Striving for Equal Opportunities: Essays on the Distribution and Transmission of Economic Resources

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Striving for Equal Opportunities: Essays on the Distribution and Transmission of Economic Resources

Dissertation

Maximilian Stockhausen

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Chapter 1

Introduction

1.1 Motivation

Market economies will always tend to generate unequal distributions of economic resources, since individuals are differently rewarded within the production process due to differences in their skills, talents, or efforts. However, the broad economic and philosophical literature on distributive justice has shown that a distinction should be made between morally acceptable and morally unacceptable inequalities; inequalities can be justified if they result from different personal efforts under otherwise identical circumstances. If inequalities are only due to circumstances that are beyond the personal control they should be treated as unacceptable and should be compensated to a certain degree Roemer (1998). For example, the young, the elderly, or the sick are not able to participate in the labour market generating a sufficient income to make their livings and they are obviously not (fully) responsible for being in such a position.

If one agrees on this argumentation, then, there is a well-founded need for a welfare state to redistribute resources from the more able to the less able. This can be achieved, for instance, by a progressive tax and transfer system that generates a public budget to provide a minimum cash income to secure a sufficient living for the needy members of a society. Furthermore, the welfare state can provide essential in-kind benefits that go beyond cash incomes, like security, health, or education at low costs or even for free to reduce existing inequalities in resources that are beyond an individual's control. However, the question arises of what should a society actually equalize and to which degree? In other words: what should the equalisandum be? Is it utility, a bundle of outcomes, or opportunities for welfare?

This is a complex normative question that has been extensively and controversially discussed for years in the literature and on economic forums. In general, there are two opposing schools of thought that differ in their principal view on what should be equalized across persons: the utilitarians and the egalitarians. The former postulate that distributive justice is best achieved by maximizing the sum of utility across all persons in a laissez-faire economy. In contrast, egalitarians stress that distributive justice is more than just maximizing the sum of welfare. Society should be concerned with the distribution of some basic goods and it is this bundle of goods that should be maximized for the least well-off person in society. In addition, interventions by the welfare state are accepted, whenever they improve the outcome of the laissez-faire market economy.

The idea of providing a specific set of material and non-material goods goes back to the seminal work of Rawls (1971). Roemer (1998) highlights the importance of this work for egalitarian theory as an important counterpart to the utilitarian approach, since Rawls introduced three new elements: the primary goods concept, the difference principle, and self-responsibility. In particular, the latter is the essential concept of the equality of opportunity theory that prevailed implicitly in Rawls for the first time and was decisively further developed and made explicit in the works of Dworkin (1981a,b) and his successors.

Rawls argues that a bundle of natural and social primary goods should represent the equalisandum, which includes intelligence, imagination, health, income, wealth as well as fundamental political freedoms. Moreover, he argues that not the sum of welfare should be maximized, but rather the welfare of the least well-off individual. With this he introduces the so-called difference principle and offers a fundamental alternative to utilitarianism. This new egalitarianism not only forms the basis for the works of Sen (1976, 1979, 1980, 1985), who accuses Rawls to have a fetishism for his primary good concept and, in addition, postulates the need to further distinguish between functionality and capability of goods.

It is similarly important in the works of Ronald Dworkin who postulates equality in the available resources rather than equality in utility, too. Dworkin also suggests focusing on a broad set of resources that even goes beyond the definition of Rawls and encompasses financial as well as non-financial resources such as talent or physical constraints. What is remarkably new to Dworkin's approach is that people are explicitly made responsible for their personal preferences. It follows from this, in brief, that it is not welfare increasing to redistribute scarce resources from a person with cheap tastes to a person with expensive tastes, as long as the latter person voluntarily identifies with his expensive tastes (Roemer and Trannoy, 2015).

Since non-financial resources are not transferable, Dworkin introduces the idea of a security equivalency to be paid that is calculated in a thought experiment behind a so-called "veil of ignorance". This is another ground-breaking element of Dworkin's theory.

Behind the veil, all individuals are aware of their preferences, but they do not know what resources they will be endowed with in life. Furthermore, each individual owns the same amount of money to buy insurance against bad luck in the birth lottery at an insurance market according to his or her preferences. The resulting allocation of goods in combination with the insurance values would produce an equitable distribution that balances the available resources. However, it is almost impossible to put this thought experiment into practice and Roemer can show that the insurance market can only lead to an equitable distribution of resources if individuals are sufficiently risk-averse. Otherwise, it may lead to the perverse result that people with expensive tastes will eventually get the bulk of the available resources (Roemer and Trannoy, 2015).

Further criticism was articulated by Arneson (1989) and Cohen (1989). Arneson argued that one should rather strive to equalize opportunities for welfare than just resources. This would allow taking account of different individual preferences, while allowing differences in the individual levels of well-being that would originate from different personal choices and, thus, would be fairer. Cohen, on the other hand, criticized Dworkin's theory at the core of the fact that people cannot be made fully responsible for their personal preferences because they may have formed under the influence of other circumstances - often during childhood - that have been strongly influenced by the available resources at that time itself. This view is referred to as *control view* and is in contrast with the stricter *preference view* of Ronald Dworkin.

In the core of the equality of opportunity theory, the question ultimately arises as to which factors contribute to circumstances and which to efforts. Roemer and Trannoy (2015, p. 277) show the different perspectives in the separation of circumstances and effort from the example of age and gender: "Under the control view, age and sex are circumstances. Under the preference view, because age and sex are important determinants of preference, they will implicitly enter as factors of effort!"

The definition of a certain point of view, then, depends primarily on social conditions and the social norms anchored in societies, and can vary widely from country to country. Parents also play a special role in the transfer and formation of preferences of their children. However, it is not unambiguously clear to what extent the transfer of parents own preferences to their children is a circumstance, which would need compensation among children. In principle, Roemer and Trannoy (2015) argue that it is morally legitimate for parents to pass on their own views and values and become immortal in their children. But if the parents already developed their preferences under limited circumstances themselves, this deficit should ultimately not have a negative impact on their children, who would be unnecessarily constrained in their electoral kites by the limited vision of their parents. This view is typical for the control view formulated by Cohen and does not exist according to the preference view of Dworkin.

At the same time, a state of perfect equality of opportunity can be equally undesirable, i.e. a state of perfect intergenerational mobility. Their essential argument against it is that it would be difficult to justify this condition, since this would ultimately lead to a collective and equal education of all children. This would be an unjustifiable intervention into personal freedom. At this point, however, Roemer and Trannoy (2015) avoid giving a concrete answer to the normative theoretical question, which degree of equality of opportunity would be just as acceptable under these assumptions, and thus remaining blurred in his analysis.

Without attempting to address the specific concepts, requirements and difficulties in measuring equality of opportunity, empirical research can, however, make a valuable contribution to providing a measure of equality of opportunity, for example, by investigating the correlation between lifetime earnings of parents and children, or by quantifying the extent of family influences on later outcomes in sibling analyses. (Roemer, 2011) further proposes that the goal should be to eliminate all inter-dynastic inequality caused by the mere luck of birth. He declares as a desirable goal for all developed economies to reach the level of Scandinavian economies, for instance Sweden, in the next decades, and thus provides an answer to the previously unanswered question about an ideal degree of equality of opportunity.

Björklund et al. (2012), among others, show for Sweden that the social conditions, which can not be influenced by individuals, constitute a proportion of 15.3 to 18.7 percent of the total Gini coefficient. The counterfactual Gini coefficient, which would result from the sole consideration of the social differences, is near zero (0.043), which is a condition that is close to a state of perfect equality of opportunity. The United States and Italy, on the other hand, show the least equality of opportunity (see Aaberge et al., 2011; Almas et al., 2011, among others).

For Germany, there are only a few studies that try to quantify the degree of equality of opportunity, so far, which is primarily due to the high demands put on data availability (see, for example, Schnitzlein, 2014; Peichl and Ungerer, 2016). However, Brunori et al. (2013) have made an initial attempt to derive a comprehensive comparison of countries that also includes Germany. The main results are briefly summarized in terms of the fact that equality of opportunity and income inequality are positively correlated with each other and negatively correlated with intergenerational mobility (see Neidhöfer, 2016, for similar results on Latin America). The latter applies for both the mobility of education and income mobility. Germany is below average among OECD countries, but the United States and Great Britain even show a somewhat lower degree of equality of opportunity than Germany. The Scandinavian countries, on the other hand, are the most equitable and take top positions. The results are robust for the various countries using different measures of equal opportunities.

Investigating sibling correlations, Schnitzlein (2014) shows in a comparative analysis of Germany, Denmark, and the USA that family and community background have the greatest impact on outcomes in Germany and he discusses the links between sibling correlations, family background - which is characterized by both monetary and non-monetary values - and equal opportunities. In particular, it is shown that the available income is an important determinant in explaining the degree of equal opportunities, but it is not the most important factor. Income and related factors together account for less than 50% of the total influence of family and neighbourhood characteristics on the economic outcomes of adult children (also see Björklund et al., 2010; Mazumder, 2008).

This is backed up by the literature on family influences on the outcomes of children, which is comprehensively summarized in Heckman and Mosso (2014). This research highlights that the skill formation of children, i.e. their capacities to act, is a highly dynamic process that is not only shaped by financial assets but also by parental time investments and parents' knowledge of effective parenting styles. Children growing up in families with low socio-economic background experience both lower material living standards as well as less supportive learning environments. At the same time, intervention studies show that high-quality investments in disadvantaged children at early childhood yield high economic returns and are effective in promoting children's skills (Heckman and Kautz, 2014).

Despite this, Atkinson (2015) also argues that promising equal opportunities and access to education might not be enough to tackle inherent socio-economic disadvantages that are not due to individual effort but circumstances. We should care about both outcomes and opportunities of a given generation and keep in mind that inputs of today's generations are the outcomes of ancient generations. Hence, there is an indispensable need to investigate the extent of inequalities in resources available to children in the current generation, which are the underlying factors of children's opportunities later in life.

1.2 Contribution

This dissertation makes three contiguous contributions to the empirical literature on economic inequality and poverty, intergenerational mobility, and equal opportunity research. Following key recommendations formulated in the Stiglitz-Sen-Fitoussi report by the Commission on the measurement of economic performance and social progress, broader measures are developed, justified and deployed to quantify the changes of economic resources available to children in Germany that are major determinants of children's opportunities Stiglitz et al. (2009).

This is accompanied by a cross-country analysis of multigenerational human capital transmission to further investigate the extent to which inequalities are inherited from one generation to the next. In the remainder of this chapter each paper is briefly described, the main results are presented, and major contributions to the existing literature are highlighted. An overview of the main research questions, methods, data sources, main results, and the distribution of work between my co-authors and me is given for each paper in Table 1.1.

The first two papers provide a comprehensive analysis of static inequality using broader concepts and different measures of resource inequality. Both papers have in common that they focus on the economic resources of dependent children living with their parents. In addition, they both exploit information on the changes in family structures that have occurred since the German reunification in 1990 to investigate their potential linkages with changes in children's access to economic resources, and in particular whether the second demographic transition has contributed to rising economic inequalities (see, for instance, Peuckert, 2012, on the second demographic transition in Germany). The general innovation of the first two papers is to go beyond the classic univariate analysis of the distribution of disposable cash income, where cash income alone is assumed to be a sufficient predictor of an individual's well-being and a key determinant of an individual's capabilities to successfully participate in society as an adult (see Aaberge et al., 2010; Garfinkel et al., 2006, among others, for a more general critique).

Hence, in both papers non-monetary resources are included into the analysis, which are known to be important determinants for the development of a child's cognitive and non-cognitive skills and, in turn, have great influence on children's capabilities to be successful later in life (see, for instance, Becker and Tomes, 1979, 1986; Heckman and Mosso, 2014). A special focus is put on the role of publicly provided childcare and education that are known to be very effective in compensating non-monetary disadvantages experienced at home (see, for instance, Verbist and Matsaganis, 2014). These in-kind benefits are likely to mitigate differences in the capabilities of parents to foster the development of their children's skills that are mainly due to differences in parents' education but also to material conditions or neighbourhood effects. These factors are highly interrelated with each other and constitute the circumstances under which children grow up. However, it is not clear *a priori*, whether they are substitutes or complements to each other. This question is investigated in the first two papers in more detail and, hence, it closes an existing knowledge gap in the literature.

The first two papers differ in the methods used to address the main research questions. The first paper applies a multidimensional approach to aggregate the chosen set of resources available to children, whereas the second paper introduces an extended income approach. Both approaches have largely in common that they consist of two steps: in a first step, all dimensions are aggregated into a real number for each child (money units or a standardized index number) and, in a second step, a univariate inequality measure from the General Entropy (GE) class is applied on the newly generated distribution of real numbers to receive a scalar that represents the degree of inequality among children in a given year.

In particular, Chapter 2 of the dissertation, which is entitled "Children's Opportunities in Germany - An Application Using Multidimensional Measures", investigates the impact of changing family structures on the distribution of disposable resources of children using data from the Socio-Economic Panel (SOEP) for 1991 to 2012. In a first step it is shown that an increasing number of children in Germany grow up in single parent families who are disadvantaged in at least three dimensions that are beyond their control but decisive for their later achievements: material standard of living, parental education, and parental childcare time. It is argued that disadvantages in parental childcare may have been cushioned by the supply of public childcare and education, which was heavily expanded since the 2000s.

To quantify the trends in inequality of economic resources of children between 1991 and 2012, a measure of multidimensional inequality and poverty is applied which belongs to the family of GE measures. As suggested by Maasoumi (1986, 1999), dimensions are first aggregated for each individual using a utility-like function. Subsequently, a univariate inequality measure from the family of GE measures is employed to aggregate the utility-like values across individuals. A major advantage of this two-stage 'ad-hoc' measure is that value judgements are made explicit and transparent regarding the degree of substitutability between each pair of dimensions, the weighting structure, as well as the degree of risk aversion.

It can be shown that both multidimensional inequality and poverty among children decreased between 1991 and 2012, despite changing family patterns. The decline is driven by expanded publicly provided childcare that reduced inequality along this dimension and more than offsets rising income inequality among children. The finding is robust to different assumptions on inequality and poverty aversion and to the degree of substitutability between dimensions. However, increasing the weight of income and decreasing the weight of publicly provided childcare takes away the declining trend in some cases.

Hence, these findings provide evidence that publicly provided childcare is crucial in equalizing existing inequalities in disposable cash income. In addition, inequality decomposition by family type reveals that the observed decline in multidimensional inequality is mainly due to reduced differences within family types. In contrast, the effect of changing family patterns on the inequality decline seems negligible. The share of multidimensionally poor children decreased for all family types and the gap between them has become smaller over time. More children are counted as poor in the multidimensional setting than if considering income only, because of low levels of non-parental and parental childcare time devoted to them.

However, multidimensional indices are known to be especially sensitive to the choice of weighting schemes and rates of substitution between each pair of dimensions. As a consequence, ambiguous orderings of multidimensional inequality can occur. Another drawback of this approach is found in the standardization of the set of well-being indicators for aggregation purposes, which can also affect the degree and ordering of multidimensional inequality (Decancq and Lugo, 2013; Lugo, 2005).

An alternative to the multidimensional approach might be found in an extended income approach. It also allows the researcher to expand his focus from disposable cash income to a broader concept of disposable resources. For this purpose, the monetary value of non-cash components can be imputed and is subsequently added up to disposable cash income. Expressing all dimensions in monetary units bears the advantages that every dimension of well-being can still be intuitively interpreted from an economic perspective, it is easier to communicate for purposes of making policy recommendations, and no weighting structures or rates of substitutions between factors have to be arbitrarily chosen and justified.

However, Lugo and Maasoumi (2008), among others, also formulate doubt on the supremacy of monetary approaches since some of the underlying market prices cannot be observed at all or they might be biased due to market imperfections. As a consequence, they tend to be not less arbitrary than explicitly chosen weighting schemes in multidimensional frameworks. All in all, both approaches exhibit a couple of inherent advantages but also disadvantages and yet there is no consensus in the literature on which approach should be used. Hence, another major contribution of this dissertation is to provide a comparison of the results when either using a multidimensional approach or an extended income approach and to identify the preconditions under which similar results occur.

Accordingly, an extended income approach is applied in Chapter 3 of the dissertation, which is entitled "The Distribution of Economic Resources to Children in Germany". In general, it assesses the redistributive impact of private and public childcare and education on children's resources in Germany between 2009 and 2013. Again, the paper draws on fundamental changes of family structures that were accompanied by a considerable increase of female labour market participation rates in Eastern and Western Germany and an extensive expansion of public childcare and education in Germany to foster the work-life-balance of families, especially for single parents.

The major methodological contribution of this paper is to unify two different strands of literature for constructing an extended income concept, namely the literature on evaluating home production and the literature on calculating the value of public in-kind benefits. It provides for the first time a comprehensive analysis of the distribution of and access to economic resources available to children in Germany and draws a picture of the circumstances under which children grow up. It takes account of the multidimensionality of children's needs and encompasses the value of education and time investments next to disposable cash income, which are all decisive indicators for a child's development and chances later in life (Heckman and Mosso, 2014). Thus, it also provides additional insights into the question of how opportunities among children are distributed.

The analysis is based on both data from the SOEP and data from the German Federal Statistical Office to calculate the value of each extended income component. In contrast to Chapter 2, the analysis only covers the income years 2009 to 2013. This is due to the use of the new Families in Germany data set provided by the DIW Berlin, which is a supplementary data set of the SOEP that has been integrated into the SOEP core data set in 2014 to increase the analytical power for subgroup analyses like single parents. Since this is crucial for the analysis, the benefits of having richer data outweigh the cost of restricting the period of analysis even though the two papers are, thus, not fully comparable anymore.

The net monetary value of public childcare and education is measured by a standard production cost approach, which relies on the assumptions that the value of public in-kind benefits is as high as the costs of providing it (Aaberge et al., 2010; Garfinkel et al., 2006). In contrast, the value of parental childcare time is imputed by using a housekeeper wage approach as well as two opportunity cost approach to derive (gross) hourly shadow wage rates for non-market workers from the SOEP. Both approaches differ in their assumption on the underlying productivity of parents doing childcare; the housekeeper wage approach assumes that all parents are similarly productive and, hence, assigns a flat wage rate to every parent, whereas the opportunity cost approach allows for heterogeneity in the productivity of parents.

The main finding of this paper is that extending the income definition by the monetized values of private and public childcare and education reduces inequality in economic resources significantly at the five percent level across all years. However, it is also shown that the extension of disposable resources does not significantly change distributional trends. Furthermore, the redistributive effect of parental childcare time is largely in line with the more general findings of, for instance, Jenkins and O'Leary (1996) for the UK, Zick et al. (2008) for the US, or Frick et al. (2012) for Germany. The latter investigate the distributional impact of adding the value of overall home production to disposable cash income for Germany in 2009. They find similar changes of income and inequality levels which are especially pronounced for households from the lower part of the initial cash income distribution. These findings are also robust to the use of different evaluation approaches of parental childcare time and show similar variations in levels.

Despite this, the results also highlight the redistributive power of publicly provided childcare and education which cushions the existing inequalities in disposable cash income. Paulus et al. (2010) and Frick et al. (2011), among others, find similar patterns on the distributional effect of adding the value of public education to disposable cash income for Germany and other European countries. This study also shows that differences in family structures are an issue: children living together with a single parent are disadvantaged in terms of disposable cash income and parental childcare, but they gain from public childcare and education the most. In contrast, parental childcare largely reproduces existing inequalities in disposable cash incomes.

All in all, these findings provide further evidence on the hypothesis that the provision of child-related public in-kind benefits, such as public childcare and education, is a key policy instrument to mitigate the economic disadvantages experienced by children from low socio-economic background. Given their equalising potential suggests that investing into the quality of public childcare may further foster equal opportunities.

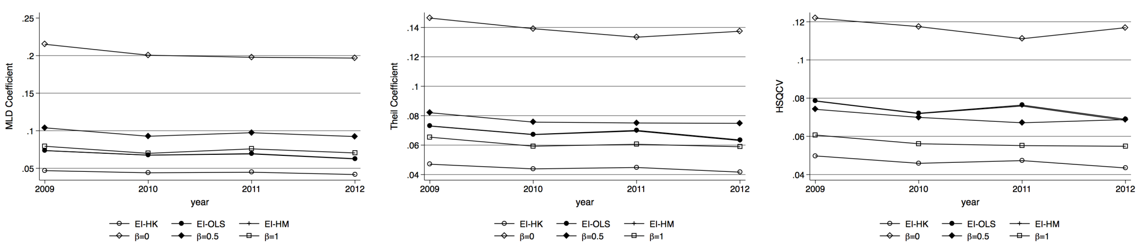
At this point, a brief comparison of the results from the multidimensional and extended income approach shall be drawn. To increase the comparability of both approaches, parental education has been excluded from the list of dimensions to compute the multidimensional inequality index value. Otherwise, results would substantially differ in levels but not in trends. This already shows that the 'right' choice of dimensions matters in multidimensional analyses and for their comparability to other findings.

As Figure 1.1 depicts, the levels and trends in multidimensional and extended income inequality are comparable to the greatest possible extent if the following preconditions are met: (i) the monetary value of parental childcare time is evaluated by applying an opportunity cost approach in the extended income framework, (ii) the rate of substitution between each pair of dimensions is assumed to be close to perfect substitution in the multidimensional approach ($0.5 < \beta < 1$), depending on the assumed degree of risk aversion, and (iii) all dimensions are equally weighted or, at least, not a single dimension receives a substantially larger weight than all the other dimensions.

It is a promising finding that both approaches are able to yield similar results in levels and trends under some narrow preconditions. At the same time, this does not mean that general conclusions can be drawn on how to set 'appropriate' parameter values in future multidimensional analyses. Furthermore, it cannot be finally said whether the assumption of a high or even perfect rate substitution fits for each pair dimensions. It seems to be plausible, for example, that parental and non-parental childcare time are close to be perfect substitutes for all possible levels of all dimensions. But this may not hold for parental income and non-parental childcare time. Since income is crucial to pay for essential needs of living it cannot be substituted for childcare time at a similar fix rate at all levels of income and time. Future research should study this in more detail by employing nested approaches that allow for different rates of substitutions between different pairs of dimensions, as described in Decancq and Lugo (2013). In addition, the assumed degree of risk aversion has a clear impact on the overall fit of both approaches. Assuming lower levels of risk aversion requires to set a lower rate of substitution between each pair of dimensions, i.e. the curvature of the underlying social welfare function has to be increased, to still fit the results of the extended income approach.

Figure 1.1: Comparison of multidimensional and extended income inequality among children, 2009-2012

(a) MLD coefficient (b) Theil coefficient (c) HSQCV



Note: The parameter β denotes the degree of substitution between each pair of dimensions in calculating the multidimensional index number. In addition, it is assumed that each dimension is weighted equally and the sum of weights is equal to one.
Abbreviations: EI = Extended Income, HK = Housekeeper wage approach, OLS = Ordinary least squares model, HM = Heckman selection correction model.
Source: SOEP (v30/v31.1), own calculations.

Finally, Chapter 4 of the dissertation has the title "Dynastic Inequality Compared: Multigenerational Mobility in the US, the UK, and Germany" and it examines the degree of intergenerational mobility across three generations using harmonized household survey data for Germany (SOEP), the US (PSID), and the UK (BHPS/UKHLS). The theoretical background for the analysis of intergenerational transmission of human capital is the Becker and Tomes model (Becker and Tomes, 1979, 1986). To test previous and recent theories of long run social mobility including various transmission channels of socio-economic status, we basically utilize the stylized and parameterized version of the Becker and Tomes model developed in Solon (2004, 2014).

In a first step, intergenerational mobility of socio-economic status is estimated by means of a standard linear regression model to receive descriptive measures for the association in outcomes between generations, i.e. we estimate persistence and correlation coefficients for each pair of generations and for all generations in a unified framework. The outcome of interest is completed years of education, since it is a widely accepted measure for the human capital stock of an individual and it is known to be highly and positively correlated with individual lifetime earnings (see, for instance, Björklund and Jäntti, 2011). In a second step, the estimates are used to identify the parameters needed to test recent theories of long run mobility proposed in Clark (2014); Clark and Cummins (2015), among others. In particular, Clark and Cummins postulate the existence of a "universal law of social mobility" and argue that long run mobility is much lower across time and countries than conventional extrapolations from classic two generations frameworks would suggest. For this purpose, we rely on the work of Braun and Stuhler (2016) who comprehensively show how to use estimates from the linear regression framework to identify the parameters of Clark's and Cummins so-called latent factor model. Furthermore, we explore whether there is a direct effect of grandparents' educational attainment on grandchildren's educational achievements, which is not mediated through their parents, and evaluate the impact of cultural capital and sex on the transmission of socio-economic status in further analyses. A major strength of our study is that we are the first to pool and harmonize data from three different household surveys which allows us to comprehensively control for institutional differences and other features of parental background that might affect intergenerational mobility across multiple generations.

In general, we find evidence against Clark's hypothesis of a universal law of intergenerational mobility. Multigenerational mobility varies with the historical and institutional context and there are substantial differences in long run mobility rates in the US, the UK, and Germany that are in line with previous findings on cross-country differences over two generations (Blanden, 2013; Chevalier et al., 2009; Hertz et al., 2007; OECD, 2015). Hence, the findings show that cross-country relationships hold aside from the timing of measurement, and short run mobility (i.e. over two generations) does not seriously over nor under predict long run mobility patterns. Another major finding of our analysis is that statistically significant differences exist between correlations and direct effects of grandparents by gender and lineages. In addition, these patterns differ across countries, confirming, again, that historical, institutional, and cultural differences matter for the process of intergenerational transmission of socio-economic status.

In sum, the results from Chapter 2 and 3 highlight the importance to consider more than one dimension in inequality and poverty analysis when conclusions about children's opportunities shall be drawn. Particularly, in-kind benefits like publicly provided childcare and education should be accounted for to get a more complete picture of non-monetary resources that shape children's opportunities. Further, such approach highlights the welfare state's role in redistributing resources and providing less unequal opportunities. However, these results should not be used to draw the final conclusion that overall inequalities among children in Germany are not severe at all, since the redistributive effects of other public goods and services, for instance public health care, or the effect of indirect taxes, for instance value added taxes, have not been considered in the presented studies. Their effect on the distribution of economic resources is not clear *a priori* and they might change the picture. This should be studied in future research. The results from Chapter 4 highlight the overall need to intensify the efforts in providing high quality childcare to every one in need and to increase the permeability of the German schooling system, especially for children with low socio-economic background, to further increase educational mobility across generations. Higher levels of mobility would help to mitigate the negative effects of today's economic inequalities on children's future outcomes and, thus, they would foster equal opportunities (Corak, 2013).

Table 1.1: Overview of chapters

	Chapter 2	Chapter 3	Chapter 4
Title	Children's Opportunities in Germany: An Application Using Multidimensional Measures	The Distribution of Economic Resources to Children in Germany	Dynastic Inequality Compared: Multigenerational Mobility in the US, the UK, and Germany
Main research question	How did multidimensional inequality and poverty evolve over time in light of an increased variety of living arrangements?	How do public provided childcare and education as well as parental childcare time affect existing inequalities in children's access to economic resources?	How has multigenerational social mobility developed in Germany, the US, and the UK and does a universal law of multigenerational mobility exist?
Data	SOEP (v30)	SOEP (v31.1), German Federal Statistical Office data	SOEP (v30), BHPS/UKHLS, PSID
Method	Descriptive analysis of multidimensional inequality and poverty using measures from the GE family; decomposition of changes in multidimensional inequality over time by family type.	Construction of an extended income concept and descriptive analysis of the distribution of extended income available to children. Inequality decomposition by income sources and subgroups.	Descriptive analysis of multigenerational mobility in the US, the UK, and Germany using an OLS regression framework; recent hypotheses of long run mobility are tested and transmission channels are investigated.
Main results	Both disposable cash income inequality and poverty among children increased. Adding parental education and care time to the picture we find that both multidimensional inequality and poverty among children decreased over time as expanded public childcare strongly reduces resource disparities among children.	Extended income inequality is found to be significantly lower than disposable cash income inequality across all years. The extension does not change distributional trends. Publicly provided childcare and schooling notably decrease inequality among children such that it cushions cash income inequality.	The hypothesis of a universal law of social mobility is rejected and the validity of a first-order Markov chain in the intergenerational transmission of human capital is very likely to be country-specific. The direct and independent effect of grandparents' social status on grandchildren's status varies by sex and institutional context.
Co-Author	Charlotte Bartels	-	Guido Neidhöfer
Author's contribution	50%	100%	50%
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Chapter 2

Children's Opportunities in Germany - An Application Using Multidimensional Measures

2.1 Introduction

Single parents and non-marital cohabitations are increasingly replacing the traditional nuclear family in many industrialized countries.[1] The greater disparity in family environments most likely leads to greater disparity in children's resources, which are major predictors of later life socio-economic success.

This paper analyses if changing family patterns in Germany create greater disparities in children's endowments along three dimensions: (1) parental income; (2) parental education; (3) and care time; all crucial determinants of children's later outcomes. Higher parental income translates into higher expected earnings for their children via investments in health and education, as argued by Becker and Tomes (1979, 1986).[2] Parental education reflects parental productivity in child-enhancing activities (Black and Devereux, 2011). There is broad evidence for strong correlations between parental education and income, on the one hand, with their children's education and income later in life, on the other hand.[3] Finally, time investment affects the development of children's cognitive and social-emotional skills.[4] We include both parental childcare

[1] See, e.g., McLanahan (2004)

[2] There was a rapidly growing theoretical literature on the relation of family behaviour and the distribution of income and wealth in the 1970s and 1980s, among which Becker and Tomes (1979, 1986) are probably the best known contributions.

[3] The large literature on intergenerational mobility since the 1990s is summarized in Black and Devereux (2011) and Jenkins and Jäntti (2015).

[4] An extensive overview of empirical studies on the importance of certain early life conditions and the evidence on critical periods for shaping multiple life skills is provided by Heckman and Mosso (2014).

time and publicly provided childcare and school time. In many industrialized countries, large welfare states play an important role in "levelling the playing field" for children both through financial redistribution via progressive taxes and monetary benefits as well as the provision of public services, such as public education, childcare, and other in-kind benefits. Verbist and Matsaganis (2014) suggest that the redistributive impact of in-kind benefits is as large as that of monetary benefits, with their relative importance in social spending seeming to increase in European countries. Since 2005, the German welfare state heavily expanded publicly provided childcare, which might have counteracted growing disparities among children.[5]

We apply Maasoumi's index for multidimensional inequality (Maasoumi, 1986, 1999) and poverty (Lugo and Maasoumi, 2008), where resources are first aggregated for each individual and then aggregated across individuals to arrive at a single index.[6] Maasoumi's proposition to first aggregate dimensions for each individual carries the benefit that low levels of one dimension can be compensated with high levels of another dimension at the individual level. E.g., lower net incomes, lower parental education and less parental time, which applies to the average child in a single parent family, may be at least partly compensated by publicly provided childcare.

We contribute to the growing literature on multidimensional inequality and poverty measurement, which promotes a shift from the sole focus on income to a broader concept of "well-being" by incorporating endowments along several dimensions into a single measure.[7] Our study is also related to the literature on equality of opportunity, which separates the influence on outcomes into circumstances beyond individual control and individual effort.[8] If people believe that inequality is caused by circumstances beyond individual control they are less willing to accept high inequality levels and support more redistribution (Fong, 2001; Corneo and Grüner, 2002). Niehues and Peichl (2014) find that a sizable share of total inequality in Germany and the US can be attributed to circumstances beyond individual control. We argue that our three dimensions are beyond the children's control.

Our main results are as follows. Both multidimensional inequality and poverty among children decreased between 1991 and 2012, despite changing family patterns. The decline is driven by expanded publicly provided childcare that reduced inequality along this dimension and more than offsets rising income inequality among children.

[5]According to Schober and Stahl (2014), the use of publicly provided childcare has disproportionately grown among single mothers and highly educated mothers since 2006.

[6]Further applications of Maasoumi's index include, e.g., Nilsson (2010); Justino (2012); Rohde and Guest (2013).

[7]Rawls (1971) and Sen (1985) first advocated a multidimensional perspective on the notion of well-being. See Aaberge and Brandolini (2015) for a summary and thorough discussion of the multidimensional approaches as well as the introduction of Decancq and Lugo (2013).

[8]The literature on equality of opportunity was pioneered by Roemer (1993, 1998).

The finding is robust to different assumptions on inequality and poverty aversion and to the degree of substitutability between dimensions. However, increasing the weight of income and decreasing the weight of publicly provided childcare takes away the declining trend in some cases.

The paper is organized as follows: In Section 2.2, we describe our data, sample and the measurement of (1) parental income; (2) parental education; as well as (3) parental and non-parental childcare time. Section 2.3 describes how these resources evolved over time by family type. The methodological approach deriving multidimensional inequality and poverty indices is described in Section 2.4. In Section 2.5, we present and discuss our results. Section 2.6 concludes.

2.2 Data

Our analysis is based on data from the Socio-Economic Panel (SOEP). The SOEP is an annual survey of German households that includes a variety of demographic and socio-economic characteristics for all years since 1984. East German households are included in the panel since 1990. By 2013, almost 11,000 households participated, which corresponds to approximately 20,000 individuals.[9]

Our sample includes East and West German children. Children are defined as individuals that are younger than 14 years and still live in the household of their parents.[10] We further differentiate between children living with married, cohabiting and single parents. We start the analysis with the year 1991 in order to include East German children that entered the sample after reunification in 1990. In order to maximize the sample size and to minimize problems like panel attrition, we use the original and all refreshment samples (A-K) of the SOEP in an unbalanced panel design excluding the migration sample from 2013. Furthermore, our sample is restricted to children, where values of all four attributes are observed, by which we lose about 2,500 observations from a total of about 77,000 observations over the entire period. In 2013, the sample includes about 3,000 observations.[11]

Children's resources are measured along three dimensions: (1) parental income; (2) parental education; (3) and care time.

1. *Parental income*

   Parental income is measured as real net equivalent household income. Net household income is the sum of households' labour earnings, asset flows, private re-

[9] For further details see Wagner et al. (2007) and Gerstorf and Schupp (2015).

[10] Sensitivity tests show that our results are robust to restricting our sample to children younger than seven years.

[11] The number of observed children by family type is provided in Appendix Table A.1.1.

tirement income, private transfers, public transfers, and social security pensions minus total household taxes including imputed rents from housing. Income is equivalized using the modified OECD scale to take into account different needs of adults and children in the household.

2. *Parental education*

   Parental education is measured as years of education completed at the time of the survey. For married and cohabiting parents, we use the value of the parent with the highest number of years of education.

3. *Childcare time*

   (a) *Parental childcare time*

   In contrast to many other surveys, where parental time can only be measured as a residual term, we are able to directly observe total time devoted to childcare activities by each parent: Every household member aged sixteen or older is asked the number of hours spent on childcare on an average weekday. Parental childcare time is the sum of hourly childcare activities of household head and spouse for all children on an average weekday. Unfortunately, we do not observe the type of childcare such that we cannot distinguish between physical and non-physical childcare (e.g. nourishing vs. teaching) or direct and indirect childcare (e.g. reading vs. doing household tasks together). Consequently, we can only measure quantity of childcare time and not quality. Empirical evidence shows that quality of childcare time depends on parents' educational level.[12] Higher quality of childcare time might thus be captured by considering parental education as a separate dimension.

   Since parents' only state the total time spend with children, we have to adjust total time to the number of children in the household. We assume that parents' caring time is not proportionally increasing with the number of children and that there are economies of scale in parenting within families. Evidence for this hypothesis is given by time use studies. In particular, Kühhirt (2012) shows that West German married and cohabiting parents do not spend significantly more time on childcare activities if there is more than one child living in the same household. To construct comparable *one child equivalent families* we apply a generalized version of the square root

[12] E.g., Doyle et al. (2009) find that children of low-educated mothers tend to have lower achievements in tests measuring cognitive, socio-emotional and behavioural skills than children from high-educated families.

scale[13] on total parental childcare time, PT, of both parents ($i = 1, 2$) such that equivalent parental childcare time, PT_{eq} is defined as:

$$PT_{eq} = \frac{\sum_{i=1}^{2} \text{Parental time}_i}{s^\theta}, \tag{2.1}$$

where s is the number of siblings living in a household and θ is an *equivalence elasticity* (Bönke and Schröder, 2012). $\theta = 0.5$ produces the well-known square root equivalence scale. Dividing total parental childcare time by the number of children (this would be equal to $\theta = 1$) would most likely underestimate parental time devoted to each child in the presence of economies of scale in parenting. On the other hand, assigning the total parental time to each child in the family (this would be equal to $\theta = 0$), would certainly overestimate parental time per child.[14]

(b) *Non-parental childcare time*

Non-parental childcare time includes total hours spent in crib, kindergarten, after school care club, with a child-minder or in school on an average weekday depending on the age of the respective child. Since the bulk of this care time is provided by the state and presumably only a small portion is spent with a private child-minder, we also refer to this dimension as publicly provided childcare time.

We only observe if children spent half- or full-day in the above mentioned institutions on an average weekday. According to information on public childcare provision, we assign four hours for half-day care and eight hours for full-day care. Since 2009 exact hours are asked in the SOEP questionnaire, but for consistency reasons we stick to our half-day and full-day categories.

Time in school is based on information from publications of the Standing Conference of the Ministers of Education and Cultural Affairs of the German Länder (*Kultusministerkonferenz der Länder*), where school hours taught per week are provided by class type, class level and federal state (*Bundesland*) for the 1992-2012 period. We take 1992 values for 1991, where no information is available. We assign school hours taught in elementary school to every child aged between six and ten in the respective *Bundesland* and year. The average of actually taught school hours over all lower secondary school types is assigned to every child aged between eleven and thirteen in

[13]We use the square root scale to consider the number of siblings only, in contrast to the modified OECD scale used for income which also considers the number of adults in the household.

[14]Our results on trends in parental childcare inequality are robust to changes of θ. Inequality levels vary in θ, but differences are not significant. Results are available from the authors upon request.

the respective *Bundesland* and year.[15]

There exist large differences within and across regions and between private and public childcare and schools (Camehl et al., 2015). SOEP data only includes questions on the quality of publicly provided childcare for children in preschool age. Information on the attended school and its respective quality is not observed. Therefore, we might underestimate disparities in non-parental childcare time.

2.3 Trends in Family Resources in Germany

Since the mid-1960s, the traditional nuclear family consisting of a married couple and their respective children is on retreat. An increasing number of children grows up in comparably disadvantaged families with only one parent.[16]

As Figure 2.1 shows, the total number of children in Germany decreased from approximately 22 million in 1991 to 19 million in 2012. Over this period, the share of children living in traditional nuclear families decreased from 84.5 percent to 73.6 percent. At the same time, the share of children living in cohabiting couple families more than doubled increasing from 2.9 percent to 6.5 and the share of children in single parent families increased from 12.6 percent to 19.9 percent. In particular, the number of female-headed single parent households has risen sharply. In contrast, the number of children per family remained fairly constant.[17]

Figure 2.2 depicts the average trends in Germany in each dimension by family type from 1991 to 2012. Graph 2.2a shows that children's average equivalent net income increased from 17,832 Euro to 21,223 Euro (+19 percent). Children living in traditional married couple families experienced both a higher level and a higher income growth rate than their counterparts in single parent families.[18] Consequently, the absolute income gap between children from married and cohabiting couple families on the one hand and children from single parent families on the other hand has widened.

[15]We also incorporate the fact that primary school usually lasts until class level six in the federal states of Berlin and Brandenburg, in contrast to four years in the other federal states. We take averages over all lower secondary school types for each year because school types and hours taught in lower secondary schools vary heavily within and between *Bundesländer* over time. Secondary school types in Germany are *Hauptschule, Realschule, Gesamtschule, Schularten mit mehreren Bildungsgängen* and *Gymnasium*.

[16]A wide sociological and demographical literature examines the general trends and causes of the so-called second demographic transition for Western countries, e.g., Peuckert (2012), Lesthaeghe (2010), and McLanahan and Percheski (2008).

[17]The share of families with one child increased from 31.4 percent in 1991 to 33.4 percent in 2012, whereas the share of families with two (three or more) children declined from 46.2 (22.4) percent to 45 (21.6) percent.

[18]Single parent families lack a second potential earner. Moreover, most single parents are females who have lower hourly wages and lower working hours than males.

Similarly, married and cohabiting couples exhibit, on average, more years of education than single parents, as can be taken from Graph 2.2b. However, although years of education increased for all family types, the education gap did not.

Parental childcare time depicted in Graph 2.2c replicates the pattern observed for parental income and education. Children in single parent families receive less care time from their parents. Of course, this gap is mostly explained by the total number of parents present in the family.[19] Equivalizing childcare time reduces the level of childcare time per child across all family types, as depicted in Graph 2.2d, but more so for children living in traditional married couple families due to the larger number of children living in this type of family. Average (equivalent) parental childcare time increased slightly from 8.0 (5.8) hours in 1991 to 8.6 (6.3) hours in 2012.[20]

Finally, Figure 2.2e shows that, in contrast to the other dimensions, the average child in a single parent family receives more non-parental childcare time than an average child living with married or cohabiting couple families. Average non-parental childcare time increased from 3.6 to 5 hours per day. A number of legislative changes expanded public childcare provision in Germany, particularly since 2005.[21] In some municipalities, special consideration is given to single parents. The observed trend indicates that expanded public supply may at least partly offset single parent children's disadvantage in parental care time.

2.4 Method

In this section, we explain and discuss how we measure inequality and poverty in a multidimensional setting.

First, we have to normalize the observed values x_{itd} for every child i, $i = 1, ..., N$, and dimension d, $d = 1, ..., D$, because of the dimensions' different measurement units, which are daily hours for childcare and schooling, Euro for income and years for education. We transform observed values x_{itd} to values between zero and one for all observation years t, where the dimension-specific maximum and minimum over all years t serve as so-called *goalposts* (see, e.g., United Nations Development Programme,

[19]Single parents spend less time on childcare since they are not able to share housework with a partner and cannot reduce their working time being the only "breadwinner."

[20]See Section 2.2 for care time equivalization.

[21]A new law in 2004 introduced a legal claim for children under three years of age for a place in a day care center if certain conditions are met. Another law in 2008 redefined this claim for children older than one. Consequently, the share of children under three in day care centres increased from 8 to 24 percent in West Germany between 1991 and 2013, while remaining at roughly 50 percent in East Germany where the use of publicly provided childcare has a stronger tradition (Schober and Stahl, 2014).

2014).[22] Transformed values $\tilde{x}_{itd}$ are obtained by the following formula:

$$\tilde{x}_{itd} = \frac{x_{itd} - \min x_d}{\max x_d - \min x_d}. \tag{2.2}$$

After normalization, we replace all zero observations with 0.001, since GE measures of inequality are not defined for zero values.[23]

Most importantly, an aggregation rule that transforms the dimensions' distributions into a single real value has to be decided upon.[24] One approach is to first aggregate across children for each single dimension and second aggregate the dimension-specific indicators. This approach is easily applicable if only aggregates are available by dimension and, thus, forms the basis for the UN's Human Development Index (HDI). If individual data are available for each dimension, the joint distribution can be taken into account and potentially compensating effects between dimensions can be considered for each child. Then, as suggested by Maasoumi (1986, 1999), dimensions are first aggregated for each individual using a utility-like function and then a univariate inequality measure is employed to aggregate the utility-like values across individuals. Maasoumi's index is an "ad-hoc" measure as compared to an axiomatic approach. The "ad-hoc" chosen parameter values make value judgements, e.g., the degree of substitutability between the dimensions and the weight of each dimension, explicit and transparent.[25]

In the first step, every child's observed endowments $\tilde{x}_{id}$ – suppressing time index t – are aggregated using aggregation function S_i, which can be interpreted as some utility-like function used to rank alternative distributions according to their social desirability (see Weymark, 2006). In our context, it measures a child's opportunities incorporating disposable income, parents' educational background and care time into a single measure. According to Maasoumi (1986) the optimal aggregation function S minimizes the distance between the joint distribution of the resources and the distribution of the index under the condition $\sum_{i=1}^{N} S_i = 1$ such that:

[22] The goalpost approach is a linear transformation that is used, for instance, to construct the Human Development Index. Of course, the transformation affects the inequality measured in each dimension, but, so far, standardization offers the best solution how to overcome different measurement units. See Decancq and Lugo (2013) for details on standardization procedures.

[23] Sensitivity tests show that our results are robust to choosing values closer to zero. Results are available from the authors upon request.

[24] The problem of choosing an appropriate well-being index including the selection of dimensions, substitution rates between each pair of dimensions, dimension weights etc., is also known as Rawl's index problem (Rawls, 1971, p. 80).

[25] Maasoumi's index satisfies the desirable properties for measuring multidimensional inequality: monotonicity, continuity, normalization, anonymity, homotheticity, subgroup decomposability, weak uniform majorization as well as individualism. See, e.g., Tsui (1999), Lugo (2007) or Weymark (2006) for a comprehensive discussion on desirable distributional and non-distributional properties of multidimensional inequality measures.

$$S_i = \Big(\sum_{d=1}^{D} w_d \tilde{x}_{id}^{\beta}\Big)^{1/\beta},\ \beta \neq 0, \tag{2.3}$$

$$S_i = \Big(\prod_{d=1}^{D} \tilde{x}_{id}^{w_d}\Big),\ \beta = 0. \tag{2.4}$$

In the second step, the utility-like function S_i to which we will refer to as opportunity indicator is aggregated to arrive at a measure of multidimensional inequality (Section 2.4.1) and of multidimensional poverty (Section 2.4.3).

2.4.1 Multidimensional Inequality

Maasoumi (1986, 1999) proposes a measure from the General Entropy (GE) family for the inequality of the distribution of $S = (S_1, ..., S_N)$. We can derive the following GE specifications to get a measure of multidimensional inequality I_α, where $\bar{S} = \sum_{i=1}^{N} S_i/N$ is the average of the aggregated well-being indicator for N children:

			GE inequality measure I_α	
GE	$(\alpha \neq 0, 1)$	=	$\frac{1}{\alpha(1-\alpha)} \frac{1}{N} \sum_{i=1}^{N} \left[1 - \left(\frac{S_i}{\bar{S}}\right)^{\alpha}\right]$	(2.5)
MLD	$(\alpha = 0)$	=	$\frac{1}{N} \sum_{i=1}^{N} \ln\left(\frac{\bar{S}}{S_i}\right)$	(2.6)
Theil	$(\alpha = 1)$	=	$\frac{1}{N} \sum_{i=1}^{N} \left[\frac{S_i}{\bar{S}} \ln\left(\frac{S_i}{\bar{S}}\right)\right]$	(2.7)
HSCV	$(\alpha = 2)$	=	$-\frac{1}{2N} \sum_{i=1}^{N} \left[1 - \left(\frac{S_i}{\bar{S}}\right)^{2}\right]$	(2.8)

The magnitude of multidimensional inequality measured crucially depends on the chosen weighting structure w (1), the substitutability between dimensions β (2), and the inequality aversion parameter α (3). We elaborate on the weighting structure in Section 2.4.4.

The parameter β determines the degree of substitution between all pairs of dimensions. If $\beta = 1$, then all dimensions are perfect substitutes, i.e., low levels of one dimension can be perfectly compensated by high levels of another. The smaller β, the smaller is the substitutability between the dimensions, i.e., the loss of one unit in one dimension can only be compensated by ever more extra units in another dimension to keep the level of well-being constant. If β converges to minus infinity, then dimensions are treated as perfect complements and the opportunity indicator depends on the dimension where the child is worst off regardless of the chosen weighting structure.

The parameter α determines the degree of concavity of the inequality measure and indicates to what extent a society values the well-being of some individuals in the distribution different from others. The lower α, the more weight is put on individuals at the bottom of the distribution and, thus, the more sensitive is the inequality measure to changes in the lower part of the distribution. The Mean Logarithmic Deviation (MLD), where $\alpha = 0$, is thus more sensitive to changes at the bottom than the Theil, where $\alpha = 1$, or the Half Squared Coefficient of Variation (HSCV), where $\alpha = 2$.

2.4.2 Decomposition of Multidimensional Inequality

To further investigate the relationship between changing family patterns and our measure for children's opportunity, we decompose the intertemporal change in multidimensional inequality by family type. Using inequality measures from the GE family in the second step of our multidimensional framework, we can additively decompose the changes in multidimensional inequality into a within group and a between group component (see Shorrocks, 1980; Maasoumi, 1986). In particular, we can decompose the MLD denoted as I_0, which is the only path independent inequality measure of that class (see Foster and Shneyerov, 2000), as follows:

$$I_0 = \underbrace{\sum_{f=1}^{F} v_f I_{0f}}_{within} + \underbrace{\sum_{f=1}^{F} v_f \ln\left(\frac{1}{\lambda_f}\right)}_{between}. \tag{2.9}$$

F is the number of family types, $v_f = n_f/n$ is the population share of family type f, I_{0f} is the family type specific level of multidimensional inequality measured by MLD, and $\lambda_f = \bar{S}_f/\bar{S}$ reflects family type f's average opportunities relative to the overall opportunity average. Since we are particularly interested in the impact of changing family patterns on the change in multidimensional inequality over time, we decompose the inequality change $\Delta I = I_{t+1} - I_t$, suppressing the GE index α, according to Mookherjee and Shorrocks (1982) as follows:

$$\Delta I = \sum_{f=1}^{F} v_{f,t+1} I_{f,t+1} - \sum_{f=1}^{F} v_{f,t} I_{f,t} - \sum_{f=1}^{F} v_{f,t+1} \ln(\lambda_{f,t+1}) + \sum_{f=1}^{F} v_{f,t} \ln(\lambda_{f,t}). \tag{2.10}$$

Extending both sides by $\sum_{f=1}^{F} v_{f,t} I_{f,t+1}$ and $\sum_{f=1}^{F} v_{f,t} \ln(\lambda_{f,t+1})$, rearranging and denoting differences between $t+1$ and t by Δ gives:

$$\Delta I = \sum_{f=1}^{F} v_{f,t}\Delta I_f + \sum_{f=1}^{F} \Delta v_f I_{f,t+1} - \sum_{f=1}^{F} \Delta v_f \ln(\lambda_{f,t+1}) - \sum_{f=1}^{F} v_{f,t}\Delta \ln(\lambda_f). \tag{2.11}$$

$v_{f,t}$, $I_{f,t+1}$ and $\ln(\lambda_{f,t+1})$ are replaced by their mean values (e.g., $\bar{v}_f = \frac{1}{2}[v_{f,t}+v_{f,t+1}]$) in order to avoid aggregating weights from different points in time which gives:

$$\Delta I = \sum_{f=1}^{F} \bar{v}_f\Delta I_f + \sum_{f=1}^{F} \bar{I}_f \Delta v_f - \sum_{f=1}^{F} \overline{\ln(\lambda_f)}\Delta v_f - \sum_{f=1}^{F} \bar{v}_f\Delta \ln(\lambda_f). \tag{2.12}$$

The first term gives the impact of the change in within family type inequality ΔI_f on the overall inequality change. However, the change in relative importance of family types Δv_f affects not only the two middle terms but also the last term through $\lambda_f = \bar{S}_f/\bar{S}$ because of $\bar{S} = \sum_{f=1}^{F} v_f \bar{S}_f$. Since we want to exactly identify the effect of Δv_f on the overall inequality change, we rearrange the last term in Equation (2.12) and then approximate the decomposition according to Mookherjee and Shorrocks (1982) as:

$$\Delta I \approx \underbrace{\sum_{f=1}^{F} \bar{v}_f\Delta I_f}_{(1)} + \underbrace{\sum_{f=1}^{F} \bar{I}_f \Delta v_f}_{(2)} + \underbrace{\sum_{f=1}^{F} \left[\bar{\lambda}_f - \overline{\ln(\lambda_f)}\right]\Delta v_f}_{(3)} + \underbrace{\sum_{f=1}^{F} \left(\bar{\theta}_f - \bar{v}_f\right)\Delta \ln(\bar{S}_f)}_{(4)}, \tag{2.13}$$

where $\theta_f = v_f\bar{S}_f/\bar{S}$ is the family type's share of total population's well-being. We can now clearly distinguish between the impact of changes in (1) within family inequality and (4) between family inequality, as well as the impact of changing relative importance of family types on the (2) within and (3) between family type inequality.

2.4.3 Multidimensional Poverty

In the view of policy implications, we might be particularly interested in the lower part of the distribution. Therefore, we also compute measures of multidimensional poverty. To stay as close as possible to our methodological framework for inequality presented above, we focus on a multidimensional poverty measure based on information theory introduced by Lugo and Maasoumi (2008).[26]

[26] See, e.g., Bourguignon and Chakravarty (2003) or Alkire and Foster (2011) for a detailed discussion of counting and multidimensional poverty measures including differences in identifying the poor (union, intersection or dual cut-off methods).

As for multidimensional inequality, we start with each child's utility-like function S_i (see equations (3) and (4)) covering the endowments in all dimensions. But to identify the children with poor opportunities we must decide on a poverty line.

One can either use dimension-specific poverty thresholds before aggregation (*component poverty line approach*) or an aggregate poverty line derived from dimension-specific poverty lines (*aggregate poverty line approach (APL)*). Since we aggregate dimensions in the first step, we construct an APL, which we denote S_z, from dimension-specific poverty lines z_d. The dimension-specific poverty lines z_d are defined as 60 percent of the median value in each dimension. E.g., children are identified as income poor if they have 60 percent of the median real equivalent net income or less. To obtain S_z we simply replace the $\tilde{x}_{id}$ in (3) and (4) with the dimension-specific poverty lines z_d:

$$S_z = \left(\sum_{d=1}^{D} w_d z_d^{\beta} \right)^{1/\beta}, \quad \beta \neq 0, \tag{2.14}$$

$$S_z = \prod_{d=1}^{D} z_d^{w_d}, \quad \beta = 0. \tag{2.15}$$

Children with an opportunity indicator S_i below the aggregate poverty line S_z are identified as poor in opportunities.[27]

Then, we aggregate the level of well-being of children identified as poor with the following function

$$P(S; z) = \frac{1}{N} \sum_{i=1}^{N} p_i^{\phi} = \frac{1}{N} \sum_{i=1}^{N} \left[\max \left\{ \frac{S_z - S_i}{S_z}; 0 \right\} \right]^{\phi}, \tag{2.16}$$

where p_i is the multi-attribute poverty function for each child i. Our poverty measure is directly related to the Foster-Greer-Thorbecke (FGT) poverty measures and satisfies the same distributional and non-distributional properties. A general formulation that allows for some substitution between dimensions above and below the poverty thresholds can be written as

[27] According to the union approach, an individual is already identified as multidimensional poor if she is deprived at least in one dimension. The intersection approach identifies an individual as multidimensional poor if it is deprived in all dimensions at the same time (see, e.g., Alkire and Foster, 2011). In contrast, we apply an intermediate approach that allows for some substitution between dimensions such that disadvantages in one or more dimensions can be compensated by advantages in other dimensions in which an individual is not deprived (Lugo and Maasoumi, 2008). However, the poverty function collapses to the union approach if β is infinitely small such that only the worst dimension is considered in S_i.

$$P(APL) = \frac{1}{N}\sum_{i=1}^{N}\left[\max\left\{\frac{S_z^{1/\beta} - S_i^{1/\beta}}{S_z^{1/\beta}}; 0\right\}\right]^{\phi}, \ \beta \neq 0. \tag{2.17}$$

The magnitude of poverty measured crucially depends on the choice of the parameters w, β and ϕ. Note that a higher ϕ in FGT poverty measures indicates higher poverty aversion putting more weight on the children identified as poor.

