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DISCUSSION PAPER SERIES

IZA DP No. 16223

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ABSTRACT

The Rising Influence of Family Background on Early School Performance*

We use administrative data from Norway to examine recent trends in the association between parents' prime age earnings rank and offspring's educational performance rank by age 15/16. We show that the intergenerational correlation between these two ranks has increased over the past decades, and that offspring from economically disadvantaged families have fallen behind. This has happened despite public policies contributing to leveling the playing field. In particular, we show that the expansion of universal childcare and, more recently, the increased teacher-pupil ratio in compulsory school, have disproportionally benefited lower class offspring. The rising influence of parents' earnings rank can partly be explained by a strengthened intragenerational association between earnings rank and education among parents, as educational achievement has an inheritable component. Yet a considerable unexplained rise in the influence of family background remains, pointing towards an impending decline in intergenerational economic mobility.

JEL Classification: I24, J62

Keywords: Intergenerational mobility, achievement gaps, parental influence, meritocracy, GPA

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1 Introduction

Equality of opportunity is a widely accepted aim of economic and social policy. From an intergenerational perspective, equal opportunities imply that offspring born into poor families have the same chances in life as those born into richer families. The empirical literature on intergenerational earnings correlations points to Norway and the other Nordic countries as being among the most socially mobile societies in the world (Corak, 2006; Jäntti et al., 2006; Bratsberg et al., 2007; Black and Devereux, 2011; Blanden, 2013; Bratberg et al., 2017). However, although the literature on mobility *trends* in these countries shows mixed results (e.g., Bratberg et al., 2005; Hansen, 2010; Pekkarinen et al., 2017), recent empirical evidence from Norway suggests that intergenerational mobility has come under pressure, particularly at the bottom of the socioeconomic class distribution (Markussen and Røed, 2020; Hoen et al., 2021). As intergenerational earnings mobility metrics typically require earnings data for both parents and offspring at mature age, there is so far no empirical evidence covering offspring born after the early 1980s. Existing studies have therefore not been able to capture any recent shift in mobility trends, e.g., arising from the massive expansion of publicly provided childcare or increased investments in school quality.

The present paper contributes to the literature by examining trends in intergenerational mobility for more recent (native) birth cohorts (born 1986-2005). Whereas parental class background is measured in terms of the parents' prime age earnings rank (PER), based on the best three earnings years during age 34-40, offspring are ranked based on their grade point average (GPA) from lower secondary school, adjusted for variation in local grading standards. The latter adjustment is made based on data on externally graded exam results and national test scores. Although observed at low age (15/16), we show that adjusted GPA is a strong predictor for adult earnings; hence it can serve as a reliable early indicator for structural shifts in intergenerational economic mobility patterns. A key finding is that the trend toward declining bottom class mobility in earnings rank seems to continue into the new millennium in terms of school performance rank. For the 1986-2005 birth cohorts, we document a widening gap in performance between offspring from different parental earnings classes, and, in particular, a significant decline for offspring born into economically disadvantaged families.

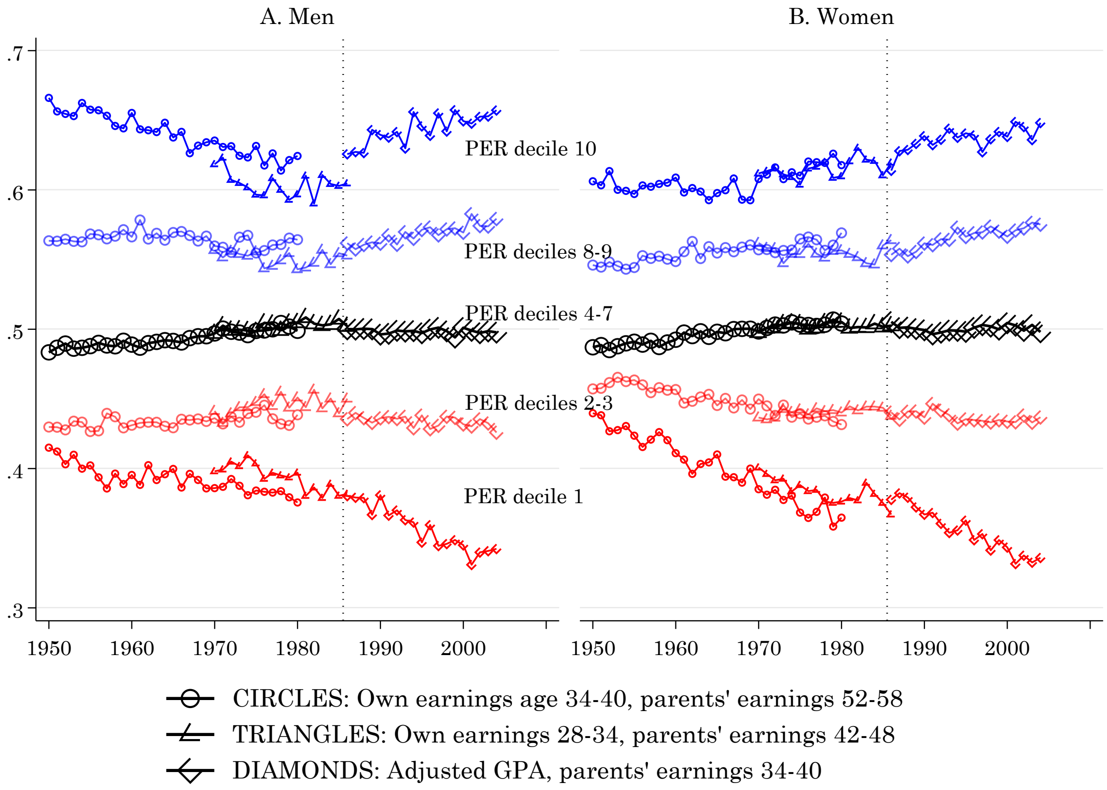

Figure 1. Parent-offspring rank-rank associations for native offspring born 1952-2005

Note: The figure shows average offspring prime-age earnings or GPA rank on a uniform [0,1] scale by parental earnings rank (PER) class. PER is divided into five classes: Bottom class (first decile), lower class (decile 2-3), middle class (decile 4-7), upper class (decile 8-9) and top class (tenth decile). Parents are ranked based on earnings age 52-58 (for offspring cohorts born 1952-1977), on earnings age 42-48 (for offspring born 1962-1986), and on earnings age 34-40 (for cohorts born 1986-2005). Offspring are ranked based on own earnings age 34-40 (for cohorts born 1952-1977), on own earnings age 28-34 (for cohorts born 1962-1986), and on grade point average (GPA) from junior high school, adjusted for local grading practices (for offspring born 1986-2005). For parents, the rankings are based on the highest three of the (up to) 14 earnings observations for the father and the mother during the indicated seven-year periods. For the offspring age 34-40 and 28-34 rankings, we also use the highest three of the (up to) seven annual earnings observations. Earnings obtained in different calendar years are inflated to a common value based on the wage growth index used by Norwegian pension system.

To put our findings into the perspective of the intergenerational economic mobility literature, Figure 1 shows how the trends in average school performance rank by parental earnings rank almost perfectly line up with the corresponding trends in prime age earnings rank outcomes observed for previous generations. Given that earnings obtained as adults and GPA score obtained at age 15/16 intuitively appears to be quite different variables, we find the similarity in the class structure of the two rank outcomes quite remarkable. Together, the observed class-specific trends in earnings ranks (for the 1952-86 birth cohorts) and adjusted GPA ranks (for the 1986-2005 cohorts) form a consistent pattern of declining bottom class mobility over more than five decades.

Our analysis of recent mobility trends relates to a large literature on socioeconomic achievement gaps in education; see, e.g., Reardon (2011), Broer et al. (2019) and Chmielewski (2019). A common finding is that the disparity in academic achievement between students from high and low socioeconomic status (SES) backgrounds has increased over time in most countries, yet with considerable disagreement about trends in each country. A study of particular interest in our context is Sandsør et al. (2023), who examine a decade of achievement gaps (2007-2018) by parental income and education using population data from Norway. They find that achievement gaps increased when parents are ranked based on income (comparing the predicted 90th and the 10th percentile), but remained stable when parents are ranked based on education (comparing master degree with at most high school degree). This illustrates a potential problem with the SES concept when used to assess changes over time, namely that the marginal distribution of variables used to define SES, such as education (or occupation), also changes over time. A notable element of our contribution to the literature is that we describe parental background as well as offspring outcomes in terms of metrics that, by construction, have the exact same marginal distributions across all parent/offspring pairs, and arguable also a stable interpretation in terms of socioeconomic status. This is also what facilitates a direct comparison of trends in socioeconomic achievement gaps with trends in other indicators of intergenerational mobility, such as the earnings rank associations shown in Figure 1.

A second contribution of our paper is that it examines empirically several mechanisms behind observed changes in the influence of parental earnings rank on offspring's early school performance. Whereas the previously identified trends in intergenerational earnings mobility may be attributed to structural changes in the labor market (e.g., skill biased changes in labor demand due to technology, trade, or immigrant competition), the fact that the trend toward lower mobility is manifested already in school results measured at age 15/16 suggests that we also have to look for explanations elsewhere.

The strengthened association between parental earnings rank and offspring school performance must either reflect that human capital investments and/or intergenerationally transferable parental characteristics have become more strongly associated with earnings rank *among parents*, or that a given set of parental characteristics have become more important for early educational performance *among offspring*. Whereas the former explanation may reflect increased social mobility over the parent generations (i.e., good news, from an equality of opportunity perspective), the latter may reflect declining mobility over the offspring generations (bad news).

To evaluate the case for a strengthened intragenerational association between earnings rank and inheritable characteristics, we examine data on parents' parental background (i.e., the earnings rank of the offspring's grandparents), on fathers' cognitive ability (IQ), and on parents' educational attainment. We find no support for the "good news" that declining mobility over the offspring cohorts is an artefact of rising intergenerational mobility over the parent cohorts; neither do we find evidence that fathers' IQ has become more strongly correlated with parents' earnings rank. To the contrary, we present evidence indicating that the parent generations in on our data (typically born between 1950 and 1980) were subjected to declining intergenerational earnings rank mobility and that the association between parents' earnings rank and father's IQ became slightly weaker. In that sense, we can reject a general trend toward meritocracy over the parent cohorts as the driving force behind declining mobility over the offspring cohorts. However, we do find that the parents' earnings ranks became more strongly associated with (relative) educational attainment, suggesting that the returns to education increased over the parent cohorts. To the extent that educational ability is an inheritable latent characteristic, this development may to some extent explain the strengthened statistical association between parents' earnings rank and offspring's school performance rank.

