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Parents' income and wealth matter more for children with low than high academic performance: Evidence from comparisons between and within families in egalitarian Norway

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ABSTRACT

Most educational mobility research assumes that the associations between parents' economic resources and children's academic performance do not vary between low- and high-performing children. Analyzing such variation increases our understanding of how family background affects children's life chances. We examine the egalitarian case of Norway, where we should expect smaller differences than in other countries. We use quantile regression models to estimate variation in the impact of parental income and wealth on children's school grades across the distribution of school grades. We compare the within-family effects of parental income and wealth on children's educational performance with the associations between families. We apply this approach to Norwegian register data, which includes information on children's school grades at age 16. For both parental income and wealth, we find a declining association with children's school grades across the distribution of school grades. This pattern is found in both between- and within-family analyses. These findings are in line with the view that parents compensate for children's low academic performance.

1. Introduction

Children perform differently in school depending on their family background (Breen & Jonsson, 2005). The influence of family background is often studied in terms of the parents' ethnic origin, educational attainments, class position, and income. But research has usually paid less attention to the role played by parental wealth (Keister & Moller, 2000; Rumberger, 1983; Spilerman, 2000). Yet, recent evidence indicates that both parental wealth and income are strongly associated with children's educational choices and performance (e.g., Conley, 2001; Duncan, Pamela, & Rodrigues, 2011; Duncan, Ariel Kalil, & Ziol-Guest, 2017; Pfeffer, 2018; Reardon, 2011). Surprisingly, such associations are even evident in more egalitarian societies such as Norway and Sweden (Grätz & Wiborg, 2020; Hällsten & Pfeffer, 2017; Hansen, 2014; Wiborg, 2017a). Despite this growing evidence, we still need to know more about how parents' financial resources affect children's educational outcomes. In this study, we fill some gaps by examining lower secondary school students in Norway. We assess whether parental income and wealth independently influence students' school performance and whether these associations differ between low- and high-performing students. We also examine how these financial resources are related to variation in children's educational performance between and within families.

To answer the question of how parental income and wealth matter, it is crucial to consider the dominant focus of most studies on academic performance or cognitive test scores. They examine how children's academic performance differs between socioeconomic groups, ethnic backgrounds, and gender on average. We think this represents a critical shortcoming in the literature. Focusing only on averages in academic and cognitive performance may be incomplete. Children whose performance is low, average, or high benefit in different ways from parents' economic resources. This has been shown to be the case for children's educational choices and social class origin (Bernardi & Cebolla-Boado, 2014; Bernardi, 2014). For performance, this means that intergenerational associations could also vary across an outcome's distribution; the strength of predictors could vary at different locations of the dependent variable (Hao & Naiman, 2007; Koenker & Bassett, 1978). Surprisingly, such variation has hardly been addressed by social stratification

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researchers. However, based on data from the United States, Germany, and Norway, recent studies found that the associations between children's academic performance and family background were stronger for low-performing children (Grätz & Wiborg, 2020; Linberg & Wenz, 2017; Wiborg, 2017a). But these studies did not disentangle the impact of parental income from wealth, and they did not take unobserved confounders into account.

These patterns can be understood in terms of two central intergenerational theories. First, social divides between families with different resource levels could be deepened by parents' compensatory behavior in aiding their children who are struggling (Bernardi & Grätz, 2015; Bernardi, 2014; Conley, 2004). Second, (dis)advantages in performance could be path-dependent and cumulate over time (Cunha & Heckman, 2007; DiPrete & Eirich, 2006) in the same way as "the rich get richer, the poor get poorer." We argue that the two models do not only predict how average school performance depends on parental income and wealth. They also predict how the effects of parental income and wealth on children's school performance vary across the performance distribution. Cumulative advantages among privileged families should strengthen the associations between parental economic resources and school performance among high-performing children. However, if families compensate for children's low school performance, associations will be stronger for those with low school performances.

Differences in compensatory behavior and accumulation of (dis) advantage might occur between families. But similar mechanisms may also work within families. Parents make equal or different investments between siblings with different abilities and demonstrated performance (Becker & Tomes, 1976; Behrman, Robert, & Taubman, 1982; Conley, 2004, 2008; Griliches, 1979). These intra-familial investment strategies may enhance the high-performing children or compensate for their lack of performance. We argue that the distinction between within- and between-family processes could be fundamental when assessing the impact of parental financial resources. One crucial example is when parental wealth is mainly tied up in the property. If this is the case, we might expect stronger associations between than within families due to sorting into neighborhoods with access to schools of different quality.

Our study contributes to the research literature in several ways. First, we address whether and how the impact of both parental income and wealth matters for children's academic performance. Parental income and wealth may have independent effects or different logics (Hällsten & Thaning, 2021; Keister & Moller, 2000). Second, we use state-of-the-art quantile regression models (Borgen, Andreas Haupt, & Wiborg, 2021; Firpo, Nicole, & Lemieux, 2009; Frölich & Melly, 2013; Powell, 2016, 2020). These models allow us to examine whether the associations between family financial resources and academic performance vary between children whose performance is low, average, or high. Third, we use family fixed effects models to explore whether children within the same family, i.e., siblings, benefit differently from parents' economic resources depending on the children's level of academic performance. Family fixed effects models are also advantageous since they account for potential confounding, unobserved characteristics shared by siblings in the same family. Finally, we contrast the family fixed effects model with models that only examine associations between families. Based on this comparison, we can tell whether the mechanisms of compensatory and cumulative advantages work mainly between or within families. This approach extends the analytical reach of the earlier studies (Grätz & Wiborg, 2020; Linberg & Wenz, 2017; Wiborg, 2017a, 2017b) that do not account for unobservable shared family characteristics nor examine processes within and between families. We apply these approaches to high-quality data from administrative education, tax, and population registers in Norway, which cover the entire population over long periods and across generations on an individual level.

2. Egalitarian Norway as a strategic test case

The egalitarian context of Norway provides an interesting test case for how parental financial resources affect educational performance. With their generous safety nets, free education, and free access to health care, Scandinavian societies represent a distinct type of welfare regime (Esping-Andersen, 1990, 1999). In these societies, the social-democratic policy predominated after World War II. Not only is the income structure more compressed than in other Western societies, but intergenerational income mobility is higher in Norway than, for instance, in the United States and the United Kingdom (Bratsberg et al., 2007).

In the Norwegian social-democratic context, parents' income and wealth should matter less for children's life chances than in other societies with higher inequality and lower intergenerational mobility. The combination of lower-income inequality, a dominant and uniform public school sector, and free access to education should reduce or remove economic barriers to academic performance and choices.

