Essays on Social Mobility

DISSERTATION
of the University of St.Gallen,
School of Management,
Economics, Law, Social Sciences,
International Affairs and Computer Science,
to obtain the title of
Doctor of Philosophy in International
Affairs and Political Economy

submitted by

Elisabeth Essbaumer

from

Germany

Approved on the application of

Prof. Dr. Christian Keuschnigg

and

Prof. Dr. Reto Föllmi

Dissertation no. 5376

D-Druck Spescha, St.Gallen 2024

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The University of St.Gallen, School of Management, Economics, Law, Social Sciences, International Affairs and Computer Science, hereby consents to the printing of the present dissertation, without hereby expressing any opinion on the views herein expressed.

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The President:

Prof. Dr. Bernhard Ehrenzeller

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St. Gallen, February 2023 Elisabeth Essbaumer

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Summary

This dissertation comprises three research papers, each addressing a specific aspect of social mobility. The first paper documents intergenerational income mobility in Austria, demonstrating that relative income mobility is high. Considering absolute income mobility, approximately half of the children in the 1990 birth cohort attain a higher income percentile rank than their fathers. Whether this translates into higher earnings largely depends on economic growth, as reflected in real wages, and as illustrated by several counterfactual scenarios. The second paper argues that family income background also matters for the translation of children's human capital into earnings. It focuses on the role of tasks as drivers of economic persistence. The results indicate that approximately 40% of economic persistence in Germany are attributable to the influence of family background on children's task level and the corresponding economic returns. Focusing on the heterogeneous socio-economic backgrounds of students at a Swiss university, the third paper provides causal evidence for their response to peer exposure. The analysis reveals that a higher share of peers with non-academic background positively impacts students' income after graduation. The effect is strongest on other students from non-academic background and works through changes in graduates' occupational choices and in their labor supply.

Zusammenfassung

Die vorliegende Dissertation besteht aus drei Kapiteln, die je eine spezifische Frage zu sozialer Mobilität in der DACH-Region behandeln. Das erste Kapitel dokumentiert intergenerationelle Einkommensmobilität in Österreich und zeigt ein hohes Level an relativer Einkommensmobilität. Ausserdem erreicht etwa die Hälfte der Kinder in der Geburtskohorte von 1990 ein höheres Einkommensperzentil als ihre Väter. Inwiefern sich dies in einem höheren absoluten Einkommen widerspiegelt, hängt stark von wirtschaftlichem Wachstum ab, welches sich in den Realeinkommen widerspiegelt, wie mehrere illustrative Beispielszenarien zeigen. Das zweite Kapitel argumentiert, dass der ökonomische Hintergrund der Kinder auch eine Rolle für die Umwandlung von Humankapital in Einkommen spielt. Die empirische Analyse konzentriert sich hierbei auf eine aufgabenbasierte Betrachtungsweise von Berufen und die Rolle von Arbeitsmärken. Die Ergebnisse demonstrieren, dass etwa 40% der Einkommenspersistenz in Deutschland dem Einfluss des Elternhauses auf die beruflichen Aufgaben des Kindes und den daraus folgenden wirtschaftlichen Erträgen zugeordnet werden kann. Das dritte Kapitel zeigt für die Schweiz, dass Studierende auf die soziale Zusammensetzung ihrer Peergruppe reagieren. Das Einkommen von Studierenden steigt, wenn sich der Anteil an Peers aus nicht-akademischen Elternhäusern erhöht. Der Effekt wirkt hierbei am stärksten auf Studierende, die selbst aus einem nicht-akademischen Elternhaus stammen und entsteht durch eine Anpassung der Berufswahl und des Arbeitsangebots.

Chapter 1

Introduction

> *"Poor kids, through no fault of their own, are less prepared by their families, their schools, and their communities to develop their God-given talents as fully as rich kids. For economic productivity and growth, our country needs as much talent as we can find, and we certainly can't afford to waste it."*[1]

Over the last decade, social mobility, or rather its lack, has been identified as key challenge in many societies. Social mobility is still only broadly conceptualized, as "upward or downward movement, between higher and lower social classes".[2] In contrast, this dissertation distinguishes two distinct concepts within this definition. First, the term income mobility encompasses relative income mobility and absolute income mobility. Relative income mobility describes the association between a child's position in the income distribution and its parents' income position. Absolute income mobility refers to children's absolute economic outcomes. Absolute mobility is measured by several indicators, such as the share of children who are better off than their parents. Secondly, I address educational mobility as the outcomes of university graduates from non-academic families.

Higher income mobility increases equal opportunities and improves the outcomes of children from less advantaged backgrounds. These children can develop their full potential, which increases productivity, improves the talent-job match in the labor market, and strengthens innovation (Aghion et al., 2017). It is estimated that between 20% and 40% of aggregated GDP per capita growth in the United States between

[1] Putnam (2016), 230.

[2] Barber (1957), 356, following the citation of Westoff et al. (1960), 376.

1960 and 2010 derived from an enhanced allocation of ability to occupation (Hsieh et al., 2019). Thus, income mobility boosts economic growth in the long run.

Furthermore, there is a significant link between economic mobility and income inequality (Hassler et al., 2007; Corak, 2013; Durlauf et al., 2022). The Great-Gatsby curve shows that countries with higher income inequality typically exhibit lower economic mobility, and vice versa. Intuitively, climbing the income ladder becomes more difficult if inequality pushes the steps further apart. This link is crucial, especially as the global COVID-19 pandemic has increased inequality along several dimensions, including income, wealth, and education. Consequently, further reductions in economic mobility can be expected in the medium to long run (Hanspal et al., 2020; Blundell et al., 2022). These findings emphasize the need for further research on income mobility, in order to establish the level of income mobility and to identify the potential barriers to and the drivers of upwards economic mobility.

Despite a growing body of research, the reliable evidence on income mobility remains limited to a small set of countries. Additionally, there is a lack of causal evidence for the mechanisms underlying upwards mobility, which is largely due to a lack of identification possibilities. Consequently, income mobility is still widely misperceived, affecting individuals preferences for public policies (Alesina et al., 2018). Therefore, each of the papers comprising this cumulative dissertation addresses the challenge to better understand social mobility.

This dissertation is a collection of three papers analyzing one specific aspect of social mobility. The first paper documents intergenerational income mobility in Austria. Using a decomposition approach, the second paper explores the role of education and occupational autonomy as drivers of economic persistence in Germany. Focusing on the heterogeneous socio-economic background of students at a Swiss university, the third paper provides causal evidence for their responses to peer exposure. Thus, the three papers are also connected by their geographical reach, with each focusing on a DACH country.

Measuring income mobility is highly demanding in terms of the data. It requires income observations over at least two generations and information on family linkages. Previous research therefore focuses almost exclusively on the United States and Scandinavian countries, where extensive administrative data sets were available early on. More recently, however, access to high-quality data is increasing. The first chapter *Income Mobility in Austria* adds to this development. It provides the first analysis of income mobility in Austria based on administrative income data and family linkages across two generations. The results imply that, on the aggregate level, relative income mobility is high in Austria. Considering absolute mobility, I find that approximately half of children reach a higher income percentile than their fathers. Whether this results in higher absolute earnings largely depends on economic growth. When relative mobility is high, the children of high-income earners are more likely to end up in a lower income position than their fathers. Therefore, higher growth in real wages is required for these children to improve their absolute earnings compared to their fathers. If Austria had experienced the same growth between 1990 and 2020 as between 1960 and 1990, absolute mobility in the 1990 birth cohort would almost be twice as large. Thus, income mobility is closely related to overall economic developments.

In the theoretical literature on intergenerational income mobility, economic persistence arises from the diverging financial resources that high- and low-income households can invest in their children's human capital (e.g., Becker and Tomes, 1986; Solon, 2004). Consequently, policy recommendations target education, as human capital directly translates into earnings. The second paper, *It's not all about Education. Intergenerational Income Mobility and Occupational Autonomy* argues that parent's economic background also matters for the translation of human capital into earnings. Hereby, it focuses on the role of children's task level, which are measured by the level of occupational autonomy. Stylized facts show that given equal education, children from the top income quintile are more likely to reach a higher task level than children from the bottom income quintile.

Using tasks to analyze drivers of economic persistence is novel in the literature on income mobility. The results show that overall, approximately 40% of economic persistence in Germany is attributable to the influence of family background on children's occupational autonomy and the corresponding economic returns. Across birth cohorts, occupational autonomy is driven by patterns in economic returns: Children with low-autonomy occupations are increasingly left behind. Looking at related mechanisms, the paper evaluates determinants of children's occupational levels and how these relate to their family income background. In doing so, it expands the analysis to the transmission of task levels from fathers to children, labor market patterns, and personality traits.

The third paper, *Peer Effects and Social Mobility*, analyzes peer effects at the University of St. Gallen (HSG). It explores whether students' outcomes are affected by the social composition of their peer groups and how this depends on students' own background. The data set combines HSG information with the Graduate Survey of the Swiss Statistical Office. The results show that students' income increases when they are exposed to a higher share of students with low socio-economic status (SES). This effect is highest on other low-SES students and functions through an adoption of students' occupational choices and their labor supply. Conversely, I find no evidence in the sample that the outcomes of low-SES students suffer due to social alienation at the university. This outcome is important because overall educational mobility in

Switzerland is low and a child's probability of entering university strongly depends on its family's income background (Chuard and Grassi, 2020). Negative peer effects on the outcomes of low-SES students would provide additional barriers to upward mobility after university entrance. Here, I find that the income of all students benefits from greater social diversity at the university.

Bibliography

Aghion, P., U. Akcigit, A. Hyytinen, and O. Toivanen. 2017. Living the American dream in Finland: The Social Mobility of Inventors.

Alesina, A., S. Stantcheva, and E. Teso. 2018. Intergenerational Mobility and Preferences for Redistribution. *American Economic Review* 108:521–554.

Barber, B. 1957. *Social Stratification.* New York: Harcourt Brace.

Becker, G. S., and N. Tomes. 1986. Human Capital and the Rise and Fall of Families. *Journal of Labor Economics* 4:S–39.

Blundell, R., M. Costa Dias, J. Cribb, R. Joyce, T. Waters, T. Wernham, and X. Xu. 2022. Inequality and the COVID-19 crisis in the United Kingdom. *Annual Review of Economics* 14:607–636.

Chuard, P., and V. Grassi. 2020. Switzer-Land of Opportunity: Intergenerational Income Mobility in the Land of Vocational Training. University of St. Gallen SEPS Discussion Paper no. 2020-11.

Corak, M. 2013. Inequality from Generation to Generation: The United States in Comparison. *The Economics of Inequality, Poverty, and Discrimination in the 21st Century* 1:107–126.

Durlauf, S. N., A. Kourtellos, and C. M. Tan. 2022. The Great Gatsby Curve. *Annual Review of Economics* 14:571–605.

Hanspal, T., A. Weber, and J. Wohlfart. 2020. Income and Wealth Shocks and Expectations during the COVID-19 Pandemic. CESifo Working Paper No. 8244.

Hassler, J., J. V. Rodríguez Mora, and J. Zeira. 2007. Inequality and Mobility. *Journal of Economic Growth* 12:235–259.

Hsieh, C.-T., E. Hurst, C. I. Jones, and P. J. Klenow. 2019. The Allocation of Talent and US Economic Growth. *Econometrica* 87:1439–1474.

Putnam, R. D. 2016. *Our Kids: The American Dream in Crisis*. Simon and Schuster.

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

Westoff, C. F., M. Bressler, and P. C. Sagi. 1960. The Concept of Social Mobility: An Empirical Inquiry. *American Sociological Review* pp. 375–385.

Chapter 2

Intergenerational Income Mobility in Austria

Elisabeth Essbaumer

This paper documents intergenerational income mobility and the access to education in Austria, using administrative data on the 1990 birth cohort and their parents. Relative economic mobility in Austria is high, with a rank-rank slope (RRS) of 0.167. The results indicate a geographic variation in economic mobility, forming an Austrian Great Gatsby curve: Inequality is low in regions where income mobility is comparatively high, and vice versa. Children's income background also affects their chances of obtaining tertiary education. Overall, children from the top income quintile are more than 3-times as likely to obtain a tertiary degree than children from the bottom income quintile. Turning to absolute mobility, I find that approximately half of children reach a higher income percentile rank than their fathers. Counterfactual scenarios illustrate that the extent to which children improve their earning level compared to their parents relates strongly to economic growth. The higher income share (HIS) would be twice as high if real GDP had grown to the same extent during the investigated children's lifetime as it did between 1960 and 1990, assuming that this growth is reflected in children's real wages.
JEL classification: D31, J62, I24.

2.1 Introduction

As income inequality grows, there is an increasing public discourse on income mobility. Equal opportunities for children relate to relative income mobility: To what extent does a child's economic position in the income distribution depends on its family's economic position? Thereby, relative mobility is distinct from absolute mobility, which concerns children's absolute outcomes and whether they are better off than their parents. Consequently, absolute income mobility allows for a more straightforward normative interpretation than relative income mobility. Relative income mobility implies that the children of higher-income earners end up in a lower income percentile so that children from lower-income earners can improve their economic position. Absolute mobility does not require that any children have to be worse off.

For most countries, the actual level of income mobility remains unknown. This is due to challenging data requirements and leads to many misconceptions about income mobility in public opinion. This in turn affects individuals' preferences for public policies (Alesina et al., 2018). Therefore, it is important to provide reliable information based on representative data sets. This analysis adds to this goal.

The following paper characterizes relative and absolute economic mobility in Austria. Hereby, it relies on administrative data of an entire Austrian birth cohort and their parents. The analysis is threefold. The first part of the paper documents income mobility at the aggregate level. Several measures of absolute mobility explore the outcomes of children from low-income households and children's chances to improve their living standard compared to their parents. The rank-rank slope (RRS) is used to characterize relative income mobility. Additionally, I explore heterogeneities in income mobility on the regional level and provide evidence for an Austrian Great Gatsby curve: When income inequality is high, then economic mobility is low, and vice versa.

The second part of the paper highlights existing inequalities in education. I illustrate how children's educational attainment depends on their father's income position. Hereby, I am particularly interested in children's chances of obtaining tertiary education which generates high economic returns.

The third part of the paper focuses on absolute mobility. Several counterfactual scenarios are provided, illustrating the relation between absolute and relative mobility, as well as income inequality and economic growth. As part of these scenarios, I also derive the level of absolute mobility in Austria if the country experiences the same level of relative mobility and income inequality as in the United States.

Overall, I find that Austria is characterized by a high level of relative economic mobility. The RRS coefficient of 0.167 implies that on average, a 1-rank increase in the father's income percentile rank is associated with a 0.167 increase in his child's income percentile rank. Thereby, relative mobility is higher than in Germany and in the United States, which are characterized by RRS values of 0.242 and 0.342, respectively (Kyzyma and Groh-Samberg, 2018; Chetty et al., 2014a). Conversely, relative income mobility is moderately lower than in Switzerland (Chuard and Grassi, 2020).

Looking at absolute mobility measures, I find that children are mobile in the middle-upper parts of the income distribution, and those children born to fathers at the 25^{th} income percentile can expect to reach rank 42 in their own distribution. Overall, approximately 50% of children reach a higher income percentile rank than their fathers. Yet, there is a persistence of poverty within the bottom income quintile. Here, children face a comparatively high chance to remain in the bottom quintile as adults themselves. Furthermore, income mobility is heterogeneous across Austrian regions and there are several clusters of low- and high-mobility regions. The wedge in economic outcomes between children from high- and low-income families is twice as high in Weinviertel (Lower Austria) than in Östliche Obersteiermark (Styria).

The second set of results relates children's economic outcomes closely to their education level. However, the access to education depends on children's income background. Children from the top income quintile are more than 3-times as likely to obtain a tertiary degree than children from the bottom income quintile. Hereby, educational inequality tends to increase from West to East Austria, with the notable exception of Mittelburgenland. The access to tertiary education is important, as it is associated with high economic returns. Having a tertiary degree increases children's economic position on average by 30.2 income ranks compared to general education. At age 30, this translates into 45.8% higher monthly earnings.

The last set of results highlights that economic growth is crucial for absolute income mobility. The counterfactual scenarios show that changes in income inequality and relative mobility only produce small changes, as the effects diverge along the father income distribution. If income inequality and relative mobility were the same in Austria as in the United States, this would improve the position of children of high-income earners. This pushes the higher income share (HIS) in the upper part of the father income distribution. Conversely, absolute mobility declines for children from the lower part of the distribution. At aggregate level, these changes largely offset each other. Overall, higher inequality leads to a small increase of absolute income mobility at the mean, and lower relative mobility to a decline.

In comparison, if real GDP had grown to the same extent during the investigated children's lifetime (1990-2020) as it did between 1960 and 1990, absolute mobility would almost be twice as high. This assumes that economic growth translates into real wage growth. High relative mobility also implies that children from the upper part of the income distribution move closer to the median rank. Growth in real wages is required if these children should still be able to improve their earnings relative to their parents. On the other hand, growth only accruing to a small number of children does not largely affect absolute mobility. Therefore, equally distributed economic growth is necessary to boost absolute mobility. This links income mobility to overall economic trends.

The present analysis relates to three literature streams. First, it relates to the existing research on relative income mobility. Corak (2006) originally establishes a relation between existing income inequality and relative income mobility on the national level, denoted as the Great Gatsby Curve. Influential work by Chetty et al. (2014a,b) transfer this concept to the regional level. They show that US regions with comparatively high income inequality are characterized by below-average mobility rates. The authors also find that mobility rates in the US strongly correlate with social structures such as family stability and social capital. Similar studies add regional evidence for Italy (Acciari et al., 2019), Sweden (Heidrich, 2017), Australia (Deutscher and Mazumder, 2020), and Switzerland (Chuard and Grassi, 2020).

The paper uses the rank-rank slope to characterize relative mobility. Several papers highlighted the advantages of this measure compared to the intergenerational income elasticity (IGE) (e.g. Dahl and DeLeire, 2008; Chetty et al., 2014a,b; Corak, 2017; Bratberg et al., 2017). The RRS is less sensitive to attenuation bias, which derives from proxying life-time income with a limited range of annual income observations (Solon, 1992). Furthermore, the measure is less prone to life-cycle bias, which refers to the life-cycle stage when children's and parent's income are measured (Haider and Solon, 2006). Other than income levels, income ranks are stable over time. Nybom and Stuhler (2017) show that the rank-based measure of intergenerational mobility shows a superior bias performance once the children reach the age of 30, which is when children's income is observed in this analysis.

The paper also adds to recent research on absolute income mobility, measured by the share of children who are better off than their parents (Chetty et al., 2017; Blanden et al., 2019; Bönke et al., 2019; Manduca et al., 2020; Kennedy and Siminski, 2022; Liss et al., 2023). Absolute mobility is declining in countries such as the United States, the United Kingdom, Australia, and Germany. Chetty et al. (2017) provide the methodology applied in the counterfactual scenarios and show that declining absolute mobility in the United States relates to lower GDP growth, which is unequally distributed among children. In more recent cohorts, Chetty et al. (2017) find that approximately 50% of children earn more than their parents. This share is substantially higher than in the United Kingdom (33% for the 1987 birth cohort, Blanden et al., 2019). For Germany, Bönke et al. (2019) show that the higher income share fell from 90% in the 1962 birth cohort to 70% in the 1983 cohort. When only considering earnings, children from high-income families are less likely their outcomes than children from the lower part of the income distribution. However, this changes once asset income are taken into account.

Conversely, absolute mobility is increasing in Sweden, where more than 80% of children are better-off than their parents. (Liss et al., 2023) show that when income inequality is higher in the father generation, more GDP growth is required to keep the level of absolute mobility. I add to the ongoing debate by adding a country for cross-country comparisons and provide counterfactual scenarios to analyze drivers of absolute income mobility.

Finally, the analysis relates to research on social mobility in Austria. Until now, no income data on two generations has existed to comprehensively analyze intergenerational mobility in Austria. Consequently, previous studies focus on the transmission of educational attainment and educational inequality (e.g. Fessler and Schneebaum, 2012, Altzinger and Schneebaum, 2018). Alternatively, Altzinger and Schnetzer (2010) and Schnetzer and Altzinger (2013) rely on the 2005 and 2011 EU-SILC surveys. Respondents were asked to classify their parents' financial situation when they, i.e., the respondents, were between 12 and 16 years of age. Based on this assessment, the parent generation is divided into five income classes. As discussed by the authors, this retrospective classification is subject to respondents' highly subjective memory. In contrast, this analysis benefits from a large data set provided by the Austrian Statistical Office which includes earnings information on two generations.

This paper adds to existing research in two ways. First, it combines two strands of research that are typically considered separately: relative income mobility and absolute income mobility. This approach provides a more complete picture of income mobility and highlights the relation between relative and absolute income mobility. Austria has a comparatively high level of relative income mobility. Yet the overall economic developments affecting real wage growth are decisive for whether children can improve their living standards compared to their parents. Second, the paper closes an important research gap on social mobility in Austria and offers a new data point for cross-country comparisons on income mobility. Compared to previous studies, it provides an in-depth analysis on income mobility based on administrative data. Together with Chuard and Grassi (2020) and Kyzyma and Groh-Samberg (2018), this paper complements the rank-based analysis of German-speaking countries. The results indicate that Austria experiences a higher level of relative mobility than Germany, and children have a greater access to tertiary education than in Switzerland.

The analysis is structured as follows. Section 2.2 discusses the methodological approach and Section 2.3 describes the data set. The results are presented in Section 2.4. These include estimates for absolute and relative income mobility, and for regional variation within Austria. I address educational inequality and provide counterfactual scenarios for absolute mobility. This is followed by alternative specifications and robustness checks in Section 2.5. Section 2.6 concludes the analysis.

2.2 Methodological Approach

The goal of this analysis is to document intergenerational income mobility in Austria. Consequently, the estimation strategy applies two types of measures: absolute mobility measures and relative mobility measures.
Relative mobility evaluates the extent to which children's economic outcomes depend on their economic background. This is obtained from the rank-rank slope (RRS), which also sets economic outcomes of children born to fathers in the top income percentile relative to those of children born to fathers in the bottom income percentile. Absolute mobility cares about absolute outcomes and whether children improve their economic position compared to their parents. Therefore, absolute mobility measures relate to children's expected economic outcomes conditional on the income position of their fathers. Hereby, the outcomes of children from low-income families are of particular interest.
In this approach, I follow the influential work of Chetty et al. (2014a) and Chetty et al. (2017) to ensure a high level of comparability between the obtained results for Austria and those for other countries.

2.2.1 Absolute Economic Mobility

The level of absolute economic mobility, and, hence, expected absolute outcomes, are investigated using three indices: (i) the income transition matrix and positional indicators, (ii) absolute upwards mobility (AUM), and (iii) higher income shares (HIS).

Income Transition Matrix

The income transition matrix summarizes the probability that a child reaches a specific income quintile, given its father's income quintile. Three indicators derive directly from the transition matrix, providing directional mobility measures which are also used in a cross-country comparison. The $P_{1,1}$ indicator provides the probability that children born to fathers in the bottom income quintile remain in the bottom income quintile of their own generation. This is a measure for the transmission of poverty across generations:

$$P_{1,1} = Pr[R_i^C < 20 | R_i^F < 20], \tag{2.1}$$

where R_i^C is the income percentile rank of child i and R_i^F is the income percentile rank of child i's father. Analogously, the $P_{5,5}$ indicator documents intergenerational privilege, that is, the probability that children remain in the top income quintile:

$$P_{5,5} = Pr[R_i^C \geq 80 | R_i^F \geq 80], \tag{2.2}$$

The "American Dream" captures the idea that a child goes "from rags to riches" and moves from the bottom income quintile to the top income quintile (Corak, 2010). Here, this is defined as $P_{1,5}$ indicator:

$$P_{1,5} = Pr[R_i^C \geq 80 | R_i^F < 20], \tag{2.3}$$

Absolute Upwards Mobility (AUM)

The absolute upwards mobility (AUM) measure reports the expected economic position of children who are born to fathers at the 25$^{\text{th}}$ income percentile. This is the mean rank in the lower half of the father income distribution:

$$\bar{R}_{25}^C = \mathbb{E}[R_i^C | R_i^F = 25]. \tag{2.4}$$

Therefore, the AUM provides a summary measure for the outcomes of children from less advantaged backgrounds. These are of particular interest for public policy makers.

Higher Income Share (HIS)

The higher income share (HIS) is used to describe to what extent children improve their living standards compared to their parents. The HIS is defined by the share of children earning more than their parents. Therefore, the HIS consists of three elements: (i) the marginal income distribution in the children generation, (ii) the marginal distribution in the father generation, and (iii) the joint distribution of father and child ranks, i.e., the copula. For the children population, the HIS is then derived by:

$$\text{HIS} = \int 1\{Q^C(R^C) \geq Q^F(R^F)\} C(R^C, R^F) \delta R^C \delta R^F \tag{2.5}$$

Where $Q^C(R^C)$ are the average earnings in the R^{th} income percentile rank of the children income distribution and $Q^F(R^F)$ are the average earnings in the R^{th} percentile rank of the father income distribution. The indicator function checks whether

$Q^C(R^C)$ is weakly higher than $Q^F(R^F)$ and the copula $C(R^C, R^F)$ provides the probability that each pair of ranks (R^C, R^F) occurs.[1] The counterfactual scenarios in Section 2.4.6 adjust the marginal income distribution and the copula, evaluating how this affects the higher income share along the father income distribution and at the aggregate level.

One limitation of this analysis is that it is not possible to observe children and fathers at the same age range. This reduces the informative value of the HIS in cross-country comparisons. However, it does not lose validity in the counterfactual scenarios where the goal is to evaluate changes in the HIS value under different assumptions.

2.2.2 Relative Economic Mobility

Relative economic mobility is measured by the rank-rank slope (RRS). The RRS coefficient is derived from regressing child i's income rank R_i^C on the father's income rank R_i^F:

$$R_i^C = \gamma_0 + \gamma_1 R_i^P + \epsilon_i, \tag{2.6}$$

where ϵ_i captures factors which affect the economic position of children independent from their parent's economic position. The intercept γ_0 defines the economic position children can expect when they are born to fathers at the bottom of the income distribution. The estimated γ_1 provides the rank-rank slope. This is the primary coefficient of interest and describes the relation between a child's and and father's economic positions: The greater the RSS value, the stronger the transmission of economic status within family dynasties. A RSS value of 1 implies that a child's economic position in life is entirely predetermined by its parents' economic position. In contrast, a RRS value close to zero indicates strong societal mobilization with little continuance of economic status from parent to child.

Additionally, $\gamma_1 * 100$ is the expected gap in economic outcomes between children born at the top and bottom income percentile ranks. Thereby, relative mobility provides a generational inequality measure: A higher RRS coefficient indicates a larger spread in expected child ranks, and hence, a higher level of outcome inequality in the children generation.

The rank-rank slope is used to describe geographic variation of economic mobility within Austria. Hereby, I estimate regional RRS coefficients based on children's income ranks in the national income distribution, as regional income distributions vary in Austria. The same applies to the AUM measure of absolute mobility, which is

[1] This approach follows Sklar's theorem, stating that any multivariate distribution can be expressed by their marginal distributions and a copula (Sklar, 1959).

also provided on the regional level. For instance, a child born to a low-income family in Tyrol might reach the 40^{th} percentile of the specific Tyrolian income distribution. Yet, the economic implications can be very different from a comparable child reaching the 40^{th} percentile of the Viennese income distribution. Therefore, using national income ranks instead of regional ranks achieves a common reference frame for the interpretation of estimated results.

2.2.3 Educational Inequality

A father's income rank does not only affect his child's economic position, but also his or her level of education. This paper documents educational inequality and describes the existing gap in the access to tertiary education between children from low-income families and children from high-income families. I focus on tertiary degrees because they relate to the highest average economic returns and thus enable upwards economic mobility (see Section 2.4.5). Also, they require higher investments than other types of education such as vocational education and training (VET). Thus, families' financial constraints are more decisive.

Consequently, the Q1 measure is defined as the probability that a child reaches tertiary education when he is born to a father in the bottom income quintile, $\mathbb{E}[Y_i^C|R_i^P \leq 20]$. A higher value indicates a higher level of absolute educational mobility. Analogously, the Q5 measure gives the probability when the child is born in the highest income quintile, that is, $\mathbb{E}[Y_i^C|R_i^P > 80]$. The ratio $Q5/Q1$ relates the chances of rich to poor children:

$$Q5/Q1 = \frac{\mathbb{E}[Y_i^C|R_i^P > 80]}{\mathbb{E}[Y_i^C|R_i^P \leq 20]} \tag{2.7}$$

This measure is used to characterize the level of educational inequality in Austria and also to describe regional variation within the country.

2.3 Data

2.3.1 Data Sources

The data is provided by Statistik Austria, the Austrian Statistical Office. Statistik Austria started systematically collecting data only in 2009, which restricts observable income information and family linkages. Consequently, the analysis targets the 1990 birth cohort only, thereby restricting the sample size. However, focusing on a recent birth cohort and current income information up to 2020 has one major advantage in terms of policy implications: The estimates provide insights into the *current* situation in Austria.

More specifically, the analysis relies on Statistik Austria's register-based employment histories RBEH ("Registerbasierte Erwerbsverläufe"). The RBEH consolidate data to construct individual employment biographies without gaps or overlaps. Thereby, the RBEH draw data from the register census ("Registerzählung"). In Austria, the register census replaced the traditional census in 2006. Instead of surveying single individuals or households, the register census assigns an identification number to every individual and combines information from several administrative registers. These include, among others, the Main Association of Austrian Social Security Institutions (HVSV), Tax Data (BMF), and the National Education Attainment Register (BSR).

Family linkages are extracted primarily from health insurance information ("Mitversichertendatei"). Children are co-insured with their parents, as long as they are underage, or pursuing education, or training. In some cases, linkages are established by the civil registry, for instance, with updates or changes that occurred after 2009.

Additional demographic variables are restricted to insurance-relevant information and the BSR. These include age, gender, highest level of education, country of birth, and place of residence. Supplementary variables contain individuals' labor market status and the industry in which they are employed. Specific occupations are not known.

Five types of educational attainment can be distinguished: general education, dual training (apprenticeships), vocational educational and training (VET) schools ("Berufsbildende Mittlere Schule"), upper secondary education ("Berufsbildende und Allgemeinbildende Höhere Schule"), and tertiary education ("Akademie, Kolleg, Universität").

Income information is derived from tax data ("Lohnzetteldaten"). These provide individuals' average monthly gross income for each employment period. The gross sample includes the labor income of children when they are between 25 and 30 years old. For the parent generation, all available income information is collected from 2009 onward. To study intergenerational mobility, the rank-based in-come measure is calculated on a subset of these income observations.

2.3.2 Main Sample Selection

The goal is to determine individuals' long-term income position. Therefore, I abstract from short term fluctuations and exclude individuals who are unemployed, on parental leave, retired, on sick leave, in training, or who are not participating in the labor market for other reasons.

The main analysis focuses on father-child pairs. Here, I do not have information on family income, nor on the civil status of the parents. The labor market participation and income of mothers is significantly lower than those of fathers in the sample and I assume that the fathers' income position is more indicative for a child's economic background. Fathers' pre-dominant region of residence is also used to analyze regional variation. Hereby, two geographical units are used: federal states and regions. The definition of an Austrian region follows Eurostat's 'Nomenclature des unités territoriales statstiques (NUTS)'. Each region represents municipalities as subdivisions of basic administrative units (NUTS-3 level). Further criteria are structural and geographical characteristics (Statistik Austria, 2009). NUTS-3 regions contain a larger number of municipalities with different residential areas and socio-economic structures. The results are therefore less prone to selection bias due to residential segregation. The robustness checks include alternative specifications based on mothers' income and place of residence.

Children's income data are collected for 2020, that is, when children turn 30. This is the earliest age in which income ranks are stable. Their income ranks are calculated relative to other children in the 1990 birth cohort. Therefore, children's earnings are used when they are likely to be affected by the Covid-19 pandemic, which is one limitation of the analysis. However, this should affect children's income levels to a larger extent than their income ranks. Alternative income specifications are evaluated as part of the robustness checks in Section 2.5.

I measure father income in the 2010-2013 period and remove fathers who are older than 59 years in 2013 or do not have an active labor market status. Fathers are ranked based on their income relative to other fathers with children in the 1990 birth cohort. The resulting sample includes 46,400 father-child pairs.

2.3.3 Summary Statistics

Table A.6.6 provides descriptive statistics for children and fathers. The average father is born in 1962 and reaches an age of 47.57 years. All children in the 1990 birth cohort are 30 years old by the end of 2020.

The age gap between the two generations is reflected in their income. The average monthly income is significantly higher for fathers and more dispersed, with 4,360 Euros compared to 2,642 Euros in the next generation. This is also illustrated by the right and left panel in figure 2.1. For fathers and children, they show the mean monthly income for each income percentile rank. There is no top-coding which is noticeable in the difference in mean income between the top income percentile rank and the next lower ranks.

Five dummy variables measure different levels of educational attainment. There is a

Table 2.1: Descriptive summary statistics

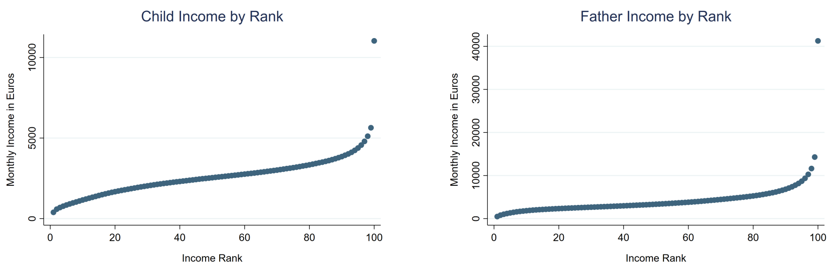
	Fathers	Children
Age	47.570	30.000
	(4.205)	(0.000)
Monthly Gross Income	4,359.85	2,641.58
	(10,228.56)	(1,789.28)
Log Monthly Gross Income	8.167	7.760
	(0.581)	(0.506)
General Education	0.116	0.091
	(0.321)	(0.288)
Dual Training	0.513	0.353
(Apprenticeships)	(0.500)	(0.478)
Vet School	0.136	0.108
	(0.343)	(0.310)
Upper Secondary Education	0.106	0.206
	(0.308)	(0.405)
Tertiary Education	0.105	0.237
	(0.306)	(0.425)
N	46,600	46,600

Note: This table shows sample means with standard deviations in parentheses. All income is measured in constant 2020 Euros.

shift from vocational training to tertiary degrees between the two generations. The share of children completing tertiary education is more than twice as large as that share in the father generation. By comparison, dual training is declining. Every second father completed an apprenticeship, but only 35% of their children. The sample statistics also indicate that the share of individuals with a general education decreases by 2.5 percentage points from the father generation to the children generation, with a share of 11.6% and 9.1%, respectively.

Additional information on employment shares for Austrian industries are presented in Table A.1.1, defined by the OENACE 2008 classification. Comparatively many fathers are employed in the manufacturing industry (22.0%), the construction sector (12.8%), and in transportation (11.3%). In the children generation, the manufacturing industry is still important (18.3%), together with the wholesale and retail industry

Figure 2.1: Father and child mean income by rank



Note: The two panels show the mean income per month for each income rank for children (left) and fathers (right). All income is in constant 2020 Euros. Note the difference in the y-axis scaling.

(14.7%). In both generations, approximately 11% are employed in the public sector.

2.4 Results

2.4.1 Absolute Economic Mobility in Austria

Transition Probabilities

How likely is it that a child reaches a certain economic position in its adult life, given its father's income position? The income transition matrix in Table 2.2 provide an answer to this question. The matrix summarizes the probability that a child reaches a specific income quintile conditional on the income quintile of his or her father.

In Austria, children are mobile in the middle part of the income distribution. Those who are born in the second- and third income quintiles exhibit similar probabilities of staying or moving up to two income quintiles in every direction. In comparison, the $P_{1,5}$ indicator, that is, the probability that a child moves from the bottom quintile to the top quintile is 13.26%.

Economic persistence is higher at the bottom and at the top. At both ends of the income distribution, children are relatively likely to remain in the same economic position as their fathers. Hereby, the $P_{5,5}$ measure equals 26.12%. Conversely, with $P_{1,1} = 27.95\%$, the staying probability is highest at the bottom income quintile, which indicates a transmission of poverty across generations.

A more detailed income transition matrix based on deciles rather than quintiles is provided in the Appendix Table A.2.3. It confirms that middle-class children, born in deciles 4-6, face fairly even chances of moving along the income ladder. The probability of moving from the bottom 10% to the top 10% of incomes equals 6.06%.

Table 2.2: Income quintile transition matrix

		Father Quintile				
		Bottom	Second	Third	Fourth	Top
Children Quintile	Bottom	27.95%	21.77%	19.20%	16.27%	14.37%
	Second	23.27%	21.19%	19.95%	18.19%	16.87%
	Third	19.41%	20.34%	20.42%	20.17%	19.75%
	Fourth	16.10%	19.12%	20.45%	21.97%	22.89%
	Top	13.26%	17.58%	19.98%	23.40%	26.12%

Note: Each cell in this table shows the probability that a child reaches a specific income quintile, conditional on its father's quintile. The likelihood of 'going from rags to riches', $P_{1,5}$, is 13.26%. Contrary, with a probability of 27.95%, it is more than twice as likely that a child born at the bottom quintile stays at the bottom quintile.

Absolute Upwards Mobility (AUM)

Absolute mobility cares about children's absolute economic outcomes - here expressed by the place in the income distribution. The AUM predicts the expected outcome of poorer children who are born to fathers at the 25^{th} income percentile. Table 2.5 reports that these children reach on average the 46^{th} income percentile, which implies a monthly salary of 2,451 Euros.

The expected economic outcomes of poor-born daughters are substantially below poor-born sons' outcomes. A daughter born to a father at the 25^{th} rank increases her

Table 2.3: Absolute upwards mobility (AUM)

	Total Sample	Sons	Daughters
Absolute Upwards Mobility (AUM)	46.405	54.437	34.678
N	46,400	26,957	19,443

Note: This table reports the level of absolute upwards mobility (AUM), that is, the expected income rank of children born to fathers in the 25^{th} income percentile. As adults, those reach on average the 46.405^{th} income percentile rank.

economic position by approximately 10 percentage points and ends-up at rank 35, where she earns an average income of 2,200 Euros. A son born in the same economic environment reaches rank 54 and is therefore entering the upper half of the children income distribution.

Higher Income Share (HIS)

To improve children's living standards compared to their parents is a central goal for parents and policy makers alike. The higher income share (HIS) reflects this ambition and documents the share of children earning weakly more than their fathers. Here, the higher income share is 0.259. This reflects that children's income is measured significantly earlier in the life cycle than fathers' income. Conversely, economic positions have already stabilized. Therefore, in terms of economic positions, 51.3% of children in the 1990 birth cohort reache a weakly higher income rank than their fathers do. This is captured by the Higher Rank Share (HRS). The results are summarized in Table 2.4.

Whether higher ranks translate into higher earnings once children reach the same age as their fathers depends on the development of their real wages and therefore also on the total economy. Changes in growth, inequality and relative economic mobility are likely to affect this outcome, which is further evaluated in Section 2.4.6.

Also, there is a significant gender gap. Separate results for daughters and sons reveal that sons are substantially more likely to reach a higher economic position than their father in their own generation. Looking at the HIS values, 32.6% of sons earn more than their fathers, compared to 16.6% of daughters.