2.4.4 Weights

The weighting structure w determines the trade-off between any pair of dimensions and reflects value judgements on which factors are viewed as more important than others for children's later achievements. We apply three methods to check the robustness of our findings to the chosen weights.[28]

First, we assign equal weights to all dimensions following an agnostic approach. Equal weighting is widely used in empirical works on multidimensional inequality and poverty, e.g., in the Human Development Index.

Second, we employ a data-driven approach and calculate frequency-based weights following Cheli and Lemmi (1995). The weights w_d are defined as

$$w_d = \ln(\frac{1}{P_d})/\sum_{d=1}^{D}\ln(\frac{1}{P_d}),$$

where P_d is the dimension-specific headcount ratio. Accordingly, the weights w_d are an inverse function of the average degree of deprivation; the lower the share of deprived children in one dimension, the greater the weight of the respective dimension.

Third, we gradually increase the weight of income from 1/4 to 9/10 and proportionally reduce the weight of the other dimensions checking if level and trends in multidimensional inequality and poverty change.

2.5 Results

We first present results how inequality of each dimension evolved between 1991 and 2012. Then we present and discuss the results from our multidimensional analysis.

[28] Deutsch and Silber (2005) describe various methods to set weights in a multidimensional framework. Decancq and Lugo (2013) comprehensively discuss the issue of weight setting in a multidimensional framework and compare the advantages and disadvantages of three existing approaches: (1) data-driven; (2) normative; and (3) hybrid. Overall, there is no unifying theoretical framework that argues in favour of one specific weighting scheme. Both studies rather conclude to rely on reasonable trade-offs between dimensions and to perform a series of robustness checks and sensitivity analyses to control for the impact of different weighting schemes on the respective results.

2.5.1 Univariate Inequality and Poverty

Univariate inequality in each dimension measured by the MLD is given in Figure 2.3. Income and parental time inequality significantly increased between 1991 and 2012 (Figures 2.3a and 2.3c).[29] In contrast, inequality of parental education did not change significantly (Figure 2.3b), while publicly provided childcare time decreased significantly (Figure 2.3d). However, differences in inequality levels across dimensions depend on the inequality measure: Inequality of non-parental time is by far the highest when measured by the MLD.[30] Non-parental time inequality decreases in the 2000s when several policy initiatives were enforced to increase the provision of public childcare in Germany, especially for children under the age of three.

The headcount ratio presented in Figure 2.4 shows the share of children by family type counted as poor in one dimension, i.e. their resource level is lower than 60 percent of the median. As we see for average numbers in Section 2.3, children living in single parent households are disadvantaged in parental income (Figure 2.4a), parental education (Figure 2.4b), and parental time (2.4c), but are better off with respect to non-parental childcare time (Figure 2.4d). About 40 percent of single parents' children is considered as income poor, contrasting to an overall income poverty risk between 7 and 14 percent in 1991 and 2012. The overall share of children with publicly provided time lower than 60 percent of the median sharply decreased over time. Interestingly, children living with cohabiting couples seem the least likely to spend much time in publicly provided childcare.

2.5.2 Multidimensional Inequality

Our results in Section 2.3 and 2.5.1 suggest that children living in single parent families are disadvantaged in parental income, parental education and parental time, but single parents make more use of publicly provided childcare time. The analysis of multidimensional inequality allows us to draw conclusions if disadvantages in one dimension are compensated by advantages in another at the individual level. Growing univariate inequality might be less of a concern if these dimensions indeed compensate each other

[29]Prior research shows that changing family structures have actually led to an increase in family income inequality. E.g., Danziger and Gottschalk (1993) find that 13 percent of the increase in U.S. family income inequality among the white population between 1969 and 1987 was due to changing family structures, the rise in female-headed single parent families in particular. Peichl et al. (2012) show that decreasing average household size in Germany between 1991 and 2007 is associated with increasing income inequality.

[30]Appendix Figure A.1.1 shows that inequality of non-parental time is similarly unequal as parental time when measured by the Gini. The share of children receiving zero non-parental childcare time declined from more than 30 percent in 1991 to less than 15 percent in 2012 which is more reflected by the MLD than by the Gini.

and multidimensional inequality does not increase. In our baseline scenario, we consider parental care time and publicly provided care time as separate dimensions since it can hardly be argued that they should be added up and, hence, treated as perfect substitutes.[31]

All in all, multidimensional inequality significantly declines between 1991 and 2012, which is largely driven by the expansion of publicly provided childcare. In the following, we vary each of the "ad-hoc" chosen parameters of the Maasoumi index and check the robustness of the declining trend in the view of reasonable parameter values. Figure 2.5 shows that the decline is robust to degrees of inequality aversion between 0 and 2, which is the interval empirically agreed on.[32] This applies to assuming dimensions to be complements (left-hand graph) or perfect substitutes (right-hand graph).

The declining trend persists for different degrees of substitutability between our four dimensions as shown by the left-hand graph in Figure 2.6. Even if we assume that all dimensions are perfectly substitutable, the declining trend remains but is smaller in size. However, the assumption of perfect substitutability seems rather far-fetched: One unit less parental time is most likely not perfectly compensated by one unit more income.[33] In contrast, one could argue that among our dimensions parental time and non-parental time are closest to being perfect substitutes. The right-hand graph of Figure 2.6 shows multidimensional inequality if we collapse both childcare time measure into one dimension and, consequently, end up with three dimensions in total. The declining trend is robust to different degrees of substitutability between the three dimensions, but changes are no longer significant for all years. With equal weighting, income now receives a weight of 1/3 and non-parental childcare a weight of 1/6 such that the equalizing effect of non-parental time is deemphasized.

As a robustness check, we also computed multidimensional inequality using frequency-based weights. We broadly find the same trends and significance levels as for equal weighting.[34]

So far we find that multidimensional inequality has decreased since the beginning of the 1990s and that this result is quite robust against different parameter settings. But how sensitive is the multidimensional inequality index to increasing the income weight, where univariate inequality increased over the past two decades. Figure 2.7 shows how our multidimensional index of inequality changes, if we gradually increase

[31] Instead, it seems to depend on the perceived quality of parental childcare time, whether one type of care should be preferred over the other.

[32] See Aaberge and Brandolini (2015) or Lambert et al. (2003) for an overview on studies that either estimate α, e.g., through the elasticity of marginal social utility of income, or use parameter ranges that seem theoretically plausible. Values vary between zero and three.

[33] For $\beta < 1$, the utility-like function is a concave function and reflects a preference for a more equal vector of (transformed) achievements (Decancq and Lugo, 2013).

[34] Figures A.1.2 are in Appendix.

the weight of income towards unity under the restriction that the remaining three dimensions are equally weighted and that all dimensions sum up to one. Assuming a low degree of substitutability ($\beta = -1$) in the left-hand graph, we still find a decline in multidimensional inequality even when weighting income by 90 percent. Assuming a slightly higher degree of substitutability ($\beta = 0$) in the right-hand graph the trend reverses when weighting income by 90 percent.

Finally, we check if our results are indeed driven by the expansion of publicly provided childcare. Figure 2.3 shows that non-parental childcare time became more equally distributed over the time period under study. In fact, the declining trend disappears once we exclude publicly provided childcare and consider only the three other dimensions as shown in Figure 2.8.

2.5.3 Decomposition of Multidimensional Inequality by Family Type

We now turn to the impact of increasing non-traditional families on children's multidimensional inequality between 1991 and 2012. Table 2.1 depicts to what extent the total change in multidimensional inequality given in the second column can be attributed to changes in the four components: changing inequality (1) within family types; (4) changing inequality between family types; and the effect of changing family patterns on (2) within and (3) between family type inequality. The observed decrease in multidimensional inequality tends to be higher for low degrees of substitutability. Reduced inequality within family types, (1), is the main explanatory component. In contrast, inequality changes between family types, (4), as well as family type's share on within, (2), and between, (3), family type inequality only negligibly contribute to the decline in multidimensional inequality and signs are not robust to different time period specifications.

2.5.4 Multidimensional Poverty

The decline of multidimensional inequality may be due to losses of the better-off children or due to gains of children at the bottom of the opportunity indicator distribution. One might argue that a combination of multiple deprivations in attributes necessary for success later in life reduces children's opportunities even more than just the sum of each. To uncover the changes for those in the bottom of the multidimensional distribution, we now turn to the trends of multidimensional poverty. We also find a decline in multidimensional poverty, which is similarly robust to different parameter values and dimension specifications.

Figure 2.9 shows multidimensional poverty trends for three different poverty measures, which are headcount ratio ($\phi = 0$), poverty gap ($\phi = 1$), and poverty intensity ($\phi = 2$). All poverty measures exhibit a significant decline between 1991 and 2012.

As Figure 2.10 depicts, differentiating between family types reveals a higher multidimensional poverty risk for children from single parent families compared to children from married and cohabiting families. Nevertheless, for both low and high degrees of substitutability we find a considerable decline in multidimensional poverty across all family types and the gap between them has become smaller over time.

The poverty decline is robust to different assumptions on the substitutability between dimensions as can be taken from the left-hand graph of Figure 2.11. The level of multidimensional poverty increases in the assumed degree of substitution between dimensions. If we assume perfect substitutability ($\beta = 1$), our measure for children's opportunities is a simple arithmetic mean of all dimensions. One unit less income can be perfectly offset by more parental time. However, this assumption does not appear very realistic. The more complementary the dimensions, the heavier is the effect of the worst dimension on the individual opportunity indicator and the higher is the number of deprived children. The declining trend mostly disappears if we sum up parental and non-parental childcare time to one dimension as shown in the right-hand graph of Figure 2.11. Again, this occurs because of the new weighting structure: when time is collapsed into one dimension, the weight of each dimension is halved in comparison to education and income. In contrast, multidimensional inequality still slightly declined for this setting, but not significantly anymore.

Figure 2.12 shows how our multidimensional poverty index changes, if we gradually increase the income weight towards unity under the restriction that the remaining three dimensions are equally weighted and that all dimensions sum up to one. It depends on the assumption on the degree of substitutability, if more or less children are deprived in the multidimensional case than in the univariate case with income only. For $\beta = 1$, e.g., low income is perfectly compensated by higher levels in childcare time or parental education and less children are counted as multidimensionally poor than in the univariate case. For $\beta = -1$, low levels in one dimensions are not outweighed by higher levels in the other dimensions and, hence, more children are counted as poor than for income only. If we judge the assumption of less than perfect substitutability as more realistic, then more children face difficult circumstances than if we would only focus on incomes. In 2012, 30 percent of all children experienced multidimensional poverty risk ($\beta = -1$), whereas the share of children living under income poverty risk was 14 percent. In comparison to income only, many children are additionally counted as poor in the multidimensional setting because of low levels of non-parental childcare time, but also low levels of parental childcare time.

As a robustness check, we compute multidimensional poverty risk using frequency-based weights. As for multidimensional inequality, we broadly find the same trends and similar levels. Multidimensional poverty risk rates based on frequency-based weights tend to be slightly lower for all rates of substitution.[35]

Finally, Figure 2.13 checks if multidimensional poverty risk is driven by the expansion of non-parental childcare time. As for multidimensional inequality, excluding non-parental childcare takes away the declining trend.

2.6 Conclusion

An increasing number of children in Germany are growing up in non-traditional families, particularly in single parent families. These children are often disadvantaged along three dimensions: parental income, parental educational and parental childcare time. Disadvantages may be partly compensated by publicly provided childcare and education. Since the mid-2000s, the German welfare state has heavily expanded publicly provided childcare.

Based on broad empirical evidence, we take parental income, parental education and childcare time as proxies for circumstances that are beyond children's control, but strongly contribute to their later achievements. We apply Maasoumi's index for multidimensional inequality and poverty to measure how the disparity of children's opportunities has evolved since the beginning of the 1990s.

Focusing on income only we find that both inequality and poverty among children increased. However, adding parental education and care time to the picture we find that both multidimensional inequality and poverty among children decreased over time. The expansion of childcare provided by the welfare state more than offsets the disequalizing trends observed for income only. This finding is robust against different parameter values for inequality and poverty aversion as well as the degree of substitutability between dimensions. However, increasing the weight of income and decreasing the weight of publicly provided childcare takes away the declining trend in some constellations. An inequality decomposition by family type reveals that the observed decline in multidimensional inequality is mainly due to reduced differences within family types. In contrast, the effect of changing family patterns on the inequality decline seems negligible. The share of multidimensional poor children decreased for all family types and the gap between them has become smaller over time. More children are counted as poor in the multidimensional setting than if considering income only, because of low

[35] Figures A.1.3 are in the Appendix.

levels of non-parental and parental childcare time devoted to them.

In sum, our analysis highlights the importance to consider more than one dimension in inequality and poverty analysis when conclusions about developments over time shall be drawn. Particularly, in-kind benefits such as publicly provided childcare and education should be accounted for to get a more complete picture of the welfare state's role in redistributing resources and providing less unequal opportunities.

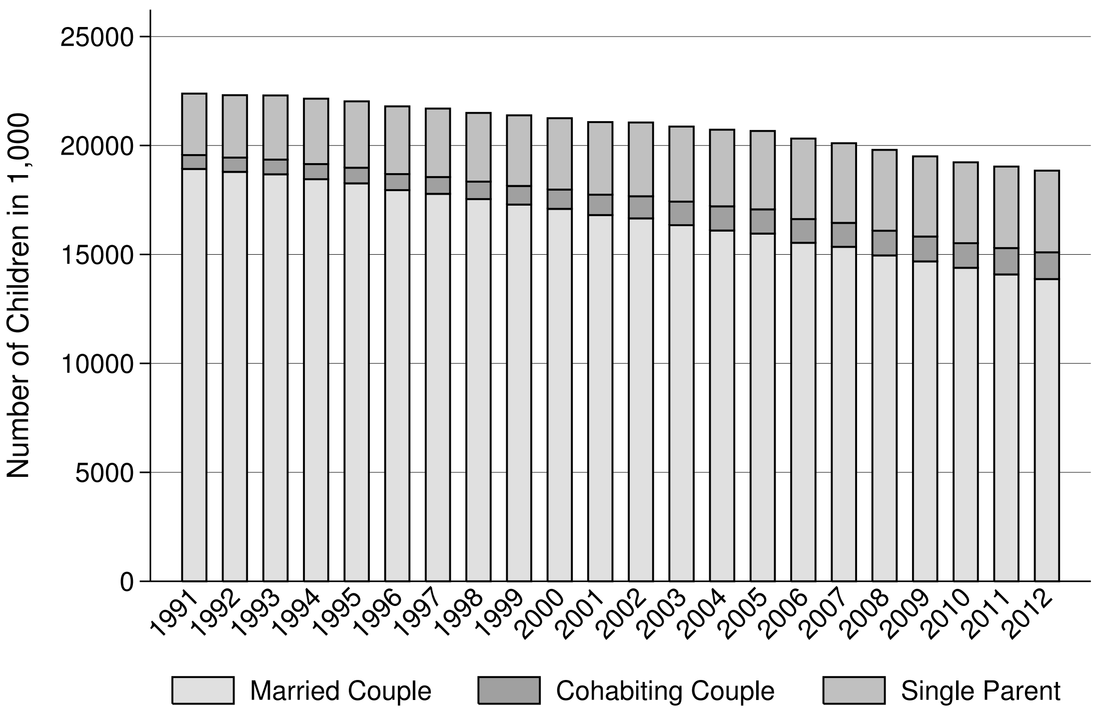
2.7 Tables and Figures

Table 2.1: Multidimensional inequality (MLD) decomposition by family type, 1991-2012

		Absolute % Change in I_0 due to			
				Family Structure	
β	Total (ΔI_0 in %)	Within I_0 (1)	Between I_0 (4)	Within I_0 (2)	Between I_0 (3)
(-10)	-33.26	-33.55	0.12	0.08	0.09
(-1)	-33.84	-34.15	0.03	0.26	0.01
0	-31.89	-32.49	0.03	0.78	-0.21
0.5	-29.39	-29.30	-0.09	0.64	-0.64
1	-27.17	-25.83	-0.06	-0.41	-0.87

Source: SOEP (v30), own calculations.
Note: Differences between ΔI_0 in % and the sum of components are due to rounding (after computation).

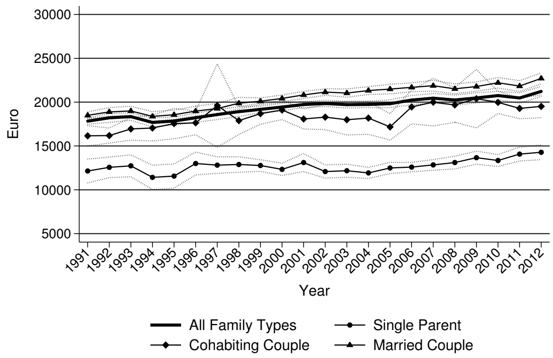
Figure 2.1: Trends in the number of children by family type



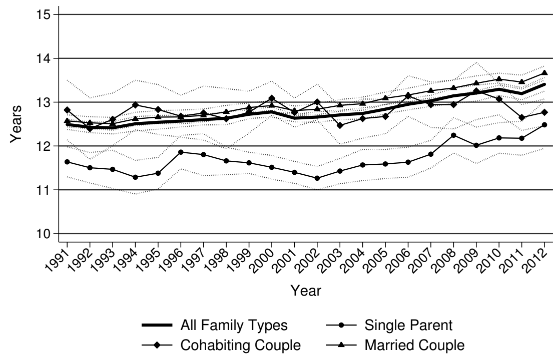
Source: Statistisches Bundesamt (2013, Table 6.5), own calculations.
Note: Values for the years 1991-1995 are not available and thus imputed using a linear trend.

Figure 2.2: Average trends by dimension

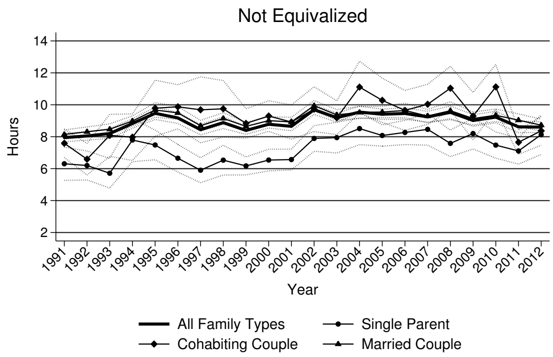
(a) Average equivalent net income



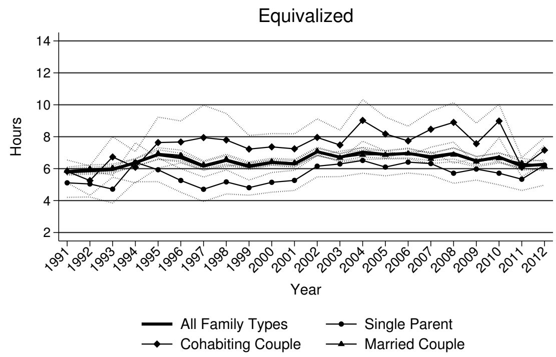
(b) Average years of parental education



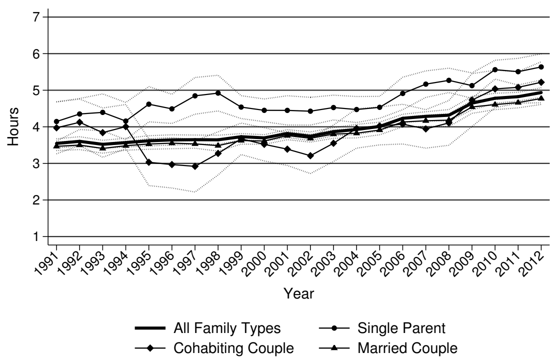
(c) Average parental childcare time



(d) Average parental childcare time

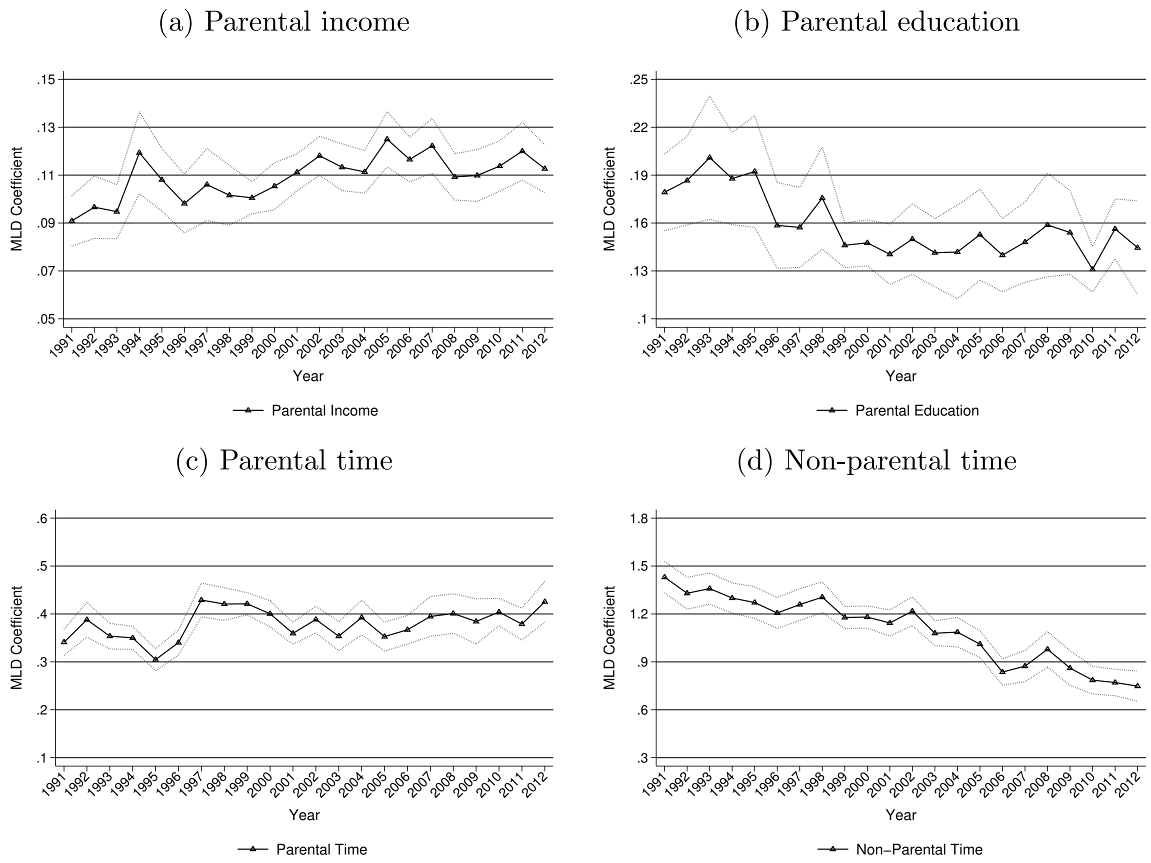


(e) Average non-parental childcare time



Source: SOEP (v30), own calculations.
Note: Incomes are in prices of 2010 and equivalized using the modified OECD scale. Education is measured as years of highest educated parent. Parental childcare time is the sum of household head's and spouse's stated childcare time on an average week day. Non-parental time is categorically coded (0,4, or 8). Significance at the five percent level is calculated using bootstrap standard errors with 100 replications. Higher volatility of the series for children in cohabiting couples is due to small sample sizes and relatively large variation of the respective sample size over time (see A.1.1).

Figure 2.3: Inequality by dimension

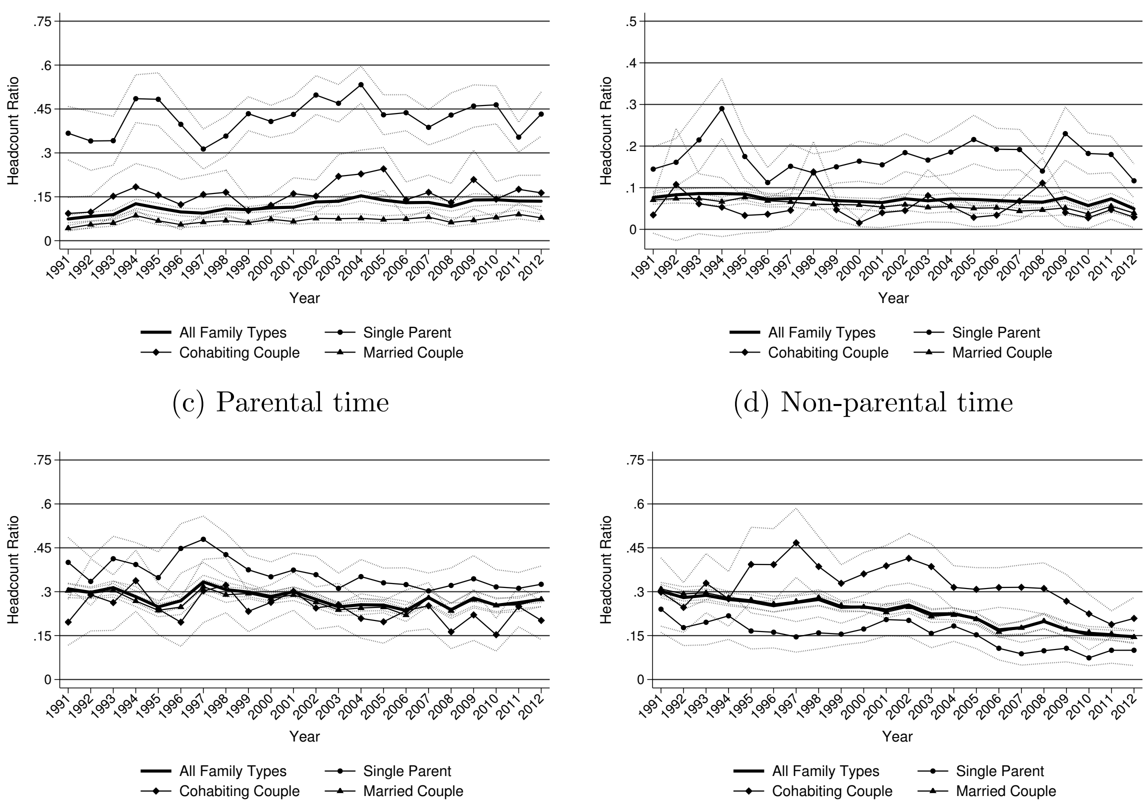


Source: SOEP (v30), own calculations.
Note: Parental time is equivalized according to the number of children in the family. Significance at the five percent level is calculated using bootstrap standard errors with 100 replications.

Figure 2.4: Poverty risk by dimension

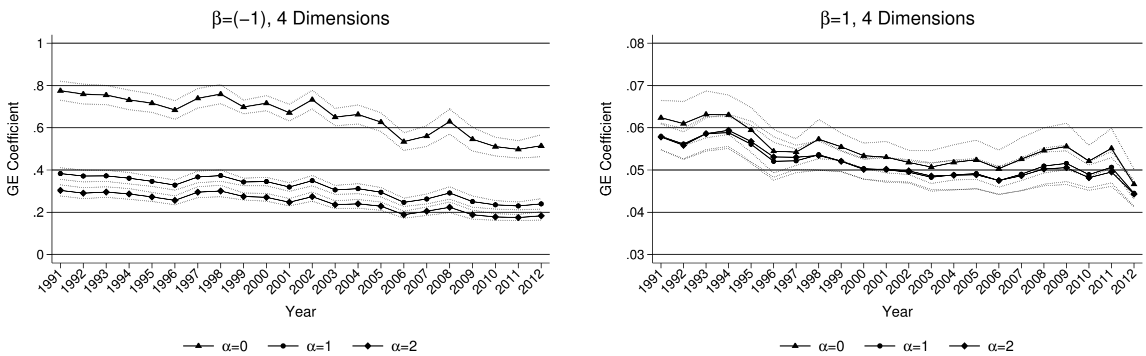
(a) Parental income (b) Parental education

(c) Parental time (d) Non-parental time



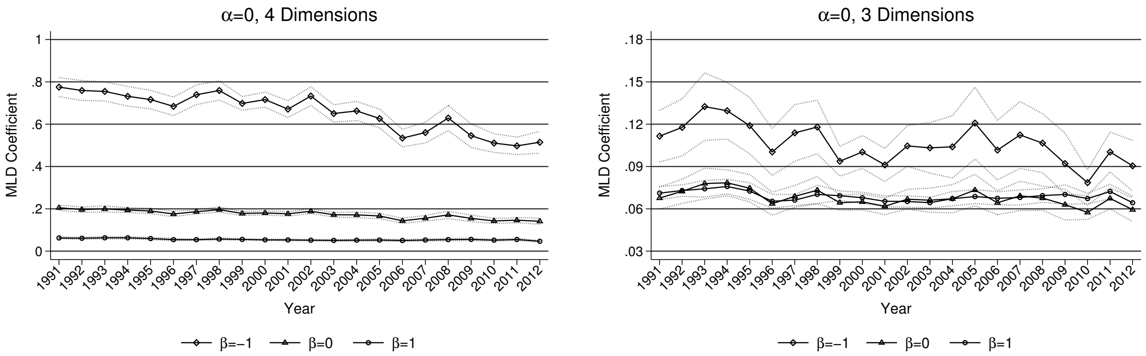
Source: SOEP (v30), own calculations.
Note: Parental time is equivalized according to the number of children in the family. Significance at the five percent level is calculated using bootstrap standard errors with 100 replications.

Figure 2.5: Multidimensional inequality with varying degrees of inequality aversion



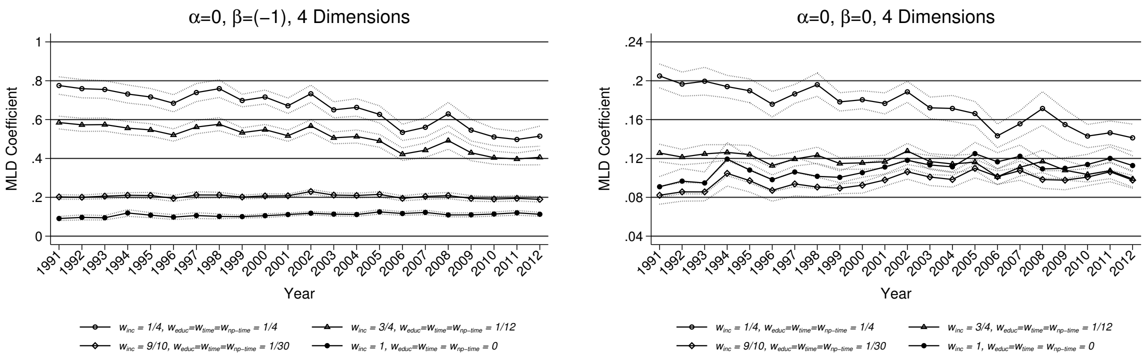
Source: SOEP (v30), own calculations.
Note: Significance at the five percent level is calculated using bootstrap standard errors with 100 replications.

Figure 2.6: Multidimensional inequality with varying degrees of substitution



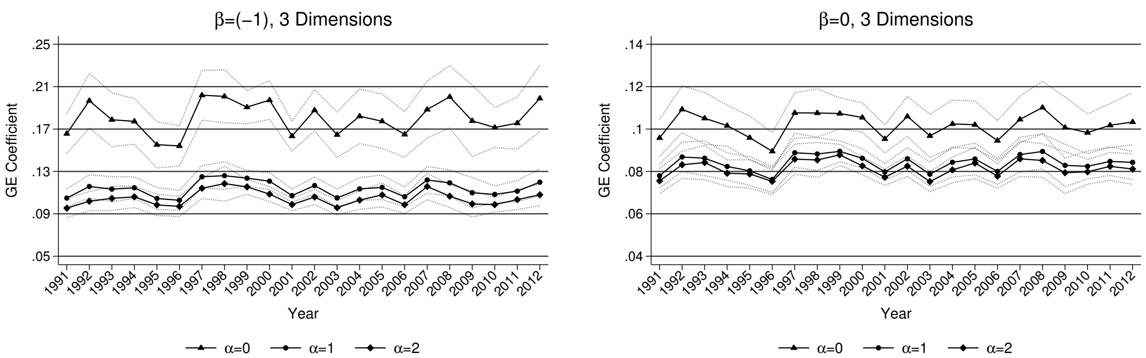
Source: SOEP (v30), own calculations.
Note: Significance at the five percent level is calculated using bootstrap standard errors with 100 replications.

Figure 2.7: Multidimensional inequality with varying income weights



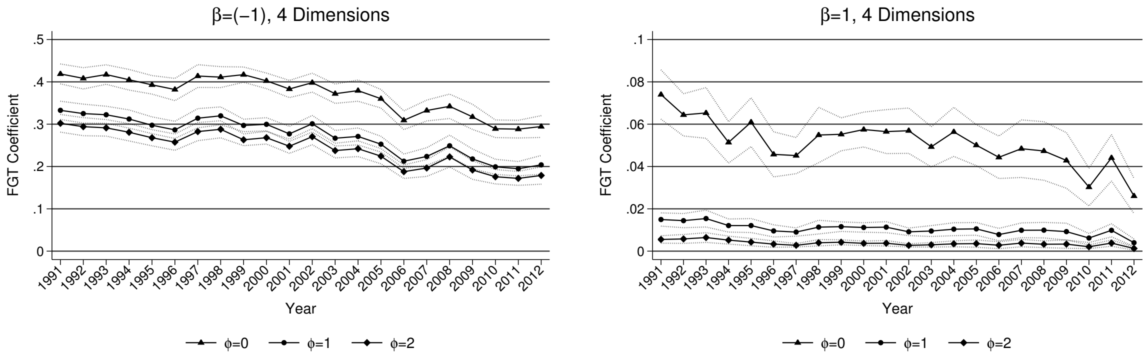
Source: SOEP (v30), own calculations.
Note: Significance at the five percent level is calculated using bootstrap standard errors with 100 replications.

Figure 2.8: Multidimensional inequality excluding non-parental childcare time



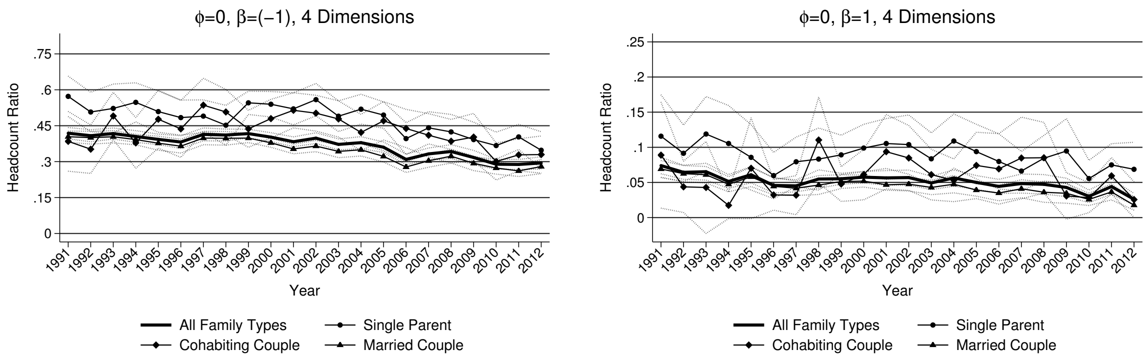
Source: SOEP (v30), own calculations.
Note: Significance at the five percent level is calculated using bootstrap standard errors with 100 replications.

Figure 2.9: Multidimensional poverty measures



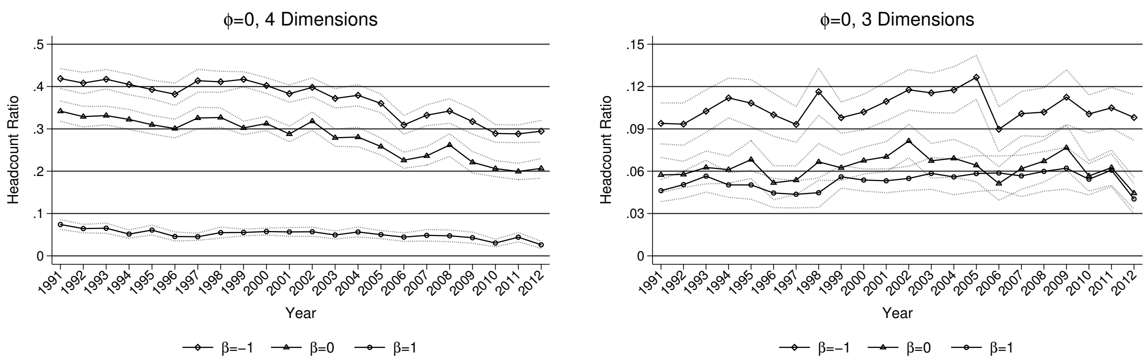
Source: SOEP (v30), own calculations.
Note: Significance at the five percent level is calculated using bootstrap standard errors with 100 replications.

Figure 2.10: Multidimensional poverty by family type



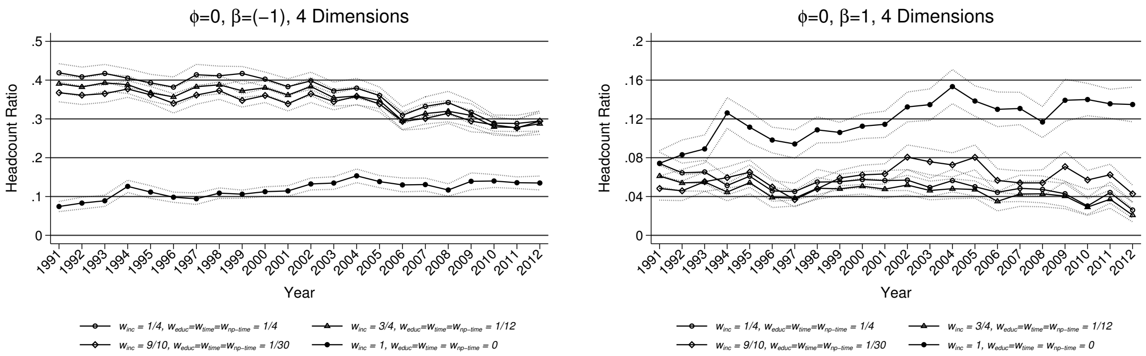
Source: SOEP (v30), own calculations.
Note: Significance at the five percent level is calculated using bootstrap standard errors with 100 replications.

Figure 2.11: Multidimensional poverty with varying degrees of substitution



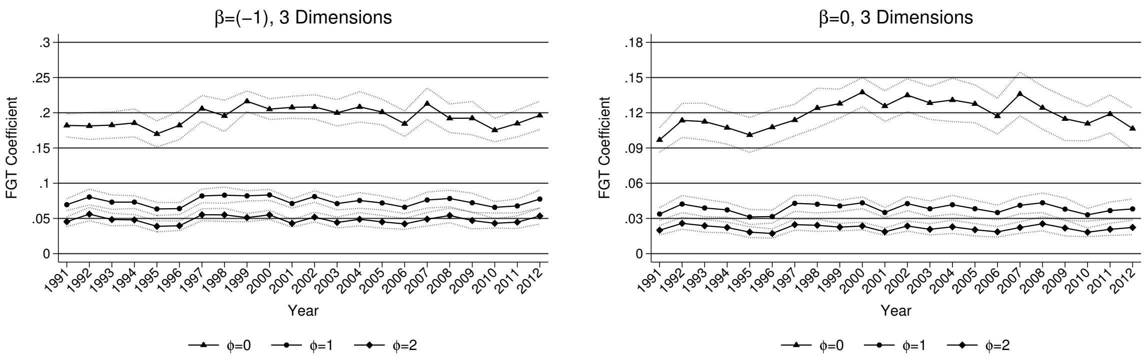
Source: SOEP (v30), own calculations.
Note: Significance at the five percent level is calculated using bootstrap standard errors with 100 replications.

Figure 2.12: Multidimensional poverty for varying income weights



Source: SOEP (v30), own calculations.
Note: Significance at the five percent level is calculated using bootstrap standard errors with 100 replications.

Figure 2.13: Multidimensional poverty excluding non-parental time



Source: SOEP (v30), own calculations.
Note: Significance at the five percent level is calculated using bootstrap standard errors with 100 replications.

Chapter 3

The Distribution of Economic Resources to Children in Germany

3.1 Introduction

Family constellations have tremendously changed over the past decades in Germany and other industrialized countries (McLanahan, 2004; Peuckert, 2012). In 2012, almost every fifth German child grew up in a single parent household (Statistisches Bundesamt, 2013). At the same time, these are the children who face the highest risk of income poverty (BMAS, 2013). But they are not only deprived in terms of disposable cash income: in many cases, they are also time-poor (McLanahan and Percheski, 2008). It is well investigated that both parental income and parental time investments are positively correlated with children's well-being and the development of a child's human capital (Heckman and Mosso, 2014).[1] Thus, children from low socio-economic backgrounds tend to accumulate disadvantages in several dimensions during their childhood which negatively affect their employment prospects and income opportunities later in life.

A key policy instrument to mitigate the disadvantages experienced by children from low socio-economic background is the provision of child-related public in-kind benefits, such as public childcare and education. On the one hand, it frees parents' time from indispensable childcare and it allows them, especially single parents, to work for pay in the labour market. This might help to cushion disadvantages in parental income and time since employment is a crucial factor to escape income poverty. On the other hand, high quality public childcare and education can function as a close substitute to parental childcare time. At its best it has a large positive effect on the formation of

[1] Human capital includes skills and abilities, personality, appearance, reputation, and appropriate credentials (Becker and Tomes, 1986)

children's cognitive and socio-emotional skills that exceeds the capabilites of parents, especially for children from low socio-economic background. At least, it helps to reduce some disadvantages that are due to different parental skills, incomes, and parenting styles (Müller et al., 2013). Indeed, Heckman (2008) can show that children from lower socio-economic backgrounds profit from publicly provided childcare services by enhancing their social development and cognition.

Therefore, disposable cash income alone appears to be an incomplete measure of children's well-being and access to economic resources (also see Aaberge et al., 2010; Garfinkel et al., 2006, for a more general critique). Accordingly, an extended income concept is derived in this study which incorporates children's disposable cash income as well as the monetized value of parental and public childcare and education to receive a more complete measure of children's well-being and access to economic resources.

An early and prominent paper that applied an extended income definition is Jenkins and O'Leary (1996) for the United Kingdom.[2] They investigate the impact of extending the cash income of households by the imputed value of household production time to consider the overall amount of economic resources. Estimating the distribution of extended income amongst non-elderly, one-family households in 1986, they find a substantially lower level of inequality in the distribution of extended income compared to disposable cash income, while overall inequality trends are similar. Furthermore, changes in the income distribution due to the extension of the income concept shift singles down the distribution relative to married couple families.

Frick et al. (2012) investigate the impact of home production on economic inequality for Germany. Their main finding is that extending cash income by the monetary value of home production has an inequality reducing effect independent of the evaluation technique and inequality measure used. Hence, their findings for Germany show the same patterns as the results of Jenkins and O'Leary (1996) for the United Kingdom. Recent U.S. studies have also found substantial inequality reducing effects if the monetary value of home production is taken into account (see, e.g., Gottschalk and Mayer, 2002; Zick et al., 2008; Frazis and Stewart, 2011). However, Frick et al. (2012) neither investigate the differences between family types nor do they consider the effects of both home production and in-kind benefits. Moreover, they do not put a special emphasis on children's available resources. This gap shall be closed by this study. Nevertheless, they show that childcare activities constitute a major part of home production whenever a household has children. Therefore, the expected transfers from parental childcare time are likely to be large among families with dependent children.

[2]Other early empirical studies are Bryant and Zick (1985) or Bonke (1992), among others. See Frick et al. (2012) for a comprehensive overview of previous studies on evaluating home production.

Another large strand of literature deals with the evaluation of public in-kind benefits, such as public education, public health services, or public housing, and investigates its distributional impact on disposable incomes (recent studies are, e.g., Garfinkel et al., 2006; Paulus et al., 2010; Koutsampelas and Tsakloglou, 2013; Higgins et al., 2015).[3] In general, all studies find substantially lower levels of disposable income inequality whenever the income concept is extended by the value of public in-kind benefits. In particular, pre-school and primary education is found to have a disproportionately high equalizing effect on the distribution of disposable income across countries (see, e.g., Antoninis and Tsakloglou, 2001; Paulus et al., 2010; Higgins et al., 2015).

So far and to the best knowledge of the author, there is no study that incorporates both the value of public in-kind benefits and parental childcare time into an extended income concept. This paper contributes to close this gap by putting special emphasis on the available resources of children in Germany and, thus, provides a more complete measure of children's current well-being and opportunities in later life. The rest of the paper is organized as follows: Section 3.2 describes the data sources used and shows how the income components under analysis are defined and measured. In Section 3.3, level and distributional effects of extending the income definition are discussed and robustness checks are performed. Finally, in Section 3.4, the results are summarized and conclusions are drawn.

3.2 Data and Measurement of Extended Income

3.2.1 Data

The analysis is based on data from the Socio-Economic Panel (SOEP) which is an annually repeated survey among German households.[4] It includes a broad range of demographic and socio-economic characteristics for all years since 1984. East German households are included in the panel since 1990. Every year, approximately 11,000 households participate in the SOEP which correspond to 20,000 individuals (Wagner et al., 2007; Schupp and Rahmann, 2013). The sample includes East and West German children and information about their parents. In this study, children are defined as individuals aged 13 or below living with their parents.[5] In 2014, the SOEP was extended by information from the SOEP-related study "Familien in Deutschland" (Families in

[3]Previous studies on the impact of public in-kind benefits are, amongst others, Ruggles and O'Higgins (1981); Le Grand (1982); Gemmell (1985); Smeeding et al. (1993); Evandrou et al. (1993); Ruggeri et al. (1994); Slesnick (1996); Antoninis and Tsakloglou (2001).

[4]DOI: 10.5684/soep.v31.1

[5]The age restriction is set in accordance with the legal definition of a child provided by the German law for the protection of the youth (§1).

Germany, FiD) which was launched in 2010. This additional survey covers more than 4.500 households every year and puts a special focus on single parents, families with more than two children, low-income families, and families with very young children in the German population (Schröder et al., 2013). Therefore, it increases the analytical power of the SOEP for the purpose of this study tremendously. However, the availability of the FiD also determines the investigation period which is limited to the survey years 2010 to 2014.[6]

Furthermore, the panel survey data is extended by official statistics provided by the German Federal Statistical Office. In particular, information on yearly expenditures on public schooling per pupil are provided for each federal state on an annual basis, including elementary and secondary schools (Statistisches Bundesamt, 2015). Public spending is defined on grounds of a 'basic funds' (*Grundmittel*) concept where revenues generated by a service (e.g. kindergarten fees) are netted out of the overall spending on that same service (e.g. kindergartens). In addition, public spending comprise expenditures on employees and administrational staff including pensions for civil servants, aid expenditures (*Beihilfeaufwendungen*), current operating expenses and capital expenditures. This definition of public spending is comparable to the OECD definition of spending on educational core services and is widely used in economic studies evaluating the distributional impact of public in-kind benefits (see, for instance, Garfinkel et al., 2006). Yearly expenditures on pre-school and after-school care clubs per child, i.e. publicly provided or subsidized childcare by cribs, kindergartens, nurseries, or childminders, are derived from combining information on the number of children enrolled in the enumerated institutions and annual total public spending on them (Statistisches Bundesamt, 2014a,b,c).[7]

3.2.2 Cash Income

Cash income is measured as real net equivalent household income including imputed rents from owner-occupied housing.[8] Net household income is the sum of a household's labour earnings, asset flows, private retirement income, private transfers, public transfers, and social security pensions minus total household taxes and social security contributions. Disposable cash income is equivalized using the modified OECD scale to account for different household sizes and composition.

[6]The survey years 2010 to 2014 correspond to the income years 2009 to 2013 which are referred to throughout the paper. This is due to the retrospective collection of income information: all incomes in survey year t refer to income year *t-1*.

[7]Data on the number of children in said institutions is generally available from 2006 onwards.

[8]Further details on the computation of imputed rent can be found in Frick and Grabka (2001) and Frick and Grabka (2003).

3.2.3 Net Monetary Value of Public Childcare and Education

The net monetary value of public childcare and education is derived by a standard production cost approach. This approach is based on the assumption that the value of public childcare provision and education is as high as the costs of providing it (Aaberge et al., 2010; Garfinkel et al., 2006). Variation in the value of publicly provided childcare and education is obtained by differences in geographical regions, in school types, and in the age of children. This also implies that the value of in-kind benefits is otherwise the same for all children no matter of where their position in the income distribution actually is. Hence, a limitation of this study is that existing differences in the quality and efficiency of childcare provision and education cannot be factored in fully. However, the largest differences are likely to occur at the federal state level in Germany, since education policy is determined at this stage, which are covered by the data available.[9] In this respect it is assumed that children living in the same federal state and attending the same educational level receive a similar amount of non-cash income from public childcare and education.

Data on public spending on childcare and schooling is provided by the German Federal Statistical Office on an annual basis for each federal state (Statistisches Bundesamt, 2014a,b,c, 2015). Average annual public expenditures on childcare per child is calculated as the sum of public expenditures on cribs, kindergartens, after-school care clubs, and other forms of publicly subsidized day care divided by the total number of children consuming these services in each federal state.[10] Average annual public expenditures on schooling per pupil are defined as the sum of public expenditures on publicly funded primary and secondary schools divided by the total number of pupils enrolled in these institutions. All expenditures are expressed in 2010 Euros and, thus, might slightly differ from official statistics which states nominal per capita spending.[11]

Since the educational in-kind benefit is consumed by the receiving child only and cannot be shared within the household, no further equalisation of the monetary transfer is done (see, e.g., Garfinkel et al., 2006, for a similar argumentation). Therefore, a child's extended income includes the full value of public childcare and/or schooling

[9] There are further differences in the quality and efficiency of public childcare and education between and within federal states that are not well explained just by the different levels of per capita spending between federal states. In this respect, Wößmann (2005, 2010, 2016) shows that there is a negative correlation between per capita spending and class size, but smaller class sizes do not automatically cause better pupil performances. Highly qualified teachers and more flexible institutional settings are rather explaining differences in performance levels between and within countries. Unfortunately, better performance indicators are not available for this analysis.

[10] Whenever a child received part-time care in the respective year of observation, yearly public expenditures on childcare are divided by two (this is commonly done; see, for instance, Frick et al., 2011)

[11] An overview of public spending on childcare and schooling by federal state is depicted in Tables A.2.1 and A.2.2 in the Appendix.

which is added to the equivalized disposable cash income and the monetary value of parental childcare time. The monetary evaluation of the latter will be explained next.

3.2.4 Monetary Value of Parental Childcare Time

Parental childcare time constitutes a major part of children's resources that is not reflected in the household's cash income flow. While the value of this time for children may differ on various dimensions, this paper will measure it in a single dimension, namely a monetary one. The main challenge in quantifying the value of parental childcare time is the absence of market prices. There are two widely used approaches to derive (gross) hourly shadow wage rates for non-market workers: (1) the housekeeper wage approach, and (2) the opportunity cost approach. Both approaches mainly differ in their assumption on the underlying productivity of individuals; the housekeeper wage approach assumes that all individuals are similarly productive, whereas the opportunity cost approach accounts for the heterogeneity in the productivity of individuals.

Both approaches rely on information on parental childcare hours on an average weekday which is the second crucial determinant of the monetary value of parental childcare time.[12] Figure 3.1a gives a brief overview on the distribution of parental childcare time on an average weekday between and within families. The majority of parents spend two to five hours on their children on an average weekday.[13] In addition, parental childcare time within couples is unequally distributed between parents (single parents excluded), as it is depicted in Figure 3.1b. Patterns have kept quite unchanged over time and it is still women who do most of childcare activities (see Figures A.2.1 and A.2.2 in the Appendix).

3.2.4.1 Housekeeper Wage Approach

The idea of the housekeeper wage approach is to assign a uniform hourly gross wage rate to all parents doing childcare activities at home by themselves. Each parent is assumed to be similarly productive such that differences in the productivity between parents, or between skilled childcare workers and unskilled parents are neglected. One way to derive the shadow price of parental childcare time is to use the average gross wage rates of employees working in sectors that provide similar services in the market. Therefore, the housekeeper approach is comparable to a market value approach, where the gross hourly wage rate is close to a market price.

[12]In the SOEP, respondents are asked how many (full) hours they spend on childcare on a typical weekday. Information on the kind of parental childcare activities are not available such that an hour of watching TV, doing homework, or reading together is evaluated similarly.

[13]The number of childcare hours is limited to eighteen hours per parent assuming parents to spend at least six hours on recreation on an average weekday.

Here, the shadow price of parental childcare time is derived from information on the average monthly gross earnings of childcare workers (ISCO-88 code 5131) provided in the SOEP for each year. In particular, mean gross hourly wage rates are calculated by dividing monthly gross earnings by the number of working weeks (factor 4.3) and actual weekly working hours.[14] This is done for each year separately.[15] The mean gross hourly wage rate is, then, multiplied by the hours of parental childcare time on an average weekday.[16] To receive the annual monetary value of parental childcare time, the monetary value of parental childcare time on an average weekday is multiplied by 258 working days ($258 days = 5 days \times 4.3 weeks \times 12 months$).[17] The annual gross income from parental childcare is not transformed into net values since a comparable service would have to be paid at gross prices in the market as well (see, for instance, Jenkins and O'Leary, 1996).

Another obstacle is the construction of equivalent one child households to make children living in families of different size and composition comparable, i.e. to eliminate all differences in the total time parents spend on childcare activities on an average weekday that are only due to the different number of siblings and adults living in the same household. For this purpose, yearly gross income from parental childcare time, D, is equivalized using an adjusted version of the square root equivalence scale: $D_{eq} = \frac{D}{p^{\theta} \times s^{\theta}}$. It considers both the number of parents living in a child's household, p, and the number of siblings aged 13 years or below, s. The parameter θ denotes an equivalence elasticity which is set to 0.5 to be in accordance with the square root scale. The rationale behind this equivalence scale is twofold: first, overall parental childcare does not increase proportionally with the number of siblings. Second, some childcare activities are likely to affect all children at the same time and some are devoted to a single child only. Since there is no specific time use information on each child, these economies of scale in parenting are approximated by applying the described equivalence scale. Finally, the annual equivalized monetary value of parental childcare time is deflated to the base year 2010 and summed up with the household's real equivalized

[14] Alternatively, information on agreed hourly gross wage rates of childcare workers and/or teachers working in the public sector could be used. This would result in much higher gross hourly wage rates than those derived from information on childcare workers in the SOEP. Therefore, the results presented in Section 3.3 provide a lower bound for the distributional impact of the housekeeper wage approach. However, sticking to the lower gross wage rates of childcare workers can also be justified as an adjustment to the lower productivity of untrained parents compared to trained workers.

[15] Distinguishing between East and West Germany is not possible since the number of observations tends to be too small to receive reliable average gross hourly wage rates.

