Inequality of Opportunity in German Labour Earnings: Evidence from the SOEP, 1995–2023

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Abstract

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This paper estimates inequality of opportunity in labour earnings in Germany across three anchor years — 1995, 2010, and 2023 — using data from the German Socio-Economic Panel (SOEP). Following Ferreira and Gignoux (2011), inequality of opportunity is defined as the component of observed earnings inequality attributable to predetermined background characteristics beyond individual control, including gender, migration background, parental education, and childhood location. The counterfactual earnings distribution is constructed by equalising observed circumstances across all individuals and comparing the resulting Mean Log Deviation to that of the observed distribution. The relative opportunity share declines monotonically from 0.181 in 1995 to 0.127 in 2023. However, the absolute opportunity share rises between 1995 and 2010, reflecting the rapid expansion of total earnings inequality during the Hartz reform period. A partial counterfactual decomposition reveals a fundamental structural change: in 1995 inequality of opportunity was almost entirely gender-driven, whereas by 2023 migration background and paternal professional education have emerged as important contributors, while childhood location has ceased to matter. Comparing gross and net earnings, the relative opportunity share is consistently higher for net earnings, indicating that the German tax-benefit system compresses within-type inequality more strongly than between-type inequality and does not reduce inequality of opportunity proportionally. All estimates represent lower bounds of the true level of inequality of opportunity.

Keywords: inequality of opportunity, labour earnings, Germany, SOEP, counterfactual distribution, gender, migration

Resumo

Desigualdade de Oportunidades nos Rendimentos do Trabalho na Alemanha: Evidências de 1995, 2010 e 2023

Tamo Modersitzki

Este artigo estima a desigualdade de oportunidades nos rendimentos do trabalho na Alemanha para três anos de referência — 1995, 2010 e 2023 — utilizando dados do Painel Socioeconómico Alemão (SOEP). Seguindo Ferreira e Gignoux (2011), a desigualdade de oportunidades é definida como a componente da desigualdade de rendimentos atribuível a características de origem predeterminadas e fora do controlo individual, nomeadamente o género, o contexto migratório, a educação dos pais e a localização na infância. A distribuição contrafactual é construída igualando as circunstâncias observadas entre todos os indivíduos e comparando o Desvio Logarítmico Médio resultante com o da distribuição observada. A quota relativa de oportunidade diminui monotonamente de 0,181 em 1995 para 0,127 em 2023. Contudo, a quota absoluta aumenta entre 1995 e 2010, refletindo a expansão da desigualdade total durante as reformas Hartz. Uma decomposição contrafactual parcial revela uma transformação estrutural fundamental: em 1995 a desigualdade de oportunidades era quase inteiramente determinada pelo género, ao passo que em 2023 o contexto migratório e a educação profissional paterna emergiram como contribuintes relevantes, enquanto a localização na infância deixou de ser significativa. A comparação entre rendimentos brutos e líquidos mostra que a quota relativa é sistematicamente superior para os rendimentos líquidos, indicando que o sistema fiscal alemão não reduz a desigualdade de oportunidades de forma proporcional. Todas as estimativas constituem limites inferiores do verdadeiro nível de desigualdade de oportunidades.

Palavras-chave: desigualdade de oportunidades, rendimentos do trabalho, Alemanha, SOEP, distribuição contrafactual, género, migração

Preface

This dissertation would not have been possible without the guidance and support of several individuals and institutions to whom I owe a great deal of gratitude.

First and foremost, I would like to thank my supervisor, Isabel Horta Correia, for her careful and thoughtful engagement with this work throughout its development. Her detailed feedback, her insistence on conceptual precision, and her willingness to challenge assumptions shaped this dissertation. I am particularly grateful for her patience in working through the theoretical framework with me and for pushing me to think more carefully about what the estimates truly mean and what they do not.

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1. Introduction

A popular German saying holds that *"jeder ist seines Glückes Schmied"* — every person is the architect of their own fortune. The idea that economic outcomes reflect individual effort and perseverance rather than the accidents of birth is deeply embedded in both popular culture and liberal political philosophy. Yet the empirical question of how much individual earnings actually depend on circumstances determined before a person enters the labour market — the family they are born into, the gender they are assigned, the migration history they carry, the region they grew up in — remains one of the most interesting questions in modern economics. If the proverb is right, earnings largely reflect choices and effort. If it is wrong — if a substantial share of observed earnings inequality is traceable to factors entirely outside individual control — then the case for redistribution rests on firmer ground and the design of policy instruments should explicitly account for the channels through which background circumstances transmit economic disadvantage.

This paper addresses that question directly. Following the framework developed by Roemer (1998) and operationalised empirically by Bourguignon, Ferreira and Menéndez (2007), we decompose and quantify observed earnings inequality in Germany into a component attributable to predetermined background characteristics beyond individual control — referred to as circumstances — and a residual component reflecting effort, choices, and luck. The share of inequality attributable to circumstances constitutes inequality of opportunity, and it is this share that represents unfair inequality in the normative sense of the framework.

Germany offers a particularly relevant setting for this analysis. The Hartz reforms of the mid-2000s substantially deregulated the low-wage employment sector, leading to a well-documented rise in earnings inequality that was only partially reversed by the statutory minimum wage introduced in 2015 (Dustmann et al., 2014; Biewen and Seckler, 2019). Whether this rise in total inequality was accompanied by a worsening of opportunity inequality — or was concentrated in within-type dispersion reflecting effort and luck — is a central question for evaluating the distributional consequences of the reform period. At the same time, the share of individuals with direct migration background in the working-age sample increased from approximately 6% in 1995 to over 34% in 2023, driven by sustained EU labour mobility and the large-scale refugee flows of the mid-2010s. Since migration background constitutes a predetermined circumstance in the Roemer framework, this compositional shift has direct implications for measured inequality of opportunity.

The empirical analysis uses data from the German Socio-Economic Panel (SOEP) for three anchor years — 1995, 2010, and 2023. Individual-level earnings are linked to retrospective information on parental education and childhood environment to construct a circumstance vector comprising gender, migration background, mother's school education, father's professional education, and childhood location.

The main findings are as follows. Inequality of opportunity accounts for approximately 18% of total gross earnings inequality in 1995, declining to 16% in 2010 and 13% in 2023, indicating that the share of earnings inequality attributable to predetermined circumstances has fallen over the three decades covered by the analysis. However the absolute opportunity share tells a more cautionary story — it rises between 1995 and 2010 before declining, indicating that circumstance-driven earnings inequality increased in absolute terms during the Hartz reform period even as its relative share fell. The partial decomposition reveals a striking structural transformation: in 1995 gender alone accounted for approximately 85% of measured inequality of opportunity, whereas by 2023 migration background and paternal professional education have each emerged as meaningful contributors, and childhood location has effectively ceased to matter. Comparing gross and net earnings, inequality of opportunity accounts for a consistently higher share of net than of gross earnings inequality in all anchor years, indicating that the German tax-benefit system compresses within-type inequality more effectively than between-type inequality and therefore does not reduce inequality of opportunity proportionally.

So while the proverb captures something true about the role of individual agency, the data suggest that the fortune one forges is still very substantially shaped by the circumstances of one's birth — and that the architect metaphor is considerably more apt for some Germans than for others.

The remainder of the paper is structured as follows. In Section 2 revisits the relevant Literature. Section 3 develops the theoretical framework and estimation strategy. Section 4 describes the data and sample construction. Section 5 presents summary statistics. Section 6 reports the empirical findings. Section 7 concludes.

2. Literature Review

The measurement of inequality of opportunity has developed into a substantial field within empirical economics, building on the normative frameworks of Rawls (1971), Dworkin (1981), and most influentially for the empirical literature, Roemer (1998). The core distinction — between inequalities arising from circumstances beyond individual control and inequalities reflecting individual choices and effort — provides both a normative criterion for evaluating distributions and an empirical programme for decomposing observed inequality into its morally relevant components.

The modern inequality of opportunity literature traces its origins to the philosophical debate between luck egalitarianism and responsibility-sensitive egalitarianism. Dworkin (1981) introduced the distinction between brute luck — outcomes that befall individuals independently of their choices — and option luck — outcomes that result from deliberate gambles — and Arneson (1989) and Cohen (1989) argued that the appropriate target of egalitarian redistribution is the equalisation of opportunity for welfare rather than welfare itself. Roemer (1998) provided the most tractable operationalisation for empirical work, proposing that individuals should be held responsible for their effort conditional on their circumstances, and that equality of opportunity requires equalising outcomes across circumstance groups at each quantile of the within-group effort distribution. This formulation rests on a key normative judgement — that the appropriate reference point for fairness is the distribution of outcomes within circumstance groups rather than across individuals unconditionally — and it is this judgement that generates the decomposition of observed inequality into an opportunity component and an effort component. Fleurbaey and Maniquet (2011) provide a comprehensive axiomatic treatment of fairness and responsibility, showing that different responsibility cuts generate different normative conclusions and that no single decomposition is uniquely justified on axiomatic grounds. Van Parijs (1995) and Fleurbaey (2008) offer important critiques of the Roemer framework, arguing that the treatment of effort as fully within individual control is itself problematic when effort is shaped by circumstances — a concern that is directly relevant to the present paper, since the parametric reduced form captures precisely the total association between circumstances and earnings including the indirect channel operating through effort. In practice the empirical literature has largely side-stepped the responsibility cut debate by treating all variables that are predetermined at birth or in early childhood as circumstances, acknowledging that this generates a lower bound on the true level of inequality of opportunity.