2.4.2 Relative Economic Mobility in Austria

Figure 2.2 visualizes the relation between the father and the child income rank. Each dot depicts the mean income rank of children for four percentile ranks in the father income distribution. The higher a father's economic position in Austria, the higher the economic position his child can expect. The plot shows that the rank relation is approximately linear, which justifies the use of the rank-rank slope to characterize the level of relative economic mobility in Austria.

The estimated rank-rank slope (RRS) is 0.167, with a constant of 42.3. Table 2.5 summarizes the results. On average, a 1-rank increase in fathers' income position is therefore associated with a 0.167-rank increase in children's economic position. The RRS can also be interpreted as wedge between children born to fathers at the bottom rank and at the top. Compared to their fathers, the gap between children's outcomes

Table 2.4: Absolute economic mobility

	Higher Income Share	Higher Rank Share	N
Total Sample	0.259***	0.513***	46,400
	(0.002)	(0.002)	
Sons	0.326***	0.618***	26,957
	(0.003)	(0.003)	
Daughters	0.166***	0.368***	19,443
	(0.003)	(0.004)	

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses. This table reports aggregate higher income shares (HIS) in the left column and higher rank shares (HRS) in the right column. Overall, 51.3% of the 1990 birth cohort reach a weakly higher income percentile rank than their fathers. This implies that at age 30, 25.9% of children earn at least the same monthly income as their fathers at age 47.6.

closes and once they become adults, they are separated by 16.7 income ranks at the mean.

How does the rank-rank slope translates into monetary units? At age 30, a child born to a father in the first income percentile can expect to reach the 43$^{\text{th}}$ income percentile of his generation, which then corresponds to a monthly income of 2,350 Euros at age 30. In comparison, children born to fathers in the top income percentile reach approximately the 60$^{\text{th}}$ income percentile, relating to a mean income of 2,761.18 Euros per month.[2] On an annual level, this gap corresponds to more than two average monthly salaries in Austria. This rank gap will continue to exist, as children's economic positions remain stable over the life cycle. Therefore, children who are separated by 16.7 income ranks at age 30 can expect to be separated by 16.7 income ranks at age 55 as well. However, the monetary implications will change, as income profiles spread further apart over time.

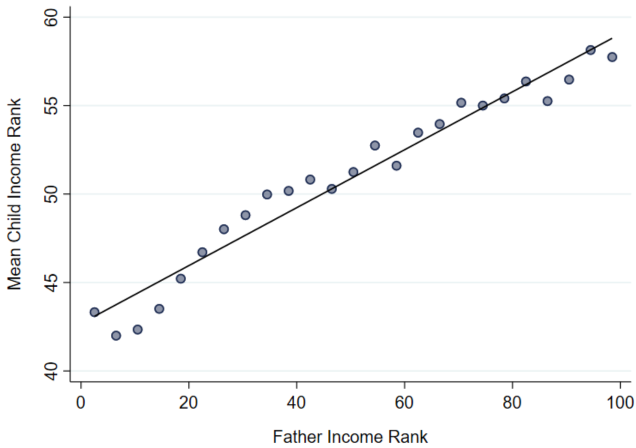
Furthermore, family income background is more important for daughters than it is for sons. The higher RRS value indicates that their income position depends more strongly on the income position of their fathers, with values of 0.208 and 0.157, respectively.

For the total sample, the adjusted R^2 equals 0.027. Low values for R^2 are common in this literature, insofar as they are reported.[3]. Thus, there is an observable and

[2] See table A.1.2 for the translation of income ranks into monthly income.

[3] For instance, Chuard and Grassi (2020) indicate a $R^2 = 0.02$ for Switzerland, values for Italy are around 0.06 (Acciari et al., 2019)

Figure 2.2: Relation between income ranks



Note: The figure plots children's income percentile rank on their fathers' income percentile rank. Each dot gives the mean rank for four father percentile ranks. The rank-rank sloe (RRS) equals 0.167.

significant relation between the economic positions of fathers and children, but there are also many other elements which are important for predicting a child's economic position.

2.4.3 Austria in International Comparison

How does economic mobility in Austria compare internationally? Below, I relate the obtained estimates to existing results for other countries (Table 2.6). Comparing Austria with the other two German-speaking DACH countries - Germany and Switzerland - is hereby of particular interest.

Austria is more comparable to Switzerland than to Germany in terms of relative and absolute economic mobility. The RRS value is slightly higher than in Switzerland yet significantly lower than in Germany. This indicates that in Austria, children's economic outcomes are less dependent on their family income background than in Germany. Also, the income position poor children can expect to attain is slightly higher in Austria and very similar to the Swiss level. All three German-speaking countries exhibit very similar $P_{1,5}$ probabilities.

However, Austria also has the most persistent poverty cycle in the DACH-region. The probability of remaining in the bottom quintile in Austria is almost 7 percentage

Table 2.5: Relative and absolute economic mobility

	Total Sample	Sons	Daughters
Rank-Rank Slope	0.167***	0.157***	0.208***
(RRS)	(0.005)	(0.006)	(0.007)
Constant	42.300***	50.512***	29.478***
	(0.274)	(0.332)	(0.416)
Adj. R^2	0.027	0.027	0.044
N	46,400	26,957	19,443

Note: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. The RRS coefficient shows that a 1-rank increase in the father's economic position relates to a 0.167-rank increase in child's economic position at the mean.

points higher than in Germany. In contrast, dynastic persistence at the top is lower than in Switzerland or Germany. The "stickiness" of Germany's top-income position is noticeable, not only compared to Austria and Switzerland, but also to other non-German speaking countries.

For a further cross-country comparison, the four right-hand columns in Table 2.6 also list characteristics for the United States, as well as for Sweden as representative of Scandinavia, and for Italy as a Southern-European country. Only Sweden has a higher share of children who improved their economic position from the bottom quintile to the top quintile ($P_{1,5}$).

Otherwise, Austria clearly provides better chances for such improvement than the United States. Nevertheless, poverty in Austria persists at a level comparable to Italy (28.0% vs. 28.7%).

2.4.4 Regional Variation

Economic Mobility in Austrian Regions

Economic mobility varies noticeable within Austria. Figure 2.3 and 2.4 visualize relative and absolute economic mobility on the regional level. For the rank-rank slope, darker colors indicate a *lower* level of relative economic mobility (Figure 2.3). For the AUM measure, darker colors imply a *higher* level of absolute economic mobility (Figure 2.4).

Relative economic mobility is heterogeneous. In East Austria, there is a regional cluster of low-mobility regions, including parts of Burgenland and Lower Austria. Overall,

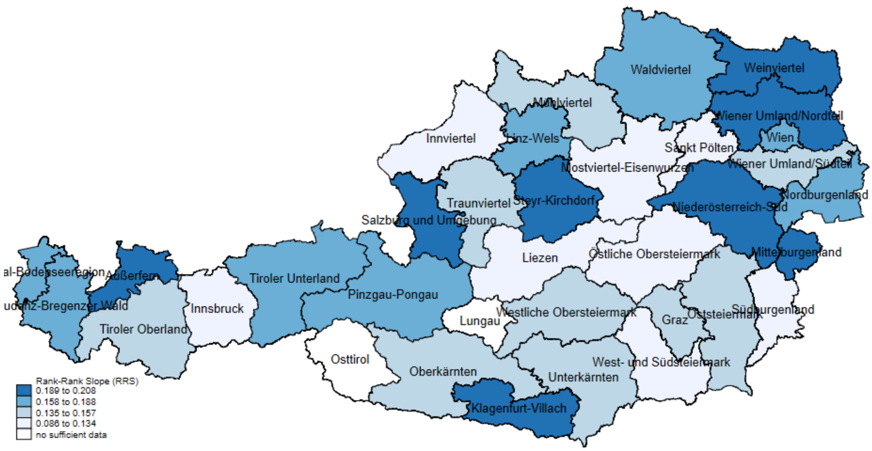
Table 2.6: Austria in international comparison

	Austria	Switzerland	Germany	United States	Sweden	Italy
RRS	0.167	0.153	0.242	0.341	0.197	0.246
AUM	46.4	46	44.0	41.4	43.6	44
$P_{1,5}$	13.3%	12.9%	11.1%	7.5%	15.7%	9.9%
$P_{1,1}$	28.0%	24.6%	21.1%	33.7%	26.3%	28.7%
$P_{5,5}$	26.1%	30.5%	42.7%	36.5%	34.5%	35.6%

Note: Based on own calcultaions for Austria, Chuard and Grassi (2020) for Switzerland, Kyzyma and Groh-Samberg (2018) for Germany, Chetty et al. (2014a) for the US, Heidrich (2017) for Sweden, and Acciari et al. (2019) for Italy.

regional RRS coefficients vary between 0.089 in Östliche Obersteiermark (Styria) and 0.208 in Weinviertel (Lower Austria). Therefore, the gap between children from the bottom and the top of the national income distribution is more than twice as large when children are born to fathers in the Östliche Obersteiermark than when they are born to fathers in Weinviertel.

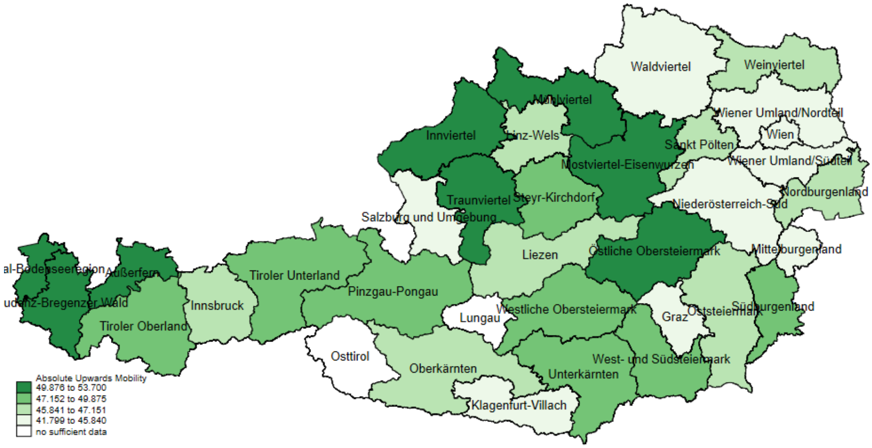
Figure 2.3: Relative economic mobility on regional level



Note: The heat map shows relative mobility on regional level, measured by the rank-rank slope (RRS). Darker shades imply higher regional RRS coefficients and thus, lower level of relative economic mobility.

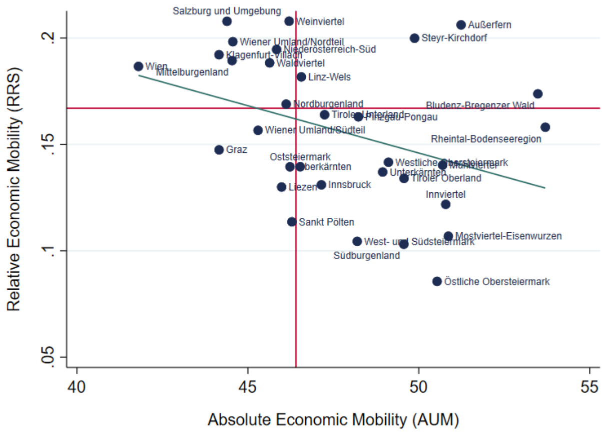
Absolute mobility reveals several regional clusters (Figure 2.4). Vienna and its neigh-

Figure 2.4: Absolute upwards mobility on regional level



Note: This heat map visualizes regional variation in the expected outcomes of poor children. Darker shades imply higher regional values for absolute upwards mobility (AUM), indicating a higher level of absolute economic mobility.

Figure 2.5: Relative and absolute mobility on regional level



Note: This figure shows that regions with high absolute mobility (AUM) tend to have high relative mobility (low RRS values) as well. The national averages for both mobility measures are indicated by the crossed red lines.

boring regions form one cluster of comparatively low absolute mobility. Adjacent to the East is a cluster of high-mobility regions. With an AUM value of 46.6, "Linz-

Wels", a comparatively weak region within this high-mobility cluster, but the region also exhibits absolute mobility that is slightly above the national average. Bordering Switzerland and Germany, Vorarlberg's regions form a second high-AUM cluster. Vienna, Pinzgau-Pongau, and Salzburg feature comparatively low levels of absolute upwards mobility, whereas "Rheintal-Bodenseeregion" in Vorarlberg features the highest: There, a child born at rank 25 can expect to reach almost the 54$^{\text{th}}$ income percentile rank.[4]

High absolute mobility tends to go hand in hand with high relative mobility (i.e., low RRS coefficients). Figure 2.5 shows relative and absolute economic mobility at the regional level. Higher AUM values on the horizontal axis indicate higher levels of absolute economic mobility, whereas lower RRS values on the vertical axis indicate higher relative mobility. The correlation coefficient for absolute and relative economic mobility is significant and equals -0.369. The crossed red lines indicate national averages for both mobility measures.

The Austrian Great-Gatsby Curve

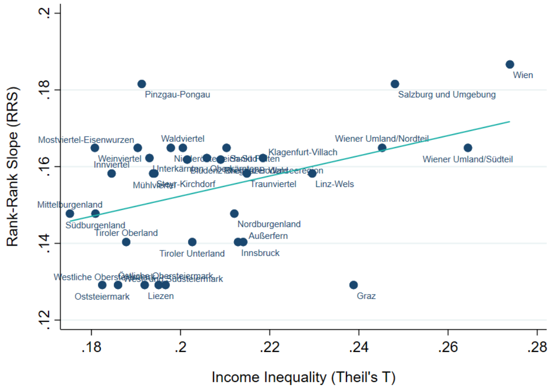
Countries with high levels of income inequality tend to face low economic mobility. This relation is called Great Gatsby Curve and for countries such as the United States, Sweden, and Italy, it is also observed on a regional level (Chetty et al., 2014a; Heidrich, 2017; Acciari et al., 2019). Therefore, Figure 2.6 shows the relation between the regional RRS coefficients Austria and the level of income inequality in 2019. Hereby, income inequality is measured by Theil's T. The Theil index is defined between zero and ∞, where higher values represent higher levels of inequality.

I find evidence for an Austrian Great Gatsby curve: It becomes more difficult to climb the income ladder when inequality is high and thus, the steps of the ladder are further apart. The blue line predicts an increasing linear relation, as higher RRS values indicate lower relative economic mobility. The significant correlation coefficient between inequality and (decreasing) relative mobility is 0.393 on the regional level.

Furthermore, Figure 2.7 illustrates how income inequality relates to absolute economic mobility. The correlation is negative, with a significant correlation coefficient of -0.486. In those Austrian regions where inequality is comparatively high, the expected economic outcomes of poor children tend to be low. For instance, Vienna and its neighboring regions (Wiener Umland / Südteil, Wiener Umland / Nordteil) exhibit the highest levels of income inequality, together with Salzburg und Umgebung. For these regions, absolute upwards mobility (AUM) is below-average.

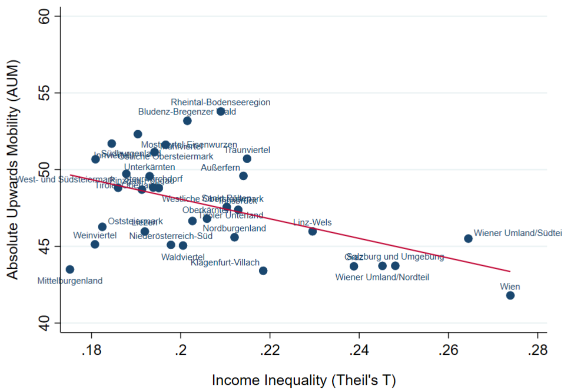
[4] Appendix A.3 aggregates results on federal state level.

Figure 2.6: The relation between income inequality and relative economic mobility



Note: For Austria, higher levels of inequality are related to lower levels of relative economic mobility, indicated by higher regional RRS coefficients. The correlation coefficient is significant at the 5% level and equals 0.393. Income inequality is measured by the Theil's T index, where higher values imply more inequality.

Figure 2.7: The relation between income inequality and absolute economic mobility



Note: For Austria, higher levels of inequality are related to lower levels of absolute economic mobility, indicated by lower AUM values. The correlation coefficient is significant at the 1% level and equals -0.486. Income inequality is measured by the Theil's T index, where higher values imply more inequality.

2.4.5 Educational Inequality in Austria

Economic Returns and the Access to Education

Education is seen as major pathway to increase income mobility, as children's education level closely relates to their economic outcomes. Tertiary degrees are associated to the largest economic gains for children. Table 2.7 reports the results of Mincer-type wage regressions where the dependent variables are children's income percentile ranks (left column) and their log income (right column). The coefficients show the average returns linked to different education levels in Austria. General education serves as a reference category.

In Austria, children holding tertiary degrees can expect to improve their income position by 30.16 percentile ranks compared to children who have completed general education. At age 30, this implies an earning advantage of 45.83%. Therefore, returns to tertiary degrees are more than twice as high as returns to completed apprenticeships, which produce an average increase of 13.46 ranks compared to general education. In general, the mean returns to VET school and upper secondary degrees are similar: 18.532 ranks and 20.043 ranks, respectively. Overall, a tertiary degree provides a significant economic advantage and increases a child's economic position, thus enabling upward economic mobility.

Conversely, children's access to education strongly depends on their economic background. Figure 2.8 shows the frequency of different education types in the children generation conditional on the income ranks of their fathers. The panels include general education (Hauptschule), apprenticeships, vocational education and training (VET) schools, upper secondary education ("Berufsbildende/ Allgemeinbildende Höhere Schulen"), and tertiary degrees ("Kolleg, Akademie, Universität").

Different types of education follow different patterns along the father income distribution. General education is present in families in the lower segment of the income distribution. Here, up to 21.5% of children obtain general education. This share decreases markedly for higher income ranks. At the 98^{th} income percentile, approximately 1% of children graduate with general education.

Apprenticeships are popular and predominant across large segments of the fathers' income distribution. After the 60^{th} income rank, the share of children who complete vocational training starts to decline and tertiary degrees become more important. VET schools exhibit a similar pattern but on a lower level (note the different scaling of the vertical axes). There is a linear trend for upper secondary degrees with a higher variation at both ends of the father income distribution. The middle-right panel of Figure 2.8 shows a downward kink occurs around the 80^{th} income percentile rank.

Starting with the 73^{th} percentile of the fathers' income distribution, more children opt

Table 2.7: Returns to education

	Income Rank	Income Level
Dual Training (Apprenticeship)	13.460***	0.209***
	(0.449)	(0.008)
VET School	18.532***	0.272***
	(0.545)	(0.010)
Upper Secondary Education	20.043***	0.281***
	(0.481)	(0.009)
Tertiary Degrees	30.156***	0.458***
	(0.476)	(0.009)
Adj. R^2	0.151	0.182
N	46,025	46,025

Note: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. This table reports economic returns to education. Those are estimated in a Mincer-type OLS regression where the dependent variables are children's income percentile rank (left column) and their monthly log income (right column). Hereby, the estimation controls for children's gender. Vocational education and training (VET) school is "Berufsbildende Mittlere Schule", upper secondary education includes "allgemeinbildende und berufsbildende höhere Schulen", and tertiary degrees "Kolleg, Akademie, Hochschule". The results imply that on average, having a tertiary degree relates to a 30.156-rank increase in the child's income position compared to general education, the reference group. In monetary terms, this translates into a 45.8% increase in the child's monthly earnings.

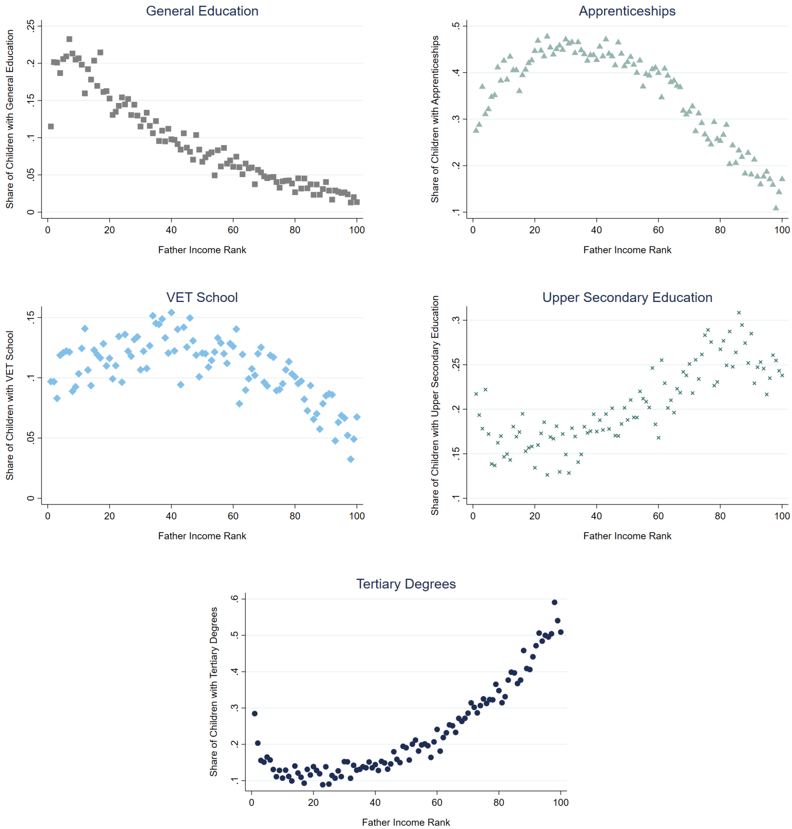
for tertiary education than for apprenticeships. The share of children with tertiary education rises sharply in the upper half of the income distribution. This makes tertiary education more accessible than in the neighboring Switzerland. Only with the 95^{th} income percentile, a higher share of children attends the gymnasium instead of vocational education and training (Chuard and Grassi, 2020), implying that the access to the gymnasium strongly depends on the (high-)income position of the parents. This indicates a higher access to tertiary education in Austria than in Switzerland.

To document the level of educational inequality in Austria, I relate the educational chances of poor-born children to the chances of rich-born children. Hereby, the Q1 measure provides the probability that a child born to a father in the bottom income quintile obtains a tertiary degree. For Austria, this equals 0.135. Conversely, the Q5 measure indicates the probability children from the top income quintile have tertiary education, which is Q5 = 0.446. Therefore, the ratio between rich and poor children, i.e., Q5/Q1, is 0.446/0.135 = 3.304. This implies that a child born to a father in the top income quintile is more than three times as likely to obtain a tertiary degree as a child born in the bottom quintile. When a father has completed tertiary education, his child very likely has, too, almost regardless of whether that father is positioned in the bottom or in the top quintile: Children at the top are 1.3 times as likely as those at the bottom to have tertiary education. This is the lowest wedge within subgroups included in the analysis. Considering separate results for sons and for daughters, I find that daughters from the top-income quintile are highly likely to obtain tertiary education. In contrast, sons raised by fathers in the bottom quintile stand the lowest chances in this respect. Table 2.8 summarizes the results.

Several studies address the transmission of education in migrant families in Austria (e.g., Oberdabernig, 2017; Altzinger and Schneebaum, 2018). Therefore, I also present reports for first- and second-generation migrants in the children generation.[5] The results are reported in Table 2.8. Economically successful migrant families care about their children's education. Especially second-generation migrant children raised by families in the top income quintile are very likely to earn a tertiary degree (54.6%). Their chances are 10 percentage points above the sample average. The Q5/Q1 ratio is high for this group, as second-generation migrant children are 41.5 percentage points more likely to have tertiary education if they are born in the top income quintile than if they are born in the bottom income quintile. Within bottom-quintile families, chances between natives and migrants vary to a smaller extent, from 10.8% for first generation migrants to 15% for native children.

[5] A child is defined as a first-generation migrant if it is born outside of Austria, and as a second-generation migrant if at least one of its parents is reportedly born abroad.

Figure 2.8: Relation between children's education and fathers' income ranks



Note: The panels of this figure show the share of children with a given education type for each percentile rank in the father's income distribution. Hereby, vocational education and training (VET) school is "Berufsbildende Mittlere Schule", upper secondary education includes "allgemeinbildende und berufsbildende höhere Schulen", and tertiary degrees "Kolleg, Akademie, Hochschule". Not the different scaling of the vertical axes.

Table 2.8: Absolute educational mobility

	Q1	Q5	Q5/Q1
Total sample	0.135	0.446	3.304
Sons	0.093	0.353	3.796
Daughters	0.197	0.558	2.833
Tertiary degree father	0.510	0.673	1.320
No tertiary degree father	0.115	0.375	3.261
Natives	0.150	0.442	2.947
First generation migrant	0.108	0.384	3.556
Second generation migrant	0.131	0.546	4.168

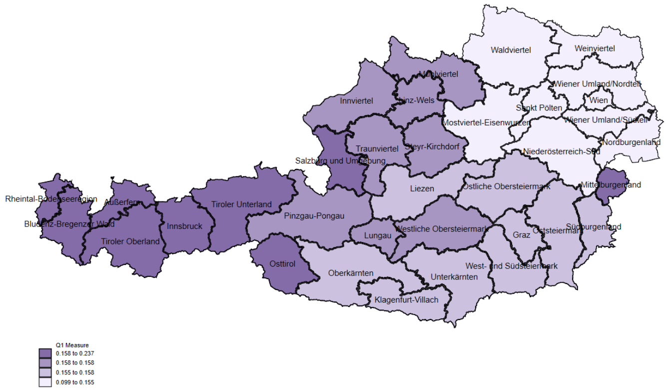
Note: This table shows the probabilities of children obtaining tertiary education when they are born to a father at first income quintile (Q1) and at the fifth income quintile (Q5). The ratio Q5/Q1 describes the level of educational inequality: Over the total sample, a child born at the top income quintile is 3.304 times as likely as a child born at the bottom quintile.

Geographical Variation

Regional variation also exists in educational inequality. Figures 2.9 and 2.10 present regional heat maps for the Q1 and Q5 measure. Darker shades indicate higher chances that children from bottom- (Q1) and top (Q5) income families obtain tertiary education. With the exception of Burgenland, the Q1 measure distinctively increases from West to East. Yet, the magnitude of this variation is moderate. In large parts of Austria, approximately 16% of poor children reach a tertiary degree, in Burgenland the share is even 23.7%. Weinviertel is the only Austrian region where less than 10% of children of bottom quintile fathers obtain tertiary education. There, it seems considerably more difficult for poor children to overcome disadvantages in terms of family background than in the rest of Austria. More variation exists when considering the share of rich children with tertiary education. The Q5 measure ranges from 30.9% in “Bludenz-Bregenzer Wald” up to 60% in “Lungau” (Salzburg), compared to the Austrian average of 44.6%.

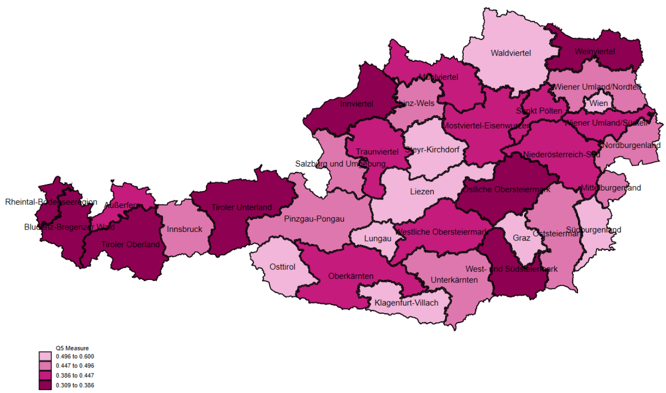
The resulting Q5/Q1 measure is visualized in Figure 2.11. Driven by the geographical pattern of the Q1 measure, educational inequality tends to increase from West to East. Yet, “Mittelburgenland” shows the lowest level of educational inequality among all Austrian regions. There, a child born to a father in the top income quintile is 1.9 times as likely to obtain a tertiary degree as a child born in the bottom quintile. In “Lungau”, the same child would be 3.8 times as likely to earn a tertiary degree. Educational mobility is also comparably high in "Östlicher Obersteiermark" and „West- und Südsteiermark". In Vienna, Q5/Q1 = 3.246, which implies that in the capital, educational inequality is slightly lower than the country's average of 3.304.

Figure 2.9: Regional variation in the Q1 measure



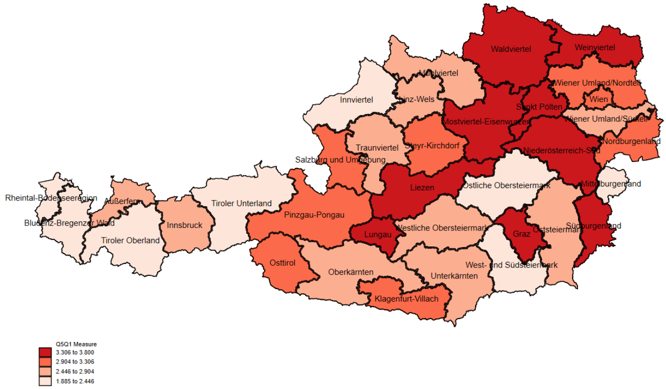
Note: This heat map illustrates regional variation in the Q1 measure. Darker shades indicate a higher probability that children born to fathers in the bottom-income quintile obtain tertiary education

Figure 2.10: Regional variation in the Q5 measure



Note: This heat map visualizes regional variation in the Q5 measure. Darker shades indicate a higher probability that children born to fathers in the top-income quintile obtain tertiary education.

Figure 2.11: Regional variation in educational inequality



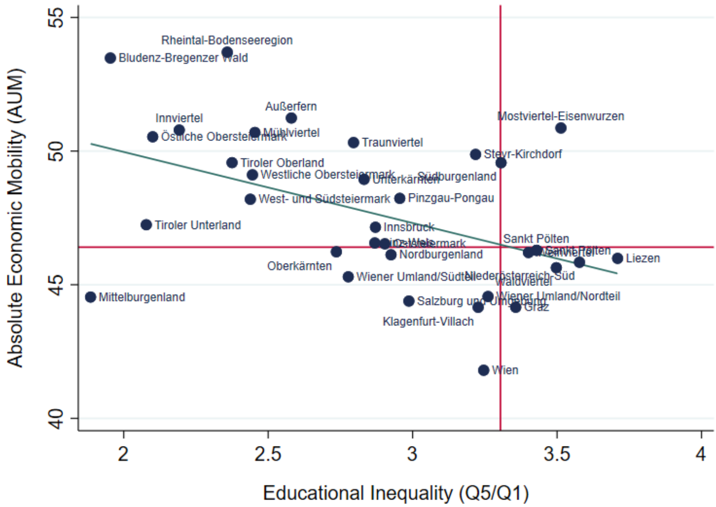
Note: This heat map visualizes regional variation in educational inequality. The darker the shade, the higher the level of educational inequality, expressed by the Q5Q1 measure. This indicates the chances of children from the top income quintile to obtain teritary education relative to children from the bottom income quintile.

Educational Inequality and Economic Mobility

Intuitively, one would expect high economic mobility to relate to high educational mobility, and vice versa. However, country-level results suggest that this is not necessarily the case. Chuard and Grassi (2020) show that Switzerland is characterized by high income mobility, but by low educational mobility. In a similar line, Dodin et al. (2021) find a stable relation between economic background and the probability of obtaining A-levels over time in Germany, despite a massive expansion of higher education. Simultaneously, income mobility in Germany is falling (Kyzyma and Groh-Samberg, 2018).

On regional level, I obtain mixed results. In regions where educational inequality is high, the expected economic outcomes of poor children tend to be low. The significant correlation coefficient between absolute upwards mobility (AUM) and educational inequality (Q5Q1) equals -0.473, which is illustrated in Figure 2.12. However, I do not find evidence for a significant relation between educational inequality and relative economic mobility, measured by the regional rank-rank slopes.

Figure 2.12: Educational inequality (Q5Q1) and absolute economic mobility (AUM)



Note: This figure illustrates a negative relation between educational inequality (Q5Q1) and absolute economic mobility (AUM). The correlation coefficient is significant on the 1% level and equals -0.473. The red lines indicate country averages for the AUM and Q5Q1 measures.

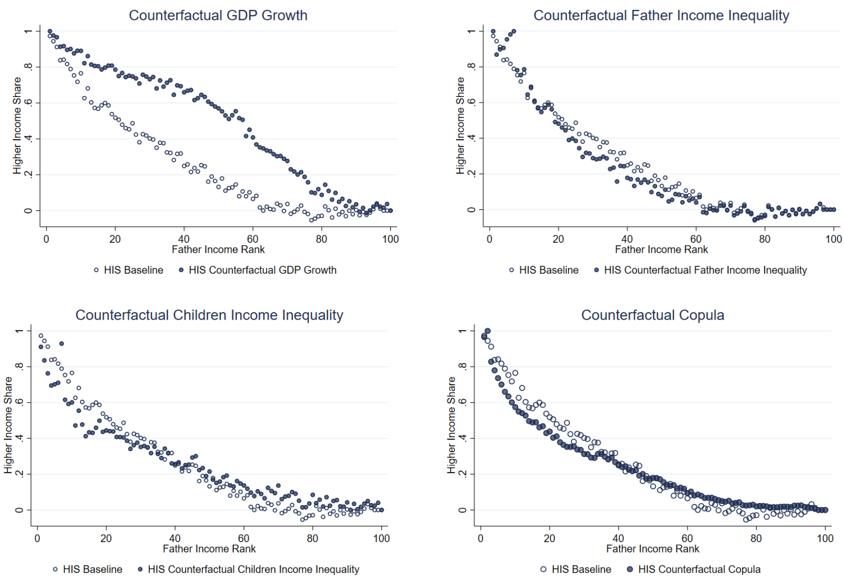
2.4.6 What drives Absolute Mobility? The Role of Growth, Inequality, and Relative Economic Mobility

For policy makers, it is important to understand how developments in the overall economy influence children's chances of improving their living standards compared to their parents. Below, I therefore provide illustrative counterfactual scenarios to describe the effect of three global trends much discussed in the public policy debate: GDP growth, higher income inequality, and declining relative income mobility.

I use the higher income share (HIS) as a measure of absolute economic mobility. The HIS consists of three elements: the two marginal income distributions in the children and father generations, and the joint distribution of income ranks, that is, the copula. Therefore, economic changes affecting one of these elements also influence the level of absolute mobility.

The counterfactual scenarios are illustrative. Therefore, they abstract (e.g.) from the relation between relative income mobility and economic growth. In the long run, relative income mobility increases economic growth, as it enables children from low-income families to develop their full potential and thus contributes to productivity and innovation (Aghion et al., 2017). Nevertheless, the counterfactuals shed light on the importance of economic growth for income mobility. So far, this has hardly found its way into the public discourse on income mobility.

Figure 2.13: Changes in absolute mobility



Note: This figure illustrates how the counterfactual assumptions on economic growth, inequality, and the copula affect absolute mobility along the father income distribution. Hereby, absolute mobility is measured by the higher income share (HIS) and each dot represents the share of children earning more than their fathers at a specific income percentile rank.

The Role of GDP Growth

In the following, I assume that Austria experienced the same economic growth between 1990 and 2020 as it did between 1960 and 1990.[6] This was a period of high economic growth, and real GDP increased by 114.8%. In comparison, real GDP grew by 52.9% during the investigated children's lifetime, which is less than half.
To obtain a counterfactual income distribution for the children generation, I multiply the income in each income percentile by the ratio of total GDP growth in the 1960-1990 period and the total GDP growth in the 1990-2020 period. This shifts the children's income distribution to the right. Consequently, average earnings increase

[6] Data on real GDP growth is provided by Wirtschaftskammer Österreich (WKO) (2022).

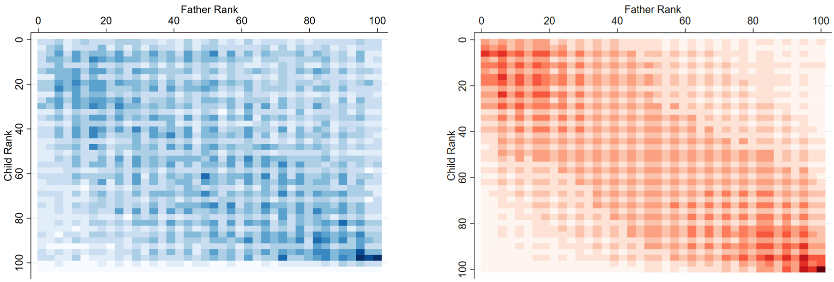
significantly from 2,631.61 Euros to 3,696.99 Euros.[7]
Higher GDP growth substantially increases absolute mobility. In this scenario, the higher income share changes from 0.259 in the main results to 0.486. Thus, almost half of all children in the 1990 birth cohort earn more than their fathers, even though they are significantly younger when their earnings are measured.
The panels of Figure 2.13 show for each father income rank the share of children earning more than their fathers. In general, it is easier for children from lower income positions to outperform their parents, whereas the share drops towards zero for higher percentile ranks. The upper left panel indicates how the HIS changes due to higher GDP growth. The share of children earning more than their fathers decreases much more slowly until the middle segment of the income distribution. At the beginning of the 6$^{\text{th}}$ income decile, approximately 60% of children outperform their fathers. Then, the share declines linearly. Overall, higher GDP growth improves absolute mobility along the entire income distribution.

An American Dream? A counterfactual scenario with US mobility rates

The previous sections indicated that Austria experiences a comparatively high level of relative economic mobility. Relative mobility is captured by the copula, which is the joint distribution of children and father income ranks. In the following counterfactual, I show how absolute mobility in Austria changes if the country would experience the same level of relative economic mobility as in the United States. For this, I exchange the Austrian copula with the US copula, leaving the marginal income distributions unchanged.[8]
Economic opportunities are distributed more evenly in Austria than in the United States. This is illustrated by the copulas' heatmaps in Figure 2.14. A darker color implies a higher probability density for the respective rank-rank constellation. The left panel visualizes the estimated copula for Austria, the right panel represents the US copula. In comparison, observed patterns are very distinct for the United States. There is a higher probability density at bottom- and top-income pairs, as well as along the diagonal, capturing the staying-probabilities. In Austria, probabilities for observing different pairs of father and child ranks are distributed more evenly, except at the very top.
When the US copula is applied to Austria, it becomes more difficult for poorer children

[7] Figure A.4.3 in the Appendix visualizes the counterfactual income distributions in all scenarios. Table A.4.4 provides additional summary statistics.
[8] The US copula is provided by Chetty et al. (2017) on `https://opportunityinsights.org/`.

Figure 2.14: Copulas of Austria and the United States



Note: This figure presents heatmaps of the copula functions. The left panel shows the 100x100 transition matrix for Austria, the right panel for the US. Darker colors indicate a higher probability of observing a specific rank combination.

to outperform their fathers as adults, whereas the share increases for children in the higher income ranks. This is illustrated by the lower right panel of Figure 2.13, showing a counterclockwise rotation of the HIS curve.

The overall effect on absolute mobility is a small decrease. The HIS slightly declines by 1.5 percentage points to a value of 0.237. In comparison, relative mobility reduces by half, given RRS coefficients of 0.167 for Austria and 0.341 for the United States (Chetty et al., 2017). This implies that the sensitivity of absolute mobility to changes in relative mobility is comparatively low.

Inequality and Absolute Income Mobility

Within Austrian regions, higher income inequality relates to lower relative income mobility. In the following, I evaluate whether this also applies to absolute economic mobility at the aggregate level. Contrary to countries like the United States, income inequality in Austria declined moderately over the last 20 years. Consequently, I provide one counterfactual scenario in which children income is distributed as in 2003, the first year in which Austria participated in the EU-SILC survey. There, gross income of young adults is slightly more dispersed than in the 1990 birth cohort. The income shares in each percentile are calculated using additional information of the 2003 EU-SILC survey on gross income.[9] These income shares are then applied to the mean income in the children generation, providing a counterfactual income distribution with a slightly higher level of income inequality. The copula and the

[9]Due to sample size, I use information on children in the age of 30-35.