[16] An overview of observed and estimated hourly gross wage rates can be found in Tables A.2.7 and A.2.8 in the Appendix.

[17] National holidays, private vacation (the minimum statutory holidays could be subtracted), and Saturdays are not considered as working days, since the vast majority of employees do not have to work on those days and public childcare services and schools are normally closed. Hence, parents face zero opportunity costs regarding the choice between paid and unpaid work.

disposable cash income and the real net monetary value of publicly provided childcare and education.

3.2.4.2 Opportunity Costs Approach

In contrast to the housekeeper wage approach, the opportunity cost approach allows for heterogeneity in the productivity of individuals and measures the foregone earnings that an individual with specific skills could have received in the labour market instead of doing childcare at home by himself. A crucial assumption to be made is that people can deliberately choose between working in the labour market or at home to satisfy a given set of needs for childcare. Thus, the decision to work at home or in the labour market depends on the individual's earnings capacity and its productivity in childcare. If parents have to work more hours in the labour market to receive an income that is large enough to buy the same amount of childcare they can provide on their own at home, they will choose not to work in the labour market. However, this rests on the very strong assumption that individuals can freely choose the amount of working hours in the labour market. Both assumptions are challenged by the presence of labour market rigidities, for instance, fixed working hours that are part of labour agreements (see Frick et al., 2012).

There are two widely used approaches to predict the shadow wage rates of home workers from the observable gross hourly wage rates of working age individuals: (i) the standard OLS regression model as well as (ii) the Heckman selection correction model. Selection correction controls for correlation between gross hourly wage rates and unobserved characteristics that influence wages and the participation decision. In both cases, a sample of private households is drawn from the SOEP to estimate the shadow prices of parental childcare time. The sample is restricted to the working age population (20-60 years) excluding all individuals who are still in education, in military or community service, in apprenticeship including trainee- and internships, who work as civil servants, who are pensioners (e.g. early retirement), and who help in family business.

OLS Regression First, a Mincerian OLS wage regression is applied to predict the shadow price of parental childcare time (Mincer, 1958). This is done separately for each year and sex (subscripts are left out for simplicity) estimating the following equation:

$$\ln(w) = \alpha + x\beta + \epsilon, \tag{3.1}$$

where w is the gross hourly wage rate of an individual. The vector x contains a broad set of commonly used covariates.[18] The estimated coefficients are, then, used for an out-of-sample prediction to derive the log of gross hourly wage rates for all men and women in the respective years.[19] Note that predicted wage rates are used only if information on gross hourly wages is missing. After exponentiating predicted log wage rates, they are multiplied with the hours of childcare activities on an average weekday. These are then annualized for each parent and summed up across all biological and non-biological parents living in the same household. A household's annual gross income from parental childcare time is, then, multiplied by the household's average tax rate to derive disposable incomes of this kind.[20]

Disposable income from parental childcare time is finally equivalized using the same equivalence scale as described in Section 3.2.4.1. The annual equivalized disposable income from parental childcare time using the OLS estimation approach is finally deflated to the base year 2010 and summed up with the household's real equivalized disposable cash income and the real net monetary value of publicly provided childcare.

Heckman Selection Correction Model In order to mitigate potential estimation bias due to self-selection into paid work, a two-step Heckman selection correction model is estimated, too. The main idea of this two-step approach is to include a correction term in the linear wage regression that takes account of any correlation between unobserved factors influencing both the decision to work and the level of observed gross wages. It is shown in Wooldridge (2013) that this correction term depends on the inverse Mills ratio which can be estimated from an unrestricted Probit model:

$$\Pr(s = 1|z) = \Phi(z\gamma), \tag{3.2}$$

where s is a binary response variable that is one if an individual is working ($s = 1[z\gamma + v \geq 0]$ with $v \sim N(0, 1)$), and zero otherwise. Φ is the cumulative distribution function of the standard normal distribution, and the vector z contains a wide set of covariates.[21] The estimates $\hat{\gamma}$ from the Probit regression are, then, used to compute

[18] It is controlled for: age and age squared, full-time and part-time working experience as well as their squared terms, schooling, vocational education, federal state, migration background, self-rated health, marital status, the number of children younger than 6 years, and the location in 1989.

[19] One percent of predicted gross wage rates is truncated at each tail to reduce potential biases from ill predicted outliers.

[20] A household's average tax rate is estimated in two steps: First, a simultaneously quantile regression of the log of a household's annual direct tax and social insurance payments on a quadratic in their log annual gross income is estimated. This is done for ten different income percentiles and for each year separately. Second, the estimated coefficients are used to predict the "adjusted" annual tax and social security payments of a household according to the sum of the household's gross cash income and its estimated income from parental childcare (annual extended gross income). Finally, a household's average tax rate is calculated by dividing the "adjusted" annual tax and social security payments by the annual extended gross income.

[21] Covariates are: age and age squared, full-time and part-time working experience as well as their

the inverse Mills ratio $\hat{\lambda} = \lambda(z_i \hat{\gamma})$ for each individual, i, working in the labour market. In a second step, the restricted OLS wage regression of the form

$$y = x\beta + u, \quad with\ E(u|x) = 0\ and\ y = ln(w), \tag{3.3}$$

is extended by a correction term that depends on the inverse Mills ratio evaluated at $z\gamma$. As long as the correlated error terms are jointly normally distributed, the conditional expectation of gross wages for persons working in the labour market can, then, be estimated by:

$$E(y|z, s = 1) = x\beta + \rho\lambda(z\gamma), \tag{3.4}$$

where ρ denotes the correlation between the error terms u and v, w is the gross hourly wage rate, and x is vector of covariates which is a strict subset of the vector z excluding self-rated health, marital status, and the number of children younger than 6 years. All regressions are, again, estimated separately for each year and sex. The estimated β coefficients are further used for an out-of-sample prediction to derive the log of gross hourly wage rates for all men and women in the respective years. Yearly equivalized disposable incomes are generated as described before in the OLS chapter.[22]

3.3 Results

Extending the income definition by income from parental childcare time, and public childcare and education has a remarkably large effect on both the level and distribution of children's disposable income. Accordingly, I will first investigate the changes in disposable income levels before describing the distributional impact of extending the income definition.

squared terms, schooling, vocational education, federal state of residence, migration background, and the location in 1989. In addition, self-rated health, marital status, and the number of children younger than 6 years are used as exclusion restrictions such that they are assumed to only influence the decision to work but not the level of earnings. This choice might be questionable, but it is widely accepted that the number of dependent children and marital status are important determinants for the choice to work, especially for women. Being mentally or physically ill is also very likely to influence the ability to work more than the level of earnings due to anti-discrimination legacy.

[22]See Tables A.2.7 to Table A.2.9 in the Appendix for an overview of estimated hourly gross wage rates according to the different approaches and for different subgroups. Again, note that predicted wage rates are only used if information on gross hourly wages is missing. One percent of predicted gross wage rates is truncated at each tail to reduce potential biases from ill predicted outliers.

3.3.1 Level Effects

Table 3.2 depicts the trends in children's yearly mean real (equivalized) disposable incomes between 2009 and 2013. First of all, mean real equivalized disposable cash incomes have been quite stable over time. They slightly decreased from 20,805 Euro in 2009 to 20,165 in 2013 which is a statistically insignificant decline of around three percent (at the 5% level). In contrast, the mean real value of in-kind benefits has increased by 4.8% over the same period: It was 4,880 Euro in 2009 (23.5% of cash income) and 5,116 Euro in 2013 (25.4% of cash income). This increase can be explained by two complementary developments: first, there was an increase of single parent households in Germany which are more likely to demand public childcare services, since they have to arrange market work and childcare without the support of a partner.[23] Second, there was a substantial expansion of publicly provided childcare in Germany during the last decade that was accompanied by a greater willingness of parents to send their children to public childcare institutions. The motives for the latter might originate from a change in role models as well as a rising economic pressure on families which resulted in a higher demand for a second earner and higher female labour market participation rates (see Schober and Stahl, 2014, among others).

Furthermore, the transfer added from parental childcare time is the largest and was 11,314 Euro in 2009 and 10,261 Euro in 2013 (-9.3%) when using the housekeeper wage approach.[24] The decline is mainly explained by the evolution of the underlying parental childcare hours which have gradually decreased over time, especially for children living with married couple parents (see Table A.2.5 in the Appendix). This declining trend could not be reversed by the simultaneous increase of the underlying housekeeper wage rate, as it is depicted in Table A.2.7 in the Appendix. Applying the two opportunity cost approaches instead yields similar results on lower levels: The transfer added when using the OLS (Heckman) approach was 9,425 Euro (9,677 Euro) in 2009 and 8,912 Euro (9,508 Euro) in 2013. This is a decline of 5.4% (1.8%). Nevertheless, annual equivalized incomes from foregone earnings still amount to 44% (OLS) and 47% (HM) of equivalized disposable cash income in 2013, which highlights the importance of considering income from non-market work in welfare analysis.

Finally, extended incomes are presented in the last three columns of Table 3.2. The negative trends in disposable cash income, and income from parental childcare also translate into a decline of total extended income which is only cushioned by the rise of

[23]See also Bartels and Stockhausen (2016) for changes in family types and family resources in Germany since the reunification.

[24]Note that income from parental childcare time is stated in gross terms when using the housekeeper wage approach, since it is a market value approach. This mainly explains the observed level differences compared to the results of the opportunity cost approaches which are net values.

transfers added from public childcare and education. As a consequence, total extended income has decreased from 36998 Euro in 2009 to 35,5542 Euro in 2013 when using the housekeeper wage approach. This is a decline of around four percent and, thereby, only slightly steeper than the change in cash income. In contrast, applying the OLS approach (Heckman approach) gives a decrease of extended income from 35,109 Euro (35,361 Euro) in 2009 to 34,194 Euro (34,790 Euro) in 2013. This is a change by around three (two) percent.

Table 3.3 shows the trends in yearly mean real (equivalized) disposable incomes by component and family type between 2009 and 2013. Differentiating between family type reveals that children living with single parents experience the lowest mean real equivalized disposable cash income. On the other hand, children living with single parents profit from in-kind benefits in absolute and relative terms the most: In 2009, their mean real income from in-kind benefits summed up to 5,781 Euro which is 38.6% of cash income. For children living with cohabiting and married couple families the same share was only 21.9% and 22.0%, respectively. In 2013, levels have increased to 6.003 Euro (44.0% of cash income) for children living with single parents, 4.286 Euro (22.2% of cash income) for children living with cohabiting parents, and 5.087 Euro (23.9% of cash income) for children living with married parents.

The monetary value of parental childcare time tends to be the lowest for children living with married couple parents. In 2009, the mean real equivalized transfer added from parental childcare time was 11,022 Euro for children living with married couple parents compared to an average of 11,986 Euro for children living with a single parent when applying the housekeeper wage approach. Similar patterns are observed on lower levels when using the opportunity cost approaches. At the same time, overall trends are unambiguous: real disposable income from parental childcare time has mostly decreased over time for all children but for children living with cohabiting parents when using the opportunity cost approaches.[25]

In addition, disposable cash income differences between children living with single parents and children living with married parents are notably reduced by the extension of the income definition. In 2009, the cash income ratio between these two groups amounted to 68.6%, whereas the extended income ratio was 86.9% when using the housekeeper wage approach. If the OLS and Heckman approaches are used, instead, the extended income ratios were 85.5% and 85.6%, respectively. In 2013, the cash income ratio decreased to 64.0%, while the extended income ratio did almost not change and was 86.5% when using the housekeeper wage approach. If the OLS and Heckman

[25]This result might just be driven by the relatively low sample size of children living with cohabiting parents which is 700 to 900 children per year.

approaches are used, the extended income ratios slightly decreased to 83.3% and 84.6%, respectively. All in all, the extended income ratios are always higher than the initial cash income ratio such that the transfers added from parental childcare time, and public childcare and education tend to equalize the income distribution. At the same time, single parents were able to slightly lower the gap in real disposable cash incomes, too. The distributional effects are discussed in more detail in the next section.

3.3.2 Distributional Effects

The results presented so far already suggest that the extension of the income definition is accompanied by large changes in the distribution of children's disposable resources. A first glimpse into the direction of the distributive effect of each extended income component can be drawn from investigating the relationship between disposable cash income and each component.

Table 3.1 depicts the pairwise correlation coefficients between disposable cash income and income from parental childcare as well as income from public childcare and education. First of all, there is a very small and positive correlation between cash income and income from in-kind benefits. This might be explained by two factors: first, the amount of transfers from schooling only depends on the federal state a child lives in at the time of the survey but not on the disposable cash income of its parents. Splitting up in-kind benefits into benefits from schooling on the one hand and benefits from publicly provided childcare on the other hand reveals that the correlation coefficient between disposable cash income and transfers from schooling is statistically insignificant different from zero at the 90% level across all years (not displayed here). Second, the small positive correlation is mainly explained by the transfers received from publicly provided childcare. This would be in line with the findings of (Schober and Stahl, 2014) who show that the probability of using publicly provided childcare is the highest among better educated, married women in East and West Germany followed by single mothers. Therefore, it seems to be plausible not to find a linear relationship between disposable cash income and transfers from public in-kind benefits.

In contrast, the correlation between income from parental childcare based on the housekeeper wage approach and cash income is unambiguously negative. Therefore, it tends to equalize the income distribution due to a simple mechanism: the housekeeper wage rate is flat and the same for all parents. Thus, it narrows the income distribution. At the same time, cash income is positively correlated with income from parental childcare time regarding both opportunity cost approaches. Therefore, the opportunity cost approaches tend to reproduce existing cash income inequalities, because it reproduces inequalities from existing differences in the productivity of children's parents that are highly correlated with their market cash income and, accordingly, their disposable cash income.

Since children from single parent families are more likely to be found in the lower part of the initial disposable cash income distribution (not shown here; also see OECD, 2011), a closer look at the different regions of the cash and extended income distribution is also of great interest. Figure 3.2 provides insights into this question by showing the relative change in mean disposable incomes by the initial cash income quintiles for each year. In general, all children benefit from adding transfers from parental childcare time, and public childcare and education, but the relative increase in extended income is the largest for children from the lowest quintile.

In 2009, extended income of the first quintile was 187% larger than cash income when using the housekeeper wage approach. Using the opportunity cost approaches has smaller effect sizes: 127% (OLS) and 131% (Heckman). Although the effect diminishes with higher quantiles, mean extended incomes are still 44% larger in the fifth quintile than the respective cash incomes when using the housekeeper wage approach. The increase of mean incomes according to the opportunity cost approaches is 49 to 50% for the fifth quintile, but differences are less severe in this quintile. In 2013, the effect size is slightly smaller such that extended income of the first quintile is 171% larger than cash income when using the housekeeper wage approach. Using the opportunity cost approaches results in an increase of 117% (OLS) and 126% (Heckman). In the fifth quintile, mean extended incomes are still 43% larger than the respective cash incomes when using the housekeeper wage approach. Again, the increase of mean incomes is larger when using the opportunity cost approaches (around 53 to 54%).

In addition to these findings, Table 3.4 depicts the weighted (cumulative) income shares by cash income deciles for each income definition and for each year. In general, extending the income definition increases the income shares of all deciles up to the 7th percentile. The magnitude of the effects slightly varies with either using the housekeeper wage approach or the opportunity cost approaches, but similar patterns can be observed across all years. Furthermore, the redistributive impact of public childcare and education is especially strong for the bottom 50% of the initial cash income distribution (column "CI+IKB"). This becomes apparent if, for example, the differences in income shares between columns "CI+IKB" and "EI(HM)" are investigated more closely: Most of the increases in income shares are already explained by adding the value of public in-kind benefits (column "CI+IKB") to disposable cash income. Adding transfers from parental childcare to cash income and income from in-kind benefits even slightly decreases income shares (column "EI(HM)") such that existing differences in cash income are reproduced. This is another hint that public in-kind benefits are highly redistributive and benefit children from low and middle income families the most. Finally, the estimated cumulative income shares already imply that the extended income Lorenz curves will lie straight above the Lorenz curve of initial cash income. Thus, extended incomes are very likely to be more equally distributed than cash incomes and have a welfare increasing effect.

Figure 3.3 shows the impact of extending the income definition on the distribution of children's disposable cash and extended incomes in Germany between 2009 and 2013. Major results are that extended income inequality is significantly lower than disposable cash income inequality across all years and that the extension does not change distributional trends significantly. Furthermore, extended income inequality is the lowest if the monetary value of childcare is measured in terms of the housekeeper wage approach. This is as expected, since applying a flat wage rate to differently productive individuals will automatically narrow the income distribution by more than any approach allowing for heterogeneity. The redistributive impact of public in-kind benefits is also noteworthy since inequality measured by the Gini coefficient is already reduced by eleven to fourteen percent. Regarding the opportunity cost approaches only, public in-kind benefits explain most of the reduction in inequality while parental childcare plays a minor role in equalizing the initial cash income distribution.

The Gini coefficient of disposable cash and extended income did not significantly change at the 5% level over time. However, a decreasing trend can be observed for cash incomes which would be in line with the increase of the cash income ratio between children from single and married parents observed before. At the same time, extended income inequality did slightly increase by 4.4% (Housekeeper), 3.5% (OLS), and 4.1% (Heckman) regarding the extended income approaches. However, this is largely driven by the increase between 2012 and 2013.[26] Before 2013, there is also a declining trend of the Gini coefficient. Adding the value of public in-kind benefits to disposable cash income yields similar results.

The inequality reducing effects of extending the income definition are even more pronounced if measures are used that are more sensitive for changes at the tails of the income distribution, namely the Mean Logarithmic Deviation (MLD) coefficient and half the squared coefficient of variation (HSQCV). As depicted in Panel b of Figure 3.3, extending the income definition reduces the Gini coefficient by around 11% to 33% across all years and approaches, while the MLD coefficient is decreased by 20% to 55%. The equalizing effect is the largest if HSQCV is considered which is more sensitive to

[26] The income year 2013 is the first year that contains valid information on childcare time for individuals from the IAB-SOEP Migration Sample. Thus, the increase between 2012 and 2013 is very likely to be driven by the integration of this new sub-sample despite the use of individual cross-sectional weighting factors provided by the SOEP.

changes at the top: income inequality is decreased by 25% to 60%. Note that the differences between the OLS and the Heckman selection correction model are, again, only marginal.

Furthermore, a decomposition of extended income inequality by income source is performed to unravel the relative contribution of each component to overall inequality. Inequality is measured by half the squared coefficient of variation (HSQCV), which can be exactly decomposed by income source, is mean independent, and can handle zero values (see Shorrocks, 1982). Income definitions remain unchanged, i.e. disposable cash income is equivalized using the modified OECD scale, disposable income from parental childcare time is equivalized using a modified square root scale, and disposable income from in-kind benefits is measured on an individual basis.

As depicted in Table 3.6, income components are differently distributed and vary in their contribution to overall extended income inequality. Disposable cash incomes are more equally distributed than incomes from parental and non-parental childcare and education. At the same time, disposable cash income contributes to total extended income inequality the most, while in-kind benefits the least. The share of cash income varies between 54% and 71% depending on the respective year and approach to evaluate parental childcare time; the share is larger if parental childcare is evaluated by the housekeeper approach, which is due to lower average wage rates given the same distribution of parental childcare hours.

An unexpected finding is the small, positive contribution of in-kind benefits to overall inequality. It varies between two and six percent and shows a slight increasing trend over time. Since inequality is remarkably lower in the joint distribution of extended income, a negative contribution of in-kind benefits was actually expected. This positive contribution is very likely to be explained by the small but positive correlation between total extended income and income from in-kind benefits. Accordingly, children with command over higher disposable cash incomes also receive a slightly higher amount of in-kind benefits. This is backed up by the finding that the absolute mean value of received in-kind benefits generally rises with disposable cash income quintiles. In 2009, for example, the first quintile received in-kind benefits of 4,655 Euro on average, while the fifth quintile got 5,164 Euro. However, the relative income increase is larger for low income children. Similar patterns are observed across all years.

Therefore, adding the monetary value of in-kind benefits to disposable cash incomes increases the absolute distance between extended incomes but, at the same time, decreases the relative distance of incomes to each other and to the mean. The latter is the crucial determinant for the reduction of inequality in extended incomes. Hence, although in-kind benefits are more unequally distributed than cash incomes and show a positive proportional contribution to extended income inequality in the decomposition framework, they reduce the relative distance between disposable extended incomes and, thus, extended income inequality.[27] The same argumentation can be applied to the income generated from parental childcare time.

Moreover, a decomposition of HSQCV by family type reveals that cash and extended income inequalities are mainly due to differences within family types (see Table A.2.10 in the Appendix). In contrast, the effect of changing family patterns seems to be negligible, although differences between family types have slightly increased over time.

However, comparing inequality coefficients is not sufficient to make reliable social welfare comparisons. Therefore, Figure 3.4 depicts generalized Lorenz curves for each year to evaluate and rank the different income distributions on welfare grounds. Since all three extended income distributions strictly lie above the cash income distribution showing no points of intersection with the said, each of them is clearly dominating the cash income distribution. Thus, they are welfare superior. Considering the cash distribution including the value of in-kind benefits only, already leads to a higher welfare level compared to the initial cash income distribution.

3.3.3 Robustness Check

So far, the value of parental childcare time has been calculated using information on parental childcare hours on an average weekday. In doing so, it has been shown that single parents spend less hours on childcare than married or cohabiting couple parents. However, it is conceivable that single parents can compensate the lack of time during the week by spending more hours with their children at the weekend. If this is the case, the equalizing effect of parental childcare time could be more pronounced. Thus, hours of parental childcare on an average Saturday and Sunday are considered in a robustness check to determine the value of parental childcare time.

However, there are some limitations to this analysis that should be mentioned. On the one hand, there is a severe difference in the decision problem parents face during the week and at the weekend. The vast majority of parents do not have to choose between paid market work and unpaid childcare at the weekend, and public childcare and schooling are not provided as a substitute for parental care. Hence,

[27]Incomes from in-kind benefits and parental childcare time tend to be more unequally distributed than cash income since the share of valid zero observations is much higher. For instance, a three year old child receives a value of zero Euro from in-kind benefits if only his parents take care of him. At the same time, a three year old is not going to school and, thus, receives no income from education. Comparing all three distributions for values larger than zero changes the picture such that cash incomes are distributed most unequal.

opportunity costs as well as the costs of professional childcare should differ substantially between the weekend and the week. On the other hand, time use information on Saturdays and Sundays is only available biannually in the SOEP core samples such that information is missing for the survey years 2010, 2012, and 2014 (income years 2009, 2011, and 2013). Nevertheless, by integrating the SOEP-related FiD survey there is at least some information for 2012 (income year 2011). However, information on the before mentioned years has to be largely imputed which introduces uncertainty into the analysis.

Imputation is done in two consecutive steps: In a first step, missing values in t, $t \in \{2010, 2012, 2014\}$, are logically imputed for parents with dependent children aged 13 or below by using the average of $t-1$ and $t+1$ whenever information on both neighbouring years is available. If information is only available for one of the two years, the information from the year available is used if the condition of a dependent child living in the household is fulfilled. In 2012, imputation is only done for sub-samples A-K, i.e. excluding sub-samples from the FiD. For 2014, either the average of $t-1$ and $t-2$ is used or just the information from $t-1$ which depends on the information available. A crucial assumption in doing this logical imputation is that parents do not change their preferences on parental childcare drastically from one year to the next. This assumption might be violated whenever there are fundamental changes in life, for example unemployment, divorce, severe illness, or other life changing events. Therefore, the results from this imputation should be treated cautiously and more attention should be drawn on the years with full information, namely 2011 and 2013 (income years 2010 and 2012).

In a second step, still missing information in t is imputed by means of a predictive means matching. This is done for both sexes separately. Since this imputation approach yields continuous estimates, these are then categorized into 19 distinct categories ranging from zero to eighteen. A transformation of this kind is necessary to receive a distribution of parental childcare time that is comparable to the original data which is categorical and only states full hours ranging from zero to eighteen.[28] Histograms on the distribution of observed and imputed parental childcare time on an average Saturday and Sunday are presented in Figure A.2.4 in the Appendix.

Doing identical analyses as before, but considering information on weekends in determining the value of parental childcare time and assuming a year to have 365 working days, reveals that single parents cannot mitigate the existing differences in childcare hours emerging during the week by additional care at the weekend. In fact, existing differences are amplified which results in even larger disparities in resources

[28] See Table A.2.11 in the Appendix for the categorisation scheme.

among children (see Table A.2.6 in the Appendix for a comparison of average childcare hours on different days.)

Table 3.5 shows the trends in yearly mean real (equivalized) disposable incomes by family type between 2009 and 2013.[29] In general, the value of parental childcare time almost doubles for children living with single parents and more than doubles for children living with married couple parents across all three evaluation approaches and all years. Accordingly, including parental childcare time at weekends raises total extended incomes between 26% to 42%. At the same time, the level increase of transfers relativises the importance of disposable cash income which translates into an increase of the extended income ratios between children living with single parents and children living with married couple parents compared to the main analysis. The extended income ratio has slightly increased from 90.2% in 2009 to 91.1% in 2013 when using the housekeeper wage approach. This is 4.6 percentage points more in 2013 compared to not considering weekends. Using the opportunity cost approaches yields similar results.

The distributional impact of incorporating childcare time done at weekends is shown in Figure 3.5. The equalizing effect of parental childcare time is weaker now and for some years it is not significantly different from the disposable cash distribution any more (at the 5% level): extending the income definition reduces the Gini coefficient by around 6% to 7% across all years when using the opportunity cost approaches; without considering weekends the inequality reducing effect was between 12% to 18%. Applying the MLD coefficient and HSQCV yields qualitatively similar results, i.e. the inequality reducing effect is less pronounced. In conclusion, considering parental childcare time done at weekends in the analysis leads to an amplification of existing differences in children's resources and cushions the inequality reducing effect of parental childcare as a whole. However, it again highlights the inequality reducing effect of public childcare and education.

3.4 Conclusion

This paper is the very first to assess the redistributive impact of both private and public childcare provision and education on children's economic resources in Germany. Combining survey data from the German Socio-Economic Panel (SOEP) with administrative data from the German Federal Statistical Office covering the years 2009 to 2013, it is shown that extended income inequality is significantly lower than disposable cash income inequality across all years and that the extension of the income definition

[29] Differences to Table 3.3 occur since the number of observations slightly differs.

does not significantly change distributional trends. This finding is robust to the use of different inequality measures, too.

Furthermore, the redistributive effect of parental childcare time is largely comparable with the more general findings of, for instance, Jenkins and O'Leary (1996) for the UK, Zick et al. (2008) for the US, or Frick et al. (2012) for Germany. The latter investigate the distributional impact of adding the value of overall home production to disposable cash income for Germany in 2009. They find similar changes of income and inequality levels which are especially pronounced for households from the lower part of the initial cash income distribution. These findings are also robust to the use of different evaluation approaches of parental childcare time. However, level effects vary largely depending on the evaluation approach; using the housekeeper approach yields the largest levelling effect since a uniform wage rate is adopted to all caring parents neglecting any differences in their skill or productivity levels.

Despite this, the results also highlight the redistributive power of publicly provided childcare and schooling which reduces relative income differentials and cushions existing inequalities in disposable cash income. Paulus et al. (2010); Garfinkel et al. (2006) and Frick et al. (2011), among others, find similar patterns on the distributional effect of adding the value of public education to disposable cash income for Germany and other European countries, but their analyses are limited to single years and they do not put special emphasis on the available resources of children.

This study also shows that differences in family structures are a notable issue: children living together with a single parent are disadvantaged in terms of disposable cash income and parental childcare, but profit from public childcare and education the most. How much a child actually gains from public childcare and education - but also from parental childcare - depends on its position in the initial cash income distribution. Children from the lowest quintiles gain by far more than children from higher quintiles, at least in relative terms. And as cross-country analyses by the (OECD, 2013), among others, show it is children from single parent families who are more likely to be found in the lower parts of the cash income distribution. However, decomposing observed cash and extended income inequalities by family type also shows that differences within family types are by far more pronounced than differences between family types.

All in all, these findings provide further evidence on the hypothesis that the provision of child-related public in-kind benefits, such as public childcare and education, is a key policy instrument to mitigate the economic disadvantages experienced by children from low socio-economic background. Their equalising potential suggests that investing into the quality of public childcare may further foster equal opportunities. However, these results cannot be used to draw the conclusion that overall inequalities among children in Germany are not severe at all, since the redistributive effects of other public goods and services, like public health care, or indirect taxes, like value added taxes, have not been considered in this study. Their effect on the distribution of economic resources is not clear *a priori* and they might change the picture into the other direction. Nevertheless, the results support the allegation that disposable cash income alone is an incomplete measure of children's well-being and a limited indicator of a child's access to economic resources shaping opportunities in life.

3.5 Tables and Figures

Table 3.1: Correlations between disposable cash income and income from parental childcare time, and public childcare and education

Year	In-kind benefits	Housekeeper	OLS	Heckman
2009	0.063	-0.166	0.176	0.161
2010	0.064	-0.167	0.173	0.157
2011	0.096	-0.150	0.223	0.200
2012	0.071	-0.195	0.190	0.165
2013	0.099	-0.153	0.257	0.215

Source: SOEP (v31.1), and Federal Statistical Office, own calculations.

Table 3.2: Mean real disposable incomes by component, 2009-2013 (in Euro)

	Cash	In-kind	HK wage	Opp. cost appr.		Total extended income		
Year	income	benefits	approach	OLS	HM	HK	OLS	HM
2009	20,805	4,880	11,314	9,425	9,677	36,998	35,109	35,361
2010	20,668	5,252	10,803	9,763	10,145	36,724	35,684	36,066
2011	20,194	5,432	10,093	9,110	9,479	35,719	34,736	35,105
2012	20,710	5,495	9,958	9,319	9,783	36,163	35,524	35,988
2013	20,165	5,116	10,261	8,912	9,508	35,542	34,194	34,790

Note: All incomes and expenditures are measured in 2010 Euros. Disposable cash income is equivalized using the modified OECD scale. Incomes from parental childcare time are equivalized using a modified square root scale. In-kind benefits are not equivalized but measured on an individual basis. Abbreviations: HK = Housekeeper, OLS = Ordinary least squares model, HM = Heckman selection correction model.
Source: SOEP (v31.1) and Federal Statistical Office, own calculations.

Table 3.3: Mean real disposable incomes by component and family type, 2009-2013 (in Euro)

Year	Family type	Cash income	In-kind benefits	Opport. cost appr. HK	OLS	HM	Total extended income HK	OLS	HM
2009	Single	14,966	5,781	11,986	10,075	10,331	32,733	30,821	31,077
	Cohabiting	19,817	4,343	12,916	8,555	8,822	37,076	32,715	32,982
	Married	21,828	4,803	11,022	9,425	9,675	37,652	36,055	36,305
2010	Single	14,807	6,176	11,362	10,369	10,757	32,345	31,352	31,740
	Cohabiting	19,969	5,009	12,620	10,416	10,910	37,598	35,394	35,888
	Married	21,716	5,128	10,502	9,587	9,956	37,346	36,432	36,801
2011	Single	14,711	6,253	11,152	9,927	10,416	32,116	30,891	31,380
	Cohabiting	19,505	5,459	9,824	8,288	8,679	34,788	33,253	33,644
	Married	21,132	5,302	9,966	9,094	9,441	36,399	35,528	35,875
2012	Single	14,820	6,223	11,460	10,144	10,694	32,503	31,186	31,736
	Cohabiting	20,184	5,073	11,133	9,218	9,789	36,390	34,476	35,047
	Married	21,804	5,429	9,529	9,191	9,625	36,763	36,425	36,859
2013	Single	13,647	6,003	11,712	9,536	10,449	31,362	29,186	30,099
	Cohabiting	19,331	4,286	11,720	10,200	10,917	35,337	33,817	34,534
	Married	21,326	5,087	9,829	8,637	9,165	36,242	35,049	35,578

Note: All incomes and expenditures are measured in 2010 Euros. Disposable cash income is equivalized using the modified OECD scale. Incomes from parental childcare time are equivalized using a modified square root scale. In-kind benefits are not equivalized but measured on an individual basis. Abbreviations: HK = Housekeeper wage approach, OLS = Ordinary least squares model, HM = Heckman selection correction model.
Source: SOEP (v31.1), and Federal Statistical Office, own calculations.

Table 3.4: Income shares, 2009-2013 (weighted)

	Income shares (in percent)					Cumul. income shares (in percent)				
Decile	CI	CI+IKB	EI(HK)	EI(OLS)	EI(HM)	CI	CI+IKB	EI(HK)	EI(OLS)	EI(HM)
2009										
1	4.2	5.6	4.7	4.7	4.6	4.2	5.6	4.7	4.7	4.7
2	5.7	7.0	6.3	6.3	6.3	9.9	12.6	11.0	11.0	11.0
3	6.8	7.8	7.4	7.3	7.2	16.6	20.4	18.5	18.3	18.3
4	7.5	8.5	8.0	8.1	8.1	24.1	28.9	26.4	26.4	26.4
5	8.4	9.2	8.9	9.0	8.8	32.6	38.1	35.4	35.4	35.4
6	9.5	10.0	9.9	9.8	9.6	42.1	48.1	45.3	45.3	45.3
7	10.8	10.7	10.7	10.7	10.7	52.8	58.8	56.0	55.9	55.9
8	12.1	11.7	11.8	11.9	12.0	64.9	70.5	67.8	67.8	67.8
9	14.3	13.1	13.7	13.8	13.7	79.2	83.6	81.5	81.6	81.6
10	20.8	16.4	18.5	18.4	19.0	100.0	100.0	100.0	100.0	100.0
2010										
1	4.3	5.6	4.9	4.9	4.7	4.3	5.6	4.9	4.9	4.7
2	5.8	7.1	6.4	6.4	6.3	10.1	12.7	11.3	11.3	11.0
3	6.8	7.9	7.4	7.4	7.3	17.0	20.6	18.7	18.7	18.3
4	7.6	8.6	8.2	8.2	8.1	24.5	29.2	26.9	26.9	26.4
5	8.4	9.3	9.0	8.9	8.8	32.9	38.5	35.9	35.9	35.2
6	9.5	9.9	9.8	9.8	9.7	42.4	48.4	45.7	45.7	44.9
7	10.6	10.7	10.6	10.6	10.7	53.0	59.1	56.3	56.3	55.6
8	11.9	11.5	11.8	11.8	11.9	65.0	70.6	68.1	68.1	67.4
9	14.2	13.0	13.5	13.5	13.8	79.2	83.6	81.6	81.6	81.2
10	20.8	16.4	18.4	18.4	18.8	100.0	100.0	100.0	100.0	100.0
2011										
1	4.4	5.7	4.9	4.9	4.8	4.4	5.7	4.9	4.9	4.8
2	5.8	7.1	6.5	6.5	6.5	10.2	12.8	11.5	11.4	11.3
3	6.7	7.9	7.3	7.4	7.3	16.9	20.7	18.8	18.8	18.5
4	7.6	8.6	8.1	8.2	8.1	24.6	29.2	26.9	27.0	26.6
5	8.5	9.2	8.9	8.9	8.9	33.1	38.5	35.8	35.9	35.5
6	9.5	9.9	9.7	9.7	9.7	42.6	48.4	45.5	45.6	45.2
7	10.8	10.7	10.6	10.6	10.7	53.4	59.1	56.2	56.2	55.9
8	12.0	11.6	11.7	11.7	11.9	65.4	70.7	67.9	68.0	67.8
9	14.3	13.0	13.6	13.5	13.6	79.6	83.7	81.5	81.5	81.4
10	20.4	16.3	18.5	18.5	18.6	100.0	100.0	100.0	100.0	100.0
2012										
1	4.5	5.8	5.1	5.1	4.9	4.5	5.8	5.1	5.1	4.9
2	5.9	7.1	6.6	6.6	6.5	10.4	13.0	11.7	11.7	11.5
3	6.9	7.9	7.5	7.5	7.4	17.3	20.9	19.2	19.2	18.8
4	7.7	8.6	8.3	8.3	8.2	25.0	29.5	27.5	27.5	27.0
5	8.8	9.3	9.0	9.0	8.9	33.8	38.7	36.5	36.5	35.9
6	9.4	10.0	9.8	9.8	9.8	43.2	48.7	46.3	46.3	45.7
7	10.6	10.7	10.7	10.7	10.7	53.8	59.4	57.0	57.0	56.4
8	12.0	11.7	11.6	11.7	11.8	65.8	71.0	68.6	68.6	68.2
9	14.1	13.0	13.5	13.3	13.6	80.0	84.0	82.1	81.9	81.8
10	20.0	16.0	17.9	18.1	18.2	100.0	100.0	100.0	100.0	100.0
2013										
1	4.3	5.1	4.4	4.4	4.5	4.3	5.1	4.4	4.4	4.5
2	5.8	6.9	6.2	6.2	6.1	10.1	12.0	10.7	10.6	10.6
3	6.7	8.1	7.3	7.3	7.2	16.8	20.1	18.0	17.9	17.8
4	7.6	8.3	8.2	8.2	8.0	24.3	28.5	26.2	26.1	25.8
5	8.5	9.2	8.9	8.9	9.1	32.8	37.7	35.0	35.0	34.8
6	9.4	10.0	9.9	9.7	9.5	42.2	47.6	44.9	44.7	44.3
7	10.6	10.8	10.6	10.7	10.7	52.8	58.5	55.5	55.4	55.0
8	12.2	11.8	11.9	11.8	12.1	64.9	70.3	67.3	67.3	67.2
9	14.3	13.2	13.7	13.6	14.0	79.3	83.4	81.1	80.9	81.1
10	20.7	16.6	18.9	19.1	18.9	100.0	100.0	100.0	100.0	100.0

Note: Deciles are calculated from the initial disposable cash income distribution. Abbreviations: CI = Cash income, IKB = In-kind benefits, EI = Extended income, HK = Housekeeper wage approach, OLS = Ordinary least squares model, HM = Heckman selection correction model. *Source*: SOEP (v31.1), and Federal Statistical Office, own calculations.

Table 3.5: Mean real disposable incomes by component and family type (including weekends), 2009-2013 (in Euro)

Year	Family type	Cash income	In-kind benefits	Housekeeper wage appr.	Opport. cost appr. OLS	Opport. cost appr. HM	Total extended income HK	Total extended income OLS	Total extended income HM
2009	Single	14,989	5,782	23,427	19,451	19,844	44,198	40,222	40,615
	Cohabiting	19,863	4,369	26,471	18,703	19,071	50,703	42,935	43,302
	Married	21,799	4,804	22,400	19,643	20,001	49,003	46,247	46,605
2010	Single	14,818	6,168	22,824	20,398	21,040	43,810	41,383	42,025
	Cohabiting	20,150	5,012	25,863	21,696	22,435	51,024	46,858	47,596
	Married	21,799	5,138	20,536	19,111	19,642	47,474	46,048	46,579
2011	Single	14,609	6,254	23,054	19,609	20,478	43,917	40,472	41,340
	Cohabiting	19,356	5,429	22,191	18,344	19,032	46,976	43,129	43,817
	Married	21,201	5,258	20,485	19,123	19,672	46,945	45,582	46,131
2012	Single	14,846	6,180	22,406	19,353	20,257	43,432	40,380	41,284
	Cohabiting	20,296	4,955	22,119	18,894	19,766	47,371	44,145	45,017
	Married	21,961	5,433	19,546	18,991	19,621	46,940	46,385	47,015
2013	Single	13,584	5,994	25,018	21,140	22,783	44,597	40,718	42,362
	Cohabiting	19,367	4,120	22,754	20,308	21,355	46,242	43,796	44,843
	Married	21,211	5,052	22,686	19,942	20,762	48,949	46,205	47,025

Note: Hours of parental childcare on Saturdays and Sundays are fully imputed for income years 2009, 2011 and 2013, and partly imputed for 2012 by means of logical imputation and predictive mean matching using information from income years 2008, 2010, and 2012. All incomes and expenditures are measured in 2010 Euros. Disposable cash income is equivalized using the modified OECD scale. Incomes from parental childcare time are equivalized using a modified square root scale. In-kind benefits are not equivalized but measured on an individual basis. Abbreviations: HK = Housekeeper, OLS = Ordinary least squares model, HM = Heckman selection correction model.
Source: SOEP (v31.1), and Federal Statistical Office, own calculations.

Table 3.6: Decomposition of GE(2) by income source

Extended Income (Housekeeper Wage Approach)

	2009 HSQCV	Share ($100 \times s\_y$)	2010 HSQCV	Share ($100 \times s\_y$)	2011 HSQCV	Share ($100 \times s\_y$)	2012 HSQCV	Share ($100 \times s\_y$)	2013 HSQCV	Share ($100 \times s\_y$)
Equival. disposable cash income	0.120	68.20	0.123	70.90	0.112	69.76	0.104	68.16	0.115	65.08
Unequival. income from in-kind benefits	0.162	1.74	0.154	2.42	0.141	4.16	0.136	4.08	0.198	5.67
Equival. income from parental care (HK)	0.239	30.06	0.238	26.68	0.232	26.09	0.253	27.76	0.264	29.25
Total	0.050	100	0.049	100	0.047	100	0.044	100	0.052	100

Extended Income (Opportunity Cost Approach - OLS)

	2009 HSQCV	Share ($100 \times s\_y$)	2010 HSQCV	Share ($100 \times s\_y$)	2011 HSQCV	Share ($100 \times s\_y$)	2012 HSQCV	Share ($100 \times s\_y$)	2013 HSQCV	Share ($100 \times s\_y$)
Equival. disposable cash income	0.120	61.73	0.123	62.43	0.112	59.39	0.104	59.65	0.115	57.63
Unequival. income from in-kind benefits	0.162	3.07	0.154	2.82	0.141	3.88	0.136	3.79	0.198	5.02
Equival. income from parental care (OLS)	0.327	35.19	0.308	34.75	0.336	36.72	0.311	36.57	0.373	37.35
Total	0.078	100	0.076	100	0.077	100	0.069	100	0.086	100

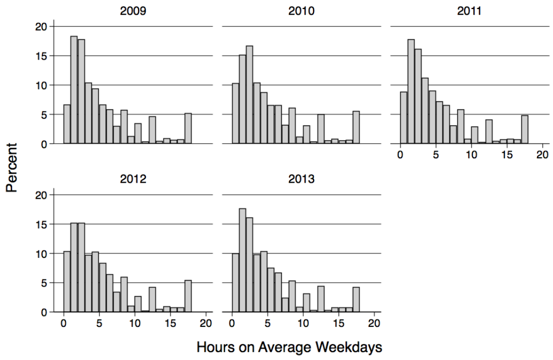
Extended Income (Opportunity Cost Approach - Heckman)

	2009 HSQCV	Share ($100 \times s\_y$)	2010 HSQCV	Share ($100 \times s\_y$)	2011 HSQCV	Share ($100 \times s\_y$)	2012 HSQCV	Share ($100 \times s\_y$)	2013 HSQCV	Share ($100 \times s\_y$)
Equival. disposable cash income	0.120	60.60	0.123	61.05	0.112	58.20	0.104	57.87	0.115	54.43
Unequival. income from in-kind benefits	0.162	2.83	0.154	2.45	0.141	3.60	0.136	3.30	0.198	4.49
Equival. income from parental care (HM)	0.335	36.57	0.313	36.50	0.339	38.20	0.319	38.83	0.402	41.08
Total	0.078	100	0.076	100	0.076	100	0.069	100	0.087	100

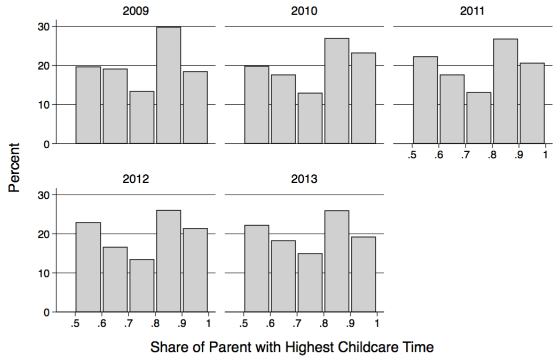
Note: Stata module ineqfac was used for decomposition (Jenkins, 2009).
Source: SOEP (v31.1), and Federal Statistical Office, own calculations.

Figure 3.1: Distribution of parental childcare time on an average weekday within and between families, 2009-2013

(a) *Between families*

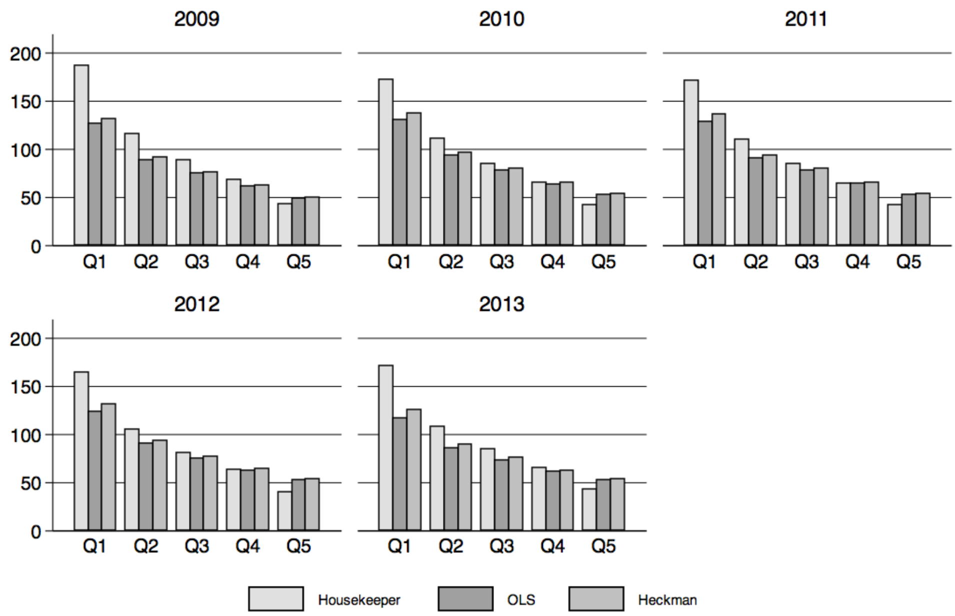


(b) *Within families (excl. singles)*



Note: Restricted to families having children aged 13 years or below.
Source: SOEP (v31.1), own calculations.

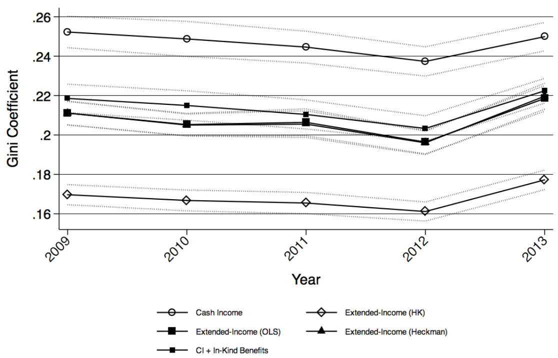
Figure 3.2: Relative change in mean real extended incomes across cash income quintiles by year



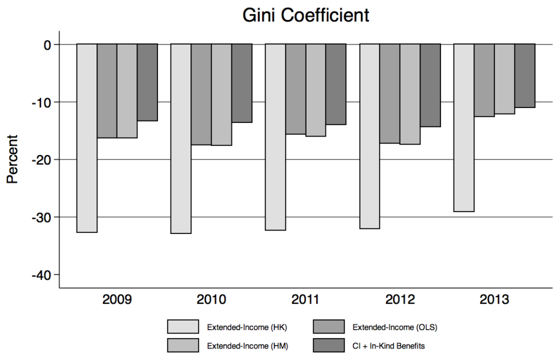
Source: SOEP (v31.1), and Federal Statistical Office, own calculations.

Figure 3.3: Trends in disposable cash and extended income inequality, 2009-2013

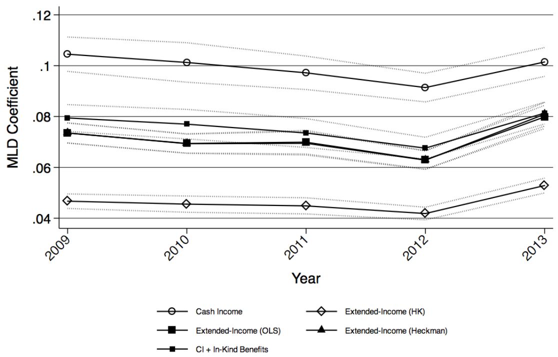
(a) Gini



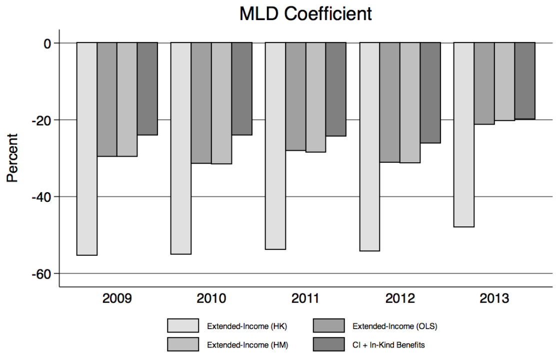
(b) Relative change of Gini coefficient



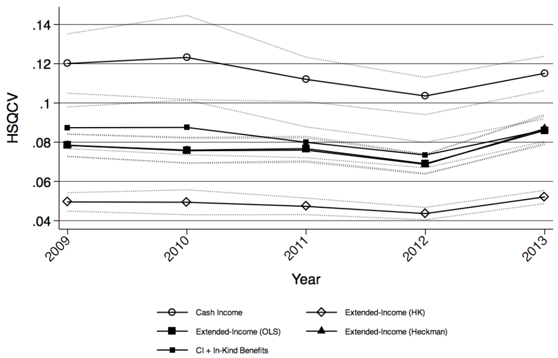
(c) MLD



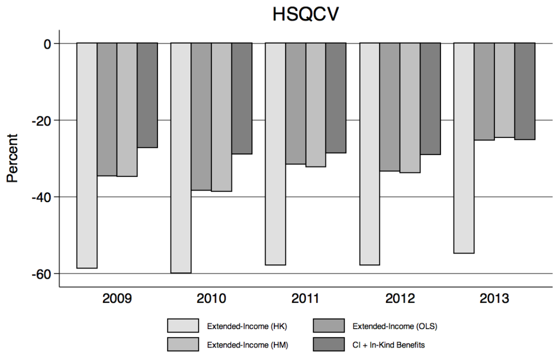
(d) Relative change of MLD coefficient



(e) HSQCV

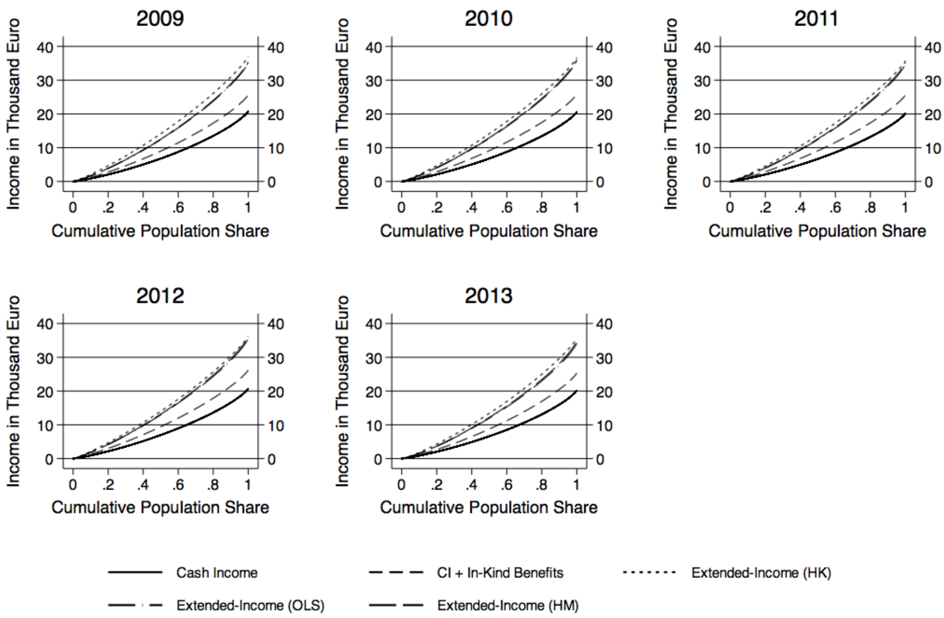


(f) Relative change of HSQCV



Note: Significance at the five percent level is calculated using bootstrap standard errors with 100 replications.
Abbreviations: HK = Housekeeper wage approach, OLS = Ordinary least squares model, HM = Heckman selection correction model.
Source: SOEP (v31.1), and Federal Statistical Office, own calculations.

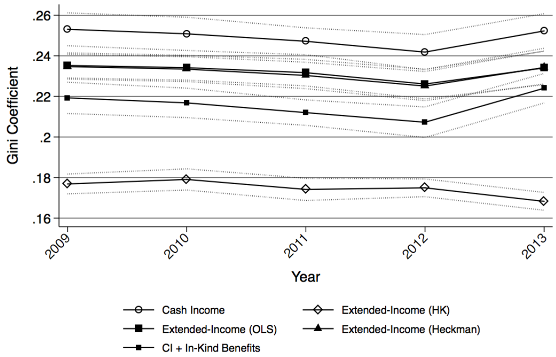
Figure 3.4: Generalized Lorenz curves of disposable cash and extended income, 2009-2013



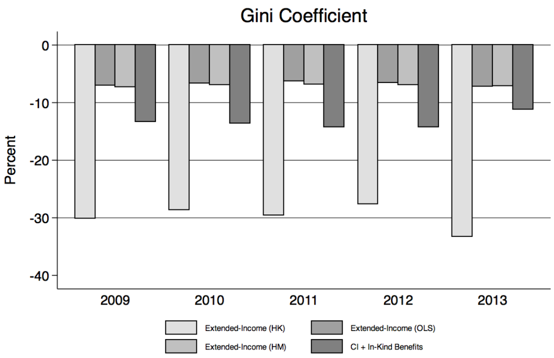
Abbreviations: HK = Housekeeper wage approach, OLS = Ordinary least squares model, HM = Heckman selection correction model.
Source: SOEP (v31.1), and Federal Statistical Office, own calculations.