Several studies have focused on the relationship between income inequality and intergenerational mobility (e.g., Björklund and Jäntti, 2009; Blanden, 2011; Corak, 2013), and Durlauf et al. (2022)

show that the negative association between inequality and mobility is consistent with a range of theoretical explanations, including family investments in human capital. We provide empirical evidence that increased income inequality has contributed moderately to the rising influence of parental background on offspring's GPA score observed in our data. The differences in net-of-tax income (during offspring age 7-15) across different parental earnings ranks increased over the 1986-2005 birth cohorts, and we show that parents' net income level is positively associated with offspring outcomes even conditional on parents' earnings rank and other parental characteristics.

Whereas changes in the composition of parental earnings ranks and increased income inequality have contributed to strengthening the association between parental earnings rank and offspring GPA, we find that the expansion of publically provided childcare and (in more recent years) increased teacher-pupil ratio in primary and lower secondary schools has worked in the opposite direction. Exploiting the idiosyncratic (and arguably random-assignment-like) expansion of universal childcare coverage – largely driven by a national policy aimed at reaching full coverage – we confirm previously reported empirical evidence (Havnes and Mogstad, 2015; Cornelissen et al., 2018; Dearing et al., 2018; Zachrisson et al., 2022) that universal childcare enhances intergenerational mobility. Our estimates imply that the observed rise in the average age 1-5 coverage rate from 38% (for the 1986-cohort) to 84% (for the 2005-cohort) has reduced the top-to-bottom-decile GPA differential by 2.9 percentiles. In line with a recent meta-analysis covering 31 "credibly causal" studies from the U.S (Jackson and Mackevicius, 2021), we also find that investments in school quality has been to the relative benefit of offspring from disadvantage families. Our estimates imply that the recent increases the teacher-pupil ratio of approximately 0.02 has reduced the top-bottom GPA differential by 1.9 percentiles.

For the bottom parental earnings decile, we find that observed changes in the composition of parental characteristics can explain roughly half of the observed five percentage point decline in GPA rank. However, as expansion of publically provided childcare and school resources has offset much of this decline, we ultimately end up with an unexplained (residual) negative trend in the bottom class

GPA rank that is close to the one we started out with. For the intergenerational rank-rank correlation, we end up with an unexplained rise that is even larger than the observed increase. Hence, our attempt to identify and quantify the mechanisms behind the rising influence of family background must be deemed a failure. We conclude that the explanation(s) must be sought in other aspects of the schools' learning environment or in an increased parental engagement in offspring's early education. Our findings are thus consistent with the mounting empirical evidence that parents' engagement in the children's schooling has increased in response to higher returns to education, and that the scale of the increased parental efforts to support their children has been positively correlated with the parents' own human capital resources; see Doepke and Zilibotti (2019).

2 Data, measurement issues, and trends

Our description and analysis of recent mobility trends is based on encrypted population data linking all residents born from 1986 through 2005 to their parents and grandparents. To ensure appropriate information about parental background, we restrict the analysis population to offspring with at least one Norwegian-born parent. We also require that the offspring were residents in Norway by birth and by ages 6 and 16. Earnings rank data for parents and grandparents are based on annual labor earnings, which are observed from 1967. Grade point averages (GPA) from lower secondary education are observed from 2002 and measured at age 15/16 in the final year of compulsory school. The Norwegian schooling system is comprehensive with a common curriculum, no tracking and no grade promotion or retention. The vast majority of students attend their local free-of-charge public school to which they are assigned based on residential address only.

Family class background as well as offspring outcomes are defined in terms of ranks within offspring birth cohorts, such that they (by construction) have exactly the same (uniform) distribution for all offspring cohorts. For parents, we use prime age earnings as the foundation for ranking. We combine observed labor earnings for mothers and fathers over the seven-year period when they were

34-40 years old, inflated to a common calendar year value based on a national wage index.[1] This gives us up to 14 annual parental earnings observations – seven for the father and seven for the mother. We pick the highest three of the available earnings observations for each parent pair, and use them to rank the parental background of offspring belonging to each birth cohort (regardless of the birth-years of the parents), such that the resultant parental earnings rank (PER) is uniformly distributed on the [0,1]-interval. In cases of ties, which in practice only occur for a low number of zero-earnings-observations, we randomize the rankings of the tied observations in order to ensure uniformity. For grandparents, we use a similar strategy, with the difference being that their earnings are measured when they were 52-58 years old. Again, we pick the highest three of the available earnings observation and use them to compute the parents' parental earnings rank (PPER).[2]

Offspring outcomes are computed as uniformly distributed GPA ranks within each offspring's complete same-sex birth cohort. GPA is a composite of grades obtained in all subjects at the final year of compulsory school, some graded by the teacher and some by external examiners. As GPA contains an element of teacher assessment, it is conceivable that the grading standards are higher in environments with many higher-achieving students, in which case GPA is not a clean performance indicator. In the main part of our analysis, we therefore adjust GPA for local grading practices by comparing the average GPA at the school-by-year level with results from anonymous written exams graded by external examiners and national test scores in Norwegian, English, and Math. As the exam subjects vary from school to school and from year to year, we first regress individual exam results on subject and take out the residuals. The residuals are then standardized within cohorts and added up at the school-

[1] We use the "Basic amount" (Grunnbeløpet), which is adjusted each year approximately in line with aggregate wage growth, and used as an important parameter in the Norwegian pension system

[2] As shown in Markussen and Røed (2020), earnings obtained around age 50 are more highly correlated with lifetime earnings than earnings obtained at earlier ages. Hence, in order to come as closely as possible to a ranking based on permanent income, it is preferable to measure earnings at a relatively high age. However, to ensure full coverage for the relatively young parent cohorts included in our analysis, we have to measure earnings at lower ages. The primary motivation for the pick-the-best-three-years approach is that we expect the relative influence of mothers and fathers to have changed over time, and by choosing the highest of all earnings (irrespective of earner), we reduce the potential distorting influence of trends in household specialization and movements into and out of the labor force (particularly by females).

by-year level together with standardized results from the 8th and 9th grade national tests.[3] Let $\overline{TEST_{st}}$ be the average of all standardized exam residuals and test scores obtained at school *s* for birth cohort *t*. Let $\overline{GPA_{st}}$ be the corresponding average of standardized GPA. To arrive at a grading-style-adjusted GPA for each offspring *i*, we compute $AdjGPA_{ist} = GPA_{it} - (\overline{GPA_{st}} - \overline{TEST_{st}})$. The adjustment factor $(\overline{GPA_{st}} - \overline{TEST_{st}})$ ensures that GPA's obtained in schools that systematically give their students better (worse) grades than indicated by the results obtained in exams and/or national tests are adjusted downwards (upwards).

Figure 2 presents our main results regarding recent trends in the statistical association between parental earnings rank (PER) and offspring (adjusted) GPA rank. As the intergenerational rank-rank associations are almost the same for boys and girls during the period covered by GPA data (as also illustrated in Figure 1), we do not distinguish by sex (although the ranks are computed within the gender-specific distributions). Gender-specific versions of Figure 2 are provided in Appendix Figure A1. Throughout the paper, we describe mobility trends in terms of rank-rank correlations and in terms of mean outcomes for specific parental rank bins. Whereas the former of these metrics provides a convenient summary measure for intergenerational mobility, the latter is motivated by the existence of non-linear trends, particularly at the bottom and the top of the PER distribution. As already anticipated in Figure 1, we divide the population into five parental earnings rank bins; i.e., decile 1 (bottom class), decile 2-3 (lower class), decile 4-7 (middle class), decile 8-9 (upper class), and decile 10 (top class).

[3] Our data include exam results for all cohorts born from 1986 through 2003, whereas national test scores are available for cohorts born from 1994 through 2005. Hence, for the first cohorts the adjustment is based on exam results only, whereas for the last cohorts it is only based on national tests. For the 1994-2003 cohorts, we use both sources.

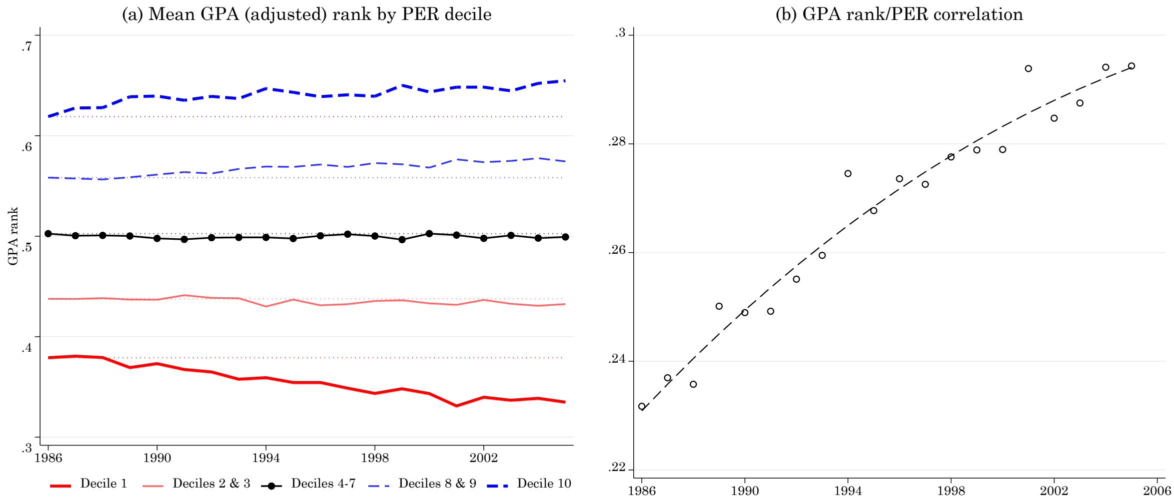

Figure 2. The statistical association between parental earnings rank (PER) and offspring GPA rank, adjusted for local grading standards. Offspring born 1986-2005.
Note: In panel (a), the dotted horizontal lines mark the starting point of each series (the 1986-cohort values). In panel (b), the dashed trend line is drawn using a third order polynomial function chosen by OLS through the annual data points.

Panel (a) illustrates both the magnitude and the trend of the differential offspring outcomes by parental earnings rank. Whereas the average adjusted GPA rank of offspring born into the bottom parental earnings decile has declined from the 38th to the 33th percentile, the rank of the top class has increased from the 62nd to the 65th percentile. The difference between the two groups has thus grown by approximately eight percentiles over the cohorts born between 1986 and 2005. Panel (b) shows that the correlation coefficient has increased from around 0.23 to almost 0.30 during the same period; i.e., by 30%. As the rank distributions for parents and offspring by construction have the same variance, the correlation coefficient can also be interpreted as the regression coefficient; hence, a coefficient equal to 0.30 implies that a one decile higher position in the parental earnings rank distribution raises the expected position in the offspring GPA distribution by 3 percentiles.