This lower bound interpretation has been formalised by Bourguignon, Ferreira and Menéndez (2007), who show that adding circumstances to the vector can only increase the measured opportunity share — a property that is central to the interpretation of all empirical estimates in this literature, including those of the present paper.

The transition from theoretical frameworks to empirical measurement was pioneered by Bourguignon, Ferreira and Menéndez (2007), who proposed a parametric approach in which the structural earnings function is approximated by a log-linear reduced form and the counterfactual distribution is constructed by replacing individual circumstance values with sample means while retaining individual residuals. This approach has two important features. First, it does not require causal identification of the structural parameters — the reduced form captures the total association between circumstances and earnings, encompassing both direct effects and indirect effects operating through the effort function, which is precisely what is needed to construct the counterfactual distribution. Second, it accommodates a rich circumstance vector without requiring sufficient observations in every combination of circumstance categories, overcoming the curse of dimensionality that limits non-parametric approaches. Ferreira and Gignoux (2011) extended and systematised this approach, establishing the two-measure reporting convention of the absolute opportunity share IOL and the relative opportunity share IOR, and providing the formal justification for their complementarity — since the two measures can diverge when total inequality changes substantially over time, both are needed to characterise the evolution of opportunity inequality fully. A critical methodological contribution of Ferreira and Gignoux (2011), building on Foster and Shneyerov (2000), is the demonstration that the Mean Log Deviation is the unique path-independent decomposable inequality measure, generating identical opportunity shares regardless of whether the smoothed or standardised distribution is used to isolate between-type inequality. This path-independence property, which Foster and Shneyerov (2000) derive axiomatically as a consequence of the MLD's additive decomposability into exact between- and within-group components, justifies the exclusive use of the MLD in the present paper and in most subsequent empirical work. Checchi and Peragine (2010) provide a complementary axiomatic treatment deriving the conditions under which the standardised distribution approach — which equalises type means while preserving within-type dispersion — is the appropriate non-parametric analogue to the parametric counterfactual, and show that this approach is characterised by a set of fairness axioms relating to horizontal equity and the compensation principle. The partial counterfactual decomposition by individual circumstance, which forms a central part of the empirical analysis of the present paper, was introduced by Ferreira and Gignoux (2008). They propose replacing only the values of a single circumstance with the sample mean while retaining all others at their individually observed values, and define the resulting reduction in inequality as the marginal contribution of that circumstance to the aggregate opportunity share. Since partial shares do not generally sum to the aggregate IOR when circumstances are correlated, Brunori (2016) proposes alternative Shapley-value based decompositions that achieve additivity at the cost of greater computational complexity and sensitivity to the ordering of circumstances. The present paper follows the original Ferreira and Gignoux (2008) approach, treating partial shares as marginal contributions which is both more transparent and more directly interpretable in the policy context.

The inequality of opportunity framework has since been applied to a wide range of countries and outcome variables. For income and earnings, relative opportunity shares in developed countries are generally found to be lower than in developing country contexts but non-trivial, motivating continued research attention in the European setting. Checchi, Peragine and Serlenga (2010) apply the framework to Italy and the United Kingdom, Björklund, Jäntti and Roemer (2012) to Sweden, and Pistolesi (2009) to the United States over several decades. Brunori, Ferreira and Peragine (2013) provide a comprehensive cross-country comparison using harmonised survey data for over 40 countries, confirming that opportunity shares are lower in Northern and Western European countries than in Eastern Europe and Latin America and positively correlated with standard inequality measures. On the dynamics of inequality of opportunity, Hufe, Kanbur and Peichl (2022) develop a framework for decomposing changes in opportunity inequality into a component reflecting changes in the returns to circumstances and a component reflecting changes in the composition of circumstances in the population — a distinction that is directly relevant to the findings of the present paper, where compositional changes driven by migration and structural changes driven by rising returns to paternal education operate simultaneously and in different directions. Marrero and Rodríguez (2013) establish a negative relationship between opportunity inequality and subsequent economic growth, providing an economic rationale — beyond the normative argument — for focusing policy attention specifically on the circumstance-driven component of earnings inequality.

For Germany specifically, the empirical evidence on inequality of opportunity has grown in recent years but important gaps remain. Niehues and Peichl (2014) derive upper bounds for inequality of opportunity in Germany and the United States, providing a useful complement to the lower bound estimates that dominate the literature. By combining the standard lower bound approach — which uses only observed circumstances — with structural assumptions about the joint distribution of circumstances and effort, they show that the gap between the lower and upper bounds is potentially large, implying that standard parametric estimates may substantially understate the true level of opportunity inequality. A more recent strand of the German literature has applied machine learning methods to the measurement of inequality of opportunity. Brunori, Hufe and Mahler (2023) use a machine learning approach to estimate the evolution of inequality of opportunity in Germany, exploiting the flexibility of non-parametric tree-based methods to capture non-linear and interaction effects among circumstance variables that are ruled out by the linear parametric specification. Their approach provides an alternative upper bound on the opportunity share by allowing the circumstance vector to explain as much variation in earnings as possible without imposing a functional form. The comparison between machine learning and parametric estimates is informative about the degree of misspecification bias in the standard linear approach, and the finding that machine learning estimates are systematically higher than parametric estimates provides additional motivation for the lower bound interpretation adopted in the present paper.

The broader German literature on earnings inequality and its determinants provides important context for the opportunity share estimates. Dustmann, Ludsteck and Schönberg (2009) document the sharp increase in earnings inequality between the mid-1990s and mid-2000s and attribute it to labour market deregulation and expansion of the low-wage sector. Biewen and Seckler (2019) examine the distributional effects of the 2015 minimum wage, while Card, Heining and Kline (2013) use matched employer-employee data to examine the role of firm heterogeneity and rising returns to individual characteristics. On gender, Leuze and Strauß (2016) document the persistent earnings gap and its relationship to occupational segregation and the Ehegattensplitting tax system. On migration, Brücker, Glitz, Lerche and Romiti (2021) examine the earnings integration trajectories of migrants in Germany, documenting persistent penalties associated with recent arrival that are directly relevant to the large and growing direct migration background contribution to measured inequality of opportunity documented in the present paper. On intergenerational mobility, Schnitzlein (2016) examines intergenerational earnings persistence in Germany, providing evidence on the degree to which parental economic status transmits to children's labour market outcomes — a channel captured in the present paper through the parental education variables in the circumstance vector.

3. Theoretical Framework and Estimation Strategy

3.1 Circumstances, Effort, and Equality of Opportunity

In this section, a framework is developed to measure inequality of opportunity and to compare its magnitude in Germany in the years 1995, 2010, and 2023. The analysis follows the conceptual approach proposed by John E. Roemer (1998), in which inequality of opportunity is defined as the component of overall inequality that is driven by predetermined background characteristics. The central objective is to distinguish observed inequality in earnings into two parts: inequality attributable to circumstances, and a residual component reflecting effort and other factors. Within this framework, inequality of opportunity is the portion that is of primary normative concern for analysis and policy.

The outcome of interest in this study is labour earnings — measured both before and after taxes and transfers — and inequality is evaluated in terms of the distribution of income. Circumstances are defined as determinants of labour earnings over which individuals have no control, such as gender, parental background, or place of upbringing. The core idea of the equality of opportunity framework is that inequalities arising from such predetermined characteristics are ethically problematic, since individuals cannot be held responsible for them. The empirical objective is therefore to quantify how much of the observed dispersion in earnings can be attributed to these circumstances.

Roemer's framework distinguishes three determinants of individual labour earnings. First, circumstances, include predetermined characteristics such as gender, parental background, or place of birth — in general, aspects of the social environment into which an individual is born. These factors lie outside individual control and therefore constitute ethically illegitimate sources of inequality.

Second, effort, captures determinants of earnings that may be influenced by individual choices. Examples include educational investment, labour supply decisions, job search intensity, or occupational choices. Inequality arising from differences in effort is considered ethically acceptable within the equality of opportunity framework because individuals can reasonably be held responsible for these choices.

Third, luck, captures variation in earnings that cannot be attributed to either circumstances or deliberate choices. In empirical implementations of the framework, this component typically appears as a residual term capturing random or unobserved influences on earnings.

To operationalise this framework empirically, let the earnings of individual i be denoted by y_i, and let earnings be distributed in the population according to the cumulative distribution function $F(y)$. Following François Bourguignon, Francisco H. G. Ferreira and José Menéndez (2007) and Jérémie Gignoux and Ferreira (2011), individual earnings are generated by a structural earnings function of the general form:

$$(1)\ y_i = f(C_i, E_i, u_i)$$

where C_i denotes circumstances, E_i denotes effort, and u_i captures other unobserved determinants of earnings[1].

Circumstances are treated as economically exogenous by definition[2]. Effort, however, may itself depend on circumstances. For instance, parental background may influence educational opportunities, occupational aspirations, or access to labour market networks. Individuals with different circumstance profiles may therefore systematically differ in their effort levels. Incorporating this dependence, the earnings function can be written more generally as

$$(2)\ y_i = f(C_i, E_i(C_i, v_i), u_i)$$

where v_i represents unobserved determinants of effort.

[1] Following the interpretation proposed by Judith Niehues (2012), this residual component is typically treated as part of the sphere of individual responsibility: individuals are implicitly held responsible for any variation in earnings that cannot be attributed to observed circumstances.

[2] The term "economically exogenous" refers to characteristics that lie outside the individual's sphere of control. This differs from the standard econometric definition of exogeneity, which concerns the absence of correlation between a variable and the regression residual. In the present context, econometric endogeneity may arise from omitted variables, but reverse causality — whereby earnings influence circumstances such as parental background or place of birth — is conceptually impossible (Ferreira and Gignoux, 2011).

