Wealth Gaps in Education in Germany

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Contents

1. General introduction

In 2019, there was a huge bribery scandal regarding college admission in the United States. Wealthy parents had paid several hundred thousand dollars to get their children into elite universities, by faking their athletic records or helping them cheat in scholastic assessment tests (Feis and Eustachewich 2019). Similarly, in Germany in 2014, a judge was accused of selling the solutions for the state law exams (Spiegel 2014).

For the United States, this likely is only the (illegal) tip of the iceberg. Usually, wealthy parents find other (and legal) ways to secure educational success for their children. Educational attainment is strongly stratified by parental wealth. For instance, in the US, less than 10% of children in the lowest wealth quintile have graduated from college at the age of 25, compared to more than 50% of children in the highest wealth quintile (Pfeffer 2018). These differences are not only caused by wealth but can in part be attributed to other differences between wealthy and less wealthy households, like education, occupation, and composition of the household. However, even when comparing households that are otherwise similar, children in wealthy households attain on average a higher level of education.

In contrast, there is to date no comprehensive evaluation of wealth gaps in education in Germany. An extensive literature documents large gaps by parental education and occupational class in educational achievement and attainment (Neugebauer et al. 2013; Neugebauer and Schindler 2012; Schindler and Reimer 2010; Schneider 2008), also in comparison to other countries (OECD 2019; Pfeffer 2008). For example, Hillmert and Jacob (2010) report that only 5% of children of less educated parents graduate from university compared to 31% of children from better educated families. However, if parental wealth provides educational advantages beyond the advantages provided by parental education, then social stratification in education is even larger than suggested by the estimates of Hillmert and Jacob.

In my work, I consider wealth as financial wealth.[1] That is, wealth is the combination of all property, assets, and debt that a household or individual owns.[2] In contrast to income, which captures the inflow of material resources in a certain time, wealth is the stock of accumulated material resources and therefore a more comprehensive measure of an entity's economic situation (Spilerman 2000).

[1] This aligns with what Mulder et al. (2009) define as 'material wealth'. I do not consider 'embodied wealth' and 'relational wealth'.

[2] I explicitly do not define wealth as the sum of all assets minus all debt (i.e., net worth) because this is only one, and probably not the best, measure of wealth (see chapter 5).

When examining wealth gaps in education, it is helpful distinguish three different concepts: 1) Raw wealth gaps in education. They describe the average difference in educational outcomes by wealth. 2) Wealth gaps in education net of income, other dimensions of socio-economic status (SES), and demographics, i.e., wealth as an *independent* source of differences in education (Moulton et al. 2021; Pfeffer 2018). 3) Causal wealth effects on education. They describe the difference between the observed educational outcome and the educational outcome that would have been observed under the counterfactual circumstance if children lived in a household with a different amount of wealth. In my dissertation, I will focus on wealth as an independent source of differences in education.[3]

In the following, I will first elaborate on why it is important to evaluate the association between parental wealth and children's education. From these considerations, I will derive the relevant research question. In a third step, I will present the four studies that I conducted to answer these research questions.

1.1 Relevance

From a sociological perspective, evaluating wealth gaps in education in Germany is important for two reasons: First, wealth is a distinct dimension of social stratification, which however has only recently been fully established in empirical research. Second, education is one important mechanism for the intergenerational transmission of advantages, but wealth effects on education may work differently in the institutional context of Germany. Moreover, trends in wealth inequality and recent changes in the German education system and welfare state may make parental wealth more important for children's education.

1.1.1 Wealth as a distinct component of social stratification

Wealth is a crucial dimension of social stratification, and played a key role in early social class schemes such as those of Karl Marx (Marx 2009) and Max Weber (Weber 2009). However, wealth has only recently been fully established in empirical research on social stratification, partially due to the difficulty in measuring wealth (Spilerman 2000).

Wealth provides several advantages to families that cannot be captured by other dimensions of SES. First, wealth – in the form of self-occupied housing, vehicles, and durable goods – can

[3] However, keep in mind that wealth as an *independent source of differences in education* is the same as the *causal wealth effect on education* if the set of control variables blocks all backdoor paths between parental wealth and children's educational outcomes (Pearl 2009).
Research designs that allow an identification of causal wealth effects under weaker assumptions like sibling/cousin fixed effects or exploiting exogenous variation in wealth shocks (e.g., lottery wins) are not feasible for Germany or do not capture all the relevant variation in wealth. I will come back to this issue in the general discussion.

create a high standard of living. These kinds of wealth can be used without consuming them (Spilerman 2000). Moreover, by owning a dwelling instead of renting it, the monthly expenses of households are reduced. In 2019, German households paid on average more than a quarter of their income for housing (Statistisches Bundesamt 2020a). Thus, households who own their dwelling may have a substantially higher disposable income.

Second, wealth can generate income (i.e., income function of wealth; Frick and Grabka 2009). This could happen in the form of returns on investment in stocks, bonds, or business assets or in the form of rents for non-self-occupied housing or land. Very wealthy families may solely live on the income generated by their wealth. Likewise, owning or inheriting wealth enables some individuals to be entrepreneurs, while those without wealth can only earn money in dependent positions. Wealth in the form of pensions serves as income during retirement.

Third, wealth can be used to smooth consumption in case of income losses (e.g., due to unemployment or illness) or to cover a short-term demand for more consumption. This 'insurance function' of wealth is not only effective if there are negative life events; families can also anticipate that their wealth will buffer against negative events that may occur in the future (Brown, Coile, and Weisbenner 2010; Shapiro 2004). This enables wealthy families to act in a more future-oriented way (Sherraden 1991).

Fourth, wealth provides political power (e.g., Gilens 2012; Rossi 2014) and access to networks that are not or rarely available to the non-wealthy (Khan 2011).

Fifth, possessing wealth changes families' attitudes and norms, particularly when this wealth was inherited (Hällsten and Pfeffer 2017) and may create a sense of educational entitlement, also among families with moderate wealth (Conley 1999).

Finally, the negative components of wealth, namely debts, create obligations that limit further investments. This may force individuals to pursue different careers (Field 2009; Mann 2011; Rothstein and Rouse 2011) or affect family transitions (Addo 2014; Nau, Dwyer, and Hodson 2015).[4]

On a macro level, the distribution of wealth may shape the social structure of societies when it comes to the concentration of political power, social cohesion, dominant norms, and the organization of the labor market (Marx 2009).

[4] The wealth functions discussed here are an adapted and extended version of the wealth functions mentioned in Frick and Grabka (2009).

Although wealth is correlated with other dimensions of SES, the functions listed above are only provided by wealth, or add to advantages provided by the other dimensions. Even when comparing two families with the same education, occupation, and earnings, the wealthier family will have a higher disposable income; more opportunities in their occupational careers; more political power and access to more networks; different norms; and will fear less severe consequences in the case of negative events. Thus, wealth is a unique dimension of social stratification. If a study ignores wealth, it will only establish an incomplete picture of social stratification (Keister and Moller 2000; Killewald, Pfeffer, and Schachner 2017; Skopek 2015; Spilerman 2000). Hällsten and Thaning (2021) consider wealth to be one of the 'Big Four' of SES dimensions in intergenerational transmission (together with education, occupation, and income).

Moreover, wealth is accumulated in a different way than other dimensions of SES. Wealth can directly be transferred over generations via gifts and inheritance. Therefore, it depends less on skill and effort than other dimensions of SES. Wealth inequalities based on inheritance stand in strong conflict with meritocratic ideals and equal opportunities (Skopek 2015:33). The process of wealth accumulation is a typical process of cumulative advantage (DiPrete and Eirich 2006), because wealth accumulates naturally due to compound interest (Pfeffer and Killewald 2017). Likewise, families at the bottom of the wealth distribution tend to remain there, whereas income poverty is less long-lasting (Elmelech 2008). Finally, taxes on wealth are often much smaller than taxes on income.

As a consequence of how wealth is accumulated, wealth correlates with the other dimensions of SES, albeit these correlations are moderate in size. For Germany, Pfeffer and Hällsten (2012:21) find a correlation of 0.29 between families' wealth and income, a correlation of 0.17 between wealth and occupational status, and a correlation of 0.22 between wealth and education. Grätz and Wiborg report a correlation of 0.42 between wealth and parental education and a correlation of 0.43 between parental wealth and parental ISEI (International Socio-Economic Index of Occupational Status) scores (Grätz and Wiborg 2020, Table S5). Correlations between income, occupational status and education are larger.

1.1.2 Wealth gaps in education in a different educational system and welfare state

Children's education is crucial for the intergenerational transmission of advantages. One main reason for the intergenerational correlation of occupational class is that children of higher occupational classes attain higher educational degrees, which in turn allows them to enter higher occupational classes themselves (Blau and Duncan 1967). If advantaged children do not manage to obtain a high-level education, they are at much higher risk of experiencing intergenerational downward mobility. Likewise, one of the main mechanisms behind the intergenerational transmission of wealth inequalities is children's education (Pfeffer and Killewald 2017).

The importance of parental wealth for educational attainment has already been shown *in other countries*. Several studies in the US report substantial wealth gaps in educational attainment, even when accounting for other measures of parental SES (e.g., Conley, 2001; Diemer, Marchand and Mistry, 2020; Jez, 2014; Lovenheim, 2011; Pfeffer, 2018; for an overview Elliott III, Destin and Friedline, 2011). Moreover, wealth gaps in educational attainment have been reported for Sweden (Hällsten and Pfeffer, 2017; Hällsten and Thaning, 2018), the UK (Karagiannaki 2017), Brazil (Torche and Costa-Ribeiro 2012), and Mexico (Torche and Spilerman 2009).

In addition, wealth gaps in cognitive competences and school performance are well documented in several studies in the US (Diemer, Marchand, and Mistry 2020; Friedline, Masa, and Chowa 2015; Orr 2003; Williams Shanks 2007; Yeung and Conley 2008; for an overview of research before 2011 see again Elliott, Destin, and Friedline 2011). Furthermore, wealth gaps in adolescents' grade point averages are reported for Norway (Wiborg 2017) and Sweden (Hällsten and Pfeffer 2017). In contrast, Cesarini et al. (2016) find no wealth effects on children's cognitive competences in Sweden, and Moulton et al. (2021) report that wealth gaps in cognitive abilities in the UK disappear once they control for parents' permanent income.

Therefore – as has been shown for other dimensions of SES like education, occupational status, and income (Bukodi and Goldthorpe 2013; Mood 2017) – it may be necessary to also take wealth into account separately in research on social stratification, because the different dimensions of SES provide different advantages to children. Excluding wealth may, on the one hand, result in an overestimation of the impact of the other dimensions, which will partially pick up wealth effects. On the other hand, it may underestimate the total stratification in educational attainment and intergenerational persistency of SES. Moreover, the effect of the different dimensions of parental SES may vary in their importance or even their direction. For instance, Hällsten and Thaning (2018) show that high wealth children favor other fields of study than children of highly educated parents.

Nevertheless, these findings can probably not be generalized to the different educational system and welfare state in Germany. Particularly in contrast to the US, there are several potential reasons why wealth may be less important for educational attainment in Germany. First, education is free of tuition fees in Germany. Therefore, everyone in Germany should be able to afford tertiary education. Second, the German welfare state is more generous than the American welfare state and fewer families should experience severe financial hardship or should be restricted in their investments in children. Moreover, the German welfare state provides more social insurance against negative events like parental job loss (DiPrete 2002), which may reduce the importance of wealth as a form of private insurance (Pfeffer and Hällsten 2012). Finally, the funding of public education in Germany is less dependent on the characteristics of a neighborhood in Germany than in the US.

However, the same applies – indeed, even more markedly so – to Sweden and Norway, where substantial wealth effects have been found. Moreover, two features of the German educational system may make it particularly vulnerable to wealth effects. First, the German system of early tracking between schools, with few opportunities for changes between tracks, increases the risk of status demotion (Pfeffer and Hällsten 2012:12). To secure status maintenance in Germany, parents have to invest in their children's education from early on, in contrast to countries with more comprehensive educational systems. Second, the German vocational education and training (VET) system provides an attractive alternative to tertiary education. Particularly children in households with little wealth may choose the risk-averse option of a VET and only start tertiary education afterwards (Hillmert and Jacob 2003).

1.1.3 Wealth inequality is large and growing over time

Wealth inequality is much larger than the more frequently studied income inequality. For example, averaged over the 15 countries in the study by Pfeffer and Waitkus (2021), the 5% of households with the highest incomes earn 17.4% of the total income. The average Gini coefficient is 0.353. In contrast, the 5% of households with the highest net worth own 38.7% of the total net worth and the Gini coefficient of net worth is 0.690 (Pfeffer and Waitkus 2021:594).

Moreover, wealth inequality is on the rise worldwide (Piketty 2014; Saez and Zucman 2016; Zucman 2019). Combined for China, Europe and the United States, the share of wealth owned by the top 1% has increased from 28% in 1980 to 33% in 2017 (Zucman 2019). During the Covid pandemic, wealth inequality seems to have risen even further (Ahmed et al. 2022).

Compared to other OECD countries, wealth inequality in Germany is high. The Global Wealth Databook (Shorrocks, Davies, and Lluberas 2021:115–18) reports a Gini of 0.78 for Germany in 2020. Thus, German wealth inequality is substantially larger than, for example, in Australia (0.66), France (0.70), Israel (0.73), Italy (0.66), Poland (0.71), and the United Kingdom (0.72). However, wealth inequality is larger in Norway (0.79), Sweden (0.87), and the United States (0.85).

The mean net worth of adults in Germany was 108k EUR in 2017. However, the net worth distribution is highly skewed, and the median is only 26k EUR. At the bottom of the distribution, 6.4% of individuals have a negative net worth and 14.5% of individuals report a net worth of exactly zero. At the top of the distribution, 10% of individuals have a net worth of more than 275k EUR, and 1% a net worth of more than 1m EUR (Grabka and Halbmeier 2019:737). About half of total gross wealth in 2018 was real estate (most of this self-occupied). Business assets account for about a quarter, and deposits and insurances each for about 12% (Albers, Bartels, and Schularick 2020:34).

Levels of wealth inequality in Germany first increased substantially after reunification in 1990, but decreased slightly between 2008 and 2018. The Gini coefficient rose from 0.69 in 1993 to 0.76 in 2008 and then shrank to 0.74 in 2018. Likewise, the share of the total wealth owned by the top 10% of wealthiest households rose from 51% to 58%, before shrinking to 56%. The total wealth of the richest 1% rose from 19% to 23% and remained there until 2018 (Albers et al. 2020:37). The increase in wealth inequality since reunification is even more dramatic when comparing the upper and lower half of the wealth distribution. The upper half has doubled their wealth since 1993, among other things due to rising housing prices. Conversely, real wealth hardly grew for the bottom half. In consequence, the wealth share of the bottom half almost halved from 5% in 1993 to 3% in 2018.

1.1.4 Changes in the educational system and welfare state

However, not only did wealth inequality increase over the last decades; some changes in the German educational system and welfare state also suggest that wealth may have become more consequential for children's educational outcomes.

On the one hand, the German educational system has extended its reach considerably. In 1980, only 22% of students in West Germany obtained secondary school degrees that granted them access to higher education, with 13% completing a higher education degree. In contrast, in 2018, 51% of students are eligible for higher education and 32% completed a higher education degree (Statistisches Bundesamt 2020b).

On the other hand, the educational system has become more flexible and now offers alternative ways to get the highest school leaving certificate or to enter university. While the difference in the costs of different school tracks are small, and scarcely contribute to social stratification as long as children are of mandatory school age (Stocké 2007), there are direct and salient opportunity costs for schooling once students might also be earning money in a dual VET or on the labor market (Schneider 2008). Therefore, one can expect the financial resources of parents to become more important, since these additional pathways delay young people's entrance into the labor market.

Lastly, more private education opportunities have emerged in recent years. The share of students in private schools in Germany has doubled from 4.8% in 1992 to 9.2% in 2018 (Statistisches Bundesamt 2019b). Although private schools are not allowed to take tuition fees that may exclude children from families with few financial resources, these rules are not rigorously implemented by the authorities, and children of families with fewer financial resources are substantially less likely to attend private schools (Dräger, Röhlke, and Stefes 2021; Görlitz, Spieß, and Ziege 2018; Wrase and Helbig 2016). The privatization of education is even more pronounced for tertiary education. In 1995, 1.1% of all students studied at one of the 25 private universities in Germany. In contrast, in 2018, the number of students at private universities has increased to 9.9% and the number of private universities to 107 (Autorengruppe Bildungsberichterstattung 2020:178).

Moreover, the changes in the German welfare state may make parental wealth more important for children's education. In general, there have been ongoing trends of privatization for social securities and a development from a social insurance system to a minimum income scheme since the reunification (Nullmeier 2018). The most notable change was the introduction of the Hartz IV reform, which replaced the previous system of unemployment support (which comprised 57% of prior income for individuals with children) with a means-tested, flat rate basic income support. This change led to worse financial conditions for the families who received these benefits and increased the gap between the educational attainment of children in families who receive these benefits and children in families who do not receive the benefits (Trinh 2021). This decline in publicly-provided insurance may make wealth more important as a source of private insurance (Pfeffer and Hällsten 2012).

Both increasing inequality in the distribution of wealth (chapter 1.1.3) or the increasing importance of wealth for educational attainment alone will lead to growing wealth gaps in education. If both processes take place at the same time, their effects will multiply (Pfeffer 2018).

1.2 Research questions

There are four broader research questions about wealth gaps in education that are still unanswered: 1) Are there wealth gaps in education in Germany? 2) At which stage in the educational system do wealth gaps emerge? 3) Where within the overall wealth distribution do differences in education emerge? 4) Which mechanisms drive wealth gaps in education?

1.2.1 Are there wealth gaps in education in Germany?

As discussed earlier, there is strong evidence that parental wealth has a unique effect on educational attainment *in other countries* than Germany; however, these results are probably not generalizable to the German context because of differences in the educational system and the welfare state. There are already three studies on wealth gaps in education in Germany based on the data of the Socio-Economic Panel (SOEP).

First, Pfeffer and Hällsten (2012) assessed the association between parental wealth measured in 1988 and children's educational and occupational attainment when they were 26 to 38 years old.[5] Parental wealth was measured as the net worth of the household. For the empirical analysis, households with zero or negative net worth were assigned a floor value of US$1000 (2011 dollars, purchasing power parity) and log-transformed. In an occupational attainment model, they find that parental wealth has a statistically significant effect on the number of years children spend in education: A one standard deviation increase in parental net worth is associated with a 0.08 standard deviation increase in children's years of education. The effect of parental wealth is as large as the effect of the income and the occupational status of parents, but only one fourth as large as the effect of parents' highest level of education. Differences in children's occupational attainment by parental SES were completely mediated by children's educational attainment. Moreover, the study evaluates separately whether parental wealth affects the probability of graduating from the highest school track (*Gymnasium*) or graduating from university. They find quite small wealth effects (odds ratio for *Gymnasium* degree=1.044; odds ratio for university degree=1.022). Due to the small analysis sample (N=703) these estimates are imprecise and not statistically significant. The authors interpret these findings as tentative support for wealth effects being of similar size across the different educational levels. Lastly, the authors find that children living in wealthy households are substantially and

[5] Similar results are reported in Pfeffer (2011).

statistically significantly less likely to experience occupational downward mobility (odds ratio=0.810) and more likely to experience upward mobility (odds ratio=1.194).

Second, Grätz and Wiborg (2020) evaluated the association between parental wealth (measured as net worth) and performance in a cognitive skills test when children were 17 years old. They found that children living in wealthy households performed substantially better. The association between test scores and parental wealth were of a similar size to those between test scores and both parental education (measured as years of education) and parental occupational status (ISEI). Parental wealth seems to be particularly relevant for compensating for low cognitive skills: A standard deviation increase in parental wealth is associated with an almost 0.4 standard deviation increase for children at the bottom of the distribution of cognitive skills. At the top of the cognitive skills distribution, a standard deviation increase in wealth is still associated with an increase in test scores of more than 0.2 standard deviations.

Third, Müller, Pforr, and Hochman (2020) evaluated the association between parental wealth and children's post-secondary transitions, particularly whether parental gross wealth affects for how long children with *Fachabitur* (school-leaving certificate that grants restricted eligibility for tertiary education) or *Abitur* (school-leaving certificate that grants full eligibility for tertiary education) stay inactive before entering the labor market, starting vocational training, or entering tertiary education. They found a non-linear association between parental gross wealth and the timing of children's transition out of inactivity: Children living in households with small amounts of gross wealth leave inactivity more quickly than children in households with zero gross wealth. However, children in households with high gross wealth seem to remain inactive for longer than children in households with medium levels of wealth. Finally, they found that wealth effects are mostly driven by housing wealth rather than by financial wealth. Like in Pfeffer and Hällsten (2012), the estimates in the study of Müller, Pforr, and Hochman (2020) are imprecise due to the low number of cases (N=1045).

These studies already suggest that wealth has an independent effect on education in Germany. While all of them make important contributions, they also have some methodological shortcomings or do not directly aim to evaluate wealth as an independent source of advantages in education. Müller, Pforr, and Hochman (2020) only consider children who obtained a school leaving certificate that grants access to tertiary education; they look at whether these children enter vocational training, tertiary education, or stay inactive. Therefore, the questions as to how wealth affects whether children obtain these school leaving certificates or not, and whether wealthy children are more likely to attend university or VET, remain unanswered. Grätz and

Wiborg (2020) do not control for the impact of the other dimensions of parental SES on children's cognitive competences when studying wealth effects. Thus, the wealth differences in competences that they report may just capture the effects of other SES dimensions on competencies. Lastly, Pfeffer and Hällsten (2012) only have data on less than 750 children, most of them born in the 1970s. Due to the changes in the educational system and the distribution of wealth, results may be different for more recent cohorts.

1.2.2 At which stage in the educational system do wealth gaps emerge?

Most of the research on wealth gaps in educational attainment looks at the highest educational level obtained or certain educational transitions (e.g., enrolling in tertiary education). For countries like the US, it is reasonable to use this as the most crucial transition because most school leavers obtain the formal qualification to enroll in tertiary education. However, in countries with early tracking like Germany, where almost half of the recent cohorts do not obtain the required secondary school certificate to attend tertiary education, other transitions may be more important. Therefore, when considering wealth gaps in educational attainment in Germany, the next important, yet unanswered, question is: At which stage in the educational system do wealth gaps emerge? For instance, upon finding in a first step that children of wealthy parents are more likely to enroll in tertiary education, it is impossible to establish *prima facie* whether this is because wealthy children are more likely to obtain an *Abitur*, or whether they are more likely to enroll in tertiary education given that they have an *Abitur*, or both. Existing research has often ignored the difference between unconditional stratification (which might lead to conclusions like '*Children of wealthy parents are more likely to enroll in tertiary education*') and conditional stratification in educational transitions (which enables conclusions like '*Among the children with* Abitur*, children of wealthy parents are more likely to enroll in tertiary education*'; Schindler 2015:516).

Furthermore, most research has focused on pathways to tertiary education (Biewen and Tapalaga 2017; Schindler 2015) and has ignored that wealth may affect the further educational and occupational pathways of the children without *Abitur*, too. Research shows that access to vocational training is also socially stratified (Protsch and Solga 2016) but differences by wealth have, to date, been ignored.

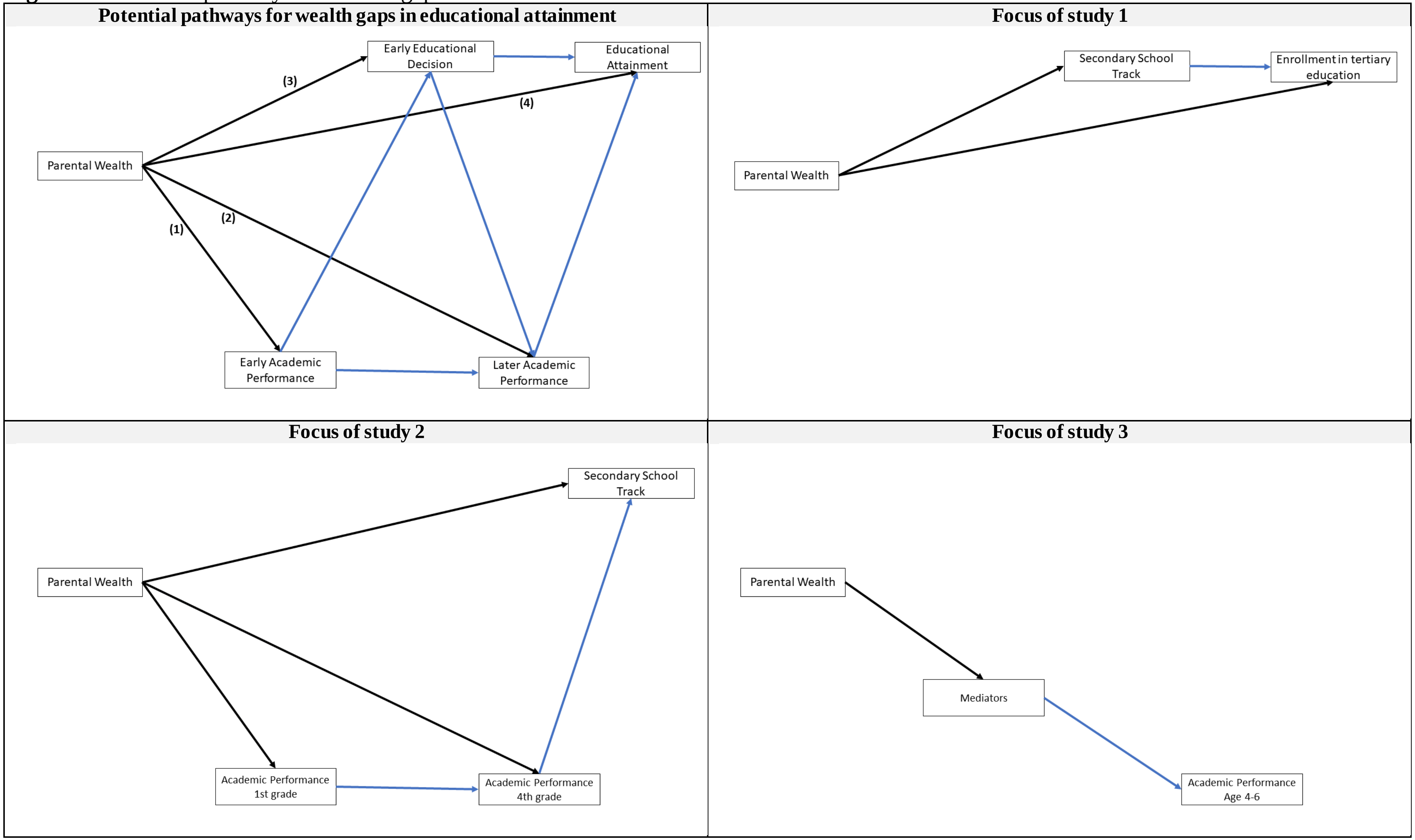
In the same vein, existing research is inconclusive regarding which measures of educational achievement and cognitive development are stratified by parental wealth and how these wealth gaps unfold over time. Wealth seems to affect cognitive outcomes in some domains but not others (Elliott et al. 2011). One reason for this inconclusiveness could be that results are based on studies with different children, rather than comparing the competences of the same children in different domains and at different ages.

The upper left part of Figure 1.1 shows a conceptual model for how parental wealth may affect children's educational attainment. The black arrows indicate direct effects of wealth and blue arrows indicate indirect effects that carry wealth effects forward. When considering only two points in time, there are four ways in which wealth gaps in educational attainment could emerge:

1. Wealthy children may have higher early performance (path (1) on the upper left part of Figure 1.1). This better academic performance may then lead to different educational decisions (*Early Academic Performance* → *Early Educational Decision,* i.e., primary effects; Boudon 1974).
2. Wealthy children may make larger learning gains during school (path (2) in Figure 1.1) and may therefore make more ambitious educational decisions at later transitions.
3. Wealthy children may be more likely to make ambitious early educational decisions (path (3) in Figure 1.1), net of differences in early academic performance (i.e., secondary effects).
4. Educational pathways are often strongly determined by earlier educational transitions (*Early Educational Decision* → *Educational Attainment;* Hillmert and Jacob 2010; Neugebauer and Schindler 2012; Schneider 2008). However, wealthy children may be more (or less) likely to diverge from the usual educational pathways after the first educational decision (path (4) in Figure 1.1).

If at least one of these processes takes place (and is not cancelled out by reverse processes), final educational attainment will be stratified by parental wealth.

Figure 1.1 Potential pathways for wealth gaps in educational attainment and focus of studies 1-3



Note: Black arrows indicate direct effects of wealth; blue arrows indicate indirect effects that carry wealth effects forward.

1.2.3 Where in the wealth distributions do differences emerge?

One further question to be answered is: For which contrasting pairs of values of wealth do gaps in education emerge? For instance, are there larger gaps in the educational attainment when comparing children in households with zero net worth to children in households with 100k EUR net worth or when comparing children in households with 100k EUR net worth to children in households with 200k EUR net worth? The college admission bribery scandal mentioned in the introduction may suggest that only very high levels of parental wealth provide educational advantages; whether families have moderate or low levels of wealth might matter less. Yet there are also reasons to expect differences in educational outcomes for other wealth contrasts. Researchers have found a variety of functional forms of wealth gaps in education: Hällsten and Pfeffer (2017) find an almost linear increase of GPA rank by parental net worth rank in Sweden. In contrast, Müller et al. (2020) find a non-linear association between parental wealth and the probability of being not in employment, education or training (NEET) after obtaining *Abitur* in Germany. They find that the wealthiest children are more likely to remain NEET when compared to those living in households with moderately high levels of wealth. In general, it may be possible that very high wealth causes moral hazard for students because they may anticipate that their parents will absorb any failure costs and provide the financial resources for additional years of study (Bodvarsson and Walker 2004). Research on income gaps in educational outcomes in Germany suggests that children in income-poor households are disadvantaged, but that income becomes less important as soon as households surpass a relatively low threshold (Schneider 2004; Schulz et al. 2017). However, in contrast to income, net worth can also be negative. What educational outcomes can be expected from children growing up in households with negative net worth? Do they have similar outcomes to children in households with little net worth – or even worse outcomes? The answer to this question is not straightforward because of the ambivalent meaning of debt. Having large amounts of debt may indicate economic deprivation, but it can also be an indicator of high economic potential and access to credit (Killewald 2013). Also, for Germany, research shows that the decile of individuals with the least net worth have *more assets* than the second decile of net worth (Grabka and Halbmeier 2019:743).

Moreover, there are several methodological challenges when considering wealth as a predictor variable, which likely contribute to the inconsistent findings in the literature. Usually, wealth is measured as net worth, but alternative measures include gross wealth, assets-to-debts ratios, or specific components of wealth. When researchers use net worth, they face the next problem: How to deal with the right-skewed distribution of wealth and the households with zero and negative net worth. Here, researchers have used wealth ranks, log-transformations, or the inverse hyperbolic sine transformation (Friedline et al. 2015). Lastly, researchers must find the correct functional form of the association between wealth and the considered outcome. The current best practice is to experiment with different specifications (Killewald et al. 2017). These decisions leave researchers with a considerable degree of freedom, resulting in the risk of misspecification or overfitting to random variation in the data.

1.2.4 Which mechanisms drive wealth effects?

Lastly, if there are wealth gaps in educational attainment in Germany, it is vital to establish which mechanisms cause these gaps if the resulting inequalities are to be effectively reduced. Since wealth is a distinct dimension of SES, it is likely that wealth gaps are also driven by other mechanisms (Hällsten and Pfeffer 2017).

While several explanations for wealth gaps in education have been proposed, they are yet to have been studied in any detail. For instance, wealth gaps in children's achievement may be caused by differences in parents' investments in children's education, differences in stress and parenting behavior (Moulton et al. 2021), or differences in educational aspirations (Conley 2001; Zhan 2006). The few studies that examine these mechanisms are based on data from the US (Diemer et al. 2020; Orr 2003). As discussed above (sections 1.1.2 and 1.2.1), it is questionable whether these results are generalizable to the German context: The lack of expensive tuition fees in Germany removes one potential hurdle to higher education, namely that non-wealthy families may feel unable to send their children to university. The psychological insurance function provided by wealth is less important when the welfare state buffers negative events like parental unemployment (Pfeffer and Hällsten 2012). Thus, non-wealthy parents should be less stressed in Germany. There should be smaller differences in parents' investment by wealth in Germany, because the more generous welfare state should allow all families to invest in their children's education.

Again, the question regarding the underlying mechanisms of wealth gaps is made even more challenging due to methodological issues. The different mediators of wealth gaps in children's education are not independent but affect each other (e.g., Coley et al. 2021). If mediators are causally related, then the difference-method and the product-method, which are usually applied for mediation analysis, give biased results (VanderWeele 2015; VanderWeele, Vansteelandt, and Robins 2014).

1.3 Approach to answering the research questions

My dissertation seeks to answer these four research questions. My general strategy is to first evaluate whether there are any wealth gaps in educational attainment or at specific educational transitions and then to focus on the transitions and processes that appear most crucial for the final wealth gaps in educational attainment. Therefore, the research questions that are asked in the later studies always depend on the results in the prior studies.

In the **first study**, I evaluate whether educational attainment in Germany is stratified by parental wealth, and at which transitions wealth gaps emerge (thus, research questions 1 and 2). Of the four potential pathways presented in the upper left part of Figure 1.1, I only evaluate pathways (3) and (4) and do not, for now, consider wealth gaps in educational achievement or any underlying mechanisms (see upper right part of Figure 1.1). For the analysis, I use data from the ninth grade starting cohort in NEPS and employ a multinomial transition model. I find substantial wealth gaps in children's educational trajectories net of other parental characteristics, particularly at the transition to the tracked secondary school and for the transition into further education after graduation from secondary school. Children in wealthy households are 20% more likely to attend the highest track after primary school and are 40% more likely to enroll in tertiary education. Among children on lower tracks, wealthy children are much less likely to leave the school without a certificate or to not enter a fully qualifying VET afterwards.

Since the first study points to the crucial role of the transition to secondary school for wealth gaps in educational attainment, the **second study** (co-authored with Nora Müller) evaluates in more detail when and how wealth gaps emerge in primary school (research questions 2 and 4). We evaluate wealth gaps in children's academic performance when they enter school, whether these gaps grow throughout primary school, and finally whether wealth gaps in educational transitions can be attributed to differences in academic abilities, or whether wealthy families make different educational decisions net of academic abilities (see the lower left part in Figure 1.1). Employing linear multilevel regressions and logistic regressions on the data of the starting cohort Kindergarten in NEPS, we find that children in wealthy households already score 0.15 standard deviations higher in first grade math tests than children living in households with little wealth. These wealth gaps remain almost constant throughout primary school. Furthermore, children living in wealthy households are 10 percentage points more likely to transition to *Gymnasium*. Around half of this wealth gap in transition rates can be attributed to wealth gaps in competences and performance in school (i.e., ‘primary effects’) and half to different decisions made at given levels of performance (i.e., ‘secondary effects’).

Based on the finding that large wealth gaps in academic competences have already emerged in the first grade, the **third study** (co-authored with Klaus Pforr) evaluates the underlying mechanisms of the academic competence gap by parental wealth and income. In this paper, we focus on pathway 1 of Figure 1.1 (see the lower right part of Figure 1.1) and test the mediators that were only discussed in the second study. Thus, the third study addresses research question 4. For this study, we apply sequential joint mediation analysis to the data of the starting cohort Newborns in NEPS. For the mediation analysis, we consider parental investment, family stress, neighborhood effects, and educational norms and aspirations. We find that at ages as early as 4 to 6 years, children in households with high wealth score up to 0.24 standard deviations higher in math and sciences tests. For grammar test scores, we only find income gaps, but not wealth gaps. In total, all mediators together mediate only 17% of the total wealth gap, but 47% of the income gap.

In the first three studies, net worth is used to measure parental wealth. Although this is by far the most common choice for research on wealth effects (Killewald et al. 2017), several reviewers in the peer-review process questioned this conceptual choice and requested robustness checks of the results, using either alternative wealth measures or other model specifications (see also the supplementary materials to the second and third chapter). However, are similar results to be expected for gross wealth and net worth? And what does it mean when using gross wealth and net worth yields different (or the same) results? Likewise, reviewers questioned whether we had chosen the correct functional form between wealth and children’s educational outcomes and asked for the robustness of the results when allowing other functional forms. Again, there is no clear rule to ascertain which of the different functional forms is to be preferred.

Therefore, the **fourth study** (co-authored with Klaus Pforr and Nora Müller) introduces a new approach to exploring wealth gaps. We propose the use of Generalized Additive Models and jointly evaluating differences by households’ gross wealth and households’ debt to overcome the implausible assumptions made when using net worth to measure wealth. By conducting a simulation study, we show that our approach describes systematic wealth gaps in more detail, and is less likely to overfit to random variation in the data than standard approaches. We then apply our approach to re-analyze wealth gaps in educational attainment in the US using data from the Panel Study of Income Dynamics.[6] In contrast to existing research, we do not find that negative net worth is associated with the worst educational prospects, but rather the combination of low gross wealth and low debt. Children in households with high gross wealth have the best prospects, almost independent of household debt.

[6] Unlike the first three studies, we want to make a methodological contribution to research on the consequences of wealth inequality. Therefore, we decided to re-analyze results for the United States, where wealth gaps in educational attainment are well established in the literature, which was not the case for Germany when we started working on this study.

2. The role of parental wealth in children's educational pathways in Germany

In this paper, I evaluate whether educational attainment in Germany is stratified by parental wealth and at which transitions stratification emerges. I propose a four-stage model to capture the emergence of stratification in the German education system, which is characterized by early between-school tracking: 1) transition to the tracked secondary school, 2) attended track in the last year of mandatory schooling, 3) highest school-leaving certificate, and 4) transition to vocational or tertiary education. Results suggest that stratification by parental wealth emerges at all four stages, and, therefore, accumulates over the stages. Children living in wealthy households are 20% more likely to attend the highest track in fifth grade and to obtain the highest school-leaving certificate and are 40% more likely to enroll in tertiary education compared to children at the bottom of the wealth distribution. Furthermore, parental wealth seems to be particularly effective in preventing negative outcomes like leaving school without a certificate or not finding a fully qualifying vocational training. Among those who do not obtain the formal requirements to enroll in tertiary education, those with wealthy parents are more likely to start dual vocational training. [7]

[7] A slightly different version of this chapter was published in *European Sociological Review*: Dräger, Jascha. 2022. "The Role of Parental Wealth in Children's Educational Pathways in Germany." *European Sociological Review* 38(1):18–36. doi: 10.1093/esr/jcab027.

2.1 Introduction

Recent research shows that parental wealth is an important determinant of educational attainment (Hällsten and Pfeffer, 2017; Karagiannaki, 2017), net of other characteristics of socioeconomic status (SES). This has important consequences for the intergenerational reproduction of wealth: About a quarter of the association between parents' and children's wealth in the US can be attributed to children's educational attainment (Pfeffer and Killewald, 2017). This issue may become even more relevant in the future as wealth gaps in educational attainment are increasing (Pfeffer 2018), while wealth inequalities are on the rise in most Western countries (Shorrocks, Davies and Lluberas, 2018).

Particularly for the US, researchers found that children of wealthy parents are more likely to graduate from high school, to enroll in and graduate from college, and to complete more years of schooling (e.g., Conley, 2001; Diemer, Marchand and Mistry, 2020; Jez, 2014; Lovenheim, 2011; Pfeffer, 2018; for an overview Elliott III, Destin and Friedline, 2011). Similar results have been found for Germany (Dräger and Müller, 2020; Pfeffer and Hällsten, 2012), Norway (Wiborg 2017), Sweden (Hällsten and Pfeffer, 2017; Hällsten and Thaning, 2018), the UK (Karagiannaki 2017), and developing countries, for instance Brazil and Mexico (Torche and Costa-Ribeiro 2012; Torche and Spilerman 2009). To advance studies in this field, I will evaluate at which points wealth stratification emerges in tracked education systems.

Most of these studies look at years of schooling or specific educational outcomes (e.g., enrolling in college), without considering the previous steps (e.g., graduating from high school). Although this allows us to evaluate the total inequality at this point, it does not allow us to assess at which educational transition the stratification occurred. Are children in wealthy households more likely to attend college because they are also more likely to graduate from high school, or because they are more likely to enroll in college conditional on high school graduation, or both?

Fewer studies examine where social stratification occurs by restricting the sample to those who fulfill the formal requirements to continue education (Conley, 2001; Haveman and Wilson, 2007; Nam and Huang, 2009), or by modeling a series of transitions (Pfeffer and Hällsten, 2012). Conley (2001) and Haveman and Wilson (2007) find social stratification by parental wealth in the US for high school graduation, college attendance, and college graduation conditional on the previous steps. Nam and Huang (2009) get similar results, except for finding no effect of parental wealth on college graduation. Pfeffer and Hällsten (2012) find wealth stratification in the US only regarding high school graduation and conditional college graduation, but not for conditional college attendance. For Sweden, they find a similar magnitude of wealth stratification for graduation from the academic secondary track, participating in tertiary education, and finishing extended tertiary education. For Germany, they had too few observations to identify where stratification occurred.

While this research provides further insights about where stratification by parental wealth occurs, it ignores that not all children fulfill the formal requirements to attend universities. Therefore, an important question remains: What happens to those children who do not achieve the required qualifications to continue to tertiary education? Although it is reasonable to assume that they are affected by parental wealth, existing research mostly focuses on pathways to tertiary education (Biewen and Tapalaga, 2017; Schindler, 2015). Wealth stratification in the educational and occupational trajectories of those who leave this path is yet to be studied.

These questions are particularly relevant in countries with early tracking like Germany, where almost half of the children do not obtain the required secondary school certificate to attend tertiary education. Yet the initial track placement does not determine the final secondary school qualification, as children may change tracks or continue secondary schooling after getting their first certificate. These alternative pathways have become more common in recent years. Furthermore, Germany provides an interesting case study for this research question thanks to its free tertiary education and attractive vocational education and training system.

Two studies on wealth stratification in educational attainment in Germany show that children of wealthy parents already have higher competencies in elementary school and are more likely to transition to the highest secondary school track (Dräger and Müller, 2020) and complete more years of schooling (Pfeffer and Hällsten, 2012). Yet it remains unknown at which points in children's educational career the differences by wealth occur. In the current paper, I aim to fill this gap by tracing the educational pathways of children born in the mid-1990s for more than ten years, and by evaluating the wealth stratification in Germany throughout tracked secondary schooling, as well as the transition to tertiary education or vocational training. By doing this, I contribute to two ongoing strands of research: first, examining the additional effect of parental wealth on the social stratification of educational attainment, and second, evaluating how alternative educational pathways affect social inequality in education. Knowing at which points stratification occurs is essential for effective interventions.

2.2 The role of parental wealth in tracked education systems

Parental wealth may affect educational attainment in two different ways: On the one hand, parental wealth may affect educational attainment indirectly by affecting children's competencies and performance in school (i.e., 'primary effects'). On the other hand, parents' wealth may affect educational decisions, net of differences in performance, by affecting the relative costs, aspirations, benefits, and perceived probability of success (i.e., 'secondary effects'). Both primary and secondary effects will affect educational trajectories, but I am interested in the total differences and do not want to decompose them here. Wealth provides further advantages for children's educational attainment through three functions, which add or substitute for the advantages provided by traditional measures of SES like parental educational, income, or occupational class (Hällsten and Pfeffer, 2017):

First, wealth allows families to buy resources and services (i.e., 'purchasing function') that help children to be more successful in their educational or occupational careers. Parents may use their wealth to invest in their child's competencies (e.g., private tutoring), cover tuition fees, or finance additional years of education. Moreover, children profit from the stable learning environment provided by the homeownership of parents.

Second, children can rely on their parents' wealth to fall back on should they fail in their educational career (i.e., 'insurance function'). Parents already anticipate that they could make further investment in children's education if this should become necessary in the future. For instance, parents know that their wealth may partially compensate for a lack of abilities by investing in private tutoring in case their child struggles in school. Therefore, wealthy families can choose more rewarding albeit riskier educational pathways, even when the prior school performance of the child was average or low. Furthermore, the insurance function of wealth may also have a positive effect on educational attainment by reducing parental stress, thereby increasing parenting quality and children's competencies (Conger and Conger, 2002).

Lastly, wealth fosters pro-educational norms and high educational aspirations (i.e., 'normative function'), as families aim to secure or increase their wealth advantage across generations (Conley 2001). Children may dissave this wealth advantage during longer periods of unemployment or when working in low-paying jobs. Families try to minimize this risk by pushing their children to higher educational attainment. Thus, like families try to avoid status decline with respect to their occupational class (Breen and Goldthorpe, 1997), they also try to avoid status decline with respect to their wealth. Moreover, wealth allows families to act more future-oriented and the outlook of attending university may motivate children, while children in households with no wealth may be discouraged by the fact that financing tertiary education may be problematic (Zhan and Sherraden, 2011).

These arguments originally were derived from the US context. Yet, they also apply to other national contexts, although wealth differences are probably less pronounced in contexts with lower costs of education and more generous welfare states (Pfeffer and Hällsten, 2012). Moreover, most research has only considered wealth stratification of educational attainment at specific ages and did not consider at which transitions these differences arise, although the mechanisms suggest that stratification results from the combination of several stratified transitions. The question of where stratification arises is particularly important in countries with (between-school) tracking, as further alternatives depend on prior educational pathways.

To assess where wealth stratification in educational trajectories occurs and to evaluate whether advantages accumulate, we must look at it from two perspectives. First, we can evaluate whether some groups are more likely to make a specific transition or to get a specific educational degree independently (*unconditional*) of prior educational trajectories. For instance, unconditional stratification of whether children have obtained the school-leaving certificate (B) from the academic track (b) is usually presented as the ratio of the unconditional probability for different groups: $\frac{\Pr(B=b \mid SES=high)}{\Pr(B=b \mid SES=low)}$.

The unconditional stratification of having obtained the academic school-leaving certificate allows us to assess total stratification as a combination of stratified transitions into the tracked system, stratified changes between tracks, and stratified dropout and graduation rates. Moreover, if the unconditional stratification is larger for obtaining the academic school-leaving certificate than for transitioning to the academic track, we can conclude that socially selective transitions took place in between. However, we cannot tell which transitions are socially selective.

Second, we can examine the outcome at one of the stages conditional on the prior educational trajectories, for instance, the initial track in secondary school (A=a):

$$\frac{\Pr(B=b \mid SES=high,\ A=a)}{\Pr(B=b \mid SES=low,\ A=a)}.$$

Thus, we look at social stratification but only among a subset of children on a specific track or with a specific school-leaving certificate. This allows us to single out specific socially selective educational decisions. Looking at the school leaving certificate - separately by the initial track

- allows us to assess stratified graduation rates net of stratification at the transition to the tracked system.

The functions of wealth imply conditional stratification at several educational transitions. Therefore, inequalities accumulate, and unconditional wealth stratification should be larger at later points in children's educational trajectories.

Yet, some mechanisms should be more important for certain educational transitions than for others. The purchasing function of wealth should be particularly important for educational decisions when there are large differences in the financial costs between the alternatives. The insurance function should be most important at transitions to educational pathways with a low probability of success and large negative consequences of failure. Lastly, the normative function should affect all transitions but should be more pronounced for earlier ones. Children become more independent with increasing age and are more likely to make educational choices on their own. Moreover, we could assume that wealthy, future-oriented parents with high educational aspirations will push their children on educational paths that will allow them a smoother transition to tertiary education later.

At which transition exactly inequalities emerge depends on the characteristics of the educational system. In the following, I will look at the German education system. Germany is an interesting case for this analysis because of its early tracking and the vocational education and training system.

2.3 The German education system

A simplified model of the German education system is shown in Figure 2.1. Children are required to stay in school for at least nine years in Germany. Additionally, they are required to be enrolled in some type of schooling or training until they are 18 years old or have a fully qualifying occupational certificate. After four years of schooling, children are tracked based on their abilities and a teacher's recommendation into a tripartite system of secondary schooling (albeit in most federal states parents are not obliged to follow the recommendation). The lowest track (*Hauptschule*) ends after ninth grade, and it prepares students for manual jobs. The middle track (*Realschule*) prepares students for skilled non-manual jobs and ends after tenth grade. The highest track (*Gymnasium*) ends after twelfth or thirteenth grade and prepares students for tertiary education. Additionally, there are schools that do not track students or offer multiple tracks.

Depending on the track that students attend they get a *Hauptschulabschluss* (lowest school-leaving certificate; 'HAS' in Figure 2.1), a *Realschulabschluss* (middle school-leaving certificate; 'RSA' in Figure 2.1), or an *Abitur* (general qualification for tertiary education) after passing their final exams. In schools with multiple tracks or without tracking, students get a *Hauptschulabschluss* and can advance to the higher certificates if their performance grants it. After passing the ninth grade, students can attend different subject-specific vocational-oriented schools ('Vocational School' in Figure 2.1), which however belong to the secondary schools of general education. In addition to the certificates already mentioned, students can obtain certificates here, which give them subject-specific or restricted qualification for tertiary education (*Fachhochschulreife*; 'FHR' in Figure 2.1).

The school-leaving certificate determines which alternatives the students have for their vocational and tertiary education. A broad summary of the available alternatives is given in Table 2.1. Within the VET system, there are three types of training: First, there is the dual system of employer-based vocational training combined with education in school (dual VET). Dual VET usually takes three years and offer vocational credentials in a broad range of jobs from lower-skilled service jobs to high-skilled jobs like bank clerk. Doing a dual VET can be an attractive option even for children with *Abitur* because it offers a salary from the first month and the outlook of a good and stable job afterward. While there are no formal eligibility criteria for most dual VET positions, they are highly competitive (Protsch and Solga, 2016). Qualifications for other occupations can only be obtained in school-based VET (e.g., nurses, kindergarten teachers). Unlike dual VET, school-based VET often requires at least a *Realschulabschluss* and is unpaid. Children under 18 who have left secondary school but are unable to find a dual or school-based VET must attend prevocational training to meet the requirements of compulsory schooling. Prevocational training should serve as preparation for a fully qualifying VET; however, a large share of attendees does not enter a fully qualifying VET afterward.

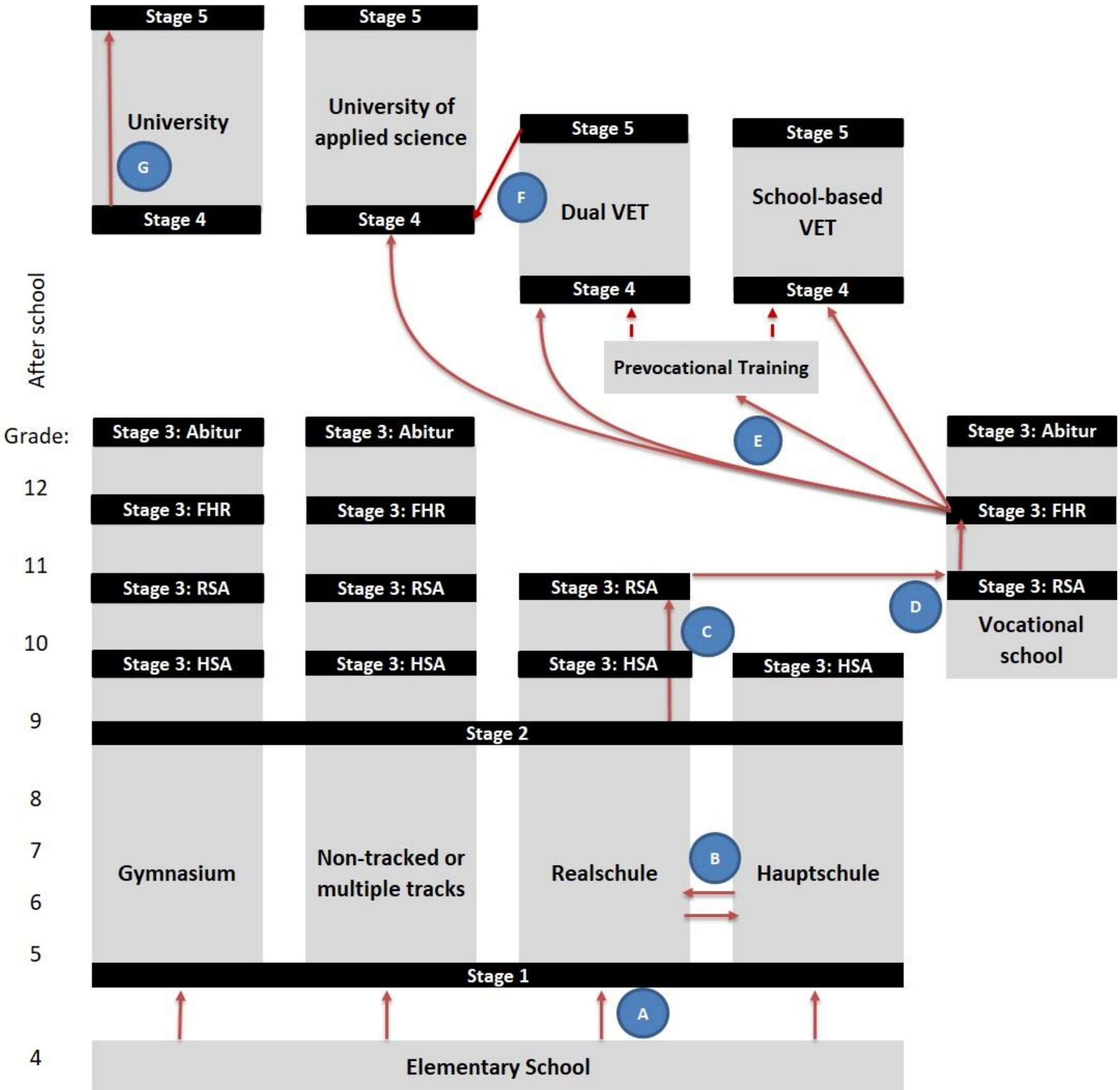
In tertiary education, a distinction is made between (academic) universities and universities of applied science. Academic universities focus more on theoretical aspects and usually require an *Abitur* or subject-specific qualification, while universities of applied science are more vocationally-oriented and require a *Fachhochschulreife*. Some programs like medicine and law are only offered at academic universities. Additionally, dual studies have become more common recently. Like dual VET, dual studies combine practical employer-based training with theoretical training at a university and are paid.

Table 2.1 Summary of vocational and tertiary education

Training	Required Certificate	Duration (Years)	Tuition Fees	Wage	Share of all new vocational training or tertiary education attendees in 2017
Dual VET Firm-based vocational training combined with education in schools	None (but competitive)	2-3.5	None	Depending on sector; on average 900 EUR per month	34%
School-based VET Theoretical vocational training in school	*Hauptschul-abschluss* (more alternatives with *Realschul-abschluss*)	2-3.5	None for public schools (60% are enrolled in public schools)	None (but exceptions for e.g., nurses)	14%
Prevocational Training Preparation for fully-qualifying VET and general education	None (but more alternatives with higher certificates)	1-2	None	None	19%
University Tertiary education with focus on theoretical aspects	*Abitur* or subject-specific qualification	3-5	Small administration fee	None	19%
University of applied science Tertiary education with focus on practical aspects	*Fachhoch-schulreife* or *Abitur*	3-5	Small administration fee	None	13%
Dual Study Firm-based vocational training combined with tertiary education	*Fachhoch-schulreife* or *Abitur* (and competitive)	3-5	Company usually pays the administration fee	Depending on sector and size of company; comparable to dual VET	2%

Numbers are taken from Autorengruppe Bildungsberichterstattung (2018) and Bundesinstitut für Berufsbildung (2019).

Figure 2.1 Simplified model of the German education system and potential points for stratification



- **A** Transition to secondary school
- **B** Mobility between tracks
- **C** Successful attainment of secondary school certificates
- **D** Continuing schooling after the first secondary school qualification
- **E** Transition to VET or tertiary education
- **F** Mobility between VET and tertiary education
- **G** Successful attainment of VET and tertiary education certificates

Note: HSA = Hauptschulabschluss, RSA = Realschulabschluss, FHR = Fachhochschulreife.

2.4 Wealth stratification in the German education system

Social stratification can occur at several points in this highly differentiated education system. This complexity cannot be captured by the sequential model of educational transitions (Mare 1980). Instead, I use an approach similar to Breen and Jonsson's (2000), whose multinomial transition model considers the education system's multiple opportunities and alternative pathways.

Based on the work of Hillmert and Jacob (2010), I distinguish seven points within the German education system where social stratification may happen. Empirical evidence for social stratification exists for all these stages, although the stages are often combined:

A. Transition to secondary school after grade four: children with high-SES parents are much more likely to transfer to *Gymnasium* (Neugebauer 2010);
B. Mobility between tracks: children with high-SES parents are more likely to transfer to a higher track and less likely to transfer to a lower track (P. Blossfeld, 2018; Jacob and Tieben, 2009);
C. Successful attainment of secondary school certificates: children with high-SES parents are more likely to graduate from *Gymnasium* and are less likely to leave *Gymnasium* before graduating (Schindler 2015; Schneider 2008);
D. Continuing schooling after the first secondary school qualification: children with high-SES parents are more likely to upgrade their initial school-leaving certificate (Biewen and Tapalaga, 2017; Buchholz and Schier, 2015);
E. Transition to VET or tertiary education: children with high-SES parents are more likely to enroll in tertiary education (Reimer and Pollak, 2010) and are less likely to not start any fully qualifying training (Protsch and Solga, 2016);
F. Mobility between VET and tertiary education: children with high-SES parents are more likely to enroll in tertiary education after finishing VET (Jacob, Steininger, and Weiss 2013);
G. Successful attainment of VET and tertiary education certificates: children with high-SES parents are less likely to drop out of (academic) universities (Müller and Schneider 2013).

