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Social mobility in Germany☆

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ABSTRACT

We characterize intergenerational mobility in Germany using census data on educational attainment and parental income for 526,000 children. Motivated by Germany's tracking system in secondary education, our measure of opportunity is the A-Level degree, a requirement for access to university. A 10 percentile increase in parental income rank is associated with a 5.2 percentage point increase in the A-Level share. This gradient remained unchanged for the birth cohorts 1980–1996, despite a large-scale expansion of upper secondary education. At the regional level, there exists substantial variation in mobility estimates. Local characteristics, rather than sorting patterns, account for most of these differences.

1. Introduction

Intergenerational social mobility is an important indicator for both fairness and economic efficiency in a society. Next to violating widely held fairness ideals, low mobility can lead to the misallocation of resources, as talented children from disadvantaged backgrounds are impeded from realizing their potential. Despite its importance, reliable mobility statistics are not available for many countries. Measuring social mobility across generations is challenging, as it requires data that links parental outcomes to a measure of opportunities for children.[1] Household panel studies may contain this information but are typically too small to deliver sufficiently precise estimates for regional comparisons or the analysis of time trends (Lee and Solon, 2009; Mazumder, 2018). An attractive alternative are administrative data sources, such as linked tax records (e.g. Chetty et al., 2014). As in many other countries, however, such data is not available in Germany, where to date no large-scale empirical study of social mobility across time and space exists.

In order to fill this gap, this paper implements a new measurement strategy for social mobility in Germany and provides estimates across time and regions. Motivated by Germany's early tracking system in secondary education, our mobility statistics measure the association between parental income and the educational opportunities of children. Our measure of opportunities captures whether a child will obtain the A-Level (Abitur), the highest secondary schooling degree in Germany. We are able to link 526,000 children to their parents, using census data spanning the years from 1997 to 2018.

Our first finding is that relative mobility, defined as the percentage point difference in the probability to obtain an A-level degree between children with different parental income ranks, has remained constant for recent birth cohorts. On average, a 10 percentile increase in parental income rank was associated with a 5.2 percentage point increase in the probability of obtaining an A-Level degree. For the birth cohorts 1980–1996, this parental income gradient has not changed despite a large-scale expansion of upper secondary education in Germany, the *Bildungsexpansion*. This long-term expansion was in parts

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[1] In the literature, the expression social mobility refers to inter-generational social mobility and in other cases also to intra-generational mobility (i.e. social mobility between different periods of a lifetime). In this paper, we focus on the relationship across generations.

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a policy response to a public debate on social mobility (Dahrendorf, 1966; Hadjar and Becker, 2006) and increased the A-level share from 39% for children born in 1980 to 53% for the 1996 birth cohort. We document that the *Bildungsexpansion* took place uniformly across the income distribution, with almost identical increases in the share of A-Level educated children in all quintiles of the parental income distribution. This enhanced the odds ratio for disadvantaged children, but left the parental income gradient unaffected. The same pattern emerges when estimating mobility trends for population subgroups typically emphasized in social mobility policies, such as children in single parent households or children of parents with low levels of formal education. Complementing our main analysis with data on test scores and grades, we find no evidence that measured ability was better for marginal students from disadvantaged backgrounds than for marginal students from affluent households. We therefore cannot draw a positive conclusion about the *Bildungsexpansion* in the sense that it revealed more hidden talent among children at the bottom of the income distribution than among those at the top.

We also document geographic variation in social mobility across German states, cities, and local labor markets. For example, the top-bottom gap in the probability of obtaining an A-Level degree between children at the top and the bottom of the income distribution is 20 percentage points larger in Bremen than in Hamburg, two city states approximately 100 km apart. We also find significant and meaningful differences within states. For example, the top-bottom gap is 8 percentage points larger in Cologne than in Düsseldorf, two large cities in North Rhine-Westphalia located approximately 40 km apart. Overall, the within-state component of the variance in the parental income gradient across local labor markets or cities is around six times higher than the between-component. This is remarkable, as education policies, which prior literature has suspected to be a key determinant of mobility, vary mainly at the state level in Germany.[2]

We show that household characteristics can explain only a small fraction of the variation in mobility measures across local labor markets. Differences in mobility estimates can arise either due to structural differences between places or due to systematic sorting of households into different local labor markets (Chetty et al., 2014). The census data employed in this paper contains rich information on the structure and characteristics of households, allowing us to directly test the importance of sorting by conditioning on an extensive set of household characteristics. We find that the mobility ranking between local labor markets is largely unchanged when conditioning on household characteristics, leading us to reject the hypothesis that sorting is the major driver of the regional variation in mobility.