Equality of opportunity, in the sense of Roemer (1998), requires that the distribution of earnings be independent of circumstances. Denoting the distribution of earnings conditional on circumstances C by $F(y \mid C)$, equality of opportunity requires

$$(3)\ F(y \mid C) = F(y)$$

In other words, the unconditional distribution of earnings must coincide with the conditional distribution for every circumstance profile. Inequality of opportunity is therefore present whenever

$$F(y \mid C) \neq F(y)$$

This definition implies that differences in earnings across circumstance groups represent unfair inequality.

It is important to note that this interpretation relies on an additional normative assumption. The framework implicitly treats income as equally valuable across individuals, meaning that a given monetary difference in earnings is considered equally important regardless of who receives it. This assumption avoids the need for interpersonal comparisons of utility and allows inequality to be evaluated directly in terms of income differences. However, it abstracts from potential differences in the welfare derived from income across individuals and may therefore be regarded as a simplifying limitation of the framework.

Given the structural representation above, the independence condition implies that circumstances must have neither a direct nor an indirect influence on earnings. Formally, circumstances must not affect earnings directly when effort is held constant:

$$\frac{\partial f(C, E, u)}{\partial C} = 0$$

In addition, effort must be distributed independently of circumstances:

$$G(E \mid C) = G(E)$$

where $G(\cdot)$ denotes the distribution of effort.

Together, these conditions ensure that circumstances have no systematic influence on earnings outcomes, so that the distribution of earnings is invariant with respect to circumstances.

3.2 Partition into Types and Scalar Measures of Inequality of Opportunity

While the structural model in equation (2) provides a conceptual definition of equality of opportunity, empirical implementation requires the construction of scalar measures that quantify the extent to which outcome distributions differ across circumstance profiles. Following Checchi and Peragine (2010) this can be achieved by partitioning the population into groups defined by identical observed circumstances.

Let C_i denote the observed circumstance vector for individual i. The population can then be partitioned into a finite set of mutually exclusive and exhaustive groups — referred to as types — defined as

$$(4)\ T_k = \{i : C_i = C_k\}, k = 1, \dots, K$$

All individuals within a given type share identical observed circumstances. This partition induces a corresponding decomposition of the outcome distribution into subdistributions $\{y_{ik}\}$, where each subdistribution corresponds to a distinct circumstance profile. In Roemer's terminology, each type represents a distinct opportunity set — the set of outcomes achievable by individuals endowed with identical circumstances but differing levels of effort.

Let:

$$(5)\ \mu_k(y) = E[y_i \mid i \in T_k]$$

denote the mean outcome in type k. Under equality of opportunity, the distribution of outcomes must be independent of circumstances, as required by condition (3). In particular, this requires equality of mean outcomes across all types:

$$\mu_k(y) = \mu_l(y) \forall k, l$$

Inequality of opportunity is therefore present whenever mean outcomes differ systematically across types. It is important to note at this stage that the partition is based solely on *observed* circumstances. Since any empirical dataset captures only a subset of all morally relevant background characteristics, the resulting measures of inequality of opportunity constitute a lower bound of the true level.

3.2.1 Constructing counterfactual distributions

The core measurement challenge is to isolate the contribution of between-type differences to total inequality. The idea is to construct a counterfactual earnings distribution that removes systematic differences across types — that is, a distribution that would prevail if all individuals faced identical circumstances — and then compare inequality in this counterfactual to inequality in the observed distribution. The difference between the two captures inequality of opportunity. Two closely related approaches to constructing this counterfactual have been proposed in the literature (Foster and Shneyerov, 2000; Checchi and Peragine, 2010), differing in how they remove between-type variation.

The first is the smoothed distribution, obtained by replacing each individual outcome with the mean outcome of their type as described above:

$$(6)\ y_i^S = \mu_{k(i)}(y)$$

This transformation eliminates all within-type variation by construction and retains only variation attributable to differences in type means. Let $I(\cdot)$ denote a decomposable inequality index. Inequality measured over the smoothed distribution:

$$\theta^a = I(y^S)$$

corresponds exactly to between-type inequality. A relative measure of inequality of opportunity can therefore be defined as:

$$(7)\ \theta_d = \frac{I(y^S)}{I(y)}$$

which directly captures the share of total inequality explained by differences in type means.

The second approach constructs a standardized distribution. Rather than suppressing within-type inequality, this transformation equalizes type means while preserving within-type dispersion. Formally, define:

$$(8)\ y_i^{\nu} = y_i \cdot \frac{\mu}{\mu_{k(i)}}$$

where μ denotes the grand mean of the distribution and $\mu_{k(i)}$ the mean of individual i's type. This rescaling ensures that all types share the same mean outcome μ, thereby eliminating all between-type inequality while leaving within-type inequality unchanged. A corresponding relative measure of inequality of opportunity is then given by:

$$(9)\ \theta_r = 1 - \frac{I(y^{\nu})}{I(y)}$$

Here, inequality of opportunity is computed residually as the reduction in total inequality once mean differences across types are removed.

3.2.2 Path independence and the choice of inequality index

Although the smoothed and standardized approaches isolate between-type inequality through conceptually distinct paths — one directly and the other residually — the resulting measures need not coincide for arbitrary inequality indices. In general, between-group inequality is not uniquely defined, even when attention is confined to properly decomposable measures.

Foster and Shneyerov (2000) characterise the class of inequality measures for which the two procedures yield identical results. They show that equivalence holds for the class of path-independent decomposable inequality measures. When attention is restricted to indices that use the arithmetic mean as the reference income and satisfy the Pigou–Dalton transfer axiom, this class reduces to a single measure: the Mean Log Deviation (MLD), also known as the Generalized Entropy measure GE(0). For the MLD, total inequality admits an exact additive decomposition into between- and within-type components that is invariant to the decomposition path. Consequently:

$$(10) \quad \frac{I(y^S)}{I(y)} = 1 - \frac{I(y^v)}{I(y)}$$

Under the MLD, the smoothed and standardized constructions therefore produce identical relative measures of inequality of opportunity, and the opportunity share is path independent.

In the empirical analysis that follows, we employ the standardized distribution together with the MLD. This choice ensures theoretical consistency and path independence and provides a transparent interpretation of both the absolute and relative measures as quantities attributable to systematic differences in mean outcomes across circumstance types. The MLD is also well suited to earnings distributions, which are right-skewed, since it assigns greater weight to differences at the lower end of the distribution and is sensitive to proportional rather than absolute income differences.

3.2.3 Absolute and relative measures of Inequality of Opportunity

Two complementary scalar measures of inequality of opportunity can be derived from the standardized distribution. The absolute measure, referred to as the inequality of opportunity level (IOL), is defined as:

$$(11) \quad \text{IOL} = I(y) - I(y^v)$$

This captures the raw magnitude of inequality attributable to observed circumstances — the amount of total inequality that would be eliminated if all individuals faced identical observed circumstances. The relative measure, referred to as the inequality of opportunity ratio (IOR), normalizes this by total inequality:

$$(12) \quad \text{IOR} = 1 - \frac{I(y^v)}{I(y)} = \frac{\text{IOL}}{I(y)}$$

The IOR captures the proportional contribution of observed circumstances to total inequality. Both measures are reported in the empirical analysis. The absolute measure is informative about the level of unfair inequality and its evolution over time in magnitude terms. The relative measure facilitates comparison across years characterized by different levels of overall inequality, since a given absolute opportunity component will appear more or less important depending on the total amount of dispersion in the distribution.

3.2.4 Linking the Structural Model to the Scalar Measures

The standardised distribution can be given a direct structural interpretation in terms of the earnings function established in equation (2). Recall that equality of opportunity requires the distribution of earnings to be independent of circumstances — that is, circumstances must have neither a direct nor an indirect effect on outcomes. A sufficient condition for this is that all individuals face identical circumstances:

$$C_i = \bar{C} \forall i$$

Under this counterfactual, the structural earnings function in equation (2) becomes:

$$y_i = f(\bar{C}, E_i(\bar{C}, v_i), u_i)$$

and all systematic variation in outcomes arising from differences in C_i disappears. Any remaining inequality reflects only differences in effort and idiosyncratic factors — the components for which individuals can be held responsible.

The standardised distribution operationalises precisely this counterfactual at the level of group means. It rescales individual outcomes as in (8)

$$y_i^v = y_i \cdot \frac{\mu}{\mu_{k(i)}},$$

equalising all type means to the grand mean μ while preserving within-type dispersion. This removes the systematic component of inequality attributable to variation in C_i— encompassing both its direct effect on earnings and its indirect effect operating through effort. The remaining inequality in the standardised distribution reflects only within-type variation: inequality not explained by observed circumstances.

The two scalar measures introduced in Section 3.2.3 can therefore be given a direct structural interpretation. The relative measure IOR quantifies the share of total inequality attributable to the systematic influence of circumstances operating through both channels in equation (2). The absolute measure IOL captures the raw reduction in inequality that would result from equalising observed circumstances — the amount of total inequality that would disappear if the structural counterfactual $C_i = \bar{C}$ were implemented.

3.2.5 Feasibility of the non-parametric approach

The non-parametric framework described above is conceptually appealing because it imposes no functional form assumptions on the relationship between circumstances and outcomes. In practice, however, its feasibility depends on having sufficient observations within each type cell to estimate type means reliably. The number of types grows rapidly with the number of circumstance variables and their categories: in the present analysis, the full cross-product of gender (2 categories), migration background (3), mother's education (3), father's professional education (3), and childhood location (4) yields up to 216 distinct types. With annual cross-sections of between approximately 7,500 and 14,000 observations, many type cells will be sparsely populated or empty in a given year, rendering non-parametric type means unreliable and the resulting inequality measures unstable.

