WORKING PAPER SERIES

Working Paper No. 138

Transmission Channels of Intergenerational Income Mobility: Empirical Evidence from Germany and the United States

Mustafa Coban
Sarah Sauerhammer

December 2017

Julius-Maximilians-UNIVERSITÄT WÜRZBURG

Chair of Economic Order and Social Policy

Transmission Channels of Intergenerational Income Mobility: Empirical Evidence from Germany and the Unites States

Mustafa Coban *Sarah Sauerhammer*

Working Paper No. 138

December 2017

University of Würzburg

Department of Economics

Chair of Economic Order and Social Policy

Sanderring 2

D-97070 Würzburg

E-Mail:

mustafa.coban@uni-wuerzburg.de

sarah.sauerhammer@uni-wuerzburg.de

Transmission Channels of Intergenerational Income Mobility: Empirical Evidence from Germany and the United States

Mustafa Coban[*] *Sarah Sauerhammer*[†]

[*,†] *University of Würzburg, Department of Economics, Sanderring 2, D-97070 Würzburg, Germany*

Abstract

Relying on harmonized individual data for Germany and the United States, we perform a country comparison regarding the underlying mechanisms of the intergenerational income mobility. By applying descriptive and structural decomposition methods, we estimate the relative importance of the transmission of financial resources and endowments within a family. Although the results from both approaches are similar, the structural decompositions rather allow a causal interpretation due to instrumenting the transmission channels. Whereas a family's financial resources and endowments almost equally contribute to the intergenerational income mobility in Germany, endowments account for solely 30 percent in the United States. Nonlinearities in the transmission channels along the income distribution in the United States indicate that the endowment effect slightly decreases in relative importance across income percentiles. In Germany, there are no significant nonlinearities at all.

Keywords:	intergenerational income elasticity, intergenerational mobility, financial resources, human capital
JEL-No.:	I24, J24, J62

[*] mustafa.coban@uni-wuerzburg.de (Corresponding author)

[†] sarah.sauerhammer@uni-wuerzburg.de

1 Introduction

The rise in income inequality in many industrialized countries over the last three decades has brought the distribution of income back onto the agenda of policy makers and economic researchers. In the United States and Germany, the inequality of market incomes increased from around 44 to 51 Gini points between 1980 and 2010 (Solt, 2016). Long-lasting or increasing income disparities raise the question of whether this persistence is passed on to the next generation. Based on the theoretical framework of Becker and Tomes (1979, 1986), a vast literature emerged in order to measure the intergenerational transmission of income and to evaluate social mobility and equality of opportunity. Motivated by Solon (1992, 2004), the intergenerational income elasticity (IGE) has been the most commonly used measure as a rationalization of the theoretical base. It quantifies the intergenerational transmission of parents' income (dis)advantages to their children. For example, an intergenerational income elasticity of 0.3 implies that an offspring's future income will be 3 percent above the filial generation's average income if his or her parents' income is 10 percent above the parental generation's average income. Since availability of multi-generational data has improved in the last decades, there are more accurate estimates of the intergenerational income elasticity for most industrialized countries, such as the United States (Solon, 1992; Zimmerman, 1992; Mazumder, 2005; Gouskova et al., 2010), France (Lefranc and Trannoy, 2005), Italy (Mocetti, 2007; Piraino, 2007), Denmark (Hussain et al., 2009), Finland (Pekkarinen et al., 2009), Norway (Nilsen et al., 2008), Sweden (Björklund and Jäntti, 1997; Björklund et al., 2012), Germany (Vogel, 2006; Eisenhauer and Pfeiffer, 2008; Schnitzlein, 2009; Coban and Sauerhammer, 2016), the United Kingdom (Blanden et al., 2004), Australia (Leigh, 2007), and Canada (Corak and Heisz, 1999), and for some developing countries (Harper et al., 2003; Nunez and Miranda, 2011). Additionally, some cross-country comparisons have been undertaken (Solon, 1999; Corak, 2006; Björklund and Jäntti, 2009; Black and Devereux, 2011; Corak et al., 2014; Bratberg et al., 2017) and the change in intergenerational income mobility over time has been investigated for certain countries (Lee and Solon, 2009; Chetty et al., 2014).

Although there has been considerable progress in economic models of intergenerational income transmission, leading to new insights into the underlying mechanisms (Solon, 2004; Hassler et al., 2007; Raaum et al., 2008), there has been limited attempts to identify the relative importance of the mechanisms underlying the intergenerational income transmission. After all, it is critical for a policy recommendation to know if the intergenerational income elasticity can be interpreted as a causal impact of a family's financial resources, some sort of human capital transmission or something else. Thus, once the size of the intergenerational income mobility is estimated, the follow-up question naturally arises: *why* do children born to wealthy families earn more than less fortunate children? By using adoption data to create a natural experiment, several studies investigated the separate impact of nature (genetic transmission) and nurture (environmental transmission) on the intergenerational transmission of income (see Björklund et al., 2006; Sacerdote, 2007, among other). Although these studies employ structural decompositions of the intergenerational transmission of income by utilizing natural experiments, they neglect the impact of a family's financial resources in shaping their children's level of human capital and future income. Therefore, the mechanisms underlying the intergenerational income mobility can be condensed to two transmission channels when nature and nurture are taken together. On the one hand, families directly pass their level of human capital through nature, e.g. the genetic transmission of certain traits, and nurture, e.g. the transmission of environmental properties, such as aspirations, skills, and at-home nonfinancial investments, to their children. When more educated families experience higher incomes within their cohort, the intergenerational transmission of incomes might be explained in part by the transmission of a family's endowments. On the other hand, more affluent families might have more and better opportunities to invest in the education of their offspring by enrolling their children in private schools and universities as well as financing additional private tuition, which might not be affordable for children from poor families. Once these divergent investments are reflected in a higher human capital and a higher adult income of the children, the intergenerational transmission of incomes might be explained in part by the transmission of a family's financial investments.

Most empirical studies employ descriptive decomposition methods in order to calculate the contribution of parents' human capital to the intergenerational income mobility. Blanden et al. (2007) find that parents' education accounts for 46 percent of the intergenerational transmission of income in the United Kingdom. Utilizing the PSID for the Unites States, one third of the intergenerational income elasticity is attributable to the transmission of education due to Eide and Showalter (1999). In Denmark, parents' health status contributes 28 percent to the relationship between the fathers' and sons income (Eriksson et al., 2005). Hirvonen (2010) depicts that the transmission of education and IQ is the major contributor to social mobility in the upper middle class of Sweden. Differing from path analysis as a decomposition method, Österbacka (2001) applies a variance decomposition method and concludes that the largest share of the intergenerational income correlation is transmitted through education and occupation in Finland. In contrast, Cardak et al. (2013) use stochastic properties of intergenerational income elasticity to decompose the estimate for the United States into the investment and endowment effect without the need for additional data. They find an investment effect of approximately one third and an endowment effect of approximately two thirds.

Since descriptive decomposition methods are common in the social mobility literature, we apply a path analysis method proposed by Blanden (2013) and compare obtained results with a more structural and causal approach developed by Lefgren et al. (2012). The former divides the intergenerational income mobility into three components: (i) the extent of intergenerational income persistence if intergenerational educational persistence were the only determinant, (ii) the impact of inequalities in parental income on filial income within education groups, and (iii) the cross-effect between parental education and children's residual earnings. The latter approach applies a structural decomposition to establish an upper and lower bound for the investment and endowment effect using suitable instruments for the transmission of a father's human capital (endowment effect) and financial resources (investment effect).

Therefore, our paper builds on the existing literature and seeks to determine the extent to which the investment and endowment effect contribute to the estimates of intergenerational income mobility in Germany and the United States. Relying on harmonized individual data allows us to perform a country comparison regarding the relative importance of the transmission channels. To the best of our knowledge, this is the first study investigating and determining the mechanisms underlying the social mobility in the United States and Germany by employing a structural decomposition method. The empirical results suggest that the investment and endowment effect almost equally contribute to the estimated intergenerational income mobility in Germany, while the investment effect is more pronounced in the United States. These findings are true for both the descriptive and the structural decomposition method. Furthermore, we make use of unconditional quantile regressions in order to reveal nonlinearities in the transmission mechanisms along the income distribution. There is a mild but steady downward trend of the endowment effect in the United States along the income distribution, whereas no clear trend can be observed in Germany. However, the endowment effect is smaller in the United States than in Germany across all income percentiles. The opposite is true for the investment effect.

The rest of the paper is organized as follow: Section 2 presents the conceptual framework of the descriptive and structural decompositions, deriving the link between the fathers' and sons' human capital and income. Section 3 describes the data and discusses possible measurement issues. The results of the estimations are presented in Section 4. Finally, Section 5 concludes.

2 Conceptual Framework

Our decomposition methods are based on the theoretical framework of Becker and Tomes (1979, 1986), where each family maximizes a utility function depending on the consumption of the parents and the future income of their children. Children's income is raised when they receive investments in human capital from their parents. In addition, children's income is influenced by a variety of inherited endowments including race, ability, and other characteristics, family reputation and connections, and knowledge, skills, and goals provided by their family environment. However, endowments and investments in human capital are not independent, as better-endowed children have a higher return to human capital than worse-endowed children and therefore the incentive to invest in their human capital is higher. The equilibrium income of children is thus determined by the income and endowment of their parents as well as by their fortuitous endowment and their luck on the labor market.

2.1 Intergenerational income and educational persistence

In the empirical literature, particular attention has been given to the intergenerational persistence of income and education. Intergenerational income persistence measures the influence of parents' income on the adult income of their children. In contrast, intergenerational educational persistence analyzes, how strongly the educational success of children depends on the educational degree of their parents. These two measures are commonly considered separately from one another, but are indeed closely related. The standard approach in order to measure intergenerational income persistence is based on the estimation of a log-linear equation of the form

$$\log(y_i^s) = \alpha_1 + \beta \log(y_i^f) + u_{1i}^s, \tag{1}$$

where y_i^s is the lifetime income of the son and y_i^f is the lifetime income of the father, respectively.[1] The intercept α_1 gives the average lifetime income in the son's generation, and the slope β is the intergenerational income elasticity. It states that an increase in father's lifetime income by 1 percent increases the expected lifetime income of his son by β percent. If $\beta = 0$, son's lifetime income is independent of his father's lifetime income. In this case, there is complete intergenerational mobility in a society. In contrast, the higher the value of β, the stronger the link between the lifetime income of a father and his son is, and consequently, the lower the intergenerational income mobility. Deviations from the expected income of the son due to factors orthogonal to the income of the father are summarized in the idiosyncratic error term u_{1i}^s.