More recently, however, this idealized portrayal of the Scandinavian model has been challenged. The trend of rising inequality in income and wealth observed in many Western societies over the last four decades (Piketty, 2013) includes the Scandinavian countries (Aaberge & Anthony, 2010; Aaberge, 2018; Hansen & Toft, 2021; Hansen, 2012; Skopek, Buchholz, & Blossfeld, 2014; Wiborg & Hansen, 2018; Wiborg, 2017b). Wiborg and Hansen (2018) found increasing impacts of observed and unobserved aspects of family background on wealth and income but declining effects on children's educational attainment. However, in the long run, sustained income and wealth inequality could lead to lower intergenerational educational mobility in Scandinavian countries, working through academic choices as well as performance. Such developments make our focus on the impact of parental income and wealth on children's performance particularly urgent.

3. Parental financial assets and children's educational performance

3.1. *Stronger effects on academic performance among income-poor families*

The role of parental financial assets for children's academic performance has mainly been addressed by focusing on parental income. Research offers at least three main explanations of why parental income is related to children's educational outcomes (Mayer, 1997). First, parental income might work through parents' financial constraints to invest in their children's education, an essential part of their human capital (Becker & Tomes, 1976, 1986). Affluent families have more resources and opportunities to invest in their children's education and cognitive development than low-income families. For example, affluent parents might increase their children's cultural consumption, hire private tutors, or send their children to summer courses. Their children might benefit from better schooling by living in high-income neighborhoods that attract more competent teachers. Second, a lack of financial resources could cause psychological stress and behavioral problems, making the parents less able to supervise, engage, and assist their children, or even generate adverse interactions within the family (Conger, Conger, & Martin, 2010; Duncan, Jean Yeung, Jeanne Brooks-Gunn, & Smith, 1998; Mayer, 1997). Third, low- and high-income parents could differ on background characteristics in relevant ways for children's educational performance. Parents might transmit knowledge, socialized norms and values to their children (Bourdieu & Passeron, 1970), and genetically based traits (Freese, 2008).

The third explanation means that other parental characteristics – which can be unobserved or observed – may partly or wholly confound the estimated impact of parental income and wealth. To account for unobserved and observed parental characteristics, Susan Mayer (1997) used several different causal identification strategies on data from the United States. After accounting for unobserved parental characteristics, parental income had moderate to minor effects. She argued that parental income does not matter much for a range of outcomes, including educational performance, above a certain income level. Instead, parents work as role models, transmitting socialized norms, values, and behaviors to their children. Primarily long-term poor parents transmit dysfunctional values and behaviors that lower the probability of succeeding in the school system.

More recent research has provided evidence of small to noteworthy causal impacts of parents' income on children's educational outcomes. For instance, Duncan et al. (2011) compared several experiments in the United States and Canada in the 1990 s. They found that a 1000 USD increase in parental income increased children's educational achievement by around 0.05 standard deviations. In Norway, Løken (2010) found minor effects of family income on children's education. In a similar national context, a Swedish study, based on a natural experiment, suggested minor to non-existing causal effects of sudden wealth increments on a range of child development indicators, including academic performance (Cesarini, Erik Lindqvist, & Wallace, 2016).

However, the impact of parental income is more substantial among low-income families in the United States (Dearing, McCartney, & Taylor, 2006; Duncan et al., 1998). Two studies found nonlinear causal effects of parental income on children's academic performance in Norway. First, Løken, Mogstad, and Wiswall (2012) demonstrated that the causal relationship between parental income and children's achievement was nonlinear and concave. Using a natural experiment, they found that the effects of parental income were more substantial for children's education for low-income families than for high-income families. They interpreted this finding as consistent with the theory of financially constrained human capital investments (Becker & Tomes, 1976, 1986).

Second, Elstad and Bakken (2015) found a similar pattern using family fixed-effects models on separate income strata. Only low-income families experienced a positive effect of parental income on their children's school performance. For the low-income families, each increase of parental income by 100,000 NOK (approx. 12,000 USD) led to an approximate 0.08 standard deviation increase in school grades in families earning less than 300,000 NOK (approx. 36,000 USD) per year. There were no positive effects of the same increase in income in families earning more than 450,000 NOK (approx. 54,000 USD) per year. In contrast to Løken et al. (2012), they interpreted their finding as consistent with the parental stress model.

In the United States, nonlinear causal effects of parental income on children's academic performance may not be astonishing, and it would contradict the role model theory of Mayer (1997). However, such a pattern is more surprising in egalitarian societies because of greater equal educational opportunities, lower economic barriers, and more significant safety nets.

3.2. Stronger effects on performance among the low-performing children

Stratification researchers have given little attention to whether intergenerational associations vary across the outcome distribution. But recent studies provide evidence from Germany, Norway, and the United States. In all countries, the associations between children's demonstrated ability (school performance and cognitive scores) and family background factors were stronger for low-performing than for high-performing students. Grätz and Wiborg (2020) examined bivariate relationships between academic performance measures and four different family background measures (parent's education, income, wealth, and occupation) in Germany, Norway, and the United States. Wiborg (2017a) found that the income and wealth of aunts and uncles affect performance in the same way as the parents, although having somewhat weaker associations in Norway. Examining language competencies at age 5, Linberg and Wenz (2017) found a similar pattern of more significant socioeconomic differences for low than high language competencies in Germany.

In addition, intergenerational income mobility research found varying associations between parental income and child income depending on location in the outcome's distribution (e.g., Bratsberg et al., 2007; Grawe, 2004; Gregg, Macmillan, & Vittori, 2019). The associations are more substantial for adult children with high and low earnings than those closer to the median.

Such evidence illustrates why it is essential to consider this form of varying associations. However, none of the earlier studies tells us whether such associations vary within or between families and whether unobserved, shared family factors confound these relationships.

4. Parental wealth might play a different role than income

Family income and wealth might play similar roles as financial assets. But parental wealth seems to affect children's education independently of parental income (Conley, 2001; Hällsten & Pfeffer, 2017; Pfeffer, 2018; Wiborg, 2017a). Parents' wealth might even play a different role than their income in shaping children's educational outcomes, as wealth differs from income in fundamental ways (Keister & Lee, 2014; Keister & Moller, 2000; Spilerman, 2000). Wealth has a greater permanence than income across the life course and multiple generations. Wealth is less influenced by job loss, promotions, and exogenous shocks in the labor market. Wealth inequality is higher than inequality in earnings (Keister & Lee, 2014), and Scandinavia is no exception (Aaberge & Anthony, 2010; Aaberge, 2018; Hansen, 2014; Skopek et al., 2014; Wiborg, 2017b). The higher permanence and inequality could make parents' wealth more influential than income regarding children's school grades. But wealth consists of various financial resources such as housing, financial assets, liquid assets, and debt (Hällsten & Pfeffer, 2017). For example, wealth could be tied up in non-liquid assets, such as housing or debt, and we might thus expect the opposite: wealth may matter less than income.