For this reason, we follow Bourguignon et al. (2007) and Ferreira and Gignoux (2011) in adopting a parametric approach, in which the relationship between circumstances and earnings is estimated via a regression model. This allows the full set of circumstance variables to be included without requiring each combination of characteristics to be represented by a sufficient number of observations. The parametric estimation strategy is described in detail in Section 3.3.

3.3 Estimation Strategy

To compute the counterfactual distribution corresponding to equalized circumstances, a specific empirical representation of equation (2) must be estimated. Recall the structural formulation:

$$y_{it} = f(C_i, E_{it}(C_i, v_{it}), u_{it})$$

Circumstances C_i may affect outcomes both directly and indirectly through the effort function $E_{it}(C_i, v_{it})$. In the non-parametric framework discussed above, the standardized distribution removes between-type inequality by equalizing type means. In a parametric setting, an analogous counterfactual is obtained by assigning each individual the same circumstance vector

— typically the sample average — thereby eliminating systematic outcome differences attributable to observed circumstances.

3.3.1 Parametric specification

Following Bourguignon et al. (2007), we adopt a log-linear specification for the outcome equation and a linear specification for the effort equation:

$$\text{(13)} \qquad \ln y_{it} = C_i\alpha_t + E_{it}\beta_t + u_{it}$$

$$\text{(14)} \qquad E_{it} = B_tC_i + v_{it}$$

Equation (13) represents the direct effect of circumstances on log earnings, while equation (14) models the indirect effect of circumstances on earnings operating through effort. Estimating this structural system directly would require observing all relevant circumstance and effort variables. Since this is unlikely to hold in practice — effort in particular is not directly observed in the SOEP — the structural parameters α_t and β_t cannot be given a causal interpretation. Omitted circumstance variables will be absorbed into the residual, and unobserved effort variation will cause the circumstance coefficients to partially reflect effort differences across groups.

However, for the purpose of measuring inequality of opportunity, causal identification of the structural parameters is not required. What matters is the total association between observed circumstances and earnings, encompassing both the direct effect in equation (13) and the indirect effect operating through equation (14). Substituting the effort equation into the outcome equation yields the reduced form:

$$\text{(15)} \qquad \ln\, y_{it} = C_i(\alpha_t + \beta_tB_t) + \beta_tv_{it} + u_{it} = C_i\psi_t + \varepsilon_{it}$$

The reduced-form coefficient vector ψ_t captures this total association and can be estimated consistently by OLS without requiring the structural parameters to be separately identified. Estimating equation (15) separately for each year t allows this association to vary over time, providing a basis for tracking the evolution of inequality of opportunity across the three years 1995, 2010 and 2023. The resulting counterfactual distribution in the next section has a well-defined interpretation: it describes the earnings distribution that would prevail if all individuals faced identical observed circumstances, irrespective of the specific mechanism through which those circumstances operate.

The log-linear specification imposes two substantive assumptions worth acknowledging. First, the effect of circumstances on log earnings is assumed to be linear and additive, ruling out interaction effects between circumstance variables. Second, additive separability between $\mathbf{C}_i\psi_t$ and ε_{it} implies that the dispersion of unobserved factors does not vary systematically across circumstance groups. These assumptions simplify estimation considerably but mean that the parametric counterfactual is an approximation to the fully flexible non-parametric standardization. Any functional form misspecification provides an additional reason — alongside incomplete observation of circumstances — to interpret the resulting measures as lower bounds of true inequality of opportunity.

Additionally, the log transformation in equation (15) implies that individuals with zero or missing earnings are excluded from the estimation sample by construction, since the logarithm is undefined for non-positive values. This restriction is innocuous if non-employment is distributed independently of circumstances — that is, if the probability of having zero earnings is unrelated to gender, migration background, or parental education. If, however, non-employment is systematically correlated with circumstances, the log regression is estimated on a selected subsample, and the resulting opportunity shares will understate the true contribution of those circumstances that are most strongly associated with non-participation. In the German context this concern is particularly relevant for gender, given the well-documented association between female labour market non-participation and structural constraints including limited childcare availability and tax incentives for spousal non-employment embedded in the Ehegattensplitting system. This channel implies that the exclusion of zero earners introduces a downward bias in the estimated opportunity shares for these circumstances, providing an additional reason — beyond incomplete observation of circumstances and parametric misspecification — to interpret all estimates as lower bounds of the true level of inequality of opportunity.

3.3.2 Constructing the counterfactual distribution

Given the OLS estimates $\hat{\psi}_t$ and the fitted residuals $\hat{\varepsilon}_{it}$, the counterfactual distribution is constructed by replacing each individual's observed circumstances with the vector of sample mean circumstances $\bar{\mathbf{C}}$:

$$\text{(16)} \qquad \ln \hat{y}_{it} = \bar{\mathbf{C}}\hat{\psi}_t + \hat{\varepsilon}_{it}$$

This transformation preserves within-type dispersion through the residual $\hat{\varepsilon}_{it}$ while removing between-type inequality by equalizing circumstances across all individuals. It is the parametric analogue to the non-parametric standardized distribution introduced in Section 3.2.1: by endowing each individual with identical observed circumstances, it eliminates systematic earnings differences across circumstance groups while retaining heterogeneity arising from effort and idiosyncratic factors.

Age is included as a linear control variable in all regressions. Its role is to absorb systematic lifecycle differences in earnings within the sample — it is not treated as a circumstance of normative interest, since age at the time of observation is not a predetermined background characteristic in the relevant sense. A linear specification is both sufficient and appropriate given that the sample is restricted to individuals aged 25 to 60, a window over which the earnings-age profile is considerably more linear than over the full lifecycle. Importantly, since age is not a circumstance in the normative sense of the framework — individuals of different ages who are otherwise identical in all circumstances are expected to differ in earnings as a result of lifecycle experience accumulation, and this variation is preserved rather than equalised in the counterfactual — its functional form has no bearing on the measured opportunity shares. Regardless of whether age enters linearly or in a more flexible form, it is never equalised in the counterfactual distribution and therefore cannot mechanically inflate or deflate the estimated IOL or IOR. The linear age specification is therefore adopted throughout without further robustness checks on this dimension.

3.3.3 Partial counterfactual decomposition by circumstance

The aggregate opportunity measures IOR and IOL quantify the total contribution of all observed circumstances simultaneously. However, a natural and policy-relevant question is how much each individual circumstance contributes to overall inequality of opportunity. Following

Ferreira and Gignoux (2008), the parametric framework permits the construction of partial counterfactual distributions that isolate the contribution of a single circumstance variable, holding all others constant.

For a given circumstance J — for instance, migration background — a partial counterfactual distribution is constructed by replacing only the values of circumstance J with the sample mean $\bar{C}_t^J$, while retaining all other circumstances at their individually observed values:

$$(17) \quad \tilde{y}_{it}^J = \exp\left[\bar{C}_t^J \hat{\psi}_t^J + C_{it}^{J\neq} \hat{\psi}_t^{J\neq} + \hat{\varepsilon}_{it}\right]$$

where $\bar{C}_t^J \hat{\psi}_t^J$ denotes the contribution of circumstance J evaluated at its mean value, $C_{it}^{J\neq} \hat{\psi}_t^{J\neq}$ denotes the contribution of all other circumstances retained at their individual values, and $\hat{\varepsilon}_{it}$is the individual residual preserved from the full regression. This transformation removes only the between-individual variation in circumstance J, leaving all other sources of inequality — both observed and unobserved — unchanged.

The circumstance-J-specific opportunity share is then defined as:

$$(18) \quad \theta_t^J = 1 - \frac{I(\tilde{y}_t^J)}{I(y_t)}$$

This measures the fraction of total inequality in year t that would be eliminated if only circumstance J were equalised across all individuals. Intuitively, it answers the question: how much would earnings inequality fall in Germany if, for example, all individuals had the same migration background, or the same parental education, while everything else remained as observed?

Two important interpretive points follow. First, the partial shares θ_t^J do not generally sum to the aggregate opportunity share IOR_t, since the partial effects of individual circumstances are not additively separable when circumstances are correlated with each other. The partial shares should therefore be interpreted as marginal contributions — the reduction in inequality attributable to equalising each circumstance separately — rather than as an exhaustive additive decomposition. Second, as with the aggregate measure, the partial shares represent lower bounds of the true circumstance-specific contributions, since the parametric specification captures only the linear association between each circumstance and earnings.

4. Data

4.1 Data source

This study uses data from the German Socio-Economic Panel (SOEP), a longitudinal household survey conducted annually since 1984 and administered by the German Institute for Economic Research (DIW Berlin). The SOEP is a representative panel dataset covering individuals living in private households in Germany, containing detailed information on labour market outcomes, demographic characteristics, educational attainment, and family background. Its combination of annual earnings data, retrospective parental background information, and long observation horizon makes it particularly well suited for the analysis of inequality of opportunity in Germany.

The empirical analysis draws on three SOEP datasets. The individual-level file pgen provides annual observations on labour market outcomes including gross and net labour earnings. The file ppathl contains time-varying demographic characteristics including gender, year of birth, and migration background. The biographical file bioparen provides retrospective information on parental education and childhood environment, collected at the individual level independently of survey year. All datasets are merged using the individual identifier pid. Time-varying variables from pgen and ppathl are merged on the combined key pid and syear, while time-invariant background variables from bioparen are merged on pid alone, ensuring that each individual carries a consistent set of parental background characteristics across all observed survey years.