In Figure 2.1, examples of these transitions are represented by the arrows and the blue dots. For all transitions in the stages (A) to (D) all transitions are possible, depending on the performance of the child.

I propose to break down the educational careers into five stages to assess where stratification occurs: (1) the track attended after elementary school (capturing A; in fifth grade); (2) the track in the last grade of mandatory schooling (capturing B; in ninth grade); (3) the highest secondary school qualification when leaving mandatory schooling (capturing C and D); (4) the first vocational or tertiary education track after leaving the mandatory schooling system (capturing E); and (5) the highest vocational or tertiary educational level obtained (capturing F and G).[8] These five stages are presented as black blocks in Figure 2.1.

In the German education system, the purchasing function of wealth should be most relevant after the ninth grade when children are not required to go to school anymore because the alternative of earning money in a dual VET creates direct and salient opportunity costs for continuing general schooling (Schneider 2008). These potential earnings may make leaving school at this stage more attractive for children in households with little wealth. After leaving school, parental wealth may allow children to start programs that are not paid, like enrolling in universities or doing a school-based VET. Furthermore, the purchasing function of wealth could increase the probability of delaying the transition to further training because of the reduced need for an own income and a higher utility of leisure time (Müller, Pforr and Hochman, 2020).

The insurance function should be most relevant for the transition to the highest track in the fifth grade and enrolling in tertiary education for which the probability of failure is comparatively high. While we can assume that this risk affinity also increases the probability of changing to a more ambitious track afterward, this may be pre-empted by risk-affine behavior at the transition to secondary school (Lucas 2001). For the transition after leaving school, the attractive dual VET system in Germany plays an important role: Particularly children in households with little wealth may choose the risk-averse option of a VET and only start tertiary education afterward (Hillmert and Jacob, 2003).

If parents want to ensure that their child has a smooth transition to tertiary education, they must set the foundation for this already at the transition into the tracked system. However, a different argument applies when parents own a business and plan to hand this over to their child: While it requires tertiary education to take over some businesses, e.g., a doctor’s practice, other businesses may require a dual VET, e.g., for handicraft.

Overall, in the first three stages, I expect that children of wealthy parents are more likely to transition to higher tracks and graduate from these, net of other characteristics of the parents and conditional on the

[8] F and G are only discussed for the sake of completeness but cannot be studied empirically with the data at hand.

prior stage. For the transition to vocational and tertiary education, the different functions of wealth predict different outcomes, but overall, wealthy children should be more likely to start a fully qualifying training and less likely to enter directly into the labor market.

2.5 Methods

2.5.1 Data

I use data from the German National Educational Panel Study (NEPS), starting cohort ninth grade (SC 4), for the empirical analysis (H.-P. Blossfeld, Roßbach, and von Maurice, 2011). The target population was all students who attended ninth grade at regular schools in fall 2010. Students were sampled using stratified cluster sampling using different types of schools. Within these strata, schools and classes within these schools are randomly selected, and all students within these classes were invited for participation. The most recent panel wave took place between October 2016 and August 2017. Thus, students who got *Abitur* after 12 years of schooling (in summer 2014) are observed for at least two years after graduating, students who leave school earlier even longer.

NEPS sampled 16,425 children. I exclude 1,361 children who attend schools for special needs, 6,512 children whose parents did not participate in the survey, 2,457 children who did not take part in any of the two most recent waves, and 53 children who are yet to leave secondary school. This leaves 6,042 students for the analysis.

To account for potentially selective non-response and panel attrition, I weight all cases by the inverse of the probability that they are included in the analysis sample. I estimate these probabilities with a Random Forest algorithm (Lee, Lessler and Stuart, 2009) using sampling characteristics, parental characteristics, meta-data about prior interviews, and children's prior educational trajectories. These weights are multiplied with the design weights offered by NEPS. Standard errors are adjusted to the stratified sampling design.

2.5.2 Variables

Tracks in fifth and ninth grade (Stages 1 and 2)

I use the retrospective information on students' track in fall 2006, when they were 11 years old, to measure the attended track in fifth grade. I distinguish between (1) *Hauptschule*, (2) *Realschule*, (3) *Gymnasium*, and (4) non-tracked. When students attend a specific track at a school that offers more than one track they are coded by this track; otherwise, they are coded as non-tracked. I make the same differentiation for tracks in the ninth grade but use the currently attended track in the first wave of the survey.

School-leaving certificate (Stage 3)

I operationalize the highest school-leaving certificate as the certificate that students have when leaving secondary schooling for the first time. I distinguish between (1) no certificate, (2) *Hauptschulabschluss*, (3) *Realschulabschluss*, (4) *Fachhochschulreife*, and (5) *Abitur*.

Activity after school (Stage 4)

I define activity after school as the first fully qualifying training attended for at least six months after leaving secondary school. Among the fully qualifying kinds of training, I distinguish between (1) school-based VET, (2) dual VET, (3) attending university of applied science, (4) attending university, or (5) dual studies. If secondary school graduates did not start a fully qualifying training, I further distinguish between those who (6) enroll in prevocational training or re-entered the secondary schooling system, (7) enter the labor market directly, and (8) do none of the above ('other'). This includes unemployment, civilian or military service, parental leave, and gaps in the data. For the respective conditional analyses, I collapse transitions to the conditionally most frequent transitions, because not all transitions are possible, and others are too rare to analyze separately.[9]

Wealth

All household assets and debts were measured – self-reported by parents – when children were in the ninth grade.[10] I use net worth (assets minus debts) to get results that are comparable with most existing research. Net worth is transformed using an inverse-hyperbolic sine transformation (Friedline, Masa, and Chowa, 2015) to deal with the highly skewed distribution of net worth and negative values.[11] I include quadratic and cubic terms to detect non-linear associations. In a sensitivity analysis, I evaluate the results when using only assets or when allowing heterogeneous effects of assets depending on the level of debts instead of net worth (see supplementary materials G).

[9] A more detailed description of the outcomes for the conditional analysis of activities after school and sequence-index plots are available in the supplementary materials C.

[10] First, parents were first asked whether they possess different kinds of assets: saving books or checking accounts; building loan agreements; life insurances and private pension insurances; fixed-interest securities; other securities such as stocks, funds, bonds; business assets; owner-occupied real estate property; and other real estate property. In the next step, they were asked to report the total values of these assets and their total liabilities

[11] Measuring wealth only once may lead to an underestimation of wealth effects (see also discussion). However, calculations with data of the German Socio-Economic Panel suggest that the net worth of families with 13 to 17-year-old-children remained rather stable between 2012 and 2017 (correlation of IHS-transformed net worth=0.82; N=1,562).

Control variables

To distinguish differences by parents' wealth from other dimensions of parents' SES, which may confound the association between wealth and educational attainment, I control for parents' highest educational level (ISCED), highest occupational class (EGP), logarithmized household income (for the correlations between these variables see supplementary materials B). Moreover, I control for household size, average age of parents, parents' migration background, marital status, and whether the family lives in eastern or western Germany. Like parental wealth, all variables were measured when children were in the ninth grade. I control for household size instead of adjusting net worth to the household size because there is no widely accepted scale for how to equivalize net worth yet.

I generate 50 imputed data sets using categorization and regression trees to deal with missing values in predictor variables (for more information on missings and the multiple imputation see supplementary materials C).

2.5.3 Methods

First, I look at differences by parental wealth unconditional on earlier educational trajectories. Therefore, I apply multinomial logistic regression for each of the four stages and present the results as predicted probabilities for different values of parental net worth (Tables 2.3, 2.5, 2.7, and 2.9). Predicted probabilities are generated for all individuals conditional on their observed values on control variables, and are then averaged.

In a second step, I use conditional analysis to disentangle which specific transitions are stratified by parental wealth. I estimate a separate multinomial logistic regression for each outcome in the first three stages (Tables 2.4, 2.6, and 2.8). For the conditional analysis, it is important to consider selection into the different tracks and certificates: The attended track in the fifth grade will depend on SES and factors that are partially unobserved like abilities and motivation. While most high-SES children will attend *Gymnasium*, even with low abilities, low-SES children will only attend *Gymnasium* if they have high abilities. Therefore, among children in *Gymnasium*, we will observe a different correlation between SES and abilities than among all children. Thus, in an extreme case, we may underestimate the effect of SES in the conditional analysis, because we compare low-SES children with high abilities to high-SES children with average abilities (Cameron and Heckman, 1998; Mare, 1980). In other words: conditioning on the collider 'track in fifth grade' changes the correlation between SES and abilities and introduces endogenous selection bias. I use latent class analysis on observed earlier measures of aspirations, academic self-conception, skills, and marks to approximate these unobserved factors and add the latent classes as control variables to reduce this bias (for more details see supplementary materials D).

2.6 Results

2.6.1 Descriptive statistics

Table 2.2 shows the distribution of variables in the weighted sample. The average net worth of families is 250k EUR. Yet, the distribution of net worth is highly unequal (Gini=0.75), and the median net worth is only 100k EUR. The level of inequality is similar to overall inequality in Germany (Shorrocks, Davies, and Lluberas, 2018). On the one hand, around 10% of parents have more debts than assets and another 8% have zero net worth. On the other hand, the 10% of the wealthiest households (ranging from 470k EUR to 9m EUR) own 59% of the total net worth.

2.6.2 Educational trajectories

Figure 2.2 shows the distribution of tracks in the fifth and ninth grade, highest certificate, and activities after school, as well as the transitions between them. About 16% of students attended *Hauptschule* in the fifth grade, 29% *Realschule*, and 46% *Gymnasium.* The vast majority are still on the same track in the ninth grade. The attended track in the ninth grade is also a very good predictor for the school-leaving certificate, particularly among those students who attend *Gymnasium*. About 85% of those at *Gymnasium* obtain *Abitur*. Of those who attended *Hauptschule* and *Realschule*, about half got the corresponding certificates. However, a substantial share also got higher certificates than that. Leaving school without a certificate is much more common among those attending *Hauptschule*.

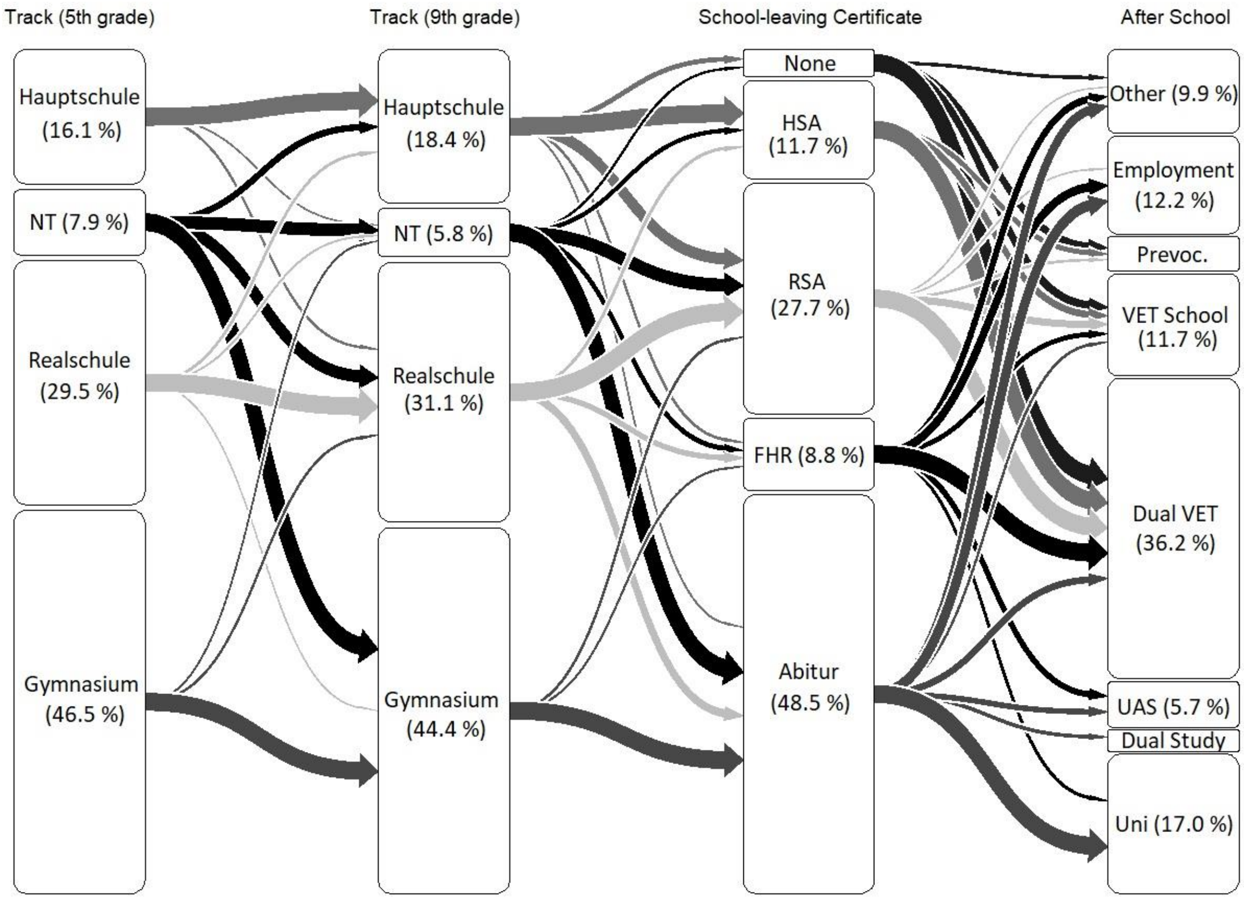
The picture gets more complicated after children leave school. Of those with *Hauptschulabschluss* or *Realschulabschluss*, about two-thirds start a dual VET, and about one-fifth start a school-based VET. Even among those with no certificate, the majority start a fully qualifying VET. Starting a dual VET is also the most common alternative for those with *Fachhochschulreife*. Less than one-fifth of children with *Fachhochschulreife* start tertiary education. Only among those with *Abitur* is enrolling in universities the most common choice. However, we also see that a large share of those with *Fachhochschulreife* or *Abitur* did not start any further training. A reason for this is that about 20% of those children are observed for less than 1.5 years after leaving school. Overall, the sample includes slightly more children in high tracks and more graduates from higher tracks than in the population of this cohort.

Table 2.2 Descriptive statistics

	Mean / Percentile / Proportion	Standard Deviation
Household net worth		
Mean	250,872	1,548,016
10. percentile	0	-
25. percentile	10,000	-
50. percentile	100,000	-
75. percentile	250,000	-
90. percentile	470,000	-
Household income		
Mean	3,527	2,366.193
10. percentile	1,700	-
25. percentile	2,400	-
50. percentile	3,100	-
75. percentile	4,000	-
90. percentile	5,000	-
Parents‘ average birthyear		
Mean	1965	5.022
Parents‘ marital status		
Married	0.800	-
Not married	0.200	-
Parents‘ migration background		
Yes	0.197	-
No	0.803	-
Region		
East	0.111	-
West	0.889	-
Parents‘ highest ISCED		
0, 1, 2	0.063	-
3	0.369	-
4	0.076	-
5B	0.210	-
5A / 6	0.282	-
Parents‘ highest EGP		
I	0.274	-
II	0.300	-
IIIa, IV	0.185	-
IIIb, V, VI, VII	0.241	-
Household size		
2	0.065	-
3	0.220	-
4	0.442	-
5	0.189	-
6 or more	0.083	-

NEPS, SC 4. N=6,042. Weighted and averaged over all imputed datasets.

Figure 2.2 Transition plot of the most frequent trajectories (proportion of categories in parenthesis)



Note: NT = Non-tracked, None (Proportion=3.3 %), HSA = Hauptschulabschluss, RSA = Realschulabschluss, FHR = Fachhochschulreife, Prevoc. = Prevocational Training (Proportion=4.4 %), UAS = University of applied science, Dual Study (Proportion=2.8 %). Only transitions with relative frequencies higher than 2.5% in each departing state are shown. The different tones of grey and black indicate where the arrows stem from.

2.6.3 Stratification by parental wealth

Track in fifth grade (Stage 1)

Table 2.3 shows the predicted probabilities of attending the different tracks for children living in households with zero net worth (10th percentile of the net worth distribution; 'low-wealth children') and children living in households with 470k EUR net worth (90th percentile; 'high-wealth children'), as well as the ratio of these predicted probabilities. Additionally, I present the ratios of the predicted probabilities in Figure 2.3 to show more intuitively where stratification emerges in the educational trajectories. The colors of the boxes imply unconditional stratification and the colors of the arrows show conditional (on the box of departure) stratification.

We already see stratification by parental wealth in the fifth grade. About 50% of high-wealth children attend *Gymnasium*, compared to only 42% of low-wealth children (the difference is statistically significant at p=0.001). Therefore, there are 1.19 times as many high-wealth children attending *Gymnasium* as there are low-wealth children (see lower left box in Figure 2.3). High-wealth children are eight percentage points less likely to attend *Hauptschule* (Ratio=0.60; p<0.001).

Transition from fifth grade to ninth grade (Stage 1 to Stage 2)

Table 2.4 shows the predicted probabilities of the attended track in grade nine by parental wealth, conditional on the track in the fifth grade. While most children stay in their track, the few occurring transitions are stratified by parental wealth. In general, high-wealth children are more likely to transfer to higher tracks and less likely to transfer to lower tracks. However, due to the smaller number of observations, these differences are only statistically significant for those children who were in *Realschule* or *Gymnasium* in the fifth grade. For instance, among those in *Realschule*, only 5.1% of high-wealth children transfer to *Hauptschule*, while 12.6% of low-wealth children do (p=0.004). Thus, the ratio of high-wealth to low-wealth children for this transition is 0.41 (see dark-red arrow from *Realschule* in fifth grade to *Hauptschule* in ninth grade in Figure 2.3). High-wealth children are eight percentage points more likely to stay in *Realschule* (p=0.023) and are five percentage points more likely to stay in *Gymnasium* (p=0.073).

Track in ninth grade (Stage 2)

The differences in transition by parental wealth result in slightly larger unconditional stratification in the ninth grade (Table 2.5). High-wealth children are ten percentage points more likely to attend

Gymnasium (p<0.001). Thus, the ratio of high-wealth to low-wealth children in *Gymnasium* increased slightly from 1.19 in the fifth grade to 1.26 in the ninth grade. Low-wealth children are ten percentage points more likely to attend *Hauptschule* (p<0.001) and three percentage points more likely to be non-tracked (p=0.023).

Transition from ninth grade to school-leaving certificate (Stage 2 to Stage 3)

For the transition from tracks in ninth grade to school-leaving certificate, a similar pattern emerges to the transition from tracks in the fifth grade to tracks in the ninth grade: There are rather few transitions, but these are stratified by parental wealth. High-wealth children are slightly more likely to get a higher certificate and are less likely to get a lower certificate, relative to their track in ninth grade (Table 2.6). This tendency is particularly pronounced among children who were in *Hauptschule*. Of those children, only 6.1% of the high-wealth children do not get any certificate compared to 15.4 % of low-wealth children (p=0.011). High-wealth children are about five percentage points more likely to still get *Fachhochschulreife* or *Abitur* (p=0.086).

School-leaving certificate (Stage 3)

The strong social stratification at the transition from ninth grade to school-leaving certificate among children attending lower tracks results in increased unconditional stratification regarding those who leave school without any certificate (Table 2.7). Low-wealth children are four times more likely to leave school without any qualifications (p<0.001). Yet, the ratio of high-wealth to low-wealth children getting *Abitur* (Ratio=1.22) remains similar to the ratio of high-wealth to low-wealth children attending *Gymnasium* in the ninth grade. High-wealth children are about nine percentage points more likely to obtain *Abitur* (p<0.001).

Transition from school-leaving certificate to activity after school (Stage 3 to Stage 4)

While the school-leaving certificate restricts the set of available alternatives after graduating from secondary school, we also see strong stratification by parental wealth, conditional on these certificates (Table 2.8). For those children who are not eligible for tertiary education (no certificate, *Hauptschulabschluss*, or *Realschulabschluss*) we can observe two important patterns: First, high-wealth children are more likely to start a fully qualifying VET (dual or school-based). Among those with no school-leaving certificate, low-wealth children are 22 percentage points more likely than high-wealth children (p=0.001) to do only prevocational training or other activities; low-wealth children with *Hauptschulabschluss* are 10 percentage points more likely to do so (p=0.017).

Second, high-wealth children are much more likely to start a dual VET. For instance, among those with *Realschulabschluss*, high-wealth children are 19 percentage points more likely to start a dual VET compared to low-wealth children (p<0.001). Low-wealth children are more likely to start school-based VET. Only among those children with Abitur, high-wealth children are slightly less likely to start a dual VET.

High-wealth children with *Fachhochschulreife* or *Abitur* are more likely to enroll in tertiary education. Among those with *Abitur*, high-wealth children are about 1.5 times more likely to enroll in universities of applied science (p=0.063) and 1.7 times more likely to start dual studies (p=0.044). However, conditional on having *Abitur*, high-wealth children are only 2.3 percentage points or 1.07 times more likely to enroll in academic universities (p=0.436).

Activity after school (Stage 4)

The higher probability of high-wealth children enrolling in tertiary education, conditional on having a qualification for tertiary education, further increases the unconditional stratification in stage 4 (Table 2.9). High-wealth children are about 2 percentage points more likely to enroll in universities of applied science or to start dual studies and 4.4 percentage points more likely to enroll in academic universities (p=0.005). Combining the predicted probabilities of attending university, universities of applied science, and dual studies, we get a ratio of high-wealth to low-wealth children of 1.40, compared to a ratio of 1.22 for obtaining *Abitur*.

A different picture emerges for starting a dual VET. Most of the children starting a dual VET have *Hauptschulabschluss* or *Realschulabschluss*. These certificates are more common among low-wealth children. However, due to the higher probability of high-wealth children starting a dual VET, conditional on having these certificates, we see that, unconditionally, high-wealth children are slightly more likely to start a dual VET (Ratio=1.09; p=0.145). Here, the conditional stratification counterbalances earlier stratification regarding the obtained school leaving certificate. Moreover, we see that high-wealth children are less likely to do school-based VET (Ratio=0.60; p<0.001) or only prevocational training (Ratio=0.42; p<0.001).

Importantly, all these stratifications by parental wealth emerge net of other differences by parental SES. For most transitions, differences by parental education or income are larger than differences by wealth. However, for the transition after leaving school, we see that wealth results in other patterns of stratification (see supplementary materials 2.F).

Table 2.3 Predicted probabilities of secondary school track in fifth grade by net worth, unconditional

	10th percentile 0 EUR		**90th percentile 470k EUR**		**p-value** of difference	**Ratio** 90th / 10th percentile
	Pred. Prob.	SE	Pred. Prob.	SE		
Hauptschule	19.589	1.175	11.791	1.080	0.000	0.602
Non-tracked	8.453	0.880	7.542	1.099	0.526	0.892
Realschule	29.791	1.460	30.360	1.817	0.817	1.019
Gymnasium	42.167	1.518	50.307	1.697	0.001	1.193

NEPS SC4. N=6,042. Predicted values based on multinomial regression. The underlying regression estimates are available in the supplementary materials Table E1.

Table 2.4 Predicted probabilities of secondary school track in ninth grade by net worth; conditional on track in fifth grade

Conditional on:	**Outcome:**	**10th percentile 0 EUR**		**90th percentile 470k EUR**		**p-value** of difference	**Ratio** 90th / 10th percentile
Track in fifth grade	Track in ninth grade	Pred. Prob.	SE	Pred. Prob.	SE		
Hauptschule	Hauptschule	90.700	2.429	87.597	2.931	0.441	0.966
	NT, RS or Gym	9.300	2.429	12.403	2.931	0.441	1.334
Non-tracked	Hauptschule	13.062	2.405	11.519	3.499	0.754	0.882
	Non-tracked	29.320	4.433	21.878	4.852	0.262	0.746
	Realschule	22.651	4.080	25.448	5.620	0.670	1.124
	Gymnasium	34.967	4.660	41.155	5.281	0.392	1.177
Realschule	Hauptschule	12.590	1.739	5.141	1.322	0.004	0.408
	Non-tracked	4.622	1.295	4.636	1.915	0.996	1.003
	Realschule	80.371	2.168	88.376	2.430	0.023	1.100
	Gymnasium	2.416	0.742	1.847	0.735	0.579	0.765
Gymnasium	HS or RS	10.043	1.480	7.777	1.396	0.329	0.774
	Non-tracked	5.146	1.800	2.236	0.720	0.128	0.435
	Gymnasium	84.812	2.105	89.987	1.502	0.073	1.061

NEPS SC4. N=6,042. Predicted values based on multinomial regression. HS=Hauptschule, RS=Realschule, NT=Non-tracked, Gym=Gymnasium. The underlying regression estimates are available in the supplementary materials Tables E2.1- E2.4.

Table 2.5 Predicted probabilities of secondary school track in ninth grade by net worth, unconditional

	10th percentile 0 EUR		90th percentile 470k EUR		p-value of difference	Ratio 90th / 10th percentile
	Pred. Prob.	SE	Pred. Prob.	SE		
Hauptschule	22.826	1.295	12.919	1.198	0.000	0.566
Non-tracked	7.487	1.350	4.232	0.799	0.023	0.565
Realschule	30.509	1.827	33.316	2.084	0.283	1.092
Gymnasium	39.178	1.607	49.532	1.865	0.000	1.264

NEPS SC4. N=6,042. Predicted values based on multinomial regression. The underlying regression estimates are available in the supplementary materials Table E3.

Table 2.6 Predicted probabilities of school-leaving certificate by net worth; conditional on track in ninth grade

Conditional on:	**Outcome:**	**10th percentile 0 EUR**		**90th percentile 470k EUR**		**p-value** of difference	**Ratio** 90th / 10th percentile
Track in ninth grade	School-leaving certificate	Pred. Prob.	SE	Pred. Prob.	SE		
Hauptschule	None	15.419	2.315	6.126	2.177	0.011	0.397
	HSA	49.012	2.703	46.259	4.616	0.619	0.944
	RSA	28.497	2.251	35.257	4.170	0.165	1.237
	FHR or Abitur	7.071	1.207	12.358	2.619	0.086	1.748
Non-tracked	FHR or lower	58.600	4.169	51.519	4.444	0.318	0.879
	Abitur	41.400	4.169	48.481	4.444	0.318	1.171
Realschule	None or HSA	8.857	2.118	4.642	1.197	0.133	0.524
	RSA	54.577	2.720	55.641	2.544	0.776	1.019
	FHR	14.395	2.078	14.935	1.965	0.877	1.037
	Abitur	22.170	1.821	24.782	2.283	0.424	1.118
Gymnasium	RSA or lower	10.482	1.353	6.871	1.036	0.057	0.655
	FHR	5.027	0.858	7.073	0.921	0.190	1.407
	Abitur	84.491	1.459	86.056	1.303	0.491	1.019

NEPS SC4. N=6,042. Predicted values based on multinomial regression. HSA=Hauptschulabschluss, RSA=Realschulabschluss, FHR=Fachhochschulreife. The underlying regression estimates are available in the supplementary materials Tables E4.1 - E4.4.

Table 2.7 Predicted probabilities of school-leaving certificate by net worth, unconditional

	10th percentile 0 EUR		**90th percentile 470k EUR**		**p-value** of difference	**Ratio** 90^{th} / 10^{th} percentile
	Pred. Prob.	SE	Pred. Prob.	SE		
None	5.280	0.756	1.330	0.378	0.000	0.252
Hauptschulabschluss	14.357	1.068	8.134	0.877	0.000	0.567
Realschulabschluss	28.473	1.240	27.552	1.520	0.674	0.968
Fachhochschulreife	8.193	0.863	9.862	0.986	0.297	1.204
Abitur	43.696	1.266	53.121	1.533	0.000	1.216

NEPS SC4. N=6,042. Predicted values based on multinomial regression. The underlying regression estimates are available in the supplementary materials Table E5.

Table 2.8 Predicted probabilities of activity after graduating from secondary school by net worth; conditional on school-leaving certificate

Conditional on:	**Outcome:**	**10th percentile 0 EUR**		**90th percentile 470k EUR**		**p-value** of	**Ratio** 90th /
School-leaving certificate	Activity after school	Pred. Prob.	SE	Pred. Prob.	SE	difference	10th percentile
None	Fully-qualifying	73.079	4.471	95.469	4.441	0.001	1.306
	Prevoc. or other	26.921	4.471	4.531	4.441	0.001	0.168
Hauptschul-abschluss	VET school	22.397	2.772	15.514	4.089	0.226	0.693
	Dual VET	59.029	3.076	76.103	4.764	0.008	1.289
	Prevoc. or other	18.574	2.539	8.383	2.692	0.017	0.451
Realschul-abschluss	VET school	29.741	2.431	16.908	2.124	0.001	0.569
	Dual VET	55.396	2.578	74.833	2.375	0.000	1.351
	Prevocational	8.857	1.523	4.632	1.136	0.060	0.523
	Other	6.006	1.147	3.627	1.018	0.190	0.604
Fachhoch-schulreife	VET	42.148	4.018	56.098	4.194	0.035	1.331
	Tertiary	16.155	3.291	19.379	3.220	0.552	1.200
	Employment	27.930	4.854	10.242	2.587	0.006	0.367
	Other	13.766	3.158	14.281	3.539	0.925	1.037
Abitur	VET school	4.319	0.833	2.744	0.477	0.139	0.635
	Dual VET	12.307	1.338	11.383	1.103	0.633	0.925
	University	32.376	2.018	34.642	1.615	0.436	1.070
	UAS	7.247	1.162	10.730	1.095	0.063	1.481
	Dual Study	3.924	0.750	6.584	0.831	0.044	1.678
	Employment	22.380	1.966	18.030	1.275	0.100	0.806
	Other	17.446	1.629	15.888	1.553	0.546	0.911

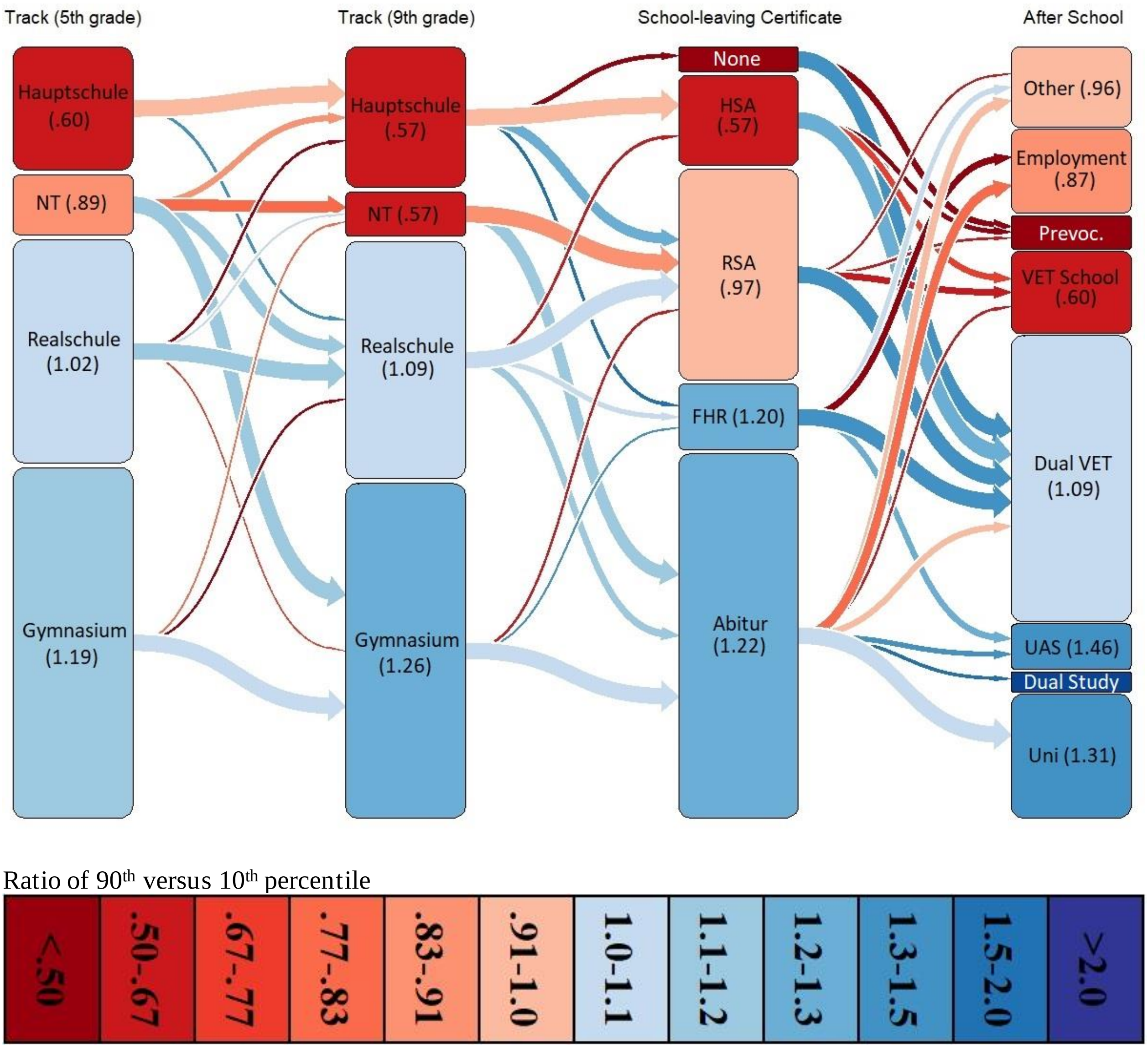
NEPS SC4. N=6,042. Predicted values based on multinomial regression. UAS=University of applied science. The underlying regression estimates are available in the supplementary materials Tables E6.1- E6.5.

Table 2.9 Predicted probabilities of activity after graduating from secondary school by net worth, unconditional

	10th percentile 0 EUR		**90th percentile 470k EUR**		**p-value** of difference	**Ratio** 90th / 10th percentile
	Pred. Prob.	SE	Pred. Prob.	SE		
Other	10.077	0.866	9.620	0.950	0.755	0.955
Employment	13.164	1.042	11.425	0.841	0.263	0.868
Prevocational	6.076	0.671	2.563	0.483	0.000	0.422
VET school	14.796	1.038	8.825	0.781	0.000	0.596
Dual VET	35.107	1.290	38.421	1.513	0.145	1.094
UAS	4.631	0.614	6.754	0.682	0.048	1.458
Dual Study	1.810	0.357	3.667	0.488	0.008	2.026
University	14.339	0.978	18.724	0.993	0.005	1.306

NEPS SC4. N=6,042. Predicted values based on multinomial regression. UAS=University of applied science. The underlying regression estimates are available in the supplementary materials Table E7.

Figure 2.3 Wealth stratification throughout the educational career (ratios of predicted probabilities of the 90th versus 10th percentile of net worth in parenthesis)



Note: NT = Non-tracked, None (Ratio=0.25), HSA = Hauptschulabschluss, RSA = Realschulabschluss, FHR = Fachhochschulreife, Prevoc. = Prevocational Training (Ratio=0.42), UAS = University of applied science, Dual Study (Ratio=2.03).

2.7 Discussion

My findings suggest that the wealth stratification of educational attainment in tracked education systems results from the accumulation of unequal transition rates throughout children's entire educational trajectories. However, in line with prior research using other measures of SES (e.g., Neugebauer and Schindler, 2012), crucial differences already occur at the transition to the tracked secondary schools in Germany. An explanation for this could be that parents already anticipate the future benefits of their wealth at the transition to secondary school, rather than reacting differently to the developments during secondary school. Transferring to *Gymnasium* in the fifth grade and staying there until obtaining *Abitur* may still be considered the easiest path to tertiary education. Ultimately, about half of wealth stratification in university enrollment can be attributed to achieving the required certificate, and half to the decision to enroll conditional on having the required qualification.

Yet the results imply that parental wealth is even more helpful in preventing negative outcomes like leaving school without a certificate or not finding a fully qualifying vocational training. This could indicate that families are especially likely to use their wealth to compensate for the disadvantages of children performing poorly at school (Bernardi and Triventi, 2020; Wiborg, 2017). Wealth seems to enable families to push their children over the low threshold of dropping out of school and thereby maintain all options for a smooth transition to vocational training.

Overall, high-wealth children are less likely to end up without a qualification for tertiary education. However, among those children ineligible for tertiary education, high-wealth children are more likely to start a dual VET. Together, these two tendencies result in dual VET attendance - unconditional on prior educational trajectories - being hardly stratified by parental wealth. Findings like these can only be obtained when doing both conditional and unconditional analysis. What we see here might be an extension of Lucas' (2001) effectively maintained inequality hypothesis: If high-wealth children fail to obtain a quantitative advantage in educational attainment (more years of education), they still manage to enter qualitatively better vocational training programs.

Wealth stratification regarding attendance of tertiary education is of a magnitude similar to the one found in the US context. For example, Pfeffer (2018) finds that children in the top quintile of the wealth distribution are 8.4 percentage points more likely to attend college compared to children in the lowest quintile. This is surprising since tertiary education is far less costly in Germany. The ten percentage points difference by parental wealth regarding attainment of *Abitur* is even larger than the difference for high school graduation in the US. On the one hand, this may be attributable to the early tracking system in Germany. Children in families with little wealth who showed average performance in primary school will likely not transfer to *Gymnasium* after the fourth grade. However, even if children show better academic performance later, they will have a much more difficult pathway to acquire the required certificate for tertiary education in comparison to education systems without early tracking. On the other hand, the dual VET system provides a secure alternative to tertiary education for the transition to the labor market, whereas in the US, alternatives to tertiary education are also rather insecure paths into the labor market.

Some limitations must be considered when interpreting the results. First, some students who attain one of the higher school-leaving certificates participate in the survey for the last time only a few months after leaving school, leading to an underestimation of the prevalence of starting a fully qualifying VET or tertiary education. However, the results barely change when controlling for the time that students have been observed after leaving school. Moreover, in this study, it was not possible to evaluate wealth stratification regarding the successful attainment of VET and tertiary education. Lastly, parental wealth was only measured once in NEPS. Therefore, the wealth measure is potentially imprecise and does not capture changes over time, which probably leads to an underestimation of stratification by wealth (Mazumder 2005).

To give recommendations on how to reduce inequality in educational attainment, we need not only to know where stratification occurs but also which mechanisms drive it. The results here give some hints: The insurance function of wealth may imply that children in less wealthy families make risk-averse decisions and do not attend higher tracks despite good academic performance. However, I do not find that they catch up on the higher certificates later. Furthermore, I do not find support for the demotivating effect of very high wealth as proposed by Müller, Pforr and Hochman (2020).[12]

These results highlight that social stratification in education emerges throughout the entire school career and beyond, and that we, therefore, must examine complete educational trajectories to better understand stratification processes. Looking only at specific transitions or educational certificates might obscure that different processes took place earlier (for unconditional analysis) or ignore these earlier processes (for conditional analysis).

[12]Separating net worth into assets and debts gives further hints on the underlying mechanisms (see supplementary materials G).

3. Wealth stratification in the early school career in Germany

Recent research has established parental wealth as an important determinant of children's educational achievement. However, parental wealth is often ignored in research on social inequality in education, or its influence is only considered at later stages of children's educational careers. Our paper contributes to this research by examining the relationship between parental wealth and (1) children's math competences at the beginning of primary school; (2) the development of children's competences throughout primary school; and (3) children's transition from primary to secondary school. We are looking at Germany, where the early ability tracking may make an early investment in education particularly important. Analyzing data from the German National Educational Panel Study, we find that parental wealth has a distinct association with children's educational outcomes that adds to social disparities by other measures of parents' socioeconomic status (SES). Our results indicate that children in wealthy households have higher competences already in the first grade. This advantage remains stable throughout primary school and translates into a higher probability to attend the highest secondary school track. Moreover, children in these wealthy households are more likely to attend the highest secondary school track, net of differences in competences and performance. Our results imply that ignoring wealth as a component of parental SES leads to an underestimation of the level of social inequality in education in Germany. [13]

[13] A slightly different version of this chapter, co-authored with Nora Müller, was published in *Research in Social Stratification and Mobility*:
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3.1 Introduction

Children's parental social background crucially shapes their educational achievement, thus reproducing social inequality between generations (Blau and Duncan 1967). Studies have found that children of parents with high socioeconomic status (SES) have on average higher competences and show better performance in school than children with low SES (Bradley and Corwyn 2002). As a consequence of their better performance, they are more likely to make more ambitious educational decisions (i.e., primary effect of social origin) and they are more likely to receive higher educational degrees. Yet, children of parents with high SES make more ambitious educational decisions even when they have the same competences and school performance as children of parents with low SES (i.e., secondary effect of social origin) (Boudon 1974; Jackson 2013).

To approximate parental SES, researchers usually use measures of parental education, income or occupational class. However, recent research on the United States, Sweden and Norway suggests that parental wealth should be added to the existing measures comprising parental SES, to better capture social inequalities in education (Elliott and Sherraden, 2013; Hällsten and Pfeffer, 2017; Pfeffer, 2018; Wiborg, 2017). Ignoring wealth as a specific dimension of SES may result in an underestimation of social stratification in education.

Wealth possesses specific features that are not captured by traditional measures of SES, but that contribute to social stratification in unique ways. Wealth can stem either from self-accumulation over one's own life-course or from transfers (e.g., inter-vivo transfers or bequests). Unlike earned income, education or occupational status, the accumulation of which generally requires time, effort, and ability, transferred wealth offers access to capital and goods independently of the individual's decisions or their abilities. Because wealth is less volatile than income, it is a more accurate indicator of an individual's or household's long-term consumption potential and capacity to maintain a particular standard of living (Spilerman, 2000). Yet, wealth does not have to be consumed in order to affect behavior. The mere expectation of incoming wealth and the potential use of wealth can impact individual behavior (Brown et al. 2010).

The association between children's competences and their educational performance with parental wealth follows the same pattern as what previous research has found for other measures of parental SES. Children of wealthy parents have higher competences and show better performance in school as compared to children of less wealthy parents. In the United States, children in wealthy households were found to have higher test scores in math than children of less wealthy households (Friedline et al. 2015; Orr 2003; Williams Shanks 2007; Yeung and

Conley 2008). The findings for the association between parental wealth and reading test scores are, however, inconsistent (Elliott et al. 2011). For Sweden, Hällsten and Pfeffer (2017) found a substantial positive association between parental wealth and children's grade point average (GPA) in the ninth grade. Wiborg (2017) observed the same for Norway. Cesarini, Lindqvist, Östling, and Wallace (2016), however, found no association between lottery wins and children's competences or GPA in Sweden. This last finding suggests that wealth may have different impacts on children's educational outcomes, depending on whether children grow up with the knowledge of the existence of parental wealth or not (Hällsten and Pfeffer, 2017, p. 331).

Additionally, parental wealth has been found to be associated with more ambitious educational decisions and higher educational attainment. Research on the United States showed that children of wealthy parents were more likely to attend college as compared to children with less wealthy parents (Conley 2001; Jez 2014; Pfeffer 2018; Zhan 2006). In Sweden, children of wealthy parents were also more likely to attend and graduate from academic secondary school tracks and to choose tertiary fields of study, which are associated with higher earnings (Hällsten and Pfeffer, 2017; Hällsten and Thaning, 2018). In the only study on Germany, Pfeffer (2011) analyzed the effect of parental wealth on children's educational attainment measured as the number of years of schooling attained. He found a positive and statistically significant association between parental wealth and children's educational attainment. While parental education shows the highest partial correlation with children's educational attainment, the correlation with parental wealth was of similar magnitude as the correlations with income and occupational class.

The relationship between parental wealth and children's educational outcomes can be expected to become even more relevant in the future, given that wealth inequality has grown during the last decades in most Western countries (Piketty and Zucman 2014). Yet, important research gaps remain. First, there is a lack of research in countries other than the United States, Norway, and Sweden. The results for these countries are probably not generalizable to most other countries because of different educational and welfare state systems.

Second, there are few studies on the relationship between parental wealth and children's early educational outcomes. But past research has shown that social stratification of competences emerges already for young children (Feinstein 2003; T. Linberg et al. 2019) and that early investments in competences are more effective than later ones (Cunha and Heckman 2008).

With regards to parental wealth, research has not yet shown when social disparities emerge, nor how these develop throughout the early years of schooling.

Third, most existing studies on wealth stratification in education looked either at performance in school or test scores or at educational decisions. Therefore, they cannot differentiate between primary and secondary effects of parental wealth or they only hinted at this differentiation (Hällsten and Pfeffer 2017; Huang et al. 2010). Policy implications, however, would differ depending on whether primary or secondary effects are more relevant for children's educational outcomes.

In this paper, we aim to make two contributions to reduce these research gaps: First, we assess the association between parental wealth and early educational outcomes in an institutional context with an early and important educational decision, namely the transition to different secondary school tracks after elementary school in Germany. This early tracking may make an early investment in education particularly important. Within this context, we examine the relationship between parental wealth and (1) children's competences[14] at the beginning of primary school; (2) the development of competences throughout primary school; and (3) children's transition to secondary school.

Second, we integrate wealth stratification in the transition to secondary school tracks in the framework of primary and secondary effects, both theoretically and empirically.

3.2 The German context

3.2.1 Educational system

Similar to Scandinavian countries and in contrast to the United States, most children in Germany attend the public education system, which is free from tuition fees. Financial resources of schools are more equally distributed in Germany as compared to the United States as schools are funded centrally by the federal states and not by taxes levied in the municipality. German citizens enjoy a more generous social security system than their American counterparts. Just like in the Scandinavian countries, in Germany private institutionalized education is of limited importance. Based on these characteristics, we expect a weak association between parental wealth and children's educational outcomes in Germany.

[14] In line with the OECD (2013), we understand competences to 'refer to the ability or capacity of an agent to act appropriately in a given situation' (p. 19), especially to someone's proficiency in performing certain tasks. In this sense, competences can be used interchangeably with skills.

However, the early tracking in the German educational system may magnify the effects of parental wealth on educational outcomes for young children. In the majority of German Federal States, after only four years of schooling, children are tracked based on their academic abilities into a tripartite system of secondary schooling. The least advanced track, *Hauptschule*, is nine grades long, and it prepares students for manual jobs. *Realschule* is the intermediate track. Ten grades long, it prepares students for skilled non-manual jobs. The most advanced track, *Gymnasium*, is twelve or thirteen grades long, and it is the only track that offers students immediate access to tertiary education. Schools usually offer one of the three tracks. Additionally, there are comprehensive schools, which combine different tracks (*Gesamtschule*).[15]

Teachers give individual track recommendations in the fourth grade based on the student's marks and the teacher's subjective evaluation of the children's academic abilities. In most Federal States, these recommendations are not binding and parents' decisions regarding which secondary school track to send their children may deviate from the teacher recommendation. In the Federal States where track recommendations are binding, children can still attend a higher track than the one recommended by the teacher, but only if they pass an entrance examination. Although it is theoretically possible for students to change tracks, these changes occur rarely, particularly changes to more advanced school tracks (Blossfeld 2018; Tamm 2007). Therefore, the initial secondary school track has major implications for access to higher education and the students' later professional career.

In contrast, tracking in Sweden starts after grade nine and there is no between-school tracking in the United States. Compared to Sweden, the United States and most other countries, the German educational system is very rigid and possesses a high level of institutional stratification (Glaesser 2008). In contrast to the considerations we made above, the early tracking in the German educational system might make parental wealth an important determinant of early educational outcomes in Germany.

3.2.2 Distribution of wealth

In 2018, the mean household gross wealth in Germany was about 215,000 USD, the median was about 35,000 USD. The mean net worth (assets minus debts) was 184,000 USD. These values are low compared to other European countries and the United States. The level of wealth inequality in Germany (Gini: 0.82; share of the top 10% of wealth: 58%) is higher than in

[15] In the school year 2016/17, 34 % of fifth-graders attended a *Gymnasium*, 21 % a *Realschule*, 10 % a *Hauptschule* and 31 % a *Gesamtschule* (Statistisches Bundesamt 2018:13).

Norway (0.79; 50%) but lower than in Sweden (0.87; 67%) and the United States (0.85; 77%) (Shorrocks et al. 2018). Yet, compared to most other European countries, wealth inequality is high in Germany. One reason for this may be that large economic differences persist between East (the former German Democratic Republic) and West Germany. During the time of the German Democratic Republic (1949-90), almost no private capital property existed and the average household wealth is still much lower in East Germany than in West Germany.

The lower end of the net worth distribution in Germany is comprised of 7% of adults with negative net worth and about 20% of adults with zero net worth (Grabka 2015:383). At this point, it is important to consider the ambivalent nature of debts (Hällsten and Pfeffer 2017:342). Having large amounts of debt may indicate economic deprivation, but it can also be an indicator of high economic potential. In order to obtain substantial credit, households usually have to provide proof of financial securities, and therefore, assets and debts are usually positively correlated (Brown and Taylor 2008). In Germany, this requirement is much stricter as compared to the United States.

The asset portfolio of all but the wealthiest households is characterized by little variation. The wealth of the households at the lower end of the gross wealth distribution consists mostly of domestic appliances and vehicles. The asset of highest value in the average German wealth portfolio is self-occupied residential property, which accounts for more than 60% of the total gross wealth (Grabka and Westermeier 2014). About 40% of all German households possess self-occupied residential property. Although about half of all adults in Germany possess some financial assets and insurance policies, these account for respectively 16% and 11% of the total gross wealth. The wealthiest households have asset portfolios that are more diverse. These households also typically hold valuable business assets and non-self-occupied real estate (Skopek et al. 2012). In contrast to other countries, in Germany, household wealth has not been substantially affected by the 2008 financial crisis (Grabka and Westermeier 2014).

Typically, wealth has a strong positive correlation with income, education, and occupational class. However, the correlation between wealth and the traditional measures of SES is relatively weak in Germany. The correlation between net worth and income is about 0.30 in Germany (Pfeffer and Hällsten 2012: 21). In comparison, this correlation is 0.35 in Sweden (Hällsten and Pfeffer 2017: 355) and ranges between 0.50 and 0.65 in the United States (Killewald et al. 2017:391). Therefore, excluding wealth in research on social stratification in education in Germany may be more problematic than in other countries because income alone is not a good indicator of a household's economic standing with the correlation being comparatively small.

3.3 Theory

3.3.1 Competence

Based on existing research, four interrelated mechanisms may explain the relationship between parental wealth and children's competences. The unit of analysis in this literature is usually the family.

1) Wealth increases resources for *families' investment* in children. Parents can invest their wealth in the purchase of resources, that foster the competences of their children (Becker and Tomes 1986). These resources include learning materials (e.g., books or educational software) as well as educational institutions (e.g., child-care facilities and private schools). Other resources in which parents can invest in their children's education are activities that stimulate learning, such as participating in extra-curricular activities, hiring private tutoring lessons and also taking part in cultural activities, like attending concerts or visiting museums (Orr 2003). For poor families, wealth may enable these families to meet all basic needs of their children (e.g., nutrition, healthcare, and housing conditions) (Bradley and Corwyn 2002).

2) Wealth reduces *family stress*. Economic hardship causes distress, as well as behavioral problems and marital conflict for parents. This reduces the warmth and quality of parenting, which may subsequently slow the competence development of their children (Conger and Conger 2002). These adverse effects of economic hardship can be softened by wealth because wealth can be used to smooth consumption in periods of economic difficulties. Even when wealth is not consumed, it can create a sense of economic security, thereby reducing family stress.

3) Wealth facilitates *residential segregation*. Wealth enables families to live in affluent neighborhoods or to relocate to neighborhoods where kindergartens and schools have more resources (Pfeffer 2018:1037). Living in these neighborhoods or being enrolled in these institutions may foster children's competence development through positive peer effects or access to higher quality urban amenities (e.g., public parks and libraries) (Owens 2016).

4) Wealth fosters *pro-educational norms and aspirations*. Wealth may create a sense of educational entitlement (Conley 1999, 2001), leading wealthy families to promote pro-educational norms among their children. These norms are likely to increase children's motivation for learning and, thereby, lead to higher educational performance (Hällsten and Pfeffer 2017). The literature proposes three reasons why wealthier parents are more likely

to have pro-educational norms: First, families aim to secure or increase their wealth advantage across generations (Conley, 2001). One way in which families may secure this wealth advantage is through (higher) education and the higher earnings and financial literacy associated with it. Second, families with high economic but low cultural capital might use education as a means to transform or legitimize their economic capital. The need to do so arises from the perception that in meritocratic societies, economic advantages achieved through educational attainment are viewed more positively than those achieved through wealth transfers (Bourdieu and Passeron 1977). Third, wealth allows families to have a more future-orientated attitude, which is correlated with having higher educational aspirations (Shobe and Page-Adams 2001; Zhan and Sherraden 2011a).

We expect parental wealth to affect investment, family stress, place of residence, and educational aspirations additionally to the effects of parents' education, class, and income. Yet, most of these proposed mechanisms are derived from research done in the United States. While we may assume that the mechanisms work similarly in the German context, they may cause less pronounced differences. German households should be less likely to suffer from severe economic hardship compared to households in the United States due to the more generous welfare state. Therefore, fewer families should be restricted in their investments in children or be affected by constant stress. We expect segregation to be a less relevant factor in Germany because educational resources are less dependent on the neighborhood in Germany than in the United States (Pfeffer 2011). Lastly, we assume that future orientation to be less stratified by wealth as education is free of tuition fees.

We expect the early tracking in Germany, however, to strongly alter the association between parental wealth and children's early competences. Early tracking may make parents' pro-educational norms more salient in the first years of schooling and may increase parents' investment in their children's competences to increase their chances of qualifying for the highest secondary school track.

In summary, we expect to find a positive relationship between parental wealth and children's competences in the early school career in Germany. Moreover, we expect that wealth stratification in competences increases throughout primary school. Pro-educational norms may become more salient the closer the children get to the important transition to secondary school. Thus, when children reach those ages, parents may invest more time and money to realize the high educational aspirations they have for their children.

3.3.2 Transition to secondary school

If children in wealthy households have higher competences and perform better in school, they should also be more likely to attend the highest track (i.e., primary effect of parental wealth). Based on previous research on traditional measures of parental SES, we expect children from wealthy families to be more likely to attend this highest track, net of competences and school marks (i.e., secondary effect of parental wealth). Importantly to mention, early educational decisions are more likely to be initiated primarily by the parents, with a less direct influence of the child as compared to later decisions in the child's educational career (Becker and Hecken 2009).

Research in Germany found that secondary effects of parents' education and occupational class account for about 40 to 60% of differences in children's transition rates to the secondary school track (Neugebauer 2010; Neugebauer et al. 2013). By comparison, in Sweden, most of the differences in educational attainment can be attributed to primary effects of wealth (Hällsten and Pfeffer 2017; Hällsten and Thaning 2018), while in the United States, the secondary effects of wealth seem to dominate (Elliott et al. 2011).

Secondary effects of parental SES can be explained by the socially stratified expectations of the costs and benefits of the different educational alternatives (Breen and Goldthorpe 1997; Erikson and Jonsson 1996), or in our case the different secondary school tracks (Becker 2003; Neugebauer 2010). Families compare their expected utility from each educational track and choose the track that maximizes it. The subjective expected utility (SEU) model proposes that the utility derived from attending a track depends on the expected benefits (B) of graduating from the specific track, on the expected probability to successfully complete this track and to obtain the expected benefits (p), and on the expected costs of this track (C). Furthermore, parents are assumed to be risk-averse regarding their current socioeconomic status, which translates into educational decisions aimed at avoiding status decline (SD). Children will experience status decline if they do not find a job with a similar occupational prestige as their parents'. For children whose parents have a high occupational class, status decline will occur with a high probability (q), if children do not manage to graduate from the highest secondary school track (Becker 2003; Breen and Goldthorpe 1997).

Originally, these theories consider the effect of parents' occupational class. We argue that it can be applied in a similar manner to parental wealth. We expect parental wealth to affect the factors of the SEU model systematically and, thus, affect educational decisions:

Wealth, like income, decreases the relative costs (*C*) of schooling. While the direct costs of all school tracks in Germany are similar, the opportunity costs of entering and staying in the highest track are higher because children have to stay in school for more years and cannot earn their living. Wealth allows parents to finance these additional years of schooling without the need for children to earn their living.

Wealth could increase the *p* or reduce its importance for the decision. Before the transition to secondary school is made, wealthy parents are likely to have been able to increase their children's achievement and performance in school by providing them with intellectually stimulating resources. Similarly, wealthy parents may also anticipate the opportunity to invest in children's achievement in the future. For instance, if their child struggles in school because of a lack of specific abilities, wealthier parents can partially compensate for this by investing in private tutoring. Importantly, parents do not actually have to invest their wealth to affect this educational decision. The potential to fall back on their wealth - the insurance function of wealth - may be sufficient to choose a more rewarding but riskier track (Hällsten and Pfeffer 2017). For instance, parents know that they could potentially use their wealth to finance the additional year of school for repeating a grade if necessary. This implies that secondary effects of parental wealth are more pronounced for children with medium or low performance in school because parents of high-performing children can be certain that their child will succeed in the highest track independent of their wealth. A so-called compensatory effect of parental background for low-performing children has been found for parents' occupational class (Bernardi and Boado 2014), education (Neugebauer 2010), as well as wealth (Prix and Pfeffer 2017).

Based on the educational entitlement argument (see section 3.1), we assume that parental wealth increases the *B* of more advanced educational tracks because these tracks can legitimize the advantages gained through economic capital (Bourdieu and Passeron 1977). Moreover, specific asset components of parents' wealth, especially having their own business, may increase the labor market returns for specific educational degrees. For instance, the returns to a medical degree are higher when the child can take over their parents' medical practice.

Wealth can reduce *q* for less advanced educational tracks. This should be true under the assumption that parents seek to avoid status decline with respect to their wealth (Conley 2001). Without obtaining a high educational degree, it is more likely that children will deplete their parents' wealth instead of increasing it.

