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Essays on Intergenerational Income Mobility in Germany and the United States

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Deutschsprachige Zusammenfassung

Die vorliegende Dissertation beschäftigt sich mit der intergenerativen Einkommensmobilität in Deutschland im Vergleich zu den USA. Im Zentrum der Analyse steht demnach die Frage, inwiefern Einkommensunterschiede zwischen armen und reichen Familien an die nächste Generation weitergegeben werden. Diese Thematik wird sowohl in der Ökonomie als auch in der Soziologie seit mehreren Jahrzehnten diskutiert, dennoch sind – auch auf Grund der unzureichenden Datenverfügbarkeit in den meisten Ländern – viele Fragestellungen offen. Die vorliegende Arbeit setzt an der vorhandenen Literatur an und gliedert sich in drei Hauptkapitel, die jeweils einen bestimmten Aspekt der intergenerativen Einkommensmobilität untersuchen und als eigenständige Forschungsarbeiten zu betrachten sind. Der Fokus liegt dabei auf der empirischen Analyse der jeweiligen Fragestellung mithilfe vorhandener Daten des sozioökonomischen Panels (SOEP) für Deutschland und der Panel Study of Income Dynamics (PSID) für die USA.

Der erste Teil der Arbeit untersucht Struktur und Ausmaß der intergenerativen Einkommensmobilität in Deutschland und den USA. Dafür werden unterschiedliche Mobilitätsmaße berechnet und die Ergebnisse für beide Länder miteinander verglichen. Im Einklang mit der bestehenden Literatur fällt die intergenerative Einkommenselastizität in Deutschland geringer aus als in den USA, was für eine höhere Mobilität in Deutschland spricht. Vergleicht man jedoch die intergenerative Rangmobilität, sind die Ergebnisse für beide Länder relativ ähnlich. Bei der intergenerativen Einkommensanteilsmobilität bestehen dagegen stärkere Unterschiede zwischen Deutschland und den USA. Mit jedem höheren Perzentil sinkt die Einkommensanteilsmobilität der Söhne im Vergleich zu ihren Vätern in Deutschland weniger stark als in den USA. Die Regression zur Mitte findet demnach in Deutschland langsamer statt als in den USA, was für eine höhere Mobilität in den USA spricht. Die Ergebnisse der bedingten und unbedingten Quantilsregression liefern für keines der beiden Länder Hinweise auf Nichtlinearitäten. Eine abschließende Dekomposition der intergenerativen Einkommensungleichheit ergibt für Deutschland sowohl eine größere Einkommensmobilität als auch ein stärkeres progressives Einkommenswachstum als für die USA. Insgesamt kann keine klare Rangfolge hinsichtlich der intergenerativen Einkommensmobilität in Deutschland und den USA festgestellt werden. Abschließend werden mögliche Politikmaßnahmen erläutert, die zur Erhöhung der intergenerativen Einkommensmobilität in Deutschland beitragen könnten.

Der zweite Teil der Dissertation beschäftigt sich mit der Frage, über welche Transmissionskanäle das Einkommen der Eltern das Einkommen ihrer Kinder beeinflusst. Dabei sind im Wesentlichen zwei Mechanismen denkbar. Zum einen können wohlhabende Familien mehr Geld in das Humankapital ihrer Kinder investieren, wodurch diese später ein höheres Einkommen auf dem Arbeitsmarkt erzielen. Dieser Kanal wird als Investitionseffekt bezeichnet und beinhaltet beispielsweise den Besuch einer privaten Schule oder Universität oder die Finanzierung privater Nachhilfestunden. Zum anderen verfügen Eltern mit einem hohen Einkommen tendenziell auch über ein höheres Humankapital, das sie auch ohne den Einsatz finanzieller Mittel an ihre Kinder weitergeben können. Darunter fallen die genetische Weitergabe bestimmter Eigenschaften, die innerfamiliär erlernten Einstellungen und Ziele, aber auch gezielte nicht-monetäre Investitionen in das Humankapital der Kinder, zum Beispiel in Form von pädagogisch hochwertiger Freizeitgestaltung oder Unterstützung bei den Hausaufgaben. Dieser Kanal wird als Humankapitaleffekt bezeichnet. Die empirische Analyse mithilfe unterschiedlicher Dekompositionsmethoden zeigt, dass der Investitionseffekt und der Humankapitaleffekt in Deutschland zu etwa gleichen Teilen zur geschätzten intergenerativen Einkommenselastizität beitragen, während in den USA der Investitionseffekt vor allem in den oberen Perzentilen deutlich stärker ausgeprägt ist. Im Hinblick auf die im Vergleich zu Deutschland deutlich höhere Privatisierung des Bildungssektors in den USA scheint dieses Resultat plausibel. Für die Politik in Deutschland bedeuten diese Ergebnisse, dass die bloße Bereitstellung finanzieller

Mittel für Kinder aus armen Familien nicht ausreicht, um ihre Aufwärtsmobilität zu fördern. Zusätzlich muss die fehlende direkte Weitergabe von Humankapital innerhalb sozioökonomisch schwacher Familien durch staatliche Angebote substituiert werden.

Während sich die bisherige Analyse auf Väter und ihre Söhne beschränkt, ist das Ziel des dritten Teils der Dissertation eine Untersuchung der intergenerativen Einkommensmobilität der Töchter. Der Hauptgrund für diese in der Literatur übliche Restriktion sind Probleme bei der statistischen Analyse, die sich aufgrund der geringeren Arbeitsmarktpartizipation von Frauen im Vergleich zu Männern ergeben. Während Männer fast immer Vollzeit arbeiten, sind nach wie vor viele – insbesondere verheiratete – Frauen nur in Teilzeit oder gar nicht berufstätig. Das individuelle Einkommen der Tochter ist daher in vielen Fällen kein geeignetes Maß für ihren tatsächlichen Wohlstand. Gerade wenn assortative Paarung stattfindet – also Töchter wohlhabender Familien tendenziell auch gutverdienende Männer heiraten und sich infolgedessen für eine geringere Anzahl an Arbeitsstunden entscheiden – kann die geschätzte Einkommenselastizität verzerrt sein. Eine erste Basisregression zeigt, dass die intergenerative Einkommenselastizität der Töchter in Deutschland höher ausfällt als die der Söhne, während es in den USA gerade umgekehrt ist. Eine Trennung nach Familienstand macht jedoch deutlich, dass in beiden Ländern unverheiratete Frauen eine höhere Einkommenselastizität aufweisen als unverheiratete Männer, wohingegen für verheiratete Frauen eine niedrigere Einkommenselastizität geschätzt wird als für verheiratete Männer. Während die geringere Mobilität der unverheirateten Töchter auf eine stärkere Humankapitaltransmission zwischen Vätern und Töchtern im Vergleich zu den Söhnen zurückgeführt werden kann, ist die höhere Mobilität verheirateter Frauen zum einen auf eine weniger starke Humankapitaltransmission und zum anderen auf eine stärkere Arbeitsstundenelastizität der Töchter im Hinblick auf das Einkommen ihres Ehepartners zurückzuführen. Um den Effekt der assortativen Paarung genauer zu untersuchen, werden anschließend die verheirateten Individuen noch einmal nach unterschiedlichen Einkommensarten untersucht.

Dabei zeigt sich, dass die intergenerative Elastizität der Haushaltseinkommen tendenziell sogar größer ausfällt als die der Individualeinkommen, was für eine starke assortative Paarung spricht. Betrachtet man die Höhe des Haushaltseinkommens als das eigentliche Wohlstandsniveau einer Person, existieren außerdem keine gravierenden Unterschiede zwischen der Einkommensmobilität von Töchtern und Söhnen. Auch das Individualeinkommen des jeweiligen Ehepartners ist stark mit dem Einkommen des Vaters korreliert, was die These der assortativen Paarung wiederum stützt. Die intergenerative Einkommenselastizität der Schwiegersöhne im Vergleich zu ihren Schwiegervätern fällt in Deutschland sogar größer aus als die intergenerative Einkommenselastizität der Söhne im Vergleich zu ihren eigenen Vätern.

Chapter 1

Introduction

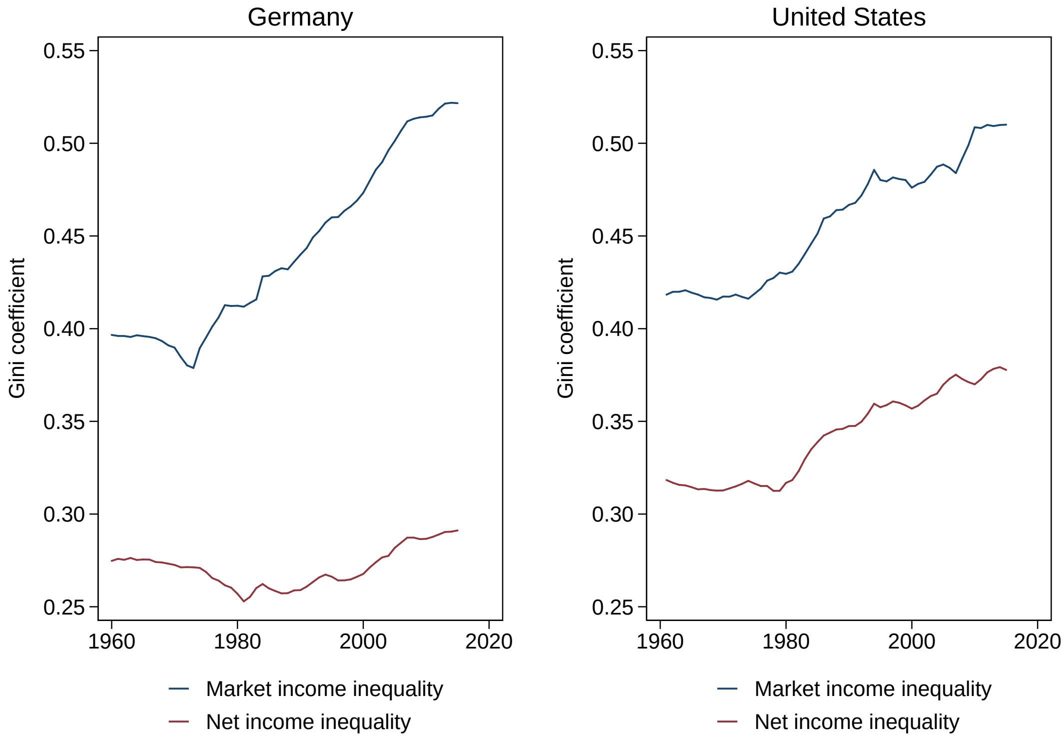
1.1 Motivation

The inequality of market incomes has risen in almost all developed countries since the 1970s. In Germany, the Gini coefficient has increased from a local minimum of 0.38 in 1973 to a local maximum of 0.52 in 2014, while the Gini coefficient in the United States has risen from a local minimum of 0.42 in 1969 to a local maximum of 0.51 in 2015 (Figure 1.1).

This development is driven by rapidly increasing incomes in the upper percentiles of the earnings distribution and has been attributed mainly to the consequences of globalization and technological progress. On the one hand, growing international division of labor has led to an increase in the demand for high-skilled labor and a decrease in the demand for low-skilled labor in developed countries (Ebenstein et al., 2014). On the other hand, a growing number of manual tasks can today be performed more efficiently by computers and robots, whereas complementary cognitive tasks are in high demand (Autor et al., 2003). Both developments have led to increasing wages for high-skilled workers and constant or even decreasing wages for low-skilled workers, resulting in an increase in the inequality of market incomes.

From a distributive point of view, an overly high level of income inequality seems "unfair" to most people. Therefore, market incomes are usually redistributed by the government, leading to significantly lower inequality of disposable incomes. However, "fairness" is a normative rather than an economic concept, and thus the optimal amount of redistribution remains unclear to both economists and policy makers. In addition, a high level of redistribution is likely to create disincentives to invest in physical and human capital and might therefore harm economic growth in a society (Muinelo-Gallo and Roca-Sagalés, 2013).

Figure 1.1: Development of market and net income inequality



Source: Solt (2016).

However, even a high level of net income inequality is less problematic if it is accompanied by a similarly high level of income mobility. To illustrate this, imagine two societies, A and B. Society A is characterized by complete income immobility, meaning that in each period, the income position of an individual is perfectly predetermined by their income position in the previous period. In contrast, society B features complete income mobility, such that in each period, every individual has an equal chance of receiving a high or low income irrespective of their income in the previous period. In the latter case, society will be more likely to accept a high level of inequality than in the first case. If there exists a high level of income mobility and thus economic success is directly dependent on talent, ability, and effort, income differences might even encourage investments in education and an extension of working hours.

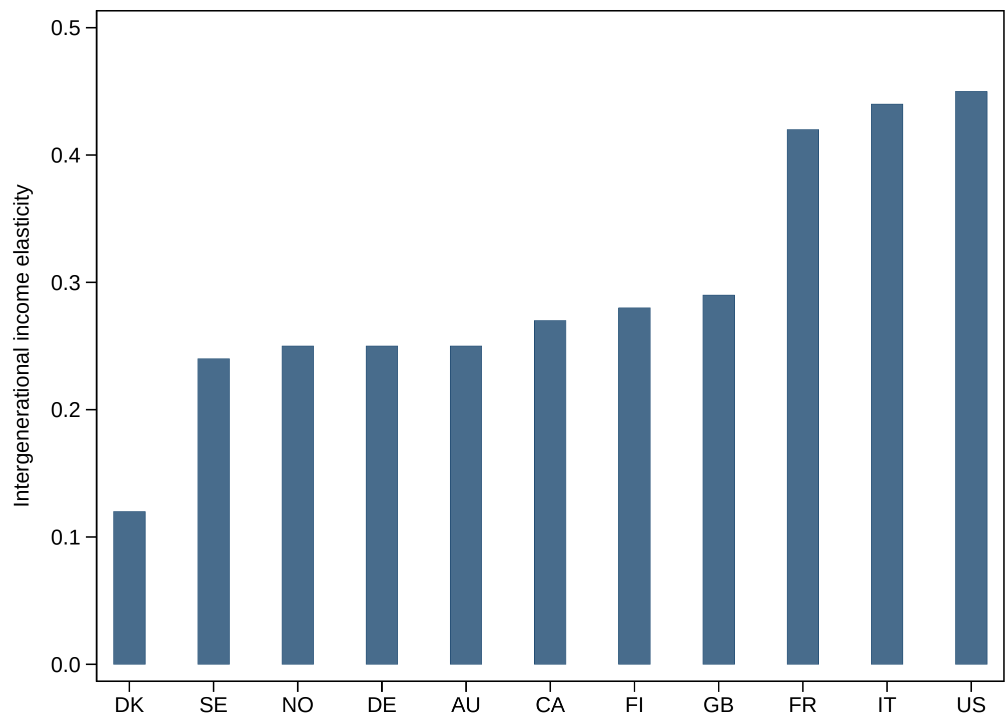
A distinction is generally made between intra- and intergenerational mobility. While *intragenerational income mobility* considers the extent to which an individual can ascend or descend the income ladder within their own working life, *intergenerational income mobility* analyzes the ascent or descent of a child relative to their parents' position in the income distribution. Intergenerational income mobility thus examines the question of whether and to what extent the future income of a child is predetermined by their family background, or, as Corak (2006) puts it: "Do poor children become poor adults?" This issue is closely related to the analysis of equality of opportunity and has been the subject of a broad strand of the economic and sociological literature for several decades. However, at least partly due to a lack of data availability in most countries, numerous questions still remain unanswered.

The present dissertation deals with intergenerational income mobility in Germany as compared to the United States and is intended to be a contribution to the currently available literature. It consists of three parts, each of which addresses a different aspect of intergenerational income mobility. The overall focus is on an empirical investigation using comparable data from the Socio-economic Panel (SOEP) for Germany and the Panel Study of Income Dynamics (PSID) for the United States. A detailed description of the structure and the main results of this dissertation is presented in Section 1.3.

1.2 Literature review

Intergenerational income mobility has been discussed in the economic literature since the 1970s. Early studies include Sewell and Hauser (1975), Bielby and Hauser (1977), and Behrman and Taubman (1985). However, the results of these first studies are likely to be systematically biased due to measurement errors and homogenous samples. Beginning with the seminal contributions of Solon (1989, 1992), more recent decades have witnessed a rapid increase in the number of studies on the transmission of income positions within families. A broad overview can, for example, be found in Solon (1999), Björklund and Jäntti (2009), and Black and Devereux (2011).

Figure 1.2: Country comparison of intergenerational income mobility



Source: Björklund and Jäntti (2009).
Notes: DK: Denmark, SE: Sweden, NO: Norway, DE: Germany, AU: Australia, CA: Canada, FI: Finland, GB: United Kingdom, FR: France, IT: Italy, US: United States.

Intergenerational income mobility is commonly estimated by the *intergenerational income elasticity*, which measures the share of parents' income advantage or disadvantage that is passed on to their children. Thus, higher values for the intergenerational income elasticity imply a higher persistence of income positions and thus a lower level of intergenerational income mobility. An international comparison of the existing literature indicates that there are major differences among the results for individual countries (Figure 1.2). Studies for the United States have ascertained values ranging from 0.09 (Behrman and Taubman, 1985) to 0.61 (Mazumder, 2001). Today the generally accepted value for the intergenerational income elasticity in the

United States is 0.4 or higher (Corak, 2006). This places the United States at the upper end of the estimated results and makes it a country with a rather low level of intergenerational income mobility.

Similarly low levels of intergenerational income mobility are found in the literature for France and Italy. Lefranc and Trannoy (2005) determine an intergenerational income elasticity of approximately 0.4 for France. Meanwhile, estimates of around 0.5 have been established for Italy (Mocetti, 2007, Piraino, 2007). For the United Kingdom, the ascertained values of approximately 0.3 are somewhat lower than those for the United States. However, they are still relatively high in the international comparison (Blanden et al., 2004, Nicoletti and Ermisch, 2007).

In contrast, the Scandinavian countries exhibit very low levels of intergenerational income persistence. The estimated elasticities for Finland (Pekkarinen et al., 2009), Norway (Nilsen et al., 2008), and Sweden (Björklund and Jäntti, 1997, Björklund et al., 2012) range from 0.2 to 0.3. Hussain et al. (2009) obtain a value of only 0.14 for Denmark. Australia and Canada also exhibit comparatively low values for the intergenerational income elasticity and thus high levels of income mobility. Leigh (2007) finds values ranging from 0.2 to 0.3 for Australia. For Canada, Corak and Heisz (1999) compute a value of approximately 0.2.

Germany is usually classified between the United States and the Scandinavian countries (Schnitzlein, 2016). Existing studies, however, calculate varying results for the intergenerational income elasticity in Germany. The estimated values range from 0.10 (Grawe, 2004) to 0.48 (Chau, 2012). However, the majority of studies find values of the order of approximately 0.2 to 0.3 (Vogel, 2006, Eisenhauer and Pfeiffer, 2008, Schnitzlein, 2009), indicating a level of intergenerational income mobility similar to that of the Scandinavian countries. Surprisingly often, however, studies conducting a direct comparison with comparable data find no significant differences between Germany and the United States (Couch and Dunn, 1997, Lillard, 2001, Couch and Lillard, 2004, Schnitzlein, 2016). The relative position of Germany in the international comparison is thus not clearly determined.

1.3 Organization of this dissertation

This dissertation consists of three contributions. Each addresses one specific aspect of intergenerational income mobility and is intended to be a stand-alone analysis. All chapters use comparable data for Germany and the United States to conduct country comparisons. As there are usually a large number of studies available for the United States, this approach is useful for comparing the empirical results to the existing literature. While the first two studies are co-authored with Mustafa Çoban, the third study is single-authored.

Structure and extent of intergenerational income mobility

Chapter 2 conducts a direct country comparison of the structure and extent of intergenerational income mobility in Germany and the United States. In line with existing results, the estimated intergenerational income mobility of 0.49 in the United States is significantly higher than that of 0.31 in Germany. While the results for the intergenerational rank mobility are relatively similar, the level of intergenerational income share mobility is higher in the United States than in Germany. There are no significant indications of a nonlinear run of intergenerational income elasticity. A final decomposition of intergenerational income inequality shows both greater income mobility and stronger progressive income growth for Germany compared to the United States. Overall, we cannot identify a clear ranking of the two countries. To conclude, several economic policy recommendations to increase intergenerational income mobility in Germany are discussed. This chapter is co-authored with Mustafa Çoban and has been published in a similar version in *ORDO Yearbook of Economic and Social Order*, 67, 101-131.

Transmission channels of intergenerational income persistence

Chapter 3 examines the transmission channels of intergenerational income persistence in Germany and the United States. In principle, there are two ways in which well-off families may influence the adult incomes of their children: first through direct investments in their children's human capital (*investment effect*), and second through the indirect transmission of human capital from parents to children (*endowment effect*). In order to disentangle these two effects, a descriptive as well as a structural decomposition method are utilized. The results suggest that the investment effect and the endowment effect each account for approximately half of the estimated intergenerational income elasticity in Germany, while the investment effect is substantially more influential in the United States with a share of around 70 percent. With regard to economic policy, these results imply that equality of opportunity for children born to poor parents cannot be reached by the supply of financial means alone. Conversely, an efficient policy must additionally substitute for the missing direct transmission of human capital within socio-economically weak families. This chapter is again co-authored with Mustafa Çoban.