The estimation of the intergenerational educational persistence provides the advantage that data on education are usually more easily available and constant over an adult's lifetime. The intergenerational educational persistence is measured equivalently to the intergenerational income persistence by estimating a linear equation of the form

$$Ed_i^s = \alpha_2 + \gamma Ed_i^f + u_{2i}^s, \tag{2}$$

where Ed_i^s and Ed_i^f correspond to son's and father's education level, respectively. The slope γ is the intergenerational educational persistence and can be interpreted in such a way that an increase in a father's education by 1 unit raises the expected education of the son by γ units. Again, the residual term u_{2i}^s captures all deviations from the expected education level of the son orthogonal to his father's education.

2.2 Descriptive decomposition

Linear threefold decomposition

It is a widely accepted stylized fact that the education level is one of the most important determinants of a person's lifetime income. The relationship between education and income

[1] Since the analyses are limited to father-son pairs, the explanations refer to the effect of father's lifetime income on son's lifetime income. In principle, the subsequent relationships apply to any parent-child pair.

can be estimated for the fathers by

$$\log(y_i^f) = \theta^f + \delta^f Ed_i^f + \nu_i^f \tag{3}$$

and for the sons by

$$\log(y_i^s) = \theta^s + \delta^s Ed_i^s + \nu_i^s, \tag{4}$$

where δ^f and δ^s correspond to the rate of return to education for the generation of the fathers and the sons, respectively. In contrast, ν_i^f and ν_i^s capture income variations that are due to a father's or son's fortune in the labor market. This includes, for example, benefits from a generous union contract, unusually good or bad job matches, or working in a firm that goes out of business (Lefgren et al., 2012). Blanden (2013) shows that in order to decompose the intergenerational income elasticity β, the simple Mincer equations (3) and (4) can be combined with the mobility measure estimations (1) and (2) to obtain

$$\beta = \left(\frac{\delta^s}{\delta^f}\gamma\right) R^2_{Edf} + \frac{\mathrm{Cov}(\log(y^s), \nu^f)}{\mathrm{Var}(\nu^f)}(1 - R^2_{Edf}) + \frac{1}{\delta^f}\frac{\mathrm{Cov}(\nu^s, Ed^f)}{\mathrm{Var}(Ed^f)} R^2_{Edf}, \tag{5}$$

where R^2_{Edf} is given by equation (3), $\mathrm{Cov}(\log(y^s), \nu^f)/\mathrm{Var}(\nu^f)$ is the estimated coefficient from a regression of the son's lifetime income $\log(y_i^s)$ on his father's income due to luck in the labor market ν_i^f, and $\mathrm{Cov}(\nu^s, Ed^f)/\mathrm{Var}(Ed^f)$ is the estimated coefficient from a regression of the luck component of son's income ν_i^s on the father's education Ed_i^f. The first term of equation (5) can thus be interpreted as the magnitude of the intergenerational income elasticity if educational persistence were the only transmission channel and therefore captures the endowment effect. Holding the intergenerational transmission of education fixed, the endowment effect increases if the relation between the rates of return to education in both generations rises or if the relationship between education and income in the fathers' generation is more pronounced. The second term of equation (5) measures the impact of the association between son's lifetime income and the within-education group inequalities in paternal incomes and can thus be interpreted as the investment effect. The investment effect increases if the within-education group income inequality increases, which might be due to divergent rates of return to education between individual occupations with the same amount of human capital or a strong regional variation in the quality of schools and universities (Blanden, 2013). Finally, the third term of equation (5) gives the cross-effect between paternal education and the residual income of the son.

Nonlinear threefold decomposition

The threefold decomposition of Blanden (2013) implicitly assumes that the relationship between fathers' and sons' lifetime income is linear, i.e., that the intergenerational income elasticity is constant along the entire income distribution. However, Becker and Tomes (1986) already pointed out that the intergenerational income elasticity can take a concave run when poor families experience credit market constraints that do not apply for rich families. Consequently, rich families will invest in the human capital of their children until the marginal costs equal the marginal rate of return, while credit-constrained families might be forced to invest less than the optimal amount in their children's education. Thus, a small increase in a poor father's income will have a stronger impact on his son's income than a small increase in a rich father's income would have. In this case, the intergenerational income persistence will be more pronounced for poor families than for rich families, resulting in a concave run of intergenerational income elasticity. However, neither does a concave run of intergenerational income elasticity need to follow from credit market constraints nor is market failure implied by concavity. If the income of a father correlates with the unobservable talent of his son, poor fathers—regardless of whether credit market constraints exist—will reduce investments in the human capital of their sons as a result of a lower expected rate of return. Likewise, a concave run is not a clear indication for credit market constraints. This relationship might be triggered by institutional, social, or unobservable circumstances which influence poor and rich families in different ways (Grawe, 2004). On the other hand, a convex run of the intergenerational income elasticity can be observed if educational policy is designed in such a way as to ensure a basic level of human capital for all sons, regardless of their father's income. Beyond this socially guaranteed level, all families experience credit market constraints, such that the total amount of human capital investment in the son is dependent on paternal income (Bratsberg et al., 2007). Assuming that the unobservable talent of children is not independent from the socio-economic status of their family, the intergenerational income persistence among poor families consequently will be lower than among rich families, resulting in a convex run of the intergenerational income elasticity (Han and Mulligan, 2001; Grawe and Mulligan, 2002).

Since the nonlinear threefold decomposition is to be undergone along the income distribution of the sons, equation (1) and (4) are estimated applying unconditional quantile or RIF regressions at different income quantiles (Firpo et al., 2009).[2] For this purpose, the values of the dependent variable $\log(y_i^s)$ are transformed into their corresponding RIF values using the estimation formula

$$\widehat{\mathrm{RIF}}(y_i, \hat{y}_q, \hat{\mathrm{F}}) = \hat{y}_q + \frac{q - 1[y_i \leq \hat{y}_q]}{\hat{\mathrm{f}}(\hat{y}_q)}, \tag{6}$$

where $\hat{\mathrm{F}}$ is the estimated cumulative income distribution of the sons, q is the unconditional income quantile, $\hat{\mathrm{f}}(\hat{y}_q)$ gives the kernel density estimate at the income value $\hat{y}_q$ and $1[y_i \leq \hat{y}_q]$ is an indicator function, which takes on a value of one if a son has an income less than or equal to $\hat{y}_q$ at the particular quantile and a value of zero otherwise. Equations (1) and (4) can then be estimated via OLS utilizing the transformed RIF values.

2.3 Structural decomposition

The descriptive decomposition methods are likely to overestimate the impact of education in the intergenerational transmission process if the residuals of the respective equations are

[2]The estimation methods of the remaining equations remain unchanged.

mutually correlated via unobservable talents or abilities (Hirvonen, 2010). To overcome this shortcoming, a more structural approach is needed that decomposes the intergenerational income elasticity into the causal effect of the fathers' financial resources, the mechanistic transmission of human capital, and the impact of fathers' human capital on their permanent income. In contrast to Blanden (2013), Lefgren et al. (2012) directly model fathers' investment in the human capital of their sons by extending and reformulating equation (2) to

$$HC_i^s = \psi + \pi_1 \log(y_i^f) + \pi_2 HC_i^f + \varepsilon_i^s, \tag{7}$$

where $HC_i^s = \delta^s Ed_i^s$ and $HC_i^f = \delta^f Ed_i^f$. Thus, son's and father's human capital are measured in Euros or US dollars, respectively. According to equation (7), a father may influence the human capital of his son via financial investments as well as through the direct transfer of human capital. Whereas the parameter π_1 represents the share of father's income that is invested in his son's human capital, multiplied by the efficacy of this investment, the parameter π_2 is the share of father's human capital that is directly passed on to his son independent of the financial investments. Substituting equation (7) into equation (4), the lifetime income of the son as a function of father's lifetime income and human capital is given by

$$\log(y_i^s) = \pi_0 + \pi_1 \log(y_i^f) + \pi_2 HC_i^f + \eta_i^s, \tag{8}$$

where $\pi_0 = \psi + \theta^s$ and $\eta_i^s = \varepsilon_i^s + \nu_i^s$. Finally, substituting equation (3) into equation (8) yields

$$\log(y_i^s) = \pi_0 + \pi_1 \theta^f + (\pi_1 + \pi_2) HC_i^f + \pi_1 \nu_i^f + \eta_i^s. \tag{9}$$

Equation (9) precisely depicts the intuition that an increase in the lifetime income of the father can influence the lifetime income of his son via two different transmission channels. If the father's income increase can be ascribed to the father's higher human capital, this raises the financial investments in the human capital and, in turn, the adult income of his son (π_1). Meanwhile, the higher human capital of the father directly influences the human capital of the son, which in turn leads to an increase in his adult income (π_2). In contrast, an increase in father's lifetime income which is solely due to a good fortune in the labor market influences the child only via higher financial investments (π_1).

Given the model of Lefgren et al. (2012), the OLS estimator $\hat{\beta}^{OLS}$ obtained from equation (1) converges in probability to

$$\text{plim}(\hat{\beta}^{OLS}) = \pi_1 + \pi_2 \frac{\text{Var}(HC^f)}{\text{Var}(HC^f) + \text{Var}(\nu^f)}. \tag{10}$$

The estimated intergenerational income elasticity thus depends on three different factors. First, π_1 is the influence of the father's income when his human capital remains constant. Second, π_2 describes the impact of the father's human capital when his income remains unchanged. Last, $\text{Var}(HC^f)/(\text{Var}(HC^f)+\text{Var}(\nu^f))$ gives the share of the variance in the fathers' income that can be explained by the variance in their human capital, which equals $R^2_{Ed^f}$ in equation (5). Thus, the first part of the sum can be interpreted as the investment effect, while the second part represents the endowment effect.