Parental wealth is thus likely to affect several factors of the SEU model above and beyond the effect of parental occupational class, education, and income. Therefore, we assume that children of wealthy parents are more likely to attend the highest track as compared to children of less wealthy parents, even if these children show similar levels of competences and performance. While most of these considerations for the SEU model are not relevant during the early school career (e.g., opportunity costs only start to become relevant when children are not required to go to school anymore), we assume that parents already anticipate the importance of the initial secondary school track for later educational decisions. Thus, wealth stratification observed at later educational decisions in other countries may be partially shifted to the transition to secondary school in Germany, because of its importance for the educational career of children.

3.4 Data, variables, and methods

3.4.1 Data

We use data from the German National Educational Panel Study (NEPS) (Blossfeld et al. 2011) for our empirical analysis.[16] NEPS provides longitudinal data on educational processes from children's birth until late adulthood by following six different starting cohorts. The NEPS is the only German dataset that includes data about parental wealth and assesses children's competences via standardized tests. This allows us to trace children's competence development and educational transitions using a large number of observations over time. For our analyses, we make use of the kindergarten cohort. The target population of this cohort was children attending kindergarten two years prior to their enrollment in elementary school in Germany in 2010/11. After kindergarten, children are followed throughout primary and secondary school. The sample was extended when children started attending primary school. By the time the most recent panel wave took place (wave seven: 2016/17), most children had reached fifth grade, which means that they had just made the transition to secondary school.

For our analyses, we include all children who participated in all three math tests in primary school and whose parents had participated in the survey at least once. This left our sample with 4,611 children for the analysis of competences (hereafter 'Sample A').

For the analysis of the transition to secondary school, we include all children that had reached secondary school by 2017, excluding those who were attending a special-needs school. If

[16] This paper uses data from the National Educational Panel Study (NEPS): Starting Cohort Kindergarten, doi:10.5157/NEPS:SC2:7.0.0. From 2008 to 2013, NEPS data was collected as part of the Framework Program for the Promotion of Empirical Educational Research that is funded by the German Federal Ministry of Education and Research (BMBF). As of 2014, NEPS is carried out by the Leibniz Institute for Educational Trajectories (LIfBi) at the University of Bamberg in cooperation with a nationwide network.

information on the attended secondary school track is not available, we substituted it with the track in which the parents enrolled their children at the end of the fourth grade. Additionally, the parents of these children have to have participated in the survey at least once. This left us with a sample of 4,572 children for the analysis of the transition to secondary school (hereafter 'Sample B').[17]

3.4.2 Variables

Competence

We operationalize our first outcome of interest using math competence test scores on standardized tests which contained between 22 and 24 items (for details, see Neumann et al., 2013). The tests took place on three occasions: in 2013 when children were enrolled in the first grade; then again in 2014 when children were in the second grade; and finally in 2016 when children had reached the fourth grade. We chose math competence for two reasons. First, previous research showed consistent findings for the relationship between parental wealth and competences only for math (Elliott et al. 2011). Using math competences thus makes it easier to compare our results to those of previous research. Second, only math competences have been measured in the NEPS at least three times throughout primary school, and thus, allow us to study changes over time. However, as a robustness check, we ran our analysis also for test scores in grammar, natural sciences, and reading.

To derive an estimate of the unobserved competence of the children from the test results, we used the weighted maximum likelihood estimates (WLE) provided by NEPS (Warm 1989). We standardized WLEs for the analysis sample to have a mean of zero and a standard deviation of one for ease of interpretation.

Secondary School Track

Our second outcome of interest is the secondary school track attended by children in the fifth grade. We distinguish between the highest track (*Gymnasium*) and all other tracks. We chose this operationalization because *Gymnasium* is the only track common to all Federal States and is the only track granting direct access to higher education.

[17] It is important to note that these two samples differ. Information about secondary school track is missing for some children who participated in all math competence tests and vice versa. We can only use 3,262 children in both analyses. Our substantive results do not change when we run the analyses only with this sub-sample.

Parental Wealth

In NEPS, parental wealth was measured when children were in the second grade during the year 2014. In a first step, NEPS participants were asked whether their household[18] possesses different kinds of assets: savings books and checking accounts; building loan agreements; life insurances and private pension insurances; fixed-interest securities; other securities such as stocks, funds, bonds; business assets; owner-occupied real estate property; and other real estate property. In a second step, participants were asked to report the total value of all these assets and the total value of all their liabilities.[19] When respondents did not report a value, they were asked to pick range categories that capture the values of their assets and debts.

In line with previous research, we use parents' net worth as a measure of wealth. Given that the distribution of net worth is highly skewed, we transformed our variable's distribution using an inverse hyperbolic sine transformation (Friedline et al. 2015). Moreover, exploratory analysis of the distribution of wealth revealed a non-linear association between categories of net worth and our outcome variables. Five polynomials of the transformed net worth were included to approximate this non-linear association, which also helped to reduce the leverage of outliers.

Parental SES and Further Controls

To account for the effect of other measures of parents' SES, we included parents' income, education, and occupational class in our analysis. Income was measured at the household level. We converted this variable into income quintile categories. We use the International Standard Classification of Education (ISCED) to measure parents' education. We use the EGP to measure occupational class. Following Erikson's (1984) dominance coding strategy, we use the highest value of the parents' ISCED and EGP to classify the household.

Furthermore, we control for potential confounders of the association between parents' wealth and children's educational outcomes. On the parental level, we use employment status, family status, mother tongue, and age. On the child level, we use the sex, age, number of siblings,

18 We are most likely underestimating the importance of parental wealth for children who are not living with both of their parents in a household. The absent parent can be expected to invest his or her wealth in the child's education, too.

19 Thus, NEPS uses a similar procedure to assess wealth as, for example, the German Socio-Economic Panel (SOEP), but with less details. Most importantly, NEPS only asks for the total value of all assets and not for the value of the different components and NEPS asks for household wealth instead of individual wealth. The average net worth of households in the SOEP who had a child in elementary school in 2012 is slightly lower than in NEPS but the distribution is similar otherwise.

whether the child lives with both biological parents, migration status, and whether the child lives in East or West Germany.

4.4.3 Imputation of missing data

We applied multiple imputation to deal with missing values. On average, 14% of the independent variables in sample A and 11% of the independent variables in sample B were missing. One reason for this high share of missing values is that parents did not participate in all panel waves. Additionally, parents did not answer all questions or did only provide rough categories regarding their assets, debts and income. Most item non-response occurred for parents' assets (36% missings in sample A, 33% in sample B) and debts (22% missings in sample A, 1 % in sample B).

We imputed missing values using chained equations to reduce the bias caused by systematic non-response and to increase the statistical power of our analysis. We impute all missing values using only cases that have no missing values in the respective dependent variable for our analysis (Von Hippel 2007). Following the approach of Burgette and Reiter (2010), we use categorization and regression trees (CART) for imputation. CART is a nonparametric recursive algorithm that uses binary splits to create groups with maximum intragroup homogeneity and minimum intergroup homogeneity. We stop the algorithm when groups become smaller than 50 cases (Aßmann et al. 2017; Burgette and Reiter 2010). Using CART for multiple imputation has the advantage that the algorithm finds the best predictors among all potential covariates, including non-linear patterns and interactions. Imputation values are drawn from the terminal nodes of the trees. This means that we replace missing values using values that have been observed for other households with similar characteristics. In our imputation model, we include all the covariates that we will use in our analyses. We also include time-varying control variables measured in 2015 and 2017, the variables measuring the existence of different kinds of assets, results of other competence tests, and the meta-data about the interviews to get plausible imputations. If information about the range categories about assets, debts or income is available and the imputed values fall outside these specified ranges, we set the imputed values to the lower or upper limit of the category. We create 100 imputed data sets and report average across all imputed datasets and apply Rubin's rules to obtain standard errors in the results section (Rubin 1987).

4.4.4 Methods

We estimate two separate models: one for the association between parents' wealth and children's test scores in math (using sample A) and one for the association between parents' wealth and children's secondary school track (using sample B). Given that our data consists of repeated measures on the child's competence, we estimate a generalized linear mixed model with random-effects for the child to evaluate the association between parental net worth and children's competence development. To predict a child's math competence, we include parental net worth and the control variables mentioned above. We also include an interaction term between year and parental net worth in order to examine whether the association between net worth and test scores varies over time.

Second, to assess the association between parental net worth and secondary school track, we apply two logistic regression models. Here, the outcome variable captures whether the child attends a *Gymnasium* or not. In a first step, we include parental net worth and all control variables. For all time-varying variables, we use the values measured in 2016. In a second step, we add math and reading competences and marks in math and German in the fourth grade to assess secondary effects of parental wealth. We present our results as the predicted probabilities to attend a *Gymnasium.* Predicted probabilities are generated for all individuals conditional on their observed values on control variables and are then averaged. Contrary to logistic regression coefficients, predicted probabilities are comparable across nested models and allow us to estimate the relative importance of primary and secondary effects (Breen, Karlson, and Holm 2018).

3.5 Results

3.5.1 Descriptive statistics

Table 3.1 shows the distribution of all the variables used in our analyses. The first three columns show the summary statistics of the variables used in the analysis of test scores (sample A), separately for each year in which a test in math took place. In sample A, parental net worth ranges from -3.75m EUR to 195m EUR, with the second-highest value being 16m EUR. The mean of net worth in sample A is 195k EUR and the median is 100k EUR. About 9% of the households in sample A have a negative net worth, 6.5% of the households have a net worth of exactly zero. Only 6.2% of the households report net worth above 500k EUR (for a more detailed picture of the net worth distribution see Figures S1 and S2 in the online supplements). The Gini coefficient of net worth in sample A is 0.70 and the wealthiest 10% of the households hold around 48% of the total net worth. Thus, net worth is more equally distributed in our sample as compared to the overall German population. Moreover, we see that household income increases and parents move into higher occupational classes over the years.

The last column shows the summary statistics of the variables used in the analysis of *Gymnasium* attendance (sample B). The average net worth is higher than in sample A (mean: 246k EUR; median: 109k EUR) and net worth is more unequally distributed (Gini: 0.74; share of wealthiest 10%: 56%) because of selective panel attrition. Additionally, there is a higher social selectivity in Sample B, with more highly educated parents and parents in higher occupational classes as compared to Sample A.

Table 3.1 Descriptive statistics

	2013	Competence 2014	2016	Track 2016
Math competence	0.000	0.000	0.000	0.000
Gymnasium	-	-	-	0.617
Net worth	195000	*constant*	*constant*	246000
HH income	3930	4404	4573	4852
No full time employment	0.051	0.051	0.074	0.066
Number of siblings	1.404	1.417	1.416	1.370
Birthyear of parents	1973	*constant*	*constant*	1973
Birthyear of child	2006	*constant*	*constant*	2006
Living with biological parents	0.838	*constant*	*constant*	0.861
Mothertongue: German	0.841	*constant*	*constant*	0.862
East	0.141	*constant*	*constant*	0.106
Girl	0.517	*constant*	*constant*	0.511
Income quintile				
1. Quintile	0.174	0.182	0.180	0.160
2. Quintile	0.146	0.123	0.206	0.197
3. Quintile	0.254	0.277	0.159	0.150
4. Quintile	0.197	0.189	0.202	0.209
5. Quintile	0.229	0.228	0.253	0.283
Highest ISCED				
2 or less	0.042	0.043	0.027	0.020
3	0.270	0.273	0.263	0.234
4	0.093	0.094	0.093	0.092
5B	0.211	0.209	0.216	0.211
5A	0.323	0.321	0.341	0.372
6	0.060	0.060	0.060	0.071
Highest EGP				
I	0.353	0.353	0.392	0.410
II	0.310	0.309	0.309	0.318
IIIa, IV	0.153	0.153	0.158	0.147
IIIb, V, VI, VII	0.184	0.184	0.141	0.125
Family status				
married	0.857	0.858	0.848	0.865
divorced or widowed	0.056	0.061	0.075	0.067
single	0.087	0.081	0.076	0.068
Generation status				
Native	0.750	*constant*	*constant*	0.770
First generation	0.021	*constant*	*constant*	0.018
Second generation	0.196	*constant*	*constant*	0.179
Third generation	0.033	*constant*	*constant*	0.033
N	4611	4611	4611	4572
Sample	A	A	A	B

Multiple imputed data (M=100) of NEPS starting cohort Kindergarten. Average values across all imputations. Means for continuous variables and proportions for categorical variables. Categories of categorical variables with more than two values are indented and in italics. '-' means that the variable is not included in the analysis. 'constant' means that value does not change over time.

In line with previous research, we find that the correlations among income, education and occupational class are higher than the correlation of net worth with each of these measures. The rank correlation between net worth and education as well as occupational class is 0.27 and 0.24, while the rank correlation between income and these measures is 0.48 and 0.44 (for Sample A, for all correlations see tables S1 and S2 in the online supplements). The correlation between net worth and income is about 0.36. Thus, we claim that income alone does not fully capture the economic resources of a household.

3.5.2 Math competence

Figure 3.1 shows the predicted values of our random-effects linear regression of math competence in the first, second and fourth grade on parental net worth and the control variables (see Table S3 in the online supplements for the underlying regression estimates).[20] The 95% confidence intervals of the predicted values are indicated by the vertical lines. A math competence level of zero, indicated by the horizontal dashed red line, stands for average math competence. The figure reveals three important findings:

First, there is a distinct association between parents' wealth and their children's math competences in primary school in Germany, even when we control for the traditional measures of parental SES. We find that children in households with zero or small amounts of negative net worth perform worst; their average math test score in the first grade is about 0.10 standard deviations (hereafter SD) below the average test score ($p<0.05$). Children in households with a moderately high net worth (between 100k EUR and 300k EUR) perform best; their average math test score is about 0.05 SD above the average test score ($p<0.05$) in the first grade. Compared to other components of parents' SES, differences in math test scores by parental net worth are of medium size. The difference in math competence between the worst- and best-performing children by parental net worth (0.15 SD) is larger than the largest competence level difference by parents' occupational class (0.09 SD) as well as by parents' income (0.07 SD). However, the strongest predictor of children's math competences in primary school is parental

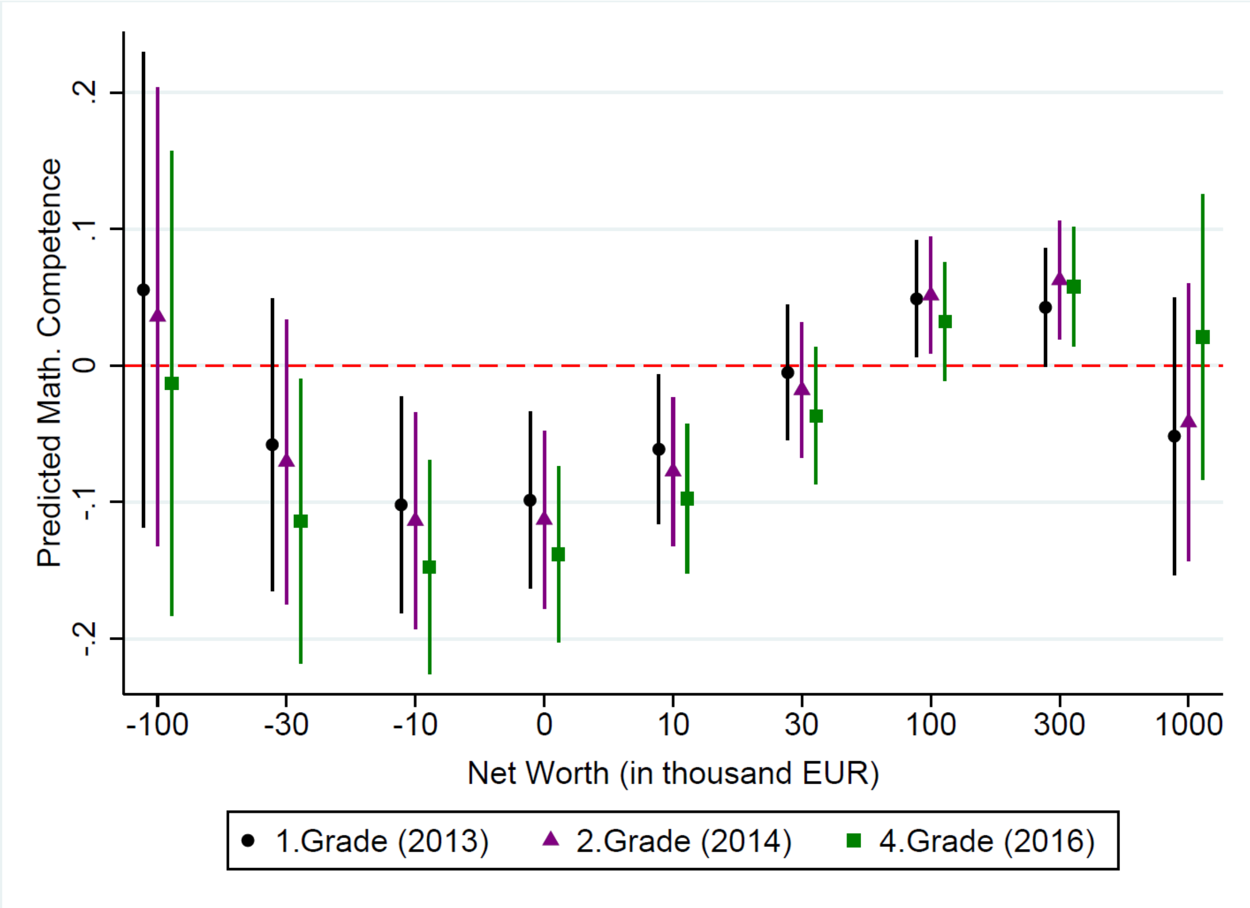
[20] Without adjusting for covariates the differences by parental net worth are about 2.5-times the size of the differences reported here. The functional form of the association remains the same, only the disadvantage of children in very wealthy households disappears (see figure A1 in the appendix). The same holds for the association between parental net worth and transition to Gymnasium.
Some of these control variables could be affected by parental wealth, and, therefore, may intro duce overcontrol-bias to our results. For instance, some households may generate a part of their income through yields of their stocks. Differences in educational outcomes by parental wealth become slightly stronger when we exclude these variables, but the general pattern remains the same.

education. The difference between parents with the lowest education compared to parents with the highest education is more than 0.50 SD (see Table A1 in the Appendix).

Second, the association between parental net worth and children's math test scores is non-linear. Children in households with a high negative net worth show higher test scores than children in households with low negative or zero net worth. For instance, in the first grade, children in households with very high net worth have slightly better than average test scores in math, while children in households with low negative net worth show a below-average test score. For households with a net worth between zero and about 100k EUR, we see a monotone increase in children's test scores with increasing parental wealth. For children in households between about 100k EUR and 300k EUR net worth, we see few differences in test scores by wealth. Children in households with even more net worth perform worse. For instance, in the first grade, the average test score of children in households with a net worth of 1m EUR is about 0.09 SD lower than the average test score of children in households with 300k EUR net worth (p=0.03). However, note that the predicted values for children with high negative or high positive net worth are imprecise.

Third, the association between parental wealth and children's math test scores remains rather constant throughout primary school (see Figure A1 in the appendix for the results without the interaction between net worth and year). Our estimates point towards a slightly bigger disadvantage of children in households with a low negative or low positive net worth in the fourth grade as compared to the first and second grade. The average test scores in math of children in households with zero or low negative net worth are about 0.20 SD lower than the average test scores of children in moderately wealthy households in the fourth grade. The disadvantage of children in very wealthy households as compared to children in moderately wealthy households becomes smaller in the fourth grade. The difference between children in households with 300k EUR and children in households with 1m EUR net worth shrinks from 0.09 SD (p=0.03) in the first grade to 0.03 SD (p=0.41) in the fourth grade. However, these changes are not of noticeable size, nor are they statistically significant.

Figure 3.1 Predicted math competence by parental net worth



N=4,611. Multiple imputed data (M=100) of NEPS starting cohort Kindergarten, Sample A. Horizontal lines show 95%-confidence intervals.

We find similar results for test scores in grammar in the first grade; for natural sciences in the first and third grades; and for reading in the fourth grade (see figure A2 in the appendix). The differences by wealth are slightly smaller for these measures. Yet, these differences are statistically significant with the exception of effects in the competence in natural sciences among first graders.

As already mentioned above, debts have an ambivalent nature, as they can indicate both economic deprivation and economic potential. To find out, whether the non-linear association between net worth and test scores in Figure 3.1 is driven by the ambivalent nature of debts, we separate net wealth into gross wealth and gross debts and run our analyses again (see figure A3 the in appendix). For gross wealth, we find a similar picture as for the positive value of net worth: Children in households with zero or very low gross wealth perform worst. Afterward, test scores increase with higher levels of wealth but the effect levels off for children in moderately wealthy households. For gross debts, we find that children in households with relatively small levels of debt perform substantially worse than children in households with no debts; and worse than children in households with very high amounts of debts.

Lastly, we try to find out, whether the association between wealth and math test scores is driven by a specific wealth component. While we do not have information about the value of the different wealth components, we do know which assets a household possesses, and use this to infer the effects of specific components of wealth. We find that it is especially the small group of children in households without a savings book or checking account who perform substantially worse (-0.24 SD, $p<0.01$), while children whose parents own their house or apartment score on average 0.08 SD higher ($p=0.01$) than children whose parents do not own their home (see Table A2). Financial assets seem to be less relevant. Children in households with fixed interest securities (0.05 SD, $p=0.21$) or those with stocks, funds or bonds (0.05 SD, $p=0.07$) seem to have slightly higher math competences than children in households without these assets.

3.5.3 Transition to secondary school

We expect the wealth-based differences in children's math competence to translate into wealth-based differences in children's likelihood of attending the *Gymnasium*. Figure 3.2 shows the predicted probabilities of attending a *Gymnasium* by parental wealth with 95% confidence intervals indicated by the vertical lines. The estimates presented with black dots and lines are based on a logistic regression of *Gymnasium* attendance on parental net worth and the control variables (see Table S4 in the online supplements for the underlying regression estimates). The blue diamonds and lines show the predicted probabilities when math and reading competences, as well as teacher assigned marks in math and German are controlled for (thus, secondary effects of parental net worth). The dashed red line shows the average probability of *Gymnasium* attendance in our analysis sample (61.7%).

The relation between parental wealth and *Gymnasium* attendance exhibits a similar pattern to the one we found between parental wealth and math test scores. Children in households with low levels of negative net worth or net worth equal to zero have the lowest predicted probability of attending a *Gymnasium*. The predicted probability of children in households with zero net worth is only about 55.7%. Thus, their probability to attend a *Gymnasium* is about 5.5 percentage points lower than the average ($p<0.01$). Children in households with about 150k EUR have the highest chances to attend a *Gymnasium* with a predicted probability of slightly above 64%. The gradient by wealth is rather flat around this part of the distribution.

As for math competence, we see that children in households with high negative net worth and children in households with the highest positive net worth deviate from the linear trend of *Gymnasium* attendance. For instance, the predicted probability to attend a *Gymnasium* of children in households with a net worth of -100k EUR is average. At the other end of the wealth distribution, children in very wealthy households are even slightly less likely to attend a *Gymnasium* as compared to the average. Again, note that the estimates are imprecise at both ends of the wealth distribution.

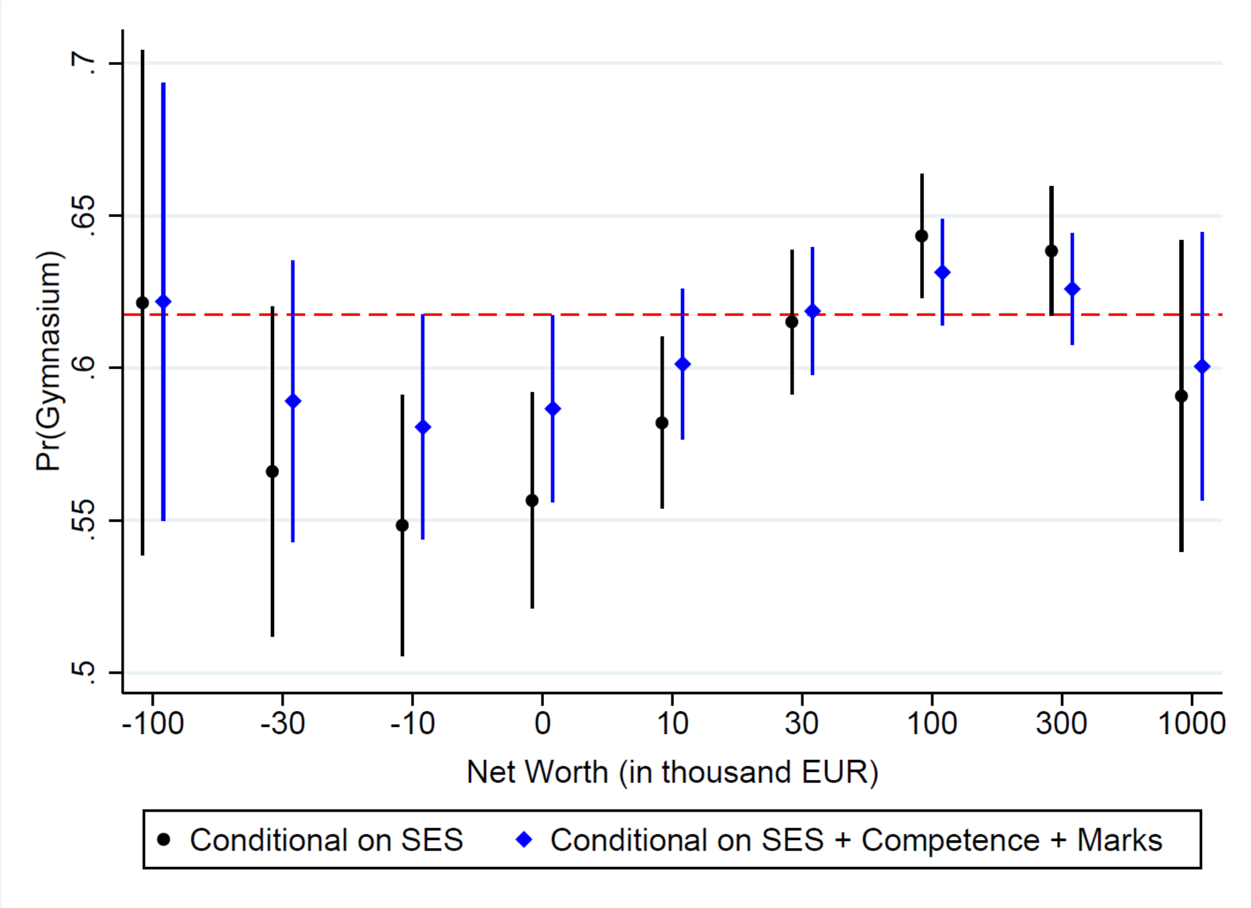
Compared to the difference in *Gymnasium* attendance based on parents' education, occupational class, and income, the difference in attendance rates that is associated with parental wealth is moderate. Again, parental education is by far the best predictor of our outcome (see Table A3). Children whose parents have an advanced research qualification (ISCED 6) are almost 40 percentage points more likely to attend a *Gymnasium* than children whose parents have lower secondary education or less (ISCED 2 or less). Yet, the nine percentage points difference found for parental wealth between about zero and 150k EUR is similar to the difference between upper service class and working class.

The difference in *Gymnasium* attendance by parental wealth shrinks when we control for the competences and marks in the fourth grade. For instance, the predicted probability of children in households with zero net worth increases from about 55.7% to 58.6%, while the predicted probability of children in households with a net worth of 100k EUR decreases from 64.3% to

63.1%. Yet, the 4.5 percentage points difference between these children is still statistically significant (p=0.02). On average, differences in competences and marks account for about half of the total difference in *Gymnasium* attendance by parental wealth. We interpret this as evidence for a distinct secondary effect of parental net worth at the transition to secondary school.

In line with previous research, we find that secondary effects of parental wealth are slightly more pronounced for children with below-average marks. These results suggest that students from households with small negative or zero net worth are less likely to attend a *Gymnasium* in all marks categories, but this relation is more pronounced among students with satisfactory or worse marks (see figure A4 in the appendix). This may indicate that parents of 'poor performing' children may use their wealth to compensate for their children's disadvantage in performance. However, these results should be interpreted with caution because the subgroups become rather small.

Figure 3.2 Predicted probability to attend the highest track by parental net worth



N=4,572. Multiple imputed data (M=100) of NEPS starting cohort Kindergarten, Sample B. Horizontal lines show 95%-confidence intervals.

3.6 Discussion

In this paper, we investigated the association between parental wealth and (1) children's competence, operationalized as test score results in math at the beginning of primary school; (2) the development of children's math competence throughout primary school; and (3) children's educational transition to secondary school, operationalized as attendance to the highest secondary school track.

In line with prior research, we find that even after controlling for traditional measures of SES, parental wealth has a distinct association with children's math competence. While most previous research focused on wealth effects for older children, we found that an association already exists for children in primary school in Germany. These wealth-driven differences in children's math competence might be the result of the early tracking component of the German educational system. Such a system incentivizes parents to invest their wealth early on in their children's competence so as to secure the opportunity for their children to attend the highest secondary school track.

Our results suggest that there is a non-linear association between parental net worth and children's competence. Children in households with high negative parental net worth perform better in math tests than children in households with low negative or zero net worth. A potential explanation for the educational disadvantage of children in households with a low negative net worth (compared to those in households with positive net worth) is that the low negative net worth was caused by having unsecured debts, which can have a negative effect on children's competence (Williams Shanks 2007). Families who have unsecured debts and, hence, struggle to make ends meet, will probably also have trouble in providing a pro-learning environment to their children at home. In additional analyses, we found that it is especially the small group of children in households without a saving book or checking account who perform substantially worse. These children are very likely to suffer from liquidity constraints if their parents do not have these common types of assets.

Children in households with high negative net worth fare somewhat better than children in households with low negative net worth. But this is probably due to these household's high levels of negative net worth as reflection of their good financial position. These households might have secured debts that are backed up by strong financial credit. In order to take out a large loan in Germany, households have to provide proof of a high level of financial securities. Thus, having high negative net worth in Germany may indicate high economic potential instead of economic disadvantage. Hällsten and Pfeffer (2017) find a similar pattern for the relationship between parental wealth and children's GPA in the ninth grade for Sweden.

The best performance is shown by children with medium to high parental net worth. Intriguingly, children in households with very high parental wealth tend to perform worse than children in households with medium or high parental wealth. This contrasts with previous findings for other countries. However, in our sample, there are few households with these high amounts of net worth. Further research is needed to establish whether wealthy households have worse educational outcomes in the early school career, and if so to investigate why this could be the case; or to establish if this is just an artifact in the data.

Contrary to our expectations, we found the association between parental wealth and math test scores to remain stable throughout primary school. One explanation for the stable association may be that the time interval we examine is too short to reveal noticeable changes. An alternative explanation may be that important investments took place before primary school, such as improving the children's learning environment or moving to a neighborhood with better schools. Finally, schooling may also decrease wealth disparities in competences because it provides all students with a standardized learning environment (Downey and Condron 2016).

Investigating the transition from primary to secondary school, we found a small but distinct association between parental wealth and children's probability of attending a *Gymnasium*. Children in wealthier households are more likely to attend a *Gymnasium*. However, like for competences, we see a non-linear association, where children in households with high negative and very high positive net worth deviate from the trend in the middle of the wealth distribution. The differences by parental wealth can be attributed in roughly equal parts to differences in competences and performance by parental wealth (primary effect of parental wealth) and to differences in educational decisions (secondary effect of parental wealth).

Similar to Pfeffer (2011), we found that parents' education is by far the strongest predictor of math competence and *Gymnasium* attendance. Differences by parental wealth are of similar size as differences by parental occupational class or income. Compared to the results found for the US, we find smaller associations between wealth and test scores (Friedline et al. 2015; Yeung and Conley 2008). The differences in secondary school track transition rates by parental wealth in Germany are of a similar magnitude to those found for Sweden (Hällsten and Thaning 2018) and only slightly smaller than the ones found for the United States (Pfeffer 2018). It might be the case that the wealth stratification which was observed at later educational decisions in other countries is partially shifted to the transition to secondary school in Germany, because of its importance for the further educational career of children. Yet, these comparisons should be interpreted with caution because of other differences between the studies and that no prior tracking took place in these countries.

Some limitations should be considered in interpreting our results. Parental wealth was only measured once in NEPS. Therefore, wealth may be measured with error (Goodman and Ittner 1992) and we are unable to detect whether household wealth changed over time. According to data from the German Socio-Economic Panel Study, wealth remained rather stable throughout the five years (2013-17) of our study (Grabka and Westermeier 2014). Yet, some families may have experienced greater wealth increases than others, for instance, families with real estate in urban areas affected by gentrification. Measurement error and treating wealth as time-constant may lead to an underestimation of the impact of wealth in our analysis. However, we assume that short-term changes in wealth are less relevant for educational achievement and attainment as compared to wealth held by families during their children's early childhood years (Cesarini et al. 2016; Hällsten and Pfeffer 2017).

Furthermore, unobserved factors may confound the association between parental wealth and children's educational outcomes. For instance, parents' cognitive and non-cognitive competences probably affect both their levels of wealth and their children's educational outcomes (Doren and Grodsky 2016); but those were not measured in the NEPS. Therefore, our results may be upwardly biased and should not be interpreted as causal estimates. However, we assume that a big part of parents' competences may be captured by their educational achievement, as well as their income. Even if there was a strong partial correlation of these unmeasured confounders with parental wealth and children's test scores, we would observe smaller, but still statistically significant differences by parental wealth. Therefore, despite these limitations, we interpret our results as support for our claim that wealth is a distinct dimension of social stratification that contributes to social inequality in education over and above the traditional measures of parental SES in Germany.

We see two open questions remaining in the study of parental wealth effects of children's educational attainment. First, we only considered the association at an early stage in the children's educational careers. Especially regarding educational decisions, we expect that parental wealth would have a stronger effect at later stages because financial considerations should become more relevant at that time. While the financial costs of attending the different secondary school tracks are similar, there are bigger differences in financial costs when students have to choose between going to university or entering the labor market (Becker and Hecken 2009). Thus, the secondary effects of parental wealth can be expected to increase at later stages of children's educational careers.

Second, more research is needed to uncover the mechanisms that drive the association between parental wealth and children's educational outcomes. In the theoretical part of our paper, we propose several such mechanisms. Family investment, family stress, residential segregation, and educational entitlement can be considered as potential causal mechanisms; and we proposed that differences in family's expected utilities could explain children's educational decisions. We encourage future research to examine these mechanisms. Knowledge of these will allow us to propose policy interventions that can more effectively reduce social inequality in education.

4. The multiple mediators of early differences in academic abilities by parental financial resources in Germany

This paper examines the mediators of differences in academic abilities by parental income and wealth among pre-schoolers in Germany. Families' investment, parental stress and parenting, neighbourhood effects, and parents' educational norms and aspirations are considered as mediators. Unlike most existing studies, we explicitly consider the interdependence of these mediators and, therefore, apply sequential joint mediation analysis. We find that children in income-poor households score up to 0.34 standard deviations lower and children in households with a negative net worth up to 0.24 standard deviations lower in tests of academic ability, even when controlling for a comprehensive set of other familial characteristics. All mediators together explain on average 47% of the differences by income, but only 17% of the wealth differences. Parental investment is the most important mediator, followed by neighbourhood effects. Parental Stress, mother-child interaction quality, and educational norms and aspirations seem to be less relevant as mediators. [21]

[21] A slightly different version of this chapter, co-authored with Klaus Pforr, was published in *Advances in Life Course Research*:
Dräger, Jascha, and Klaus Pforr. 2022. "The multiple mediators of early differences in academic abilities by parental financial resources in Germany." *Advances in Life Course Research* 52 (100476). doi: 10.1016/j.alcr.2022.100476.

4.1 Introduction

There is strong evidence that children of parents with high socioeconomic status have higher cognitive skills, perform better in school, and achieve higher educational degrees. The social stratification of academic abilities occurs even before children enter school, and it is almost never fully redressed (e.g., Feinstein 2003; Linberg et al. 2019; Skopek and Passaretta 2020). These early differences in academic abilities have crucial consequences for children's further cognitive development and long-term consequences for their educational and occupational career.

Families' financial resources play an important role in the early social stratification of academic abilities. Children in families at the top of the income distribution score more than one standard deviation higher in standardised test scores in the US compared to children in families at the bottom of the income distribution (Reardon 2011). These differences get smaller when adjusting for other parental characteristics, or when applying fixed-effects or instrumental variables approaches, but important disparities remain (e.g., Dahl and Lochner 2012; Duncan and Murnane 2011). Yet, income alone is not sufficient to capture the financial resources of families. Recent research shows that parental wealth contributes to differences in academic abilities, even when controlling for income and other familial characteristics. In the US, children in wealthy households were found to display substantially higher cognitive abilities and academic achievement than their less wealthy peers (Diemer, Marchand, and Mistry 2020; Friedline, Masa, and Chowa 2015; Orr 2003; Williams Shanks 2007; Yeung and Conley 2008). However, the size of the wealth effect seems to depend on the domain of academic achievement (Elliott, Destin, and Friedline 2011). For Sweden (Hällsten and Pfeffer 2017) and for Norway (Wiborg 2017) substantial differences in adolescents' grade point average by parental wealth were found. These differences in cognitive abilities and academic achievement later lead to lower educational attainment (Diemer, Marchand, and Mistry 2020; Hällsten and Pfeffer 2017; Karagiannaki 2017). In contrast to these findings, for the UK, Moulton et al. (2021) found only small differences in cognitive abilities of 11-year-old children by parental wealth, once they adjusted for parents' permanent income.

To fully understand and potentially reduce these disparities, knowledge regarding their underlying mechanisms is needed. Important progress has already been made analysing the underlying mechanisms of the differences in academic ability by parental income. Substantial proportions of these academic ability-income differences can be explained by parents' investment in children (i.e., the Family Investment Model; Becker and Tomes 1986), parental stress and parenting behaviour (i.e., the Family Stress Model; Conger and Conger 2002), and neighbourhood differences (Leventhal and Brooks-Gunn 2000).

Despite this progress, crucial research gaps remain three of which we address in this paper. First, we evaluate whether academic ability differences by parental wealth are caused by the same mechanisms as differences by income. Only a few studies have evaluated the underlying mechanisms of wealth disparities in academic abilities (Diemer, Marchand, and Mistry 2020; Orr 2003), even though they are likely caused by other mechanisms than income disparities (Hällsten and Pfeffer 2017).

Second, we test the mediators of academic ability differences in a different institutional context, namely Germany. Most of the theories aiming to explain these disparities are derived from and evaluated in the US context. Yet, it is questionable whether they can be generalised to other countries. Germany provides an interesting case study for this research question. On the one hand, we could expect less pronounced differences by financial resources due to the more generous welfare state and the fact that public resources are less dependent on the neighbourhood one lives in (Pfeffer and Hällsten 2012). On the other hand, educational attainment is strongly stratified and the German system of early ability tracking in school may make early investment more important. Few studies that have explicitly examined the impact of parents' financial resources on early academic abilities in Germany. These studies found that there are disadvantages regarding the academic abilities of children living in income-poor households or households with negative or zero net worth (Biedinger 2011; Schulz et al. 2017). These differences later translate into a lower educational attainment (Dräger 2021; Dräger and Müller 2020; Schneider 2004).

Third and most importantly, we take into account that the different mediators of academic ability differences by parents' financial resources are likely not independent but affect each other causally (e.g., Coley et al. 2021; Layte 2017). Since the different explanations for the disparities come from different disciplines, they are often tested separately, or in comparison to each other. However, as pointed out by the development in causal mediation analysis in the last decade, analysing causally related mediators as if they were independent gives biased results, because mediators early in the causal chain serve as confounders for the effect of other mediators on the outcome. Moreover, common approaches for mediation analysis, like the difference method (Baron and Kenny 1986), assume that there are no interactions between exposure and mediators or among the mediators. Here, we apply sequential joint mediation analysis to overcome these issues (VanderWeele and Vansteelandt 2014; VanderWeele et al. 2014).

4.2 Background

There exist several explanations for the association between parents' financial resources and children's academic abilities. We consider the family investment model, the family stress model, the neighbourhood, and educational norms and aspirations.

4.2.1 Family investment model

The family investment model (FIM) proposes that parents invest their resources (time and money) in the development of their children to increase their children's human capital (Becker and Tomes 1986). These investments increase children's academic abilities. Since families with more financial resources are less constrained in their investments, their children will have higher academic abilities than children in families with fewer financial resources. Investment in several components enhances the cognitive development of children and partially mediates the differences in academic abilities by parents' financial resources: These components include children's basic needs (e.g., housing and food), learning materials, and stimulating activities and services, including organised leisure activities and cultural activities. Empirical studies have identified parental investment as the main mediator of income differences in children's cognitive development for the US (e.g., Davis-Kean 2005; Guo and Harris 2000; Yeung, Linver, and Brooks–Gunn 2002) but also for the UK (Layte 2017; Violato et al. 2011). Similarly, differences by parental wealth are partially mediated by parental investment (Orr 2003).

For Germany, we expect smaller differences in parental investment as households are less likely to suffer from economic hardship because of the more generous welfare state. The few empirical studies on financial resources and investment in Germany have mixed results: Income was found to be associated with more activities and materials promoting literacy, but not for activities and materials promoting numeracy (Kluczniok et al. 2013). Other studies found that higher income is associated with more participation in informal activities like early music education, but not with the frequency of visiting places of cultural learning like concerts or theatres (Mudiappa and Kluczniok 2015).

4.2.2 Family stress model

The family stress model (FSM) proposes that economic hardship causes stress for families, thereby disrupts children's social-emotional and cognitive development. In the first step, economic hardship puts families under economic pressure. This increases parents' emotional stress and the probability of behavioural problems, which may result in feelings of depression and increased conflict between parents. Parental stress leads to less parental warmth, inconsistency in parenting, and less involved parenting. Ultimately, this reduction of interaction quality inhibits cognitive development and causes behavioural problems in children (Conger and Conger 2002).

Existing research usually finds that differences in academic abilities by socio-economic background are mostly mediated through parental investment, while differences in socio-emotional behaviour are mostly mediated through parenting behaviour (Gershoff et al. 2007). However, several studies also found that parental stress and parenting behaviour affect children's cognitive development (e.g., Iruka, LaForett, and Odom 2012; Kiernan and Mensah 2011; Layte 2017; Nievar et al. 2014; Violato et al. 2011). Parental wealth may be particularly important to consider for this process in addition to parental income because debts seem to have a substantial negative effect on psychological distress (Brown, Taylor, and Wheatley Price 2005; Dunn and Mirzaie 2016), while assets create a buffer and reduce stress (Rothwell and Han 2010).

For Germany, research on the mediating role of parental stress and parenting is rare and results are inconsistent. Weinert, Attig, and Rossbach (2017) find a negative effect of income-poverty on mother-child interaction quality. Conversely, Attig and Weinert (2018) find no effect of income on mothers' interaction behaviour with toddlers. Walper and Grgic (2013) find only a negative effect of poverty on activities related to education, but not for interaction quality.

4.2.3 Neighbourhood

Parents with sufficient financial resources can afford to reside in or relocate to neighbourhoods that are better suited to foster their children's development (Owens 2018). On the one hand, the infrastructure and composition of a neighbourhood affect children's cognitive development directly: Children will develop better when there are high-quality public facilities available, when they play with other children with high cognitive abilities (Justice et al. 2011), and when they are not exposed to noise and air pollution (Evans 2006). On the other hand, the neighbourhood affects children's development indirectly by affecting parents: Parents will be more stressed when they are exposed to the threat of crime or when the neighbourhood provides them with few opportunities for recreation (Leventhal and Brooks-Gunn 2000) and will be more likely to invest in high-quality childcare, activities, and services that foster cognitive development when these are close by.

For Germany, recent research shows that families with a high socioeconomic status move to less deprived neighbourhoods when the nearby elementary schools are deemed unsuitable (Oeltjen and Windzio 2019). However, we assume neighbourhood effects to be smaller in Germany because the financial situation of a neighbourhood is less dependent on the financial resources of its residents than in the US.

4.2.4 Educational norms and aspirations

Lastly, some existing studies claim that educational norms and aspirations mediate the effect of parents' financial resources, particularly of parents' wealth. Wealth may create a sense of educational entitlement, leading wealthy families to promote pro-educational norms among their children and to have higher educational aspirations for them (Conley 2001). This can be partially attributed to families trying to secure their wealth advantage throughout generations through (higher) education, and partially to wealth enabling families to invest more in the future in general (Zhan and Sherraden 2011). To conform to these educational norms and high aspirations, children have to perform well in school (Hällsten and Pfeffer 2017), which will be easier if children already have high academic abilities before entering school. In consequence, it can be expected that parents with pro-educational norms and high aspirations will invest more resources and time in their child. Diemer, Marchand, and Mistry (2020) found that parental expectations mediate more than half of the wealth differences in the achievement test scores of 6 to 12-year-old children in the US.

4.2.5 Interdependencies between mediators

The current state of research often considers the aforementioned mediators as being separate and independent causal pathways between parents' financial resources and children's academic abilities. However, as already noted, we assume that investment, stress, parent-child interaction quality, norms and aspirations, and neighbourhood affect each other.

The neighbourhood where a family lives defines the context for other processes that affect children's development (Williams Shanks and Robinson 2013). First, the neighbourhood affects parents' stress. Parents will be more stressed when they are exposed to the threat of crime or when the neighbourhood provides them with few recreational opportunities. Second, parents might to a lesser degree abide by pro-educational norms, if their peers in the neighbourhood value education negatively. Finally, the neighbourhood may constrain investments: Even if parents have the required financial resources for services that foster cognitive development, they cannot invest in them without ready access to these services (Leventhal and Brooks-Gunn 2000).

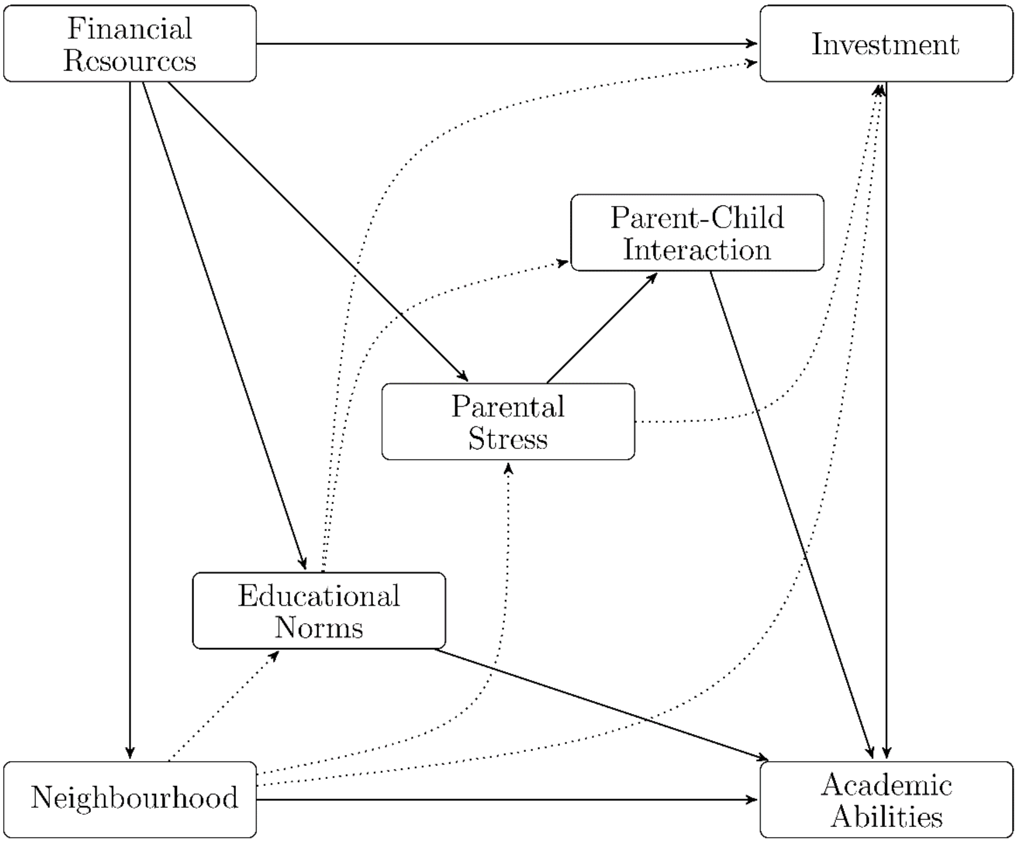
Secondly, parents' educational norms affect their parenting behaviour and investment. We assume that parents with high educational aspirations and a positive attitude towards education will try to implement these attitudes by using parenting styles that foster cognitive development (Davis-Kean 2005) and will be more willing to invest or undertake joint activities with their children (Kim et al. 2015).

Lastly, parental stress affects family investment. Parents with high levels of stress will invest less in their children (Gershoff et al. 2007).

These expected effects among the mediators are presented in Figure 4.1. Solid arrows show the effects as they are expected in the current literature, while dotted arrows show the potential effects between the different mediators that are yet to be examined in detail. The described interdependencies among the mediators result in a chain of mediators, with the neighbourhood as the first mediator and parents' investment as the last mediator. This chain of mediators will be used for the mediation analysis.

Although our structural model is comprehensive, there may be additional paths that we did not consider. For instance, parents with high educational aspirations might be more likely to move to neighbourhoods that provide higher school quality and a better environment for cognitive development (Kim, Pagliara, and Preston 2005). Our model cannot account for these alternative paths.

Figure 4.1 Theoretical path model with interdependent mediators.



4.3 Methods

Data

For our analysis, we use data from the newborn cohort of the German National Educational Panels Study (hereafter NEPS; Blossfeld, Roßbach, and von Maurice 2011). The target population of this cohort sample were children born in Germany between February and June 2012. The data contains information about parents' socio-demographic characteristics and multiple standardised competency tests for children. Most importantly it has rich data on all potential mediators of the effect of parents' socio-economic characteristics and children's academic abilities. At the time of the most recent panel wave (2018, wave seven), the children were six years old. For our analysis, we use all children that had participated in at least one of the competency tests in waves five, six or seven. This leaves us with an analysis sample of 2,377 children out of the initial sample of 3,481 children.

We use the weighting factors offered by the NEPS to account for selective participation in the first wave of the survey and multiply these weights with the inverse of the probability to be included in the analysis sample to account for selective panel attrition. For the estimation of the probability of attrition, we use a categorisation tree (Hastie, Tibshirani, and Friedman 2009; Hayes et al. 2015) on the same variables that were used by the NEPS to estimate weights.

We generate multiple imputations for missing values in parental financial resources, mediators, control variables, and test scores for children with at least one observed test score. We create 50 imputed data sets using categorisation and regression trees (Burgette and Reiter 2010).

Academic abilities

We use the results of all four standardised competency tests that were assessed in the fifth, sixth, and seventh wave of NEPS. We use four different measures of children's academic abilities, assessing their competencies in math, science, and verbal ability, because the effect of parents' financial resources may depend on the domain (Elliott, Destin, and Friedline 2011). For math abilities (measured in wave five, when children were four years old and sixth wave, when they were six years old) and scientific abilities (measured in wave six when children were five years old), we use the weighted maximum likelihood estimates provided by NEPS, which were derived from performances in a standardised test with 20 tasks (Hahn et al. 2013; Peterson and Gerken 2018). Verbal ability is measured in the sixth wave by children's scores in the German adaptation of the Peabody Picture Vocabulary Test (PPVT).

Financial resources: wealth

Parents participating in NEPS are asked to estimate the value of all real estate and financial assets of their household and then to estimate the value of their debts and liabilities. Parental wealth was measured in the third wave when children were two years old. In line with existing research, we use parents' net worth (assets minus debts) as a measure of wealth. In our sample, net worth ranges from -400k EUR to 10m EUR and is with a mean of 310k EUR and a median of 50k EUR strongly right-skewed (see appendix A). We categorise net worth into five categories to capture potential non-linear effects:

(1) Negative net worth / 1. Quintile [-400k EUR; 0 EUR),

(2) 2. Quintile [0 EUR; 20k EUR),

(3) 3. Quintile [20k EUR; 100k EUR),

(4) 4. Quintile [100k EUR; 210k EUR),

(5) 5. Quintile [210k EUR; 10m EUR].

This categorisation corresponds roughly to the quintiles in the weighted data set. The first group is smaller than the other categories (14%) to allow us to differentiate between negative and positive net worth. [22]

Financial resources: income

We use the average of the net household monthly income over the first three waves and equivalise it to the household size using the OECD-modified scale. The reported equivalised household incomes range from 506 EUR to 10,902 EUR per month. Like for parental wealth, we categorise equivalised household income into five categories:

(1) Income-poor / 1. Quintile [506 EUR; 980 EUR),

(2) 2. Quintile [980 EUR; 1,389 EUR),

(3) 3. Quintile [1,389 EUR; 1,694 EUR),

(4) 4. Quintile [1,694 EUR; 2,111 EUR),

[22] We use this parsimonious way to model non-linearities to keep the mediation analysis with multiple mediators comprehendible. With non-linear total effects, there are different indirect effects for each potential wealth (or income) contrast. Additionally, using the five net worth and income categories results in better model fit (AIC) and captures more variance in children's academic abilities than when using linear, quadratic, or cubic specifications for income and net worth.

(5) 5. Quintile [2,111 EUR; 10,902 EUR].

The first threshold corresponds to 60% of the median equivalised household income in Germany in 2013 (Statistisches Bundesamt 2019a). Households below this threshold count as income-poor. As for the categorisation of wealth, this first group (16%) is slightly smaller than the other groups.

Mediator: neighbourhood

We chose mediators and the time-point of measurement (when multiple measures were available) based on our theoretical model presented in Figure 4.1. Whenever possible, we measured the proposed mediators with multiple items and applied factor analysis to items that are supposed to measure latent constructs. The measurements of all mediators are summarised in Table 4.1, including all items used, the wave of their measurement, and the type of factor analysis applied.

We operationalise the quality of a neighbourhood with five variables about the composition of the neighbourhood, like the share of academics, an index of its purchasing power and the unemployment rate. This data was provided by a private marketing firm (Schönberger and Koberg 2017) for the time when the first wave took place. Except for the unemployment rate, all variables were measured on the street-level. Unlike the items assessed in the survey, the neighbourhood variables were not constructed to measure one latent construct. Therefore, we applied (exploratory) principal factor analysis. We extract the first factor to measure the composition of the neighbourhood, which captures most of the common variance of the variables (Eigenvalue=3.21; KMO=0.81).

Mediator: educational norms and aspirations

On the one hand, we use measures of parents' general attitude towards education by applying confirmatory factor analysis (CFA) on items like '*To go to school is a waste of time*' (Cronbach's α=0.56). On the other hand, we consider parents' idealistic aspirations for the school leaving certificate of the child. Here we only distinguish between aspirations for the highest school leaving certificate and all other certificates. Both, parents' attitudes and their aspirations were only measured in the fourth wave.[23]

[23] An earlier measurement of parents' attitudes and aspirations would have been preferable with respect to our theoretical model. With the available measurement of parents' attitudes and aspirations, we have to assume that these attitudes are reasonably time-constant and not affected by parental stress and parenting style. The weak association between parents' attitudes and aspirations with parental stress and parenting style seem to support this.

Mediator: parental stress

We use the mothers' self-reported feelings to measure parental stress. In the second wave, mothers were surveyed about depressive feelings, whether they feel like they are running out of energy, whether they feel restricted by their role as a mother, and whether they feel lonely (Cronbach's α=0.67). We apply CFA to these items.

Mediator: mother-child interaction quality

To measure the interaction quality, mothers were given age-adequate toys and were asked to '*play with the child as you would normally do, if you were alone with the child and have some time to play*'. This semi-standardised play situation was recorded on video and the video material was later rated with respect to different interaction behaviours of mother and child (for more details see A. Linberg et al. 2019). Here, we use the ratings of interaction in the third wave, the last wave that these measures took place. At this point, children were on average 27 months old. We apply CFA on the rating of mother's sensitivity to non-distress, positive attention, emotionality, and sensitivity (Cronbach's α=0.70; Weinert et al. 2016).

Mediator: investment

We measure different aspects of parental investment using three constructs: materials, investment in cultural activities and time investment in joint activities. All items were measured in wave five. For investment in material, NEPS only offers the number of children's books. Time investment is measured by the frequency of different learning-related activities like reading to the child or showing them letters (Cronbach's α=0.57). Investment in cultural activities is measured using four items that assess the frequency of different activities, like visiting concerts or theatres for children (Cronbach's α=0.53). Unlike the time investment, these activities are usually not free of costs for parents. For parental investment in learning-related activities and investment and cultural activities, we apply CFA.

Table 4.1 Measurement of mediators

	Construct	Items	Wave	Loading	Method
Neighbourhood	Neighbourhood Composition	Share of academics	1	0.638	EFA
		Social Status		0.966	
		Probability of default in payment		-0.725	
		Index of purchasing power		0.864	
		Unemployment rate		-0.775	
Educational Norms and Aspirations	Norms	To go to school longer is a waste of time.	4	-0.302	CFA
		Without Abitur you have to feel a little bit ashamed		0.642	
		A high level of education expands a person's horizons.		0.636	
		Education is indispensable to the cultural life of our country.		0.708	
		Students should take the Abitur no matter what the cost.		0.495	
	Aspirations	What school-leaving qualification would you like for the child?	4	-	Single Item
Parental Stress	Parental Stress	How often in the last 4 weeks did you feel depressed or sad?	2	0.655	CFA
		I often feel like I am running out of energy.		0.758	
		I often feel alone.		0.700	
		I am suffering from being restricted to my role as a mother.		0.581	
Parent-Child Interaction Quality	Parent-Child Interaction Quality	Sensitivity to non-stress	3	0.311	CFA
		Stimulation		0.557	
		Positive regard		0.827	
		Emotionality		0.918	
Investment	Materials	Number of children's books	5	-	Single Item
	Cultural activities	Frequency of museum visits	5	0.485	CFA
		Frequency of visiting zoos or wildlife parks		0.414	
		Frequency of attending concerts for children		0.531	
		Frequency of watching theatre plays for children		0.627	
	Time investment	Read out	5	0.441	CFA
		Dealing with letters		0.547	
		Dealing with numbers		0.610	
		Learning rhymes		0.525	

Painting	0.423

NEPS, starting cohort Newborns. N=2,377. Weighted and averaged over 50 imputed datasets. EFA = Exploratory factor analysis; CFA = Confirmatory factor analysis.