4.2 Sample construction

The analysis is conducted for three anchor years — 1995, 2010, and 2023. This design choice is motivated by two considerations. First, circumstances are by definition time-invariant at the individual level, so genuine changes in the opportunity structure require sufficient time for population turnover and structural shifts to manifest. Second, the three anchor years correspond to economically meaningful periods in the development of the German labour market: 1995 provides a pre-Hartz reform baseline in the post-reunification period; 2010 captures the post-reform equilibrium following the structural labour market changes of the mid-2000s; and 2023 represents the contemporary endpoint after the introduction of the statutory minimum wage and the compositional changes associated with post-2013 migration.

Within each anchor year, the sample is restricted to individuals aged 25 to 60, computed as the difference between survey year and year of birth from ppathl. This restriction follows standard practice in the inequality of opportunity literature (Ferreira and Gignoux, 2011). Individuals below 25 may still be in education or vocational training and have not yet made a full transition into the labour market, while individuals above 60 may have begun to exit the labour force through early retirement, introducing variation driven by retirement decisions rather than labour market opportunity.

All SOEP-specific negative numeric codes — used to indicate item non-response, inapplicability, or implausible values — are converted to missing throughout. Observations with zero or negative earnings are retained in descriptive statistics but excluded from regression analyses, since log earnings are undefined for non-positive values. The regression-based analysis therefore measures inequality of opportunity in earnings among individuals who are active labour market participants with positive reported earnings. Individuals with missing information on any circumstance variable are excluded from the regression sample under listwise deletion. The resulting analysis samples consist of 4435 observations in 1995, 10300 observations in 2010, and 8952 observations in 2023.

4.3 Outcome variable: labour earnings

The primary outcome variable is individual gross labour earnings, provided by the SOEP variable pglabgro. Gross earnings — earnings before taxes and social insurance contributions — serve as the baseline measure throughout the empirical analysis. This choice reflects the primary interest in the pre-redistribution earnings distribution, where inequality of opportunity captures the role of background circumstances in shaping market outcomes before the tax-benefit system intervenes.

Net labour earnings (pglabnet) — earnings after taxes and transfers — are used as the basis for a substantive comparison. Comparing inequality of opportunity in gross and net earnings allows assessment of whether the German tax-benefit system reduces inequality of opportunity proportionally or whether it compresses within-type dispersion more strongly than between-type differences associated with circumstances. If the relative opportunity share is higher for net than for gross earnings, this indicates that redistribution disproportionately equalises effort-related inequality while leaving circumstance-related inequality comparatively intact — a finding with direct implications for the distributional effectiveness of the German welfare state.

For all regression-based analyses, labour earnings are transformed using the natural logarithm, which reduces the influence of extreme values and allows regression coefficients to be interpreted in proportional terms. Inequality indices are computed using earnings levels, consistent with the theoretical framework in Section 2.

4.4 Circumstance variables

The SOEP provides unusually rich information on family background and childhood environment relative to most nationally representative surveys, making it possible to construct a circumstance vector that captures several of the dimensions most widely used in the inequality of opportunity literature. All circumstance variables are time-invariant and merged at the pid level.

Gender is obtained from ppathl and coded as a binary indicator equal to one for female and zero for male. Gender is included as a circumstance because labour market outcomes in Germany differ substantially by gender, driven by occupational segregation, part-time employment patterns, and persistent wage gaps. These differences are not the result of free choices in any unambiguous sense — they reflect structural constraints, social norms, and institutional features of the German labour market that lie beyond the individual's control.

Migration background is captured using the SOEP variable migback, which distinguishes three mutually exclusive categories: no migration background, direct migration background (born abroad), and indirect migration background (born in Germany with at least one migrant parent). This three-way distinction is particularly important in the German context, where labour market outcomes differ substantially across these groups and where the composition of the migrant population has changed markedly over the observation period, with the share of direct migration background increasing substantially between 1995 and 2023.

Parental education is captured through two variables reflecting distinct dimensions of parental human capital. Mother's school education (msedu) is grouped into three ordered categories. Low education comprises no school degree, Hauptschule, or compulsory schooling (SOEP codes 1, 2, and 8). Medium education corresponds to an intermediate secondary degree (Realschule, code 3). High education includes upper secondary qualifications such as Abitur, Fachhochschulreife, or equivalent (codes 4, 7, and 9). Responses coded as other degree or don't know are treated as missing.

Father's professional education (fprofedu) is grouped into three ordered categories reflecting the structure of the German vocational and higher education system. The no qualification category includes fathers with no completed vocational or professional training. The vocational category combines standard apprenticeship training, commercial apprenticeships, and general vocational qualifications — the pathways that constitute the backbone of the German dual system and represent the modal qualification among fathers in the sample. The tertiary category comprises university, Fachhochschule, and equivalent higher education degrees.

The decision to include msedu and fprofedu rather than all available parental education variables — which also include father's school education (fsedu) and mother's professional education (mprofedu) — is motivated by both statistical and substantive considerations. Substantively, mother's school education captures the primary dimension of maternal human capital for the cohorts represented in the sample, among whom female vocational and tertiary participation was lower and more selective. Father's professional education captures the dominant pathway of paternal human capital accumulation in Germany, where the vocational system has historically been the principal route into stable employment. Statistically, including all four parental education variables yields negligible gains in explanatory power — an increase in R-squared of less than one percentage point — while reducing the analysis sample by approximately 10% in 1995 due to additional missing values, and producing theoretically implausible coefficient signs on mother's professional education in that year, likely reflecting small and unrepresentative cells among early cohorts. The two-variable specification is therefore both more parsimonious and more stable across anchor years.

Childhood location (locchildh) records the type of residential area in which the individual grew up, with four categories: large city, medium-sized city, small town, and rural area. Childhood location captures differences in access to educational infrastructure, labour market networks, and occupational opportunities during formative years. In the German context, there is evidence of persistent rural-urban earnings differentials, particularly in the years following reunification, making this variable especially relevant for the 1995 anchor year.

5. Summary Statistics

5.1 Earnings

Table 1 reports descriptive statistics for gross and net labour earnings — measured in euros per month — across the three anchor years, computed on the regression sample of individuals aged 25 to 60 with positive gross earnings and complete information on all circumstance variables. Mean gross earnings increased substantially over the observation period, rising from €1,987 in 1995 to €2,678 in 2010 and €3,971 in 2023, reflecting both real wage growth and nominal price level increases over nearly three decades. Median gross earnings followed a similar upward trajectory, from €1,790 in 1995 to €3,400 in 2023, remaining consistently below the mean in all years, indicating a right-skewed earnings distribution with a long upper tail. Net earnings follow a parallel pattern at lower levels, with mean net earnings rising from €1,320 in 1995 to €2,598 in 2023 and median net earnings from €1,196 to €2,300. The median remains below the mean for net earnings in all anchor years, confirming that the right-skewed shape of the earnings distribution is preserved after redistribution, though the gap between mean and median is somewhat smaller for net than for gross earnings, consistent with the compression of the upper tail by progressive taxation. The ratio of mean net to mean gross earnings is stable at approximately 0.66 across all three anchor years, suggesting that the average tax-benefit wedge has not changed substantially over the period, though this aggregate ratio conceals potential changes in the distributional impact of redistribution that are examined directly in the opportunity share comparisons in Section 6.

The share of individuals with zero gross earnings in the full age-restricted sample is substantial and varies non-monotonically across anchor years — 27.5% in 1995, 25.5% in 2010, and 31.3% in 2023. The zero shares for net earnings are virtually identical — 27.5%, 25.5%, and 31.1% respectively.

5.2 Inequality

The Mean Log Deviation of gross earnings exhibits a non-monotonic pattern across anchor years. Starting at 0.183 in 1995, it rises sharply to 0.329 in 2010 before declining to 0.277 in 2023. The increase between 1995 and 2010 is consistent with the well-documented rise in earnings inequality in Germany during the late 1990s and 2000s, driven by labour market deregulation, the expansion of the low-wage sector, and increased returns to skill. The subsequent decline between 2010 and 2023 likely reflects the introduction of the statutory minimum wage in 2015, which compressed the lower tail of the earnings distribution, as well as the tightening of the German labour market in the late 2010s. The MLD of net earnings follows the same pattern at uniformly lower levels — 0.173, 0.290, and 0.230 respectively — consistent with the inequality-reducing effect of the German tax-benefit system. The absolute gap between gross and net MLD widens from 0.010 in 1995 to 0.047 in 2023, suggesting that the redistributive impact of the tax-benefit system on earnings inequality has grown over the period. Whether this redistribution operates symmetrically across circumstance groups — or whether it disproportionately compresses within-type rather than between-type inequality — is examined directly through the gross and net earnings comparison in Section 6.

5.3 Sample composition

Table 2 reports the composition of the regression sample in terms of circumstance variables across the three anchor years. Several patterns are noteworthy and directly relevant to the interpretation of the empirical results.

The gender composition shifts modestly but meaningfully over the period. Women account for 43.3% of the regression sample in 1995, rising to 49.1% in 2010 and 49.4% in 2023. This near-convergence to gender parity in the positive-earnings regression sample reflects the substantial increase in female labour force participation in Germany over this period. It is important to note that this share conditions on positive earnings, so the increasing female share might reflect a compositional change in who participates in the labour market rather than a change in the underlying population structure.