In Appendix Figure A2, we show that the trends described in Figure 2 are similar if we use unadjusted instead of adjusted GPA, with the important exception that the top class no longer experience a noticeable rise in average rank. As shown in Appendix Figure A3, the latter reflects that there is a social gradient in the difference between adjusted an unadjusted GPA, which has become much steeper over time, most likely as a result of increased school segregation (a phenomenon we return to in the next section). In view of the fact that GPA is a high-stake outcome, which directly affects the students' likelihood of being admitted to the upper secondary education of choice, unadjusted GPA is an important outcome in its own right. As shown in Appendix figures A4 and A5 for the 1986-cohort (whose earnings now can be traced until age 34), both adjusted an unadjusted GPA ranks are powerful predictors for adult earnings rank, and the relationship is stronger for women than for men. For women, the correlation between adjusted GPA rank at age 15/16 and earnings rank during age 28-34 (three best years) is as high as 0.47, whereas it is 0.31 for men. The patterns shown in Figure 2 may thus be taken as an early warning that the young people born into the bottom parental earnings class in our data are going to lose out, not only in GPA rank, but also in future adult earnings rank.

3 Trends in the composition of parental earnings rank cells and their association with offspring opportunities

There are two very different interpretations of the widening gap in early educational performance across offspring with different parental earnings ranks. The first is that something happened over the parent generations that strengthened the association between earnings rank and other traits transferred to the offspring generations. A hypothesis of particular interest is that the parent generations experienced a shift toward a more meritocratic society (Nybom and Stuhler, 2022), such that the intragenerational association between earnings rank and the ability to offer a good learning environment for own children became stronger. The reason why we observe a stronger association between parental earnings rank and offspring outcomes is then simply that earnings rank has become a better proxy for parental traits that are important for the intergenerational transmission of human capital – not that the influence of these traits has changed. The second interpretation is that a given set of parental characteristics has become more important for offspring outcomes, such that opportunities have become more strongly related to family background. The reason(s) why we observe a stronger association between parental earnings rank and offspring outcomes must then most likely be sought in current circumstances or institutions.

Whereas the first interpretation is a tail of rising mobility among parents, the second is a tail of declining mobility among offspring. From a policy perspective, it is important to find out which interpretation is the most empirically relevant.

3.1 The composition of parental earnings rank cells: The meritocracy hypothesis

Has the statistical association between parents' earnings ranks and other inheritable traits that influence offspring's educational performance become stronger over time? We focus on three variables that may provide some answers to this question; i.e., the parents' own parental background, the fathers' cognitive ability (as measured in IQ tests), and the parents' educational attainment. As we measure mobility in terms of rank associations, all the parental background variables used in this section are measured in terms of ranks within parenthood cohorts (i.e., ranks made among parents to each offspring birth cohort). In cases of ties (two or more parent couples have the same characteristics), we randomize ranks to ensure the exact same uniform distribution for all variables.

We first examine trends in the parents' economic mobility; i.e., the association between the parents' own earnings rank and that of their parents (the offspring's grandparents). We define the parents' parental earnings rank (PPER) as the average of the father's and the mother's parents' ranks. For the oldest generation, we measure earnings during age 52-58, and for each grandparent pair pick the three highest out of the 14 potential earnings-years. As shown in Figure 3, panels (a) and (b), we find no evidence of increasing intergenerational mobility over the parent generations. To the contrary, the correlation between the parents' earnings rank and that of the parents' parents has displayed an increase over the relevant period, suggesting a decline in intergenerational mobility. In particular, we note that bottom class parents to an increasing extent come from lower class families. Hence, it does not appear to be the case that the declining mobility recorded for the offspring generations born after 1985 is an artefact of higher intergenerational mobility experienced by their parents.

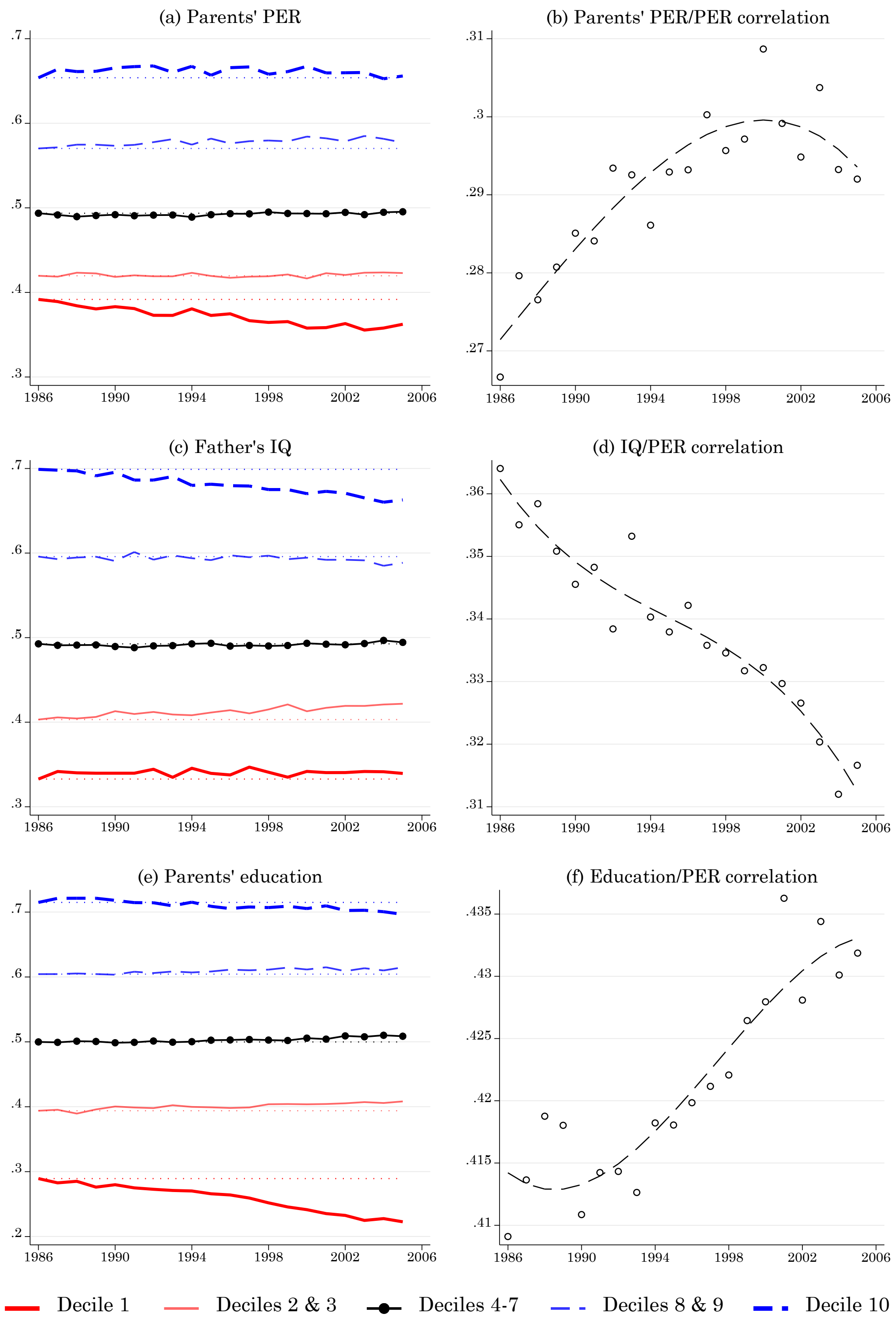

Figure 3. Parents' characteristics by earnings rank decile and offspring birth year.

Note: In panels (a), (c), and (e), the dotted horizontal lines mark the starting point of each series (the 1986-cohort values). Parents' PER is the parent's parental earnings rank, defined as the average of the father's and the mother's parents' ranks. Father's IQ and parents' education (at age 30) are also measured in terms of ranks, and are obtained by projecting IQ scores or average education of the two parents onto uniform [0,1] distributions, using a rank lottery among fathers/parents with the same score/attainment. Ranks are in all cases made among parents of the same offspring birth-cohort. In panels (b), (d), and (f), the dashed trend lines are drawn using third order polynomial functions chosen by OLS through the annual data points.

To facilitate a more direct examination of a potential movement toward meritocracy in the parent generation, we apply a measure of fathers' cognitive ability (IQ), as recorded in tests administered by the armed forces to all men at military conscription around age 18/19. As cognitive ability is genetically inheritable and also likely to be of importance for creating a productive learning environment at home, a strengthened relationship between ability and earnings rank in the parent generations could explain the strengthened relationship between parental earnings rank and offspring outcomes as a statistical artefact of a stable intergenerational transmission of genetically or socially inherited ability traits. IQ test-takers receive an integer score running from 1 to 9, which is a composite of three tests, on arithmetic, word similarities and pattern recognition. We have transformed the test results to uniformly distributed ranks within each fatherhood cohort, and show in Figure 3, panels (c) and (d), how the association between IQ rank and earnings rank has developed for the fathers to offspring born from 1986 through 2005. There is clearly a strong association between IQ and earnings rank. Whereas the average IQ rank in the top earnings decile is around the 65th-70th percentile, the average IQ rank of the bottom earnings decile is around the 33d percentile. However, there is no indication that the relationship between earnings rank and IQ has become stronger. To the contrary, the correlation between the father's IQ rank and the parents earnings rank has declined. Whereas the upper decile in the parental earnings distribution has lost some of its IQ premium, there is no clear indication that the bottom earnings decile has fallen more behind.

Finally, we examine trends in the association between earnings rank and educational attainment among parents. Previous evidence has indicated that the returns to education increased over the parent generations covered in this study (Markussen and Røed, 2020), implying that the distribution of educational attainment may have become more skewed toward the higher earnings ranks. In Figure 3, panels (e) and (f), we examine the intragenerational associations between parents' educational attainment rank and earnings rank, where attainment is defined as the sum of the mother's and the father's non-compulsory education years (measured at their age 30). Here, we do see an increase in the correlation between attainment rank and earnings rank (panel (f)), and it is primarily the bottom class that to an increasing extent consists of those with lowest education (panel (e)). Although existing empirical evidence indicates that the causal effects of parental education on offspring outcomes are modest (Black et al., 2005; Holmlund et al., 2011; Lundborg et al., 2014), it seems plausible that educational ability is genetically and socially inheritable, and consequently that a rise in the returns to education in the parent generation has translated into a stronger association between parental earnings rank and offspring education.

3.2 Economic inequality

To examine trends in income inequality relevant for offspring outcomes, we compute for each offspring, the parents' average total net income during the offspring's age 7-15.[4] This income concept deviates from the one used to compute parental earnings rank both in its timing (referring to a specific period in the offspring's lives instead of in the parents' lives) and in its content (including all incomes over a given period and net of tax instead of gross labor earnings in the best three out of 14 years), as it is designed to represent economic living conditions during adolescence. Figure 4, panel (a), shows that the income inequality between households belonging to different earnings ranks has indeed increased. In particular, the top earnings decile has pulled away from the others, whereas the bottom class has fallen behind. The rise in income inequality is also pictured in panel (b), showing that the Gini coefficient has increased by approximately 12%.