Figure 3.5: Trends in disposable cash and extended income inequality (including weekends), 2009-2013

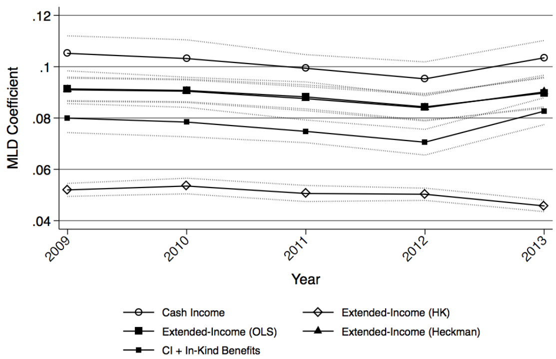
(a) Gini



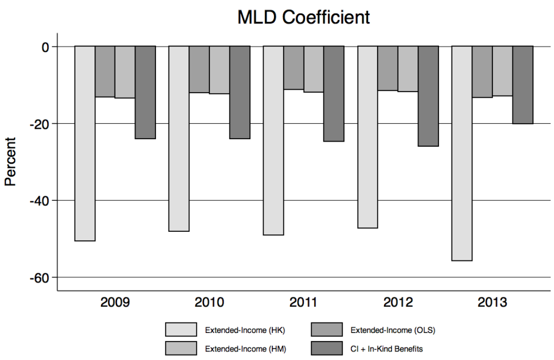
(b) Relative change of Gini coefficient



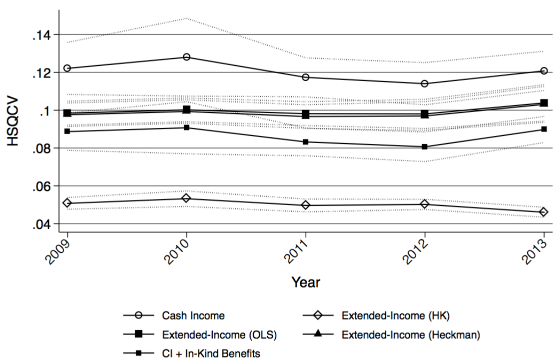
(c) MLD



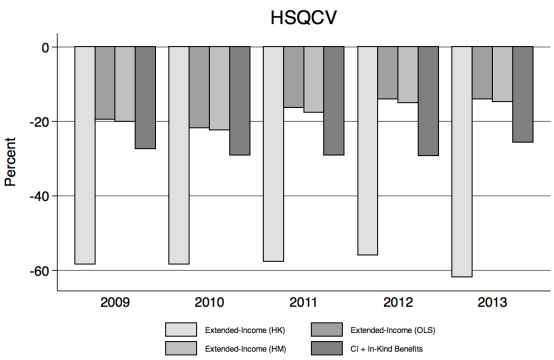
(d) Relative change of MLD coefficient



(e) HSQCV



(f) Relative change of HSQCV



Note: Significance at the five percent level is calculated using bootstrap standard errors with 100 replications. Hours of parental childcare on Saturdays and Sundays are fully imputed for income years 2009, 2011 and 2013, and partly imputed for 2012 by means of logical imputation and predictive mean matching using information from income years 2008, 2010, and 2012.
Abbreviations: HK = Housekeeper wage approach, OLS = Ordinary least squares model, HM = Heckman selection correction model.
Source: SOEP (v31.1), and Federal Statistical Office, own calculations.

Chapter 4

Dynastic Inequality Compared: Multigenerational Mobility in the US, the UK, and Germany

4.1 Introduction

In many developed countries, the levels of income concentration experienced by current generations are as high as those experienced by their ancestors at the beginning of the 20th century (Piketty, 2014). Although trends of cross sectional inequality are informative in themselves, they neglect the movement of families within the income distribution - as well as their opportunities to improve their socio-economic status - over the course of time. Indeed, theories of justice suggest to focus on both dimensions of inequality: the static dimension, i.e. the income distribution at a given point in time, and the dynamic dimension (Rawls, 1971). The latter can be evaluated analysing the persistence of inequality between generations, or rather its antonym: social intergenerational mobility.

Recently, the relevance of the intergenerational dimension for distributional analyses has gained increasing attention by researchers and policy makers. A growing number of studies evaluates social intergenerational mobility measuring the degree of association between parents' and children's outcomes (e.g. income, earnings, occupation, or educational attainment). However, while this procedure seems to be suitable as a broad measure for equality of opportunity in a society (Chetty et al., 2014b; Corak, 2013), it is still not clear whether it leads to erroneous conclusions about the persistence of inequality in the long run. For instance, empirical studies show that long run mobility tends to be overestimated if it is extrapolated from the canonical two-generational mobility framework (e.g. Lindahl et al., 2015). Generally, the existing evidence is still mixed and refers to single countries. Researchers drew contrasting conclusions about, first, the long run persistence of socio-economic status, and, second, the existence of a direct effect that grandparents exert on the economic outcomes of their grandchildren. Therefore, it is of scientific importance and political relevance to add further evidence and to empirically verify different facets of intergenerational mobility over multiple generations. One of the main contributions of this study is to provide a comprehensive analysis on the subject in a common framework using harmonized data for three countries with different welfare regimes, the US, the UK, and Germany.

From a normative perspective, the analysis of long run intergenerational persistence of social status is crucial for a social planner who strives to *level the playing field*. Inasmuch, as the degree of intergenerational mobility of today's adults reflects the distribution of opportunities of yesterday's children, the analysis of mobility over three consecutive generations mirrors the circumstances faced by parents investing in their children's human capital. Hereby, since the vast recent literature on multigenerational persistence mainly focuses on single countries, it is valuable to evaluate the role played by the historical and institutional context. In this work, we therefore analyse the long run transmission of social status in three countries with very different institutional characteristics and historical backgrounds, providing comparable and consistent estimates of intergenerational mobility over three generations.

We perform the analysis with data from nationally representative household surveys that allow us to link individuals to their parents' and grandparents', and to reconstruct the educational history of families over three consecutive generations. The surveys are highly comparable and enable us to perform a harmonized cross-country analysis, testing recent theories of multigenerational persistence like Gregory Clark's controversial hypothesis of a "universal law of social mobility" (Clark, 2014). Furthermore, we test for the existence of a direct and independent effect that grandparents exert on their grandchildren, i.e. the part of the association between outcomes which is not mediated by parents. Additionally, to the best of our knowledge, we are the first to empirically account for ethnic capital – i.e the quality of the ethnic environment in which parents make their investments (Borjas, 1992) – within a multigenerational set-up.

Our main findings are the following: We find the strongest association between grandparents' and grandchildren's educational attainment in Germany and substantially lower associations in the UK. The US lies in between. Furthermore, we provide evidence that questions Clark's hypothesis of a fairly low and constant rate of social mobility over time and space. Although we cannot reject all implications of Clark's hypothetical construct, his strongest conclusion that the long run persistence of social status is independent of the specific historical and institutional context finds no support in our data. In particular, we even find cross-country differences in the effect of direct interaction between grandparents and grandchildren.

The remainder of this paper is organized as follows: In Section 4.2 we review the literature on multigenerational mobility and introduce some of the most influential theories of long run persistence. Section 4.3 describes the data. Section 4.4 presents descriptive evidence on intergenerational mobility over two and three generations in the US, the UK, and Germany: First, assessing multigenerational mobility as equalizer of dynastic inequality in 4.4.1; Then, accounting for short-run and long-run mobility trends in 4.4.2; Last, applying non-parametric approaches in 4.4.3. Our test results on the theories of multigenerational persistence are presented and discussed in Section 4.5. Section 4.6 concludes.

4.2 Conceptual Framework and Literature Review

A widely accepted approach to measure intergenerational persistence of socio-economic status is to estimate the following linear regression model:

$$y_{it} = \alpha + \beta_{-m} \cdot y_{it-m} + \varepsilon_{it}, \tag{4.1}$$

where y_{it} is an outcome indicator of the socio-economic status of individual i belonging to generation t, and y_{it-m} of her ancestors' outcomes that date back m generations. The slope coefficient β_{-m} describes how much of the outcome advantage or disadvantage is transmitted within families over m generations on average. Thus, it can be interpreted as the persistence of inequality between families over the course of time.

Such analysis is usually performed on two subsequent generations, i.e. on parents and children. Since parents are arguably the most influential source for the formation of human capital, the association between parents' and children's outcomes is certainly of primary interest. Furthermore, although the channels of transmission are still not fully investigated, it generally seems plausible to assume a direct effect of parents on their children. Indeed, seminal theoretical contributions in economics on the intergenerational transmission of inequality build on a mainly two generational set up (Becker and Tomes, 1979, 1986; Loury, 1981; Solon, 1992). In addition, in many available data sets it is possible and less complicated to link parents and children, in contrast to higher ordered ancestors.

If the aim is to predict or extrapolate long run mobility patterns, the straightforward method that follows from the regression based procedure presented in equation (4.1) relies on a restrictive assumption, namely that the process is autoregressive of order one, and implies that

$$\beta_{-m} \approx (\beta_{-1})^m \quad \forall m \epsilon \mathbb{N}^+.$$

The finding of a directly estimated coefficient which is higher than the extrapolation would suggest ($\beta_{-m} > (\beta_{-1})^m$) was defined as "iterated regression fallacy". Stuhler (2012), who introduced the term, proves and extensively discusses the drawbacks of the iteration based extrapolation procedure for the analysis of multigenerational mobility (see also Braun and Stuhler, 2016).

The topic came up recently because of an increasing interest in the long run persistence of economic inequality. A new wave of studies by economists and sociologists emerged that analyses intergenerational mobility over three or more generations with different methodologies. While older studies mostly did not reject the hypothesis that the underlying process of intergenerational transmission of socio-economic status is of Markovian nature – i.e. that the socio-economic status of grandparents and older ancestors is totally mediated by the status of parents – recent studies basically reject this hypothesis and agree that the iterated extrapolation underestimates the long run persistence of economic inequality. For instance, earlier empirical works on multigenerational mobility did not find any significant association between grandparents' and grandchildren's outcomes, when controlling for parental outcomes (Behrman and Taubman, 1985; Peters, 1992; Ridge, 1974; Warren and Hauser, 1997).[1] This first line of research was, however, more focused on testing the implication of a negative grandparental coefficient as theorized by Becker and Tomes (1979) or finding a direct causal effect of grandparents.

In contrast, recent studies test the iteration procedure against direct or grouped observational data over three or more generations. One of the first empirical studies to show that an extrapolation by iteration might not fully capture the actual degree of intergenerational persistence is Lindahl et al. (2015) using longitudinal data from the Swedish Malmö study. Other recent studies mainly support these findings measuring intergenerational associations over three, four, or even more generations.[2] Two promi-

[1]One exemption is Hodge (1966) who rejects the hypothesis of a first-order Markov chain in the transmission of occupations. For a review of earlier literature on multigenerational mobility, see also Warren and Hauser (1997).

[2]Recent studies evaluate the intergenerational persistence of distinct outcomes over three or more generations, such as earnings (Lindahl et al., 2015; Lucas and Kerr, 2013), wealth (Adermon et al., 2015), occupation (Chan and Boliver, 2013; Hertel and Groh-Samberg, 2014; Knigge, 2016), education (Braun and Stuhler, 2016; Celhay and Gallegos, 2015; Kroeger and Thompson, 2016), cognitive abilities (Hällsten, 2014), longevity (Piraino et al., 2014), and mental health (Johnston et al., 2013). Studies that measure the transmission over more than four generations mostly do not rely on direct family linkages, but instead use the informative content of surnames (Barone and Mocetti, 2016; Clark and Cummins, 2015; Collado et al., 2013). Olivetti et al. (2014) estimate intergenerational mobility over three generations using first names. The only studies, apart from the present work, to analyse multigenerational mobility in a framework including more than one country are Clark (2014) and

nent approaches try to explain this divergence between the predicted and the actual degree of intergenerational persistence. The first argues in favour of a so-called *latent factor* that determines the transmission of socio-economic status (Clark, 2014; Clark and Cummins, 2015). The second states that there is a direct and causal effect that grandparents exert on their grandchildren (Mare, 2011, among others).

A commonly adopted way to evaluate the statistical association between grandparents and grandchildren, abstracting from the mediating role of parents, is to estimate a regression which includes both the socio-economic status of parents and grandparents:

$$y_{it} = a + b_{-1} \cdot y_{it-1} + b_{-2} \cdot y_{it-2} + \vartheta_{it}. \tag{4.2}$$

Hereby, a positive significant coefficient of grandparents is often interpreted in the sense that an independent effect of grandparents persists over and above the effect of parents. However, as Braun and Stuhler (2016), Solon (2014), and Stuhler (2012) point out, the observation of a significant coefficient for grandparental outcomes does not automatically signalize a causal relationship. A direct causal effect of grandparents is a possible explanation, but omitted variable bias could explain a positive grandparental coefficient as well. Omitted variables could be, for instance, the education or occupational status of the other parent. *Ethnic capital*, understood as the quality of the ethnic environment in which parents make their investments, might be another factor of interest, which has been found to play an important role for the intergenerational transmission of human capital (Borjas, 1992). Indeed, the *latent factor model* argues that b_{-2} is positive and significantly larger than zero when estimating equation (4.2), because the variable included to measure the socio-economic status of grandparents captures an unobserved part of parents' socio-economic status which is fundamental for the intergenerational transmission mechanism; i.e. any kind of endowment, like abilities, preferences, or cultural heritage (see Clark and Cummins, 2015).

4.2.1 The Latent Factor Model

Braun and Stuhler (2016) formalize the association between the observable outcome y_{it} and the unobservable endowment e_{it} following the *latent factor model* as

$$y_{it} = \rho e_{it} + u_{it} \tag{4.3}$$

$$e_{it} = \lambda e_{it-1} + v_{it} \tag{4.4}$$

Hertel and Groh-Samberg (2014). For recent exhaustive overviews, see Pfeffer (2014); Solon (2014).

in a one-parent one-offspring family setting, assuming that both error terms u_{it} and v_{it} are uncorrelated with other variables and past values. The parameter λ can be interpreted as a "heritability" coefficient and captures the degree of unobservable endowments passed on from generation $t-1$ to generation t. The parameter ρ is called "transferability" coefficient and measures the scope of inherited endowments that can be converted into the observed outcome. If the variances of y_{it} and e_{it} are normalized to one, the observed correlation in outcome y between generation t and generation $t-m$ comes up to

$$\beta_{-m} = \rho^2 \lambda^m. \tag{4.5}$$

Therefore, multigenerational persistence is higher if both the degree of inheritability λ and transferability ρ is higher. As Braun and Stuhler (2016) show, estimating equation (4.1) for children's on parents' status and grandparents' status separately, using direct individual observations which can be linked over three generations (instead of grouped observations over surname groups as in Clark and Cummins, 2015), λ and ρ can be identified as

$$\frac{\beta_{-2}}{\beta_{-1}} = \frac{\rho^2\lambda^2}{\rho^2\lambda} = \lambda, \tag{4.6}$$

$$\sqrt{\frac{(\beta_{-1})^2}{\beta_{-2}}} = \rho. \tag{4.7}$$

Since constant variances are assumed, the regression coefficients equal the correlation coefficients. Adopting this specification, Braun and Stuhler (2016) test the hypothesis made by Clark (2014) on the heritability coefficient λ, and on the existence of a "universal law" of multigenerational persistence, i.e. the true rate of intergenerational persistence is almost the same in every country and time period. Using their own estimated correlations for Germany and the estimates in Lindahl et al. (2015) for Sweden, they find evidence against a constant heritability coefficient. Besides, their estimates for λ are significantly lower than the value suggested by Clark (0.75).[3]

4.2.2 The Grandparental Effect Model

Another branch of research tries to explain the excess persistence arguing that differences in status inequality across generations are not exclusively transmitted from

[3]Further evidence against such a high heritability coefficient is provided in a recent study by Nybom and Vosters (2015) within a two-generational set up. Including multiple proxy measures of parental background into a single estimate of status persistence, the authors find no evidence of bias in prior estimates of social intergenerational mobility in Sweden.

parents to children. Grandparents might exert a direct and independent effect on their grandchildren, too, for example by investing in their grandchildren's human capital and by shaping their preferences while living in the same multigenerational household (e.g. Mare, 2011; Pfeffer, 2014). Other sorts of direct effects of grandparents could lie in the genetic transmission of certain traits that "jump" a generation, the strength of family networks or reputation, and the role of inheritances.[4] All these are possible explanations of a positive significant grandparental coefficient in equation (4.2) which go beyond technical issues like measurement error and omitted variable bias as discussed above.[5] So, to test for a direct effect of grandparents, abstracting from merely technical reasons driving the statistical relationship, requires an extension of the baseline model displayed in equation (4.2).

A common approach is to include additional variables to control for other socio-economic characteristics of the parents. For instance, information on the outcomes of both fathers and mothers are included in the regression instead of taking only the highest or the mean of the two. This way, unobserved characteristics that might explain the underlying transmission of status are covered more properly and a positive significant grandparental coefficient is a closer indicator of a direct relationship. However, the grandparental coefficient could still be biased upward due to the omission of other characteristics. *Ethnic capital* is an important feature that has been found to largely explain the different patterns of intergenerational transmission from parents to children between blacks and whites or natives and immigrants (e.g. Borjas, 1992). A similar relationship might also exist in a three-generational framework and is, thus, of particular importance. Our data allows to analyse this aspect controlling for migration background and race of individuals.

Another approach is to use information on direct contact between grandparents and grandchildren – or on a higher likelihood of contact between them – and compare the regression coefficients of individuals with and without direct contact to their grandparents. This method allows to account for intergenerational effects from grandparents to grandchildren generated by direct contact abstracting from those direct links that should be the same for individuals with and without a direct contact to their grandparents, which includes the genetic transmission of traits or the role of family networks. When information on exposure or co-residence are directly available, the analysis is straightforward. For example, Zeng and Xie (2014) show for rural China

[4] A discussion of the ways in which grandparents can affect their grandchildren can be found e.g. in Kroeger and Thompson (2016) and Solon (2014).

[5] For an overview of factors that might explain the excess persistence see, among others, Solon (2014). A recent theoretical examination of multigenerational persistence based on *careers* can be found in Zylberberg (2016).

that the effect of grandparental education on school drop-out is significantly stronger for coresident grandparents than for those who are not living in the same household as their grandchildren. However, when this information is not available, a common procedure is to use information on the year of death of the grandparents and check if the grandparent died before the grandchild was born, which is the identification strategy adopted also in the present study. Braun and Stuhler (2016) apply this strategy, too, and find no significant difference between the regression coefficients of grandparents who died before their grandchildren were born and grandparents who were still alive.[6]

4.2.3 Universal Law of Social Mobility and the Role of Institutions

A remarkable difference between the *latent factor model* and the *grandparental effect model* is related to their implications about the role of institutions to affect intergenerational mobility and the persistence of inequality. While the former argues that social policy interventions can only change short run patterns of social mobility, without having any effect on the long run effects of dynasties, the latter stresses the importance of the environment. Mare (2011) argues, for example, that the effect of grandparents on their grandchildren might vary between and within countries, and depend on the historical and institutional context. Indeed, recent empirical findings for different countries seem to confirm this theory. For instance, while Zeng and Xie (2014)'s findings point at the existence of a direct effect of co-resident grandparents on their grandchildren in rural China, the application of LaFave and Thomas (2017) to Indonesia shows no effect of grandparental resources on grandchildren's human capital.

To investigate the importance of the institutional context and to test the hypothesis of a "universal law" of social intergenerational mobility, we propose a novel approach. First, we analyse time trends in the intergenerational persistence of human capital over two and three generations for different cohorts. Then, we pool the samples of the three countries and allow for country-specific intercepts. Technically, this procedure should reduce the omitted variable bias deriving from differences in institutions and enable to evaluate whether a common behaviour exists between societies in the transmission of inequality over two and three generations, while abstracting from characteristics which should be equally transmitted from grandparents and parents to children across countries. In addition, as mentioned above, our data allows us to control for migration or ethnic background. Thus, we are able to model potential between-group differences

[6]Since Braun and Stuhler (2016) find a significant correlation between year of death and the education of grandparents, they present further applications using World War II as an exogenous source of variation in the time of death. All tests on this behalf confirm their main results.

in intercepts (see Solon, 2014).

4.3 Data

Our analysis is based on three very similar and nationally representative longitudinal household surveys: i) the *German Socio-Economic Panel* (SOEP) for Germany, ii) the *Panel Study of Income Dynamics* (PSID) for the US, and iii) the *British Household Panel Survey* (BHPS) for the UK which we extend by information from the follow up survey *Understanding Society* (UKHLS). Using these surveys has several advantages for our analysis: First, the data sets are highly comparable and they are designed upon similar schemes. Indeed, SOEP, PSID and BHPS/UKHLS are part of the Cross-National Equivalent File (CNEF) where different data sets are harmonized for cross-national comparisons (see Frick et al., 2007). Second, socio-economic conditions of respondents and their family members are carefully reported over time, even when children leave their initial household. Third, the three data sets entail retrospective questions on parental characteristics. These information allow us to reconstruct the educational history of families over three consecutive generations. Since important structural differences affected individuals living in East and West Germany before and after reunification we restrict our German sample to families residing in West Germany before reunification.

The main challenge is to find a measure for human capital and socio-economic status that is i) available for grandparents, parents and children, and ii) comparable across countries and generations. An ideal measure would account for generation-specific differences due to educational institutions as well as country- and time-specific differences in the capability to generate income in the labour market. We approximate these concepts with a widely accepted measure for the human capital stock of an individual: completed years of education. Completed years of education includes the regular years of schooling needed to obtain the indicated educational degree (measured in ISCED levels) and accounts for vocational training and tertiary education as well as for the skill level (measured in ISCO levels). Using education to measure socio-economic status reduces potential measurement error in intergenerational mobility estimates since individuals tend to be well informed about their own and their parents' highest obtained educational attainment (Black and Devereux, 2011).[7] Detailed information on the data and the exact codification of completed years of education for children, parents, and grandparents can be found in the Supplemental Material.

[7]Furthermore, in contrast to earnings, the highest educational attainment is obtained relatively early in life and is less volatile over the life-cycle.

For a matter of fact, due to the structure of the educational system, in the UK it might be less appropriate to adopt a continuous measure like years of education when measuring intergenerational mobility (Dearden et al., 1997). We address this issue measuring mobility also by correlation coefficients and by adopting an outcome variable that indicates the relative standing of individuals and their ancestors. To obtain this measure, which is conceptually even closer to the notion of human capital and comparable across countries and time periods, we perform a linear transformation of the relevant outcome variables for grandparents, parents, and children. The transformation yields the standard score (z-score) of educational achievements by cohorts:

$$z_{ijT} = \frac{y_{ijT} - \bar{y}_{jT}}{\sigma_{jT}}. \tag{4.8}$$

Here, $\bar{y}_{jT}$ and σ_{jT} are the mean and standard deviation of completed years of education of all individuals from generation $T \epsilon \{t, t-1, t-2\}$ in cohort j. The cohort refers to the cohort of the children's generation. This measurement gives the relative standing (in standard deviations) of an individual, his parents, and grandparents with respect to their reference groups, i.e. people competing with them in the labour market.

The main strength of this approach is the higher comparability between countries and time periods, accounting especially for the expansion of educational attainment in the second half of the 20th century that took place in all three countries under examination.[8] The z-score is adopted to built quantiles of children's, parents', and grandparents' relative educational position that are used to display transition matrices and mobility curves. As further robustness check, we also run the complete analysis using the z-score of educational attainment instead of the completed years of education. As usually done in the literature, we will refer to the parents' and grandparents' education (educational position) as the completed years of education (the z-score) of the parent and grandparent with the highest educational attainment (educational position) within the family (Black and Devereux, 2011). In further analyses we also disentangle this measurement and analyse the education (educational position) of fathers, mothers, and all four grandparents, separately.

We draw the same sample in each survey. For our analysis, we need families that participated in the respective survey for at least two generations and where the first participating generation (parents; generation *t-1*) has available retrospective information

[8] Standardizing the outcome variables by adopting z-scores yields regression estimates which are similar to the correlation coefficients (reported below the tables) with one important difference: The correlation coefficient is standardized by the variances of the entire sample, while our transformation compares individuals with their respective cohort. Furthermore, applying the transformation on the outcome variables instead of the estimated parameter allows us to test the coefficient of grandparents against zero, controlling for parents, within a simple regression.

on their father's or mother's educational attainments and occupation. We integrate this information to a measure for grandparents' education (generation *t-2*) and associate it to adult children (generation t) with available information on educational attainment. Our samples consist of individuals born between 1960 and 1985 with available information on the educational attainment of at least one of their parents as well as grandparents. In addition, individuals have to be at least 28 years old at the time of their last interview. The age restriction helps us to reduce bias due to uncompleted educational biographies and is justified empirically by observing patterns in our data: the mean of completed years of education is stable from the age of 28 onwards.

Table 4.1 shows the weighted means and standard deviation of completed years of education observed in our samples over three generations. In all three countries, educational attainment has substantially increased over generations. The US sample shows the highest averages, while educational attainments are lower and rather similar in Germany and in the UK. These patterns match with the ones found in other data sets on cross-national educational achievements.[9]

4.4 Descriptive Evidence on Multigenerational Mobility

4.4.1 Dynastic inequality

First, we look at changes in the distribution of educational attainment over time. For this purpose, we measure the degree of inequality in the distribution of completed years of education for each generation and the degree of inequality in the distribution of family means across generations. The resulting analysis is close to the one proposed by Shorrocks (1978b) and mirrors the concept of dynastic inequality (Jäntti and Jenkins, 2015). Table 4.2 shows short and long-run (dynastic) inequality for each country, as well as two indices to account for multigenerational mobility as an equalizer of long term inequality. Three different inequality measures are applied that share the characteristic of strong Lorenz-dominance, but differ in their sensitivity towards changes along the distribution: i) Gini coefficient, which reacts stronger to changes at the middle of the distribution; ii) Theil index, which is sensitive to changes at the lower middle of the distribution; and iii) Coefficient of Variation (CV), which is more sensitive to changes at the top of the distribution. The two computed mobility measures are the ones proposed by Shorrocks (1978a) and Fields (2010). The first relates dynastic inequality

[9] A comparison of mean years of schooling observed in the Barro-Lee data on educational attainment as well as an analysis of selectivity issues regarding the analysed sample are included in the Supplemental Material.

to the weighted inequality in all generations, the second evaluates mobility as equalizer of long term outcomes relative to the initial shape of the distribution.

In all countries, we find decreasing inequality in completed years of education from the grandparents' to the children's generation. The UK shows relatively high inequality of educational attainments in the grandparents' and parents' generation, but also the highest degree of mobility. Inequality in children's completed years of education tends to be the largest in Germany. The US tend to be the country with the lowest educational inequality. The evaluation of differences in mobility between Germany and the US depends on the applied measure. Measuring mobility relative to the initial level of inequality – i.e. in the grandparents generation – Germany is less mobile to a larger extent than measuring it with respect to the overall distribution.

It is expedient to compare short-run inequality with dynastic inequality. It has been argued that whenever dynastic inequality is less than inequality in any given generation there was some equalizing mobility between generations (Jäntti and Jenkins, 2015). In our analysis, Germany is the only country with dynastic inequality being lower than cross-sectional inequality in every generation and for all measures. In the US, inequality in the children's generation is lower than dynastic inequality if measured by the Gini and Theil index. In the UK, inequality in generation t is lower than dynastic inequality measured by the Gini index, but higher or equally large for the other two measures. In conclusion, mobility acts as an equalizer of dynastic inequality in all three countries, especially in Germany, although the impacts on the distribution are of distinct magnitude.

4.4.2 Multigenerational Mobility Trends

In this part, we show trends of multigenerational mobility. Figure 4.1 depicts two indicators which measure the degree of intergenerational mobility over two and three generations experienced by different cohorts: i) The regression coefficient, β_{-m}, obtained by regressing children's education on parents' ($m = 1$) or grandparents' ($m = 2$) education, measured in completed years of education; ii) The correlation coefficient, r_{-m}, which accounts for changes in the distribution of educational attainments ($r_{-m} = (\sigma_{-m}/\sigma_0)\beta_{-m}$).[10]

Mobility patterns generally differ between countries and confirm earlier findings on cross country comparisons of educational correlations (see e.g. Hertz et al., 2007). Panel A shows the two generation case, i.e. parents and children. Educational mobility is the lowest in Germany with an average regression coefficient of 0.49, and is higher in the US and the UK where coefficients are 0.42 and 0.21, respectively. The development

[10] σ_0 is the standard deviation of educational attainment in the children's generation.

of mobility rates is, however, different between the US and the UK. Older cohorts show a relatively high degree of mobility in both countries, but mobility decreased in the US by far more for younger cohorts than in the the UK where it remained almost unchanged. Correlation coefficients show similar patterns within countries. A major difference is that correlation coefficients tend to be smaller than regression coefficients in Germany while they tend to be higher in the US and the UK. This relates to changes in the variance of educational attainment over time.[11]

Panel B shows intergenerational mobility over three generations, i.e. grandparents and grandchildren. Although coefficients are substantially smaller and somewhat more stable within countries, the ranking between countries is basically unchanged. On average, ten years of grandparental education are associated to an increase in grandchildren's education of about three years in Germany, one and a half years in the US and less than one year in the UK.

4.4.3 Transition Matrices & Mobility Curves

Deeper insights into intergenerational mobility in a cross-country analysis can be derived from non-parametric approaches (Corak et al., 2014). These give further insights on how structural mobility – e.g. because of educational expansion – affects intergenerational mobility in each country and in which parts of the distribution mobility takes place.

First, we construct mobility matrices which show the percentage of children with low, middle, and high educational attainment for each class of grandparents' educational position; depicted in Figure 4.2. Educational position is based on the z-scores of educational attainment by cohorts as explained in Section 4.3. The three quantiles – low, middle, and high – display the position within the respective distribution of the cohort's educational attainment. The highest upward mobility from the bottom to the top of the distribution is observed in the US, the lowest in Germany; 31.7 and 21.9 % of children with high education have grandparents with low education, respectively. Interestingly, both countries show a similar persistence at the bottom of the distribution. For instance, in our samples for Germany and the US about 53 and 54 percent of children with low educational position have grandparents in the bottom part of the distribution. In contrast, only 37 percent of the individuals in our UK sample show this pattern. Furthermore, Germany shows the highest persistence at the top of the distribution with 47 percent, while in the US and the UK it is about 37 and 39 percent, respectively.

[11] The relatively low number of observations in our UK sample makes the analysis less reliable than in the two other countries.

Second, we compute *mobility curves* over three generations.[12] Figure 4.3 displays the average years of education and educational position of grandchildren for each level of grandparents' education and educational position. Hereby, the former accounts for absolute changes while relative changes within the distribution are registered in the second. This method has the advantage to show how absolute mobility differs over the distribution of grandparents' status. We find differences between countries – especially between Germany and the US – to be marked in the lower part of the distribution. For instance, the average education of grandchildren in the bottom part of the grandparents' distribution is substantially lower in Germany. In contrast, in the upper part of the distribution differences are smaller. Our sample for the UK shows a much flatter curve signalizing higher mobility within the distribution. Generally, differences between countries are less pronounced measuring social status by educational positions rather than years of education. For instance, for lower than average educational attainment of grandparents the mean educational position of the children is lower than the mean of their reference group in all three countries.

4.5 Testing Theories of Multigenerational Persistence

4.5.1 Iterated Regression Fallacy

Table 4.3 shows our estimates of equation (4.1) where we separately regress children's education on parents' and grandparents' education, and equation (4.2) where we regress children's education on both parents' and grandparents' education. As commonly done in the literature, we only consider the education of the parent and grandparent with the highest educational level within the family (Black and Devereux, 2011).[13] Intergenerational correlation coefficients are reported below the tables. The outcome variable is completed years of education.

The regression coefficients of parents' education in column (1) and grandparents' education in column (2) confirm the patterns observed before; the UK shows the highest degree of intergenerational mobility, Germany the lowest. In the regression analysis including both, parents and grandparents education, in column (3), the grandparental coefficient is positive in each application, but only significantly different from zero for Germany and the UK. According to these first results, we cannot reject the hypothesis

[12] Mobility curves are usually applied to measure the mean income rank of children for each rank of their parents (see e.g. Bratberg et al., 2016). See also Chetty et al. (2014a).

[13] Estimates for Grandfather-Father-Son and Grandmother-Mother-Daughter lineages are included in the Appendix (Tables A.3.5-A.3.8) and discussed below.

for the US that the intergenerational transmission of human capital follows an AR(1) process, while we reject it for Germany and the UK.

Next, we test if the directly estimated coefficients of grandparents are equal to the ones predicted by the iterative regression procedure, i.e. squaring the coefficient of parents ($H_0 : \beta_{-2} = \beta_{-1}^2$). The tests are reported below the Tables. Although the estimated grandparental coefficients in columns (2) are always greater than the squared parental coefficient, we cannot reject the hypothesis that they are equal for Germany and the US. Performing the same analysis for each cohort separately, we find that the squared parental coefficient neither systematically over nor under predicts the directly estimated grandparental coefficient (see Panel B of Figure 4.1).

As further robustness check, we perform the same analysis adopting the z-score of educational attainment measured in comparison to individuals of the same cohort. The observed patterns are the same and results do not change qualitatively applying either measurement.[14] An insightful finding is that applying the z-score of educational attainment changes the country ranking between Germany and the US regarding the association between parents' and children's outcomes. Interestingly, our results as well as previous studies on educational mobility found the US to be more mobile than Germany (e.g. Chevalier et al., 2009; OECD, 2015), while studies on income mobility over two generations mostly found the opposite or, at least, no significant differences between the two countries (e.g. Couch and Dunn, 1997; Schnitzlein, 2015). Thus, we interpret our finding in the sense that the z-score yields a better approximation of social status which, indeed, was our primary goal when applying this transformation.

So far, our cross-country results are mixed and show that the validity of the iterated regression procedure to extrapolate long-run mobility estimates varies by countries. The evidence for the US suggests that there is no direct effect of grandparents on grandchildren. However, such a clear statement cannot be made for Germany and the UK at this point of the analysis.

4.5.2 Latent Factor Model

Table 4.4 entails the parameter estimates to test the hypotheses of Clark's latent factor model described in Section 4.2.1. Using the correlation coefficients between children and parents, and children and grandparents, we calculate the heritability coefficient λ and the transferability coefficient ρ as in equation (4.6) and (4.7). Figure 4.4 sums up the estimated coefficients for each country.

In our application, λ varies between 0.560 and 0.726 and ρ between 0.692 and

[14] Tables A.3.1-A.3.4 show the main results with this alternative outcome variable, all other estimations applying the z-score can be found in the Supplemental Material.

0.899. Clark's hypothesis that λ is larger than the correlation in observed outcomes is confirmed. However, differences between countries are statistically significant.[15] The same is true applying the z-score instead of completed years of education as outcome variable; the range for the z-score is 0.506 to 0.725 for λ and 0.717 to 0.937 for ρ. Furthermore, the heritability coefficient varies also over time: Performing the analysis for different cohorts separately we obtain different values of λ.[16] Hereby, in some of our estimations we cannot reject the hypothesis of a heritability coefficient being close, equal, or higher than 0.75. In Germany, for instance, some cohorts even display values of λ which are close to unity. However in the US, λ is constantly and significantly lower than 0.75 for the cohorts 1965-69 to 1980-84. The results for the UK also suggest λ to be smaller than 0.75. All in all, we find no clear evidence in favour of Clark's hypothesis that the historical and institutional context does not matter for the movements of families along the distribution in the long run.[17]

4.5.2.1 Extensions: Lineages, Assortative Mating and Sample Selectivity

As further extensions, we account for lineages within families and estimate the rates of assortative mating. When we disentangle the intergenerational transmission in different lineages following son-father-grandfather and daughter-mother-grandmother triplets, the overall results basically do not change (see Tables A.3.5-A.3.8). However, gender specific pathways in the transmission of social status across two and three generations are revealed to some degree. For instance, in all three countries the regression coefficient of maternal education on the education of the daughter is higher than the coefficient of paternal education on sons, while the coefficient of grandfathers on fathers is higher than the coefficient of grandmothers on mothers. Regarding the transmission over three generations, the size of the coefficients of grandfathers on sons and granddaughters on daughters is rather similar in all three countries.

In Germany the positive and significant effect of grandparents on grandchildren, controlling for parents, seems to be mainly driven by the influence of grandfathers on their grandsons. The coefficient of grandmothers on their granddaughter is not significant when controlling for mother's education. These diverging findings might be explained by progressive changes in gender roles, as well as women's educational

[15] Differences between the estimates for Germany and the US are statistically significant at the 10% level.

[16] Figure A.3.1 shows the heritability coefficient estimated for different cohorts.

[17] As Braun and Stuhler (2016) point out, large variation in ρ among generations might lead to bias in the estimation of λ. We find large variations in ρ among cohorts in the children's generation, but cannot determinate the direction of the bias, since we have no information on the magnitude of ρ in the parents' and grandparents' generation. For a clear identification of Clark's hypothesis of time varying λ, these information are necessary. Future research with more comprehensive data on three ore more generations over multiple cohorts should address this point.

attainment and labour market participation experienced in industrialized countries in the last decades that led to a decrease in the association in observed outcomes between grandmothers and granddaughters. The results on the US in this sense are even more pronounced. In our previous analysis, we did not find any significant positive effect of grandparents on grandchildren, controlling for the social status of parents. However, there is a significant positive effect of both, grandfathers on grandsons, and grandmothers on granddaughters, if analysed separately. These results indicate that there might be a direct, gender-specific grandparental effect on the educational attainment of grandchildren in the US. The fact that for both lineages we reject the hypothesis of an AR(1) process for the US gives further support to this hypothesis. Finally, in the UK the coefficients of grandfathers on grandsons and grandmothers on granddaughters are both not significant. This might however just be the result of relatively small sample sizes which result in larger standard errors. Finally, although some common behaviours of the intergenerational transmission exist, the country-specific differences found in the main analysis persist when disentangling by different lineages. Regarding the test of the latent factor model, the results point even stronger at different heritability coefficients between countries which are smaller than the hypothesized 0.75.[18]

The analysis of assortative mating – understood as non-random selection of individuals becoming parents – is relevant for the study of intergenerational persistence because the degree of spouse correlation in a society influences mobility parameters (Chadwick and Solon, 2002; Ermisch et al., 2006). Although the baseline model by Becker and Tomes assumes perfect assortative mating, the implications of the latent factor model crucially depend on this feature. Higher spouse correlations in endowments cause higher heritability coefficients. Therefore, large values of λ depend on high and constant rates of assortative mating (see Braun and Stuhler, 2016). Since endowments are unobservable characteristics, in order to analyse assortative mating we focus on spouse correlations in observable outcomes, i.e. completed years of education and the z-score of educational attainment. However, since we mostly have information on both father's and mother's outcomes in our data, our intergenerational mobility parameters are estimated taking the parent with highest education, as usually done in the literature on educational mobility when the characteristics of both parents are available.[19] The highest observable outcome should be an useful approximation of the average unobservable endowment of the two parents. So, the issue of assortative

[18]Hereby, the coefficient r_{-1} used to estimate the heritability coefficient λ is the average of the correlation coefficients of sons (daughters) on fathers (mothers) and of fathers (mothers) on grandfathers (grandmothers).

[19]Estimates of income mobility instead mostly focus on son-father pairs, because lower labour-force participation rates among women cause their earnings to be a unreliable indicator of social status.

mating in unobservable endowments should influence less our results in comparison to studies that only have information on one parent. Still, it is an interesting dimension to account for; especially its differences between countries and over time.

Indeed, we find substantial differences in assortative mating between countries and generations.[20] Spouse correlations in the parents' and grandparents' generation are about 0.6 and 0.8 in Germany, about 0.4 and 0.8 in the UK, and about 0.6 in both generations in the US, respectively. Hence, assortative mating decreased in all three countries – with the UK showing the largest changes between the grandparents' and parents' generation – but is still a prevalent phenomenon, possibly fostering the intergenerational transmission of social status.[21] Interestingly, among the three countries under evaluation there seems to be a negative association between intergenerational mobility and assortative mating: In our analysis, the UK is the country with highest mobility and lowest assortative mating in the parents' generation, while Germany is the one with lowest mobility and highest assortative mating. Another interesting finding is the difference in correlation coefficient among both grandfathers and both grandmothers that is high in Germany and, particularly, in the US, and very low in the UK. A possible reason for the higher degree of intergenerational mobility found in our UK sample could therefore be the weaker intermarriage of elites in the grandparent's generation, which seems to be substantially stronger in the other two countries.

Finally, a sensitivity analysis shows that samples drawn from household surveys might be positively selected in educational attainments. We find that the average years of education of individuals in our samples – restricted by the condition of available information on parents' and grandparents' education – is higher than the mean of the unrestricted sample, weighted by the inverse probability of selection. Furthermore, restricting the sample on the condition to have just information on parental education yields lower regression coefficients. Therefore, our results might be understood as an upper bound for intergenerational persistence. Since the selectivity issue and the direction of a potential bias seem to be the same in the three surveys, the cross-country analysis should hold, as well as the following identification of mechanisms.

[20]The results discussed in this part of the analysis can be found in the Supplemental Material.

[21]These findings are in line with earlier studies on educational assortative mating (alias educational *homogamy*) for the cohorts included in our analysis. In the UK, past studies show a decreasing trend from the cohorts around 1925 to 1960 (Chan and Halpin, 2003). In the US, despite of a general rising trend, assortative mating decreased from 1940 to 1960, which should be exactly the time of marriage of the grandparents and parents in our sample (Schwartz and Mare, 2005). In Germany, assortative mating in education has been rising constantly among natives in the last decades (Grave and Schmidt, 2012). Excluding people with migration background from our analysis we come to the same result.

4.5.3 Direct Grandparental Effect

Next, we test for the presence of a direct and independent effect of grandparents following two different strategies. First, we include more variables capturing different features of parental background to test whether the positive significant coefficient of grandparental outcomes is just an artefact of omitted variable bias or not. Second, we test if the grandparental coefficient varies with the likelihood of grandchild's exposure to the respective grandparent. For this purpose, we use the time of death of the grandparent as exogenous source of variation.[22]

4.5.3.1 Omitted Variables

First, we test for the general existence of a grandparental effect. For this exercise, we pool all data sets and perform a similar analysis as before; results can be found in Table 4.5. Our data is particularly suitable to control for omitted variable bias, since we mostly have information on both parents and all four grandparents. Furthermore, we can control for the influence of ethnic capital, an essential parental background characteristic, as a possible source of omitted variable bias.[23] In column (1), the coefficient of grandparental education is positive and significant, and gets slightly smaller when allowing country-specific intercepts and slopes as in column (2). To control for ethnic capital, in column (3) a dummy is included in the regression which is one if the individual is non-white in the US and the UK, or has migration background in Germany, and zero otherwise. This dummy is then interacted with the country fixed effects in column (4) to control for country-specific ethnic capital. The coefficient of grandparents decreases when controlling for ethnic capital and country-specific ethnic capital, but is still positive and significantly different from zero.

The next four columns (5) to (8) control successively for the same characteristics as above, but include the completed years of education of both father and mother, instead of only including information of the parent with the highest degree. The resulting coefficient of grandparental education in columns (5) is still positive and statistically

[22] As argued, for example, by Braun and Stuhler (2016), time of death might be correlated with unobserved factors that influence the intergenerational transmission and is, therefore, not suitable as exogenous source of variation. However, in our samples we do not find any clear association. The regression coefficient of time of death and grandparental education, measured in completed years of education and by the z-score, is mostly not significantly different from zero. Also, the association between year of death and educational attainment when controlling for year of birth is very weak and mostly not statistically significant.

[23] Borjas (1992) originally controls for ethnic capital in the regressions by including the average skill level (measured in earnings) of migrant groups, clustered by their national origin. We adopt a more general approach grouping individuals by their migration status in Germany or ethnicity in the US and the UK. As has been shown in previous studies, the intergenerational mobility of these groups differ significantly from the average mobility of the native population. Hence, controlling for these characteristics should reduce omitted variable bias substantially.

significant, but rather small. The coefficient becomes not significantly different from zero when father's and mother's education is interacted with the country dummies in the subsequent estimations, shown in columns (6) to (8). The coefficients of the control variables are mostly significantly different from zero and their inclusion increases the adjusted R-squared of the regressions. So, the persistence of a positive and significant coefficient for grandparental education observed before seems to be mainly driven by omitted variables which cause bias in the estimation of the grandparental effect. We try to further reduce the bias caused by unobserved characteristics of parental social status performing the same analysis applying the z-scores of educational attainments. Indeed, in the joint analysis pooling the three samples, the coefficient of grandparental educational position measured by the z-score is not significantly different from zero as soon as we control for the education of both parents (see Table A.3.3). The evidence, so far, points therefore against the existence of an independent and direct effect of grandparents, once parental social status is accounted for properly.

However, the fact that a general rule regarding the direct effect of grandparents might not exist does not rule out specific differences caused by institutions. As argued, for instance, by Mare (2011), the effect of grandparents might vary by context and institutional characteristics could determine the magnitude of the effect. Indeed, we find heterogeneous profiles comparing the three countries. Table 4.6 reports the estimated coefficients country wise. For Germany, the coefficient of grandparents is significantly different from zero when controlling, first, for the parent with highest education, and, then, for the education of both parents. The last evidence seems initially to be in contrast with the findings of Braun and Stuhler (2016) who find statistically insignificant coefficients in most of their applications controlling for both parents. However, Braun and Stuhler (2016) find, indeed, a positive significant coefficient in two of their five samples which are closer to our sample in terms of the years of birth of individuals and their grandparents. In our analysis, the coefficient of grandparents for Germany is no longer significantly different from zero if we additionally control for ethnic capital, besides mother's and father's educational attainment. The results on the UK show a positive and significant coefficient of grandparents controlling for parents and ethnic capital. The coefficient is, however, substantially smaller and not significantly different from zero as soon as we control for the education of both parents. Our results, therefore, only partly confirm the findings of Chan and Boliver (2013) on the persistence of social status over three generations in the UK. For the US, the coefficient is persistently not significantly different from zero in all applications. This pattern confirms earlier findings on older cohorts for the US by Behrman and Taubman (1985); Peters (1992); Warren and Hauser (1997).

Our results are qualitatively similar for the three countries when the outcome variable is the z-score of educational attainment (see Table A.3.4). Interestingly, the results adopting the z-score for the US show a negative coefficient of grandparents when controlling for both father and mother, as found by previous studies on income mobility over three generations (Peters, 1992; Behrman and Taubman, 1985) and hypothesized by Becker and Tomes (1979). We interpret this as further evidence in favour of our supposition that the z-score mirrors socio-economic status properly.

4.5.3.2 Death of Grandparents

For the second exercise, we test whether the coefficient of grandparental education varies with the likelihood of interaction between grandparents and grandchildren (following Braun and Stuhler, 2016). Here, we use the information on the year of death of grandparents and the year of birth of grandchildren to check if a direct interaction was possible between the two or not. Since the information on parental year of death is only available in the SOEP and the PSID we restrict our analysis for this exercise to Germany and the US.

The estimation strategy is straightforward: Equation (4.2) is estimated interacting the education of the respective grandparent with a dummy variable which is one if there was no possibility of direct interaction – i.e. the grandparent died before the grandchild turned one year old – and zero otherwise. The results are shown in Table 4.7. If a direct interaction has a substantial effect, we would expect the coefficient of "dead grandparents" to be significantly lower than the coefficient of grandparents who were alive when the grandchild was born.

This hypothesis does not find a clear support in our findings. Only dead grandparents on the mother's side show the expected negative coefficient with respect to the coefficient of living grandparents. If we subdivide the analysis, it is evident that this result is completely driven by our German sample. Again, we find cross-country differences in the evaluation of a direct effect of grandparents. Identical patterns are observed when applying the z-score as outcome variable.[24] Of course, this strategy rules only those effects out that depend on direct interaction. There still might be important and persistent effects which derive from grandparents regardless of whether they were alive or not; for instance, family wealth, reputation, networks, as well as genetic traits that skip one generation. These cannot be clearly ruled out in this analysis. Our results show that direct interaction might only have a limited effect on grandchildren's human capital and confirm that these effects might vary with the cultural, historical, or institutional context.

[24]These results are furthermore robust to the exclusion of people with migration background.

Our findings for Germany regarding maternal grandparents seem, however, to confirm earlier findings and the hypotheses raised by family sociologists and human evolutionary scientists on differential effects of maternal and paternal grandparents on grandchildren. The former argue that the emotional closeness between mothers and their parents explains the stronger effect of maternal grandparents on grandchildren. Evolutionary explanations instead mostly focus on the degree of assumed genetic relatedness. One theory states, for example, that the bias in grandparental investment might depend on *paternity uncertainty*: maternal grandparents know for sure that their daughter is the mother of their grandchild (although in the case of the maternal grandfather there might still be some uncertainty about genetic relatedness), while the probability of relatedness on the father's side is usually smaller than one. However, to go deeper into the exact reasons and mechanisms of differences in grandparental effects would go beyond the scope of this work.[25]

4.6 Conclusions

This study evaluated multigenerational mobility in a cross-country setting using harmonized survey data sets. On grounds of highly comparable estimates we found some clear patterns: First, multigenerational mobility tends to vary with the historical and institutional context. We even find different effects of grandparental exposure on grandchildren's socio-economic status by country and gender. Second, our finding of different heritability parameters across countries and time does not support the existence of a "universal law of social mobility". Third, the differences in long run mobility rates in the US, the UK, and Germany are in line with previous findings on cross-country differences over two generations (Blanden, 2013; Chevalier et al., 2009; Hertz et al., 2007; OECD, 2015). Hence, our findings show that cross-country relationships, at least in this small sample of countries, hold aside from the timing of measurement, and short-run mobility (i.e. over two generations) does not seriously over nor under predict long-run mobility patterns.

A strength of our findings, apart from the cross-country perspective, lies in the adoption of measures which should be suitable as *omnibus measures* for latent socio-economic status with less measurement error (see Nybom and Vosters, 2015; Solon, 2014). Especially, our analysis using the relative position of grandparents, parents, and children should be particularly useful in that sense, since it allows to compare individuals and their ancestors with the corresponding reference group, namely people

[25] For a recent review of theories and empirical findings on differential grandparental effects, see Danielsbacka et al. (2015).

competing in the labour market broadly at the same time. An issue challenging our findings, and generally the analysis of intergenerational mobility with household survey data, turned out to be sample selectivity. We find that higher educated people are more likely to have available information on parents' and grandparents' education. Especially, families with higher education (which tend to have lower intergenerational mobility) are more likely i) to participate in household surveys for more than one generation and ii) to answer retrospective questions about their parents' education. Our intergenerational persistence estimates over two and three generations might, thus, be understood as an upper bound. Even with these upper bound estimates we found no support for a strong unobserved intergenerational transmission of socio-economic status that is constant across time and space. Furthermore, since selectivity is the same in all three countries, the cross-country analysis should still be valid. On top of this, the identification of the mechanisms of multigenerational persistence should not be affected. Nevertheless, it might be important to address the issue of sample selectivity in future studies dealing with intergenerational transmission using survey data.

Other points worth mentioning are the uncovered different effects by gender and family lineages. Decomposing the analysis by the effect of (grand)fathers and (grand) mothers on (grand)sons and (grand)daughters we find that significant differences exist between correlations and even direct effects. Interestingly, we find these patterns to differ across countries, confirming that historical, institutional, and cultural features matter for the intergenerational transmission of socio-economic status.

Concluding, a relevant point is how our findings are related to income mobility. Previous studies covering two generations have shown that rates of intergenerational mobility in education and income show the same broad picture, but are less than perfectly correlated. Since data on permanent income over three generations is rare, we cross-checked our results adopting a transformation that yields an outcome measure which is intuitively closer to the concepts of human capital and socio-economic status than completed years of education. Our analysis showed that our results adopting this transformation mirror past findings on intergenerational income mobility. It might therefore be useful to deepen this methodological aspect in future.