Table 2.9: Counterfactual outcomes for the higher income share (HIS)

Scenario	HIS
Baseline Higher Income Share	0.259^{***}
	(0.028)
Higher GDP growth	0.486^{***}
	(0.031)
Higher inequality in children generation	0.253^{***}
	(0.022)
US level of relative mobility	0.237^{***}
	(0.023)
US level of inequality in children generation	0.271^{***}
	(0.017)

Note: $*(p < 0.05)$, $**(p < 0.01)$, $***(p < 0.001)$. Standard errors in parentheses. This table summarizes the outcomes of the counterfactual scenarios. Compared to the baseline value of 0.259, a higher GDP growth relates to a substantial increase in absolute mobility, measured by the higher income share. Higher inequality or lower relative mobility affects the HIS value to a smaller extent.

income distribution in the father generation remains unchanged.[10]

Higher inequality does not lead to large changes on the aggregate level of absolute mobility, the HIS coefficient shifts from 0.259 to 0.253. The lower left panel of Figure 2.13 shows that the higher level of income inequality enables more children in the upper part of the income distribution to earn more than their fathers, which is offset by declining shares in the lower part of the income distribution.

However, the difference in income inequality between 2003 and 2020 is only of limited magnitude. To illustrate how larger changes in income inequality in the children generation affect absolute mobility, I provide an additional scenario where children in Austria experience the same level of income inequality as in the United States.

Already at age 30, children's income is substantially more dispersed in the United States than in Austria. Analogously to the previous counterfactual, I scale the income share in each children income percentile to the US level but keep the copula and the marginal distribution of father income constant.[11]

[10] See Appendix A.4 for further information on the counterfactual income distribution and a corresponding density plot.

[11] I refer to the income shares of the 1984 birth cohort in the United States, which is the most recent one included in Chetty et al. (2017). The data is publicly available on `https://opportunityinsights.org/`.

The observed patterns in absolute mobility resemble the 2003 scenario, but they become more pronounced. The share of children earning more than their parents drops substantially in the lower part of the income distribution. Approximately with the 40$^{\text{th}}$ income percentile, the higher income shares start to rise. At the aggregate level, this leads to an increase in absolute mobility by 1.2 percentage points.
Table 2.9 summarizes the results of the counterfactual scenarios. The counterfactual scenarios demonstrate that even comparatively large changes in relative mobility or inequality lead to only small effects on absolute mobility at the aggregate level, as changes are ambiguous: Higher inequality benefits children from high-income families but deteriorates absolute mobility for children at the bottom tail. Then, the net effect depends on the density in each part of the income distribution. Here, the net effect of high income inequality is positive.
This suggests that policymakers should focus not only on whether children earn more than their parents, but also on *which* children. The same applies to the counterfactual copula scenario, where, however, the aggregate HIS value slightly decreases compared to the baseline scenario. In contrast, higher economic growth, in which all children participate in the form of gains in real income, significantly increases absolute mobility and substantially improves the higher income share along the entire distribution. Following the argument of Manduca et al. (2020), in a country where relative income mobility is high, the children of high-income earners are more likely to end up in a lower income percentile rank than their fathers. Thus, more economic growth is required to increase these children's living standards compared to their parents.

2.5 Robustness Checks and Alternative Specifications

2.5.1 Intergenerational Income Elasticity

The main analysis uses the rank-based RRS coefficient as measure for relative economic mobility. In comparison, the intergenerational income elasticity (IGE) is level based. The IGE is estimated by regressing child i's log income ($logY_i^C$) on the father's log income ($logY_i^F$), controlling for ages in linear and quadratic form. Consequently, the IGE can be expressed as:

$$\text{IGE} = \rho_{\text{CF}} \frac{SD(logY_i^C)}{SD(logY_i^F)}, \tag{2.8}$$

where ρ_{CF} is the Pearson correlation coefficient between children's and fathers' log earnings. $SD(logY_i^F)$ and $SD(logY_i^C)$ are the standard deviation of father and child income, respectively. Therefore, the IGE coefficient does not only describe the association between parent and child income, but also reflects changes in inequality across generations.

Table A.5.5 shows IGE-based results for relative mobility. The IGE equals 0.101 for the entire sample. The IGE value implies that a 1% increase in father income is associated with a 0.101% increase in child income. As in the main results, the IGE coefficient is higher for daughters than for sons (0.091 vs. 0.132).

Therefore, the IGE is smaller than the RRS coefficient in the main results. Typically, the literature finds larger IGE coefficients. For instance, Kyzyma and Groh-Samberg (2018) report an earning elasticity of 0.368 for Germany together with a RRS coefficient of 0.242. In Switzerland, corresponding values are 0.166 for the income elasticity and 0.141 for the rank-rank slope (Chuard and Grassi, 2020).

Here, the sample is not optimal for a level-based analysis of intergenerational income mobility. As discussed in the data section, children and fathers are not in the same stage of their life cycle when income is observed. Children are comparatively young and consequently, their income is less dispersed than father income ($SD(logY_i^C) < SD(logY_i^F)$), which decreases the IGE compared to the correlation coefficient. Furthermore, income observations in the children generation are observable for less than five years, which makes them prone to attenuation bias additional to life cycle bias. This confirms the use of the rank-based RRS coefficient as measure for relative economic mobility in the main analysis.

2.5.2 Results for Mother-Child Pairs

I expect that mothers' earnings are less predictive for children's economic outcomes than fathers' earnings. In Austria, female labor market participation has been substantially lower than male labor market participation, which also applies to the observed parent generation. Therefore, their earnings are less reflective of the socioeconomic environment a child grew-up in. Their average monthly earnings are significantly lower than fathers' earnings (2,383.16 Euros vs. 4,359.85 Euros).[12] The share of mothers with tertiary education is comparable to the share of fathers. Almost twice as much have obtained general education and a substantially lower share of mothers completed an apprenticeship (31.2% vs. 51.3% of fathers).

Table A.6.7 summarizes the results for the estimated rank-rank slope. As expected, the association between children's economic positions and their mothers' economic

[12] Table 2.1 provides additional information on mother sample statistics. Analogous to the main specification, I calculate a mother's economic position relative to other mothers with children in the 1990 birth cohort and use their average earnings between 2010 and 2013, given that they participate in the labor market.

position is weaker than in the main results. For the total mother-child sample, the RRS value equals 0.067, compared to 0.167 in the father-child sample. Especially for sons, mothers' economic positions do not have much predictive power for their own economic outcomes. A similar conclusion can be drawn from the income transition matrices in the Appendix Table A.6.8. Children's chances of reaching a specific income quintile conditional on their mother's income quintile appear to be quite evenly distributed.

Next, I implement different lower income bounds on the mothers' earnings. Table A.6.9 summarizes the results, restricting the sample to mothers with a minimal income of 500 Euros, 1,000 Euros, 2,000 Euros, and 3,000 Euros, respectively. The results are very similar for the first and second specification, as well as for the third and fourth. The rank-rank slope estimates remain largely unchanged for a lower bound of 500 or 1,000 Euros, whereas higher income bounds lead to similar coefficients converging to the level of the main results.

2.5.3 Location Choice

The main specification relies on father-child pairs. Consequently, children are assigned to the fathers' place of living at the NUTS3-level. In the following, I test the sensitivity of the results towards different specifications by implementing the mothers' place of living and the child' own place of living in 2020 as alternative geographic assignments. The results are summarized in Table A.7.10.

The coefficients are similar in size to those in the main specification when children are assigned to their mothers' location. Styria remains the federal state with the highest RRS coefficient, and Vienna remains the one with the highest. The magnitude of Vienna's RRS coefficient remains almost unchanged in all three specifications. Otherwise, results vary more for children's place of living. However, it seems less likely that children's current place of living reflects the region in which they grew-up in - except perhaps for the capital.

2.5.4 Lower Income Bounds

Table A.8.11 provides results on the rank-rank slope for different lower income bounds ranging from 500 Euros to 3,000 Euros. Overall, the RRS estimates are not sensitive towards the implementation of lower bounds. The coefficient values show no substantial variation except when the lower bound is raised to 3,000 Euros on monthly earnings, which is more than the mean income in the 39^{th} income percentile of the father income distribution. Then, the RRS coefficient decreases from 0.167 to 0.139, as the sample excludes low-income fathers and their children. Thus, this income bound would cover the transmission of low economic positions.

2.5.5 Life-cycle Bias and Attenuation Bias

Life-cycle bias arises when the observed income at a specific life-cycle state systematically deviates from lifetime income. In general, the level of current income is below the life-time average when individuals are still very young adults. This particularly applies to highly educated individuals with steep income profiles. In late adulthood, the current income tends to exceed life-time income. Consequently, income levels should be measured when individuals are in their prime age (Grawe, 2006; Haider and Solon, 2006).

Nybom and Stuhler (2017) show that life-cycle bias is small in rank-based mobility measures. Other than income levels, percentile ranks stabilize once children reach the age of 30 (Chetty et al., 2014a). To check whether results are sensible for fathers' age, I adjust the observation years for parental income. Table A.9.12 shows the results. The average father was 47.6 years old by the end of 2010, the first year of income observation. Different specifications increase the mean age up to 56.6 years by the end of 2019. Thus, their current income level exceeds their average life-time income. Yet, the RRS coefficients remain comparatively stable, ranging between 0.168 and 0.174. The table also presents results on the intergenerational income elasticity. In comparison, the magnitude of the IGE coefficient almost doubles in its magnitude across the different specifications.

The second line in Table A.9.12 shows the RRS coefficient when father income is measured over six years between 2010 and 2015. This refers to attenuation bias. This bias derives from measurement errors in the income variables due to transitory income shocks (Solon, 1992; Mazumder, 2005). Income is often observed for a restricted time-period only, in which short-term fluctuations of income can occur. This bias leads to a downwards estimate of intergenerational persistence, especially for level-based mobility measures such as the intergenerational income elasticity. The bias diminishes with increasing number of years that are used to calculate income averages, assuming that transitory fluctuations are not serially correlated (Björklund and Jäntti, 1997). Here, I work with income ranks. Nybom and Stuhler (2017) show that for the RRS measure, the bias is small if there is measurement error either in the child rank or in the father rank, and moderate if there are errors at both sides of the regression equations. When increasing the number of observation years in the father generation, neither the RRS nor the IGE show large changes.

Table A.9.13 presents results for children income. The available data is limited to observations in 2018 to 2020, when children are between 28 and 30 years old. Due to life-cycle concerns, income in 2020 is used in the main specification, when children reach the age of 30. Then, children's income percentile ranks should be comparatively stable. Expanding the number of observation years reduces children's age below the threshold of 30 years. The RRS coefficient slightly increases from 0.167 up to 0.172. Conversely, the IGE value decreases as children become younger, which hints a downwards directed life-cycle bias. Note that in all specifications of father and children income, the obtained rank-rank slope equals approximately 0.17 as in the main results.

2.6 Conclusion

This paper uses administrative data on the entire 1990 birth cohort and their parents to document relative and absolute income mobility in Austria. It also explores regional differences and characterizes educational inequality. Furthermore, the analysis involves counterfactual scenarios to explore the role of economic growth, income inequality, and relative mobility for children's chances of improving their living standards compared to their parents.

In Austria, the level of relative mobility is comparatively high. The rank-rank slope (RRS) equals 0.167 for father-child pairs, and children born at the 25^{th} income percentile can expect to reach the 47^{th} income percentile of their own generation. Compared to Germany, Austria is characterized by higher relative mobility at the mean and by lower persistence at the top of the income distribution.

However, the income transition matrix reveals poverty cycles. Children born in the bottom income quintile are more likely to remain there as adults than in other German-speaking countries (to a similar extent as in Italy). Also, there is substantial geographical variation with several clusters of high- and low-mobility regions. On an annual level, the gap in children's economic outcomes between regions exhibiting the highest and lowest relative mobility corresponds to more than one average monthly salary in Austria. I also find evidence of an Austrian Great-Gatsby curve. At the regional level, high income inequality correlates with low economic mobility, and vice versa.

A father's income position also relates to children's chances of obtaining tertiary education. On average, children from the top income quintile are more than 3-times as likely to reach a tertiary degree than children from the bottom income quintile. A geographical gradient is also evident, except for "Mittelburgenland": In Austria, educational inequality rises from West to East. This finding is important for the transmission of economic status, as economic returns to tertiary education are large.

Having a tertiary degree increases the average child's position by 30.2 income ranks compared to general education. At age 30, this translates into an increase of 45.8% in monthly earnings.

One important result for policymakers is that high relative mobility does not automatically translate into a high share of children improving their living standard compared to their parents. This finding is illustrated by a counterfactual scenario that adopts relative mobility in Austria to the US level. The RRS coefficient is twice as high in the United States than in Austria, indicating that relative mobility is substantially lower. When, however, the joint distribution of income and father ranks is applied, absolute mobility decreases by only 2 percentage points. Similar applies to changes in income inequality in the children generation, as a result of divergent changes along the father's income distribution: Lower relative mobility and higher income inequality both deteriorate absolute mobility for children from lower-income families. However, this effect is almost completely offset by increases in the higher income shares for children from higher-income ranks.

In comparison, higher GDP growth, as reflected in equally distributed real wage growth, benefits all children and significantly increases absolute mobility. For the 1990 birth cohort, absolute mobility would almost double if Austria had experienced the same growth during the investigated children's lifetime as it did between 1960 and 1990. Consequently, if policy makers want to enhance absolute mobility, they should focus on real wages and on fostering GDP growth, while distributing this growth equally along the distribution.

However, it is also necessary to keep in mind that absolute mobility is no measure for equality of opportunities. In this respect, policymakers must reduce unequal education access to maintain high relative economic mobility and to target poverty cycles. Overall, Austria is a country with high innovative potential (Kletzan-Slamanig et al., 2009). Its policymakers are therefore advised to ensure that the country does not lose talents due to missing access to educational and economic opportunities.

Bibliography

Acciari, P., A. Polo, and G. L. Violante. 2019. "And Yet It Moves": Intergenerational Mobility in Italy. NBER Working Paper 25732.

Aghion, P., U. Akcigit, A. Hyytinen, and O. Toivanen. 2017. The Social Origins of Inventors. NBER Working Paper No. 24110.

Alesina, A., S. Stantcheva, and E. Teso. 2018. Intergenerational Mobility and Preferences for Redistribution. *American Economic Review* 108:521–54.

Altzinger, W., and A. Schneebaum. 2018. Austria: Intergenerational Mobility among Children of Immigrants. In *Catching Up? Country Studies on Intergenerational Mobility and Children of Immigrants.* OECD.

Altzinger, W., and M. Schnetzer. 2010. Intergenerational Income Mobility - An Empirical Investigation for Austria and the European Union. Vienna University of Economics and Business Department of Economics.

Björklund, A., and M. Jäntti. 1997. Intergenerational Income Mobility in Sweden compared to the United States. *The American Economic Review* 87:1009–1018.

Blanden, J., S. Machin, and S. Rahman. 2019. Falling Real Wages: The Effect on Absolute Earnings Mobility. mimeo.

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

Bönke, T., A. Harnack, and H. Luthen. 2019. Are Children Better off? Intergenerational Mobility of Living Standards. mimeo.

Chetty, R., D. Grusky, M. Hell, N. Hendren, R. Manduca, and J. Narang. 2017. The fading American dream: Trends in absolute income mobility since 1940. *Science* 356:398–406.

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

Chetty, R., N. Hendren, P. Kline, E. Saez, and N. Turner. 2014b. Is the United States still a Land of Opportunity? Recent Trends in Intergenerational Mobility. *American Economic Review* 104:141–47.

Chuard, P., and V. Grassi. 2020. Switzer-Land of Opportunity: Intergenerational Income Mobility in the Land of Vocational Training. University of St. Gallen SEPS Discussion Paper no. 2020-11.

Corak, M. 2006. Do Poor Children Become Poor Adults? Lessons from a Cross-Country Comparison of Generational Earnings Mobility. *Research on Economic Inequality* 13:143–188.

Corak, M. 2010. Chasing the Same Dream, Climbing Different Ladders: Economic Mobility in the United States and Canada. Pew Charitable Trusts.

Corak, M. 2017. *Divided Landscapes of Economic Opportunity: The Canadian Geography of Intergenerational Income Mobility.* Research Group on Human Capital-Université du Québec à Montréal.

Dahl, M., and T. DeLeire. 2008. The Association between Children's Earnings and Father's Lifetime Earnings: Estimates Using Administrative Data. Institute for Research on Poverty Discussion Paper No. 1342-08.

Deutscher, N., and B. Mazumder. 2020. Intergenerational Mobility across Australia and the Stability of Regional Estimates. *Labor Economics* 101861.

Dodin, M., S. Findeisen, L. Henkel, D. Sachs, and P. Schüle. 2021. Social Mobility in Germany. University of Konstanz Working Paper Series No. 04.

Fessler, P., and A. Schneebaum. 2012. Gender and Educational Attainment Across Generations in Austria. *Feminist Economics* 18:161–188.

Grawe, N. 2006. Lifecycle Bias in Estimates of Intergenerational Earnings Persistence. *Labour Economics* 13:551–570.

Haider, S., and G. Solon. 2006. Life-Cycle Variation in the Association Between Current and Lifetime Earnings. *American Economic Review* 96:1308–1320.

Heidrich, S. 2017. Intergenerational mobility in Sweden: A Regional Perspective. *Journal of Population Economics* 30:1241–1280.

Kennedy, T., and P. Siminski. 2022. Are We Richer than Our Parents were? Absolute Income Mobility in Australia. *Economic Record* 98:22–41.

Kletzan-Slamanig, D., A. Reinstaller, and I. Stadler. 2009. Assessment of ETAP roadmaps withregard to their eco-innovation potential: Country Profile. ENV-MAP Project Task 2 for the OECD.

Kyzyma, I., and O. Groh-Samberg. 2018. Intergenerational Economic Mobility in Germany: Levels and Trends. Mimeo.

Liss, E., M. Korpi, and K. Wennberg. 2023. Absolute Income Mobility and the Effect of Parent Generation Inequality: An extended Decomposition Approach. *European Economic Review* 152:104359.

Manduca, R., M. Hell, A. Adermon, J. Blanden, E. Bratberg, A. C. Gielen, H. van Kipepersluis, K. B. Lee, S. Machin, M. D. Munk, M. Nybom, Y. Ostrovsky, S. Rahman, and O. Sirniö. 2020. Trends in Absolute Income Mobility in North America and Europe. IZA Discussion Paper 2020:11.

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

Nybom, M., and J. Stuhler. 2017. Biases in Standard Measures of Intergenerational Income Dependence. *Journal of Human Resources* 52:800–825.

Oberdabernig, A., Doris; Schneebaum. 2017. Catching Up? The Educational Mobility of Migrants' and Natives' Children in Europe. *Applied Economics* 49:3701–3728.

Schnetzer, M., and W. Altzinger. 2013. Intergenerational Transmission of Socioeconomic Conditions in Austria in the Context of European Welfare Regimes. *Momentum Quarterly* 2:108–126.

Sklar, A. 1959. Fonctions de Repartition an Dimensions et Leurs Marges. *Publ. inst. statist.univ. Paris* 8:229 – 231.

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

Statistik Austria. 2009. Regionaldaten Österreichs in NUTS-Gliederung. *Statistisches Jahrbuch* pp. 492–518.

Wirtschaftskammer Österreich (WKO). 2022. BIP und Wirtschaftswachstum. WKO Statistik.

Appendix

A.1 Supplementary Descriptive Statistics

Table A.1.1: Employment shares

Industry	Fathers	Children	Industry	Fathers	Children
Agriculture, forestry and fishing	0.005	0.003	Financial and insurance activities	0.034	0.026
	(0.070)	(0.058)		(0.182)	(0.160)
Mining and quarrying	0.005	0.002	Real estate activities	0.011	0.009
	(0.069)	(0.041)		(0.104)	(0.010)
Manufacturing	0.220	0.183	Professional, scientific and	0.029	0.074
	(0.415)	(0.387)	technical activities	(0.168)	(0.262)
Electricity, gas, steam and air	0.015	0.006	Administrative and support	0.059	0.059
conditioning supply	(0.121)	(0.078)	service activities	(0.235)	(0.236)
Water supply, sewerage, waste	0.010	0005	Public administration and defence,	0.111	(0.112)
management, remediation activities	(0.100)	(0.070)	compulsory social security	(0.314)	(0.316)
Construction	0.128	0.080	Education	0.043	0.053
	(0.334)	(0.271)		(0.202)	(0.224)
Wholesale and retail trade, repair	0.108	0.147	Health and social services sector	0.036	0.084
of motor vehicles and motorcycles	(0.310)	(0.354)		(0.185)	(0.277)
Transportation and storage	0.113	0.047	Arts, entertainment and	0.010	0.012
	(0.317)	(0.213)	recreation activities	(0.099)	(0.108)
Accommodation and food	0.028	0.041	Other service activities	0.014	0.019
service activities	(0.166)	(0.197)		(0.119)	(0.138)
Information and communication	0.021	0.037	Activities of households as employers	0.000	0.000
	(0.145)	(0.188)		(0.012)	(0.016)

Note: This table reports children's employment shares in Austrian industries, following the 1-digit OENACE 2008 classification. Standard deviations in parentheses.

Table A.1.2: Mean income by income percentile rank

Rank	Child Income	Father Income	Rank	Child Income	Father Income
1	391.47	483.21	51	2,562.51	3,381.96
2	586.14	801.70	52	2,583.80	3,424.96
3	688.68	1,015.15	53	2,604.54	3,468.38
4	770.77	1,184.23	54	2,626.39	3,512.92
5	843.77	1,329.64	55	2,648.91	3,558.69
6	911.22	1,459.51	56	2,671.08	3,608.37
7	973.76	1,580.97	57	2,692.21	3,657.19
8	1,032.87	1,675.13	58	2,714.60	3,704.97
9	1,094.55	1,755.82	59	2,738.84	3,755.33
10	1,156.01	1,835.08	60	2,761.18	3,808.02
11	1,211.48	1,905.94	61	2,784.49	3,861.42
12	1,268.33	1,971.83	62	2,805.80	3,918.58
13	1,323.86	2,028.51	63	2,829.30	3,974.19
14	1,378.15	2,077.71	64	2,853.76	4,039.22
15	1,433.40	2,123.06	65	2,878.70	4,106.81
16	1,486.96	2,168.76	66	2,904.29	4,175.86
17	1,535.94	2,209.81	67	2,932.26	4,241.53
18	1,583.30	2,251.16	68	2,958.96	4,308.06
19	1,630.34	2,291.92	69	2,984.83	4,378.05
20	1,671.79	2,329.00	70	3,011.71	4,450.04
21	1,712.71	2,364.07	71	3,041.84	4,522.46
22	1,751.75	2,399.70	72	3,072.39	4,596.45
23	1,788.84	2,432.56	73	3,102.84	4,675.03
24	1,825.12	2,466.56	74	3,131.15	4,751.97
25	1,862.34	2,498.34	75	3,161.73	4,831.08
26	1897.90	2,532.84	76	3,194.09	4,912.20
27	1935.24	2,563.76	77	3,228.73	4,994.40
28	1969.24	2,595.25	78	3,266.76	5,079.82
29	2001.52	2,627.63	79	3,300.14	5,173.76
30	2033.29	2,658.13	80	3,337.91	5,267.50
31	2064.72	2,689.14	81	3,378.20	5,369.02
32	2096.02	2,720.51	82	3,421.13	5,481.65
33	2126.22	2,751.66	83	3,464.71	5,607.63
34	2153.38	2,780.18	84	3,505.67	5,737.42
35	2181.58	2,810.99	85	3,553.91	5,879.79
36	2205.84	2,840.99	86	3,601.44	6,022.48
37	2231.80	2,874.63	87	3,658.05	6,182.41
38	2258.39	2,906.56	88	3,717.75	6,383.10
39	2284.47	2,940.45	89	3,781.97	6,585.61
40	2306.57	2,973.88	90	3,848.85	6,814.45
41	2331.10	3,010.25	91	3,931.68	7,088.93
42	2354.31	3,045.64	92	4,015.66	7,393.23
43	2379.40	3,080.91	93	4,115.09	7,756.57
44	2402.04	3,116.79	94	4,235.71	8,168.15
45	2426.71	3,151.97	95	4,380.85	8,686.39
46	2,450.73	3,187.46	96	4,562.34	9,355.82
47	2,474.65	3,224.32	97	4,792.29	10,274.78
48	2,494.63	3,262.28	98	5,113.41	11,625.94
49	2,515.83	3,301.63	99	5,638.87	14,291.47
50	2,538.81	3,341.35	100	11,029.79	41,263.39

Note: This table gives the mean income in every percentile rank of the income distribution of children and fathers, respectively. All amounts are measured in constant 2020 Euros.

A.2 Income Decile Transition Matrix

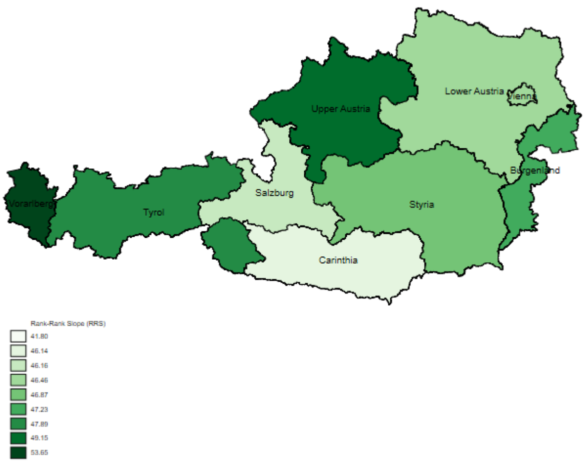
Table A.2.3: Income Decile Transition Matrix

		Fathers' Decile									
		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Children's Decile	1.	15.13%	14.05%	11.61%	10.29%	9.94%	9.08%	8.17%	7.64%	7.23%	6.48%
	2.	13.62%	13.00%	11.31%	10.32%	10.04%	9.35%	8.59%	8.12%	7.77%	7.08%
	3.	12.33%	11.99%	11.01%	10.35%	10.16%	9.65%	9.05%	8.67%	8.36%	7.76%
	4.	11.17%	11.08%	10.69%	10.34%	10.23%	9.91%	9.50%	9.22%	9.00%	8.52%
	5.	10.11%	10.22%	10.33%	10.28%	10.25%	10.13%	9.94%	9.78%	9.64%	9.33%
	6.	9.14%	9.40%	9.93%	10.15%	10.20%	10.30%	10.34%	10.33%	10.31%	10.20%
	7.	8.26%	8.62%	9.49%	9.97%	10.09%	10.39%	10.69%	10.85%	10.96%	11.13%
	8.	7.46%	7.90%	9.03%	9.74%	9.93%	10.44%	11.01%	11.35%	11.62%	12.12%
	9.	6.73%	7.22%	8.56%	9.46%	9.72%	10.43%	11.27%	11.82%	12.26%	13.16%
	10.	6.06%	6.57%	8.05%	9.12%	9.44%	10.33%	11.44%	12.21%	12.85%	14.22%

Note: Analogous to table 2.2, this transition matrix shows the probability that a child reaches a specific income decile conditional on the father's income decile. For instance, the probability is 15.15% that a child born to a father at the bottom decile remains at the bottom decile in his own generation.

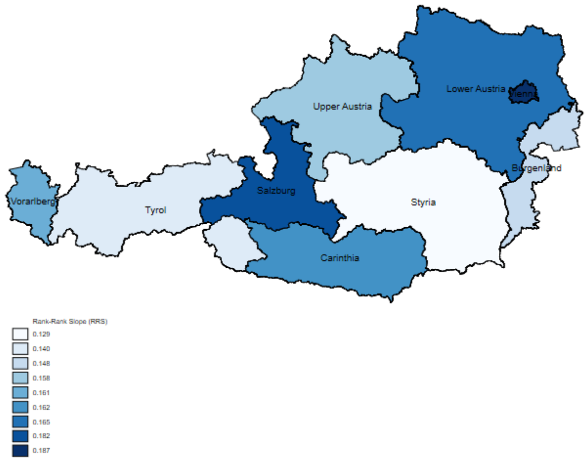
A.3 Regional Variation on Federal State Level

Figure A.3.1: Absolute upwards mobility (AUM) on federal level



Note: This heat map shows absolute upwards mobility (AUM) for Austrian federal states. The higher the value, the higher the level of absolute upwards mobility (AUM).

Figure A.3.2: Relative mobility on federal level (RRS)



Note: This heat map visualizes relative mobility for Austrian federal states, measured by the rank-rank slope (RRS). The higher the value, the lower the level of relative mobility.

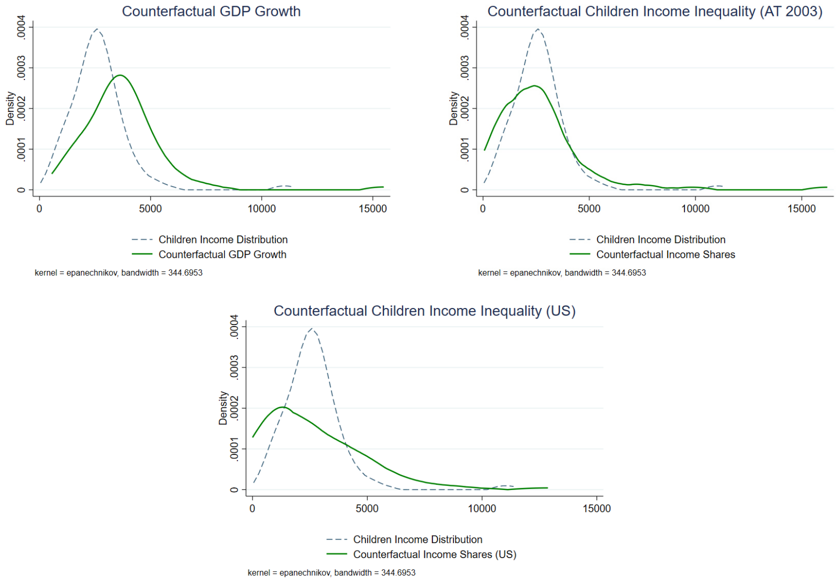
A.4 Counterfactual Income Distributions

Table A.4.4: Mean children income in the counterfactual scenarios

Scenario	Mean Income	N
Baseline Higher Income Share	2.631.61 (1.324.77)	100
Higher GDP growth	3.696.99 (1.861.06)	100
Higher inequality in children generation	2.659.27 (2.188.78)	100
US level of inequality in children generation	2.641.58 (2.285.92)	100

Note: This table reports the mean of the counterfactual income distribution with standard errors in parentheses. The income distribution does not change when the US copula is applied and therefore, children's mean income is not reported separately to the baseline scenario. The calculation of the higher income shares is based on the mean income in each income percentile, which implies a sample size of 100.

Figure A.4.3: Children income distributions in the counterfactual scenarios



Note: Each panel visualizes the children income distribution in one of the counterfactual scenarios.

A.5 The Intergenerational Income Elasticity (IGE)

Table A.5.5: The intergenerational income elasticity (IGE)

	All children	Sons	Daughters
Rank-Rank-Slope (RRS)	0.101*** (0.004)	0.091*** (0.005)	0.132*** (0.007)
Age Controls	Yes	Yes	Yes
N	47,790	26,957	19,443

Note: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. This table summarizes results for the intergenerational income elasticity (IGE). The coefficient implies that on average, a 1% increase in father income relates to a 0.101% increase in his child's income. Hereby, I control for father age in linear and squared form. There is no variation in children's age.

A.6 Results for Mother-Child Pairs

Table A.6.6: Descriptive summary statistics for mothers

	Mothers
Age in 2010	45.787
	(4.315)
Monthly Gross Income	2,383.164
	(2,653.964)
Log Monthly Gross Income	7.576
	(0.601)
General Education	0.221
	(0.415)
Vocational Training	0.312
	(0.463)
Lower Secondary Education	0.227
	(0.419)
Upper Secondary Education	0.103
	(0.304)
Tertiary Education	0.127
	(0.333)
N	47,790

Note: This table shows sample means, with standard deviations in parentheses. Mothers' monthly gross earnings is measured in constant 2020 Euros.

Table A.6.7: RRS results for mother-child pairs

	All children	Sons	Daughters
Rank-Rank Slope (RRS)	0.067*** (0.005)	0.026*** (0.006)	0.142*** (0.007)
Constant	47.867*** (0.267)	50.512*** (0.332)	34.383*** (0.403)
N	47,790	27,379	20,411

Note: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. This table shows results for the rank-rank slope (RRS) based on mother-child pairs. For the total sample, a 1-percentile rank increase in the mother's economic position is associated with a mean increase of 0.067 percentile ranks in the child's economic position.

Table A.6.8: Income quintile transition matrix for mothers and children

		Mother Quintile				
		Bottom	Second	Third	Fourth	Top
Children Quintile	Bottom	21.85%	21.34%	21.19%	18.82%	16.76%
	Second	20.92%	20.70%	20.63%	19.44%	18.23%
	Third	20.00%	20.03%	20.04%	20.04%	19.85%
	Fourth	19.09%	19.34%	19.42%	20.61%	21.63%
	Top	18.14%	18.59%	18.73%	21.09%	23.53%

Note: Each cell in this table shows the probability that a child reaches a specific income quintile, conditional on the mother's quintile.

Table A.6.9: Lower income bounds on mother income

	no restr.	500 EUR	1,000 EUR	2,000 EUR	3,000 EUR
Rank-Rank Slope (RRS)	0.067*** (0.005)	0.067*** (0.005)	0.076*** (0.006)	0.138*** (0.014)	0.142*** (0.041)
N	47,790	47,307	42,441	22,947	11,193

Note: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. This table shows estimates for the rank-rank slope (RRS) when different lower income bounds are applied to mothers' earnings.

A.7 Alternative Location Choice

Table A.7.10: Alternative location assignments

	Father	N	Mother	N	Child	N
Burgenland	0.148***	1.709	0.155***	1.713	0.163***	1.462
	(0.024)		(0.024)		(0.026)	
Lower Austria	0.165***	9.772	0.158***	9.759	0.164***	8.823
	(0.010)		(0.010)		(0.011)	
Vienna	0.187***	6.248	0.185***	6.137	0.182***	9.253
	(0.011)		(0.011)		(0.009)	
Carinthia	0.162***	3.047	0.159***	3.051	0.157***	2.683
	(0.019)		(0.019)		(0.020)	
Styria	0.129***	6.685	0.132***	6.716	0.121***	6.876
	(0.013)		(0.013)		(0.012)	
Upper Austria	0.158***	8.801	0.154***	8.805	0.176***	8.481
	(0.011)		(0.011)		(0.012)	
Salzburg	0.182***	2.857	0.178***	2.849	0.192***	2.830
	(0.029)		(0.019)		(0.019)	
Tyrol	0.140***	3.871	0.133***	3.873	0.136***	3.939
	(0.017)		(0.017)		(0.016)	
Vorarlberg	0.162***	1.812	0.164***	1.799	0.205***	1.765
	(0.026)		(0.026)		(0.026)	

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. This table presents results on the rank-rank slope for Austrian federal states for alternative location assignments. The first two columns show the RRS coefficients and sample sizes of the main specification where children are assigned to their fathers' regions. Alternatively, children are assigned to their mothers' regions. The last two columns provide results when children's own place of living is applied as geographical unit.

A.8 The Implementation of Lower Income Bounds

Table A.8.11: Lower income bounds on father income

	no restr.	500 EUR	1,000 EUR	2,000 EUR	3,000 EUR
Rank-Rank Slope	0.167***	0.167***	0.170***	0.162***	0.139***
(RRS)	(0.005)	(0.005)	(0.006)	(0.006)	(0.010)
N	46,600	46,213	45,479	41,657	28,664

Note: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. This table shows estimates for the rank-rank slope (RRS) when different lower income bounds are applied to fathers' earnings.

A.9 Attenuation Bias and Life-Cycle Bias

Table A.9.12: Sample selection rules for father income

Observed Income Period	RRS	IGE	N
2010-2013	0.167***	0.106***	46,400
(Baseline)	(0.005)	(0.004)	
2010-2015	0.171***	0.104***	46,802
	(0.005)	(0.004)	
2011-2014	0.170***	0.106***	45,791
	(0.005)	(0.004)	
2012-2015	0.168***	0.106***	45,056
	(0.005)	(0.004)	
2013-2016	0.166***	0.106***	44,378
	(0.005)	(0.004)	
2014-2017	0.168***	0.110***	43,488
	(0.005)	(0.004)	
2015-2018	0.170***	0.114***	42,550
	(0.005)	(0.004)	
2016-2019	0.174***	0.119***	41,456
	(0.005)	(0.005)	

Note: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. This table show RRS and IGE results when different sample selection rules are applied to father earnings. The second line shows results when the number of observed income year is increased to six years.

Table A.9.13: Sample selection rules for children income

Observed Income Period	RRS	IGE	N
2020	0.167***	0.106***	46,400
(Baseline)	(0.005)	(0.004)	
2019-2020	0.170***	0.095***	52,456
	(0.005)	(0.004)	
2018-2020	0.172***	0.095***	52,456
	(0.005)	(0.004)	

Note: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. This table show RRS and IGE results when different sample selection rules are applied to children earnings.

Chapter 3

It's not all about Education. Income Mobility and Occupational Autonomy

Elisabeth Essbaumer [1]

This paper explores the role of education and occupational autonomy as pathway channels of economic persistence in Germany. Hereby, economic persistence is measured by the rank-rank slope (RRS) and occupations are ranked according to their task structure. Using a decomposition approach, the analysis focuses on the influence of families' income position on children's education and occupational level, and the corresponding economic returns to these characteristics. The results suggest that approximately 40% of the level of economic persistence is attributable to the occupational autonomy pathway. When looking at time trends, I find that the occupational autonomy pathway is driven by patterns of economic returns, linking economic mobility closer to the labor market policies. Also, there is evidence for a transmission of low task levels across generations, contributing to intergenerational poverty cycles.

JEL classification: I24, I26, J24, J62.

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3.1 Introduction

Efforts to understand what drives income mobility have largely focused on education. According to economic theory, financial constraints prevent low-income households from optimally investing in the education of their children (Becker and Tomes, 1979, 1986; Solon, 2004). As education translates into earnings, children from low-income households earn less than children from high-income households and thus, income persistence arises. Consequently, public policies focus on overcoming this financial disadvantage by reducing the costs of education, for example, through subsidies and scholarships. However, high-income households also improve their children's economic outcomes in other ways, for instance, by providing social capital, networks and knowledge to get their children access to high-paid jobs (e.g., Rivera, 2016). This implies that a children's socio-economic background also matters for the translation of human capital into their economic outcomes.

Consequently, this paper explores how the influence of family background on children's occupational level and their corresponding economic returns contribute to economic persistence in Germany. It shows that a family's income position influences children's task level beyond education. Therefore, I distinguish between children's education and their task level: Children apply their education to perform different tasks in exchange for earnings. This distinction is important, because with equal education, children from high-income families are more likely to perform a job with a higher task-level, which translates into higher economic returns.

In the following, children's task level is expressed by the level of occupational autonomy, a novel variable in the literature on income mobility. Occupational autonomy groups children according to their responsibilities and task structure. This measure allows grouping and categorizing children performing different occupations.

The empirical analysis uses a decomposition approach to evaluate which part of economic persistence can be attributed to the education pathway, and which part to the occupational autonomy pathway. It measures the level of intergenerational persistence using the rank-rank slope (RRS), which describes the relation between a child's income rank and that of its family. The RRS value is decomposed into two parts. One part derives from the direct influence of parental background on children's economic position, while the other part is mitigated by education and occupational autonomy. The latter part relates to how economic background influences children's education and occupational level, and to how these translate into economic returns.