[4] To avoid too much noise from outliers, we have winsorized incomes at the first and the 99th percentiles.

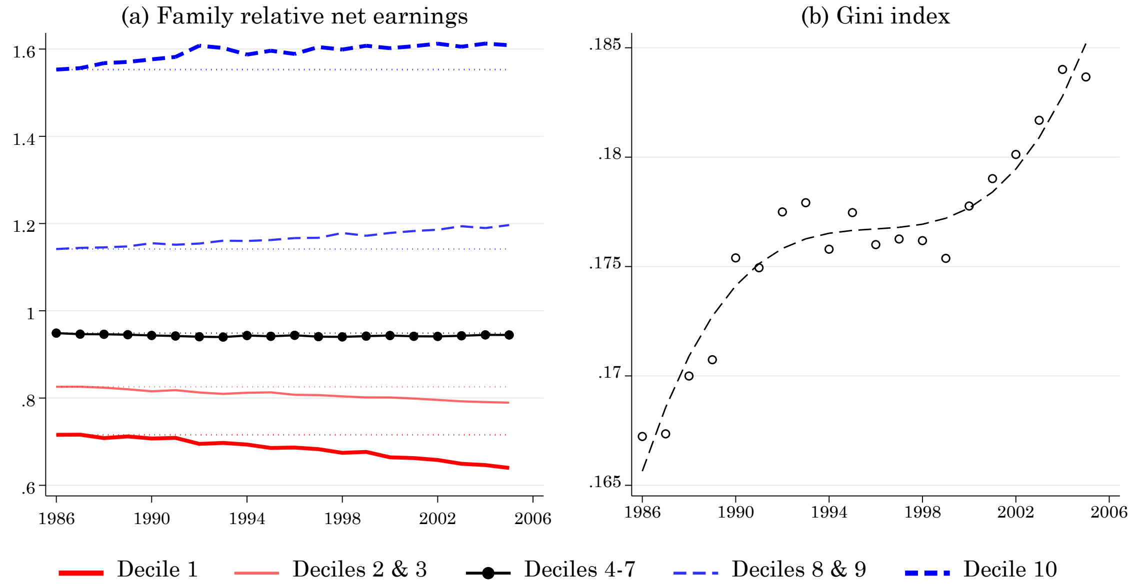

Figure 4. Parents' relative net-of-tax income during offspring age 7-15 by earnings rank and offspring birth-year

Note: Income is measured relative to the average of all parents to the respective offspring birth cohort. In panel (a), the dotted horizontal lines mark the starting point of each series (the 1986-cohort values). In panel (b), the dashed trend line is drawn using a third order polynomial function chosen by OLS through the annual data points.

3.3 School segregation

The degree of school segregation may affect the relationship between parental earnings rank and offspring school performance both through a positive peer effect (arising from socializing with people who are resourceful in terms of human capital and family support) and a negative relative deprivation effect (arising from experiencing a lower relative position, possibly with less attention from teachers and peers); see Markussen and Røed (2023) and references therein. To examine trends in the degree of school segregation, we compute, for each birth cohort, the average parental earnings rank among all final-year students at each junior high school, and compare own parental earnings rank with the school average. Figure 5 shows that there is a considerable degree of school segregation in Norway, which, given that almost all children attend their local public school, largely reflects residential segregation. There has also been a trend toward increasing segregation, as reflected in the widening gap between the top and bottom classes (panel (a)) and the monotonically increasing correlation between own and co-students parental ranks.

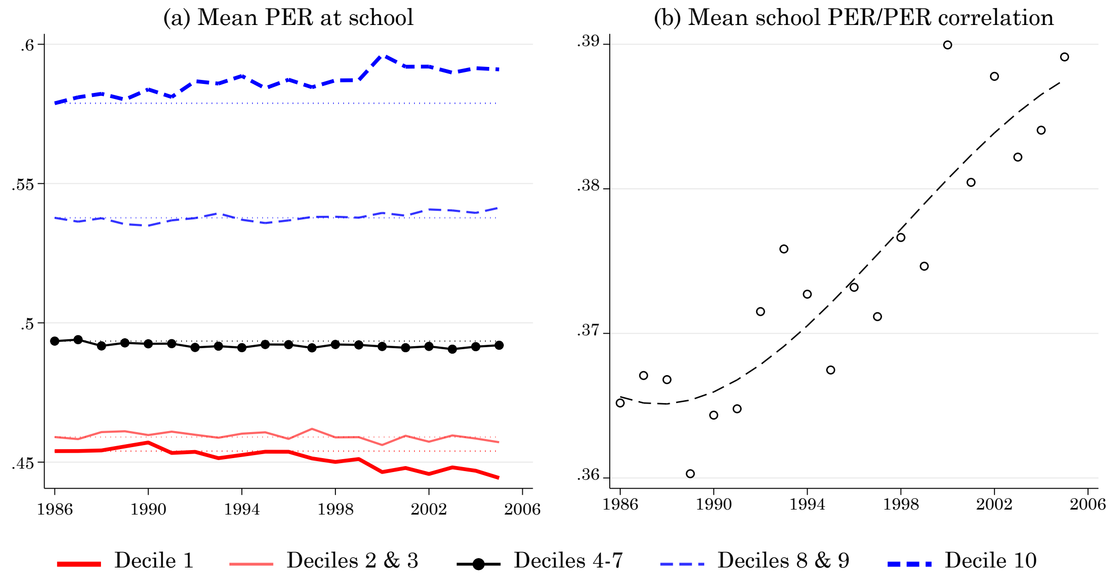

Figure 5. Average parental earnings rank among pupils in junior high-school by parental earnings rank decile and birth-year

Note: In panel (a), the dotted horizontal lines mark the starting point of each series (the 1986-cohort values). In panel (b), the dashed trend line is drawn using a third order polynomial function chosen by OLS through the annual data points.

3.4 Public policies related to universal childcare and school quality

The period covered by our analysis was a period of massive expansion of universal high-quality childcare as well as hours taught in primary school. We identify variation in universal childcare coverage and overall teaching hours at the municipal level. Moreover, as a proxy for overall investments in public schools, we compute teacher-pupil ratios. To compute childcare coverage rates, we assign the municipality of residence at birth, whereas to compute school resources, we assign the municipality of residence at age 6. During most of the period covered by our analysis, there were 435 municipalities in Norway, with population sizes varying from just 600 to more than 600,000 inhabitants (average size approximately 12,500). Figure 6 shows trends in the publically provided learnings environment, as experienced by offspring with different parental class backgrounds. Note that the differences related to class background are entirely generated by differences in residential patterns across municipalities – we do not use data on individual exposure. Childcare coverage is for each birth cohort defined as the average coverage rate in the municipality of residence from age 1 through 5. Panel (a) in Figure 6 shows that the coverage rate increased from 38% for the 1986 cohort to almost 84% for the 2005 cohort, and that the rise has eliminated initial (small) differences in coverage by the municipalities' socioeconomic compositions. As a result, panel (b) shows that the correlation between parental earnings rank and municipal childcare coverage has declined and reached a level slightly below zero.

Data on hours taught in primary and lower secondary school are obtained from "Grunnskolenes Informasjonssystem" (GSI). For each offspring, we have added up the number of hours taught in the municipality of residence at age six from age seven through age 15, and then computed the annual average.[5] Panel (c) shows that hours taught increased considerably over the cohorts covered by our analysis. Panel (d) in Figure 6 indicates that teaching hours are weakly positively correlated with parental earnings rank, with no clear trend in the correlation pattern. From GSI, we also compute the average teacher-pupil ratio by cohort and municipality. Panel (e) in Figure 6 shows that this ratio is higher in lower-class municipalities, reflecting the redistributive nature of the Norwegian welfare state; see, e.g., Borge (2010; 2013) for a description of equalization mechanisms in the Norwegian system for allocation of resources across municipalities. The average teacher-pupil ratio declined over the first offspring cohorts in our data, from around 0.063 to 0.059 (corresponding to an increase in the number of pupils per teacher from 17 to 18), and then gradually returned to its initial level. These fluctuations largely reflect (unaccommodated) fluctuations in the sizes of birth cohorts. In addition, whereas the first years of our data period was characterized by centralization and a restructuring of primary schools toward larger entities and thus fewer very small classes, recent trends in the teacher-pupil ratio have been more strongly influenced by the rise in the number of teaching hours.

[5] Note that there was a school reform in Norway in 1997 which reduced the school starting age from age 7 to age 6 and extended compulsory school from 9 to 10 years. For most affected children, the alternative to school start at age 6 in 1997 would have been participation in universal childcare, and, according to Drange et al. (2016), the added school year was designed as a low-intensity kindergarten program, and its introduction did not have any effect on subsequent educational outcomes. To avoid that our variable "annual teaching hours" is dominated by the increased school hours due to the reform, we include the nine years from age 7 to age 15 only.