In the following, it will be assumed that there exists an instrument Z_i^f for the income of the father which can be used in an instrument variables (IV) estimation of equation (1). The estimated parameter $\hat{\beta}^{IV}$ then converges in probability to

$$\text{plim}(\hat{\beta}^{IV}) = \pi_1 + \pi_2 \frac{\text{Cov}(HC^f, Z^f)}{\text{Cov}(HC^f, Z^f) + \text{Cov}(\nu^f, Z^f)}. \tag{11}$$

Equivalently to equation (10), π_1 and π_2 are the ceteris paribus influences of the father's income and human capital, respectively, while $\text{Cov}(HC^f, Z^f)/(\text{Cov}(HC^f, Z^f) + \text{Cov}(\nu^f, Z^f))$ represents the share of the covariance between paternal income and the instrument that is attributable to human capital. From equations (10) and (11) it follows that $\hat{\beta}^{OLS} = \hat{\beta}^{IV}$ if and only if $\pi_2 = 0$ or

$$\frac{\text{Var}(HC^f)}{\text{Var}(HC^f) + \text{Var}(\nu^f)} = \frac{\text{Cov}(HC^f)}{\text{Cov}(HC^f, Z^f) + \text{Cov}(\nu^f, Z^f)}. \tag{12}$$

Since equation (12) does not generally hold, a significant difference between the OLS and the IV estimator implies $\pi_2 \neq 0$. If thus a Hausman test for endogeneity is rejected, it may be assumed that in addition to the pure investment effect, the intergenerational transfer of income is also carried out via the direct transfer of human capital. In this case, different instruments Z_i^f should yield different estimates of $\hat{\beta}^{IV}$, depending upon their covariance with the human capital and luck component of the father's lifetime income. This circumstance can be used to determine the magnitude of the investment effect and the endowment effect, respectively. Consider first the cases, where the chosen instrument is correlated solely with the human capital component of father's income and thus $\text{Cov}(HC^f, Z^f)/(\text{Cov}(HC^f, Z^f) + \text{Cov}(\nu^f, Z^f)) = 1$. In this case, $\hat{\beta}^{IV}$ converges in probability to $\pi_1 + \pi_2$. In contrast, if Z_i^f is exclusively correlated with the luck component of father's income and thus $\text{Cov}(HC^f, Z^f)/(\text{Cov}(HC^f, Z^f) + \text{Cov}(\nu^f, Z^f)) = 0$, $\hat{\beta}^{IV}$ converges to π_1. A direct comparison of the two IV estimators in combination with the OLS estimator $\hat{\beta}^{OLS}$ then allows for the identification of the investment and the endowment effect.

Unfortunately, one will generally not be able to find perfect instruments for the father's human capital and luck component. However, on the monotonicity condition that $\text{Cov}(HC^f, Z^f)$ and $\text{Cov}(\nu^f, Z^f)$ have the same sign, each estimate for β^{IV} lies in the range between π_1 and $\pi_1 + \pi_2$. Thus, if one chooses an instrument that is highly correlated with the luck component of father's income, $\hat{\beta}^{IV}$ can be interpreted as an upper bound for π_1. In contrast, an instrument which is primarily correlated with the human capital component of the father's income yields a lower bound for $\pi_1 + \pi_2$. Finally, the difference between the two estimators gives a lower bound for π_2. A complementary bounding procedure is possible using only instruments for the human capital of the father. In this case, the IV estimator $\hat{\beta}^{IV}$ again captures a lower bound for $\pi_1 + \pi_2$. A direct estimation of R^2_{Edf} via equation (3) then yields a lower bound for $\mathrm{Var}(HC^f)/(\mathrm{Var}(HC^f)+\mathrm{Var}(\nu^f))$. These results in conjunction with the OLS estimator $\hat{\beta}^{OLS}$ then again allow to estimate an upper bound of π_1 and a lower bound of π_2.

3 Data and measurement issues

To examine the intergenerational income mobility empirically, long-term panel data of two-generation households, that capture information on children while they are still living with their parents and follow them into adulthood, are required (Corak, 2006). For a valid country comparison, data also need to be highly comparable. We therefore decide to use the Socio-economic Panel (SOEP) for Germany and the Panel Study of Income Dynamics (PSID) for the United States. Both studies collect information on all adult persons of a household and survey them repeatedly in the subsequent years. Further, the SOEP and the PSID are part of the Cross-National Equivalent File (CNEF) project, which offers a harmonized panel data set of the underlying national household surveys (Frick et al., 2007).

3.1 Measurement errors and life-cycle bias

In order to measure lifetime income exactly, all of a respondent's income statements over the entire working life would be required. However, within very long-lasting surveys the number of people who continue to participate is often considerably reduced. This so-called *panel mortality* can correlate with certain characteristics of a person (e.g., income or education), resulting in a relatively homogeneous longitudinal sample (Fitzgerald et al., 1998). This circumstance can lead to substantial distortions of the estimation parameters (*panel attrition bias*) (Solon, 1989, 1992).

For this reason, lifetime incomes are usually approximated by means of annual income observations, which consist of a permanent as well as a fluctuating component (Solon, 1989, 1992; Zimmerman, 1992). If parental income is approximated by income data from only one particular point in time, the classical *errors-in-variables* problem occurs and leads to a systematic downward bias of the estimated elasticity (*attenuation bias*) (Wooldridge, 2010). Therefore, Solon (1992) proposes to form an average of five valid annual income observations for the parental generation in order to reduce the variance of the fluctuating component. This procedure does not completely eliminate the bias, but can significantly reduce it. The estimator for the intergenerational income elasticity can then be interpreted as a lower bound for the true estimation parameter.[3]

Haider and Solon (2006) additionally point out that the approximation of children's lifetime income depends on the chosen stage of life. Since individual income during a person's working life assumes a hump-shaped run, income observations at young ages are lower and thus the lifetime income of a person is underestimated. Meanwhile, income

[3] In the approximation of the children's lifetime income, measurement errors only lead to higher standard errors.

differences between high- and low-skilled workers are smaller at the beginning of their working lives and only increase over time. If incomes are thus observed at the beginning of the working life, this in turn leads to a downward bias of intergenerational income elasticity (*life-cycle bias*). This circumstance is verified by Böhlmark and Lindquist (2006) for Sweden and Brenner (2010) for Germany. Haider and Solon (2006) show that for the sons the age range between mid-30s and mid-40s produces a good approximation of the life-time income. Schnitzlein (2016) uses the income of sons between 35 and 42 years of age.

3.2 Sample definition and variables

The selected samples from the SOEP and the PSID are defined congruently so as to ensure reliable comparability of the results. The analysis is based on data from the years from 1984 to 2013. The individual annual labor income is used, which includes wages and salaries from both paid employment and self-employment as well as bonus payments, income from overtime, and profit sharing (Grabka, 2014; Lillard, 2013). The SOEP sample does not include imputed income data.[4] All income statements are deflated to 2010.[5] In order to be able to compare the results with the existing literature, annual real incomes of less than 1,200 Euro/US dollar are not included in the estimates. To avoid a bias due to wage developments in East Germany after reunification, the analysis for Germany is limited to the persons who lived in West Germany in 1989 (Schnitzlein, 2009). In order to estimate the intergenerational educational persistence, the individual years of education are utilized as an approximation for father's and son's education.[6]

The generation of the parents is restricted to the income observations of the fathers and the generation of the children to the income observations of the sons.[7] Fathers' incomes are drawn from the period from 1984 to 1993, from which at least five valid income observations must be available. The lifetime income of the fathers is approximated by the formation of the average of the annual incomes. Only income observations from the age of 30 to 55 years are considered. Thus, the fathers belong to the birth cohorts of the period from 1933 to 1959. The income observations of the sons are drawn from the years from 2003 to 2013, during which time period at least one valid income observation must be available. Again, the lifetime income of the sons is approximated by the formation of the average of the annual incomes. Only incomes from the age of 35 to 42 years are taken into account. Thus, the sons belong to the birth cohorts of the period from 1961 to 1978, which do not overlap with the cohorts of their fathers.

[4] Missing income statements are estimated in the SOEP with the help of personal and household characteristics as well as past income data (Frick et al., 2012). The CNEF-PSID features no imputed income data.

[5] For the SOEP, the Consumer Price Index and, for the PSID, the Consumer Price Index of All Urban Consumers and All Items based on the recommendation of Grieger et al. (2009) are utilized.

[6] This approach implicitly assumes that the impact of one more year of education on the level of education is linear and constant across nations and generations. Since there is no harmonized measure of education levels in the data, nonlinearities or discontinuities in the transmission of years of education to the level of education cannot be investigated (Chevalier et al., 2009).

[7] This limitation is due to the divergent labor market participation of women in both countries, which can lead to a bias of differences in intergenerational income elasticity.