The decomposition relates to the theoretical framework of Solon (2004) where an altruistic household faces a trade-off between its own consumption and investing in its child's human capital. The optimal investment depends on the child's earnings returns, which partly derive from inherent abilities. Further, investments increase with parental income: High income always invest more in their children. Existing credit constraints further amplify this linkage. Therefore, persistence derives (i) from parental investments which increase in income, and (ii) from the corresponding economic return on these investments. Both arguments are captured by the decomposition analysis. However, here I assume that they additionally invest in children's task level, e.g., by providing job networks and social capital.

Based on the Socio-Economic Panel (SEOP), I find that occupational autonomy is an important driver of economic persistence in Germany. The results indicate that approximately 40% of the RRS coefficient are attributable to task-based occupational patterns, and additional 20% to education. The explanatory power of the decomposition is higher with daughters than with sons. For daughters, 72.5% of the RRS coefficient relate to the two channels. Observed time trends across birth cohorts suggests that (i) economic persistence is rising for more recent birth cohorts, and (ii) the importance of education and occupational autonomy is increasing. For occupational autonomy, the attributable share of the RRS coefficient increases from 27.6% up to 49.4%. The share of the education pathway more than doubles across cohorts (from 10% to 23.9%). Understanding how family income affects children's occupational outcomes is also important because intragenerational occupational mobility is low. This implies that at age 45, children are very likely to being working at the same task level as at age 32, although the specific job might have changed. For instance, the probability of remaining in a low-autonomy occupation is 62%, a percentage that even rises to 76.26% with high-autonomy occupations.

This study explores several mechanisms for how family background impacts children's occupational level. I evaluate the direct transmission of task levels from fathers to children. Taking their education and other characteristics into account, children tend to follow their fathers in low-autonomy occupations. This mechanism contributes to low-income persistence, especially as economic returns to low-autonomy occupations are declining across birth cohorts. Similar applies to medium-level occupations. Children are significantly more likely to work in a medium task level when their father already have a medium autonomy level. Also, I find that working part-time and past unemployment episodes contribute to the task downgrading which is observed in the occupational mobility matrix. Furthermore, there are gender-specific patters. The higher the income rank, the more likely are daughters to work in medium-level occupations. In comparison, sons born to high income families tend to work in high-autonomy occupations with high economic returns. Finally, I examine psychological factors and find that certain personality traits (e.g., risk tolerance) increase in family income and positively correlate with high-autonomy occupations. Conversely, chil-

dren become less anxious, which is associated with low-autonomy occupations.
Thereby, this paper adds to existing research in three ways. First, it applies a task-based approach to children's occupational structure, thus contributing a novel measure to the literature on intergenerational income mobility. The results indicate that the level of occupational autonomy has significant explanatory power for the existing level of economic persistence. Second, it provides a new data point for analyzing the channels transmitting economic persistence across countries. Germany is a particularly interesting case to study how occupational patterns contribute to economic persistence. The country boasts a widely recognized vocational education and training (VET) system, and it is possible to reach high levels of occupational autonomy also without academic degrees. Germany thus differs from countries such as the United States, where persistence is largely driven by educational inequality. And third, the results address a new policy field. The results on the occupational autonomy pathway indicate that policy makers should not only focus on education, but also on the labor market. In this respect, it is especially important to consider the transfer of human capital into occupational levels when children enter the labor market.
The paper is structured as follows. Section 3.2 reviews the relevant literature. Section 3.4 outlines the empirical strategy for measuring intergenerational persistence and the decomposition. Section 3.3 describes the data used while Section 3.5 presents the main findings. These include the baseline results for intergenerational persistence in Germany. I use the decomposition to explore how education and the level of occupational autonomy drive economic persistence. Section 3.6 explores how the role of the pathway variables changes over time. Section 3.7 analyzes related mechanisms, including the transmission of task levels across generations, labor market characteristics, and personality traits. Section 3.8 presents the robustness checks, before Section 3.9 concludes the analysis.

3.2 Literature Review

This paper applies a labor market concept to understand intergenerational income mobility. In labor economics, an increasing body of research is using a task-based approach to analyze how wages are affected by technological innovations and changing job requirements. Occupations are classified by core activities. Introduced by Autor et al. (2003), a central idea is that technological innovation automizes medium-level tasks, which involve much routine work (e.g., accounting). This affects individuals with medium education levels and polarizes the skills demanded by industries. Related work includes David et al. (2006); Goos and Manning (2007); Acemoglu and Autor (2011); Black and Spitz-Oener (2010) and Autor and Handel (2013). Here, I use a task-based measure to explore drivers of economic persistence. The results indicate that a considerable share of economic persistence is attributable to the influence of family background on a child's task level. Thus, the theoretical assumption that economic persistence arises exclusively from financial restrictions on human capital investments falls short of the mark.

In the literature on economic mobility, several studies analyze the role of education for intergenerational income mobility. Hirvonen (2010) shows that 46.1% of the intergenerational earnings elasticity in Sweden can be attributed to the education channel. This share decreases to 30% once other transmission channels are accounted for (e.g., ability and health). Occupations are not included as a potential driver of economic persistence. In a cross-country comparison, Blanden (2005) finds that in the United Kingdom, the United States, and Germany one-third to one-half of earnings elasticity can be attributed to educational attainment. Bloome and Western (2011) explore changes over time. Blanden et al. (2014) find that the primary transmission channel for income persistence in the United Kingdom is provided by occupations, whereas in the United States, education is the main driver. Bloome et al. (2018) examine how the expansion of higher education adds to the comparatively stable rank mobility in the United States over time. They find that the educational expansion on low-income families partly offsets rising inequalities in the access to education and increasing returns. Additionally, parental income is less predictive of adult income within different education levels. Overall, this literature strongly emphasizes the role of education, although Blanden et al. (2014) also include an occupation pathway.

In comparison to these studies, I focus on the role of tasks as driver of economic persistence. The share attributable to the education pathway decreases when the influence of family background on children's occupational autonomy level is accounted for. Furthermore, I use the rank-rank slope as measure for economic mobility, whereas existing decomposition results are based on the intergenerational income elasticity (IGE). The rank-rank slope overcomes several disadvantages of income-level based measures such as the IGE. Economic positions stabilize earlier in the life-cycle and their calculation is less prone to attenuation bias. Nor do they require a monotonic relation between children's economic outcomes. By definition, ranks are distributed uniformly and thus abstract from changes in the income distribution across generations inequality across generations (Dahl and DeLeire, 2008; Chetty et al., 2014; Nybom and Stuhler, 2017).

Finally, this paper adds to the existing literature on income mobility in Germany. Several studies include Germany as a reference country for the United States, the United Kingdom, and Scandinavian countries (Couch and Dunn, 1997; Lillard, 2001; Couch, 2004; Comi, 2004; Schnitzlein, 2016; Bratberg et al., 2017). In general, these papers conclude that income persistence in Germany is less pronounced than in the US, but more pronounced than in Scandinavian countries. Other contributions address bias profiles (Vogel, 2006; Brenner, 2010), or the economic mobility of migrants (Yuksel, 2009; Flake, 2013). Kyzyma and Groh-Samberg (2018), the only paper using a rank-based mobility measure, report a decline of economic mobility over time. The estimated values of the intergenerational income elasticity in Germany increase over the respective year of publication and range from an IGE value of 0.112 (Couch and Dunn, 1997) to 0.368 (Kyzyma and Groh-Samberg, 2018). An important reason for this variation is that research relies almost exclusively on the Socio-Economic Panel (SOEP), which began gathering data in 1984. Consequently, the second generation of respondents was still very young (i.e. a mean age of 22.80 years) when Couch and Dunn (1997) conducted the first analysis of intergenerational earnings mobility in Germany. Early results are therefore subject to life-cycle and further attenuation bias. The second generation reached adult age only recently, a fact benefiting this analysis. Additionally, the use of percentile ranks instead of income levels further improves the quality of estimation results.

3.3 Data

This paper relies on data from the German Socio-Economic Panel (SOEP). The SOEP is a representative annual survey of German households. Its data collection provides high-quality information on a wide range of income variables and socio-demographic characteristics at the individual level and at the household level. The SOEP data files are part of international data-infrastructures, including the Cross National Equivalent Files (CNEF).[2]

The SOEP fulfills the demanding data requirements for analyzing intergenerational income mobility. The data collection started in 1984 and thus provides a sufficiently long time horizon to compare the economic outcomes of two generations. Once a household participates in the survey, the SOEP follows every household member as long as they are willing to participate and live in Germany. Therefore, the sample includes children also after they leave their original household. A special biography file connects them to their parents which enables tracing child-parent pairs over time. However, the number of traceable pairs with adult children is still limited and consequently, all birth cohorts are pooled together to increase the sample size. Hereby, children's mean birth year is 1972, ranging from 1958 to 1984.

[2] See Goebel et al. (2019) for detailed information on SOEP data quality and methodology.

Income Definitions and Sample Selection

Children's income level is defined by their annual labor earnings. These include salaries and wages from all employment and self-employment, as well as income from bonuses, overtime, and profit sharing. Income ranks stabilize comparatively early in the life cycle (Nybom and Stuhler, 2017). Consequently, earnings are measured when children are between 32 and 38 years old and at least three observations are available, which are averaged.

According to the theoretical background, intergenerational persistence arises due to financial constraints preventing low-income parents to optimally invest in their children (Becker and Tomes, 1986; Solon, 1999, 2004). To reflect a family's financial abilities, the disposable household income is used as family income measure. This is defined as sum of all income after taxes, private and government transfers. To account for family structures, the disposable household income is adjusted with OECD equivalence weights. The first adult living in the household is assigned a weight of 1, every additional adult a weight of 0.7, and underage children a weight of 0.5 each. The income is measured when the parent is between 35 and 45 years old, and income averages are calculated when at least five observations are observable. The main specification relies on the mothers' family income. Alternative income specifications such as fathers' individual earnings are part of the robustness checks.

All income is converted to constant 2015 Euros, then, family and child income is transformed into income percentile ranks. Hereby, the ranks are calculated relative to the income of all other respondents in the same birth cohort, regardless of them being part of a child-parent pair. Following Kyzyma and Groh-Samberg (2018), ranks are calculated separately by children's gender, using information of the entire panel. The sample is restricted to pairs where children's years of schooling and their occupational autonomy level are available. The resulting sample includes 1,247 children from 926 families.

Summary Statistics

Table 3.1 presents the sample's descriptive summary statistics. On average, fathers and mothers are 42 years old when their respective income is measured, and have an annual income of 40,181.30 Euros at their disposal. After adjusting this for family composition, the average family income equals 17,935.52 Euros per year.

Children reach a mean age of 35 years, which is well above the threshold of 30 years when income ranks stabilize in their life cycle (Nybom and Stuhler, 2017). At this age, children earn a mean income of 29,309.20 Euros per year, which ranges up to 205,533.90 Euros in the sample. The sample is approximately balanced between

Table 3.1: Descriptive statistics

	Mean	N
Family:		
Mother age	42.061	926
	(1.897)	
Father age	42.310	577
	(1.932)	
Family income	40,181.33	926
	(19,440.48)	
Adjusted family income	17,935.52	926
	(6,360.00)	
Children:		
Children age	35.064	1,247
	(1.088)	
Female share	0.486	1,247
	(0.500)	
Children income	29,309.20	1,247
	(21,574.58)	
Years of Schooling	12.959	1,247
	(2.832)	
Secondary level I	0.242	1,247
	(0.429)	
Secondary level II	0.407	1,247
	(0.491)	
University entry exam	0.095	1,247
	(0.293)	
Academic degree	0.257	1,247
	(0.437)	
Low occupational autonomy	0.084	1,247
	(0.278)	
Lower occupational autonomy	0.213	1,247
	(0.409)	
Medium occupational autonomy	0.315	1,247
	(0.465)	
High occupational autonomy	0.388	1,247
	(0.488)	

Note: This table shows sample means, standard deviations in parentheses. All amounts are in constant 2015 Euros. Age refers to the mean age when income is observed. Secondary level I defines "Hauptschulabschluss", secondary level II "Realschule", and the university entry exam includes "Abitur" and "Fachabitur".

genders, with 48.6% of children being daughters.

The main specification uses years of schooling as measure for educational attainment, with an average of 12.96 years. As alternative measure, dummy variables indicating different education levels are used. A share of 24.2% completed the secondary level I ("Hauptschule"). Additional 40.7% of children attended institutions at secondary level II ("Realschule"). A minority of 9.5% obtained a qualification for university entrance ("Abitur", Fachhochschulabschluss"). Finally, 25.7% have academic degrees.

The level of occupational autonomy describes the task structure of occupations. This variable is designed specifically for the German SOEP. The goal was to create a simple and meaningful measure that captures the task structure of occupations. The classification is based on occupational positions. Self-employed persons are categorized by company size, except for farmers (who are categorized by acres of land). Civil servants are classified according to civil service legislation, which defines duties and tasks in that sector. Workers and employed persons are grouped by the tasks they can be expected to perform and by the related responsibilities.[3]

Here, occupations are categorized into four groups: (i) low-autonomy occupations, (ii) lower-autonomy occupations, (iii) medium autonomy occupations, and (iv) high-autonomy occupations. The low autonomy group includes employees with the lowest autonomy level (i.e., unspecialized manual labor). Lower-autonomy occupations include manufacturing, farm work, services, and only require minimum specialization. Employees and government officials are classified as having medium autonomy once they are given a limited amount of responsibility. High-autonomy occupations involve greater responsibility (e.g. managers). Self-employed persons are defined as having either medium or high-occupational autonomy, depending on the number of employees in their organization.

Here, 38.8% of children work in occupations with high-autonomy level. They less frequently work in medium- and lower-autonomy occupations, with shares of 31.5% and 21.3%, respectively. In contrast, 8.4% have low-autonomy occupations. This group serves as baseline in the decomposition. Table A.1.2 provides supplementary information on industries in which these occupations are performed.

Table A.1.1 reports the sample statistics separately by children's gender. On average, daughters earn less than sons (19,421.94 Euros vs. 38,656.60 Euros). Also, a higher share of daughters works in medium level jobs rather than in high level occupations. For sons, high-autonomy occupations dominate.

In section 3.7, I use additional information on father's occupational structure. Descriptive statistics are provided in Table A.1.4. In comparison to the children generation, a higher share of fathers has been working in low-autonomy occupations,

[3]See Hoffmeyer-Zlotnik and Geis (2003) for more details on this variable.

whereas high-autonomy occupations were less prevalent. Furthermore, I evaluate children's personality traits. These include risk tolerance along several dimensions, and standard variables to measure children's level of neuroticism, agreeableness, conscientiousness, and openness (Gerlitz and Schupp, 2005). The personality traits are measured on a 1-7 scale, and risk tolerance from 0 to 10. All values are self-reported, and a higher value indicates that children perceive their trait as more pronounced. Table A.1.3 shows corresponding sample means.

3.3.1 Supplementary Data

I use supplementary data from the SOEP to provide aditional evidence on the persistence of task levels of children's life cycle. This is a pooled sample of the 1984-2015 SOEP survey waves and includes all available information on children's characteristics and outcomes. The resulting sample provides 19,683 observations, with summary statistics reported in Table A.1.6 in the Appendix.

3.4 Empirical Strategy

The empirical strategy consists of two steps. First, I estimate the rank-rank slope (RRS) to document the level of economic persistence across generations in Germany. Secondly, I explore to what extent the transmission of economic status is driven by education and occupational autonomy. To do so, the RRS value is decomposed into two components: One component is attributable to the influence of the pathway variables, the other component derives from the direct influence of children's economic background.

3.4.1 Measuring Economic Persistence

The rank-rank slope is a positional measure which relates children's economic position to the economic position of their families. Accordingly, the income level in both generations is transformed into percentile ranks R_i^C and R_i^F. Then, child i's income rank R_i^C is regressed on the family's income rank R_i^F:

$$R_i^C = \beta_0 + \beta R_i^F + u_i, \tag{3.1}$$

where u_i denotes the error term. Income ranks are stable over time and thus, age controls which are typically included in level-based mobility measures do not enter here.

The estimated parameter β provides the rank-rank slope (RRS) and is the main parameter of interest. The RRS value indicates the expected change in a child's economic position when the family's economic position increases by one income percentile rank. Hence, the higher the RRS value, the stronger the linkage between two generations, and the higher the level of economic persistence. The RRS coefficient $\beta * 100$ can also be interpreted as the expected economic gap between children born to families in the highest and lowest income rank. This concept also implies that over the course of generations, children approach the economic mean. Neither the advantages nor the disadvantages of their parents' economic situation are fully transmitted to the next generation.

3.4.2 Decomposing Intergenerational Mobility

The goal of this decomposition is to explore how far economic persistence is attributable to the education pathway and to the occupational autonomy pathway. In general, a pathway combines the influence of children's economic background on a specific characteristic with the economic return to this characteristic while accounting for the direct influence of the families' income position.

The Education Pathway

The decomposition starts with education as a single pathway variable. To derive the first component, the analysis evaluates the influence of families' economic position on their children's educational attainment:

$$Edu_i^C = \alpha_E + \lambda_E R_i^F + \epsilon_i, \tag{3.2}$$

where Edu_i refers to child i's years of schooling. The coefficient λ_E indicates the influence of children's economic background on their education level. Then, children's returns to education are derived while including the direct influence of R^F, that is, the families' income rank:

$$R_i^C = \omega + \gamma_E Edu_i^C + \gamma_R R_i^F + v_i \tag{3.3}$$

Consequently, the RRS coefficient β can be decomposed into:

$$\beta = \lambda_E * \gamma_E + \gamma_F \tag{3.4}$$

The first term $\lambda_E * \gamma_E$ captures how education as transmission pathway contributes to economic persistence. The second term γ_F is the direct component deriving from the influence of children's economic background which cannot be attributed to the education pathway.

The Occupational Autonomy Pathway

Now the children's task level is added. This is measured by the level of occupational autonomy. Three dummy variables are used to characterize children's level of occupational autonomy. The reference group consists of children employed in occupations with low autonomy level. Section 3.5.1 indicates an approximately linear relation between family income ranks and children's occupational outcomes. Consequently, the influence of family background is derived from the following equations:

$$Aut^C_{L,i} = \alpha_L + \lambda_L R^F_i + \epsilon_{L,i} \tag{3.5a}$$

$$Aut^C_{M,i} = \alpha_M + \lambda_M R^F_i + \epsilon_{M,i} \tag{3.5b}$$

$$Aut^C_{H,i} = \alpha_H + \lambda_H R^F_i + \epsilon_{H,i} \tag{3.5c}$$

Where Aut^C_{Li} equals 1 if child i's occupation is characterized by at least lower occupational autonomy, and 0 otherwise. The dummy variables Aut^C_{Mi} and Aut^C_{Hi} are defined analogously for occupations with at least medium level and with high level occupational autonomy.

Then, the economic returns to different occupational levels are estimated, accounting for children's education and the direct influence of family background:

$$R^C_i = \omega + \varphi_E Edu^C_i + \varphi_L Aut^C_{L,i} + \varphi_M Aut^C_{M,i} + \varphi_H Aut^C_{H,i} + \varphi_F R^F_i + v_i \tag{3.6}$$

The coefficients φ_E and $\varphi_L - \varphi_H$ provide children's economic returns to education and occupational autonomy. Note that due to the specific definition of the dummy variables, $\varphi_L - \varphi_H$ indicate the economic gains from a given occupational autonomy level compared to the next lower level. Otherwise, when estimating the influence of family income background on child's occupational autonomy level, occupations with the two intermediate levels would be compared to a baseline group including both lower- and higher-ranked occupations. Additionally, φ_F captures the influence of children's family background on their economic outcomes. This is the direct component. It contributes to economic persistence and cannot neither be explained by the education pathway nor by the occupational pathway.

Thus, the RRS value is now decomposed into the three parts: (i) the education pathway, (ii) the occupational autonomy pathway, and (iii) the direct influence of family background:

$$\underbrace{\hat{\beta}}_{\text{Rank-Rank Slope}} = \underbrace{\hat{\lambda}_E\hat{\varphi}_E}_{\text{Education Pathway}} + \underbrace{\hat{\lambda}_A\hat{\varphi}_A}_{\text{Occupational Autonomy Pathway}} + \underbrace{\hat{\varphi}_F}_{\text{Direct Influence}} \tag{3.7}$$

with

$$\hat{\lambda}_A\hat{\varphi}_A = \hat{\lambda}_L\hat{\varphi}_L + \hat{\lambda}_M\hat{\varphi}_M + \hat{\lambda}_H\hat{\varphi}_H.$$

So overall, the decomposition illustrates the extent to which intergenerational economic persistence is driven by mechanisms relating to education and occupational autonomy, and to what extent it is attributed to the direct component relating to family background, following Blanden et al. (2014). In comparison, this analysis is based on the rank-based RRS to measure economic persistence, whereas Blanden et al. (2014) rely on the intergenerational income elasiticity (IGE). Using the RRS provides an advantage. The relation between economic positions can be approximated by a linear form, whereas the IGE varies substantially along the income distribution and is sensitive towards changes in income inequality across generations (Chetty et al., 2014; Nybom and Stuhler, 2017). For a linear decomposition, using income ranks rather than log income is thus preferable, although additional results based on the IGE are shown in the robustness checks in Section 3.8. Furthermore, I introduce a novel pathway variable to the literature on intergenerational income mobility, that is, the task-based level of occupational autonomy.

This approach faces several limitations. The children's years of schooling increase linearly in their families' income position (see Section 3.5.1). Therefore, it is used as measure for children's educational attainment in the main specification. However, the decomposition assumes constant returns to the pathway variables. To mitigate this for education, I provide additional results which are based on different educational categories rather than on the years of schooling. Also, the analysis is sequential and includes pathway variables by occurrence in the children's life cycle - first education, then their task level. Consequently, education is independent of occupational autonomy, but the latter correlates with educational attainment. This dependence can somewhat be mitigated by using the tasked based occupation measure. Section 3.5.1 illustrates that all occupational levels are accessible with every education type. In Germany, vocational education and training (VET) is highly established and allows to obtain high occupational autonomy levels also without academic degrees. However, the correlation between education and occupational autonomy is larger for the high autonomy level. Yet, the corresponding variance inflation factors (VIF) are smaller

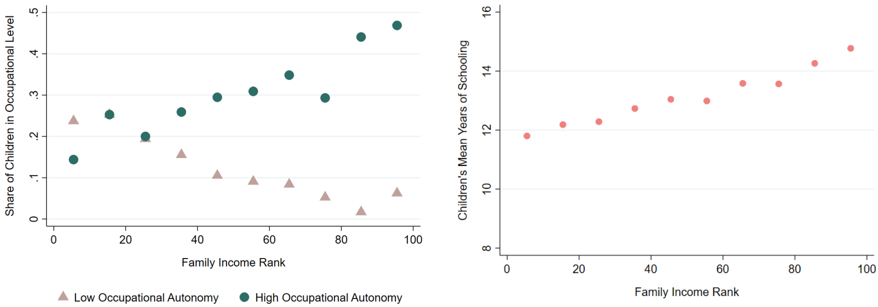
than 2 and therefore, they remain well below the suggested threshold of 10, which would indicate a problematic level of multicollinearity.
Furthermore, the decomposition focuses on the influence of only two transmission channels. This approach highlights the importance of occupational patterns but implies that numerous intergenerational mobility factors are not included in the analysis. They are captured by the error terms and by the second component of the decomposition. For instance, cognitive and non-cognitive skills are influenced by parental resources and contribute essentially to the economic outcomes (Carneiro and Heckman, 2003; Cunha and Heckman, 2007, 2008; Almlund et al., 2011). Unfortunately, information on these characteristics is not available for the children generation studied here, as the SOEP provides the respective information only for selected subsamples. However, including years of schooling might be mitigating, given that Blanden et al. (2007) implement several proxy variables for cognitive and non-cognitive abilities and find that their influence is minimized once education is included. Nor can early childhood and care (ECEC) be included as pathway variables, as ECEC information are available only for a small minority of children in the sample.
Finally, children's economic outcomes are also influenced by numerous unobserved factors. Therefore, this analysis is impaired by the likely correlation between the error terms and the covariates. Nevertheless, they illustrate mechanisms underlying the intergenerational transmission of earnings. Until now, strong emphasis has been placed on education as a main driver of intergenerational mobility. Yet, an important occupation pathway indicates that policy makers must look beyond educational attainment and target the labor market, which forms task structures.

3.5 Results

3.5.1 Patterns in Family Income, Education and Occupational Autonomy

Distinct patterns are evident in the relation between a child's occupational autonomy level and its family's income background. The left panel of Figure 3.1 illustrates this for low- and high-autonomy occupations. The higher the family income rank, the higher the share of children being employed in occupations with high autonomy levels. Conversely, the share of children with low occupational autonomy decreases, and the relation between family income and children's occupational task levels is approximately linear. In the top family income decile, over 60% of children perform high-

Figure 3.1: The relation between family income and children's occupational level and education

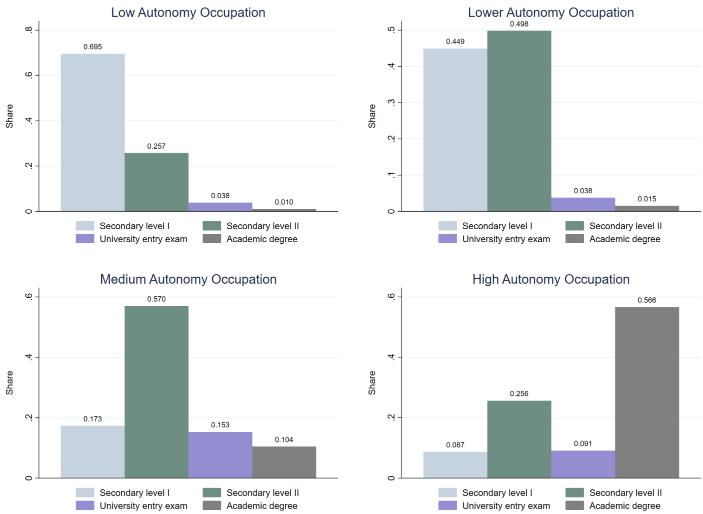


Note: The left panel shows that the share of children working in high-autonomy occupations linearly increases in family income. Simultaneously, the share of children with low-autonomy jobs linearly declines. Each point represents the mean share of children working in low- and high-autonomy occupations for four family income ranks. The right panel illustrates that children's schooling years linearly increase in their families' income position. Hereby, each point represents the mean years of schooling for four family income ranks.

autonomy occupations, while only 4% are employed in low-autonomy jobs. Similar applies to children with medium-level and with lower-level occupations, respectively.[4] Intuitively, children's occupational autonomy and their education correlate. Nevertheless, occupational autonomy varies within education levels (Figure 3.2). High occupational autonomy is accessible with every education level. Although academic degrees dominate, almost half of children have lower education levels. For instance, 25.6% of children working in high-autonomy occupations graduate with upper secondary education. This is linked to Germany's vocational education and training system (VET). Primarily targeting children with a secondary education, VET enables them to attain higher occupational autonomy levels also without a university degree. Moreover, a linear relation exists between children's years of schooling and family income ranks, which is well suited to the linear decomposition approach (right panel of Figure 3.1).

[4]See Appendix Figure A.1.1.

Figure 3.2: Accessibility of occupational autonomy levels



Note: The four panels illustrate the composition of occupational autonomy by education levels, indicating a high variation of schooling degrees across children's task levels.

Furthermore, the access to different task levels differs for children from high- and low-income families also within education levels. The panels in Figure 3.3 display the composition of autonomy levels for children from the bottom- and top-income quintile conditional on children's education level.

With a lower secondary education, children from bottom-quintile families perform predominately low- and lower-level tasks. Of them, 9.2% reach high occupational autonomy. This share is more than 2-times as high among children from top-income quintile families, who are also more likely perform medium-level tasks rather than low-level tasks.

The occupational distribution also differs among children holding an upper secondary certificate (which qualifies them to enter university). With equal education levels, children from top-income families are generally more likely to attain a high-autonomy occupation than children from low-income families. Among children from high-income families, a shift occurs toward high-autonomy occupations at upper secondary level. Although eligible to enter university, 17.3% of children from bottom-income families work in low- or lower autonomy jobs. These types of occupations are not present among children from high-income families. Only for academic degrees, the share of high-autonomy occupations is approximately equal. Nevertheless, 5.6% of children

Figure 3.3: Differences in occupational outcomes by family income and education

Note: The four panels illustrate differences in the task structure of children from families in the bottom- and top income quintile, conditional on their education level.

from low-income families work in jobs with lower occupational autonomy despite holding an academic degree.

Additionally, there are gender-specific patterns. Across all education types, daughters are less likely to perform high-autonomy occupations. Among children with lower secondary education, 32.6% of daughters work in low-autonomy occupations, compared to 13.9% of sons. With this education level, only 3.2% of daughters reach high-level occupations, compared to 13.9% of sons. This is further illustrated by Figure A.2.2 in the Appendix.

Overall, this descriptive evidence indicates that children's economic background matters not only for their education level, but also for their occupational autonomy, i.e., for their task level. Consequently, this mechanism contributes to economic persistence.

3.5.2 Intragenerational Occupational Mobility

The influence of family background on children's occupational outcomes is also relevant because little occupational mobility occurs over time. Occupational autonomy levels are highly persistent over children's life cycle. Based on the pooled SOEP

sample, Table 3.2 shows an occupational mobility matrix. This summarizes the probability of an individual reaching a certain occupational autonomy level at age 45 conditional on their occupational autonomy level at age 32. These ages are selected to match the main sample specification: 32 is the first year where children's income is taken into account, and 45 is the last year for observing parental income.
Even though children's specific job might differ during this time, their task level is quite likely the same. Overall, 61.62% of individuals remain in a low-autonomy job, and even 76.26% in a high-autonomy occupation. Less than 1% improve their task level from a low-autonomy to a high-autonomy occupation. Also, the task level of individuals working in intermediate levels at age 32 is more likely to deteriorate than improve over time. This makes the influence of family background on children's initial occupational level even more decisive.

Table 3.2: Intragenerational occupational mobility

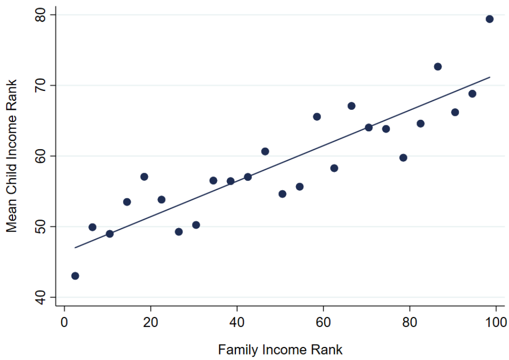
		Age 45			
		Low Autonomy	Lower Autonomy	Medium Autonomy	High Autonomy
Age 32	Low Autonomy	61.62%	25.70%	9.51%	3.17%
	Lower Autonomy	12.55%	54.94%	24.33%	8.17%
	Medium Autonomy	1.08%	12.02%	63.94%	22.96%
	High Autonomy	0.80%	3.22%	19.72%	76.26%

Note: This table shows the probability that an individual reaches a given occupational autonomy level by the age of 45, conditional on the occupational autonomy level he has at age 32. This transition matrix suggests that occupational autonomy is persistent over individuals' employment biography. The probability that they work in a job with the same autonomy level varies between 54.94% and 76.26%.

3.5.3 Decomposing Economic Persistence in Germany

The relation between children's income ranks and the income ranks of their families is approximately linear (Figure 3.4). Every dot shows the mean children income rank for four family income ranks. This implies that the linear rank-rank slope is a suitable summary statistic for economic persistence in Germany.
The estimated RRS coefficient is 0.235 (Table 3.3). Therefore, a 1 percentile rank increase in the family's income position is associated with an average increase of 0.235 percentile ranks in the child's income position. The gender-specific coefficients are of

Figure 3.4: The relation between family and children income ranks



Note: Each point shows the mean child rank for four family ranks. Ranks are income percentiles. The blue line derives from regressing a child's income rank on the family's income rank, with a slope of 0.235, which is denoted as rank-rank slope (RRS). The higher the RRS, the more children's income position depends on their family's income position.

similar magnitude, with values of 0.254 for sons and 0.227 for daughters.

In the following, economic persistence is decomposed into two parts: The first part is mitigated by the pathway variables education and occupational autonomy, while the second part derives from the direct influence of family background on children's economic outcomes.

Table 3.3: Economic mobility in Germany

	Total Sample	Sons	Daughters
Rank-Rank Slope (RRS)	0.235*** (0.029)	0.254*** (0.042)	0.227*** (0.040)
N	1,247	641	606

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on the family level. On average, a 1 percentile increase in the family's economic position is associated with a 0.235 percentile increase in the child's economic position. The higher the estimated RRS, the higher the level of economic persistence and therefore, the lower the level of income mobility.

The Role of Education

Education is an important mechanism for the transmission of economic status (e.g., Solon, 2014; Bloome et al., 2018). Therefore, education is first included as singular pathway variable. The education pathway combines the influence of family background on a child's education level with the economic returns to this education.

Table 3.4 summarizes the results. The standard errors are also clustered on the family level to account for sibling relations. The left column of Table 3.4 shows to which extent intergenerational persistence can be attributed to the education path-

Table 3.4: Decomposing the influence of education

	Total Sample		Sons		Daughters	
	Part of RRS	Percentage of RRS	Part of RRS	Percentage of RRS	Part of RRS	Percentage off RRS
Education Pathway Variable	0.102*** (0.013)	43.27% (0.067)	0.094*** (0.018)	37.19% (0.087)	0.109*** (0.019)	48.17% (0.101)
Direct Effect of Economic Background	0.134*** (0.028)	56.73% (0.067)	0.159*** (0.041)	62.81% (0.087)	0.117*** (0.037)	51.83% (0.101)
RSS	0.235*** (0.027)	100.00%	0.254*** (0.041)	100.00%	0.227*** (0.039)	100.00%
N	1,247		641		606	

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Bootstrapped standard errors (1,000) in parentheses, clustered on family level. The education pathway coefficient combines the influence of fathers' economic position on children's education with the children's economic returns that are associated to education. When only taking education into account, this combination accounts for 43.27% of the economic persistence, measured by the RRS. Consequently, 56.73% of the RRS value are attributed to the direct influence of the family's economic position.

Table 3.5: Underlying values of the single pathway decomposition

	Influence of Families' Economic Position on Children's Education	Children's Economic Return to Education	N
Total Sample	0.029***	3.474***	1,247
	(0.003)	(0.266)	
Sons	0.028***	3.376***	641
	(0.005)	(0.387)	
Daughters	0.031***	3.533***	606
	(0.005)	(0.346)	

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on family level. The left column shows the association between children's years of education and their family background. The right column shows the economic return to education. For the entire sample, a 1-rank increase in the family's economic position is associated with a 0.029 increase in children's schooling years. In turn, an additional schooling year increases the children's income rank by 3.474 ranks. Combining the coefficients in the first line gives the pathway coefficient value for education. The table also shows separate results for sons and daughters. For daughters, both the influence of their family income background and the returns to education are larger than for sons, resulting in a higher pathway coefficient.

way when occupational structures are not accounted for. Then, with an estimated pathway coefficient of 0.102, the education pathway amounts to 43.27% of the RRS coefficient, measuring economic persistence. Thus, 56.73% of the RRS value remain unexplained by the single pathway decomposition. This share is attributed to the family background directly affecting the child's income rank.

The education pathway is more influential for daughters than for sons. With a numerical value of 0.109, approximately half of the daughters' RRS coefficient relates to the education pathway. The explanatory power of education is 10 percentage points lower lower with sons, where the coefficient equals 37.19% of the gender-specific RRS value.

Table 3.5 presents the underlying regression results for the decomposition. The left column shows the association between children's years of schooling and their families' income rank. The right column indicates children's returns to education, measured by the mean increase in children's income ranks. On average, a 1-rank increase in the family's income rank relates to additional 0.028 schooling years for their children. In turn, one additional schooling year raises children's income position on average by 2.960 percentile ranks. Combining coefficients provides the education pathway value.

For daughters, the higher share attributable to the education pathway derives from a stronger influence of family background on their educational outcomes (0.031 vs.

0.026). Additionally, the associated returns to education are higher when the direct family influence is accounted for. For daughters, one additional schooling year relates to a 3.533 increase in their income rank, compared to 3.376 for sons.

The Role of Occupational Autonomy

Occupational autonomy is now added to the decomposition. Table 3.6 reports the results. The influence of the education pathway diminishes substantially and then accounts for 19.18% of the overall RRS value, which is approximately half of the share in the single pathway specification. Therefore, the impact of the earlier education pathway is partly transmitted through the occupational pathway which occurs later in children's life.

The occupational autonomy channel is highly influential and has a larger explanatory power than the education pathway. A coefficient value of 0.091 implies that overall, 38.73% of the RRS value is attributable to the influence of family background on children's occupational level and to the corresponding economic returns. For daughters, the explanatory power is approximately 17 percentage points (pp) higher than for sons. With an estimated pathway coefficient of 0.115, half of the rank persistence level relates to the occupational autonomy pathway. For sons, the obtained result of 0.086 amounts to 33.74% of the gender specific RRS level.

The underlying coefficients for the occupational autonomy pathway are presented in Table 3.7. Sons and daughters do not show large differences in the relation between their families' income ranks and their occupational levels. A 1-rank increase in the family's income position relates to a 0.2 percentage points higher probability that a child reaches at least lower occupational autonomy. For daughters, the influence is higher on medium-level occupations than on high-level occupations.

The average child is in the 32^{th} income percentile when working in a low-autonomy occupation. Given this baseline, switching to a lower-autonomy occupation increases the child's economic position by 10.955 income ranks at the mean (see Table 3.8). The relative gain between lower and medium-level occupations is of similar magnitude (10.663 ranks), whereas having a high-autonomy occupation increases the child's income position by another 8.592 ranks.

The structure of economic returns shows gender-specific patterns. For sons, the highest relative gain occurs when they switch to a high-level occupation. This relates to an additional increase of 16.657 income ranks. For them, the increase between lower- and medium-level occupations is comparatively small and equals 4.056 ranks. At this stage, daughters experience substantially higher gains (13.781 ranks), whereas there is only an additional increase of 6.711 ranks when they change from a medium-level to a high-level occupation.

The education channel remains important. For the total sample, the education pathway coefficient amounts to 19.18% of the RRS value. The associated influence of family background on children's education remains unchanged, as the coefficient derives from a univariate regression (see Equation 3.2 and results in Table 3.5). However, the returns to education change. When taking into account the child's task level, an additional year of schooling increases the child's income position by 1.540 ranks, compared to 2.960 ranks in the single pathway specification. Daughters experience higher returns to schooling than sons (1.579 vs. 1.060 ranks). Therefore, education provides economic returns in addition to tasks children are performing.