Intergenerational income mobility among daughters

Chapters 2 and 3 of this dissertation are restricted to the analysis of fathers and their sons, whereas Chapter 4 explicitly focuses on the intergenerational income mobility among daughters. The restriction to men is commonly made in the empirical literature due to women's lower labor market participation. While most men work full-time, the majority of (married) women still work only part-time or not at all. Especially with the occurrence of assortative mating, daughters from well-off families are likely to marry rich men and might decide to reduce their labor supply as a result. Thus, the individual labor income of a daughter might not be a good indicator for her actual economic status. The baseline regression analysis shows a higher intergenerational income elasticity in Germany and a lower intergenerational income elasticity in the United States for women as compared to men. However, a separation by marital status reveals that in both countries unmarried women exhibit a higher intergenerational income elasticity than unmarried men, while married women feature a lower intergenerational income elasticity than married men. The reason for the lower mobility of unmarried women turns out to be a stronger human capital transmission from fathers to daughters than to sons. The higher mobility of married women is driven by a weaker human capital transmission and a higher labor supply elasticity with respect to spousal income for women as compared to men. In order to further study the effects of assortative mating, the subsample of married children is analyzed by different types of income. It shows that the estimated intergenerational income elasticity of children's household incomes is even higher than that of their individual incomes. This can be seen as an indication for strong assortative mating. If household income is interpreted as a measure of children's actual economic welfare, there are barely any differences between sons and daughters. The intergenerational income elasticity of spousal income with respect to parental income is again relatively high, which in turn supports the hypothesis of strong assortative mating. The elasticity of the sons-in-law with respect to their fathers-in-law in Germany is even higher than that of the sons with respect to their own fathers.

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Chapter 2

Structure and Extent of Intergenerational Income Mobility*

2.1 Introduction

The high level of income inequality is currently one of the most important socio-political issues in both Germany and the United States. Closely related to income inequality but less intensely discussed in public is the topic of income mobility. The relationship between income inequality and income mobility can be illustrated with the help of a simple image. If one imagines the interpersonal income distribution as a ladder upon the rungs of which the respective income earners are located, then income inequality determines the distance between the individual rungs. In contrast, income mobility represents the probability of an individual to ascend or descend from a particular rung on the ladder (Chetty et al., 2014).

Generally, one distinguishes between intra- and intergenerational income mobility. While *intragenerational income mobility* considers the extent to which an individual person can ascend or descend the income ladder within their own working life, *intergenerational income mobility* describes the ascent or descent of a child relative to their parents' position on the income ladder. Intergenerational income mobility thus examines the question of whether and to what extent the adult income of a child is determined by their background. Put more simply: Do poor children become poor adults and vice versa?

* This chapter is co-authored with Mustafa Çoban and has been published in a similar version in *Ordo Yearbook of Economic and Social Order*, 67, 101–131.

A high level of intergenerational income mobility is desirable from both a distributive and an allocative point of view. On the one hand, society perceives it as "unfair" when the income of a child is determined to a large extent by that of their parents, and thus the future prospects of children from low-income families are largely eliminated. On the other hand, if one assumes that initial abilities are equally distributed among income classes, but children from low-income families are unable to obtain well-paid employment reflective of their abilities, then society is failing to use its resources in an efficient manner (Schnitzlein, 2008).

However, high intergenerational income persistence cannot generally be interpreted as a lack of equal opportunity. Instead, children from wealthier households may on average demonstrate a stronger preference for human capital investments than children from poorer households. Reasons for this may be the intergenerational transfer of aspirations, skills, and occupational choices within the family. Inequalities that are driven by these determinants are accepted within a market economy (Roemer, 2004). In contrast, high intergenerational income persistence is indicative of a lack of equal opportunity if it is exogenously influenced by institutional conditions, credit market constraints for poor households, or other social factors that are beyond the control of the individual.

Intergenerational income mobility is commonly estimated by the *intergenerational income elasticity* (Section 2.2.3), where, for example, a value of 0.3 means that 30 percent of the income advantage or disadvantage of the parents is passed on to their children. Thus, if a father's income is 10 percent higher than the average income in the parents' generation, the expected income of his children is 3 percent higher than the average income in the children's generation. Higher values for the intergenerational income elasticity therefore imply a higher persistence of income positions and thus a lower level of intergenerational income mobility. A comparison of the existing literature on intergenerational income mobility shows that there are considerable differences between individual countries (Solon, 1999, Björklund and Jäntti, 2009, Black and Devereux, 2011). The consensus estimate for the intergenerational income elasticity in the United States lies between 0.4 and 0.5 (Corak, 2006). Thus, in the international comparison, the United States is located at the upper end of the ascertained values and is therefore a country with a rather low level of intergenerational income mobility. The Scandinavian countries, in contrast, exhibit very low levels of intergenerational income elasticity with values estimated at around 0.2 (Nilsen et al., 2008, Hussain et al., 2009, Pekkarinen et al., 2009, Björklund et al., 2012). Germany is generally classified between the United States and the Scandinavian countries. The estimates obtained are of the order of approximately 0.2 to 0.3 (Vogel, 2006, Eisenhauer and Pfeiffer, 2008, Schnitzlein, 2009). However, Schnitzlein (2016) finds no significant differences between the intergenerational income elasticities in Germany and the United States.

This chapter conducts a direct comparison of the structure and extent of intergenerational income mobility in Germany and the United States. Consistent with existing results, the intergenerational income elasticity in the United States is found to be higher than in Germany. When comparing intergenerational rank mobility, however, the results for the two countries are relatively similar. In terms of intergenerational income share mobility, greater differences exist between Germany and the United States. With each higher percentile, the income share mobility of the sons in the United States drops by a higher amount when compared to their fathers than in Germany. For both countries, the results of the quantile regressions provide no evidence of nonlinearities. The final decomposition of intergenerational income inequality shows both greater income mobility and stronger progressive income growth for Germany than for the United States. Section 2.2 subsequently describes the data used and provides an overview of the various mobility measures. The results of the estimates are presented in Section 2.3. Finally, Section 2.4 includes several economic policy recommendations to increase intergenerational income mobility in Germany and is followed by a brief summary in Section 2.5.

2.2 Data and mobility measures

In order to examine intergenerational income mobility empirically, individual data are required for at least two generations. Long-term panel surveys of households that start capturing information on children while they are still living with their parents and follow them into the older adult years are suitable for this purpose (Corak, 2006). In addition, in order to conduct a country comparison, it is necessary that the data used are highly comparable regarding the survey design, the survey method, and the survey period. In this study, we use the Socio-economic Panel (SOEP) for Germany and the Panel Study of Income Dynamics (PSID) for the United States. Both records collect information on all adult persons of a household and survey them repeatedly in the subsequent years. Thus, children who leave their parents' homes and establish their own households can continue to be covered over time. Both surveys 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). In particular, it provides a reliable data basis for international comparisons of income, taxes, and transfers. The individual annual labor income in the CNEF used in this study includes wages and salaries from both paid employment and self-employment as well as bonus payments, income from overtime, and profit sharing (Lillard, 2013, Grabka, 2014).

2.2.1 Measurement errors and life-cycle bias

In order to measure lifetime income, all of a respondent's income statements over the entire working life would be required.[1] In the case of an academic, for example, income observations over the course of 35 to 40 years would need to be available (Schnitzlein, 2009). However, with such a long survey period, the number of people

[1] The lifetime income of a person generally includes both labor and capital income. Since in surveys the collection of capital income is linked to problems, here the concept of income refers to the labor income of a person.

who continue to participate in the survey is reduced. This so-called *panel mortality* can correlate with certain characteristics of the respondents (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).

Therefore, lifetime incomes are approximated by means of annual income observations. These income statements consist of a permanent as well as a fluctuating component, where the second causes lifetime income to be determined with measurement errors (Solon, 1989, 1992, Zimmerman, 1992). Thus, if parental income is approximated by income data from only one particular point in time, the classical *errors-in-variables* problem occurs (Wooldridge, 2010). This leads to a systematic downward bias of the estimated intergenerational income elasticity (*attenuation bias*). 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 it can significantly reduce it. Since the direction of the bias is known, an estimate of the intergenerational income elasticity can be interpreted as a lower bound for the true estimation parameter. In the approximation of children's lifetime income, measurement errors only lead to higher standard errors.

In addition, Haider and Solon (2006) point out that the approximation of children's lifetime income depends on the chosen stage of life. On the one hand, individual income during the working life assumes a hump-shaped run, so that the income at the beginning of the working life is lower and thus the lifetime income of a person is underestimated. On the other hand, differences in income 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 leads to an underestimation of intergenerational income elasticity (*life-cycle bias*). This circumstance is verified by Böhlmark and Lindquist (2006) for Sweden and Brenner (2010) for Germany. For the United States, Haider and Solon (2006) show that for the sons, the age range between the mid-30s and the mid-40s produces a good approximation of the lifetime income. Schnitzlein (2016) uses the income of sons between 35 and 42 years of age for Germany.

2.2.2 Sample definition

The selected baseline 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 of 1984 to 2013. The individual annual labor income is used. We exclude imputed income data from the SOEP sample.[2] All income statements are deflated to the year 2010.[3] 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 baseline samples. 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).

The generation of the parents is restricted to the income observations of the fathers and the generation of the children to the income observation of the sons.[4] Fathers' incomes are drawn from the period of 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 ages of 30 to 55 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 of 2003 to 2013, during which time period at least one valid income observation must be available. Again, the lifetime income of the

[2] 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.

[3] 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.

[4] 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. While in the United States female labor market participation was on average at 54.2 percent in the 1980s and at 59.5 percent in the 2000s, Germany features values of 41.4 percent and 50.8 percent, respectively (World Bank, 2017).

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 from 1961 to 1978, which do not overlap with the cohorts of their fathers.

Table 2.1: Descriptive statistics

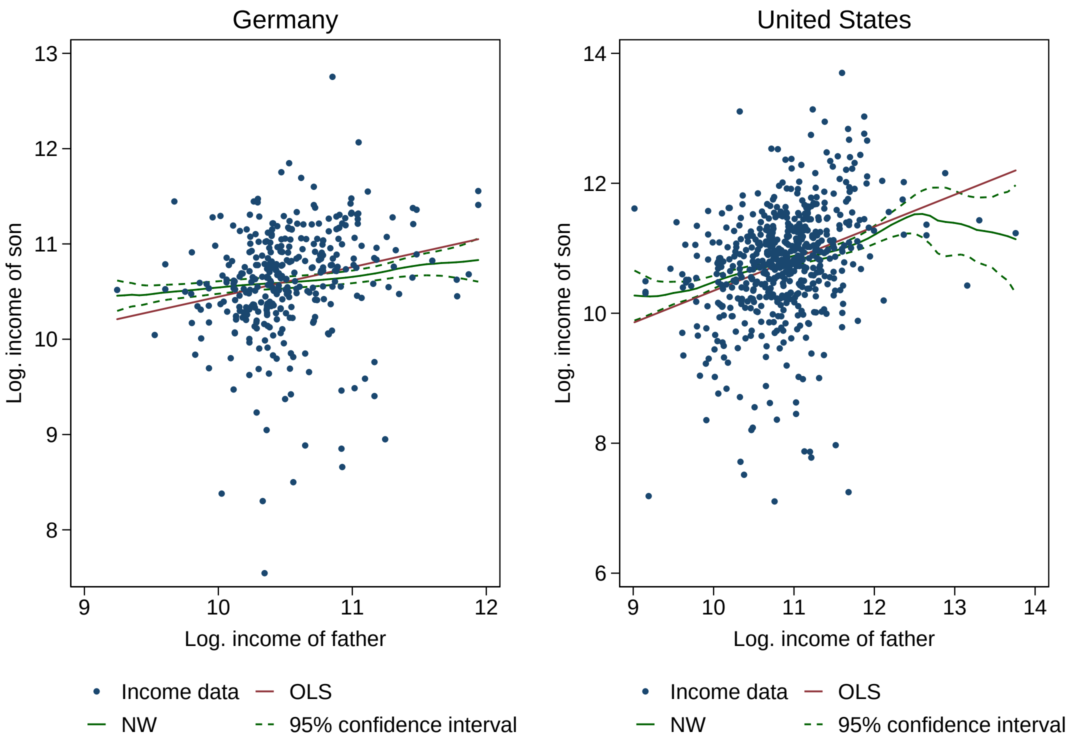
		Fathers		**Sons**	
		Mean	Std. Dev.	Mean	Std. Dev.
SOEP					
Income		40,441.96	19,611.62	46,868.19	27,724.28
Age		46.84	4.53	38.13	1.80
Father-son pairs	354				
PSID					
Income		64,070.24	59,633.14	67,199.29	69,580.75
Age		43.76	5.42	37.89	1.88
Father-son pairs	601				

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

A total of 354 father-son pairs are thus recorded in the SOEP and 601 father-son pairs in the PSID (Table 2.1). On average, the sons earn more than their fathers in both countries. The average income of the sons is 15.9 percent higher than the average income of the fathers in Germany, while it is only 4.9 percent higher in the United States. The average age of the fathers is mid-40s in both countries, older than the sons, whose average age is late-30s. The younger age of the sons might also determine the observed higher variance in incomes.

The logarithmized incomes of the fathers and sons exhibit a positive correlation (Figure 2.1). The slope of the line of best fit from the bivariate ordinary least squares (OLS) regression is higher for the United States than for Germany. However, it also becomes clear that the income data points in both countries are heavily scattered around the regression line. In order to examine the simple linear relationship more closely, the course of the bivariate Nadaraya-Watson (NW) estimation is additionally depicted. Both countries show deviations compared to the OLS estimation. However, the 95 percent confidence intervals include the OLS regression line over nearly the entire distribution of paternal income and deviations on the upper and lower ends might be caused by influential outliers. Thus, it cannot be concluded from the bivariate evidence that the intergenerational income elasticity changes significantly along the income distribution of the fathers.

Figure 2.1: Intergenerational income correlation



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

2.2.3 Intergenerational mobility measures

Intergenerational income elasticity

The theoretical basis for the relationship between the income of parents and the income of their children is expressed by the model of Becker and Tomes (1979, 1986). The starting point is a family comprising two generations which maximizes its utility by dividing its disposable income between consumption and investment in the human capital of its children. Solon (2004) simplifies this approach in order to rationalize the intergenerational income elasticity usually estimated in empirical studies by

$$\log(y_i^s) = \beta_0 + \beta_1 \log(y_i^f) + \gamma x_i' + \varepsilon_i^s. \tag{2.1}$$

For each family i, the lifetime income of the son y_i^s and the lifetime income of the father y_i^f are logarithmized. The intercept β_0 can then be interpreted as the average logarithmized lifetime income in the generation of the son, and the slope β_1 is the searched-for intergenerational income elasticity. It states that an increase in the father's lifetime income by 1 percent increases the son's lifetime income by an average of β_1 percent. If $\beta_1 = 0$, the lifetime income of the son is independent of the father's lifetime income and assumes the average value of the son's generation. The higher the value of β_1, the stronger the link between the lifetime income of a father and his son is, and consequently, the lower the intergenerational income mobility. If the variance of the logarithmized lifetime incomes of the fathers and sons is approximately equal, β_1 can also be interpreted as the correlation between the logarithmized lifetime incomes of the two generations (Solon, 2004). In the selected samples, the income observations of the sons and the fathers are sometimes measured at different times of their lives. Moreover, the number of valid observations varies between respondents. Thus, the vector x_i includes polynomials of the average age of the father and the son, respectively, as well as the number of valid observations of the son (Schnitzlein, 2016).[5] Deviations from the predicted value due to factors orthogonal to the income of the father are summarized in the idiosyncratic error term ε_i^s.

[5] If the generation of the fathers and the generation of the sons exhibit different age-income profiles, the estimated intergenerational income elasticity might be biased (Fertig, 2003). However, the bootstrapped Hausman test for the intergenerational income elasticity with commonly estimated age-income profiles and separately estimated age-income profiles yields no significant difference for Germany ($p = 0.6460$) and the United States ($p = 0.1672$), respectively.

Intergenerational transition matrices

While the intergenerational income elasticity is a useful summary measure of relative intergenerational mobility, it has some limitations. For example, it is not informative regarding differences between upward and downward mobility and does not consider nonlinearities along the income distribution (Bratberg et al., 2017). As a starting point to overcome these issues, estimated transition matrices provide the possibility of an illustrative representation. Here, the position of the son in the children's income distribution is conditioned to the position of the father in the parents' income distribution. More specifically, each cell c_{jk} of the estimated transition matrix can be interpreted as the probability that a son born to a father from quintile j reaches quintile k. Again, the vector x_i includes polynomials of the average age of the father and the son as well as the number of valid observations of the son (Fertig, 2003).

$$c_{jk} = \mathrm{P}(q_i^s = k \mid q_i^f = j, x_i), \quad j, k = 1, ..., 5 \tag{2.2}$$

Intergenerational transition matrices provide detailed information about the upward and downward mobility at certain income quintiles. They thus supplement the intergenerational income elasticity by determining to where sons from different backgrounds migrate within the income distribution.

Intergenerational rank mobility

Since estimated transition matrices cannot illustrate movements of the sons within the respective quintiles, intergenerational rank mobility provides another way to determine upward and downward mobility in more detail (Aaberge and Mogstad, 2014, Bratberg et al., 2017). Intergenerational rank mobility (RM) measures the expected difference between the percentile of a son p_i^s and the percentile of his father p_i^f conditioned to the percentile affiliation of the father:

$$\mathrm{RM}(p) = \mathrm{E}(p_i^s - p_i^f \mid p_i^f = p), \quad p = 1, ..., 100 \tag{2.3}$$

It thus provides additional information on how the mobility of the sons varies along the income distribution of the fathers (Bhattacharya and Mazumder, 2011, Chetty et al., 2014, Mazumder, 2014). A further advantage of intergenerational rank mobility in comparison to intergenerational income elasticity is that it is relatively robust to measurement issues and life-cycle bias (Nybom and Stuhler, 2016).[6]

Countries with similarly high levels of intergenerational income elasticity may exhibit different levels of intergenerational rank mobility if they differ greatly in terms of income inequality. This is due to the fact that for income recipients in countries with higher income inequality, it is more difficult to reach higher ranks, because the absolute income limits of the percentiles are further apart from one another than in a country with lower income inequality. Thus, combining intergenerational rank mobility with income inequality allows further conclusions for a country comparison.

Intergenerational income share mobility

While intergenerational rank mobility measures relative positional movements, it does not consider the distance between individual ranks in terms of absolute income differences. In contrast, intergenerational income share mobility provides a hybrid measure containing aspects of both absolute and relative mobility. In addition, it also allows us to compare absolute income changes that are measured using different currencies (Bratberg et al., 2017).

Intergenerational income share mobility (IS) is defined as the expected difference between a child's income relative to their generation's average income and their parents' income relative to the parental generation's average income conditioned to

[6] According to Chetty et al. (2014), rank persistence stabilizes at the age of 30. Mazumder (2014) shows that by the age of 40, the rank persistence in the PSID no longer exhibits a downward bias. Thus, by limiting our sample, we meet both requirements.

the percentile affiliation of the father:

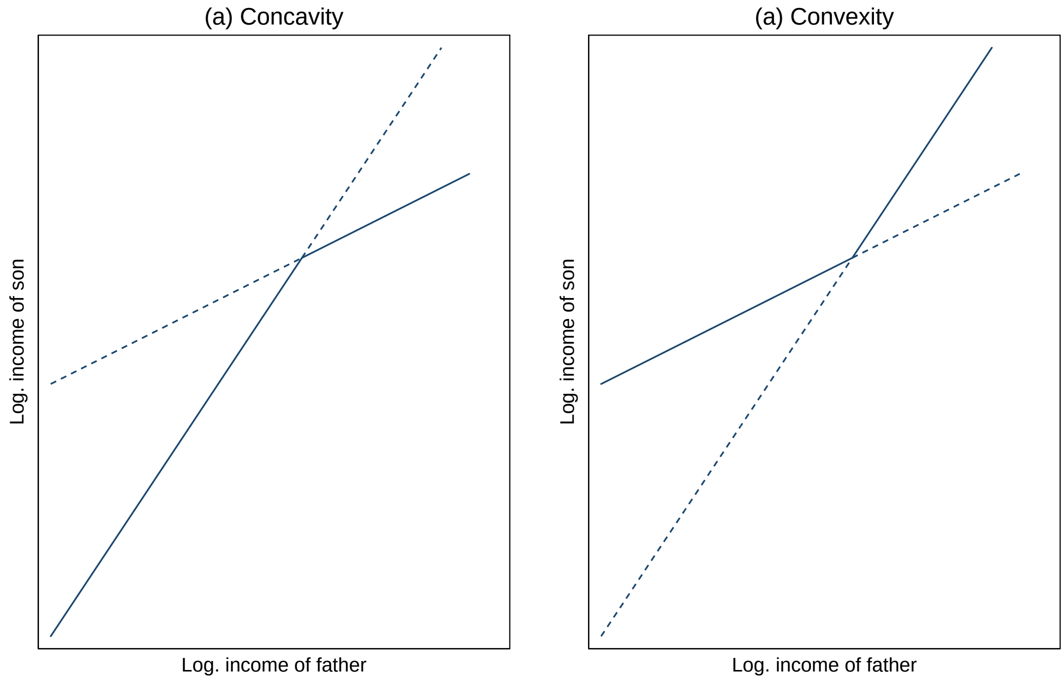
$$\mathrm{IS}(p) = \mathrm{E}\left(\frac{y_i^s}{\mathrm{E}(y_i^s)} - \frac{y_i^f}{\mathrm{E}(y_i^f)} \,\middle|\, p_i^f = p \right), \quad p = 1, ..., 100 \tag{2.4}$$

As we use a balanced panel of families in each generation, this measure is equal to the change in a family's share of their generation's total income scaled by the population of the generation. The estimation of the intergenerational income rank mobility and the intergenerational income share mobility is carried out with the aid of nonparametric mobility curves with the respective OLS estimator being used as a benchmark (Aaberge and Mogstad, 2014).