Finally, a total of 353 and 602 father-son pairs are recorded in the SOEP and PSID, respectively (Table 1). On average, the sons earn more than their fathers in both countries. In

Table 1: Descriptive statistics

		Father		Son	
		Mean	Std.Dev.	Mean	Std.Dev.
SOEP					
Income		40590.37	19576.16	46941.29	27652.96
Age		46.78	4.54	38.17	1.79
Years of Education		10.93	2.55	12.75	2.94
Father-Son Pairs	*353*				
PSID					
Income		64019.61	59658.27	67280.92	69782.23
Age		43.82	5.46	37.87	1.88
Years of Education		13.20	2.41	13.82	2.03
Father-Son Pairs	*602*				

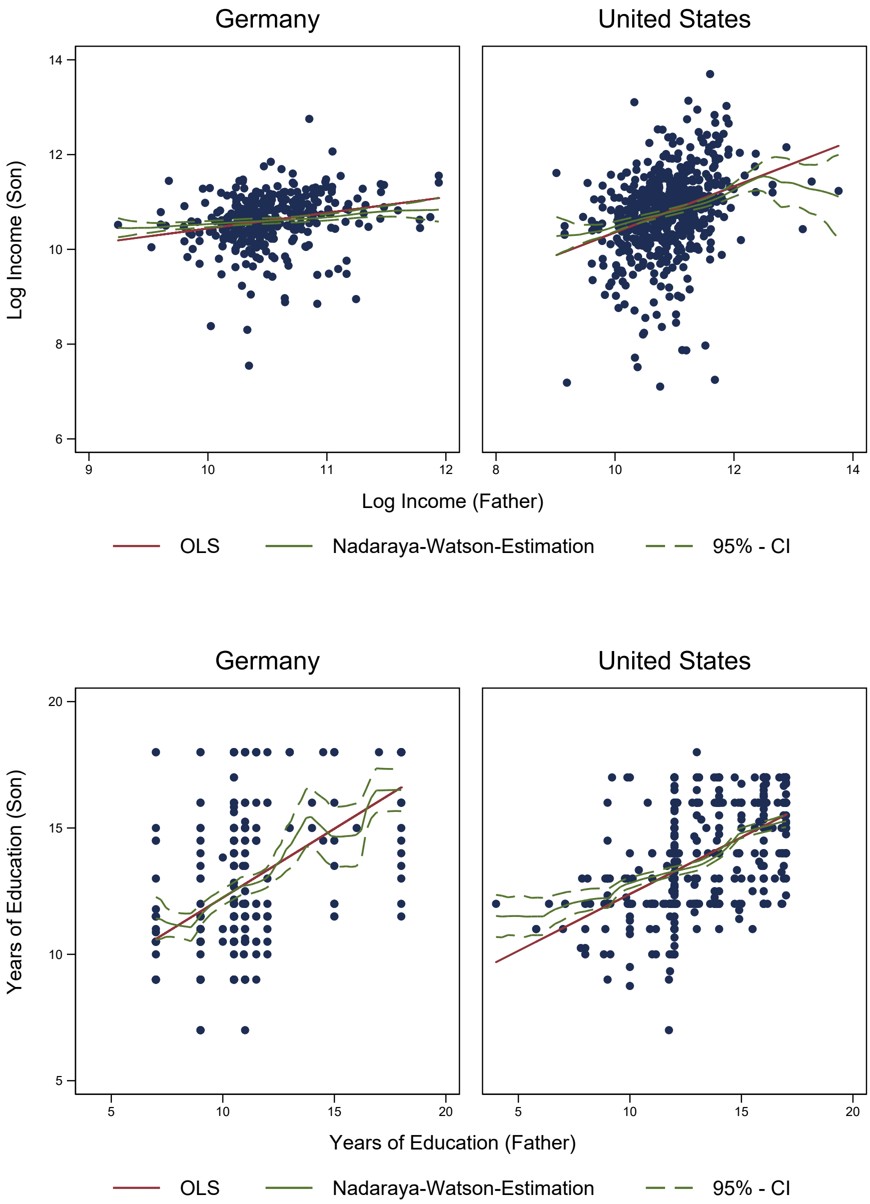
Source: SOEP (1984-2013), PSID (1984-2013).

Germany the income of the sons is 15.6 percent higher, while in the United States it is only 5.1 percent higher than the average income of the fathers. The average age of the fathers is mid-40s in both countries, older than that of the sons, whose average age is late-30s. The younger age of the sons also explains the higher variance in incomes. German fathers on average spent 10.93 years in education, while their sons exhibit 12.75 years of education. In the United States, fathers' and sons' educational attainment is relatively similar with 13.20 and 13.82 education years, respectively. One the one hand, the higher educational years of the fathers in the United States might be due to a higher compulsory school attendance. While in most German federal states 9 years of schooling are mandatory, most US states require children to stay in school until the age of 16 to 18. On the other hand, the aftermath of World War II significantly contributed to the lower educational attendance of the German fathers.

3.3 Descriptive evidence

Taking a closer look at the bivariate relationship between fathers' and sons' incomes shows that there is a considerable positive correlation in both countries (see Figure 1, upper Panel). The slope of the OLS regression is higher for the United States than for Germany. However, income data points in both countries are heavily scattered around the regression line. In order to examine nonlinearities in the bivariate relationship, a Nadaraya-Watson estimation is additionally depicted. Both countries show deviations compared to the OLS estimation.

Figure 1: Intergenerational income and educational correlation



Source: SOEP (1984-2013), PSID (1984-2013).
Notes: The Nadaraya-Watson estimation uses the Epanechnikov kernel with a bandwidth based on Silverman's rule of thumb.

However, the 95 percent confidence intervals include the OLS regression line over nearly the entire distribution of paternal income. From the bivariate evidence, therefore, it cannot be concluded that the intergenerational income elasticity changes significantly along the income distribution of the fathers. Regarding the correlation between the fathers' and sons' years of education, the slope of the OLS estimation is larger for Germany than the United States, implying that son's years of education depends more strongly on the education years of his father in Germany than in the United States (see Figure 1, lower Panel). However, while the 95 percent confidence interval of the Nadaraya-Watson estimation always completely contains the OLS estimator in Germany, the results significantly deviate from linearity in the lower education percentiles in the United States. Thus, sons from low-skilled fathers experience a better education than the OLS estimation would predict. This nonlinearity might also explain the lower OLS slope in the United States.

4 Empirical results

The bivariate estimations already give a first impression of the differences in the intergenerational income and educational persistence between Germany and the United States. However, in order to avoid distortions of the estimators due to divergent age and cohort structures, additional control variables are considered (Schnitzlein, 2016). Including polynomials for the fathers' and sons' age, their birth years and the number of valid observations of the sons, the obtained estimates slightly decreases (see Table 2). Notwithstanding, Germany

Table 2: Intergenerational income elasticity and educational persistence

			Germany			
β	0.331***	0.331***	0.331***			
	(0.083)	(0.081)	(0.081)			
γ				0.545***	0.530***	0.535***
				(0.054)	(0.054)	(0.056)
Cohort Controls	No	Yes	Yes	No	Yes	Yes
Age Controls	No	No	Yes	No	No	Yes
Obs.	353	353	353	353	353	353
R^2	0.053	0.083	0.089	0.224	0.236	0.243

			United States			
β	0.486***	0.455***	0.452***			
	(0.069)	(0.071)	(0.071)			
γ				0.449***	0.441***	0.435***
				(0.029)	(0.030)	(0.030)
Cohort Controls	No	Yes	Yes	No	Yes	Yes
Age Controls	No	No	Yes	No	No	Yes
Obs.	602	602	602	602	602	602
R^2	0.108	0.140	0.143	0.284	0.295	0.297

Source: SOEP (1984-2013), PSID (1984-2013).
Notes: The table contains estimates of intergenerational income elasticity β and educational persistence γ for the PSID and SOEP sample without annual imputed individual labor earnings data. Intergenerational income elasticity estimates are based on a lower annual earnings limit of 1,200 Euro/US dollar. Cohort Controls include: Birth cohort of fathers and sons. Age controls include: the number of years in sons' earnings average and two polynomials of average age for fathers and sons. Standard errors are clustered at family level and are estimated by paired bootstrapped approach with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

still shows a lower intergenerational income persistence with an estimate of 33 percent than the United States with an obtained value of 45 percent. In contrast, families in the United States experience a lower educational persistence than families in Germany. While one more of father's education year provides his son with 0.44 additional years of education in the United States, the education years of German sons increases by 0.54 years. These contrasting results already illustrate that intergenerational educational persistence cannot be perfectly transformed into intergenerational income persistence. Instead, additional determinants might strongly influence intergenerational income persistence, such that countries can even switch positions in the ranking of intergenerational mobility.

4.1 Descriptive decompositions

Since the educational attainment of an individual is most important in predicting his or her current income and income growth, the descriptive threefold decomposition involves the fathers' and sons' rate of return to education and connects them with both intergenerational persistence measures. In the United States, the return to education is for both generations higher than in Germany (see Table 3). While each year of education raises a father's (son's)

Table 3: Linear threefold decomposition

	β	γ	δ^f	δ^s	R^2_{Edf}	$\frac{\mathrm{Cov}\left(\log(y_i^s),\nu_i^f\right)}{\mathrm{Var}\left(\nu_i^f\right)}$	$\frac{\mathrm{Cov}\left(\nu_i^s,Ed_i^f\right)}{\mathrm{Var}\left(Ed_i^f\right)}$
Germany	0.331***	0.545***	0.089***	0.087***	0.320***	0.254**	-0.005
	(0.083)	(0.054)	(0.010)	(0.008)	(0.044)	(0.104)	(0.012)
United States	0.486***	0.449***	0.167***	0.115***	0.229***	0.374***	0.024**
	(0.069)	(0.029)	(0.017)	(0.011)	(0.033)	(0.074)	(0.012)

	β	$\left(\frac{\delta^s}{\delta^f}\gamma\right)R^2_{Edf}$	$\frac{\mathrm{Cov}\left(\log(y_i^s),\nu_i^f\right)}{\mathrm{Var}\left(\nu_i^f\right)}\left(1-R^2_{Edf}\right)$	$\frac{1}{\delta^f}\frac{\mathrm{Cov}\left(\nu_i^s,Ed_i^f\right)}{\mathrm{Var}\left(Ed_i^f\right)}R^2_{Edf}$
Germany	0.331***	0.179***	0.172**	-0.020
	(0.083)	(0.032)	(0.071)	(0.046)
United States	0.486***	0.149***	0.289***	0.048**
	(0.069)	(0.023)	(0.057)	(0.024)
Difference	**-0.155**	**0.03**	**-0.117**	**-0.068**

Source: SOEP (1984-2013), PSID (1984-2013).
Notes: The table contains estimates of intergenerational income elasticity β and educational persistence γ for the PSID and SOEP sample without annual imputed individual labor earnings data. Intergenerational income elasticity estimates are based on a lower annual earnings limit of 1,200 Euro/US dollar. Standard errors are clustered at the family level and are estimated by paired bootstrapped approach with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

income by 8.9 (8.7) percent in Germany, the United States exhibits a value of 16.7 (11.5) percent for the fathers (sons). Thus, the rate of return to education has declined in both countries over time, but the drop is stronger in the United States than in Germany. In contrast, the variation in years of education explains a greater portion of the variation in parental income in Germany than in the United States. Whereas 32 percent of income differences are attributable to the fathers' education in Germany, merely 23 percent of the fathers' income variance can be traced back to education differences in the United States. However, the correlation between the sons' income and the estimated luck component of the fathers' income is stronger in the United States with a value of 0.37 than in Germany with a value of 0.25. Linking these results to the estimates of the intergenerational educational persistence, the linear descriptive decomposition reports a higher endowment effect for Germany than the United States. Whereas almost 54 percent of the intergenerational income persistence is attributable to endowments in Germany, 31 percent are merely due to endowments in the United States. Since the components of the linear descriptive decomposition, measured as a percentage, sum up to 100, the opposite is true regarding the investment effect. The cross-effect of the father's education on the son's residual is rather negligible. Regarding the difference between the intergenerational income elasticity in Germany and the United States of 47 percent, more than three quarters are due to the difference in the investment effect. Thus, if the investment effect were the same in both countries, the gap between Germany and the United States would merely be 11 percent.