4.7 Tables and Figures

Table 4.1: Descriptive statistics

	Germany				USA				UK			
	Year of Birth	Education	s.d.	N	Year of Birth	Education	s.d.	N	Year of Birth	Education	s.d.	N
Children	1972	12.56	2.609	3210	1970	13.95	2.258	6303	1975	12.87	2.724	1532
Fathers	1942	11.53	2.445	2893	1942	12.88	3.226	5589	1946	10.84	4.066	1413
Mothers	1945	10.68	2.057	3135	1944	12.86	2.563	6268	1948	10.21	3.965	1516
GF-F	1917	10.71	3.450	2672	1927	11.06	3.962	5539	1920	9.74	3.922	964
GM-F	1913	9.08	3.133	2677	1925	11.64	3.355	5319	1917	8.14	3.651	960
GF-M	1913	10.73	3.305	2913	1924	11.01	4.005	6202	1918	9.72	4.008	1374
GM-M	1910	9.24	2.980	2948	1923	11.50	3.473	6068	1914	8.29	3.797	1368

Notes: Means, standard deviations, and number of observations. Education measured in completed years of education.
GF/GM-F/M: Grandfather/Grandmother-Father's/Mother's side.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table 4.2: Multigenerational mobility as an equalizer of dynastic inequality

(a) Germany

	t	*t-1*	*t-2*	*Family Mean*	*M(S)*	*M(F)*
Gini	0.117	0.107	0.136	0.101	0.719	0.256
s.e.	*0.0011*	*0.0015*	*0.0033*	*0.0016*	*0.0033*	*0.0144*
Theil	0.022	0.020	0.047	0.017	0.811	0.642
s.e.	*0.0004*	*0.0005*	*0.0033*	*0.0005*	*0.0090*	*0.0134*
CV	0.209	0.204	0.276	0.182	0.736	0.339
s.e.	*0.0020*	*0.0023*	*0.0062*	*0.0029*	*0.0052*	*0.0113*

(b) USA

	t	*t-1*	*t-2*	*Family Mean*	*M(S)*	*M(F)*
Gini	0.089	0.100	0.144	0.090	0.711	0.376
s.e.	*0.0011*	*0.0013*	*0.0024*	*0.0012*	*0.0075*	*0.0069*
Theil	0.012	0.018	0.046	0.014	0.769	0.693
s.e.	*0.0003*	*0.0006*	*0.0013*	*0.0005*	*0.0160*	*0.0076*
CV	0.166	0.187	0.276	0.162	0.722	0.412
s.e.	*0.0035*	*0.0027*	*0.0038*	*0.0022*	*0.0087*	*0.0067*

(c) UK

	t	*t-1*	*t-2*	*Family Mean*	*M(S)*	*M(F)*
Gini	0.100	0.153	0.208	0.113	0.754	0.454
s.e.	*0.0029*	*0.0036*	*0.0032*	*0.0020*	*0.0163*	*0.0130*
Theil	0.024	0.049	0.073	0.021	0.854	0.707
s.e.	*0.0017*	*0.0020*	*0.0027*	*0.0010*	*0.0147*	*0.0154*
CV	0.202	0.291	0.375	0.201	0.768	0.463
s.e.	*0.0054*	*0.0054*	*0.0052*	*0.0042*	*0.0114*	*0.0125*

Notes: Gini, Theil and Coefficient of Variation. *t, t-1, t-2* are the generation of children, parents and grandparents, respectively. *Family mean* is the mean of completed years of education over three generations. *M(S)* is the mobility index proposed by Shorrocks: $M(S) = 1 - \frac{I(\sum_{T=t-2}^{t} y_T)}{\sum_{T=t-2}^{t} w_T I(y_T)}$ with $w_T = \bar{y_T}/\bar{y_F}$. *M(F)* is the mobility index proposed by Fields: $M(F) = 1 - \frac{I(\sum_{T=t-2}^{t} y_T)}{I(y_{t-2})}$. $I()$ denotes the inequality index, y_T is the outcome in generation T, and $\bar{y_F}$ the family mean. The closer the value is to one, the greater is mobility in both indices. Bootstrapped s.e. with 100 replications.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table 4.3: Regression analysis - outcome: completed years of education

(a) Germany

	(1)	(2)	(3)
Parents (β_{-1})	0.484***		0.413***
	(0.0295)		(0.0394)
Grandparents (β_{-2})		0.258***	0.101***
		(0.0243)	(0.0297)
Observations	3210	3210	3210

Correlation coefficients: $r_{-1} = 0.451$, $r_{-2} = 0.327$

Test $(\beta_{-1})^2{=}\beta_{-2}$: F = 0.8984, Prob > F = 0.3433 ; $(\beta_{-1})^2 = 0.235$

(b) USA

	(1)	(2)	(3)
Parents (β_{-1})	0.400***		0.386***
	(0.0169)		(0.0195)
Grandparents (β_{-2})		0.167***	0.021
		(0.0137)	(0.0150)
Observations	6303	6303	6303

Correlation coefficients: $r_{-1} = 0.453$, $r_{-2} = 0.254$

Test $(\beta_{-1})^2{=}\beta_{-2}$: F = 0.2221, Prob > F = 0.6375 ; $(\beta_{-1})^2 = 0.160$

(c) UK

	(1)	(2)	(3)
Parents (β_{-1})	0.208***		0.189***
	(0.0284)		(0.0288)
Grandparents (β_{-2})		0.111***	0.047**
		(0.0210)	(0.0197)
Observations	1532	1532	1532

Correlation coefficients: $r_{-1} = 0.279$, $r_{-2} = 0.163$

Test $(\beta_{-1})^2{=}\beta_{-2}$: F = 10.4645, Prob > F = 0.0012 ; $(\beta_{-1})^2 = 0.043$

Notes: Tables show regressions of children's educational outcomes on the outcomes of the parent or grandparent with highest education within the family. Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table 4.4: Estimated correlation (r), heritability (λ), and transferability (ρ) coefficients

	Years of Education		
	GER	*USA*	*UK*
r_{-1}	0.451	0.453	0.279
r_{-2}	0.327	0.254	0.163
λ	0.726	0.560	0.584
s.e.	*0.0602*	*0.0314*	*0.0937*
ρ	0.788	0.899	0.692
s.e.	*0.0464*	*0.0274*	*0.0832*

Notes: Bootstrapped s.e. (200 replications).
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table 4.5: Testing for a grandparental effect: controlling for multiple features of parental background

***Outcome**: Completed years of education*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Grandparents	0.060***	0.046***	0.046***	0.042***	0.029**	0.016	0.018	0.014
	(0.0114)	(0.0116)	(0.0117)	(0.0117)	(0.0120)	(0.0122)	(0.0123)	(0.0124)
Parents	0.315***	0.369***	0.368***	0.369***				
	(0.0172)	(0.0186)	(0.0191)	(0.0195)				
GER (0/1) × Parents		0.083**	0.083**	0.077**				
		(0.0336)	(0.0336)	(0.0353)				
UK (0/1) × Parents		-0.180***	-0.179***	-0.176***				
		(0.0333)	(0.0335)	(0.0339)				
Father					0.170***	0.189***	0.192***	0.192***
					(0.0138)	(0.0179)	(0.0180)	(0.0182)
GER (0/1) × Father						0.128***	0.129***	0.122**
						(0.0472)	(0.0471)	(0.0477)
UK (0/1) × Father						-0.082***	-0.084***	-0.081***
						(0.0282)	(0.0284)	(0.0285)
Mother					0.188***	0.226***	0.227***	0.228***
					(0.0152)	(0.0237)	(0.0236)	(0.0238)
GER (0/1) × Mother						0.065	0.067	0.061
						(0.0489)	(0.0488)	(0.0490)
UK (0/1) × Mother						-0.109***	-0.110***	-0.110***
						(0.0313)	(0.0313)	(0.0313)
Country F.E.	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Non-white or Migrant	No	No	Yes	Yes	No	No	Yes	Yes
- (interacted with country f.e.)	No	No	No	Yes	No	No	No	Yes
Adj. R^2	.1788	.2069	.207	.2085	.1912	.2217	.222	.2237
Observations	11045	11045	11039	11039	9769	9769	9764	9764
Clusters	5768	5768	5762	5762	5168	5168	5163	5163

Notes: Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table 4.6: Testing for a grandparental effect: controlling for multiple features of parental background – country-wise

***Outcome**: Completed years of education*

	(1) USA	(2) USA	(3) USA	(4) GER	(5) GER	(6) GER	(7) UK	(8) UK	(9) UK
Grandparents	0.020	0.001	0.002	0.096***	0.049*	0.048	0.044**	0.018	0.016
	(0.0152)	(0.0161)	(0.0162)	(0.0316)	(0.0296)	(0.0323)	(0.0198)	(0.0212)	(0.0211)
Parents	0.383***			0.414***			0.192***		
	(0.0202)			(0.0394)			(0.0290)		
Father		0.193***	0.195***		0.304***	0.304***		0.107***	0.110***
		(0.0177)	(0.0180)		(0.0463)	(0.0463)		(0.0223)	(0.0225)
Mother		0.233***	0.233***		0.270***	0.270***		0.117***	0.118***
		(0.0249)	(0.0249)		(0.0437)	(0.0438)		(0.0216)	(0.0215)
Non-white or Migrant (0/1)	-0.095		0.074	-0.081		-0.025	0.763*		0.984**
	(0.1040)		(0.1096)	(0.1724)		(0.1853)	(0.4097)		(0.3921)
Adj. R^2	.2055	.2267	.2267	.2149	.23	.2297	.08382	.08496	.09016
Observations	6303	5554	5554	3210	2818	2818	1526	1397	1392
Clusters	2065	1898	1898	2192	1890	1890	1505	1380	1375

Notes: Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table 4.7: Testing for a grandparental effect: grandparents' death as exogenous source of variation in the likelihood of interaction

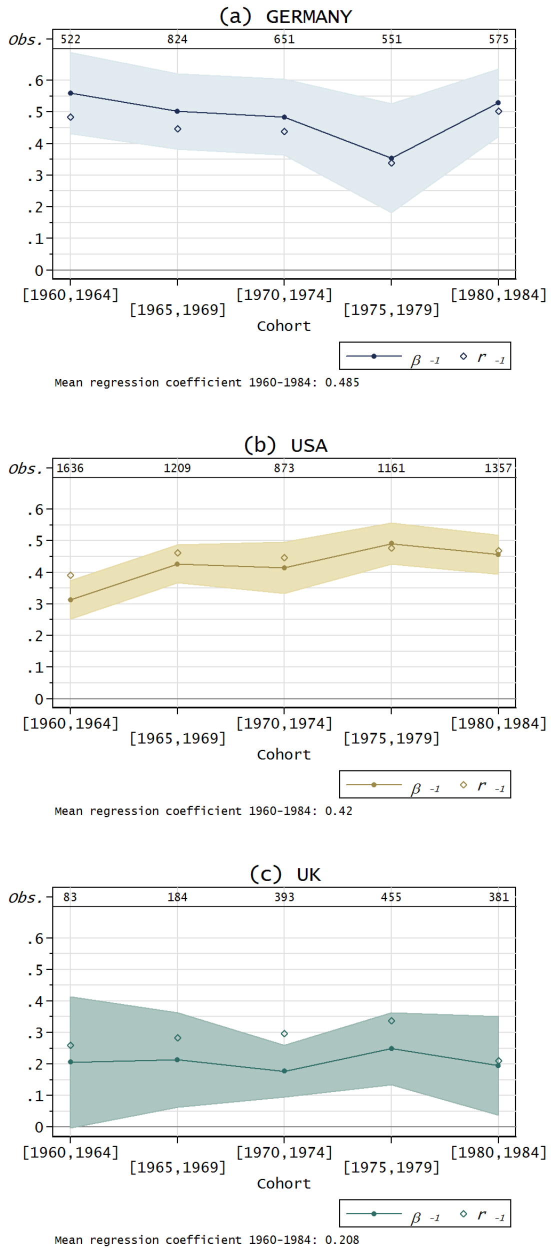
Outcome*: Completed years of education*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Father	0.368***	0.367***	0.330***	0.359***				
	(0.0250)	(0.0296)	(0.0266)	(0.0306)				
Mother					0.391***	0.373***	0.431***	0.430***
					(0.0290)	(0.0350)	(0.0328)	(0.0366)
GF-F	0.047**	0.029						
	(0.0186)	(0.0220)						
GM-F			0.055**	0.033				
			(0.0229)	(0.0236)				
GF-M					0.086***	0.106***		
					(0.0200)	(0.0241)		
GM-M							0.040	0.048
							(0.0278)	(0.0333)
Death=1 × GF-F		0.047						
		(0.0355)						
Death=1 × GM-F				0.075				
				(0.0521)				
Death=1 × GF-M						-0.067*		
						(0.0378)		
Death=1 × GM-M								-0.033
								(0.0571)
Death=1		-0.479						
		(0.5481)						
Death=1 × Father		0.003						
		(0.0462)						
Death=1				0.459				
				(0.7046)				
Death=1 × Father				-0.093*				
				(0.0518)				
Death=1						-0.084		
						(0.5402)		
Death=1 × Mother						0.064		
						(0.0463)		
Death=1								0.425
								(0.8073)
Death=1 × Mother								0.005
								(0.0770)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3360	3360	2241	2241	2973	2973	2147	2147
Clusters	1871	1871	1309	1309	1797	1797	1311	1311

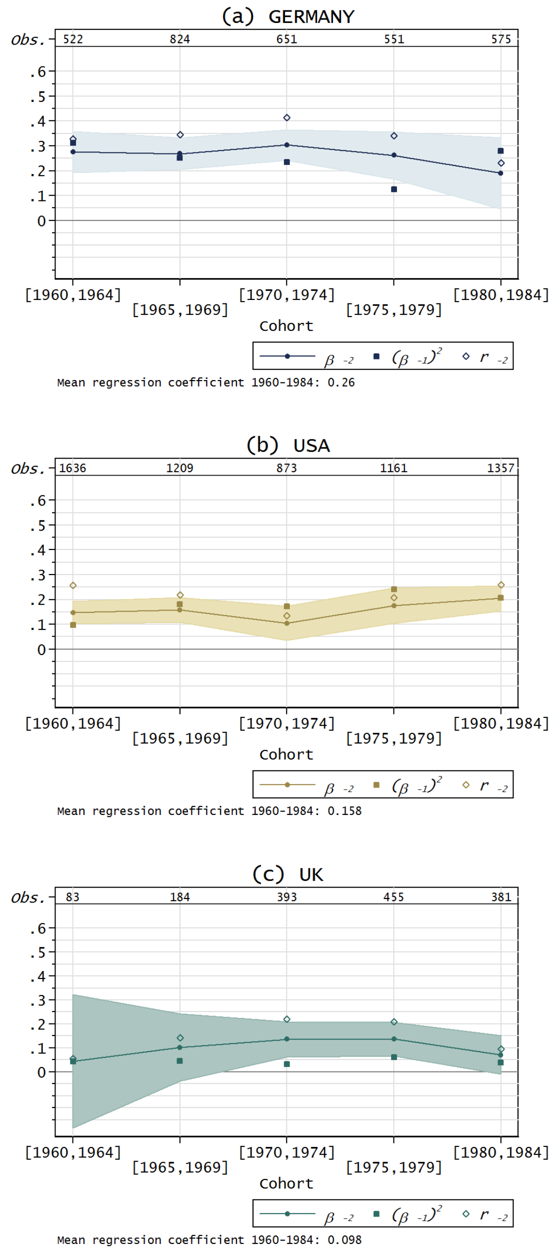
Notes: GF/GM-F/M: Grandfather/Grandmother-Father's/Mother's side. Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Figure 4.1: Multigenerational mobility trends – regression (β) and correlation (r) coefficients

(a) *Panel A – Two generations; parents' on children's education*

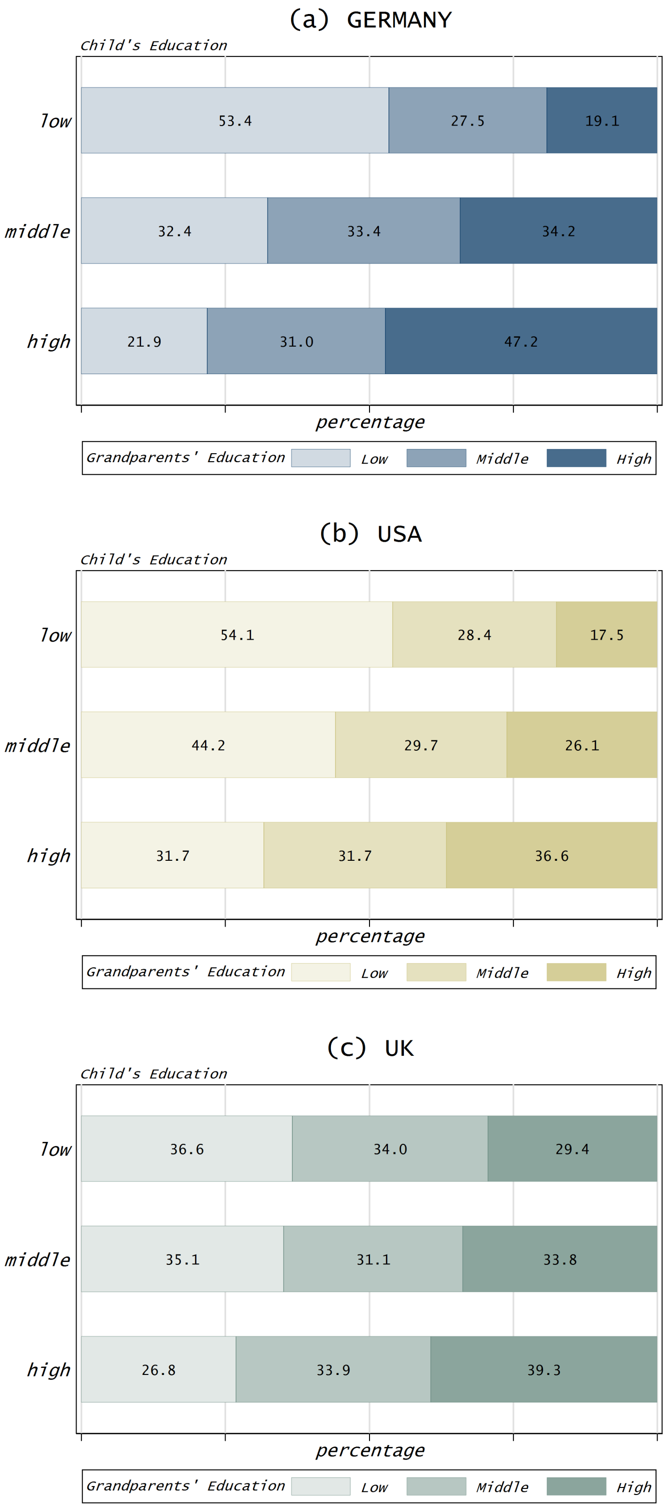


(b) *Panel B – Three generations; grandparents' on grandchildren's education*



Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

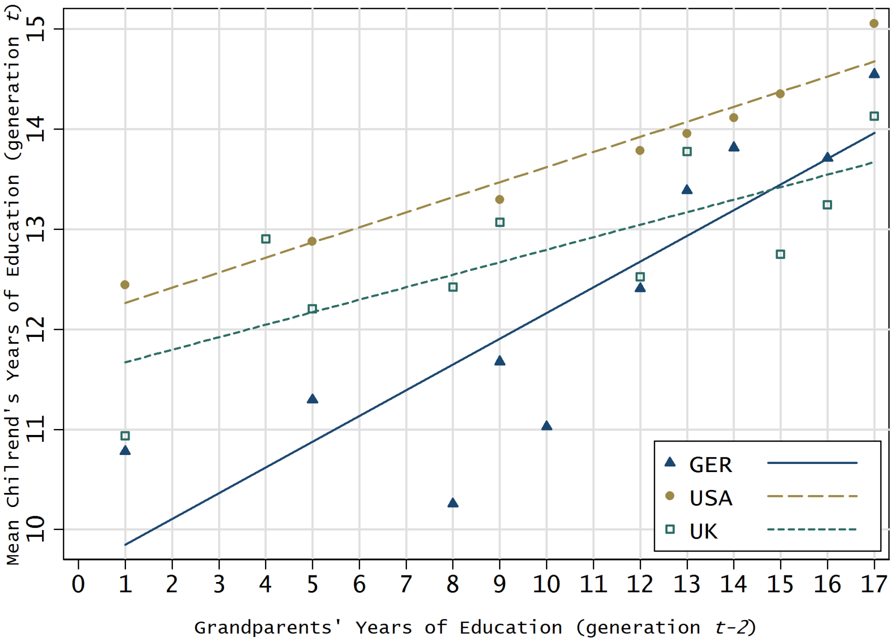
Figure 4.2: Transition matrices by quantiles of the z-score of educational attainment



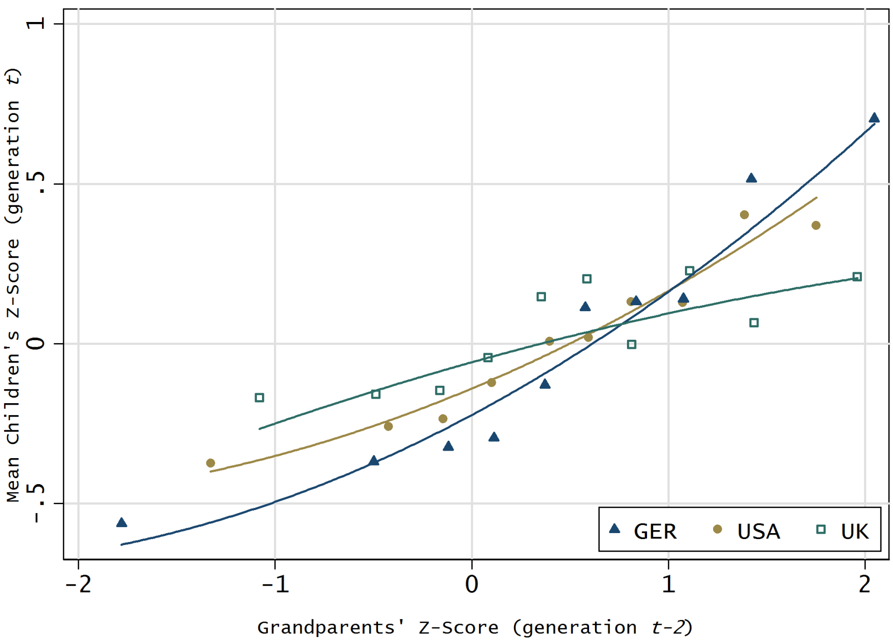
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Figure 4.3: Mobility curves – mean education of grandchildren by grandparents' education

(a) *Completed years of education - Linear fit*

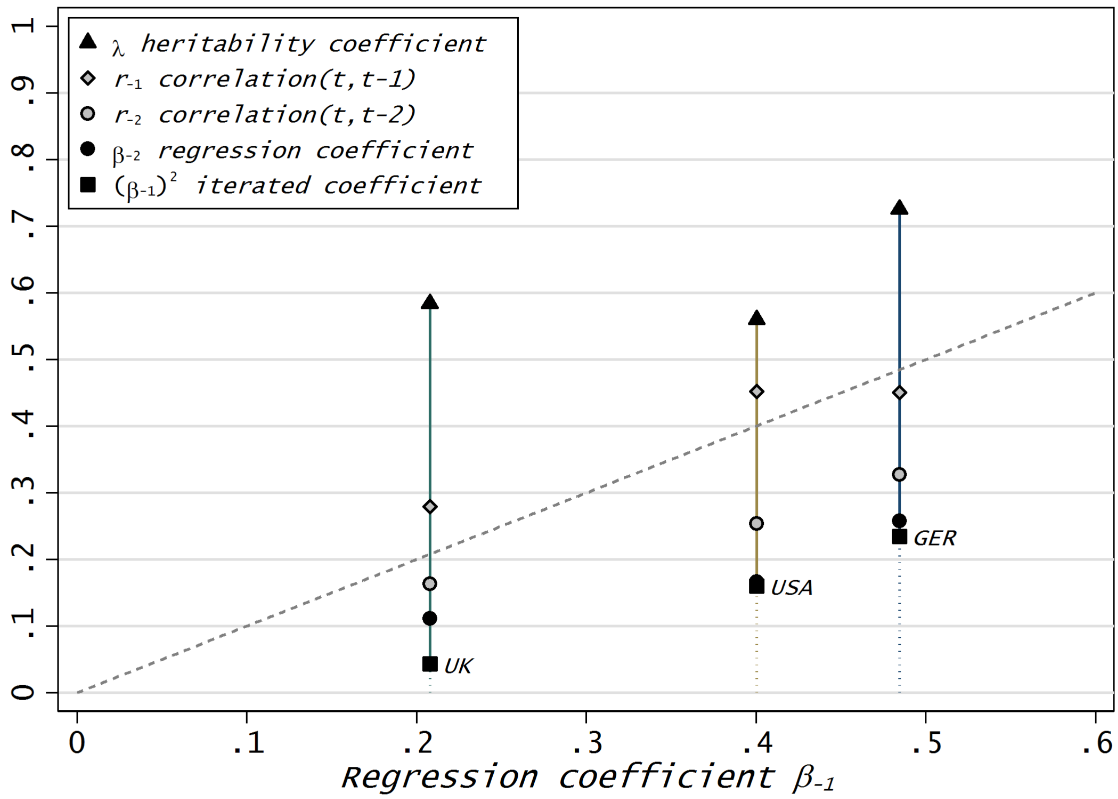


(b) *Educational position (z-score) - Quadratic fit*



Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Figure 4.4: Summary and comparison of the estimated coefficients



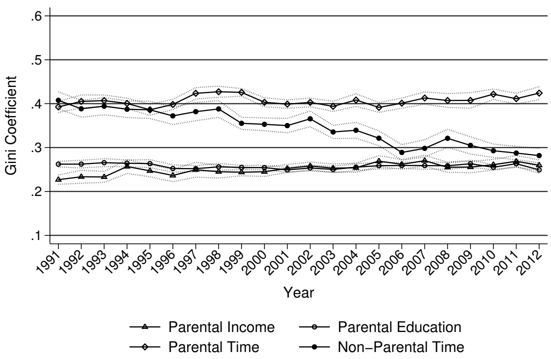
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Appendix A

Appendicies

A.1 Appendix of Chapter 2

Figure A.1.1: Inequality by dimension (Gini coefficient)



Source: SOEP (v30), own calculations.
Note: Parental time is equivalized according to the number of children in the family. Significance at the five percent level is calculated using bootstrap standard errors with 100 replications.

Table A.1.1: Number of observed children (aged 0-14) by family type (unweighted)

Year	Single Parent	Cohabiting Parents	Married Parents	Total
1991	208	99	2,723	3,030
1992	198	110	2,586	2,894
1993	197	123	2,645	2,965
1994	219	133	2,657	3,009
1995	209	122	2,526	2,857
1996	234	137	2,408	2,779
1997	245	173	2,522	2,940
1998	269	200	2,420	2,889
1999	479	278	4,230	4,987
2000	393	307	3,650	4,350
2001	371	310	3,754	4,435
2002	361	312	3,406	4,079
2003	348	320	3,107	3,775
2004	375	307	2,853	3,535
2005	440	317	2,978	3,735
2006	399	315	2,739	3,453
2007	376	294	2,447	3,117
2008	429	331	2,583	3,343
2009	381	281	2,236	2,898
2010	432	296	2,426	3,154
2011	449	354	2,373	3,176
2012	373	325	2,111	2,809
Total	7,385	5,444	61,380	74,209

Source: SOEP (v30), own calculations.
Note: Children with missing information on at least one of the four dimensions are excluded.

Table A.1.2: Descriptive statistics (weighted)

		Parental Income				Parental Education				Parental Time				Non-Parental Time				Total Time			
Year	Family Type	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
	Single	12,144	6,963	1,913	36,590	12	2	7	18	5	5	0	24	4	3	0	12	9	5	0	28
1991	Cohabiting	16,155	5,409	6,321	40,319	13	3	9	18	6	4	0	19	4	3	0	8	10	4	0	23
	Married	18,491	7,610	1,550	70,415	13	3	7	18	6	4	0	30	3	3	0	14	9	4	0	32
	Single	12,565	6,567	721	34,536	12	2	7	18	5	5	0	24	4	3	0	14	9	4	1	24
1992	Cohabiting	16,186	5,021	6,569	36,210	12	3	9	18	5	3	0	24	4	3	0	12	9	4	0	24
	Married	18,890	9,234	4,942	166,946	13	3	7	18	6	5	0	28	4	3	0	12	9	4	0	32
	Single	12,736	7,143	1,012	38,680	11	3	7	18	5	4	0	24	4	3	0	12	9	4	1	24
1993	Cohabiting	16,944	5,987	6,315	37,069	13	2	9	18	7	7	0	48	4	3	0	12	11	7	2	52
	Married	18,994	8,864	3,190	140,065	13	3	7	18	6	5	0	28	3	3	0	12	9	4	0	35
	Single	11,420	7,165	438	46,137	11	2	7	18	6	6	0	24	4	3	0	12	11	6	0	29
1994	Cohabiting	17,050	7,809	4,310	67,208	13	3	9	18	6	5	0	25	4	3	0	12	10	5	0	30
	Married	18,374	9,672	1,418	156,218	13	3	7	18	6	5	0	39	3	3	0	14	10	5	0	39
	Single	11,563	7,007	1,172	42,267	11	2	7	18	6	5	0	24	5	3	0	14	11	5	1	32
1995	Cohabiting	17,553	7,668	3,511	43,797	13	2	9	18	8	6	0	25	3	3	0	12	11	5	0	25
	Married	18,563	8,701	2,437	115,170	13	3	7	18	7	5	0	40	4	3	0	14	10	5	0	40
	Single	13,000	7,113	2,444	43,178	12	2	7	18	5	5	0	24	4	3	0	12	10	5	0	29
1996	Cohabiting	17,635	6,230	4,710	36,106	13	2	9	18	8	6	0	25	3	3	0	12	11	6	0	29
	Married	18,980	8,943	836	118,622	13	3	7	18	7	5	0	48	4	3	0	14	10	5	0	48
	Single	12,816	6,019	2,608	54,962	12	3	7	18	5	5	0	24	5	3	0	14	10	5	0	28
1997	Cohabiting	19,611	21,549	4,814	162,390	13	3	7	18	8	7	0	28	3	3	0	12	11	7	0	36
	Married	19,266	9,792	1,551	132,912	13	3	7	18	6	5	0	34	4	3	0	14	10	5	0	34
	Single	12,886	5,996	3,047	45,522	12	2	7	18	5	5	0	24	5	3	0	14	10	5	0	36
1998	Cohabiting	17,893	8,472	4,392	61,854	13	3	7	18	8	7	0	48	3	3	0	12	11	7	0	48
	Married	19,876	9,651	4,164	102,715	13	3	7	18	7	5	0	32	3	3	0	14	10	5	0	33
	Single	12,772	6,002	3,354	51,097	12	2	7	18	5	4	0	24	5	3	0	14	9	4	0	28
1999	Cohabiting	18,686	7,911	3,788	56,687	13	2	7	18	7	7	0	48	4	3	0	12	11	6	1	52
	Married	20,104	9,230	3,660	144,416	13	3	7	18	6	5	0	36	4	2	0	14	10	5	0	36
	Single	12,331	5,694	2,231	42,240	12	2	7	18	5	4	0	24	4	3	0	14	10	4	0	28
2000	Cohabiting	19,103	8,012	6,266	67,381	13	2	7	18	7	6	0	36	4	3	0	13	11	6	0	41
	Married	20,422	9,487	2,506	94,653	13	3	7	18	6	5	0	30	4	2	0	14	10	5	0	42
	Single	13,109	7,582	352	76,733	11	2	7	18	5	5	0	24	4	3	0	13	10	5	0	29
2001	Cohabiting	18,081	8,857	5,653	100,565	13	2	9	18	7	6	0	27	3	3	0	13	11	6	1	31
	Married	20,823	11,278	2,112	269,016	13	3	7	18	6	5	0	32	4	2	0	13	10	5	0	37

Table A.1.3: Continued: Descriptive statistics (weighted)

		Parental Income				Parental Education				Parental Time				Non-Parental Time				Total Time			
Year	Family Type	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
	Single	12,082	6,286	1,727	62,231	11	2	7	18	6	5	0	24	4	3	0	13	11	5	1	32
2002	Cohabiting	18,289	9,478	4,938	104,115	13	3	9	18	8	6	0	45	3	3	0	13	11	6	0	45
	Married	21,147	10,292	4,262	131,635	13	3	7	18	7	5	0	36	4	3	0	15	11	5	0	41
	Single	12,177	5,918	1,004	61,793	11	2	7	18	6	5	0	24	5	3	0	13	11	5	0	36
2003	Cohabiting	17,992	9,587	4,742	83,652	12	2	7	18	7	6	0	29	4	3	0	14	11	6	0	34
	Married	21,035	10,029	3,715	207,782	13	3	7	18	7	5	0	48	4	2	0	13	10	5	0	60
	Single	11,927	5,428	2,538	77,639	12	2	7	18	7	6	0	24	4	3	0	13	11	5	1	28
2004	Cohabiting	18,183	9,182	3,515	111,304	13	3	9	18	9	7	0	31	4	3	0	13	13	7	0	39
	Married	21,321	9,991	1,269	166,880	13	3	7	18	7	5	0	48	4	2	0	13	11	5	0	54
	Single	12,491	5,812	2,498	111,617	12	3	7	18	6	5	0	24	5	3	0	14	11	5	1	38
2005	Cohabiting	17,172	8,907	2,217	59,178	13	2	9	18	8	6	0	30	4	3	0	13	12	6	0	31
	Married	21,490	11,785	2,187	158,590	13	3	7	18	7	5	0	48	4	2	0	14	11	5	0	48
	Single	12,591	5,418	2,521	92,204	12	3	7	18	6	5	0	24	5	3	0	14	11	6	1	38
2006	Cohabiting	19,452	9,406	3,726	67,915	13	3	7	18	8	6	0	36	4	3	0	12	12	6	0	42
	Married	21,689	11,574	3,902	182,342	13	3	7	18	7	5	0	48	4	2	0	14	11	5	0	52
	Single	12,839	5,258	2,208	56,365	12	3	7	18	6	5	0	24	5	3	0	14	11	5	0	30
2007	Cohabiting	19,998	13,250	3,108	70,051	13	3	9	18	8	7	0	40	4	3	0	14	12	6	0	40
	Married	21,875	11,451	4,496	129,508	13	3	7	18	7	5	0	36	4	2	0	14	11	5	0	42
	Single	13,110	5,881	1,616	65,233	12	3	7	18	6	4	0	24	5	2	0	13	11	5	0	28
2008	Cohabiting	19,683	9,905	4,318	50,624	13	3	7	18	9	7	0	48	4	3	0	12	13	7	0	48
	Married	21,520	10,125	4,056	107,732	13	3	7	18	7	5	0	36	4	2	0	12	11	5	0	40
	Single	13,663	5,919	1,493	42,507	12	3	7	18	6	5	0	24	5	2	0	14	11	5	0	32
2009	Cohabiting	20,391	12,578	907	65,367	13	3	7	18	8	7	0	48	5	3	0	12	12	6	2	48
	Married	21,779	9,964	3,891	128,101	13	3	7	18	6	5	0	34	5	3	0	12	11	5	0	42
	Single	13,345	5,999	2,233	53,494	12	3	7	18	6	5	0	24	6	2	0	14	11	5	0	32
2010	Cohabiting	19,972	8,147	2,744	57,932	13	3	7	18	9	8	0	48	5	3	0	12	14	7	1	52
	Married	22,210	11,097	3,490	132,710	14	3	7	18	7	5	0	48	5	3	0	13	11	5	0	52
	Single	14,075	7,913	3,696	99,350	12	3	7	18	5	5	0	24	6	3	0	15	11	5	0	33
2011	Cohabiting	19,285	8,238	1,798	146,790	13	2	7	18	6	5	0	48	5	3	0	14	11	5	0	48
	Married	21,833	11,952	2,880	137,571	13	3	7	18	6	5	0	34	5	2	0	14	11	5	0	42
	Single	14,279	7,178	2,357	55,967	12	3	7	18	6	6	0	24	6	2	0	13	12	6	0	30
2012	Cohabiting	19,517	9,475	1,757	106,335	13	2	7	18	7	6	0	48	5	3	0	13	12	5	0	48
	Married	22,707	11,461	2,850	129,842	14	3	7	18	6	5	0	48	5	2	0	12	11	5	0	48

Source: SOEP (v30), own calculations.

Table A.1.4: Multidimensional inequality (weighting scheme: $w_{inc} = \frac{1}{4}$, $w_{educ} = \frac{1}{4}$, $w_{time} = \frac{1}{4}$, and $w_{np-time} = \frac{1}{4}$)

$\alpha = 0$									
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.775	0.730	0.820	0.205	0.193	0.217	0.062	0.058	0.066
1992	0.759	0.712	0.806	0.197	0.184	0.209	0.061	0.056	0.066
1993	0.755	0.710	0.800	0.200	0.185	0.214	0.063	0.058	0.069
1994	0.732	0.685	0.778	0.194	0.182	0.206	0.063	0.058	0.068
1995	0.716	0.673	0.760	0.190	0.177	0.202	0.059	0.054	0.065
1996	0.684	0.640	0.728	0.176	0.163	0.189	0.054	0.049	0.060
1997	0.739	0.693	0.786	0.186	0.177	0.196	0.054	0.051	0.057
1998	0.759	0.714	0.804	0.196	0.184	0.208	0.057	0.053	0.062
1999	0.698	0.666	0.731	0.178	0.169	0.188	0.055	0.052	0.059
2000	0.716	0.680	0.752	0.180	0.171	0.190	0.053	0.050	0.056
2001	0.671	0.632	0.711	0.177	0.166	0.187	0.053	0.049	0.057
2002	0.733	0.689	0.777	0.189	0.178	0.199	0.052	0.049	0.055
2003	0.650	0.609	0.692	0.172	0.161	0.183	0.051	0.047	0.055
2004	0.663	0.618	0.708	0.171	0.158	0.185	0.052	0.048	0.056
2005	0.627	0.582	0.671	0.166	0.154	0.179	0.052	0.048	0.057
2006	0.534	0.493	0.576	0.143	0.131	0.155	0.050	0.046	0.055
2007	0.560	0.511	0.609	0.156	0.142	0.169	0.053	0.048	0.058
2008	0.629	0.570	0.689	0.171	0.154	0.189	0.055	0.049	0.060
2009	0.546	0.490	0.601	0.155	0.139	0.170	0.056	0.050	0.061
2010	0.511	0.467	0.555	0.143	0.131	0.155	0.052	0.048	0.056
2011	0.498	0.456	0.539	0.146	0.134	0.159	0.055	0.050	0.060
2012	0.515	0.463	0.566	0.141	0.127	0.155	0.047	0.043	0.050

$\alpha = 1$									
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.383	0.355	0.411	0.160	0.150	0.170	0.058	0.055	0.061
1992	0.371	0.344	0.399	0.153	0.143	0.163	0.056	0.052	0.060
1993	0.372	0.346	0.398	0.156	0.145	0.167	0.059	0.054	0.063
1994	0.361	0.334	0.388	0.152	0.142	0.162	0.059	0.055	0.063
1995	0.346	0.322	0.370	0.149	0.140	0.158	0.056	0.052	0.061
1996	0.329	0.305	0.352	0.139	0.129	0.149	0.052	0.048	0.057
1997	0.367	0.340	0.395	0.150	0.141	0.159	0.052	0.049	0.055
1998	0.373	0.347	0.400	0.155	0.145	0.164	0.054	0.050	0.057
1999	0.343	0.325	0.361	0.141	0.134	0.148	0.052	0.050	0.055
2000	0.345	0.325	0.365	0.142	0.135	0.150	0.050	0.048	0.053
2001	0.319	0.299	0.340	0.138	0.130	0.146	0.050	0.047	0.053
2002	0.350	0.325	0.374	0.148	0.140	0.157	0.049	0.047	0.052
2003	0.306	0.284	0.327	0.134	0.125	0.142	0.048	0.045	0.052
2004	0.312	0.288	0.335	0.134	0.124	0.144	0.049	0.045	0.052
2005	0.295	0.273	0.317	0.129	0.120	0.138	0.049	0.046	0.053
2006	0.247	0.227	0.267	0.111	0.103	0.120	0.047	0.044	0.051
2007	0.263	0.239	0.286	0.119	0.110	0.128	0.049	0.045	0.053
2008	0.291	0.262	0.321	0.132	0.119	0.144	0.051	0.047	0.055
2009	0.250	0.224	0.277	0.117	0.106	0.128	0.052	0.047	0.056
2010	0.235	0.215	0.255	0.110	0.101	0.118	0.049	0.046	0.052
2011	0.230	0.211	0.249	0.110	0.101	0.118	0.051	0.047	0.054
2012	0.240	0.215	0.264	0.109	0.098	0.119	0.044	0.041	0.048

$\alpha = 2$									
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.303	0.277	0.330	0.145	0.135	0.155	0.058	0.055	0.061
1992	0.290	0.265	0.316	0.138	0.129	0.148	0.056	0.053	0.059
1993	0.296	0.271	0.320	0.142	0.131	0.153	0.059	0.055	0.062
1994	0.287	0.261	0.312	0.138	0.128	0.148	0.059	0.056	0.063
1995	0.273	0.251	0.294	0.136	0.126	0.145	0.057	0.052	0.062
1996	0.256	0.235	0.278	0.127	0.117	0.137	0.053	0.048	0.058
1997	0.295	0.269	0.321	0.138	0.128	0.148	0.053	0.050	0.056
1998	0.301	0.274	0.328	0.141	0.132	0.151	0.053	0.050	0.057
1999	0.275	0.258	0.291	0.129	0.122	0.136	0.052	0.050	0.054
2000	0.271	0.252	0.289	0.129	0.122	0.136	0.050	0.048	0.052
2001	0.247	0.230	0.265	0.123	0.116	0.131	0.050	0.047	0.053
2002	0.274	0.252	0.296	0.135	0.126	0.144	0.050	0.047	0.052
2003	0.236	0.217	0.254	0.120	0.112	0.128	0.049	0.045	0.052
2004	0.240	0.219	0.261	0.120	0.111	0.130	0.049	0.045	0.052
2005	0.229	0.209	0.248	0.116	0.108	0.124	0.049	0.046	0.052
2006	0.189	0.172	0.205	0.099	0.092	0.107	0.048	0.044	0.051
2007	0.205	0.185	0.225	0.106	0.098	0.115	0.049	0.045	0.052
2008	0.224	0.199	0.249	0.117	0.106	0.129	0.050	0.046	0.054
2009	0.188	0.167	0.209	0.102	0.092	0.112	0.051	0.047	0.055
2010	0.178	0.162	0.194	0.097	0.089	0.104	0.048	0.045	0.051
2011	0.175	0.160	0.190	0.096	0.088	0.103	0.050	0.046	0.053
2012	0.183	0.163	0.203	0.096	0.087	0.106	0.044	0.041	0.047

Source: SOEP (v30), own calculations.

Table A.1.5: Multidimensional inequality (weighting scheme: $w_{inc} = \frac{1}{2}$, $w_{educ} = \frac{1}{6}$, $w_{time} = \frac{1}{6}$, and $w_{np-time} = \frac{1}{6}$)

	$\alpha = 0$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.585	0.552	0.618	0.126	0.117	0.135	0.055	0.052	0.059
1992	0.573	0.539	0.607	0.121	0.113	0.129	0.055	0.050	0.059
1993	0.574	0.540	0.608	0.125	0.115	0.134	0.056	0.052	0.061
1994	0.556	0.523	0.590	0.126	0.118	0.134	0.058	0.054	0.062
1995	0.547	0.515	0.579	0.124	0.115	0.133	0.055	0.050	0.060
1996	0.521	0.489	0.552	0.113	0.103	0.122	0.050	0.046	0.055
1997	0.562	0.527	0.596	0.119	0.112	0.127	0.051	0.048	0.054
1998	0.576	0.543	0.610	0.123	0.115	0.132	0.053	0.049	0.057
1999	0.533	0.508	0.557	0.115	0.109	0.121	0.052	0.049	0.055
2000	0.548	0.521	0.575	0.115	0.109	0.122	0.050	0.048	0.053
2001	0.517	0.488	0.545	0.117	0.110	0.123	0.051	0.048	0.054
2002	0.567	0.535	0.600	0.128	0.120	0.136	0.050	0.048	0.053
2003	0.506	0.476	0.536	0.117	0.109	0.125	0.049	0.045	0.052
2004	0.513	0.479	0.547	0.114	0.105	0.123	0.049	0.046	0.053
2005	0.490	0.457	0.523	0.116	0.108	0.125	0.051	0.047	0.055
2006	0.422	0.390	0.454	0.101	0.093	0.109	0.049	0.045	0.052
2007	0.443	0.406	0.480	0.111	0.102	0.120	0.051	0.047	0.056
2008	0.492	0.448	0.536	0.117	0.105	0.129	0.052	0.047	0.057
2009	0.429	0.388	0.471	0.108	0.098	0.118	0.053	0.048	0.058
2010	0.404	0.371	0.437	0.104	0.096	0.111	0.050	0.047	0.054
2011	0.397	0.366	0.428	0.107	0.099	0.116	0.054	0.049	0.058
2012	0.406	0.367	0.444	0.099	0.091	0.107	0.045	0.042	0.049
	$\alpha = 1$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.340	0.316	0.363	0.108	0.101	0.116	0.052	0.049	0.055
1992	0.330	0.306	0.353	0.104	0.098	0.111	0.052	0.048	0.055
1993	0.332	0.309	0.356	0.109	0.101	0.117	0.054	0.050	0.058
1994	0.326	0.303	0.349	0.110	0.103	0.116	0.055	0.052	0.059
1995	0.317	0.295	0.339	0.109	0.101	0.117	0.053	0.049	0.057
1996	0.299	0.278	0.319	0.100	0.091	0.109	0.049	0.045	0.053
1997	0.331	0.306	0.356	0.109	0.101	0.116	0.050	0.047	0.053
1998	0.335	0.311	0.359	0.110	0.102	0.117	0.051	0.047	0.054
1999	0.308	0.292	0.324	0.102	0.096	0.107	0.050	0.047	0.052
2000	0.313	0.295	0.331	0.102	0.096	0.107	0.048	0.046	0.050
2001	0.292	0.274	0.309	0.103	0.097	0.108	0.049	0.047	0.052
2002	0.322	0.301	0.344	0.112	0.105	0.118	0.049	0.046	0.052
2003	0.284	0.266	0.302	0.102	0.096	0.108	0.047	0.044	0.050
2004	0.288	0.267	0.309	0.100	0.093	0.107	0.047	0.044	0.051
2005	0.278	0.258	0.298	0.103	0.096	0.110	0.049	0.046	0.053
2006	0.236	0.218	0.255	0.090	0.083	0.097	0.047	0.044	0.050
2007	0.250	0.228	0.271	0.097	0.090	0.105	0.049	0.045	0.053
2008	0.274	0.248	0.299	0.102	0.092	0.111	0.049	0.045	0.054
2009	0.236	0.213	0.259	0.093	0.085	0.101	0.050	0.046	0.054
2010	0.222	0.204	0.240	0.090	0.083	0.096	0.048	0.045	0.051
2011	0.222	0.205	0.238	0.093	0.086	0.100	0.051	0.047	0.054
2012	0.226	0.204	0.247	0.088	0.080	0.095	0.044	0.041	0.047
	$\alpha = 2$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.284	0.260	0.308	0.105	0.097	0.112	0.053	0.050	0.055
1992	0.271	0.248	0.294	0.100	0.094	0.106	0.052	0.049	0.056
1993	0.279	0.254	0.304	0.106	0.097	0.116	0.055	0.051	0.059
1994	0.275	0.251	0.299	0.107	0.100	0.114	0.057	0.052	0.061
1995	0.270	0.245	0.295	0.107	0.097	0.117	0.054	0.049	0.058
1996	0.252	0.230	0.274	0.100	0.089	0.110	0.051	0.046	0.055
1997	0.287	0.259	0.316	0.110	0.100	0.121	0.052	0.049	0.055
1998	0.287	0.258	0.317	0.109	0.099	0.119	0.051	0.047	0.055
1999	0.261	0.244	0.278	0.101	0.095	0.107	0.050	0.048	0.052
2000	0.260	0.242	0.279	0.099	0.093	0.105	0.048	0.046	0.051
2001	0.242	0.226	0.258	0.101	0.096	0.107	0.050	0.048	0.053
2002	0.271	0.250	0.292	0.110	0.103	0.117	0.050	0.047	0.053
2003	0.235	0.218	0.252	0.100	0.094	0.106	0.048	0.045	0.051
2004	0.238	0.219	0.257	0.098	0.090	0.105	0.048	0.044	0.051
2005	0.235	0.214	0.256	0.102	0.094	0.111	0.050	0.046	0.053
2006	0.199	0.181	0.217	0.089	0.082	0.097	0.048	0.045	0.051
2007	0.213	0.192	0.234	0.096	0.088	0.105	0.049	0.046	0.053
2008	0.228	0.203	0.252	0.099	0.090	0.109	0.049	0.045	0.053
2009	0.192	0.172	0.212	0.089	0.081	0.097	0.050	0.046	0.054
2010	0.181	0.166	0.196	0.087	0.080	0.093	0.048	0.045	0.051
2011	0.185	0.170	0.200	0.092	0.084	0.099	0.051	0.047	0.054
2012	0.187	0.167	0.206	0.086	0.078	0.095	0.045	0.042	0.048

Source: SOEP (v30), own calculations.

Table A.1.6: Multidimensional inequality (weighting scheme: $w_{inc} = \frac{3}{4}$, $w_{educ} = \frac{1}{12}$, $w_{time} = \frac{1}{12}$, and $w_{np-time} = \frac{1}{12}$)

	$\alpha = 0$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.585	0.354	0.394	0.085	0.076	0.093	0.050	0.047	0.054
1992	0.573	0.348	0.388	0.085	0.078	0.092	0.052	0.047	0.057
1993	0.574	0.351	0.394	0.087	0.079	0.095	0.053	0.048	0.058
1994	0.556	0.344	0.385	0.099	0.089	0.108	0.057	0.052	0.063
1995	0.547	0.340	0.382	0.095	0.085	0.105	0.054	0.049	0.059
1996	0.521	0.322	0.362	0.084	0.075	0.094	0.050	0.045	0.055
1997	0.562	0.347	0.392	0.090	0.081	0.099	0.053	0.048	0.058
1998	0.576	0.355	0.397	0.089	0.081	0.097	0.052	0.047	0.057
1999	0.533	0.336	0.368	0.087	0.082	0.091	0.053	0.050	0.056
2000	0.548	0.345	0.379	0.088	0.081	0.095	0.052	0.049	0.056
2001	0.517	0.332	0.365	0.092	0.087	0.097	0.055	0.052	0.058
2002	0.567	0.364	0.403	0.102	0.095	0.109	0.055	0.052	0.059
2003	0.506	0.328	0.365	0.095	0.087	0.103	0.052	0.049	0.056
2004	0.513	0.327	0.369	0.092	0.085	0.099	0.052	0.049	0.056
2005	0.490	0.320	0.362	0.100	0.092	0.108	0.057	0.053	0.062
2006	0.422	0.279	0.321	0.090	0.083	0.097	0.053	0.049	0.057
2007	0.443	0.291	0.338	0.098	0.089	0.106	0.057	0.052	0.062
2008	0.492	0.312	0.367	0.094	0.085	0.103	0.054	0.050	0.059
2009	0.429	0.278	0.328	0.091	0.082	0.100	0.056	0.050	0.061
2010	0.404	0.268	0.310	0.092	0.085	0.099	0.054	0.050	0.058
2011	0.397	0.269	0.308	0.097	0.088	0.105	0.058	0.053	0.063
2012	0.406	0.266	0.313	0.087	0.080	0.094	0.050	0.046	0.054
	$\alpha = 1$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.272	0.255	0.289	0.079	0.072	0.086	0.049	0.046	0.052
1992	0.266	0.249	0.283	0.081	0.074	0.087	0.052	0.046	0.057
1993	0.271	0.252	0.290	0.084	0.076	0.093	0.053	0.048	0.059
1994	0.268	0.251	0.285	0.093	0.085	0.102	0.057	0.051	0.064
1995	0.266	0.246	0.287	0.091	0.080	0.102	0.054	0.049	0.059
1996	0.251	0.232	0.269	0.083	0.071	0.095	0.050	0.045	0.056
1997	0.278	0.255	0.302	0.093	0.081	0.106	0.055	0.049	0.062
1998	0.276	0.256	0.296	0.089	0.079	0.099	0.053	0.047	0.058
1999	0.256	0.243	0.270	0.084	0.079	0.090	0.052	0.050	0.055
2000	0.261	0.247	0.276	0.084	0.078	0.090	0.052	0.048	0.055
2001	0.251	0.238	0.264	0.092	0.086	0.097	0.056	0.053	0.059
2002	0.277	0.261	0.293	0.098	0.092	0.104	0.055	0.052	0.059
2003	0.248	0.234	0.262	0.091	0.085	0.098	0.053	0.049	0.056
2004	0.249	0.233	0.266	0.089	0.082	0.096	0.052	0.048	0.056
2005	0.249	0.232	0.267	0.100	0.091	0.109	0.058	0.053	0.063
2006	0.218	0.201	0.234	0.091	0.083	0.099	0.054	0.050	0.058
2007	0.229	0.210	0.248	0.097	0.088	0.106	0.057	0.052	0.062
2008	0.242	0.221	0.262	0.092	0.083	0.101	0.054	0.049	0.058
2009	0.214	0.196	0.232	0.088	0.079	0.097	0.054	0.049	0.059
2010	0.204	0.189	0.220	0.089	0.082	0.097	0.053	0.049	0.057
2011	0.209	0.194	0.224	0.097	0.087	0.106	0.058	0.053	0.063
2012	0.207	0.190	0.225	0.087	0.079	0.096	0.051	0.046	0.055
	$\alpha = 2$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.252	0.232	0.272	0.082	0.074	0.090	0.051	0.047	0.054
1992	0.243	0.224	0.263	0.085	0.077	0.094	0.055	0.047	0.063
1993	0.253	0.229	0.278	0.091	0.079	0.102	0.057	0.049	0.065
1994	0.253	0.231	0.274	0.100	0.088	0.112	0.062	0.052	0.072
1995	0.259	0.224	0.293	0.099	0.081	0.116	0.057	0.050	0.064
1996	0.244	0.212	0.276	0.092	0.073	0.112	0.054	0.046	0.062
1997	0.280	0.240	0.320	0.111	0.088	0.134	0.062	0.052	0.072
1998	0.266	0.233	0.299	0.099	0.083	0.115	0.056	0.049	0.064
1999	0.242	0.225	0.259	0.091	0.084	0.098	0.055	0.052	0.058
2000	0.244	0.226	0.262	0.089	0.082	0.097	0.054	0.050	0.057
2001	0.240	0.224	0.255	0.106	0.097	0.114	0.062	0.058	0.067
2002	0.265	0.246	0.284	0.107	0.099	0.114	0.059	0.055	0.063
2003	0.233	0.217	0.249	0.100	0.093	0.107	0.056	0.053	0.060
2004	0.234	0.215	0.252	0.097	0.087	0.106	0.055	0.050	0.059
2005	0.244	0.220	0.268	0.114	0.099	0.128	0.063	0.056	0.070
2006	0.213	0.193	0.233	0.104	0.093	0.115	0.059	0.054	0.064
2007	0.225	0.201	0.250	0.109	0.096	0.123	0.061	0.055	0.068
2008	0.229	0.206	0.251	0.099	0.088	0.110	0.056	0.050	0.061
2009	0.199	0.179	0.219	0.094	0.082	0.106	0.056	0.050	0.062
2010	0.191	0.174	0.208	0.097	0.086	0.107	0.056	0.051	0.061
2011	0.204	0.184	0.223	0.109	0.095	0.123	0.062	0.055	0.069
2012	0.197	0.176	0.218	0.097	0.085	0.109	0.055	0.049	0.060

Source: SOEP (v30), own calculations.