Quantile regressions

Until now, it has been assumed that the relationship between the logarithmized income of fathers and their sons 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 relationship can assume a concave run when poor families experience credit market constraints that do not apply for rich families. Rich families will then invest in the human capital of their children until the marginal costs equal the marginal rate of return. Therefore, the expected relation between earnings of parents and children in rich families depends solely on the expected relation between their endowments λ. In contrast, credit-constrained families might be forced to invest less than the optimal amount in their children's human capital. This means that a small increase in a poor father's income will increase his child's income by more than λ. The intergenerational income persistence will then be more pronounced for poor families than for rich families, creating a concave intergenerational earnings relationship (Figure 2.2.a).

Figure 2.2: Nonlinearities in intergenerational income elasticity



Source: Bratsberg et al. (2007).

However, a concave run of the intergenerational income elasticity neither needs 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, credit market constraints do not necessarily imply a concave relationship. In this case, 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. The 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 fathers' income. Then, particularly at the bottom of the parents' earnings distribution, the slope of the regression line is equal to λ. 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, i.e., the slope of the regression line is again higher than λ (Bratsberg et al., 2007).[7] Consequently, the intergenerational income persistence among poor families will be lower than among rich families, resulting in a convex run of the intergenerational income elasticity (Figure 2.2.b).

According to this reasoning, countries with a largely public education system will likely exhibit a convex run of the intergenerational income elasticity, while in countries with a high level of privatization of the education system, a concave run is assumed. In 2013, the share of private spending in the German education system amounted to 13.5 percent, whereas the United States exhibited a share of 31.8 percent (OECD, 2016). The curve of intergenerational income elasticity is thus assumed to feature a rather convex run in Germany and a rather concave run in the United States.

Decomposition of intergenerational income inequality

If the observed fathers and sons are interpreted as representatives of their respective families at two different points in time, income inequality and intergenerational income mobility can be considered together. Jenkins and Van Kerm (2006) provide an analytical framework within which changes in income inequality $\mathrm{G}(\nu)$ over time can be additively decomposed into a progressivity component $\mathrm{P}(\nu)$ and a mobility component $\mathrm{R}(\nu)$:

$$\Delta\mathrm{G}(\nu) = \mathrm{R}(\nu) - \mathrm{P}(\nu), \tag{2.5}$$

where ν represents the inequality aversion of the society.[8] While Jenkins and Van Kerm (2006) utilize intragenerational income mobility to decompose income inequality, we transfer this method to intergenerational income mobility. We thus interpret the progressivity component $\mathrm{P}(\nu)$ as the change in income inequality when relative

[7] This situation can be accounted for by the fact that the optimal human capital investment of the fathers grows with the increasing talent of the sons (Han and Mulligan, 2001, Grawe and Mulligan, 2002).

[8] The conventional Gini coefficient is obtained with $\nu = 2$.

incomes between families change, but all sons take on the respective income ranks of their fathers. If income growth is more pronounced among the lower income quantiles, i.e., income growth is progressive (*pro-poor*), $\mathrm{P}(\nu) > 0$ and therefore leads to a reduction of income inequality. If, in contrast, income growth is concentrated among the upper income quantiles, i.e., income growth is regressive (*pro-rich*), $\mathrm{P}(\nu) < 0$ and thus reinforces income inequality. In the same manner, the mobility component $\mathrm{R}(\nu)$ is interpreted as the change in income inequality when the income ranks of the sons in comparison to those of their fathers change but the relative incomes of the sons equal the relative incomes of their fathers. When there is no reranking, $\mathrm{R}(\nu) = 0$, and otherwise, $\mathrm{R}(\nu) > 0$. Thus, for a given level of $\mathrm{P}(\nu)$, a higher $\mathrm{R}(\nu)$ will lead to a rise in income inequality.

In conclusion, Equation (2.5) states that income inequality is reduced by progressive income growth unless more than offset by concomitant income mobility. These mutually compensatory effects can also explain the paradox that increasing income inequality is compatible with progressive income growth. If poor families benefit relatively more from income growth, they move upward within the income distribution and the income gap between poor and rich families diminishes such that the overall income inequality declines. However, some of the initially poor families might not only be able to catch up relative to richer families, but also overtake some of them. This situation counteracts the reduction in income inequality.

2.3 Empirical results

2.3.1 Descriptive evidence

Comparing income inequality in the fathers' and the sons' generations in Germany and the United States, respectively, it can be observed that the Gini coefficient is lower in Germany in both generations but has increased in both countries over time (Table 2.2). While in the United States income inequality rose by 7.84 Gini points

(23.42 percent) from an initial value of 33.48 Gini points to a final value of 41.32 Gini points, it increased by 9.11 Gini points (42.49 percent) from an initial value of 21.44 Gini points to a final value of 30.55 Gini points in Germany. Thus, the level of income inequality has increased more sharply in Germany both in terms of absolute and relative values.

Table 2.2: Income inequality

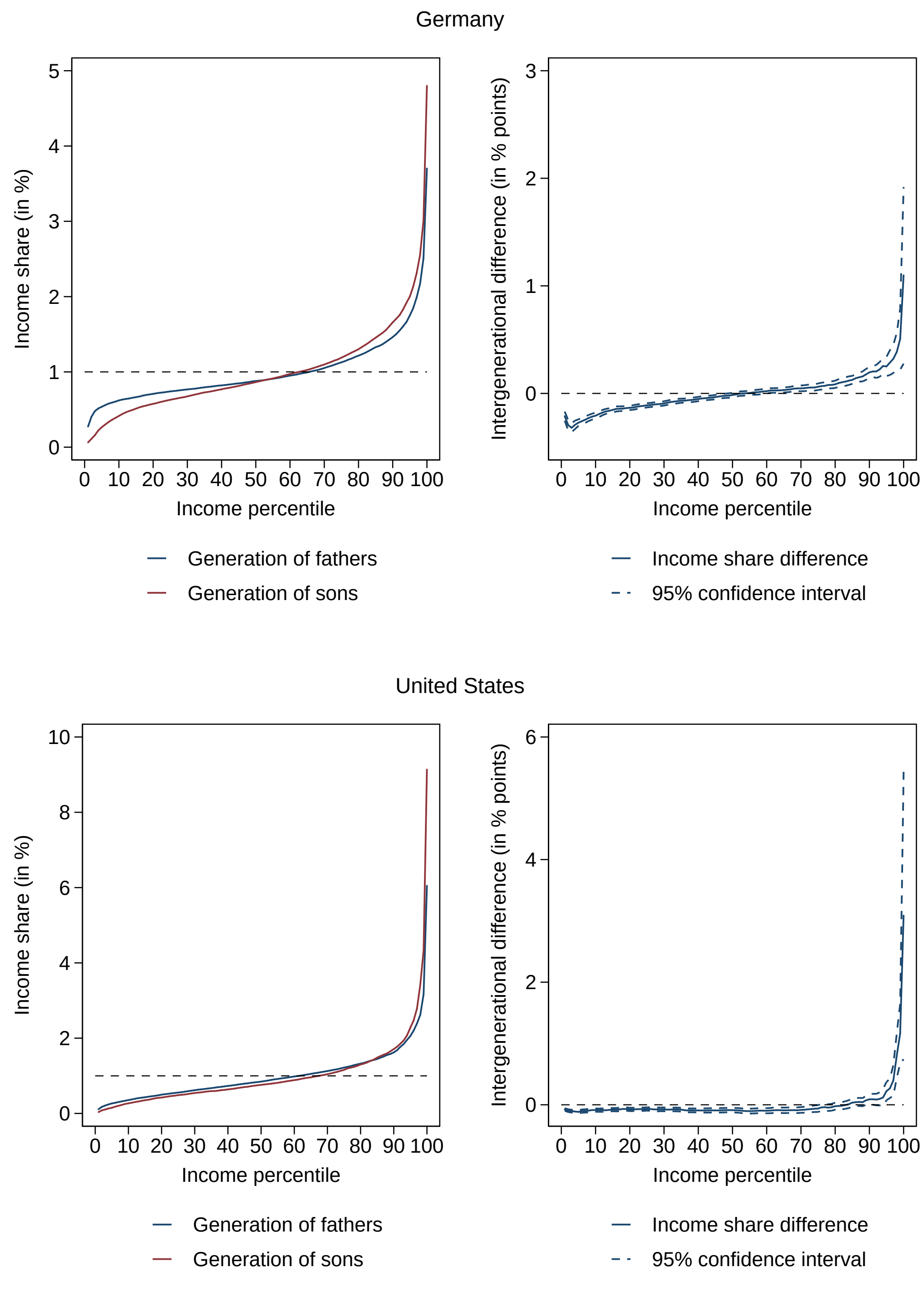
	Generation of the fathers (1984-1993)	**Generation of the sons (2003-2013)**
Germany	21.44	30.55
United States	33.48	41.32

Source: SOEP (1984-2013), PSID (1984-2013).
Notes: Income inequality is estimated based on unweighted samples. A comparison with weighted values shows that the effects of panel mortality and selection bias are minor. The demarcations from Section 2.2.2 were applied, but the sample was not limited to father-son pairs.

Figure 2.3 shows that there were both winners and losers as a result of this development. The quantile curves for Germany and the United States show the share of the total income covered by the respective percentile of the income distribution (left partial figure). Percentiles with values smaller than one claim a disproportionately low share of the total income for themselves, while percentiles with values greater than one claim a disproportionately high share. The income share curves assume a slightly s-shaped run in Germany, while the United States exhibits rather convex curves. In Germany, fathers from the 65th and sons from the 62nd percentile on possess a disproportionate share of total income, while in the United States fathers from the 61st and sons from the 67th percentile on receive a disproportionate share of total income. Thus, the two countries do not differ much with regard to the proportionality limit. However, the empirical picture changes when considering the top income percentile. The top 1 percent of income earners in Germany receive 3.7 percent of the total income in the fathers' generation and 4.8 percent in the sons' generation, while in the United States these values are found to be 6.0 percent for the fathers and 9.1 percent for the sons.[9] The quantile curves of the two generations intersect at the 53rd percentile in Germany and at the 83rd percentile in the United States. This means that in Germany, just over half of the sons' generation is poorer compared to their fathers' generation. In the United States, this share reaches four-fifths of the sons' generation (right partial figure). Measured in percentage points, the lower percentiles of the sons' generation must accept greater losses in Germany than in the United States. The percentile with the greatest loss in Germany loses 0.32 percentage points (66.65 percent) in comparison to the percentile of the fathers' generation, while the maximum loss in the United States is 0.12 percentage points (43.42 percent). Thus, on the one hand, the drop at the lower end of the income distribution in Germany is stronger than in the United States. On the other hand, the share of losers in the total population in the United States is greater than in Germany.

[9] The analysis of the top incomes in the SOEP and the PSID should be treated with caution, since high-income earners are systematically less likely to provide information about their income. The values can thus be biased downwards and are to be regarded as a lower limit for the true parameter.

Figure 2.3: Income share curves



Source: SOEP (1984-2013), PSID (1984-2013).
Notes: Confidence intervals were calculated using paired bootstrap resampling with 1,000 replications.

2.3.2 Intergenerational income elasticity

If the samples of the two countries are limited to the observed father-son pairs, the simple intergenerational income elasticity can be determined using OLS estimations (Table 2.3).

Table 2.3: Intergenerational income elasticity

	Germany		**United States**	
Dependent variable: Log. income (son)				
Log. income (father)	0.3114***	0.3180***	0.4929***	0.4639***
	(0.0801)	(0.0777)	(0.0722)	(0.0723)
Age (son)		0.3025		-1.2207
		(1.2841)		(1.2906)
Age^2 (son)		-0.0039		0.0163
		(0.0167)		(0.0168)
Age (father)		-0.0347		0.0208
		(0.1258)		(0.1070)
Age^2 (father)		0.0005		-0.0002
		(0.0014)		(0.0012)
Observations (son)		0.0291		0.1336**
		(0.0280)		(0.0544)
Observations	354	354	601	601
R^2	0.0448	0.0722	0.1080	0.1397

Source: SOEP (1984-2013), PSID (1984-2013).
Notes: Estimations for the SOEP are based on non-imputed income data. The intergenerational income elasticities have been determined for an annual lower income limit of 1,200 Euro/US dollar. Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

For Germany, a value of 0.3114 is obtained, while in the United States, the value is 0.4929. According to this, 31 percent of the father's income advantage or disadvantage is passed on to his son in Germany and 49 percent of the father's income advantage or disadvantage is passed on to his son in the United States. Including polynomials of the average age of the father and the son as well as the number of valid observations of the son, the estimates change only slightly. Therefore, we can assume that the selected age limits are chosen correctly. Thus, at first glance, intergenerational income elasticity is higher in the United States than in Germany.

Table 2.4: Intergenerational income elasticity for different lower income limits

	Germany		**United States**
	Without imputed income data	With imputed income data	
Income > 1,200 Euro/US dollar			
IIE	0.3180***	0.2889***	0.4639***
	(0.0777)	(0.0809)	(0.0723)
Observations	354	392	601
R^2	0.0722	0.0743	0.1397
Income > 6,000 Euro/US dollar			
IIE	0.3238***	0.3360***	0.4600***
	(0.0711)	(0.0739)	(0.0622)
Observations	348	387	583
R^2	0.1032	0.1199	0.1688
Income > 12,000 Euro/US dollar			
IIE	0.3591***	0.3666***	0.4187***
	(0.0704)	(0.0667)	(0.0606)
Observations	337	376	557
R^2	0.1299	0.1515	0.1533

Source: SOEP (1984-2013), PSID (1984-2013).
Notes: Other control variables include polynomials of the father's and the son's age as well as the number of valid observations of the son. Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. IIE: Intergenerational income elasticity.

The baseline estimations include observations with earned incomes of at least 1,200 Euro/US dollar per year. However, such a low income is not sufficient for the survival of a single individual in either country without additional income sources or social transfers. Thus, the estimates are repeated for lower income limits of 6,000 Euro/US dollar and 12,000 Euro/US dollar per year (Table 2.4). For Germany, the estimates were conducted both with and without imputed income data. The two countries show different developments of intergenerational income elasticity.

The intergenerational income elasticity in the United States decreases with a rising lower income limit from an estimated value of 0.4639 to an estimated value of 0.4187. The intergenerational income elasticity in Germany increases from 0.3180 to 0.3591 without imputed incomes and from 0.2889 to 0.3666 with imputed incomes. Thus, the gap between the United States and Germany is shortened by an increase in the income limit, even though the United States exhibits higher intergenerational income elasticities across all lower income limits. Since with a rising lower income limit, an increasingly larger piece is cut off at the left-hand side of the income distribution, the estimates provide evidence that the intergenerational income elasticity might differ along the income distribution.[10]

2.3.3 Intergenerational rank and income share mobility

As a starting point, estimated transition matrices offer the possibility to further examine intergenerational income mobility by providing information about nonlinearities along the income distribution and differences between upward and downward mobility. Here, the position of the son in the children's income distribution is conditioned to the position of his father in the parents' income distribution. More specifically, each value indicates the probability of a son to reach a certain quintile depending on his father's quintile affiliation. Thus, in a completely mobile society, all cells should assume a value of 0.2. The income position of the son is then independent of the income position of his father. In a completely immobile society, on the other hand, the main diagonal assumes a value of one with a value of zero being assigned to all remaining cells. In this case, the income position of the son can be perfectly predicted from the income position of his father.

[10] Considering the birth cohorts of the fathers and sons as well as including periods of unemployment, we find no major differences in the intergenerational income elasticity in Germany and the United States after accounting for influential observations according to Belsley et al. (1980) (see Table 2.8 in the Appendix).

Table 2.5: Estimated transition matrices

	Germany				
	Income quintile (son)				
Income quintile (father)	1	2	3	4	5
1	**27.31**	24.52	21.87	16.19	10.11
2	26.53	**24.31**	22.08	16.59	10.48
3	15.28	18.88	**23.24**	23.52	19.08
4	11.57	15.85	22.11	**25.95**	24.51
5	7.66	11.73	19.13	27.70	**33.78**

	United States				
	Income quintile (son)				
Income quintile (father)	1	2	3	4	5
1	**39.16**	21.79	18.33	11.49	9.23
2	27.89	**20.52**	21.26	15.82	14.51
3	17.12	16.30	**21.70**	20.74	24.14
4	13.20	13.81	20.52	**22.31**	30.15
5	8.29	9.77	17.02	22.92	**42.01**

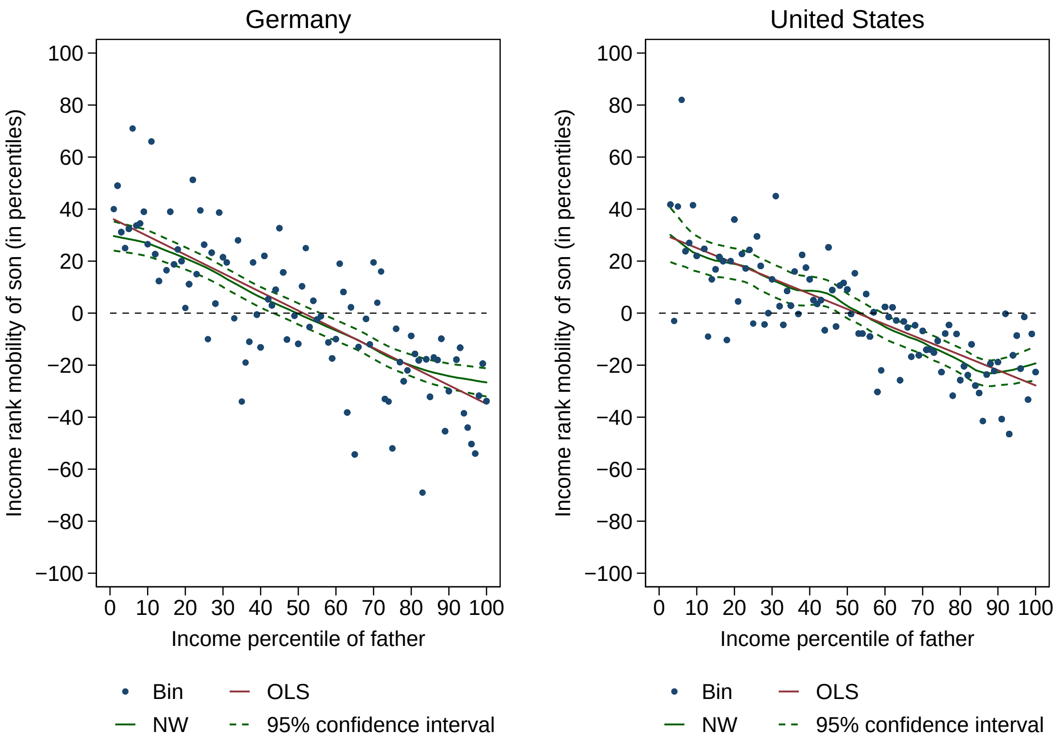
Source: SOEP (1984-2013), PSID (1984-2013).
Notes: The income positions of fathers and sons are based on the unweighted income distribution of their respective generation. Other control variables include polynomials of the father's and the son's age as well as the number of valid observations of the son.

Along the main diagonal, the results for Germany and the United States differ strongly from one another only in the lowest and the highest quintiles (Table 2.5).[11] In the United States, the probability of a son whose father is located in the lowest quintile remaining in that quintile is 39.16 percent, whereas the probability is 27.31 percent in Germany. Likewise, the probability of a son whose father is located in the highest quintile remaining in that quintile is 42.01 percent in the United States and 33.78 percent in Germany, respectively. However, the upward mobility of sons from the higher quintiles is more pronounced in the United States. Consequently, the downward mobility of sons from the higher quintiles is slightly higher in Germany. Overall, intergenerational persistence at the bottom and the top of the income dis-

[11] Since income quintiles are an ordinal variable, the transition probabilities of the sons are estimated using ordered logistic regressions (Fertig, 2003, Schnitzlein, 2009). Subsequently, the estimated transition probabilities are averaged over the entire sample.

tribution appears to be stronger in the United States than in Germany, although the differences are not very pronounced.