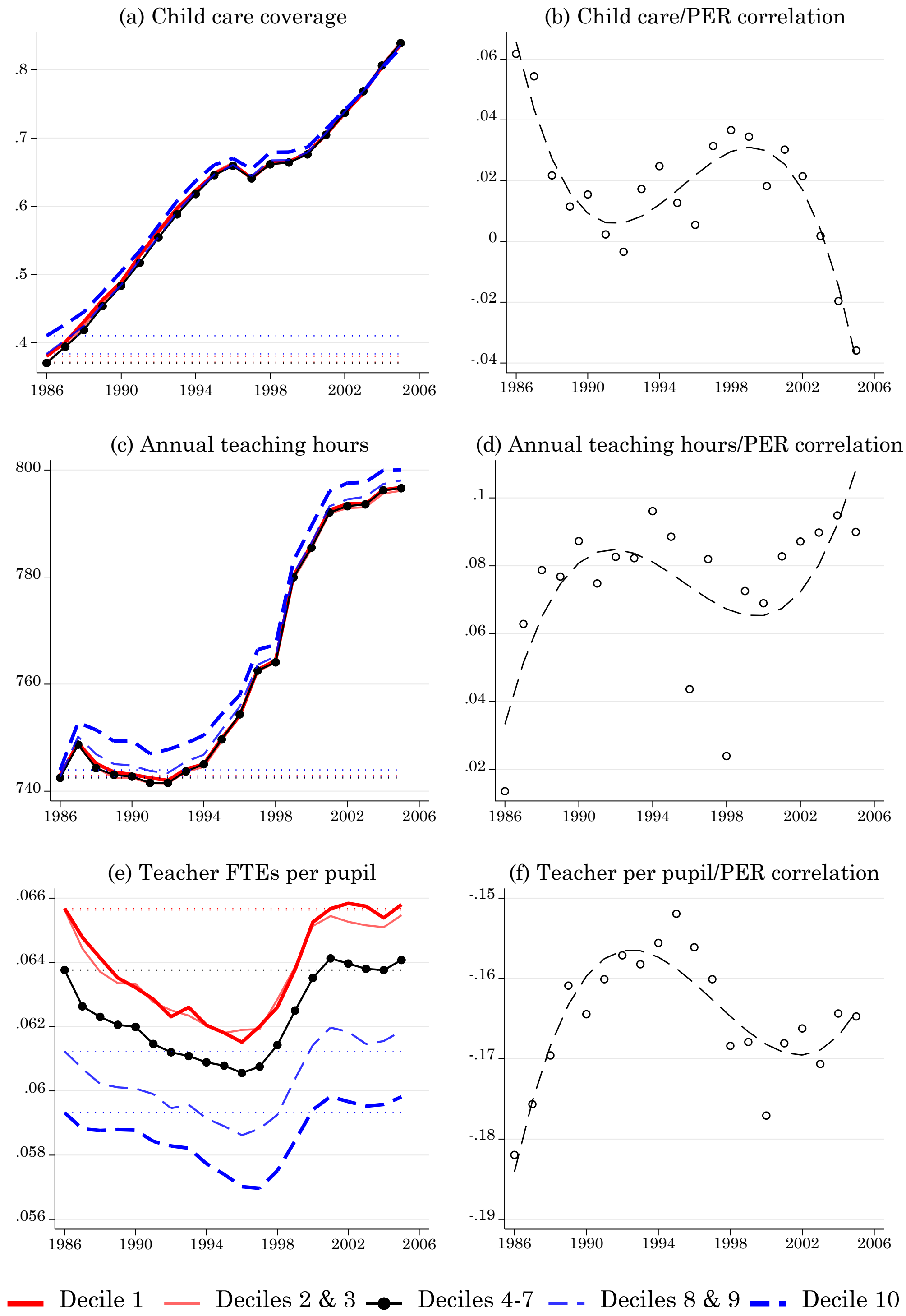

Figure 6. Universal childcare coverage (age 1-5), annual teaching hours (age 7-15) and teacher-pupil ratio (age 6-15). Municipality characteristics by parental earnings rank decile and offspring birth year.

Note: In panels (a), (c) and (e), the dotted lines mark the starting point of each series (the 1986-cohort values). Childcare coverage (panels (a) and (b)) is for each birth cohort defined as the average coverage rate in the municipality of residence from age 1 through 5. Annual teaching hours (panels (c) and (d)) and teacher-pupil ratio (panels (e) and (f)) are computed as the average over the relevant ages. The teacher-pupil ratio is measured in full time equivalents (FTE) and excludes teachers assigned to pupils with special needs. In the panels to the right, dashed trend lines are drawn using third order polynomial functions chosen by OLS through the annual data points.

4 Empirical analysis

To examine the mechanisms behind the observed changes in the association between family background and AdjGPA rank, we set up regression models based on individual data. The purpose of the analysis is to identify the impacts of each of the variables discussed in the previous section, and to examine their roles in explaining the mobility trends reported in Section 2.

4.1 Statistical model

The determination of a rank outcome is a zero-sum game. One person's gain must be someone else's loss. To incorporate this property into the regression model, explanatory variables are either included as deviation from the cohort average (such that there is no trend) or with a restriction ensuring that positive and negative rank movements cancel out. Let y_{tmi} be the adjusted GPA rank obtained by offspring *i* belonging to birth cohort *t,* and municipality *m.* Let $\mathbf{x_{ti}}$ be the vector of parental/family and school peer characteristics (parents' parental earnings rank, fathers IQ rank, parents' education rank, parents' relative income, and average PER among pupils in offspring's junior high-school) and let $\mathbf{z_{tm}}$ be the vector of municipality-by-cohort characteristics (universal childcare coverage, hours taught through compulsory school, and average teacher-pupil ratio). We specify two alternative models, one based on linear interaction terms between PER and time trends and one based on separate effects for the five different class background categories. The linear model has the following structure:

$$y_{tmi} = \alpha_t + \delta_t(PER_{ti} - \overline{PER_t}) + (\mathbf{x_{ti}} - \overline{\mathbf{x}}_\mathbf{t})\boldsymbol{\pi}_\mathbf{x} + \mu_m + (\mathbf{z_{tm}} - \overline{\mathbf{z}}_\mathbf{t})\boldsymbol{\pi}_\mathbf{z} + \mathbf{z_{tm}}(PER_{ti} - \overline{PER_t})\boldsymbol{\gamma} + \varepsilon_{tmi}, \quad (1)$$

where $(\overline{\mathbf{x}}_\mathbf{t}, \overline{\mathbf{z}}_\mathbf{t})$ are the cohort-specific averages of the explanatory variables, PER_{ti} is offspring i's parental earnings rank measured on the [0,1] uniform scale, and $\overline{PER_t}$ is its cohort average (by construction equal to 0.5). The categorical class model has the following structure:

$$y_{tmci} = \alpha_{tc} + (\mathbf{x_{ti}} - \overline{\mathbf{x}}_\mathbf{t})\boldsymbol{\beta}_\mathbf{x} + \theta_m + (\mathbf{z_{tm}} - \overline{\mathbf{z}}_\mathbf{t})\boldsymbol{\beta}_\mathbf{z} + \sum_{c \neq 4-7} \mathbf{z_{tm}}\boldsymbol{\sigma}_c + \zeta_{ctmi}, \quad (2)$$

where *c* denotes the five parental earnings class bins defined on the *PER*-distribution (decile 1, deciles 2-3, deciles 4-7, decile 8-9, and decile 10), and with the following set of linear restrictions:

$$\alpha_{t1} + 2\alpha_{t2\&3} + 4\alpha_{t4-7} + 2\alpha_{t8\&9} + \alpha_{t10} = 0 \quad \forall t = 1986,...,2005. \tag{3}$$

The restrictions in (3) ensures that if the expected GPA rank of one class increases, the expected rank of at least one other class must decline.

4.2 Identification and interpretation

The variables included in Equations (1) and (2) naturally falls into two categories; i) variables characterizing the parents or the consequences of decisions made by them, and ii) variables characterizing public policies.

Parental characteristics can largely be considered predetermined, such that we can rule out reverse causation as an important factor. The influence of family background can thus be interpreted as causal, although the estimated effect of each specific trait will capture the effect of that particular trait as well as its (unaccounted for) correlates. The latter will include latent inheritable traits as well as influences operating through, e.g., residential decisions, family networks, and school choice. Parents' relative income during the offspring's adolescence, as well as the socioeconomic status of schoolmates, may be correlated with unobserved parental characteristics, and also be subjected to reverse causation (children's schooling experiences may potentially affect parents' labor supply). Hence, the purpose of including these variables in the regression is not to identify and quantify distinct causal mechanisms related to particular aspects of family characteristics/decisions, but to examine how controlling for them affects the estimated time trends in the influence of parental earnings rank.

For the second group of variables, we aim at a causal interpretation. Public investments in kindergartens and schools may be important tools in efforts to promote equality of opportunities; hence, it is of considerable interest to identify and quantify their causal impacts. The municipalities' decisions regarding universal childcare capacity, teaching hours, and teacher-pupil ratios are arguably exogenous with respect to the performance of each individual kid, yet in order to identify their impacts on the class gradient in school performance based on Equations (1) and (2), we face a couple of challenges. The first is that achievement gaps may vary across municipalities in a way that exhibits a spurious correlation with resource allocation. The inclusion of municipality-fixed effects in Equations (1) and (2) ensures that differences in average achievement *levels* across municipalities are not erroneously attributed to differences in class composition.[6] However, spatial differences in achievement *gaps* that are spuriously correlated with differences in resource allocation may still undermine a causal interpretation of estimated effects. We assess the empirical relevance of this potential problem through robustness/sensitivity analyses where we add into the models controls for geographically differentiated (time-invariant) class gradients (at the county- or municipal level), essentially removing much of the cross-sectional variation from the sources of identification.

A second challenge is that the allocation of resources to kindergartens and schools may be subjected to some form of reverse causation, e.g., such that poor GPA performance locally trigger demand for more spending. This is probably not a serious problem for universal child care, as the rapid expansion that took place over the 1986-2005 birth cohorts was largely driven by a national policy aimed at reaching full coverage; see Andresen and Havnes (2019). The exogeneity of hours taught and the teacher-pupil ratio in compulsory schools is probably more questionable. However, whereas it appears likely that municipal spending on schools may respond to local changes in average school results, it seems less probable (but not impossible) that there is a direct effect of changes in the (unobserved) class gradient in these results. Given our focus on the class gradient, it is only the latter that could undermine the causal interpretation. Moreover, the longitudinal changes in the teacher-pupil ratio are largely driven by fluctuations in cohort sizes, which are not fully accommodated by corresponding changes in the number of teachers.

[6] The municipality structure has changed during the period covered by our data. In 2020, several of the smallest municipalities were merged, such that the total number of municipalities was reduced from 422 to 356. For the municipality-fixed effects, we use the most recent municipality structure.

4.3 Results

To examine how the mechanisms discussed in the previous section have affected trends in the estimated influence of parental earnings rank (PER), we include the explanatory variables in Equations (1) and (2) in a step-by-step fashion. We do this in four steps, first including only parental background characteristics, then add parents' relative income level and PER of schoolmates, then add municipality-fixed effects (based on the municipality of residence by age 15/16), and finally add the municipalities' child-care coverage rates and school characteristics (based on the municipalities of residence by age 0 and 6, respectively), allowing the latter variables to affect offspring differently depending on class background.

The estimated effects of explanatory variables are shown in Table 1, whereas the estimated trends in the (remaining) influence of *PER*, as captured by δ_t in Equation (1) and by $\{\alpha_{t1}, \alpha_{t2\&3}, \alpha_{t4-7}, \alpha_{t8\&9}, \alpha_{t10}\}$ in Equation (2) are shown in Figure 7 (for the linear correlation model) and Figure 8 (for the categorical class model). The trend estimates are normalized to zero for the first birth-cohort (1986) such that the figures illustrate the changes over time in rank-rank correlation and class-specific rank outcomes.

Starting with parental background characteristics, we note that the estimated effects of parents' parental earnings rank, father's IQ, and parents' educational attainment are all significant, and that point estimates are almost the same regardless of model (linear or categorical) and choice of control variables. Since all three variables are specified as uniform ranks, their coefficients are directly comparable, and it is notable that parents' joint educational attainment is the characteristic that has the greatest influence on offspring's school performance. Starting with Figure 7, we note that the estimated effect of PER (the correlation coefficient α_{tc}) has trended upwards by approximately 0.055; see the solid black line. When we include controls for parental background characteristics, the estimated trend in the intergenerational correlation is dampened, suggesting that parts of the increase can indeed by explained by changes in the composition of earnings rank cells in the parent generation. A closer inspection (not shown) reveals that this is almost entirely related to parents' education; i.e., that educational attainment has become more strongly associated with earnings rank, see Figure 4, panels (e) and (f). Considering the results from the categorical model in Figure 8, it is notable that the changes in the composition of parental earnings rank cells can account for a large fraction of the declining performance ranks for the bottom class. In fact, what Figure 8 tells us is that both the bottom and the top classes have become less positively selected in terms of inheritable characteristics relevant for offspring school performance.