Hällsten and Pfeffer (2017) argue that family wealth influences children's educational performance and decisions in three different ways. Wealth increases purchasing power, provides insurance against future uncertainty, and affects normative expectations. First, parental financial resources, both income and wealth, allow various goods and services to be purchased, for example, to support learning and success in education. The purchasing mechanism should be more effective in societies with high than low economic barriers to education. Second, (significant) family wealth can function as an insurance, a safety net, for later educational careers, thereby reducing the risks of making educational choices with uncertain career benefits. This means that families with a high-social class standing, usually coupled with significant wealth, can take greater risks in educational decisions and investments. The relative risk aversion theory makes similar predictions (Breen & Goldthorpe, 1997). The third mechanism is the normative character of wealth across generations. In line with Thurow (1975), Hällsten and Pfeffer (2017) argue that since wealth is associated with power and privilege, affluent families strive to secure advantages for their offspring. Affluent families develop pro-educational norms, expecting family members to achieve higher education. By establishing their belief in higher education as a conventional goal, this mechanism extends beyond wealthy families. This way, pro-education norms create higher ambitions for educational attainment and achievements—the higher levels of wealth, the more significant pro-educational norms.

All three mechanisms will likely be at work in Norway. Contrary to Hällsten and Pfeffer (2017), we believe that the purchasing mechanism may also operate in egalitarian Scandinavian countries. For instance, parents can hire private tutors or send their children to private schools to retake exams to improve their GPAs to get into prestigious academic professions such as medicine and law (Hansen, 2005). Such investments could lead to significant differences not only between families but also within families. A more important reason for family wealth to matter, and perhaps more so than income, is that neighborhoods' housing prices are strongly correlated with the quality of primary and secondary schools in Norway (Hansen, 2017). Affluent families tend to concentrate in expensive areas with access to good schools that influence their children's school performances (Wiborg, 2017b). This self-selection could make the effects of wealth on educational outcomes perhaps more pronounced between than within families. In addition, the insurance and the normative function would have similar implications for family wealth. Norms will likely work similarly for all siblings in the same family. It is also likely that the prospects of a significant inheritance, ensured by the law, will be distributed (relatively) equally between the children.

5. Compensatory and cumulative advantages between and within fami lies

Intergenerational stratification research often examines how averages in children's outcomes vary according to parental characteristics. But two intergenerational mobility models seem to imply that the associations between parental resources and their children's educational performance vary between children whose performance is low, average, or high. We argue that these models also have implications for social processes operating between as well as within families.

The first model describes "compensatory advantage" (Bernardi & Cebolla-Boado, 2014; Bernardi & Grätz, 2015; Bernardi, 2014; Conley, 2004). This model imply that parents use their resources to boost their low-achieving children's academic performance. Parents may be motivated to ensure that their children should not experience downward mobility (Boudon, 1973; Breen & Goldthorpe, 1997). Much of this literature has focused on educational decision-making (Bernardi & Cebolla-Boado, 2014; Bernardi, 2014). However, parents may anticipate the consequences of poor performance and attempt to prevent downward mobility for their children by affecting their children's academic performance, for example, by hiring private tutors (Bernardi & Grätz, 2015; Grätz & Bernardi, 2017). Compensatory advantage predicts a stronger association between parental resources and children's educational performance at the bottom than at the middle or top of the performance distribution.

The second model describes social inequalities in terms of a path-dependent "cumulative advantage" (DiPrete & Eirich, 2006). Skills and human capital, economic resources, privilege and advantages, and other resources accumulate faster in high-status families because they have more resources initially. On the one hand, this theory implies that high-status families can invest more in their children, increasing inequalities between families. But at the same time, this theory also implies that children with higher academic performance levels will accumulate human capital more quickly than those with lower academic performance, given the same level of parental resources and investments. This view is also in line with the idea that skills learned at a younger age make it easier to develop more skills later in life (Cunha & Heckman, 2007). However, von Hippel and Hamrock (2019) concluded that earlier studies overestimated the effects of cumulative (dis)advantage. They found that social gaps in cognitive and school performance form mainly in early childhood before schooling begins. After the children entered the school system, most social gaps largely remained unchanged. Virtually identical findings were reported for Germany (Skopek & Passaretta, 2021). Despite such evidence, the cumulative advantage mechanism implies a stronger association between parental resources and children's academic performance at the top than at the middle or the bottom of the performance distribution.

The two sociological models above do not specifically address siblings with different needs and endowments within the same families. But related theories from other disciplines focus on whether parents treat their children differently or equally (Becker & Tomes, 1976, 1986; Behrman, Pollak, & Taubman, 1982; Conley, 2004, 2008; Griliches, 1979). These theories are consistent with the models of cumulative and compensatory advantage. But they provide more specific explanations of how parents allocate their investments in their children's human capital within families depending on the children's endowments.

The literature on resource allocation within families distinguishes between three main parental resource allocation strategies. These strategies have implications for how the associations between parental resources and children's educational performance vary across the performance distribution.

First, parents may invest equally in all children, ensuring equal opportunities rather than equal outcomes. High-performing children profit more from the same amount of parental resources than the children with lower performance (Becker & Tomes, 1986). Second, parents may focus their investments on the more endowed children to maximize the family's overall outcome (Becker & Tomes, 1976). Based on these family strategies, we would expect parental income and wealth to affect children's educational performance more at the top than at the middle than at the bottom of the performance distribution.

Third, families can function as "mini welfare states" that attempt to achieve equal outcomes between siblings (Behrman, Pollak, and Taubman, 1982; Conley, 2004, 2008; Griliches, 1979). In other words, parents may compensate for differences in siblings' initial abilities. If so, the influence of parental income and wealth on children's educational performance should be stronger at the bottom than at the middle than at the top of the performance distribution.[1]

6. Data, variables, and analytical strategy

6.1. Data

We use data on siblings and their parents derived from various Norwegian administrative registers. Data on children's school grades at age 16 is available from 2001 to 2018. Our analytical samples include 1070,493 individuals from 593,439 families. The children were born between 1985 and 2002.

6.2. Variables

6.2.1. Grade Point Average (GPA)

The dependent variable in our analysis is children's GPA at age 16. The students receive these school grades on leaving lower secondary school. These grades are very influential for their later educational careers. We standardize this measure of academic performance within each graduation year, allowing us to adjust for possible distributional changes in grades between the cohorts studied. The resulting measurement is normally distributed around a mean of 0 and has a standard deviation of 1.