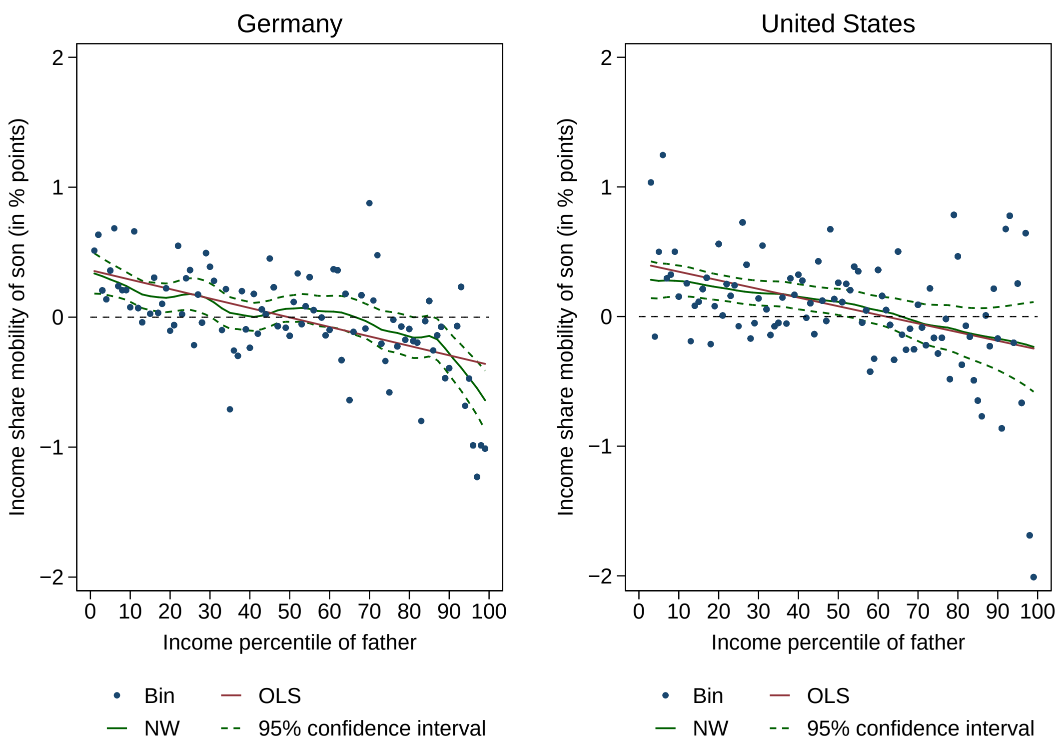
Figure 2.4: Intergenerational rank mobility



Source: SOEP (1984-2013), PSID (1984-2013).
Notes: The Nadaraya-Watson estimation uses the Epanechnikov kernel with a bandwidth according to Silverman's rule of thumb. OLS: Ordinary least squares, NW: Nadaraya-Watson.

The analysis of intergenerational mobility curves refines the picture of upward and downward mobility along the income distribution. The intergenerational rank mobility measures by how many percentiles the son is expected to ascend or descend dependent on the income position of his father. The estimated curves show a negative slope in both countries, with an OLS estimate of -0.7167 for Germany and -0.5873 for the United States (Figure 2.4). Thus, if the father's income position increases by one percentile, the absolute rank mobility of the son is reduced by 0.72 percentiles in Germany and 0.59 percentiles in the United States. Sons whose fathers rank in the lowest five percentiles ascend on average by 33-36 percentiles in Germany and by 28-30 percentiles in the United States. Sons whose fathers rank in the highest five percentiles descend on average by 32-35 percentiles in Germany and by 25-28 percentiles in the United States. Thus, the upward and downward mobility of the sons located at the bottom and the top of the paternal income distribution is again more pronounced in Germany than in the United States. Comparing the OLS estimates with the results of the Bin estimation and the Nadaraya-Watson estimation, it can be concluded for both countries that there is no evidence of nonlinearities in the development of intergenerational rank mobility along the income distribution of the fathers.

Figure 2.5: Intergenerational income share mobility



Source: SOEP (1984-2013), PSID (1984-2013).
Notes: The Nadaraya-Watson estimation uses the Epanechnikov kernel with a bandwidth according to Silverman's rule of thumb. OLS: Ordinary least squares, NW: Nadaraya-Watson.

In contrast, the intergenerational income share mobility measures the expected change in a family's share of the total income over two generations dependent on the income position of the father.[12] Similar to the finding of mean reversion in

[12] Incomes of sons with the same father were averaged to ensure a family comparison.

ranks, there is also mean reversion in income shares. Families that start at higher percentiles in the income distribution experience a smaller increase in income share than families that start at lower percentiles. The OLS estimation yields values of -0.0091 in Germany and -0.0121 in the United States, respectively (Figure 2.5). Thus, if the father's income position increases by one percentile, the income share mobility of the son is reduced by 0.0091 percentage points in Germany and 0.0121 percentage points in the United States. The income share of the sons whose fathers rank in the lowest five percentiles increases on average by 0.38-0.42 percentage points in Germany and by 0.58-0.62 percentage points in the United States. The income share of the sons whose fathers rank in the highest five percentiles decreases on average by 0.45-0.49 percentage points in Germany and 0.53-0.57 percentage points in the United States. However, the income drop in the United States is not statistically significant. Therefore, regarding intergenerational income share mobility, the United States is more mobile than Germany. Unlike intergenerational rank mobility, intergenerational income share mobility tends to exhibit nonlinearities in Germany. In particular, the sons located at the top of the paternal income distribution experience an abrupt reduction in income share. Thus, the empirical picture suggests that the OLS estimator actually overestimates intergenerational income share mobility due to outliers at the upper end of the fathers' income distribution.

2.3.4 Quantile regressions

For a valid assessment of nonlinearities in the relationship between the incomes of fathers and sons, estimates along the income distribution of the sons are necessary.[13] For this purpose, the intergenerational income elasticity is estimated using conditional and unconditional quantile regressions at selected percentiles of the income distribution of the sons (Table 2.6).

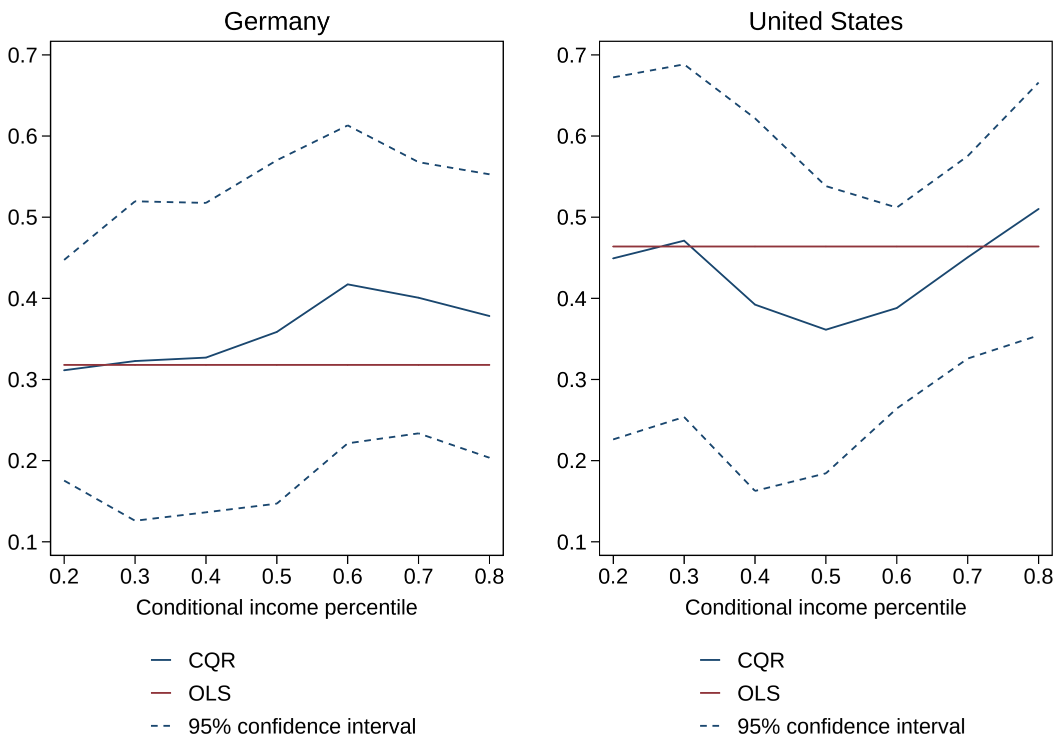
[13] The empirical picture is mixed for both Germany and the United States. Lillard (2001) and Couch and Lillard (2004) find evidence of a nonlinear run of intergenerational income elasticity for both countries. Bratsberg et al. (2007) determine a more or less linear relationship for the United States. Schnitzlein (2009, 2016) also finds no significant difference along the conditional income distribution in Germany.

Table 2.6: Quantile regressions

	Germany		**United States**	
	CQR	UQR	CQR	UQR
20th percentile				
IIE	0.3114***	0.2483**	0.4493***	0.4268***
	(0.1036)	(0.1034)	(0.0868)	(0.1044)
Pseudo R^2	0.0476	0.0351	0.0701	0.0583
40th percentile				
IIE	0.3270***	0.4178***	0.3923***	0.3765***
	(0.0891)	(0.0862)	(0.0908)	(0.0702)
Pseudo R^2	0.0623	0.1049	0.0634	0.0925
50th percentile				
IIE	0.3586***	0.4093***	0.3613***	0.3935***
	(0.0968)	(0.0809)	(0.0798)	(0.0657)
Pseudo R^2	0.0719	0.1221	0.0665	0.1067
60th percentile				
IIE	0.4173***	0.4068***	0.3881***	0.4000***
	(0.0934)	(0.0876)	(0.0614)	(0.0666)
Pseudo R^2	0.0731	0.1132	0.0737	0.0961
80th percentile				
IIE	0.3782***	0.4420***	0.5101***	0.4782***
	(0.0716)	(0.1106)	(0.0707)	(0.0926)
Pseudo R^2	0.0856	0.0768	0.0883	0.0924
Observations	354	354	601	601

Source: SOEP (1984-2013), PSID (1984-2013).
Notes: Other control variables include polynomials of the father's and the son's age as well as the number of valid observations of the son. Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. IIE: Intergenerational income elasticity, CQR: Conditional quantile regression, UQR: Unconditional quantile regression.

Figure 2.6: Conditional quantile regressions



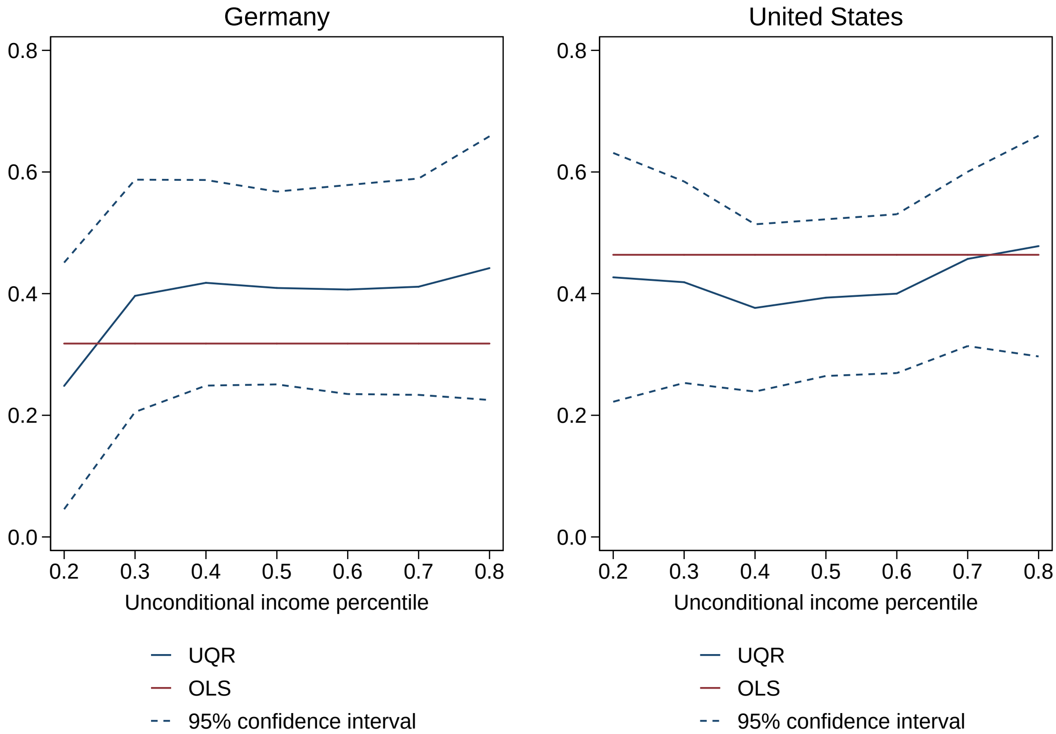
Source: SOEP (1984-2013), PSID (1984-2013).
Notes: Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1,000 replications. CQR: Conditional quantile regression, OLS: Ordinary least squares.

The conditional quantile regressions show a slightly hump-shaped run for Germany and a u-shaped curve for the United States over the conditional income quantiles of the sons.[14] Using conditional quantile regressions, however, statements about a nonlinear run of the intergenerational income elasticity can only be made when the monotonicity of the estimation parameter along the income distribution is unambiguous.[15] Likewise, for both Germany and the United States, the 95 percent confidence interval completely covers the OLS estimator of intergenerational income elasticity (Figure 2.6). Thus, neither a concave nor a convex run of the intergenerational income elasticity in Germany and the United States can be verified.

[14] The conditional quantile regression defines the income quantile of the son conditional on the income of his father and estimates the intergenerational income elasticity on the conditional quantile of the income distribution of the son (Koenker and Bassett, 1978, Koenker, 2005).

[15] Simple Wald tests show that the estimates do not differ significantly across the percentiles either for Germany ($p = 0.7857$) or for the United States ($p = 0.1793$).

Figure 2.7: Unconditional quantile regressions



Source: SOEP (1984-2013), PSID (1984-2013).
Notes: Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1,000 replications. UQR: Unconditional quantile regression, OLS: Ordinary least squares.

Using conditional quantile regressions, insights into how strong the effect of parental income is for the sons at the selected quantile of the marginal income distribution cannot be obtained. For such questions, the unconditional quantile regression or RIF regression is suitable (Firpo et al., 2009). In Germany, the intergenerational income elasticity assumes an s-shaped curve along the ascending quantiles. Between the 40th and the 60th percentile, it is relatively constant at about 0.4, whereas it is lower for the 20th percentile and higher for the 80th percentile. The intergenerational income mobility is therefore higher at the lower end of the income distribution of the sons and slightly decreases when moving upward through the quantiles. In the United States, the development of the estimation parameters across the quantiles takes on a slightly u-shaped form. According to this, intergenerational income mobility is higher in the middle range of the income distribution of the sons than at the lower and upper end of the income distribution. While the curve for Germany indicates a convex development, the United States displays an initially concave and then a convex course. However, the deviations from proportionality must be interpreted with caution since the confidence bands for both countries are relatively large and always contain the respective OLS estimator (Figure 2.7). Overall, the results of the conditional and unconditional quantile regressions provide no clear indication of nonlinearities in the development of intergenerational income elasticity over the income distribution of the sons either for Germany or for the United States.

2.3.5 Decomposition of intergenerational income inequality

Viewing the fathers and the sons as representatives of their families at different points in time, the income inequality between families for two generations can be measured.[16] In Germany, income inequality has risen by 3.11 Gini points (13.54 percent) from an initial value of 22.94 Gini points to a final value of 26.05 Gini points. In the United States, income inequality has increased by 7.35 Gini points (21.98 percent) from an initial value of 33.43 Gini points to a final value of 40.77 Gini points (Table 2.7).[17] Thus, in both countries, income inequality has increased over time, but the increase was stronger in the United States than in Germany.

In principle, the smaller rise in income inequality in Germany could reflect a pattern of either progressive income growth being offset by significant reranking or simply fewer changes overall. Our results show that the former was the case: income growth was more pro-poor in Germany than in the United States. The decomposition according to Jenkins and Van Kerm (2006) shows that progressive income growth has reduced income inequality by 14.71 Gini points (64.14 percent) in Germany and by 15.43 Gini points (46.16 percent) in the United States. Thus, in the case of unchanged income positions of the families in the second generation,

[16] Since a father can have several economically active sons, the incomes of the sons of a family were averaged in the calculations.

[17] Note that the obtained Gini coefficients differ from those presented in Section 2.3.1 because in-sample rather than overall observations are used.

there should have been a strong reduction in income inequality. However, income mobility in both countries overcompensates for progressive income growth, such that income inequality between families ultimately increases. In Germany, income mobility raises income inequality by 17.82 Gini points (77.68 percent), whereas in the United States, income inequality is increased by 22.78 Gini points (68.14 percent). Thus, Germany exhibits both more progressive income growth and higher income mobility as measured by percentage of the initial Gini coefficients in comparison to the United States.

Table 2.7: Decomposition of intergenerational income inequality

	Germany	**United States**
Initial Gini of the fathers	22.94	33.43
Final Gini of the sons	26.05	40.77
	Sizes in Gini points	
Δ Gini	3.11	7.35
Mobility	17.82	22.78
Progressive income growth	14.71	15.43
	Sizes in percent of initial Gini	
Δ Gini	13.54	21.98
Mobility	77.68	68.14
Progressive income growth	64.14	46.16

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

2.4 Recommendations for economic policy

Our results suggest that paternal income has a strong influence on the future income of the sons both in Germany and the United States. Although there are no indications of nonlinearities which might be caused by credit market constraints, the substantially lower intergenerational income elasticity in, e.g., the Scandinavian countries indicates the additional influence of exogenous determinants on the success of children from poor households. Thus, measures to mitigate these exogenous influences can reduce intergenerational income elasticity and facilitate a more efficient use of the human capital in society.

However, stronger redistribution of income via the tax and transfer system does not necessarily have a positive effect on the level of social mobility. Although the disposable incomes of poor and rich families converge as a result of more redistribution, a more progressive tax and transfer system leads to a declining return to human capital in the labor market, and thus to a reduction in the incentive to invest in education. While this is true for all families, it affects poor households relatively more strongly than it does rich households. In sum, a higher level of redistribution could even reduce intergenerational income mobility. The method of choice should therefore be an improvement in the institutional design of the preschool and school system to increase equality of opportunity without severe distortion of market processes.

Early childhood education

The barriers to the later income of relatively poor children are not found in the late stages of education, but rather in early childhood care. Stimulation that children experience in the early stages of brain development greatly influences the limits of future mental capability. A stimulating environment thus results in improved cognitive development, better social skills, and better health (Knudsen et al., 2006).

While children whose families have above-average incomes and human capital are able to receive this stimulation at home, this support often falls by the wayside in less well-off families. Lee and Burkam (2002) show that there are already severe differences in education between children from different social backgrounds at the beginning of preschool. As these differences are expected to grow over the course of the children's education, this means that early childhood care is of great importance. Thus, for children from socio-economically weak households, incentives and opportunities must be created for their earlier attendance of public or private childcare facilities where they can be supported according to their abilities.

This particularly applies to those children with an immigration background who first come into contact with the German language at day care centers or in kindergarten. In 2016, however, only 21 percent of children under 3 years of age with a migrant background visited day care, while 38 percent of under-3-year-olds with no migration background did so (Federal Statistical Office, 2017). An expansion of childcare facilities especially for children under 3 years of age as well as a good staff-to-student ratio with well-trained educators would therefore be conductive to higher intergenerational income mobility. The German *Betreuungsgeld*, a childcare subsidy for parents who raise their under-3-year-olds at home, is obviously not.

Desegregation

Another starting point is the pronounced segregation of children according to their social background. This problem is particularly evident in the strong heterogeneity of the quality of schools in Germany. The variation in the 2009 PISA scores between schools is 68 percent, which is well above the average of 42 percent for the OECD countries. At the same time, the variance in the results within the individual schools is only 45 percent, which is considerably below the OECD average of 65 percent (OECD, 2012). Thus, pupils at the respective schools are at a comparable level, while the variation between the performance of pupils in good and bad schools is substantial.

Musset (2012) illustrates that a large part of educational segregation can be traced back to local segregation. On the one hand, families with a lower educational level spend less time choosing a school for their children and often suffer from a considerable information deficit with regard to the educational system and the quality of schools (Hastings et al., 2005). Thus, families with a weaker socio-economic status tend to send children to the locally nearest school, while wealthy families choose the subjectively best school for their children and tend to avoid schools with a high number of children from socially vulnerable families (Schneider and Buckley, 2002, Raveaud and Zanten, 2007). On the other hand, a strong variation in school quality means that the demand for spots at good schools exceeds the existing capacities. In such cases, the risk of so-called *cream skimming*, i.e., the selection of subjectively better pupils, is high (Lubienski, 2006). Here, the location of children's homes is an indicator of their social background, which can be used by schools as a basis for the selection of pupils. Thus, if cities become increasingly segregated by social background, this intensifies the problem of intergenerational income persistence.