Moving on to the impacts of parental income *levels,* the results shown in Table 1 indicate that higher income during the offspring's childhood (relative to the cohort average) improves educational performance, even conditional on earnings rank and other parental background characteristics. It is also notable that the inclusion of relative income in the regression does not at all change the estimated impacts of the parental background characteristics. As income inequality rose over the period considered here, this contributes to explaining the strengthened associations between parents' earnings rank and offspring's educational performance.

Attending a school with higher average PER is associated with slightly higher own performance; hence the trend toward increasing segregation also contributes to steepen the social gradient. At this point, the model based on unadjusted GPA rank gives the complete opposite result; see Appendix Table A1. This is probably the reason why the top class has not pulled apart from the other classes when unadjusted GPA is used for ranking (Figure A2). The rising segregation illustrated in Figure 5 has intensified the grade completion among upper class offspring and contributed to level the gradient in unadjusted GPA. Apart from the impact of PER among co-students , it is notable that the estimation results are similar for rank outcomes based on adjusted and unadjusted GPA; compare Table 1 and Table A1.

Table 1. Estimation results for linear (LIN) and categorical (CAT) models (standard errors in parentheses)
Outcome is adjusted GPA rank

	LIN1	LIN2	LIN3	LIN4	CAT1	CAT2	CAT3	CAT4
Parents' PER	0.050	0.045	0.048	0.048	0.050	0.045	0.048	0.048
	(0.004)	(0.002)	(0.001)	(0.001)	(0.004)	(0.002)	(0.001)	(0.001)
Father's IQ	0.165	0.164	0.162	0.162	0.166	0.165	0.163	0.163
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Parents' education rank	0.347	0.344	0.339	0.339	0.346	0.342	0.338	0.337
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Parents' rel. income		0.012	0.011	0.011		0.013	0.012	0.012
		(0.003)	(0.003)	(0.003)		(0.003)	(0.003)	(0.003)
Mean school PER		0.037	0.053	0.053		0.041	0.056	0.056
		(0.031)	(0.025)	(0.024)		(0.031)	(0.026)	(0.025)
Public childcare cov.				-0.039				-0.041
				(0.046)				(0.055)
× PER (uniform)				-0.060				
				(0.019)				
× Decile 1								0.033
								(0.021)
× Deciles 2-3								0.020
								(0.022)
× Deciles 8-9								-0.010
								(0.017)
× Decile 10								-0.029
								(0.015)
Annual teaching hours				0.013				0.014
				(0.005)				(0.008)
× PER (uniform)				0.001				
				(0.010)				
× Decile 1								0.001
								(0.012)
× Deciles 2-3								-0.009
								(0.013)
× Deciles 8-9								0.008
								(0.010)
× Decile 10								-0.013
								(0.009)
Teacher-pupil ratio				0.003				-0.002
				(0.088)				(0.106)
× PER (uniform)				-0.973				
				(0.166)				
× Decile 1								0.378
								(0.117)
× Deciles 2-3								0.417
								(0.079)
× Deciles 8-9								-0.330
								(0.087)
× Decile 10								-0.551
								(0.142)
Municipality-fixed eff.	No	No	Yes	Yes	No	No	Yes	Yes
R-squared	0.250	0.251	0.256	0.256				
No. observations	1043525	1043525	1043525	1043525	1043525	1043525	1043525	1043525

Note: The regressions also include dummy variables indicating missing values of father's IQ (1.9% of observations), parents' PER (2,2%), public childcare coverage (2.4%), public school resources (1,1%).

The rapid expansion of universal childcare has disproportionally benefited offspring from the lower parental earnings ranks. The point estimates reported in Table 1 (LIN4 and CAT4) imply, for example, that the observed increase in the average age 1-5 public childcare coverage rate of 46 percentage points has reduced the rank-rank correlation by 0.060×0.46=0.028 and the top-to-bottom-class GPA differential by (0.033+0.029)×0.46=0.029; i.e., 2.9 percentiles. Our results also indicate that higher teacher-pupil ratio in primary and lower secondary school disproportionally benefits lower class offspring. The point estimates imply that the recent increase in the teacher-pupil ratio by approximately 0.02 has reduced the rank-rank correlation by 0.973×0.02=0.019 and the top-to-bottom-class GPA differential by (0.378+0.551)×0.02=0.019; i.e., 1.9 percentiles. By contrast, the number of teaching hours does not appear to influence the GPA ranking of offspring from different parental earnings rank cells; hence, it appears to be the *intensity* rather than the *quantity* of the teaching that is important for the achievement gap.

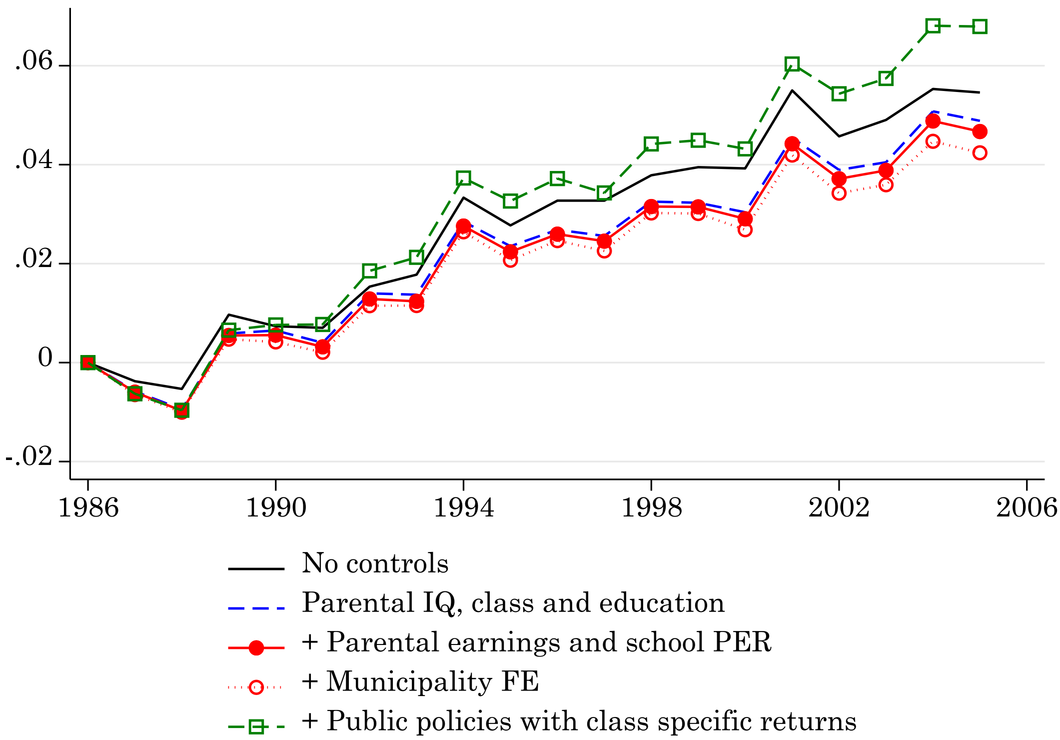

Figure 7. Rank-rank correlation under alternative control variable sets.

Note: The figure shows estimated linear associations between offspring GPA rank and parental earnings rank ($\hat{\delta}_t$ from Equation (1)) after controlling for additional sets of variables in a cumulative fashion. Public policies include childcare coverage, annual teaching hours, and teacher-pupil ratio in the municipality.

The fact that the influence of parents' earnings rank has increased over time despite public policies that have had large effects in the opposite direction implies that other forces are at work, which have more than offset their opportunity-equalizing effects.

It is notable that the mechanisms examined with our models have had very different impacts on the bottom and top classes. For the bottom class, we see from Figure 8, panel (a), that changes in the parent composition explain a considerable part of the decline in performance rank, whereas public policies have contributed in the opposite direction. For the top class, most of the mechanisms we have studied here have contributed to a negative trend in outcomes (panel (e)): Members of the top class have on average become less positively selected in terms of both IQ and education, and the recent expansion of universal childcare and school resources has unequivocally been to their relative disadvantage. Only the rise in economic inequality and school segregation has worked to their advantage, but the influence of these forces have been small and is hardly visible in Figure 8. Hence, when we control for all our explanatory variables, we end up with a much larger unexplained trend in favor of the top class than what we have seen in observed outcomes.

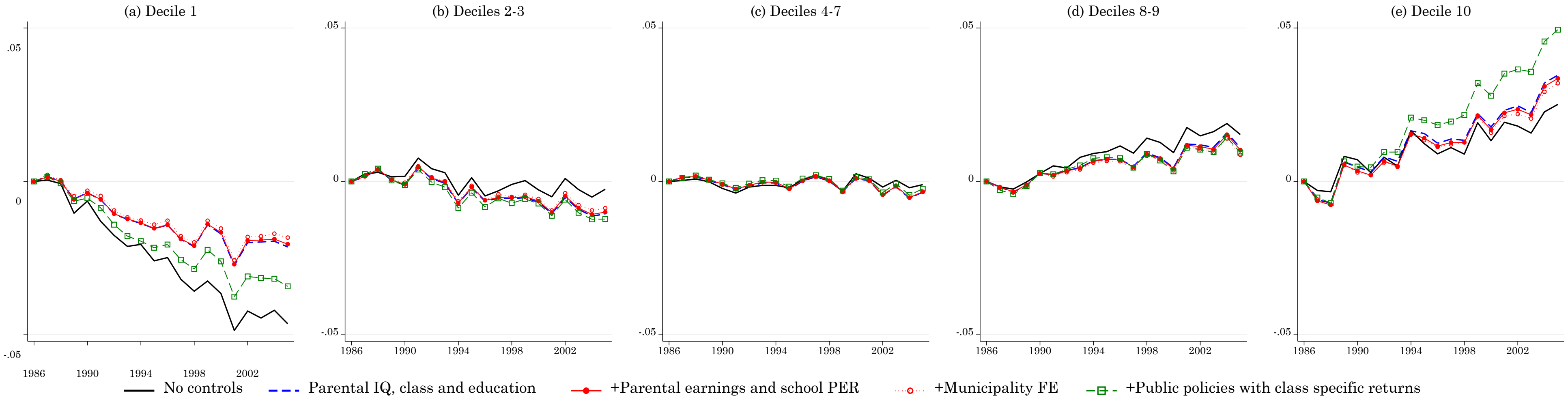

Figure 8. Expected offspring GPA rank by parental earnings rank under alternative control variable sets.