Control variables

To get unbiased estimates for the mediation analysis we have to control for all potential confounders between parents' financial resources, mediators, and children's academic abilities. Therefore, we control for parents' highest education (ISCED) and occupational class (EGP), migration status, age, marital status, family structure, number of siblings, child's gender, child's age, and whether the family lives in east or west Germany. Controlling for parental education and occupational class is necessary because we are only interested in the effect of financial resources and not in other advantages that may be associated with high socioeconomic status. All these variables were measured in the first wave. Descriptive statistics of parents' income and wealth and all control variables are provided in Table A1.

Analysis plan

In a first step, we estimate the differences in children's test scores (Math, PPVT, and Science; Y) by parents' financial resources (income and net worth; A) using ordinary least squares (OLS) regressions. In these models, we include both income and net worth[24] and all the control variables (C).

In a second step, we apply causal mediation analysis. In causal mediation analysis, the focus of interest is usually on the natural indirect effects (NIE) and the remaining natural direct effects. NIEs are defined as the difference in an outcome that would have occurred if the individuals had the observed values of exposure (α), but the values of a mediator (M) that would have arisen under a counterfactual level of exposure (M_{α^*}), instead of the observed values for exposure and mediator (M_α): $E[Y_{\alpha M_\alpha} - Y_{\alpha M_{\alpha^*}}]$.

Four no confounding assumptions must hold to get unbiased estimates VanderWeele (2015):

(1) There are no unmeasured confounders of the relation between exposure and outcomes;

(2) There are no unmeasured confounders of the relation between exposure and mediators;

(3) There are no unmeasured confounders of the relation between mediators and outcomes;

[24] A high income may allow households to accumulate more wealth, and, at the same time, returns to investment may generate income. We decided to include both income and net worth in the same model to get conservative estimates for their unique contributions (see Pfeffer 2018 and Moulton et al. 2021 for a similar approach). Total differences are only slightly larger when excluding net worth for the estimation of income effects and vice versa (see appendix E).

(4) There is no mediator-outcome confounder that is affected by the exposure.

If these assumptions hold, estimates can be interpreted as causal effects.[25] Due to the rich set of control variables, we assume that assumptions 1-3 hold. Therefore, we will talk about indirect *effects* from here on. Potential violations of these assumptions are addressed in the discussion.

Unlike assumptions 1-3, assumption 4 also applies to *observed* mediator-outcome confounders. Therefore, only the joint indirect effect via all mediators together and the NIE via the first mediator in the causal chain, here the neighbourhood, are statistically identified (VanderWeele, Vansteelandt, and Robins 2014). The NIEs via educational norms and aspirations, stress, parent-child interaction quality, and parental investment are not statistically identified because there are mediators earlier in the causal chain. On the one hand, we have to control for these early mediators, like the neighbourhood, when estimating the effect of the other mediators on the outcome because the neighbourhood is a confounder of the association between the other mediators and the outcome (e.g., Investment ← Neighbourhood → Academic Abilities). On the other hand, we must not control for the neighbourhood because this would capture a part of the indirect effect of these other mediators (e.g., Financial Resources → Neighbourhood → Investment → Academic Abilities). Either way, the results will be biased.

Therefore, we follow the sequential joint mediation approach by VanderWeele, Vansteelandt, and Robins (2014) and estimate partial indirect effects (PIE) for these mediators. PIEs give us the indirect effects through a specific mediator that bypasses all prior mediators (Steen et al. 2017). It shows us how much of the total effect of parents' financial resources we could erase by a hypothetical intervention that sets the effect of financial resources on this mediator to zero.

This decomposition is achieved by comparing joint indirect effects in a nested subset of mediators:

(1) Neighbourhood,

(2) Neighbourhood + Educational Norms & Aspirations,

[25] Additionally, we must make consistency and positivity assumptions (Hernán and Robins 2020). For mediation analysis, these assumptions also apply to all mediators (Zhou 2021). We evaluate the common support for net worth, income, and all mediators in the appendix C by comparing the distribution of the propensity scores between exposed and non-exposed cases. If certain ranges of propensities are only observed for exposed or non-exposed cases this indicates a lack of common support. The propensities of exposed and non-exposed cases largely overlap for net worth and most mediators. Only for income-poverty and low values in learning materials, there are few non-exposed cases with high propensities. Estimates for these cases are based on extrapolations.

(3) Neighbourhood + Educational Norms & Aspirations + Parental Stress,

(4) Neighbourhood + Educational Norms & Aspirations + Parental Stress + Parent-child Interaction Quality,

(5) Neighbourhood + Educational Norms & Aspirations + Parental Stress + Parent-child Interaction Quality + Investment.

The indirect effect in model 5 gives us the joint indirect effect via all mediators together and the indirect effect in model 1 gives us the NIE of neighbourhood. PIEs can be estimated as the difference in indirect effects between consecutive models: The PIE of educational norms and aspirations can be estimated as the difference in the indirect effects between model 1 and 2, PIE of parental stress as the differences between model 2 and 3, PIE of parent-child interaction quality as the differences between model 3 and 4, and the PIE of investment as the difference between model 4 and 5. Note that NIE and PIE also capture indirect effects via mediators later in the causal chain. For instance, the NIE of neighbourhood also captures indirect effects like Financial Resources → Neighbourhood → Investment → Academic Abilities (see also appendix B for a graphical presentation of all indirect effects).

We use '*Natural Effect Models*' to estimate direct and indirect effects (Steen et al. 2017). The underlying idea of this approach is to impute nested counterfactual values for the outcomes ($Y_{\alpha M_{\alpha^*}}$) and then estimating direct and indirect effects by regressing $Y_{\alpha M_{\alpha^*}}$ on the actual exposure (a) and the counterfactual exposure ($a\,*$) (for more details see Vansteelandt, Bekaert, and Lange 2012, and Steen et al. 2017). We use lasso regressions to select the covariates (Tibshirani 1996) for the imputation of $Y_{\alpha M_{\alpha^*}}$ from the set of financial resources, control variables, mediators, interaction-terms between financial resources and mediators (i.e., exposure-mediator interactions), and interaction-terms among the mediators. We choose the penalisation parameter that yields the lowest AIC for the lasso regressions.

Standard errors are estimated using bootstraps on the imputed data (Schomaker and Heumann 2018). Individuals are sampled into the bootstrap by the inverse of their probability to be included in the analysis sample.

4.4 Results

4.4.1 Differences in academic abilities by financial resources

Results for all four measures of academic abilities are presented in Figures 4.2.1 to 4.2.4. We see substantial differences for all measures of children's academic abilities by both parental income and net worth (see '*Total Differences*' in Figures 4.2.1 to 4.2.4). Already at an age of four years, children in income-poor households score 0.22 standard deviations (SD) lower in the standardised math test scores than children living in households with the highest incomes. Similarly, children in income-poor households score up to 0.30 SD lower in the math test at an age of six, up to 0.23 SD lower in science, and up to 0.34 SD lower in PPVT.

A similar pattern emerges for parental net worth, but with smaller effect sizes. Children with a negative net worth score up to 0.22 SD lower in the math test at an age of four, up to 0.23 SD lower in math at an age of six, and up to 0.24 SD lower in the science test. Differences in PPVT scores are much smaller and none of them is statistically significant.[26]

The differences in academic abilities by parents' financial resources are non-linear. The largest contrast appears between children growing up in households below the income-poverty threshold and children growing up in households above this threshold. The differences in academic abilities among children in the second to fifth income quintile are much smaller. For instance, for math test scores at age four, children in households in the second income-quintile score 0.211 SD higher (95%-CI: 0.012 - 0.408), while children in the fifth income-quintile score 0.224 SD higher (95%-CI: 0.002 - 0.440) compared to income-poor children.

Likewise, for parental net worth, we see the largest contrasts between children in households with negative net worth and children in households with zero or positive net worth. Moreover, we see for all outcomes that children in the highest net worth quintile score lower than children in the fourth net worth quintile. This pattern is most pronounced for math test scores at an age of six. Children in the second net worth quintile score 0.110 SD higher (95%-CI: -0.058 - 0.284), and children in the fourth net worth quintile even 0.230 SD higher (95%-CI: 0.041 - 0.436) than children in households with negative net worth. However, children in the highest net worth quintile score only 0.131 SD higher (95%-CI: -0.073 - 0.338) than children in households with negative net worth, and, thus, almost 0.10 SD lower than children in the fourth

[26] Raw differences (without adjusting for control variables) by income are up to three times larger and raw differences by wealth are up to two times larger than the adjusted differences (see appendix D).

net worth quintile. Importantly, all these differences emerge after controlling for the comprehensive set of other parental characteristics.

4.4.2 Mediation analysis

In the next step, we analyse which factors mediate these differences in academic abilities by parents' financial resources. In general, we see that the indirect effects are much more consistent over the different measures of academic abilities than the total income differences. Moreover, in contrast to the total differences, all joint indirect effects are statistically significant. All mediators together mediate between 0.041 and 0.097 SD of the difference between children in income-poor households and children in the second income quintile and even 0.094 to 0.185 SD of the differences between children in income-poor households and children in the highest income quintiles (see '*Joint Indirect*' in Figures 4.2.1 to 4.2.4). On average, all mediators together account for 47% of the disparities by parental income.[27]

Parental investment and the composition of the neighbourhood seem to be the most important mediators of income differences. Differences in parental investment account for 0.031 to 0.080 SD of the income differences for math (age 6), science and PPVT scores. Indirect effects via investment are less relevant for math test scores at age 4 (see '*PIE Investment*'). On average, 23% of the differences by parental income can be attributed to parental investment.

The neighbourhood composition mediates between 0.026 and 0.054 SD of the income differences in math test and PPVT scores (see '*NIE NBH*'). This corresponds, on average, to 23% of the total differences for these outcomes.

All other indirect effects are much smaller and occur only for some measures of academic abilities and some income contrasts. Parents' educational norms mediate a small share of the difference between children in the highest quartile in contrast to the lowest quintile for math test scores at age four (PIE=0.023; 95%-CI: -0.010 - 0.058) and math test scores at age six (PIE=0.025; 95%-CI: -0.006 - 0.060). Lastly, there are small indirect effects via parent-child interaction quality for math test scores at age six and science test scores. Yet, it is important to keep in mind that all indirect effects except for the PIE via parental investment also include indirect effects via the mediators later in the causal chain (see appendix B).

The indirect effects of wealth differences are much smaller than indirect effects of income differences and most are not statistically significant. The largest joint indirect effect emerges

[27] We only consider outcomes and income / wealth contrasts, for which the *Total Difference* is larger than 0.1 for the calculation of the average proportion mediated.

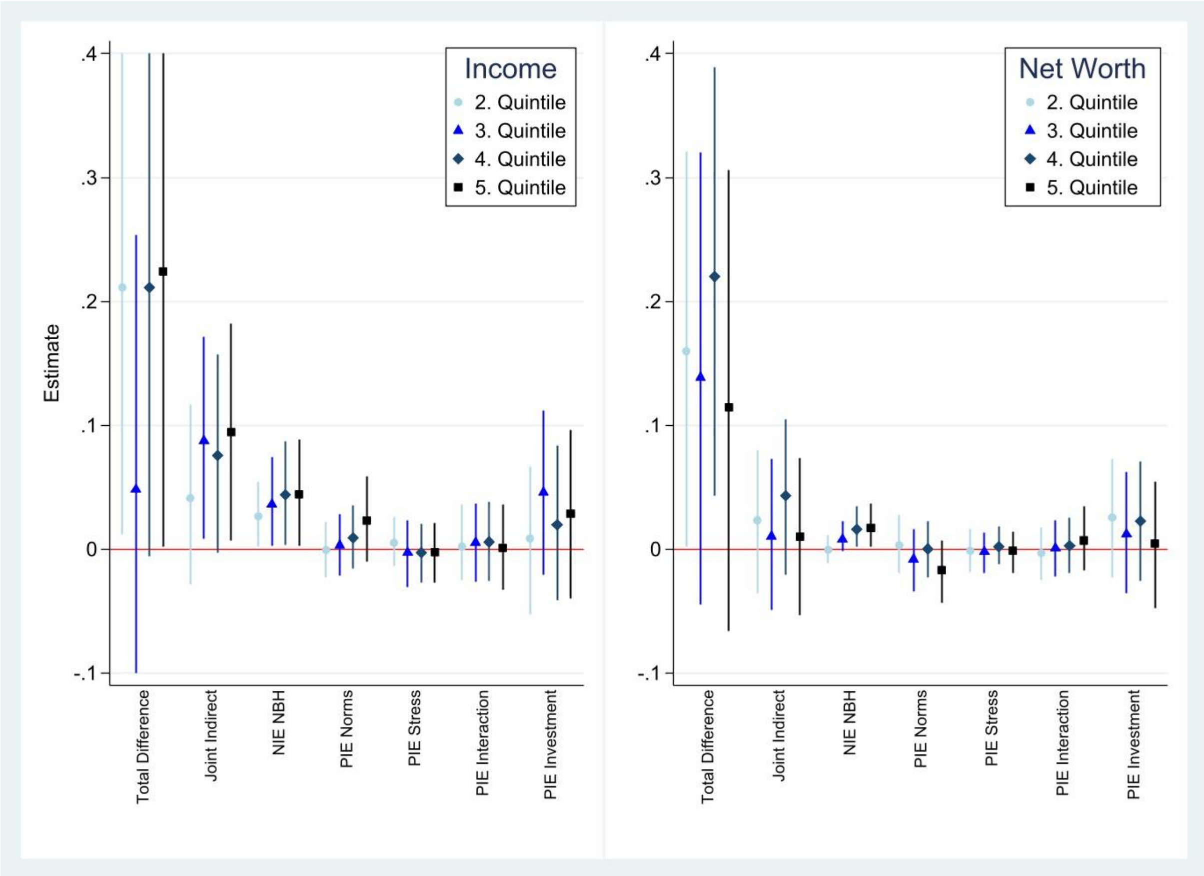
for the contrast between children in the fourth net worth quintile and children in households with negative net worth: 0.032 SD (95%-CI: -0.021 - 0.105) for math test scores at age four, 0.053 SD (95%-CI: -0.007 - 0.117) for math test scores at age six, and 0.039 SD (95%-CI: -0.017 - 0.094) for PPVT scores. On average, all mediators together account for 17% of the total difference in academic abilities by parental net worth.

Like for income, the most important mediators seem to be parental investment (on average 12% of total differences by wealth) and neighbourhood effects (on average 8%). Surprisingly, differences in parental investment seem to contribute most to the differences in academic abilities between children in the second net worth quintile and children in households with a negative net worth (e.g., for science: 0.036 SD; 95%-CI: -0.013 - 0.088) and less for the differences between children in the households with the highest net worth in contrast to those with negative net worth.

Indirect effects via the neighbourhood composition emerge only for math and PPVT scores. The largest indirect effect emerges for the differences in math test scores at age six for the contrast between children in the highest net worth quintile and children in households with negative net worth: 0.034 SD (95%-CI: 0.011 - 0.062). Indirect effects of parental net worth via parental Stress, mother-child interaction quality, and educational norms and aspirations seem to be negligible.

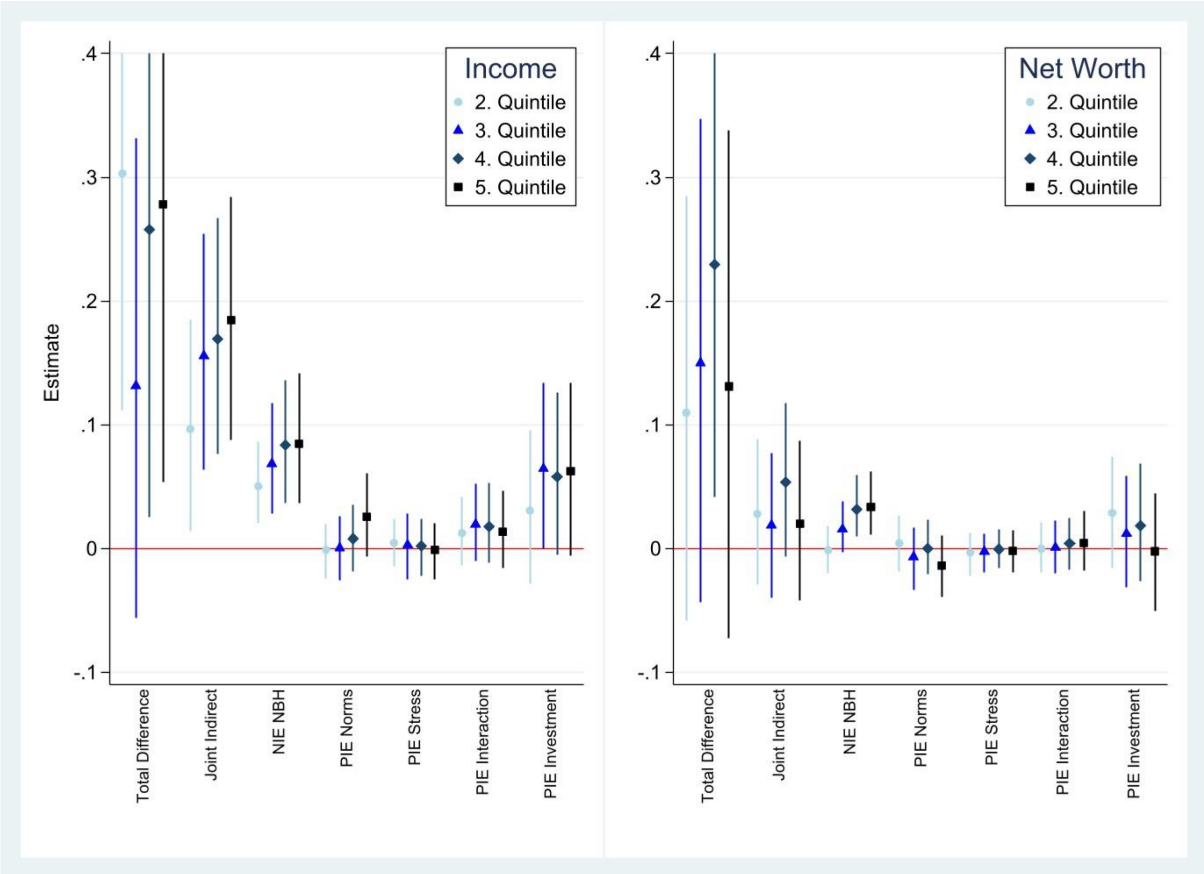
We would have gotten different results if we had used the difference method instead of the sequential mediation approach (see Table 4.2). Recall that the results of these two methods may differ for two reasons: 1) interdependencies between the mediators and 2) interactions between financial resources and mediators or interactions among the mediators.

Figure 4.2.1 Mediation analysis of math test scores differences by parental income and wealth at age four



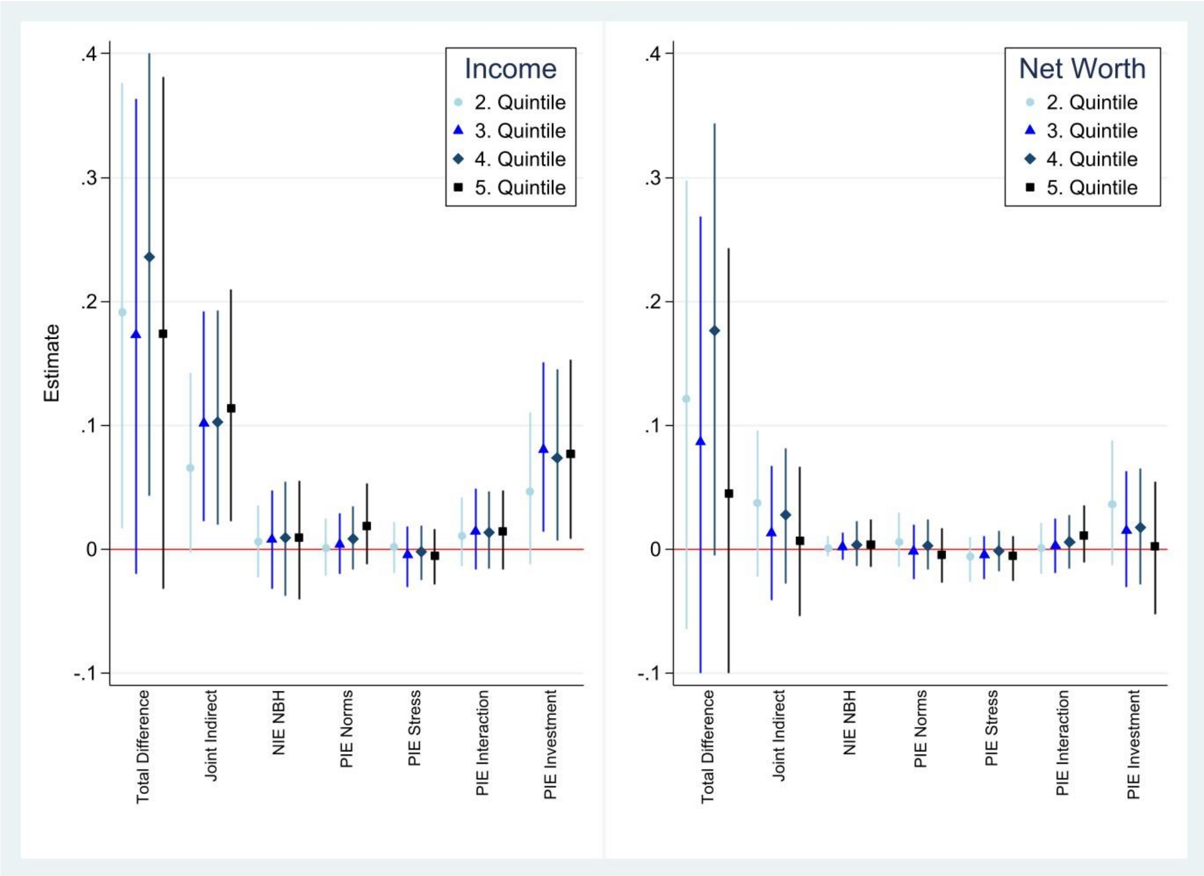
NEPS, starting cohort Newborns. N=2,377. Weighted and averaged over 50 imputed datasets.
Reference categories: Income = Income-poor. Net Worth = Negative.

Figure 4.2.2 Mediation analysis of math test scores differences by parental income and wealth at age six



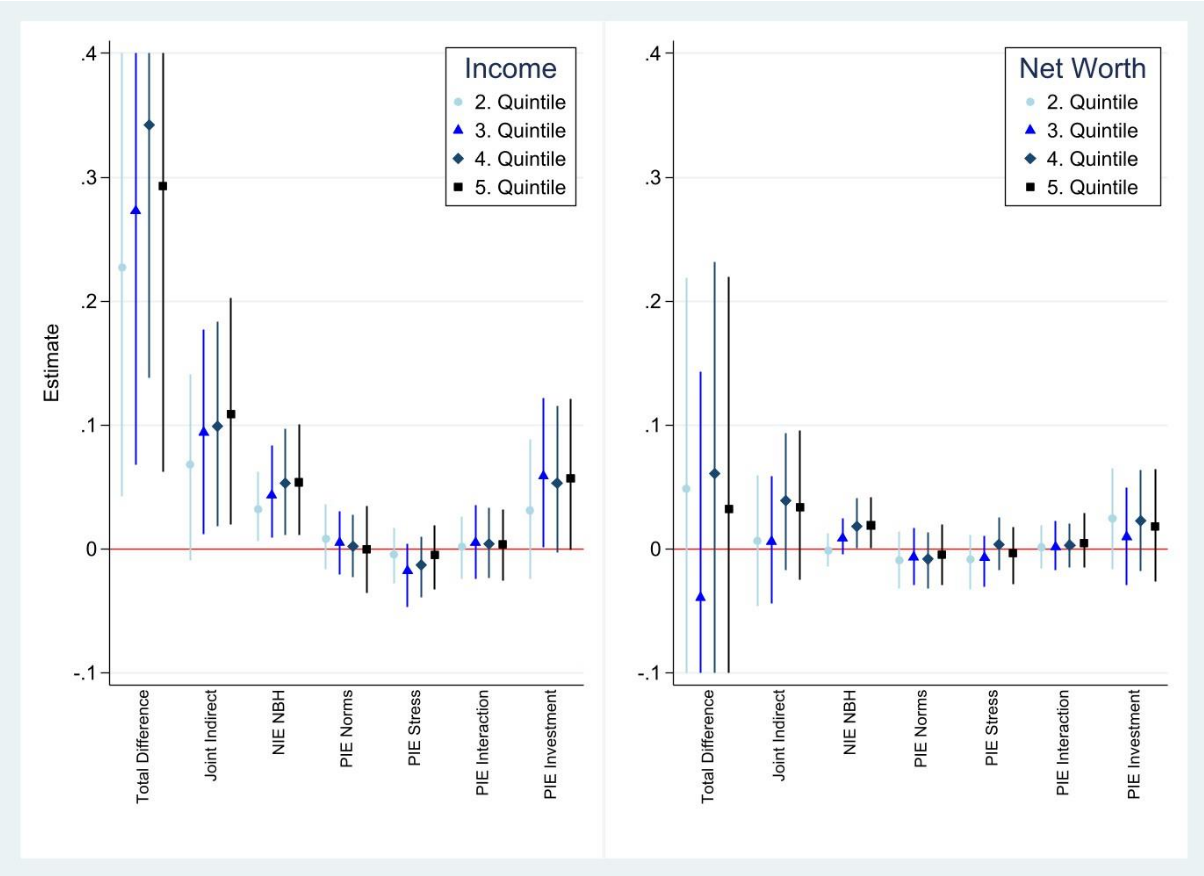
NEPS, starting cohort Newborns. N=2,377. Weighted and averaged over 50 imputed datasets.
Reference categories: Income = Income-poor. Net Worth = Negative.

Figure 4.2.3 Mediation analysis of science test scores differences by parental income and wealth



NEPS, starting cohort Newborns. N=2,377. Weighted and averaged over 50 imputed datasets.
Reference categories: Income = Income-poor. Net Worth = Negative.

Figure 4.2.4 Mediation analysis of PPVT scores differences by parental income and wealth



NEPS, starting cohort Newborns. N=2,377. Weighted and averaged over 50 imputed datasets.
Reference categories: Income = Income-poor. Net Worth = Negative.

We observe four main differences when comparing the results of the two methods. First, when using the sequential mediation approach, the joint indirect effect equals the sum of the indirect effects via the five mediators (by definition). This is not the case for the difference method. The sum of the indirect effects via neighbourhood, norms, parental stress, interaction quality and parental investment is 0.011 SD larger than the joint indirect effect for income and 0.005 SD larger for wealth when using the difference methods. Second, on average over all outcomes, the difference method overestimates the indirect effect via parental investment by 0.01 SD (see row 'Investment', column 'Average of differences' in Table 4.2) i.e., by about 20%. Third, the joint indirect effects of income differ between the methods on average by 0.009 SD (row 'Joint indirect', column 'Average of absolute difference'). However, the average difference between the methods is almost zero because of overestimations for some outcomes but underestimations for other outcomes. Lastly, the standard errors of the indirect effect estimates are larger when applying the sequential mediation analysis. For example, the standard errors of the joint indirect effects are 1.4 times larger when using the sequential mediation approach than when using the difference method. This reflects the bias-variance trade-off that we face when allowing for exposure-mediator and mediator-mediator interactions in the sequential mediation approach, which are assumed to be zero when using the difference method.

Table 4.2 Difference between indirect effects with the sequential mediation approach and the difference method.

	Average of differences	Average of absolute differences	Ratio of SEs
Income			
Joint Indirect	-0.001	0.009	1.425
NBH	0.000	0.003	1.028
Norms	0.001	0.003	1.709
Stress	-0.003	0.005	3.285
Interaction Quality	-0.001	0.003	1.756
Investment	-0.010	0.010	1.548
Net Worth			
Joint Indirect	-0.002	0.006	1.480
NBH	0.001	0.001	1.164
Norms	-0.004	0.004	1.379
Stress	-0.002	0.003	2.703
Interaction Quality	0.000	0.002	1.869
Investment	-0.002	0.005	1.504

Differences averaged over all four outcomes and four income / net worth contrasts. Average of differences = Indirect effects obtained with sequential mediation approach – Indirect effect obtained with difference method. Ratio of SEs = Standard errors of the indirect effects obtained with the sequential mediation approach / standard errors of the indirect effects obtained with the difference method.

4.5 Discussion

In this paper, we evaluate the association between parents' financial resources and the academic abilities of pre-school children in Germany and test potential mediators of these associations. Even when controlling extensively for other socio-demographic parental characteristics, we find that children growing up in income-poor households score up to 0.33 SD lower in math, science and PPVT. Yet, differences by income do not give the complete picture of the stratification by parents' economic resources: On top of the differences by parental income, we also find a substantial difference in math and science test scores by parental wealth. Consistently with the literature (Elliott, Destin, and Friedline 2011), we do not find wealth differences in PPVT scores.

Both, differences by parental income and wealth emerge particularly at the lower end of the distribution. Children in income-poor households or households with negative net worth score substantially worse than their peers above these thresholds. This threshold effect is in line with other research on income effects in Germany (e.g., Schneider 2004). Thus, a lack of financial resources hinders children's academic abilities, while more financial resources do not result in higher academic abilities once families have surpassed a relatively low threshold.

Based on the existing literature, we test five potential mediators of the association between parents' financial resources and children's academic abilities: family investment, parental stress and parenting, neighbourhood effects, and educational norms and aspirations. Importantly, these different mediators are interdependent, which has to be considered for their analysis. Traditional approaches to mediation analysis give biased results if mediators are causally related.

Applying a sequential joint mediation approach, we find that all mediators together explain on average 47% of the differences in academic abilities by parental income, but only 17% of the differences by parental wealth. The most important mediator of the differences by parents' financial resources is parental investment. This finding is in line with existing results which demonstrate that investment is more important in driving income effects on academic abilities than family stress and parenting behaviour (Guo and Harris 2000; Yeung, Linver, and BrooksGunn 2002). Besides family investment, the most important mediator seems to be the neighbourhood composition. One explanation for this could be that the neighbourhood composition will be reflected in the composition of day-care groups, which have been shown to affect children's cognitive development (Becker and Schober 2017). Parents' educational norms and aspirations, their stress levels and the parent-child interaction quality do not seem to contribute substantially to differences in academic abilities by parents' economic resources, even when considering their indirect effects on parental investment behaviour. Particularly the negligible contribution of educational aspirations stands in strong contrast to the finding of Diemer, Marchand, and Mistry (2020) for the US. One explanation for this could be that Diemer, Marchand, and Mistry (2020) did not consider other mediators. Moreover, educational aspirations may become more important for educational decisions when children are older.

Overall, our results raise the question as to why the proposed mediators explain a much smaller proportion of the wealth differences than they do for income differences. This finding highlights again that wealth differences in academic abilities are caused by other underlying mechanisms than income differences. Further mechanisms that may drive wealth effects may be housing conditions and housing stability. Housing is by far the largest component of the wealth portfolio of most households (Grabka and Westermeier 2014). At the same time, it has been shown that child development is harmed by bad housing conditions and instability (Evans 2006; Ziol-Guest and McKenna 2014). Housing quality was, however, not evaluated in NEPS.

Importantly, our results have to be interpreted in the context of Germany, where children's differences in academic ability resulting from other socioeconomic characteristics of their parents - like their parents' educational levels - are larger than differences caused by financial resources. The extent to which these results can be generalised to other countries remains an open question. The magnitude of disparities in academic abilities will vary according to how stratified the mediators are by financial resources.

Some limitations should be considered for the interpretation of our results. First, even though a comprehensive set of variables was measured in NEPS, the timing of measurement was not optimal for our research questions. Parental wealth was only measured in the third wave. Although wealth could have potentially changed during this time and may have been affected by the neighbourhood in which parents live, we assume that no large bias arises from this because of our categorical operationalisation of net worth and because there were no substantial changes to the distribution of wealth during this period (Grabka and Westermeier 2014). A similar argument applies to parents' educational norms, which were measured only in the fourth wave. Nevertheless, the potential bias arising from this would not change the substantive results, because the association of norms with all outcomes and mediators is negligible small.

Second, both parents' financial resources, particularly wealth, and mediators are probably measured with error. Wealth was self-reported by parents, which is often inaccurate (Goodman and Ittner 1992). Measurement error in parents' financial resources will lead to an underestimation of the total differences in children's academic abilities (Mazumder 2005). Since wealth is likely measured with more error than income, underestimation will be larger for wealth. Among the mediators, particularly parents' investment in learning materials could have been measured in more detail. Measurement error in mediators will lead to an underestimation of the indirect effects (VanderWeele 2015).

Third, the interpretation of the results of the mediation analysis depends crucially on whether its assumptions are met, particularly that there are no unmeasured confounders. One potential unmeasured confounder of parents' economic resources and children's academic abilities could be parents' cognitive and non-cognitive competencies, which were not assessed in NEPS. Although parents' competencies may be partly captured by parents' education and occupational class, this could have resulted in an overestimation of effects. However, if only parents' economic resources and children's academic abilities are confounded, only total differences and direct effects are biased, while the indirect effects remain unbiased. If this were the case, we could apply the front-door criterion (Pearl 2009) and interpret the joint indirect effect as an unbiased estimate of parents' economic resources' effect.

Fourth, as already mentioned in the background section, there may be additional causal paths between mediators that we did not consider, like educational norms affecting the choice of the residence. Testing these additional pathways would require longitudinal data on all mediators.

Despite these limitations, our research suggests once more that wealth is a unique dimension of social stratification and that ignoring it may lead to an underestimation of inequalities. Yet, even when using a rich set of the proposed mediators of wealth differences, surprisingly little of the differences can be explained. To reduce the stratifying consequences of wealth inequality, further research is needed to test the underlying mechanisms of wealth stratification in other contexts and to test further potential mediators like housing conditions.

Moreover, our results highlight that individual mediating factors of social stratification cannot be studied in isolation when mediators are causally related. Not including a mediator which occurs early in the causal pathway may cause confounding between later mediators and the outcome. The problem of causally related mediators does not only apply to our analysis but to most mediation processes in the social sciences. The bias from ignoring other mediators will be particularly severe in contexts where mediators are strongly related.

5. Wealth 2D – An alternative approach to explore wealth effects

The analysis of wealth as a predictor variable comes with several conceptual and methodological challenges with important consequences for results. We propose employing Generalized Additive Models and jointly evaluating gross wealth and debt to overcome the dependence of wealth effects on implausible assumptions. By conducting a simulation study, we show that our approach describes systematic wealth differences in more detail and overfits less to random variation in the data than standard approaches. We then apply our approach to re-analyze wealth gaps in educational attainment in the US. In contrast to existing research, we find that not negative net worth is associated with the worst educational prospects but the combination of low gross wealth and low debt. Children in households with high gross wealth have the best prospects, almost independent of household debt. Our approach can be easily adapted to other research questions. [28]

[28] A slightly different version of this chapter, co-authored with Klaus Pforr and Nora Müller, is currently in preparation for submission to a peer-reviewed journal.

5.1 Introduction

Recent research has established wealth as a unique dimension of socio-economic status, working differently from education, occupation, and income (Hällsten and Thaning 2021; Keister and Moller 2000; Killewald et al. 2017; Skopek 2015; Spilerman 2000). Wealth plays a major role in reproducing intergenerational inequality in various dimensions, including education, income, occupational status, health, or general well-being. Consequently, ignoring wealth effects leads to an underestimation of the level of intergenerational inequality.

However, the analysis of wealth as a predictor variable in social stratification research includes several conceptual and methodological challenges with important consequences for results (see Killewald et al. 2017). In our paper, we discuss two of them: the multidimensional nature of the wealth measure and non-linearities in the relationship between wealth and any outcome variable of interest (in the following Y) and propose an alternative approach to overcome these problems. Next, we employ a simulation study to evaluate whether our approach discovers the (in observed data unknown) systematic wealth differences in Y. Finally, we showcase the usefulness of our approach by re-analyzing parts of Pfeffer's (2018) work on 'Growing Wealth Gaps in Education'.

5.2. Two challenges when studying wealth effects

5.2.1 Wealth as a multidimensional measure

In contrast to income, wealth has a positive (assets) and a negative (debt) dimension. Assets and debt are strongly correlated (Brown and Taylor 2008) and debt is not just the inverse of assets (Dew 2007). While higher assets are related to a higher economic status, debt can indicate economic hardship as well as economic potential (Spilerman 2000). Different amounts of debt can indicate household differences in access to credit, accumulation strategies, tendencies for risk-taking, and possession of knowledge of investment strategies (Dwyer 2018; Fourcade and Healy 2013; Hansen and Toft 2021).

In most surveys that measure wealth, it is possible to differentiate between assets and debt.[29] Yet, empirical researchers mostly measure wealth as a one-dimensional measure by subtracting debt from assets, resulting in net worth (Killewald et al. 2017). The use of net worth is so widespread that newcomers to the field of wealth research may mistakenly assume that wealth is defined as net worth and not that net worth is only one measure of wealth. Using net worth to measure wealth can be problematic because it assigns households with very different

[29] From the 30 surveys with wealth data listed in Killewald, Pfeffer, and Schachner (2017), only in four surveys it is not possible to differentiate between assets and debt.

combinations of assets and debt to the same net worth values. By measuring wealth as net worth, researchers implicitly assume that households with the same values of net worth will, on average, have the same outcomes, no matter from what combinations of assets and debt these net worth values result. These assumptions are hardly discussed in past research. We illustrate them in Figure 5.1.

Let's assume we have three households: household A has zero gross wealth and zero debt, household B has $500k gross wealth – consisting of a well-located apartment – and – which is a bank credit to finance the apartment – and household C has $500k gross wealth – consisting of an inherited apartment – and no debt. By measuring wealth as net worth (see upper left part of Figure 5.1), we implicitly assume that children who grow up in household A will have, on average, the same outcome as children who grow up in household B because both households have a net worth of zero. This assumption seems implausible.

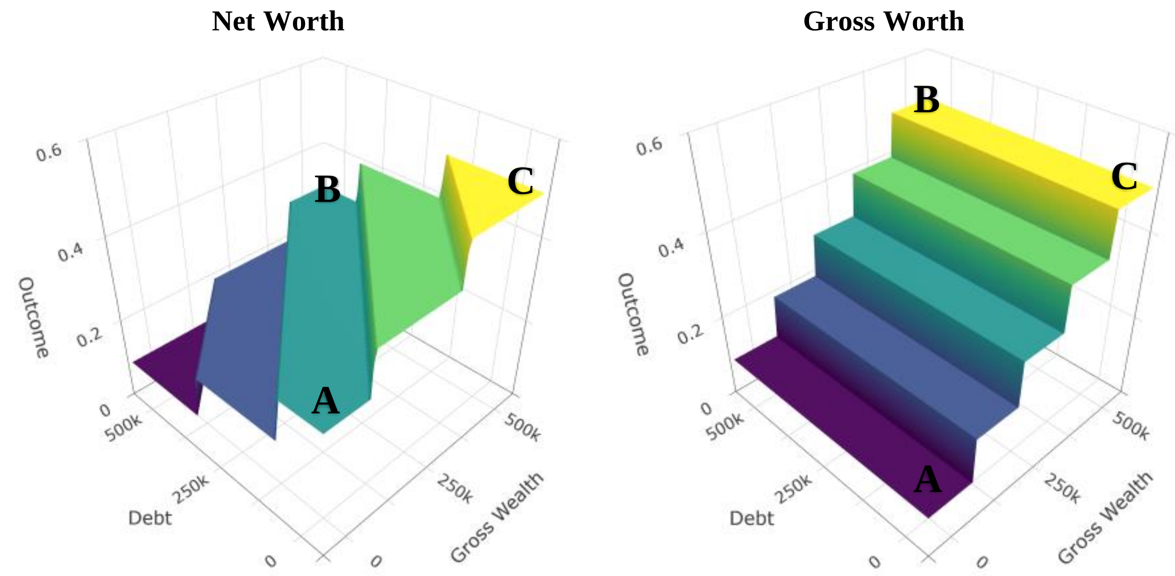
First, children may profit much more from their parents' assets than that they suffer from their debt. In that sense, children in household B will grow up in an environment more similar to that of children in household C. Unlike children in household A, children in households B and C can profit from growing up in the stable environment of a self-owned apartment, from living in a peaceful neighborhood which may provide a stimulating environment in terms of cultural and social capital and are likely to attend similar well-financed schools. Moreover, the differences in gross wealth and debt between households A and B may indicate differences in terms of their general economic situation, including creditworthiness. A household that was not deemed worthy to get the credit for an apartment may not get credit for investment in their children's education neither.

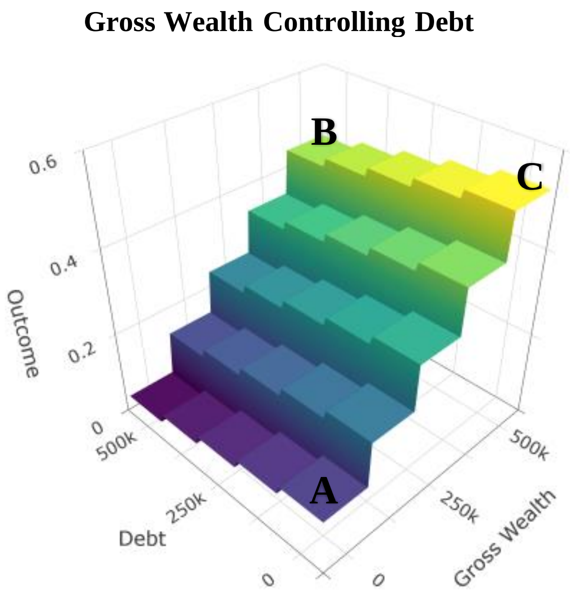
Other one-dimensional measures of wealth like gross wealth (e.g., Conley 2001; Schneider 2011; Wiborg 2017) or asset-to-debt ratios (e.g., Conger et al. 1992) make different but equally strong assumptions. As illustrated in the upper right part in Figure 5.1, by measuring wealth as gross wealth, we implicitly assume that all families with the same gross wealth values have on average the same outcome, independent of their amounts of debt. Thus, for instance, we assume that children in household B will have, on average, the same outcomes as children in household C. Again, this assumption is likely to miss relevant differences in household B and C's potential to support their children's educational careers. While household B has a large bank loan to handle, household C is free from any financial obligations, which should make it much easier for household C to support its child.

A less restrictive approach is to estimate the effect of gross wealth while controlling for the effect of debt as done by Dew (2007), Hochman and Skopek (2013), or Müller et al. (2020) and illustrated in the lower left part of Figure 5.1. Unlike when using gross wealth or net worth, applying this operationalization, researchers do not assume that different combinations of gross wealth and gross debt will result, on average, in the same outcome. Applied to the example in Figure 5.1, this means that the children in households A, B, and C could all have different outcomes. In our example in the lower left part of Figure 5.1, the effect of gross wealth is five times larger than the (negative) effect of debt, and, therefore, the pattern resembles our example with the gross wealth operationalization in the upper right part. Yet also this approach makes an unplausible assumption: The slope of a certain change in gross wealth (debt) is equally large regardless of a household's amount of debt (gross wealth). In technical terms, what we are missing is the interaction between gross wealth and debt.

Currently, researchers deal with the problem of the multiple components of wealth by checking the robustness of their results to a few other measures of wealth. However, differences by gross wealth and differences by net worth have very different implications and there is no reliable decision rule on which wealth measure gives the more relevant results.

Figure 5.1 Implicit assumptions of wealth effects with different measures of wealth





	Gross Wealth	Debt	Net Worth
A	0	0	0
B	500k	500k	0
C	500k	0	500k

5.2.2 Functional form

Wealth effects are usually considered to be non-linear: Households with little wealth benefit more from an additional unit of wealth than wealthy households (Gibson-Davis and Hill 2021; Killewald et al. 2017). Non-linear wealth effects are usually implemented in two ways:

First, researchers model non-linear wealth effects by transforming wealth, most commonly, by taking the natural logarithm of net worth. Doing this, researchers assume that every log unit increase (about a 2.7-fold increase) in wealth leads to the same change in the outcome (Miller et al. 2021:159). Yet, the natural logarithm is not defined for zero or negative values that are common in the distribution of net worth. In recent years, researchers often used the inverse hyperbolic sine transformation (Friedline et al. 2015; Pence 2006) for net worth, which behaves similar to the natural logarithm, but allows to retain zero- and negative-valued observations:

$$IHS\ (x) = \frac{\log\left(\theta x + \sqrt{\theta^2 x^2 + 1}\right)}{\theta}$$

where θ is an arbitrary scale parameter with recommended values of 0.0001, 0.00003, and 0.00001 (Pence 2006). When θ is close to 1 the IHS-transformation resembles the natural logarithm. Alternatively, some researchers use wealth-ranks (e.g., Grätz and Wiborg 2020; Hällsten and Pfeffer 2017; Hällsten and Thaning 2018, 2021).

Second, in addition, or alternative to transforming wealth, researchers explicitly specify non-linear associations. They do this by (1) categorizing wealth (7 out of the 25 papers that consider wealth as a predictor reviewed in Killewald et al. 2017), (2) including polynomials of wealth in the specification (2 out of 25 papers in Killewald et al. 2017), or (3) using splines (4 out of 25 papers in Killewald et al. 2017).

Within these approaches, the researchers decide in advance how to specify the functional form of their wealth effect. Since it is not clear which specification provides the best fit between wealth and Y and how complex the specification should be (e.g., how many wealth categories; which order of polynomials; how many and at which position to place the knots for splines), the currently recommended practice is to experiment with different specifications (Killewald et al. 2017). However, finding the best fitting function involves finding a compromise between describing the functional form in detail and not fitting the functional form to random noise in the data (i.e., the 'bias-variance trade-off'; e.g. Hastie, Tibshirani, and Friedman 2009). For instance, let's assume that the true functional form is that Y first increases linearly with wealth but decreases for very high values of wealth (potentially through moral hazard for children's outcomes). If we try to fit this unknown function with a linear effect only, we will not find the decrease in Y for very high wealth. On the other extreme, if we fit a complex functional form (e.g., higher-order polynomials), we may find a more complex association than the true functional form because of random variation in the sample. Based on this too complex association, we may mistakenly infer that households in a certain wealth range fare better than they actually do in the population. The bias-variance trade-off is rarely considered in research on wealth effects yet.

5.3 An alternative approach

Instead of this tedious and error-prone procedure of experimenting with different measures and specifications, we propose to consider how the joint distribution of the two main dimensions of wealth – gross wealth and debt – is associated with Y. Thus, we suggest exploring which groups on the 'surface' defined by their gross wealth and gross debt are advantaged and which groups are disadvantaged with respect to Y without making the strong homogeneity assumptions discussed above. Moreover, we propose to employ Generalized Additive Models (GAM; Hastie and Tibshirani 1999; Wood 2017) to overcome the issues of model specification and over-fitting.

GAMs are generalized linear models in which Y depends on the additive combination of unknown smoothing functions (and potentially parametric functions) of the predictor variables. Interactions between predictor variables are only considered if explicitly specified. GAMs combine linear mixed models, generalized linear models (McCulloch, Searle, and Neuhaus 2008), and smoothers (Cleveland 1979). In general, GAMs can be described as (Wood 2017:249):

$$\mathrm{g}(\mu) = \mathbf{Z}ß + \sum_j f_j(x_j)$$

$$\text{with} \quad \mu = \mathrm{E}(\mathrm{Y})$$

$$\text{and} \quad \mathrm{Y} \sim \text{Exponential family}(\mu, \text{shape parameters}),$$

where $\boldsymbol{Z}$ is a vector of variables that are considered parametrically, $\boldsymbol{ß}$ is the corresponding vector of parameters, and f is the smooth function of the j variables that are considered non-parametrically (x). On the left-hand side, we have a link function $g(\cdot)$ that connects the dependent variable with the right-hand side. The dependent variable itself follows a distribution from the exponential family. For our analyses, we use the mgcv-package in R (Wood 2017).

Smooth functions can be estimated with different spline functions. We use thin plate regression splines which we do not have to choose explicit sets of knots (Duchon 1977).

The wiggliness of the smooths is penalized to avoid overfitting. The wiggliness penalties are estimated either by cross-validation or with a random effect maximum likelihood algorithm.

We propose to consider the combination of gross wealth and debt to explore wealth stratification. Thus, we want to evaluate

$$\mathrm{g}(\mu) = \mathbf{Z}ß + f(Gross\ Wealth, Debt)$$

Here $f(Gross\ Wealth, Debt)$ is the sum of a thin plate regression spline smoother of gross wealth, a thin plate regression spline smoother of debt, and a thin plate tensor product smoother of gross wealth and debt (Wood 2006). The tensor product smoother over gross wealth and gross debt is used to allow for more flexible non-linear interaction terms.

In our application, we consider whether children have obtained a BA degree or not:

$$\Pr(BA\ Degree) = \frac{\exp\left(\mathbf{Z}ß + f(Gross\ Wealth, Debt)\right)}{1 + \exp\left(\mathbf{Z}ß + f(Gross\ Wealth, Debt)\right)}$$

GAMs have important advantages over alternative methods. In contrast to unregularized regression approaches, the complexity of the association between wealth and the outcome of interest is not restricted by the researchers' decisions (e.g., the number of wealth categories). At the same time, unregularized regression approaches do not consider issues of overfitting. In contrast to classical Machine Learning approaches like regression trees, GAMs can consider control variables. Regularized regression approaches (i.e., Ridge and Lasso regressions) can fit flexible associations, can include control variables, and avoid overfitting. However, regularized regression approaches are not helpful with splines specifications, because regularizing splines does not change the number and location of knots. Although regularized regressions with polynomial approximation can successfully regularize the wiggliness part, they are imprecise at the extreme ends of a distribution.

The flexibility of GAMs comes at the cost of larger standard errors. Moreover, note that GAMs do not summarize differences by wealth in one or a few regression coefficients. Instead, we can obtain a predicted value for each combination of gross wealth and debt and can contrast the predicted values of these different combinations.

5.4 Data and variables

First, we will conduct a simulation study (section 5.5) to test whether our approach describes wealth differences in more detail and makes more accurate predictions in cross-validation compared to the methods that are currently used to estimate wealth effects. Second, we apply our approach to re-analyze wealth stratification in educational attainment in the US (section 5.6). Both, the simulation study, and the showcase application are based on the data of the Panel Study of Income Dynamics (2021; PSID) used in Pfeffer (2018). We base the simulation study on real wealth data to have a more realistic distribution of the wealth components. We use the publicly available data and code provided in Pfeffer (2018)[30] and augment it with the data on wealth components. In the following, we will shortly summarize the data and variables used for Pfeffer's and our analyses. We will focus on our proposed alternative wealth measures.

5.4.1 Data and wealth measures in Pfeffer (2018)

Pfeffer analyzed wealth gaps in the educational attainment of 20- and 25-year-old individuals using the data of the PSID 2017. He included all children of PSID households who were 10-14 years old when parental wealth was measured (1984, 1989, 1994, and 1999) and for whom information about their educational attainment is available at age 20 (N=5,025) or age 25 (N=4,344). Pfeffer analyzes four outcomes: high school graduation, college attendance, college graduation, and college graduation conditional on attendance.

The predictor of interest in his analysis is household net worth. He inflated all net worth values to $2015 and categorized households into quintiles for most of his analyses. The net worth of the lowest quintile ranges between -$1278k and $5k and of the top quintile between $273.4k and $26m. To distinguish wealth effects from the effects of other parental SES dimensions, Pfeffer additionally considers permanent household income, parents' highest education, and the socio-economic index score. He further controls for household size, the number of children in the household, the household head's marital state, mother's age, and the individuals' sex.

Pfeffer reports an almost linear increase in the probability of high school graduation (from 72.8% in the lowest quintile to 91.1% in the highest quintile), the probability of college attendance (21.3% to 53.3%), and the probability of obtaining a BA degree (9.1% to 53.7%) over net worth quintiles. Adjusted for covariates, there remains a gap of 6.4 percentage points

30 The data are available from: https://simba.isr.umich.edu/data/data.aspx.
The replication files for the analysis of Pfeffer (2018) are available from: https://www.openicpsr.org/openicpsr/project/101105/version/V2/view.

between the lowest and the highest net worth quintile for high school graduation, 7.2 percentage points for college attendance, and 10.5 percentage points for obtaining a BA degree.

5.4.2 Our modifications

For our showcase analyses reported under section 5.6, we will focus on whether children have obtained a BA degree at the age of 25 years, for which Pfeffer finds the largest wealth gaps. Our analysis can be considered a 'test of robustness' (Freese and Peterson 2017:152) because we only change the measurement of wealth and specification of wealth effects.

In 1984, 1989, and 1994, the PSID measured nine components of wealth: 1) the value of the main house 2) the net value of farm and business assets, 3) the value of checking and savings accounts, 4) the net value of real estate other than the main home, 5) the value of shares of stock, 6) the net value of vehicles, 7) the value of investments in trusts or estates, bonds, life insurances, 8) the remaining mortgage on the main house, 9) the value of debts other than mortgages (such as credit card and student loans). Additionally, in 1999, private annuities and IRAs were assessed separately rather than jointly with checking and savings accounts.

Instead of combining these nine components to net worth, we differentiate between gross wealth and gross debt. We define *gross wealth* as the sum of the wealth components 1-7 (plus the value of IRAs for children born after 1985). We define *gross debt* as the sum of mortgages and other debt (wealth components 8 and 9). We transform gross wealth and gross debt using the inverse hyperbolic sine transformation with a scale parameter of $\theta = 0.0001$ to start from a smoother association between wealth and Y.

We had to drop three cases from our sample that were included in the net worth measure as applied by Pfeffer (2018), because of missing values in the wealth components.[31] This leaves us with an analysis sample of N=4,341.

5.4.3 Joint distribution of gross wealth and debt

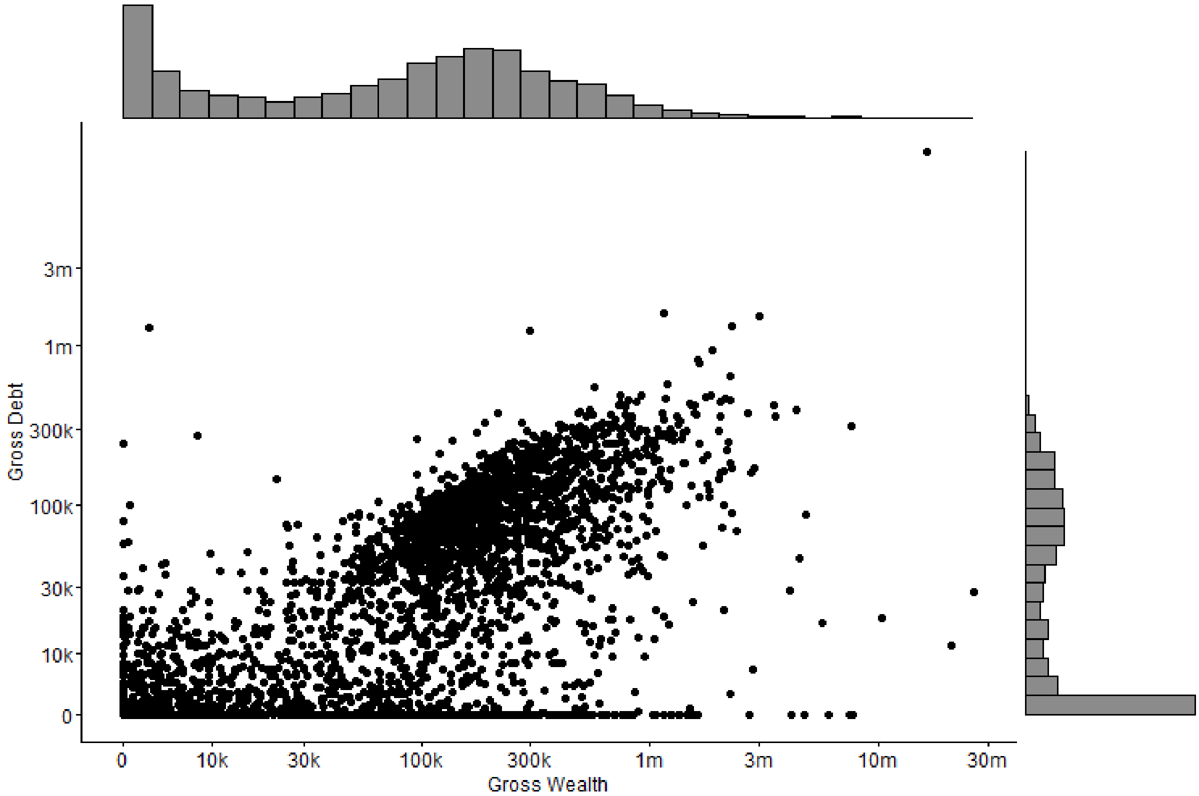
Figure 5.2 shows the resulting joint distribution of gross wealth (x-axis) and gross debt (y-axis), which we will use both for the simulation study and the replication of Pfeffer (2018). The distribution of gross wealth and debt are both highly skewed. Gross wealth ranges from \$0 to about \$26m, with the 90th percentile possessing around \$640k. The average gross wealth is \$298k and the median gross wealth is \$144k. The distribution of gross debt looks rather similar.

