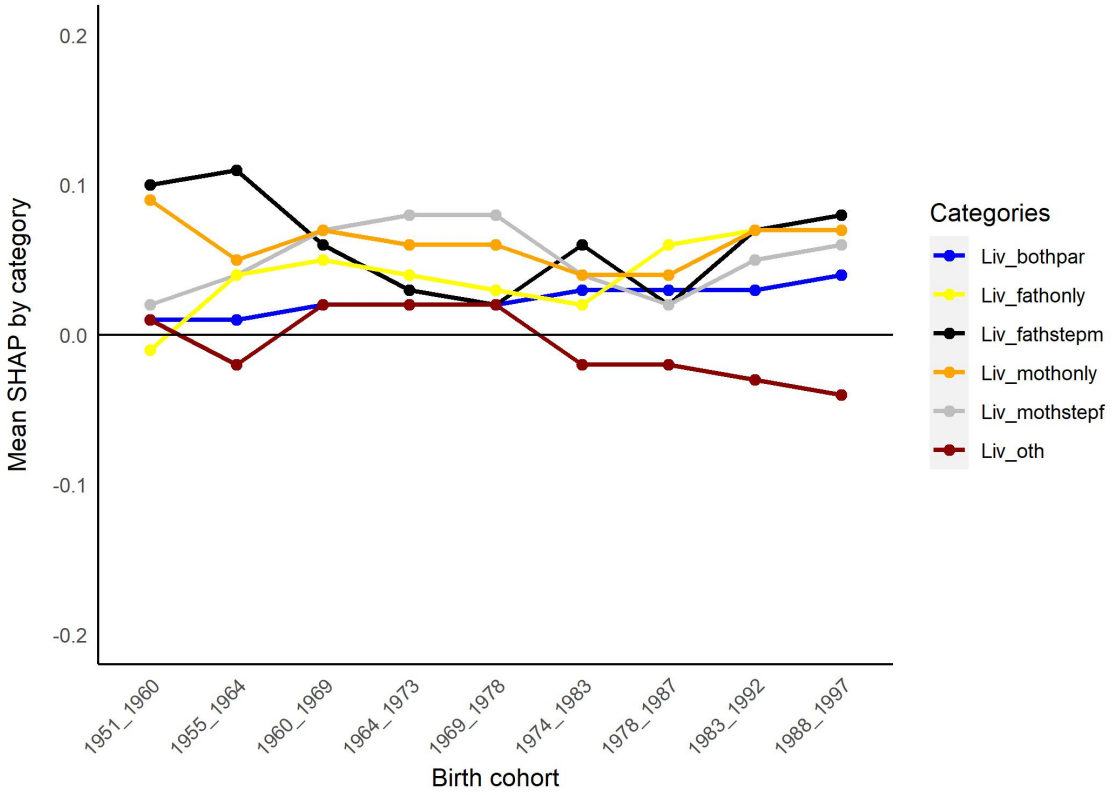
Source: own elaboration with data from HILDA
Each dot is obtained averaging the individual SHAP values of the predictor *mother occupation* over the individuals who show a specif category of that circumstance (for instance, the *dark red* dot is given by the average of the SHAP values of *mother occupation* across the individuals whose mother had an occupation as "plant operator").

Figure 15: SHAP values - Mother/Father country of birth



Source: own elaboration with data from HILDA
Each dot is obtained averaging the individual SHAP values of the predictor *mother country of birth (/father)* over the individuals who show a specif category of that circumstance (for instance, the *dark green* dot is given by the average of the SHAP values of *mother country of birth* across the individuals whose mother was born abroad).

Figure 16: SHAP values - Living with parents when 14



Source: own elaboration with data from HILDA
Each dot is obtained averaging the individual SHAP values of the predictor *living with parents* over the individuals who show a specif category of that circumstance (for instance, the *dark red* dot is given by the average of the SHAP values of *living with parents* across the individuals who did not live with any of the parents when 14).