To increase intergenerational income mobility, investments in the education system must therefore primarily promote equal opportunity and desegregation. A simple enhancement in educational spending is not an adequate means of increasing social mobility: the higher the average level of human capital, the more difficult the process of catching up is for pupils from disadvantaged families (Hanushek, 2003). A so-called *formula funding* based on the Dutch model could help to decrease cream skimming and reduce the segregation of children according to social status. Here, a weight is assigned to each student and the financial resources allocated to a certain school are calculated based on the sum of the weights of its students. If pupils from disadvantaged families are assigned a higher weight, there is an incentive for schools to accept these pupils. This also takes account of the fact that due to the more intensive support they require, the admission of disadvantaged children may be more cost-intensive in some circumstances.

Secondary school tracking

Another issue often discussed in politics is the division of pupils into various secondary school tracks after only four years of elementary school in Germany. Thus, while the median age of first formal selection is 15 years in the OECD countries, selection in Germany takes place when students are only 10 years old (OECD, 2012). As a consequence, the decision as to whether a child apprentices to learn a trade or attends university is made very early in most cases. However, children's level of education is one of the most important determinants for their adult income and heavily influences the probability of becoming unemployed during their working life.

In 2015, the unemployment rate of persons aged between 15 and 74 who earned a degree below the secondary education level was 11.2 percent in Germany. In contrast, the possession of a secondary (4.3 percent) or tertiary education level (2.3 percent) leads to a significantly lower probability of unemployment (European Commission, 2017).

However, the decision to attend a particular type of secondary school depends heavily on the education level of the parents. While 43.8 percent of the parents of children at the German *Hauptschule* also attended this institution, only 7.2 percent of the parents of pupils at the *Gymnasium* did so. Similarly, 62.5 percent of the parents of children at the *Gymnasium* achieved a high school diploma, while only 14.5 percent of the parents of children at the *Hauptschule* have (Federal Statistical Office, 2017). Therefore, later secondary school tracking, e.g., at the age of 12 instead of 10, as a measure to support equality in the schooling system has been discussed for some time. A similar school reform in Finland has led to a reduction of intergenerational income elasticity by 23 percent (Pekkarinen et al., 2009). Hanushek and Wößmann (2006) confirm that early tracking is associated with a significantly larger inequality of performance between pupils, while there are no significant effects on the overall performance. In contexts where there is reluctance to delay early tracking in the short term, the negative effects could be lessened by an improvement of the selection methods for the different tracks, a limitation of grouping to specific subjects, and an increase in the flexibility to change tracks.

2.5 Conclusion

The present study examines the structure and extent of intergenerational income mobility in Germany and the United States with the help of different statistical concepts. In line with existing results, intergenerational income elasticity in the United States is higher than in Germany. While the results for intergenerational rank mobility are relatively similar, the level of intergenerational income share mobility is higher in the United States than in Germany. There are no indications of a nonlinear run of the intergenerational income elasticity. The decomposition of intergenerational income inequality shows both higher income mobility and stronger progressive income growth for Germany compared to the United States. Overall, we cannot identify a clear ranking of the two countries. In order to increase the level of social mobility, policy needs to focus on equality of opportunity in the educational system. This solution is more incentive-compatible in the long run than a policy of pure redistribution.

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Appendix

Table 2.8: Intergenerational income elasticity (robustness checks)

	Germany		**United States**	
	Without unemployment periods	With unemployment periods	Without unemployment periods	With unemployment periods
Dependent variable: Log. income (son)				
Log. income (father)	0.3428***	0.3283***	0.4613***	0.4433***
	(0.0776)	(0.0790)	(0.0731)	(0.0657)
Age (son)	-0.0747	1.1732	-1.3013	0.6606
	(1.2985)	(1.1114)	(1.2942)	(1.0109)
Age^2 (son)	0.0003	-0.0157	0.0175	-0.0087
	(0.0168)	(0.0143)	(0.0169)	(0.0132)
Age (father)	-0.0729	-0.0151	0.0317	0.0354
	(0.1365)	(0.1310)	(0.1081)	(0.0975)
Age^2 (father)	0.0003	-0.0003	0.0000	0.0003
	(0.0013)	(0.0013)	(0.0013)	(0.0012)
Observations (son)	0.0437	0.0047	0.1368**	-0.0114
	(0.0297)	(0.0238)	(0.0539)	(0.0450)
Birth cohort (son)	-0.0296*	-0.0230	0.0063	-0.0166
	(0.0160)	(0.0159)	(0.0187)	(0.0156)
Birth cohort (father)	-0.0436	-0.0433	0.0236	0.04944
	(0.0479)	(0.0465)	(0.0547)	(0.0495)
Observations	354	353	601	597
R^2	0.0847	0.0788	0.1402	0.1222

Source: SOEP (1984-2013), PSID (1984-2013).
Notes: Estimations for the SOEP are based on non-imputed income data. The intergenerational income elasticities have been determined for an annual lower income limit of 1,200 Euro/US dollar. Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Chapter 3

Transmission Channels of Intergenerational Income Persistence†

3.1 Introduction

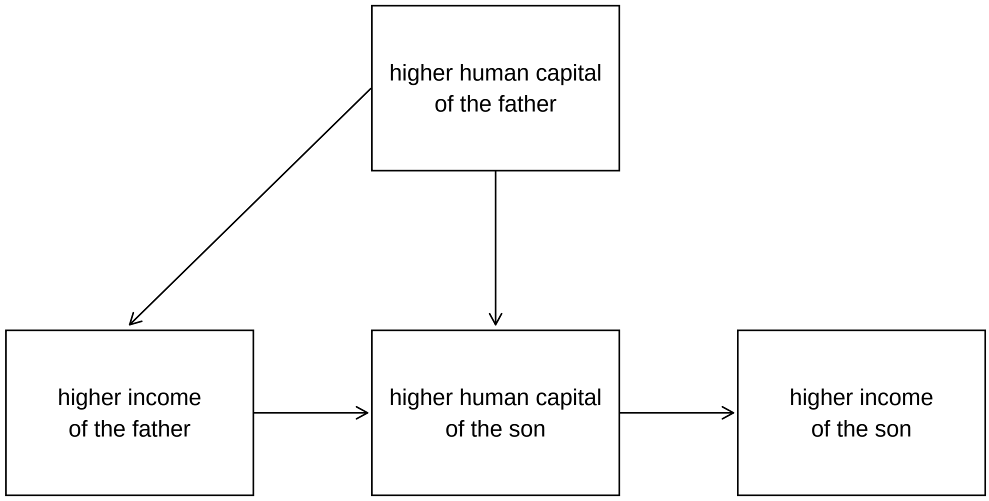
Intergenerational income persistence—the fact that children from rich families tend to have higher adult incomes themselves than children from poor families—has been extensively discussed in the economic literature since the 1980s.[18] A wide range of studies analyze the extent of intergenerational income persistence (Solon, 1992, Björklund and Jäntti, 1997, Schnitzlein, 2016), the development of intergenerational income persistence over time (Fertig, 2003, Lee and Solon, 2009, Chetty et al., 2014), and differences in the intergenerational income persistence between individual countries (Corak, 2006, Corak et al., 2014, Bratberg et al., 2017). The measure commonly estimated in order to quantify intergenerational income persistence is the *intergenerational income elasticity*, where, for example, a value of 0.3 means that 30 percent of the parents' income advantage or disadvantage is passed on to their children. Thus, if a family's income is 10 percent higher than the average income in the parental generation, the expected income of their children is 3 percent higher than the average income in the filial generation.[19]

† This chapter is co-authored with Mustafa Çoban.

[18] For a broad literature review, see Solon (1999), Björklund and Jäntti (2009), and Black and Devereux (2011).

[19] The intergenerational income elasticity is described in detail in Section 3.2.1.

Figure 3.1: Transmission channels of intergenerational income persistence



So far, however, little is known about the underlying transmission channels of intergenerational income persistence. Why exactly do children born to wealthy families earn more than less fortunate children? Essentially, there are two conceivable mechanisms (Figure 3.1). On the one hand, well-off families can use their financial resources to invest in the education of their offspring, which is then reflected in their children's higher human capital and thus higher income in adulthood (*investment effect*). This includes, for example, the attendance of private schools and universities as well as additional private lessons, which might not be affordable for children from poor families. On the other hand, if the higher parental income is at least partially determined by a higher parental human capital, more affluent families may in addition directly pass on this human capital to their children (*endowment effect*). Possible examples are the genetic transmission of certain traits, the intergenerational transfer of aspirations and skills, and at-home nonfinancial investments such as reading books or assisting with children's homework.

The economic literature is limited to very few studies that explicitly analyze the transmission channels described above. Blanden (2013) proposes a descriptive decomposition to estimate (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. She concludes that the majority of the differences in intergenerational income persistence between the United Kingdom and the United States are due to the second effect. Lefgren et al. (2012) use a structural decomposition to establish an upper and lower bound for the investment and endowment effects using data from a 35 percent sample of Swedish sons and their fathers. They show that only a minority of the intergenerational income elasticity can be plausibly attributed to the causal effect of fathers' financial resources. Cardak et al. (2013) use stochastic properties of the intergenerational income elasticity to decompose the estimate for the United States into the investment and endowment effects without the need for additional data. They find an investment effect of approximately one third and an endowment effect of approximately two thirds.

A complementary strand of the economic and sociological literature deals with the intergenerational transmission of certain characteristics that might help to explain the transmission channels of intergenerational income persistence. For example, Behrman and Rosenzweig (2002), Oreopoulos et al. (2006), and Holmlund et al. (2011) study the intergenerational transmission of education, Hauser and Logan (1992) discuss the intergenerational transmission of occupational status, and Blau (1999), Blanden and Gregg (2004), and Dahl and Lochner (2012) analyze the causal effects of parental income on children's educational achievement.

This chapter builds on the existing literature and seeks to determine the extent to which the investment and endowment effects contribute to the estimates of intergenerational income persistence in Germany and the United States. We use a linear and a nonlinear version of the Blanden (2013) descriptive decomposition method as well as a structural decomposition method as presented in Lefgren et al. (2012). Overall, we find that while the investment and the endowment effects in Germany contribute more or less equally to the estimated intergenerational income persistence, the investment effect is more pronounced in the United States. In light of the higher level of privatization in the education system of the United States, this result seems reasonable. Furthermore, we use unconditional quantile regressions in order to reveal nonlinearities in the transmission mechanisms along the income distribution. While there is a mild but steady downward trend of the endowment effect along the increasing percentiles in the United States, no clear trend can be observed in Germany. Section 3.2 subsequently presents the theoretical background which establishes the link between income and human capital. Section 3.3 describes the data used and discusses possible measurement issues. The results of the estimations are presented in Section 3.4. To conclude, Section 3.5 includes a brief summary as well as several economic policy recommendations, which can be derived from our results.

3.2 Theoretical framework

Our decomposition methods are based on the theoretical framework of Becker and Tomes (1979, 1986), wherein each family maximizes a utility function dependent on the parents' consumption and their children's future income. 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 from one another, as children who receive more parental endowments have a higher return to human capital than those who receive less 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.

3.2.1 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 their parents' degree of education. These two measures are commonly considered separately from one another, though they are indeed closely related. The standard approach in order to measure intergenerational income persistence is based on the estimation of a log-linear equation in the form of

$$\log(y_i^s) = \alpha_1 + \beta \log(y_i^f) + u_{1i}^s, \tag{3.1}$$

where y_i^s is the lifetime income of the son and y_i^f is the lifetime income of the father.[20] The intercept α_1 represents the average lifetime income in the son's generation, and the slope β is the searched-for intergenerational income elasticity. It states that an increase in a father's lifetime income by 1 percent increases the expected lifetime income of his son by β percent. If $\beta = 0$, sons' lifetime incomes are independent of their fathers' lifetime incomes. In this case, a society has complete intergenerational income mobility. 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, just like the intergenerational income persistence, by estimating a linear equation in the

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

form of

$$Ed_i^s = \alpha_2 + \gamma Ed_i^f + u_{2i}^s, \tag{3.2}$$

where Ed_i^s and Ed_i^f correspond to the son's and the father's education level, respectively. The slope γ is the searched-for intergenerational educational persistence and can be interpreted in such a way that an increase in the father's education by 1 unit raises the expected education of his 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.

3.2.2 Descriptive decomposition

Linear descriptive decomposition

It is a widely accepted fact that the education level is one of the most important determinants of a person's lifetime income. The relationship between education and income can be estimated for the fathers by

$$\log(y_i^f) = \theta^f + \delta^f Ed_i^f + \nu_i^f \tag{3.3}$$

and for the sons by

$$\log(y_i^s) = \theta^s + \delta^s Ed_i^s + \nu_i^s, \tag{3.4}$$

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 (3.3) and (3.4) can be combined with the mobility measure equations (3.1) and (3.2) to obtain

$$\beta = \left(\frac{\delta^s}{\delta^f}\gamma\right) R^2_{Ed^f} + \frac{\mathrm{Cov}(\log(y^s), \nu^f)}{\mathrm{Var}(\nu^f)}(1 - R^2_{Ed^f}) + \frac{1}{\delta^f}\frac{\mathrm{Cov}(\nu^s, Ed^f)}{\mathrm{Var}(Ed^f)} R^2_{Ed^f}, \quad (3.5)$$

where $R^2_{Ed^f}$ is given by Equation (3.3), $\mathrm{Cov}(\log(y^s), \nu^f)/\mathrm{Var}(\nu^f)$ is the estimated coefficient from a regression of the son's lifetime income $\log(y^s_i)$ on his father's income due to luck in the labor market ν^f_i, 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^s_i on the father's education Ed^f_i. The first term of Equation (3.5) can thus be interpreted as the magnitude of the intergenerational income elasticity if educational persistence were the only transmission channel, therefore capturing the endowment effect described in Section 3.1. Holding the intergenerational transmission of education constant, 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 (3.5) measures the impact of the association between the son's lifetime income and the within-education group inequalities in paternal incomes and can thus be interpreted as the investment effect described in Section 3.1. 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 (3.5) yields the cross-effect between paternal education and the residual income of the son.

Nonlinear descriptive 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) point out that the intergenerational income elasticity can assume 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, a concave run of the intergenerational income elasticity neither needs 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 fathers' 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 will consequently 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 descriptive decomposition is to be performed along the income distribution of the sons, Equations (3.1) and (3.4) are estimated by applying unconditional quantile or RIF regressions at different income quantiles (Firpo et al., 2009).[21] For this purpose, the values of the dependent variable $\log(y_i^s)$ are transformed into their corresponding RIF values using the estimation formula

$$\widehat{\mathrm{RIF}}(y_i, \hat{y}_q, \hat{\mathrm{F}}) = \hat{y}_q + \frac{q - \mathbb{1}[y_i \leq \hat{y}_q]}{\hat{\mathrm{f}}(\hat{y}_q)}, \tag{3.6}$$

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 $\mathbb{1}[y_i \leq \hat{y}_q]$ 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 (3.1) and (3.4) can then be estimated via ordinary least squares (OLS) utilizing the transformed RIF values.

3.2.3 Structural decomposition

The descriptive decomposition method described in Section 3.2.2 is likely to overestimate the impact of education in the intergenerational transmission process if the residuals of the respective equations are mutually correlated via, e.g., unobservable talents or abilities (Hirvonen, 2010). To overcome this problem, a structural approach to decompose the intergenerational income elasticity into the causal effect of financial resources, the mechanistic transmission of human capital, and the impact of human capital in the determination of fathers' permanent incomes is presented in Lefgren et al. (2012). 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 (3.2) to

$$HC_i^s = \psi + \pi_1 \log(y_i^f) + \pi_2 HC_i^f + \varepsilon_i^s, \tag{3.7}$$

[21] The estimation method of Equations (3.2) and (3.3) remains unchanged.

where $HC_i^s = \delta^s Ed_i^s$ and $HC_i^f = \delta^f Ed_i^f$. Thus, sons' and fathers' human capital are measured in Euro or US dollar, depending on their country of residence. According to Equation (3.7), a father may influence the human capital of his son via financial investments as well as through the direct transfer of human capital. The first parameter π_1 represents the share of a father's income which he invests in the human capital of his son, multiplied by the efficacy of this investment. The second parameter π_2 can be interpreted as the share of a father's human capital which is directly passed on to his son independent of financial investments (Lefgren et al., 2012). Substituting Equation (3.7) into Equation (3.4), the lifetime income of a son as a function of his father's lifetime income and human capital is expressed by

$$\log(y_i^s) = \pi_0 + \pi_1 \log(y_i^f) + \pi_2 HC_i^f + \eta_i^s, \tag{3.8}$$

where $\pi_0 = \psi + \theta^s$ and $\eta_i^s = \varepsilon_i^s + \nu_i^s$. Finally, substituting Equation (3.3) into Equation (3.8) yields

$$\log(y_i^s) = \pi_0 + \pi_1 \theta^f + (\pi_1 + \pi_2) HC_i^f + \pi_1 \nu_i^f + \eta_i^s. \tag{3.9}$$

Equation (3.9) precisely depicts the notion 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 a father's lifetime income which is due solely to his 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 (3.1) converges in probability to

$$\text{plim}(\hat{\beta}^{OLS}) = \pi_1 + \pi_2 \frac{\text{Var}(HC^f)}{\text{Var}(HC^f) + \text{Var}(\nu^f)}. \tag{3.10}$$

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. Finally, $\text{Var}(HC^f)/(\text{Var}(HC^f) + \text{Var}(\nu^f))$ represents 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 (3.5). Thus, the first part of the sum can be interpreted as the investment effect, while the second part represents the endowment effect.

Hereinafter, 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 (3.1). The estimated parameter $\hat{\beta}^{IV}$ then converges in probability to

$$\text{plim}(\hat{\beta}^{IV}) = \pi_1 + \pi_2 \frac{\text{Cov}(HC^f, Z^f)}{\text{Cov}(HC^f, Z^f) + \text{Cov}(\nu^f, Z^f)}. \tag{3.11}$$

As in Equation (3.10), 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 can be ascribed to human capital. From Equation (3.10) and (3.11), it follows that $\hat{\beta}^{OLS} = \hat{\beta}^{IV}$ if and only if $\pi_2 = 0$ or

$$\frac{\text{Var}(HC^f)}{\text{Var}(HC^f) + \text{Var}(\nu^f)} = \frac{\text{Cov}(HC^f)}{\text{Cov}(HC^f, Z^f) + \text{Cov}(\nu^f, Z^f)}. \tag{3.12}$$

Since Equation (3.12) does not generally hold, a significant difference between the OLS and the IV estimator implies $\pi_2 \neq 0$. If a Hausman test for endogeneity is rejected, it may thus be assumed that in addition to the pure investment effect, the intergenerational transfer of income is 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. Consider first the cases where the chosen instrument is correlated solely with the human capital component of the 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 the 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 in probability 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 effects.

Unfortunately, one will generally not be able to find perfect instruments for the father's human capital and luck income components. 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} should lie 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 the 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 provides 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 $R^2_{Ed^f}$ via Equation (3.3) yields a lower bound for $\text{Var}(HC^f)/(\text{Var}(HC^f)+\text{Var}(\nu^f))$. These results in conjunction with the OLS estimator $\hat{\beta}^{OLS}$ in turn allow for the estimation of an upper bound of π_1 and a lower bound of π_2.

3.3 Data and measurement issues

To examine intergenerational income mobility empirically, long-term panel data of 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 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).

3.3.1 Measurement errors and life-cycle bias

In order to measure lifetime income exactly, all of a respondent's income statements over their entire working life would be required. Thus, in the case of an academic, income observations over the course of 35 to 40 years would need to be available (Schnitzlein, 2009). 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 component and 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 intergenerational income elasticity (*attenuation bias*) (Wooldridge, 2010). Therefore, Solon (1992) proposes to form an average of five 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 it can significantly reduce it. The estimator for the intergenerational income elasticity can then be interpreted as a lower bound for the true estimation parameter.[22]

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 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 son's 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 the age range between the mid-30s and mid-40s produces a good approximation of the sons' lifetime income. Schnitzlein (2016) uses the income of sons between 35 and 42 years of age.

3.3.2 Sample definition and variables

The selected samples from the SOEP and the PSID are defined congruently so as to ensure the 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.[23] All income

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

[23] 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.

statements are deflated to 2010.[24] 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 persons who lived in West Germany in 1989 (Schnitzlein, 2009). In order to estimate the intergenerational educational persistence, we utilize years of schooling as an approximation for fathers' and sons' level of education.[25]

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.[26] 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 ages of 30 to 55 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 ages of 35 to 42 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.