Although the decomposition is informative in terms of the average endowment and investment effect in both countries, there might be considerable nonlinearities in the relative importance of the two components along the income distribution (see Table 4). Applying unconditional quantile regressions to the equation (1) and (4) provides insights into possible shifts in the relative importance of the components and into divergent patterns between the United States and Germany. In Germany, intergenerational income persistence increases with a higher income of the sons until the 40th income quantile and remains relatively constant hereafter at about 0.4. In contrast, the United States exhibits a u-shaped run of the intergenerational income elasticity, indicating that parental income is more important at the edges of the sons' income distribution than in the middle.

In conclusion, two suggestions can be drawn from these results. First, the Bratsberg et al. (2007) conjecture of a convex run of intergenerational income elasticity rather applies to Germany than to the United States. This seems reasonable, as the education system in Germany is largely funded by the public sector, while there is a strong privatization in the United States. Thus, there might be a compensating effect at the lower end of the income distribution in Germany. Assuming that low-income sons have also lower education and income is mainly driven by educational attainment, this would imply that there should be lower intergenerational educational persistence at the lower end of educational distribution. Applying unconditional quantile regressions to the intergenerational educational persistence confirms this suggestion for Germany (see Figure 3 in the Appendix). Second, the pattern of the intergenerational income elasticity in the United States at least partially reflects the Becker and Tomes (1986) conjecture, as the estimated values decrease at the upper end of the sons' income distribution. Remarkably, the intergenerational educational persistence exhibits an exactly inverse shape across the ascending percentiles. The highest estimates are obtained in the middle of the educational distribution of the sons, while the values at the two ends are notably smaller.

Table 4: Nonlinear threefold decomposition

Germany

	β	$\left(\frac{\delta^s}{\delta^f}\gamma\right)R^2_{Ed^f}$	$\frac{\mathrm{Cov}\left(\log(y_i^s),\nu_i^f\right)}{\mathrm{Var}\left(\nu_i^f\right)}\left(1-R^2_{Ed^f}\right)$	$\frac{1}{\delta^f}\frac{\mathrm{Cov}\left(\nu_i^s,Ed_i^f\right)}{\mathrm{Var}\left(Ed_i^f\right)}R^2_{Ed^f}$
20th Percentile	0.262**	0.148***	0.089	0.024
	(0.103)	(0.032)	(0.084)	(0.055)
40th Percentile	0.424***	0.184***	0.237***	0.003
	(0.076)	(0.031)	(0.065)	(0.040)
50th Percentile	0.411***	0.188***	0.228***	-0.005
	(0.076)	(0.032)	(0.067)	(0.036)
60th Percentile	0.399***	0.189***	0.191***	0.019
	(0.080)	(0.034)	(0.069)	(0.037)
80th Percentile	0.418***	0.190***	0.191**	0.038
	(0.106)	(0.040)	(0.086)	(0.051)

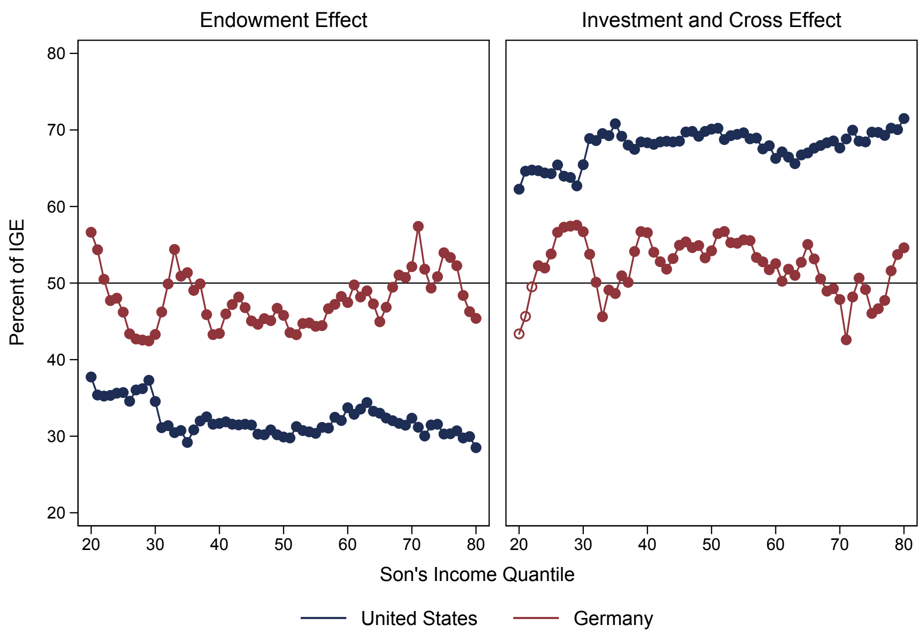
United States

	β	$\left(\frac{\delta^s}{\delta^f}\gamma\right)R^2_{Ed^f}$	$\frac{\mathrm{Cov}\left(\log(y_i^s),\nu_i^f\right)}{\mathrm{Var}\left(\nu_i^f\right)}\left(1-R^2_{Ed^f}\right)$	$\frac{1}{\delta^f}\frac{\mathrm{Cov}\left(\nu_i^s,Ed_i^f\right)}{\mathrm{Var}\left(Ed_i^f\right)}R^2_{Ed^f}$
20th Percentile	0.442***	0.167***	0.236***	0.039
	(0.086)	(0.030)	(0.075)	(0.034)
40th Percentile	0.406***	0.129***	0.224***	0.053**
	(0.054)	(0.019)	(0.049)	(0.025)
50th Percentile	0.407***	0.122***	0.223***	0.063***
	(0.051)	(0.019)	(0.045)	(0.022)
60th Percentile	0.392***	0.132***	0.202***	0.058***
	(0.052)	(0.020)	(0.045)	(0.022)
80th Percentile	0.467***	0.133***	0.256***	0.078**
	(0.079)	(0.023)	(0.062)	(0.030)

Source: SOEP (1984-2013), PSID (1984-2013).
Notes: The table contains estimates of intergenerational income elasticity β and the nonlinear decompositions for the PSID and SOEP sample without annual imputed individual labor earnings data. Intergenerational income elasticity estimates are based on a lower annual earnings limit of 1,200 Euro/US dollar. Standard errors are clustered at family level and estimated by paired bootstrapped approach with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Turning the attention back to the decomposition results reveals that the endowment effect is significantly smaller than the investment effect over the entire income distribution in the United States (see Figure 2). Furthermore, there is a mild but steady downward trend of the endowment effect in the United States. In contrast, there is no clear trend for the endowment and investment effect across percentiles in Germany. Although the endowment effect is slightly larger than the investment effect at the lower end of the income distribution, the relative importance of both components oscillate around 50 percent across percentiles in Germany. Overall, the endowment effect is stronger across all income percentiles in Germany, while the investment effect is continuously higher in the United States. Since

Figure 2: Descriptive decomposition of intergenerational income elasticity along the income distribution



Source: SOEP (1984-2013), PSID (1984-2013).
Notes: The figure contains estimates of the nonlinear decompositions for the PSID and SOEP sample without annual imputed individual labor earnings data. Estimates are based on a lower annual earnings limit of 1,200 Euro/US dollar. Standard errors are clustered at family level and estimated by paired bootstrapped approach with 1,000 replications. Full circles: $p \leq 0.05$, hollow circles: $p > 0.05$.

the parameters of equation (2) and (3) take on the same values across the entire income distribution, deviations in the relative importance of the endowment effect can be traced back to nonlinearities in the intergenerational income elasticity or in the rate of return to sons' educational attainment. The latter is almost constant across the sons' income distribution in Germany and only slightly deviates downwards at the 20th percentile (see Table 8 in the Appendix). In contrast, in the United States the sons' rate of return to education takes on a slightly u-shaped curve over the ascending income deciles.