The reported results indicate that occupational patters are an important mechanism for the transmission of economic status across generations. When including children's task levels, approximately 60% of the RRS coefficient are attributable to the pathway variables. Therefore, the explanatory power of the decomposition increases compared to the single pathway specification which only focuses on education. This implies that the occupational autonomy pathway contributes to the deeper understanding

Table 3.6: The joint decomposition of education and occupational autonomy

	Total Sample		Sons		Daughters	
	Part of RRS	Percentage of RRS	Part of RRS	Percentage of RRS	Part of RRS	Percentage off RRS
Education Pathway Variable	0.045^{***} (0.010)	19.18% (0.047)	0.030^{**} (0.013)	11.68% (0.057)	0.049^{***} (0.015)	21.53% (0.072)
Occupational Autonomy Pathway Variable	0.091^{***} (0.013)	38.73% (0.057)	0.086^{***} (0.018)	33.74% (0.071)	0.115^{***} (0.020)	50.92% (0.105)
Pathway Total	0.136^{***} (0.015)	57.90% (0.075)	0.115^{***} (0.022)	45.42% (0.095)	0.164^{***} (0.023)	72.45% (0.130)
Direct Effect of Economic Background	0.099^{***} (0.025)	42.10% (0.075)	0.138^{***} (0.038)	54.58% (0.095)	0.062^{*} (0.035)	27.55% (0.130)
RSS	0.235^{***} (0.028)	100.00%	0.254^{***} (0.040)	100.00%	0.227^{***} (0.039)	100.00%
N	1,247	1,247	641	641	606	606

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Bootstrapped (1,000) standard errors in parentheses, clustered on family level. This table summarizes the results of the joint decomposition, including the education and occupational autonomy pathways. Hereby, each pathway coefficient combines the influence of the family's income position on child's education and occupational autonomy with the child's corresponding economic returns. For the total sample, these combinations account for 57.90% of the economic persistence, measured by the rank-rank slope. Hereby, 38.73% are attributable to the occupational autonomy pathway alone. Consequently, 42.10% of the estimated RRS coefficient are attributed to the direct influence of the family's economic position. For daughters, the decomposition has a higher explanatory power as for sons (72.45% vs. 45.42%).

Table 3.7: The influence of family background on children's occupational level

	Total Sample	Sons	Daughters
Lower Occupational Autonomy	0.002***	0.001***	0.002***
	(0.000)	(0.000)	(0.001)
Medium Occupational Autonomy	0.004***	0.003***	0.005***
	(0.001)	(0.001)	(0.001)
High Occupational Autonomy	0.003***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)
N	1,247	641	606

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Bootstrapped (1,000) standard errors in parentheses, clustered on family level. The table shows how a child's probability of working in a specific occupational level changes when the family income position improves. For instance, a 1-rank increase in the family income rank is associated with a 0.3 percentage point increase in the child's chances of having a high-autonomy job.

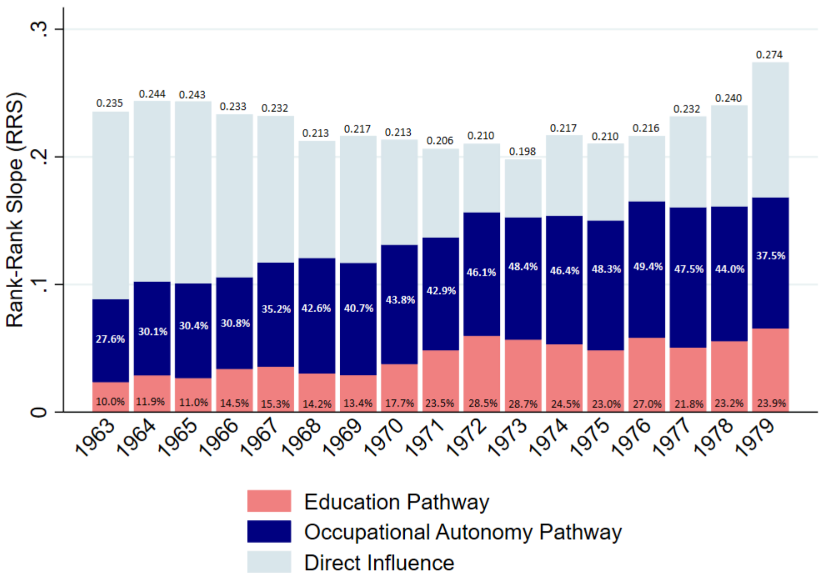
Table 3.8: Economic returns in the joint decomposition

	Total Sample	Sons	Daughters
Education	1.540***	1.060***	1.579***
	(0.315)	(0.455)	(0.430)
Lower Occupational Autonomy	10.955***	12.864***	11.035***
	(2.538)	(3.767)	(3.278)
Medium Occupational Autonomy	10.663***	4.056***	13.781***
	(1.836)	(2.592)	(2.565)
High Occupational Autonomy	8.592***	16.657***	6.711***
	(1.805)	(2.618)	(2.421)
N	1,247	641	606

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Bootstrapped (1000) standard errors in parentheses, clustered on family level. This table provides the additional economic returns for an occupational autonomy level, compared to the next lower one. The average child's income position increases by 10.955 ranks when they switch from a low-autonomy occupation (the reference group) to a lower-autonomy occupation.

of income persistence and does not only absorb variation otherwise attributed to education.

Figure 3.5: Time trends in economic persistence



Note: The figure shows the rank-rank slope and the contribution of the education and occupational autonomy pathways over time. Hereby, the vertical axis indicates absolute coefficient values, and the cohort-specific RRS values are depicted above the bars. The shares attributable to the pathways coefficients are depicted inside the bars. Hereby, the birth cohorts are overlapping where each cohort covers one birth decade. The direct influence captures children's economic returns to their families' income position once their education and occupational level are accounted for. The contribution of the education pathway more than doubles over time, and the share attributable to occupational autonomy varies between 27.6% in the 1963 cohort to up to 49.4% in the 1974 cohort.

3.6 Time Trends

The role of education and occupational autonomy for economic persistence changes across birth cohorts. Figure 3.5 illustrates the rank-rank-slope and the coefficient values of the two pathway variables over time. Due to the limited sample size, I estimate results for overlapping birth cohorts, where each cohort covers one decade. Therefore, the 1963 cohort includes children born between 1958 and 1968, the 1964 cohort those born between 1959 and 1969, and so on.

Economic persistence is rising for more recent cohorts. At the beginning, a moderate decline occurs in the rank-rank slope until the 1973 cohort, where a 1-rank increase in the family income position is associated with a 0.198 increase in the child's income rank. Then, the RRS coefficient increases and reaches a value of 0.274 for the last observed birth cohort. This implies an increasing gap between children born at the bottom and at the top of the family income distribution. In the 1973 birth cohort, the wedge between rich and poor children is 19.8 income ranks. In the 1984 birth cohort, this gap raises to 27.4 ranks. The higher the level of income inequality, the greater the gap in absolute monetary terms.

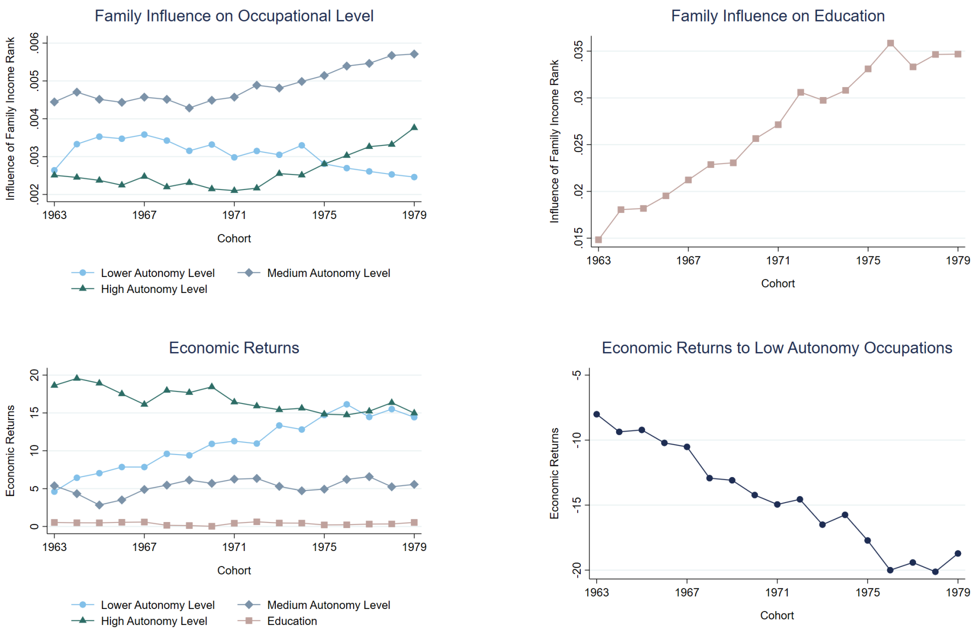
Education and occupational autonomy become increasingly important for the transmission of economic status across birth cohorts. The share of the RRS coefficient attributable to the education pathway more than doubles from 10% in the 1963 cohort to 24% in the 1979 cohort. Similar applies to the occupational autonomy pathway, where the share rises from 27% to approximately 50% for children born around 1975.

Why is the share attributable to the pathway variables increasing over time? One reason might be that a child's income background becomes more important for its education and task level. Also, there could be changes in the economic returns to education and occupational autonomy. Therefore, Figure 3.6 shows the underlying coefficients of the pathway variables across cohorts. They indicate that children's economic background is becoming more important for their education level over time, implying rising educational inequality. In comparison, the returns to education are comparatively stable across cohorts when children's occupational level is accounted for. This is shown by the lower left panel of Figure 3.6.

With the early 1970 cohorts, family background becomes also more influential for children's propensity of working in medium- and high-autonomy occupations. The economic markups for these occupations seem comparatively stable and even to be somewhat decreasing for high-autonomy occupations. For the first birth cohort, having a high-autonomy occupation relates to an additional gain of 18.63 income ranks, compared to 14.98 in the last observed birth cohort.

However, returns to lower-autonomy occupations are rising over time. This implies that the expected *absolute* outcomes of medium- and high-autonomy occupations are rising as well, because the returns are measured as additional gains in income ranks compared to the next lower group. The increasing returns to lower-autonomy occupations therefore imply an increasing wedge in economic outcomes to children in the reference group, that is, children with low-autonomy occupation. This is further highlighted by the lower right panel in Figure 3.6, plotting the mean economic returns to low-autonomy occupations relative to those of higher autonomy levels. For the first cohort covered in the sample, a gap of 8 income ranks between the average income rank of children working in low-autonomy occupations and those in higher task levels. This gap more than doubles over time and equals approximately 20 income ranks

Figure 3.6: Time trends in underlying coefficients



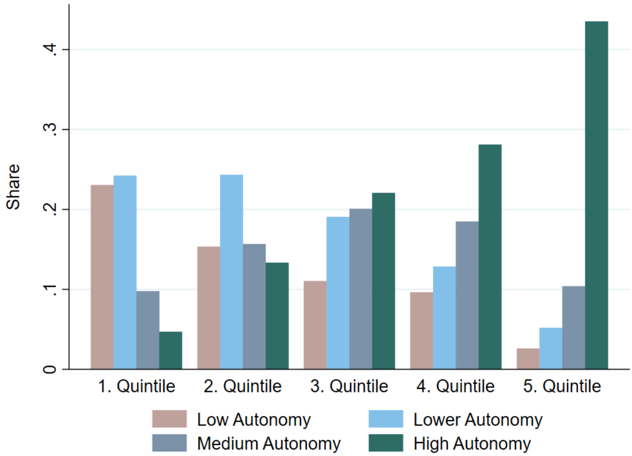
Note: This figure shows the underlying coefficients for the decomposition over time. The upper panels indicate how the influence of family income background on children's education and occupational level changes over time. The lower left panel shows children's economic returns to education and occupational level over time. Economic returns to occupational autonomy are measured as relative gain to the next lower level. The lower right panel illustrate the economic returns to the reference group, that is, to occupations with the lowest autonomy level. There is a stable economic mark-up to medium- and high-autonomy occupations, whereas the economic gap to children with the lowest autonomy level is more than doubling between the 1968 and 1984 birth cohort.

for the more recent cohorts. Consequently, children with low-autonomy occupations become increasingly detached in terms of economic outcomes.

3.7 Related Mechanisms

The previous sections have demonstrated that the influence of family background on children's occupational outcomes is an important pathway for economic persistence. For policy makers, it is important to understand which mechanisms contribute to the relation between family income background and children's task levels. The following

Figure 3.7: The distribution of tasks in the father generation



Note: The figure displays the distribution of task levels in the father generation conditional on the family income quintile. As in the children generation, the share of fathers with high-autonomy occupations increases for higher income quintiles, whereas the share of low-autonomy occupations declines.

analysis cannot resolve this issue fully but shreds light on several contributing factors that affect children's task levels.

3.7.1 The Transmission of Task-Levels

It is well documented that the children of lawyers, doctors, and pharmacists are more likely than others to follow in their parents' footsteps (Lentz and Laband, 1989; Laband and Lentz, 1992; Dunn and Holtz-Eakin, 2000; Sørensen, 2007; Lindquist et al., 2015; Gubler et al., 2017; Aina and Nicoletti, 2018) This has been related to the lower costs needed to acquire occupation-specific human capital — and to nepotism (e.g., Lentz and Laband, 1989).

Here, I consider children's task level rather than specific occupations. Figure 3.7 displays the distribution of task levels in the father generation conditional on the family income quintile. With a share of over 40%, high-level jobs clearly dominate the top income quintile. The variation of occupational autonomy is comparatively balanced for middle incomes, whereas fathers in the bottom income quintile typically perform lower- or low-level occupations. The distribution of task-levels is therefore similar to the children's generation.

Table 3.9: The intergenerational transmission of tasks

	Low Autonomy Level	Lower Autonomy Level	Medium Autonomy Level	High Autonomy Level
Father with lower autonomy occupation	-0.073^{**} (0.033)	0.031 (0.043)	0.148^{***} (0.046)	−0.056 (0.038)
Father with medium autonomy occupation	-0.080^{**} (0.035)	−0.001 (0.044)	0.205^{***} (0.046)	−0.043 (0.039)
Father with high autonomy occupation	-0.092^{**} (0.041)	−0.062 (0.047)	0.113^{**} (0.051)	0.028 (0.043)
Years of schooling	-0.067^{***} (0.009)	-0.045^{***} (0.006)	-0.017^{***} (0.006)	0.069^{***} (0.003)
Family income rank	-0.002^{***} (0.001)	0.000 (0.001)	0.002^{***} (0.001)	−0.000 (0.001)
Controls	Yes	Yes	Yes	Yes
Pseudo R^2	0.365	0.174	0.097	0.354
N	773	826	821	818

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors (shown in parentheses) are clustered on the family level. The control variables include children's age, gender, and industry. Having a father in a higher task level significantly reduces the likelihood that a child has a low-autonomy job, controlling for education, family income and other characteristics. Conversely, a child is 20.5 pp more likely to work in a medium-autonomy occupation when the father is already working at this task level, compared to when the father has a low-autonomy job.

Are children born to fathers with (e.g.) low-autonomy occupations more likely to also work in low-level occupations, even when accounting for their education? This mechanism reduces upwards income mobility when children end-up in jobs with lower task levels although their acquired human capital would enable accessing higher autonomy occupations with higher economic returns.

Table 3.9 reports average marginal effects obtained from logit regressions. They indicate the extent to which the father's occupational level influences a child's task level once its education and family income rank are taken into account. The set of control variables includes children's age, gender, and the industry they are working in. The results indicate that the father's task-level significantly affect whether a child is working in a low- and medium-level occupation, but not in lower- and high-autonomy occupations.[5]

There is evidence for a transmission of low-autonomy occupations. Each higher task

[5]The results remain qualitatively unchanged when looking at mothers' task level instead of fathers' task level, see Appendix Table A.3.7.

level in the father generation significantly reduces the child's probability of working in a low-autonomy occupation, additional to education and the family income background. Having a father in a lower-autonomy occupation, the next-higher task level, already reduces the probability by 7.3 percentage points, keeping the child's schooling years and the family income rank constant.

This result is important for understanding economic persistence at the bottom of the income distribution. It implies that low-autonomy occupations are not only resulting from children's (low) educational achievement. Additionally, children tend to choose the same job type as their fathers before them, that is, jobs with low task levels and low economic returns. Consequently, this mechanism contributes to intergenerational poverty cycles, especially as the time trends in Section 3.6 indicate a rising gap in economic outcomes between children with low-autonomy occupations and children with higher task levels.

Similar applies to medium-level occupations. Children of fathers with medium-autonomy occupations are on average 20.5 percentage points more likely to work in a medium-autonomy occupation than children from low-autonomy fathers, keeping their education level and family income position constant. This implies a strong transmission of medium-level occupations across generations.

When controlling for the child's education, its father's occupational level is not significantly affecting its chances of working in a high-autonomy occupation. The coefficient for the family income position is also not significant. Appendix Table A.3.8 provides a second set of results where education is not included. Then, having a father with a high-autonomy job would be associated with a 28.1 pp increase. This hints that on average, children born to fathers with high-autonomy occupations do not work in a high-level occupation because they follow their fathers' footsteps, but because they have access to education which allows them to work at an equally high task level. Education seems to be also a primary determinant for children's propensity of working in a lower-autonomy occupation.[6]

3.7.2 Labor Market Patterns

One result of the occupational mobility matrix in Section 3.5.2 is that if children at intermediate task levels experience a change in their occupational autonomy, a deterioration is more likely than an improvement. Below, I explore potential drivers

[6] Otherwise, the results for low- and medium-autonomy occupations are very similar to Table 3.9. When not accounting for education, then the advantage of having a father in a higher-autonomy position becomes larger on the child's likelihood of working in a low-autonomy occupation. The transmission of medium-level occupations remains largely unaffected by the education control (17.8 pp. vs. 20.5pp).

Table 3.10: Labor-market related drivers of occupational autonomy

	Low Autonomy Level	Lower Autonomy Level	Medium Autonomy Level	High Autonomy Level
Working part-time	0.041***	0.034**	−0.032**	−0.069***
	(0.007)	(0.013)	(0.013)	(0.008)
Unemployment experience	0.020***	−0.005	−0.026**	−0.033***
	(0.004)	(0.007)	(0.010)	(0.009)
Full time work experience	0.000	−0.001	0.007***	−0.001
	(0.001)	(0.002)	(0.002)	(0.002)
Family income rank	−0.000	−0.002***	0.001***	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Female	−0.013	−0.021	0.146***	−0.073***
	(0.010)	(0.019)	(0.022)	(0.014)
Controls	Yes	Yes	Yes	Yes
Pseudo R^2	0.247	0.099	0.087	0.356
N	19,683	19,683	19,683	19,683

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The table reports average marginal effects from logit regressions. This is a pooled sample including all available observations on children and their outcomes. The dependent variables are children's current occupational autonomy level in a given survey year. The set of control variables includes individual's age, year of schooling, region, industry, marital status, and year effects. Standard errors are clustered on the individual level. The results indicate, for instance, that an additional year of past unemployment includes the child's probability of working in a low-autonomy occupation by 2.0 percentage points.

of task downgrading at the labor market and evaluate whether these relate to children's family income background. While a background-dependent task downgrading might indicate direct or indirect discrimination, it could also derive from different job networks and job searching strategies after children become unemployed.

To explore the influence of family background over children's employment career, I use the pooled SOEP sample which includes all available observations for children's characteristics and outcomes over their life cycle, keeping the family income rank constant.[7] Table 3.10 reports average marginal effects from four logistic regressions. The dependent variables are dummies indicating children's occupational autonomy level in a given survey year. The set of control variables includes cohort effects, children's years of schooling, age, region, and their industry of employment (1-digit-level). All standard errors are clustered on the individual level to account for the pooled sample structure.

[7] See Table A.1.6 for additional descriptive statistics.

Working Part-time, Unemployment, and the Influence of Work Experience

A lower labor supply relates to occupational downgrading. Conditional on education and other characteristics, working part-time makes children more likely to work in the two lower task levels and reduces their probability of working in a medium- or high-autonomy occupations by 3.2 and 6.9 percentage points, respectively. Similar applies to past unemployment episodes. An additional year of unemployment increases the propensity for working in a low-autonomy job by 2 percentage points, and it significantly decreases the likelihood of having a medium- and high-autonomy occupation.

Conversely, there is not much evidence that full-time work experience substantially affects children' s task levels. There is, however, a significant effect on medium-level occupations. On average, every additional year of work experience increases the child's probability of having a medium-level job by 0.7 pp.

These results match the occupational mobility matrix (Section 3.5.2). Children's task levels are not strongly affected by their work experience and thus, they remain stable over their life cycle. However, when children reduce their labor supply or are affected by unemployment, they face a risk of task downgrading, which reflects in the occupational transition matrix.

There is no evidence that children from low-income families are affected to a larger extent from task downgrading than children from high-income families. Figures A.4.3 - A.4.5 in the Appendix visualize the marginal effects of working part-time, unemployment, and work experience conditional on the child's family income rank. There is no large variation and at several segments of the family income distributions, the interaction effects are not significant.

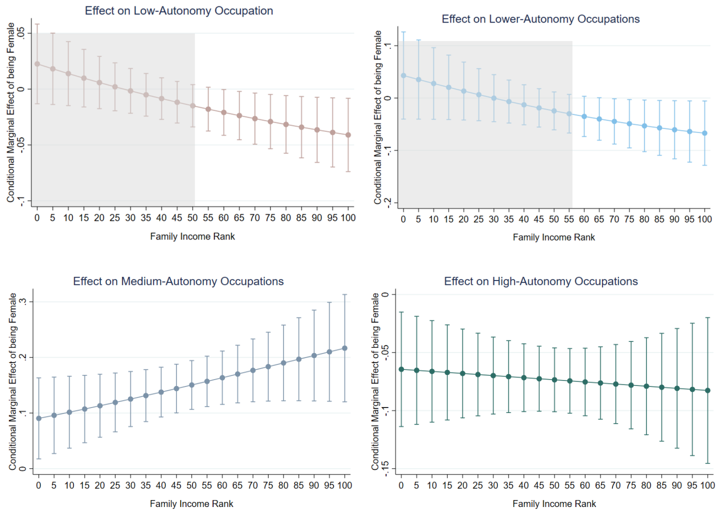
Gender-specific Patterns

Figure 3.8 provides additional evidence on gender-specific patterns along the family income distribution. This highlights the role of medium-level occupations for daughters' income mobility.

In the lower half of the family income distribution, daughters and sons do not differ in their likelihood of having low- and lower-autonomy job, conditional on their other characteristics. Afterwards, daughters are significantly less likely to work in low- and lower-autonomy occupations. This effect becomes more pronounced in higher family income ranks (see upper panels in Figure 3.8).

Being female is highly predictive for medium-level occupations. On average, daughters are 14.6 percentage points more likely to work in medium-autonomy occupations than

Figure 3.8: Effects of children's gender conditional on family income rank



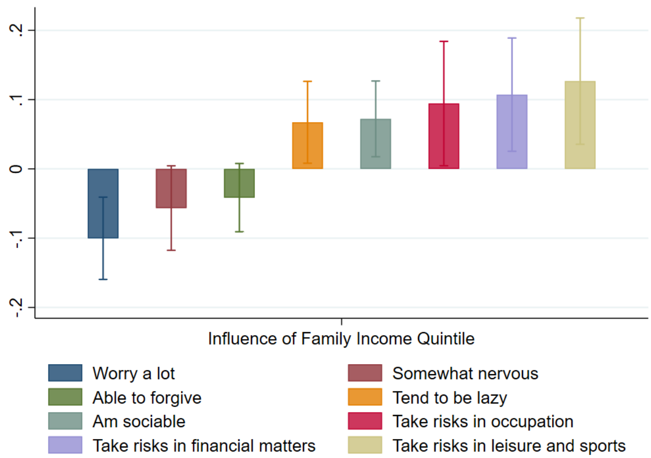
Note: The figure shows the total effects of being female on children's task levels conditional on the family income rank. The marginal effects are not significant in areas with grey background.

sons (Table 3.10). This effect increases with families' income rank. At the top of the family income distribution, daughters are 21.7 pp. more likely to work in a medium-level task than sons. Simultaneously, they become less likely to have high-autonomy occupations.

This implies that daughters from high-income families are substantially more likely to work in medium-level occupations, although they are typically higher educated than comparable sons.[8] On average, these medium-level occupations relate to lower earning returns than high-autonomy occupations. Consequently, daughters' income percentile ranks are likely to decrease compared to their families' income rank. This increases the average level of income mobility and explains why the RRS coefficient is somewhat lower for daughters than for sons. In comparison, sons from high-income families tend to work in high-autonomy positions and therefore reach a higher income percentile themselves, which contributes to the transmission of economic status.

[8]Table 3.5 in Section 3.5.3 predicts that at a given family income rank, daughters reach on average a higher number of schooling years than sons.

Figure 3.9: The associated influence of children's income background on their personality traits



Note: This figure illustrates the influence of family income quintile on children's personality traits. Hereby, children's traits are measured on a 1-to-7 scale, and their risk tolerance on a 0-to-10 scale. For instance, a 1-quintile increase in the family's income position is associated with a 0.057 decrease in the child's level of nervousness, which is a measure for neuroticism. The underyling OLS regressions control for children's education, gender, and age.

3.7.3 Personality Traits

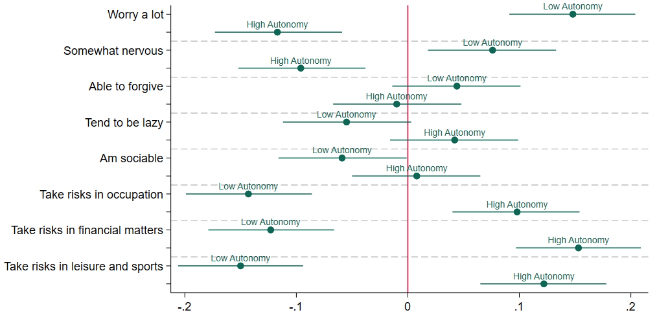
Finally, I turn to psychological factors as potential mechanism. The importance of personality traits for occupational choices and career outcomes is well documented in the literature (e.g., Seibert et al., 1999; Hurtz and Donovan, 2000; Judge and Kammeyer-Mueller, 2007; George et al., 2011; Xu, 2020). A high-income background might enhance personality traits that facilitate children to obtain and perform occupations with high task levels, which would contribute to economic persistence.

I evaluate this claim by exploring how family income influences different personality traits. These include risk tolerance and standard variables to measure children's level of neuroticism, agreeableness, conscientiousness, and openness (Gerlitz and Schupp, 2005). Personality traits are measured on a 1-7 scale, and risk tolerance from 0 to 10. The values are self-reported, with higher values indicating that children perceive their traits as more pronounced, and are more willing to take risks along several dimensions.[9]

Family income background is highly relevant for children's risk tolerance on the one

[9]See Table A.1.3 in the Appendix for further descriptive statistics.

Figure 3.10: Correlation between personality traits and occupation types



Note: This figure shows correlation coefficients between children's personality traits and low- and high-autonomy occupations. Measures for neuroticism (worry a lot, somewhat nervous) are positively correlated with low-autonomy occupations and negatively correlated with high-autonomy occupations, whereas the reverse applies to children's willingness to take risks along different dimensions.

side, and for indicators of neuroticism on the other side. Additionally, a higher family income rank increases children's openness, but reduces their conscientiousness and agreeableness. This is highlighted by Figure 3.9, which shows how a family's income quintile influences their child's reported personality traits at the mean. Children's education level is already accounted for.[10]

Ceteris paribus, a higher income quintile is associated with lower values for worrying and nervousness, that is, traits indicating neuroticism. Children indicate a mean value of 4.401 when they are asked whether they worry a lot. With this baseline, a 1-quintile increase in the family's income position is associated with a decrease by 0.100, which is significant at the 1 % level. Furthermore, an increase in the family income quintile reduces the extent to which children are able to forgive others. This relates to children's level of agreeableness. Being lazy is a standardized measure for low conscientiousness (Gerlitz and Schupp, 2005). Therefore, the positive influence on laziness indicates that higher family income relates to a lower level of conscientiousness. Higher family income is also associated with a significantly higher level of sociability, implying more openness. In particularly, a family's income position positively affects children's willingness to take risks along different dimensions. This affects taking risks in occupational matters and financial affairs, but the influence is largest on their private life (leisure and sports). Overall, these results suggest that children's economic background affect their personality traits.

In turn, personality traits correlate with occupational types. This is shown by Figure

[10] See Appendix Table A.5.9 for the estimated coefficient values.

3.10, which illustrates the Point-Biserial correlation coefficients between traits and high- and low-autonomy occupations.[11]

Correlation coefficients are highest for those traits that are most affected by children's family income background, that is, risk tolerance and neuroticism. High-autonomy occupations are positively correlated with the willingness to take risks in occupational and financial matters, as well as in leisure and sports. Conversely, they are negatively correlated with worrying a lot and with being nervous. For low-autonomy occupations, the correlation coefficients move in the reverse direction, and are also highly significant. The correlation with other traits is less pronounced and close to zero.[12] These traits are also less affected by children's economic background.

This implies that children from high-income families grow-up in a socio-economic environment that makes them more willing to take risks and less anxious. This in turn is favorable for their occupational outcomes. Simultaneously, children from low-income families have a lower risk tolerance and worry more, traits which are typically observed in individuals working in low-autonomy occupations. Thereby, this mechanism contributes to the transmission of economic status across generations. However, the correlation between occupational outcomes and personality traits is, although highly significant, moderate in its magnitude. This also applies to the associated influence of family background on traits, suggesting that personality traits might not be the primary mechanism behind the observed effects.

3.8 Robustness Checks

3.8.1 Alternative Income Measures

In the following, I implement alternative income measures for the parent generation to estimate the rank-rank slope. These include fathers' individual earnings, the disposable household income in non-equalized form, and gross household in equivalized and non-equivalized form (Table 3.11). The children income measure remains unchanged and is defined by children's labor earnings. The obtained RRS coefficients are slightly higher when the income measure is adjusted for the number of adults and children in the family, that is, when OECD equivalence weights are implemented. Therefore, the relation between economic outcomes is stronger for income measures reflecting more closely the financial resources available for investments into one child. Yet, the magnitude of the obtained coefficients is overall very similar in size, indicating that

[11] The Point-Biserial correlation coefficient is used to estimate the correlation between continuous variables and binary variables such as children's occupational level.

[12] See Appendix Table A.5.10 for the estimated values of the correlation coefficients.

the rank-rank slope is robust towards the implemented income measure.

Table 3.11: Alternative income measures for RRS estimates

Parent Income Measure	HH Disposable Income	HH Disposable Income	Father Earnings	HH Gross Income	HH Gross Income
RRS	0.235*** (0.029)	0.152*** (0.030)	0.225*** (0.044)	0.227*** (0.029)	0.174*** (0.029)
Equalized Parent Income Measure	Yes	No	No	Yes	No
N	1,247	1,247	856	1,247	1,247

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on family level. This table presents estimated coefficients for the rank-rank slope (RRS) based on alternative income measures. These include disposable household income (main analysis), fathers' individual earnings, and household gross income in equalized and non-equalized form. Hereby, equalized income is adjusted to the household composition regarding the number of adults and minors.

Table 3.12: Decomposition with alternative income measures

Decomposition with Alternative Income Measures						
	Total Sample		Sons		Daughters	
	Part of RRS	Father Earnings of RRS	Part of RRS	HH Gross of RRS	Part of RRS	Percentage off RRS
Education Pathway Variable	0.067*** (0.015)	29.92% (0.084)	0.041*** (0.010)	17.96% (0.046)	0.031*** (0.008)	20.36% (0.059)
Occupational Autonomy Pathway Variable	0.096*** (0.018)	42.58% (0.093)	0.081*** (0.012)	35.35% (0.058)	0.063*** (0.012)	41.46% (0.089)
Direct Effect of Economic Background	0.062 (0.038)	27.50% (0.138)	0.106*** (0.026)	46.45% (0.075)	0.058** (0.025)	38.19% (0.119)
RSS	0.235*** (0.028)	100.00%	0.227*** (0.028)	100.00%	0.152*** (0.028)	100.00%
Family Income Measure	Individual Father Earnings		Household Gross Income		Household Disposable Income	
Equivalence Weights	No		Yes		No	
N	856		1,247		1,247	

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Bootstrapped (1000) standard errors in parentheses, clustered on family level. This table summarizes the results of the joint decomposition for different income measures in the parent generation. The right column shows decomposition results for disposable household income without OECD equivalence weights.

This is further confirmed when looking at decomposition results obtained with father earnings, gross household income, and disposable household income without the implemented equivalence weights. When using fathers' individual labor earnings, the share attributable to the education pathway is moderately higher than in the main

Table 3.13: IGE-based decomposition results

	Total Sample			
	Part of RRS	Percentage of RRS	Part of RRS	Percentage off RRS
Education Pathway Variable	0.217*** (0.031)	36.56% (0.067)	0.015 (0.023)	2.59% (0.041)
Occupational Autonomy Pathway Variable			0.302*** (0.049)	50.81% (0.079)
Direct Effect of Economic Background	0.376*** (0.086)	63.44% (0.067)	0.277*** (0.078)	46.60% (0.083)
IGE	0.593*** (0.089)	100.00%	0.593*** (0.092)	100.00%
N	1,245		1,245	

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Bootstrapped (1000) standard errors in parentheses, clustered on family level. The obtained coefficient of 0.593 indicates that on average, a 10% increase in disposable family income relates to a 5.93% increase in the child's income. In the single pathway specification, 36.56% of the estimated IGE coefficient is attributable to the education pathway. In the joint decomposition, the explanatory power shifts to the occupational autonomy pathway. For pathway coefficient is equivalent to 50.81% of the IGE value.

specification and accounts for 29.92% of the RRS coefficient. Otherwise, the results remain very close to the main specification, especially for the occupational autonomy pathway.

3.8.2 The Intergenerational Income Elasticity (IGE)

Alternative to the rank-rank slope, I derive decomposition results based on the intergenerational income elasticity (IGE). In the earlier literature, this is a conventional measure to express the level of income persistence at the mean. The IGE derives from regressing children's averages of log income on the families' averages of log income, controlling for age and squared age in both generations to account for income variations over the life cycle. As with the rank-rank slope, a higher IGE value indicates a higher level of intergenerational persistence and a lower level of economic mobility.

Here, the estimated IGE is 0.593, using family log income as parental income measure. This implies that on average, a 10% increase in disposable family income is associated with a 5.93% increase in children's income. Hence, the absolute level of the IGE is noticeable higher than the estimated RRS coefficient of 0.221, which is in the line

Table 3.14: Alternative income measures for IGE estimates

Parent Income Measure	HH Disposable Income	Father Earnings	HH Gross Income	HH Gross Income	HH Disposable Income
IGE	0.593*** (0.087)	0.282*** (0.069)	0.340*** (0.050)	0.330*** (0.054)	0.505*** (0.087)
Age Controls	Yes	Yes	Yes	Yes	Yes
Equalized Parent Income Measure	Yes	No	Yes	No	No
N	1,245	838	1,244	1,244	1,245

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on family level. This table presents estimated coefficients for the intergenerational income elasticity (IGE) based on alternative income measures. These include disposable household income (main analysis), fathers' individual earnings, and household gross income in equalized and non-equalized form. Hereby, equalized income is adjusted to the household composition regarding the number of adults and minors. The results indicate that the IGE is more sensitive towards the implemented income measure than the RRS (see Table 3.11).

with the existing literature (e.g., Chetty et al., 2014).

Table 3.13 reports the IGE coefficient and summarizes the decomposition results based on the intergenerational income elasticity. In the single pathway specification, education accounts for 36.56% of the estimated IGE, compared to 43.27% in the RRS-based main results. As in the main results, the explanatory power shifts to the occupational autonomy pathway in the joint decomposition. Here, the education pathway is not significant.

Furthermore, the magnitude of the estimated IGE value is noteworthy. The coefficient of 0.593 is well above other results for Germany (e.g., Couch and Dunn, 1997; Bratberg et al., 2017; Kyzyma and Groh-Samberg, 2018). This relates to the selected income measure. Existing studies on Germany conventionally rely on individual earnings rather than household income. In some cases, household gross income is used (Kyzyma and Groh-Samberg, 2018). Therefore, I provide additional IGE results based on these alternative income measures.

The corresponding results are reported in Table 3.14. They show that the IGE value strongly depends on the income measure. For instance, the obtained IGE coefficient is 0.282 based on father earnings, compared to the baseline IGE coefficient of 0.593. As with the RRS, the equalization with OECD weights increases IGE estimates, but to a larger extent. This indicates that the IGE is more sensitive towards implemented sample specification rules, confirming that the RRS is a more suitable summary measure to analyze the transmission of economic status across generations.

Table 3.15: The alternative education measure

	Total Sample			
	Part of RRS	Percentage of RRS	Part of RRS	Percentage off RRS
Education Pathway Variable	0.066*** (0.011)	27.61% (0.055)	0.019** (0.008)	8.33% (0.037)
Occupational Autonomy Pathway Variable			0.102*** (0.013)	43.88% (0.061)
Direct Effect of Economic Background	0.169*** (0.029)	72.39% (0.055)	0.112*** (0.027)	47.79% (0.072)
RSS	0.235*** (0.029)	100.00%	0.235*** (0.029)	100.00%
N	1,247		1,247	

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Bootstrapped (1000) standard errors in parentheses, clustered on family level. Here, the decomposition relies on dummy variables indicating children's education levels. In the single pathway specification, the obtained results indicate that 28.17% of the RRS is attributable to the education pathway, and 8.33% in the joint decomposition.

3.8.3 Alternative Measure for Children Education

The main specification uses years of schooling as measure for children's education. They increase linearly in family income ranks and are therefore well suited for the linear decomposition. Alternatively, children's education is expressed by dummy variables, indicating their highest educational degree (see Section 3.3 for additional information). Compulsory education serves as baseline. Table 3.15 summarizes the results. In the joint decomposition, the magnitude of the education pathway coefficient somewhat decreases from 0.049 in the main specification to 0.021. The occupational autonomy pathway remains on a very similar level (0.102 vs. 0.091 in main results) and represents a central pathway contributing to the level of economic persistence in Germany.

3.9 Conclusion

This paper explores the role of occupational autonomy as pathway for intergenerational income persistence in Germany. Occupational autonomy is a task-based measure that categorizes occupations by autonomy and responsibility. The analysis relies on a decomposition approach to show the extent to which economic persistence is attributable to the influence of families' income position on their children' level of education and occupational autonomy, as well as to the corresponding economic returns to these characteristics.

Task structures are important for understanding the transmission of economic status across generations. For Germany, the results show that approximately 40% of the rank-rank slope (RRS) are attributable to the occupational autonomy pathway, and 20% to the education pathway. Furthermore, observed time trends indicate that both channels become more important across birth cohorts. For the education pathway, this relates to an increasing influence of family income background on children's educational outcomes. The role of the occupational autonomy pathway is further driven by patterns in the economic returns to children's task levels, thus connecting intergenerational income mobility to the labor market. Children with low-autonomy jobs are increasingly left behind.

Simultaneously, children face a significantly higher risk of ending up in a low-autonomy occupation when their fathers already have a low-autonomy job, taking education and other characteristics into account. This implies a transmission of low task levels across generations and contributes to intergenerational poverty cycles.

The obtained results also highlight the role of medium-autonomy occupations. Similar to low-autonomy occupations, there is evidence for a transmission of medium task levels from father to child. Additionally, gender-specific patterns are evident. The higher the family income rank, the more likely daughters are to work in a medium-autonomy job. At the top of the family income distribution, daughters are 24.1 percentage points more likely to work in a medium-autonomy occupation than sons, although they are better educated. This provides an interesting starting point for future research, e.g., on the influence of assortative mating on daughter's task levels.

These findings have important policy implications. In general, there is no evidence for a transmission of high-autonomy occupations once children's education is taken into account. Thus, when policies aim at increasing the access to high-autonomy occupations, they should indeed target the access to higher education and reduce existing inequalities between children from low-and high-income households. However, policies should simultaneously target children's transition to the labor market, i.e., when children make their initial career choices. In general, children's task levels remain stable over their life cycle or even tend to deteriorate, which makes their initial autonomy level even more important. The results imply that especially children whose parents work at low task levels are an important target group to avoid poverty cycles. For instance, these children might benefit from further career counseling during secondary education. This could provide information on career paths, funding opportunities, and job networks which can not be provided by the family background and support children to translate their human capital into higher economic outcomes. So far, efforts in this direction have been limited.