Table A.1.7: Multidimensional inequality (weighting scheme: $w_{inc} = \frac{9}{10}$, $w_{educ} = \frac{1}{30}$, $w_{time} = \frac{1}{30}$, and $w_{np-time} = \frac{1}{30}$)

	$\alpha = 0$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.202	0.190	0.214	0.082	0.073	0.091	0.058	0.053	0.062
1992	0.200	0.190	0.211	0.086	0.076	0.095	0.062	0.054	0.069
1993	0.206	0.192	0.219	0.086	0.076	0.095	0.062	0.055	0.069
1994	0.210	0.197	0.224	0.105	0.092	0.118	0.071	0.062	0.080
1995	0.209	0.193	0.225	0.097	0.085	0.109	0.067	0.059	0.074
1996	0.195	0.179	0.210	0.087	0.076	0.098	0.061	0.054	0.069
1997	0.212	0.195	0.229	0.094	0.081	0.106	0.068	0.059	0.077
1998	0.212	0.197	0.226	0.091	0.080	0.101	0.065	0.057	0.072
1999	0.201	0.192	0.211	0.089	0.084	0.095	0.066	0.062	0.070
2000	0.207	0.196	0.218	0.092	0.084	0.101	0.067	0.061	0.072
2001	0.208	0.199	0.217	0.098	0.092	0.104	0.071	0.067	0.076
2002	0.230	0.219	0.241	0.106	0.099	0.114	0.074	0.069	0.079
2003	0.211	0.200	0.223	0.101	0.092	0.110	0.070	0.064	0.075
2004	0.209	0.197	0.221	0.098	0.091	0.106	0.068	0.063	0.074
2005	0.215	0.201	0.228	0.110	0.100	0.120	0.077	0.070	0.084
2006	0.195	0.182	0.208	0.101	0.093	0.109	0.071	0.066	0.077
2007	0.204	0.190	0.219	0.107	0.098	0.117	0.076	0.069	0.083
2008	0.209	0.193	0.225	0.098	0.089	0.107	0.069	0.063	0.075
2009	0.194	0.180	0.209	0.098	0.088	0.107	0.070	0.063	0.078
2010	0.191	0.178	0.204	0.101	0.092	0.110	0.070	0.065	0.076
2011	0.195	0.181	0.208	0.106	0.096	0.117	0.076	0.068	0.083
2012	0.190	0.176	0.203	0.098	0.089	0.106	0.068	0.062	0.075
	$\alpha = 1$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.181	0.170	0.192	0.079	0.071	0.087	0.058	0.053	0.063
1992	0.179	0.168	0.190	0.086	0.074	0.098	0.065	0.054	0.075
1993	0.185	0.171	0.199	0.086	0.075	0.097	0.065	0.055	0.074
1994	0.189	0.177	0.201	0.102	0.088	0.117	0.074	0.061	0.087
1995	0.192	0.172	0.211	0.095	0.082	0.109	0.068	0.059	0.077
1996	0.180	0.160	0.199	0.088	0.074	0.103	0.064	0.054	0.075
1997	0.204	0.181	0.228	0.103	0.084	0.122	0.075	0.061	0.089
1998	0.195	0.178	0.212	0.094	0.081	0.107	0.068	0.058	0.078
1999	0.183	0.173	0.194	0.090	0.084	0.096	0.067	0.063	0.072
2000	0.186	0.175	0.198	0.091	0.083	0.099	0.068	0.062	0.073
2001	0.191	0.182	0.200	0.103	0.095	0.110	0.077	0.071	0.082
2002	0.207	0.196	0.218	0.105	0.098	0.112	0.075	0.070	0.080
2003	0.190	0.180	0.199	0.100	0.092	0.107	0.072	0.067	0.076
2004	0.188	0.176	0.201	0.098	0.089	0.107	0.070	0.064	0.076
2005	0.200	0.183	0.216	0.114	0.101	0.126	0.082	0.073	0.090
2006	0.180	0.166	0.194	0.106	0.096	0.116	0.076	0.069	0.083
2007	0.188	0.172	0.205	0.112	0.100	0.123	0.080	0.071	0.089
2008	0.187	0.172	0.202	0.099	0.089	0.108	0.070	0.064	0.077
2009	0.173	0.159	0.188	0.097	0.086	0.108	0.071	0.063	0.079
2010	0.170	0.157	0.184	0.102	0.091	0.112	0.072	0.065	0.080
2011	0.179	0.164	0.194	0.111	0.098	0.124	0.080	0.071	0.089
2012	0.172	0.157	0.187	0.101	0.090	0.112	0.072	0.064	0.080
	$\alpha = 2$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.188	0.173	0.203	0.085	0.075	0.094	0.062	0.056	0.069
1992	0.187	0.171	0.202	0.101	0.080	0.122	0.077	0.057	0.097
1993	0.197	0.175	0.218	0.100	0.079	0.120	0.075	0.057	0.093
1994	0.203	0.184	0.222	0.121	0.092	0.150	0.089	0.063	0.115
1995	0.214	0.173	0.255	0.109	0.084	0.134	0.076	0.061	0.092
1996	0.203	0.162	0.244	0.105	0.077	0.132	0.074	0.057	0.092
1997	0.246	0.194	0.298	0.135	0.096	0.175	0.095	0.068	0.122
1998	0.216	0.183	0.249	0.111	0.088	0.134	0.079	0.064	0.095
1999	0.197	0.182	0.213	0.101	0.092	0.110	0.074	0.068	0.080
2000	0.200	0.183	0.217	0.101	0.090	0.112	0.075	0.067	0.082
2001	0.217	0.201	0.234	0.131	0.115	0.146	0.096	0.084	0.107
2002	0.228	0.213	0.243	0.120	0.111	0.129	0.085	0.079	0.091
2003	0.206	0.193	0.219	0.115	0.106	0.124	0.082	0.076	0.088
2004	0.204	0.185	0.222	0.112	0.098	0.125	0.079	0.070	0.088
2005	0.231	0.201	0.261	0.140	0.117	0.163	0.098	0.083	0.114
2006	0.206	0.184	0.229	0.130	0.113	0.147	0.091	0.080	0.102
2007	0.215	0.186	0.244	0.134	0.114	0.154	0.094	0.081	0.107
2008	0.202	0.182	0.222	0.112	0.099	0.124	0.078	0.069	0.086
2009	0.186	0.164	0.207	0.110	0.094	0.126	0.078	0.067	0.088
2010	0.184	0.163	0.204	0.117	0.101	0.133	0.081	0.071	0.092
2011	0.205	0.179	0.230	0.135	0.114	0.156	0.094	0.080	0.109
2012	0.190	0.166	0.213	0.119	0.102	0.136	0.083	0.071	0.094

Source: SOEP (v30), own calculations.

Table A.1.8: Multidimensional inequality (weighting scheme: $w_{inc} = \frac{1}{3}$, $w_{educ} = \frac{1}{3}$, $w_{time} = \frac{1}{3}$, and $w_{np-time} = 0$)

	$\alpha = 0$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.166	0.147	0.184	0.096	0.087	0.105	0.082	0.077	0.088
1992	0.197	0.171	0.223	0.109	0.098	0.120	0.086	0.080	0.093
1993	0.179	0.153	0.204	0.105	0.093	0.117	0.086	0.080	0.093
1994	0.177	0.156	0.199	0.102	0.092	0.111	0.085	0.079	0.090
1995	0.155	0.133	0.177	0.096	0.086	0.106	0.084	0.077	0.090
1996	0.154	0.135	0.173	0.090	0.081	0.098	0.076	0.070	0.082
1997	0.202	0.178	0.225	0.108	0.098	0.117	0.079	0.074	0.084
1998	0.201	0.176	0.226	0.108	0.096	0.119	0.081	0.074	0.089
1999	0.191	0.175	0.206	0.107	0.100	0.115	0.084	0.079	0.088
2000	0.197	0.179	0.216	0.105	0.099	0.112	0.081	0.077	0.085
2001	0.163	0.149	0.178	0.095	0.089	0.102	0.078	0.073	0.082
2002	0.188	0.168	0.207	0.106	0.097	0.115	0.080	0.074	0.086
2003	0.165	0.143	0.186	0.097	0.087	0.107	0.078	0.072	0.085
2004	0.182	0.156	0.208	0.102	0.091	0.114	0.080	0.074	0.087
2005	0.177	0.152	0.203	0.102	0.091	0.113	0.082	0.076	0.089
2006	0.165	0.143	0.186	0.095	0.085	0.104	0.081	0.075	0.087
2007	0.188	0.162	0.215	0.105	0.094	0.116	0.082	0.075	0.089
2008	0.200	0.171	0.230	0.110	0.098	0.123	0.084	0.078	0.090
2009	0.178	0.144	0.211	0.101	0.086	0.115	0.085	0.077	0.092
2010	0.171	0.153	0.190	0.098	0.090	0.107	0.082	0.077	0.088
2011	0.176	0.151	0.200	0.102	0.092	0.112	0.089	0.083	0.096
2012	0.199	0.168	0.230	0.103	0.090	0.117	0.081	0.072	0.090
	$\alpha = 1$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.105	0.096	0.113	0.078	0.072	0.084	0.078	0.074	0.082
1992	0.116	0.105	0.127	0.087	0.080	0.094	0.081	0.076	0.085
1993	0.113	0.102	0.125	0.086	0.078	0.094	0.082	0.076	0.087
1994	0.115	0.104	0.125	0.082	0.076	0.089	0.079	0.075	0.083
1995	0.104	0.094	0.115	0.080	0.073	0.087	0.078	0.073	0.083
1996	0.103	0.093	0.112	0.076	0.070	0.082	0.072	0.067	0.076
1997	0.125	0.115	0.135	0.089	0.082	0.096	0.074	0.070	0.078
1998	0.126	0.113	0.139	0.088	0.081	0.096	0.075	0.070	0.081
1999	0.124	0.116	0.131	0.089	0.084	0.094	0.077	0.074	0.081
2000	0.121	0.113	0.129	0.086	0.082	0.091	0.074	0.071	0.078
2001	0.107	0.101	0.113	0.080	0.076	0.084	0.073	0.070	0.076
2002	0.117	0.109	0.125	0.086	0.081	0.091	0.074	0.070	0.077
2003	0.105	0.097	0.113	0.079	0.073	0.084	0.072	0.068	0.076
2004	0.114	0.103	0.124	0.084	0.077	0.091	0.075	0.070	0.080
2005	0.115	0.103	0.126	0.086	0.078	0.093	0.077	0.072	0.082
2006	0.106	0.097	0.115	0.080	0.074	0.086	0.076	0.071	0.080
2007	0.122	0.109	0.135	0.088	0.080	0.096	0.076	0.071	0.082
2008	0.119	0.107	0.131	0.089	0.081	0.098	0.078	0.073	0.082
2009	0.110	0.096	0.124	0.083	0.073	0.093	0.078	0.072	0.084
2010	0.108	0.100	0.116	0.082	0.076	0.088	0.076	0.072	0.080
2011	0.111	0.101	0.121	0.085	0.078	0.091	0.081	0.076	0.086
2012	0.120	0.107	0.133	0.084	0.076	0.092	0.072	0.067	0.078
	$\alpha = 2$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.095	0.086	0.104	0.076	0.070	0.081	0.080	0.076	0.084
1992	0.102	0.093	0.111	0.083	0.077	0.090	0.083	0.079	0.088
1993	0.105	0.093	0.116	0.084	0.076	0.092	0.085	0.079	0.090
1994	0.106	0.096	0.116	0.079	0.073	0.085	0.080	0.076	0.085
1995	0.098	0.088	0.108	0.079	0.072	0.085	0.080	0.075	0.085
1996	0.097	0.088	0.106	0.075	0.069	0.082	0.074	0.069	0.078
1997	0.114	0.105	0.124	0.086	0.079	0.093	0.076	0.071	0.080
1998	0.118	0.102	0.135	0.085	0.077	0.094	0.076	0.071	0.081
1999	0.115	0.108	0.122	0.088	0.083	0.093	0.079	0.075	0.082
2000	0.109	0.102	0.116	0.083	0.078	0.087	0.075	0.072	0.078
2001	0.099	0.093	0.104	0.077	0.073	0.081	0.074	0.071	0.077
2002	0.106	0.099	0.113	0.082	0.078	0.087	0.074	0.071	0.078
2003	0.096	0.089	0.103	0.075	0.070	0.080	0.072	0.068	0.076
2004	0.103	0.094	0.112	0.081	0.075	0.087	0.076	0.071	0.080
2005	0.108	0.096	0.119	0.084	0.077	0.091	0.078	0.073	0.082
2006	0.099	0.090	0.107	0.078	0.072	0.083	0.076	0.072	0.080
2007	0.116	0.103	0.128	0.086	0.078	0.094	0.076	0.071	0.082
2008	0.107	0.096	0.117	0.085	0.077	0.093	0.078	0.073	0.082
2009	0.099	0.087	0.112	0.079	0.069	0.089	0.077	0.071	0.083
2010	0.099	0.092	0.106	0.080	0.074	0.086	0.075	0.071	0.080
2011	0.103	0.094	0.113	0.082	0.076	0.089	0.080	0.075	0.084
2012	0.108	0.098	0.118	0.081	0.074	0.088	0.071	0.066	0.076

Source: SOEP (v30), own calculations.

Table A.1.9: Multidimensional poverty (weighting scheme: $w_{inc} = \frac{1}{4}$, $w_{educ} = \frac{1}{4}$, $w_{time} = \frac{1}{4}$, and $w_{np-time} = \frac{1}{4}$)

	$\phi = 0$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.419	0.395	0.442	0.342	0.318	0.366	0.074	0.062	0.086
1992	0.408	0.383	0.434	0.329	0.305	0.353	0.064	0.054	0.074
1993	0.417	0.394	0.440	0.331	0.309	0.353	0.065	0.053	0.077
1994	0.405	0.381	0.429	0.322	0.299	0.346	0.051	0.042	0.061
1995	0.393	0.371	0.415	0.310	0.288	0.332	0.061	0.049	0.072
1996	0.382	0.356	0.408	0.301	0.279	0.323	0.046	0.035	0.056
1997	0.414	0.387	0.441	0.326	0.301	0.351	0.045	0.037	0.054
1998	0.411	0.386	0.436	0.327	0.304	0.350	0.055	0.042	0.068
1999	0.417	0.399	0.435	0.302	0.287	0.318	0.055	0.047	0.063
2000	0.402	0.384	0.421	0.313	0.296	0.330	0.057	0.049	0.066
2001	0.383	0.363	0.403	0.288	0.269	0.307	0.056	0.046	0.067
2002	0.398	0.376	0.420	0.318	0.297	0.340	0.057	0.046	0.068
2003	0.372	0.349	0.395	0.279	0.259	0.299	0.049	0.040	0.059
2004	0.379	0.354	0.404	0.281	0.258	0.304	0.056	0.045	0.068
2005	0.360	0.338	0.382	0.258	0.238	0.278	0.050	0.040	0.060
2006	0.309	0.287	0.331	0.226	0.207	0.245	0.044	0.034	0.054
2007	0.332	0.308	0.357	0.236	0.214	0.258	0.048	0.035	0.062
2008	0.342	0.313	0.371	0.262	0.235	0.289	0.047	0.034	0.061
2009	0.317	0.288	0.347	0.221	0.196	0.246	0.043	0.030	0.056
2010	0.289	0.268	0.310	0.206	0.187	0.225	0.030	0.021	0.039
2011	0.288	0.267	0.309	0.199	0.180	0.219	0.044	0.033	0.055
2012	0.294	0.269	0.320	0.207	0.183	0.230	0.026	0.018	0.034
	$\phi = 1$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.333	0.311	0.354	0.179	0.165	0.192	0.015	0.012	0.018
1992	0.325	0.303	0.347	0.170	0.157	0.183	0.014	0.011	0.018
1993	0.322	0.302	0.342	0.171	0.158	0.185	0.015	0.011	0.019
1994	0.312	0.291	0.334	0.163	0.151	0.176	0.012	0.009	0.015
1995	0.297	0.278	0.317	0.158	0.146	0.170	0.012	0.009	0.015
1996	0.287	0.266	0.307	0.148	0.136	0.161	0.010	0.007	0.012
1997	0.314	0.292	0.337	0.161	0.149	0.173	0.009	0.007	0.011
1998	0.320	0.299	0.341	0.165	0.152	0.177	0.011	0.008	0.015
1999	0.297	0.282	0.312	0.150	0.141	0.159	0.012	0.009	0.014
2000	0.300	0.284	0.315	0.153	0.144	0.162	0.011	0.009	0.013
2001	0.277	0.259	0.295	0.145	0.134	0.156	0.011	0.009	0.014
2002	0.301	0.281	0.321	0.158	0.146	0.170	0.009	0.007	0.011
2003	0.267	0.248	0.285	0.140	0.129	0.150	0.010	0.007	0.012
2004	0.271	0.251	0.291	0.140	0.127	0.152	0.010	0.007	0.013
2005	0.253	0.234	0.271	0.129	0.118	0.141	0.011	0.008	0.014
2006	0.213	0.196	0.229	0.107	0.097	0.116	0.008	0.005	0.011
2007	0.224	0.203	0.244	0.114	0.102	0.126	0.010	0.006	0.013
2008	0.249	0.224	0.274	0.129	0.114	0.144	0.010	0.006	0.014
2009	0.218	0.194	0.241	0.111	0.097	0.125	0.009	0.005	0.013
2010	0.199	0.181	0.217	0.098	0.088	0.108	0.006	0.004	0.008
2011	0.195	0.178	0.212	0.100	0.089	0.111	0.010	0.007	0.013
2012	0.204	0.182	0.226	0.099	0.086	0.112	0.004	0.002	0.006
	$\phi = 2$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.302	0.281	0.323	0.103	0.094	0.111	0.006	0.004	0.007
1992	0.294	0.273	0.315	0.097	0.089	0.105	0.006	0.004	0.008
1993	0.291	0.272	0.311	0.098	0.090	0.107	0.006	0.004	0.009
1994	0.281	0.260	0.301	0.092	0.084	0.099	0.005	0.003	0.007
1995	0.268	0.249	0.287	0.089	0.082	0.097	0.004	0.003	0.006
1996	0.258	0.238	0.277	0.083	0.075	0.091	0.003	0.002	0.005
1997	0.283	0.261	0.304	0.088	0.081	0.095	0.003	0.002	0.004
1998	0.288	0.268	0.308	0.092	0.084	0.100	0.004	0.002	0.005
1999	0.263	0.249	0.277	0.083	0.077	0.089	0.004	0.003	0.005
2000	0.268	0.253	0.283	0.085	0.079	0.091	0.004	0.003	0.005
2001	0.248	0.231	0.265	0.082	0.075	0.089	0.004	0.002	0.005
2002	0.270	0.252	0.289	0.090	0.082	0.097	0.003	0.002	0.003
2003	0.238	0.220	0.255	0.079	0.072	0.086	0.003	0.002	0.004
2004	0.242	0.223	0.261	0.078	0.070	0.086	0.003	0.002	0.005
2005	0.224	0.206	0.242	0.073	0.066	0.080	0.004	0.002	0.005
2006	0.188	0.172	0.204	0.059	0.052	0.066	0.003	0.001	0.004
2007	0.196	0.177	0.216	0.065	0.057	0.073	0.004	0.002	0.006
2008	0.223	0.199	0.247	0.073	0.063	0.083	0.003	0.002	0.005
2009	0.192	0.170	0.214	0.063	0.054	0.072	0.003	0.001	0.005
2010	0.176	0.159	0.193	0.054	0.047	0.060	0.002	0.001	0.003
2011	0.172	0.156	0.188	0.058	0.051	0.065	0.004	0.002	0.005
2012	0.179	0.158	0.199	0.055	0.047	0.063	0.001	0.001	0.002

Source: SOEP (v30), own calculations.

Table A.1.10: Multidimensional poverty (weighting scheme: $w_{inc} = \frac{1}{2}$, $w_{educ} = \frac{1}{6}$, $w_{time} = \frac{1}{6}$, and $w_{np-time} = \frac{1}{6}$)

	$\phi = 0$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.391	0.368	0.413	0.317	0.293	0.340	0.061	0.050	0.072
1992	0.382	0.358	0.407	0.303	0.279	0.326	0.054	0.046	0.062
1993	0.393	0.371	0.415	0.306	0.282	0.329	0.055	0.046	0.064
1994	0.388	0.366	0.411	0.297	0.276	0.318	0.045	0.036	0.054
1995	0.367	0.346	0.389	0.296	0.275	0.318	0.054	0.043	0.066
1996	0.357	0.333	0.381	0.282	0.258	0.306	0.039	0.029	0.049
1997	0.383	0.359	0.407	0.294	0.270	0.318	0.038	0.030	0.046
1998	0.388	0.365	0.411	0.300	0.278	0.322	0.049	0.037	0.060
1999	0.373	0.355	0.390	0.279	0.263	0.294	0.048	0.041	0.055
2000	0.380	0.362	0.399	0.281	0.264	0.298	0.051	0.043	0.059
2001	0.362	0.342	0.381	0.264	0.245	0.283	0.048	0.038	0.057
2002	0.384	0.360	0.407	0.304	0.281	0.327	0.052	0.042	0.062
2003	0.355	0.333	0.376	0.270	0.250	0.290	0.046	0.037	0.056
2004	0.359	0.336	0.383	0.264	0.242	0.286	0.048	0.038	0.058
2005	0.348	0.327	0.368	0.257	0.237	0.277	0.047	0.038	0.056
2006	0.295	0.273	0.318	0.208	0.188	0.227	0.035	0.025	0.045
2007	0.314	0.287	0.341	0.218	0.196	0.240	0.043	0.030	0.055
2008	0.320	0.293	0.347	0.242	0.216	0.267	0.043	0.029	0.056
2009	0.309	0.279	0.339	0.211	0.187	0.234	0.040	0.027	0.053
2010	0.280	0.258	0.301	0.185	0.167	0.204	0.029	0.020	0.038
2011	0.278	0.256	0.300	0.186	0.167	0.205	0.037	0.028	0.046
2012	0.288	0.260	0.315	0.191	0.167	0.214	0.021	0.014	0.028
	$\phi = 1$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.307	0.286	0.327	0.104	0.095	0.114	0.011	0.008	0.014
1992	0.299	0.278	0.320	0.099	0.091	0.107	0.011	0.008	0.014
1993	0.296	0.277	0.316	0.100	0.091	0.109	0.011	0.008	0.015
1994	0.289	0.269	0.309	0.098	0.090	0.106	0.010	0.007	0.013
1995	0.277	0.258	0.295	0.094	0.085	0.102	0.010	0.007	0.012
1996	0.264	0.245	0.283	0.085	0.076	0.094	0.007	0.005	0.010
1997	0.287	0.266	0.309	0.090	0.083	0.097	0.007	0.005	0.008
1998	0.293	0.273	0.313	0.096	0.087	0.105	0.009	0.006	0.011
1999	0.271	0.257	0.285	0.086	0.080	0.093	0.009	0.007	0.011
2000	0.278	0.263	0.293	0.089	0.082	0.096	0.009	0.007	0.011
2001	0.255	0.239	0.272	0.086	0.078	0.094	0.009	0.007	0.011
2002	0.281	0.262	0.300	0.098	0.089	0.106	0.008	0.006	0.010
2003	0.250	0.233	0.268	0.085	0.077	0.092	0.008	0.006	0.010
2004	0.253	0.234	0.271	0.084	0.075	0.093	0.009	0.006	0.011
2005	0.238	0.221	0.256	0.079	0.072	0.087	0.009	0.006	0.012
2006	0.197	0.181	0.213	0.063	0.056	0.071	0.007	0.004	0.009
2007	0.205	0.185	0.225	0.069	0.062	0.077	0.008	0.005	0.011
2008	0.230	0.206	0.254	0.077	0.067	0.088	0.008	0.005	0.011
2009	0.201	0.179	0.223	0.068	0.059	0.077	0.008	0.005	0.012
2010	0.184	0.168	0.201	0.060	0.052	0.067	0.005	0.004	0.007
2011	0.180	0.164	0.197	0.063	0.055	0.070	0.008	0.005	0.011
2012	0.187	0.166	0.207	0.058	0.050	0.067	0.003	0.002	0.005
	$\phi = 2$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.268	0.249	0.287	0.045	0.039	0.050	0.004	0.002	0.005
1992	0.261	0.242	0.280	0.042	0.038	0.047	0.004	0.002	0.006
1993	0.259	0.241	0.276	0.043	0.038	0.048	0.004	0.003	0.006
1994	0.250	0.231	0.268	0.042	0.037	0.046	0.004	0.002	0.005
1995	0.240	0.223	0.257	0.040	0.035	0.045	0.003	0.002	0.004
1996	0.229	0.211	0.246	0.035	0.030	0.039	0.002	0.001	0.004
1997	0.249	0.230	0.269	0.035	0.032	0.038	0.002	0.001	0.003
1998	0.256	0.237	0.274	0.040	0.035	0.044	0.003	0.002	0.004
1999	0.233	0.221	0.246	0.036	0.032	0.039	0.003	0.002	0.004
2000	0.241	0.227	0.254	0.037	0.033	0.041	0.003	0.002	0.004
2001	0.221	0.206	0.236	0.036	0.032	0.040	0.003	0.002	0.004
2002	0.243	0.226	0.260	0.042	0.037	0.047	0.002	0.002	0.003
2003	0.214	0.199	0.230	0.036	0.032	0.040	0.002	0.001	0.003
2004	0.217	0.200	0.234	0.036	0.031	0.041	0.003	0.002	0.004
2005	0.202	0.186	0.219	0.034	0.029	0.038	0.003	0.001	0.004
2006	0.168	0.154	0.183	0.027	0.022	0.031	0.002	0.001	0.003
2007	0.175	0.157	0.193	0.031	0.026	0.035	0.003	0.002	0.004
2008	0.199	0.177	0.221	0.033	0.027	0.039	0.002	0.001	0.004
2009	0.172	0.152	0.192	0.029	0.024	0.035	0.003	0.001	0.004
2010	0.157	0.142	0.173	0.025	0.022	0.029	0.002	0.001	0.002
2011	0.154	0.139	0.169	0.028	0.024	0.033	0.003	0.002	0.004
2012	0.159	0.140	0.178	0.024	0.020	0.028	0.001	0.000	0.001

Source: SOEP (v30), own calculations.

Table A.1.11: Multidimensional poverty (weighting scheme: $w_{inc} = \frac{3}{4}$, $w_{educ} = \frac{1}{12}$, $w_{time} = \frac{1}{12}$, and $w_{np-time} = \frac{1}{12}$)

	$\phi = 0$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.391	0.347	0.393	0.163	0.145	0.180	0.047	0.036	0.059
1992	0.382	0.336	0.385	0.164	0.146	0.183	0.039	0.032	0.046
1993	0.393	0.346	0.391	0.178	0.158	0.198	0.045	0.037	0.054
1994	0.388	0.357	0.400	0.177	0.161	0.193	0.048	0.038	0.058
1995	0.367	0.344	0.387	0.179	0.159	0.199	0.046	0.037	0.055
1996	0.357	0.314	0.363	0.162	0.143	0.181	0.032	0.025	0.039
1997	0.383	0.339	0.386	0.159	0.143	0.175	0.025	0.019	0.032
1998	0.388	0.344	0.390	0.177	0.157	0.197	0.037	0.027	0.047
1999	0.373	0.334	0.368	0.170	0.156	0.183	0.043	0.036	0.049
2000	0.380	0.346	0.382	0.171	0.155	0.187	0.048	0.039	0.057
2001	0.362	0.320	0.358	0.171	0.154	0.188	0.041	0.032	0.050
2002	0.384	0.347	0.392	0.190	0.171	0.208	0.050	0.040	0.059
2003	0.355	0.320	0.362	0.192	0.173	0.211	0.041	0.032	0.050
2004	0.359	0.337	0.380	0.183	0.163	0.203	0.046	0.035	0.056
2005	0.348	0.318	0.360	0.194	0.176	0.212	0.052	0.042	0.061
2006	0.295	0.272	0.316	0.143	0.126	0.161	0.040	0.029	0.050
2007	0.314	0.274	0.326	0.168	0.150	0.186	0.044	0.032	0.056
2008	0.320	0.287	0.339	0.161	0.141	0.182	0.042	0.029	0.054
2009	0.309	0.265	0.319	0.158	0.138	0.177	0.048	0.034	0.061
2010	0.280	0.258	0.302	0.146	0.129	0.164	0.033	0.025	0.040
2011	0.278	0.248	0.290	0.156	0.139	0.174	0.041	0.031	0.051
2012	0.288	0.263	0.316	0.145	0.125	0.165	0.026	0.018	0.033
	$\phi = 1$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.261	0.243	0.279	0.040	0.033	0.046	0.008	0.005	0.010
1992	0.255	0.237	0.273	0.039	0.033	0.045	0.008	0.005	0.010
1993	0.254	0.237	0.271	0.039	0.034	0.044	0.008	0.006	0.010
1994	0.248	0.232	0.265	0.044	0.038	0.050	0.008	0.006	0.010
1995	0.239	0.223	0.255	0.042	0.036	0.048	0.007	0.005	0.009
1996	0.227	0.210	0.244	0.035	0.030	0.040	0.005	0.003	0.007
1997	0.244	0.226	0.262	0.031	0.027	0.035	0.004	0.003	0.006
1998	0.253	0.235	0.270	0.038	0.032	0.043	0.005	0.004	0.007
1999	0.233	0.220	0.245	0.036	0.033	0.040	0.007	0.006	0.009
2000	0.242	0.229	0.255	0.040	0.035	0.045	0.008	0.006	0.010
2001	0.222	0.208	0.237	0.036	0.032	0.041	0.007	0.006	0.009
2002	0.245	0.229	0.262	0.047	0.041	0.053	0.009	0.007	0.011
2003	0.220	0.205	0.235	0.043	0.037	0.049	0.007	0.005	0.009
2004	0.222	0.206	0.238	0.041	0.035	0.046	0.008	0.005	0.010
2005	0.210	0.195	0.226	0.042	0.037	0.047	0.008	0.006	0.011
2006	0.173	0.159	0.187	0.032	0.027	0.037	0.006	0.004	0.008
2007	0.180	0.163	0.198	0.035	0.030	0.040	0.007	0.004	0.010
2008	0.201	0.180	0.221	0.036	0.029	0.043	0.006	0.004	0.009
2009	0.178	0.159	0.197	0.034	0.028	0.041	0.008	0.005	0.011
2010	0.164	0.149	0.178	0.032	0.027	0.036	0.005	0.003	0.006
2011	0.160	0.146	0.174	0.034	0.029	0.039	0.006	0.004	0.008
2012	0.166	0.148	0.184	0.026	0.022	0.030	0.003	0.002	0.004
	$\phi = 2$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.197	0.183	0.211	0.016	0.011	0.020	0.002	0.001	0.003
1992	0.193	0.179	0.207	0.014	0.011	0.017	0.003	0.001	0.004
1993	0.192	0.178	0.205	0.014	0.011	0.016	0.002	0.001	0.003
1994	0.184	0.171	0.197	0.017	0.014	0.021	0.002	0.002	0.003
1995	0.177	0.165	0.189	0.015	0.012	0.019	0.002	0.001	0.003
1996	0.169	0.157	0.182	0.012	0.010	0.015	0.002	0.001	0.003
1997	0.183	0.169	0.196	0.010	0.008	0.012	0.001	0.001	0.002
1998	0.191	0.177	0.205	0.012	0.010	0.014	0.001	0.001	0.002
1999	0.174	0.165	0.184	0.012	0.011	0.014	0.002	0.002	0.003
2000	0.183	0.173	0.193	0.015	0.013	0.018	0.002	0.002	0.003
2001	0.167	0.156	0.179	0.013	0.011	0.015	0.002	0.001	0.003
2002	0.186	0.173	0.199	0.019	0.016	0.022	0.002	0.002	0.003
2003	0.165	0.153	0.176	0.016	0.012	0.019	0.002	0.001	0.003
2004	0.166	0.153	0.179	0.015	0.012	0.017	0.002	0.001	0.003
2005	0.155	0.143	0.167	0.015	0.012	0.017	0.002	0.001	0.003
2006	0.129	0.118	0.140	0.011	0.009	0.013	0.001	0.001	0.002
2007	0.134	0.120	0.148	0.012	0.009	0.015	0.002	0.001	0.003
2008	0.151	0.135	0.168	0.013	0.009	0.016	0.002	0.001	0.003
2009	0.132	0.117	0.148	0.012	0.009	0.015	0.002	0.001	0.003
2010	0.122	0.110	0.133	0.011	0.009	0.013	0.001	0.001	0.002
2011	0.119	0.107	0.130	0.011	0.010	0.013	0.002	0.001	0.002
2012	0.123	0.109	0.137	0.008	0.007	0.010	0.001	0.000	0.001

Source: SOEP (v30), own calculations.

Table A.1.12: Multidimensional poverty (weighting scheme: $w_{inc} = \frac{9}{10}$, $w_{educ} = \frac{1}{30}$, $w_{time} = \frac{1}{30}$, and $w_{np-time} = \frac{1}{30}$)

	$\phi = 0$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.368	0.344	0.391	0.098	0.083	0.112	0.048	0.036	0.060
1992	0.361	0.337	0.385	0.098	0.081	0.115	0.046	0.036	0.056
1993	0.365	0.343	0.387	0.112	0.097	0.128	0.055	0.045	0.065
1994	0.377	0.356	0.399	0.139	0.125	0.154	0.060	0.048	0.071
1995	0.362	0.341	0.383	0.131	0.113	0.148	0.065	0.053	0.078
1996	0.340	0.315	0.365	0.104	0.091	0.118	0.050	0.041	0.059
1997	0.361	0.338	0.385	0.099	0.084	0.114	0.037	0.029	0.044
1998	0.373	0.351	0.395	0.114	0.099	0.128	0.048	0.038	0.057
1999	0.347	0.331	0.364	0.121	0.111	0.132	0.059	0.051	0.067
2000	0.360	0.342	0.379	0.126	0.112	0.139	0.062	0.052	0.072
2001	0.339	0.321	0.357	0.121	0.107	0.134	0.063	0.053	0.074
2002	0.365	0.342	0.387	0.147	0.131	0.162	0.081	0.068	0.093
2003	0.344	0.323	0.365	0.142	0.125	0.160	0.076	0.062	0.089
2004	0.358	0.337	0.379	0.147	0.131	0.163	0.073	0.060	0.085
2005	0.339	0.318	0.359	0.152	0.136	0.169	0.080	0.068	0.093
2006	0.294	0.271	0.316	0.135	0.119	0.152	0.057	0.045	0.069
2007	0.301	0.275	0.327	0.137	0.120	0.154	0.054	0.042	0.066
2008	0.315	0.288	0.341	0.127	0.109	0.145	0.054	0.041	0.068
2009	0.294	0.267	0.322	0.132	0.112	0.151	0.071	0.055	0.086
2010	0.285	0.263	0.306	0.129	0.114	0.144	0.057	0.047	0.067
2011	0.277	0.257	0.297	0.135	0.119	0.150	0.062	0.052	0.073
2012	0.294	0.268	0.321	0.128	0.109	0.148	0.043	0.034	0.052
	$\phi = 1$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.169	0.157	0.180	0.025	0.018	0.032	0.009	0.006	0.012
1992	0.167	0.154	0.179	0.025	0.018	0.031	0.008	0.006	0.011
1993	0.167	0.156	0.178	0.025	0.021	0.028	0.008	0.006	0.010
1994	0.164	0.154	0.175	0.033	0.028	0.038	0.011	0.008	0.013
1995	0.158	0.148	0.168	0.030	0.025	0.036	0.011	0.008	0.013
1996	0.150	0.139	0.161	0.026	0.021	0.030	0.007	0.005	0.010
1997	0.158	0.147	0.169	0.020	0.016	0.023	0.005	0.004	0.007
1998	0.169	0.157	0.181	0.025	0.020	0.029	0.006	0.005	0.008
1999	0.156	0.148	0.165	0.026	0.023	0.029	0.010	0.008	0.011
2000	0.166	0.157	0.175	0.031	0.026	0.036	0.012	0.009	0.015
2001	0.152	0.143	0.162	0.027	0.024	0.031	0.011	0.009	0.012
2002	0.172	0.160	0.184	0.038	0.032	0.043	0.015	0.012	0.018
2003	0.156	0.145	0.167	0.035	0.029	0.041	0.012	0.009	0.015
2004	0.157	0.145	0.168	0.034	0.029	0.038	0.012	0.010	0.014
2005	0.149	0.139	0.160	0.035	0.031	0.040	0.012	0.010	0.015
2006	0.123	0.114	0.133	0.027	0.023	0.031	0.009	0.006	0.011
2007	0.128	0.116	0.140	0.028	0.023	0.032	0.009	0.006	0.012
2008	0.139	0.125	0.154	0.026	0.021	0.032	0.009	0.006	0.012
2009	0.127	0.114	0.140	0.029	0.024	0.034	0.012	0.009	0.015
2010	0.118	0.108	0.128	0.028	0.024	0.032	0.008	0.006	0.010
2011	0.116	0.106	0.126	0.027	0.023	0.031	0.008	0.006	0.010
2012	0.120	0.108	0.132	0.024	0.020	0.027	0.006	0.005	0.008
	$\phi = 2$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.084	0.077	0.091	0.011	0.007	0.015	0.003	0.001	0.004
1992	0.083	0.076	0.090	0.010	0.007	0.013	0.003	0.002	0.004
1993	0.083	0.077	0.089	0.009	0.007	0.011	0.002	0.001	0.003
1994	0.081	0.075	0.087	0.014	0.011	0.017	0.003	0.002	0.004
1995	0.077	0.071	0.083	0.012	0.009	0.016	0.003	0.002	0.004
1996	0.073	0.068	0.079	0.010	0.007	0.012	0.002	0.001	0.003
1997	0.076	0.070	0.082	0.006	0.005	0.008	0.001	0.001	0.002
1998	0.085	0.078	0.092	0.008	0.006	0.010	0.001	0.001	0.002
1999	0.078	0.074	0.083	0.009	0.008	0.011	0.003	0.002	0.003
2000	0.085	0.080	0.091	0.013	0.010	0.015	0.004	0.003	0.005
2001	0.077	0.072	0.083	0.010	0.008	0.011	0.003	0.002	0.004
2002	0.091	0.084	0.097	0.016	0.013	0.019	0.005	0.003	0.006
2003	0.081	0.074	0.087	0.014	0.010	0.017	0.003	0.002	0.005
2004	0.080	0.074	0.087	0.012	0.010	0.014	0.003	0.002	0.004
2005	0.075	0.069	0.081	0.012	0.010	0.015	0.003	0.002	0.004
2006	0.062	0.057	0.068	0.009	0.007	0.011	0.002	0.001	0.003
2007	0.065	0.059	0.072	0.009	0.007	0.012	0.003	0.001	0.004
2008	0.072	0.064	0.080	0.009	0.007	0.012	0.002	0.001	0.003
2009	0.065	0.057	0.072	0.010	0.007	0.012	0.003	0.002	0.004
2010	0.061	0.055	0.067	0.009	0.007	0.011	0.002	0.001	0.003
2011	0.059	0.054	0.065	0.009	0.007	0.010	0.002	0.001	0.003
2012	0.061	0.054	0.068	0.007	0.006	0.009	0.001	0.001	0.002

Source: SOEP (v30), own calculations.

Table A.1.13: Multidimensional poverty (weighting scheme: $w_{inc} = \frac{1}{3}$, $w_{educ} = \frac{1}{3}$, $w_{time} = \frac{1}{3}$, and $w_{np-time} = 0$)

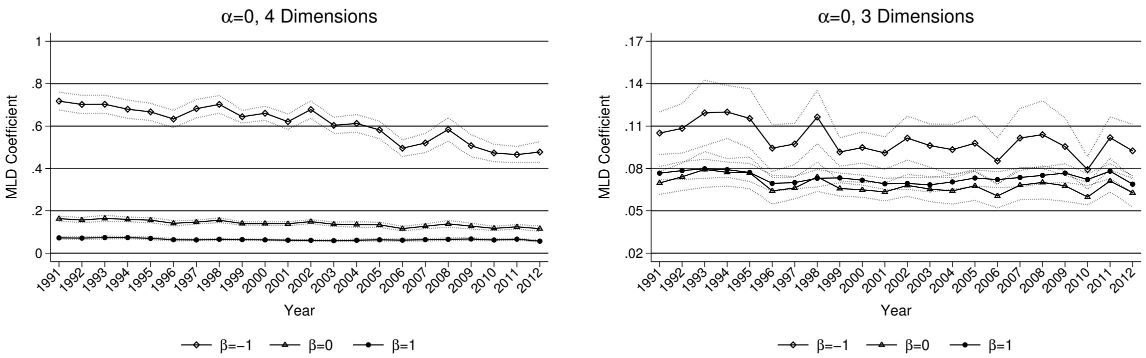
	$\phi = 0$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.182	0.166	0.198	0.097	0.087	0.107	0.054	0.045	0.062
1992	0.181	0.162	0.200	0.114	0.099	0.128	0.054	0.045	0.064
1993	0.183	0.164	0.201	0.112	0.097	0.128	0.064	0.052	0.076
1994	0.186	0.166	0.205	0.107	0.093	0.121	0.057	0.048	0.066
1995	0.170	0.151	0.188	0.101	0.086	0.116	0.052	0.041	0.063
1996	0.182	0.162	0.202	0.108	0.093	0.123	0.049	0.039	0.059
1997	0.206	0.187	0.224	0.114	0.100	0.127	0.051	0.041	0.061
1998	0.196	0.173	0.218	0.124	0.107	0.141	0.049	0.039	0.059
1999	0.216	0.202	0.231	0.128	0.116	0.140	0.059	0.051	0.068
2000	0.205	0.191	0.220	0.137	0.125	0.150	0.058	0.050	0.067
2001	0.208	0.192	0.223	0.126	0.113	0.139	0.055	0.047	0.063
2002	0.208	0.191	0.226	0.135	0.121	0.149	0.069	0.059	0.079
2003	0.200	0.181	0.219	0.128	0.114	0.142	0.067	0.055	0.079
2004	0.208	0.187	0.230	0.131	0.112	0.149	0.066	0.054	0.078
2005	0.201	0.183	0.219	0.128	0.112	0.144	0.068	0.055	0.081
2006	0.184	0.166	0.203	0.117	0.102	0.133	0.063	0.050	0.077
2007	0.213	0.190	0.235	0.136	0.117	0.155	0.069	0.054	0.085
2008	0.192	0.172	0.212	0.124	0.106	0.143	0.067	0.053	0.081
2009	0.192	0.169	0.216	0.115	0.096	0.133	0.072	0.057	0.087
2010	0.175	0.159	0.192	0.111	0.096	0.126	0.056	0.045	0.067
2011	0.185	0.166	0.204	0.119	0.103	0.135	0.067	0.054	0.080
2012	0.196	0.176	0.216	0.107	0.089	0.124	0.049	0.038	0.060

	$\phi = 1$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.070	0.061	0.078	0.034	0.028	0.039	0.014	0.011	0.017
1992	0.080	0.069	0.092	0.042	0.035	0.050	0.016	0.013	0.020
1993	0.073	0.063	0.083	0.039	0.032	0.046	0.017	0.013	0.021
1994	0.073	0.064	0.082	0.037	0.031	0.044	0.016	0.013	0.020
1995	0.063	0.054	0.073	0.031	0.025	0.038	0.016	0.011	0.020
1996	0.064	0.056	0.072	0.032	0.026	0.037	0.013	0.009	0.017
1997	0.082	0.072	0.092	0.043	0.036	0.050	0.013	0.010	0.016
1998	0.083	0.072	0.095	0.042	0.035	0.050	0.014	0.009	0.018
1999	0.082	0.075	0.089	0.041	0.036	0.046	0.016	0.013	0.018
2000	0.083	0.076	0.091	0.043	0.038	0.048	0.015	0.013	0.017
2001	0.071	0.065	0.078	0.035	0.031	0.039	0.014	0.011	0.017
2002	0.081	0.073	0.089	0.043	0.037	0.049	0.016	0.012	0.019
2003	0.071	0.062	0.080	0.038	0.032	0.045	0.017	0.013	0.021
2004	0.075	0.064	0.087	0.042	0.034	0.050	0.017	0.012	0.021
2005	0.072	0.062	0.082	0.038	0.031	0.046	0.016	0.012	0.020
2006	0.066	0.057	0.075	0.035	0.029	0.041	0.014	0.010	0.018
2007	0.076	0.065	0.087	0.041	0.034	0.048	0.016	0.011	0.020
2008	0.078	0.066	0.090	0.043	0.035	0.052	0.015	0.011	0.019
2009	0.072	0.059	0.086	0.038	0.028	0.048	0.017	0.012	0.022
2010	0.066	0.058	0.074	0.033	0.028	0.039	0.011	0.009	0.014
2011	0.068	0.058	0.078	0.037	0.029	0.044	0.017	0.013	0.021
2012	0.077	0.065	0.090	0.038	0.030	0.047	0.014	0.009	0.018

	$\phi = 2$								
	$\beta = -1$			$\beta = 0$			$\beta = 1$		
Year	Coeff.	Conf. Interval		Coeff.	Conf. Interval		Coeff.	Conf. Interval	
1991	0.045	0.038	0.052	0.020	0.016	0.024	0.007	0.005	0.009
1992	0.056	0.047	0.066	0.026	0.021	0.031	0.008	0.006	0.010
1993	0.048	0.040	0.057	0.024	0.018	0.029	0.007	0.005	0.009
1994	0.048	0.040	0.055	0.022	0.018	0.027	0.008	0.005	0.010
1995	0.039	0.031	0.047	0.018	0.014	0.023	0.007	0.005	0.009
1996	0.040	0.033	0.046	0.017	0.013	0.021	0.006	0.004	0.008
1997	0.055	0.047	0.064	0.025	0.020	0.029	0.006	0.004	0.007
1998	0.055	0.046	0.064	0.024	0.019	0.029	0.006	0.003	0.009
1999	0.051	0.045	0.057	0.023	0.019	0.026	0.007	0.005	0.008
2000	0.055	0.049	0.062	0.024	0.020	0.027	0.006	0.005	0.008
2001	0.043	0.038	0.048	0.019	0.016	0.022	0.006	0.004	0.008
2002	0.052	0.045	0.059	0.024	0.019	0.028	0.007	0.004	0.009
2003	0.044	0.037	0.052	0.021	0.016	0.026	0.007	0.005	0.009
2004	0.049	0.039	0.058	0.023	0.017	0.029	0.006	0.004	0.009
2005	0.045	0.036	0.054	0.020	0.015	0.026	0.006	0.004	0.009
2006	0.042	0.035	0.050	0.019	0.014	0.023	0.005	0.003	0.008
2007	0.049	0.039	0.058	0.022	0.017	0.027	0.006	0.003	0.008
2008	0.054	0.044	0.065	0.025	0.019	0.031	0.006	0.004	0.008
2009	0.047	0.035	0.059	0.022	0.015	0.029	0.006	0.003	0.009
2010	0.043	0.036	0.050	0.018	0.015	0.022	0.004	0.003	0.005
2011	0.045	0.036	0.054	0.021	0.016	0.026	0.007	0.005	0.009
2012	0.053	0.042	0.065	0.022	0.016	0.029	0.007	0.003	0.010

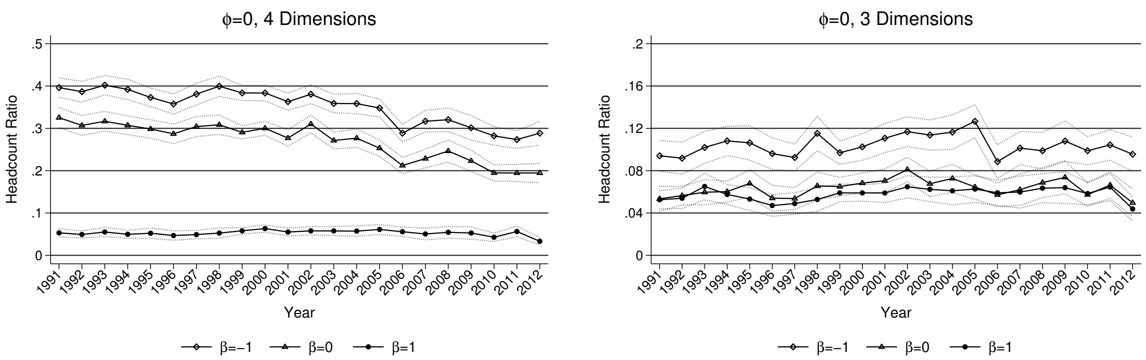
Source: SOEP (v30), own calculations.

Figure A.1.2: Multidimensional inequality (with frequency-based weights)



Source: SOEP (v30), own calculations.
Note: Significance at the five percent level is calculated using bootstrap standard errors with 100 replications. Frequency-based weights, 4 dimensions: $w_{inc} = .2835$, $w_{educ} = .3492$, $w_{time} = .1699$, and $w_{np-time} = .1974$. Frequency-based weights, 3 dimensions: $w_{inc} = .3091$, $w_{educ} = .3819$, and $w_{total-time} = .3090$.

Figure A.1.3: Multidimensional poverty (with frequency-based weights)



Source: SOEP (v30), own calculations.
Note: Significance at the five percent level is calculated using bootstrap standard errors with 100 replications. Frequency-based weights, 4 dimensions: $w_{inc} = .2835$, $w_{educ} = .3492$, $w_{time} = .1699$, and $w_{np-time} = .1974$. Frequency-based weights, 3 dimensions: $w_{inc} = .3091$, $w_{educ} = .3819$, and $w_{total-time} = .3090$.

A.2 Appendix of Chapter 3

Table A.2.1 depicts the evolution of mean yearly real public expenditures per child on childcare including spending on cribs, kindergarten, after school care clubs and publicly subsidized child minders. In 2009, Berlin spent most with an average of 7,367 Euro per child followed by Hamburg with 7,189 Euro. In contrast, Mecklenburg Western Pomerania and Saxony Anhalt spent least. Their mean expenditures amounted to 3,416 Euro and 3,950 Euro per child, respectively. In 2013, Berlin was still in the leading position spending an average of 8,802 Euro per child followed by Northrhine-Westphalia (7,659 Euro) and Bremen (7,611 Euro). Mecklenburg Western Pomerania (3,701 Euro), Saxony Anhalt (3,872 Euro), and Saxony (4,031 Euro) spent least on childcare per child in 2013. However, almost all German federal states increased their real per capita spending on childcare over the past years except of Saxony, Saxony Anhalt, and Hamburg. The latter might be the consequence of less demand of childcare provision due to a decreasing number of children in these federal states. At the same time, West German states increased their real per capita expenditures by more than the East German states. The former spent on average 5,587 Euro in 2009 per child on childcare and increased their spending to 6,715 Euro in 2013 (+20%), while the latter increased their mean real expenditures from 4,718 Euro in 2009 to 5,187 Euro in 2013 (+10%).

Table A.2.2 shows the trend in average yearly real public expenditures per child on schooling between 2009 and 2013. In 2009, the highest per capita spending on schooling is observed in Thuringia and Saxony Anhalt: on average they spent 8,190 Euro and 7,685 Euro per child, respectively. In contrast, Northrhine-Westphalia and Schleswig Holstein spent least with 5,460 Euro and 5,561 Euro, respectively. In 2013, Hamburg, Thuringia and Berlin spent the most: mean per capita spending on schooling amounted to 8,420 Euro in Hamburg and 8,042 Euro both in Thuringia and Berlin. The lowest mean spending is observed in Northrhine-Westphalia with 5,866 Euro and Schleswig-Holstein with 5,960 Euro. Again, almost all federal states managed to raise their real per capita expenditures on schooling over the past years but Saxony and Thuringia. However, these two countries operate on high levels and still spend more than other federal states. At the same time, all East German federal states together spent more on schooling on average than the West German states. Nevertheless, the latter were able to increase their mean real spending by around eight percent, which is six percentage points more compared to Eastern states. Therefore, a convergence in spending can be observed.

Table A.2.1: Mean real public expenditures per child on childcare services by region (in Euro)

Region	2009	2010	2011	2012	2013
Baden-Württemberg	4,703	5,406	5,342	6,354	6,823
Bavaria	4,759	5,152	5,411	5,452	5,958
Berlin	7,367	7,944	8,342	8,594	8,802
Brandenburg	4,234	4,343	4,567	4,480	4,490
Bremen	6,265	6,638	6,718	7,257	7,611
Hamburg	7,189	6,991	6,713	7,062	6,969
Hesse	5,666	6,198	6,293	6,360	6,506
Mecklenburg Western Pomerania	3,416	3,486	3,614	3,837	3,701
Lower Saxony	4,880	5,156	5,404	5,471	5,700
Northrhine-Westphalia	5,835	6,546	7,016	7,885	7,659
Rhineland Palatinate	6,082	6,733	6,970	6,990	7,049
Saarland	5,564	7,137	6,622	6,981	7,147
Saxony	4,334	4,359	4,041	3,995	4,031
Saxony Anhalt	3,950	4,053	3,842	3,783	3,872
Schleswig-Holstein	4,926	5,840	5,357	5,392	5,729
Thuringia	5,007	5,600	5,960	5,833	6,227

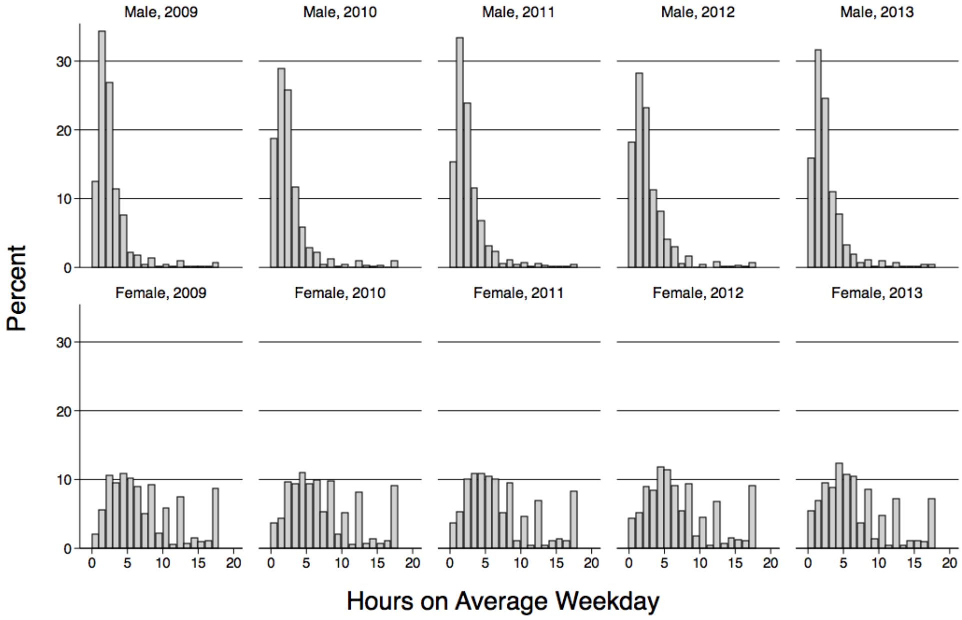
Note: All expenditures are in 2010 Euros.
Source: Statistisches Bundesamt (2014a), own calculations.

Table A.2.2: Mean real public expenditures per child on schooling by region (in Euro)

Region	2009	2010	2011	2012	2013
Baden-Württemberg	6,370	6,500	6,562	6,436	6,528
Bavaria	6,673	7,100	7,150	7,301	7,663
Berlin	7,381	7,800	8,031	7,877	8,042
Brandenburg	6,269	6,900	6,954	6,724	6,623
Bremen	6,471	7,200	7,248	7,109	7,001
Hamburg	7,583	7,900	8,129	8,165	8,420
Hesse	6,471	7,000	7,052	6,820	6,906
Mecklenburg Western Pomerania	6,370	6,900	6,758	6,532	6,717
Lower Saxony	5,966	6,300	6,268	6,244	6,528
Northrhine-Westphalia	5,460	5,600	5,681	5,764	5,866
Rhineland Palatinate	5,865	6,200	6,366	6,340	6,339
Saarland	5,966	6,400	6,268	6,436	6,149
Saxony	7,078	7,900	7,444	6,916	6,717
Saxony Anhalt	7,685	8,400	8,325	7,877	7,758
Schleswig-Holstein	5,561	5,900	5,779	5,860	5,960
Thuringia	8,190	8,800	8,521	8,165	8,042

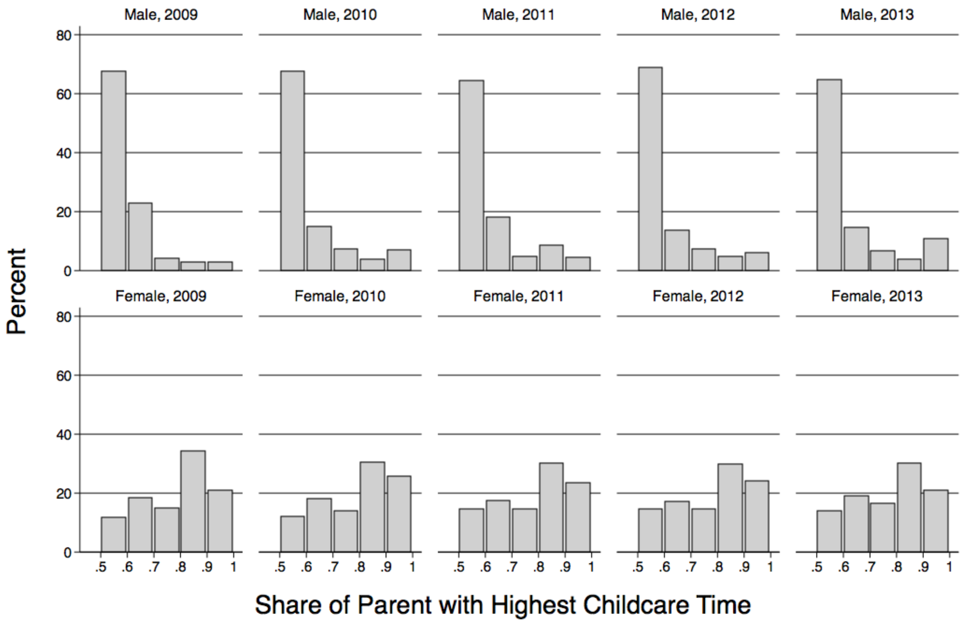
Note: Expenditures on employees and administrational staff including social contributions for civil servants, aid expenditure (Beihilfeaufwendungen), current operating expenses and capital expenditures. All expenditures are in 2010 Euros.
Source: Statistisches Bundesamt (2015).