Finally, a total of 353 and 602 father-son pairs are recorded in the SOEP and the PSID, respectively (Table 3.1). On average, the sons earn more than their fathers in both countries. In Germany the average income of the sons is 15.6 percent higher than the average income of the fathers, while in the United States it is only 5.1 percent higher than the average income of the fathers. The average age of the

[24] 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.

[25] This approach implicitly assumes that the impact of one more year of schooling on the level of education is linear and constant across nations and generations.

[26] 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.

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 might also determine the higher variance in incomes. German fathers on average spent 10.93 years in school, while their sons received 12.75 years of schooling. In the United States, fathers' and sons' educational attainment is relatively similar, with 13.20 and 13.82 years of schooling, respectively. On the one hand, the fathers in the United States might spend more years in school due to the longer compulsory school attendance period. While in most German federal states, 9 years of schooling are mandatory, most U.S. states require children to stay in school until the age of 16 or 18. On the other hand, the aftermath of World War II might have significantly contributed to the fathers' fewer years in education in Germany.

Table 3.1: Descriptive statistics

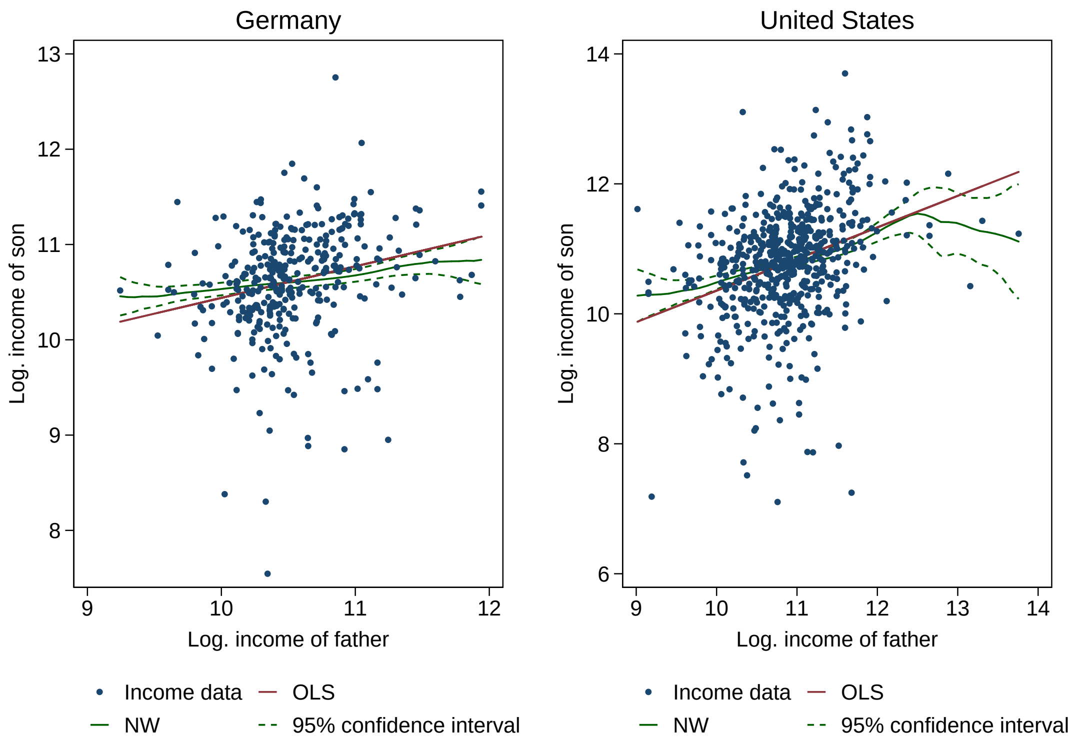
		Fathers		**Sons**	
		Mean	Std. Dev.	Mean	Std. Dev.
SOEP					
Income		40,590.37	19,576.16	46,941.29	27,652.96
Age		46.78	4.54	38.17	1.79
Education years		10.93	2.55	12.75	2.94
Father-son pairs	353				
PSID					
Income		64,019.61	59,658.27	67,280.92	69,782.23
Age		43.82	5.46	37.87	1.88
Education years		13.20	2.41	13.82	2.03
Father-son pairs	602				

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

3.3.3 Descriptive evidence

The logarithmized incomes of the fathers and sons exhibit a positive correlation (Figure 3.2). The slope of the line of best fit from the bivariate OLS regression is higher for the United States than for Germany. However, it is also obvious that the income data points in both countries are heavily scattered around the regression line. In order to examine the simple linear relationship more closely, a bivariate Nadaraya-Watson (NW) estimation is additionally depicted. Both countries show deviations compared to the OLS estimation. 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.

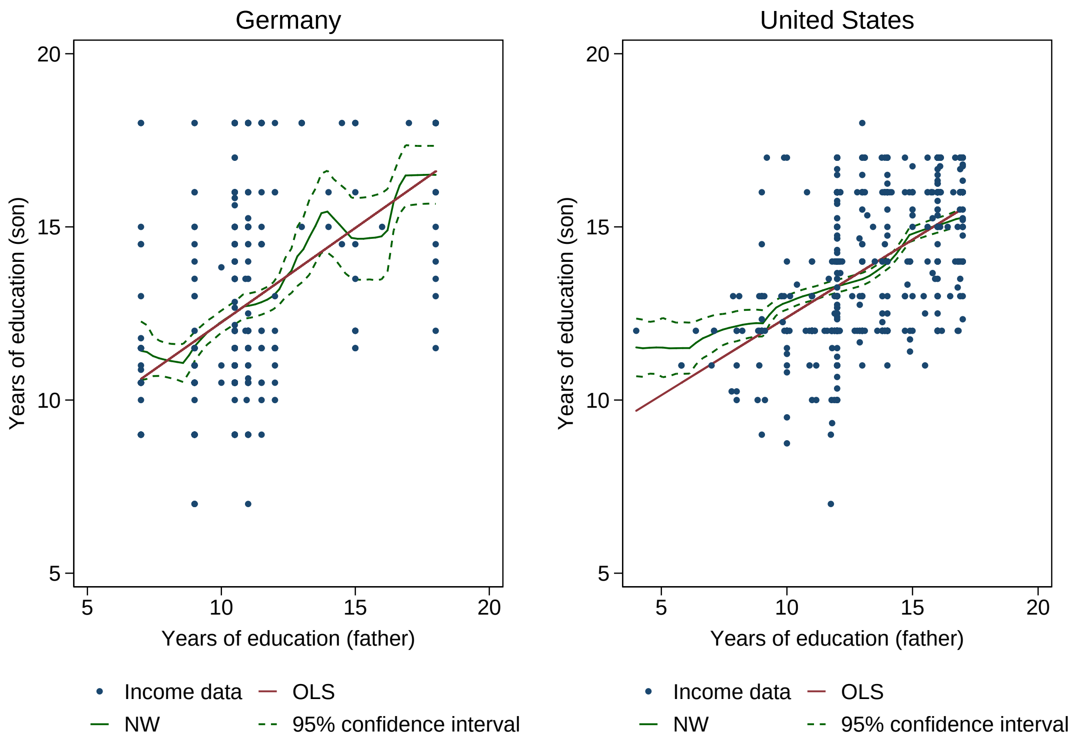
Figure 3.2: Intergenerational income correlation



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

Figure 3.3 shows the correlation between the education years of fathers and their sons. Here, the slope for Germany is higher than that of the United States, implying that sons' years of schooling depend more strongly on the education years of their fathers in Germany than in the United States. However, while the 95 percent confidence interval of the NW estimation almost completely contains the OLS estimator in Germany, the results significantly deviate from linearity in the lower education percentiles in the United States. Thus, sons of low-skilled fathers receive better education than the OLS estimation would predict. This nonlinearity might also explain the lower OLS regression slope in the United States.

Figure 3.3: Intergenerational educational correlation



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

3.4 Empirical results

The bivariate estimations in the previous section 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 in accordance with Schnitzlein (2016). With the inclusion of age polynomials and the birth years of fathers and sons as well as the number of valid observations of the son, the obtained estimators slightly decrease (Table 3.2). Notwithstanding, Germany still shows a lower intergenerational income persistence, with an estimate of 33 percent, than the United States, with an obtained value of 45 percent.

Table 3.2: Intergenerational income 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
R^2	0.053	0.083	0.089	0.224	0.236	0.243
Obs.	353	353	353	353	353	353
			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
R^2	0.108	0.140	0.143	0.284	0.295	0.297
Obs.	602	602	602	602	602	602

Source: SOEP (1984-2013), PSID (1984-2013).
Note: Cohort controls include birth years of the fathers and the sons. Age controls include polynomials of the average age of fathers and sons as well as the number of valid observations of the sons. Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In contrast, families in the United States experience a lower intergenerational educational persistence than families in Germany. While one more education year of a father in the United States provides his sons with an average of 0.44 additional years of schooling, the education years of German sons increase by 0.54 years. These contrasting results 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.

3.4.1 Descriptive decomposition

Table 3.3 shows the results of the linear descriptive decomposition as described in Equation (3.5). In Germany, the return to education is lower in both generations than in the United States. While in Germany, each year of education raises a father's (son's) income by 8.9 percent (8.7 percent), the United States exhibits a value of 16.7 percent (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.

Table 3.3: Linear descriptive decomposition

	β	γ	δ^f	δ^s	$R^2_{Ed^f}$	$\frac{\mathrm{Cov}(\log(y^s),\nu^f)}{\mathrm{Var}(\nu^f)}$	$\frac{\mathrm{Cov}(\nu^s,Ed^f)}{\mathrm{Var}(Ed^f)}$
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	Endowment effect	Investment effect	Cross-effect
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**	**0.030**	**-0.117**	**-0.068**

Source: SOEP (1984-2013), PSID (1984-2013).
Note: Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In contrast, the variation in years of schooling explains a greater portion of the variation in parental income in Germany than in the United States. While in Germany, 32 percent of income differences are attributable to fathers' education, in the United States only 23 percent of the income variance can be traced back to educational differences. However, the relationship between sons' income and the predicted luck component of their fathers' income is stronger in the United States, with a value of 0.37, than in Germany, with a value of 0.25. The estimated coefficient from a regression of the luck component of a son's income on the education years of his father does not significantly deviate from zero either in Germany or in the United States. Linking these results to the estimates of intergenerational income and educational persistence, the linear descriptive decomposition reports a higher endowment effect for Germany, with a value of 54 percent of the intergenerational income elasticity, than for the United States, with a value of 31 percent. In contrast, the United States exhibits a higher investment effect, with a value of 59 percent, than Germany, with a value of 52 percent. The cross-effect of the father's education on the son's residual income amounts to 10 percent in the United States and -6 percent in Germany. However, the value for Germany is statistically insignificant. Regarding the 47 percent difference in intergenerational income elasticity between Germany and the United States, more than three quarters is 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.

The linear descriptive decomposition estimates the average endowment and investment effects in both countries. However, there might be considerable nonlinearities in the relative importance of the two components across the income distribution. Thus, in a further step we apply unconditional quantile regressions to Equations (3.1) and (3.4) (Table 3.4). In Germany, intergenerational income persistence increases with the son's income 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.

Table 3.4: Nonlinear descriptive decomposition

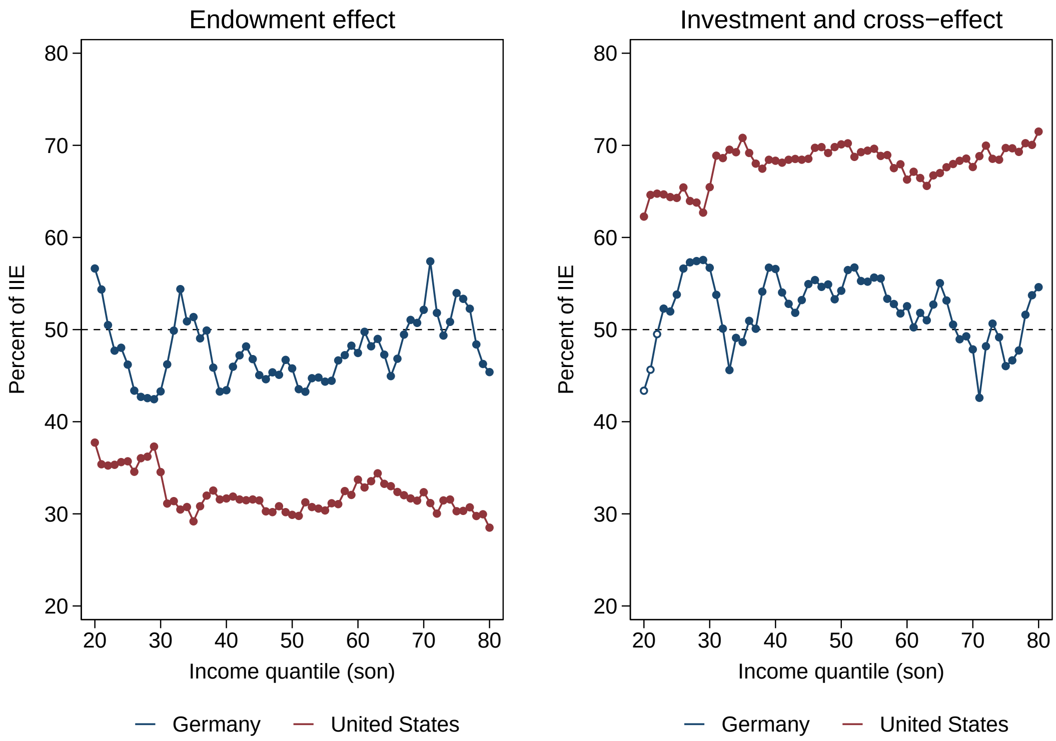
Germany	β	Endowment effect	Investment effect	Cross-effect
20th percentile	0.262**	0.148***	0.089	0.024
	(0.103)	(0.032)	(0.084)	(0.055)
40th percentile	0.424***	0.184***	0.237***	0.003
	(0.076)	(0.031)	(0.065)	(0.040)
50th percentile	0.411***	0.188***	0.228***	-0.005
	(0.076)	(0.032)	(0.067)	(0.036)
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	Endowment effect	Investment effect	Cross-effect
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).
Note: Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In conclusion, two suggestions can be drawn from these results. Firstly, the Bratsberg et al. (2007) conjecture of a convex run of intergenerational income elasticity applies to Germany rather than to the United States. This seems reasonable, as the education system in Germany is largely funded by the public sector, while privatization in the United States is strong. Thus, there might be a compensating effect at the lower end of the income distribution in Germany. Applying unconditional quantile regressions to the intergenerational educational persistence confirms this suggestion.[27] Secondly, 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.

Figure 3.4: Nonlinear descriptive decomposition



Source: SOEP (1984-2013), PSID (1984-2013).
Notes: Hollow circles are insignificant estimates at $p = 0.05$. IIE: Intergenerational income elasticity.

Figure 3.4 shows the development of the endowment and investment effects across the ascending income deciles of the sons. In the United States, the endowment effect is significantly smaller over the entire income distribution, with a value of around 30 percent, than the investment effect, with a value of approximatly 70 percent. At the

[27] See Figure 3.5 in the Appendix.

lower end of the income distribution, the endowment effect is slightly higher and, consequently, the investment effect is somewhat lower. In Germany, the endowment and investment effects are relatively constant at approximately 50 percent. Overall, the endowment effect is stronger across all income percentiles in Germany, while the investment effect is continuously higher in the United States. Since the parameters of Equations (3.2) and (3.3) 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.[28] 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.

3.4.2 Structural decomposition

Although descriptive decomposition methods are a good starting point for first insights into the transmission 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 have to be constructed.

For the human capital component of fathers' incomes, we employ years of education, level of education, and educational attainment. Fathers' 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 a father's years of education.[29] In contrast, educational attainment indicates the level of fathers' education with respect to high school education.[30]

[28] See Table 3.8 in the Appendix.

[29] (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, (5) more than 17.4 years.

[30] (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' incomes, two instruments are constructed based on fathers' months of unemployment in the observation period. This variable is likely to be highly correlated with fathers' human capital, though unemployment might also occur by chance due to exogenous shocks such as mass layoffs or changing family commitments. Therefore, in the first stage, months of unemployment are regressed on fathers' past income, level of education, and further human capital variables such as occupation and industry. Ultimately, the residuals from this regression are used as an instrument for fathers' fortune on the labor market. In addition, a second instrumental variable indicating the probability that a father—depending on his income, level of education, occupation, and industry in the first three years of the observation period—was unemployed at least once in the subsequent two or more observed years is constructed.[31] The obtained residuals should thus be orthogonal to the father's human capital by construction.

Table 3.5 shows the results of an IV estimation of Equation (3.1) using the above instrument variables. Instrumenting paternal income with years of education, level of education, and educational attainment yields quite similar results for both countries. Regardless of the chosen instrument, the obtained values 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 still do not

[31] Since the dependent variable is binary, generalized residuals from a probit regressions are calculated following the approach of Gourieroux et al. (1987).

support a rejection of the null hypothesis of equal values for Germany. Nevertheless, Lefgren et al. (2012) show that an imperfect instrument for luck which is a valid measure for an upper bound of π_1 is sufficient.

Table 3.5: IV estimation of intergenerational income elasticity

Germany	Years of education	Level of education	Educational attainment	Unemployment residuals	Employment status residuals
β	0.495***	0.527***	0.554***	0.188	0.390
	(0.177)	(0.170)	(0.192)	(0.472)	(1.113)
p-value Durbin-Wu-Hausman test	0.280	0.150	0.203	0.280	0.280
First-stage F-statistic	172.750***	45.646***	64.575***	20.134***	8.141***

United States	Years of education	Level of education	Educational attainment	Unemployment residuals	Employment status residuals
β	0.863***	0.899***	0.869***	0.341	0.401
	(0.146)	(0.160)	(0.160)	(0.288)	(0.289)
p-value Durbin-Wu-Hausman test	0.006	0.006	0.014	0.006	0.006
First-stage F-statistic	177.933***	44.121***	60.834***	38.364***	31.282***

Source: SOEP (1984-2013), PSID (1984-2013).
Note: Other control variables include the father's and the son's year of birth as well as the number of valid observations of the son. Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Since the results for the various human capital variables are of equal size, we 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 IV estimations are combined with the OLS estimation, $\text{Var}(HC^f)/(\text{Var}(HC^f) + \text{Var}(\nu^f))$ can be calculated via Equation (3.10). The results of this first bounding procedure are presented in Table 3.6.

Table 3.6: Structural decomposition I

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

Source: SOEP (1984-2013), PSID (1984-2013).
Note: Other control variables include the father's and the son's year of birth as well as the number of valid observations of the son. Standard errors are clustered at family level and were calculated using paired bootstrap resampling with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The structural decomposition suggests an upper bound for the mechanistic effect of fathers' financial resources (π_1) of 0.19 in Germany and 0.34 in the United States. In contrast, the estimated lower bound for the mechanistic effect of fathers' 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 a father's income within the given data set has turned 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 descriptive decomposition in Section 3.4.1.

The results of the alternative bounding procedure avoiding the direct estimation of π_1 are presented in Table 3.7. While a lower bound for $\pi_1 + \pi_2$ is again estimated using fathers' years of education as an instrument for human capital, a lower bound for R^2_{Edf} is now directly drawn from a Mincer regression of the father's income on several human capital variables such as level of education, occupation, and industry. Thus, in combination with the OLS results, an upper bound for π_1 and a lower bound for π_2 can be calculated using Equation (3.10). This approach produces more precise coefficients for the United States. The same is true for the variation of fathers' income due to human capital in Germany, though the results for the investment and endowment effects are still not significant at the 10 percent level.

Table 3.7: Structural decomposition II

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

Source: SOEP (1984-2013), PSID (1984-2013).
Note: Other control variables include the father's and the son's year of birth as well as the number of valid observations of the son. Standard errors are clustered at the family level were calculated using paired bootstrap resampling with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 (3.3) yields a lower bound for R^2_{Edf} of 45 percent in Germany and 27 percent in the United States. Consequently, a lower bound for 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 increases slightly, to 59 percent in Germany and 71 percent in the United States. Hence, the obtained lower bounds for the endowment effect decrease slightly to 41 percent and 29 percent, respectively. Overall, the obtained values are very similar to those in Table 3.6.

In total, the results of the structural decomposition support the findings of the descriptive decomposition with an investment effect and an 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.

3.5 Conclusion

This chapter analyzes the transmission channels of intergenerational income persistence in Germany and the United States. Using a descriptive decomposition method, we find that the mechanistic effects of fathers' financial resources and human capital are about equally high in Germany, while the investment effect in the United States accounts for approximately 70 percent of the intergenerational income elasticity. We estimate stronger nonlinearities only in the lower income quantiles in the United States, where the endowment effect is somewhat more pronounced. The results of the structural decomposition method using different bounding procedures support this supposition. However, the values should be interpreted with caution since they are insignificant for the most part.