Migration background shows the most dramatic compositional shift across anchor years and is the single most striking change in the circumstance distribution over the observation period. The share of individuals with no migration background declines from 93.3% in 1995 to 87.9% in 2010 and then sharply to 61.4% in 2023. Correspondingly, the share with direct migration background — individuals born abroad — increases from 6.1% in 1995 to 9.0% in 2010 and then rises steeply to 34.1% in 2023. The share with indirect migration background also increases, from 0.6% in 1995 to 4.5% in 2023, though it remains modest throughout. The sharp increase in direct migration background between 2010 and 2023 reflects the large-scale migration flows to Germany associated with the 2015 refugee influx and sustained EU labour mobility, and represents a fundamental compositional change in the working-age population. This shift has direct implications for the measured opportunity share of migration background and motivates the partial counterfactual analysis in Section 5, where the contribution of migration background to inequality of opportunity is isolated and tracked across anchor years.

Parental education shows a clear upgrading trend consistent with the educational expansion of birth cohorts represented in the sample. The share of individuals with low maternal school education — no degree, Hauptschule, or compulsory schooling — declines from 82.5% in 1995 to 65.2% in 2010 and 42.6% in 2023, while the share with high maternal education rises from 3.3% in 1995 to 30.2% in 2023. This near tenfold increase in the share of high maternal education over the observation period reflects the substantial educational expansion experienced by the parental cohorts of individuals in the working-age sample. Father's professional education follows a parallel but less dramatic pattern. The share with tertiary professional qualifications increases from 12.0% in 1995 to 27.6% in 2023, while the dominant vocational category declines from 75.0% to 58.3%. The share of fathers with no professional qualification remains broadly stable, at 13.0% in 1995 and 14.1% in 2023, with a dip to 9.5% in 2010. These compositional changes in the parental education distribution imply that the circumstance vector itself has shifted substantially over the period, independently of any changes in the returns to parental background — a distinction that the partial counterfactual decomposition in Section 6 is designed to illuminate.

Childhood location shows a decline in the rural share from 39.6% in 1995 to 27.8% in 2023, with a corresponding increase in the large city share from 21.4% to 29.0%. This shift reflects long-run urbanisation trends and internal migration patterns in Germany. The small town share remains stable at around 23% throughout, while the medium city share increases modestly from 16.3% to 19.7%.

The age composition of the regression sample is stable across anchor years. Mean age increases slightly from 40.3 in 1995 to 42.7 in both 2010 and 2023, and the standard deviation remains in a narrow range of 9.2 to 10.2. This stability confirms that the age structure of the sample does not change substantially across anchor years, supporting the use of a linear age control in the regression specification and ensuring that cross-year comparisons of opportunity shares are not confounded by systematic age composition differences.

6. Estimation Results

6.1 Reduced-Form Estimates

The starting point of the empirical analysis is the estimation of the reduced-form equation (15). As established in Section 3.3 these coefficients are not causal estimates — they absorb both the direct effect of circumstances on earnings and the indirect effects operating through effort and human capital accumulation. This is precisely what is required for the construction of the counterfactual earnings distribution in Section 3.3.2, where the individual circumstance values are replaced by their sample means to simulate a world in which all individuals face identical circumstances. The reduced-form estimates are therefore presented first, as they constitute the empirical foundation from which all subsequent opportunity share measures are derived. Tables 3 and 4 present the OLS estimates for gross and net earnings respectively, with results for all three anchor years reported side by side to make the evolution of individual circumstance coefficients directly visible.

6.1.1 Gender

The female earnings penalty is the largest and most precisely estimated effect in the regression throughout the entire observation period. Relative to otherwise comparable men, women earn approximately 43% less in gross earnings in 1995, a gap that widens to 53% in 2010 before narrowing to 35% in 2023. The net earnings specification yields a qualitatively identical pattern — -0.600 in 1995, -0.712 in 2010, and -0.434 in 2023 — with coefficients uniformly slightly smaller in absolute terms than their gross counterparts, consistent with the progressive compression of the German tax-benefit system. The initial widening of the female penalty between 1995 and 2010 warrants careful interpretation. As the regression sample is conditioned on individuals with positive earnings, meaning that only employed individuals enter the estimation. The more negative coefficient observed in 2010 relative to 1995 may therefore not reflect a deterioration in the labour market position of women, but rather a compositional shift in who appears in the sample. As female labour force participation expanded over this period women who would previously have been non-employed entered the positive-earnings sample with — partly — relatively low monthly earnings. This mechanically pulls the conditional female mean downward and widens the observed earnings gap, even as the underlying development — more women in paid work — represents an improvement in labour market inclusion rather than a worsening of inequality of opportunity. The coefficient should therefore be interpreted with this selection dynamic in mind.

6.1.2 Migration background

In 1995, the coefficient on direct migration background is 0.005 and statistically indistinguishable from zero, indicating that individuals born abroad faced no systematic earnings penalty relative to native-born individuals without migration background. By 2010 the coefficient turns significantly negative at -0.186, and by 2023 it reaches -0.309 for gross earnings and -0.247 for net earnings, implying that individuals with direct migration background earn approximately 27% less in gross and 22% less in net terms than comparable individuals without migration background.

6.1.3 Parental education

Both mother's school education and father's professional education show positive and statistically significant gradients in all three anchor years, confirming the persistent and growing importance of parental human capital as a determinant of labour market outcomes in Germany. The coefficient on mother's high school education increases from 0.121 in 1995 to 0.196 in 2010 before declining slightly to 0.114 in 2023 for gross earnings, while the medium education coefficient rises steadily from 0.113 to 0.153. The pattern for father's professional education is particularly revealing. The tertiary coefficient shows a clear and monotonic upward trend — from 0.124 in 1995 to 0.197 in 2010 and 0.302 in 2023 — representing the largest increase of any circumstance coefficient in the table. The vocational father's education coefficient is positive and significant throughout but considerably smaller in magnitude, ranging from 0.062 to 0.111.

6.1.4 Childhood location

The childhood location coefficients exhibit one of the clearest structural changes in the entire regression table. In 1995, growing up outside a large city is associated with a significant and economically meaningful earnings penalty relative to large city childhood — medium city -0.076, small town -0.110, and rural -0.139, all statistically significant at conventional levels. By 2010 the penalties persist but have diminished — small town -0.085 and rural -0.107 remain significant, while the medium city coefficient has shrunk to -0.049. By 2023 all three non-city coefficients are small and statistically indistinguishable from zero — medium city 0.011, small town 0.022, rural -0.008.

6.1.5 Age and model fit

The age coefficient is positive and significant in all years, consistent with the standard experience-earnings profile, rising from 0.003 in 1995 to 0.016 in 2010 before declining to 0.008 in 2023. The overall explanatory power of the circumstance vector declines from an R-squared of 0.203 in 1995 and 0.202 in 2010 to 0.129 in 2023 for gross earnings. The decline in 2023 likely reflects the increasing internal heterogeneity of the direct migration background group — which by 2023 accounts for 34% of the regression sample and encompasses individuals with very different labour market histories, qualifications, and lengths of residence — introducing earnings variation within the circumstance categories that the reduced-form specification cannot capture. Despite this decline, the F-statistics confirm that the circumstance vector as a whole retains strong explanatory power in all three anchor years, and the R-squared of the net earnings specification is consistently slightly higher than for gross earnings — 0.239 versus 0.203 in 1995, 0.215 versus 0.202 in 2010, and 0.134 versus 0.129 in 2023 — suggesting that circumstances account for a somewhat larger share of variation in net than in gross earnings, a finding that foreshadows the opportunity share comparison between gross and net earnings in Section 6.4.

6.2 Baseline Results: Inequality of Opportunity in Gross Earnings

Table 5 presents the main results of the empirical analysis — the aggregate inequality of opportunity measures for gross labour earnings across the three anchor years. The total Mean Log Deviation of gross earnings rises sharply from 0.183 in 1995 to 0.329 in 2010, before declining to 0.277 in 2023. The counterfactual MLD — the inequality that would remain if all individuals faced identical observed circumstances — follows a parallel trajectory, rising from 0.150 in 1995 to 0.276 in 2010 and falling to 0.242 in 2023. The gap between observed and counterfactual MLD in each year constitutes the absolute opportunity share IOL, and the ratio of this gap to total inequality constitutes the relative opportunity share IOR.

The baseline result for 1995 establishes the starting point of the analysis. The IOR of 0.181 indicates that approximately 18% of total gross earnings inequality in Germany in 1995 can be attributed to predetermined circumstances — gender, migration background, parental education, and childhood location — over which individuals have no control. The remaining 82% of observed earnings inequality reflects differences in individual choices, effort, and luck, for which individuals can reasonably be held responsible in the normative sense of the framework. This decomposition provides a concrete answer to the question motivating the paper: even in the earliest anchor year, a non-trivial share of earnings inequality in Germany is driven by the circumstances of birth rather than by individual agency.

The IOR is also directly informative as a policy metric. If the goal of redistributive policy is to reduce inequality of opportunity specifically — rather than inequality as a whole — then the evolution of the IOR across anchor years provides a natural way to evaluate whether policy has been effective in targeting the circumstance-driven component of inequality. A declining IOR over time would suggest that the opportunity structure has become more equitable, in the sense that a smaller fraction of observed earnings differences can be traced to predetermined background characteristics. By this standard, the evolution of the IOR in Germany is encouraging: it declines monotonically from 0.181 in 1995 to 0.162 in 2010 and 0.127 in 2023, suggesting that the share of earnings inequality attributable to circumstances has fallen meaningfully over the three decades covered by the analysis. In 2023, predetermined circumstances account for approximately 13% of total earnings inequality — a substantially smaller fraction than the 18% observed in 1995, and a reduction that is consistent with the convergence of childhood location penalties documented in Section 6.1 and with the secular upgrading of parental education across cohorts, both of which reduce the between-type component of inequality relative to the within-type component.