Figure A.2.1: Distribution of parental childcare time on an average weekday by sex



Source: SOEP (v31.1), own calculations.

Figure A.2.2: Distribution of parental childcare time within couples on an average weekday by sex (excluding single parents)



Source: SOEP (v31.1), own calculations.

Table A.2.3: Number of children (aged 0-13) by family type (unweighted)

Year	Single parents	Cohabiting parents	Married parents	Total
2009	1,285	939	6,626	8,850
2010	1,598	840	7,075	9,513
2011	1,448	852	6,535	8,835
2012	1,219	763	5,707	7,689
2013	969	730	5,969	7,668
Total	6,519	4,124	31,912	42,555

Source: SOEP (v31.1), own calculations.

Table A.2.4: Relative number of children (aged 0-13) by family type (weighted)

Year	Single parents	Cohabiting parents	Married parents	Total
2009	12.2	9.2	78.6	100
2010	12.9	9	78.1	100
2011	12	10.4	77.6	100
2012	13.1	10.9	75.9	100
2013	12.4	10.5	77.1	100
Total	12.5	10	77.5	100

Source: SOEP (v31.1), own calculations.

Table A.2.5: Average hours of parental childcare time, and public childcare and education on an average weekday by family type (weighted)

		Total parental time				Parental time per child				Public childcare & education			
Year	Family type	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
2009	Single	5.8	4.5	0	18	3.7	3.3	0	18	5.3	2.3	0	14.6
	Cohabiting	9	6.4	0	36	6.1	5.3	0	36	4.5	3.2	0	13.1
	Married	8.5	5.5	0	36	4.5	3.7	0	36	4.6	2.5	0	13.7
	Total	8.2	5.5	0	36	4.6	3.9	0	36	4.6	2.6	0	14.6
2010	Single	5.8	4.2	0	18	3.9	3.5	0	18	5.5	2.3	0	13.7
	Cohabiting	9.2	6.5	0	36	6.4	5.4	0	36	4.8	3.1	0	11.5
	Married	8.6	5.6	0	36	4.5	3.7	0	36	4.6	2.5	0	13.1
	Total	8.3	5.6	0	36	4.6	3.9	0	36	4.7	2.5	0	13.7
2011	Single	5.8	4.2	0	18	3.8	3.2	0	18	5.7	2.3	0	13.7
	Cohabiting	7.5	5.3	0	31	4.9	4	0	31	5.1	3	0	14.2
	Married	8.3	5.4	0	36	4.3	3.5	0	34	4.7	2.4	0	12.9
	Total	7.9	5.4	0	36	4.3	3.5	0	34	4.9	2.5	0	14.2
2012	Single	6.1	4.7	0	18	4	3.5	0	18	5.6	2.3	0	13.7
	Cohabiting	8.5	6.2	0	36	5.6	4.6	0	32	4.9	3.1	0	12.6
	Married	8	5.4	0	36	4.2	3.5	0	36	4.7	2.4	0	12.7
	Total	7.8	5.4	0	36	4.3	3.7	0	36	4.9	2.5	0	13.7
2013	Single	5.8	4.4	0	18	3.7	3.4	0	18	5.2	2.7	0	13.6
	Cohabiting	8.3	5.3	0	36	5.4	4.2	0	24	4	3.3	0	12.5
	Married	7.5	5.2	0	36	4	3.5	0	30	4.4	2.7	0	13.7
	Total	7.4	5.2	0	36	4.1	3.6	0	30	4.4	2.8	0	13.7

Source: SOEP (v31.1), own calculations.

Table A.2.6: Average hours of parental childcare time on weekdays and weekends (weighted)

		Weekday				Saturday				Sunday				Week average			
Year	Family type	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
2009	Single	5.9	4.6	0	18	8.9	5.3	0	18	9.3	5.2	0	18	8	4.4	0	18
	Cohabiting	9	6.4	0	36	15.7	6.5	0	36	17.1	7	0	36	12.8	5.9	0	36
	Married	8.5	5.6	0	36	14.1	6.9	0	36	15.2	7	0	36	11.9	6	0	36
	Total	8.2	5.6	0	36	13.6	6.9	0	36	14.6	7.1	0	36	11.5	5.9	0	36
2010	Single	5.9	4.2	0	18	9.2	5.2	0	18	9.5	5.1	0	18	8.2	4.5	0	18
	Cohabiting	9.5	6.7	0	36	14.6	7.6	0	36	15.4	7.8	0	36	13.2	6.7	0	36
	Married	8.7	5.7	0	36	13	7.5	0	36	13.9	7.7	0	36	11.8	6.5	0	36
	Total	8.4	5.7	0	36	12.7	7.4	0	36	13.5	7.6	0	36	11.5	6.5	0	36
2011	Single	5.8	4.2	0	18	9.2	5.3	0	18	9.6	5.2	0	18	8.2	4.5	0	18
	Cohabiting	9.5	5.7	0	36	14.9	7.4	0	36	15.7	7.4	0	36	13.4	6.4	0	36
	Married	9.3	5.3	0	36	14.7	7.2	0	36	15.5	7.4	0	36	13.2	6.1	0	36
	Total	8.7	5.3	0	36	13.7	7.2	0	36	14.4	7.4	0	36	12.2	6.2	0	36
2012	Single	6.2	4.8	0	18	9.3	5.4	0	18	9.6	5.4	0	18	8.3	4.8	0	18
	Cohabiting	8.7	6.3	0	36	13.3	7.9	0	36	13.7	8.2	0	36	11.9	6.9	0	36
	Married	8	5.5	0	36	12.8	7.6	0	36	13.5	7.8	0	36	11.4	6.6	0	36
	Total	7.9	5.6	0	36	12.4	7.5	0	36	13	7.7	0	36	11.1	6.5	0	36
2013	Single	5.8	4.4	0	18	10.5	5.1	0	18	10.7	5	0	18	9	4.1	0	18
	Cohabiting	8.5	5.5	0	36	15.4	6.4	0	36	15.5	6.5	0	36	11.8	5.2	0.3	29.7
	Married	7.6	5.4	0	36	14.5	6.6	0	36	15.6	6.8	0	36	11.7	5.6	0	36
	Total	7.5	5.4	0	36	14.1	6.6	0	36	14.9	6.7	0	36	11.4	5.5	0	36

Note: Hours of parental childcare on Saturdays and Sundays are fully imputed for income years 2009, 2011 and 2013, and partly imputed for 2012 by means of logical imputation and predictive mean matching using information from income years 2008, 2010, and 2012.
Source: SOEP (v31.1), own calculations.

Table A.2.7: Imputed average gross wage rates (weighted)

Year	Observed		Housekeeper		OLS		Heckman	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2009	14.28	8.06	9.48	0.00	12.74	7.25	13.87	7.57
2010	14.32	7.97	9.00	0.00	12.85	7.20	13.78	7.37
2011	14.56	8.01	9.01	0.00	13.30	7.18	14.51	7.59
2012	14.84	8.38	9.19	0.00	13.41	7.59	14.67	7.93
2013	15.28	8.50	10.15	0.00	13.87	7.74	15.73	9.06

Note: Observed gross wage rates are just weighted sample means of the working age population.
Source: SOEP (v31.1), own calculations.

Table A.2.8: Imputed average gross wage rates by sex (weighted)

				Men				
Year	Observed		Housekeeper		OLS		Heckman	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2009	15.71	8.63	9.48	0.00	14.19	7.86	16.05	8.17
2010	15.75	8.56	9.00	0.00	14.53	7.72	15.84	7.92
2011	15.96	8.58	9.01	0.00	14.86	7.74	16.74	8.23
2012	16.34	8.98	9.19	0.00	15.09	8.11	16.97	8.47
2013	16.77	9.04	10.15	0.00	15.56	8.21	18.43	10.24
				Women				
Year	Observed		Housekeeper		OLS		Heckman	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2009	12.78	7.10	9.48	0.00	11.34	6.32	11.77	6.27
2010	12.78	6.97	9.00	0.00	11.24	6.25	11.81	6.20
2011	13.07	7.05	9.01	0.00	11.80	6.23	12.37	6.21
2012	13.27	7.38	9.19	0.00	11.80	6.66	12.48	6.68
2013	13.73	7.59	10.15	0.00	12.26	6.88	13.20	6.91

Note: Observed gross wage rates are just weighted sample means of the working age population.
Source: SOEP (v31.1), own calculations.

To gain further insights into the reasons for rising extended income inequality, half the squared coefficient of variation (HSQCV) is decomposed by family type. The decomposition of HSQCV is comprehensively explained in Mookherjee and Shorrocks (1982). The decomposition equation is $GE(2) = \sum_k v_k(\lambda_k)^2 I_2^k + \frac{1}{2}\sum_k v_k[(\lambda_k)^2 - 1]$, where k is the number of subgroups, $v_k = n_k/n$ is the proportion of the population in subgroup k, and $\lambda_k = \mu_k/mu$ is the mean income of subgroup k in relation to the overall population mean.

The results of the decomposition by family types are depicted in Table A.2.10. While disposable cash income has slightly decreased between 2009 and 2013, all extended incomes have decreased over time. However, all income approaches have in

Table A.2.9: Imputed average gross wage rates by family type (weighted)

	Singles							
Year	Observed		Housekeeper		OLS		Heckman	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2009	11.32	6.77	9.48	0.00	10.99	6.26	11.53	6.48
2010	11.75	7.29	9.00	0.00	11.27	6.72	11.68	6.75
2011	11.56	7.01	9.01	0.00	11.17	6.49	11.76	6.66
2012	11.76	7.19	9.19	0.00	11.36	6.65	12.00	6.85
2013	12.14	7.63	10.15	0.00	11.79	7.10	12.53	7.57
	Cohabiting							
Year	Observed		Housekeeper		OLS		Heckman	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2009	12.83	7.77	9.48	0.00	12.55	7.46	12.87	7.56
2010	13.22	7.75	9.00	0.00	12.89	7.30	13.28	7.36
2011	13.40	7.73	9.01	0.00	13.11	7.37	13.50	7.45
2012	13.91	8.28	9.19	0.00	13.66	7.78	14.23	7.95
2013	14.90	8.23	10.15	0.00	14.67	7.72	15.26	8.01
	Married							
Year	Observed		Housekeeper		OLS		Heckman	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2009	14.10	8.41	9.48	0.00	13.70	7.87	14.23	8.07
2010	14.24	8.31	9.00	0.00	13.82	7.82	14.26	7.91
2011	14.60	8.50	9.01	0.00	14.20	7.99	14.73	8.17
2012	14.97	8.70	9.19	0.00	14.59	8.27	15.16	8.45
2013	15.53	8.98	10.15	0.00	15.20	8.56	15.95	9.06

Note: Observed gross wage rates are just weighted sample means of the working age population.
Source: SOEP (v31.1), own calculations.

common that inequality is largely explained by differences within family types. Extending the income definition even fortifies the explanatory power of within differences in relative terms and, hence, lowers income inequalities between children from different family types. It is especially noteworthy that between family type inequality has increased across all income approaches such that the change of family structures tends to have a distributional impact on children's economic resources. However, the changes are not statistically significant

Furthermore, extending the income definition also reduces inequalities for each family type; the effect is the largest when the housekeeper wage approach is used to quantify the monetary value of parental childcare time. All in all, adding the value of public childcare and education as well as the monetary value of parental childcare time to the disposable cash income of children in Germany reduces both the level of inequality between and within different family types.

Furthermore, extending the income definition also reduces inequalities for each family type; the effect is the largest when the housekeeper wage approach is used to quantify the monetary value of parental childcare time. All in all, adding the value of public childcare and education as well as the monetary value of parental childcare time to the disposable cash income of children in Germany reduces both the level of inequality between and within different family types.

Table A.2.10: Decomposition of HSQCV by family type

Cash Income

Year	HSQCV	HSQCV Within	HSQCV Between	HSQCV: Singles	HSQCV: Cohab.	HSQCV: Married
2009	0.1201	0.1142	0.0059	0.1244	0.1441	0.1091
2010	0.1232	0.1170	0.0062	0.0896	0.1048	0.1186
2011	0.1120	0.1067	0.0053	0.1099	0.0996	0.1060
2012	0.1036	0.0972	0.0064	0.1093	0.0938	0.0951
2013	0.1151	0.1073	0.0078	0.0966	0.1070	0.1061

Extended Income (Housekeeper Wage Approach)

Year	HSQCV	HSQCV Within	HSQCV Between	HSQCV: Singles	HSQCV: Cohab.	HSQCV: Married
2009	0.0496	0.0486	0.0009	0.0574	0.0553	0.0467
2010	0.0494	0.0483	0.0011	0.0436	0.0424	0.0495
2011	0.0473	0.0465	0.0008	0.0485	0.0432	0.0466
2012	0.0436	0.0428	0.0008	0.0500	0.0383	0.0424
2013	0.0521	0.0511	0.0010	0.0565	0.0442	0.0512

Extended Income (Opportunity Cost Approach - OLS)

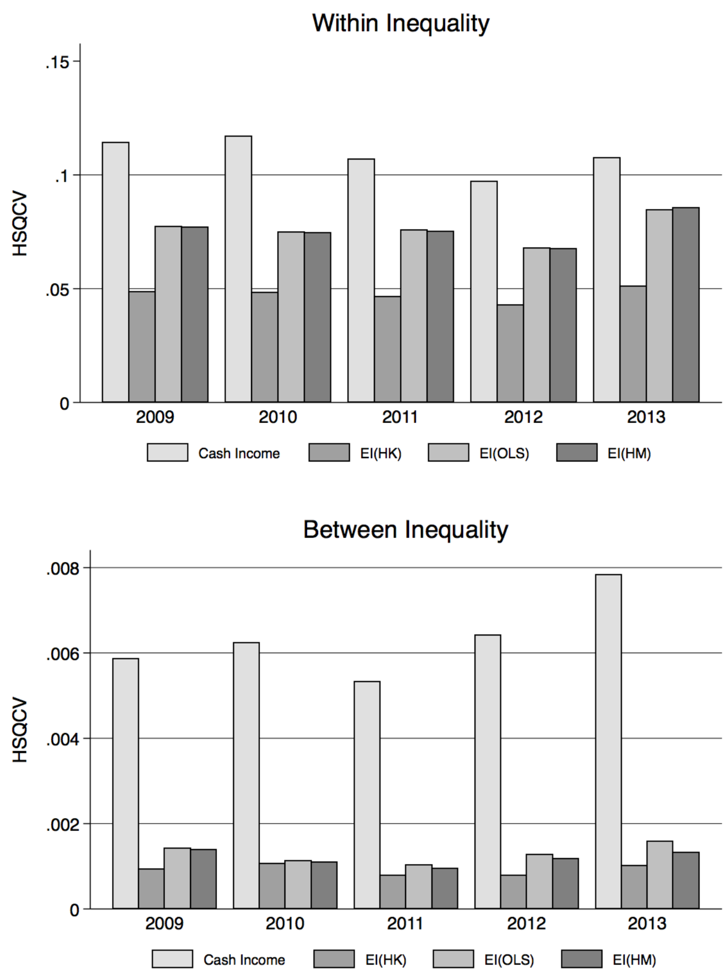
Year	HSQCV	HSQCV Within	HSQCV Between	HSQCV: Singles	HSQCV: Cohab.	HSQCV: Married
2009	0.0785	0.0771	0.0014	0.0737	0.1006	0.0749
2010	0.0760	0.0748	0.0011	0.0627	0.0650	0.0772
2011	0.0767	0.0757	0.0010	0.0723	0.0724	0.0763
2012	0.0690	0.0678	0.0013	0.0698	0.0590	0.0684
2013	0.0860	0.0844	0.0016	0.0735	0.0750	0.0865

Extended Income (Opportunity Cost Approach - Heckman)

Year	HSQCV	HSQCV Within	HSQCV Between	HSQCV: Singles	HSQCV: Cohab.	HSQCV: Married
2009	0.0784	0.0770	0.0014	0.0747	0.1000	0.0748
2010	0.0757	0.0746	0.0011	0.0634	0.0646	0.0768
2011	0.0760	0.0750	0.0010	0.0716	0.0712	0.0757
2012	0.0687	0.0675	0.0012	0.0701	0.0590	0.0680
2013	0.0868	0.0855	0.0013	0.0808	0.0756	0.0870

Note: Stata module INEQDEC0 was used for decomposition (Jenkins, 1999).
Source: SOEP (v31.1), and Federal Statistical Office, own calculations.

Figure A.2.3: GE(2) Within and between inequality by income definition



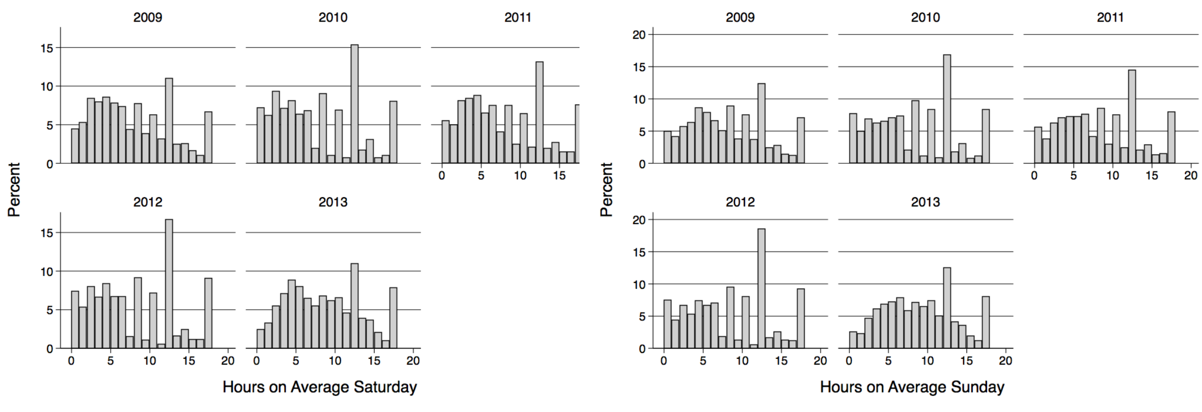
Note: Stata module INEQDEC0 was used for decomposition (Jenkins, 1999).
Abbreviations: EI = Extended Income, HK = Housekeeper wage approach, OLS = Ordinary least squares model, HM = Heckman selection correction model.
Source: SOEP (v31.1), and Federal Statistical Office, own calculations.

Table A.2.11: Conversion scheme of parental childcare hours, h

$$h = \begin{cases} 0 & if \quad 0 \leq h < 0.5 \\ 1 & if \quad 0.5 \leq h < 1.5 \\ 2 & if \quad 1.5 \leq h < 2.5 \\ 3 & if \quad 2.5 \leq h < 3.5 \\ 4 & if \quad 3.5 \leq h < 4.5 \\ 5 & if \quad 4.5 \leq h < 5.5 \\ 6 & if \quad 5.5 \leq h < 6.5 \\ 7 & if \quad 6.5 \leq h < 7.5 \\ 8 & if \quad 7.5 \leq h < 8.5 \\ 9 & if \quad 8.5 \leq h < 9.5 \\ 10 & if \quad 9.5 \leq h < 10.5 \\ 11 & if \quad 10.5 \leq h < 11.5 \\ 12 & if \quad 11.5 \leq h < 12.5 \\ 13 & if \quad 12.5 \leq h < 13.5 \\ 14 & if \quad 13.5 \leq h < 14.5 \\ 15 & if \quad 14.5 \leq h < 15.5 \\ 16 & if \quad 15.5 \leq h < 16.5 \\ 17 & if \quad 16.5 \leq h < 17.5 \\ 18 & if \quad h \geq 17.5 \end{cases}$$

Figure A.2.4: Distribution of parental childcare time on an average Saturday and Sunday

(a) Saturday (b) Sunday



Note: Hours of parental childcare on Saturdays and Sundays are fully imputed for income years 2009, 2011 and 2013, and partly imputed for 2012 by means of logical imputation and predictive mean matching using information from income years 2008, 2010, and 2012.
Source: SOEP (v31.1), own calculations.

Table A.2.12: OLS regression of logged gross hourly wages (2009)

	Male			Female		
	Coeff.	**t**	**p-value**	**Coeff.**	**t**	**p-value**
Age	0.011	1.0	0.315	0.019	2.5	0.014
Age Squared	-0.000	-2.8	0.006	-0.000	-3.9	0.000
Part-Time Working Experience	-0.040	-4.2	0.000	0.005	1.4	0.173
Part-Time Working Experience Squared	0.003	4.0	0.000	0.001	3.8	0.000
Full-Time Working Experience	0.042	8.2	0.000	0.039	12.5	0.000
Full-Time Working Experience Squared	-0.000	-3.5	0.000	-0.000	-5.1	0.000
Schooling (Ref.: Lower Secondary)						
Intermediate	0.134	7.5	0.000	0.136	6.3	0.000
College	0.311	12.1	0.000	0.303	11.8	0.000
Vocational Education (Ref.: None)						
Basic Vocational	0.092	3.1	0.002	0.080	2.5	0.012
Higher Vocational	0.195	6.1	0.000	0.154	4.5	0.000
Tertiary	0.493	13.6	0.000	0.397	10.7	0.000
Marital Status (Ref.: Married)						
Single	-0.090	-4.3	0.000	-0.006	-0.3	0.789
Divorced	-0.130	-4.1	0.000	-0.000	-0.0	0.984
Widowed	-0.073	-0.7	0.466	-0.004	-0.1	0.949
No. of Children < 6 *in HH* (Ref.: None)						
One Child < 6	-0.047	-2.5	0.011	0.016	0.6	0.528
Two or More Children < 6	-0.003	-0.1	0.896	0.076	2.0	0.051
Self-Rated Health (Ref.: Very Good)						
Good	-0.024	-1.1	0.271	-0.053	-2.4	0.019
Satisfactory	-0.053	-2.2	0.025	-0.081	-3.3	0.001
Bad	-0.106	-3.3	0.001	-0.116	-3.8	0.000
Very Bad	-0.303	-3.8	0.000	-0.029	-0.4	0.707
Migration (Ref.: No)						
1st Generation Immigrant	-0.011	-0.3	0.736	-0.038	-0.9	0.395
2nd Generation Immigrant	-0.001	-0.1	0.959	-0.003	-0.1	0.898
Location in 1989 (Ref.: GDR)						
FRG	0.174	5.6	0.000	0.098	3.5	0.000
Abroad	0.068	1.0	0.320	0.039	0.5	0.614
Constant	1.904	9.4	0.000	1.607	9.7	0.000
Federal State	Yes			Yes		
Adj. R-Square	0.356			0.244		
Number of Observations	4837			4555		

Note: * $p<0.05$, ** $p<0.01$, *** $p<0.001$
Source: SOEP (v31.1), own calculations.

Table A.2.13: Heckman regression of logged gross hourly wages (2009)

	Male Coeff.	t	p-value	Female Coeff.	t	p-value
Wage Regression						
Age	0.020	2.0	0.040	0.014	2.0	0.047
Age Squared	-0.000	-3.2	0.001	-0.000	-3.7	0.000
Part-Time Working Experience	-0.040	-5.2	0.000	0.008	1.9	0.058
Part-Time Working Experience Squared	0.003	5.2	0.000	0.000	3.2	0.002
Full-Time Working Experience	0.033	6.4	0.000	0.042	12.6	0.000
Full-Time Working Experience Squared	-0.000	-3.7	0.000	-0.000	-6.0	0.000
Schooling (Ref.: Lower Secondary)						
Intermediate	0.115	6.0	0.000	0.145	6.8	0.000
College	0.263	9.3	0.000	0.332	12.7	0.000
Vocational Education (Ref.: None)						
Basic Vocational	0.075	2.5	0.013	0.070	2.5	0.014
Higher Vocational	0.163	4.7	0.000	0.147	4.7	0.000
Tertiary	0.457	12.6	0.000	0.380	11.0	0.000
Location in 1989 (Ref.: GDR)						
FRG	0.180	5.9	0.000	0.111	3.9	0.000
Abroad	0.138	2.1	0.032	0.031	0.4	0.673
Migration (Ref.: No)						
1st Generation Immigrant	0.009	0.2	0.811	-0.044	-1.1	0.278
2nd Generation Immigrant	-0.006	-0.3	0.802	0.005	0.2	0.841
Constant	1.725	9.4	0.000	1.663	11.2	0.000
Selection Regression						
Age	0.024	0.8	0.426	-0.003	-0.2	0.880
Age Squared	-0.001	-4.0	0.000	-0.001	-4.0	0.000
Part-Time Working Experience	0.052	1.8	0.071	0.210	21.0	0.000
Part-Time Working Experience Squared	0.002	0.8	0.399	-0.004	-8.6	0.000
Full-Time Working Experience	0.105	7.7	0.000	0.114	13.6	0.000
Full-Time Working Experience Squared	0.000	0.2	0.831	-0.000	-0.6	0.569
Schooling (Ref.: Lower Secondary)						
Intermediate	0.163	2.4	0.015	0.274	4.7	0.000
College	0.655	7.0	0.000	0.476	6.5	0.000
Vocational Education (Ref.: None)						
Basic Vocational	0.281	3.1	0.002	0.224	3.1	0.002
Higher Vocational	0.532	4.8	0.000	0.292	3.5	0.000
Tertiary	0.563	4.8	0.000	0.523	5.4	0.000
Location in 1989 (Ref.: GDR)						
FRG	-0.139	-1.2	0.221	-0.226	-2.5	0.011
Abroad	-0.267	-1.3	0.195	-0.359	-2.0	0.050
Migration (Ref.: No)						
1st Generation Immigrant	-0.081	-0.7	0.515	0.085	0.8	0.428
2nd Generation Immigrant	0.180	1.9	0.056	0.042	0.6	0.573
Marital Status (Ref.: Married)						
Single	0.078	1.0	0.335	0.293	4.0	0.000
Divorced	-0.132	-1.3	0.192	0.037	0.6	0.576
Widowed	-0.012	-0.0	0.977	0.062	0.3	0.736
No. of Children < 6 *in HH* (Ref.: None)						
One Child < 6	-0.442	-6.1	0.000	-1.066	-18.0	0.000
Two or More Children < 6	-0.668	-7.6	0.000	-1.573	-19.7	0.000
Self-Rated Health (Ref.: Very Good)						
Good	0.220	2.8	0.005	0.012	0.2	0.862
Satisfactory	0.227	2.6	0.009	-0.001	-0.0	0.989
Bad	-0.146	-1.4	0.165	-0.108	-1.2	0.222
Very Bad	-0.684	-4.2	0.000	-0.777	-4.7	0.000
Constant	0.799	1.3	0.182	0.780	1.7	0.083
Mills						
Lambda	-0.269	-3.8	0.000	0.045	1.3	0.180
Federal State	Yes			Yes		
Number of Observations	5128			5973		

Note: * $p<0.05$, ** $p<0.01$, *** $p<0.001$
Source: SOEP (v31.1), own calculations.

Table A.2.14: OLS regression of logged gross hourly wages (2010)

	Male			Female		
	Coeff.	**t**	**p-value**	**Coeff.**	**t**	**p-value**
Age	0.018	1.9	0.053	0.018	2.8	0.005
Age Squared	-0.000	-3.0	0.002	-0.000	-4.6	0.000
Part-Time Working Experience	-0.034	-5.1	0.000	0.008	2.8	0.004
Part-Time Working Experience Squared	0.002	4.5	0.000	0.000	3.7	0.000
Full-Time Working Experience	0.032	7.7	0.000	0.033	12.8	0.000
Full-Time Working Experience Squared	-0.000	-2.9	0.004	-0.000	-3.7	0.000
Schooling (Ref.: Lower Secondary)						
Intermediate	0.146	9.6	0.000	0.158	8.6	0.000
College	0.320	14.9	0.000	0.333	15.1	0.000
Vocational Education (Ref.: None)						
Basic Vocational	0.090	3.5	0.000	0.099	3.7	0.000
Higher Vocational	0.172	6.2	0.000	0.184	6.3	0.000
Tertiary	0.459	14.6	0.000	0.437	13.9	0.000
Marital Status (Ref.: Married)						
Single	-0.050	-2.9	0.004	0.012	0.6	0.529
Divorced	-0.093	-3.6	0.000	0.046	2.7	0.008
Widowed	-0.076	-0.8	0.452	-0.022	-0.5	0.648
No. of Children < 6 in HH (Ref.: None)						
One Child < 6	0.010	0.6	0.517	0.029	1.5	0.128
Two or More Children < 6	0.037	1.7	0.085	0.031	0.8	0.438
Self-Rated Health (Ref.: Very Good)						
Good	-0.020	-1.1	0.274	-0.037	-1.8	0.074
Satisfactory	-0.065	-3.3	0.001	-0.066	-3.0	0.003
Bad	-0.119	-4.5	0.000	-0.072	-2.6	0.009
Very Bad	-0.188	-2.7	0.007	-0.126	-2.3	0.021
Migration (Ref.: No)						
1st Generation Immigrant	0.004	0.1	0.883	0.044	1.3	0.200
2nd Generation Immigrant	0.013	0.7	0.503	0.010	0.5	0.620
Location in 1989 (Ref.: GDR)						
FRG	0.134	5.3	0.000	0.084	3.8	0.000
Abroad	0.059	1.1	0.273	-0.009	-0.2	0.873
Constant	1.735	9.8	0.000	1.607	11.7	0.000
Federal State	Yes			Yes		
Adj. R-Square	0.375			0.257		
Number of Observations	5560			5767		

Note: * p<0.05, ** p<0.01, *** p<0.001
Source: SOEP (v31.1), own calculations.

Table A.2.15: Heckman regression of logged gross hourly wages (2010)

	Male Coeff.	t	p-value	Female Coeff.	t	p-value
Wage Regression						
Age	0.035	3.9	0.000	0.013	2.0	0.046
Age Squared	-0.001	-5.1	0.000	-0.000	-3.9	0.000
Part-Time Working Experience	-0.040	-6.1	0.000	0.008	2.1	0.034
Part-Time Working Experience Squared	0.002	5.3	0.000	0.000	3.1	0.002
Full-Time Working Experience	0.021	4.2	0.000	0.034	11.3	0.000
Full-Time Working Experience Squared	-0.000	-1.6	0.109	-0.000	-4.0	0.000
Schooling (Ref.: Lower Secondary)						
Intermediate	0.130	7.6	0.000	0.162	8.6	0.000
College	0.307	13.0	0.000	0.341	14.6	0.000
Vocational Education (Ref.: None)						
Basic Vocational	0.077	3.0	0.002	0.101	4.0	0.000
Higher Vocational	0.154	5.3	0.000	0.195	7.0	0.000
Tertiary	0.428	13.5	0.000	0.437	14.3	0.000
Location in 1989 (Ref.: GDR)						
FRG	0.129	5.1	0.000	0.107	4.4	0.000
Abroad	0.123	2.2	0.026	-0.002	-0.0	0.971
Migration (Ref.: No)						
1st Generation Immigrant	0.008	0.2	0.812	0.026	0.7	0.490
2nd Generation Immigrant	0.002	0.1	0.933	0.014	0.6	0.530
Constant	1.494	9.0	0.000	1.691	12.4	0.000
Selection Regression						
Age	-0.096	-3.2	0.001	-0.048	-2.5	0.013
Age Squared	0.000	0.2	0.858	-0.000	-2.2	0.030
Part-Time Working Experience	0.094	4.1	0.000	0.214	24.5	0.000
Part-Time Working Experience Squared	-0.002	-1.3	0.187	-0.004	-10.2	0.000
Full-Time Working Experience	0.133	10.5	0.000	0.118	15.7	0.000
Full-Time Working Experience Squared	-0.001	-2.6	0.011	-0.000	-1.2	0.230
Schooling (Ref.: Lower Secondary)						
Intermediate	0.285	4.5	0.000	0.208	4.0	0.000
College	0.512	6.1	0.000	0.455	7.1	0.000
Vocational Education (Ref.: None)						
Basic Vocational	0.230	2.7	0.006	0.256	4.0	0.000
Higher Vocational	0.435	4.2	0.000	0.303	4.2	0.000
Tertiary	0.593	5.5	0.000	0.635	7.6	0.000
Location in 1989 (Ref.: GDR)						
FRG	-0.144	-1.3	0.180	-0.130	-1.8	0.078
Abroad	-0.286	-1.5	0.145	0.050	0.3	0.757
Migration (Ref.: No)						
1st Generation Immigrant	-0.084	-0.7	0.478	-0.034	-0.3	0.736
2nd Generation Immigrant	0.091	1.1	0.286	0.064	1.0	0.331
Marital Status (Ref.: Married)						
Single	-0.059	-0.8	0.398	0.056	1.0	0.314
Divorced	-0.075	-0.8	0.452	0.010	0.2	0.861
Widowed	-0.520	-1.6	0.117	-0.022	-0.2	0.880
No. of Children $<$ *6 in HH* (Ref.: None)						
One Child $<$ 6	-0.401	-6.2	0.000	-0.923	-18.4	0.000
Two or More Children $<$ 6	-0.562	-6.9	0.000	-1.603	-21.8	0.000
Self-Rated Health (Ref.: Very Good)						
Good	-0.019	-0.2	0.812	0.077	1.3	0.210
Satisfactory	-0.041	-0.5	0.638	-0.004	-0.1	0.956
Bad	-0.310	-3.0	0.003	-0.070	-0.9	0.382
Very Bad	-1.015	-6.3	0.000	-0.493	-3.7	0.000
Constant	3.185	5.3	0.000	1.537	3.8	0.000
Mills						
Lambda	-0.165	-2.2	0.025	-0.002	-0.1	0.949
Federal State	Yes			Yes		
Number of Observations	5858			7367		

Note: * $p<0.05$, ** $p<0.01$, *** $p<0.001$
Source: SOEP (v31.1), own calculations.

Table A.2.16: OLS regression of logged gross hourly wages (2011)

	Male			**Female**		
	Coeff.	**t**	**p-value**	**Coeff.**	**t**	**p-value**
Age	0.008	0.8	0.431	0.002	0.3	0.785
Age Squared	-0.000	-2.2	0.027	-0.000	-2.0	0.046
Part-Time Working Experience	-0.034	-5.1	0.000	0.010	3.4	0.001
Part-Time Working Experience Squared	0.002	3.9	0.000	0.000	3.6	0.000
Full-Time Working Experience	0.036	8.3	0.000	0.040	16.1	0.000
Full-Time Working Experience Squared	-0.000	-3.6	0.000	-0.000	-6.7	0.000
Schooling (Ref.: Lower Secondary)						
Intermediate	0.127	8.3	0.000	0.162	9.2	0.000
College	0.328	14.9	0.000	0.323	14.8	0.000
Vocational Education (Ref.: None)						
Basic Vocational	0.076	2.9	0.004	0.075	3.0	0.002
Higher Vocational	0.177	6.1	0.000	0.155	5.8	0.000
Tertiary	0.439	13.5	0.000	0.415	14.2	0.000
Marital Status (Ref.: Married)						
Single	-0.051	-2.9	0.003	-0.007	-0.4	0.693
Divorced	-0.068	-2.7	0.007	0.022	1.3	0.200
Widowed	-0.242	-2.0	0.048	-0.034	-0.8	0.435
No. of Children < 6 in HH (Ref.: None)						
One Child < 6	-0.002	-0.1	0.887	0.017	0.9	0.344
Two or More Children < 6	0.032	1.5	0.141	0.058	1.6	0.103
Self-Rated Health (Ref.: Very Good)						
Good	0.001	0.1	0.955	-0.018	-0.9	0.390
Satisfactory	-0.042	-2.0	0.050	-0.066	-3.0	0.003
Bad	-0.067	-2.4	0.018	-0.119	-4.2	0.000
Very Bad	-0.030	-0.5	0.590	-0.153	-2.4	0.018
Migration (Ref.: No)						
1st Generation Immigrant	-0.005	-0.2	0.855	0.063	2.0	0.049
2nd Generation Immigrant	-0.012	-0.6	0.544	-0.005	-0.3	0.788
Location in 1989 (Ref.: GDR)						
FRG	0.122	5.2	0.000	0.080	3.5	0.000
Abroad	0.100	2.1	0.038	-0.043	-0.8	0.416
Constant	1.979	10.9	0.000	1.882	12.8	0.000
Federal State	Yes			Yes		
Adj. R-Square	0.374			0.276		
Number of Observations	5318			5745		

Note: * p<0.05, ** p<0.01, *** p<0.001
Source: SOEP (v31.1), own calculations.

Table A.2.17: Heckman regression of logged gross hourly wages (2011)

	Male			Female		
	Coeff.	**t**	**p-value**	**Coeff.**	**t**	**p-value**
Wage Regression						
Age	0.019	2.2	0.030	0.007	1.1	0.260
Age Squared	-0.000	-3.0	0.002	-0.000	-2.9	0.004
Part-Time Working Experience	-0.040	-6.4	0.000	0.007	1.9	0.053
Part-Time Working Experience Squared	0.002	5.4	0.000	0.000	3.5	0.000
Full-Time Working Experience	0.026	5.6	0.000	0.038	13.6	0.000
Full-Time Working Experience Squared	-0.000	-3.2	0.001	-0.000	-6.4	0.000
Schooling (Ref.: Lower Secondary)						
Intermediate	0.109	6.5	0.000	0.156	8.6	0.000
College	0.289	12.2	0.000	0.324	14.5	0.000
Vocational Education (Ref.: None)						
Basic Vocational	0.045	1.7	0.089	0.074	3.0	0.003
Higher Vocational	0.138	4.6	0.000	0.145	5.4	0.000
Tertiary	0.400	12.4	0.000	0.407	13.7	0.000
Location in 1989 (Ref.: GDR)						
FRG	0.111	4.4	0.000	0.078	3.4	0.001
Abroad	0.114	2.1	0.036	-0.005	-0.1	0.936
Migration (Ref.: No)						
1st Generation Immigrant	-0.002	-0.1	0.953	0.041	1.1	0.261
2nd Generation Immigrant	-0.011	-0.6	0.577	-0.012	-0.6	0.570
Constant	1.820	11.0	0.000	1.781	13.0	0.000
Selection Regression						
Age	-0.047	-1.4	0.164	-0.044	-2.0	0.045
Age Squared	-0.001	-1.8	0.065	-0.001	-2.5	0.011
Part-Time Working Experience	0.117	4.7	0.000	0.232	24.8	0.000
Part-Time Working Experience Squared	-0.002	-1.8	0.075	-0.004	-11.2	0.000
Full-Time Working Experience	0.137	9.8	0.000	0.118	14.7	0.000
Full-Time Working Experience Squared	-0.001	-1.6	0.114	-0.000	-0.1	0.915
Schooling (Ref.: Lower Secondary)						
Intermediate	0.191	2.6	0.008	0.235	4.3	0.000
College	0.620	6.1	0.000	0.509	7.4	0.000
Vocational Education (Ref.: None)						
Basic Vocational	0.335	3.6	0.000	0.229	3.4	0.001
Higher Vocational	0.599	5.0	0.000	0.346	4.4	0.000
Tertiary	0.668	5.4	0.000	0.656	7.2	0.000
Location in 1989 (Ref.: GDR)						
FRG	0.102	0.9	0.370	-0.044	-0.6	0.575
Abroad	-0.081	-0.4	0.720	-0.031	-0.2	0.859
Migration (Ref.: No)						
1st Generation Immigrant	0.107	0.7	0.486	0.065	0.6	0.568
2nd Generation Immigrant	-0.012	-0.1	0.902	-0.020	-0.3	0.774
Marital Status (Ref.: Married)						
Single	-0.130	-1.6	0.102	0.148	2.5	0.014
Divorced	-0.195	-1.9	0.057	0.115	1.8	0.066
Widowed	-0.527	-1.4	0.149	0.373	2.3	0.022
No. of Children < 6 in HH (Ref.: None)						
One Child < 6	-0.190	-2.4	0.015	-0.707	-12.9	0.000
Two or More Children < 6	-0.389	-3.8	0.000	-1.554	-19.5	0.000
Self-Rated Health (Ref.: Very Good)						
Good	-0.011	-0.1	0.914	-0.081	-1.1	0.261
Satisfactory	-0.079	-0.7	0.456	-0.151	-2.0	0.046
Bad	-0.489	-4.0	0.000	-0.315	-3.5	0.000
Very Bad	-1.271	-7.7	0.000	-0.525	-3.6	0.000
Constant	2.247	3.3	0.001	1.885	4.0	0.000
Mills						
Lambda	-0.257	-3.8	0.000	-0.007	-0.2	0.845
Federal State	Yes			Yes		
Number of Observations	5596			7109		

Note: * p<0.05, ** p<0.01, *** p<0.001
Source: SOEP (v31.1), own calculations.

Table A.2.18: OLS regression of logged gross hourly wages (2012)

	Male			Female		
	Coeff.	**t**	**p-value**	**Coeff.**	**t**	**p-value**
Age	0.008	0.8	0.400	0.021	2.9	0.004
Age Squared	-0.000	-2.3	0.023	-0.000	-4.6	0.000
Part-Time Working Experience	-0.021	-3.5	0.000	0.008	2.6	0.009
Part-Time Working Experience Squared	0.001	3.5	0.000	0.000	4.1	0.000
Full-Time Working Experience	0.039	9.6	0.000	0.032	13.0	0.000
Full-Time Working Experience Squared	-0.000	-4.2	0.000	-0.000	-2.7	0.007
Schooling (Ref.: Lower Secondary)						
Intermediate	0.127	8.2	0.000	0.154	8.7	0.000
College	0.312	14.0	0.000	0.331	15.5	0.000
Vocational Education (Ref.: None)						
Basic Vocational	0.117	4.4	0.000	0.133	5.2	0.000
Higher Vocational	0.205	6.9	0.000	0.232	8.4	0.000
Tertiary	0.465	14.3	0.000	0.451	14.9	0.000
Marital Status (Ref.: Married)						
Single	-0.066	-3.7	0.000	-0.002	-0.1	0.927
Divorced	-0.080	-3.2	0.001	0.013	0.7	0.459
Widowed	-0.135	-1.0	0.336	-0.045	-1.1	0.273
No. of Children < 6 in HH (Ref.: None)						
One Child < 6	0.006	0.4	0.714	0.022	1.2	0.235
Two or More Children < 6	0.035	1.6	0.104	-0.022	-0.6	0.570
Self-Rated Health (Ref.: Very Good)						
Good	0.025	1.3	0.208	-0.018	-0.9	0.393
Satisfactory	-0.027	-1.3	0.201	-0.069	-3.1	0.002
Bad	-0.090	-3.1	0.002	-0.080	-3.0	0.003
Very Bad	-0.220	-3.2	0.002	-0.165	-2.6	0.010
Migration (Ref.: No)						
1st Generation Immigrant	-0.059	-2.2	0.025	0.005	0.2	0.870
2nd Generation Immigrant	-0.007	-0.4	0.719	-0.009	-0.5	0.643
Location in 1989 (Ref.: GDR)						
FRG	0.124	5.0	0.000	0.116	5.2	0.000
Abroad	0.150	3.4	0.001	0.039	0.9	0.394
Constant	1.934	10.7	0.000	1.528	9.9	0.000
Federal State	Yes			Yes		
Adj. R-Square	0.360			0.274		
Number of Observations	5302			5677		

Note: * p<0.05, ** p<0.01, *** p<0.001
Source: SOEP (v31.1), own calculations.

Table A.2.19: Heckman regression of logged gross hourly wages (2012)

	Male Coeff.	t	p-value	Female Coeff.	t	p-value
Wage Regression						
Age	0.016	1.8	0.075	0.024	3.5	0.001
Age Squared	-0.000	-2.7	0.007	-0.000	-5.1	0.000
Part-Time Working Experience	-0.037	-5.7	0.000	0.004	1.0	0.309
Part-Time Working Experience Squared	0.002	4.9	0.000	0.000	3.7	0.000
Full-Time Working Experience	0.027	5.7	0.000	0.029	10.2	0.000
Full-Time Working Experience Squared	-0.000	-3.1	0.002	-0.000	-2.5	0.013
Schooling (Ref.: Lower Secondary)						
Intermediate	0.132	7.5	0.000	0.163	8.6	0.000
College	0.302	12.7	0.000	0.334	14.4	0.000
Vocational Education (Ref.: None)						
Basic Vocational	0.032	1.1	0.257	0.113	4.4	0.000
Higher Vocational	0.113	3.5	0.001	0.214	7.5	0.000
Tertiary	0.379	11.2	0.000	0.435	14.0	0.000
Location in 1989 (Ref.: GDR)						
FRG	0.139	5.4	0.000	0.118	5.0	0.000
Abroad	0.292	5.0	0.000	0.014	0.2	0.815
Migration (Ref.: No)						
1st Generation Immigrant	0.052	1.3	0.186	0.031	0.8	0.426
2nd Generation Immigrant	0.079	2.8	0.006	0.003	0.1	0.892
Constant	1.945	10.4	0.000	1.458	9.5	0.000
Selection Regression						
Age	0.022	0.7	0.461	0.025	1.2	0.239
Age Squared	-0.001	-3.1	0.002	-0.001	-4.5	0.000
Part-Time Working Experience	0.172	7.9	0.000	0.229	25.0	0.000
Part-Time Working Experience Squared	-0.005	-4.2	0.000	-0.005	-12.7	0.000
Full-Time Working Experience	0.128	10.2	0.000	0.101	12.9	0.000
Full-Time Working Experience Squared	-0.001	-2.5	0.014	0.000	0.1	0.935
Schooling (Ref.: Lower Secondary)						
Intermediate	0.193	3.0	0.002	0.166	3.0	0.002
College	0.445	5.4	0.000	0.402	6.0	0.000
Vocational Education (Ref.: None)						
Basic Vocational	0.333	4.2	0.000	0.268	4.1	0.000
Higher Vocational	0.697	6.6	0.000	0.377	5.0	0.000
Tertiary	0.633	6.1	0.000	0.613	7.2	0.000
Location in 1989 (Ref.: GDR)						
FRG	-0.105	-1.0	0.326	-0.159	-2.0	0.047
Abroad	-0.479	-3.0	0.003	-0.549	-4.0	0.000
Migration (Ref.: No)						
1st Generation Immigrant	-0.976	-10.3	0.000	-0.513	-5.5	0.000
2nd Generation Immigrant	-0.920	-14.2	0.000	-0.653	-11.5	0.000
Marital Status (Ref.: Married)						
Single	0.029	0.4	0.679	0.131	2.3	0.022
Divorced	-0.060	-0.6	0.546	0.277	4.3	0.000
Widowed	-0.371	-1.1	0.273	0.051	0.4	0.724
No. of Children < 6 in HH (Ref.: None)						
One Child < 6	0.134	2.0	0.048	-0.407	-7.6	0.000
Two or More Children < 6	0.308	3.0	0.003	-1.133	-13.7	0.000
Self-Rated Health (Ref.: Very Good)						
Good	0.406	5.6	0.000	0.294	4.5	0.000
Satisfactory	0.403	5.0	0.000	0.203	2.9	0.004
Bad	0.076	0.8	0.441	0.100	1.2	0.225
Very Bad	-0.576	-3.7	0.000	-0.444	-3.2	0.001
Constant	-0.416	-0.7	0.492	-0.064	-0.1	0.890
Mills						
Lambda	-0.232	-3.5	0.000	-0.036	-0.8	0.397
Federal State	Yes			Yes		
Number of Observations	5599			6946		

Note: * p<0.05, ** p<0.01, *** p<0.001
Source: SOEP (v31.1), own calculations.

Table A.2.20: OLS regression of logged gross hourly wages (2013)

	Male			Female		
	Coeff.	**t**	**p-value**	**Coeff.**	**t**	**p-value**
Age	0.002	0.2	0.854	0.021	2.7	0.007
Age Squared	-0.000	-1.8	0.080	-0.000	-4.1	0.000
Part-Time Working Experience	-0.021	-4.1	0.000	0.011	3.7	0.000
Part-Time Working Experience Squared	0.001	3.9	0.000	0.000	2.8	0.005
Full-Time Working Experience	0.042	9.8	0.000	0.032	13.0	0.000
Full-Time Working Experience Squared	-0.000	-4.7	0.000	-0.000	-3.0	0.003
Schooling (Ref.: Lower Secondary)						
Intermediate	0.129	8.3	0.000	0.181	9.5	0.000
College	0.300	13.9	0.000	0.364	16.1	0.000
Vocational Education (Ref.: None)						
Basic Vocational	0.081	3.1	0.002	0.094	3.3	0.001
Higher Vocational	0.173	5.8	0.000	0.176	5.8	0.000
Tertiary	0.453	13.8	0.000	0.406	12.3	0.000
Marital Status (Ref.: Married)						
Single	-0.072	-4.3	0.000	0.026	1.4	0.148
Divorced	-0.077	-3.1	0.002	0.002	0.1	0.933
Widowed	-0.080	-0.9	0.395	-0.068	-1.4	0.165
No. of Children < 6 *in HH* (Ref.: None)						
One Child < 6	0.040	2.4	0.017	0.032	1.5	0.125
Two or More Children < 6	0.050	2.1	0.037	0.047	1.2	0.242
Self-Rated Health (Ref.: Very Good)						
Good	-0.012	-0.6	0.545	-0.000	-0.0	0.993
Satisfactory	-0.055	-2.5	0.013	-0.046	-1.9	0.056
Bad	-0.104	-3.6	0.000	-0.080	-2.7	0.007
Very Bad	-0.247	-3.8	0.000	-0.088	-1.5	0.141
Migration (Ref.: No)						
1st Generation Immigrant	-0.036	-1.4	0.163	-0.005	-0.2	0.869
2nd Generation Immigrant	0.008	0.4	0.676	-0.016	-0.8	0.435
Location in 1989 (Ref.: GDR)						
FRG	0.110	4.8	0.000	0.092	3.8	0.000
Abroad	0.089	2.1	0.038	0.005	0.1	0.912
Constant	2.239	11.0	0.000	1.478	8.7	0.000
Federal State	Yes			Yes		
Adj. R-Square	0.380			0.282		
Number of Observations	4635			5011		

Note: * p<0.05, ** p<0.01, *** p<0.001
Source: SOEP (v31.1), own calculations.

Table A.2.21: Heckman regression of logged gross hourly wages (2013)

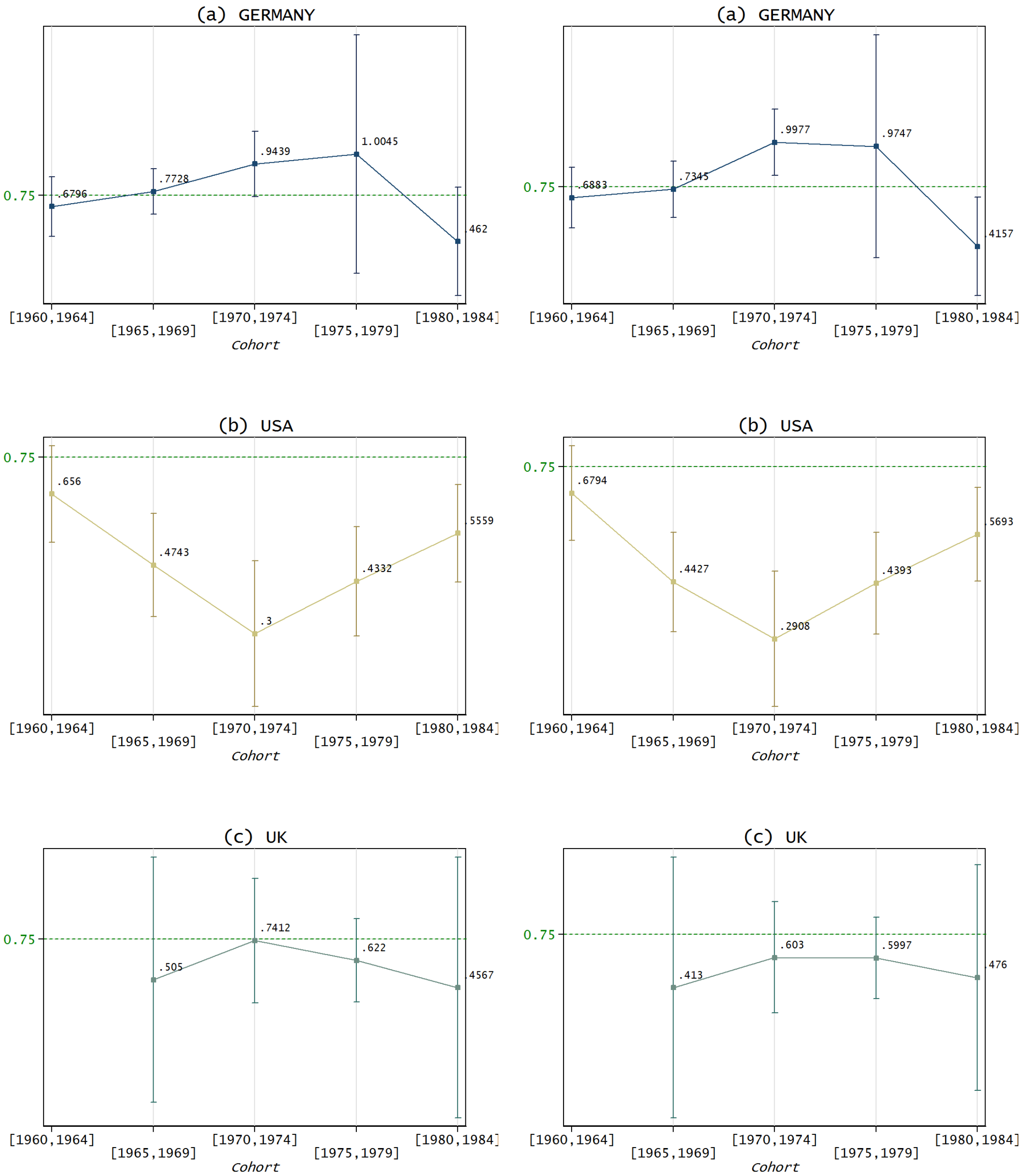
	Male			Female		
	Coeff.	**t**	**p-value**	**Coeff.**	**t**	**p-value**
Wage Regression						
Age	0.014	1.5	0.130	0.019	2.5	0.011
Age Squared	-0.000	-2.3	0.021	-0.000	-3.9	0.000
Part-Time Working Experience	-0.026	-4.9	0.000	0.005	1.1	0.260
Part-Time Working Experience Squared	0.001	3.7	0.000	0.000	3.3	0.001
Full-Time Working Experience	0.027	6.5	0.000	0.030	10.1	0.000
Full-Time Working Experience Squared	-0.000	-4.0	0.000	-0.000	-3.3	0.001
Schooling (Ref.: Lower Secondary)						
Intermediate	0.104	6.1	0.000	0.179	9.2	0.000
College	0.249	11.1	0.000	0.356	15.0	0.000
Vocational Education (Ref.: None)						
Basic Vocational	0.072	2.9	0.003	0.094	3.7	0.000
Higher Vocational	0.156	5.5	0.000	0.176	6.2	0.000
Tertiary	0.433	14.4	0.000	0.406	13.2	0.000
Location in 1989 (Ref.: GDR)						
FRG	0.118	4.8	0.000	0.104	4.3	0.000
Abroad	0.083	1.8	0.074	0.024	0.5	0.647
Migration (Ref.: No)						
1st Generation Immigrant	-0.020	-0.7	0.506	0.000	0.0	0.998
2nd Generation Immigrant	0.022	1.1	0.268	-0.017	-0.8	0.412
Constant	2.056	11.4	0.000	1.545	9.5	0.000
Selection Regression						
Age	0.037	0.8	0.416	-0.023	-0.9	0.380
Age Squared	-0.002	-3.6	0.000	-0.001	-2.5	0.011
Part-Time Working Experience	0.080	2.8	0.005	0.220	21.1	0.000
Part-Time Working Experience Squared	0.001	0.6	0.529	-0.004	-10.4	0.000
Full-Time Working Experience	0.168	9.8	0.000	0.112	12.6	0.000
Full-Time Working Experience Squared	-0.001	-2.0	0.045	-0.000	-0.5	0.630
Schooling (Ref.: Lower Secondary)						
Intermediate	0.399	4.0	0.000	0.186	3.0	0.003
College	0.657	5.2	0.000	0.519	6.7	0.000
Vocational Education (Ref.: None)						
Basic Vocational	0.126	1.0	0.302	0.172	2.3	0.020
Higher Vocational	0.354	2.1	0.033	0.317	3.7	0.000
Tertiary	0.595	3.6	0.000	0.458	4.6	0.000
Location in 1989 (Ref.: GDR)						
FRG	-0.094	-0.6	0.552	-0.172	-1.9	0.059
Abroad	0.219	0.8	0.440	-0.192	-1.1	0.253
Migration (Ref.: No)						
1st Generation Immigrant	-0.240	-1.2	0.213	0.119	1.0	0.316
2nd Generation Immigrant	-0.229	-2.0	0.047	-0.093	-1.3	0.191
Marital Status (Ref.: Married)						
Single	-0.341	-3.4	0.001	0.139	2.0	0.043
Divorced	-0.454	-3.6	0.000	0.185	2.5	0.011
Widowed	7.991	.	.	0.021	0.1	0.900
No. of Children < 6 *in HH* (Ref.: None)						
One Child < 6	0.008	0.1	0.945	-0.665	-10.4	0.000
Two or More Children < 6	-0.079	-0.5	0.638	-1.348	-14.1	0.000
Self-Rated Health (Ref.: Very Good)						
Good	0.121	0.9	0.384	0.002	0.0	0.980
Satisfactory	-0.015	-0.1	0.917	-0.117	-1.3	0.179
Bad	-0.481	-3.0	0.002	-0.262	-2.7	0.008
Very Bad	-1.254	-6.1	0.000	-0.958	-6.1	0.000
Constant	0.719	0.8	0.438	1.684	2.9	0.003
Mills						
Lambda	-0.382	-6.6	0.000	-0.076	-1.8	0.080
Federal State	Yes			Yes		
Number of Observations	4832			5948		

Note: * p<0.05, ** p<0.01, *** p<0.001
Source: SOEP (v31.1), own calculations.