6.2.2. Parental income

Our parental income measure is based on parental earnings, i.e., labor market incomes when the children were aged 0–16. They represent the sum of the mother's and father's average earnings during these years. The resulting measure is ranked into relative cumulative density function ranks (CDF-RANKS) within each child's birth year. The ranking has two advantages. First, this way, we compare changes in the relative position in the income distribution over time. Second, we reduce the influence of extreme values of the very high-income earners (*see Online Supplements*, Table S11).

6.2.3. Parental wealth

Similar to parental earnings, we measured parental wealth when children were aged 0–16. Parental wealth is measured via parental net

[1] We are aware of three studies analyzing socioeconomic differences in parental responses to ability differences between twins or siblings (Grätz & Torche, 2016; Hsin, 2012; Restrepo, 2016). If there are socioeconomic differences in parental responses, these may lead to variations in the association between parental resources and children's education across the performance distribution. However, these three empirical studies have shown contradictory results, so it is unclear whether parental responses to ability differences do indeed differ by family socioeconomic background.

worth, i.e., gross wealth (real assets and financial wealth) minus debt. The sum of the wealth of both parents during their children's whole childhood is used. Of the same reasons for using a relative income measure, we rank wealth into relative CDF-ranks within each year of birth of the children.

6.2.4. Control variables

Gender and birth order are included as control variables in all models. Girls often have higher academic performance than boys, and parents might treat them differently. Birth order is established as a vital factor measuring parents' differential treatment (Grätz, 2018; Härkönen, 2014). Mainly, the firstborn receives more attention and resources than other siblings. Birth order is also correlated with cognitive and non-cognitive differences, which would be relevant for success in academic performance. More importantly, controlling for birth order is very important when including families with many siblings. Large families get disproportionally considerable weight in the family-fixed effects models. The between-family models control for family size measured as the number of siblings. Family size would be especially important for available financial resources for each child. In some models, parents' education, measured as both parents' average number of years of education, is also taken into account.

We do not include other control variables in the main analyses, such as birth spacing, family structure, or ethnicity. Some of these variables may be endogenous to the included independent variables, in particular family structure. Birth spacing is also highly correlated with mothers' age and birth order, especially in the within-family regressions. Ethnicity is already controlled for in the family fixed effects models. Adding these control variables is therefore not necessary. However, as described in Section 7.3 below we estimated models controlling for birth spacing and ethnicity, which resulted in virtually identical estimates.

The descriptive statistics for all variables included in our analysis are reported in Table 1.

6.3. Analytical strategy

The analyses use quantile regression models, allowing us to examine the associations between parental resources and children's school grades at different parts of the distribution of school grades. First, these models assess whether the associations are more substantial for low or high-performing children, thus clarifying predictions based on cumulative and compensatory advantage. Second, we examine how these associations vary between and within families. The family level is defined by having the same mother. The maternal line ensures that the siblings are biologically related, and it also includes single mothers in the selection.

The family fixed effects models have the additional advantage of controlling for all unobserved characteristics shared by siblings, including effects at the family level and at the broader level of the environment, e.g., neighborhoods and schools. These within-family models could still omit relevant characteristics that vary between siblings, such as attending different schools, having other friends and classroom peers, and birth spacing, which might limit our ability for causal inference. Furthermore, the fixed effects estimator provides the average treatment effect on the treated (Allison 2009; Angrist & Pischke, 2009). In our case, nearly everyone receives different amounts of treatment. The within-family variation in income and wealth is relatively small (see *Online Supplement*, Table S11), which makes the large number of cases especially important for consistency and efficiency.

To address whether the theoretical expectations hold up to confounding and independent effects of parental income and wealth, we set up fixed- and between-family effects models as follows in all analyses:

a. First, we report results from two base models, including parental wealth or income, and controls for gender, the number of siblings, and birth order.
b. Then, we expand the base models by controlling for parental education.
c. Finally, we include both parental wealth and income in the same models.

The first analyses (7.1) assume that income and wealth are linear predictors. In our second set of analyses (7.2), we assume a functional free form and explore whether the associations also vary with the level of parents' financial resources (income and wealth). Here we divide income and wealth into a set of dummy variables according to deciles of income and wealth.

Recent studies have addressed methodological issues that arise when conditional quantile regression models are combined with a fixed-effects approach (Firpo et al., 2009; Killewald & Bearak, 2014). Conditional quantile regression models enable us to assess whether parental resources are more strongly associated with school grades in the lower than the higher parts of the distribution of school grades (Hao & Naiman, 2007; Koenker & Bassett Jr., 1978). However, known problems arise when using more than one predictor variable within the conditional quantile regression framework (Angrist & Pischke, 2009). These issues are particularly problematic when using a fixed-effects approach (Killewald & Bearak, 2014).

We employ an unconditional quantile regression method specifically designed to handle more than one predictor variable (Firpo et al., 2009). Firpo et al. (2009) proposed a two-step approach. The first step creates a new binary variable relying on the re-centered influence function (RIF) according to equation [1] below. The binary variable, $RIF(X; q_\tau, F_x)$, created by the following formula:

$$RIF(X; q_\tau, F_x) = q_\tau + \frac{\tau - 1\{X \leq q_\tau\}}{f_x(q_\tau)} \quad (1)$$

In Eq. (1), X is the original dependent variable, and q_τ represents its value at a specific quantile τ.F_X is the cumulative distribution function of X and $f_x(q_\tau)$ is the density of the dependent variable at the quantile q_τ.

Table 1
Descriptive Statistics.

	Mean	SD	Min	Max	N
Graduation year (age 16)	2009.72	5.09	2001	2018	1,081,166
GPA (unstandardized)	40.22	11.2	0	66	1,081,165
GPA (unstandardized) (standardized)	0.00	1.00	–4.65	2.46	1,081,165
Parental Income(NOK, hundred thousands)	7.29	4.13	0	459.9	1,078,119
Parental income (cdf-ranked)	0.51	0.28	0.00	1.00	1,078,119
Parental Net Wealth (NOK, hundred thousands)	22.77	129.3	–1467.5	6,2748.1	1,080,342
Parental Net Wealth (cdf-ranked)	0.51	0.29	0.00	1.00	1,080,342
Parental education (years)	12.78	2.60	9	22	1,072,474
Birth Year	1993.69	5.08	1985	2002	1,081,166
Gender (Female = 1)	0.49	0.50	0	1	1,081,166
Number of siblings	2.02	1.29	0	18	1,081,166
Birth order (ref=1)	0.90	1.01	0	16	1,081,166
Analytical selection without missing obs.	N_i = 1070,493	Nij= 593,439			

Whether the value of the outcome variable is below q_τ or not is identified by the indicator function $1\{X \le q_\tau\}$.