The overall result of a stronger impact of the investment effect in the United States seems reasonable in light of a significantly higher level of privatization in the education system than in Germany. The large cross-country differences in the relative contribution of the two transmission channels emphasize that policy makers should not only focus on the level of intergenerational income mobility alone, but also on the underlying transmission mechanisms. If the endowment effect—as in the case of Germany—is very pronounced, equality of opportunity for children born to poor parents cannot be reached by the supply of financial means alone. Conversely, an efficient policy must additionally substitute for the missing direct transmission of human capital within socio-economically weak families. Appropriate means to improve intergenerational income mobility in this case might be the expansion and improvement of early childcare facilities, kindergartens, and (full-time) schools with a good staff-to-student ratio and well-trained educators.

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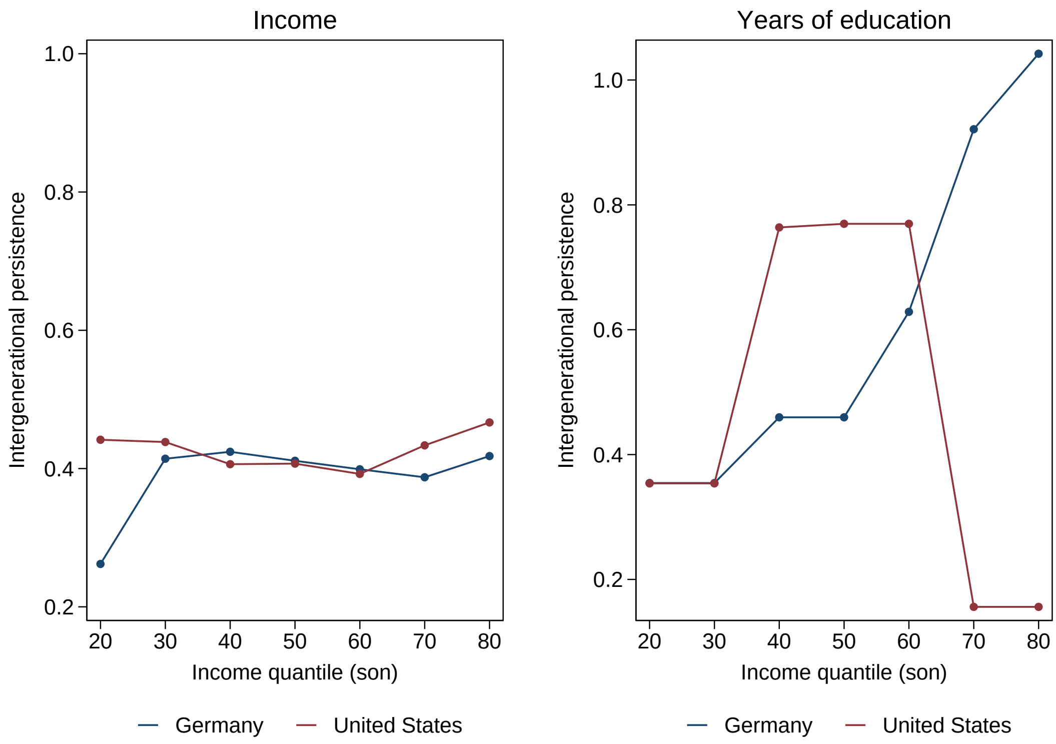
Appendix

Figure 3.5: Intergenerational persistence along the income distribution



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

Table 3.8: Nonlinear descriptive decomposition (detailed estimates)

Germany	β	γ	δ^f	δ^s	$R^2_{Ed^f}$	$\frac{Cov(\log(y^s),\nu^f)}{Var(\nu^f)}$	$\frac{Cov(\nu^s,Ed^f)}{Var(Ed^f)}$
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	$R^2_{Ed^f}$	$\frac{Cov(\log(y^s),\nu^f)}{Var(\nu^f)}$	$\frac{Cov(\nu^s,Ed^f)}{Var(Ed^f)}$
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: Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Chapter 4

Intergenerational Income Mobility among Daughters

4.1 Introduction

Intergenerational income mobility as measured by the extent to which children's adult income is predetermined by their parents' income has been discussed in the economic literature for several decades (Solon, 1999, Björklund and Jäntti, 2009, Black and Devereux, 2011). However, the majority of empirical studies focus on the association between fathers and their sons. This restriction is commonly made due to the lower labor market participation of women as compared to men. While most men work full-time, married women in particular still tend to work only part-time or not at all. Thus, the individual labor income of a daughter might be an unreliable indicator for her actual economic status. This is especially true under the assumption of assortative mating, i.e., if daughters from well-off families are likely to marry rich men and decide to reduce their labor supply as a result of their husbands' higher income (Chadwick and Solon, 2002).[32]

Studies that consider daughters are relatively rare and the results vary substantially. A comprehensive literature review is, for example, presented by Raaum et al. (2007). Early analyses that consider *individual labor income* of daughters, such as

[32] The expression "assortative mating" refers to any nonrandomness in the process of who marries whom (Chadwick and Solon, 2002). The reasons for systematic mate selection are discussed in the theoretical analyses of Lam (1988) and Becker (1991). The mostly noneconomic empirical literature documents positive correlations between spouses with respect to age, physical size, intelligence test scores, religion, ethnicity, and other personality traits (Epstein and Guttman, 1984). Empirical research by economists has focused mainly on educational attainment and earnings (Kremer, 1997).

Altonji and Dunn (1991), Peters (1992), Couch and Dunn (1997), and Mazumder (2005), estimate about equally high intergenerational elasticities for sons and daughters in the United States. In contrast, Österberg (2000), Österbacka (2001), Bratberg et al. (2005, 2007), Holmlund (2006), Jäntti et al. (2006), and Hirvonen (2008) estimate lower elasticities for women than for men in the Scandinavian countries. Dearden et al. (1997) and Blanden et al. (2004) report higher elasticities for daughters than for sons using data for the United Kingdom. For Germany, Couch and Dunn (1997) find a very low and at times even negative elasticity of women's individual earnings with respect to their parents' income. However, the cross-country pattern of daughters is similar to that of sons, with smaller estimated elasticities in the Nordic countries and larger values in the United States and the United Kingdom (Raaum et al., 2007).

Chadwick and Solon (2002) show that in the United States, the elasticity of daughters' *household labor income* with respect to her parents' income is of the same magnitude as the elasticity typically found for individual earnings of sons and their fathers. Raaum et al. (2007) find similar elasticities of family earnings with respect to parental earnings as the elasticities of individual earnings. They argue that these somewhat surprising results can be explained by strong assortative mating, which ensures that the earnings of the spouse are as closely correlated with parents' income as the children's own earnings. Atkinson et al. (1983) estimate the elasticity of the daughters' *husbands' individual income* with respect to their fathers' earnings to be just as great as the elasticity of sons' income with respect to their own fathers' earnings. Altonji and Dunn (1991) and Chadwick and Solon (2002) support these findings.

This chapter contributes to the literature on intergenerational income mobility among daughters in Germany and the United States by presenting new results based on data from the Socio-economic Panel (SOEP) and the Panel Study of Income Dynamics (PSID). The baseline regression analysis shows a higher intergenerational income elasticity in Germany and a lower intergenerational income elasticity in the

United States for women as compared to men. However, a separation by marital status reveals that in both countries, unmarried women exhibit a higher intergenerational income elasticity than unmarried men, while married women feature a lower intergenerational income elasticity than married men. The reason for the lower mobility of unmarried women turns out to be a stronger human capital transmission from fathers to daughters than to sons. The higher mobility of married women is driven by a weaker human capital transmission and a higher labor supply elasticity with respect to the spouse's income of women as compared to men. In order to further study the effects of assortative mating, the subsample of married children is analyzed by different types of income. It shows that the estimated intergenerational income elasticity of children's household incomes is even higher than that of their individual incomes. This can be seen as an indication for strong assortative mating. If household income is interpreted as a measure of children's actual economic welfare, there are barely any differences between sons and daughters. The intergenerational income elasticity of spouses' income with respect to fathers' income is again relatively high, which in turn supports the hypothesis of strong assortative mating. The elasticity of the sons-in-law with respect to their fathers-in-law in Germany is even higher than that of the sons with respect to their own fathers. In the following, Section 4.2 presents a theoretical model for the interpretation of the differences in the intergenerational income elasticity. Section 4.3 discusses potential measurement errors and reports some descriptive statistics of the data used. Section 4.4 presents the empirical results before Section 4.5 concludes.

4.2 Theoretical framework

Raaum et al. (2007) provide a framework to understand why intergenerational income elasticities may differ between women and men, wherein the primary mechanisms are assortative mating and labor supply responses both with respect to a person's own hourly wage and with respect to the spouse's wage. In a two-adult household, family earnings z_i consist of a person i's own earnings y_i and those of the spouse y_i^s, i.e., $z_i = y_i + y_i^s$. If earnings are written as the product of an average hourly wage w_i and hours worked l_i, then $\log(y_i) = \log(w_i) + \log(l_i)$. To represent the intergenerational association between parents and their children, it is assumed that the logarithmized wage of the child is a function of the logarithmized income of their parents $\log(y_i^p)$ and a term ε_i capturing the combined effect of factors orthogonal to parental earnings:

$$\log(w_i) = \alpha + \lambda \log(y_i^p) + \varepsilon_i, \tag{4.1}$$

where $0 < \lambda < 1$. The positive correlation between the economic status of parents and their children might be due to the genetic transmission of certain traits and talents, the endowments a child receives at home, and financial investments in the human capital of the child (Becker and Tomes, 1979, 1986).

Raaum et al. (2007) emphasize that the matching of spouses into marriage is not a completely random process, as it takes place in numerous private and professional environments. Educational institutions are, for example, important meeting places where the density of potential partners is high and search costs are low (Blossfeld and Timms, 2003). Evidence from different countries indicates that about 20 percent have met their spouse in school, college, or university (Lewis and Oppenheimer, 2001, Skyt Nielsen and Svarer, 2006). Another reason might be that marriage is motivated by the economic resources and the risk insurance it provides (Hess, 2004). Finally, assortative mating may also arise if individual traits and skills are complements in household production (Becker, 1973, 1974). In this model, the degree of assortative mating is captured by means of wage resemblance within partnerships:

$$\log(w_i^s) = \pi \log(w_i) + (1 - \pi) \log(\bar{w}^s) + \xi_i, \tag{4.2}$$

where $0 < \pi < 1$. Equation (4.2) expresses how the logarithmized wage of the spouse is composed of a weighted average of a person's own logarithmized wage and the average logarithmized wage in the pool of potential matches $\log(\bar{w}^s)$ plus a residual term ξ_i representing factors orthogonal to wages, where the parameter π captures the extent of assortative mating.[33] Assume further that logarithmized hours worked are a linear function of a person's own and their spouse's logarithmized wages represented by

$$\log(l_i) = \eta \log(w_i) - \eta^s \log(w_i^s) + \kappa_i, \tag{4.3}$$

where $\eta > 0$ denotes the elasticity of labor supply with respect to a person's own wage, $\eta^s > 0$ is the cross-elasticity with respect to the wage of the spouse, and κ_i includes any individual labor supply components orthogonal to wages.[34]

Combining Equations (4.1) to (4.3) and allowing η and η^s to differ between men and women, the logarithmized income of a daughter $\log(y_i^f)$ can be expressed by

$$\log(y_i^f) = \beta^f \log(y_i^p) + K_i, \tag{4.4}$$

where $\beta^f = ((1 + \eta^f) - \pi\eta^{sf})\lambda$ denotes the intergenerational earnings elasticity of the daughter with respect to her parents' income and $K_i = \kappa_i + ((1 + \eta^f) - \pi\eta^{sf})(\alpha + \varepsilon_i) - \eta^{sf}((1 - \pi)\log(\bar{w}^s) + \xi_i)$ is the combined residual term. Thus, the elasticity of daughters' earnings with respect to parents' income is increased by the intergenerational transmission of human capital λ as well as by their own wage labor supply elasticity η^f, and is lowered by the strength of assortative mating π as well as by the cross-elasticity η^{sf}. Assortative mating and family labor supply decisions are therefore important components of intergenerational income mobility, even if the analysis is restricted to individual earnings. In the same manner, Equations (4.1) to (4.3) can be utilized to derive the association between the income of the daughter's

[33] Note that assortative mating is defined in terms of *potential* incomes rather than *realized* incomes. When spouses make joint decisions with respect to labor supply, even a close matching on potential earnings will not necessarily imply that actual earnings are highly correlated as a higher spousal wage induces a negative own labor supply response (Raaum et al., 2007).

[34] In principle, wage elasticities can be positive or negative as long as leisure is a normal good. The assumption of positive elasticities is justified by empirical results indicating that a person's own wage elasticity is positive but close to zero for men and strictly positive for married women (Killingsworth, 1983, Blundell and MaCurdy, 1999), whereas the elasticity with respect to the partner's wage is close to zero for men and significantly negative for women (Lundberg, 1988, Juhn and Murphy, 1997, Eckstein and Wolpin, 1989, Devereux, 2004, Blau and Kahn, 2007).

husband and that of her parents:

$$\log(y_i^{sf}) = \beta^{sf} \log(y_i^p) + K_i^s, \tag{4.5}$$

where $\beta^{sf} = ((1+\eta^m)\pi - \eta^{sm})\lambda$ denotes the elasticity of the husband's earnings with respect to the income of his parents-in-law and $K_i^s = \kappa_i + ((1+\eta^m)\pi - \eta^{sm})(\alpha + \varepsilon_i) - (1+\eta^{sm})((1-\pi)\log(\bar{w}^s) + \xi_i)$ is the combined error term. Thus, the in-law elasticity depends positively on the intergenerational transmission of human capital between a daughter and her parents λ, the husband's own wage labor supply elasticity η^m, and the degree of marital sorting π, while it is affected negatively by the cross-elasticity of husbands' labor supply with respect to their wives' hourly wages η^{sm}. The elasticity of the husband's earnings may exceed that of the daughter's earnings if $(1 + \eta^m + \eta^{sf})\pi > 1 + \eta^f + \eta^{sm}$, i.e., if the degree of marital sorting is strong, if the wife's labor supply is highly responsive to her husband's wage while being less influenced by her own wage, and if the husband's labor supply responds more strongly to his own wage than to the wage of his wife. The association between parental earnings and combined earnings of partners μ^f is finally represented by a weighted average of daughters' and husbands' elasticities:

$$\mu^f = (1-\theta)\beta^f + \theta\beta^{sf}, \tag{4.6}$$

where $0 \leq \theta = \bar{y}^s/(\bar{y} + \bar{y}^s) \leq 1$ is the husbands' average share of household earnings. As men on average work longer market hours and frequently receive higher wages than women, θ will typically exceed one half.

4.3 Data and measurement issues

In order to analyze intergenerational income mobility, individual data for at least two generations of parents and their children are required. For a valid country comparison, it is also necessary that the data used are highly comparable. Therefore, the

Socio-economic Panel (SOEP) for Germany and the Panel Study of Income Dynamics (PSID) for the United States are utilized in this study. Both data sets represent long-term household surveys that capture information on children while they are still living with their parents and follow them into adulthood. Thus, children who leave their homes and establish their own households can continue to be covered over time. In addition, both household surveys are part of the Cross-National Equivalent File (CNEF) project, which offers a harmonized individual data set of the underlying national household surveys. In particular, it provides a reliable data basis for international comparisons of incomes, taxes, and transfers (Frick et al., 2007).

4.3.1 Measurement errors and life-cycle bias

To exactly measure the lifetime incomes of parents and their children, all income statements of a respondent over their entire working life would be required. Thus, in the case of an academic, for example, income observations of 35 to 40 years would need to be available (Schnitzlein, 2009). However, with such a long survey period, the number of people who continue to participate is often significantly reduced. This so-called *panel mortality* might correlate with certain characteristics of a respondent (e.g., income or education), resulting in a relatively homogeneous longitudinal sample (Fitzgerald et al., 1998). Solon (1989, 1992) shows that this homogeneity leads to substantial downward distortions of the estimated parameters (*panel attrition bias*).

Lifetime incomes are thus typically approximated by means of annual income observations. However, these income statements consist of a permanent as well as a fluctuating component, where the second causes lifetime income to be determined with measurement errors (Solon, 1989, 1992, Zimmerman, 1992). Thus, if parental income is approximated by income data from only one particular point in time, the classical *errors-in-variables* problem occurs (Wooldridge, 2010). This, in turn, leads to a systematic downward bias of the estimated intergenerational income elasticity (*attenuation bias*). Solon (1992) proposes to form an average of five valid annual income statements 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. Since the direction of the bias is known, an estimate of the intergenerational income elasticity can be interpreted as a lower bound for the true estimation parameter. In the approximation of the children's lifetime income, measurement errors only lead to higher standard errors.

In addition, Haider and Solon (2006) point out that the observations of children's lifetime incomes depend on the chosen stage of life. On the one hand, individual income during the working life assumes a hump-shaped run, so that the income at the beginning of the working life is lower and thus the lifetime income of a person is underestimated. On the other hand, differences in income between high- and low-skilled workers are smaller at the beginning of their working lives and steadily increase over time. If incomes are thus observed at the beginning of the children's working life, this leads to an underestimation of intergenerational income elasticity (*life-cycle bias*). This circumstance is verified by Böhlmark and Lindquist (2006) for Sweden and Brenner (2010) for Germany. For the United States, Haider and Solon (2006) show that for sons the age range between mid-30s and mid-40s produces a good approximation of the lifetime incomes. Schnitzlein (2016) uses the income of sons between 35 and 42 years of age for Germany.

4.3.2 Sample definition

Taking the previously mentioned problems into consideration, a sample for the analysis of intergenerational income mobility has to be formed. 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 of 1984 to 2013. All income statements are deflated to the year 2010.[35] In the baseline sam-

[35] 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.

ple, individual labor earnings are used.[36] Imputed income data are excluded from the SOEP sample.[37] In order to be able to compare the results with the existing literature, annual real individual 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 persons who lived in West Germany in 1989 (Schnitzlein, 2009).

Fathers' incomes are drawn from the period of 1984 to 1993, from which at least five valid income observations must be available. The lifetime income of the father 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 from the period of 1933 to 1958. The incomes of the children 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 children 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 children belong to the birth cohorts from the period of 1961 to 1978, which do not overlap with the cohorts of their fathers.

A total of 354 (601) father-son and 261 (623) father-daughter pairs are thus recorded in the SOEP (PSID). In Germany (the United States), sons' incomes average to 46,868 Euro (68,599 US dollar) and are thus higher than daughters' average incomes of 21,553 Euro (39,937 US dollar). Fathers' incomes average to 40,333 Euro (66,418 US dollar) and are thus slightly lower than the income average of the sons. The average age of the fathers is mid-40s in both countries, while the children's average age is late 30s (Table 4.1).

[36] This variable captures wages and salaries from employees as well as self-employed individuals, and includes bonus payments, overtime pay, and shares in profits (Lillard, 2013, Grabka, 2014).

[37] 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.