Our paper is the first to provide a comprehensive account of social mobility in Germany, characterizing its evolution over time, heterogeneity across regions, estimates for many subgroups, and disentangling sorting versus place effects. Due to its early-age tracking system, Germany is particularly suited for studying social mobility through the lens of educational opportunities. Only completion of the highest track grants the A-Level degree and thus direct access to the tuition-free national university system, opening up the full range of career prospects. As a result, the A-Level wage premium amounts to more than 40%. Besides the economic benefits, having obtained an A-Level is also an important sign of social distinction in the German society. More broadly, a large literature shows that educational attainment has intrinsic value and predicts a wide range of non-pecuniary outcomes (Oreopoulos and Salvanes, 2011; Lochner, 2011). Educational attainment as a measure of opportunity is thus a strong and comprehensive indicator for the opportunities of an individual in the German context. Beyond Germany, this approach to measure mobility may also prove useful in other countries where the highest secondary school degree plays a similarly important role in shaping future career options.

The remainder of this paper is organized as follows. Section 2 discusses the related literature and relevant aspects of the German institutional framework. In Section 3, we describe data and measurement strategy. Section 4 reports our results at the national level. Regional estimates, including the analysis of local labor markets, are presented in Section 5. Section 6 concludes.

2. Related literature and institutional background

2.1. Related literature

The study of intergenerational social mobility has a long tradition in economics, sociology and educational research. While early sociological studies focused on measuring occupational transitions between generations, educational research studied intergenerational correlations in educational attainment. The literature in economics has traditionally measured social mobility by the intergenerational elasticity of (lifetime) earnings, or, more recently, by rank-rank correlations in lifetime income, making use of linked administrative tax data (e.g. Chetty et al., 2014; Acciari et al., 2022; Corak, 2020).

In Germany, it is not possible to link individual tax returns. For that reason, most empirical evidence on income mobility is based on the German Socio-Economic Panel (SOEP), a household survey with limited sample size. Time trends or more fine-grained geographic variation in social mobility hence cannot be documented in the SOEP with a sufficient degree of statistical confidence. Schnitzlein (2016) shows that estimates of the national IGE based on the SOEP are sensitive to small variations in sampling criteria, resulting in a wide range of plausible estimates. It is therefore not surprising that the empirical evidence regarding the level of social mobility in Germany is not coherent. Studies that investigate intergenerational income mobility in the SOEP include Eisenhauer and Pfeiffer (2008), Riphahn and Heineck (2009), Eberharter (2013) and Bratberg et al. (2017). These studies typically find higher levels of income mobility in Germany than in the US, and lower levels of mobility in East than in West Germany, albeit with high statistical uncertainty. On the other hand, sibling correlations (Schnitzlein, 2014) or measures of educational mobility have placed Germany closer to the immobile end of the scale in an international comparison.

Our measurement approach focuses on children's educational opportunities, while retaining the interpretability advantages of income based measures of parental socioeconomic status. This allows us to draw on the German census data, providing us with the statistical power necessary to conduct a more comprehensive study of social mobility in Germany.[3] At the same time, we can document social mobility for very recent cohorts, because – unlike lifetime income – the A-Level degree can be measured already relatively early in the lifecycle. An additional advantage of our measurement approach is that it works great even in the presence of non-labor force participation or zero earnings in the child generation. Therefore, while much of the intergenerational mobility literature focuses on men, our method is well suited at including women.

Hilger (2015) employed a comparable approach for the US, examining mobility statistics based on census data linking children's years of schooling to parental income. Unlike our study, their focus on later-life outcomes raises sample selection concerns, requiring an imputation procedure due to most children leaving the parental household.

[2] Helbig and Nikolai (2015) provide a comprehensive account of state level school reforms in Germany since 1949. Studies trying to evaluate their effects on social mobility include Betthäuser (2017), Büchler (2016), and Jähnen and Helbig (2015).

[3] A less comprehensive version of the German Census data has previously been used to document differences in the intergenerational correlation in educational attainment between East and West Germany (Riphahn and Trübswetter, 2013; Klein et al., 2019).

Emphasizing years of schooling is justified in the US, where almost all children attend academic high school programs. In contrast, the German system's academic and vocational tracks make it ideal for our outlined census-based social mobility analysis.

2.2. Institutional background

The salient feature of Germany's system of secondary education is early age tracking, where only the successful completion of the highest track results in the award of an A-Level degree (Abitur) and grants direct access to the tuition-free national university system. After finishing the four-year[4] elementary school around the age of 10, children are allocated into one of three tracks. While the highest track, the Gymnasium (grades 5-12/13), provides general academic education that aims to prepare children for college, the lower two tracks (grades 5–9/10) provide vocational training with a focus on preparing students for an apprenticeship.[5] The specific design of the tracking system in secondary education can vary across the 16 federal states, which bear the main responsibility for the education system. However, there exist only minor differences in state-provided financing. In addition, the Standing Conference of State Education Secretaries has the stated goal to ensure a high degree of comparability of educational qualifications across German states and there are no legal differences between the A-Level degrees issued from different states.