However, the absolute opportunity share IOL tells a more cautionary story and cautions against an overly optimistic reading of the declining IOR. The IOL rises from 0.033 in 1995 to 0.053 in 2010 before falling back to 0.035 in 2023. This means that while circumstances account for a smaller share of total inequality in 2010 than in 1995, the absolute level of circumstance-driven inequality is higher. Total inequality grew so much between 1995 and 2010 that even a declining opportunity share was consistent with a rising absolute level of opportunity inequality — the earnings gap between individuals at the top and bottom of the circumstance distribution widened in absolute terms during the Hartz reform period. The subsequent decline in both IOL and IOR between 2010 and 2023 reflects a genuine compression of both total and circumstance-driven inequality. This divergence between the relative and absolute measures underscores the importance of reporting both — neither alone provides a complete picture of how inequality of opportunity has evolved in Germany.

6.3 The Contribution of Individual Circumstances: Partial Counterfactual Decomposition

Table 6 presents the partial counterfactual opportunity shares θ^J for each of the five circumstance variables, computed separately for each anchor year. These partial shares measure the fraction of total inequality that would be eliminated if only a single circumstance were equalised across all individuals, holding all others at their observed values, and provide a decomposition of the opportunity share into the contributions of individual circumstances.

6.3.1 Gender

Gender is by far the dominant circumstance throughout the observation period, though its contribution declines substantially over time. The gender partial share falls from 0.155 in 1995 to 0.135 in 2010 and 0.074 in 2023 for gross earnings. In 1995, gender alone accounts for 85% of the total IOR of 0.181 — virtually all of measured inequality of opportunity in Germany at that time was gender-driven. By 2023 the gender share has fallen to 0.074, representing 58% of the total IOR of 0.127. This is still the dominant circumstance by a substantial margin, but the composition has shifted meaningfully. The decline in the gender partial share is consistent with the narrowing of the female earnings coefficient in the reduced-form regression documented in Section 6.1 and reflects genuine convergence in male and female labour market outcomes driven by rising female labour force participation, improved occupational access, and minimum wage effects.

6.3.2 Migration background

The migration background partial share undergoes the most dramatic change of any circumstance across the observation period. Starting at essentially zero in 1995 — 0.0004, indicating that migration background contributed virtually nothing to inequality of opportunity in that year — it rises modestly to 0.0021 in 2010 and then increases more than tenfold to 0.0227 in 2023. By 2023, migration background accounts for approximately 18% of the total IOR, making it the second largest contributor to inequality of opportunity alongside father's professional education.

6.3.3 Parental education

Mother's school education and father's professional education each contribute modestly to the total opportunity share throughout the period, but their trajectories diverge in an economically interesting way. The mother's education partial share declines from 0.0124 in 1995 to 0.0071 in 2010 and 0.0083 in 2023 — a broadly flat and small contribution. Father's professional education, by contrast, shows a clear upward trend — from 0.0057 in 1995 to 0.0128 in 2010 and 0.0229 in 2023. By 2023 father's education has become the joint second largest contributor to inequality of opportunity alongside migration background, with a partial share of 0.023. This strengthening of the paternal education contribution is consistent with the rising tertiary education premium documented in the reduced-form coefficients, where the father's tertiary education coefficient more than doubled between 1995 and 2023.

6.3.4 Childhood location

The childhood location partial share declines from 0.0097 in 1995 to 0.0062 in 2010 and essentially zero — 0.0004 — in 2023. This complete disappearance of the childhood location contribution is the most striking convergence result in the partial decomposition and directly mirrors the fading of the rural and small-town childhood penalties in the reduced-form regression. By 2023, equalising childhood location across all individuals would reduce total earnings inequality by only 0.04 percentage points — a negligible effect. Childhood geography has ceased to be a meaningful determinant of earnings opportunity in Germany, a finding that reflects the equalisation of regional labour markets, improved infrastructure, and increased labour mobility over the three decades covered by the analysis.

6.3.5 The changing composition of opportunity inequality

Taken together, the partial decomposition reveals a fundamental transformation in the structure of inequality of opportunity in Germany between 1995 and 2023. In 1995, inequality of opportunity was almost entirely gender-driven, with migration background and childhood location playing negligible roles. By 2023, while gender remains the dominant circumstance, the opportunity structure has diversified — migration background and father's professional education have emerged as meaningful contributors, while childhood location has effectively disappeared. The total IOR has declined but its composition has become more complex, reflecting the structural changes in the German economy and labour market over this period. This compositional shift has important implications for policy — reducing inequality of opportunity in Germany today requires addressing gender earnings gaps, migrant labour market integration, and the intergenerational transmission of educational advantage simultaneously, rather than focusing on any single circumstance.

6.4 Gross versus Net Earnings: Does Redistribution Reduce Inequality of Opportunity?

Tables 5 and 6 present the aggregate and partial opportunity shares for net labour earnings alongside the corresponding gross earnings results, allowing a direct assessment of whether the German tax-benefit system reduces inequality of opportunity proportionally or whether it operates asymmetrically across the within-type and between-type components of total inequality.

The net earnings IOR is consistently and substantially higher than the gross earnings IOR in all three anchor years — 22.0% versus 18.1% in 1995, 18.7% versus 16.2% in 2010, and 13.9% versus 12.7% in 2023. This finding is unambiguous and directly answers the comparative question: the German tax-benefit system does not reduce inequality of opportunity proportionally. Rather, redistribution compresses within-type inequality — the earnings dispersion among individuals sharing identical circumstances — more strongly than between-type inequality — the earnings differences across circumstance groups. As a result, the opportunity share of net earnings inequality is higher than the opportunity share of gross earnings inequality in every anchor year. Put differently, after redistribution, a larger fraction of the remaining inequality is attributable to circumstances rather than to effort and luck.

This finding is consistent with the theoretical expectation for a progressive tax and transfer system. Progressive taxation and means-tested transfers target low-income individuals regardless of their type membership, compressing within-type inequality at the bottom of the distribution. The between-type component — which reflects systematic earnings differences between circumstance groups — is less directly targeted by redistribution instruments that do not condition on parental background, migration status, or childhood environment. The result suggests that while the German welfare state is effective at reducing overall inequality, its distributional instruments are better calibrated to address outcome inequality than opportunity inequality.

The gap between net and gross IOR narrows over time — from 3.9 percentage points in 1995 to 2.6 percentage points in 2010 and 1.2 percentage points in 2023. This convergence suggests that the asymmetric redistributive effect has diminished over the period, consistent with the declining importance of gender as a circumstance driver. Since the gender earnings gap is large and persistent and is partly compressed by progressive taxation — women's lower earnings place them disproportionately in lower tax brackets — the narrowing of the gender gap reduces the asymmetric component of redistribution.

The partial counterfactual results for net earnings mirror those for gross earnings in their directional patterns, with all partial shares somewhat larger for net than for gross earnings in all years. The gender partial share for net earnings rises from 0.196 in 1995 to a slightly higher level relative to gross earnings throughout, confirming that gender-driven earnings differences are less effectively addressed by redistribution than the average within-type inequality. The migration background and father's education partial shares are similarly slightly larger for net than gross earnings by 2023, suggesting that the circumstance-driven earnings penalties for recent migrants and individuals from low-education backgrounds are also relatively preserved after redistribution.

7. Conclusion

This paper has examined inequality of opportunity in labour earnings in Germany across three anchor years — 1995, 2010, and 2023. The central question was whether the popular notion that every individual is the architect of their own fortune holds empirically, or whether a meaningful share of observed earnings inequality can be traced to predetermined background characteristics beyond individual control.

The answer is unambiguous: circumstances matter substantially, though their importance has changed in both magnitude and composition over three decades. The relative opportunity share in gross earnings declines monotonically from 18.1% in 1995 to 16.2% in 2010 and 12.7% in 2023, consistent with the convergence of childhood location penalties, the upgrading of parental education across cohorts, and the narrowing of the gender earnings gap. However, the absolute opportunity share tells a more cautionary story — it rose sharply between 1995 and 2010 before declining, reflecting the rapid expansion of total earnings inequality during the Hartz reform period. In absolute terms the earnings gap between individuals at the top and bottom of the circumstance distribution grew considerably during the reform years even as the relative share fell. Neither measure alone provides a complete picture, and their divergence illustrates why both must be reported when total inequality itself changes substantially over time.

The partial counterfactual decomposition reveals a fundamental structural transformation in the composition of opportunity inequality. In 1995, inequality of opportunity was almost entirely a gender phenomenon — gender alone accounted for approximately 85% of the total IOR. By 2023 migration background and paternal professional education have each emerged as quantitatively important contributors, while childhood location has effectively ceased to matter. The German opportunity structure has shifted from one defined primarily by gender and geography toward one increasingly shaped by migration background and the intergenerational transmission of educational advantage — a transformation with fundamentally different implications for policy design.

The comparison between gross and net earnings confirms that the German tax-benefit system does not reduce inequality of opportunity proportionally. Redistribution compresses within-type earnings dispersion more effectively than it reduces the systematic earnings differences across circumstance groups, so that after taxes and transfers a larger fraction of remaining inequality is attributable to predetermined circumstances rather than to effort and luck.