4.2 Structural decomposition

Although descriptive decomposition methods are a good starting point for first insights into the transmissions channels of intergenerational income persistence, they neglect the transfer of unobserved determinants within the family. In order to overcome this weakness using the structural decomposition method of Lefgren et al. (2012), valid instrument variables for the endowment and the investment transmission channel have to be constructed. In order to accurately instrument the human capital transmission, the fathers' years of education, level of education and educational attainment are employed as instrument variables. Father's years of education measure total years of schooling, vocational training and university education. As this variable exhibits peaks at certain values due to the organization of the national education system, the level of education is defined as an ordered variable with five levels based on the fathers' years of education. (1) less than 9.5 years, (2) 9.5 to 11.4 years, (3) 11.5 to 13.4 years, (4) 13.5 to 17.4 years, and (5) more than 17.4 years. In turn, educational attainment indicates the level of fathers' education with respect to high school education: (1) less than high school education, (2) high school education, (3) more than high school education. These instruments should be highly correlated with fathers' human capital, but can be considered more or less independent of fathers' fortune on the labor market. In order to measure the luck component of fathers' income, two instruments are constructed based on a father's unemployment spells in the observation period and employment status utilizing calendar data from Germany and the United States. These variables are likely to be highly correlated with human capital level, however, unemployment might also occur by chance due to exogenous shocks such as mass layoffs or changing family commitments. Therefore, unemployment spells and employment status have to be adjusted for the influence of human capital. First, a father's unemployment duration is regressed on his level of education, occupation, and industry. The residuals from this regression are used as an instrument for the fathers' misfortune on the labor market. Second, a father's employment status, which indicates whether a father was unemployed at least once after the third valid observation in the data, is regressed on his level of education, occupation, industry and past income in the first three valid observations. Since employment status is binary, generalized residuals from a probit regression are calculated following the approach of Gourieroux et al. (1987) and used as instruments for the fathers' misfortune in the labor market. Since the obtained residuals from both approaches are orthogonal to the fathers' human capital, they capture the variation in unemployment duration and employment status that is due to exogenous factors. Although such instruments might be imperfect, they account for a certain extent the income loss of fathers due to misfortune in the labor market.

Alternative instrument variable estimations of the intergenerational income mobility are employed using human capital instruments and constructed luck instruments for the fathers' permanent income (see Table 5). Instrumenting the paternal permanent income with years of education (Col. 2), level of education (Col. 3), and educational attainment (Col. 4) yields quite similar results. Regardless of the chosen instrument, the obtained estimates are always higher than the corresponding OLS estimates. However, the bootstrapped Durbin-Wu-Hausman test indicates a significant difference between $\hat{\beta}^{OLS}$ and $\hat{\beta}^{IV}$ only for the United States. As the high standard errors in Germany are likely to occur due to the relatively small number of observations, we nevertheless consider it reasonable to reject a one-factor model of intergenerational income transmission. Using the residuals of unemployment and employment status as instrument variables results in lower estimates for the intergenerational income elasticity compared to the corresponding OLS values. However, the IV estimates do not significantly differ from zero in both countries and the results of the Durbin-Wu-Hausman test do not support a rejection of the null hypothesis of equal values for Germany. Nevertheless, Lefgren et al. (2012) show that an imperfect instrument

Table 5: Instruments for the Structural Decomposition of Intergenerational Income Elasticity and Rank Association

	Years of Education	Level of Education	Educational Attainment	Unemployment Spell Residuals	Employment Status Residuals
Germany					
Father's Income	0.495***	0.527***	0.554***	0.188	0.390
	(0.177)	(0.170)	(0.192)	(0.472)	(1.113)
p-value of Bootstrapped	0.280	0.150	0.203	0.280	0.280
Durbin-Wu-Hausmann Test					
First-Stage F-statistic	172.750***	45.646***	64.575***	20.134***	8.141***
United States					
Father's Income	0.863***	0.899***	0.869***	0.341	0.401
	(0.146)	(0.160)	(0.160)	(0.288)	(0.289)
p-value of Bootstrapped	0.006	0.006	0.014	0.006	0.006
Durbin-Wu-Hausmann Test					
First-Stage F-statistic	177.933***	44.121***	60.834***	38.364***	31.282***

Source: SOEP (1984-2013), PSID (1984-2013).
Note: PSID and SOEP Sample without annual imputed individual labor earnings data are applied. Estimations are based on a lower annual earnings limit of 1200 Euro/US-Dollar. Controls include: Birth cohort of fathers and sons and number of valid annual income observations of the sons. Standard errors are clustered at family level and estimated by paired bootstrapped approach with 1000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

for luck, that is a valid measure for an upper bound of π_1, is sufficient. In Germany, the insignificant difference might be due to the small number of observations. Thus, we suggest that the one-factor model of intergenerational income transmission should still be rejected. Furthermore, these instrument variable estimates can be used as plausible values for the sum of the parameters $\pi_1 + \pi_2$ of the structural model, since they isolate the variation in fathers' permanent income due to human capital.

Within the structural approach, the intergenerational income elasticity is a function of paternal financial resources (π_1), fathers' transmission of human capital (π_2), and the explained variance of the fathers permanent income due to their human capital levels (R^2). Once two components of the model are given or estimated, the third factor can be determined. Thus, there are two alternative approaches to calculate the endowment and investment effect. First, a suitable measure of the lower bound of the sum $\pi_1 + \pi_2$ is required, in order to detect the variation in the fathers' permanent income only on account of human capital. Since the results for the various human capital variables are of equal size, we decide to use fathers' years of education as an instrument to establish a lower bound for $\pi_1 + \pi_2$. In order to obtain an upper bound for π_1, we use fathers' unemployment residuals, because the respective IV estimates for both Germany and the United States are smaller than those obtained with fathers' employment status residuals. Once these two components are estimated and combined with the OLS estimates, the fraction of the fathers' income attributable to solely human capital $R^2 = \left(\hat{\beta}^{OLS} - \hat{\beta}^{IV}_{lk}\right) \Big/ \left(\hat{\beta}^{IV}_{hc} - \hat{\beta}^{IV}_{lk}\right)$ can be calculated via equation (7). The structural decomposition suggests an upper bound for the mechanistic effect of a father's financial resources (π_1) of 0.19 in Germany and 0.34 in the United States (see Table 6). In contrast, the estimated lower bound for the mechanistic effect of father's

Table 6: Structural Decomposition I of Intergenerational Income Elasticity and Rank Association

	π_1	$\pi_1 + \pi_2$	π_2	R^2	Endowment Effect	Investment Effect
Germany	0.188	0.495***	0.307	0.466	0.432	0.568
	(0.472)	(0.177)	(0.520)	(30.265)	(1.712)	(1.712)
United States	0.341	0.863***	0.523*	0.278	0.299	0.701
	(0.288)	(0.146)	(0.317)	(4.456)	(0.543)	(0.543)

Source: SOEP (1984-2013), PSID (1984-2013).
Note: PSID and SOEP Sample without annual imputed individual labor earnings data are applied. Estimations are based on a lower annual earnings limit of 1200 Euro/US-Dollar. Controls include: Birth cohort of fathers and sons and number of valid annual income observations of the sons. Standard errors are clustered at family level and estimated by paired bootstrapped approach with 1000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

human capital (π_2) is substantially higher with a value of 0.31 in Germany and a value of 0.52 in the United States. Combining these estimates with the respective OLS estimator, an upper bound for the investment effect in Germany of 57 percent is obtained, while the value of 70 percent for the United States is markedly higher. Consequently, a lower bound for the endowment effect is estimated to be 43 percent in Germany and 30 percent in the United States. However, the investment and endowment effects are insignificant for both countries. Overall, the direct estimation of π_1 suffers from two problems. On the one hand, constructing a valid instrument for the luck component of father's income within the given data set turns out to be somewhat problematic. On the other hand, the relatively small number of observations produces high standard errors of the estimation parameters. Nevertheless, the values are in line with the results of the linear descriptive decomposition.

In order to avoid the direct estimation of π_1, an alternative bounding procedure is employed. While a lower bound for the sum $\pi_1 + \pi_2$ is again estimated using fathers' years of education as an instrument for human capital, a lower bound for R^2 is now directly drawn from a Mincer regression of father's income on his level of education, occupation, and industry. Thus, in combination with the OLS estimate an upper bound for $\pi_1 = \left(\hat{\beta}^{OLS} - \hat{R}^2 \cdot \hat{\beta}^{IV}_{hc}\right) \Big/ \left(1 - \hat{R}^2\right)$ and a lower bound for $\pi_2 = \left(\hat{\beta}^{IV}_{hc} - \hat{\beta}^{OLS}\right) \Big/ \left(1 - \hat{R}^2\right)$ can be calculated using equation (7). This approach produces more precise coefficients for the United States. The same is true for the variation of father's income due to human capital in Germany, however, the results for the investment and endowment effect are insignificant (see Table 7). The second decomposition yields an upper bound for π_1 of 0.20 in Germany and 0.34 in the United States. The estimation of the extended version of equation (3) gives a lower bound for R^2 of 45 percent in Germany and 27 percent in the United States. Consequently, a lower bound for the π_2 is estimated to be 0.30 in Germany and 0.52 in the United States. In both countries, the upper bound for the investment effect slightly increases to 59 percent in Germany and 71 percent in the United States. Hence, the obtained lower bounds for the endowment effect slightly

Table 7: Structural Decomposition II of Intergenerational Income Elasticity and Rank Association

	π_1	$\pi_1 + \pi_2$	π_2	R^2	Endowment Effect	Investment Effect
Germany	0.196	0.495***	0.299	0.452***	0.409	0.591
	(0.159)	(0.177)	(0.285)	(0.050)	(0.497)	(0.497)
United States	0.344***	0.863***	0.519***	0.273***	0.292**	0.708***
	(0.094)	(0.146)	(0.184)	(0.039)	(0.127)	(0.127)

Source: SOEP (1984-2013), PSID (1984-2013).
Note: PSID and SOEP Sample without annual imputed individual labor earnings data are applied. Estimations are based on a lower annual earnings limit of 1200 Euro/US-Dollar. Controls include: Birth cohort of fathers and sons and number of valid annual income observations of the sons. Standard errors are clustered at family level and estimated by paired bootstrapped approach with 1000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

decrease to 41 percent and 29 percent, respectively. Overall, the obtained values are very similar to the first structural approach. In total, the results of the structural decompositions support the findings of the descriptive decompositions with an investment and endowment effect of approximately equal size in Germany and a significantly higher investment effect in the United States. Thus, we conclude that sons in the United States are more reliant on the financial resources of their fathers, whereas the transmission of human capital within the family is more substantial in Germany.