Note: The figures show estimated expected offspring GPA rank by parental earnings rank ($\hat{\alpha}_{tc}$ from Equation (2)) after controlling for additional sets of variables. Public policies include childcare coverage, annual teaching hours, and teacher-pupil ratio in the municipality.

4.4 Robustness

To address the concern that local class gradients in school performance may correlate spuriously with childcare coverage and school resources, we extend the models with controls that incorporate such cross-sectional differences. For the linear models, this is done by adding interaction terms between parental earnings rank and dummy variables indicating either county or municipality of residence. For the categorical model, it is done by adding class-by-county or class-by-municipality fixed effects. The motivation for using counties in this context is that many of the municipalities in Norway are extremely small, with just a handful of students in the relevant age group; hence, separate class gradients for each municipality may absorb much of the required identifying variation in public policies. By using the 19 counties instead, we account for regional variation in the class gradients in a less “costly” fashion.

The robustness results are presented in Appendix Table A2. When we allow for county-specific gradients (Models LIN5 and CAT5), the estimated effects of childcare coverage and the teacher-pupil ratio on the class gradients remain stable (or increases). With municipality-specific gradients, the point estimates become smaller and the standard errors become considerably larger (LIN6 and CAT6). Yet, viewed as a whole, the main conclusions seem robust. Higher childcare coverage and a larger teacher-pupil ratio significantly reduces the achievement gap between pupils from high and low class families.

5 Discussion and concluding remarks

Based on population data from Norway, we have shown that the association between parents’ earnings rank and offspring early school performance has become stronger over the past decades. We have provided evidence that the rising influence of parental earnings rank is not an artefact of a general trend toward meritocracy and increased mobility in the parent generations, which could have resulted in a tighter relationship between earnings rank and (inheritable) ability in the parent generation. To the contrary, exploiting data on the parents’ parental earnings rank, we show that intergenerational mobility declined slightly over the parent cohorts and that the association between parents’ earnings rank and father's IQ became slightly weaker. On the other hand, we do find that earnings rank became more closely associated with educational attainment among parents, suggesting that the returns to education increased and thus made educational attainment a more important determinant of earnings rank. To the extent that educational achievement is socially or genetically inherited, even conditional on cognitive ability, this may explain parts of rising influence of parental earnings rank on offspring outcomes. However, the increased role of parental education has been more than offset by the huge expansion of publically provided childcare and, more recently, the rise in the teacher-pupil ratio in primary and lower secondary schools. We show that these policies have been to the relative advantage of bottom and lower class offspring.

Viewed as a whole, our analysis has not been able to explain why the influence of family background has risen so much. To the contrary, the estimated joint influence of all the mechanisms and variables examined in this paper has been to reduce the influence of parental earnings rank, whereas the observed association has increased. Hence, our analysis has added to an unexplained force of declining intergenerational mobility. It appears that policies aimed at equalizing offspring opportunities have to deal with fundamental societal trends working in the opposite direction.

In a paper documenting the widening achievement gap between offspring from rich and poor families in the U.S., Reardon (2011) referred to empirical evidence showing that parents have become increasingly focused on children's cognitive development during the last 50 years. There is now ample empirical evidence from many countries indicating that parents have become more involved in their children's lives. Doepke and Zilibotti (2019) compare time-use data from six different countries (Canada, Spain, Italy, UK, Netherlands, and the US), and show that parents' time spent with their kids has increased sharply over the past decades in all countries. In the US, for example, hours per week spent by mothers and fathers on childrearing increased from 10 (mother) and 4 (father) around 1990 to 14 (mother) and 7 (father) in 2011, and the increase was larger for parents with high education (Doepke and Zilibotti, 2019, pp. 55-57). Parents' time spent directly on helping their kids with homework has increased from 17 minutes per week in the mid-1970s to more than an hour and a half in 2012. Based on two recent meta-analyses, Curran and Hill (2022, p. 107) argue that increased parental involvement reflects a response to "escalating societal competitiveness, individualism, inequality, and pressures to excel at school and college."

Time-use data from Norway indicate more stability in parents' average time spent on childrearing (Egge-Hoveid and Sandnes, 2013), yet there are indications that the difference in involvement between parents with high and low education has increased, particularly among fathers (Ellingsæter and Kitterød, 2021). There is also evidence that the nuclear family plays an increasing role in the lives of Norwegian adolescents more generally. For example, according to the Norwegian youth survey, the fraction of 13-18-year olds that spent at least two evenings out with friends during the last week has declined from 62% in 2002 to 34% in 2018-20, whereas the fraction who spent at least two evenings home alone with mother, father, and/or siblings increased from 54% to 73% (Bakken et al., 2021).

Irrespective of the precise mechanism, the rising influence of family background on early school performance represents a challenge for policies aimed at achieving equal opportunities for all. Our findings suggest that policies designed to expand access to publically provided childcare have successfully contributed to leveling the playing field, yet been insufficient to offset other and more powerful trends contributing to lower intergenerational mobility. Our results also indicate that investment in school quality (in our model represented by the teacher-pupil ratio) has the potential for leveling the playing field.

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Appendix

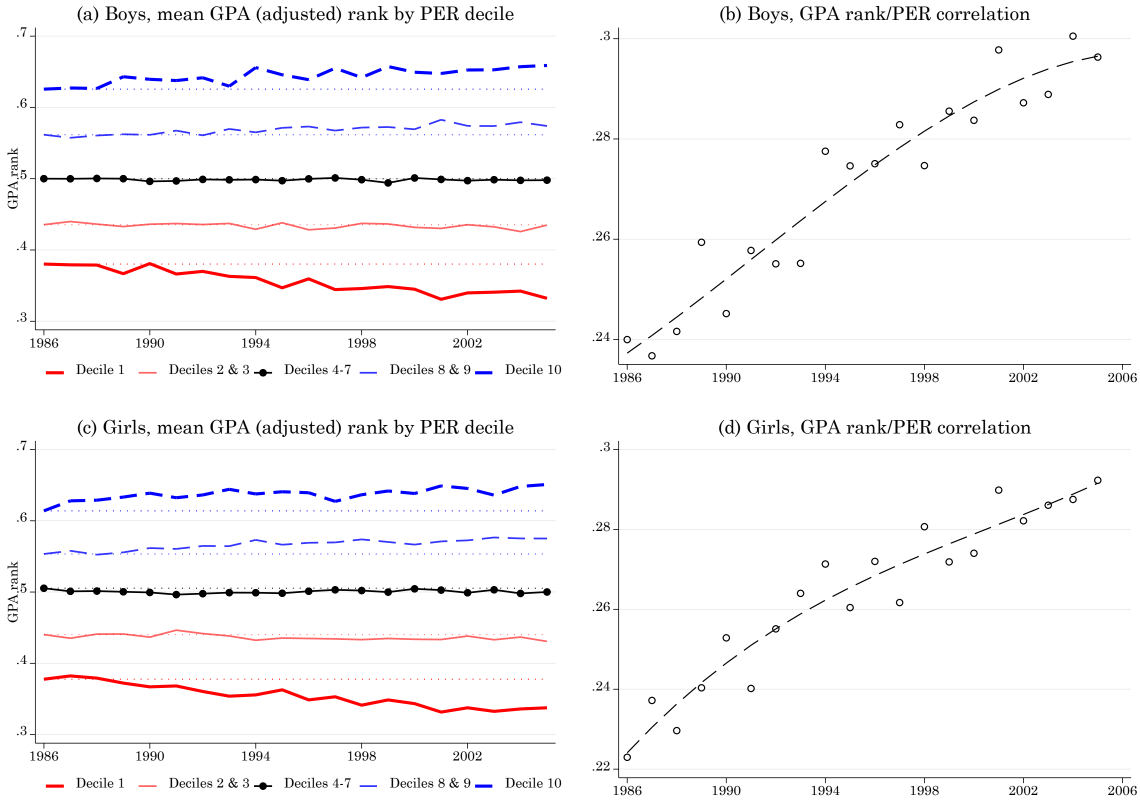

Figure A1. The statistical association between parental earnings rank (PER) and standard-adjusted off-spring GPA rank for offspring born 1986-2005. By sex.

Note: In panels (a) and (c), the dotted horizontal lines mark the starting point of each series (the 1986-cohort values). In panels (b) and (d), the dashed trend line is drawn using a third order polynomial function chosen by OLS through the annual data points.

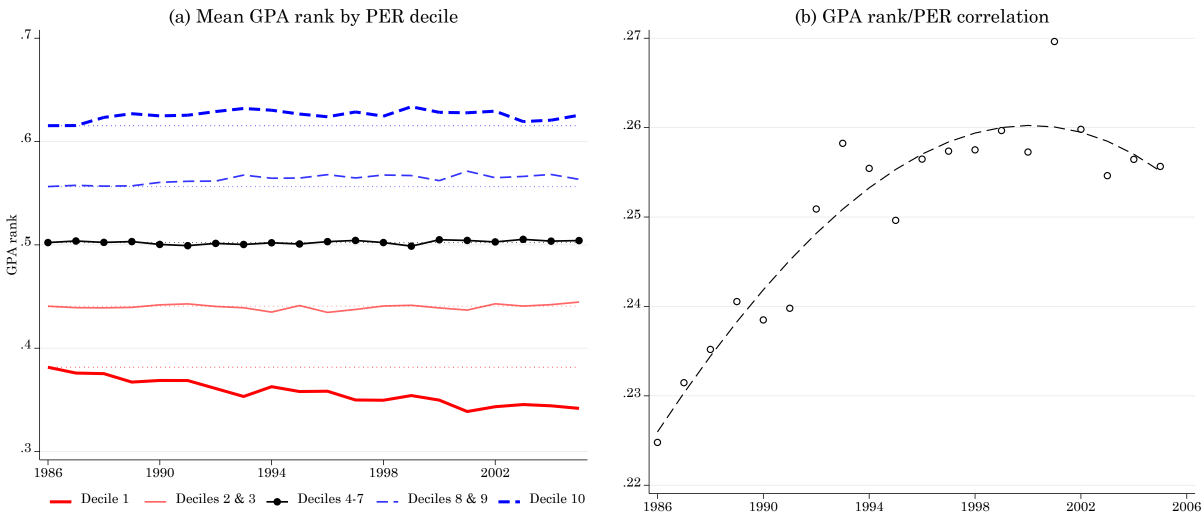

Figure A2. The statistical association between parental earnings rank (PER) and unadjusted offspring GPA rank for offspring born 1986-2005.

Note: In panel (a), the dotted horizontal lines mark the starting point of each series (the 1986-cohort values). In panel (b), the dashed trend line is drawn using a third order polynomial function chosen by OLS through the annual data points.