A.3 Appendix of Chapter 4

Figure A.3.1: Estimated heritability coefficient (λ) by cohorts

Panel A – Completed years of education *Panel B – Z-Score of educational attainment*



Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A.3.1: Regression analysis - outcome: z-score of educational attainment

(a) Germany

	(1)	(2)	(3)
Parents (β_{-1})	0.423***		0.365***
	(0.0241)		(0.0329)
Grandparents (β_{-2})		0.331***	0.115***
		(0.0285)	(0.0366)
Observations	3210	3210	3210

Correlation coefficients: $r_{-1} = 0.444$, $r_{-2} = 0.322$

Test $(\beta_{-1})^2$=β_{-2} : F = 28.4403, Prob ¿ F = 0.0000 ; $(\beta_{-1})^2 = 0.179$

(b) USA

	(1)	(2)	(3)
Parents (β_{-1})	0.491***		0.480***
	(0.0197)		(0.0222)
Grandparents (β_{-2})		0.256***	0.024
		(0.0236)	(0.0237)
Observations	6303	6303	6303

Correlation coefficients: $r_{-1} = 0.445$, $r_{-2} = 0.225$

Test $(\beta_{-1})^2$=β_{-2} : F = 0.4075, Prob ¿ F = 0.5233 ; $(\beta_{-1})^2 = 0.241$

(c) UK

	(1)	(2)	(3)
Parents (β_{-1})	0.313***		0.290***
	(0.0421)		(0.0422)
Grandparents (β_{-2})		0.148***	0.056**
		(0.0303)	(0.0281)
Observations	1532	1532	1532

Correlation coefficients: $r_{-1} = 0.276$, $r_{-2} = 0.148$

Test $(\beta_{-1})^2$=β_{-2} : F = 2.7467, Prob ¿ F = 0.0977 ; $(\beta_{-1})^2 = 0.098$

Notes: Tables show regressions of children's educational outcomes on the outcomes of the parent or grandparent with highest education within the family. Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A.3.2: Z-score - estimated correlation (r), heritability (λ), and transferability (ρ) coefficients

	Z-Score		
	GER	*USA*	*UK*
r_{-1}	0.444	0.445	0.276
r_{-2}	0.322	0.225	0.148
λ	0.725	0.506	0.537
s.e.	*0.0529*	*0.0298*	*0.1041*
ρ	0.783	0.937	0.717
s.e.	*0.0377*	*0.0375*	*0.0839*

Notes: Bootstrapped s.e. (200 replications).
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A.3.3: Z-score - testing for a grandparental effect: controlling for multiple features of parental background (outcome: z-score of educational attainment)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Grandparents	0.057***	0.056***	0.055***	0.050***	0.012	0.012	0.015	0.011
	(0.0163)	(0.0165)	(0.0168)	(0.0167)	(0.0171)	(0.0173)	(0.0177)	(0.0177)
Parents	0.395***	0.466***	0.465***	0.465***				
	(0.0176)	(0.0210)	(0.0216)	(0.0222)				
GER (0/1) × Parents		-0.071**	-0.071**	-0.076**				
		(0.0310)	(0.0311)	(0.0326)				
UK (0/1) × Parents		-0.176***	-0.173***	-0.169***				
		(0.0466)	(0.0466)	(0.0472)				
Father					0.253***	0.283***	0.286***	0.287***
					(0.0176)	(0.0233)	(0.0236)	(0.0238)
GER (0/1) × Father						0.028	0.028	0.021
						(0.0437)	(0.0437)	(0.0442)
UK (0/1) × Father						-0.113***	-0.116***	-0.112***
						(0.0414)	(0.0418)	(0.0418)
Mother					0.227***	0.249***	0.249***	0.250***
					(0.0166)	(0.0238)	(0.0237)	(0.0238)
GER (0/1) × Mother						-0.032	-0.030	-0.036
						(0.0401)	(0.0400)	(0.0402)
UK (0/1) × Mother						-0.068*	-0.070*	-0.069*
						(0.0386)	(0.0385)	(0.0386)
Country F.E.	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Non-white or Migrant	No	No	Yes	Yes	No	No	Yes	Yes
- (interacted with country f.e.)	No	No	No	Yes	No	No	No	Yes
Adj. R^2	.1563	.161	.1612	.1622	.1769	.1817	.1819	.183
Observations	11045	11045	11039	11039	9769	9769	9764	9764
Clusters	5768	5768	5762	5762	5168	5168	5163	5163

Notes: Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A.3.4: Z-score - testing for a grandparental effect: controlling for multiple features of parental background – country-wise (outcome: z-score of educational attainment)

	(1) USA	(2) USA	(3) USA	(4) GER	(5) GER	(6) GER	(7) UK	(8) UK	(9) UK
Grandparents	0.021	-0.006	-0.004	0.106***	0.057	0.055	0.053*	0.010	0.008
	(0.0241)	(0.0253)	(0.0256)	(0.0387)	(0.0348)	(0.0378)	(0.0280)	(0.0307)	(0.0306)
Parents	0.477***			0.365***			0.294***		
	(0.0230)			(0.0330)			(0.0423)		
Father		0.287***	0.290***		0.299***	0.299***		0.171***	0.175***
		(0.0231)	(0.0236)		(0.0387)	(0.0387)		(0.0351)	(0.0352)
Mother		0.253***	0.254***		0.199***	0.199***		0.181***	0.182***
		(0.0248)	(0.0247)		(0.0340)	(0.0340)		(0.0308)	(0.0307)
Non-white or Migrant (0/1)	-0.038		0.044	-0.044		-0.011	0.248		0.310*
	(0.0455)		(0.0464)	(0.0644)		(0.0689)	(0.1583)		(0.1621)
Adj. R^2	.198	.2208	.2209	.2056	.2258	.2256	.08014	.0876	.09126
Observations	6303	5554	5554	3210	2818	2818	1526	1397	1392
Clusters	2065	1898	1898	2192	1890	1890	1505	1380	1375

Notes: Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A.3.5: Lineages - regression analysis by son/daughter – father/mother – grandfather/grandmother (outcome: completed years of education)

(a) Germany

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.486***		0.439***	
	(0.0355)		(0.0455)	
Grandfather		0.225***	0.076**	0.338***
		(0.0314)	(0.0342)	(0.0233)
Observations	1625	1503	1497	1497

Test $\beta^f_{-1} \cdot \beta^s_{-1}=\beta^f_{-2}$: F = 3.6893, Prob ¿ F = 0.0550 ; $\beta^f_{-1} \cdot \beta^s_{-1} = 0.164$

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.539***		0.513***	
	(0.0421)		(0.0506)	
Grandmother		0.215***	0.051	0.321***
		(0.0345)	(0.0359)	(0.0250)
Observations	1391	1311	1310	1310

Test $\beta^m_{-1} \cdot \beta^d_{-1}=\beta^m_{-2}$: F = 1.5214, Prob ¿ F = 0.2177 ; $\beta^m_{-1} \cdot \beta^d_{-1} = 0.173$

(b) USA

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.281***		0.262***	
	(0.0220)		(0.0268)	
Grandfather		0.147***	0.039**	0.412***
		(0.0158)	(0.0184)	(0.0238)
Observations	2705	2681	2681	2681

Test $\beta^f_{-1} \cdot \beta^s_{-1}=\beta^f_{-2}$: F = 3.8558, Prob ¿ F = 0.0498 ; $\beta^f_{-1} \cdot \beta^s_{-1} = 0.116$

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.363***		0.335***	
	(0.0187)		(0.0241)	
Grandmother		0.168***	0.056***	0.333***
		(0.0172)	(0.0184)	(0.0275)
Observations	3250	3153	3153	3153

Test $\beta^m_{-1} \cdot \beta^d_{-1}=\beta^m_{-2}$: F = 7.3774, Prob ¿ F = 0.0067 ; $\beta^m_{-1} \cdot \beta^d_{-1} = 0.121$

(c) UK

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.145***		0.084**	
	(0.0304)		(0.0356)	
Grandfather		0.076**	0.046	0.357***
		(0.0306)	(0.0332)	(0.0481)
Observations	734	506	506	506

Test $\beta^f_{-1} \cdot \beta^s_{-1}=\beta^f_{-2}$: F = 0.6329, Prob ¿ F = 0.4267 ; $\beta^f_{-1} \cdot \beta^s_{-1} = 0.052$

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.157***		0.147***	
	(0.0318)		(0.0343)	
Grandmother		0.085***	0.046	0.265***
		(0.0312)	(0.0299)	(0.0475)
Observations	721	651	651	651

Test $\beta^m_{-1} \cdot \beta^d_{-1}=\beta^m_{-2}$: F = 1.9852, Prob ¿ F = 0.1593 ; $\beta^m_{-1} \cdot \beta^d_{-1} = 0.041$

Notes: Tables show regressions of sons'/daughters' educational outcomes on the outcomes of father/mother and grandfather/grandmother. Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01. $\beta^{s/d}$ regression coefficient of the education of fathers/mothers on sons/daughters. $\beta^{f/m}$ regression coefficient of the education of grandfathers/grandmothers on fathers/mothers.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A.3.6: Lineages - estimated correlation (r), heritability (λ), and transferability (ρ) coefficients (outcome: completed years of education)

	GER		*USA*		*UK*	
	Sons	*Daughters*	*Sons*	*Daughters*	*Sons*	*Daughters*
r_{-1}	0.456	0.455	0.451	0.451	0.286	0.240
r_{-2}	0.286	0.256	0.251	0.275	0.121	0.118
λ	0.627	0.563	0.557	0.609	0.424	0.491
s.e.	*0.0712*	*0.0770*	*0.0457*	*0.0472*	*0.1613*	*0.1508*
ρ	0.853	0.899	0.900	0.861	0.821	0.699
s.e.	*0.0506*	*0.0635*	*0.0425*	*0.0348*	*0.5916*	*0.4914*

Notes: Bootstrapped s.e. (200 replications). r_{-1} is here the average of the correlation coefficients of son (daughter) on father (mother) and of father (mother) on grandfather (grandmother).
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A.3.7: Lineages - regression analysis by son/daughter – father/mother – grandfather/grandmother (outcome: z-score of educational attainment)

(a) Germany

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.444***		0.399***	
	(0.0331)		(0.0410)	
Grandfather		0.302***	0.108***	0.486***
		(0.0365)	(0.0402)	(0.0297)
Observations	1625	1503	1497	1497

Test $\beta^f_{-1} \cdot \beta^s_{-1}=\beta^f_{-2}$: F = 5.6279, Prob ¿ F = 0.0178 ; $\beta^f_{-1} \cdot \beta^s_{-1}$ = 0.216

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.396***		0.374***	
	(0.0356)		(0.0421)	
Grandmother		0.232***	0.064	0.451***
		(0.0384)	(0.0401)	(0.0339)
Observations	1391	1311	1310	1310

Test $\beta^m_{-1} \cdot \beta^d_{-1}=\beta^m_{-2}$: F = 1.9480, Prob ¿ F = 0.1631 ; $\beta^m_{-1} \cdot \beta^d_{-1}$ = 0.179

(b) USA

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.410***		0.391***	
	(0.0290)		(0.0335)	
Grandfather		0.232***	0.056*	0.450***
		(0.0291)	(0.0302)	(0.0282)
Observations	2705	2681	2681	2681

Test $\beta^f_{-1} \cdot \beta^s_{-1}=\beta^f_{-2}$: F = 2.6858, Prob ¿ F = 0.1015 ; $\beta^f_{-1} \cdot \beta^s_{-1}$ = 0.184

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.396***		0.371***	
	(0.0210)		(0.0259)	
Grandmother		0.229***	0.078***	0.409***
		(0.0257)	(0.0257)	(0.0348)
Observations	3250	3153	3153	3153

Test $\beta^m_{-1} \cdot \beta^d_{-1}=\beta^m_{-2}$: F = 6.8630, Prob ¿ F = 0.0089 ; $\beta^m_{-1} \cdot \beta^d_{-1}$ = 0.162

(c) UK

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.233***		0.137**	
	(0.0501)		(0.0575)	
Grandfather		0.124***	0.080	0.320***
		(0.0451)	(0.0502)	(0.0482)
Observations	734	506	506	506

Test $\beta^f_{-1} \cdot \beta^s_{-1}=\beta^f_{-2}$: F = 1.1846, Prob ¿ F = 0.2769 ; $\beta^f_{-1} \cdot \beta^s_{-1}$ = 0.075

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.209***		0.197***	
	(0.0424)		(0.0455)	
Grandmother		0.105**	0.057	0.245***
		(0.0431)	(0.0417)	(0.0455)
Observations	721	651	651	651

Test $\beta^m_{-1} \cdot \beta^d_{-1}=\beta^m_{-2}$: F = 1.5634, Prob ¿ F = 0.2116 ; $\beta^m_{-1} \cdot \beta^d_{-1}$ = 0.051

Notes: Tables show regressions of sons'/daughters' educational outcomes on the outcomes of father/mother and grandfather/grandmother. Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01. $\beta^{s/d}$ regression coefficient of the education of fathers/mothers on sons/daughters. $\beta^{f/m}$ regression coefficient of the education of grandfathers/grandmothers on fathers/mothers.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A.3.8: Lineages - estimated correlation (r), heritability (λ) and transferability (ρ) coefficients (outcome: completed years of education)

	GER		*USA*		*UK*	
	Sons	*Daughters*	*Sons*	*Daughters*	*Sons*	*Daughters*
r_{-1}	0.456	0.433	0.428	0.418	0.276	0.227
r_{-2}	0.292	0.240	0.227	0.243	0.131	0.105
λ	0.641	0.555	0.531	0.581	0.476	0.464
s.e.	*0.0631*	*0.0776*	*0.0496*	*0.0506*	*0.1668*	*0.1676*
ρ	0.844	0.883	0.897	0.849	0.761	0.699
s.e.	*0.0419*	*0.0650*	*0.0468*	*0.0388*	*0.2216*	*0.3099*

Notes: Bootstrapped s.e. (200 replications). r_{-1} is here the average of the correlation coefficients of son (daughter) on father (mother) and of father (mother) on grandfather (grandmother).
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Data

The SOEP is an annually repeated longitudinal study of private households in Germany that was launched in 1984. Since 1991, it also includes a sample of the East German population.[1] For the current study we restrict our sample to people residing in West Germany. The PSID is a representative sample of the US population and was annually repeated between 1968 and 1995. Since 1995, it is repeated biennial only and was reduced in its scope.[2] The BHPS is an annually repeated longitudinal study of private households in Great Britain and was run between 1991 and 2008.[3] In 2009, the BHPS was detached by Understanding Society which is an annually repeated longitudinal study of private households in Great Britain and covers an even larger array of people's social and economic circumstances, attitudes, behaviours and health.[4] It builds on the BHPS and a large number of former BHPS respondents were incorporated into Understanding Society from the second wave of interviews onwards. We

[1]See: Wagner, Gert G., Joachim R. Frick, and JÃ¼rgen Schupp (2007) The German Socio-Economic Panel Study (SOEP) - Scope, Evolution and Enhancements. *Journal of Applied Social Science Studies* 127 (1), 139-169.

[2]Panel Study of Income Dynamics, public use dataset. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI (2016).

[3]Since 2001, the BHPS is also representative of the United Kingdom. This was achieved by adding 1,500 additional households from Scotland and 1,500 households from Wales in 1999 and another 2,000 households from Northern Ireland in 2001. See: University of Essex. Institute for Social and Economic Research. (2010). British Household Panel Survey: Waves 1-18, 1991-2009. 7th Edition. UK Data Service. SN: 5151.

[4]See: University of Essex. Institute for Social and Economic Research, NatCen Social Research. (2015). Understanding Society: Waves 1-5, 2009-2014. [data collection]. 7th Edition. UK Data Service. SN: 6614.

treat information collected from BHPS sample members in Understanding Society as if it were information collected in successive BHPS waves.[5]

Harmonization

We maximize the comparability of our educational measure by following the harmonization procedures adopted in the Cross-National Equivalent File (CNEF).[6]

PSID provides detailed information on completed years of education for each family unit member at the time of the interview. It encompasses information on primary, secondary, and tertiary education as well as vocational training. We use this information to construct both the variables on schooling and education for parents (generation t-1) and children (generation t). In addition, retrospective questions on parental education are available. In this case, the answer of the responding household head is categorized into one of eight possible grade categories. We use this information to attribute the completed years of education of grandparents (generation t-2) to their grandchildren. Since we can directly observe generation *t* and *t-1* in our samples, we use these retrospective information to compute the completed years of education for generation *t-2* (grandparents). Also, whenever individual response on completed years of education is not available for parents, we take the information given by retrospective questions.

SOEP provides a comparable measure of completed years of education for each household member at the time of the interview. In contrast to the PSID, the scale of completed years of education is restricted to values ranging from seven years of education to eighteen years of education. We limit the scale at the upper bound to be consistent with the scale from the PSID. Retrospective questions on the educational level of both mothers and fathers are also available, at which the respondents have to refer to school leaving degrees ranging from "secondary school degree" to "did not attend school". As described before, the available information on the respondent and its parents is, then, transformed to our common scale of years of education.

The panel surveys for the UK, BHPS and Understanding Society, can be combined with each other for longitudinal analyses. Both do not provide a direct measure of completed years of education, but information on the highest educational qualification of a respondent and its respective parents.[7] This variable combines both information on the highest school leaving degree as well as information on vocational training. Again, the information provided in the retrospective questions on parents are less detailed

[5]There is no information on BHPS sample members for 2009.

[6]The CNEF project provides a harmonized subset of the information included in various household surveys and suitable for international comparisons. For information on CNEF, see Frick et al. (2007).

[7]Information on parents are provided in Wave 13 in the BHPS and in Wave 2 of Understanding Society.

and contain only five different categories. By using additional information on parental occupation and skills, measured in ISCO levels, we are however able to construct comparable measures of schooling and education for children, parents and grandparents. Figure A.3.2 shows the codification scheme applied in each survey, Figure A.3.3 the mean completed years of education by age and a comparison with the Barro-Lee data on educational attainment.

Finally, the household surveys are non-random draws of the population and oversample certain groups, like PSID does with low-income households and SOEP with migrants. Sample design weights are therefore provided to represent the actual population. Computing descriptive statistics and performing regressions without using weighting factors would results in inconsistent estimates. Our estimates are, therefore, obtained by weighting each observation by its inverse probability of selection into the sample. Since we pool several waves of the surveys, we normalize these weights for every survey year to maintain its relative population share. To account for heteroscedasticity, standard errors are obtained by clustering observations within the household of origin. For comprehensive overviews on household survey design and weighting procedures, see Deaton (1997) and Solon et al. (2015).

Figure A.3.2: Codification of completed years of education

(a) PSID - USA

$$Years\,of\,Schooling = \begin{cases} 1 & if\,school\,not\,attended \\ 5 & if\,school\,dropout\,and\,no\,school\,degree \\ 9 & if\,secondary\,school\,degree \\ 10 & if\,intermediate\,school\,degree \\ 12 & if\,technical\,school\,degree \\ 13 & if\,upper\,secondary\,school\,degree \end{cases}$$

$$Years\,of\,Education = \begin{cases} 1 & if\,0-5\,grades \\ 5 & if\,6-8\,grades\,or\,\text{''}grade\,school\text{''} \\ 9 & if\,9-11\,grades\,(some\,high\,school)\,or\,junior\,high \\ 12 & if\,12\,grades\,(completed\,high\,school) \\ 13 & if\,12\,grades\,plus\,nonacademic\,training\,or\,R.N.\,(no\,further \\ & elaboration) \\ 14 & if\,some\,college,\,no\,degree\,or\,Associate's\,degree \\ 15 & if\,College\,BA\,and\,no\,advanced\,degree\,mentioned\,or\,normal\,school\,or \\ & R.N.\,with\,3\,years\,college \\ 17 & if\,College,\,advanced\,or\,professional\,degree,\,some\,graduate\,work\,or \\ & close\,to\,receiving\,degree \end{cases}$$

(b) SOEP - Germany

$$Years\,of\,Schooling = \begin{cases} 1 & if\,school\,not\,attended \\ 5 & if\,school\,dropout\,and\,no\,school\,degree \\ 9 & if\,secondary\,school\,degree \\ 10 & if\,intermediate\,school\,degree \\ 12 & if\,technical\,school\,degree \\ 13 & if\,upper\,secondary\,school\,degree \end{cases}$$

$$Years\,of\,Education = \begin{cases} Years\,of\,Schooling & if\,no\,vocational\,degree \\ Years\,of\,Schooling+3 & if\,vocational\,degree \\ Years\,of\,Schooling+4 & if\,Tech\,Engineer,\,Civil\,Service\,Training, \\ & Special\,Tech\,School \\ 17 & if\,College,\,University \end{cases}$$

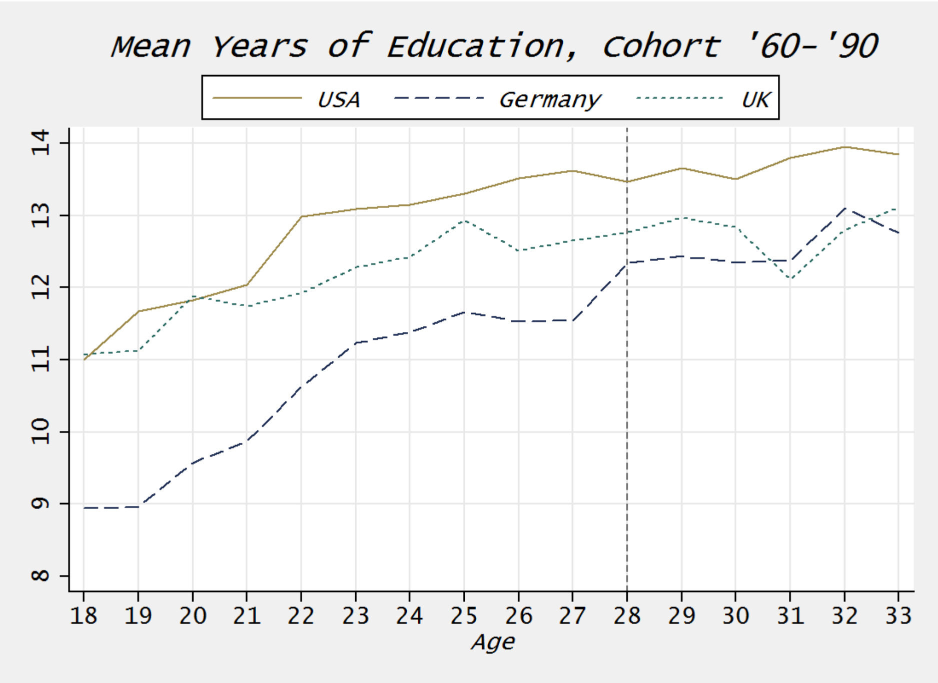
(c) BHPS/UKHLS - UK

$$Years\,of\,Schooling = \begin{cases} 1 & if\,did\,not\,go\,to\,school\,at\,all \\ 5 & if\,left\,school\,with\,no\,qualifications\,or\,certificates \\ 9 & if\,left\,school\,with\,some\,qualifications\,or\,certificates \\ 12 & if\,post\,school\,quals\,or\,certs\,(e.g.\,city\,\&\,guilds) \\ 13 & if\,university\,degree\,or\,higher\,degree \end{cases}$$

$$Years\,of\,Education = \begin{cases} Years\,of\,Schooling & if\,ISCO\,level\,9\,(skill\,level\,1) \\ Years\,of\,Schooling+3 & if\,ISCO\,levels\,4-8\,(skill\,level\,2) \\ Years\,of\,Schooling+4 & if\,ISCO\,level\,0,1\,and\,3\,(skill\,level\,3) \\ 17 & if\,ISCO\,levels\,2\,(skill\,level\,4) \end{cases}$$

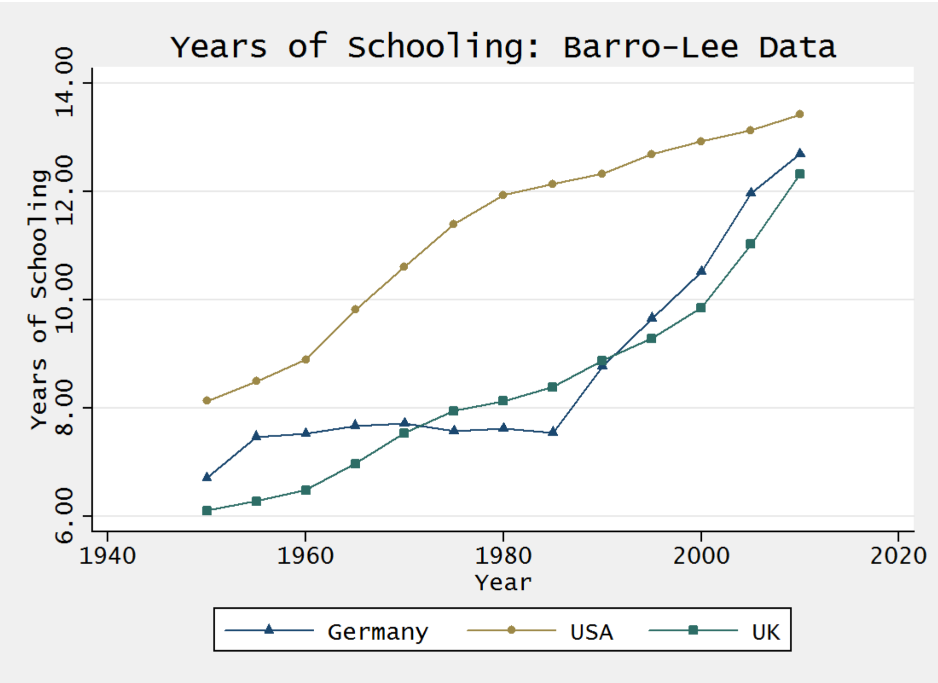
Figure A.3.3: Mean education by age and comparison with other data sets on mean educational attainment

(a) *Mean Education by Age*



Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

(b) *Barro-Lee Data on Years of Schooling (see Barro and Lee, 2013)*



Selectivity of Sample

A sensitivity analysis shows that the samples might be positively selected in educational attainments. We find that the weighted mean years of education of individuals in our sample – restricted by the condition of available information on parents' and grandparents' education – is higher than the weighted mean of the unrestricted sample. Restricting the sample on the condition to have information on parental education retrieved from retrospective questions – and not necessarily grandparental education – yields lower regression coefficients. These differences are statistically significant at the 1 % level for SOEP, at the 5 % level for BHPS/UKHLS and not significant for PSID. The interpretations and consequences of this bias for our study are discussed in the paper.

Table A.3.9: Testing selection into sample (cohort 1960-1985), weighted statistics

Sample 1: Sample used in this study (parents and children in survey and information on grandparental education).
Sample 2: Parental information retrieved from retrospective questions; information on grandparental education not necessarily available.

Mean years of education	*Sample 1*	*Sample 2*	*p-value*	*Unrestricted*	*p-value*
GER	12.552	12.497	0.2261	12.141	0.0000
USA	13.660	13.181	0.0000	13.088	0.0000
UK	12.673	12.630	0.5094	12.008	0.0000

First p-value shows the probability that the weighted means of sample 1 and sample 2 are equal. Second p-values shows the probability that the weighted mean of sample 1 and of the unrestricted sample are equal.

Regression coefficient (β_{-1})	*Sample 1*	*N*	*Sample 2*	*N*	*p-value*
GER	0.484	3,210	0.380	12,044	0.0004
USA	0.400	6,299	0.378	10,475	0.1931
UK	0.208	1,532	0.169	4,757	0.1774

P-value shows the probability that the weighted regression coefficient of sample 1 and sample 2 are equal.

Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

ADDITIONAL MATERIAL

Analysis performed applying the z-score of educational attainment

To obtain a measure that is conceptually even closer to the notion of human capital – and comparable across countries and time periods – we perform a linear transformation of the dependent and independent variables constructing the z-score of educational achievements by cohorts:

$$z_{ijT} = \frac{y_{ijT} - \bar{y}_{jT}}{\sigma_{jT}} \tag{A.1}$$

where $\bar{y}_{jt}$ and σ_{jt} are the mean and standard deviation of completed years of education of all individuals from generation $T \epsilon \{t, t-1, t-2\}$ in cohort j. The cohort refers hereby to the cohort of the children's generation. This measurement gives the relative standing (in standard deviations) of an individual, his parents, and grandparents with respect to their reference groups, i.e. people competing with them in the labour market.

Testing for a grandparental effect

Table A.3.10: Testing for a grandparental effect: grandparents' death as exogenous source of variation in the likelihood of interaction (outcome: z-score of educational attainment)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Father	0.433***	0.450***	0.402***	0.440***				
	(0.0280)	(0.0346)	(0.0311)	(0.0369)				
Mother					0.381***	0.361***	0.409***	0.412***
					(0.0283)	(0.0356)	(0.0298)	(0.0339)
GF-F	0.079***	0.048						
	(0.0285)	(0.0367)						
GM-F			0.084***	0.076**				
			(0.0299)	(0.0337)				
GF-M					0.152***	0.183***		
					(0.0302)	(0.0371)		
GM-M							0.064*	0.076*
							(0.0377)	(0.0452)
Death=1 × GF-F		0.077						
		(0.0536)						
Death=1 × GM-F				0.023				
				(0.0667)				
Death=1 × GF-M						-0.105*		
						(0.0607)		
Death=1 × GM-M								-0.047
								(0.0757)
Death=1		0.042						
		(0.0455)						
Death=1 × Father		-0.039						
		(0.0553)						
Death=1				0.058				
				(0.0605)				
Death=1 × Father				-0.128**				
				(0.0640)				
Death=1						-0.014		
						(0.0493)		
Death=1 × Mother						0.064		
						(0.0527)		
Death=1								0.073
								(0.0707)
Death=1 × Mother								-0.013
								(0.0735)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3360	3360	2241	2241	2973	2973	2147	2147
Clusters	1871	1871	1309	1309	1797	1797	1311	1311

GF/GM-F/M: Grandfather/Mother-Father's/Mother's side. Own estimations based on pooled sample of SOEP and PSID.
Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	USA	USA	USA	USA	GER	GER	GER	GER
Father	0.501***	0.459***			0.394***	0.423***		
	(0.0503)	(0.0517)			(0.0482)	(0.0525)		
Mother			0.349***	0.395***			0.357***	0.420***
			(0.0551)	(0.0565)			(0.0464)	(0.0417)
GF-F	0.022				0.092			
	(0.0420)				(0.0737)			
GM-F		0.047				0.122*		
		(0.0394)				(0.0668)		
GF-M			0.131***				0.285***	
			(0.0474)				(0.0580)	
GM-M				0.038				0.135**
				(0.0647)				(0.0628)
Death=1 × GF-F	0.070				0.129			
	(0.0642)				(0.1049)			
Death=1 × GM-F		0.047				0.045		
		(0.0844)				(0.1154)		
Death=1 × GF-M			-0.036				-0.220**	
			(0.0780)				(0.1049)	
Death=1 × GM-M				0.029				-0.170
				(0.0935)				(0.1461)
Death=1	0.104*				-0.052			
	(0.0588)				(0.0740)			
Death=1 × Father	-0.034				-0.047			
	(0.0732)				(0.0838)			
Death=1		0.171**				-0.090		
		(0.0818)				(0.0861)		
Death=1 × Father		-0.097				-0.178*		
		(0.0905)				(0.0958)		
Death=1			0.034				-0.049	
			(0.0678)				(0.0753)	
Death=1 × Mother			0.083				0.057	
			(0.0817)				(0.0701)	
Death=1				0.110				0.057
				(0.0951)				(0.1110)
Death=1 × Mother				-0.015				-0.006
				(0.1106)				(0.1005)
Observations	1832	1105	1390	931	1528	1136	1583	1216
Clusters	811	501	646	434	1060	808	1151	877

Own estimations based on SOEP and PSID.
Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

Table A.3.11: Testing for a grandparental effect: grandparents' death as exogenous source of variation in the likelihood of interaction (outcome: completed years of education)

	(1) USA	(2) USA	(3) USA	(4) USA	(5) GER	(6) GER	(7) GER	(8) GER
Father	0.341***	0.302***			0.440***	0.453***		
	(0.0357)	(0.0331)			(0.0547)	(0.0580)		
Mother			0.297***	0.339***			0.462***	0.520***
			(0.0485)	(0.0514)			(0.0547)	(0.0518)
GF-F	0.016				0.063			
	(0.0235)				(0.0557)			
GM-F		0.020				0.107*		
		(0.0246)				(0.0563)		
GF-M			0.070**				0.240***	
			(0.0283)				(0.0469)	
GM-M				0.025				0.137**
				(0.0409)				(0.0595)
Death=1 × GF-F	0.040				0.139			
	(0.0403)				(0.0875)			
Death=1 × GM-F		0.044				0.102		
		(0.0640)				(0.1113)		
Death=1 × GF-M			-0.020				-0.187**	
			(0.0457)				(0.0842)	
Death=1 × GM-M				0.041				-0.200
				(0.0663)				(0.1218)
Death=1	-0.185				-0.698			
	(0.6549)				(0.9900)			
Death=1 × Father	-0.002				-0.084			
	(0.0555)				(0.0962)			
Death=1		0.534				1.168		
		(0.9010)				(1.2223)		
Death=1 × Father		-0.049				-0.208**		
		(0.0639)				(0.1012)		
Death=1			-0.712				1.535	
			(0.7458)				(0.9382)	
Death=1 × Mother			0.078				0.036	
			(0.0703)				(0.0833)	
Death=1				0.062				1.607
				(1.0757)				(1.3930)
Death=1 × Mother				-0.024				0.042
				(0.1004)				(0.1137)
Observations	1832	1105	1390	931	1528	1136	1583	1216
Clusters	811	501	646	434	1060	808	1151	877

Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Lineages

Table A.3.12: Lineages - pooled sample (outcome: completed years of education)

Sons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father	0.212***	0.212***			0.203***		0.132***
	(0.0203)	(0.0212)			(0.0219)		(0.0239)
Mother			0.246***	0.253***		0.244***	0.182***
			(0.0230)	(0.0230)		(0.0237)	(0.0264)
GF-F	0.061***				0.045***		0.027
	(0.0149)				(0.0173)		(0.0276)
GM-F		0.067***			0.034		0.019
		(0.0179)			(0.0213)		(0.0345)
GF-M			0.070***			0.055***	0.011
			(0.0143)			(0.0179)	(0.0281)
GM-M				0.067***		0.027	-0.003
				(0.0160)		(0.0199)	(0.0335)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4684	4559	5318	5263	4507	5180	4216
Clusters	3123	3061	3533	3508	3027	3457	2789

GF/GM-F/M: Grandfather/Mother-Father's/Mother's side. Own estimations based on pooled sample of SOEP, PSID and UKHLS/BHPS. Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

Daughters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father	0.237***	0.251***			0.243***		0.184***
	(0.0182)	(0.0187)			(0.0193)		(0.0206)
Mother			0.233***	0.239***		0.230***	0.154***
			(0.0222)	(0.0224)		(0.0231)	(0.0229)
GF-F	0.066***				0.046***		0.016
	(0.0140)				(0.0172)		(0.0244)
GM-F		0.064***			0.030		0.014
		(0.0150)			(0.0188)		(0.0262)
GF-M			0.080***			0.062***	0.028
			(0.0138)			(0.0176)	(0.0238)
GM-M				0.074***		0.027	0.010
				(0.0148)		(0.0189)	(0.0259)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4480	4386	5164	5114	4328	5039	4095
Clusters	2831	2790	3244	3228	2752	3174	2572

GF/GM-F/M: Grandfather/Mother-Father's/Mother's side. Own estimations based on pooled sample of SOEP, PSID and UKHLS/BHPS. Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A.3.13: Lineages - pooled sample (outcome: z-score of educational attainment

Sons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father	0.329***	0.332***			0.323***		0.209***
	(0.0232)	(0.0236)			(0.0246)		(0.0270)
Mother			0.328***	0.338***		0.329***	0.251***
			(0.0221)	(0.0220)		(0.0227)	(0.0264)
GF-F	0.078***				0.062**		0.044
	(0.0211)				(0.0253)		(0.0353)
GM-F		0.069***			0.031		0.001
		(0.0219)			(0.0265)		(0.0392)
GF-M			0.098***			0.087***	0.003
			(0.0211)			(0.0256)	(0.0363)
GM-M				0.077***		0.021	-0.003
				(0.0201)		(0.0243)	(0.0383)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4683	4557	5318	5263	4505	5180	4214
Clusters	3122	3059	3533	3508	3025	3457	2787

GF/GM-F/M: Grandfather/Mother-Father's/Mother's side. Own estimations based on pooled sample of SOEP, PSID, and UKHLS/BHPS. Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

Daughters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father	0.361***	0.379***			0.372***		0.283***
	(0.0224)	(0.0225)			(0.0233)		(0.0257)
Mother			0.316***	0.321***		0.312***	0.194***
			(0.0218)	(0.0217)		(0.0226)	(0.0246)
GF-F	0.079***				0.048*		0.008
	(0.0209)				(0.0267)		(0.0347)
GM-F		0.069***			0.039		0.010
		(0.0204)			(0.0261)		(0.0356)
GF-M			0.102***			0.076***	0.034
			(0.0201)			(0.0256)	(0.0331)
GM-M				0.088***		0.038	0.018
				(0.0204)		(0.0259)	(0.0362)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4475	4379	5164	5113	4321	5038	4090
Clusters	2826	2784	3244	3228	2746	3174	2568

GF/GM-F/M: Grandfather/Mother-Father's/Mother's side. Own estimations based on pooled sample of SOEP, PSID, and UKHLS/BHPS. Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A.3.14: Correlation of parents' and grandparents' education. Spouse correlations (**Assortative Mating**) are Father/Mother, GF-F/GM-F, and GF-M/GM-M.

Panel A – Outcome: Completed years of education

(a) GER	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	*1.000*	*0.598*	*0.469*	*0.416*	*0.440*	*0.404*
Mother	*0.598*	*1.000*	*0.484*	*0.428*	*0.520*	*0.486*
GF-F	*0.469*	*0.484*	*1.000*	*0.792*	*0.686*	*0.659*
GM-F	*0.416*	*0.428*	*0.792*	*1.000*	*0.665*	*0.706*
GF-M	*0.440*	*0.520*	*0.686*	*0.665*	*1.000*	*0.783*
GM-M	*0.404*	*0.486*	*0.659*	*0.706*	*0.783*	*1.000*

(b) USA	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	*1.000*	*0.559*	*0.481*	*0.450*	*0.429*	*0.407*
Mother	*0.559*	*1.000*	*0.449*	*0.437*	*0.479*	*0.477*
GF-F	*0.481*	*0.449*	*1.000*	*0.637*	*0.877*	*0.585*
GM-F	*0.450*	*0.437*	*0.637*	*1.000*	*0.565*	*0.870*
GF-M	*0.429*	*0.479*	*0.877*	*0.565*	*1.000*	*0.636*
GM-M	*0.407*	*0.477*	*0.585*	*0.870*	*0.636*	*1.000*

(c) UK	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	*1.000*	*0.409*	*0.332*	*0.302*	*0.302*	*0.280*
Mother	*0.409*	*1.000*	*0.253*	*0.228*	*0.306*	*0.284*
GF-F	*0.332*	*0.253*	*1.000*	*0.839*	*0.293*	*0.295*
GM-F	*0.302*	*0.228*	*0.839*	*1.000*	*0.290*	*0.278*
GF-M	*0.302*	*0.306*	*0.293*	*0.290*	*1.000*	*0.823*
GM-M	*0.280*	*0.284*	*0.295*	*0.278*	*0.823*	*1.000*

Panel B – Outcome: z-score of educational attainment

(a) GER	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	*1.000*	*0.577*	*0.468*	*0.410*	*0.443*	*0.390*
Mother	*0.577*	*1.000*	*0.502*	*0.443*	*0.539*	*0.490*
GF-F	*0.468*	*0.502*	*1.000*	*0.776*	*0.674*	*0.643*
GM-F	*0.410*	*0.443*	*0.776*	*1.000*	*0.641*	*0.693*
GF-M	*0.443*	*0.539*	*0.674*	*0.641*	*1.000*	*0.760*
GM-M	*0.390*	*0.490*	*0.643*	*0.693*	*0.760*	*1.000*

(b) USA	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	*1.000*	*0.540*	*0.439*	*0.412*	*0.380*	*0.359*
Mother	*0.540*	*1.000*	*0.389*	*0.384*	*0.421*	*0.424*
GF-F	*0.439*	*0.389*	*1.000*	*0.587*	*0.860*	*0.525*
GM-F	*0.412*	*0.384*	*0.587*	*1.000*	*0.507*	*0.847*
GF-M	*0.380*	*0.421*	*0.860*	*0.507*	*1.000*	*0.582*
GM-M	*0.359*	*0.424*	*0.525*	*0.847*	*0.582*	*1.000*

(c) UK	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	*1.000*	*0.384*	*0.316*	*0.299*	*0.295*	*0.269*
Mother	*0.384*	*1.000*	*0.228*	*0.210*	*0.287*	*0.266*
GF-F	*0.316*	*0.228*	*1.000*	*0.837*	*0.271*	*0.264*
GM-F	*0.299*	*0.210*	*0.837*	*1.000*	*0.269*	*0.253*
GF-M	*0.295*	*0.287*	*0.271*	*0.269*	*1.000*	*0.815*
GM-M	*0.269*	*0.266*	*0.264*	*0.253*	*0.815*	*1.000*

Note: Assortative mating is an important characteristic to account for studying the intergenerational persistence of socio-economic status. Higher spouse correlations in endowments cause higher heritability coefficients and large values of λ depend on high and constant rates of assortative mating. Here, we report spouse correlations in observable outcomes.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

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English Summary (Abstracts)

Chapter 2: Children's Opportunities in Germany - An Application Using Multidimensional Measures

Single parents and unmarried couples are increasingly replacing the traditional nuclear family. This paper investigates if the greater variety in living arrangements contributes to increased resource disparities among children in Germany. Children in single parent families are disadvantaged in at least three dimensions decisive for their later achievements: material standard of living, parental education, and parental childcare time. We compute multidimensional inequality and poverty indices using SOEP data from 1991 to 2012. We distinguish between parental and publicly provided childcare, which is an increasingly important in-kind benefit in Germany. We find that both multidimensional inequality and poverty declined as expanded public childcare strongly reduces resource disparities among children.

Chapter 3: The Distribution of Economic Resources to Children in Germany

This paper investigates the redistributive impact of private and public childcare provision and education on children's resources in Germany between 2009 and 2013. It takes account of the multidimensionality of children's needs and access to economic resources by applying an extended income approach. Combining survey data from the Socio-Economic Panel (SOEP) with administrative data from the German Federal Statistical Office, extended disposable income inequality is found to be significantly lower than disposable cash income inequality at the five percent level across all years. However, the extension does not significantly change distributional trends. At the same time, publicly provided childcare and schooling notably decrease inequality among children such that it cushions cash income inequality. One major reason for this effect is that public in-kind benefits profit children living with single parents, which are deprived in terms of cash incomes, most. This gives additional evidence on the importance of publicly provided childcare and schooling as a policy instrument to equalize economic resources and opportunities in children's lives.

Chapter 4: Dynastic Inequality Compared: Multigenerational Mobility in the US, the UK, and Germany

Using harmonized household survey data, we analyse long run social mobility in the US, the UK, and Germany and test recent theories of multigenerational persistence of socio-economic status. Our results show that the long run persistence of socio-economic status and the validity of a first-order Markov chain in the intergenerational transmission of human capital might be country-specific. Furthermore, we find that the direct and independent effect of grandparents' social status on grandchildren's status tends to vary by gender and institutional context.

German Summary

Die vorliegende Dissertation ist ein Beitrag zur empirischen Ungleichheits- und Armutsforschung. Sie beinhaltet sowohl statische als auch dynamische Analysen zum Ausmaß der Ungleichheit in Deutschland und anderen entwickelten Volkswirtschaften. Ein besonderer Schwerpunkt wird dabei auf die Verteilung von Ressourcen gelegt, die Kindern in der frühen Phase ihres Lebens zur Verfügung stehen und die für die Entwicklung ihrer kognitiven und nicht-kognitiven Fähigkeiten sowie ihren späteren Lebenschancen von großer Bedeutung sind. Dies umfasst sowohl das elterliche Geldeinkommen, aber auch andere nicht monetäre Größen wie elterliche Zeitinvestitionen oder das Bildungsniveau des Elternhauses, wobei letzteres eng mit der Qualität der elterlichen Erziehung verknüpft ist. Darüber hinaus wird die Rolle öffentlicher Kinderbetreuung und Bildung genauer betrachtet, die als Substitut oder Komplement zur elterlichen Zeit fungieren kann.

Die ersten beiden Studien schließen sich damit der Kritik an, dass das Wohlbefinden von Kindern nur unzureichend durch die verfügbaren Geldeinkommen der Eltern abgebildet wird und es einer breiteren Betrachtung ökonomischer Ressourcen bedarf, welche die Entwicklungsmöglichkeiten von Kindern maßgeblich mitbestimmen. Es braucht umfassendere multidimensionale oder monetäre Maße zur Quantifizierung der tatsächlichen Ungleichheit in den verfügbaren Ressourcen von Kindern in Deutschland. Diese werden in den ersten beiden Arbeiten mithilfe unterschiedlicher Aggregationsverfahren entwickelt und angewendet. Darüber hinaus befasst sich die dritte Arbeit mit der Fragestellung, wie mobil die deutsche Gesellschaft im Vergleich zu den USA und Großbritannien ist. Dazu werden die Zusammenhänge in der Weitergabe von Bildungserfolgen über drei Generationen in diesen drei Ländern untersucht und einander gegenübergestellt. Die vorliegende Dissertation besteht dementsprechend aus drei Arbeiten, die inhaltlich eng miteinander verknüpft sind, aber in Form von eigenständigen Artikeln erschienen sind. Im Folgenden werden die wesentlichen Bestandteile und Erkenntnisse aller drei Beiträge kurz vorgestellt.

Der erste Beitrag der Dissertation untersucht für Deutschland, in welchem Maße die Veränderung von Familienstrukturen mit einer Veränderung der Ressourcenungleichheit unter Kindern in Deutschland seit der Wiedervereinigung einhergegangen ist. Dabei stehen vor allem Kinder von Alleinerziehenden im Vordergrund, die oftmals in dreierlei Hinsicht benachteiligt sind: beim materiellen Lebensstandard, beim Bildungsniveau des Elternhauses und bei den elterlichen Betreuungszeiten. Zur Beschreibung der Veränderungen der Ressourcenungleichheit werden multidimensionale Ungleichheits- und Armutsindizes aus der Familie der allgemeinen Entropiemaße verwendet und auf die Daten des Sozio-ökonomischen Panels (SOEP) angewendet. Der Untersuchungszeitraum umfasst dabei die Einkommensjahre von 1991 bis 2012. Des Weiteren wird bei den Betreuungszeiten von Kindern zwischen der elterlichen und der öffentlichen bzw. öffentlich geförderten Kinderbetreuung unterschieden, die im Verlauf der letzten zwei Jahrzehnte in Deutschland immer wichtiger geworden ist, insbesondere in Westdeutschland. Die Untersuchungen zeigen, dass unter bestimmten Annahmen sowohl die multidimensionale Ungleichheit als auch das Armutsrisiko unter Kindern zurückgegangen ist, da die Ausweitung der öffentlichen Kinderbetreuung die Ressourcenunterschiede bei den Kindern stark reduzieren konnte.

Der zweite Beitrag untersucht die umverteilende Wirkung von privater und öffentlicher Kinderbetreuung und Bildung auf die verfügbaren Ressourcen von Kindern in Deutschland. Auch hier wird die Multidimensionalität der Bedürfnisse von Kindern und deren Zugang zu wesentlichen, ihre Fähigkeiten bestimmenden ökonomischen Ressourcen berücksichtigt. In Abgrenzung zum ersten Beitrag wird jedoch ein erweitertes Einkommenskonzept verwendet, bei dem der konkrete Geldwert der privaten und öffentlichen Kinderbetreuung ermittelt und zum verfügbaren Geldeinkommen eines Kindes hinzuaddiert wird. Der Geldwert elterlicher und öffentlicher Betreuungszeiten wird auf Grundlage vorhandener öffentlicher Ausgabedaten sowie mithilfe von multivariaten Schätzmethoden bestimmt und ist durch die Kombination von Erhebungsdaten aus dem SOEP mit administrativen Daten des Statistischen Bundesamtes möglich. Diese Informationen stehen für die Einkommensjahre 2009 bis 2013 zur Verfügung und geben damit den Analysezeitraum vor. Die Arbeit zeigt, dass die Ungleichheit in den verfügbaren erweiterten Einkommen statistisch signifikant niedriger ausfällt als die Ungleichheit in den verfügbaren Geldeinkommen. Die Erweiterung des Einkommenskonzeptes ändert jedoch die Verteilungstrends nicht wesentlich. Gleichzeitig kann die besondere Rolle öffentlicher bzw. öffentlich geförderter Kinderbetreuung und Bildung hervorgehoben werden, da diese den Großteil der Verringerung der gemessenen Ungleichheit erklärt. Ein wichtiger Grund für diesen Effekt ist, dass die öffentliche Kinderbetreuung relativ stärker von Kindern von Alleinerziehenden in Anspruch genommen wird, die gleichzeitig über durchschnittlich geringere Geldeinkommen verfügen. Dies zeigt ein weiteres Mal auf, welch bedeutende Rolle der öffentlich bereitgestellten Kinderbetreuung und Bildung als ein politisches Instrument zur Angleichung ökonomischer Lebensverhältnisse und zur Herstellung von Chancengleichheit in Deutschland zukommt. Das darf jedoch nicht darüber hinwegtäuschen, dass die Unterschiede in den verfügbaren Geldeinkommen weiterhin bestehen und Haushalte durch andere Abgaben oder indirekte Steuern, bspw. der Mehrwertsteuer, die in dieser Analyse nicht erfasst wurden, unterschiedlich betroffen sind und der positiven Wirkung öffentlicher Sachleistungen, wie der hier diskutieren Kinderbetreuung und Bildung, entgegenwirken könnten. Weitere Untersuchungen würden sich an dieser Stelle für die Zukunft anbieten.

Der dritte Beitrag analysiert mithilfe harmonisierter Paneldaten die langfristige soziale Mobilität in den USA, dem Vereinigten Königreich und Deutschland. Gleichzeitig werden aktuelle Theorien zur multigenerationalen Persistenz getestet. Die Ergebnisse zeigen, dass das von Clark und Cummins postulierte Gesetz einer universell konstanten Rate der sozialen Mobilität nicht uneingeschränkt zutreffen kann. So ist die langfristige Persistenz des sozio-ökonomischen Status' in der intergenerationalen Weitergabe von Humankapital länderspezifisch, sodass institutionelle als auch kulturelle Unterschiede zwischen den Ländern einen Einfluss auf die langfristige Transmission des sozialen Status' haben. Darüber hinaus kann gezeigt werden, dass die direkte und unabhängige Wirkung der sozialen Stellung der Großeltern auf die Stellung der Enkel nach Geschlecht und institutionellem Kontext variiert. Aus dem Ländervergleich ergibt sich auch, dass die Bildungsmobilität in Deutschland geringer ist als in den USA und Großbritannien. Damit können frühere Befunde verifiziert werden, die dem deutschen Bildungssystem eine verhältnismäßig geringe Durchlässigkeit attestieren. Eine politische Empfehlung könnte folglich lauten, den Umfang, aber insbesondere auch die Qualität öffentlicher Kinderbetreuung und Bildung weiter zu erhöhen, gezielte Förderangebote für Kinder aus sozio-ökonomisch schwachen Elternhäusern kostenlos anzubieten, um somit den Einfluss der sozialen Herkunft eines Schülers in Bezug auf die schulische Teilhabe und den schulischen Erfolg zu reduzieren. In der Konsequenz würden sich dadurch mit großer Wahrscheinlichkeit sowohl die Arbeitsmarktchancen vieler Kinder langfristig verbessern lassen, als auch die Chancengleichheit in Deutschland insgesamt steigen.