Bibliography

Acemoglu, D., and D. Autor. 2011. Skills, Tasks and Technologies: Implications for Employment and Earnings. In *Handbook of Labor Economics*, vol. 4, pp. 1043–1171. Elsevier.

Aina, C., and C. Nicoletti. 2018. The Intergenerational Transmission of Liberal Professions. *Labour Economics* 51:108–120.

Almlund, M., A. L. Duckworth, J. J. Heckman, and T. Kautz. 2011. *Handbook of Economics of Education*, vol. 4, chap. Personality Psychology and Economics, pp. 1–181. Elsevier.

Autor, D. H., and M. J. Handel. 2013. Putting Tasks to the Test: Human Capital, Job Tasks, and Wages. *Journal of Labor Economics* 31:S59–S96.

Autor, D. H., F. Levy, and R. J. Murnane. 2003. The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics* 118:1279–1333.

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

Becker, G. S., and N. Tomes. 1986. Human Capital and the Rise and Fall of Families. *Journal of Labor Economics* 4:S–39.

Black, S. E., and A. Spitz-Oener. 2010. Explaining women's success: Technological change and the skill content of women's work. *Review of Economics and Statistics* 92:187–194.

Blanden, J. 2005. International Evidence on Intergenerational Mobility. London School of Economics, Centre for Economic Performance.

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

Blanden, J., R. Haveman, T. M. Smeeding, and K. Wilson. 2014. Intergenerational Mobility in the United States and Great Britain: A Comparative Study of Parent-Child Pathways. *Review of Income and Wealth* 60:425–429.

Bloome, D., S. Dyer, and X. Zbou. 2018. Educational Inequality, Educational Expansion, and Intergenerational Income Persistence in the United States. *American Sociological Review* 83:1215–1253.

Bloome, D., and B. Western. 2011. Conort Change and Racial Differences in Educational and Income Mobility. *Social Forces* 90:375–395.

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

Brenner, J. 2010. Life-cycle Variations in the Association Between Current and Lifetime Earnings: Evidence for German Natives and Guest Workers. *Labour Economics* 17:392–406.

Carneiro, P., and J. J. Heckman. 2003. Human Capital Policy. IZA Discussion Papers No. 821.

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

Comi, S. 2004. Intergenerational Mobility in Europe: Evidence from ECHP. Centre for Household, Income, Labour, Demographic Economics Working Paper 18/2004.

Couch, D., Kenneth; Lillard. 2004. Nonlinear Patterns of Intergenerational Mobility in Germany and the United States. In M. Corak (ed.), *Generational Income Mobility in North America and Europe*. Cambridge: Cambridge University Press.

Couch, K., and T. Dunn. 1997. Intergenerational Correlations in Labor Market Status: A Comparison of the United States and Germany. *Journal of Human Resources* pp. 210–232.

Cunha, F., and J. Heckman. 2007. The Technology of Skill Formation. *American Economic Review* 97:31–47.

Cunha, F., and J. J. Heckman. 2008. Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation. *The Journal of Human Resources* 43:738–782.

Dahl, M., and T. DeLeire. 2008. The Association between Children's Earnings and Father's Lifetime Earnings: Estimates Using Administrative Data. Institute for Research on Poverty Discussion Paper No. 1342-08.

David, H., L. F. Katz, and M. S. Kearney. 2006. The Polarization of the US Labor Market. *American Economic Review* 96:189–194.

Dunn, T., and D. Holtz-Eakin. 2000. Financial Capital, Human Capital, and the Transition to Self-Employment: Evidence from Intergenerational Links. *Journal of Labor Economics* pp. 282–305.

Flake, R. 2013. Gender Differences in the Earnings Mobility of Migrants. *Labour* 27:58–79.

George, L. G., R. Helson, and O. P. John. 2011. The "CEO" of Women's Work Lives: How Big Five Conscientiousness, Extraversion, and Openness predict 50 Years of Work Experiences in a Changing Sociocultural Context. *Journal of Personality and Social Psychology* 101:812.

Gerlitz, J.-Y., and J. Schupp. 2005. Zur Erhebung der Big-Five-basierten Persönlichkeitsmerkmale im SOEP. *DIW Research Notes* 4.

Goebel, J., M. M. Grabka, S. Liebig, M. Kroh, D. Richter, C. Schröder, and J. Schupp. 2019. The German Socio-Economic Panel (SOEP). *Jahrbücher für Nationalökonomie und Statistik* 239:345–360.

Goos, M., and A. Manning. 2007. Lousy and Lovely Jobs: The Rising Polarization of Work in Britain. *Review of Economics and Statistics* 89:118–133.

Gubler, M., T. Biemann, and S. Herzog. 2017. An Apple doesn't Fall Far from the Tree - Or does it? Occupational Inheritance and Teachers' Career Patterns. *Journal of Vocational Behavior* 100:1–14.

Hirvonen, L. 2010. Accounting for Intergenerational Earnings Persistence: Can We Distinguish between Education, Skills, and Health? SOFI Working Paper 2/2010.

Hoffmeyer-Zlotnik, J. H. P., and A. J. Geis. 2003. Berufsklassifikation und Messung des beruflichen Status / Prestige. *ZUMA Nachrichten* 27:125–138.

Hurtz, G. M., and J. J. Donovan. 2000. Personality and Job Performance: The Big Five Revisited. *Journal of Applied Psychology* 85:869.

Judge, T. A., and J. D. Kammeyer-Mueller. 2007. Personality and Career Success. *Handbook of Career Studies* 9:59.

Kyzyma, I., and O. Groh-Samberg. 2018. Intergenerational Economic Mobility in Germany: Levels and Trends. Mimeo.

Laband, D. N., and B. F. Lentz. 1992. Self-Recruitment in the Legal Profession. *Journal of Labor Economics* 10:182–201.

Lentz, B. F., and D. N. Laband. 1989. Why So Many Children of Doctors Become Doctors: Nepotism vs. Human Capital Transfers. *The Journal of Human Resources* 24:396–413.

Lillard, D. 2001. Cross-National Estimates of the Intergenerational Mobility in Earnings. *Vierteljahreshefte zur Wirtschaftsforschung* 70:51–58.

Lindquist, M. J., J. Sol, and M. Van Praag. 2015. Why do Entrepreneurial Parents have Entrepreneurial Children? *Journal of Labor Economics* 33:269–296.

Nybom, M., and J. Stuhler. 2017. Biases in Standard Measures of Intergenerational Income Dependence. *Journal of Human Resources* 52:800–825.

Rivera, L. A. 2016. *Pedigree: How Elite Students get Elite Jobs*. Princeton University Press.

Schnitzlein, D. D. 2016. A New Look at Intergenerational Mobility in Germany Compared to the U.S. *Review of Income and Wealth* 62:650–667.

Seibert, S. E., J. M. Crant, and M. L. Kraimer. 1999. Proactive Personality and Career Success. *Journal of Applied Psychology* 84:416.

Solon, G. 1999. Intergenerational Mobility in the Labor Market. In D. Ashenfelter, Orley; Card (ed.), *Handbook of Labor Economics*, vol. 3, pp. 1761–1800. Elsevier.

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

Solon, G. 2014. Theoretical Models of Inequality Transmission Across Multiple Generations. *Research in Social Stratification and Mobility* 35:13–18.

Sørensen, J. B. 2007. Closure and Exposure: Mechanisms in the Intergenerational Transmission of Self-Employment. In *The Sociology of Entrepreneurship*. Emerald Group Publishing Limited.

Vogel, T. 2006. Reassessing Intergenerational Mobility in Germany and the United States: The Impact of Differences in Lifecycle Earnings Patterns. SFB 649 Discussion Paper No. 2006-55.

Xu, H. 2020. Big Five Personality Traits and Ambiguity Management in Career Decision-Making. *The Career Development Quarterly* 68:158–172.

Yuksel, M. 2009. Intergenerational Mobility of Immigrants in Germany: Moving with Natives or Stuck in Their Neighborhoods? IZA Discussion Paper No. 4677.

Appendix

A.1 Descriptive Statistics

Table A.1.1: Descriptive statistics for sons and daughters

	Sons	Daughters
Age	35.089	35.037
	(1.096)	(1.088)
Income	38,656.60	19,421.94
	(22,646.02)	(15,020.60)
Years of Schooling	12.932	12.988
	(2.855)	(2.809)
Low Educational Attainment	0.236	0.157
	(0.425)	(0.364)
Medium Educational Attainment	0.183	0.263
	(0.387)	(0.441)
Medium-High Educational Attainment	0.067	0.078
	(0.250)	(0.268)
High Educational Attainment	0.278	0.234
	(0.448)	(0.424)
Low Occupational Autonomy	0.072	0.097
	(0.258)	(0.297)
Lower Occupational Autonomy	0.229	0.195
	(0.421)	(0.396)
Medium Occupational Autonomy	0.236	0.399
	(0.425)	(0.490)
High Occupational Autonomy	0.463	0.309
	(0.499)	(0.462)
N	641	606

Note: This table shows sample means, standard deviations in parentheses.

Table A.1.2: Industry shares

	Mean
Agriculture	0.011
	(0.105)
Energy	0.015
	(0.120)
Mining	0.003
	(0.057)
Manufacturing	0.174
	(0.379)
Construction	0.128
	(0.335)
Trade	0.141
	(0.348)
Transport	0.056
	(0.230)
Bank and Insurance	0.044
	(0.205)
Services	0.428
	(0.495)
Same industry as father	0.164
	(0.379)
N	1,231

Note: This table shows sample means, standard deviations in parentheses.

Table A.1.3: Descriptive statistics of children's personality traits

	Mean	N
Worry a lot	4.405	1,141
	(1.363)	
Somewhat nervous	3.486	1,141
	(1.379)	
Able to forgive	5.318	1,142
	(1.081)	
Tend to be lazy	2.497	1,141
	(1.311)	
Am sociable	5.123	1,141
	(1.207)	
Take risks in occupations	4.203	1,159
	(2.028)	
Take risks in financial matters	2.599	1,160
	(1.871)	
Take risks in leisure and sports	4.167	1,162
	(2.092)	

Note: Standard deviation in parentheses. The table summarizes descriptive statistics of children's personality traits. The first five traits are measured on a 1-to-7 scale. Children's willingness to take risks in occupations, financial matters, and in leisure and sports are measured on a 0-to-10 scale.

Table A.1.4: The level of occupational autonomy in the father generation

Fathers' Occupational Level	Mean
Low Occupational Autonomy	0.201
	(0.401)
Lower Occupational Autonomy	0.279
	(0.449)
Medium Occupational Autonomy	0.225
	(0.418)
High Occupational Autonomy	0.295
	(0.457)
N	623

Note: This table shows sample means, with standard deviations in parentheses.

Table A.1.5: Variance inflation factors (VIF)

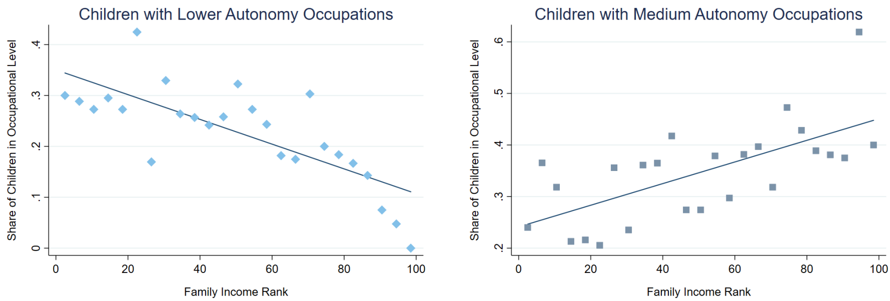
	VIF	1/VIF
Years of Schooling	1.74	0.574
Having at least medium occupational autonomy	1.69	0.591
Having at least medium-high occupational autonomy	1.69	0.592
Having high occupational autonomy	1.29	0.775
Family Income Rank	1.09	0.915

Table A.1.6: Pooled children sample statistics

	Mean		Mean
Socio-demographic characteristics		**Industry**	
Age	31.108 (7.555)	Agriculture	0.012 (0.107)
Female share	0.446 (0.497)	Energy	0.013 (0.113)
Years of schooling	12.240 (2.743)	Mining	0.007 (0.080)
East Germany	0.159 (0.366)	Manufacturing	0.205 (0.404)
West Germany	0.841 (0.366)	Construction	0.145 (0.352)
Working part-time	0.255 (0.436)	Trade	0.154 (0.361)
Unemployment experience	0.148 (0.355)	Transport	0.050 (0.218)
Full-time working experience	15.495 (11.785)	Bank,Insurance	0.044 (0.205)
Married	0.631 (0.483)	Services	0.371 (0.483)
Individuals' Level of Occupational Autonomy			
Low Occupational Autonomy	0.127 (0.333)	Medium Occupational Autonomy	0.295 (0.456)
Lower Occupational Autonomy	0.284 (0.451)	High Occupational Autonomy	0.205 (0.402)
N	19,683	N	19,683

Note: This table shows sample means, standard deviations in parentheses.

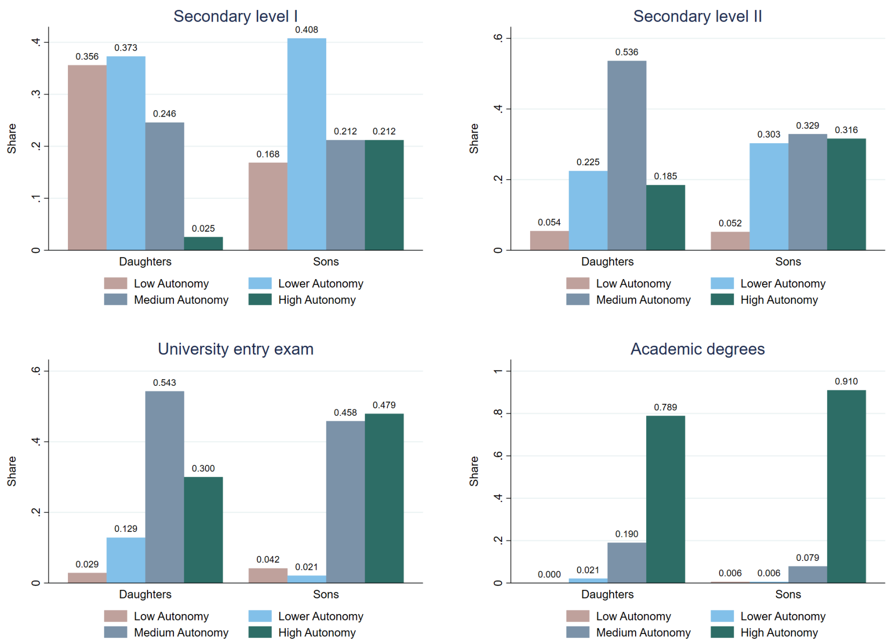
Figure A.1.1: The relation between family income ranks and children working in lower- and medium-autonomy occupations



Note: The two panels of the figure show that the share of children working in medium-autonomy occupations linearly increases in family income. Simultaneously, the share of children with lower-autonomy jobs linearly declines. The family income position is measured by income percentile ranks, and each dot presents the mean years of schooling for two family income ranks.

A.2 Gender-specific patterns in children's occupational level

Figure A.2.2: Gender-specific patterns in the occupational distribution



Note: The four panels illustrate gender-specific occupational structures. With the same education level, daughters are less likely to work in high-autonomy occupations.

A.3 Transmission of Occupational Level from Mother to Child

Table A.3.7: The transmission of task levels from mother to child

	Low Autonomy Level	Lower Autonomy Level	Medium Autonomy Level	High Autonomy Level
Mother with lower autonomy occupation	-0.082^{***} (0.026)	0.017 (0.037)	0.115^{***} (0.042)	-0.012 (0.034)
Mother with medium autonomy occupation	-0.117^{***} (0.026)	-0.025 (0.036)	0.132^{***} (0.041)	-0.013 (0.033)
Mother with high autonomy occupation	-0.119^{***} (0.040)	-0.022 (0.053)	0.007 (0.053)	0.065 (0.053)
Years of schooling	-0.028^{***} (0.004)	-0.035 (0.006)	-0.010^{*} (0.005)	0.066^{***} (0.005)
Family income rank	-0.002^{***} (0.000)	-0.001 (0.001)	0.002^{**} (0.001)	0.001 (0.001)
Controls	Yes	Yes	Yes	Yes
Pseudo R^2	0.245	0.149	0.079	0.290
N	875	927	927	927

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors (shown in parentheses) are clustered on the family level. The control variables include children's age, gender, and industry. This table shows average marginal effects, obtained from logit regressions.

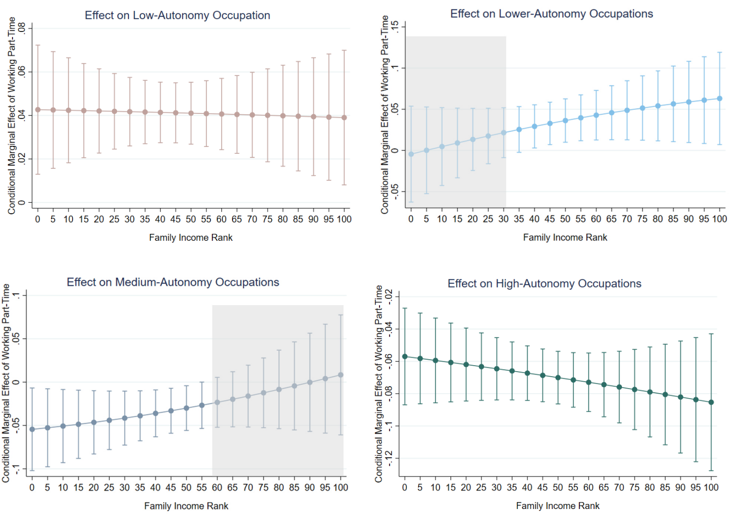
Table A.3.8: The transmission of task levels without education controls

	Low Autonomy Level	Lower Autonomy Level	Medium Autonomy Level	High Autonomy Level
Father with lower autonomy occupation	-0.128^{***} (0.041)	0.004 (0.047)	0.133^{***} (0.047)	0.008 (0.042)
Father with medium autonomy occupation	-0.161^{***} (0.042)	-0.051 (0.047)	0.178^{***} (0.047)	0.065 (0.044)
Father with high autonomy occupation	-0.207^{***} (0.041)	-0.152^{***} (0.046)	0.065 (0.049)	0.281^{***} (0.051)
Family income rank	-0.003^{***} (0.001)	-0.000 (0.001)	0.002^{**} (0.001)	0.000 (0.001)
Controls	Yes	Yes	Yes	Yes
Pseude R2	0.195	0.119	0.085	0.132
N	780	833	833	824

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors (shown in parentheses) are clustered on the family level. The control variables include children's age, gender, and industry. Here, I do not control for children's education.

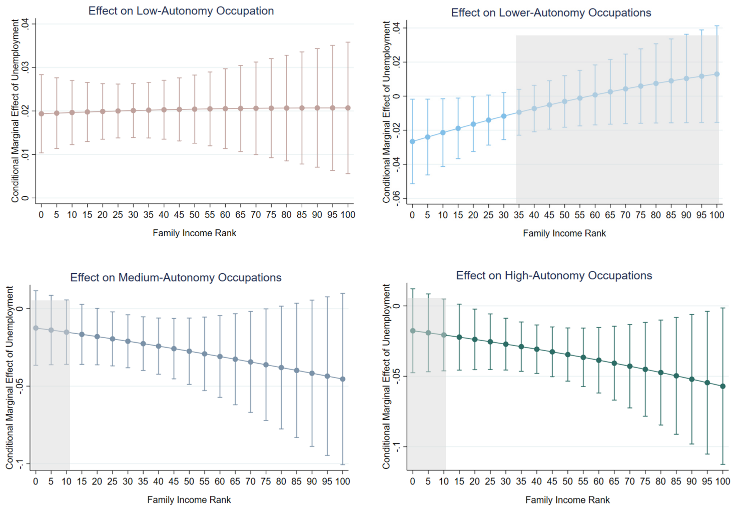
A.4 Part-time Work, Unemployment, and Work Experience

Figure A.4.3: Effects of working part-time conditional on family income rank



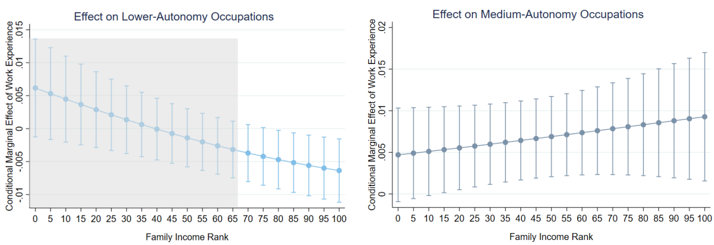
Note: The figure displays the total effects of working part-time on children's task levels conditional on the family income rank. The marginal effects are not significant in areas with grey background.

Figure A.4.4: Effects of unemployment conditional on family income rank



Note: The figure displays the total effects of an additional year of unemployment on children's task levels conditional on the family income rank. The marginal effects are not significant in areas with grey background.

Figure A.4.5: Effects of work experience conditional on family income rank



Note: The figure displays the total effects of an additional year of full-time work experience on children's task levels conditional on the family income rank. The marginal effects are not significant in areas with grey background. Past work experience has no significant effects on children's chances of working in a low- or high-autonomy occupation. The corresponding marginal effects are therefore not included in this figure.

A.5 Personality Traits and Family Income Background

Table A.5.9: The influence of income background on children's personality traits

	Worry a lot	Somewhat nervous	Able to forgive	Tend to be lazy
Family Income Quintile	-0.100^{***} (0.030)	-0.057^{*} (0.031)	-0.042^{*} (0.025)	0.067^{**} (0.030)
Controls	Yes	Yes	Yes	Yes
N	1,152	1,152	1,153	1,152
	Am sociable	**Take risks in occupations**	**Take risks in financial matters**	**Take risks in leisure and sports**
Family Income Quintile	0.072^{**} (0.028)	0.094^{**} (0.046)	0.107^{**} (0.042)	0.127^{***} (0.047)
Controls	Yes	Yes	Yes	Yes
N	1,152	1,170	1,171	1,173

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This tables shows the influence of family's income quintile on children's self-reported personality traits. For instance, a 1-quintile increase in the family's income position decreases the scale for worrying a lot by 0.100 units. The set of control variables includes children's years of education, gender, and age.

Table A.5.10: Correlation between children's personality traits and occupation types

	Low Autonomy Occupation	High Autonomy Occupation	N
Worry a lot	0.148***	−0.117***	1.152
	(5.076)	(−3.985)	
Somewhat nervous	0.076**	−0.096***	1.152
	(2.569)	(−3.255)	
Able to forgive	0.044	−0.010	1.153
	(1.486)	(−0.325)	
Tend to be lazy	−0.055*	0.042	1.152
	(−1.853)	(1.408)	
Am sociable	−0.059**	0.008	1.152
	(−1.999)	(0.259)	
Take risks in occupations	−0.143***	0.098***	1.153
	(−4.931)	(3.327)	
Take risks in financial matters	−0.123***	0.153***	1.171
	(−4.235)	(5.294)	
Take risks in leisure and sports	−0.150***	0.122***	1.173
	(−5.201)	(4.202)	

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. This table shows the Point-Biserial correlation coefficients between children's personality traits and high- and low-autonomy occupations. The corresponding t-statistics are provided in the parentheses.

Chapter 4

Peer Effects and Social Mobility

Elisabeth Essbaumer [1]

This paper analyzes peer effects at the University of St. Gallen (HSG) in Switzerland. The identification strategy relies on randomized student groups to investigate how graduates' outcomes are affected by the social composition of their peer groups. The results indicate that a 10 percentage points higher share of peers with low socio-economic status (SES) leads to a 4.87% increase in graduates' income one year after graduation. The effect is strongest on other low-SES students and functions primarily through an adoption of occupational choices and labor supply. I do not find evidence in this sample that the outcomes of low-SES students are negatively affected by high-SES peer exposure.

JEL Classification: D64, J62, I24.

[1] I am grateful for the constructive comments by Christian Keuschnigg, Niklas Potrafke, seminar participants of the LMU and ifo Institute's Public Economics Workshop on July 1, 2022, and of the Internal FGN Workshop on September 8, 2022.

4.1 Introduction

In most countries, a significant proportion of top-income earners graduate from a small number of elite universities. Access to these institutions depends on children's socio-economic background. In the United States, children from families in the top income percentile are 77-times as likely to attend an Ivy League School than children born to families in the bottom income quintile (Chetty et al., 2017). However, educational inequality does not necessarily stop at the access to elite institutions. Michelman et al. (2022) find that high-status peer exposure at Harvard benefits other high-status students – with zero or even negative effects for students with lower socio-economic status (SES). Evidence also indicates that students from less privileged backgrounds are excluded from peer networks determining the access to high-income jobs after graduation (Zimmermann, 2019). Thus, peer effects at elite universities might provide additional barriers for upwards economic mobility at the top of the income distribution.

This paper analyzes peer effects at the University of St. Gallen (HSG). The HSG is one of Europe's leading business schools.[2] The average earnings of HSG graduates are the highest of all graduates in Switzerland, and its alumni belong to the top decision makers in various sectors of the Swiss economy. Of the 100 largest Swiss companies, 80% have at least one HSG graduate on their board or executive committee, 20% of CEO are HSG graduates, the highest percentage from any single university.[3] Simultaneously, the share of HSG graduates with non-academic background is the second-lowest in Switzerland. Therefore, peer effects occurring at this institution are relevant for upwards economic mobility when exposure to high-status peers negatively affects the labor market outcomes of less privileged students.

In general, peer effects are defined as spillover effects on students' outcomes arising from exposure to their peers' characteristics or behavior. Here, the analysis explores how students' outcomes are affected by the social composition of their HSG peer group, measured by the combined education level of students' parents. The analysis focuses on two outcomes of interest: students' academic achievements and their income one year after graduation. Both outcomes are important determinants for graduates' subsequent employment biography. Thus, peer influences during the transition to the labor market affect economic outcomes also in the long run.

I find that a higher share of low-SES students benefits graduates' early labor market

[2] The University of St. Gallen is ranked as the strongest business school among German-speaking countries in the Financial Times European Busines School Ranking 2022. In Europe, HSG is at the 5th place, see https://rankings.ft.com/rankings/2943/european-business-school-rankings-2022.

[3] Guttmann (2020), 3.

outcomes. This confirms hypotheses derived from the literature. More specifically, a 10 percentage points higher share of low-SES peers increases students' income on average by 4.87 %, which is equivalent to approximately 3,961 Swiss Francs in their annual income. This peer effect is strongest among other low-SES students, but it is positive and significant for all student types. The effect functions primarily through students adopting their occupational choices and labor supply. Students are drawn to careers in the high-paid finance and insurance sector. Additionally, higher-status students are less likely to work in education and the public sector, which relate to below-average earnings. Graduates also adjust their labor supply and are on average less likely to work part-time. Conversely, I also find evidence for a small negative effect on medium-SES students' academic achievement from low-SES peer exposure. This negative effect is driven by low-SES students with low ability. Low-SES students with high ability do not significantly affect students' final grades.

This study finds no evidence that high-status peer exposure negatively affects the outcomes of students from non-academic backgrounds, nor other types of students. This is contrary to a hypothesis on social alienation and downwards shifts in self-confidence. There is an effect on graduates' probability of working over-time on a regular basis, but without significantly changing their income.

The identification strategy relies on a random assignment of student groups at the beginning of the undergraduate studies. These groups compete against each other in an incentivized business case. The specific design enhances social interactions within groups, and existing survey data shows that close friendships are formed between former group members (Thiemann, 2022). Consequently, the setting can be exploited to causally identify peer effects. The analysis combines administrative data from the University of St. Gallen with the Graduate Survey conducted by the Swiss Federal Statistical Office. This full survey of Swiss graduates provides rich information on students' characteristics, their socio-economic background and on early labor market outcomes.

Thereby, this analysis adds to two strands on the literature: (i) the literature on peer effects and (ii) the literature on social mobility and elite formation. First, there exists a large empirical literature analyzing how individuals react to peer exposure. The dominant share of the literature focuses on educational outcomes and finds heterogeneous peer effects regarding students' ability, gender, and race (Hoxby, 2000; Epple and Romano, 2011; Sacerdote, 2014; Bostwick and Weinberg, 2022; Bramoullé et al., 2020). Overall, the magnitude and direction of existing peer effects depend on the specific setting in question. For instance, results by Stinebrickner and Stinebrickner (2006) and Oosterbeek and van Ewijk (2014) suggest that pairing high- and low-ability students leads to positive spillover effects when low-ability students mimic good study behavior or more effective time management of their higher-ability peers. Conversely, low-ability students might also be discouraged by a high-ability environment which leads to negative peer effects on students' outcomes (Feld and Zölitz, 2017; Fischer, 2017; Thiemann, 2022).

This paper builds on Thiemann (2022). As in the following analysis, the orientation week at the University of St. Gallen is used to identify heterogeneous peer effects regarding students' abilities. She shows that pairing high- and low-ability peers leads to lower performance during the first year and an increased drop-out probability for low-ability students. Furthermore, Thiemann (2022) provides friendship survey data and additional information on tutorial groups showing that former orientation week group members are significantly more likely to become close friends and repeatedly interact with each other later on. In comparison to Thiemann (2022), I focus on heterogeneous effects regarding students' social background rather than on their abilities. Also, I expand the scope of the analysis to students' labor market outcomes. The existing papers on occupational preferences find gender-specific effects. For female students, being exposed to a higher share of female classmates in business schools increases the probability of pursuing careers where they work less hours and experience slower wage growth. There are no comparable effects at the labor market for male students, however, male students are more likely to choose male-dominated majors and less likely to choose female-dominated majors (Zölitz and Feld, 2021). In a similar line, Markussen and Røed (2017) show that same-sex peer exposure affects the probability of becoming an entrepreneur. Conversely, when looking at occupational preferences in general, Jones and Kofoed (2020) do not find significant peer effects in a military setting. Their survey results suggest that mentors and internships, rather than peers, shape cadets' occupational preferences. Here, I find that peers are influential for initial career decisions, which are likely to affect students' economic outcomes also in the long run.

Furthermore, this paper relates to the literature on elite formation at universities (Arcidiacono, 2005; Bertrand et al., 2010; Rivera, 2016; Chetty et al., 2017; Zimmermann, 2019; Barrios Fernández et al., 2021). In general, universities contribute to upwards economic mobility in the long run. For the United States, Chetty et al. (2017) show that within elite institutions, the earning gradient between graduates from low- and high-income families is 76% smaller than the national average. Mid-trier public institutions are often more successful in providing access to low-income students while their graduates also reach the top income quintile if not the top 1% percentile. There is also evidence that peer interactions and social networks at elite institutions affect the access to top-income jobs, and how graduates perform in these jobs. Zimmermann (2019) finds that the admission to elite business degree programs in Chile raises the probability of belonging to the top 0.1% income percentile by 51% - but only for male graduates from private high schools. He provides supportive evidence that this result is driven by peer networks to which female graduates and male graduates from public high school have no access to. Marmaros and Sacerdote (2002) explore the use of peer ties and social networks for job searches of Darthmouth College graduates, finding significant peer effects on graduates' salaries. They also show that students networking with fraternity members and alumni are most likely to obtain high-income jobs. Once high-income positions are obtained, peer effects continue to influence managerial behavior and decision making (Useem and Karabel, 1986; Shue, 2013; Fracassi and Tate, 2012; Fracassi, 2016). Here, I show how peer effects contribute to elite formation by influencing choices students make at the transition to the labor market, thus affecting their initial income level after graduation.

This analysis relates most closely to Michelman et al. (2022). They show that high-status peer exposure leads to large positive effects for former private school students, but to zero or negative effects for other social groups. Michelman et al. (2022) rely on randomized housing assignments and historical data on Harvard students matched with census records from 1910 to 1940. Michelman et al. (2022) estimate causal effects with historical data on Harvard students matched with census records from 1910 to 1940. Here, I provide causal effects for current cohorts in Switzerland. Additionally, the intervention differs which is used in the identification strategy. Conditional on the timing, I can show that even a short-term intervention is sufficient to create lasting peer effects affecting students' outcomes at the transition to the labor market.

The paper contributes to existing research in two main aspects. First, the paper documents the formation of the economic elite in Switzerland. First, this is the first analysis showing that a short-term peer intervention produces lasting effects which contributes to upwards economic mobility. In general, there exists only little evidence on causal effects relating to economic mobility. Here, the specific setting enables the identification of significant peer effects which are heterogeneous across students' social background. Secondly, it provides evidence on educational mobility in a country where a child's chances of entering the university strongly depends on the income position of the parents (Chuard and Grassi, 2020). This makes an understanding of a mechanism affecting the outcomes of graduates from less privileged households to an important policy target.

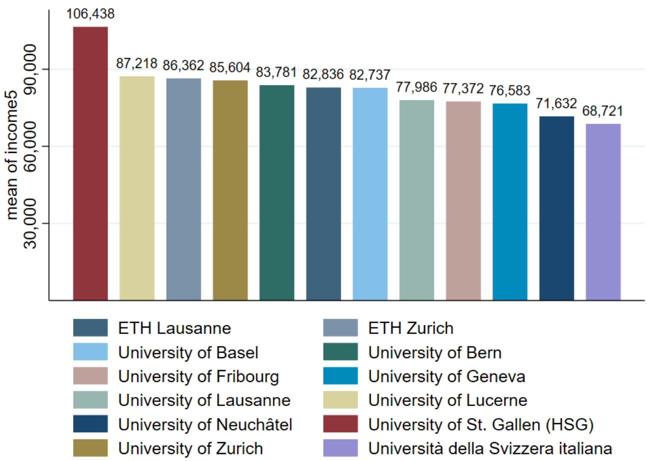
The paper is structured as follows. Section 4.2 describes the institutional background and the setting in which peer effects are identified. Section 4.3 discusses expected responses to peer exposure. Then, Section 4.4 and Section 4.5 introduce the data set and the empirical strategy. The main results are presented in Section 4.6. Section 4.7 explores underlying mechanisms. Alternative specifications and robustness checks are evaluated in Section 4.8. Section 4.9 discusses the results and concludes.

4.2 Institutional Background

4.2.1 The University of St. Gallen (HSG)

The University of St. Gallen (HSG) is a public university in German-speaking Switzerland. It offers undergraduate programs in business administration, economics, law, law and economics, and international affairs. As decreed by the Canton of St. Gallen, the governing body, access to HSG is restricted for students without a Swiss high school diploma ('Bildungsausländer'). These are required to take an entrance exam (lasting 4.5 hours) and pay higher fees. Additionally, the share of foreign students must not exceed 25% of enrollments.

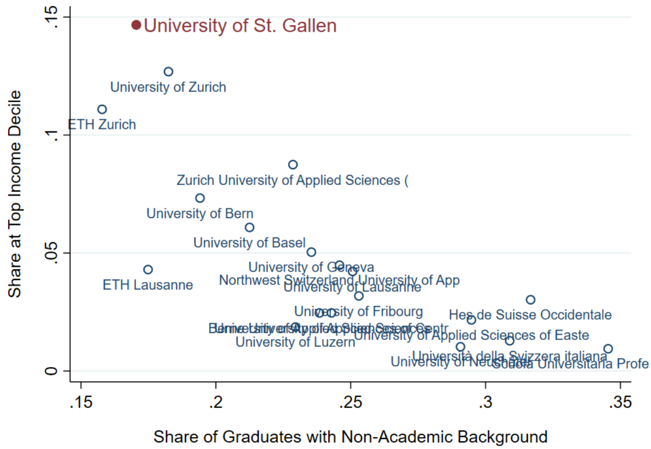
Figure 4.1: Average income of Swiss graduates



Note: The figure displays differences in graduates' mean income between Swiss universities. Hereby, sample weights are applied and income is measured in gross annual earnings five year after graduation in the 1980-1990 birth cohort (n=33,321). All amounts are in constant 2020 Swiss Francs (CHF). The mean income across all tertiary institutions is 80,348.43 CHF (including applied universities which are not displayed in this figure). The average income of HSG graduates is 106,438 CHF, which is more than 30% higher than the Swiss average.

On average, HSG graduates achieve the highest earnings among all Swiss university graduates. This is illustrated by Figure 4.1, showing the mean annual gross incomes five years after graduation. HSG graduates can expect an income of 106,438 Swiss

Figure 4.2: The composition of graduates' top income decile.



Note: The figure visualizes that 14.7% of graduates in the top income decile studied at HSG. This is the highest share from any single university (vertical axis). Simultaneously, the share of graduates without academic background in the parent generation is the second lowest across public universities (horizontal axis). The figure is based on a sample including all graduates in the 1980-1990 birth cohort who studied at a Swiss tertiary institution. The income is measured in constant 2020 CHF and is obtained five years after graduation with sample weights applied (n=33,321).

Francs (CHF), which is more than 30% above the average of 80,348 CHF. Consequently, a disproportional large share of graduates in the top income positions studied at the University of St. Gallen.

They represent 14.7% of graduates in the top income decile, although less than 4% of Swiss graduates come from HSG. Simultaneously, the access for students from less advantaged households is low. Figure 4.2 visualizes the composition of graduates' top income decile. The vertical axes show the share of top income earners by tertiary institution. This measures an institution's economic success. The horizontal axes give the share of graduates where no parent has a tertiary degree, thereby indicating access levels among children from non-academic backgrounds. HSG has the second lowest share across all Swiss tertiary institutions. Only ETH Zurich has a slightly lower share.[4] Overall, this implies that the University of St. Gallen can be described as an institution with high economic success, but comparatively low access for students from

[4]ETH Zurich and the University of Zurich show similar patterns as the University of St. Gallen. The shares of graduates in the top income deciles coming from these two universities are high, but the shares of children from non-academic backgrounds are low.

less advantaged social backgrounds. Consequently, peer effects influencing students across different social groups are not only relevant at this institution, but also for the formation of Switzerland's high-income earners in general.

4.2.2 The Orientation Week

The first undergraduate year is called "Assessment Year". All students follow exactly the same curriculum and take the same classes. The identification strategy used in this paper relies on one specific feature of the Assessment Year, the mandatory orientation week ('Startwoche'). This takes place in week 1 of the Assessment Year. All students are allocated to fixed student groups. Every cohort comprises approximately 60 to 65 groups, each having an average of 16 students. The main task during this week is to solve an incentivized business case. After working on this case for 60 hours, student groups compete in front of a jury to provide the best solution and to win the annual prize. Hence, the orientation week aims to enhance within-group social ties rather than between-group social ties.

Student allocation to groups is randomized conditional on gender and the entry exam. First, the organization team divides all first-year students into four groups, depending on their gender and on whether they have taken the mandatory entrance exam for students without a Swiss high-school diploma. Distribution results in four strata: (female / entry test), (female / no entry test), (male / entry test), (male / no entry test). Second, within each stratum, students are sorted alphabetically by surname. Third, students are distributed to the available groups. Starting with the first stratum, student 1 is allocated to group 1, student 2 goes to group 2, etc., until the first stratum is emptied. This procedure is performed for all strata, such that students with similar surnames are less likely to end-up in the same group.[5]

The HSG distribution mechanism implies that for students, the group allocation is exogenous. They are not allowed to pick specific groups or to switch groups once the orientation week has started. Thus, the conditionally randomized allocation provides a quasi-experimental setting that enables identifying peer effects.