31 Composite measures of wealth were imputed in PSID, but not all wealth components. Unlike Pfeffer, we lose these cases with missing values in wealth components since we need full information on the wealth components to separately measure gross wealth and debt.

Mean gross debt is about $77k and median gross debt equals $36k. About 19% of households have zero debt, while the most indebted 10% of the households have more than $188k gross debt, and one outlier even reports $16m debt.

Gross wealth and debt are highly correlated. Their Pearson correlation is 0.398 and their Spearman correlation is 0.725. Most of the households are clustered around the main diagonal (close to zero net worth) or to the right of it (larger gross wealth than gross debt).

Figure 5.2 Joint distribution of gross wealth and debt (on IHS scale)



Note: Data of the Panel Survey of Income Dynamics; N=4,341.

5.5 Simulation

To test whether our new approach performs better in capturing systematic wealth variation in the data as compared to common approaches, we apply a simulation study. In contrast to analyzing observed outcomes, using a simulation study allows us to define the wealth effects. If one of the models we include in our simulation predicts values in a certain wealth range that differ from the pre-defined values in this range, this can unambiguously be defined as a biased prediction.

5.5.1 Design of the simulation

We follow the reporting scheme for simulation studies proposed by Morris, White, and Crowther (2019).

Aims: The aims of the simulation study are 1) to evaluate how well the different combinations of methods, wealth measures, and specifications (see Table 5.2; in the following referred to as 'combinations') capture the association between wealth and Y in the analysis sample, and 2) to evaluate how well the different combinations can predict Y in cross-validation.

Cross-validation is a method to approximate the prediction accuracy of a statistical model for new data from the same population. This can be achieved by estimating the model with a random subset of the data (i.e., the 'training data'), predicting the values for the subset of the data that has not been used for estimating the model (i.e., the 'test data') and then calculating the prediction error in the test data (Hastie et al. 2009). Here, we use 5-fold cross-validation. Thus, the data is split into five parts. Four of these five parts serve as training data and are used to estimate the model. Their predictions are tested in the remaining part. This is repeated five times until each part has served as test data once. The cross-validation prediction error is then calculated as the average prediction error.

Data-generating mechanisms: We consider four data-generating mechanisms. These are based on the observed values of net worth, gross wealth, and debt in the PSID.

$$Y_1 = Net\ Worth\ (IHS\ transformed;\ \theta = 0.0001)$$

$$Y_2 = Gross\ Worth\ (IHS\ transformed;\ \theta = 0.0001)$$

$$Y_3 = 2 * Gross\ Wealth\ (Rank) - Debt(Rank)$$

$$Y_4 = \begin{cases} -1 + Debt\ (Rank)\ if\ Gross\ Wealth < \$50{,}000 \\ 1\ if\ \$50{,}000 \leq Gross\ Wealth < \$100{,}000 \\ 3 - Debt\ (Rank)\ if\ Gross\ Wealth \geq \$100{,}000 \end{cases}$$

Next, $Y_1 to\, Y_4$ are standardized to have a mean of 0 and a standard deviation of 1. The resulting true values are displayed in the supplementary materials A. Last, we add $\sqrt{9}$-times random normally distributed noise to the true value and standardize again. Thus, the true value accounts for 10% of the variance in the noisy variable. Data is generated $n_{sim} = 500$ times for all $n_{obs} = 4{,}341$.

Y_1 depends only on the net worth of the household and Y_2 depends only on the gross wealth of the household. These data-generating mechanisms are very parsimonious and should be easily detectable if the correct measure of wealth is used. Y_3 is a function of the linear combination of gross wealth and debt with gross wealth being twice as important as debt. In the following, we will refer to this data generating mechanism as 'Additive (Ranks)'. This data-generating mechanism is slightly more complex and can already not be fully captured by only using one measure of wealth. We use the ranks of gross wealth and debt to get a functional form that can only be captured by a non-linear association of the original values of gross wealth and debt. The fourth data-generating mechanism is almost unrealistically complex because it combines threshold effects and interactions. Therefore, we will refer to the fourth data generating mechanism as 'Complex Interaction' in the following. For households with little gross wealth, higher debt is associated with larger values in Y_4. For households with moderate levels of gross wealth, debt is unrelated to Y_4. For households with high gross wealth, higher debt is associated with smaller values in Y_4. Unrealistic data-generating mechanisms are helpful to assess the breaking points of methods (Morris et al. 2019:2078).

Estimand: The estimand of interest for both our research aims is the Mean Squared Error (MSE). It measures how close the predicted values of the different combinations are to the true values of Y. Since $Y_1\ to\ Y_4$ are standardized to an SD of 1.00, a MSE of 1.00 indicates that the model does not make better predictions of Y than if we just had ignored wealth and predicted the mean value of Y for everyone. An MSE of 0.90 indicates that the model captures all the systematic wealth variation in the data and predicts the true value of Y perfectly because 90% of the variation in Y is just noise and 10% systematic variation by wealth.

Methods: For each simulated dataset, we consider 15 combinations of methods, wealth measures, and specifications. The first 12 of those combinations are GLMs. Models 1-3 consider only net worth, model 4-6 gross wealth, model 7-9 linear combinations of gross wealth and debt, and models 10-12 the interaction between gross wealth and debt. For each of these four measures of wealth, we consider three different specifications: models 1, 4, 7, and 10 use only linear effects, models 2, 5, 8, and 11 use quintiles, and models 3, 6, 9, and 12 a cubic specification. The last three models are GAMs with different wealth transformations. We consider different transformations for gross wealth and debt for the GAM because the different transformations of wealth may yield different results (Aihounton and Hennigsen 2020). Transformed versions of gross wealth and debt may require less wiggliness to capture effects that roughly correspond to the transformation.[32]

Performance measures: On the one hand, we estimate the MSEs for the sample that has been used to estimate the model ('In-sample MSE'). On the other hand, we estimate the MSEs for the prediction accuracy in new data using cross-validation ('Out-of-sample MSE') (e.g., Hastie, Tibshirani, and Friedman 2009).

We use the same 15 combinations of methods, wealth measures, and specifications explained above for the simulated data to evaluate wealth gaps in educational attainment in the real data. Combination 2 corresponds to the specification used by Pfeffer (2018). Since we consider binary outcomes (BA degree vs. no BA degree), we use mean logarithmized errors instead of MSEs to evaluate prediction accuracy here. We decided for the mean log errors instead of the proportion of correct classifications because both the GLMs and the GAMs try to minimize log errors. Correct classification additionally depends on the arbitrary decision which predicted values are classified as being a prediction of getting a BA degree (usually those with a predicted probability ≥50%).

32 We assume that wealth effects can be better approximated by a linear effect on the transformed scale than by a linear effect on the untransformed scale. The reason behind that assumption is that describing the association between wealth and Y requires less wiggliness when wealth was transformed. Since wiggliness is penalized in GAM, transforming wealth will result in a closer approximation of the association between wealth and Y.

Table 5.1 Evaluated combinations of methods, wealth measures, and specifications

No.	Method	Wealth measure	Specification	Equation
1	GLM	NW	linear	$Y = ß_0 + ß_1 * NW\ (IHS) + \varepsilon$
2	GLM	NW	categorical	$Y = ß_0 + ß_1 * NW\ (Quintiles) + \varepsilon$
3	GLM	NW	cubic	$Y = ß_0 + ß_1 * NW\ (IHS) + ß_2 * NW(IHS)^2 + ß_3 * NW(IHS)^3 + \varepsilon$
4	GLM	GW	linear	$Y = ß_0 + ß_1 * GW\ (IHS) + \varepsilon$
5	GLM	GW	categorical	$Y = ß_0 + ß_1 * GW\ (Quintiles) + \varepsilon$
6	GLM	GW	cubic	$Y = ß_0 + ß_1 * GW\ (IHS) + ß_2 * GW(IHS)^2 + ß_3 * GW(IHS)^3 + \varepsilon$
7	GLM	GW + Debt	linear	$Y = ß_0 + ß_1 * GW\ (IHS) + ß_2 * Debt\ (IHS) + \varepsilon$
8	GLM	GW + Debt	categorical	$Y = ß_0 + ß_1 * GW\ (Quintiles) + ß_2 * Debt\ (Quintiles) + \varepsilon$
9	GLM	GW + Debt	cubic	$Y = ß_0 + ß_1 * GW\ (IHS) + ß_2 * GW(IHS)^2 + ß_3 * GW(IHS)^3 + ß_4 * Debt\ (IHS) + ß_5 * Debt(IHS)^2 + ß_6 * Debt(IHS)^3 + \varepsilon$
10	GLM	GW * Debt	linear	$Y = ß_0 + ß_1 * GW(IHS) + ß_2 * Debt(IHS) + ß_3 * GW(IHS) * Debt(IHS) + \varepsilon$
11	GLM	GW * Debt	categorical	$Y = ß_0 + ß_1 * GW(Quintiles) + ß_2 * Debt(Quintiles) + ß_3 * GW(Quintiles) * Debt(Quintiles) + \varepsilon$
12	GLM	GW * Debt	cubic	$Y = ß_0 + ß_1 * GW\ (IHS) + ß_2 * GW(IHS)^2 + ß_3 * GW(IHS)^3 + ß_4 * Debt\ (IHS) + ß_5 * Debt(IHS)^2 + ß_6 * Debt(IHS)^3 + ß_7 * GW\ (IHS) * Debt(IHS) + ß_8 * GW(IHS)^2 * Debt(IHS) + ß_9 * GW(IHS)^3 * Debt(IHS) + ß_{10} * GW\ (IHS) * Debt(IHS)^2 + ß_{11} * GW\ (IHS) * Debt(IHS)^3 + ß_{12} * GW(IHS)^2 * Debt(IHS)^2 + ß_{13} * GW(IHS)^3 * Debt(IHS)^2 + ß_{14} * GW(IHS)^2 * Debt(IHS)^3 + ß_{15} * GW(IHS)^3 * Debt(IHS)^3 + \varepsilon$
13	GAM	GW & Debt	undefined	$Y = f(GW, Debt) + \varepsilon$
14	GAM	GW & Debt	undefined	$Y = f\big(GW(log), Debt(log)\big) + \varepsilon$
15	GAM	GW & Debt	undefined	$Y = f\big(GW(IHS), Debt(IHS)\big) + \varepsilon$

Note: GAM=Generalized additive model; GLM=Generalized linear model, GW=Gross wealth; IHS=Inverse hyperbolic sine; NW=Net worth.

5.5.2 Results of the simulation

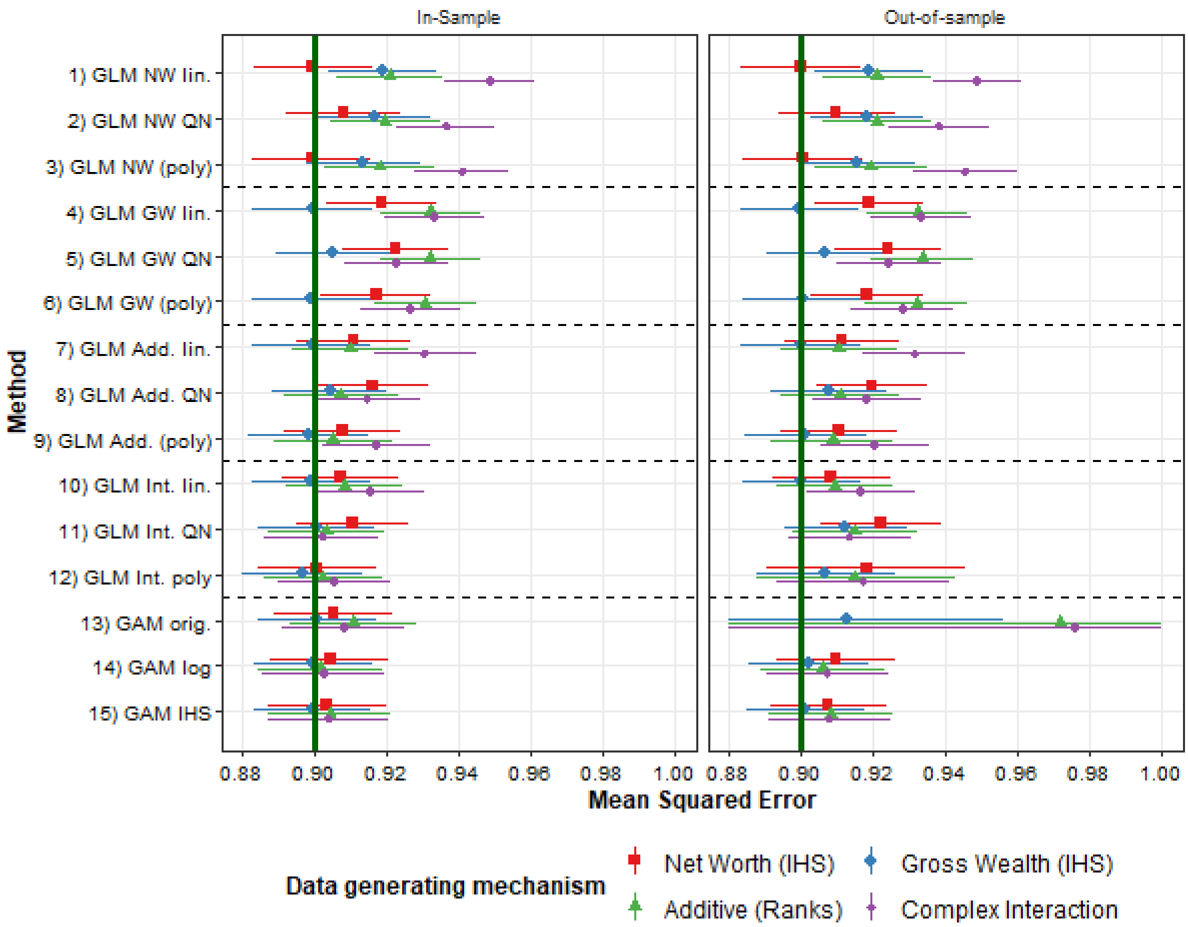
Figure 5.3 shows the results of the simulation. The colored dots indicate the average MSE over the 500 simulations for the 15 different combinations (on the y-axis). The vertical lines around the colored dots indicate the Monte Carlo 95% confidence intervals. The left panel shows the in-sample MSEs of the combinations, the right panel the out-of-sample MSEs. The green vertical line indicates the ‘target’ MSE of 0.90.

Overall, we see that the in-sample MSEs of GAMs are similar and, in most cases better compared to the GLMs. GLMs using only net worth (models 1-3) or only gross wealth (models 4-6) only capture wealth effects well if the data generating mechanism exactly corresponds to this one-dimensional measure of wealth. For instance, if net worth is the data generating mechanism (red squares), we obtain an MSE of 0.90 when using an GLM with net worth. In contrast, we miss a lot of the systematic wealth differences if there is another data-generating mechanism. We only get MSEs of around 0.92 if the data is generated by gross wealth (blue dots) or by an additive combination of gross wealth and debt (green triangles) and an MSE of around 0.94 if the data was generated by the interaction of gross wealth and debt (purple diamonds). Models that consider the linear combination of gross wealth and debt (models 7-9) capture most of the wealth effects if the data generating effect is either ‘Gross Wealth IHS’ or ‘Additive (Ranks)’. However, MSEs are larger if there exists an interaction between gross wealth and debt. The most complex GLMs (model 11-12) detect most of the systematic variation for all four data-generating mechanisms under consideration. Likewise, the three GAMs with the different transformations of gross wealth and debt (models 13-15) have in-sample MSEs of close to 0.90. Thus, the predicted values of the complex GLMs and the GAMs are close to the simulated values (see supplementary materials B).

At the same time, GAMs are better in predicting outcomes for new data than the complex GLMs, as indicated by the lower cross-validation MSEs. The more parsimonious GLMs (models 1-10) have almost the same MSEs both in-sample and out-of-sample. In contrast, both the complex GLMs and the three GAMs have higher out-of-sample MSEs than in-sample MSEs for all four data-generating mechanisms because they overfit the data. The largest overfitting emerges for the GAM using gross wealth and debt on their original scales (MSE>0.97 for three data-generating mechanisms) followed by the complex GLMs (MSEs between 0.906 and 0.922). The GAMs with log and IHS transformed wealth overfit least. Their MSEs range from 0.901 to 0.909.

Taken together, GAMs capture most of the systematic wealth variation for all four data-generating mechanisms, which gives them an edge over all parsimonious GLMs. At the same time, GAMs with log- or IHS-transformed gross wealth and debt make a more accurate prediction in the cross-validation, which gives them an edge over the complex GLMs.

Figure 5.3 MSEs of different combinations of methods, wealth measures, and specifications in the simulation analysis



Note: Add.=Additive (Gross Wealth + Debt); GAM=Generalized additive model; GLM=Generalized linear model, GW=Gross wealth; IHS=Inverse hyperbolic sine; Int.=Interaction (Gross Wealth × Debt); NW=Net worth; QN=Quintile. The out-of-sample MSE of GAM with original values of gross wealth and debt (MSE=1.12) is not shown.

5.6 Showcase analysis

Yet, the advantage of GAM with transformed gross wealth and debt may only apply to the specific data-generating mechanisms considered in the simulation study and may not apply to the association between wealth and the outcome of interest in observed data. Moreover, differences in the substantial results derived from the different approaches might be too small to be meaningful. Therefore, we next turn to the association between parental wealth and children's educational attainment in the PSID. We focus on the outcome of a BA degree at the age of 25 years, for which Pfeffer finds the largest wealth gaps.

5.6.1 Wealth gaps in educational attainment

Unlike in the simulation study, we do not know the data-generating mechanism and how well we could predict whether children will obtain a BA degree when choosing the optimal wealth measure. The only reference is how well we would predict whether children will obtain a BA degree if we predict the average probability to obtain a BA degree in the sample for all cases (22.9%): In this case, we have a mean log error of 0.538 (see Table 5.2).

Overall, we see a similar picture as for the simulation study: The most complex models explain most variance (in-sample) in whether children obtain a BA degree. The GAMs with log- or IHS transformed gross wealth and debt have the lowest mean log error (0.457) followed by the GLM with the interaction between gross wealth and debt (mean log error=0.458). In contrast, a GLM with net worth explains substantially less variance (mean log error 0.474 to 0.479).

The GLM using only gross wealth performs best in the cross-validation with a mean log error of 0.466. The GAM with IHS transformed gross wealth and debt comes with a mean log error of 0.472 rather close to this. The out-of-sample mean log errors for the GAMs with untransformed wealth (mean log error=0.506) or log gross wealth and debt are higher (mean log error=0.483). The complex GLMs overfit the data and produce mean log errors (0.520 and 0.624) close to or even worse than predicting the average probability for all children.

Table 5.2 In-sample and out-of-sample prediction accuracy of different combinations of methods, wealth measures, and specifications.

No.	**Method**	**Wealth measure**	**Specification**	In-sample performance Mean log. error	Out-of-sample performance (5-fold cross validation) Mean log. error
-	GLM	-	only intercept	0.538	0.538
1	GLM	NW	linear	0.479	0.481
2	GLM	NW	categorical	0.475	0.483
3	GLM	NW	cubic	0.474	0.483
4	GLM	GW	linear	0.467	0.469
5	GLM	GW	categorical	0.464	0.468
6	GLM	GW	cubic	0.462	0.466
7	GLM	GW + Debt	linear	0.466	0.469
8	GLM	GW + Debt	categorical	0.463	0.475
9	GLM	GW + Debt	cubic	0.462	0.475
10	GLM	GW * Debt	linear	0.466	0.470
11	GLM	GW * Debt	categorical	0.460	0.624
12	GLM	GW * Debt	cubic	0.458	0.520
13	GAM	GW & Debt	undefined	0.460	0.506
14	GAM	GW & Debt	undefined	0.457	0.483
15	GAM	GW & Debt	undefined	0.457	0.472

Note: Data of the Panel Survey of Income Dynamics; N=4,341. GLM=Generalized Linear Model; GAM=Generalized Additive Model; NW=Net Worth; GW=Gross Wealth.

Depending on which method, wealth measure, and specification we choose our conclusions about who is advantaged or disadvantaged for obtaining a BA degree substantially differ. Figure 5.4 shows the predicted probabilities for all observed combinations of gross wealth (on the x-axis) and debt (on the y-axis) for the different methods and wealth measures. The colors of the dots indicate the predicted probabilities ranging from less than 5% (dark red dots) to more than 50% (dark green dots). The exact predicted probabilities and their standard errors are available in supplementary materials C; the underlying regression coefficients of the GLMs and smoothing parameters of the GAMs are available in supplementary materials D.

If we use net worth as a measure of wealth (see the upper left part in Figure 5.4), we get the common result that children in households with the lowest net worth show the lowest probability to obtain a BA degree and children in households with high net worth the highest probability. Children in households with net worth of less than -$10k have a predicted probability of less than 5% and children in households with more than $600k have a probability of more than 50% of obtaining a BA degree.

Contrary, if we use gross wealth (see the upper middle part in Figure 5.4), we find that children in households between $5k and $20k gross wealth have the lowest probability and children in households of more than $500k the highest. We would draw a similar conclusion when using gross wealth and controlling for debt (see upper right part of Figure 5.4).

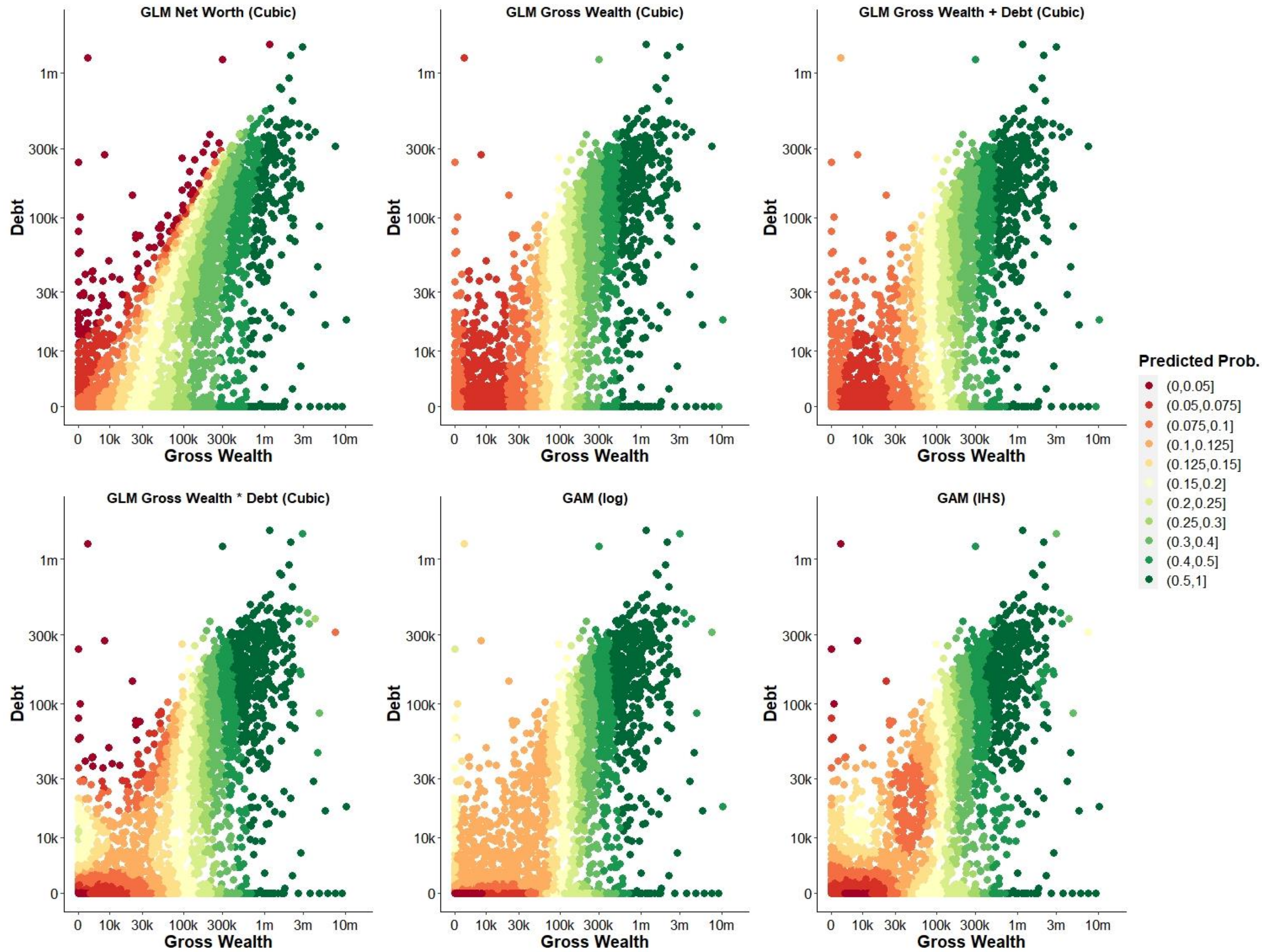
When we additionally consider the interaction between gross wealth and debt (see the lower parts of Figure 5.4) we see two things: First, among households with a gross wealth of $100k or more, the GLM with the interactions of gross wealth and debt and the two GAMs, largely resemble the results of the GLM with gross wealth only. Thus, even these complex models suggest the probability of obtaining a BA degree is well described by using only gross wealth for households with high gross wealth. For example, when using GAM with IHS transformed gross wealth and debt (see the lower right part in Figure 5.4), children in households with $300k gross wealth and $10k debt have a predicted probability of 37.7% (SE=4.6%), compared to 41.2% (SE=2.5%) among children in household with $300k gross wealth and $100k debt, or 43.9% (SE=5.2%) among children in households with $300k gross wealth and $300k debt. It even looks like that for households with high gross worth higher debt is related to an even higher probability to obtain a BA degree.

Second, for the households with low gross wealth, the results obtained from the more complex models differ substantially from the GLMs that do not consider the interaction between gross wealth and debt. Thus, the more flexible models in the lower parts of Figure 5.4 suggests that both gross wealth and debt matter for the probability of obtaining a BA degree among the children in households with low gross wealth. Children in households with less than $10k gross wealth and no or little debt have the lowest probability to obtain a BA degree. Even children in households with low wealth but some debt have a higher predicted probability than children in households with no gross wealth and no debt. For instance, looking at the GAM with IHS transformed wealth, children in households with $10k gross wealth and zero debt have a predicted probability of 4.6% (SE=1.1%) while children in households with $10k gross wealth and $10k debt have a predicted probability of 15.8% (SE=3.0%).

This pattern of wealth differences in educational attainment cannot be captured when measuring wealth as net worth. This becomes most obvious when comparing households with zero net worth but different combinations of gross wealth and debt. For instance, looking at the GAM with IHS transformed wealth, children in households with zero gross wealth and zero debt have a predicted probability of obtaining a BA degree of 6.1% (SE=1.3%) and children in households with $300k gross wealth and $300k debt have a predicted probability of 43.9% (SE=5.2%). In contrast, when using net worth (upper left part of Figure 5.4), both children have the same predicted probability of 8.0% and the same SEs of 0.6%.

There are also some differences between the GLM that includes the interaction of gross wealth and debt, the GAM with log-transformed wealth, and the GAM with IHS-transformed wealth. The GLM (lower left part in Figure 5.4) suggests that children in households with zero gross wealth and $10k debt have a higher probability to obtain a BA degree than children in households with higher gross wealth or less or more debt. Here, the GLM likely overfits the data. The GAM with log-transformed wealth (lower middle part of Figure 5.4) indicates a large difference between households with zero gross wealth and debt and households with little gross wealth and debt but smaller differences among households with nonzero gross wealth and debt. This results in a large group of children in households with $100 to about $50k gross wealth and debt all having a rather similar predicted probability. In contrast, GAM with IHS transformed wealth (lower right part in Figure 5.4) results in more gradual differences between these households. Based on the out-of-sample mean log errors, the gradual differences (GAM with IHS transformed wealth) seem to provide more accurate predictions than the large differences between zero and small values of gross wealth and debt.

Figure 5.4 Predicted probabilities of having obtained a bachelor's degree at age 25 with different combinations of methods, wealth measures, and specifications



Note: Data of the Panel Survey of Income Dynamics; N=4,341.

Compared to wealth gaps in obtaining a BA degree, slightly different patterns emerge when using GAM to evaluate wealth stratification in high school graduation or college attendance rates (see supplementary materials E). However, also for these outcomes, we find that it is particularly those children in households with high gross wealth who have higher probabilities (independent of debt) and children in households with zero or little gross wealth and debt who have the lowest probabilities.

Moreover, researchers are usually interested in the wealth gaps when adjusting for other measures of socio-economic status or potential confounders. Also, Pfeffer evaluates 'wealth as an independent source of educational advantage'. Wealth gaps in obtaining a BA degree shrink drastically when adjusting for other measures of parental SES and demographics (see supplementary materials F). Yet, we still see a similar picture to the one for unadjusted wealth gaps regarding the combinations of gross wealth and debt that result in higher probabilities to obtain a BA degree.

Based on the results of our alternative approach, we can draw more fine-grained conclusions about the wealth gaps in educational attainment than Pfeffer (2018). Our approach shows that by ignoring the two-dimensional nature of wealth, Pfeffer defines the group of disadvantaged children as too ample and the group of advantaged children as too narrow. Regarding the disadvantaged group, not the children in the households in the lowest net worth quintile have the worst educational prospects, but children in the households with little assets and little debt, which is only part of the children in the lowest net worth quintile. As to the most advantaged children, our results suggest that it is not only the group of children in the highest net worth quintile – as reported by Pfeffer – that have the best educational prospects, but also children in households with high and similar amounts of gross wealth and gross debt. Those with high and similar amounts of gross wealth and gross debt are exactly the children who Pfeffer 'falsely' assigned to the group of children with the lowest educational prospects based on their net worth. For instance, children in households with \$300k gross wealth and \$300k debt belong to the lowest net worth quantile and have a predicted probability of obtaining a college degree of 9.1% (Pfeffer 2018, Table A2). Contrary, the results of GAMs with IHS-transformed gross wealth and debt suggest that these children belong to the group of children with the highest probability of 43.9% to obtain a BA degree.

5.6.2 Cohort differences

Another important finding of Pfeffer's work was that gaps in educational attainment by parental wealth have grown over cohorts. Applying GAMs with IHS-transformed gross wealth and debt supports this claim but allow us to make a more nuanced analysis of which wealth contrasts increased and by how much. The upper part of Figure 5.5 shows the predicted probability of having obtained a BA degree at age 25 for children born in the 1970s, the lower part for children born in the 1980s.

The general pattern of which households are advantaged or disadvantaged remained similar in both cohorts. Children in households with no or little gross wealth combined with no or little gross debt are least likely to obtain a BA degree and children in households with gross wealth are most likely to do so. However, the predicted probability to obtain a BA degree increased over cohorts particularly for children in the households with high gross wealth, as indicated by the darker shades of green in the lower part of Figure 5.5 as compared to the upper part.

For example, the predicted probability of obtaining a BA degree in households with $300k gross wealth and $300k debt increased from 28.6% (SE=8.0) for children born in the 1970s to 45.8% (SE=6.8) for children born in the 1980s. In contrast, for children in households with zero gross wealth and zero debt the probability only increased from 3.2% (SE=1.3) for children born in the 1970s to 8.9% (SE=2.1) for children born in the 1980s.

Figure 5.5 Predicted probabilities of having obtained a bachelor's degree at age 25 by birth cohort

Note: Data of the Panel Survey of Income Dynamics; N=4,341. Based on GAM with IHS-transformed gross wealth and debt.

5.7 Discussion

Existing research on wealth effects on all kinds of outcomes is restricted by conceptual decisions about how wealth effects may look like. Researchers can only find what their research design allows them to find. By measuring wealth as net worth, researchers make strong, and often implicit, assumptions about which combinations of wealth components will result on average in similar outcomes. Likewise, the scope of results that can be obtained is restricted.

We propose to explore wealth effects on the surface of gross wealth × gross debt using Generalized Additive Models (GAM) to overcome two challenges in the analysis of wealth effects: the selection of the relevant wealth measure and the non-linearity of wealth effects. In a simulation study, we show that our suggested approach performs better in discovering systematic wealth differences than parsimonious parametric models and at the same time overfits less and produces more generalizable results than complex parametric models.

Applying our approach to wealth gaps in educational attainment, we find that we must partly revise our understanding of how wealth shapes children's educational opportunities. Results based on our approach show substantial systematic variation in educational attainment among children in households with the same net worth value but different combinations of gross wealth and debt. Most importantly, our approach shows that children from households with similar and high values of gross wealth and gross debt belong to the group of the most privileged children in terms of educational prospects, while previous research assigned them to the least privileged group. At the same time, children with low net wealth are most disadvantaged if they live in households that possess neither assets nor debt. Children in households with low assets combined with higher amounts of debt fare similar well as children from households with medium amounts of assets.

Studying wealth stratification on the surface of gross wealth × gross debt using GAMs can also deepen our theoretical understanding of the mechanisms underlying the relationship studied. Our analyses on wealth effects on educational outcomes in the US showed that in the middle and the top of the wealth distribution, gross wealth is a better predictor of obtaining a college degree than net worth. As the largest asset and debt components of households in the middle and the top of the wealth distribution are real estate (in the middle this is mostly owner-occupied housing, at the top other real estate) and mortgages on them, we repeated our analyses on the surface of gross housing wealth × mortgages. We find that the value of the house is much more relevant for obtaining a college degree than the remaining mortgage, which is in line with the findings of Boen, Keister, and Aronson (2020) and Wagner et al. (2020). This could mean that children benefit from stable housing conditions and a good neighborhood, independent of how much mortgage debt their parents owe. Our findings that debt is a disadvantage only for households with little or no assets while for households with medium or large wealth high debt is not related to educational attainment might indicate that another factor causes the observed differences: access to credit. High debt might be an indicator of access to credit, while no debt may indicate low creditworthiness. Also, it might indicate two different types of debt underlying these relationships, namely productive or wealth-generating debt (i.e., mostly mortgage debt) as compared to unproductive or consumption debt (e.g., credit card debt; Hiilamo 2020) or to different kinds of indebtedness, such as over- and under-indebtedness (Betti et al. 2007) or secured and unsecured loan. As to the latter one, Zhan and Sherraden (2011b) found college completion to be positively affected by secured loans and negatively by unsecured loans. Cai et al. (2021) find secured debt to be related to other dimensions of well-being as unsecured debt. From a conceptual perspective, Hansen and Toft (2021) refer to a undertheorizing of debt in social stratification research in general and in the analysis of social classes in particular. They state that raising debt can be a strategy to accumulate wealth that requires access to credit. Debt might even constitute an additional dimension of social inequality reinforcing already existing social inequalities, as credit institutes are likely to facilitate debt-based accumulation by the already advantaged groups while providing high-interest consumer credit to the already disadvantaged ones (Hansen and Toft 2021).

While our approach avoids several pitfalls in the analysis of wealth effects, it also has some limitations. Most importantly, the choice of the scale parameter in the IHS transformation can affect the results (Aihounton and Hennigsen 2020) even when using GAM. Therefore, researchers still have to check the robustness of their results to the choice of the scale parameter. The results of the re-analysis of Pfeffer (2018) are robust when using the other recommended scale parameters of 0.00003 and 0.00001 (Pence 2006). Second, there may not only be large heterogeneities between households with the same net worth but also differences between households with similar amounts of gross wealth and debt but different wealth portfolios, i.e., different types of assets (e.g., homeownership wealth, other real estate, stocks, bonds, business assets) and debt (e.g., mortgage, consumption debt). Theoretically, GAMs can also be applied to three or more wealth components. However, the interpretation of these models becomes very difficult when considering more than two components and their interactions.

Based on our findings, what are our suggestions for social stratification scholars studying wealth as an independent variable? We suggest analyzing differences on the surface of gross wealth × debt using GAM as the first step, whenever researchers consider combining assets and debt to net worth. If the resulting pattern aligns with the net worth assumptions, this analysis justifies the use of net worth. Likewise, the resulting pattern may suggest the use of other one-dimensional measures of wealth. Analyzing differences on the surface of gross wealth × debt using GAM can replace the common procedure to check the robustness of wealth effects to several one-dimensional wealth measures.

Wealth has to be measured with sufficient detail to check how wealth should be measured and if and how certain wealth components should be combined into a single measure. Therefore, we recommend surveys that cover wealth to separately ask at least for assets and debt, instead of only asking for net worth. First, our paper supports the claim that net worth is not always the most relevant measure of wealth. Second, to report net worth, individuals have to subtract their debt from their assets, which means they have to look up or calculate these measures anyway.

Our approach is easily implementable using the R-package mgcv (Wood 2017) and can be applied to most outcomes of interest. Applying our approach may challenge existing results also for other outcome variables affected by wealth such as health, or general well-being. On the downside, our approach is likely to make subsequent analyses more complicated. This comes, however, at the virtue of being more likely to correctly identify advantaged and disadvantaged groups. Only if such groups are identified correctly, policymakers can install targeted measures to reduce potential inequalities.

6. General discussion

Based on these four studies I can now answer the four broader research questions of the dissertation. Moreover, I will elaborate on the limitations of my studies, and discuss potential future research and the implications of my findings.

6.1 Answering the research questions

6.1.1 Are there wealth gaps in education in Germany?

There are substantial wealth gaps in education in Germany, net of differences by other dimensions of SES. I found wealth gaps for almost all educational outcomes that I considered: Children growing up in wealthy households score up to 0.26 SD higher in standardized achievement tests, are about 10 percentage points more likely to leave secondary school with the highest school leaving certificate (43.7% of children at the bottom of the wealth distribution vs. 53.1% of children at the top of the distribution), are four times less likely to leave secondary school without any certificate (5.2% vs. 1.3%), and are eight percentage points more likely to attend higher education (20.8% vs. 29.2%).

Since I have analyzed some outcomes with different starting cohorts of NEPS, these also serve as robustness checks for each other (see the overlap between the red, yellow, and blue squares in Figure 6.1). Despite differences in the model specification, results are similar. With the data of the starting cohort Newborns, I find a maximal wealth gap in children's achievement of 0.24 SD. With starting cohort Kindergarten, I find a maximal wealth gap of 0.15 SD. Likewise, I find very similar wealth gaps in the likelihood of attending the highest secondary school track in both the prospective data from the starting cohort Kindergarten (wealthy children from this cohort are about 8 percentage points more likely to attend *Gymnasium*: 55.7% vs. 64%) and in the retrospective data of starting cohort 9th graders (also about 8 percentage points: 42.2% vs. 50.3%).[33]

Wealth gaps in enrollment in tertiary education in Germany seem to be larger than in Sweden, and of similar magnitude as in the United States, although the relevant studies are not directly comparable due to differences in the outcome, specification of wealth effects, selection of control variables, and sample selection. For Sweden, Hällsten and Thaning (2018, Table 3) report that students at the 90th percentile of the net worth distribution are about six percentage points more likely to graduate from tertiary education than students at the 10th percentile. For

[33] The larger average proportion of students attending the *Gymnasium* can be attributed to selective panel attrition in starting cohort Kindergarten.

the United States, Pfeffer (2018, Table 1) finds that children in the top quintile of the wealth distribution are about eight percentage points more likely to attend college compared to children in the lowest quintile.

Compared to the other dimensions of SES, wealth gaps in education are smaller than gaps by parental education but comparable in size to gaps by EGP class or income. Ultimately, the importance of different dimensions of SES depends on the outcome under consideration.

Researchers will underestimate social stratification in education when ignoring wealth since educational outcomes are stratified by parental wealth, net of the other dimensions of SES. The joint contribution of multiple variables can be evaluated based on their partial eta-squared (i.e., their contribution to R^2; Olejnik and Algina 2003) or the distribution of predicted values based on the SES dimensions (holding control variables constant).[34] Table 6.1 exemplarily shows this underestimation for enrollment in tertiary education. Compared to a model with only the control variables as predictors, the explained variance increases by 9.11% when adding all four dimensions of SES as predictor variables (see row 'All four SES dimensions'; column 'partial eta-squared' in Table 6.1). Children with high values on all four SES dimensions are almost 40 percentage points more likely to enroll in tertiary education than children with low values on all four dimensions (see column '90^{th} vs. 10^{th} percentile'). In contrast, if we only use one dimension of SES, we capture at most 7.41% of the variance (parental education). Thus, by only considering parental education, we underestimate the eta-squared of SES by 15.2%. The difference in predicted probabilities by parental education is only about 30 percentage points. If we use parental education, occupational class, and households' income, but ignore wealth (row 'Education, EGP, & Income'), we still underestimate the partial eta-squared of SES by 4.2% and the difference between the most and least advantaged children by 6.6%.

[34] Researchers who only consider linear effects of all SES dimensions could also apply the method proposed by Lubotsky and Wittenberg (2006).

Table 6.1 Partial eta-squared of different SES dimensions for enrollment in tertiary education

Considered SES dimensions	Partial eta-squared	Percent of partial eta-squared with all four SES dimensions	90th vs. 10th percentile of SES-based predicted values	Percent of 90th vs. 10th percentile with all four SES dimensions
Only Education	7.41	84.75	29.84	75.26
Only EGP	4.90	62.17	26.64	67.19
Only Income	3.63	50.83	21.05	53.09
Only Net Worth	2.55	41.13	19.71	49.71
EGP, Income, & Net Worth	6.75	78.76	33.20	83.72
Education, Income, & Net Worth	8.54	94.83	37.88	95.53
Education, EGP, & Net Worth	8.96	98.67	39.27	99.05
Education, EGP, & Income	8.65	95.82	37.11	93.58
All four SES dimensions	9.11	100.00	39.65	100.00

Based on linear probability models of enrollment in tertiary education on different dimensions of SES and control variables (household size, average age of parents, parents' migration background, marital status, and whether the family lives in eastern or western Germany).

6.1.2 At which stage in the educational system do wealth gaps emerge?

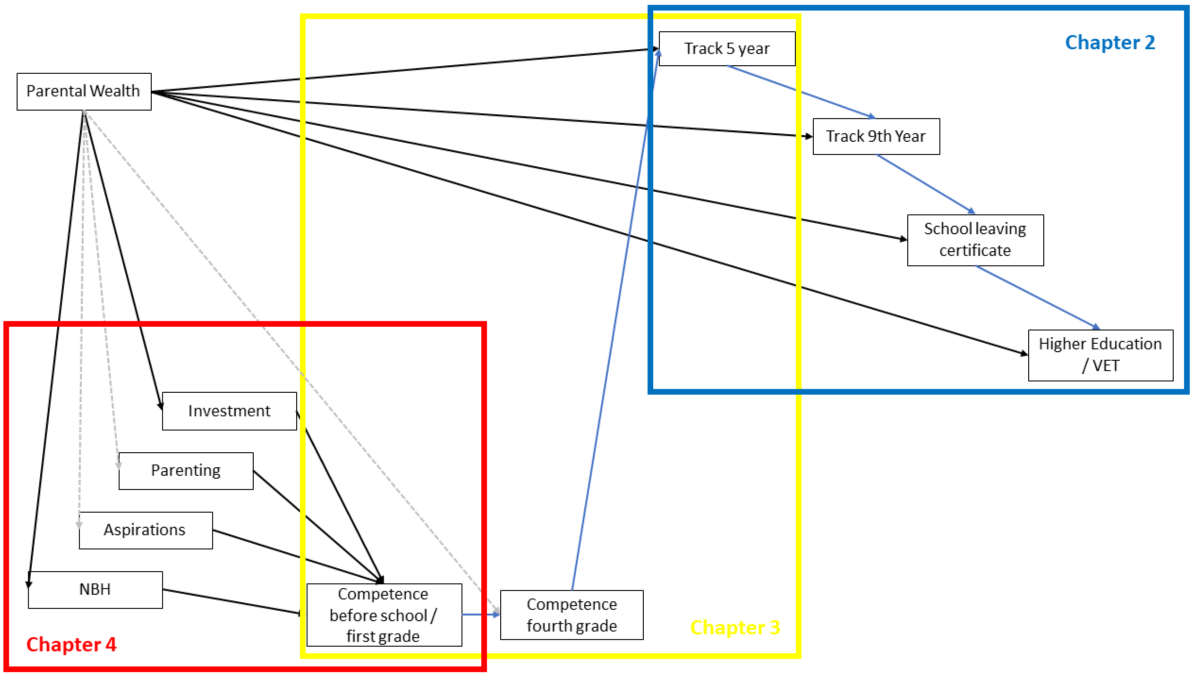
Wealth gaps accumulate throughout children's educational trajectories. However, there seem to be three crucial phases.

First, wealth gaps in achievement already occur before children enter school. In line with the results for the US (Elliott et al. 2011), I find larger wealth gaps in math and science competencies than in reading and grammar. These wealth gaps persist at later ages but do not seem to grow (as indicated by the dashed grey arrow *Parental Wealth → Competence fourth grade* in Figure 6.1). This is in line with the results that Skopek and Passaretta (2020) found for the development of achievement gaps by parental education. However, keep in mind that I have not considered entire school careers when analyzing wealth gaps in achievement. Wealth gaps in achievement may get larger because wealthy children are more likely to attend higher secondary school tracks and children have larger achievement gains on higher tracks (Guill, Lüdtke, and Köller 2017; Retelsdorf et al. 2012).

Second, wealthy children are substantially more likely to transfer to the highest school track after elementary school. About half of the wealth gap in transition rates by wealth can be attributed to differences in performance (i.e., primary effects) and the other half to differences in educational decisions by wealth, net of differences in school performance (i.e., secondary effects). In contrast to the intuitive expectation that these academically ambitious educational decisions might lead to lower success rates in secondary school, wealthy children are slightly more likely to transfer to higher tracks and less likely to transfer to lower tracks during secondary school. Instead, high parental education or occupational class compensate for less academic preparedness (Dräger, Röhlke, and Dippel 2021). This seems to apply to parental wealth, too.

Third, there are substantial wealth gaps at the transition to vocational training or higher education. Wealth gaps emerge for all students, including those students with no or the lowest school leaving certificate. In the subset of students with the lowest school leaving certificate, high wealth is associated with a higher likelihood of starting dual VET. Among the students with the highest school leaving certificate, wealthy students are more likely to enroll in universities.

Figure 6.1: Summary of the results in chapters 2 to 4



Note: Black arrows indicate hypotheses about wealth effects that are supported by the results; dashed grey arrows indicate hypotheses about wealth effects that are not supported; blue arrows indicate effects that carry wealth effects forward.

6.1.3 Where within the wealth distribution do differences emerge?

Most of the wealth gaps in education emerge at the bottom of the *net worth* distribution. In particular, children in households with zero net worth or little negative net worth have, on average, worse outcomes than children in the middle of the net worth distribution. There are also differences between children in the middle and the top of the net worth distribution, albeit these are less pronounced (see chapters 3 and 4). However, keep in mind that there are few households with a very high net worth in NEPS and most other surveys.

Yet net worth is not the best measure of wealth gaps in education. As shown in chapter 5 for the United States, wealth gaps in education can be better described by the two-dimensional combination of gross wealth and debt, rather than by any one-dimensional measure of wealth. Children in households with few assets and little debt have the worst educational prospects, while children in households with high assets have the best educational prospects almost independently of their debt.

Moreover, I evaluated which wealth components are associated with children's educational outcomes (approximated by the existence of different assets; chapter 3). I find substantially worse achievements in the small group of children living in households without a savings book or checking account and higher achievements in children whose parents own their house.

6.1.4 Which mechanisms drive wealth gaps?

Throughout my studies, I used three different approaches to investigate the underlying mechanisms of wealth gaps in education.

First, I tried establishing the mechanisms directly, by testing the mediators between wealth and children's academic performance (neighborhood effects, parental aspirations, family stress, parental investment; chapter 4). Although I considered all central mechanisms proposed in the literature, these mechanisms explain only 17% of the wealth gaps in academic performance. Among the mediators I considered, parental investment seems to be most relevant. For some measures of academic performance, neighborhood effects are of similar importance. At least for these young children, I did not find evidence for a contribution of educational aspirations or family stress processes.[35]

Second, I tried to examine the mechanisms indirectly, based on assumptions about which mechanisms are more important for which outcomes and at different ages for the child (chapters

[35] Still, educational aspirations may be more relevant for educational decisions.

2 and 3). The finding that large wealth gaps already emerge at the transition to secondary school implies that parents may anticipate that this is an easier way to tertiary education. The finding that children in high wealth households are much less likely to experience poor educational outcomes, such as not graduating from secondary school, may imply that parental wealth compensates for poor educational performance (Wiborg 2017).

Third, one can infer potential mechanisms based on where in the wealth distribution differences in children's educational outcomes emerge and which wealth components are more important for educational outcomes (chapters 2, 3, and 5). I find that children in households with negative net worth often have better prospects than children in households with few debts but also few assets. This may indicate that children profit from stable housing conditions and suffer from liquidity constraints and restricted access to credit rather than suffering from debt. This argument is supported by the substantially worse outcomes of children in households without savings books or checking accounts. I did not find that children in households at the top of the wealth distribution are demotivated to enter vocational training or enroll in university after graduating from secondary school as proposed by Müller, Pforr, and Hochman (2020) or that they are negatively affected by moral hazard.

6.2 Limitations

There are some limitations that apply to all four studies.

First, wealth is likely measured with error. In NEPS, only total gross wealth and total debt were measured. On the one hand, this may lead to worse net worth estimates than when surveying more components of wealth. On the other hand, it does not allow us to evaluate in more detail which wealth components drive the wealth gaps. Furthermore, wealth was only measured once in each starting cohort of NEPS. While household wealth is likely to be reasonably stable over time, it would have been helpful to quantify the stability and potentially evaluate the impact of changes in household wealth. Moreover, the timing of the wealth measure was not optimal for my research questions. In starting cohort Newborns, wealth was measured when children were two years old; in starting cohort Kindergarten, wealth was only measured when children were in the second grade. Thus, wealth was only measured after some of the outcome of interest.

In general, there are only two data sets that allow the analysis of wealth gaps in children's education in Germany: NEPS and SOEP. There is a clear trade-off between these two data sets. NEPS has excellent data on children's achievements and educational pathways but only one somewhat imprecise measure of wealth. In contrast, SOEP measures wealth repeatedly and with more detail but has less information on children's education, and the number of households that can be analyzed is much smaller (see Grätz and Wiborg 2020; Müller et al. 2020; Pfeffer and Hällsten 2012). Therefore, the analyses in studies 1-3 would not have been possible with SOEP data.

Second, like in most survey data, the households with high wealth are underrepresented and the households with very high wealth are missing. Children in households with wealth measurable in millions of euros may differ in their educational outcomes from the outcomes of children of moderately wealthy households, for example, due to moral hazard (Bodvarsson and Walker 2004) or because their inheritance may secure children's social position without requiring high educational attainment (Müller et al. 2020). I could not study this with the data at hand. However, it may be possible to evaluate the educational trajectories of children from very wealthy households using the recently collected data of the 'Wealth-holders at the top', which sampled households with very high business assets (Schröder et al. 2020).

Third, my dissertation describes wealth gaps in children's education, but I cannot make causal claims because not all relevant confounders were measured in NEPS. For example, parents' skills are likely a confounder of the association between parental wealth and children's education (Doren and Grodsky 2016) but parents' skills were not measured in NEPS. Because of this, the causal effect of wealth on children's education is likely smaller than the wealth gaps reported here. Only a handful of studies make claims about the causal effect of wealth based on lottery wins (Bleakley and Ferrie 2016; Bulman et al. 2021; Cesarini et al. 2016). However, these studies probably do not capture the consequences of the normative function of wealth, which likely only arises when wealth is passed on over generations and not when it is won in the lottery (Hällsten and Pfeffer 2017). Sibling fixed effects models have the same problem and there are not enough households in the SOEP to obtain reliable estimates. Sibling fixed effects are not feasible with NEPS because wealth was only measured once.

6.3 Future research

My studies leave several questions unanswered which future research may consider.

1. Does wealth affect further educational outcomes that were not studied here? The latest stage in children's educational trajectories that I evaluated here is which kind of further education or training children enroll in after graduating from secondary school. Yet wealth may also affect whether children graduate from these programs and continue to further education after finishing their vocational training or their bachelor's degree

(paths F and G in the chapter 2). Moreover, parental wealth may affect the choice of field of study (Hällsten and Thaning 2018) and whether children attend private schools or private universities.

2. How large are wealth gaps in education in Germany compared to wealth gaps in other countries? Existing single country studies are hardly comparable, because of different outcomes under consideration, different measures of wealth and different specifications of wealth effects, and restrictions to different subgroups of the population.
3. Which mechanisms cause wealth gaps in educational decisions? In the third chapter, I elaborate on how wealth may affect the cost and benefit considerations of families. The different parameters of the subjectively expected utility theory were measured in NEPS and future studies could test whether these components account for wealth gaps in educational decisions (Stocké 2007; Zimmermann 2019).
4. What role does the insurance function of wealth play for children's educational outcomes? In my dissertation, I assumed that the insurance function is an important reason why wealth has a unique effect on children's outcomes, but I only tested the contribution of the purchasing function (parental investment) and the normative function (educational aspirations and norms in chapter 4). One way to learn more about the importance of the insurance function could be to test whether wealthy families react differently to negative life events (e.g., parental unemployment, parental divorce).
5. What role do teachers and peers play in wealth gaps in education? In my dissertation, I have focused on the perspective of families. However, teachers function as gatekeepers in the educational system and peers have important consequences for children's outcomes. An alternative mechanism that explains the better educational outcomes of wealthy children could be the preferential treatment of wealthy students by teachers and classmates.
6. Do families perceive the processes that are assumed to cause wealth gaps? I assume that families without wealth are restricted in their investments, feel forced to make risk-averse educational decisions, and hold different educational norms and aspirations. Particularly the assumption about risk aversion assumes farsighted decisions of families. Qualitative studies could evaluate whether families perceive these restrictions and consider them in their educational decisions.
7. Do different dimensions of SES interact in their effect on children's education? In my studies, I have assumed that wealth has an additive effect on children's education. However, the effect of wealth may depend on other characteristics. For instance, wealth

may have different effects for children with a migration background or may depend on the birth order.

8. Does it matter in which generation wealth was accumulated? Families who have been wealthy for several generations may behave differently than families who have only recently accumulated wealth. The difference between dynastic wealth and self-earned wealth may also explain why studies that use lottery wins often find much smaller effects than studies that use other approaches to test the causal effects of wealth on children's outcomes (Hällsten and Pfeffer 2017). Comparing families who accumulated their wealth over several generations to families who accumulated their wealth in one generation may thereby give us an idea of the importance of the normative function of wealth.
9. Which role does restricted access to credit play for children's outcomes in Germany? One explanation for the better educational prospects for children with negative net worth might be that negative net worth indicates access to credit (Killewald 2013). Thus, it may not be wealth that causes children's outcomes, but that wealth gaps may just capture differences in the access to credit. However, most research to date on the effect of access to credit focuses on the United States (Dwyer 2018).
10. How important is education for the intergenerational transmission of wealth in Germany? In my dissertation, I have assumed that one of the main reasons for the higher educational attainment of wealthy children is that wealthy parents invest in their children's education to ensure the intergenerational transmission of advantages. However, education is only one way in which advantages can be passed on over generations. Thus, future research should evaluate the relative importance of education for the intergenerational transmission of wealth relative to other channels of transmission like inheritances and gifts, assortative mating, etc.

6.4 Implications

Despite these limitations and unanswered questions, the findings of my studies have important implications for both research and policy.

6.4.1 Implications for research

Based on my results, I suggest that four practices in research on social stratification in education be reconsidered.

Use a comprehensive measure of SES when studying social stratification in education. Researchers are often interested in describing social inequalities in education comprehensively instead of only describing inequalities by one dimension of SES. However, in practice, researchers often only use one dimension (parental education, class, or income) or combine several factors of social background to create an index. For example, PISA summarizes students' SES in an additive index based on parents' ISEI score, years of education, and home possessions. My results suggest that these approaches result in an underestimation of social stratification in education because they do not consider wealth.

Ignoring wealth when measuring SES may also be problematic for country comparisons because both the correlation between wealth and other dimensions of SES and the effect of wealth on education may differ between countries. Thus, country-rankings of inequality will likely differ if wealth is included as a dimension of SES (for a similar argument see also Brunori, Peragine, and Serlenga 2019; Marks 2011).

Indicators that consider wealth, like the recently proposed typology of socio-economic layers (Groh-Samberg, Büchler, and Gerlitz 2021), are a step in the right direction but only partially solve the problem. The authors propose a typology based on households' income and living conditions. Household living conditions are again an indicator based on each household's wealth, the characteristics of the dwelling, and the individuals' employment situations, which are all considered to be equally important. Thus, for the typology of socio-economic layers, income is three times more important than wealth. This may be appropriate for the study of some outcomes in some contexts but not for others.

If education, occupational class, income, and wealth are seriously considered to represent distinct dimensions of SES, they cannot be collapsed into a single indicator. Instead, I recommend that researchers who are interested in describing social inequalities comprehensively (and are not interested in the contribution of the components) include all relevant dimensions of SES in the same model. This approach incorporates the correlations between the dimensions and allows researchers to estimate the effects of the different components from the data, instead of making assumptions about their relative importance. The joint effect of all SES dimensions can then be evaluated by the partial eta-squared (Olejnik and Algina 2003) of the model with all SES dimensions compared to the model without the SES dimensions, as shown exemplarily in chapter 6.1.1. Yet using multiple dimensions to measure

SES may also lead to overfitting of the data, and thus an overestimation of social stratification. This problem can be addressed by applying cross-validation (Brunori et al. 2019).[36]

Use a comprehensive measure of wealth when studying wealth effects.