5 Conclusion

There has been vast research on and interest in the intergenerational transmission of economic status in the last years. Estimates of the intergenerational income elasticity for developed and developing countries differ widely sometimes, leading to the question of the origins and mechanisms of intergenerational income transmission. Therefore, determining the relative importance of the transmission channels of the intergenerational income elasticity is crucial for understanding social mobility and designing government policy in areas such as redistribution and education. Utilizing harmonized income data from the United States and Germany, we estimated the relative importance of the transmission of financial resources and endowments within the family. By applying a descriptive decomposition technique, we detect a higher endowment effect in Germany than in the United States, whereas the opposite is true in case of the investment effect. Furthermore, there is a slight positive trend of the endowment effect across the income distribution in the United States, whereas no clear trend can be confirmed in Germany. Since path analysis measure rather correlation than causalities due to the strict exogeneity assumption of the error terms, a more structural approach has been applied to check the results of the twofold decompositions. However, the overall results are similar when both the investment and endowment transmission channel are instrumented with suitable instruments from the fathers' employment history and educational level. In the United States the endowment effect account for about 30 percent of the intergenerational transmission of income, whereas in Germany a family's endowments contribute between 40 and 45 percent to the intergenerational income elasticity. Although these results are in line with the findings of the descriptive decompositions, they have to be interpreted with caution, since solely the estimates for the United States in the structural decomposition II are significant. Nevertheless, the large cross-country difference in the contribution of the transmission channels emphasizes that it is not the level of the intergenerational income elasticity, but rather the relative importance of the underlying mechanisms, that has to be decisive for policymakers. The greater contribution of endowments to the intergenerational income mobility in Germany indicates that an increase in intergenerational income mobility can be more effectively achieved through educational policies that enhance the environmental transmission. In contrast, the large investment effect in the United States calls for more financial subsidies that promote the human capital accumulation of children from low-income families.

References

Becker, G. S. and Tomes, N. (1979). An Equilibrium Theory of the Distribution of Income and Intergenerational Mobility, *Journal of Political Economy* **87**(6), pp.1153–1189.

Becker, G. S. and Tomes, N. (1986). Human Capital and the Rise and Fall of Families, *Journal of Labor Economics* **4**(3), pp.S1–39.

Björklund, A. and Jäntti, M. (1997). Intergenerational Income Mobility in Sweden Compared to the United States, *American Economic Review* **87**(5), pp.1009–18.

Björklund, A. and Jäntti, M. (2009). Intergenerational Income Mobility and the Role of Family Background, *in* W. Salverda, B. Nolan and T. Smeeding (eds), *Oxford Handbook of Economic Inequality*, pp. 91–121, Oxford University Press.

Björklund, A., Lindahl, M. and Plug, E. (2006). The Origins of Intergenerational Associations: Lessons from Swedish Adoption Data, *The Quarterly Journal of Economics* **121**(3), pp.999–1028.

Björklund, A., Roine, J. and Waldenström, D. (2012). Intergenerational top income mobility in Sweden: Capitalist dynasties in the land of equal opportunity?, *Journal of Public Economics* **96**(5), pp.474–484.

Black, S. E. and Devereux, P. J. (2011). Recent Developments in Intergenerational Mobility, *in* O. Ashenfelter and D. Card (eds), *Handbook of Labor Economics*, Vol. 4B, pp. 1487–1541, North-Holland.

Blanden, J. (2013). Cross-Country Rankings In Intergenerational Mobility: A Comparison Of Approaches From Economics And Sociology, *Journal of Economic Surveys* **27**(1), pp.38–73.

Blanden, J., Goodman, A., Gregg, P. and Machin, S. (2004). Changes in Intergenerational Mobility in Britain, *in* M. Corak (ed.), *Generational Income Mobility in North America and Europe*, pp. 122–146, Cambridge University Press.

Blanden, J., Gregg, P. and Macmillan, L. (2007). Accounting for Intergenerational Income Persistence: Noncognitive Skills, Ability and Education, *Economic Journal* **117**(519), pp.C43–C60.

Böhlmark, A. and Lindquist, M. J. (2006). Life-Cycle Variations in the Association between Current and Lifetime Income: Replication and Extension for Sweden, *Journal of Labor Economics* **24**(4), pp.879–900.

Bratberg, E., Davis, J., Mazumder, B., Nybom, M., Schnitzlein, D. D. and Vaage, K. (2017). A Comparison of Intergenerational Mobility Curves in Germany, Norway, Sweden, and the US, *The Scandinavian Journal of Economics* **119**(1), pp.72–101.

Bratsberg, B., Røed, K., Raaum, O., Naylor, R., Jäntti, M., Eriksson, T. and Österbacka, E. (2007). Nonlinearities in Intergenerational Earnings Mobility: Consequences for Cross-Country Comparisons, *Economic Journal* **117**(519), pp.72–92.

Brenner, J. (2010). Life-cycle variations in the association between current and lifetime earnings: Evidence for German natives and guest workers, *Labour Economics* **17**(2), pp.392–406.

Cardak, B. A., Johnston, D. W. and Martin, V. L. (2013). Intergenerational earnings mobility: A new Decomposition of investment and endowment effects, *Labour Economics* **24**(C), pp.39–47.

Chetty, R., Hendren, N., Kline, P. and Saez, E. (2014). Where is the land of Opportunity? The Geography of Intergenerational Mobility in the United States, *The Quarterly Journal of Economics* **129**(4), pp.1553–1623.

Chevalier, A., Denny, K. and McMahon, D. (2009). A Multi-country of Intergenerational Educational Mobility, *in* P. Dolton, R. Asplund and E. Barth (eds), *Education and Inequality across Europe*, pp. 260–281, Edward Elgar.

Coban, M. and Sauerhammer, S. (2016). Intergenerative Einkommensmobilität in Deutschland und den USA, *ORDO - The Ordo Yearbook of Economic and Social Order* **67**(1), pp.101–131.

Corak, M. (2006). Do Poor Children Become Poor Adults? Lessons from a Cross-Country Comparison of Generational Earnings Mobility, *in* J. Creedy and G. Kalb (eds), *Dynamics of Inequality and Poverty*, Vol. 13 of *Research on Economic Inequality*, pp. 143–188, Emerald.

Corak, M. and Heisz, A. (1999). The Intergenerational Earnings and Income Mobility of Canadian Men: Evidence from Longitudinal Income Tax Data, *Journal of Human Resources* **34**(3), pp.504–533.

Corak, M., Lindquist, M. J. and Mazumder, B. (2014). A comparison of upward and downward intergenerational mobility in Canada, Sweden and the United States, *Labour Economics* **30**(C), pp.185–200.

Eide, E. R. and Showalter, M. H. (1999). Factors Affecting the Transmission of Earnings across Generations: A Quantile Regression Approach, *The Journal of Human Resources* **34**(2), pp.253–267.

Eisenhauer, P. and Pfeiffer, F. (2008). Assessing intergenerational earnings persistence among German workers, *Journal for Labour Market Research* **41**(2/3), pp.119–137.

Eriksson, T., Bratsberg, B. and Raaum, O. (2005). Earnings persistence across generations: Transmission through health?, *Memorandum 35/2005*, Oslo University.

Firpo, S., Fortin, N. M. and Lemieux, T. (2009). Unconditional Quantile Regressions, *Econometrica* **77**(3), pp.953–973.

Fitzgerald, J., Gottschalk, P. and Moffitt, R. (1998). An Analysis of Sample Attrition in Panel Data: The Michigan Panel Study of Income Dynamics, *Journal of Human Resources* **33**(2), pp.251–299.

Frick, J. R., Grabka, M. M. and Groh-Samberg, O. (2012). Dealing With Incomplete Household Panel Data in Inequality Research, *Sociological Methods & Research* **41**(1), pp.89–123.

Frick, J. R., Jenkins, S. P., Lillard, D. R., Lipps, O. and Wooden, M. (2007). The Cross-National Equivalent File (CNEF) and its Member Country Household Panel Studies, *Journal of Applied Social Science Studies* **127**(4), pp.627–654.

Gourieroux, C., Monfort, A., Renault, E. and Trognon, A. (1987). Generalised residuals, *Journal of Econometrics* **34**(1), pp.5 – 32.

Gouskova, E., Chiteji, N. and Stafford, F. (2010). Estimating the intergenerational persistence of lifetime earnings with life course matching: Evidence from the PSID, *Labour Economics* **17**(3), pp.592–597.

Grabka, M. M. (2014). SOEP 2013 - Codebook for the PEQUIV File 1984-2013: CNEF Variables with Extended Income Information for the SOEP, *SOEP Survey Papers 204*, German Institute for Economic Research (DIW).

Grawe, N. D. (2004). Reconsidering the Use of Nonlinearities in Intergenerational Earnings Mobility as a Test for Credit Constraints, *Journal of Human Resources* **39**(3), pp.813–827.

Grawe, N. D. and Mulligan, C. B. (2002). Economic Interpretations of Intergenerational Correlations, *Journal of Economic Perspectives* **16**(3), pp.45–58.

Grieger, L. D., Schoeni, R. F. and Danziger, S. H. (2009). Accurately Measuring the Trend in Poverty in the United States Using the Panel Study of Income Dynamics, *Journal of Economics and Social Measurement* **34**(2-3), pp.105–117.

Haider, S. and Solon, G. (2006). Life-Cycle Variation in the Association between Current and Lifetime Earnings, *American Economic Review* **96**(4), pp.1308–1320.

Han, S. and Mulligan, C. B. (2001). Human Capital, Heterogeneity and Estimated Degrees of Intergenerational Mobility, *Economic Journal* **111**(470), pp.207–243.

Harper, C., Marcus, R. and Moore, K. (2003). Enduring Poverty and the Conditions of Childhood: Lifecourse and Intergenerational Poverty Transmissions, *World Development* **31**(3), pp.535 – 554. Chronic Poverty and Development Policy.

Hassler, J., Rodriguez Mora, J. V. and Zeira, J. (2007). Inequality and mobility, *Journal of Economic Growth* **12**(3), pp.235–259.

Hirvonen, L. (2010). Accounting for Intergenerational Earnings Persistence: Can We Distinguish Between Education, Skills, and Health?, *Working Papers 2*, SOFI - Swedish Institute for Social Research.