In the second step, the new transformed binary variable replaces the original dependent variable in an OLS regression with control variables. This estimator is called the RIF-OLS. According to this two-step procedure, one advantage is that the inclusion of control variables does not change how quantiles are defined since the transformed dependent variable (RIF) is created ahead of the second step (Firpo et al., 2009). By including control variables in the second step, the estimator may be used to account for selection bias, control for mediators, and even increase the estimates' precision.

To estimate the between- and within-family fixed-effects models, we use the binary variable from the first step in fixed-effects and between-effects regression models (Borgen, 2016). These estimations assess the relative importance of between- and within-family variations in the effects of parental income and wealth on academic performance.

The RIF-OLS estimator is highly flexible, fast, and easy to compute. After the Killewald and Bearak (2014) study, the estimator was established as the field's default. Therefore, we use this estimator in our main analyses. However, there is one important caveat about the RIF-based estimates. Even if we account for significant selection bias, the within-family estimates from the RIF-OLS estimator do not necessarily reflect causal estimates for other reasons than selection bias. The RIF-OLS identifies unconditional quantile partial effect (Firpo et al., 2009), and not the quantile treatment effect (Borgen, Andreas Haupt, & Wiborg, 2022; Firpo, 2007; Frölich & Melly, 2010, 2013; Powell, 2016, 2020). Much of the motivations behind these estimators are similar. Still, there might be significant practical differences in possible interpretations of the estimated predictors (Borgen et al., 2021, 2022). In the growing literature on both conditional and unconditional quantile estimators for fixed effects, there is no clear consensus about best practices. For example, Wenz (2019) demonstrated that the RIF-OLS provides similar estimates as other quantile treatment estimators. Therefore, we have performed several sensitivity checks using different quantile estimators (see Section 7.3) to interpret parental income and wealth as quantile treatment effects in the *Online Supplement* (Figs. S1 and S2, Tables S7–S10).

7. Results

7.1. Do associations vary with children's level of performance between and within families?

The analyses examine whether low or high-performing children benefit most from parents' financial resources (income and wealth), thus addressing the compensatory and cumulative advantage theories. The analyses also shed light on whether these processes occur between and within families. The first set of our analyses relies on linear predictors, and the results are presented in Figs. 2 and 3. Fig. 2 reports the models that only use variation between families.

The left-hand panel in Fig. 1 shows how the association between parental earnings and children's academic performance varies according to children's academic performance. The right-hand panel shows the variation in the association between parental wealth and children's academic performance. The point estimates and standard errors of the models used in Fig. 1 are reported in Table S1 in the *Online Supplement*. The three lines in both panels correspond to the "base", "education," and the "full" models. In the "base" models, we do not control for the other type of parental resource. In the "education" models, we include a control for parents' education. In the "full" models, we additionally control for parental earnings when estimating the effects of parental wealth and vice versa.

The strength of the associations between parents' economic resources and children's academic performance declines with higher quantiles in the distribution of children's school grades. For both parental income and wealth, the estimated associations are much stronger for low-performing children, especially at the 10th and 20th quantiles. In the base models, the CDF-rank coefficients indicate that the difference in school performance between children who originate in the first and top percentiles of parental income is 1.317 (10th quantile) and 1.254 (20th quantile) standard deviations. For parental wealth, the comparable differences are slightly smaller, with effect sizes varying between 1.047 (10th quantile) and 1.019 (20th quantile) standard deviations. The associations decline systematically with increasing levels of school performance. At the 90th quantile, the associations are only 0.550 standard deviations for parental earnings and 0.453 standard deviations for parental wealth. The declining strengths across the performance distribution support predictions based on the compensatory

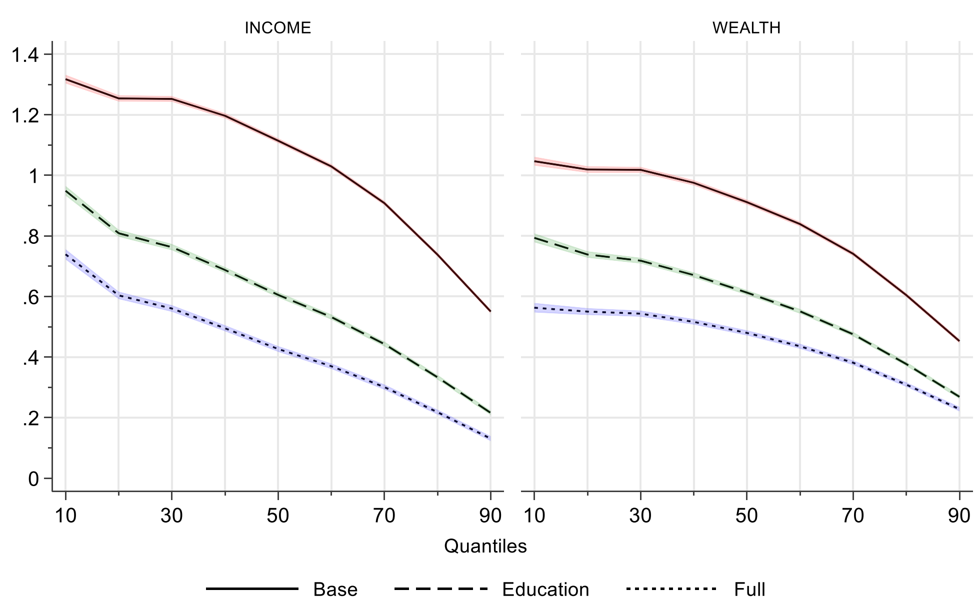

Fig. 1. Unconditional Quantile Regression Models Predicting School Grades, between Families, *Notes:* The "Base" model includes the following control variables: gender, birth order, and family size. The "Education model" includes a control for the average parental education measured in years. The "Full" model controls for parental earnings when analyzing parental wealth and vice versa. 95%-confidence intervals are based on robust standard errors.