The same problem emerges when evaluating wealth effects and when comparing wealth effects across countries. Net worth can be thought of as an additive index of wealth: $Net\ Worth = 1 * Assets - 1 * Debt$. As shown in the fifth chapter, we obtain different results if we do not make this overly restrictive assumption. Particularly if researchers have no strong theory for how wealth may affect their outcome of interest, they should explore which wealth components are associated with the difference in the outcome. Wealth must be measured in sufficient detail in surveys to make these kinds of analyses.

Consider stratification throughout entire educational careers.

To get a better understanding of how inequalities in education emerge, educational trajectories must be examined in their entirety; inequalities will only be wholly understood if considered both unconditionally and conditionally on earlier educational pathways. Inequalities will not always accumulate over consecutive transitions because making ambitious early educational decisions may result in a higher likelihood of failing (see also Dräger, Röhlke, and Dippel 2021). Important inequalities may also emerge for those children who initially attend lower secondary school tracks or who obtain lower-level school-leaving degrees. The existing research on Germany has mostly focused on the pathways towards tertiary education, although social stratification in the transition to VET may be equally important.

Consider interdependencies between mediators.

Researchers are often interested in the underlying mechanisms or mediators of the association between parental SES and children's outcomes. As shown in chapter 4, it is crucial to consider the interdependencies between potential mediators for this analysis. If interdependencies between mediators are not considered, the results of the mediation analysis will be biased because earlier mediators may confound the association between the mediator of interest and the outcome (VanderWeele et al. 2014). Interdependencies between mediators are probably the rule rather than the exception in the social sciences. Besides the approach used in chapter 4 (Steen et al. 2017), several approaches to deal with causally related mediators have been proposed (Daniel et al. 2015; Vansteelandt and Daniel 2017; Zhou 2021). Researchers can

[36] Alternatively, social stratification can be described comprehensively by using machine learning tools like random forests (Brunori, Hufe, and Mahler 2018), which, however, do not allow researchers to adjust for control variables.

choose from these approaches, based on which assumptions seem to be most plausible for their research question.

6.4.2 Implications for policy

There are substantial wealth gaps in children's educational opportunities, even in the German context where education is mostly free of tuition fees. Since most existing studies have ignored wealth, social stratification in education may be even larger than initially thought. This stands in contrast to ideas of equality of opportunity and results in inefficient use of human capital.

Based on the trends of rising wealth inequality and privatization of education (chapters 1.1.3 and 1.1.4), as well as the consequences of the Covid-19 pandemic, wealth gaps in education will likely grow rather than shrink in the future. Wealth inequalities increased throughout the Covid-19 pandemic (Ahmed et al. 2022). While many families at the bottom of the wealth distribution may have dissaved wealth to smooth consumption due to job loss or reduced working hours, families at the top of the wealth distribution may have profited from the rising stock markets. Moreover, wealth may have become even more crucial for educational outcomes. Children of low SES families have suffered larger learning losses than high SES families (e.g., Engzell, Frey, and Verhagen 2021) and particularly students from low-income families report that they may drop out of their studies because they cannot finance them anymore (Becker and Lörz 2020).

In my dissertation, I only show that substantial wealth gaps in educational outcomes exist. The next goal should be to reduce these inequalities. In general, there are two ways in which wealth gaps in education could be reduced. On the one hand, wealth inequality could be reduced. At the top of the wealth distribution, one potential solution might be to reinstate wealth taxes. At the bottom of the distribution, more could be done to help families accumulate wealth. The current rules for the receipt of welfare benefits produce the opposite effect: Families do not receive welfare benefits if they have too much wealth, which prevents families from accumulating wealth (for a similar argument in the United States see Gibson-Davis and Hill 2021).

On the other hand, the consequences of wealth for education could be reduced. I will outline some suggestions as to how this could be achieved based on my finding that large wealth gaps emerge before children enter school, at the transition to secondary school, and at the transition to tertiary education or VET (see chapter 6.1.2). However, more research is needed to explicitly test these hypotheses.

Investments made by non-wealthy parents in their children's development could be increased by making access to the already existing *Bildungs- und Teilhabepaket* (education and participation package) easier. Currently, only 15% of the 2.5 million eligible families receive these benefits (Aust et al. 2019).

Similarly, extending the eligibility for *Bafög* (Germany's federal financial support program for education) to more years of study, reducing the requirement for a timely graduation and the minimum number of credits required in early semesters, and making subject changes easier, might reduce the economic risk of tertiary education and therefore allow more non-wealthy students to enroll.

Finally, since early between-school tracking seems one of the main reasons for the large social stratification in education (e.g., Pfeffer 2008; Van de Werfhorst 2019; Van de Werfhorst and Mijs 2010), it may be worthwhile to reconsider tracking. For example, Matthewes (2021) found that prolonged comprehensive schooling results in smaller social stratification in achievement and more efficient learning. In general, the decentral organization of education in Germany may allow us to find educational policies that reduce social stratification in education. Federal states with high levels of social stratification in education could adopt the educational policies of federal states with less social stratification. This requires the systematic evaluation of differences in the social stratification between federal states, which has been done for example in Switzerland (Stadelmann-Steffen 2012). In contrast, there are only a few studies which compare achievement across federal states in Germany (Köller et al. 2010; Pant et al. 2013; Schlicht 2011) and only one study that compares social stratification in educational attainment attendance across federal states (Dodin et al. 2021). I am not aware of any study that systematically links differences in social stratification to differences in the educational policies of the German federal states. One reason for this is that the *Kultusministerkonferenz* (conference of the ministers of education) impedes comparisons between federal states (Riphahn and Wößmann 2016). For example, it is prohibited to use NEPS data to explicitly compare federal states. Not only do these restrictions prevent competition for the best educational policies, but they also prevent us from learning how to equalize educational opportunities.

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Supplementary materials to chapter 2

A. Missing data and multiple imputation

I use multiple imputation in order to deal with the missing data. Most missings occur for net worth (almost 30% missing) and income (about 17% missing; see Table A1). Using listwise deletion would have reduced the sample size to 3,863 or about 64% of the sample that can be analyzed when using multiple imputation.

Following the approach of Burgette and Reiter (2010), I use categorization and regression trees (CART) to impute missing data (see also Aßmann et al. 2017). CART is a nonparametric recursive algorithm that uses binary splits to create groups with maximum intragroup homogeneity and minimum intergroup homogeneity. Imputations are drawn from the resulting groups. Therefore, imputation values are taken from households that have similar values in variables which are good predictors of the missing variable. Compared to parametric algorithms for multiple imputation, CART has the advantage that it automatically finds the best predictors among all covariates and includes non-linear associations and interactions. I include all variables used for any of these analyses in the imputation model. Additionally, I include and additionally whether households ever paid for fees for education and which kind of assets the households own because these may help to predict household wealth. I create 50 imputed datasets using the R-package "mice" (van Buuren and Groothuis-Oudshoorn, 2011).

Analyzing only cases with complete information results in slightly larger differences by parental wealth and larger confidence intervals. However, the substantial results remain the same. Problematically, some transitions for the conditional analysis have to be collapsed when using only cases with complete information.

Table A1: Distribution of variables before and after multiple imputation

	Mean / Percentile / Proportion in multiple imputed dataset	Missings (% missings)	Mean / Percentile / Proportion before multiple imputation
Household net worth		1798 (29.76%)	
Mean	250,872		271,414
10. percentile	0		0
25. percentile	10,000		10,000

50. percentile	100,000		100,000
75. percentile	250,000		250,000
90. percentile	470,000		490,000
Household income		1020 (16.89%)	
Mean	3,527		3,515
10. percentile	1,700		1,650
25. percentile	2,400		2,300
50. percentile	3,100		3,100
75. percentile	4,000		4,000
90. percentile	5,000		5,300
Parents‘ average birthyear		2 (0.03%)	
Mean	1965		1965
10. percentile	1959		1959
25. percentile	1962		1962
50. percentile	1965		1965
75. percentile	1968		1968
90. percentile	1971		1971
Parents‘ marital status		1 (0.02%)	
Married	0.800		0.800
Not married	0.200		0.200
Parents‘ migration background		0 (0.00%)	
Yes	0.197		0.197
No	0.803		0.803
Region		0 (0.00%)	
East	0.111		0.111
West	0.889		0.889
Parents‘ highest ISCED		5 (0.08%)	
0, 1, 2	0.063		0.063
3	0.369		0.369
4	0.076		0.076
5B	0.210		0.210
5A / 6	0.282		0.282
Parents‘ highest EGP		148 (2.44%)	
I	0.274		0.275
II	0.300		0.300
IIIa, IV	0.185		0.185
IIIb, V, VI, VII	0.241		0.240
Household size		1 (0.02%)	
2	0.065		0.065
3	0.220		0.220
4	0.442		0.442
5	0.189		0.189
6 or more	0.083		0.083

NEPS, SC 4. N=6,042.

B. Correlation between net worth, income, highest education, and highest occupational class

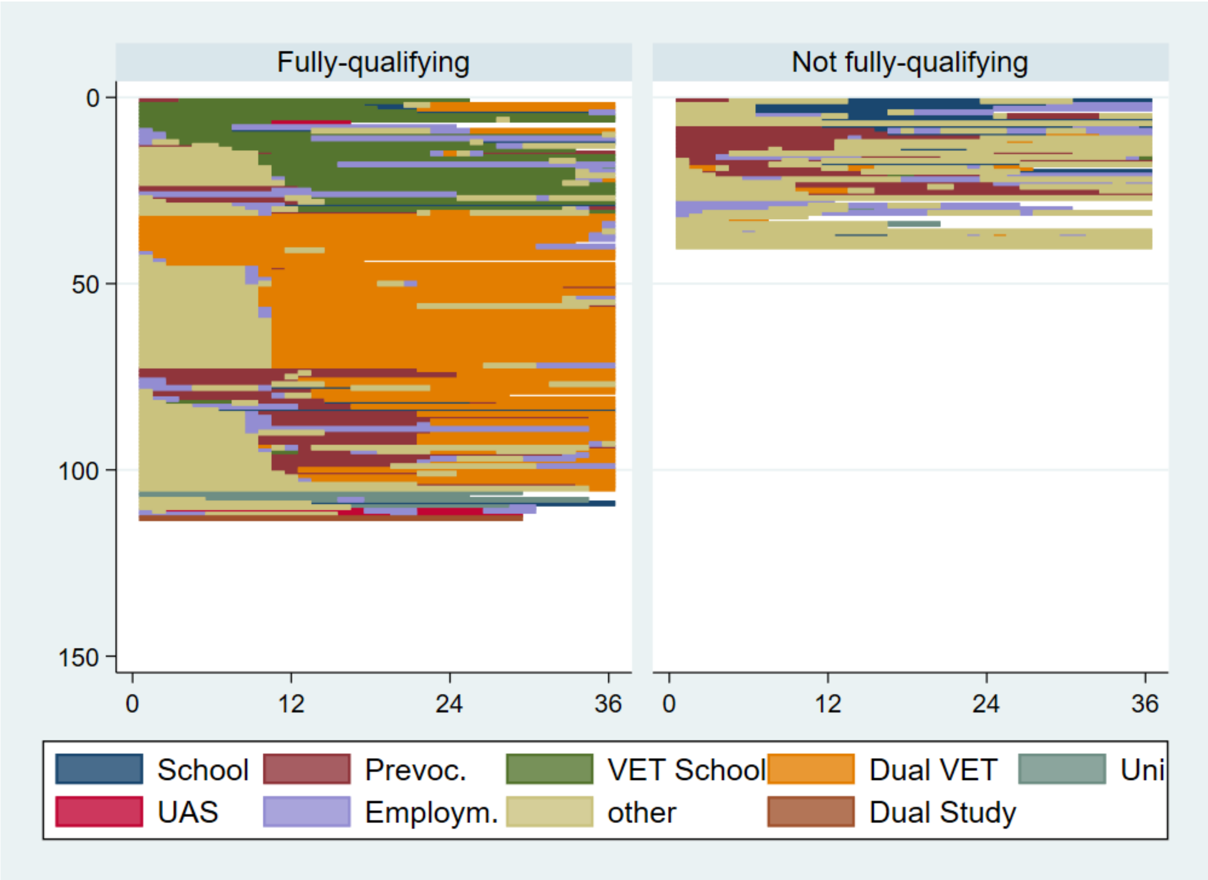
Table B1: Correlations between net worth, income, highest education (ISCED), and highest occupational class (EGP)

	Net Worth	Income	ISCED
Income	0.476		
ISCED	0.374	0.527	
EGP	0.327	0.480	0.566

NEPS, SC 4. N=6,042. Weighted and averaged over all imputed datasets. Spearman's rank correlations. Average values across all imputations. All values are significant at 1% level.

C. Collapsed activities after school for conditional analysis

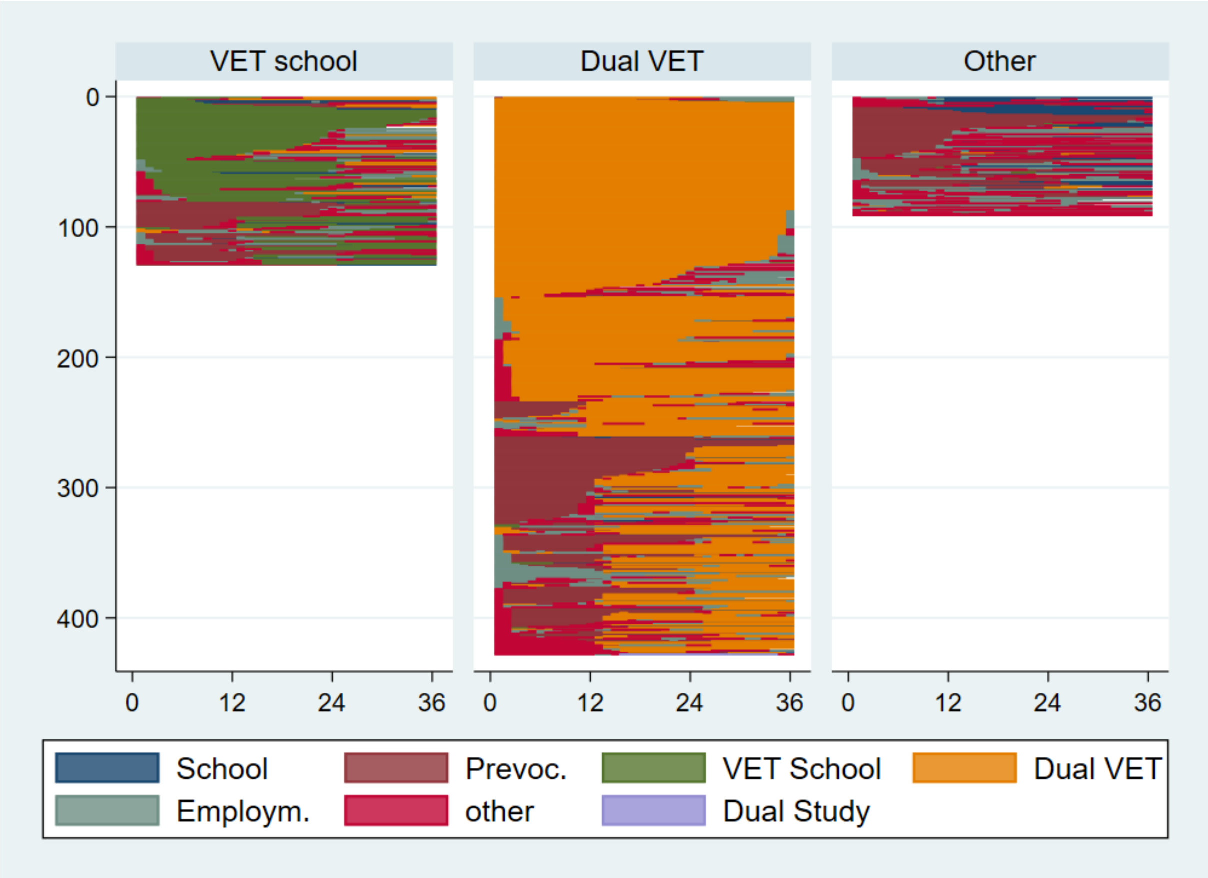
Figure C1: Sequence index plot of activities in three years after leaving school without a certificate



Fully-qualifying: VET school, dual VET, university, UAS, or dual studies for at least six consecutive months.

Not fully-qualifying: School, prevocational training, employment, or other activities.

Figure C2: Sequence index plot of activities in three years after leaving school with the lowest school-leaving certificate

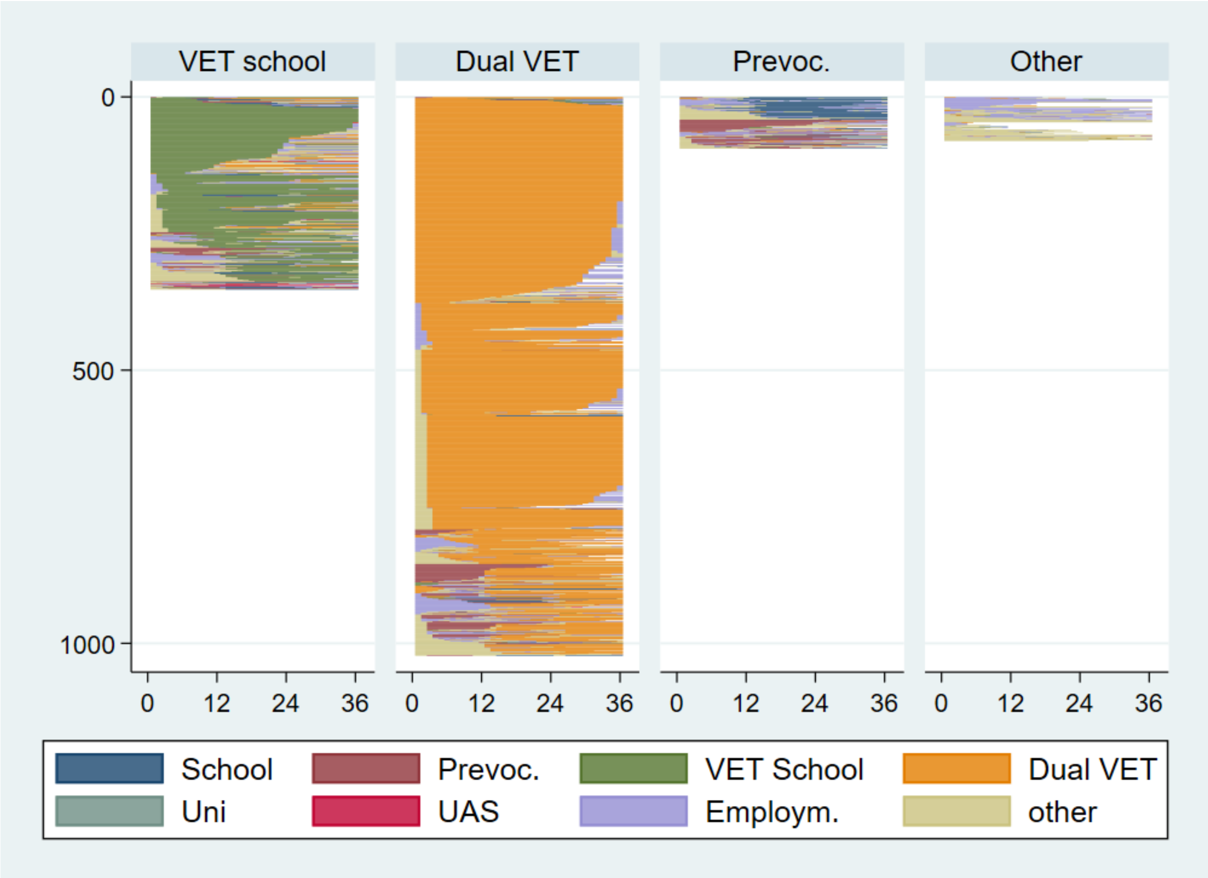


VET school: VET school for at least six consecutive months.

Dual VET: Dual VET for at least six consecutive months.

Other: School, prevocational training, employment, university, UAS or dual studies, or other activities.

Figure C3: Sequence index plot of activities in three years after leaving school with the middle school-leaving certificate



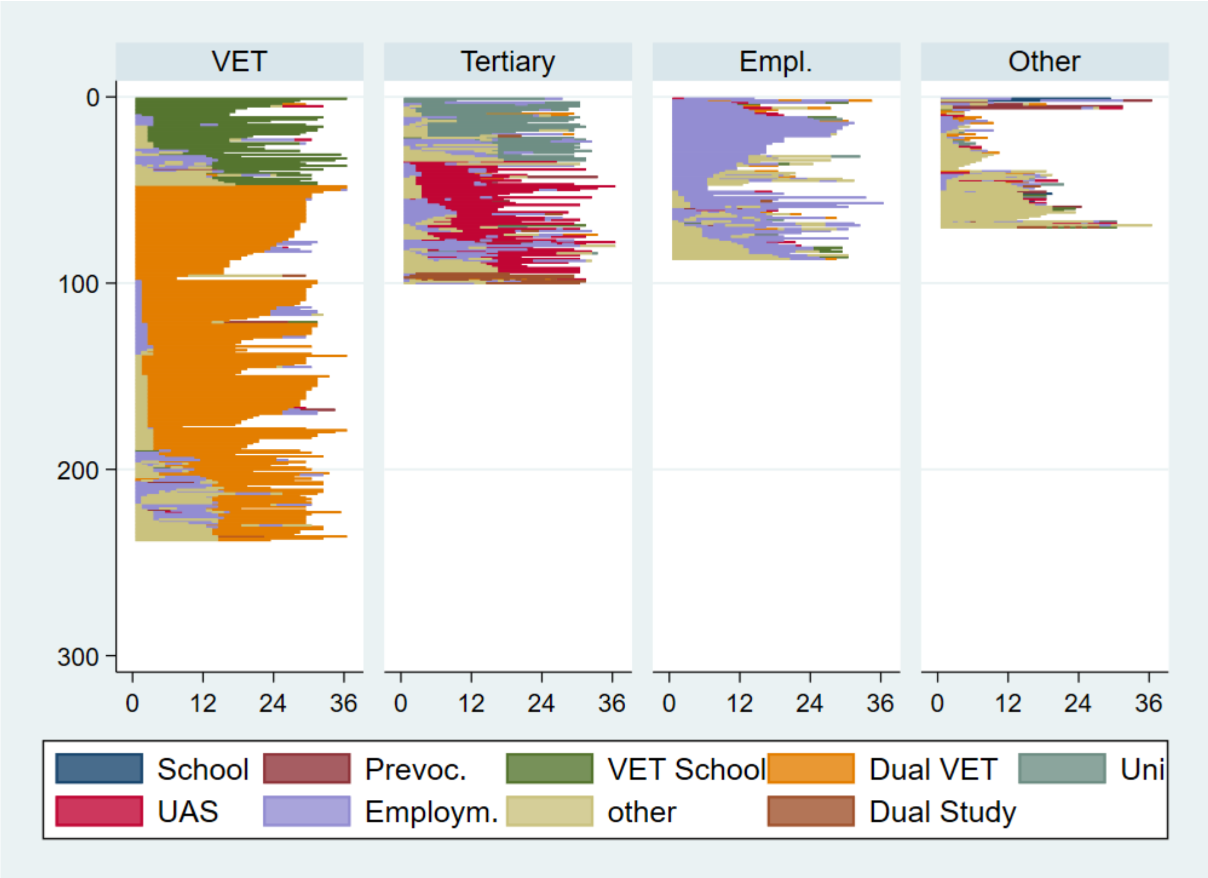
VET school: VET school for at least six consecutive months.

Dual VET: Dual VET for at least six consecutive months.

Prevoc.: Prevocational training or re-entering the general schooling system for at least six consecutive months, without starting a fully-qualifying training afterward.

Other: Employment, university, UAS or dual studies, or other activities.

Figure C4: Sequence index plot of activities in three years after leaving school with the restricted qualification for tertiary education



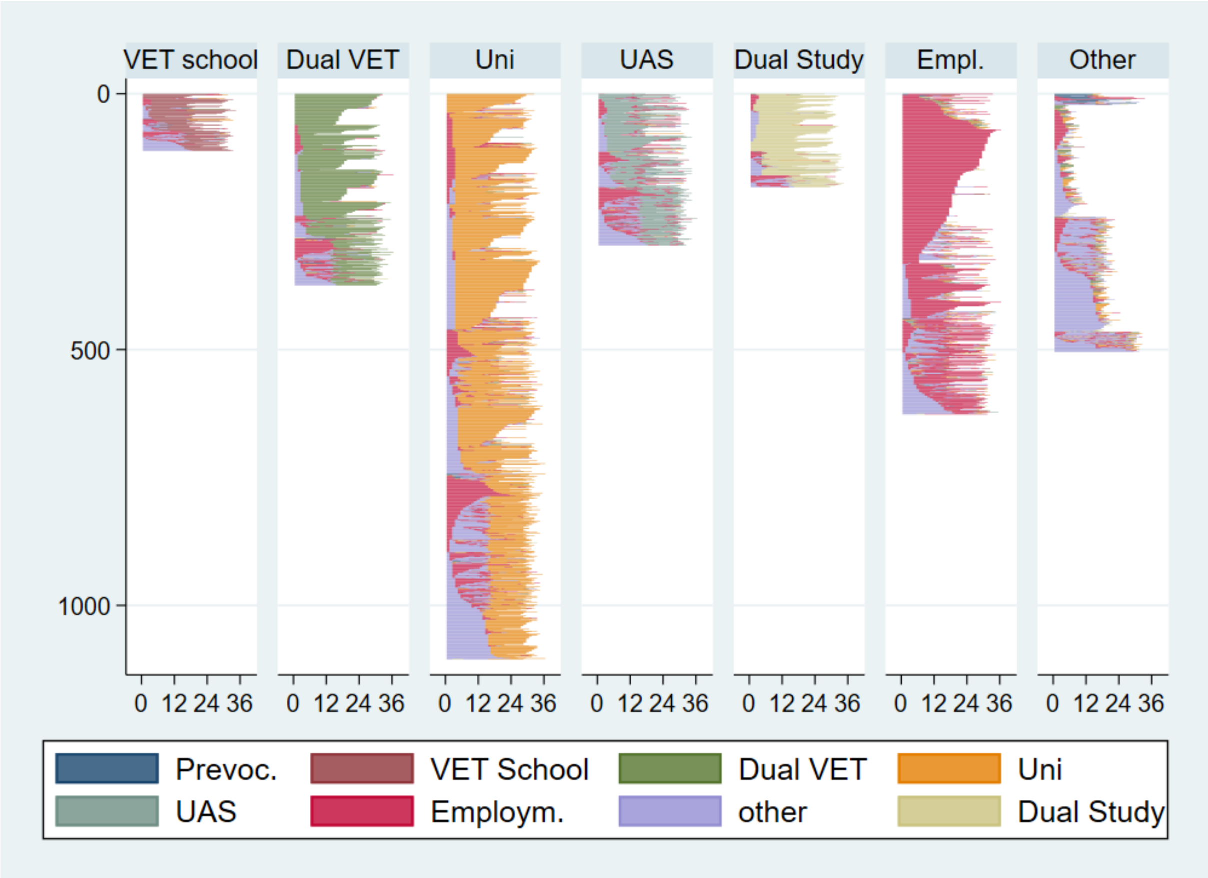
VET: VET school or Dual VET for at least six consecutive months.

Tertiary: University of applied science, university, or dual studies for at least six consecutive months.

Empl.: Employment for at least six consecutive months, without starting a fully-qualifying training afterward.

Other: School, prevocational training, or other activities.

Figure C5: Sequence index plot of activities in three years after leaving school with the general qualification for tertiary education



VET school: VET school for at least six consecutive months.

Dual VET: Dual VET for at least six consecutive months.

Uni: University for at least six consecutive months.

UAS: University of applied science for at least six consecutive months.

Dual Study: Dual study for at least six consecutive months.

Empl.: Employment for at least six consecutive months, without starting a fully-qualifying training afterward.

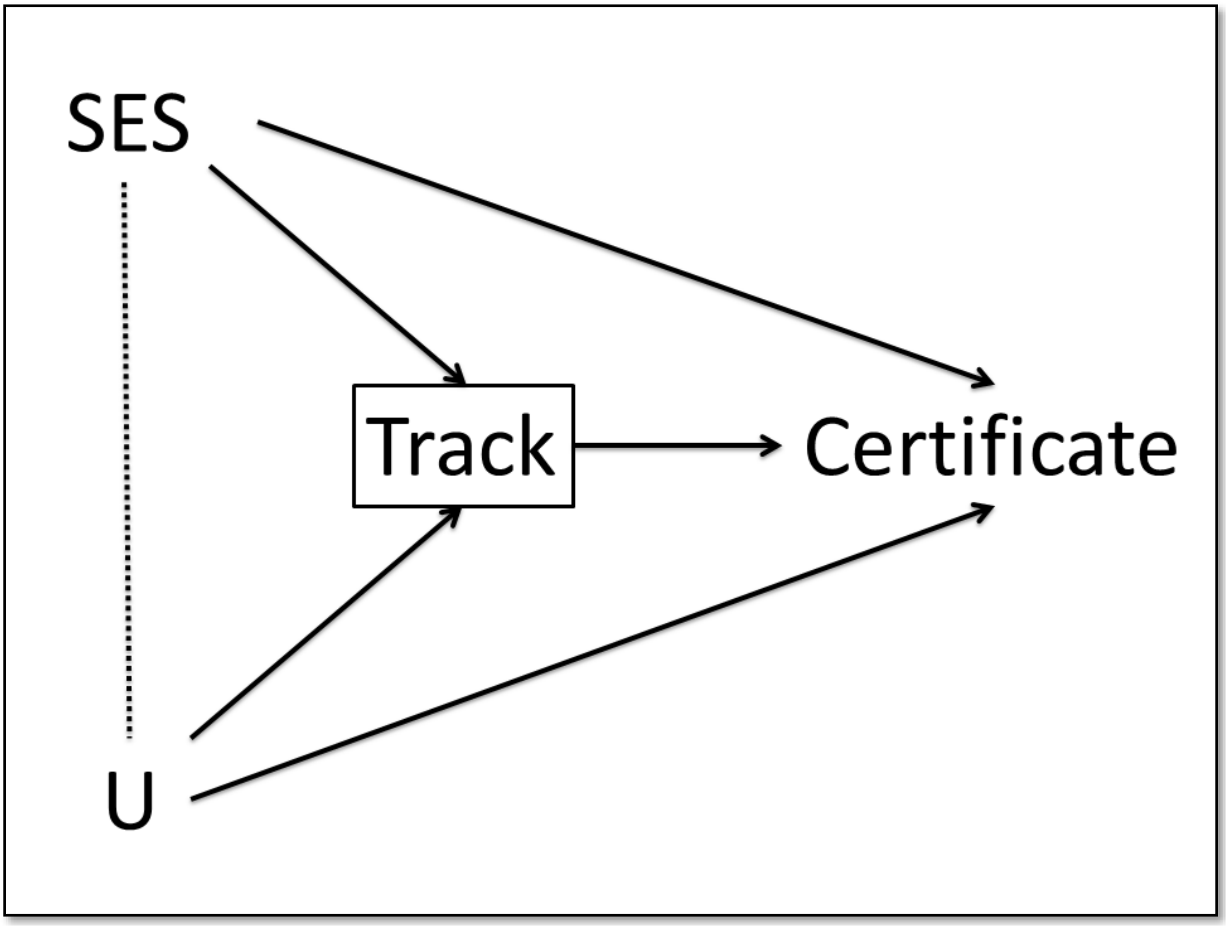
Other: School, prevocational training, or other activities.

D. Selection on unobserved heterogeneity and Latent Class Analysis

Figure D1 shows a directed acyclic graph (DAG) of the endogenous selection bias, which may occur in the conditional analysis. Arrows represent causal effects, boxes around variables indicate that they have been conditioned on, and dashed lines represent spurious associations introduced by conditioning on colliders (Elwert and Winship, 2014). For instance, for the conditional analysis, we are interested in the effect of *SES* on the school-leaving *CERTIFICATE* when conditioning on the attended *TRACK*. For now, we assume that the attended track is only affected by SES and partially unobserved characteristics (*U*) like abilities and aspirations of the student. Furthermore, we assume that *SES* and *U* are initially independent (Cameron and Heckman, 1998, p. 272). The effect of interest is

SES → *CERTIFICATE*.

Figure D1: DAG of endogenous selection bias in educational trajectories



In this DAG, *TRACK* is a common-outcome of SES and *U*. Therefore, when we are interested in the direct effect of SES on *CERTIFICATE, TRACK* is a collider. Conditional on *TRACK*, *SES* and *U* are not independent anymore and endogenous selection bias arises. Therefore, by conditioning on *TRACK*, we have unblocked the non-causal pathway

SES → *TRACK* ← *U* → *CERTIFICATE*,

which will bias the estimation of the effect of SES on *CERTIFICATE*. To reduce this bias, I try to approximate *U* and control for it in the regressions models.

I use latent class analysis (LCA) to approximate U. LCA is a technique to discover clusters of observations with similar values in specified variables. Like in factor analysis, the basic idea is that the correlation of the observed variables can be explained by a single latent (unobserved) factor. In LCA this unobserved factor is categorical. The underlying assumption of LCA is that the associations among the manifest variables are only caused by the unobserved categories ("classes"), and, therefore, that the manifest variables are mutually independent within the latent classes.

For the estimation of latent classes, we use J polytomous categorical outcomes, which contain K_J possible outcomes, for the individuals $i = 1, \ldots, N$. Y_{ijk} denotes the observed values, where $Y_{ijk} = 1$ indicates that respondent i gave response k to variable j and otherwise $Y_{ijk} = 0$. R denotes the number of latent classes and π_{jrk} denotes the class-conditional probability that an observation in class $r = 1, \ldots, R$ produces outcome k on variable j. p_r refers to the prior or unconditional probability that an individual belongs to a certain class before taking into account the manifest variables. Therefore, the probability that individual i in the latent class r produces the combination of J outcomes on the manifest variables is defined as:

$$f(Y_i;\pi_r) = \prod_{j=1}^{J} \prod_{k=1}^{K_j} (\pi_{rjk})^{Y_{ijk}}.$$

The probability density function across all classes is:

$$P(Y_i|\pi, p) = \sum_{r=1}^{R} p_r \prod_{j=1}^{J} \prod_{k=1}^{K_j} (\pi_{rjk})^{Y_{ijk}}.$$

The latent class model is then estimated by maximizing the log-likelihood function

$$\ln L = \sum_{i=1}^{N} \ln \sum_{r=1}^{R} p_r \prod_{j=1}^{J} \prod_{k=1}^{K_j} (\pi_{rjk})^{Y_{ijk}}$$

using the expectation-maximization algorithm (Linzer and Lewis, 2011). The number of classes must be defined by the user and can be evaluated by their model fit (e.g., BIC). I used the R-package "poLCA" (Linzer and Lewis, 2011).

For the LCA for the conditional analysis of the transition from the track in fifth grade to track in ninth grade, I could only use four vague indicators because this transition took place before the survey started. I use the track that was recommended by the elementary school, whether there were some special needs of the child discovered and whether the child had skipped or repeated a class until then. I tried LCAs with a different number of latent classes. The BIC indicated that the two-class solution fits the data best.

Table D1: LCA for the transition from track in fifth grade to track in ninth grade

	Class 1	**Class 2**
Recommendation in fourth grade		
Hauptschule	0.246	0.008
Realschule	0.293	0.202
Gymnasium	0.053	0.644
Non-tracked	0.068	0.017
Special needs	0.004	0.000
No Recommendation	0.336	0.128
Special needs discovered before 2006	0.157	0.019
Repeated class until fourth grade	0.143	0.000
Skipped class until fourth grade	0.000	0.015
Proportion	0.172	0.828

For the transition from track in ninth grade to school-leaving certificate, I can use much more variables for the latent class analysis: children's self-concept about Math, German and school in general, their idealistic and realistic aspirations, their marks in Math and German in the eighth grade, test scores in science, Math, ICT, and Reading, as well as their track in the fifth grade. The continuous measures (self-concepts and test scores) were collapsed to quintiles. Higher quintiles imply that students rate their own abilities higher and that they perform better in the tests. Due to the high number of indicators, the BIC indicated that the best solution would be obtained using eight latent classes. However, I choose to differentiate between five latent classes only to avoid having classes with no or very few observations for the conditional analysis.

Table D2: LCA for the transition from track in ninth grade to school-leaving certificate

	Class 1	Class 2	Class 3	Class 4	Class 5
Self-concept Math					
1. Quintile	0.227	0.147	0.243	0.004	0.188
2. Quintile	0.336	0.181	0.22	0.045	0.242
3. Quintile	0.262	0.225	0.241	0.178	0.251
4. Quintile	0.148	0.213	0.164	0.229	0.180
5. Quintile	0.027	0.234	0.132	0.545	0.138
Self-concept German					
1. Quintile	0.111	0.184	0.178	0.076	0.114
2. Quintile	0.232	0.256	0.302	0.124	0.218
4. Quintile	0.307	0.301	0.282	0.258	0.314
5. Quintile	0.350	0.259	0.238	0.542	0.354
Self-concept school					
1. Quintile	0.136	0.108	0.186	0.006	0.117
2. Quintile	0.337	0.287	0.327	0.067	0.249
4. Quintile	0.388	0.402	0.349	0.382	0.415
5. Quintile	0.139	0.204	0.138	0.546	0.218
Idealistic Aspirations					
No Certifcate	0.000	0.000	0.003	0.000	0.000
Hauptschulabschluss	0.000	0.011	0.149	0.001	0.000
Realschulabschluss	0.000	0.699	0.683	0.002	0.010
Abitur	1.000	0.290	0.166	0.997	0.990
Realistic Aspirations					
No Certifcate	0.001	0.002	0.007	0.000	0.002
Hauptschulabschluss	0.006	0.080	0.407	0.002	0.002
Realschulabschluss	0.162	0.911	0.571	0.033	0.296
Abitur	0.831	0.007	0.015	0.965	0.701
Math mark					
Very good	0.000	0.055	0.018	0.305	0.036
Good	0.099	0.328	0.164	0.595	0.276
Satisfactory	0.540	0.355	0.391	0.099	0.411
Sufficient	0.317	0.212	0.321	0.000	0.226
Poor	0.044	0.050	0.101	0.001	0.049
Deficient	0.000	0.001	0.004	0.000	0.002
German mark					
Very good	0.013	0.010	0.005	0.168	0.018
Good	0.308	0.243	0.162	0.532	0.352
Satisfactory	0.534	0.526	0.522	0.257	0.474
Sufficient	0.143	0.202	0.286	0.042	0.156
Poor	0.002	0.018	0.023	0.002	0.000
Deficient	0.000	0.001	0.002	0.000	0.000

Science Test Score Quintile					
1. Quintile	0.005	0.067	0.655	0.005	0.249
2. Quintile	0.083	0.26	0.273	0.05	0.355
3. Quintile	0.248	0.314	0.056	0.125	0.287
4. Quintile	0.354	0.224	0.011	0.282	0.103
5. Quintile	0.310	0.136	0.004	0.539	0.007
Math Test Score Quintile					
1. Quintile	0.015	0.112	0.624	0.001	0.224
2. Quintile	0.123	0.309	0.269	0.020	0.300
3. Quintile	0.276	0.280	0.088	0.101	0.289
4. Quintile	0.347	0.204	0.019	0.244	0.149
5. Quintile	0.240	0.095	0.000	0.635	0.038
ICT Test Score Quintile					
1. Quintile	0.009	0.076	0.658	0.003	0.233
2. Quintile	0.080	0.272	0.254	0.051	0.361
3. Quintile	0.216	0.300	0.076	0.139	0.304
4. Quintile	0.359	0.225	0.009	0.312	0.092
5. Quintile	0.336	0.127	0.003	0.495	0.011
Reading Test Score Quintile					
1. Quintile	0.019	0.124	0.636	0.013	0.197
2. Quintile	0.085	0.277	0.243	0.062	0.362
3. Quintile	0.200	0.271	0.083	0.132	0.245
4. Quintile	0.348	0.230	0.032	0.300	0.140
5. Quintile	0.347	0.097	0.006	0.493	0.056
Track in fifth grade					
Non-tracked	0.041	0.045	0.085	0.064	0.138
Hauptschule	0.001	0.183	0.552	0.003	0.020
Realschule	0.027	0.674	0.34	0.072	0.246
Gymnasium	0.931	0.098	0.023	0.861	0.597
Proportion	0.207	0.188	0.215	0.211	0.179

For the transition from school-leaving certificate to activity after school, I use the same indicators as for the transition to the school-leaving certificate and additionally the GPA of the leaving certificate, as well as the track in the ninth grade. Again, I differentiate between five latent classes.

Table D3: LCA for the transition from school-leaving certificate to activity after school

	Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 5**
Self-concept Math					
1. Quintile	0.020	0.193	0.215	0.097	0.267
2. Quintile	0.085	0.175	0.287	0.155	0.268
3. Quintile	0.202	0.245	0.247	0.203	0.250
4. Quintile	0.214	0.200	0.158	0.235	0.145
5. Quintile	0.479	0.186	0.093	0.31	0.070
Self-concept German					
1. Quintile	0.052	0.183	0.142	0.147	0.149
2. Quintile	0.099	0.274	0.252	0.203	0.308
4. Quintile	0.264	0.275	0.302	0.288	0.324
5. Quintile	0.585	0.268	0.304	0.362	0.218
Self-concept school					
1. Quintile	0.004	0.147	0.151	0.055	0.186
2. Quintile	0.046	0.291	0.346	0.179	0.368
4. Quintile	0.386	0.374	0.377	0.451	0.349
5. Quintile	0.565	0.188	0.125	0.315	0.097
Idealistic Aspirations					
No Certifcate	0.000	0.001	0.000	0.000	0.002
Hauptschulabschluss	0.001	0.205	0.000	0.003	0.004
Realschulabschluss	0.000	0.649	0.010	0.461	0.564
Abitur	0.999	0.145	0.990	0.536	0.430
Realistic Aspirations					
No Certifcate	0.000	0.009	0.001	0.000	0.003
Hauptschulabschluss	0.002	0.542	0.009	0.026	0.064
Realschulabschluss	0.016	0.429	0.178	0.770	0.798
Abitur	0.982	0.02	0.813	0.204	0.134
Math mark					
Very good	0.297	0.033	0.011	0.090	0.008
Good	0.531	0.236	0.187	0.429	0.118
Satisfactory	0.162	0.382	0.460	0.317	0.419
Sufficient	0.009	0.247	0.293	0.136	0.369
Poor	0.001	0.097	0.049	0.028	0.083
Deficient	0.000	0.006	0.000	0.000	0.003
German mark					
Very good	0.177	0.009	0.011	0.018	0.003
Good	0.577	0.186	0.266	0.37	0.182
Satisfactory	0.227	0.509	0.543	0.478	0.535
Sufficient	0.019	0.265	0.178	0.123	0.269
Poor	0.000	0.028	0.003	0.01	0.012
Deficient	0.000	0.003	0.000	0.000	0.000
Science Test Score Quintile					
1. Quintile	0.006	0.604	0.075	0.049	0.429
2. Quintile	0.049	0.258	0.185	0.192	0.36
3. Quintile	0.112	0.085	0.282	0.312	0.161

4. Quintile	0.278	0.041	0.269	0.257	0.045
5. Quintile	0.554	0.013	0.188	0.19	0.006
Math Test Score Quintile					
1. Quintile	0.003	0.598	0.06	0.062	0.441
2. Quintile	0.023	0.252	0.184	0.24	0.354
3. Quintile	0.101	0.109	0.278	0.314	0.165
4. Quintile	0.247	0.037	0.286	0.259	0.037
5. Quintile	0.626	0.005	0.192	0.125	0.003
ICT Test Score Quintile					
1. Quintile	0.007	0.618	0.066	0.059	0.419
2. Quintile	0.048	0.247	0.188	0.208	0.347
3. Quintile	0.119	0.102	0.270	0.308	0.170
4. Quintile	0.311	0.028	0.268	0.258	0.051
5. Quintile	0.515	0.006	0.209	0.169	0.013
Reading Test Score Quintile					
1. Quintile	0.010	0.62	0.061	0.091	0.398
2. Quintile	0.039	0.224	0.200	0.231	0.346
3. Quintile	0.111	0.093	0.241	0.255	0.178
4. Quintile	0.301	0.051	0.275	0.285	0.063
5. Quintile	0.539	0.011	0.224	0.138	0.015
Track in fifth grade					
Non-tracked	0.070	0.049	0.064	0.045	0.147
Hauptschule	0.000	0.857	0.000	0.100	0.020
Realschule	0.022	0.094	0.006	0.749	0.704
Gymnasium	0.908	0.000	0.930	0.106	0.128
GPA of Certificate					
1. Quintile	0.609	0.037	0.086	0.154	0.027
2. Quintile	0.173	0.159	0.134	0.195	0.111
3. Quintile	0.141	0.258	0.281	0.28	0.237
4. Quintile	0.051	0.154	0.212	0.151	0.213
5. Quintile	0.025	0.392	0.287	0.221	0.411
Track in ninth grade					
Hauptschule	0.001	0.941	0.002	0.163	0.025
Realschule	0.038	0.033	0.013	0.802	0.759
Gymnasium	0.903	0.005	0.94	0.011	0.071
Non-tracked	0.039	0.018	0.025	0.014	0.084
Unclear	0.009	0.003	0.007	0.003	0.023
Waldorf-school	0.01	0.000	0.014	0.000	0.032
Other	0.001	0.000	0.000	0.007	0.006
Proportion	0.202	0.162	0.304	0.165	0.168

The differences in transitions rates by parental net worth get slightly smaller when including the latent classes as control variables. This may imply that these latent classes are affected by parental net worth and therefore, that controlling for them introduces overcontrol bias (Mare, 2011, p. 243-244). However, the substantial results remain the same.

E. Multinomial Regression Coefficients

Table E1: Logit estimates of multinomial logistic regression of track in fifth grade - unconditional

Outcome	Hauptschule		Non-tracked		Realschule	
	b	p-value	b	p-value	b	p-value
Net worth (IHS)	$-8.620*10^{-6}$	(0.000)	$-4.880*10^{-6}$	(0.054)	$-3.840*10^{-6}$	(0.016)
Net worth (IHS)^2	$-1.36*10^{-11}$	(0.584)	$9.30*10^{-12}$	(0.778)	$1.21*10^{-11}$	(0.606)
Net worth (IHS)^3	$2.14*10^{-16}$	(0.087)	$5.72*10^{-17}$	(0.670)	$3.18*10^{-17}$	(0.763)
Income (log.)	3.202	(0.112)	0.346	(0.418)	0.345	(0.325)
Income (log.)^2	-0.265	(0.043)	-0.0383	(0.253)	-0.0558	(0.030)
ISCED						
3	-0.378	(0.054)	-1.173	(0.000)	-0.00526	(0.980)
4	-2.122	(0.000)	-1.789	(0.000)	-0.886	(0.000)
5B	-1.129	(0.000)	-1.392	(0.000)	-0.366	(0.098)
5A or 6	-2.420	(0.000)	-1.659	(0.000)	-1.211	(0.000)
EGP						
IIIa, IV	-0.787	(0.000)	-0.423	(0.054)	-0.323	(0.014)
II	-1.165	(0.000)	-0.299	(0.129)	-0.533	(0.000)
I	-0.991	(0.000)	-0.614	(0.009)	-0.670	(0.000)
Migration Background	-0.315	(0.039)	0.192	(0.288)	-0.309	(0.011)
Parents' age	-0.00935	(0.401)	-0.0178	(0.209)	-0.000337	(0.970)
East Germany	-1.267	(0.003)	2.182	(0.000)	0.0254	(0.923)
Married	-0.233	(0.107)	-0.423	(0.026)	0.0291	(0.813)
Household Size						
3	0.687	(0.003)	0.106	(0.706)	0.348	(0.049)
4	0.950	(0.000)	0.121	(0.692)	0.601	(0.002)
5	1.256	(0.000)	0.108	(0.720)	0.533	(0.009)
6 or more	1.553	(0.000)	0.541	(0.112)	0.606	(0.011)
Constant	11.73	(0.616)	32.66	(0.238)	1.631	(0.927)

NEPS SC4. N=6,042. Reference outcome: Gymnasium. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2.

Table E2.1: Logit estimates of logistic regression of track in ninth grade – conditional on being in Hauptschule in fifth grade

Outcome	Realschule, non-tracked, or Gymnasium	
	b	p-value
Net worth (IHS)	$1.31*10^{-5}$	(0.047)
Net worth $(IHS)^2$	$-3.60*10^{-11}$	(0.704)
Net worth $(IHS)^3$	$-4.77*10^{-16}$	(0.507)
Income (log.)	3.150	(0.672)
Income $(log.)^2$	-0.183	(0.698)
ISCED		
3	0.229	(0.739)
4	0.809	(0.325)
5B	0.702	(0.337)
5A or 6	1.381	(0.120)
EGP		
IIIa, IV	0.175	(0.702)
II	0.0184	(0.958)
I	0.716	(0.145)
Migration Background	0.0500	(0.888)
Parents' age	-0.0203	(0.517)
East Germany	2.167	(0.006)
Married	0.292	(0.483)
Household Size		
3	-0.464	(0.414)
4	-0.160	(0.810)
5	0.268	(0.695)
6 or more	-1.198	(0.136)
Latent Class		
Class 2	0.0707	(0.802)
Constant	20.92	(0.741)

NEPS SC4. N=948. Reference outcome: Hauptschule. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2; Latent Class: 1.

Table E2.2: Logit estimates of multinomial logistic regression of track in ninth grade – conditional on being non-tracked in fifth grade

Outcome	Hauptschule		Non-tracked		Realschule	
	b	p-value	b	p-value	b	p-value
Net worth (IHS)	$-9.66*10^{-6}$	(0.418)	$-5.04*10^{-6}$	(0.420)	$-8.60*10^{-7}$	(0.894)
Net worth (IHS)^2	$-4.05e*10^{-11}$	(0.888)	$-2.20*10^{-11}$	(0.814)	$2.49*10^{-11}$	(0.762)
Net worth (IHS)^3	$8.46*10^{-16}$	(0.616)	$1.87*10^{-16}$	(0.757)	$-2.40*10^{-16}$	(0.715)
Income (log.)	-12.83	(0.142)	-3.478	(0.613)	2.886	(0.752)
Income (log.)^2	0.769	(0.164)	0.211	(0.626)	-0.181	(0.755)
ISCED						
3	-0.145	(0.870)	-0.130	(0.857)	0.0404	(0.952)
4	-1.986	(0.165)	0.0864	(0.922)	-0.436	(0.626)
5B	-1.801	(0.072)	0.00822	(0.991)	-0.942	(0.232)
5A or 6	-2.693	(0.010)	0.155	(0.850)	-0.940	(0.264)
EGP						
IIIa, IV	-0.0935	(0.895)	0.159	(0.767)	-0.433	(0.398)
II	-1.127	(0.111)	0.283	(0.558)	-0.295	(0.559)
I	0.391	(0.509)	0.309	(0.570)	-0.540	(0.322)
Migration Background	-0.999	(0.140)	0.145	(0.734)	-0.553	(0.193)
Parents' age	0.0109	(0.820)	-0.00465	(0.886)	0.0167	(0.635)
East Germany	-2.093	(0.004)	-2.106	(0.001)	-0.964	(0.099)
Married	-0.209	(0.712)	0.0740	(0.855)	-0.153	(0.716)
Household Size						
3	0.526	(0.564)	-0.448	(0.557)	-0.429	(0.514)
4	0.146	(0.869)	-0.584	(0.435)	-0.431	(0.550)
5	1.098	(0.284)	-0.169	(0.839)	-0.559	(0.440)
6 or more	-0.416	(0.685)	-0.605	(0.404)	-0.992	(0.173)
Latent Class						
Class 2	-3.644	(0.000)	-2.555	(0.000)	-3.288	(0.000)
Constant	38.10	(0.720)	28.67	(0.685)	-38.76	(0.639)

NEPS SC4. N=447. Reference outcome: Gymnasium. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2; Latent Class: Class 1.

Table E2.3: Logit estimates of multinomial logistic regression of track in ninth grade – conditional on being in Realschule in fifth grade

Outcome	Hauptschule		Non-tracked		Gymnasium	
	b	p-value	b	p-value	b	p-value
Net worth (IHS)	$-8.25*10^{-7}$	(0.845)	$-2.77*10^{-7}$	(0.950)	$4.88*10^{-6}$	(0.635)
Net worth (IHS)^2	$-1.09*10^{-10}$	(0.056)	$-9.40*10^{-12}$	(0.897)	$7.42*10^{-11}$	(0.187)
Net worth (IHS)^3	$2.94*10^{-16}$	(0.484)	$2.62*10^{-17}$	(0.935)	$-1.34*10^{-15}$	(0.095)
Income (log.)	1.491	(0.575)	25.34	(0.086)	10.87	(0.212)
Income (log.)^2	-0.102	(0.534)	-1.591	(0.088)	-0.738	(0.176)
ISCED						
3	-1.007	(0.010)	-0.129	(0.837)	-1.176	(0.085)
4	-1.274	(0.028)	-0.785	(0.361)	-0.614	(0.491)
5B	-1.810	(0.000)	-0.335	(0.583)	-0.671	(0.310)
5A or 6	-0.856	(0.122)	-1.593	(0.068)	-1.124	(0.090)
EGP						
IIIa, IV	0.280	(0.346)	-0.0515	(0.911)	-0.340	(0.493)
II	0.0410	(0.881)	0.158	(0.712)	-0.230	(0.642)
I	-0.682	(0.107)	0.0828	(0.841)	-0.0136	(0.973)
Migration Background	0.0584	(0.857)	0.586	(0.098)	-0.154	(0.759)
Parents' age	0.00406	(0.861)	0.0366	(0.271)	0.0594	(0.129)
East Germany	-0.503	(0.363)	-0.229	(0.728)	1.460	(0.025)
Married	-0.165	(0.567)	-0.0682	(0.882)	-0.308	(0.571)
Household Size						
3	0.628	(0.180)	-0.903	(0.093)	0.0291	(0.960)
4	0.476	(0.304)	-0.693	(0.219)	-0.0103	(0.990)
5	0.506	(0.337)	-1.533	(0.020)	0.456	(0.524)
6 or more	0.967	(0.090)	-0.734	(0.393)	-0.971	(0.450)
Latent Class						
Class 2	-0.811	(0.001)	-0.522	(0.079)	-0.431	(0.251)
Constant	-13.24	(0.780)	-173.7	(0.054)	-159.9	(0.029)

NEPS SC4. N=1,599. Reference outcome: Realschule. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2; Latent Class: Class 1.

Table E2.4: Logit estimates of multinomial logistic regression of track in ninth grade – conditional on being in Gymnasium in fifth grade

Outcome	Hauptschule or Realschule		Non-tracked	
	b	p-value	b	p-value
Net worth (IHS)	$3.59*10^{-7}$	(0.899)	$1.56*10^{-5}$	(0.138)
Net worth (IHS)^2	$-5.12*10^{-11}$	(0.264)	$-3.21*10^{-10}$	(0.033)
Net worth (IHS)^3	$1.84*10^{-16}$	(0.302)	$9.48*10^{-16}$	(0.019)
Income (log.)	0.967	(0.570)	0.447	(0.587)
Income (log.)^2	-0.0673	(0.551)	-0.0344	(0.617)
ISCED				
3	-0.501	(0.201)	-0.392	(0.320)
4	-0.447	(0.323)	-0.498	(0.323)
5B	-0.877	(0.030)	-0.243	(0.613)
5A or 6	-1.751	(0.000)	-0.532	(0.336)
EGP				
IIIa, IV	-0.236	(0.404)	-0.145	(0.689)
II	-0.245	(0.361)	-0.271	(0.333)
I	0.0967	(0.763)	0.0859	(0.813)
Migration Background	-0.406	(0.100)	0.644	(0.072)
Parents' age	0.0293	(0.154)	-0.0198	(0.416)
East Germany	-0.250	(0.558)	-0.903	(0.165)
Married	-0.353	(0.134)	0.139	(0.661)
Household Size				
3	0.754	(0.072)	0.178	(0.701)
4	0.411	(0.320)	-0.316	(0.596)
5	0.423	(0.350)	-0.662	(0.356)
6 or more	0.535	(0.256)	-1.006	(0.088)
Latent Class				
Class 2	-1.350	(0.000)	-1.833	(0.000)
Constant	-60.27	(0.145)	37.76	(0.433)

NEPS SC4. N=3,048. Reference outcome: Gymnasium. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2; Latent Class: Class 1.