Table 4.1: Descriptive statistics

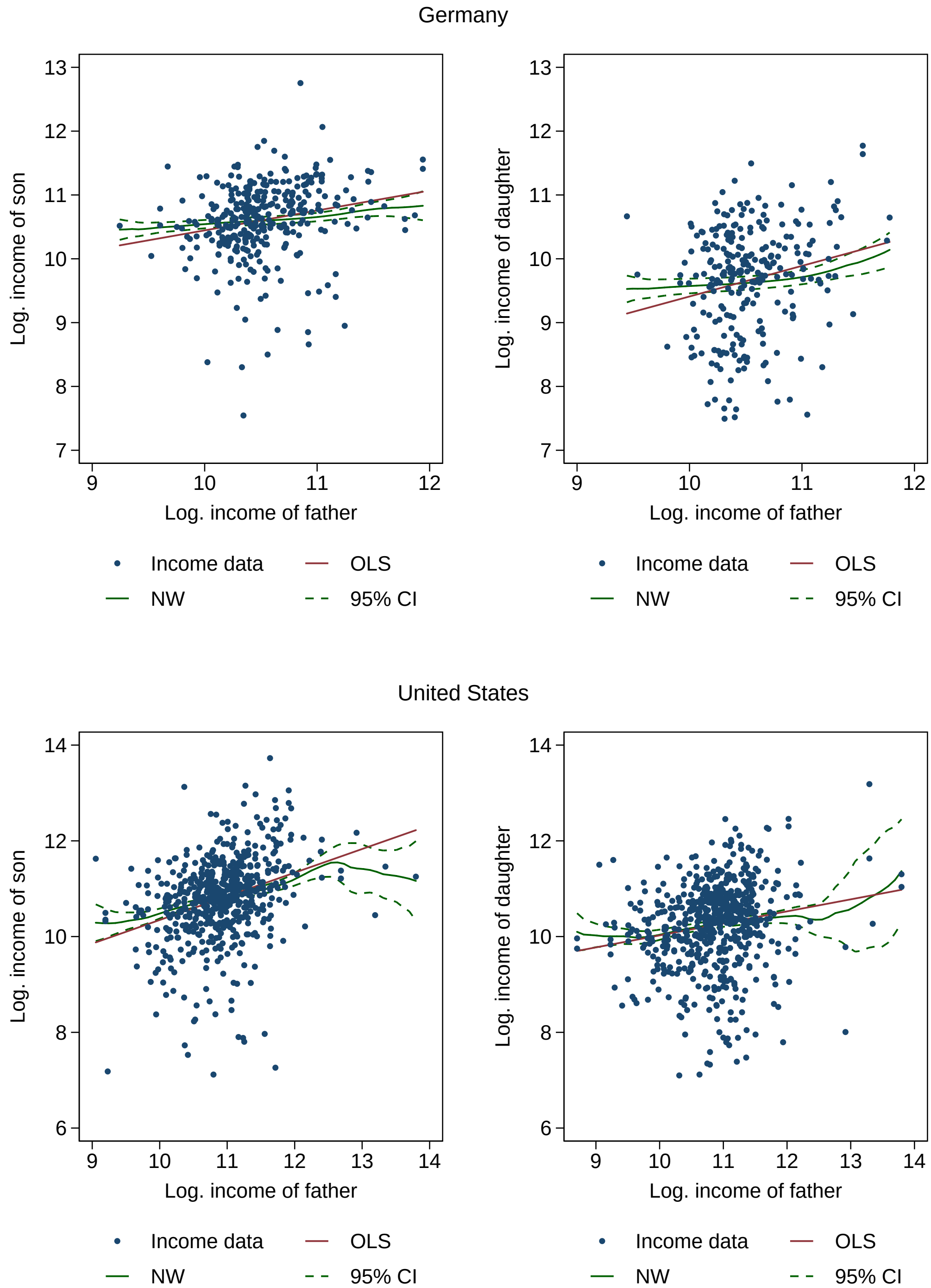
SOEP	Mean	Std. Dev.	Min.	Max.	N
Fathers					
Income	40,332.98	18,668.57	10,347.98	153,308.70	615
Age	46.55	4.68	32	53	615
Sons					
Income	46,868.19	27,724.28	1,891.89	345,753.30	354
Age	38.13	1.80	35	42	354
Daughters					
Income	21,552.95	17,488.95	1,798.41	129,572.60	261
Age	37.90	1.83	35	42	261

PSID	Mean	Std. Dev.	Min.	Max.	N
Fathers					
Income	66,418.02	68,892.81	6,026.50	981,877.40	1,224
Age	43.80	5.60	32	53	1224
Sons					
Income	68,599.45	71,238.90	1,234.57	915,955.40	601
Age	37.90	1.88	35	42	601
Daughters					
Income	39,936.94	39,241.34	1,212.12	532,325.60	623
Age	37.89	1.89	35	42	623

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

Figure (4.1) shows the intergenerational income correlation between sons and fathers and daughters and fathers, respectively. The univariate ordinary least squares (OLS) estimation implies a higher intergenerational income elasticity for the daughters in Germany, while in the United States, the OLS estimate of the sons seems to be stronger. The Nadaraya-Watson (NW) estimation shows slight deviations at the lower and upper ends of the income distribution. However, they are most likely caused by single outliers in the top and bottom income quantiles. Overall, the income data points are heavily scattered around the respective regression lines, indicating that parental earnings are not the only determinant for sons' and daughters' incomes.

Figure 4.1: Intergenerational income correlation by gender



Source: SOEP (1984-2013), PSID (1984-2013).
Notes: The Nadaraya-Watson estimation uses the Epanechnikov kernel with a range based on Silverman's rule of thumb. OLS: Ordinary least squares, NW: Nadaraya-Watson, CI: Confidence interval.

4.4 Empirical results

4.4.1 Baseline estimation

As a starting point, the intergenerational income elasticity of men and women is estimated using a lower income bound of 1,200 Euro/US Dollar per year in order to compare the results to the available literature (Table 4.2). In Germany, the intergenerational income elasticity appears to be lower for the sons, with a value of 0.3428, than for the daughters, with a value of 0.4980. These results can be interpreted in such a way that 34 percent (50 percent) of the income advantage or disadvantage of a father is transmitted to his son (daughter). Thus, if a father's income is twice as high as the average income in the parental generation, the expected income of his son (daughter) will exceed the average income of the filial generation by 34 percent (50 percent). The German sons are therefore more mobile than the German daughters. In the United States, in contrast, the sons exhibit a higher intergenerational income elasticity, with an estimate of 0.4624, than the daughters, with an estimate of 0.2607, and are therefore less mobile.

To further explore the effect of divergent labor market participation, the elasticities are re-estimated for married and unmarried sons and daughters, respectively. In both countries, unmarried women show a higher elasticity than unmarried men. In Germany, the value for unmarried daughters is 0.4791, while the value for unmarried sons does not significantly differ from zero. In the United States, unmarried daughters exhibit a value of 0.4699, whereas the estimate for unmarried sons is 0.3213. In contrast, married sons exhibit a higher elasticity than married daughters in both countries. While for married sons, a value of 0.4804 is estimated, the estimate for married daughters is lower, with a value of 0.3918, in Germany. In the United States, married sons exhibit a value of 0.4350, while the value for married daughters does not significantly deviate from zero. Thus, the higher overall elasticity for daughters in Germany is driven by unmarried children, while the higher value for sons in the

United States is driven by married children. However, the differences between sons and daughters are only statistically significant in the case of the United States for all sons and daughters ($p = 0.0341$) and for married sons and daughters ($p = 0.0064$).[38]

Table 4.2: Intergenerational income elasticity by gender and marital status

	Germany		**United States**	
	Sons	Daughters	Sons	Daughters
All				
IIE	0.3428***	0.4980***	0.4624***	0.2607***
	(0.0785)	(0.1484)	(0.0702)	(0.0662)
R^2	0.0847	0.1419	0.1412	0.0783
N	354	261	601	623
Not married				
IIE	0.2024	0.4791**	0.3213***	0.4699***
	(0.1513)	(0.1858)	(0.1179)	(0.0877)
R^2	0.1198	0.3401	0.1227	0.1624
N	134	89	203	252
Married				
IIE	0.4804***	0.3918*	0.4350***	0.1194
	(0.0929)	(0.2025)	(0.0780)	(0.0855)
R^2	0.1347	0.1324	0.1380	0.0576
N	220	172	398	371

Source: SOEP (1984-2013), PSID (1984-2013).
Notes: Covariates include polynomials of fathers' and children's age as well as their birth year and the number of valid observations of the children. Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. IIE: Intergenerational income elasticity.

The model described in Section 4.2 suggests that the intergenerational income elasticity of unmarried children is positively influenced by the impact of fathers' income on their own hourly wages λ and by the elasticity of hours worked with respect to their own wages η. To explore these determinants, λ and η are estimated for the subsamples of unmarried sons and daughters, respectively (Table 4.3). In Germany,

[38] Utilizing mothers' individual incomes, the obtained estimates are mostly insignificant.

the elasticity of hourly wages with respect to fathers' income is 0.3519 for unmarried daughters, while the estimate for unmarried sons is not statistically significant. The elasticity of hours worked with respect to their own hourly wages is about equally high for unmarried sons (0.2049) and daughters (0.2031). In the United States, the effect of fathers' income on children's hourly wages is again lower for unmarried sons (0.3238) than for unmarried daughters (0.4642). The elasticity of hours worked with respect to a person's own hourly wages is, however, not statistically significant for either gender. Thus, the higher intergenerational income elasticity of unmarried daughters is driven by a higher estimated impact of fathers' incomes on daughters' hourly wages in both countries.

Table 4.3: Determinants of intergenerational income mobility

	Germany		**United States**	
	Sons	Daughters	Sons	Daughters
Not married				
λ	0.0510	0.3519**	0.3238***	0.4642***
	(0.0926)	(0.1472)	(0.0845)	(0.0851)
η	0.2049***	0.2031**	-0.0284	0.0689
	(0.0661)	(0.0820)	(0.1584)	(0.0800)
Married				
λ	0.3524***	0.2731**	0.4149***	0.2860***
	(0.0876)	(0.1266)	(0.0661)	(0.0626)
η	0.1262*	0.1735*	-0.0433	0.0436
	(0.0737)	(0.0915)	(0.0707)	(0.0575)
η^s	0.0097	-0.1710***	-0.0113	-0.0958***
	(0.0196)	(0.0638)	(0.0207)	(0.0297)

Source: SOEP (1984-2013), PSID (1984-2013).
Notes: Covariates include polynomials of fathers' and children's age as well as their birth year and the number of valid observations of the children. In the estimation of η and η^s, the number of children age 0-14 in the household is additionally included. Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1,000 replications.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

For married children, in addition to λ and η, the intergenerational income mobility is presumably negatively influenced by the cross-elasticity of working hours with respect to the spouse's income η^s.[39] For married daughters in Germany, the effect of fathers' income on hourly wages is smaller (0.2731) than for married sons (0.3524). While the elasticity of hours worked with respect to one's own wages is slightly higher for women (0.1735) than for men (0.1262), there exist stronger differences in the elasticity of hours worked with respect to the partner's income. While sons do not react significantly to their wives' higher wages, daughters tend to reduce their labor supply with their husbands' increasing income (-0.1710). In Germany, the higher intergenerational income mobility of married daughters as compared to married sons is thus driven by a lower impact of fathers' income on hourly wages and a stronger reduction of hours worked with respect to their partner's income. These effects are counteracted though not offset by a higher elasticity of daughters' hours worked with respect to their own wages. In the United States, the impact of father's income on the hourly wage is higher for sons (0.4149) than for daughters (0.2860). The elasticity of hours worked with respect to their own hourly wages is insignificant for both genders. The elasticity of hours worked with respect to their partner's income is not statistically significant for the sons, however, daughters again reduce their labor supply with their husbands' rising income (-0.0958). Interestingly, the absolute value of this estimate is markedly lower than in Germany, implying that German women react more strongly to the income of their husbands than American women. Thus, the higher income elasticity of married sons as compared to married daughters in the United States is driven by a higher impact of fathers' income on hourly wages and a weaker reduction of hours worked with respect to partners' income.

[39] Spouses' incomes are approximated by the difference between children's household incomes and their individual incomes. In principle, partners in the SOEP and the PSID could also be matched via their personal identification number. However, this procedure further reduces the size of the already small sample. In addition, the effect of η^s is moderated by the level of assortative mating π (see Section 4.2). However, as hourly wages of the spouse cannot be observed, the comparison implicitly assumes that the strength of assortative mating is approximately equal in Germany and the United States.

4.4.2 Effects of assortative mating

The common restriction of the sample to incomes higher than 1,200 Euro/US dollar seems reasonable as an income of less than 100 Euro/US dollar per month is not sufficient for the subsistence of an individual person in either country. However, married individuals might indeed have an individual income of less than 1,200 Euro/US dollar if the labor division within the family is designed in such a way that primarily one of the spouses is active in the labor market. Therefore, the intergenerational income elasticities for married sons and daughters are re-estimated without the lower income limit of 1,200 Euro/US dollar (Table 4.4). The estimated elasticities are somewhat lower than those presented in Table 4.2, with a value of 0.2006 (0.1531) for married sons (daughters) in Germany and a value of 0.2860 (0.1451) for married sons (daughters) in the United States. However, married sons still exhibit a higher intergenerational income elasticity than married daughters in both countries.[40]

To further analyze the effects of assortative mating, the elasticity of children's household incomes with respect to fathers' incomes are additionally reported in Table 4.4. In Germany, the estimates are about equally high for sons and daughters, with values of 0.2269 and 0.2360, respectively. In the United States, the estimates are also very similar for men and women, with values of 0.2744 for the sons and 0.2671 for the daughters, though they appear to be somewhat higher when compared to Germany. Thus, although married women's individual incomes depend less strongly on their family background than those of married men, the genders do not differ much with regard to household incomes. If household income is interpreted as the actual economic status of a child, sons and daughters in the respective countries are therefore about equally mobile.

[40] If an individual features an income of zero, the logarithmized income cannot be calculated and is thus dropped from the regression analysis. To control for a sample selection bias due to this issue, a parallel Heckman estimation with the number of children younger than 14 years of age as the selection variable is performed (see Table 4.5 in the Appendix).

Table 4.4: Intergenerational income elasticities by type of income

	Germany		**United States**	
	Sons	Daughters	Sons	Daughters
Own individual income				
IIE	0.2006***	0.1531***	0.2860***	0.1451
	(0.0771)	(0.1187)	(0.0693)	(0.1056)
R^2	0.0763	0.0459	0.0973	0.0523
N	230	188	408	398
Household income				
IIE	0.2269***	0.2360***	0.2744***	0.2671***
	(0.0684)	(0.0527)	(0.0485)	(0.0563)
R^2	0.1101	0.1351	0.1172	0.1073
N	235	226	417	441
Spouse's individual income				
IIE	0.4029***	0.3755**	0.0474	0.2561***
	(0.1531)	(0.1808)	(0.0913)	(0.0613)
R^2	0.0742	0.1430	0.0244	0.0772
N	193	222	366	427

Source: SOEP (1984-2013), PSID (1984-2013).
Notes: Covariates include polynomials of fathers' and children's age as well as their birth year and the number of valid observations of the children. Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. IIE: Intergenerational income elasticity.

Because the elasticity of household incomes with respect to parental earnings is a weighted average of the children's and their spouses' elasticities (Section 4.2), the observed differences between the elasticities of individual incomes and household incomes are driven by the correlation between fathers-in-law and their children-in-law. This suggestion is supported by the estimated elasticities from a regression of the logarithmized incomes of children's spouses on the logarithmized incomes of the fathers. The elasticity of the son-in-law is estimated to be 0.3755 in Germany and is thus even higher than the corresponding value of the sons. Surprisingly, the income of the daughter-in-law is also strongly correlated with the income of her husband's father with an estimated elasticity of 0.4029. In the United States, there is no significant impact of a father's income on his daughter-in-law's income. However, the elasticity of sons-in-law with respect to their fathers-in-law is again relatively strong with an estimated value of 0.2561. This estimate is again equal in size to the corresponding value for the sons. Overall, the results imply a considerable extent of assorative mating in both countries.[41]

4.5 Conclusion

This chapter analyzes intergenerational income mobility among daughters in Germany and the United States. The baseline estimation shows a higher intergenerational income elasticity in Germany and a lower intergenerational income elasticity in the United States for women as compared to men. However, a separation by marital status reveals that in both countries, unmarried women exhibit a higher intergenerational income elasticity than unmarried men, while married women feature a lower intergenerational income elasticity than married men. The reason for the lower mobility of unmarried women appears to be a stronger human capital transmission from fathers to daughters than to sons. The higher mobility of married women is driven by a weaker human capital transmission and a higher labor supply elasticity with respect to spousal income. The estimated intergenerational income elasticity of married children's household incomes is even higher than that of their individual incomes. This can be seen as an indication for strong assortative mating. If household income is interpreted as a measure of children's actual economic welfare, there are barely any differences between sons and daughters. The intergenerational income elasticity of spousal income with respect to parental income is again relatively high, which in turn supports the hypothesis of strong assortative mating. The elasticity of the sons-in-law with respect to their fathers-in-law in Germany is even higher than that of the sons with respect to their own fathers.

[41] In the cases of the daughters-in-law in Germany and the sons-in-law in the United States, the Heckman estimation reports a significant sample selection bias. However, the results are relatively similar with values of 0.4574 and 0.2439, respectively (Table 4.5).

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Appendix

Table 4.5: Heckman estimation of intergenerational income elasticity

	Germany		**United States**	
	Sons	Daughters	Sons	Daughters
Own individual income				
IIE	0.1921**	0.2101*	0.2628***	0.1458
	(0.0777)	(0.1261)	(0.0860)	(0.1127)
N	236	228	421	443
$p(\lambda)$	1.000	0.102	0.449	0.970
Household income				
IIE	0.2264***	0.2372***	0.27722***	0.2672***
	(0.0705)	(0.0522)	(0.0514)	(0.0566)
N	236	228	421	443
$p(\lambda)$	0.639	1.000	1.000	1.000
Spouse's individual income				
IIE	0.4574**	0.3631*	-0.1203	0.2439***
	(0.1872)	(0.1886)	(0.2534)	(0.0672)
N	236	228	421	443
$p(\lambda)$	0.006	1.000	0.391	0.069

Source: SOEP (1984-2013), PSID (1984-2013).
Notes: Covariates include polynomials of fathers' and children's age as well as their birth year and the number of valid observations of the children. The number of children age 0-14 in the household is used as the selection variable. Standard errors are clustered at the family level and were calculated using paired bootstrap resampling with 1,000 replications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. IIE: Intergenerational income elasticity.

Chapter 5

Conclusive remarks

The present dissertation deals with intergenerational income mobility in Germany and the United States. The transmission process of income differences from one generation to the next is an important aspect of income inequality as it captures the dynamic component of the income distribution. A high level of intergenerational income elasticity implies that income differences are mainly caused by divergent talents, abilities, and preferences. In this case, income inequality is less problematic and might even encourage investments in human capital and efforts to increase earnings. On the contrary, if children's future level of income is predetermined for the most part by their family background, future prospects of poor children are literally eliminated. This means that a high level of intergenerational income mobility and, closely related to this, equality of opportunity should be a primary goal for economic policy in light of the rising level of interpersonal income inequality.

The analyses in the previous chapters use comparable data from Germany and the United States in order to contrast the results for the two countries. Thus, they contribute to the empirical literature on intergenerational income mobility in both countries as well as to the literature on country comparisons. The first part is motivated by an unclear position of Germany in the international ranking of intergenerational mobility levels. We therefore conduct a direct comparison of the structure and extent of intergenerational income mobility in Germany as compared to the United States. The results support the widely accepted view that the intergenerational income elasticity is higher in the United States than in Germany. However, while the results for the intergenerational rank mobility do not differ much between the two countries, Germany exhibits a higher intergenerational income share persistence than the United States. We find no indications for a nonlinear run of the intergenerational income elasticity which might point to credit market constraints. A final decomposition of intergenerational income inequality shows both higher income mobility and stronger progressive income growth for Germany compared to the United States. Overall, we cannot identify a clear ranking between the two countries.

The second contribution examines the transmission channels of intergenerational income persistence. To deduce concrete economic policy actions, it is important to know *why* intergenerational income persistence is present in a certain country. Firstly, income differences could be inherited due to the actual higher income of parents allowing them to directly invest in the human capital of their children. Secondly, human capital might also be transferred from parents to children without financial expenditures. We perform a descriptive as well as a structural decomposition and find that the direct effect of a father's financial means is much more important in the United States, whereas the indirect effect of a father's nonmonetary human capital transmission is predominant in Germany. These results are in line with the fact that the share of private expenditures in the American education system is significantly higher than in Germany. In conclusion, equality of opportunity in Germany cannot be reached by the supply of financial means for poor children alone. Rather, social policy must substitute for the missing direct human capital transmission within low-income families.

The third analysis deals with the differences in intergenerational income mobility between sons and daughters. Individual incomes are likely to be an unreliable measure of daughters' actual economic status in most cases because married women in particular tend to reduce their working hours as a result of joint decisions on household labor division. The existence of assortative mating—the tendency of women from well-off families to marry rich men—aggravates this problem. The baseline analysis shows that women in Germany exhibit higher elasticities and thus lower mobility levels than men, while in the United States this relation is reversed. A detailed analysis by marital status suggests that in both countries unmarried women exhibit higher elasticities than unmarried men, while married women show lower elasticities. This is obviously due to a stronger human capital transmission from fathers to their daughters as compared to their sons in the case of unmarried children, and due to a lower human capital transmission and a higher cross-elasticity with respect to husbands' wages for daughters in the case of married children. Overall, there appears to be a significant extent of assortative mating as spouses' incomes as well as overall household incomes are likewise highly correlated with parental earnings.

Nevertheless, the statistical analyses in this dissertation suffer from at least two problems concerning the available data sets. On the one hand, the number of observation in the parent-child samples is relatively small such that the estimated standard errors are often quite large. This becomes especially obvious in the structural decomposition analysis in Chapter 3.4.2, where hardly any significant estimates can be obtained. A further restriction to more specific subsamples is thus often not possible. On the other hand, data for Germany is only available for one generation of parents and their children. A dynamic analysis of intergenerational income mobility, as performed in several studies available for the United States and the Scandinavian countries, is thus not feasible and the implications derived in this dissertation might not be transferable to past and future generations. Here, an improvement of data availability might enable future researchers to obtained more detailed results.

Lebenslauf

Persönliche Daten

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Ausgewählte Veröffentlichungen

2018	„Potenzial des griechischen Exportsektors: Neues Wirtschaftswachstum zur Eindämmung der Schuldenkrise?“, WiSt – Wirtschaftswissenschaftliches Studium 47 (1), S. 30-37 (mit Julia Rumler)
2017	„Do Expectations Matter? Reassessing the Effect of Government Spending on Key Macroeconomic Variables in Germany“, Applied Economics Letters, im Erscheinen (mit Klaus Gründler)
2016	„Intergenerative Einkommensmobilität in Deutschland und den USA“, ORDO Jahrbuch für die Ordnung von Wirtschaft und Gesellschaft 67, S. 101-131 (mit Mustafa Çoban)