Group members are significantly more likely to become close friends after the orientation week than non-group members. Thiemann (2022)'s friendship survey and the additional data on bachelor's tutorial groups further show that group members repeatedly interact with each other. Former group members are overrepresented in students' five best friends and among members of tutorial groups in which students select themselves. Thus, while the orientation week is merely a short-term peer inter-

[5] Students' final grades are compared to test for 'alphabetical discrimination' (Einav and Yariv, 2006). No significant difference in academic performance exists between the first 15 groups and the last 15 groups in the cohorts.

vention, it is meaningful for the formation of peer groups at the university. Therefore, potential peer effects not only derive from the intervention itself, but are likely to be mitigated by repeated peer interactions over time.

4.3 Expected Responses to Peer Exposure

Peer effects are defined as any externalities which spill-over from peers' characteristics or their behavior and thereby affect students' outcomes. In this analysis, the peer characteristic is students' family background. In the following, I discuss different possible mechanisms through which the social composition of peer groups could affect students' academic achievements and their early labor market outcomes.

Social alienation

The first potential mechanism is social alienation. For the United States, it is well documented that students from low-income households feel socially alienated at Ivy League schools which also affects their career choices after university (Rivera, 2016; Jack, 2019; Michelman et al., 2022). Such effects could also materialize at the University of St. Gallen. An internal report indicates that students experience the social environment at the university as competitive and elitist (Egger, 2018). The report includes anonymous interviews with students from the 2016 and 2010 Assessment Year cohorts, of which the latter is also part of this sample. These interviews are selective, but they illustrate that the University of St. Gallen provides an institutional setting in which the social composition of peer groups might credibly create externalities on students' outcomes. Social alienation might affect low-SES graduates' career choices and push them towards jobs which are seen as less elitist. When these jobs are in industries that typically relate to lower earnings, their income declines.

Shifts in self-confidence

A second and related mechanism are shifts in students' self-confidence, which is a strong predictor of academic achievements (Stankov et al., 2014). In the education literature, there is evidence that being exposed to higher-ability students discourage students with lower ability and hurt their self-esteem. Consequently, they become demotivated and exert lower effort, which negatively affects their academic achievements (see Sacerdote, 2011; Epple and Romano, 2011 and Wennberg and Norgren, 2021 for reviews). In a social setting, students might also reinforce each other's confidence levels, especially among underrepresented groups. For instance, female PhD students are a minority in science, technology, engineering, and mathematics (STEM). Bostwick and Weinberg (2022) show that for female PhD students in STEM, a higher share of other female peers is beneficial because it substantially reduces the drop-out probability during the first PhD year. Similar effects might derive from a higher share of students with non-academic backgrounds. This could also reinforce the confidence levels of higher-SES students.

Peer pressure and social conformity

A third mechanism is peer pressure and social conformity. When individuals care about social status, they tend to act in conformity with their peers, also when their preferences deviate (Bernheim, 1994; Akerlof and Kranton, 2000). At the University of St. Gallen, Egger (2018) describes that HSG students relate overall performance at the university not only to academic achievements, but also to a common habitus regarding appearance, self-confidence and professional ambitions.[6] Students might feel pressured to increase their effort choices regarding their academic outcomes. Furthermore, they might adopt their career goals to fit to perceived social norms. Peer conformity is known to drive peer effects on workers' reservation wages and labor supply (Falk and Ichino, 2006; Mas and Moretti, 2009; Fu et al., 2019). In this line, high-SES peer exposure at HSG might increase graduates' reservation wage and their labor supply at the intensive margin, thus leading to a rise in gross income after graduation.

Job networks

Job networks provide a fourth underlying mechanism, driving peer effects on labor market outcomes. In general, evidence indicates that more than 1/3 of employees obtained their jobs through social networks and informal referrals (Granovetter, 1973, 1995; Addison and Portugal, 2002; Ioannides and Loury, 2004; Dustmann et al., 2016). At the transition to the labor market, students might therefore share their access to networks or other valuable information with their peers, e.g., where to search and how to successfully apply for a job. This could lead to a positive peer effect on their initial income after graduation. For instance, Marmaros and Sacerdote (2002) show that students who actively network are more likely to obtain highly paid jobs. Conversely, relying on family and friends could also signal a limited range of alternatives, as proposed by Loury (2006), thus leading to lower earnings.

[6] Egger (2018), 72.

Social skills

Social competence and skills are a fifth potential mechanism. There is an increasing complementarity between cognitive and social skills at the labor market, reflected in higher wage growth for jobs which combine both skill sets (Weinberger, 2014; Borghans et al., 2014; Deming and Kahn, 2018). One reason for this is that technological change is (yet) not very successful in replacing social interactions (Autor, 2015). However, digitization substitutes non-coordinate tasks and leads to a reallocation of high-skilled workers into agile, team-based settings which focus on problem-solving (David et al., 2002; Bresnahan et al., 2002; Bühlmann et al., 2017). Social skills become increasingly important as they lead to a reduction of coordination costs and increase efficient collaboration (Deming, 2017). Students' social skills might benefit from a higher social diversity at the university, as it teaches them to include different perspectives and approach questions from a variety of angles.[7] In the HSG setting, student groups resemble Swiss society and its labor force more closely when the share of low-SES students increases. This could lead to positive spill-over effects on students' outcomes, particularly at the labor market.

Peer-learning

Finally, a seventh mechanism is peer-learning which is seen as fundamental for creating spillover-effects on students' educational outcomes (Balestra et al., 2021; Kimbrough et al., 2022). In this setting, students might learn more efficient exam preparation strategies and presentation skills from their peers. Especially low-SES students could benefit, as knowledge of an academic learning environment cannot be shared by their parents. Peer learning might also occur at the transition to the labor market when students share knowledge about job searching strategies and wage negotiation. This could increase their income one year after graduation.

The following empirical analysis will show whether these mechanisms are present at the institutional setting of the University of St. Gallen. Hereby, the mechanisms are not mutually exclusive and might occur simultaneously. If upwards shifts in self confidence and social skills dominate, I expect to find a positive peer effect on the outcomes of all student types:

Hypothesis 1: *Low-SES peer exposure positively affects the outcomes of all student types.*

[7] This is included in the model framework of Epple et al. (2002, 2003) on peer effects.

However, following the results of Bostwick and Weinberg (2022), I expect that the confidence shift is higher in other low-SES students, which are a minority at this institutional setting. This leads to the following hypothesis:

Hypothesis 2: *The positive spill-over effects from low-SES peer exposure are larger on other low-SES students' outcomes than on higher-SES students' outcomes.*

If social alienation and downward shifts in self-confidence dominate peer responses, then high-SES peer exposure leads to a negative effect on the outcomes of lower-SES students:

Hypothesis 3: *High-SES peer exposure leads to a negative spill-over effect on the outcomes of lower-SES students.*

Conversely, if peer learning and job networks drive peer responses, then the opposite occurs. Without making any welfare statements, a positive spill-over effect on graduates' outcomes would also occur if peer pressure and social conformity act as a main driver, thus increasing labor supply and income of all student types. This predicts:

Hypothesis 4: *High-SES peer exposure leads to a positive spill-over effect on the outcomes of all student types.*

4.4 Data

4.4.1 Data Sources

The analysis combines two data sets: (i) administrative data from the University of St. Gallen and (ii) the Graduate Survey of the Swiss Federal Statistical Office.
The Graduate Survey is conducted every second year as a full survey among all tertiary graduates in Switzerland. The first data collection took place in 1977 and electronic files are available for graduates from 2002 onwards. Graduates are contacted twice, that is, one and five years after their graduation. The average response rates is 60% for the first wave and of those, 65% for the second wave. The first wave of the Graduate Survey offers detailed information on students' characteristics, their university outcomes such as final grades, and on their transition to the labor market. This also includes job searching strategies and students' beliefs and preferences regarding potential jobs. Additionally, graduates' occupations and income one year

after graduation are available. The second wave focuses on the subsequent employment biography. This paper addresses university outcomes and students' transition to the labor market. Therefore, the analysis relies on variables from the first data collection one year after graduation.

The University of St. Gallen provides the second data source. This data covers students enrolled in the assessment year between 2002 and 2014 and includes the allocation of student to groups and major choices. Students select their major only after they have passed the assessment year and choose between Business Administration, Economics, Law and Economics, Law, and International Affairs.

The two data sources can be combined via students' matriculation numbers. Once enrolled, students keep their matriculation number also when they switch their studies or transfer to a different university. The gross sample contains 5,300 students. I restrict the sample to groups where at least 9 out of 15 students are present. This reduces the main sample to 1,199 student observations. Missing observations are therefore one limitations of the analysis. Section 4.8.3 provides estimates based on alternative specifications to test whether results are sensitive towards the implemented cut-off rule regarding the number of group observations. These confirm the main results. A second limitation is that the sample only covers HSG graduates who also participated in the Graduate Survey. Otherwise, information on graduates' labor market outcomes would not be available. Additionally, the included questions vary across survey waves which affects the number of observations for labor market outcomes.

4.4.2 Sample Statistics

Students' Socioeconomic Status (SES)

The main analysis uses the combination of mother and father education as measure for students' socio-economic status (SES). Hereby, I distinguish between three cases. Students whose parents both have tertiary degrees are categorized as students with high SES, which applies to 24.9% of the students in the sample. Students where no parent has a tertiary degree are categorized as low-SES student (12.3%). All other combinations are categorized as medium SES. With a share of 62.9%, this is the largest group in the sample and used as reference group in all regressions.

Correspondingly, I rely on the share of high- and low-SES peers to describe students' peer group composition. These fractions are calculated as leave-own-out means, that is, they exclude the student him- or herself. Consequently, the mean share of low- and high-SES students in each group are 12.2% and 24.5%, respectively.

Ability

Table 4.1: Descriptive statistics

Low SES	0.123 (0.328)	1,199	Share of Low-SES peers	0.122 (0.141)	1,199
Medium SES	0.629 (0.483)	1,199	Share of High-SES peers	0.245 (0.179)	1,199
High SES	0.249 (0.432)	1,199	Ability	0.000 (1.000)	1,199
Final Grade	0.536 (0.169)	1,199	Income	81,335.66 (23,175.93)	458
Female Share	0.344 (0.475)	1,199	Log income	11.243 (0.427)	458
Entry Exam	0.092 (0.289)	1,199	Responding to Job Advertisements	0.141 (0.348)	434
Age	26.294 (2.326)	1,199	Use university contacts	0.323 (0.468)	434
Non-German Speaker	0.192 (0.394)	1,199	Use personal contacts	0.401 (0.491)	474
Group Size	10.392 (1.545)	1,199	Working over-time	0.140 (0.347)	487
Working Hours	39.825 (7.433)	462	Working part-time	0.380 (0.486)	487
Working full-time	0.481 (0.500)	487			

Note: This table shows sample means, standard deviations in parentheses. Graduate income is measured in constant 2019 Swiss Francs (CHF).

The sample does not include information on students' high school grades or other pre-university ability measures. Consequently, I rely on in-sample predicted final grades as ability measure, following Carrell et al. (2013) and Thiemann (2022). To predict the ability measure for students in a given cohort, I use the gross data on all other cohorts of the Graduate Survey to regress final grades on a set of student characteristics (n = 89,175). This set includes students' age, gender, mother tongue, region, degree, area, and university. Then, the estimated coefficients are used to predict the final grades in the cohort of interest. This is repeated for all cohorts. The resulting ability measure is standardized to a zero mean and a standard deviation of one for the core sample.

Outcomes

There are two outcomes of interest: Students' final grades and their income one year after graduation. The final grade is standardized between 0 and 1, which results in an average final grade of 0.536. One year after graduation from their Master's, former students achieve an average income of 81,335.66 Swiss Francs per year. The income is measured in constant 2019 Swiss Francs (CHF). This corresponds to a log income of 11.243 and includes gross earnings at the labor market, bonuses, and overtime payments.

Student Characteristics

Gender and participation in the entry exam are the two stratification variables in the allocation process. The share of female students in the sample is 34.4%, which is consistent with the actual share of female students at the University of St. Gallen. A total of 9.2% of the students participated in the entry exam, indicating a high school diploma obtained abroad. Therefore, the share is noticeable below the imposed foreigner quota and points towards one sample limitation: It includes only students who respond to the Graduate Survey and therefore only those living in Switzerland after their graduation. Students who participated in the entry exam are more likely than the average to leave Switzerland after their graduation. Thus, they are underrepresented in the sample.

Additionally, I include age, German as first language and students' group sizes as pretreatment characteristics. The average sample group includes 10.4 students. Overall, 19.2% of students have a different language than German as their first language, reflecting Switzerland's multilingual character. Finally, students are on average 26.3 years old when they participate in the Graduate Survey.

Additional Information on Labor Market Outcomes

To find a job, students apply different search strategies after graduating. Binary dummy variables show that 14.1% of students responded to traditional job advertisements, and 32.3% used personal connections which they established during their studies. Additionally, 40.1% of students indicate that they relied on family and friends, i.e., on personal contacts.

After their graduation, students are employed in 17 industries, following the Swiss NOGA-1 classification. The employment shares are provided in Table A.1.1. In total, 30.95% of graduates work in "Professional, Scientific and Technical Activities", which also includes corporate consulting. This is followed by the finance and insurance industry with 22.08%. In all other industries, the employment shares are smaller than 10%.

Furthermore, graduates are asked for their average number of working hours per week. These range between 1 to 65 hours per week, with a mean of 39.83 hours. Hereby, three cases are distinguished: Overall, 48.1% of graduates report that their average workload is equivalent to a full-time position of 42 working hours per week. 38.0% work less than that, which is denoted as working part-time. Additionally, 14.0% of graduates indicate that they work overtime on a regular basis.

4.5 Empirical Strategy

The goal of the empirical strategy is twofold: First, I evaluate the associated influence of abilities on students' outcomes and how these interact with students' social background. Then, I estimate the causal effect of peers' social status on students' final grades and on their income one year after graduation.

The Role of Abilities and Social Background

First, the associated influence of students' abilities on their outcome of interest is derived by the following OLS regression framework:

$$\begin{aligned} Y_{ic} = \beta_0 + \beta_1 \text{low}_{ic} + \beta_2 \text{high}_{igc} + \beta_3 \text{ability}_{ic} + \beta_4 \text{low}_{ic} \text{ability}_{ic} \\ + \beta_5 \text{high}_{ic} \text{ability}_{ic} + \delta G_{ic} + u_{ic} \end{aligned} \tag{4.1}$$

Hereby, Y_{ic} is the continuous outcome of interest for student i in cohort c. The two dummy variables *low* and *high* indicate whether a student is categorized as having a low educational background or high educational background. This makes students with medium status the baseline category. The vector G provides a set of control variables, including students' age, their mother tongue, gender, and cohort effects. Here, the coefficients of interest are $\beta_3 - \beta_5$. Thereby, β_3 indicates how a 1-standard deviation increase in a student's abilities affects his outcome. The coefficients β_4 and β_5 display whether the effect of abilities further depends on the student's own social background, that is, whether the influence of abilities is further increased or decreased when the student has a high or low social background compared to students in the reference group.

Linear-in-Means Peer Effects

The main interest of this paper is to estimate the causal impact of peers' social background on students' two outcomes of interest, that is, on their final grade and on their income one year after graduation. First, peer effects are estimated in a conventional linear-in-means model:

$$Y_{igc} = \beta_0 + \beta_1 \text{low}_{igc} + \beta_2 \text{high}_{igc} + \beta_3 \text{ability}_{igc} + \beta_4 \text{low}_{igc} \text{ability}_{igc} + \beta_5 \text{high}_{igc} \text{ability}_{igc} + \beta_6 \text{SL\_}_{igc} + \beta_7 \text{SH\_}_{igc} + \eta s_{gc} + \delta D_{igc} + u_{igc} \tag{4.2}$$

Where Y_{igc} is the outcome of interest for student i in group g and cohort c. Therefore, equation 4.5 is extended by $SL\_{}_{igc}$ and $SH\_{}_{igc}$. These are the share of low-SES students and high-SES students in each group, excluding student i. Furthermore, s_{gc} controls for the group sizes in each cohort. The vector D includes cohort dummies, students' age, their first language, and the two stratification variables gender and participation at the HSG entry exam. All standard errors are clustered at the group-year level. Note that whether students' abilities are included in the regression equation should not affect the estimated peer effects, as students are allocated randomly to their groups. Consequently, the inclusion of pre-treatment characteristics such as abilities and the control variables in vector D should only affect the precision of the estimator.[8]

Heterogeneous Peer Effects

The linear-in-means model implicitly assumes that all students are equally affected by the social background of their peers. However, I assume that the response to peer exposure also depends on students' own social background. To account for heterogeneous peer effects, I include interaction terms between students' own social background and the social background of their peers:

$$\begin{aligned} Y_{igc} = {} & \lambda_0 + \gamma_1 \text{low}_{igc} + \gamma_2 \text{high}_{igc} + \gamma_3 \text{ability}_{igc} + \gamma_4 \text{low}_{igc} \text{ability}_{igc} + \gamma_5 \text{high}_{igc} \text{ability}_{igc} \\ & + \lambda_{1L} \text{low}_{igc} \text{SL\_}_{igc} + \lambda_{1H} \text{low}_{igc} \text{SH\_}_{igc} + \lambda_{2L} \text{medium}_{igc} \text{SL\_}_{igc} \\ & + \lambda_{2H} \text{medium}_{igc} \text{SH\_}_{igc} + \lambda_{3L} \text{high}_{igc} \text{SL\_}_{igc} + \lambda_{3H} \text{low}_{igc} SH\_{}_{igc} \\ & + \eta s_{gc} + \delta D_{igc} + \epsilon_{igc} \end{aligned} \tag{4.3}$$

The main coefficients of interested are λ_{1L} - λ_{3H}, providing the estimated peer effects. In the interaction terms, all three dummy variables for students' social background are included, that is, $\text{low}_{igc}, \text{medium}_{igc}$ and high_{igc}, highlighting the role of peer effects also for students with medium-level background. There is no multicollinearity problem because the interaction term with the share of medium-status students is

[8] The robustness checks in Section 4.8 provide additional estimation results obtained without control variables.

excluded. The coefficients of the interaction terms show how different student types react to changes in the group composition.
A change in the group composition arises when the share of high-SES students increases marginally while keeping the share of low-SES students constant. Therefore, the share of students in the reference group adjusts. This implies that in an existing student group, students with medium status (the reference group) are replaced by students with high status. The coefficients $\lambda_{1H}, \lambda_{2H}$ and λ_{3H} indicate how this affects the outcomes of a student, depending on whether he himself has low-, medium-, or high educational background. Correspondingly, the group composition can also be changed by increasing the share of low-SES students. Then, medium-SES students are replaced by low-SES students, and the coefficients $\lambda_{1H}, \lambda_{2H}$ and λ_{3H} capture the outcome change for low-, medium-, and high-SES students.
The causal identification of peer effects is affected by four potential issues: (i) the selection problem, (ii) the reflection problem, (iii) common shocks, and (iv) measurement problems.
The selection problem states that that in general, peer groups are self-selected and hence, they are formed endogenously. Consequently, it is difficult to separate peer effects from selection effects. However, several publications show that random assignments of students to groups allow to identify peer effects without selection bias (Lyle, 2007; Carrell et al., 2009; Duflo et al., 2011; Carrell et al., 2013). As HSG students are randomly allocated to their groups, the selection problem does consequently not affect the identification. Also, it is not possible for students to bypass the allocation mechanism as they are prohibited to switch their groups.
The reflection problem describes that individuals mutually influence each other simultaneously (Manski, 1993). In most cases, this makes it impossible to distinguish between the influence of peers on the student and, vice versa, the influence of the student on his peers.[9] Therefore, empirically estimated coefficients encompass an exogenous and endogenous peer effect. The exogenous part captures how students' outcomes change in response to peer exposure. This effect is either strengthened or weakened by mutual peer interactions, the endogenous part. Therefore, the obtained results from Equation 4.2 and 4.3 identify such combined peer effects.
The common shock problem is also discussed by Manski (1993). He argues that even in the absence of true peer effects, group members' outcomes are always correlated when they are exposed to the same unobserved factors, that is, to common shocks. For example, farmers in the same village face the same weather conditions and the

[9]It is possible to identify the exogenous peer effect separately when the group influences individual behavior with a time lag, as it is the case in directed social network models. See Bramoullé et al. (2020) for a review of this literature.

same soil quality, which affects their harvesting behavior. Consequently, the outcomes of farmers within one village is always more similar than between villages, also when farmers do not influence each other's behavior. In this analysis, I look at different student groups within one university. I cluster all standard errors at the group-year level to adjust for potential correlations in the outcomes of students within each group. A common shock problem would still arise when students' input varies at the group level. However, at HSG, group supervisors are strictly instructed to give exactly the same information and input to each group. Consequently, common shocks do not impair the estimation strategy.

Finally, Angrist (2014) describes how measurement errors lead to an overestimation of peer effects. The intuition behind this result is as follows. Angrist (2014) and previous work by Acemoglu and Angrist (2000) show that the peer effect estimator can approximately be expressed by the difference between an IV estimator and an OLS estimator, that is $\beta_{peer} = \beta_{IV} - \beta_{OLS}$. A measurement error leads to a downwards bias in both estimators but the OLS estimator decreases to a larger extent than the IV estimator. Consequently, the size of the estimated peer effect coefficient increases and thus overestimates the true peer effect. However, more recent work by Feld and Zölitz (2017) shows that the direction and magnitude of this bias depends on the assignment mechanism. Under random assignment, the estimated peer effects are biased downwards when measurement errors exist, which also apply to this analysis. Here, I express students' social status by the educational background of their parents, as parental income is not available. Parental education is an imperfect proxy for social status and therefore very likely to be affected by measurement error. Consequently, the obtained results should be interpreted as lower bounds of the true peer effects regarding students' social status.

4.6 Results

4.6.1 Final Grades

The first outcome of interest is students' final grades. The included set of control variables contains pre-university characteristics, that is, students' age, whether German is their native tongue, and the two stratification variables gender and participation in the entry exam. Also, I account for group sizes and cohort effects. The robust standard errors are clustered on the group-year level. The results are reported in Table 4.2. The obtained peer effects are identified by the random assignment of students to groups. Therefore, the inclusion of control variables only affects the precision of the estimate but not the size of the coefficients.[10] However, control variables influence the adjusted R^2 which varies between 0.216 and 0.222.

Columns (1) – (3) focus on the influence of students' ability, their social background, and potential interaction effects between these factors. The average standardized final grade in the sample is 0.536. Hereby, a 1-standard deviation higher ability level increases the average students' final grade by 4%. Students with a high SES background do not benefit from an additional advantage compared to students with medium SES. The corresponding estimator is not significant in any specification.

There is evidence for a disadvantage for students with low SES. For a student, having a low-SES relates to a 2.7% decrease in his final grade. Therefore, students with low SES have to overcome a disadvantage whose absolute size amounts to approximately 60% of a 1-standard deviation change in the ability level. In general, the negative effect

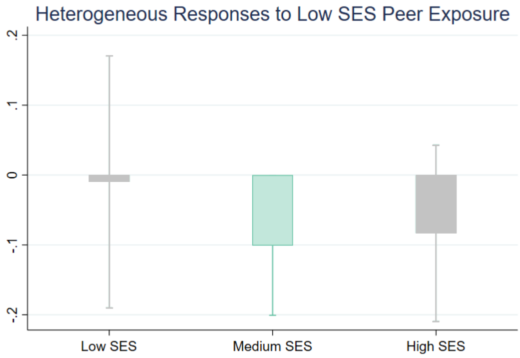
Table 4.2: The role of ability, SES, and peer effects for students' final grades

Final Grade	(1)	(2)	(3)	(4)	(5)
Low SES		-0.027^{**}	-0.027^{*}	-0.027^{*}	-0.027^{*}
		(0.014)	(0.014)	(0.014)	(0.014)
High SES		0.002	0.002	0.003	-0.003
		(0.011)	(0.011)	(0.011)	(0.011)
Low SES x Ability			-0.011		-0.009
			(0.016)		(0.015)
High SES x Ability			-0.004		-0.003
			(0.010)		(0.010)
Ability	0.042^{***}	0.042^{***}	0.045^{***}	0.043^{***}	0.045^{***}
	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)
Share of low SES students				-0.086^{**}	-0.085^{**}
				(0.039)	(0.039)
Share of high SES students				-0.026	-0.025
				(0.032)	(0.032)
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.216	0.219	0.219	0.222	0.222
N	1,199	1,199	1,199	1,199	1,199

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on the group-year level. The table shows the influence of ability, socio-economic status (SES), and peers on students' final grades. On average, a 1-standard deviation increase in students' ability level increases their final grade by 0.042 on a 0 to 1 scale. Columns (4) and (5) add peer effects. A marginal increase in the share of low-SES peers decreases a student's final grade by 0.009 units at the mean. The set of control variables includes students' age, gender, entry exam participation, mother tongue, group size and cohort effects.

[10] See Section 4.8.2 for estimation results obtained without control variables.

Figure 4.3: Heterogeneous low-SES peer effects on student's final grades



Note: The figure displays heterogeneous responses to low-SES peer exposure, conditional on students' own social background. The peer effect is only significant for medium-level students. For them, a 10 percentage points increase in the share of low-SES peers in their group leads to a 0.0101 decrease in their final grades. The corresponding regression results are reported in Table A.2.3. There are no significant effects from high-SES peer exposure.

of a low-SES does not depend on a student's ability level. There is no evidence for a significant interaction effect between students' ability and their social background.

The main interest of this paper is to establish whether students influence each other's academic outcomes. Column (4) and (5) show the average student's reaction to a change in the social composition of his peer group, captured either by (i) a higher share of low SES peers, or by (ii) a higher share of high SES peers. The results indicate that a higher share of high SES peers does not influence the average student's final grade. However, a 10-percentage points (pp) higher share of low-SES peers decreases the final grade by $0.0085 \approx 0.01 = 1\%$. Hereby, a 10-pp increase is approximately equal to replacing 1 out of 6 medium SES students by one low SES student. This implies that the obtained peer effect is statistically significant but marginal.

To check whether the peer effect at the mean covers heterogeneity between student types, I estimate heterogeneous peer effects following Equation 4.3 in Section 4.5. Figure 4.3 displays the effect of a higher share of low-SES in students' peer groups conditional on students' own background. The coefficient values are additionally reported in Table A.2.3. The negative peer effect at the mean is driven by the reaction of medium-SES students. The estimated coefficient suggests that a 10-pp larger share of low-SES peers decreases the final grades of medium-SES students by 1.01%. The final grades of other students are not affected.

Also, no student type shows significant responses to high-SES peer exposure. This could partly be driven by a compositional effect. The sample only includes students who successfully completed their studies and participated in the graduate surveys of the Federal Statistical Office. Students who reacted strongly to high SES students could have dropped their studies entirely and would consequently not be included in the sample.

4.6.2 Graduates' Income

The second outcome of interest is students' income one year after graduation. Table 4.3 indicates the extent to which this is determined by their abilities, their social background, and the impact of their peers.

Unlike final grades, having a low socio-economic status does not negatively affect graduate income. For upwards social mobility, this implies that the university successfully equalizes students' economic outcomes, at least at the beginning their employment biography. Also, on a general note, the correlation between graduates' final grades and their initial income is low, with a correlation coefficient of 0.082. Thus, other factors determine students' labor market outcomes than their academic success.

Inherent ability is important. When looking at unconditional effects, a 1-standard deviation increase in student ability relates to an average income increase of 10.1-10.5% (Columns (1) and (4)). However, the interaction terms hint that employers might not be very successful in distinguishing between ability and high socio-economic background. Note, in this regard, that the ability measure is standardized with zero mean and a standard deviation of one. Therefore, having a high SES increases the income of a student whose ability lies exactly at the mean by 20.2%. This equals more than a 1-standard deviation increase in students' ability level. For every higher ability level, the advantage of having a high socio-economic status fades out. But for lower ability levels, the income gap increases. Then, ability < 0 and thus, the conditional effect becomes positive.

That especially lower-ability students benefit from high socio-economic status might also be related to their parents' behavior. For instance, high-SES parents may support their children in securing highly-paid jobs, otherwise only accessible to graduates with higher ability levels.

Columns (4) and (5) add linear-in-means peer effects. As with final grades, a significant peer effect derives from a higher exposure to low-SES peers. The coefficient for high-SES peer exposure is not significant. However, unlike the peer effects on final grade, the impact is positive: The results show that a 10-pp higher exposure to low-status peers increases the income by 4.9% at the mean. This is equivalent to an increase of 3,985.45 Swiss Francs, given the mean annual gross income in the sample.

Table 4.3: The role of ability, SES, and peer effects for students' income

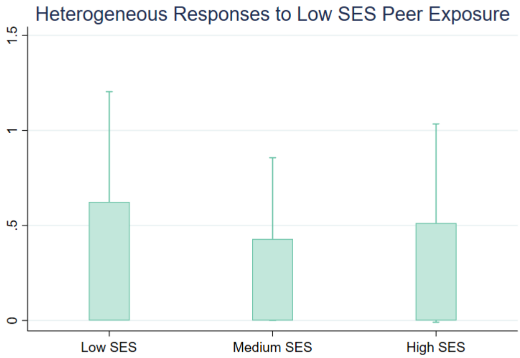
Income	(1)	(2)	(3)	(4)	(5)
Low SES		0.009	0.001	−0.011	−0.027
		(0.067)	(0.156)	(0.065)	(0.148)
High SES		0.017	0.202**	0.027	0.195**
		(0.041)	(0.088)	(0.043)	(0.084)
Low SES x Ability			0.006		0.017
			(0.132)		(0.126)
High SES x Ability			−0.195**		−0.179**
			(0.075)		(0.072)
Ability	0.105**	0.104**	0.193***	0.101**	0.182***
	(0.050)	(0.050)	(0.052)	(0.048)	(0.047)
Share of low SES students				0.485***	0.487***
				(0.180)	(0.182)
Share of high SES students				−0.175	−0.111
				(0.158)	(0.150)
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.044	0.045	0.071	0.072	0.094
N	462	462	462	462	462

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on the group-year level. This table reports the influence of ability, socio-economic status (SES), and students' peers on their annual gross income one year after graduation. A 1-standard deviation increase in the graduates' ability level increases the income by 10.5%. Columns (4) and (5) indicate that a 10-pp higher share of low-SES peers leads to a significant income increase of 4.87%. The set of control variables includes students' age, gender, entry exam participation, mother tongue, group size and cohort effects.

Compared to the peer effect on students' final grades, the peer effect on their income level is meaningful in size.

Furthermore, the positive peer effect on students' income applies to all student types. Figure 4.4 shows the heterogeneous responses to low-SES peer exposure. The positive effect on students' income is significant for low-, medium- and high-SES students. The effect is strongest for low-SES students, who benefit in particular from a stronger presence of other low-SES peers. Their income increases on average by 6.32% for a 10-pp increase in the share of low-SES peers in their group. For medium- and high-status students, the effect equals 4.29% and 5.12%, respectively. The regression results are also reported in Table A.2.3.

Figure 4.4: Heterogeneous low-SES peer effects on student's income



Note: The figure visualizes heterogeneous effects from low-SES peer exposure conditional on students' own social background. The positive effect of a 10-pp higher share of low-SES peers in students' groups is significant for all student types and varies between 4.29% and 6.32%. The corresponding regression coefficients are reported in Table A.2.3. There are no significant effects from high-SES peer exposure.

4.7 Related Responses and Choices

The main results show that a higher share of low-SES peers affects the outcomes of their fellow students. Furthermore, the peer effects on students' final grades and their income are disparate: There is a negative peer effect of low-SES students on academic achievement, but a positive peer effect on income. None of the derived hypotheses in Section 4.3 are consistent with the negative low-SES peer effect on students' academic achievement. Conversely, the spill-over effects on graduates' income confirm the first two hypotheses. They are consistent with upwards shifts in self-confidence and social skills. Furthermore, the effect is stronger for low-SES students.

Below, I explore ability effects as a potential mechanism for these findings and provide further evidence for the channels underlying the positive peer effects on graduates' income.

4.7.1 Social Background versus Ability

An important question is whether students' social background creates the negative peer effect on students' final grades. An important question is whether students' social background creates the negative peer effect on students' final grades. An alternative explanation is provided by the bad-apple model of peer effects, arguing that the presence of less disciplined students leads to negative peer effects because they

Table 4.4: Low-SES peers with high and low ability levels

	(1)	(2)
Ability	0.048***	0.064***
	(0.007)	(0.005)
Low SES	−0.022	−0.021
	(0.025)	(0.027)
High SES	0.001	0.020
	(0.022)	(0.020)
Peers with low SES and low ability		
Share of students with low SES and low ability x low SES students	−0.218	
	(0.183)	
Share of students with low SES and low ability x medium SES students	−0.172**	
	(0.087)	
Share of students with low SES and low ability x high SES students	0.080	
	(0.121)	
Peers with low SES and high ability		
Share of students with low SES and high ability x low SES students		0.016
		(0.160)
Share of students with low SES and high ability x medium SES students		−0.012
		(0.078)
Share of students with low SES and high ability x high SES students		−0.176
		(0.119)
High SES peers x low SES students	−0.075	−0.087
	(0.081)	(0.085)
High SES peers x medium SES students	−0.013	−0.009
	(0.039)	(0.039)
High SES peers x high SES students	0.011	−0.023
	(0.052)	(0.049)
Controls	Yes	Yes
N	1,199	1,199

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on the group-year level. The table reports effects arising from exposure to low SES peers with high and low ability level. The results indicate that low-SES peers negatively affect students' final grades when they also have a low ability level. The coefficient of low-SES peers with high ability level is not significant. The set of control variables includes students' age, gender, mother tongue, entry exam, group size, and cohort effects.

distract or encourage bad behavior (Sacerdote, 2011; Wennberg and Norgren, 2021). In this line, Lavy et al. (2012) find that students' performance is negatively affected by low achieving peers. A higher share of low-achieving peers deteriorates teacher quality, weakens teacher-pupil relationships, and increases classroom disruptions. In this sample, the ability level of low SES students is on average lower than that of high SES students, with mean values of -0.021 and 0.110, respectively. Therefore, the negative spillover effects might arise from low-SES students with low ability.

Consequently, I re-estimate peer effects on students' final grades and distinguish low-SES students with high and low ability. Following the bad apple model of peer effects, low-SES students with high ability should not negatively affect students' academic achievements. I separate students with low-SES and ability in the top quartile and those in the bottom quartile. Table 4.4 shows the estimates for heterogeneous peer effects deriving from a higher exposure to these groups. They confirm that peers with low-SES and high ability do not significantly affect students' final grade. Conversely, the estimator of low-SES students with low-ability level is significant for medium-SES students. A 10 percentage points higher share in students with low ability and low SES reduces medium-SES students' final grades by 1.72%. This is in line with the argument that the negative peer effect works through ability rather than through peers' social background *per se*.

4.7.2 Career Choices

The main results indicate a significant and positive effect of low-SES peer exposure on students' income. One potential explanation for this result is that low-SES students shape their fellow students' career choices, e.g., due to peer conformity and job networks. Below, I therefore assess whether students affect each other's job searching strategies and initial occupational choices. These include the industry graduates start working in and their labor supply.

Job Searching Strategies

For HSG graduates, using social networks is a very popular strategy for entering the labor market. More than 40% of graduates indicate that they relied on family and friends, while 32% used contacts established during their studies. In comparison, only 15% responded to traditional job advertisements.

Whether students use their social networks relates to their socio-economic background. High-SES students are 11.4 percentage points more likely to rely on their family and friends than students with medium SES. In comparison, low-SES students are substantially less likely to use university or personal contacts – by 16.9 pp. and

Table 4.5: Heterogeneous peer effects on graduates' job searching strategies

	Job Advertisements	University Contacts	Personal Contacts
Ability	0.002	0.025	−0.040
	(0.019)	(0.029)	(0.029)
Low SES	0.012	−0.169**	−0.195**
	(0.065)	(0.069)	(0.080)
High SES	0.029	0.048	0.114**
	(0.039)	(0.055)	(0.058)
Total low SES peer effect on low SES students	0.195	0.783***	0.493*
	(0.273)	(0.280)	(0.286)
Total low SES peer effect on medium SES students	0.308**	0.267	−0.138
	(0.121)	(0.217)	(0.202)
Total low SES peer effect on high SES students	0.418	0.418	0.503
	(0.264)	(0.412)	(0.397)
Total high SES peer effect on low SES students	−0.179	0.470	−0.268
	(0.382)	(0.406)	(0.322)
Total high SES peer effect on medium SES students	0.138	0.225	−0.011
	(0.100)	(0.161)	(0.177)
Total high SES peer effect on high SES students	0.164	0.190	0.125
	(0.225)	(0.252)	(0.276)
Controls	Yes	Yes	Yes
N	434	434	434

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on the group-year level. The table reports heterogeneous peer effects on students' job searching behavior, estimated in a logit regression framework. When the share of low-SES peers increases by 10 pp, other low-SES students are 4.93 pp more likely to rely on their family and friends to obtain a job, and 7.83 pp more likely to use contacts they have acquired during their studies. Medium-SES students' probability of responding to job advertisement is affected as well. The set of control variables includes students' age, gender, mother tongue, entry exam, group size, and cohort effects.

19.5 pp., respectively. These results are reported as average marginal effects from logit regressions in Table 4.5.

However, the probability of low-SES students using social networks increases when other low-SES peers are present in their peer group. A 10-pp. higher exposure to

Figure 4.5: Graduates' average income by job searching strategy

Note: The figure shows graduates' mean income conditional on applied job searching strategies. Mean earnings are significantly higher when students have relied on university contacts instead of using their family and friends. Other income gaps are not significant.

low SES peers increases the probability of low-SES student using personal contacts by 4.93 pp., and by 7.83 pp. for using contacts established at HSG. There is also a significant effect on medium-SES students, who are 3.08 pp. more likely to respond to traditional job advertisement. The behavior of high-SES students is not affected, nor does a significant impact arise from high-SES peer exposure.

The observed effects on graduates' job searching behavior are consistent with peer learning, conformity and gains in self-confidence. Low-SES students might be more confident and apply strategies they have learned from higher-SES students when other low-SES peers are present. Then, they rely more on social networks for job searching. It might also be the case that they consider their family and friends as less helpful for obtaining jobs they are interested in, and therefore tend to rely more on contacts they have acquired during their studies, e.g., in internships. This might explain why the peer effect on using university contacts is higher than on using personal contacts.

The use of family and friends is less rewarded than other strategies. On average, graduates who relied on their personal networks earn 7,671 Swiss Francs less per year than those who used personal contacts acquired during their studies. A t-test shows that the income gap is significant. Figure 4.5 displays the mean income of students conditional on their job searching strategy. No statistically significant income gap exists between students who responded to traditional job advertisements and those who used either university contacts or used social networks.

Industry Choices

Peers affect not only how students are search for jobs, but also in which industry. At graduation, the average HSG student has 1.8 job offers, ranging from 0 to 10 in this sample. Therefore, HSG graduates can at least to some extent choose their industry and job.

In the following, I explore whether peers affect the probability of students working in selected industries. Graduates are dispersed across industries, and this paper therefore focuses on three selected industries: (i) Finance and Insurance, (ii) Education, and (iii) the Public Sector in general.[11] Table 4.6 presents average marginal effects, estimated from logit regressions and evaluated at mean values.

Students are strongly influenced by their peers regarding the industry in which they are working in. Parental background and ability play no role in this, or, in case of the education sector, only a minor one. As with the main results, low-SES peers are more influential than high-SES peers. A 10-pp higher share in low-SES peers increase the probability of a student working in finance and insurance by 5.93 percentage points, given a baseline share of 21.23%. Concurrently, they are 3.05-pp less likely to work in the public sector. This also affects students' decision to work in education. Here, both peer effects are negative and significant. Therefore, a socially less diverse peer group composition decreases the probability that a student starts his career in education. Considering coefficient sizes, however, the influence of low-SES peers is larger than the influence of high-SES peers.