Table E3: Logit estimates of multinomial logistic regression of track in ninth grade - unconditional

Outcome	Hauptschule		Non-tracked		Realschule	
	b	p-value	b	p-value	b	p-value
Net worth (IHS)	$-7.80*10^{-6}$	(0.000)	$-2.31*10^{-6}$	(0.460)	$-1.97*10^{-6}$	(0.202)
Net worth (IHS)^2	$-4.69*10^{-11}$	(0.043)	$-8.52*10^{-11}$	(0.055)	$-9.55*10^{-12}$	(0.673)
Net worth (IHS)^3	$3.32*10^{-16}$	(0.003)	$3.25*10^{-16}$	(0.035)	$7.83*10^{-17}$	(0.457)
Income (log.)	1.238	(0.010)	0.908	(0.522)	0.271	(0.435)
Income (log.)^2	-0.128	(0.000)	-0.0687	(0.455)	-0.0454	(0.073)
ISCED						
3	-0.485	(0.020)	-0.491	(0.095)	0.169	(0.458)
4	-1.944	(0.000)	-1.030	(0.007)	-0.542	(0.045)
5B	-1.396	(0.000)	-0.594	(0.045)	-0.204	(0.387)
5A or 6	-2.499	(0.000)	-1.104	(0.005)	-1.083	(0.000)
EGP						
IIIa, IV	-0.665	(0.000)	-0.254	(0.319)	-0.361	(0.004)
II	-1.048	(0.000)	-0.261	(0.206)	-0.501	(0.000)
I	-1.068	(0.000)	-0.206	(0.343)	-0.507	(0.000)
Migration Background	-0.318	(0.046)	0.354	(0.100)	-0.348	(0.005)
Parents' age	-0.00159	(0.876)	-0.00771	(0.667)	0.000912	(0.916)
East Germany	-1.703	(0.000)	-0.441	(0.315)	-0.370	(0.233)
Married	-0.295	(0.033)	-0.0305	(0.889)	-0.0216	(0.867)
Household Size						
3	0.868	(0.000)	0.00852	(0.977)	0.375	(0.056)
4	0.915	(0.000)	-0.131	(0.686)	0.473	(0.025)
5	1.086	(0.000)	-0.146	(0.684)	0.391	(0.080)
6 or more	1.586	(0.000)	0.0335	(0.926)	0.424	(0.092)
Constant	4.365	(0.828)	12.18	(0.730)	-0.368	(0.983)

NEPS SC4. N=6,042. Reference outcome: Gymnasium. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2.

Table E4.1: Logit estimates of multinomial logistic regression of highest school-leaving certificate – conditional on being in Hauptschule in ninth grade

Outcome	None		Realschulabschluss		Fachhochschulreife or Abitur	
	b	p-value	b	p-value	b	p-value
Net worth (IHS)	$-3.79*10^{-6}$	(0.479)	$3.43*10^{-6}$	(0.295)	$1.13*10^{-5}$	(0.102)
Net worth (IHS)^2	$-1.80*10^{-10}$	(0.101)	$-1.77*10^{-11}$	(0.662)	$-1.12*10^{-10}$	(0.268)
Net worth (IHS)^3	$1.28*10^{-15}$	(0.064)	$1.06*10^{-16}$	(0.747)	$6.63*10^{-16}$	(0.224)
Income (log.)	17.92	(0.048)	1.816	(0.604)	5.654	(0.155)
Income (log.)^2	-1.153	(0.050)	-0.116	(0.608)	-0.388	(0.124)
ISCED						
3	0.0912	(0.847)	-0.147	(0.578)	-0.864	(0.063)
4	-1.573	(0.187)	0.861	(0.065)	-0.108	(0.862)
5B	-0.287	(0.597)	-0.0167	(0.962)	-0.444	(0.474)
5A or 6	0.426	(0.548)	0.0736	(0.852)	-0.0270	(0.975)
EGP						
IIIa, IV	0.262	(0.397)	-0.127	(0.598)	-0.0593	(0.883)
II	0.396	(0.165)	-0.0680	(0.772)	0.328	(0.395)
I	-0.274	(0.584)	0.245	(0.421)	0.513	(0.309)
Migration Background	-0.0286	(0.936)	0.254	(0.231)	0.871	(0.018)
Parents' age	-0.0436	(0.081)	-0.00415	(0.795)	0.0158	(0.532)
East Germany	-0.683	(0.469)	-0.379	(0.573)	-0.834	(0.405)
Married	-0.0834	(0.795)	-0.205	(0.266)	0.404	(0.380)
Household Size						
3	0.258	(0.718)	0.0399	(0.903)	0.122	(0.860)
4	0.233	(0.752)	0.0962	(0.766)	0.635	(0.383)
5	0.310	(0.686)	-0.239	(0.516)	0.524	(0.491)
6 or more	0.296	(0.715)	0.136	(0.741)	0.776	(0.328)
Latent Class						
Class 2	0.256	(0.771)	0.808	(0.183)	3.240	(0.000)
Class 3	0.295	(0.361)	0.922	(0.000)	1.144	(0.001)
Class 4	2.244	(0.044)	2.532	(0.008)	5.429	(0.000)
Constant	15.54	(0.779)	1.005	(0.975)	-54.44	(0.279)

NEPS SC4. N=1,102. Reference outcome: Hauptschulabschluss. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2; Latent Class: 1.

Table E4.2: Logit estimates of logistic regression of highest school-leaving certificate – conditional on being non-tracked in ninth grade

Outcome	Abitur	
	b	p-value
Net worth (IHS)	$3.17*10^{-5}$	(0.038)
Net worth (IHS)^2	$-4.95*10^{-10}$	(0.149)
Net worth (IHS)^3	$2.30*10^{-15}$	(0.252)
Income (log.)	-9.485	(0.373)
Income (log.)^2	0.580	(0.377)
ISCED		
3	0.789	(0.198)
4	2.043	(0.014)
5B	0.973	(0.159)
5A or 6	1.515	(0.059)
EGP		
IIIa, IV	-0.105	(0.827)
II	0.0614	(0.863)
I	0.536	(0.381)
Migration Background	0.658	(0.115)
Parents' age	0.0938	(0.004)
East Germany	-0.0184	(0.977)
Married	1.404	(0.006)
Household Size		
3	-0.343	(0.587)
4	-0.789	(0.201)
5	-0.629	(0.314)
6 or more	-0.0392	(0.955)
Latent Class		
Class 2	3.815	(0.000)
Class 3	0.611	(0.526)
Class 4	4.736	(0.000)
Class 5	5.553	(0.000)
Constant	-152.8	(0.077)

NEPS SC4. N=348. Reference outcome: Fachhochschulreife or lower. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2; Latent Class: 1.

Table E4.3: Logit estimates of multinomial logistic regression of highest school-leaving certificate – conditional on being in Realschule in ninth grade

Outcome	Hauptschulabschluss or none		Fachhochschulreife		Abitur	
	b	p-value	b	p-value	b	p-value
Net worth (IHS)	$4.50*10^{-6}$	(0.508)	$-5.12*10^{-7}$	(0.867)	$5.23*10^{-7}$	(0.848)
Net worth (IHS)^2	$-1.75*10^{-10}$	(0.111)	$1.27*10^{-11}$	(0.738)	$1.38*10^{-11}$	(0.732)
Net worth (IHS)^3	$6.80*10^{-16}$	(0.109)	$-4.88*10^{-17}$	(0.819)	$-6.23*10^{-17}$	(0.757)
Income (log.)	7.007	(0.246)	0.00965	(0.989)	-0.821	(0.060)
Income (log.)^2	-0.429	(0.263)	0.0221	(0.669)	0.0847	(0.017)
ISCED						
3	0.489	(0.545)	-0.664	(0.101)	-0.430	(0.253)
4	0.550	(0.558)	-0.335	(0.541)	0.145	(0.749)
5B	0.582	(0.441)	-0.571	(0.181)	-0.212	(0.607)
5A or 6	1.019	(0.268)	-0.307	(0.527)	0.0939	(0.829)
EGP						
IIIa, IV	-0.659	(0.129)	0.212	(0.394)	0.162	(0.506)
II	-0.565	(0.129)	0.361	(0.141)	0.208	(0.360)
I	-0.537	(0.229)	0.186	(0.527)	-0.0126	(0.965)
Migration Background	0.116	(0.762)	0.458	(0.061)	0.369	(0.138)
Parents' age	-0.0348	(0.166)	-0.0272	(0.159)	-0.0535	(0.003)
East Germany	-0.101	(0.781)	-1.709	(0.000)	-0.217	(0.407)
Married	-1.191	(0.000)	-0.0971	(0.747)	-0.302	(0.145)
Household Size						
3	0.0104	(0.982)	-0.726	(0.091)	-0.274	(0.481)
4	0.00663	(0.990)	-0.485	(0.236)	0.0522	(0.893)
5	-0.0681	(0.902)	-0.611	(0.147)	0.128	(0.745)
6 or more	-0.0987	(0.877)	-0.473	(0.359)	-0.0178	(0.969)
Latent Class						
Class 2	-0.974	(0.044)	0.588	(0.026)	2.575	(0.000)
Class 3	-1.416	(0.000)	-0.00247	(0.992)	1.324	(0.000)
Class 4	-19.13	(0.000)	0.561	(0.236)	2.562	(0.000)
Class 5	-0.861	(0.221)	0.208	(0.667)	3.344	(0.000)
Constant	40.76	(0.455)	53.35	(0.164)	104.6	(0.003)

NEPS SC4. N=1,682. Reference outcome: Realschulabschluss. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2; Latent Class: 1.

Table E4.4: Logit estimates of multinomial logistic regression of highest school-leaving certificate – conditional on being in Gymnasium in ninth grade

Outcome	Realschulabschluss, Hauptschulabschluss, or none		Fachhochschulreife	
	b	p-value	b	p-value
Net worth (IHS)	$-2.29*10^{-6}$	(0.576)	$1.12*10^{-6}$	(0.760)
Net worth (IHS)^2	$-1.03*10^{-11}$	(0.844)	$3.22*10^{-11}$	(0.543)
Net worth (IHS)^3	$-9.76*10^{-17}$	(0.789)	$-1.58*10^{-16}$	(0.526)
Income (log.)	8.247	(0.094)	20.16	(0.033)
Income (log.)^2	-0.516	(0.096)	-1.265	(0.032)
ISCED				
3	0.280	(0.666)	1.090	(0.091)
4	-0.596	(0.398)	0.132	(0.868)
5B	0.156	(0.826)	0.704	(0.295)
5A or 6	-0.478	(0.492)	0.486	(0.484)
EGP				
IIIa, IV	-0.400	(0.164)	-0.796	(0.005)
II	-0.579	(0.021)	-0.906	(0.001)
I	-0.717	(0.019)	-0.955	(0.002)
Migration Background	-0.452	(0.121)	0.310	(0.216)
Parents' age	0.0159	(0.526)	0.0302	(0.209)
East Germany	0.302	(0.285)	0.103	(0.652)
Married	-0.296	(0.263)	0.0137	(0.961)
Household Size				
3	-0.829	(0.039)	-0.384	(0.398)
4	-0.750	(0.047)	-0.664	(0.147)
5	-0.734	(0.088)	-0.655	(0.167)
6 or more	-0.749	(0.160)	-1.324	(0.039)
Latent Class				
Class 2	-2.624	(0.000)	-0.961	(0.205)
Class 3	-0.722	(0.200)	-0.596	(0.498)
Class 4	-3.169	(0.000)	-1.675	(0.029)
Class 5	-4.807	(0.000)	-2.569	(0.001)
Constant	-61.55	(0.250)	-140.1	(0.018)

NEPS SC4. N=2,910. Reference outcome: Abitur. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2; Latent Class: 1.

Table E5: Logit estimates of multinomial logistic regression of school-leaving certificate - unconditional

Outcome	None		Hauptschulabschluss		Fachhochschulreife		Abitur	
	b	p-value	b	p-value	b	p-value	b	p-value
Net worth (IHS)	$-9.12*10^{-6}$	(0.004)	$-4.20*10^{-6}$	(0.042)	$1.13*10^{-6}$	(0.597)	$2.74*10^{-6}$	(0.100)
Net worth (IHS)^2	-9.77e-11	(0.055)	-2.61e-11	(0.303)	1.41e-11	(0.642)	9.02e-12	(0.712)
Net worth (IHS)^3	6.17e-16	(0.002)	1.46e-16	(0.343)	-3.56e-17	(0.805)	-6.09e-17	(0.607)
Income (log.)	9.977	(0.069)	0.704	(0.342)	1.423	(0.647)	-0.841	(0.018)
Income (log.)^2	-0.664	(0.061)	-0.0604	(0.253)	-0.0683	(0.730)	0.0885	(0.000)
ISCED								
3	0.00924	(0.982)	-0.331	(0.113)	-0.199	(0.453)	-0.141	(0.470)
4	-1.320	(0.037)	-1.201	(0.000)	0.142	(0.695)	0.851	(0.001)
5B	-0.282	(0.518)	-0.709	(0.005)	-0.0433	(0.882)	0.305	(0.157)
5A or 6	0.276	(0.599)	-0.744	(0.022)	0.374	(0.256)	1.313	(0.000)
EGP								
IIIa, IV	-0.0373	(0.886)	-0.268	(0.084)	0.0248	(0.891)	0.427	(0.000)
II	0.0376	(0.878)	-0.356	(0.017)	0.188	(0.285)	0.668	(0.000)
I	-0.208	(0.530)	-0.460	(0.034)	0.0919	(0.669)	0.642	(0.000)
Migration Background	-0.141	(0.620)	-0.0860	(0.624)	0.589	(0.000)	0.421	(0.000)
Parents' age	-0.0366	(0.137)	-0.00921	(0.466)	0.000278	(0.983)	-0.0172	(0.049)
East Germany	-0.488	(0.135)	-0.622	(0.048)	-0.506	(0.069)	0.132	(0.531)
Married	-0.167	(0.533)	-0.295	(0.046)	0.110	(0.577)	0.107	(0.343)
Household Size								
3	0.417	(0.373)	0.275	(0.267)	-0.393	(0.138)	-0.290	(0.149)
4	0.264	(0.617)	0.402	(0.101)	-0.378	(0.162)	-0.281	(0.152)
5	0.498	(0.369)	0.721	(0.007)	-0.366	(0.197)	-0.254	(0.215)
6 or more	0.746	(0.233)	0.751	(0.012)	-0.569	(0.091)	-0.361	(0.126)
Constant	33.52	(0.518)	17.10	(0.493)	-8.266	(0.768)	34.21	(0.050)

NEPS SC4. N=6,042. Reference outcome: Realschulabschluss. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2.

Table E6.1: Logit estimates of logistic regression of activity after school – conditional on having left school without certificate

Outcome	No fully-qualifying training	
	b	p-value
Net worth (IHS)	$2.48*10^{-5}$	(0.053)
Net worth (IHS)^2	$1.08*10^{-10}$	(0.479)
Net worth (IHS)^3	$-4.66*10^{-15}$	(0.029)
Income (log.)	12.42	(0.455)
Income (log.)^2	-0.862	(0.428)
ISCED		
3	-0.196	(0.796)
4	0.309	(0.853)
5B	-0.805	(0.495)
5A or 6	0.171	(0.893)
EGP		
IIIa, IV	-0.716	(0.294)
II	-1.149	(0.076)
I	0.599	(0.505)
Migration Background	-0.267	(0.638)
Parents' age	-0.116	(0.005)
East Germany	0.398	(0.594)
Married	-0.140	(0.801)
Household Size		
3	1.558	(0.140)
4	1.407	(0.188)
5	1.029	(0.428)
6 or more	1.563	(0.209)
Latent Class		
Class 2	1.505	(0.291)
Class 3	0.817	(0.402)
Class 4	0.909	(0.266)
Class 5	0.499	(0.440)
Constant	181.0	(0.073)

NEPS SC4. N=153. Reference outcome: fully-qualifying training. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2; Latent Class: 1.

Table E6.2: Logit estimates of multinomial logistic regression of activity after school – conditional on having Hauptschulabschluss

Outcome	VET school		Other	
	b	p-value	b	p-value
Net worth (IHS)	-7.31×10^{-6}	(0.092)	-9.07×10^{-6}	(0.120)
Net worth (IHS)^2	2.62×10^{-11}	(0.589)	-1.21×10^{-10}	(0.116)
Net worth (IHS)^3	-1.16×10^{-16}	(0.776)	9.78×10^{-16}	(0.111)
Income (log.)	6.161	(0.267)	1.389	(0.753)
Income (log.)^2	-0.342	(0.329)	-0.102	(0.717)
ISCED				
3	-0.415	(0.275)	-0.956	(0.008)
4	-0.440	(0.492)	-0.935	(0.197)
5B	-0.368	(0.417)	-1.847	(0.002)
5A or 6	-0.370	(0.612)	-1.018	(0.140)
EGP				
IIIa, IV	0.114	(0.715)	-0.0467	(0.922)
II	0.0381	(0.917)	0.546	(0.161)
I	-0.684	(0.153)	0.112	(0.842)
Migration Background	-0.0176	(0.948)	0.180	(0.627)
Parents' age	-0.0106	(0.640)	-0.0345	(0.158)
East Germany	0.494	(0.286)	0.168	(0.773)
Married	-0.745	(0.038)	-0.169	(0.590)
Household Size				
3	0.0214	(0.971)	-0.794	(0.150)
4	0.0659	(0.911)	-1.091	(0.080)
5	0.0173	(0.977)	-0.126	(0.844)
6 or more	-0.441	(0.535)	-0.812	(0.281)
Latent Class				
Class 3	-0.709	(0.572)	1.825	(0.055)
Class 4	-0.0721	(0.898)	-0.245	(0.689)
Class 5	-0.372	(0.429)	-0.864	(0.064)
Constant	-5.960	(0.893)	64.20	(0.205)

NEPS SC4. N=648. Reference outcome: Dual VET. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2; Latent Class: 1.

Table E6.3: Logit estimates of multinomial logistic regression of activity after school – conditional on having Realschulabschluss

Outcome	VET school		Prevocational Training		Other	
	b	p-value	b	p-value	b	p-value
Net worth (IHS)	$-4.86*10^{-6}$	(0.113)	$-8.97*10^{-6}$	(0.034)	$-1.46*10^{-6}$	(0.803)
Net worth (IHS)^2	$-8.78*10^{-11}$	(0.089)	$-6.20*10^{-11}$	(0.252)	$-1.34*10^{-10}$	(0.111)
Net worth (IHS)^3	$5.21*10^{-16}$	(0.055)	$5.28*10^{-16}$	(0.049)	$6.97*10^{-16}$	(0.047)
Income (log.)	-1.560	(0.025)	-1.363	(0.162)	-1.339	(0.140)
Income (log.)^2	0.112	(0.029)	0.111	(0.126)	0.112	(0.147)
ISCED						
3	0.477	(0.214)	0.0279	(0.959)	0.121	(0.854)
4	0.799	(0.081)	0.584	(0.422)	1.090	(0.153)
5B	0.432	(0.313)	-0.639	(0.339)	0.626	(0.369)
5A or 6	0.967	(0.034)	1.011	(0.142)	0.652	(0.382)
EGP						
IIIa, IV	0.101	(0.641)	-0.567	(0.157)	0.137	(0.723)
II	0.107	(0.599)	-0.562	(0.200)	0.161	(0.686)
I	0.0128	(0.957)	0.0489	(0.909)	0.376	(0.381)
Migration Background	0.368	(0.073)	0.891	(0.015)	0.940	(0.005)
Parents' age	-0.0217	(0.188)	-0.0261	(0.386)	-0.0451	(0.123)
East Germany	-0.0398	(0.858)	-0.883	(0.065)	-0.564	(0.224)
Married	0.0855	(0.705)	-0.0245	(0.955)	-0.818	(0.037)
Household Size						
3	-0.502	(0.137)	-0.495	(0.376)	-0.375	(0.545)
4	-0.229	(0.539)	-0.213	(0.713)	0.303	(0.649)
5	-0.425	(0.275)	-0.180	(0.790)	0.367	(0.608)
6 or more	-0.252	(0.582)	-0.674	(0.447)	0.570	(0.446)
Latent Class						
Class 2	0.241	(0.768)	1.333	(0.081)	-16.92	(0.000)
Class 3	0.744	(0.008)	1.418	(0.001)	0.644	(0.107)
Class 4	0.594	(0.001)	0.325	(0.340)	-0.748	(0.033)
Class 5	0.0833	(0.714)	-0.0191	(0.962)	-0.335	(0.392)
Constant	46.51	(0.152)	54.19	(0.364)	91.36	(0.111)

NEPS SC4. N=1,548. Reference outcome: Dual VET. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2; Latent Class: 1.

Table E6.4: Logit estimates of multinomial logistic regression of activity after school – conditional on having Fachhochschulreife

Outcome	Tertiary		Employment		Other	
	b	p-value	b	p-value	b	p-value
Net worth (IHS)	$-5.68*10^{-6}$	(0.402)	$-6.62*10^{-6}$	(0.320)	$-8.74*10^{-6}$	(0.901)
Net worth (IHS)^2	$3.53*10^{-11}$	(0.735)	$-1.41*10^{-10}$	(0.197)	$1.27*10^{-11}$	(0.916)
Net worth (IHS)^3	$6.68*10^{-18}$	(0.991)	$7.74*10^{-16}$	(0.114)	$-2.77*10^{-16}$	(0.707)
Income (log.)	-9.843	(0.129)	-5.313	(0.518)	-2.040	(0.785)
Income (log.)^2	0.610	(0.131)	0.363	(0.470)	0.132	(0.773)
ISCED						
3	0.527	(0.406)	0.746	(0.289)	0.836	(0.234)
4	-0.0811	(0.924)	-0.282	(0.759)	0.0703	(0.934)
5B	0.507	(0.460)	0.0550	(0.948)	0.378	(0.592)
5A or 6	1.899	(0.012)	1.549	(0.069)	1.080	(0.184)
EGP						
IIIa, IV	0.291	(0.541)	0.0532	(0.913)	-0.114	(0.801)
II	0.683	(0.148)	0.455	(0.328)	0.263	(0.564)
I	-0.0727	(0.891)	-0.0894	(0.844)	0.191	(0.708)
Migration Background	0.887	(0.016)	0.847	(0.023)	0.866	(0.065)
Parents' age	-0.00656	(0.812)	0.00229	(0.941)	-0.0425	(0.220)
East Germany	-0.955	(0.121)	-0.697	(0.262)	-0.924	(0.199)
Married	-0.434	(0.334)	-0.519	(0.249)	-0.935	(0.046)
Household Size						
3	-0.408	(0.541)	-0.281	(0.635)	0.0925	(0.881)
4	-0.0773	(0.911)	-0.579	(0.378)	-0.257	(0.679)
5	-0.0731	(0.924)	-0.154	(0.821)	0.301	(0.697)
6 or more	0.734	(0.384)	-0.849	(0.358)	0.924	(0.240)
Latent Class						
Class 2	1.768	(0.004)	1.026	(0.172)	1.330	(0.119)
Class 3	0.355	(0.367)	1.085	(0.009)	1.171	(0.008)
Class 4	-0.464	(0.183)	0.201	(0.629)	0.715	(0.084)
Class 5	-0.462	(0.428)	-0.0552	(0.940)	1.187	(0.052)
Constant	52.13	(0.396)	15.06	(0.828)	91.03	(0.227)

NEPS SC4. N=495. Reference outcome: VET. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2; Latent Class: 1.

Table E6.5 (part 1): Logit estimates of multinomial logistic regression of activity after school – conditional on having Abitur

Outcome	VET school		Dual VET		UAS	
	b	p-value	b	p-value	b	p-value
Net worth (IHS)	$-6.00*10^{-7}$	(0.913)	$-2.41*10^{-6}$	(0.500)	$2.15*10^{-6}$	(0.562)
Net worth (IHS)^2	$-7.54*10^{-11}$	(0.282)	$-6.81*10^{-12}$	(0.884)	$2.02*10^{-11}$	(0.728)
Net worth (IHS)^3	$3.29*10^{-16}$	(0.147)	$1.33*10^{-16}$	(0.504)	$-1.23*10^{-16}$	(0.625)
Income (log.)	-3.535	(0.170)	-4.896	(0.021)	-1.489	(0.631)
Income (log.)^2	0.219	(0.153)	0.290	(0.022)	0.0797	(0.662)
ISCED						
3	0.189	(0.773)	-0.144	(0.768)	0.144	(0.828)
4	-0.305	(0.675)	-0.0281	(0.955)	0.587	(0.373)
5B	-0.290	(0.673)	-0.180	(0.712)	-0.0440	(0.945)
5A or 6	-0.722	(0.309)	-0.769	(0.138)	0.432	(0.514)
EGP						
IIIa, IV	0.380	(0.345)	-0.109	(0.685)	-0.0612	(0.861)
II	0.385	(0.371)	-0.206	(0.411)	-0.0395	(0.912)
I	0.116	(0.773)	-0.615	(0.022)	-0.567	(0.133)
Migration Background	-0.574	(0.066)	-0.932	(0.000)	-0.122	(0.542)
Parents' age	-0.0288	(0.334)	0.0388	(0.023)	0.0303	(0.064)
East Germany	0.140	(0.729)	0.182	(0.507)	0.101	(0.693)
Married	1.149	(0.009)	0.512	(0.025)	-0.0427	(0.860)
Household Size						
3	-0.732	(0.245)	0.262	(0.538)	-0.160	(0.715)
4	-0.526	(0.402)	0.372	(0.388)	0.244	(0.579)
5	-0.270	(0.682)	0.201	(0.648)	0.226	(0.624)
6 or more	-0.785	(0.328)	0.274	(0.574)	-0.330	(0.537)
Latent Class						
Class 2	-0.825	(0.128)	-1.625	(0.000)	-0.905	(0.001)
Class 3	0.336	(0.486)	-0.247	(0.353)	-0.598	(0.029)
Class 4	1.624	(0.018)	0.321	(0.424)	-0.0537	(0.917)
Class 5	-17.79	(0.000)	-1.152	(0.387)	-1.321	(0.312)
Constant	67.08	(0.261)	-56.62	(0.103)	-53.72	(0.101)

Table E13 continues on next page.

Table E6.5 (part 2): Logit estimates of multinomial logistic regression of activity after school – conditional on having Abitur

Table E13 continues here.

Outcome	Dual Study		Employment		Other	
	b	p-value	b	p-value	b	p-value
Net worth (IHS)	$-8.44*10^{-7}$	(0.820)	$-4.42*10^{-6}$	(0.080)	$5.49*10^{-7}$	(0.884)
Net worth (IHS)^2	$1.17*10^{-10}$	(0.009)	$3.85*10^{-11}$	(0.264)	$-5.57*10^{-11}$	(0.297)
Net worth (IHS)^3	$-6.56*10^{-16}$	(0.037)	$-2.05*10^{-16}$	(0.314)	$3.21*10^{-16}$	(0.118)
Income (log.)	10.80	(0.136)	-3.360	(0.124)	-3.138	(0.169)
Income (log.)^2	-0.662	(0.133)	0.201	(0.127)	0.186	(0.171)
ISCED						
3	-0.238	(0.726)	-0.165	(0.677)	0.429	(0.397)
4	-0.533	(0.494)	-0.145	(0.735)	0.629	(0.246)
5B	-0.334	(0.647)	-0.330	(0.394)	0.0980	(0.855)
5A or 6	-0.995	(0.178)	-0.228	(0.575)	0.432	(0.407)
EGP						
IIIa, IV	-0.691	(0.036)	-0.0451	(0.839)	0.261	(0.333)
II	-0.285	(0.286)	-0.0369	(0.861)	0.0178	(0.943)
I	-0.499	(0.092)	-0.403	(0.083)	-0.277	(0.279)
Migration Background	-0.850	(0.010)	-0.0580	(0.727)	-0.254	(0.202)
Parents' age	0.0338	(0.122)	0.0301	(0.018)	0.0331	(0.042)
East Germany	-0.274	(0.343)	-0.413	(0.016)	-0.170	(0.524)
Married	0.286	(0.335)	0.135	(0.478)	-0.0816	(0.699)
Household Size						
3	-0.286	(0.569)	0.0884	(0.788)	-0.335	(0.259)
4	-0.501	(0.319)	0.298	(0.372)	-0.0831	(0.791)
5	-0.533	(0.312)	0.0936	(0.795)	-0.209	(0.530)
6 or more	-0.647	(0.283)	0.240	(0.527)	-0.123	(0.762)
Latent Class						
Class 2	-0.881	(0.004)	-0.944	(0.000)	-1.759	(0.000)
Class 3	-0.711	(0.020)	-0.397	(0.134)	-1.027	(0.000)
Class 4	-0.150	(0.780)	0.581	(0.140)	1.003	(0.003)
Class 5	-18.06	(0.000)	-18.89	(0.000)	0.674	(0.449)
Constant	-110.5	(0.030)	-44.51	(0.080)	-51.18	(0.119)

NEPS SC4. N=3,198. Reference outcome: University. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2; Latent Class: 1.

Table E7 (part 1): Logit estimates of multinomial logistic regression of activity after school – unconditional

Outcome	Other		Prevocational Training		VET School		Dual VET	
	b	p-value	b	p-value	b	p-value	b	p-value
Net worth (IHS)	$3.85*10^{-6}$	(0.207)	$-4.23*10^{-6}$	(0.192)	$-2.40*10^{-6}$	(0.326)	$1.63*10^{-6}$	(0.418)
Net worth (IHS)^2	-6.62e-11	(0.128)	-7.92e-11	(0.042)	-4.52e-11	(0.167)	-1.22e-11	(0.675)
Net worth (IHS)^3	3.50e-16	(0.079)	5.03e-16	(0.006)	3.09e-16	(0.071)	1.22e-16	(0.435)
Income (log.)	0.209	(0.730)	0.674	(0.277)	-0.183	(0.721)	0.0946	(0.829)
Income (log.)^2	-0.0178	(0.654)	-0.0805	(0.079)	-0.00256	(0.944)	-0.0383	(0.219)
ISCED								
3	0.332	(0.381)	-0.562	(0.130)	0.260	(0.393)	0.0189	(0.945)
4	0.564	(0.181)	-1.457	(0.007)	-0.374	(0.344)	-0.700	(0.046)
5B	0.274	(0.501)	-1.363	(0.003)	0.0410	(0.906)	-0.240	(0.431)
5A or 6	0.209	(0.610)	-1.198	(0.013)	-0.791	(0.035)	-1.353	(0.000)
EGP								
IIIa, IV	0.0840	(0.702)	-0.392	(0.131)	-0.192	(0.359)	-0.277	(0.101)
II	-0.156	(0.435)	-0.721	(0.008)	-0.484	(0.010)	-0.582	(0.000)
I	-0.0547	(0.799)	-0.323	(0.294)	-0.514	(0.018)	-0.447	(0.009)
Migration Background	-0.0634	(0.700)	-0.368	(0.177)	-0.456	(0.008)	-0.805	(0.000)
Parents' age	-0.0105	(0.486)	-0.0138	(0.496)	-0.00188	(0.891)	0.0175	(0.107)
East Germany	0.231	(0.386)	0.156	(0.666)	0.393	(0.148)	0.193	(0.363)
Married	-0.0984	(0.609)	-0.0106	(0.965)	0.0726	(0.705)	0.160	(0.284)
Household Size								
3	-0.0945	(0.742)	0.109	(0.785)	0.156	(0.598)	0.496	(0.041)
4	-0.230	(0.466)	-0.0324	(0.938)	0.0893	(0.776)	0.359	(0.162)
5	-0.107	(0.746)	0.336	(0.490)	0.0902	(0.790)	0.443	(0.110)
6 or more	0.0433	(0.903)	0.0120	(0.982)	0.161	(0.665)	0.476	(0.097)
Constant	19.66	(0.508)	27.32	(0.496)	5.377	(0.843)	-31.62	(0.138)

Table E14 Continues on next page.

Table E7 (part 2): Logit estimates of multinomial logistic regression of activity after school – unconditional

Outcome	UAS		Dual VET		Uni	
	b	p-value	b	p-value	b	p-value
Net worth (IHS)	$4.21*10^{-6}$	(0.148)	$4.93*10^{-6}$	(0.198)	$5.32*10^{-6}$	(0.034)
Net worth (IHS)^2	3.17e-12	(0.942)	9.40e-11	(0.017)	-1.83e-11	(0.586)
Net worth (IHS)^3	1.28e-17	(0.952)	-6.24e-16	(0.053)	4.40e-17	(0.801)
Income (log.)	0.171	(0.826)	15.18	(0.046)	3.113	(0.087)
Income (log.)^2	-0.0203	(0.705)	-0.923	(0.046)	-0.184	(0.085)
ISCED						
3	0.122	(0.799)	0.261	(0.713)	0.0395	(0.906)
4	0.552	(0.308)	0.215	(0.782)	0.274	(0.477)
5B	0.170	(0.739)	0.544	(0.476)	0.362	(0.292)
5A or 6	0.498	(0.343)	-0.0773	(0.920)	0.386	(0.292)
EGP						
IIIa, IV	0.171	(0.574)	-0.604	(0.053)	0.180	(0.383)
II	0.149	(0.579)	-0.159	(0.561)	0.177	(0.360)
I	-0.0237	(0.934)	-0.0673	(0.828)	0.542	(0.010)
Migration Background	-0.121	(0.536)	-0.600	(0.035)	-0.0401	(0.770)
Parents' age	0.0000751	(0.996)	0.0171	(0.377)	-0.0266	(0.018)
East Germany	0.388	(0.168)	0.163	(0.537)	0.529	(0.002)
Married	0.0580	(0.801)	0.0964	(0.746)	-0.00501	(0.976)
Household Size						
3	-0.211	(0.592)	-0.0974	(0.841)	0.0791	(0.778)
4	-0.00815	(0.983)	-0.594	(0.203)	-0.106	(0.709)
5	0.0697	(0.869)	-0.461	(0.370)	-0.0104	(0.973)
6 or more	-0.112	(0.818)	-0.602	(0.303)	0.0194	(0.954)
Constant	-2.104	(0.941)	-97.75	(0.042)	38.05	(0.087)

NEPS SC4. N=6,042. Reference outcome: Employment. Reference categories: ISCED: 3; EGP: IIIb, V, VI or VII, Household size: 2. UAS = University of applied science.

Table E14 continues here.

F. Differences by other measures of SES

Table F1: Predicted probabilities of track in fifth grade, track in ninth grade school-leaving certificate, and activity after school by household income, parental education and occupational class - unconditional

Stage	Outcome	Income		Education (ISCED)		Occupational Class (EGP)	
		10th percentile 1,700 EUR	90th percentile 5,000 EUR	0, 1, or 2	5A or 6	IIIb, V, VI, or VII	I
Track in fifth grade	Hauptschule	20.2	11.1	21.4	6.2	22.1	14.1
	Non-tracked	7.9	8.4	7.4	8.4	8.5	7.2
	Realschule	33.1	27.5	36.2	21.5	33.0	26.7
	Gymnasium	38.9	52.9	35.1	63.9	36.3	52.0
Track in ninth grade	Hauptschule	20.2	11.1	21.4	6.2	22.1	14.1
	Non-tracked	7.9	8.4	7.4	8.4	8.5	7.2
	Realschule	33.1	27.5	36.2	21.5	33.0	26.7
	Gymnasium	38.9	52.9	35.1	63.9	36.3	52.0
School-leaving certificate	None	4.4	1.9	4.1	2.9	3.8	2.7
	Hauptschulabschluss	14.0	9.0	15.4	5.4	15.8	8.8
	Realschulabschluss	31.7	25.1	35.2	17.1	32.4	26.8
	Fachhochschulreife	8.6	9.4	9.6	7.9	9.9	8.5
	Abitur	41.4	54.6	35.6	66.6	38.2	53.2
Activity after school	Other	9.3	10.6	8.6	12.8	9.2	10.0
	Employment	10.9	13.5	10.1	16.9	10.8	12.3
	Prevocational	5.2	3.6	4.8	4.5	5.3	4.7
	VET school	11.8	12.1	14.1	8.7	13.5	9.9
	Dual VET	42.1	31.8	45.6	20.6	42.5	33.6
	UAS	5.7	5.9	3.8	9.3	4.8	5.2
	Dual Study	1.7	3.4	2.5	2.9	2.9	3.1
	University	13.3	19.1	10.6	24.3	11.1	21.2

NEPS SC4. N=6,042. Predicted values based on multinomial regression.

G. Sensitivity to the measurement of parental wealth as net worth

Although most research uses net worth as a measure of wealth, net worth may not capture all relevant features of wealth. Most importantly, high debts may indicate access to credit and economic potential rather than economic disadvantage (Killewald, 2013). This is particularly true for Germany, where parents will only be able to get large loans if they can prove a high level of financial security. Therefore, I check the sensitivity of my results using three alternative operationalizations of parental wealth: 1) assets (see results in Table G1); 2) assets controlling for debts (Table G2); and 3) assets, debts, and their interaction (Table G3).

Overall, the differences by assets are slightly larger than the differences by net worth. However, the substantial results remain the same. Conversely, Table G3 shows that there are substantial differences between families that have the same net worth but different levels of assets and debts. Children in households with no assets and high debts (30k EUR debts is the 90th percentile of debts among families with no assets) are by far the least like to attend *Gymnasium*, to receive an *Abitur*, and to enter tertiary education. Children in households with high assets and zero debts are the most likely to receive an *Abitur* and to enter tertiary education. Children in households with zero net worth fall in between. However, children in households with 500k EUR assets and 500k EUR debts are much more successful in their educational career than children in households with zero assets and zero debts. For instance, children in households with 500k EUR assets and 500k EUR debts are seven percentage points more likely to obtain an Abitur and four percentage points more like to enroll in an academic university. In fact, the educational careers of children in households with high assets and high debts resemble much more children with high assets and zero debts than those of children with zero assets and zero debts.

These results give us some further hints on the underlying mechanisms that drive the disparities by parental wealth: For both exemplary families with zero assets (0 assets / 0 debts and 0 assets / -30k EUR debts), we can assume that their children neither profit from high educational aspirations nor that wealth could serve as private insurance. Therefore, the lower educational attainment of children in households with high debts can probably be attributed to severe liquidity constraints and, thus, less investment in children’s education and stress caused by economic hardship.

The advantages of children in households with high assets and high debts compared to children in households with zero assets and zero debts may indicate that children profit much more from the benefits of the assets (e.g., the stable environment of owning a house) than being negatively affected by debts caused by the purchase. Moreover, these families with high assets and high debts seem to be able to plan ahead, and it seems unlikely that these families are severely restricted in their investment into their children's education. These findings are in line with prior findings showing that unsecured debts indicate economic deprivation and have negative consequences for educational outcomes, while secured debts indicate economic capacities, which may even have positive effects on educational attainment (Nam and Huang, 2009; Zhan and Sherraden, 2011).

Table G1: Predicted probabilities of track in fifth grade, track in ninth grade, school-leaving certificate, and activity after school by assets – unconditional

Stage	**Outcome**	**10th percentile 0 EUR** Pred. Prob.	SE	**90th percentile 500k EUR** Pred. Prob.	SE	**p-value** of difference
Track in fifth grade	Hauptschule	20.986	1.635	12.516	1.163	0.000
	Non-tracked	9.375	1.258	7.604	1.061	0.263
	Realschule	30.092	2.105	29.789	1.661	0.908
	Gymnasium	39.548	2.205	50.091	1.578	0.000
Track in ninth grade	Hauptschule	24.761	1.863	13.901	1.240	0.000
	Non-tracked	8.902	1.863	4.755	0.830	0.021
	Realschule	30.335	2.319	33.230	1.948	0.294
	Gymnasium	36.002	2.270	48.114	1.708	0.000
School-leaving certificate	None	6.160	1.139	1.889	0.462	0.001
	Hauptschulabschluss	15.489	1.561	9.091	0.897	0.000
	Realschulabschluss	27.889	1.711	26.624	1.339	0.580
	Fachhochschulreife	10.189	1.385	10.115	0.936	0.966
	Abitur	40.273	1.910	52.280	1.387	0.000
Activity after school	Other	8.942	1.241	9.342	0.829	0.799
	Employment	15.213	1.652	12.734	0.940	0.193
	Prevocational	6.104	0.930	2.777	0.471	0.002
	VET school	15.531	1.546	9.229	0.765	0.000
	Dual VET	33.634	1.782	37.622	1.432	0.099
	UAS	5.711	1.088	6.562	0.639	0.505
	Dual Study	1.946	0.598	3.601	0.520	0.045
	University	12.919	1.475	18.133	0.952	0.004

NEPS SC4. N=6,042. Predicted values based on multinomial regression.

Table G2: Predicted probabilities of track in fifth grade, track in ninth grade school-leaving certificate, and activity after school by assets when controlling for debts – unconditional

Stage	Outcome	10th percentile 0 EUR Pred. Prob.	SE	90th percentile 500k EUR Pred. Prob.	SE	**p-value** of difference
Track in fifth grade	Hauptschule	21.965	1.896	12.140	1.233	0.000
	Non-tracked	8.738	1.263	8.067	1.236	0.720
	Realschule	29.572	2.217	29.920	1.802	0.906
	Gymnasium	39.725	2.337	49.874	1.679	0.001
Track in ninth grade	Hauptschule	26.079	2.075	13.357	1.298	0.000
	Non-tracked	8.660	1.749	4.847	0.937	0.037
	Realschule	29.835	2.437	33.333	2.065	0.260
	Gymnasium	35.426	2.406	48.463	1.812	0.000
School-leaving certificate	None	7.292	1.536	1.703	0.434	0.001
	Hauptschulabschluss	16.312	1.783	8.392	0.943	0.000
	Realschulabschluss	27.350	1.876	27.027	1.481	0.904
	Fachhochschulreife	9.822	1.476	10.340	1.002	0.791
	Abitur	39.224	2.041	52.537	1.489	0.000
Activity after school	Other	8.513	1.238	9.840	0.979	0.453
	Employment	16.471	1.920	12.112	0.898	0.049
	Prevocational	6.821	1.254	2.493	0.487	0.004
	VET school	16.899	1.867	8.815	0.804	0.000
	Dual VET	33.230	1.903	37.359	1.509	0.120
	UAS	4.929	0.913	7.027	0.730	0.080
	Dual Study	1.720	0.549	3.801	0.574	0.015
	University	11.416	1.408	18.553	1.007	0.000

NEPS SC4. N=6,042. Predicted values based on multinomial regression.

Table G3: Predicted probabilities of track in fifth grade, track in ninth grade, school-leaving certificate, and activity after school by assets, debts and their interaction - unconditional

		Assets = 0 Debts = 0		**Assets = 500k Debts = 0**		**Assets = 0 Debts = 30k**		**Assets = 500k Debts = 500k**	
		Net Worth = 0		**Net Worth = 500k**		**Net Worth = -30k**		**Net Worth = 0**	
Stage	**Outcome**	Pred. Prob.	SE	Pred. Prob.	SE	Pred. Prob.	SE	Pred. Prob.	SE
Track in fifth grade	Hauptschule	20.128	1.694	12.868	1.754	25.204	3.273	10.906	3.100
	Non-tracked	8.889	1.291	9.315	1.679	10.555	2.610	8.952	2.693
	Realschule	29.393	2.247	29.667	2.640	30.622	3.944	30.056	3.791
	Gymnasium	41.590	2.441	48.150	2.233	33.619	3.697	50.086	3.874
Track in ninth grade	Hauptschule	23.801	1.933	13.756	1.752	30.226	3.440	13.768	3.110
	Non-tracked	8.926	2.007	4.795	1.219	9.235	3.185	6.274	2.646
	Realschule	30.133	2.568	32.825	2.736	28.740	3.908	34.368	4.122
	Gymnasium	37.140	2.526	48.624	2.389	31.798	3.481	45.590	3.907
School-leaving certificate	None	5.624	1.220	0.831	0.414	9.335	3.282	2.361	1.511
	Hauptschulabschluss	14.576	1.614	8.383	1.445	19.017	3.149	14.502	3.649
	Realschulabschluss	27.087	1.924	28.994	2.214	31.848	3.813	23.285	3.526
	Fachhochschulreife	9.481	1.388	9.041	1.360	8.777	2.689	9.814	2.319
	Abitur	43.232	2.188	52.752	2.116	31.023	3.363	50.038	3.542
Activity after school	Other	9.336	1.464	11.066	1.589	11.425	2.601	7.190	1.892
	Employment	15.399	1.779	9.616	1.086	10.640	2.910	15.491	2.878
	Prevocational	5.071	0.910	2.694	0.972	12.180	3.121	3.709	1.313
	VET school	14.888	1.705	8.049	1.385	20.072	3.731	10.227	2.389
	Dual VET	33.202	2.007	36.646	2.238	33.848	3.545	37.425	3.672
	UAS	6.232	1.267	7.164	0.953	2.204	1.002	5.500	1.451
	Dual Study	1.967	0.653	4.146	0.753	0.700	0.552	2.444	1.219
	University	13.904	1.635	20.618	1.393	8.931	2.354	18.016	2.463

NEPS SC4. N=6,042. Predicted values based on multinomial regression.

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Supplementary materials to chapter 3

Table S1: Association between parental net worth and parental SES (in 2014)

	Net Worth	Income	ISCED
Income	0.360		
ISCED	0.267	0.476	
EGP	0.243	0.437	0.555

N=4,611. Multiple imputed data (M=100) of NEPS starting cohort Kindergarten, Sample A. Spearman's rank correlations. Average values across all imputations. All values are significant at 1% level.

Table S2: Association between parental net worth and parental SES (in 2014)

	Net Worth	Income	ISCED
Income	0.372		
ISCED	0.271	0.480	
EGP	0.249	0.431	0.543

N=4,572. Multiple imputed data (M=100) of NEPS starting cohort Kindergarten, Sample B. Spearman's rank correlations. Average values across all imputations. All values are significant at 1% level.

Table S3: Random-effects regression of math competence (unstandardized coefficients, standard errors in parenthesis)

	b	SE
Year		
2014	-0.014	(0.029)
2016	-0.040	(0.029)
Net worth (IHS)	$2.59 * 10^{-6}$	$2.13 * 10^{-6}$
Net worth (IHS)^2	$2.23 * 10^{-10}$ **	$8.65 * 10^{-11}$
Net worth (IHS)^3	$-3.69 * 10^{-15}$ +	$1.98 * 10^{-15}$
Net worth (IHS)^4	$-6.19 * 10^{-20}$ +	$3.33 * 10^{-20}$
Net worth (IHS)^5	$7.64 * 10^{-25}$	$4.77 * 10^{-25}$
Year*Net worth		
*2014 * Net worth (IHS)*	$-3.39 * 10^{-7}$	$1.94 * 10^{-6}$
*2014 * Net worth (IHS)^2*	$4.38 * 10^{-12}$	$7.83 * 10^{-11}$
*2014 * Net worth (IHS)^3*	$1.12 * 10^{-15}$	$1.86 * 10^{-15}$
*2014 * Net worth (IHS)^4*	$2.31 * 10^{-21}$	$3.03 * 10^{-20}$
*2014 * Net worth (IHS)^5*	$-3.71 * 10^{-25}$	$4.54 * 10^{-25}$
*2016 * Net worth (IHS)*	$4.99 * 10^{-7}$	$1.97 * 10^{-6}$
*2016 * Net worth (IHS)^2*	$-1.87 * 10^{-11}$	$8.22 * 10^{-11}$
*2016 * Net worth (IHS)^3*	$5.96 * 10^{-16}$	$1.82 * 10^{-15}$
*2016 * Net worth (IHS)^4*	$1.73 * 10^{-20}$	$3.18 * 10^{-20}$
*2016 * Net worth (IHS)^5*	$-2.09 * 10^{-25}$	$4.51 * 10^{-25}$
Income category (in EUR)		
2. Quintile	-0.027	(0.029)
3. Quintile	-0.003	(0.029)
4. Quintile	0.040	(0.032)
5. Quintile	0.046	(0.034)
Highest ISCED		
3	0.057	(0.066)
4	0.200^{*}	(0.078)
5B	0.223^{**}	(0.076)
5A	0.431^{***}	(0.076)
6	0.541^{***}	(0.096)
Highest EGP		
II	-0.000	(0.026)
IIIa, IV	-0.057+	(0.032)
IIIb, V, VI, VII	-0.092^{*}	(0.037)
Generation status		
First generation	-0.082	(0.086)

Second generation	-0.133**	(0.048)
Third generation	-0.152*	(0.069)
Family status		
divorced or widowed	-0.040	(0.045)
single	-0.058	(0.042)
Number of siblings	-0.054***	(0.012)
East	-0.060	(0.035)
Unemployed	-0.007	(0.035)
Parent's age	-0.008**	(0.002)
Mothertongue: German	0.105+	(0.055)
Biological parents	0.101*	(0.040)
Girl	-0.188***	(0.024)
Child's age	-0.004+	(0.003)
Constant	17.337***	(5.058)
Person-years	13,833	
N	4,611	

Multiple imputed data (M=100) of NEPS starting cohort Kindergarten; Sample A. Reference categories: Year: 2013; Income: 1. Quintile; ISCED: 2 or less; EGP: I; Generation Status: native; Family Status: Married. Significance levels: *** = p<0.001, ** = p<0.01, * = p<0.05, + = p<0.10.

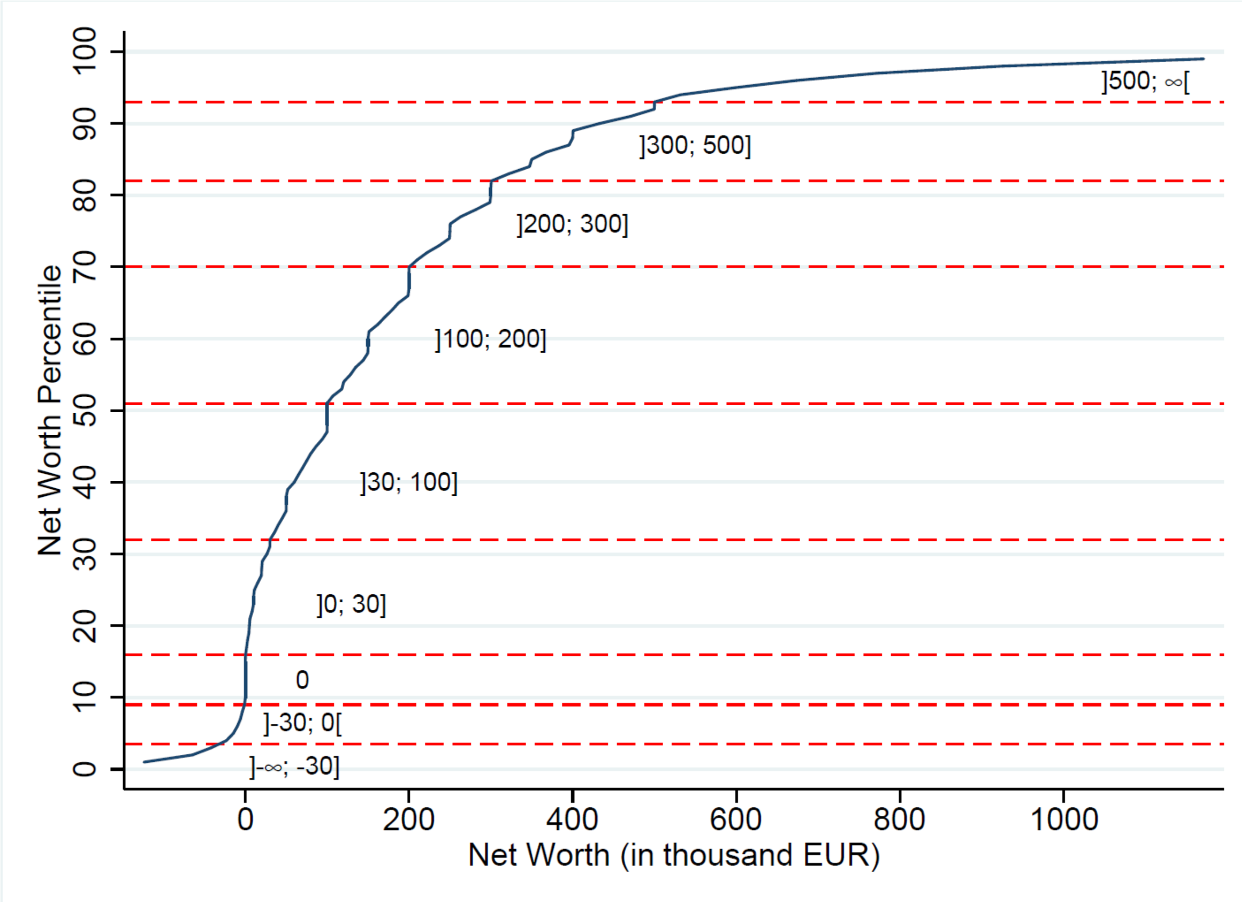
Table S4: Logistic regression of attending the highest secondary school track (log odds; standard errors in parenthesis)

	Model 1		Model 2	
	b	SE	b	SE
Net worth (IHS)	$9.54 * 10^{-6}$ *	$4.86 * 10^{-6}$	$8.21 * 10^{-6}$	$5.87 * 10^{-6}$
Net worth $(IHS)^2$	$5.24 * 10^{-10}$ **	$2.02 * 10^{-10}$	$3.67 * 10^{-10}$	$2.46 * 10^{-10}$
Net worth $(IHS)^3$	$-1.06 * 10^{-14}$ *	$4.74 * 10^{-15}$	$-9.47 * 10^{-15}$	$5.80 * 10^{-15}$
Net worth $(IHS)^4$	$-1.44 * 10^{-19}$ +	$7.50 * 10^{-20}$	$-8.42 * 10^{-20}$	$8.99 * 10^{-20}$
Net worth $(IHS)^5$	$2.13 * 10^{-24}$ +	$1.12 * 10^{-24}$	$1.67 * 10^{-24}$	$1.38 * 10^{-24}$
Income category (in EUR)				
2. Quintile	0.071	(0.133)	0.018	(0.168)
3. Quintile	0.306^{*}	(0.133)	0.219	(0.167)
4. Quintile	0.413^{**}	(0.131)	0.288+	(0.161)
5. Quintile	0.638^{***}	(0.134)	0.556^{***}	(0.167)
Highest ISCED				
3	0.655^{*}	(0.277)	0.570+	(0.339)
4	1.072^{***}	(0.295)	0.739^{*}	(0.362)
5B	1.066^{***}	(0.287)	0.818^{*}	(0.350)
5A	1.584^{***}	(0.291)	1.081^{**}	(0.352)
6	1.831^{***}	(0.331)	1.131^{**}	(0.398)
Highest EGP				
II	-0.191^{*}	(0.086)	-0.270^{**}	(0.102)
IIIa, IV	-0.190+	(0.112)	-0.160	(0.136)
IIIb, V, VI, VII	-0.513^{***}	(0.131)	-0.395^{*}	(0.155)
Generation status				
First generation	0.543+	(0.278)	0.708^{*}	(0.356)
Second generation	0.227+	(0.132)	0.286+	(0.159)
Third generation	-0.171	(0.187)	-0.189	(0.228)
Family status				
divorced or widowed	0.101	(0.173)	0.186	(0.209)
single	-0.101	(0.146)	-0.107	(0.170)
Number of siblings	-0.061+	(0.034)	-0.022	(0.041)
East	0.035	(0.109)	-0.288^{*}	(0.129)
Unemployed	0.190	(0.142)	0.233	(0.176)
Parent's age	-0.020^{**}	(0.007)	-0.017^{*}	(0.008)
Mother tongue: German	-0.475^{**}	(0.155)	-0.717^{***}	(0.190)
Biological parents	0.165	(0.126)	0.065	(0.154)
Girl	0.175^{**}	(0.066)	0.078	(0.084)
Child's age	0.022^{**}	(0.008)	0.020^{*}	(0.010)
Math test score	-		0.416^{***}	(0.057)

Math test score^2	-		-0.075*	(0.035)
Reading test score	-		0.333***	(0.056)
Reading test score^2	-		-0.074*	(0.035)
Math mark				
2	-		-0.231+	(0.126)
3	-		-1.420***	(0.165)
4	-		-3.006***	(0.712)
5 or 6	-		-0.685	(0.760)
German mark				
2	-		-0.280*	(0.130)
3	-		-1.120***	(0.159)
4	-		-2.347***	(0.464)
5 or 6	-		-1.293+	(0.758)
Constant	26.248+	(14.143)	23.342	(17.119)
N	4572		4572	

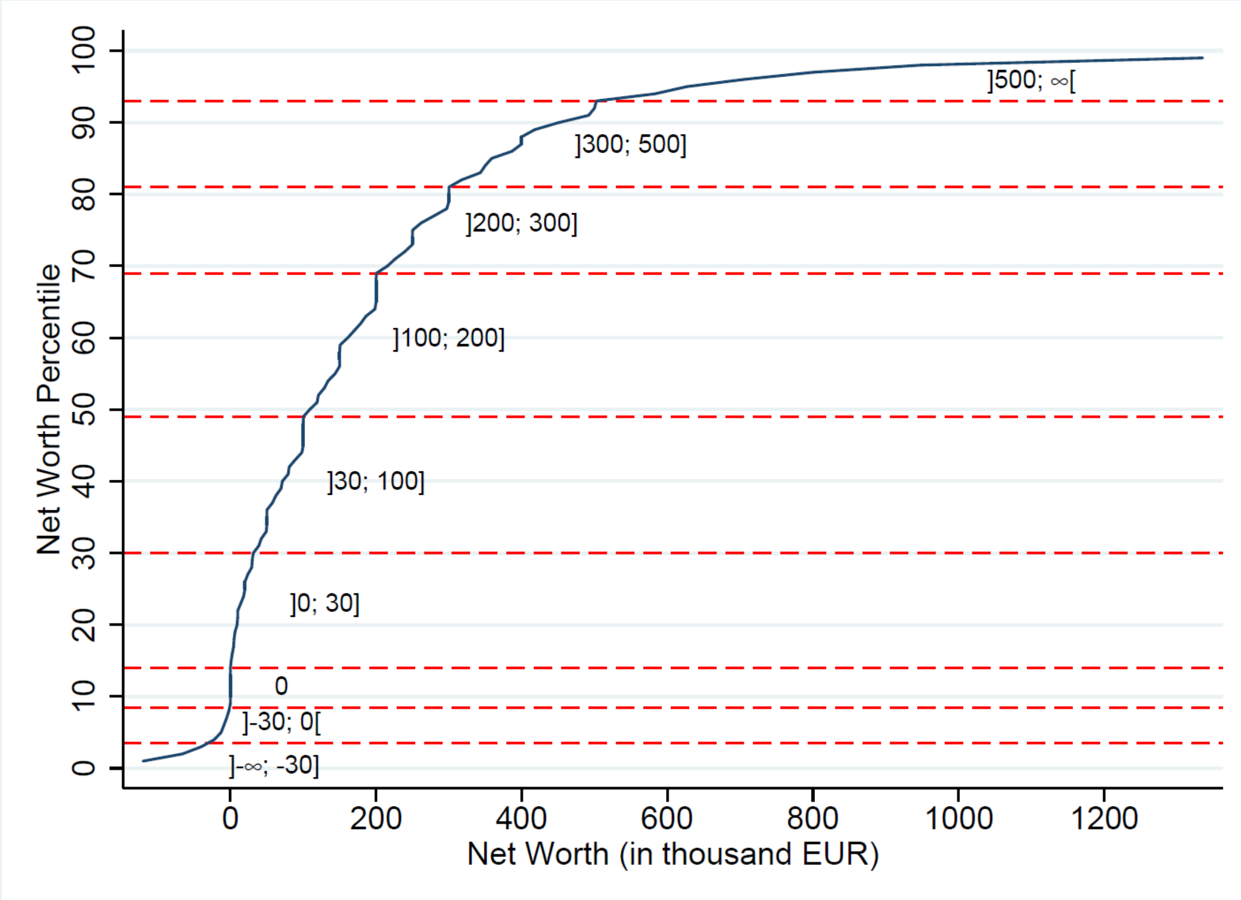
Multiple imputed data (M=100) of NEPS starting cohort Kindergarten; Sample B. Reference categories: Income: 1. Quintile; ISCED: 2 or less; EGP: I; Generation Status: native; Family Status: Married; Math mark: 1; German mark: 1. Significance levels: *** = p<0.001, ** = p<0.01, * = p<0.05, + = p<0.10.