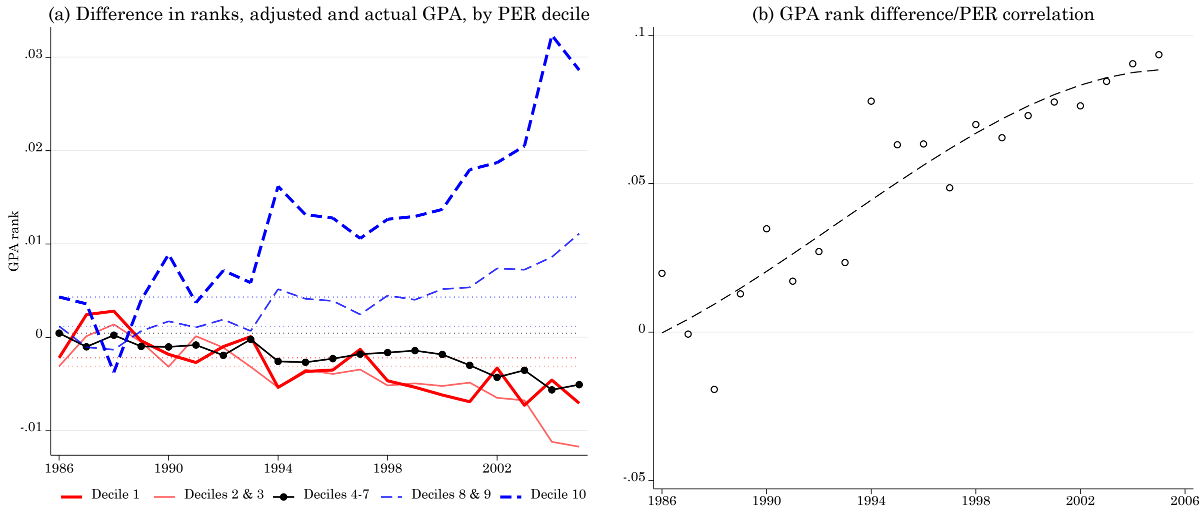

Figure A3. The GPA standard adjustment factor and its association with parental earnings rank. Offspring born 1986-2005.

Note: In panel (a), the dotted horizontal lines mark the starting point of each series (the 1986-cohort values). In panel (b), the dashed trend line is drawn using a third order polynomial function chosen by OLS through the annual data points.

Fig. A4 Gender-specific associations between GPA rank at age 15/16 and earnings rank age 28-34 for offspring born 1986-2005.

Note: The slope lines through the mean points show the linear regression line from a regression with adult earnings rank as outcome and Adjusted GPA rank as explanatory variable. Slope coefficient equals 0.312 (0.006) for men and 0.469 (0.006) form women (standard errors in parentheses).

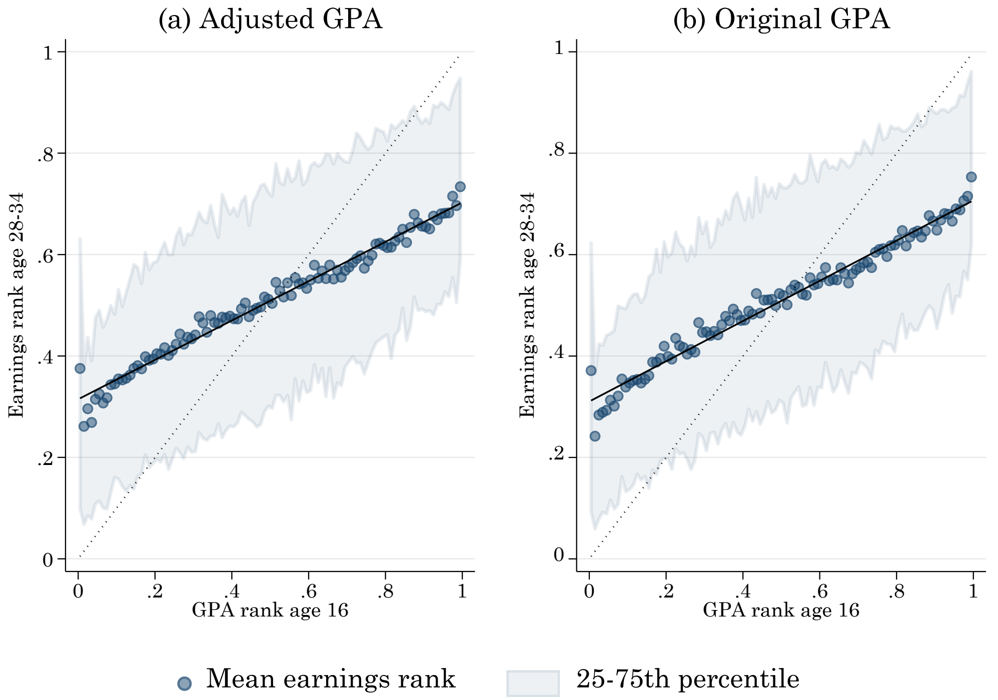

Fig. A5 Associations between adjusted and unadjusted GPA rank at age 15/16 and earnings rank age 28-34 for offspring born 1986-2005.

Note: The slope lines through the mean points show the linear regression line from a regression with adult earnings rank as outcome and Adjusted GPA rank as explanatory variable. Slope coefficient equals 0.389 (0.005) for adjusted and 0.397 (0.006) form unadjusted GPA rank (standard errors in parentheses).

Table A1. Estimation results for linear and categorical models (standard errors in parentheses)

Dependent variable: Unadjusted GPA rank	LIN1	LIN2	LIN3	LIN4	CAT1	CAT2	CAT3	CAT4
Parents' PER	0.036	0.042	0.044	0.045	0.037	0.042	0.045	0.045
	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
Father's IQ	0.160	0.161	0.160	0.160	0.161	0.162	0.162	0.162
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Parents' ed. rank	0.343	0.342	0.342	0.342	0.341	0.341	0.341	0.340
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Parents' rel. income		0.011	0.010	0.010		0.012	0.011	0.011
		(0.003)	(0.003)	(0.003)		(0.003)	(0.003)	(0.003)
Mean school PER		-0.092	-0.066	-0.052		-0.087	-0.063	-0.048
		(0.024)	(0.016)	(0.014)		(0.024)	(0.016)	(0.015)
Public childcare cov.				-0.012				-0.014
				(0.018)				(0.022)
× PER (uniform)				-0.056				
				(0.019)				
× Decile 1								0.027
								(0.014)
× Deciles 2-3								0.020
								(0.010)
× Deciles 8-9								-0.011
								(0.013)
× Decile 10								-0.025
								(0.014)
Annual teaching hours				-0.000				0.001
				(0.005)				(0.005)
× PER (uniform)				-0.006				
				(0.009)				
× Decile 1								0.007
								(0.008)
× Deciles 2-3								-0.007
								(0.007)
× Deciles 8-9								0.005
								(0.006)
× Decile 10								-0.014
								(0.007)
Teacher-pupil ratio				0.882				0.884
				(0.077)				(0.092)
× PER (uniform)				-0.489				
				(0.158)				
× Decile 1								0.111
								(0.127)
× Deciles 2-3								0.314
								(0.085)
× Deciles 8-9								-0.285
								(0.093)
× Decile 10								-0.255
								(0.146)
Municipality-fixed eff.	No	No	Yes	Yes	No	No	Yes	Yes
R-squared	0.231	0.233	0.239	0.239				
No. observations	1050794	1050794	1050794	1050794	1050794	1050794	1050794	1050794

Note: The regressions also include dummy variables indicating missing values of father's IQ (1.9% of observations), parents' PER (2,2%), public childcare coverage (2.4%), public school resources (1,1%).

Table A2. Estimation results for linear and categorical models (standard errors in parentheses)
Dependent variable: Adjusted GPA rank

	LIN4	LIN5	LIN6	CAT4	CAT5	CAT6
Parents' PER	0.048	0.048	0.047	0.048	0.046	0.048
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Father's IQ	0.162	0.162	0.162	0.163	0.164	0.163
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parents' education rank	0.339	0.338	0.338	0.337	0.340	0.337
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Parents' rel. income	0.011	0.011	0.011	0.012	0.012	0.012
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mean school PER	0.053	0.052	0.053	0.056	0.041	0.057
	(0.024)	(0.024)	(0.023)	(0.025)	(0.026)	(0.025)
Public childcare cov.	-0.039	-0.039	-0.039	-0.041	0.016	-0.041
	(0.046)	(0.046)	(0.047)	(0.055)	(0.037)	(0.057)
× PER (uniform)	-0.061	-0.084	-0.068			
	(0.019)	(0.024)	(0.042)			
× Decile 1				0.033	0.035	0.013
				(0.021)	(0.025)	(0.031)
× Deciles 2-3				0.019	0.024	0.031
				(0.022)	(0.027)	(0.033)
× Deciles 8-9				-0.010	-0.018	-0.003
				(0.017)	(0.016)	(0.016)
× Decile 10				-0.029	-0.034	-0.055
				(0.015)	(0.014)	(0.019)
Annual teaching hours	0.013	0.013	0.013	0.014	0.016	0.014
	(0.005)	(0.005)	(0.005)	(0.008)	(0.009)	(0.008)
× PER (uniform)	0.001	-0.010	-0.008			
	(0.010)	(0.015)	(0.014)			
× Decile 1				0.001	0.002	0.002
				(0.012)	(0.017)	(0.014)
× Deciles 2-3				-0.009	-0.007	-0.002
				(0.013)	(0.018)	(0.014)
× Deciles 8-9				0.008	0.007	0.006
				(0.010)	(0.010)	(0.009)
× Decile 10				-0.013	-0.011	-0.017
				(0.009)	(0.010)	(0.009)
Teacher-pupil ratio	0.003	0.007	0.020	-0.002	0.332	0.019
	(0.088)	(0.086)	(0.087)	(0.106)	(0.118)	(0.131)
× PER (uniform)	-0.973	-0.916	-0.697			
	(0.166)	(0.147)	(0.174)			
× Decile 1				0.378	0.391	0.200
				(0.117)	(0.119)	(0.150)
× Deciles 2-3				0.417	0.427	0.285
				(0.079)	(0.099)	(0.119)
× Deciles 8-9				-0.330	-0.338	-0.153
				(0.087)	(0.104)	(0.127)
× Decile 10				-0.551	-0.730	-0.394
				(0.142)	(0.167)	(0.220)
Municipality-FE.	Yes			Yes		
Class-by-county grad. or FE		Yes			Yes	
Class-by-municip grad. or FE			Yes			Yes
R-squared	0.256	0.256	0.257			
No. observations	1043525	1043525	1043525	1043525	1043525	1043525

Note: LIN 4 and CAT for are repeated from Table 2. The regressions also include dummy variables indicating missing values of father's IQ (1.9% of observations), parents' PER (2,2%), public childcare coverage (2.4%), public school resources (1,1%).