Table 4.7 summarizes heterogeneous responses conditional on students' own background. These estimates can be compared to the average peer effects in Table 4.6. The positive peer effect on the probability of working in finance and insurance affects all types of students. The reaction of other low-SES students is particularly pronounced: a 10-pp increase in the share of other low-SES peers changes the probability by 8.53 pp. In comparison, the decision (not) to work in the public sector derives exclusively from high-SES students. These are 5.11% less likely to work in the public sector when the share of low SES peers in their group increases by 10 pp. The negative peer effect influences high-SES students' industry choice most in education. Additionally, a significant negative peer effect is evident regarding the likelihood of medium-SES students to work in education. As regards education, Table 4.6 also indicates a negative effect from high-status peer exposure. Looking at the heterogeneous results, this effect does not clearly derive from the reaction of any single type.

[11] Table A.3.4 provides additional results on peer effects for graduates' probability of working in trade and professional, scientific and technical activities. Peer effects are not significant for these industries. Together with Table 4.6, this table provides results on all industries where employment shares are higher than 8%.

Table 4.6: Peer effects on graduates' industry of employment

	Finance and Insurance	Public Sector	Education
Low SES	0.026	0.021	0.005
	(0.063)	(0.067)	(0.030)
High SES	−0.019	−0.051	0.005
	(0.042)	(0.042)	(0.023)
Ability	0.038	0.026	0.024**
	(0.027)	(0.025)	(0.010)
Share of low SES students	0.593***	−0.305**	−0.224***
	(0.190)	(0.152)	(0.073)
Share of high SES students	0.118	0.054	−0.131**
	(0.110)	(0.102)	(0.066)
Controls	Yes	Yes	Yes
N	462	462	462

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on the group-year level. The table reports significant peer effects on students' industry choices, estimated in a logit regression framework and evaluated at mean values. Industries are categorized according to the NOGA-1 classification. The set of control variables includes students' age, gender, mother tongue, entry exam, group size, and cohort effects. For instance, the average student is 5.93 pp more likely to work in finance and insurance when the share of low-SES peers increases by 10 pp.

For students from all three backgrounds, the total peer effect has a negative sign but is not significant.

Figure 4.6 compares graduates' mean income in finance and insurance, where graduates achieve above-average earnings, with education and the public sector, where incomes are comparatively low. This implies that a higher exposure to low SES peers increases the probability of all graduates starting their careers in a very well-paid industry and pushes medium- and high-SES students away from industries where earnings are low. The heterogeneous responses also match the peer effects on graduates' income. The positive effect is highest on the income of low-SES students, whose probability of working in the highly paid finance and insurance sector increases the most.

Importantly, I do not find evidence that students' initial career choices are affected by social alienation. At Harvard, Michelman et al. (2022) show that lower-status

Table 4.7: Heterogeneous peer effects on graduates' industry

	Finance and Insurance	Public Sector	Education
Total low SES peer effect on low SES students	0.853** (0.367)	−0.234 (0.390)	−0.116 (0.189)
Total low SES peer effect on medium SES students	0.523** (0.230)	−0.252 (0.187)	−0.180** (0.089)
Total low SES peer effect on high SES students	0.681** (0.288)	−0.511* (0.295)	−0.338*** (0.122)
Total high SES peer effect on low SES students	0.250 (0.425)	0.111 (0.130)	−0.169 (0.147)
Total high SES peer effect on medium SES students	0.145 (0.143)	−0.521 (0.381)	−0.052 (0.084)
Total high SES peer effect on high SES students	0.032 (0.167)	0.043 (0.159)	−0.222 (0.139)
Controls	Yes	Yes	Yes
N	462	462	462

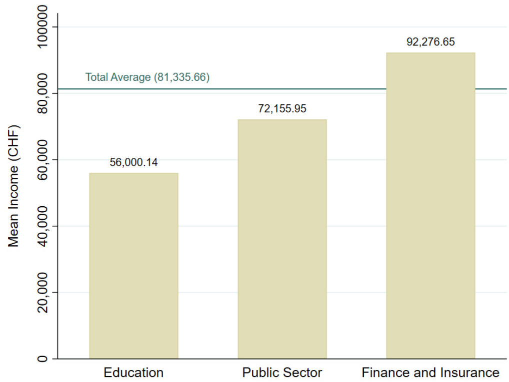
Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on the group-year level. The table summarizes heterogeneous peer effects on students' industry choices, obtained from logit regressions and evaluated at mean values. Industries are categorized according to the NOGA-1 classification. The set of control variables includes students' age, gender, mother tongue, entry exam, group size, and cohort effects. Exposure to low-SES peers affect the probability of working in finance and insurance across all student types. Only specific types adopt their decision to work in the public sector or in education.

students shrink away from a career in finance due to high-status peer exposure. Here, all students are more likely to work in finance and insurance. Several of the proposed mechanisms are consistent with this observation, including peer conformity, peer learning, and job networks.

Intensive Labor Supply

Furthermore, the positive peer effect on graduates' income might be related to labor supply. In this regard, this paper works with information on the average number of working hours per week. These refer to the actual number of working hours rather than the contractual number of working hours. I distinguish between three cases, depending on whether the average number of working hours is lower or higher than,

Figure 4.6: Average income in selected industries



Note: The figure displays differences in graduates' mean income across selected industries. The average income of graduates working in finance and insurance is above the sample mean. Conversely, earnings in the public sector and in education are comparatively low.

or equal to, full-time employment.

Higher exposure to low SES-peers significantly increases the probability of graduates working full-time instead of part-time (see Table 4.8). More specifically, a 10-percentage point increase in the share of low-SES peers increases the probability of working full-time (42 hours per week) by 4.1 pp. At the same time, it decreases the probability of working part-time by 5.3 pp. In general, this result is in line with the positive peer effect on students' income: When exposed to a higher share of low SES peers, students choose to increase their intensive labor supply after graduation, which in turn might increase their income, especially if they enter a highly-paid industry such as finance and insurance.

Additionally, there is evidence that higher exposure to high-SES peers increases the probability of working overtime on a regular basis, which is consistent with peer pressure as an underlying mechanism. Overall, 14.8% of graduates indicate that their regular number of working hours per week exceeds 42 hours. The probability of working overtime increases by 1.39 pp when the share of high SES peers is increased by 10 pp. It is unclear whether these overtime hours are paid or unpaid. In any case, the high-SES peer effect on graduates' income is not significant. Therefore, exposure to high-SES students might influence working attitudes rather than the actual outcome (i.e., income).

Notably, higher ability level is associated with a higher probability of working less than 42 hours per week. At the same time, the coefficient for working 42 hours is

Table 4.8: Linear-in-means peer effects on labor supply

	Full-time Working Hours	Part-time Working Hours	Overtime Working Hours
Low SES	0.033	−0.065	0.034
	(0.086)	(0.076)	(0.056)
High SES	−0.005	−0.003	0.006
	(0.062)	(0.062)	(0.034)
Ability	-0.077^{**}	0.074^{***}	−0.001
	(0.032)	(0.028)	(0.020)
Share of low SES students	0.409^{**}	-0.528^{***}	0.111
	(0.188)	(0.162)	(0.129)
Share of high SES students	−0.122	−0.073	0.139^{*}
	(0.133)	(0.126)	(0.083)
Controls	Yes	Yes	Yes
N	487	487	487

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on group-year level. The table shows linear-in-means peer effects on graduates' labor supply. The coefficients derive from logit regressions and are evaluated at mean values. The set of control variables includes students' age, gender, mother tongue, entry exam, group size, and cohort effects. A 10 pp higher share of low-SES peers increases the probability of working full-time by 4.09 pp and reduces the probability of working part-time by 5.28 pp. Additionally, higher exposure to high-SES peers increases the likelihood of working overtime.

Table 4.9: Heterogeneous peer effects on labor supply

	Full-time Working Hours	Part-time Working Hours	Overtime Working Hours
Total low SES peer effect on low SES students	1.598^{***} (0.498)	-1.367^{**} (0.588)	-0.253 (0.425)
Total low SES peer effect on medium SES students	0.094 (0.228)	-0.231 (0.200)	0.125 (0.143)
Total low SES peer effect on high SES students	0.800^{*} (0.423)	-1.309^{***} (0.407)	0.361 (0.224)
Total high SES peer effect on low SES students	0.751 (0.690)	-0.580 (0.558)	-0.306 (0.389)
Total high SES peer effect on medium SES students	-0.306 (0.196)	-0.026 (0.157)	0.226^{**} (0.096)
Total high SES peer effect on high SES students	0.078 (0.232)	-0.032 (0.263)	-0.034 (0.146)
Controls (incl. cohort effects)	Yes	Yes	Yes
N	487	487	487

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on group-year level. The table summarizes heterogeneous peer effects conditional on students' own type. The coefficients are estimated in a logit framework and evaluated at mean values. The set of control variables includes students' age, gender, mother tongue, entry exam, group size, and cohort effects. The linear-in-means peer effects on working full-time and part-time in Table 4.8 derive from the reaction of low- and high-SES students. Medium-SES students react to high-SES peer exposure: A 10-pp increase in the share of high-SES students makes them 2.26 pp more likely to work overtime on a regular base.

negative. One potential explanation for this observation might be a higher efficiency, which allows graduates to work somewhat less than 42 working hours to perform the tasks of a full-time position.[12]

The effect of high-SES peer exposure on working overtime derives from medium-SES students (Table 4.9). Their labor supply is not significantly influenced by low-SES peer exposure. Therefore, the positive effect from low-SES peer exposure on medium-SES students' income in the main results cannot be explained by an adoption in the number of working hours because they only react to high-SES students.

The heterogeneous peer effects reported in Table 4.9 show that the other peer effects at the mean are driven by very strong responses of low- and medium-SES students.

[12]The average number of working hours is 40.18 hours per week when ability is above average, which would count as part-time as this figure is below 42 hours per week. Figure A.4.1 shows the corresponding density plot.

This finding is consistent with prior research indicating that peer pressure and norm compliance are important for labor supply at the extensive and intensive margin (see e.g., Falk and Ichino, 2006; Mas and Moretti, 2009; Fu et al., 2019).

4.8 Alternative Specifications and Robustness

4.8.1 Standardized Income

The previous section implies that changes in labor supply contributed to the estimated peer effects on graduates' income level. Below, I use the standardized income as alternative income measure to abstract from these variations in weekly working hours. The standardized income is provided by the Swiss Federal Statistical Office and defines the annual gross income, calculated based on full-time employment. Table 4.10 summarizes the results.

Table 4.10: Peer effects on standardized students' income

	Standardized Income
Low SES	−0.064
	(0.054)
High SES	−0.002
	(0.037)
Ability	0.089***
	(0.026)
Share of low SES students	0.277**
	(0.124)
Share of high SES students	−0.031
	(0.091)
Controls	Yes
Adj. R^2	0.088
N	458

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on the group-year level. The table reports peer effects on graduates' income, which is standardized to full-time employment. The set of control variables includes students' age, gender, mother tongue, entry exam, group size, and cohort effects.

The estimated peer effect of low-SES peer exposure remains significant but decreases in size. Here, a marginal increase in the share of low-SES students increases the average graduate's income by 2.79%, compared to 4.87% in the main specification. This suggests that approximately 40% of the peer effect on income is driven by the adjustment of labor supply, and 60% by other channels such as graduates' industry choice.

4.8.2 Estimation Results without Control Variables

The identification strategy relies on the randomized allocation of students to groups. Hence, including control variables and cohort fixed effects should increase the precision of the peer effects estimators but not affect the obtained coefficients otherwise. Therefore, I repeat the estimations without control variables and without cohort fixed effects. The results show that the estimated peer effect on students' income level one year after graduation moderately decreases in size. A 10-pp. increase in the share of low-SES students increases students' income by 3.03%, compared to 4.87% in the main specification. Otherwise, the results are not affected (see Tables 4.11 and 4.12).

Table 4.11: Estimation results for students' final grades without controls

Final Grade	(1)	(2)	(3)	(4)	(5)
Low SES		-0.040^{***}	-0.041^{***}	-0.035^{**}	-0.035^{**}
		(0.014)	(0.014)	(0.014)	(0.014)
High SES		0.015	0.013	0.014	0.013
		(0.010)	(0.010)	(0.010)	(0.010)
Low SES x Ability			-0.004		-0.001
			(0.017)		(0.016)
High SES x Ability			-0.010		-0.010
			(0.013)		(0.013)
Ability	0.075^{***}	0.074^{***}	0.078^{***}	0.075^{***}	0.079^{***}
	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
Share of low SES students				-0.088^{**}	-0.088^{**}
				(0.036)	(0.036)
Share of high SES students				-0.023	-0.022
				(0.030)	(0.031)
Controls	No	No	No	No	No
Adj. R^2	0.161	0.170	0.170	0.174	0.175
N	1,199	1,199	1,199	1,199	1,199

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on the group-year level. The table displays results for students' final grades which are obtained without control variables and cohort fixed effects.

Table 4.12: Estimation results for students' income without controls

Income	(1)	(2)	(3)	(4)	(5)
Low SES		−0.001	0.006	−0.043	−0.036
		(0.059)	(0.119)	(0.057)	(0.117)
High SES		0.021	0.161**	0.039	0.166**
		(0.040)	(0.073)	(0.044)	(0.072)
Low SES x Ability			−0.019		0.014
			(0.128)		(0.127)
High SES x Ability			−0.203**		−0.190**
			(0.081)		(0.080)
Ability	0.110**	0.109**	0.200***	0.106**	0.191***
	(0.055)	(0.055)	(0.067)	(0.132)	(0.065)
Share of low SES students				0.296**	0.303**
				(0.132)	(0.130)
Share of high SES students				−0.142	−0.073
				(0.153)	(0.145)
Controls	No	No	No	No	No
Adj. R^2	0.033	0.034	0.034	0.051	0.073
N	462	462	462	462	462

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on the group-year level. The table displays results for graduates' income which are obtained without control variables and cohort fixed effects.

4.8.3 Group Selection Rules

The main sample includes observations on student groups where at least 9 out of 15 students are part of the sample. To test whether results are robust to different cut-off rules, I calculate results when at least 11 or 12 observations of each group are available. Table 4.13 presents the results.

In general, the peer effect estimators are robust to higher restrictions on group size. All results remain qualitatively the same, although the coefficient increases moderately, indicating the impact of low SES peer exposure on students' final grade when the cut-of is set to 12 students per group. Looking at the peer effects on students' income level, the precision of the estimator decreases due to the considerable reduction in sample size. When n=100, the size of the coefficient remains unchanged, but it is not significant anymore.

Table 4.13: Alternative group selection rules

Group Size	Final Grade at least 11 observations	Final Grade at least 12 observations	Income at least 11 observations	Income at least 12 observations
Low SES	-0.042^{**}	-0.051^{*}	0.087	0.098
	(0.021)	(0.028)	(0.141)	(0.169)
High SES	-0.016	-0.007	0.177^{*}	0.237
	(0.014)	(0.019)	(0.099)	(0.150)
High SES x Ability	0.011	0.013	-0.153	-0.135
	(0.023)	(0.035)	(0.137)	(0.164)
Low SES x Ability	0.006	0.008	-0.205^{**}	-0.224
	(0.017)	(0.023)	(0.097)	(0.162)
Ability	0.057^{***}	0.055^{***}	0.279^{***}	0.340^{**}
	(0.019)	(0.020)	(0.088)	(0.141)
Share of low SES students	-0.154^{**}	-0.218^{**}	0.432^{*}	0.451
	(0.067)	(0.094)	(0.249)	(0.700)
Share of high SES students	0.003	0.035	-0.398	-0.588
	(0.042)	(0.034)	(0.393)	(0.555)
Controls	Yes	Yes	Yes	Yes
Adj. R^2	0.256	0.147	0.251	0.299
N	429	250	168	100

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on the group-year level. The table summarizes results when alternative sample selection rules are applied. Then, at least 11 or 12 observations of one student group must be available. The set of control variables includes students' age, gender, mother tongue, entry exam, group size, and cohort effects.

4.8.4 Alternative SES Measure

The main specification uses the combination of paternal and maternal education as measure for students' SES. Here, I explore how the obtained results change when the education level of only one parent is used to describe the peer group composition. Consequently, I first use (i) the fraction of students with fathers having a low- or high educational background, and (ii) the fraction of students with mothers having a low- or high educational background as peer measure. Students' own SES is defined correspondingly.

In general, the results can be expected to differ due to the varying combinations of parental education. For instance, assume a students' father has a tertiary degree,

Table 4.14: Alternative SES measure

SES Measure	Final Grade: Father Education	Final Grade: Mother Education	Income: Father Education	Income: Mother Education
Low SES	−0.015	−0.017	0.031	−0.056
	(0.013)	(0.013)	(0.113)	(0.099)
High SES	−0.004	0.001	0.094	0.173**
	(0.010)	(0.011)	(0.090)	(0.077)
Low SES x Ability	0.001	−0.008	−0.050	0.099
	(0.015)	(0.013)	(0.134)	(0.119)
High SES x Ability	−0.006	−0.010	−0.153	−0.211***
	(0.010)	(0.011)	(0.115)	(0.077)
Ability	0.049***	0.051***	0.234***	0.215***
	(0.011)	(0.011)	(0.084)	(0.059)
Share of low SES students	−0.065	−0.103***	0.322	0.405***
	(0.044)	(0.0836)	(0.222)	(0.111)
Share of high SES students	−0.010	−0.044	−0.156	0.031
	(0.039)	(0.033)	(0.138)	(0.137)
Controls	Yes	Yes	Yes	Yes
Adj. R^2	0.225	0.232	0.085	0.132
N	1,135	1,135	420	421

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on the group-year level. The table summarizes estimation results when either father's or mother's education are used as alternative measures for students' socio-economic status. The set of control variables includes students' age, gender, mother tongue, entry exam, group size, and cohort effects.

whereas the mother has obtained compulsory education only. The baseline specification would categorize this student as member of the reference group, that is, as having a medium SES. However, he ranks in the high-SES category when considering only father education, in the low-SES category when considering only the mother's education.

Table 4.14 presents the results. The obtained peer effects using the mothers' education as a measure of socio-economic status resemble the results of the main specification. The second and fourth column show a negative effect from low SES peer exposure on students' final grades, and a positive effect on their income one year after graduation. Overall, the results are qualitatively equal, and the obtained peer effects have a similar size.

Using father's education as measure of SES yields no significant results. Also, the coefficient size is smaller than the main results indicate. Yet, the estimated peer effects work in the same direction and the p-values are not far away from the implemented significance levels. They equal 0.148 and 0.150 for the impact of a higher share of low-SES peers on students' final grade and on their income level, respectively.
The results of using the mother's education to measure SES more strongly resemble the main results due to assortative mating. Females tend to have partners with equal or higher education levels.[13] Therefore, well-educated mothers are comparatively likely to have well-educated spouses, while a still significant share of low-educated mothers have low-educated spouses. Consequently, this definition leads to similar categories for describing a student's SES as in the main specification. Conversely, for higher-educated fathers, the variation in mothers' education increases, and thus diverges more strongly from the main specification.
Overall, this suggests that when family income is not available, the education levels of both parents should be used measure of SES. The distinction between (low-low) and (high-high) education types prevents arbitrarily ranking either the mother's or the father's education as higher or lower than the other.

4.9 Conclusion

This paper analyzes how the social composition of students' peer groups affect their academic and early labor market outcomes. The identification strategy relies on a short-term peer intervention with randomized student groups at the University of St. Gallen (HSG) in Switzerland. On average, students' income after graduation increases when they are exposed to a higher share of peers with low socio-economic status (SES). The effect is highest on other low-SES students, as they increase their labor supply and become more likely to work in finance and insurance, an industry relating to above-average earnings. Consequently, a 10-percentage point higher share of low-SES peers in other low-SES students' groups leads to a 6.32% increase in their gross income one year after graduation. The positive effect of low-SES peer exposure on income is also observable for other student types, although to a smaller extent. As low-SES students, they are more likely to work in finance and insurance. Additionally, the probability of them working in the public sector and in education decreases.
Regarding academic outcomes, I find peers less influential than with initial occupational choices. In general, low-SES students experience a moderate disadvantage compared to other students. With equal ability level and other characteristics, low

[13] Table A.1.2 shows the relation between the father's and mother's education in the sample.

SES decreases students' final grade by 2.7%. Furthermore, low-SES peer exposure has a small yet significant negative peer effect (driven by low-ability students) on medium-SES students.

One key result of this paper is that peer effects arise primarily from exposure to low-SES students rather than from high-SES students. Higher exposure to high-SES peers increases the probability of medium-SES graduates working more than 42 hours per week, but without significantly affecting income or other outcomes. Therefore, I do not find evidence in this sample that social alienation negatively affects the outcomes of low-SES students, which would be an obstacle for social mobility after university entrance. Compositional effects might partly contribute to this. The sample used here only includes students who successfully graduated from university but not ones who dropped their studies due to high-SES peer exposure and who instead chose a different career path. Furthermore, students' SES is proxied by parents' combined education level as family income is not available, making further research with additional information on drop-outs and students' income background desirable.

Overall, the results indicate that the university is successful in equalizing students' economic outcomes. There is no earning gap between different student types which are not conditional on their ability level. This paper has observed graduates' occupational choices only shortly after students transitioned from university to the labor market. However, for social mobility, these initial choices are important, because this is where the paths are laid for children's subsequent careers and therefore for upwards economic mobility in the long run. Students' peers are very influential at this stage. In comparison, students' own abilities play no role or only a minor one for selecting the industry in which students start their professional careers. In this sense, peers shape social mobility after university entrance.

Bibliography

Acemoglu, D., and J. Angrist. 2000. How Large are Human-Capital Externalities? Evidence from Compulsory Schooling Laws. *NBER Macroeconomics Annual* 15:9–59.

Addison, J. T., and P. Portugal. 2002. Job Search Methods and Outcomes. *Oxford Economic Papers* 54:505–533.

Akerlof, G. A., and R. E. Kranton. 2000. Economics and Identity. *Quarterly Journal of Economics* 115:715–753.

Angrist, J. D. 2014. The Perils of Peer Effects. *Labour Economics* 30:98–108.

Arcidiacono, S., Peter; Nicholson. 2005. Peer Effects in Medical School. *Journal of Public Economics* 89:327–350.

Autor, D. H. 2015. Why are there still so many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives* 29:3–30.

Balestra, S., A. Sallin, and S. C. Wolter. 2021. High-Ability Influencers? The Heterogeneous Effects of Gifted Classmates. *Journal of Human Resources* pp. 0920–11170R1.

Barrios Fernández, A., C. Neilson, and S. D. Zimmerman. 2021. Elite Universities and the Intergenerational Transmission of Human and Social Capital. SSRN Working Paper 4071712.

Bernheim, B. D. 1994. A Theory of Conformity. *Journal of Political Economy* 102:841–877.

Bertrand, M., C. Goldin, and L. F. Katz. 2010. Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors. *American Economic Journal: Applied Economics* 2:228–55.

Borghans, L., B. Ter Weel, and B. A. Weinberg. 2014. People Skills and the Labor-Market Outcomes of Underrepresented Groups. *Industrial and Labor Relations Review* 67:287–334.

Bostwick, V. K., and B. A. Weinberg. 2022. Nevertheless she persisted? Gender Peer Effects in Doctoral STEM Programs. *Journal of Labor Economics* 40:397–436.

Bramoullé, Y., H. Djebbari, and B. Fortin. 2020. Peer Effects in Networks: A Survey. *Annual Review of Economics* 12:603–629.

Bresnahan, T. F., E. Brynjolfsson, and L. M. Hitt. 2002. Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-level Evidence. *The Quarterly Journal of Economics* 117:339–376.

Bühlmann, F., M. Beetschen, T. David, S. Ginalski, and A. Mach. 2017. Elites in Switzerland: the rise and fall of a model of elite coordination. *Tempo Social* .

Carrell, S. E., R. L. Fullerton, and J. E. West. 2009. Does Your Cohort Matter? Measuring Peer Effects in College Achievement. *Journal of Labor Economics* 27:439–464.

Carrell, S. E., B. I. Sacerdote, and J. E. West. 2013. From Natural Variation to Optimal Policy? The Importance of Endogenous Peer Group Formation. *Econometrica* 81:855–882.

Chetty, R., D. Grusky, M. Hell, N. Hendren, R. Manduca, and J. Narang. 2017. The fading American dream: Trends in absolute income mobility since 1940. *Science* 356:398–406.

Chuard, P., and V. Grassi. 2020. Switzer-Land of Opportunity: Intergenerational Income Mobility in the Land of Vocational Training. University of St. Gallen SEPS Discussion Paper no. 2020-11.

David, H., F. S. Levy, and R. J. Murnane. 2002. Upstairs, Downstairs: Computer-skill Complementarity and Computer-Labor Substitution on two Floors of a large Bank. *Industrial and Labor Relations Review* 55:432–447.

Deming, D., and L. B. Kahn. 2018. Skill Requirements Across Firms and Labor Markets: Evidence from Job Postings for Professionals. *Journal of Labor Economics* 36:S337–S369.

Deming, D. J. 2017. The Growing Importance of Social Skills in the Labor Market. *The Quarterly Journal of Economics* 132:1593–1640.

Duflo, E., P. Dupas, and M. Kremer. 2011. Peer Effects, Teacher Incentives, and the Impact of Tracking: Evidence from a Randomized Evaluation in Kenya. *American Economic Review* 101:1739–74.

Dustmann, C., A. Glitz, U. Schönberg, and H. Brücker. 2016. Referral-Based Job Search Networks. *Review of Economic Studies* 83:514–546.

Egger, S. 2018. Diversity Report.

Einav, L., and L. Yariv. 2006. What's in a Surname? The Effects of Surname Initials on Academic Success. *Journal of Economic Perspectives* 20:175–187.

Epple, D., R. Romano, and H. Sieg. 2002. On the Demographic Composition of Colleges and Universities in Market Equilibrium. *American Economic Review* 92:310–314.

Epple, D., R. Romano, and H. Sieg. 2003. Peer Effects, Financial Aid and Selection of Students into Colleges and Universities: An Empirical Analysis. *Journal of Applied Econometrics* 18:501–525.

Epple, D., and R. E. Romano. 2011. *Peer Effects in Education: A Survey of the Theory and Evidence*, vol. 1B, chap. Handbook of Social Economics, pp. 1053–1163.

Falk, A., and A. Ichino. 2006. Clean Evidence on Peer Effects. *Journal of Labor Economics* 24:39–57.

Feld, J., and U. Zölitz. 2017. Understanding Peer Effects: On the Nature, Estimation, and Channels of Peer Effects. *Journal of Labor Economics* 35:387–428.

Fischer, S. 2017. The Downside of Good Peers: How Classroom Composition differentially affects Men's and Women's STEM Persistence. *Labour Economics* 46:211–226.

Fracassi, C. 2016. Corporate Finance Policies and Social Networks. *Management Science* 63:2420–2438.

Fracassi, C., and G. Tate. 2012. External Networking and Internal Firm Governance. *The Journal of Finance* 67:153–194.

Fu, J., M. Sefton, and R. Upward. 2019. Social Comparisons in Job Search. *Journal of Economic Behavior & Organization* 168:338–361.

Granovetter, M. 1995. *Getting a Job: A Study of Contacts and Careers*. University of Chicago Press.

Granovetter, M. S. 1973. The Strength of Weak Ties. *American Journal of Sociology* 78:1360–1380.

Guttmann, G. 2020. Swiss Alumni Index: Educational Background of Switzerland's Corporate Directors. University of St. Gallen (HSG).

Hoxby, C. 2000. Peer Effects in the Classroom: Learning from Gender and Race Variation. NBER Working Paper 7867.

Ioannides, Y. M., and L. D. Loury. 2004. Job Information Networks, Neighborhood Effects, and Inequality. *Journal of Economic Literature* 42:1056–1093.

Jack, A. A. 2019. *The Privileged Poor.* Harvard University Press.

Jones, T. R., and M. S. Kofoed. 2020. Do Peers influence Occupational Preferences? Evidence from Randomly-Assigned Peer Groups at West Point. *Journal of Public Economics* 184:104154.

Kimbrough, E. O., A. D. McGee, and H. Shigeoka. 2022. How do Peers Impact Learning? An Experimental Investigation of Peer-to-Peer Teaching and Ability Tracking. *Journal of Human Resources* 57:304–339.

Lavy, V., M. D. Paserman, and A. Schlosser. 2012. Inside the Black Box of Ability Peer Effects: Evidence from Variation in the Proportion of Low Achievers in the Classroom. *The Economic Journal* 122:208–237.

Loury, L. D. 2006. Some Contacts are More Equal than Others: Informal Networks, Job Tenure, and Wages. *Journal of Labor Economics* 24:299–318.

Lyle, D. S. 2007. Estimating and Interpreting Peer and Role Model Effects from Randomly Assigned Social Groups at West Point. *Review of Economics and Statistics* 89:289–299.

Manski, C. F. 1993. Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies* 60:531–542.

Markussen, S., and K. Røed. 2017. The Gender Gap in Entrepreneurship – The Role of Peer Effects. *Journal of Economic Behavior & Organization* 134:356–373.

Marmaros, D., and B. Sacerdote. 2002. Peer and Social Networks in Job Search. *European Economic Review* 46:870–879.

Mas, A., and E. Moretti. 2009. Peers at Work. *American Economic Review* 99:112–145.

Michelman, V., J. Price, and S. D. Zimmerman. 2022. Old Boys' Clubs and Upward Mobility among the Educational Elite. *Quarterly Journal of Economics* 137:845–909.

Oosterbeek, H., and R. van Ewijk. 2014. Gender Peer Effects in University: Evidence from a Randomized Experiment. *Economics of Education Review* 38:51–63.

Rivera, L. A. 2016. *Pedigree: How Elite Students get Elite Jobs*. Princeton University Press.

Sacerdote, B. 2011. Peer Effects in Education: How Might They Work, How Big Are They and How Much Do We Know Thus Far? In *Handbook of the Economics of Education*, vol. 3, pp. 249–277.

Sacerdote, B. 2014. Experimental and Quasi-Experimental Analysis of Peer Effects: Two Steps Forward? *Annual Review of Economics* 6:253–272.

Shue, K. 2013. Executive Networks and Firm Policies: Evidence from the Random Assignment of MBA Peers. *Review of Financial Studies* 26:1401–1442.

Stankov, L., S. Morony, and Y. P. Lee. 2014. Confidence: The Best Non-Cognitive Predictor of Academic Achievement? *Educational Psychology* 34:9–28.

Stinebrickner, R., and T. R. Stinebrickner. 2006. What Can Be Learned about Peer Effects Using College Roommates? Evidence from New Survey Data and Students from Disadvantaged Backgrounds. *Journal of Public Economics* 8:1435–1454.

Thiemann, P. 2022. The Persistent Effects of Short-Term Peer Groups on Performance: Evidence from a Natural Experiment in Higher Education. *Management Science* 68:1131–1148.

Useem, M., and J. Karabel. 1986. Pathways to Top Corporate Management. *American Sociological Review* pp. 184–200.

Weinberger, C. J. 2014. The Increasing Complementarity between Cognitive and Social Skills. *Review of Economics and Statistics* 96:849–861.

Wennberg, K., and A. Norgren. 2021. Models of Peer Effects in Education. Stockholm School of Economics, Center for Educational Leadership and Excellence Working Papers No. 21/3.

Zimmermann, S. D. 2019. Elite Colleges and Upward Mobility to Top Jobs and Top Incomes. *American Economic Review* 109:1–47.

Zölitz, U., and J. Feld. 2021. The Effect of Peer Gender on Major Choice in Business School. *Management Science* 67:6963–6979.

Appendix

A.1 Supplementary Descriptive Statistics

Table A.1.1: Students' industry one year after graduation

Industry	Graduate Share
Manufacturing	4.76%
Electricity, gas, steam and air-conditioning supply	0.65%
Construction	0.43%
Wholesale and retail trade; repair of motor vehicles and motorcycles	8.44%
Transportation and storage	1.95%
Accommodation and food service activities	1.08%
Information and communication	6.28%
Financial and insurance activities	22.08%
Real estate activities	0.65%
Professional, scientific and technical activities	30.95%
Administrative and support service activities	1.08%
Public administration and defence; compulsory social security	8.01%
Education	8.44%
Human health and social work activities	2.81%
Arts, entertainment and recreation	0.22%
Other service activities	1.73%
Activities of extraterritorial organisations and bodies	0.43%
N	462

Note: This table shows employment shares in different industries, standard deviations in parentheses. Hereby, industries are classified according to the Swiss NOGA-1 classification system.

Table A.1.2: Parental education

		Mother		
		Non-tertiary degrees	Tert. non-ac. education	Academic degrees
Father	Non-tertiary	48.61%	32.38%	10.55%
	Tert. non-ac. degrees	8.35%	47.14%	2.37%
	Academic degrees	43.04%	20.48%	87.07%

Note: This table shows the relation between mothers' and fathers' education levels. Swiss higher vocational training ("Höhere Berufsbildung") are tertiary non-academic degrees. The columns add up to 100%. Thus, 87.07% of mothers with academic degrees have partners who have academic degrees as well.

A.2 Heterogeneous Peer Effects

Table A.2.3: Heterogeneous peer effects

	Final Grade	Income
Share low SES peers x low SES students	-0.010 (0.091)	0.624^{**} (0.293)
Share low SES peers x medium SES students	-0.101^{**} (0.051)	0.429^{**} (0.216)
Share low SES peers x high SES students	-0.083 (0.064)	0.512^{*} (0.264)
Share high SES peers x low SES students	-0.081 (0.085)	0.189 (0.268)
Share high SES peers x medium SES students	-0.023 (0.041)	-0.306 (0.218)
Share high SES peers x high SES students	-0.014 (0.051)	0.193 (0.163)
Controls	Yes	Yes
N	1,199	462

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on the group-year level. The table displays heterogeneous peer effects conditional on students' own type. The regression controls for student's ability, SES, interaction effects between students' ability and SES, as well as age, gender, mother tongue, entry exam, group size, and cohort effects.

A.3 Peer Effects on Graduates' Industry Choices

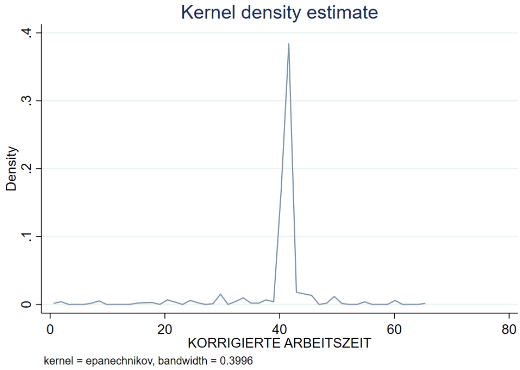
Table A.3.4: Additional results for peer effects on industry choices

	Wholesale and Retail Trade	Professional, Scientific and Technical Activities
Low SES	−0.028	−0.050
	(0.039)	(0.068)
High SES	−0.016	0.065
	(0.026)	(0.052)
Ability	0.013	-0.107^{***}
	(0.012)	(0.034)
Share of low SES students	−0.098	−0.095
	(0.101)	(0.204)
Share of high SES students	0.057	0.145
	(0.068)	(0.132)
Controls	Yes	Yes
N	462	462

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors in parentheses, clustered on group-year level. Students' industries are categorized according to the NOGA-1 classification. This table reports additional results on peer effects on students' industry choices. There is no evidence for significant peer effects on students' decision to start their career in trade and professional, scientific, and technical activities. The set of control variables includes students' age, gender, mother tongue, entry exam, group size, and cohort effects.

A.4 The distribution of average working hours per week

Figure A.4.1: The distribution of weekly working hours for high-ability graduates



Note: This figure visualizes the distribution of working hours for graduates with above-average ability levels. On average, they work 40.181 hours per week, ranging from 1 to 65 hours.

Chapter 5

Concluding Remarks

This dissertation contributes empirical evidence on German-speaking countries to the academic debate on social mobility. It provides new evidence for intergenerational income mobility and task-based occupational patterns as drivers of economic persistence on the one hand, and for the externalities on students' outcomes, which arise from the social composition of their peer groups after university entrance, on the other.

The first paper comprising this cumulative dissertation documents high relative income mobility in Austria. Looking at absolute income mobility, I find that approximately half of children in the 1990 birth cohort reach a higher income rank than their fathers. Another important finding is that whether children are better off than their parents largely depends on economic growth, as reflected by an equally distributed increase in real wages.

The second paper finds that task-based occupational patterns are an important driver of economic persistence in Germany. Almost 40% of the rank-rank slope (RRS) coefficient are attributable to the influence of family income background on a child's task level and the corresponding economic returns.

The third paper shows that higher exposure to peers from low socio-economic backgrounds (SES) increases students' income one year after graduation. This effect is highest on other low-SES students and driven by peer effects on their occupational choices and labor supply. The results are consistent with peer-to-peer learning and peer conformity. Based on the data set, I find no evidence that social alienation negatively affects the outcomes of low-SES students after university entry.

In recent years, concerns in the DACH-countries about lacking social mobility have grown. In Austria, the debate has been fuelled by the fact that, in 2018, an OECD report identified below-average income mobility in the country, based on estimates of the intergenerational income elasticity (OECD, 2018). However, these results were obtained without income data spanning two generations. The report relied on a methodology which is known to overestimate income persistence.[1] In contrast, the first paper offers a more positive perspective on the level of equal opportunities. These diverging results highlight the importance of researchers having access to large-scale administrative data to obtain reliable results on income mobility. Given that Austria exhibits lower income inequality than other OECD countries, the obtained results also align with the prediction of the Great-Gatsby Curve: Low income inequality relates to high income mobility.

The second paper takes a different angle on income mobility. Economic persistence arises due to the existing inequalities in the access to education, but also due to the structure of economic returns to children's task levels. Income mobility declines if technological changes induce a polarization at the labor market and economic returns shift stronger towards occupations with high autonomy levels. Simultaneously, when children born to families at the bottom of the income distribution continue to work in low-autonomy occupations as their fathers before them, income mobility for these children is determined by changes in the economic returns across generations. Therefore, policies which aim at increasing income mobility should also target occupational patterns and children's transition to the labor market, which is a crucial period for their subsequent employment biography.

Finally, the third paper shows that the university equalizes children's economic outcomes. Unconditional on their abilities, no significant earning gaps exist between children from different social backgrounds, at least at the beginning of their labor market career. In Switzerland, several initiatives have aimed to increase social diversity at Swiss tertiary institutions, such as "Diversity, inclusion, and equity in higher education development (2021-2024)" and the preceding "Equal opportunities and university development (2017-2020)".[2] The results obtained at the University of St. Gallen (HSG) support these goals: Graduates' income benefits from a higher share of students with non-academic background.

[1] OECD (2018) use a sample of synthetic fathers to predict earnings in the parent generation. This methodology is based on Björklund and Jäntti (1997), in order to provide an upper bound of the IGE coefficient. See OECD (2018), 193.

[2] `https://www.swissuniversities.ch/themen/chancengleichheit-diversity`.

Overall, the three papers presented in this dissertation make a substantial contribution to better understanding income mobility, the drivers of income persistence, and the factors shaping upward mobility after university entrance. As such, this dissertation provides a solid foundation for future research on how public policies can promote equal opportunities and improve the chances enhancing their living standards compared to their parents.

Bibliography

Björklund, A., and M. Jäntti. 1997. Intergenerational Income Mobility in Sweden compared to the United States. *The American Economic Review* 87:1009–1018.

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