Figure S1: Net Worth Distribution



N=4,611. Multiple imputed data (M=100) of NEPS starting cohort Kindergarten, Sample A.

Figure S2: Net Worth Distribution



N=4,572. Multiple imputed data (M=100) of NEPS starting cohort Kindergarten, Sample B.

Supplementary materials to chapter 4

A. Descriptive Statistics

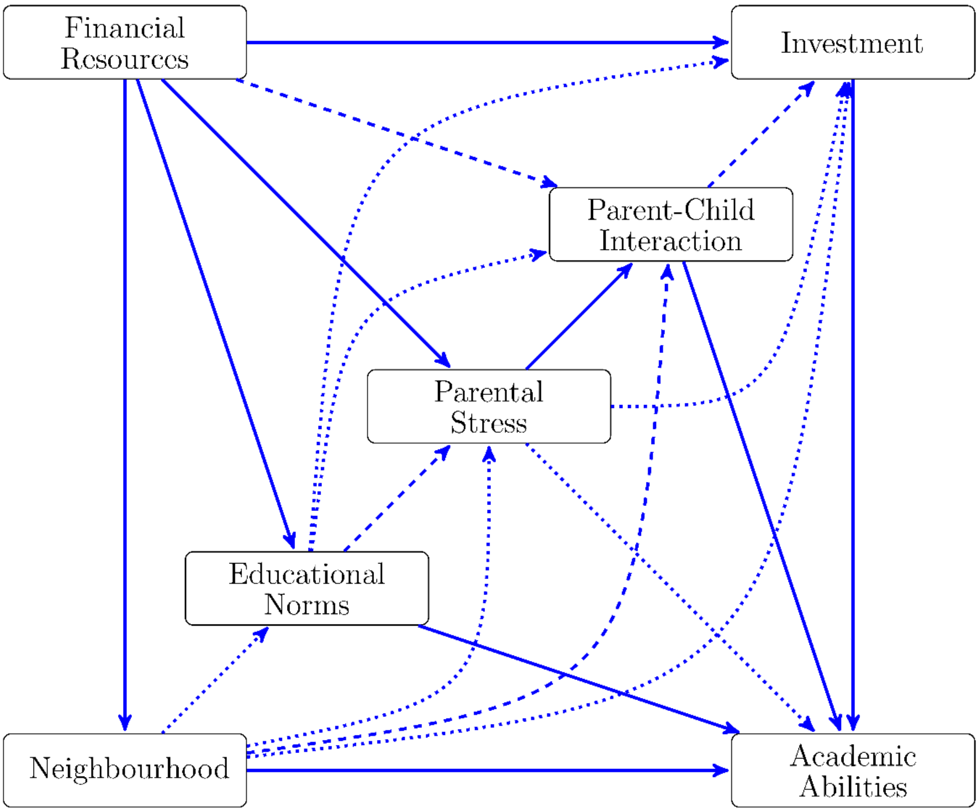
Variable	Mean / Median / Proportion	Minimum	Maximum
Household Net Worth			
Mean	310,997	-400k	10m
Median	50,000	-	-
Negative / 1. Quintile [-400k; 0)	13.86 %	-	-
2. Quintile [0; 20k)	25.22 %	-	-
3. Quintile [20k; 100k)	19.80 %	-	-
4. Quintile [100k; 210k)	21.10 %	-	-
5. Quintile [210k; 10m]	20.02 %		
Equivalized Household Income			
Mean	1,659	506	10,902
Median	1,540	-	-
Income-poor / 1. Quintile [506; 980)	15.90 %	-	-
2. Quintile [980; 1389)	24.38 %	-	-
3. Quintile [1,389; 1,694)	19.62 %	-	-
4. Quintile [1,694; 2,111)	19.79 %	-	-
5. Quintile [2,111; 10,902]	20.32 %		
Parents' highest ISCED			
0-3	32.10 %	-	-
4	7.68 %	-	-
5B	19.25 %	-	-
5A / 6	40.96 %	-	-
Parents' highest EGP			
I	37.00 %	-	-
II	30.91 %	-	-
IIIa, IV	12.62 %	-	-
IIIb, V, VI, VII	19.47 %	-	-
At least one parent was born abroad	26.57 %	-	-
Single parent	6,06 %	-	-
Parents' average birthyear (Mean)	1979	1958	1995.5
Child is a boy	50.76 %	-	-
Child's month of birth (Mean)	04 / 2012	02 / 2012	06 / 2012
Number of older siblings (Mean)	0.77	0	6

Table A1. Descriptive Statistics

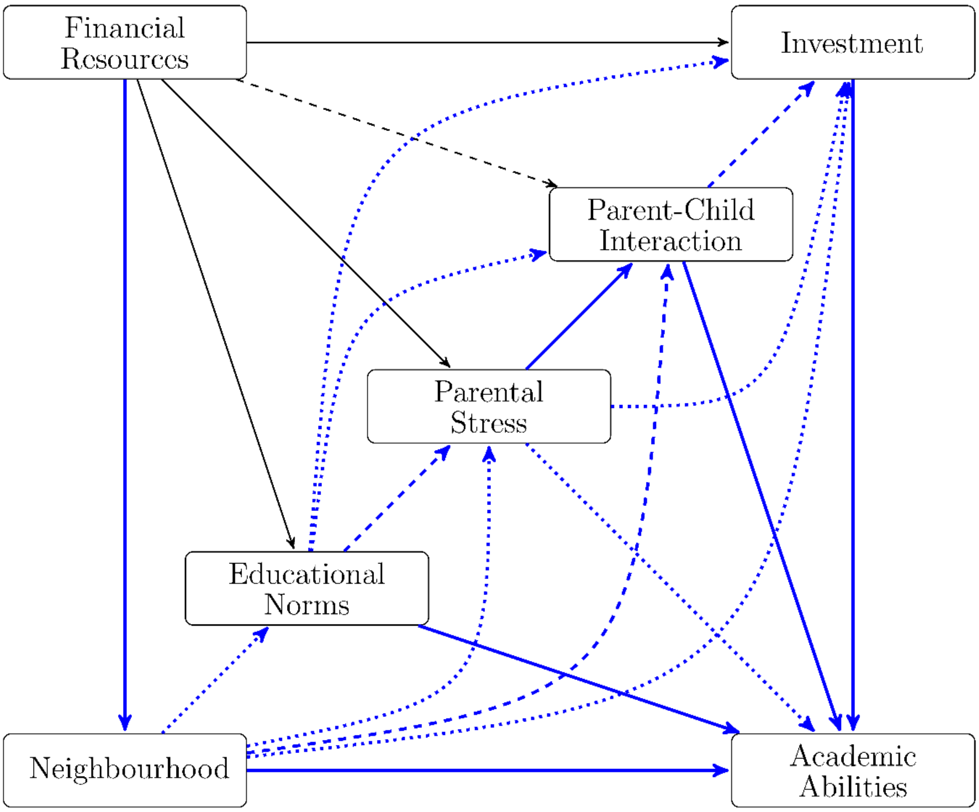
NEPS, starting cohort Newborns. N=2,377. Weighted and averaged over 50 imputed datasets.

B. Indirect Effects

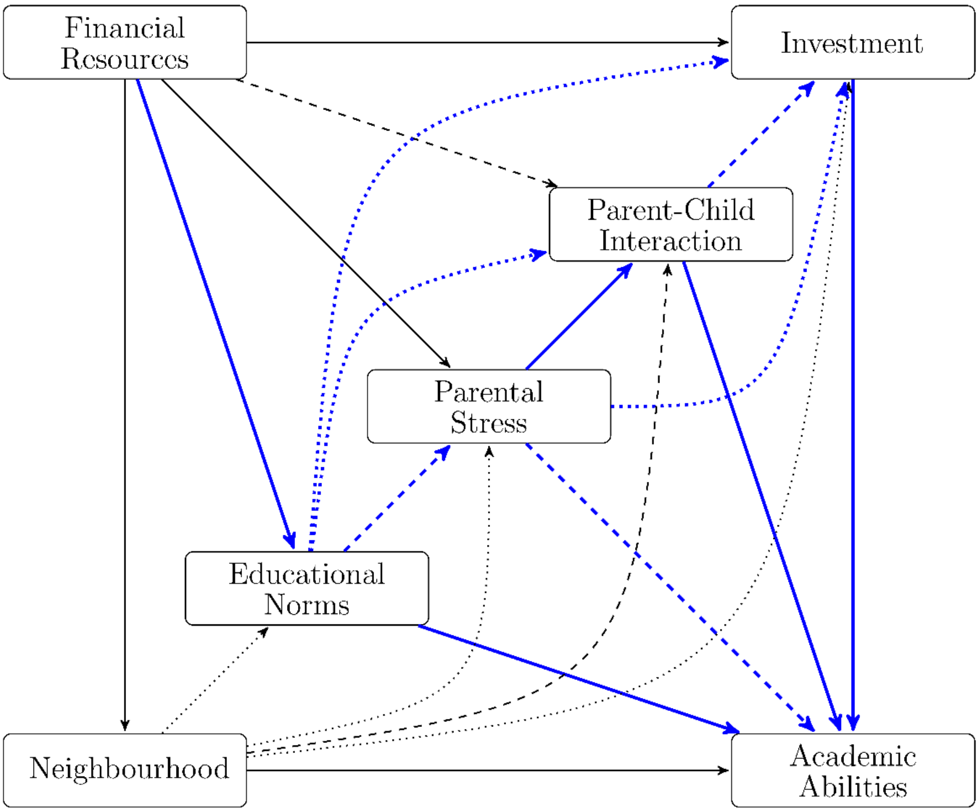
Joint Indirect



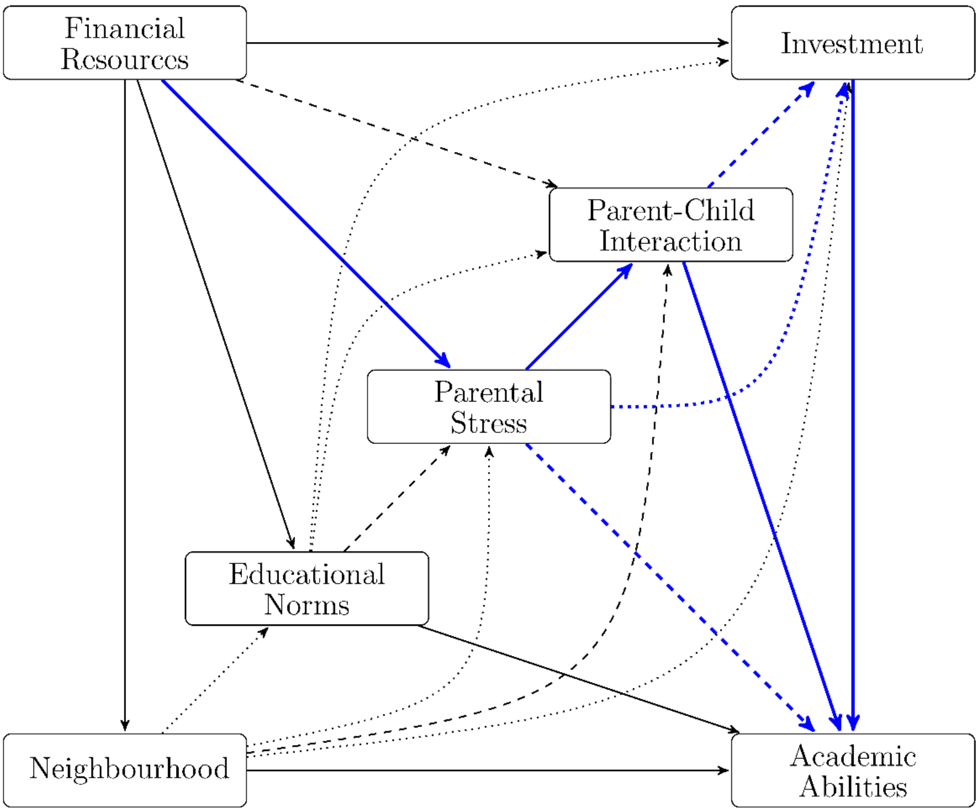
NIE Neighbourhood



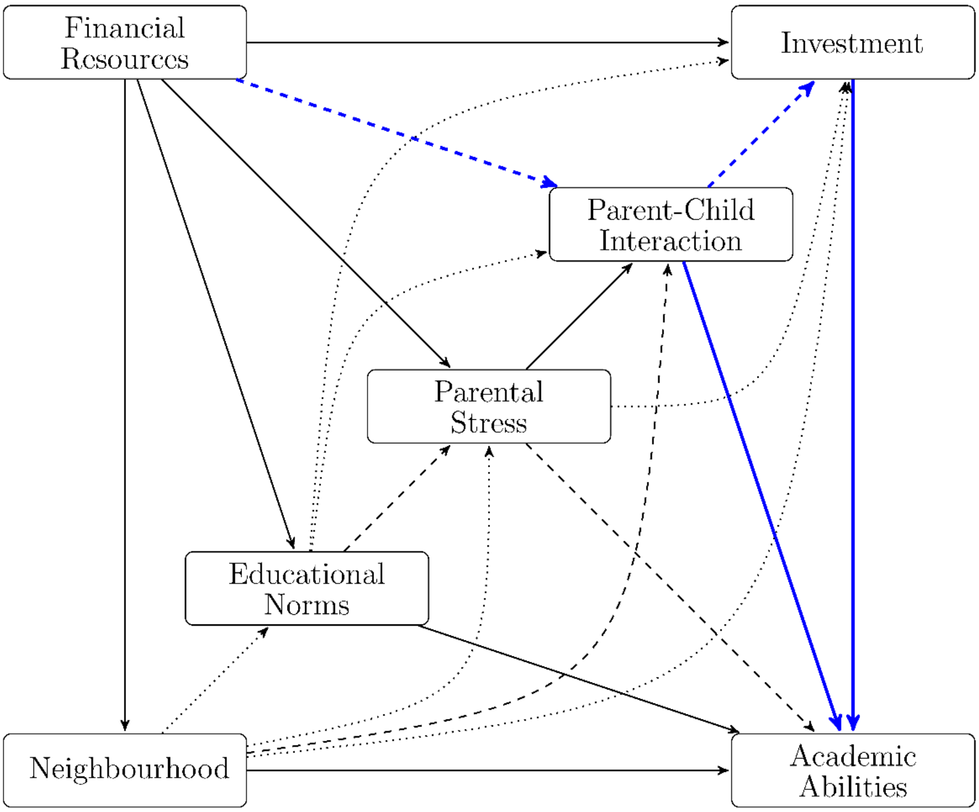
PIE Educational Norms and Aspirations



PIE Stress



PIE Parent-Child Interaction Quality



PIE Investment

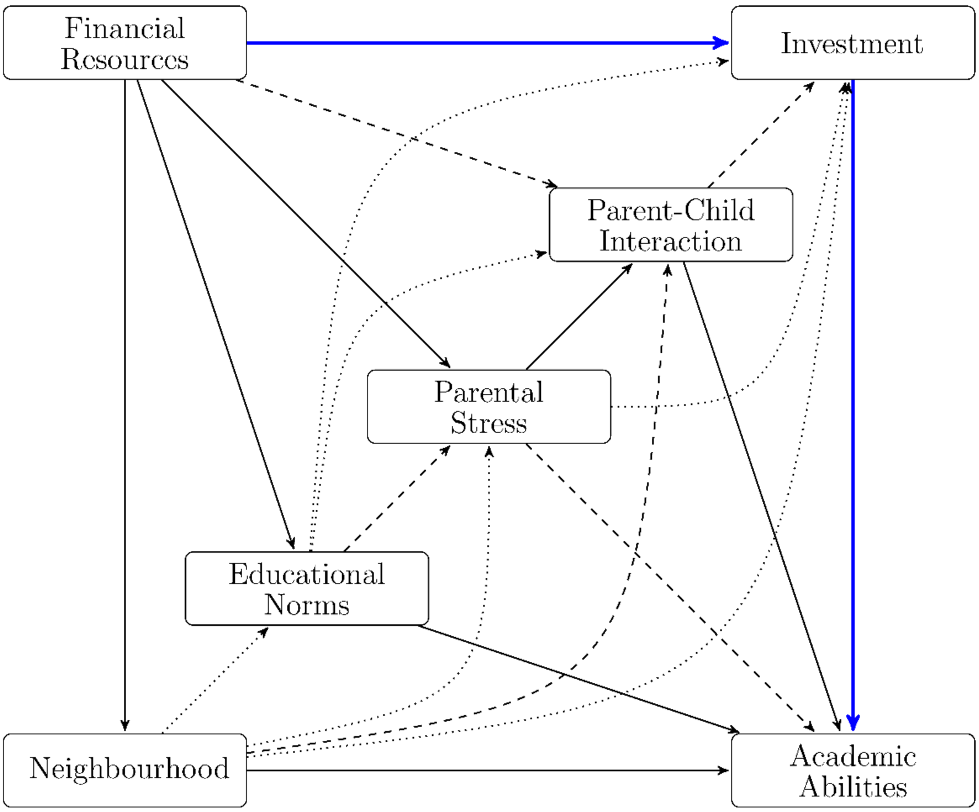


Figure B1. Paths captured by different indirect effects

Blue lines indicate pathways that are captured by the different indirect effect, black lines indicate pathways that are not captured. Dashed lines represent potential empirical effects that are, however, not considered theoretically.

C. Evaluating common support for financial resources and mediators

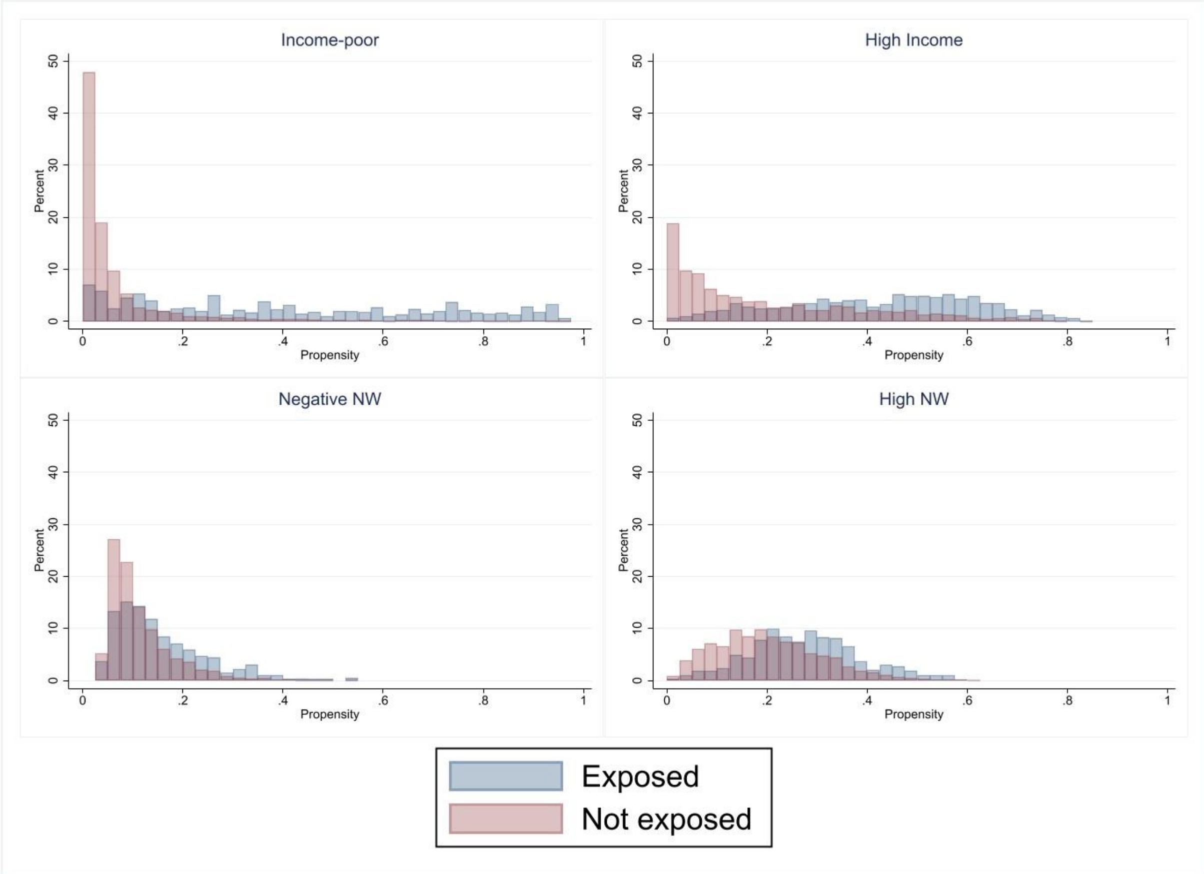


Figure C1. Estimated propensities of being exposed to extreme income or net worth levels by observed exposure.

Propensities are estimated with logistic regressions of being exposed to extreme income or net worth levels on control variables and net worth or income.

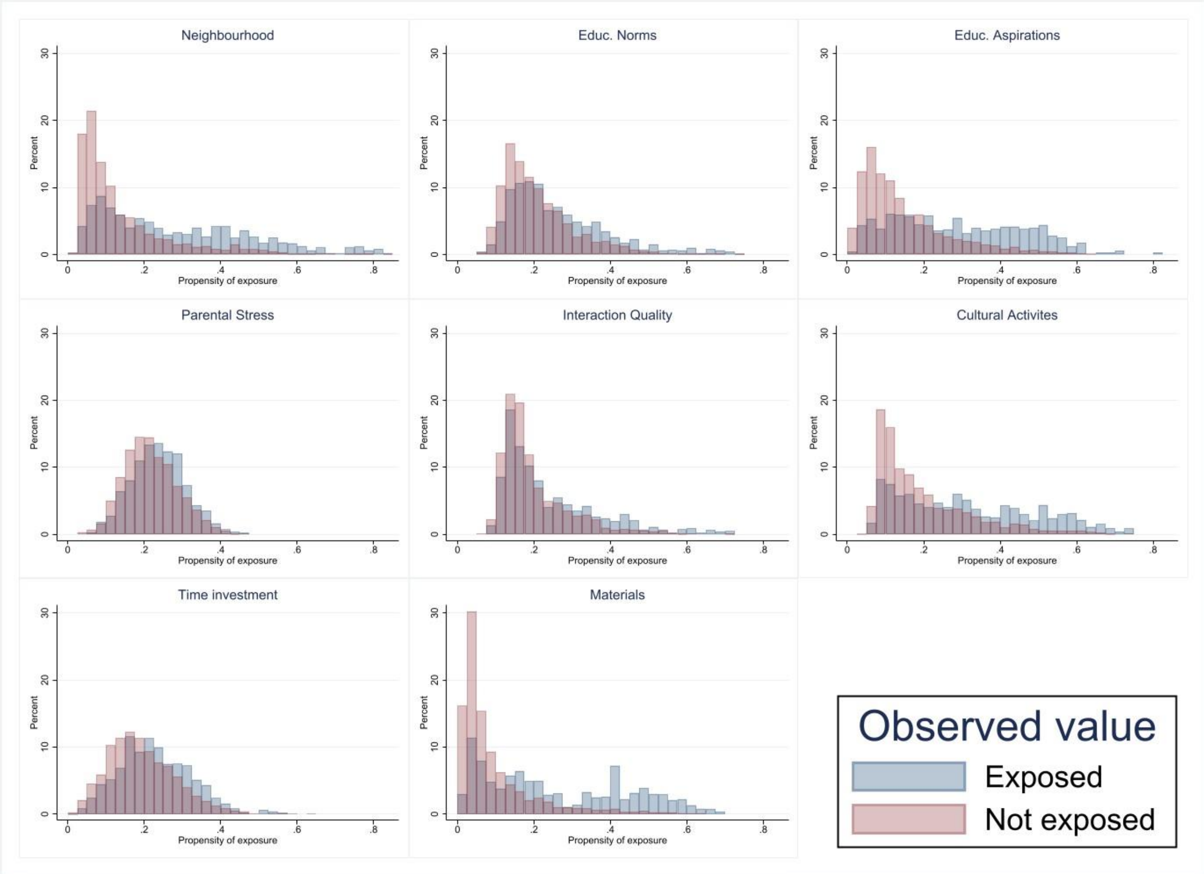


Figure C2. Estimated propensities of being exposed to the lowest quintile of the mediators by observed exposure.

Propensities are estimated with logistic regressions of being exposed to the lowest quintile of the mediators on parents' income, net worth, control variables, and all mediators earlier in the causal chain.

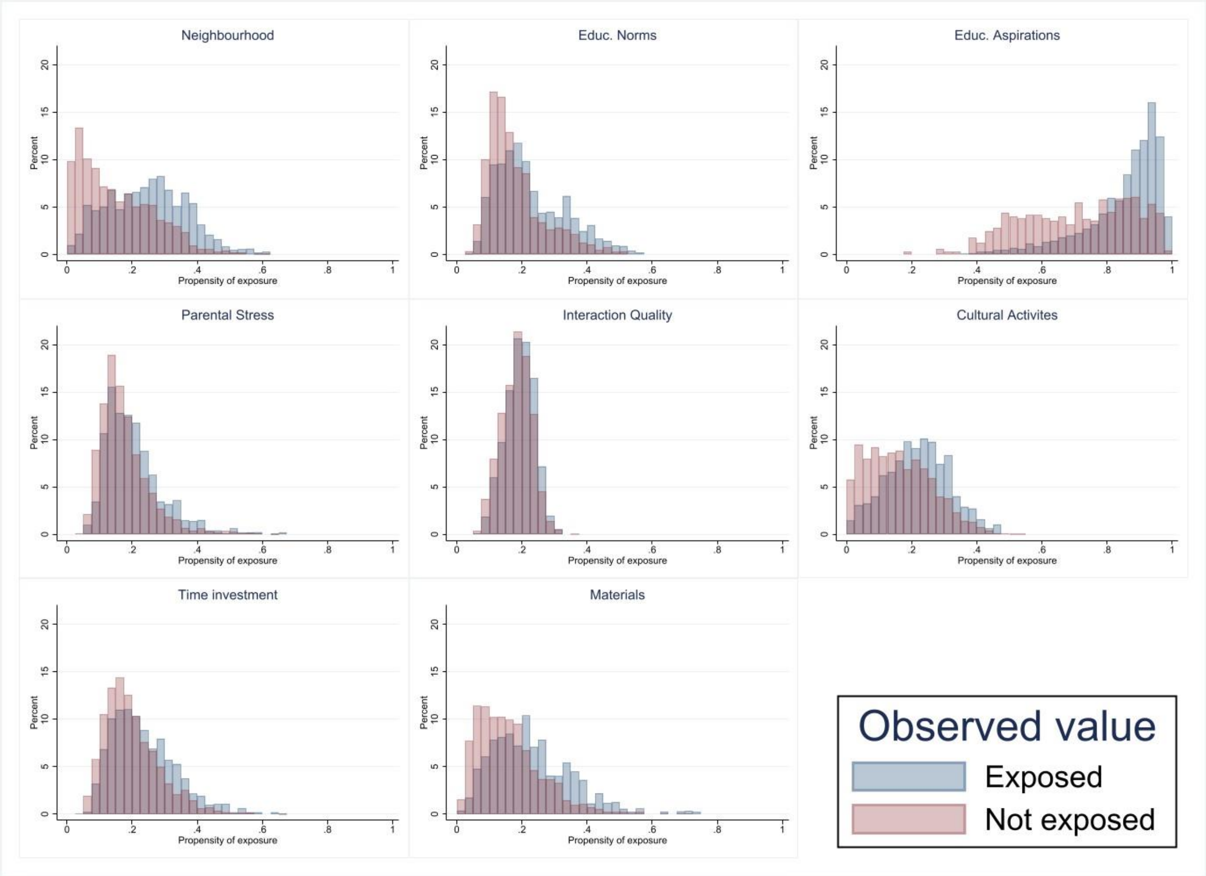


Figure C3. Estimated propensities of being exposed to the highest quintile of the mediators by observed exposure.

Propensities are estimated with logistic regressions of being exposed to the highest quintile of the mediators on parents' income, net worth, control variables, and all mediators earlier in the causal chain.

D. Total differences without adjusting for control variables

	Math (Age 4)	Math (Age 6)	Science	PPVT
2. Quintile	0.454	0.493	0.395	0.435
	[0.204,0.704]	[0.245,0.741]	[0.160,0.631]	[0.193,0.676]
3. Quintile	0.424	0.524	0.515	0.664
	[0.182,0.666]	[0.280,0.767]	[0.279,0.750]	[0.425,0.904]
4. Quintile	0.690	0.765	0.672	0.830
	[0.453,0.928]	[0.505,1.026]	[0.432,0.913]	[0.595,1.064]
5. Quintile	0.800	0.896	0.700	0.877
	[0.576,1.024]	[0.657,1.134]	[0.477,0.923]	[0.647,1.107]

Table D1. Difference in academic abilities by parental income without adjusting for control variables. Reference category: income-poor.

	Math (Age 4)	Math (Age 6)	Science	PPVT
2. Quintile	0.194	0.149	0.139	0.064
	[-0.040,0.428]	[-0.114,0.412]	[-0.099,0.376]	[-0.167,0.295]
3. Quintile	0.396	0.426	0.331	0.280
	[0.145,0.647]	[0.169,0.683]	[0.092,0.571]	[0.032,0.528]
4. Quintile	0.459	0.499	0.415	0.398
	[0.219,0.699]	[0.241,0.757]	[0.187,0.642]	[0.158,0.637]
5. Quintile	0.413	0.440	0.326	0.415
	[0.175,0.652]	[0.187,0.694]	[0.090,0.561]	[0.169,0.661]

Table D2. Difference in academic abilities by parental net worth without adjusting for control variables. Reference category: negative net worth.

E. Total differences without adjusting for income/net worth

	Math (Age 4)	Math (Age 6)	Science	PPVT
2. Quintile	0.219	0.321	0.197	0.222
	[-0.039,0.478]	[0.075,0.568]	[-0.044,0.438]	[-0.011,0.454]
3. Quintile	0.062	0.165	0.181	0.267
	[-0.202,0.327]	[-0.087,0.418]	[-0.082,0.444]	[0.018,0.516]
4. Quintile	0.228	0.297	0.244	0.334
	[-0.049,0.504]	[0.017,0.577]	[-0.020,0.508]	[0.071,0.597]
5. Quintile	0.232	0.312	0.172	0.291
	[-0.044,0.509]	[0.041,0.584]	[-0.098,0.441]	[0.025,0.557]

Table E1. Difference in academic abilities by parental income when adjusting for control variables but not for net worth. Reference category: income-poor.

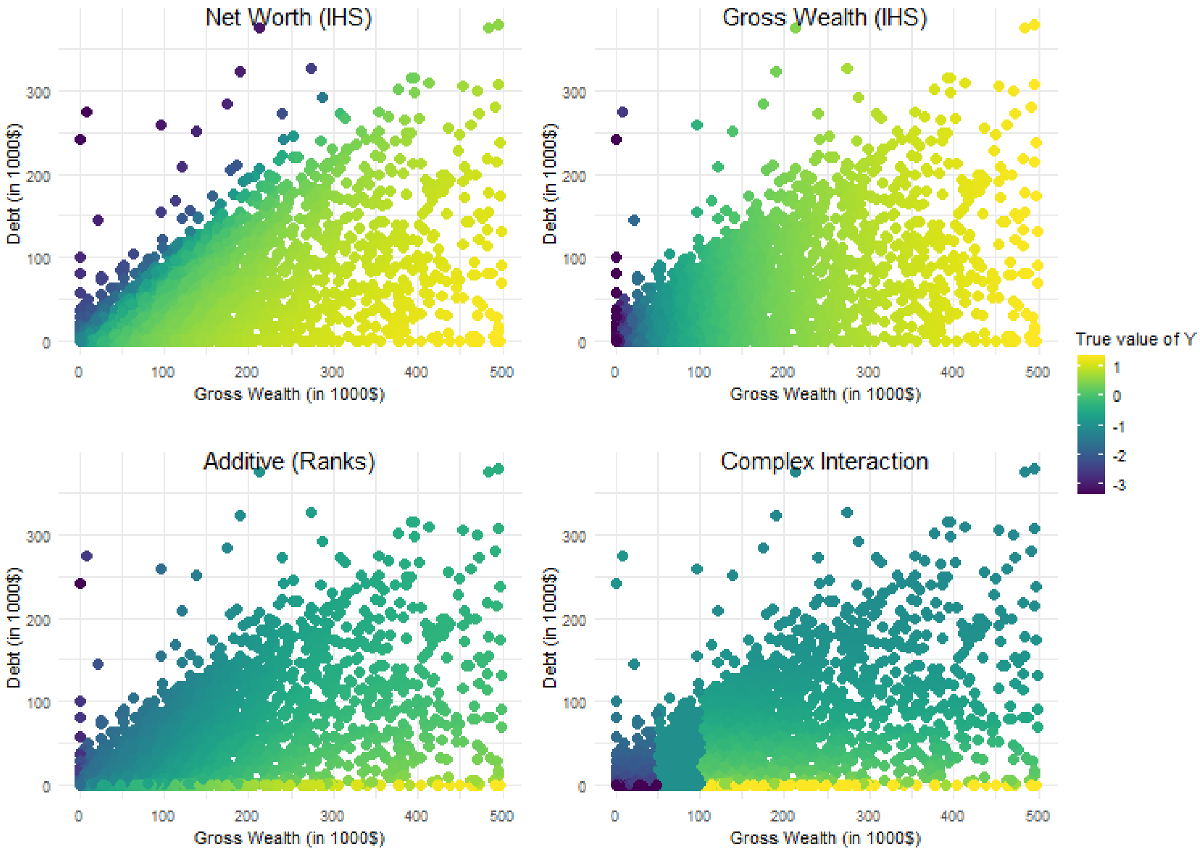
	Math (Age 4)	Math (Age 6)	Science	PPVT
2. Quintile	0.155	0.103	0.116	0.039
	[-0.063,0.373]	[-0.135,0.341]	[-0.115,0.347]	[-0.175,0.254]
3. Quintile	0.155	0.171	0.111	-0.004
	[-0.086,0.395]	[-0.068,0.409]	[-0.124,0.346]	[-0.234,0.226]
4. Quintile	0.234	0.245	0.196	0.094
	[-0.003,0.470]	[0.000,0.489]	[-0.034,0.426]	[-0.132,0.320]
5. Quintile	0.131	0.147	0.060	0.065
	[-0.110,0.372]	[-0.103,0.396]	[-0.191,0.312]	[-0.176,0.307]

Table E2. Difference in academic abilities by parental net worth when adjusting for control variables but not for income. Reference category: negative net worth.

Supplementary materials to chapter 5

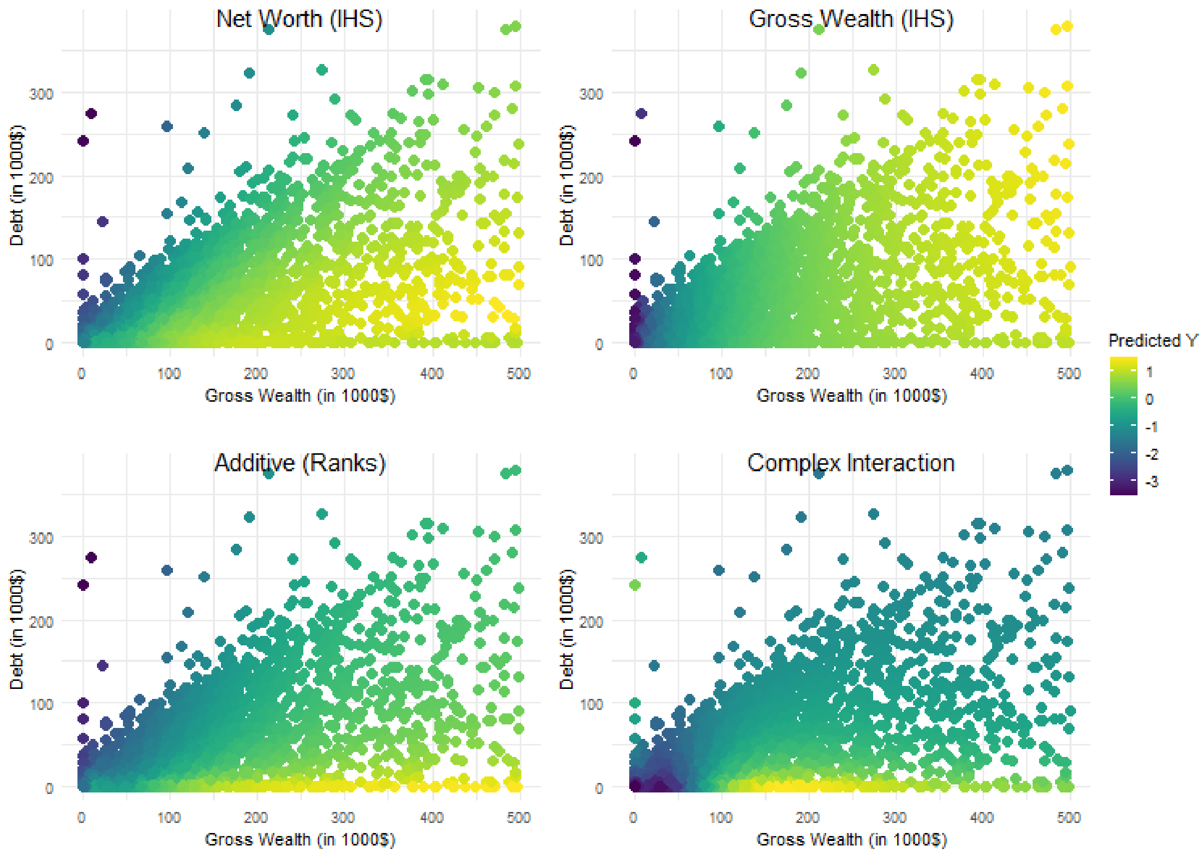
A. True values of Y in the simulation

Figure A1: True values of Y by gross wealth and debt in the simulation analysis



B. Predicted values of Y when using GAM

Figure B1: Predictions of Y by GAM f(Gross Wealth(IHS), Debt (IHS)) in the simulation



C. Predicted probabilities of obtaining a bachelor's degree with different methods

Table C1: Predicted probabilities of obtaining a bachelor's degree and their standard errors of GLM with net worth polynomials (Model 3) for exemplary combinations of gross wealth and debt.

	Gross Wealth						
Debt	0	10k	30k	100k	300k	1m	3m
1m	0.58	0.59	0.59	0.62	0.7	8	64.7
	(0.12)	(0.12)	(0.12)	(0.13)	(0.14)	(0.63)	(1.78)
300k	1.07	1.09	1.13	1.31	8	51.79	68.11
	(0.19)	(0.19)	(0.20)	(0.22)	(0.63)	(1.41)	(1.83)
100k	1.86	1.96	2.21	8	36.23	54.98	68.89
	(0.28)	(0.29)	(0.32)	(0.63)	(0.89)	(1.52)	(1.84)
30k	3.33	4	8	25.03	39.82	55.92	69.15
	(0.41)	(0.45)	(0.63)	(0.72)	(1.00)	(1.55)	(1.85)
10k	5.26	8	15.34	27.48	40.7	56.17	69.22
	(0.52)	(0.63)	(0.72)	(0.74)	(1.02)	(1.56)	(1.85)
0	8	11.98	17.98	28.56	41.12	56.3	69.26
	(0.63)	(0.70)	(0.72)	(0.75)	(1.04)	(1.56)	(1.85)

Table C2: Predicted probabilities of obtaining a bachelor's degree and their standard errors of GLM with gross worth polynomials (Model 6) for exemplary combinations of gross wealth and debt.

	Gross Wealth						
Debt	0	10k	30k	100k	300k	1m	3m
1m	8.37	6.63	8.71	18.72	38.31	59.83	65.46
	(1.20)	(0.59)	(0.71)	(0.90)	(1.05)	(1.68)	(3.72)
300k	8.37	6.63	8.71	18.72	38.31	59.83	65.46
	(1.20)	(0.59)	(0.71)	(0.90)	(1.05)	(1.68)	(3.72)
100k	8.37	6.63	8.71	18.72	38.31	59.83	65.46
	(1.20)	(0.59)	(0.71)	(0.90)	(1.05)	(1.68)	(3.72)
30k	8.37	6.63	8.71	18.72	38.31	59.83	65.46
	(1.20)	(0.59)	(0.71)	(0.90)	(1.05)	(1.68)	(3.72)
10k	8.37	6.63	8.71	18.72	38.31	59.83	65.46
	(1.20)	(0.59)	(0.71)	(0.90)	(1.05)	(1.68)	(3.72)
0	8.37	6.63	8.71	18.72	38.31	59.83	65.46
	(1.20)	(0.59)	(0.71)	(0.90)	(1.05)	(1.68)	(3.72)

Table C3: Predicted probabilities of obtaining a bachelor's degree and their standard errors of GLM with gross wealth polynomials + gross debt (Model 9) for exemplary combinations of gross wealth and debt.

	Gross Wealth						
Debt	0	10k	30k	100k	300k	1m	3m
1m	11.33	8.67	10.85	21.87	42.31	63.61	69.53
	(3.05)	(2.29)	(2.81)	(4.65)	(6.16)	(5.51)	(5.65)
300k	10.06	7.67	9.62	19.68	39.09	60.47	66.63
	(1.85)	(1.19)	(1.39)	(1.99)	(2.21)	(2.09)	(3.79)
100k	9.93	7.57	9.5	19.45	38.75	60.13	66.31
	(1.73)	(0.94)	(1.00)	(1.16)	(1.17)	(1.92)	(3.92)
30k	9.91	7.55	9.48	19.42	38.7	60.08	66.26
	(1.73)	(0.86)	(0.88)	(1.11)	(1.79)	(2.72)	(4.31)
10k	9.38	7.14	8.97	18.49	37.27	58.62	64.89
	(1.51)	(0.70)	(0.76)	(1.13)	(2.02)	(2.91)	(4.36)
0	8.13	6.17	7.77	16.24	33.68	54.76	61.24
	(1.18)	(0.64)	(0.86)	(1.56)	(2.61)	(3.25)	(4.52)

Table C4: Predicted probabilities of obtaining a bachelor's degree and their standard errors of GLM with gross wealth polynomials * gross debt (Model 12) for exemplary combinations of gross wealth and debt.

	Gross Wealth						
Debt	0	10k	30k	100k	300k	1m	3m
1m	0.42	1	3.8	20.46	51.01	64.34	41.47
	(2.10)	(3.14)	(8.81)	(23.60)	(10.78)	(11.04)	(19.75)
300k	0.05	0.25	1.71	14.35	44.42	60.79	41.98
	(0.14)	(0.42)	(1.49)	(4.86)	(3.35)	(2.97)	(8.48)
100k	0.34	0.83	2.95	14.97	40.93	59.26	48.32
	(0.67)	(0.83)	(1.21)	(1.57)	(1.37)	(2.51)	(7.53)
30k	7.77	5.86	7.79	17.76	37.8	58.67	60.93
	(5.20)	(1.98)	(1.26)	(1.39)	(1.99)	(3.71)	(7.87)
10k	20.8	12.53	11.87	18.6	34.48	58.41	73.35
	(4.56)	(1.74)	(1.61)	(1.72)	(2.05)	(3.83)	(6.29)
0	4.56	6.04	8.77	15.8	29.92	57.89	84.14
	(1.04)	(0.95)	(1.45)	(1.89)	(3.07)	(5.17)	(7.18)

Table C5: Predicted probabilities of obtaining a bachelor's degree and their standard errors of GAM with f(Gross Wealth (log), Debt(log)) (Model 14) for exemplary combinations of gross wealth and debt.

	Gross Wealth						
Debt	0	10k	30k	100k	300k	1m	3m
1m	26.03	11.85	11.05	16.53	44.58	60.86	48.28
	(14.25)	(4.29)	(3.06)	(2.53)	(3.07)	(4.17)	(7.87)
300k	22.92	11.71	10.95	16.21	43.15	59.14	50.69
	(11.15)	(3.27)	(2.39)	(1.85)	(2.07)	(2.61)	(5.71)
100k	20.32	11.55	10.85	15.95	41.81	57.35	52.59
	(8.78)	(2.46)	(1.89)	(1.41)	(1.59)	(2.42)	(5.17)
30k	17.73	11.31	10.72	15.75	40.28	55.76	55.2
	(6.68)	(1.78)	(1.54)	(1.25)	(1.78)	(3.36)	(5.92)
10k	15.59	10.99	10.55	15.71	38.82	54.62	57.97
	(5.21)	(1.38)	(1.41)	(1.38)	(2.27)	(4.53)	(7.20)
0	4.67	5.05	6.58	18.94	27.58	58.98	86.94
	(1.66)	(1.10)	(1.77)	(3.76)	(4.56)	(7.17)	(7.13)

Table C6: Predicted probabilities of obtaining a bachelor's degree and their standard errors of GAM with f(Gross Wealth (IHS), Debt(IHS)) (Model 15) for exemplary combinations of gross wealth and debt.

	Gross Wealth						
Debt	0	10k	30k	100k	300k	1m	3m
1m	1.41	3.13	8.4	26.31	47.05	64.77	43.65
	(3.93)	(6.32)	(12.47)	(18.61)	(11.70)	(7.67)	(14.03)
300k	2.35	3.93	7.64	20.01	43.91	62.81	47.09
	(4.17)	(4.80)	(6.84)	(8.39)	(5.21)	(3.48)	(7.28)
100k	4.55	6.5	8.92	16.69	41.2	55.47	44.16
	(4.60)	(4.13)	(3.69)	(2.45)	(2.50)	(4.90)	(8.66)
30k	10.2	12.77	9.66	13.56	41.82	56.62	57.97
	(4.70)	(3.75)	(2.27)	(1.92)	(3.61)	(6.88)	(10.14)
10k	12.64	15.8	10.33	15.08	37.66	46.55	58.7
	(3.32)	(2.98)	(2.10)	(2.52)	(4.57)	(8.58)	(12.37)
0	6.11	4.55	9.32	18.41	27.26	59.96	82.48
	(1.28)	(1.13)	(1.93)	(3.23)	(4.20)	(6.75)	(6.77)

D. Regression coefficients and smoothing parameters for different methods

Table D: Regression coefficients of the GLMs (standard errors in parantheses) and smooth parameters of GAMs

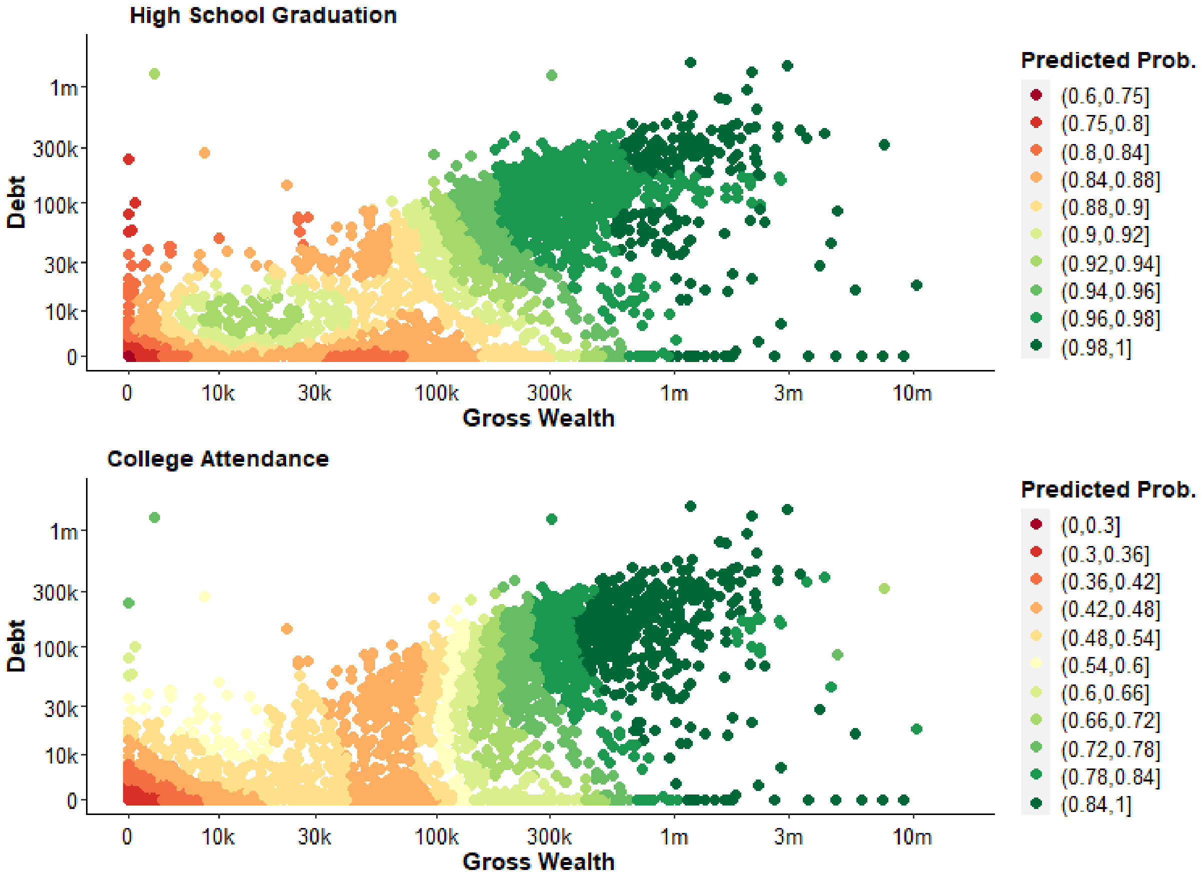
	Method 3) GLM NW (poly)	6) GLM GW (poly)	9) GLM GW + Debt (poly)	12) GLM GW × Debt (poly)	14) GAM log.	15) GAM IHS
Regression coefficients						
NW (IHS)	57.237***	-				
	(3.025)					
NW (IHS)^2	13.736***					
	(2.566)					
NW (IHS)^3	-12.519***					
	(2.783)					
GW (IHS)		61.001***	56.932***	90.543***		
		(3.550)	(4.233)	(19.195)		
GW (IHS)^2		12.662***	13.939***	1.896		
		(2.736)	(3.031)	(9.318)		
GW (IHS)^3		-16.136***	-15.828***	-10.803**		
		(2.582)	(2.649)	(4.745)		
Debt (IHS)			6.019*	-25.732		
			(3.351)	(16.691)		
Debt (IHS)^2			-1.760	-7.766		
			(2.510)	(8.915)		
Debt (IHS)^3			2.453	23.621**		
			(2.186)	(9.293)		
GW (IHS) × Debt (IHS)				2,444.011*		
				(1,380.776)		
GW (IHS)^2				-1,247.979*		

× Debt (IHS)				(655.021)		
GW (IHS)^3				-542.194		
× Debt (IHS)				(346.268)		
GW (IHS)				667.477		
× Debt (IHS)^2				(657.254)		
GW (IHS)^2				-245.929		
× Debt (IHS)^2				(366.387)		
GW (IHS)^3				211.746		
× Debt (IHS)^2				(280.350)		
GW (IHS)				-1,718.806**		
× Debt (IHS)^3				(758.027)		
GW (IHS)^2				673.665		
× Debt (IHS)^3				(462.107)		
GW (IHS)^3				-183.695		
× Debt (IHS)^3				(328.058)		
Intercept	-1.368***	-1.418***	-1.424***	-1.868***	-1.477***	-1.465***
	(0.046)	(0.048)	(0.048)	(0.228)	(0.054)	(0.051)
Smooth parameters						
Effective degrees of freedom of the smooth terms					14.03	23.47
χ^2 of the smooth terms					582.8***	603.2***
AIC	4,006.384	3,915.877	3,916.315	3,884.243	3876.490	3871.951

Note: GAM=Generalized additive model; GLM=Generalized linear model, GW=Gross wealth; IHS=Inverse hyperbolic sine; NW=Net worth. Data of the Panel Survey of Income Dynamics; N=4,341. Significance Levels: *** p<0.001; ** p<0.01; * p<0.05.

E. Wealth differences in high school graduation and college attendance

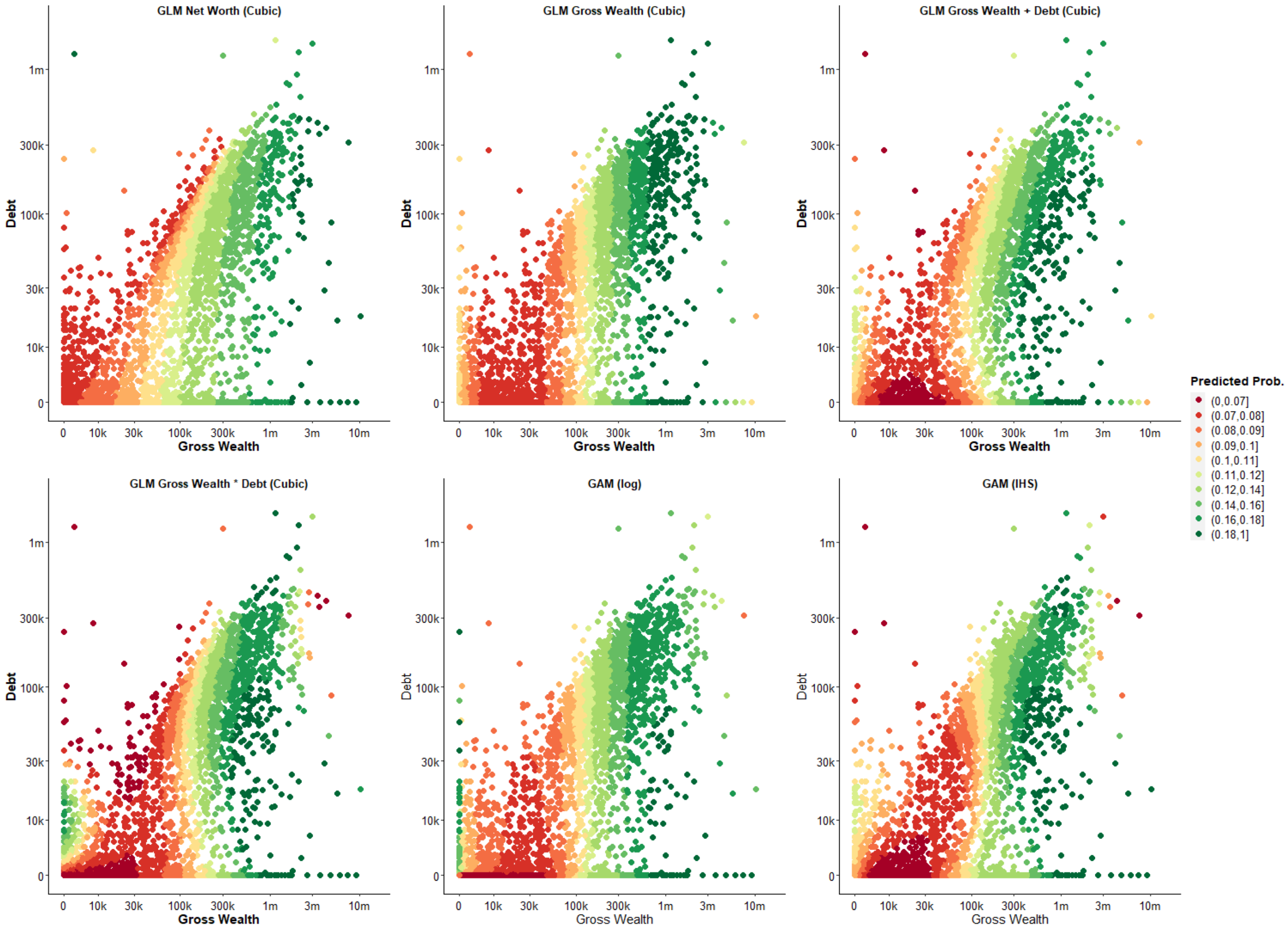
Figure E: Predicted probability of high school graduation and college attendance



Note: Data of the Panel Survey of Income Dynamics; N=4,341.

F. Predicted probability of attending a bachelor's degree when adjusting for other measures of parental SES and demographics

Figure F: Predicted probability of obtaining a bachelor's degree by gross wealth and debt when adjusting for covariates



Note: Data of the Panel Survey of Income Dynamics; N=4,341. Control variables are held constant at their mean or median.