Hussain, M. A., Munk, M. D. and Bonke, J. (2009). Intergenerational Earnings Mobilities - How Sensitive are they to Income Measures?, *Journal of Income Distribution* **18**(3-4), pp.79–92.

Lee, C.-I. and Solon, G. (2009). Trends in Intergenerational Income Mobility, *The Review of Economics and Statistics* **91**(4), pp.766–772.

Lefgren, L., Lindquist, M. J. and Sims, D. (2012). Rich Dad, Smart Dad: Decomposing the Intergenerational Transmission of Income, *Journal of Political Economy* **120**(2), pp.268 – 303.

Lefranc, A. and Trannoy, A. (2005). Intergenerational earnings mobility in France: Is France more mobile than the US?, *Annals of Economics and Statistics* **78**(2), pp.57–77.

Leigh, A. (2007). Intergenerational Mobility in Australia, *The B.E. Journal of Economic Analysis & Policy* **7**(2), pp.1–28.

Lillard, D. R. (2013). *Codebook for the Cross-National Equivalent File 1970-2013. BHPS - HILDA - KLIPS - PSID - RLMS - HSE - SHP - SLID - SOEP*.

Mazumder, B. (2005). Fortunate Sons: New Estimates of Intergenerational Mobility in the United States Using Social Security Earnings Data, *The Review of Economics and Statistics* **87**(2), pp.235–255.

Mocetti, S. (2007). Intergenerational Earnings Mobility in Italy, *The B.E. Journal of Economic Analysis & Policy* **7**(2), pp.1–25.

Nilsen, Ø. A., Vaage, K., Aakvik, A. and Jacobsen, K. (2008). Estimates of Intergenerational Elasticities Based on Lifetime Earnings, *IZA Discussion Papers 3709*, Institute for the Study of Labor (IZA).

Nunez, J. and Miranda, L. (2011). Intergenerational income and educational mobility in urban Chile, *Estudios de Economia* **38**(1 Year 20), pp.195–221.

Österbacka, E. (2001). Family Background and Economic Status in Finland, *Scandinavian Journal of Economics* **103**(3), pp.467–484.

Pekkarinen, T., Uusitalo, R. and Kerr, S. (2009). School tracking and intergenerational income mobility: Evidence from the Finnish comprehensive school reform, *Journal of Public Economics* **93**(7-8), pp.965–973.

Piraino, P. (2007). Comparable Estimates of Intergenerational Income Mobility in Italy, *The B.E. Journal of Economic Analysis & Policy* **7**(2), pp.1–27.

Raaum, O., Bratsberg, B., Roed, K., Österbacka, E., Eriksson, T., Jäntti, M. and Naylor, R. A. (2008). Marital Sorting, Household Labor Supply, and Intergenerational Earnings Mobility across Countries, *The B.E. Journal of Economic Analysis & Policy* **7**(2), pp.1–49.

Sacerdote, B. (2007). How Large are the Effects from Changes in Family Environment? A Study of Korean American Adoptees, *The Quarterly Journal of Economics* **122**(1), pp.119–157.

Schnitzlein, D. D. (2009). Struktur und Ausmaß der intergenerationalen Einkommensmobilität in Deutschland, *Journal of Economics and Statistics* **229**(4), pp.450–466.

Schnitzlein, D. D. (2016). A New Look at Intergenerational Mobility in Germany compared to the U.S., *Review of Income and Wealth* **62**(4), pp.650–667.

Solon, G. (1989). Biases in the Estimation of Intergenerational Earnings Correlations, *The Review of Economics and Statistics* **71**(1), pp.172–174.

Solon, G. (1992). Intergenerational Income Mobility in the United States, *American Economic Review* **82**(3), pp.393–408.

Solon, G. (1999). Intergenerational mobility in the labor market, *in* O. Ashenfelter and D. Card (eds), *Handbook of Labor Economics*, Vol. 3, pp. 1761–1800, Elsevier.

Solon, G. (2004). A Model of Intergenerational Mobility Variation over Time and Place, *Generational Income Mobility in North America and Europe*, pp. 38–47, Cambridge University Press.

Solt, F. (2016). The Standardized World Income Inequality Database*, *Social Science Quarterly* **97**(5), pp.1267–1281.

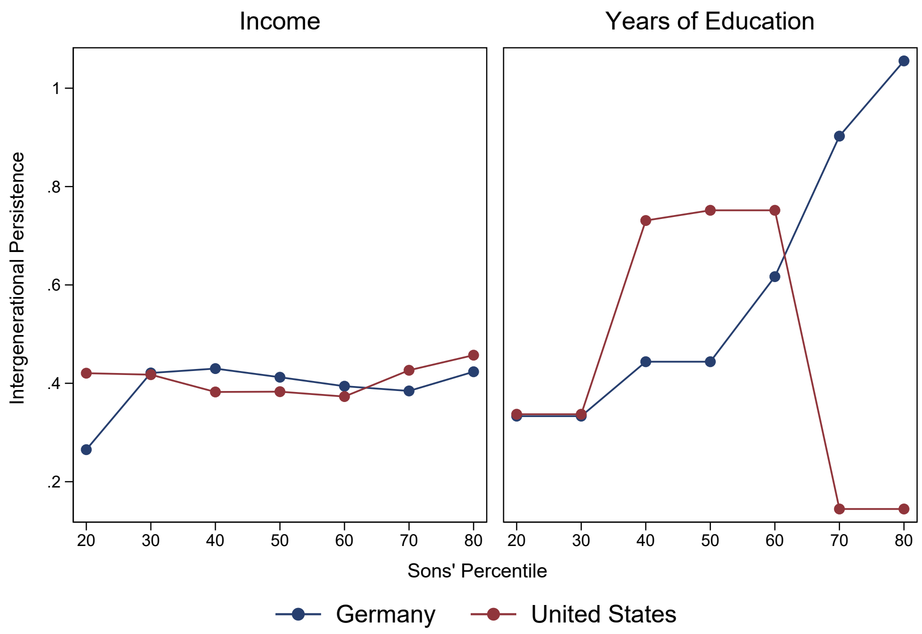
Vogel, T. (2006). Reassessing Intergenerational Mobility in Germany and the United States: The Impact of Differences in Lifecycle Earnings Patterns, *SFB 649 Discussion Papers 55*, Sonderforschungsbereich 649, Humboldt University, Berlin, Germany.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*, MIT Press.

Zimmerman, D. J. (1992). Regression toward Mediocrity in Economic Stature, *American Economic Review* **82**(3), pp.409–429.

Appendix

Figure 3: Intergenerational income elasticity and educational persistence along the income distribution



Source: SOEP (1984-2013), PSID (1984-2013).
Notes: Estimates are based on the PSID and SOEP sample without imputed annual labor earnings data.

Table 8: Nonlinear threefold decomposition

Germany

	β	γ	δ^f	δ^s	R^2_{Edf}	$\frac{\mathrm{Cov}\left(\log(y_i^s),v_i^f\right)}{\mathrm{Var}\left(v_i^f\right)}$	$\frac{\mathrm{Cov}\left(v_i^s,Ed_i^f\right)}{\mathrm{Var}\left(Ed_i^f\right)}$
20th Percentile	0.262**	0.545***	0.087***	0.074***	0.320***	0.131	0.007
	(0.103)	(0.054)	(0.008)	(0.012)	(0.044)	(0.124)	(0.015)
40th Percentile	0.424***	0.545***	0.087***	0.092***	0.320***	0.349***	0.001
	(0.076)	(0.054)	(0.008)	(0.008)	(0.044)	(0.094)	(0.011)
50th Percentile	0.411***	0.545***	0.087***	0.094***	0.320***	0.336***	-0.001
	(0.076)	(0.054)	(0.008)	(0.008)	(0.044)	(0.098)	(0.010)
60th Percentile	0.399***	0.545***	0.087***	0.094***	0.320***	0.280***	0.005
	(0.080)	(0.054)	(0.008)	(0.009)	(0.044)	(0.100)	(0.010)
80th Percentile	0.418***	0.545***	0.087***	0.095***	0.320***	0.280**	0.010
	(0.106)	(0.054)	(0.008)	(0.013)	(0.044)	(0.125)	(0.014)

United States

	β	γ	δ^f	δ^s	R^2_{Edf}	$\frac{\mathrm{Cov}\left(\log(y_i^s),v_i^f\right)}{\mathrm{Var}\left(v_i^f\right)}$	$\frac{\mathrm{Cov}\left(v_i^s,Ed_i^f\right)}{\mathrm{Var}\left(Ed_i^f\right)}$
20th Percentile	0.442***	0.449***	0.115***	0.186***	0.229***	0.306***	0.019
	(0.086)	(0.029)	(0.011)	(0.024)	(0.033)	(0.097)	(0.017)
40th Percentile	0.406***	0.449***	0.115***	0.144***	0.229***	0.291***	0.027**
	(0.054)	(0.029)	(0.011)	(0.015)	(0.033)	(0.063)	(0.012)
50th Percentile	0.407***	0.449***	0.115***	0.136***	0.229***	0.289***	0.031***
	(0.051)	(0.029)	(0.011)	(0.015)	(0.033)	(0.059)	(0.010)
60th Percentile	0.392***	0.449***	0.115***	0.148***	0.229***	0.262***	0.029***
	(0.052)	(0.029)	(0.011)	(0.015)	(0.033)	(0.058)	(0.010)
80th Percentile	0.467***	0.449***	0.115***	0.149***	0.229***	0.331***	0.039***
	(0.079)	(0.029)	(0.011)	(0.020)	(0.033)	(0.082)	(0.014)

Source: SOEP (1984-2013), PSID (1984-2013).
Notes: The table contains estimates of intergenerational income elasticity β and educational persistence γ for the PSID and SOEP sample without annual imputed individual labor earnings data. Intergenerational income elasticity estimates are based on a lower annual earnings limit of 1,200 Euro/US dollar. Standard errors are clustered at the family level and are estimated by paired bootstrapped approach with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.