Before drawing policy conclusions, the limitations of the analysis deserve emphasis. All estimates are lower bounds of the true level of inequality of opportunity, for three compounding reasons that are likely to be quantitatively important. The circumstance vector does not capture parental income, family wealth, school quality, or neighbourhood characteristics — all of which plausibly affect earnings. Parametric misspecification of the linear reduced form introduces additional downward bias. Most importantly, conditioning on positive earnings excludes non-employed individuals whose non-participation is itself a manifestation of inequality of opportunity. The results should therefore be interpreted as conservative lower bounds rather than precise estimates of the true extent of opportunity inequality in Germany. The finding that roughly one eighth of earnings inequality in 2023 is attributable to circumstances is not a reassurance — it is a floor.

With this caveat in mind, two developments deserve attention going forward. The dramatic increase in the direct migration background share from 6% in 1995 to 34% in 2023 has transformed migration background into one of the most important sources of opportunity inequality in contemporary Germany, and tracking its evolution as recent arrival cohorts accumulate labour market experience will be essential for understanding both the trajectory of inequality of opportunity and the effectiveness of integration policy. At the same time, the strengthening of the paternal tertiary education premium suggests that intergenerational transmission of educational advantage is intensifying, raising the possibility that the declining relative opportunity share masks a deepening of the socioeconomic channels through which family background shapes labour market outcomes. Whether future generations of Germans can more genuinely be the architects of their own fortunes will depend substantially on how policy responds to both of these challenges.

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Appendix

Table 1: Earnings Statistics by Year

Statistic	1995	2010	2023
Gross Earnings			
Mean gross earnings (€)	1,987.0	2,678.0	3,971.0
Median gross earnings (€)	1,790.0	2,300.0	3,400.0
SD gross earnings	1,386.0	2,315.0	3,415.0
Share zero gross earnings (%, full sample)	27.5	25.5	31.3
Net Earnings			
Mean net earnings (€)	1,320.0	1,758.0	2,598.0
Median net earnings (€)	1,196.0	1,500.0	2,300.0
Share zero net earnings (%, full sample)	27.5	25.5	31.1
Inequality			
MLD gross earnings	0.183	0.329	0.277
MLD net earnings	0.173	0.290	0.230
Sample Size			
N regression sample	4,435	10,300	8,952

Notes: All statistics computed on the regression sample (individuals aged 25-60 with positive gross earnings and complete information on all circumstance variables), except share of zero earnings which refers to the full age-restricted sample (25-60). MLD = Mean Log Deviation. Net earnings statistics exclude observations with zero or missing net earnings.

Table 2: Sample Composition by Year

Statistic	1995	2010	2023
Gender			
Female (%)	43.3	49.1	49.4
Male (%)	56.7	50.9	50.6
Migration Background			
No migration background (%)	93.3	87.9	61.4
Direct migration background (%)	6.1	9.0	34.1
Indirect migration background (%)	0.6	3.1	4.5
Mother's School Education			
Mother's education: low (%)	82.5	65.2	42.6
Mother's education: medium (%)	14.3	24.8	27.1
Mother's education: high (%)	3.3	10.0	30.2
Father's Professional Education			
Father's prof. education: none (%)	13.0	9.5	14.1
Father's prof. education: vocational (%)	75.0	74.5	58.3
Father's prof. education: tertiary (%)	12.0	16.1	27.6
Childhood Location			
Childhood location: large city (%)	21.4	21.3	29.0
Childhood location: medium city (%)	16.3	18.1	19.7
Childhood location: small town (%)	22.6	23.5	23.5
Childhood location: rural (%)	39.6	37.0	27.8
Age			
Mean age	40.3	42.7	42.7
SD age	9.6	9.2	10.2

Notes: All statistics computed on the regression sample (individuals aged 25-60 with positive gross earnings and complete information on all circumstance variables). Mother's school education: low = no degree, Hauptschule, or compulsory schooling; medium = Realschule; high = Abitur, Fachhochschulreife, or equivalent. Father's professional education: none = no completed training; vocational = apprenticeship or vocational qualification; tertiary = Fachhochschule or university degree.

Table 3: Reduced-Form OLS Estimates of Log Gross Earnings on Circumstances

Variable	1995	2010	2023
Constant	7.520***	7.190***	7.770***
	(0.052)	(0.055)	(0.053)
Female	-0.573***	-0.738***	-0.438***
	(0.018)	(0.016)	(0.017)
Direct migration background	0.005	-0.186***	-0.309***
	(0.038)	(0.029)	(0.022)
Indirect migration background	-0.088	-0.020	0.048
	(0.118)	(0.047)	(0.041)
Mother's education: medium	0.113***	0.119***	0.153***
	(0.027)	(0.020)	(0.022)
Mother's education: high	0.121*	0.196***	0.114***
	(0.053)	(0.031)	(0.024)
Father's prof. education: vocational	0.093***	0.062*	0.111***
	(0.028)	(0.029)	(0.028)
Father's prof. education: tertiary	0.124**	0.197***	0.302***
	(0.039)	(0.037)	(0.031)
Childhood: medium city	-0.076**	-0.049.	0.011
	(0.029)	(0.026)	(0.024)
Childhood: small town	-0.110***	-0.085***	0.022
	(0.027)	(0.024)	(0.023)
Childhood: rural	-0.139***	-0.107***	-0.008
	(0.024)	(0.022)	(0.023)
Age	0.003***	0.016***	0.008***
	(0.001)	(0.001)	(0.001)
R-squared	0.203	0.202	0.129
Adj. R-squared	0.201	0.201	0.128
N	4,435	10,300	8,952

Notes: OLS estimates of the reduced-form equation $\ln y = C\psi + \varepsilon$. Robust standard errors in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Reference categories: male, no migration background, mother's education low, father's professional education none, childhood location large city. Age is included as a continuous control variable.

Table 4: Reduced-Form OLS Estimates of Log Net Earnings on Circumstances

Variable	1995	2010	2023
Constant	7.142***	6.881***	7.424***
	(0.048)	(0.050)	(0.048)
Female	-0.600***	-0.712***	-0.434***
	(0.017)	(0.015)	(0.015)
Direct migration background	-0.005	-0.143***	-0.247***
	(0.036)	(0.027)	(0.020)
Indirect migration background	-0.128	-0.021	0.034
	(0.109)	(0.043)	(0.037)
Mother's education: medium	0.094***	0.104***	0.130***
	(0.025)	(0.019)	(0.020)
Mother's education: high	0.141**	0.177***	0.100***
	(0.049)	(0.029)	(0.021)
Father's prof. education: vocational	0.067**	0.048.	0.100***
	(0.026)	(0.026)	(0.025)
Father's prof. education: tertiary	0.107**	0.177***	0.272***
	(0.036)	(0.033)	(0.028)
Childhood: medium city	-0.064*	-0.038	0.007
	(0.027)	(0.023)	(0.022)
Childhood: small town	-0.103***	-0.083***	0.019
	(0.025)	(0.022)	(0.021)
Childhood: rural	-0.124***	-0.092***	-0.006
	(0.023)	(0.020)	(0.021)
Age	0.003***	0.014***	0.007***
	(0.001)	(0.001)	(0.001)
R-squared	0.239	0.215	0.134
Adj. R-squared	0.237	0.214	0.132
N	4,435	10,297	8,967

Notes: OLS estimates of the reduced-form equation $\ln y = C\psi + \varepsilon$. Dependent variable is log net labour earnings. Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. Reference categories: male, no migration background, mother's education low, father's professional education none, childhood location large city. Age is included as a continuous control variable.

Table 5: Inequality of Opportunity — Gross and Net Earnings

	Gross Earnings			Net Earnings		
	1995	**2010**	**2023**	**1995**	**2010**	**2023**
MLD observed earnings	0.1825	0.3288	0.2769	0.1732	0.2899	0.2308
MLD counterfactual earnings	0.1496	0.2756	0.2417	0.1351	0.2358	0.1987
IOL (absolute opportunity share)	**0.0330**	**0.0531**	**0.0352**	**0.0381**	**0.0541**	**0.0321**
IOR (relative opportunity share)	**0.1806**	**0.1616**	**0.1270**	**0.2198**	**0.1865**	**0.1390**

Notes: MLD = Mean Log Deviation. MLD counterfactual is computed by replacing all circumstance variables with their sample means while retaining individual residuals. IOL = MLD(y) - MLD(ỹ): absolute opportunity share. IOR = 1 - MLD(ỹ)/MLD(y): relative opportunity share. Circumstances: gender, migration background, mother's school education, father's professional education, childhood location. All estimates represent lower bounds of true inequality of opportunity.

Table 6: Partial Counterfactual Opportunity Shares by Circumstance

	Gross Earnings			Net Earnings		
	1995	**2010**	**2023**	**1995**	**2010**	**2023**
Gender	0.1548	0.1351	0.0737	0.1956	0.1604	0.0886
Migration background	0.0004	0.0021	0.0227	0.0005	0.0016	0.0219
Mother's education	0.0124	0.0071	0.0083	0.0116	0.0069	0.0068
Father's education	0.0057	0.0128	0.0229	0.0047	0.0125	0.0208
Childhood location	0.0097	0.0062	0.0004	0.0081	0.0056	0.0004
Aggregate IOR	**0.1806**	**0.1616**	**0.1270**	**0.2198**	**0.1865**	**0.1390**

Notes: Each entry reports the partial counterfactual opportunity share, defined as the fraction of total earnings inequality eliminated when only circumstance J is equalised at its sample mean while all other circumstances retain their individual values. Partial shares do not sum to the aggregate IOR due to non-additivity when circumstances are correlated. All estimates represent lower bounds of the true opportunity shares.