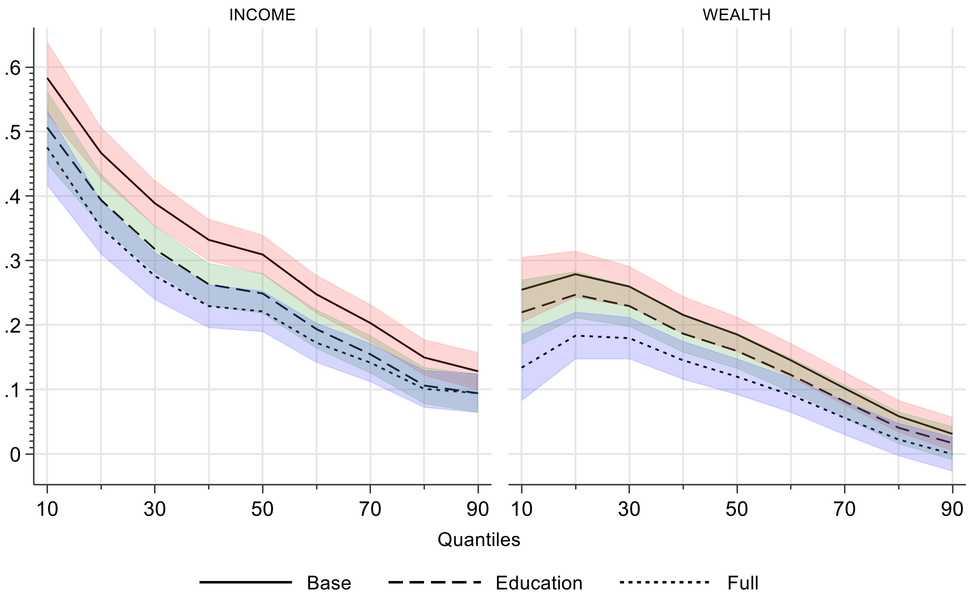

Fig. 2. Unconditional Quantile Regression Models Predicting School Grades, Family Fixed Effects (FE), *Notes:* The "Base" model includes the following control variables: gender and birth order. The "Base" model includes the following control variables: gender, birth order, and family size. The "Education" model includes controls for average parental education measured in years. The "Full" model controls for parental earnings when analyzing parental wealth and vice versa. 95%-confidence intervals are based on robust standard errors.

advantage theory: the parents' economic resources seem to compensate for lower performance.

The associations between parental financial resources (income and wealth) and academic performance are weaker when we control for parental education and the other financial resource. However, the effects are still substantive in size, and the variation in the associations across the performance distribution is unaffected by controlling for the other economic resource. Controlling for parental education affects the associations between parental income and academic performance more than parental wealth and academic performance.

Fig. 2 reports the models that only use variation within families. The models include the same predictors as the models reported in Fig. 1 but include family fixed effects. This analytical strategy rules out unobserved confounders that vary between families but not within families. More importantly, these analyses examine the processes occurring within families, and they could indicate whether parents treat their children differently. The point estimates and standard errors of the models used in Fig. 2 are reported in Table S2 in the *Online Supplement.*

We can observe the same pattern of variation in the association between parental economic resources and children's academic performance as in the between-family analyses. The associations between parents' resources and academic performance are strongest for low-performing children, and they decline in strength with increasing quantiles of the distribution of academic performance. However, the strength of the associations in the within-family analyses is much smaller than the comparable associations between families. This result is unsurprising given that the variation in parental earnings and wealth is lower within than between families. However, it is more surprising that we find the same pattern within and between families. This result suggests that the variation between families is partly driven by variation within families.

7.2. Do associations vary with the amount of parents' financial resources?

In the analyses above, we used linear estimates of parental income and wealth. This section explores their associations with performance without assuming a specific functional form. This strategy links our study to previous Norwegian studies that found the effects of parental income on school grades and cognitive skills stronger for low-income families than for their high-income counterparts (Løken et al., 2012; Elstad & Bakken, 2014). Fig. 4 and 5 report analyses that rely on a set of dummy variables indicating different levels of parental economic resources. Again, we report the point estimates and standard errors in Tables S3 and S4 in the *Online Supplement*.

The models in Figs. 3 and 4 divide parental income and wealth into five dummy variables, cutting their distribution into six intervals of quantiles: 0–10, 10–25, 25–50, 50–75, 75–90, and 90–100. The effects are compared to families with low income and wealth (0−10) in all graphs. We report the impact of the dummy variables as separate graphs to simplify the presentation of results.

The models in Figs. 3 and 4 confirm the linear estimates obtained through the models reported in Figs. 1 and 2. Proceeding from the left-hand to the right-hand panels of Figs. 3 and 4, we can see that the effects of parental earnings and wealth increase gradually in tandem with higher levels of such. The results do not suggest strong nonlinear relationships based on these predictors, measuring relative income and wealth ranks. Although relative measures are beneficial due to extreme outliers and significant changes in the period, they are not easily translatable to absolute increments in NOK (see *Online Supplements*, Table S12).

The dummy variables also show substantial differences between those at the top and those at the bottom based on parents' economic resources. For example, the graph in the upper right corner of Fig. 3 shows that low-performing students who have parents in the 90th–100th percentiles of the earnings distribution have 1.373 (10th quantile) to 1.240 (20th quantile) standard deviations higher school grades than low-performing students with parents in the bottom 0–10th percentiles. After controlling for parental education and wealth, these differences decrease to between 0.964 (10th quantile) and 0.767 (20th quantile) standard deviations, which is still a large difference between low-performing students with high- and low-earning parents. A similar pattern can be observed for differences based on parental wealth. Adding controls for parental education and earnings does not reduce the gap between students with wealthy and poor parents as much as for parental earnings.

7.3. Robustness checks

We conducted several robustness checks. First, results from standard conditional quantile regression models and the unconditional quantile regression models provided similar patterns (see *Online Supplement*, Tables S5, and S6).

Second, we examined whether ceiling effects drive the patterns. The raw grade points range from 0 to 66 and are normally distributed around

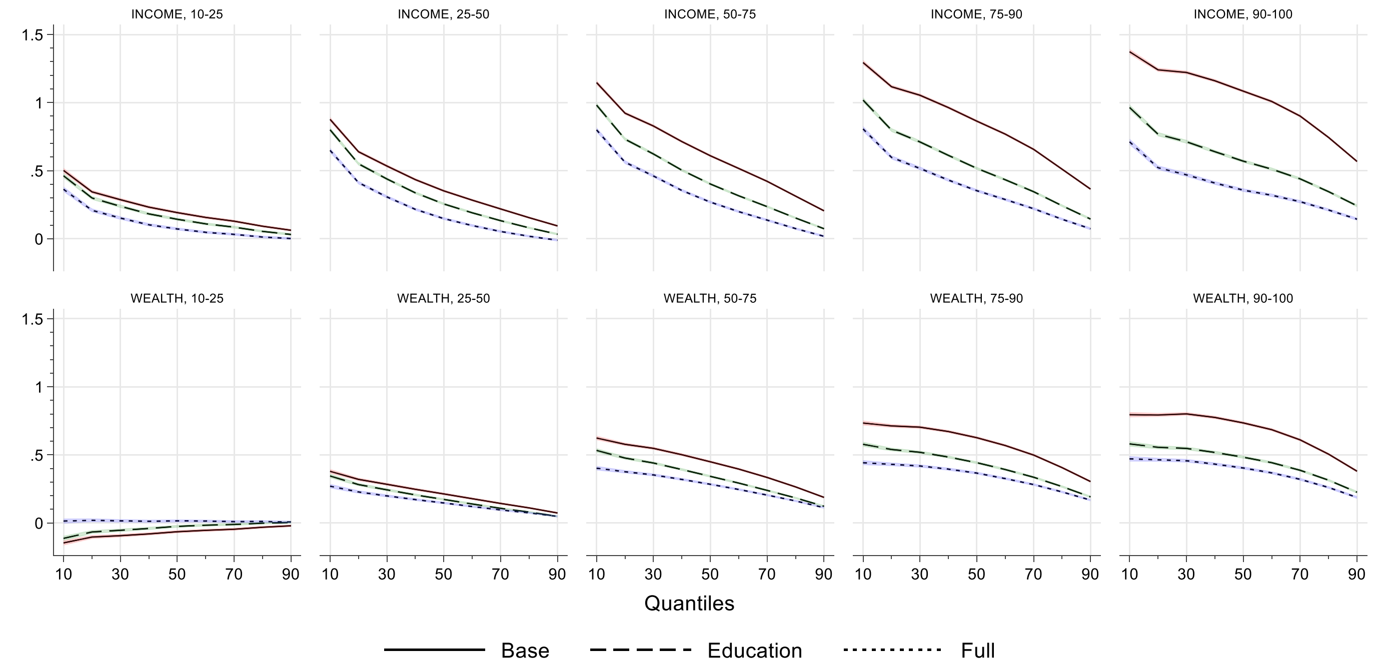

Fig. 3. Unconditional Quantile Regression Models Predicting School Grades by Parents' Location in the Income and Wealth Distribution, Between Families, *Notes:* The reference category for all models is the 0–10th percentile of parental income or wealth. The "Base" model includes the following control variables: gender, birth order, and family size. The "Education" model includes controls for average parental education measured in years. The "Full" model controls for parental earnings when analyzing parental wealth and vice versa. 95%-confidence intervals are based on robust standard errors.

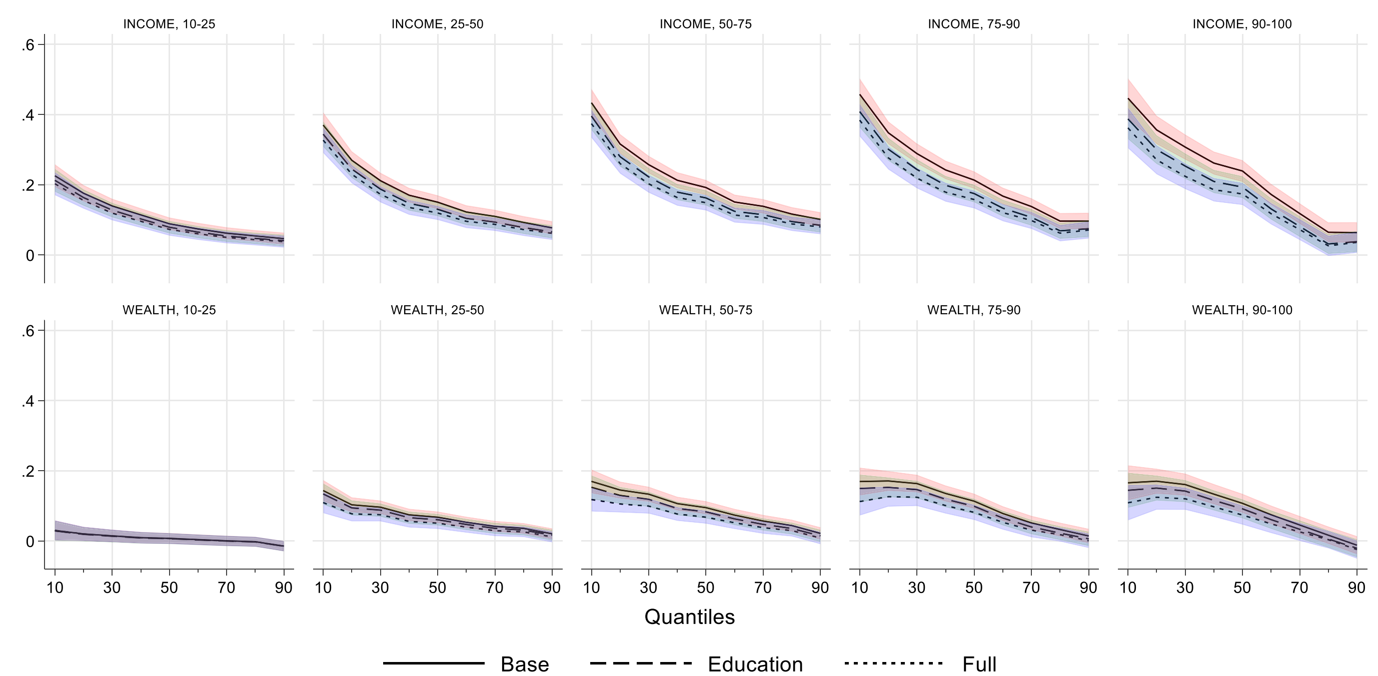

Fig. 4. Unconditional Quantile Regression Models Predicting School Grades by Parents' Location in the Income and Wealth Distribution, Family Fixed Effects (FE), *Notes:* The reference category for all models is the 0–10th percentile of parental income or wealth. The "Base" model includes the following control variables: gender, birth order, and family size. The "Education" model includes controls for average parental education measured in years. The "Control" model controls for parental earnings when analyzing parental wealth and vice versa. 95%-confidence intervals are based on robust standard errors.

a mean of 44. Fig. S3 (*Online Supplement*) breaks down the distributions according to extremes in family background characteristics (education, income, and wealth). The distributions indicate some, but not necessarily strong tendency of ceiling effects. Strong ceiling effects would make the distributions of students with advantaged backgrounds to be severely more left-skewed than the distributions of the students with less advantaged backgrounds. There is some tendency of more left skewness among students with advantage backgrounds, which suggests that we cannot rule out some degree of ceiling effects, although they do not seem to be very strong. In robustness checks of the family-fixed effects models, we removed families where all siblings had top scores on the performance (see *Online Supplement*, Fig. S4, lower graphs). The results did not differ from our primary analyses. In addition, the gradually declining associations across the performance distribution (see Figs. 1 and 2) do not suggest a sudden ceiling effect. However, we cannot rule out ceiling effects completely, as there is some tendency of nonlinearity pattern across the quantiles in the coefficient sizes.

Third, we also assessed the influence of birth spacing. We examined two different definitions of birth spacing: (i) measured as distance to the firstborn and (ii) the number of closely spaced siblings (Grätz, 2018): The number of siblings born within the one year before and after own birth year. The first definition was problematic since it is highly correlated with birth order (r = 0.9 for within-family correlations). The second definition did not change the estimates in our primary analyses (*Online Supplement*, Fig. S4).

(4) We also assessed whether the patterns were driven by ethnicity. We conducted two tests. First, we included a dummy variable for being an immigrant and a set of dummy variables indicating the region of parents' origin (Nordic countries, Western countries, Oceania, Asia, and Africa). Second, we also ran analyses without children with immigrant backgrounds. Neither strategy changed the results noteworthy (*Online Supplement*, Fig. S4).

(5) We also made sensitivity checks using alternative quantile estimators, many of which allow researchers to interpret estimates as quantile treatment effects. Powell (2016, 2020) new generalized quantile regression model (GQR) represents another recent extension of quantile estimators allowing the estimation of quantile treatment effects for both discrete and continuous predictors and control variables. In the *Online Supplement*, we report additional sensitivity tests building on Powell (2020) generalized quantile estimator (GQR) for cross-sectional data (see Table S7, GENQREG). We also did additional testing with Powell (2016) quantile estimator for panel data (see Table S8, QREGPD) for non-additive fixed effects. However, Powell's quantile estimator command for panel data provided volatile results, especially for parental wealth, when more than one control variable was included in the primary model. One possible reason for the instability is that qregpd is designed for panel data with additional non-additive fixed effects for time points. Our family and sibling level data does not necessarily fit this model. We, therefore, also report results based on a new estimator in development (Borgen et al., 2021), the so-called residualized quantile regression (RQR) estimator. This estimator seems to tackle better the family fixed effects (see Figs. S1 and S2) than the estimator by Powell (2016). Except for the QREGPD-estimator, the patterns are similar within and between families.

7. Discussion and conclusion

This study shows that the associations between parents' economic resources, measured by parental earnings and wealth, and school grades vary according to children's school grades. The findings are very robust to different model specifications. Both between and within the families, parental income and wealth play a more important role in children's school grades in the lower parts of the grades distribution. These processes play out stronger between than within families. Within families, parental income seems to matter more than parental wealth. We also examined possible nonlinear relationships between parental financial resources and school grades by dividing up parental income and wealth into dummy variables for different deciles. These results did not suggest strong nonlinear relationships.

Our findings align with the compensatory advantage theory (Bernardi, 2014; Bernardi & Grätz, 2015). The results support the notion that parents use income and wealth to compensate for low academic performance since the associations between parental financial resources are stronger for low-performing children than high-performing children. Our findings also support the claim that parents not only influence children's decision-making in education, which was the focus of most previous research (Bernardi & Cebolla-Boado, 2014; Breen & Goldthorpe, 1997). But parents also seem to use their resources to influence children's educational performance (Bernardi & Grätz, 2015; Grätz & Bernardi, 2017). This result implies that theories should consider that parents may strategically influence their children's academic performance.

In the family fixed effects models, the effects of parental income and wealth are significantly reduced compared to the between-family comparisons. However, parental income and wealth still affect children's educational performance within families. The within-family differences suggest that parental resources are also used to compensate for differences in academic performance between siblings in the same family. Our results align with Behrman et al.'s (1982) separable earnings-bequest model with inequality aversion. In this model, inequality-averse parents compensate for ability differences between siblings. Our findings support the notion that socioeconomically advantaged families use their resources to compensate for, rather than reinforce, ability differences within families (Conley, 2004, 2008; Griliches, 1979; Hsin, 2012; Restrepo, 2012).

The family fixed effects models have another advantage. They control for shared and unobserved family factors. They thus may allow us to come closer to providing causal estimates of the effects of parental income and wealth on children's education than most previous research. Nevertheless, we might have omitted important, relevant characteristics that vary between the siblings, limiting our ability to reach a strong causal inference. Furthermore, a recent concern is that estimates in the unconditional quantile model (relying on the RIF-estimator) may be confounded with compositional characteristics of the predictor variables (Borgen et al., 2022).[2] However, our sensitivity tests, relying on other estimators, do not indicate that this is a severe problem in our study.

Our study's further contribution to research on the intergenerational transmission of educational advantage is that we compare the effects of parental income and wealth on children's academic performance. These resources have independent effects of each other on children's educational performance. We have shown that these effects are mostly similar when assessing the associations between families. Within families, however, parental income seems to matter more than parental wealth.

The more significant effects of parental income than wealth on the academic performance we observe within the families could suggest that parental wealth is tied up in non-liquid assets such as property, consistent with the purchasing mechanism (Hällsten & Pfeffer, 2017). The greater parental wealth estimates between the families could suggest that affluent families are sorted into neighborhoods with access to good schools (Hansen, 2017). However, the more significant parental wealth estimates between the families could also indicate that wealthy families enforce similar educational norms in their families or that prospects of equal inheritance, ensured by law, function as security of educational choice and performance.

Our study supports previous research claiming that parental wealth is an essential but often overlooked resource affecting the intergenerational transmission of advantage (Conley, 2001; Hällsten & Pfeffer, 2017; Pfeffer, 2018; Wiborg, 2017a). However, our findings are mixed about the relative size of parental income and wealth effects. Still, our study suggests that parents' wealth and income are essential resources that should be taken into account when studying the intergenerational transmission of advantage.

It is worth mentioning a limitation of our study. The administrative register data allows us to examine parental and children characteristics. But we do not directly observe specific parental behaviors implied by the theories of differential treatment of the children (Becker & Tomes, 1976, 1986; Behrman et al., 1982; Conley, 2008). Studies that have more directly analyzed specific parental responses to ability differences between siblings or twins and how these responses vary by family socioeconomic status have found inconclusive evidence (Grätz & Torche,

[2] With its RIF estimator, the unconditional quantile model provides the quantile partial effect (Firpo et al., 2009) and not necessarily the quantile treatment effects (Firpo et al., 2007; Powell, 2016, 2020; Frölich & Melly, 2010)

2016; Hsin, 2012; Restrepo, 2016). More research on these mechanisms is thus required.

Finally, as discussed above, we cannot completely rule out that ceiling effects influence our findings. We have tried some approaches to address this issue but they all have their limitations. Future research could employ other strategies than those we have employed to completely rule out ceiling effects. However, it may also be noted that ceiling effects are often part of measures of academic performance, as there is often a limit on how well you can perform. Therefore, ceiling effects may be substantively important and not only a statistical artifact.

Our study examines a strategic case. There are good reasons to expect cross-country variation in how parental financial resources affect children's educational performance. Due to the relatively egalitarian Norwegian welfare and education regime (Esping-Andersen, 1990, 1999), our findings may provide lower-bound estimates. Parental resources and children's academic performance may be associated more strongly in other countries. Therefore, our results regarding between- and within-family processes provide a vital benchmark.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.rssm.2022.100692.

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