Since the early educational careers of children have important consequences for the choices available to them at later stages, and early track choices are heavily influenced by parental characteristics (Dustmann, 2004), the German institutional framework is particularly suited for studying social mobility through the lens of educational opportunities. The importance of track choices for social mobility is reinforced by the fact that almost all primary and secondary schools as well as universities are state-funded, mostly based on student headcounts, resulting in a comparatively large equality in the endowments and quality between different schools and universities.

Consequently, the A-Level degree is by far the most important qualification in the German education system, and individuals who obtain it enjoy substantially above-average economic outcomes. Using data on full-time workers aged 30–45, we find an A-Level wage premium of 42% for monthly net income.[6] This estimate mirrors Schmillen and Stüber (2014) who report a 44% A-Level wage premium for total gross lifetime earnings. An A-Level degree is also associated with a lower risk of being unemployed (Hausner et al., 2015) and a higher life expectancy (Gärtner, 2002). Furthermore, it constitutes a beneficial factor for obtaining vocational training in certain white-collar occupations (Klein et al., 2019) and marks an important sign of social distinction in the German society. Overall, this illustrates that, for children in Germany, the A-Level degree is a compelling measure of their social and economic opportunities.

3. Data and measurement strategy

Our analysis is based on data of the German Microcensus (Mikrozensus, hereafter MZ), a large-scale annual representative survey of the German population administered by the Federal Statistical Office of Germany (FDZ, 1997-2018). The survey was first administered in West Germany in 1957 and includes East Germany since 1991. The MZ has several features that make it particularly suited for our research question. First, it allows us to reliably match children to their parents as long as they are still registered at their parents' household. By law, it is compulsory for individuals living in Germany to register at their place of residence, and the sampled households are obliged to provide information on each person registered in their household. Second, it contains fine-grained geographic information and is sufficiently large to permit the estimation of mobility statistics for single cohorts and regions.

Each year, a randomly selected 1% sample of the population living in Germany is asked to participate in the survey. By law, participation is mandatory for members of the selected households, which remain in the survey for at most four subsequent years. The primary sampling units consist of clusters of neighboring buildings, and all households belonging to a sampled cluster are interviewed. The unit non-response rate is approximately 3%.[7] Each year, one quarter of the initially sampled clusters are replaced by new clusters, resulting in partial overlap of sampling units. Appendix A contains additional information on the survey and sampling design of the MZ. The detailed nature of the questionnaire together with the low non-response rate and the large sample size allow us to mitigate measurement and sample selection concerns often brought forward in the context of survey data.

3.1. Variable definition

Measuring opportunities of children. Motivated by the importance of the A-Level degree for children's future educational and labor market opportunities in the German institutional framework, we measure opportunities by a binary variable Y_i that is equal to one if a child has obtained, or is on track to obtain, a degree that is equivalent to an A-Level, and zero otherwise. Specifically, our outcome variable is equal to one if (i) a child has obtained a degree that qualifies for tertiary education[8] or if (ii) a child is enrolled in the last 2–3 years of a track which leads to such a degree at the successful completion of school.[9] In the following, we refer to this outcome as an A-Level degree and characterize intergenerational mobility in terms of the conditional probabilities of obtaining an A-Level degree for children of different parental backgrounds.

Our outcome definition takes into account three considerations. First, while the MZ survey is conducted on a rolling basis, A-Level degrees are typically awarded in the second quarter of the calendar year. Back of the envelope calculations suggest that, if we only count children who have already obtained an A-Level degree, we would misscount our outcome for around 40% of the graduating cohort in each survey year. Second, since the share of children failing the final examination in a given year is low,[10] including upper stage students

[4] In the states of Berlin and Brandenburg, elementary school lasts six years.

[5] The rigor of the tracking system is mediated by the possibility of switching tracks. In particular, it is common that talented students from the medium track switch to the general high track or attend a specialized high track after they finish their vocational degree when they are around 16 years old. A more detailed overview of the tracking system and track switching in Germany is provided in Biewen and Tapalaga (2017) and Dustmann et al. (2017).

[6] We use the waves 1997–2018 of the German Microcensus (described below) and compute the A-Level wage premium by regressing the log of net monthly personal income of full-time workers aged 30–45 on an A-Level dummy, controlling for a full set of age and year fixed effects to implicitly account for job experience.

[7] The non-response rate is driven by households that could not be reached and residents in shared accommodations (Statistisches Bundesamt, 2018), which we exclude from our sample. The item non-response rate in our sample for the survey questions that we utilize is typically below 1%.

[8] We classify educational qualifications as equivalent to an A-Level if they grant access to the tuition-free national university system. This includes *Allgemeine Hochschulreife (Abitur)*, *Fachgebundene Hochschulreife* and *Fachhochschulreife*.

[9] The MZ data contains information on the type of school and grade level attended by all sampled children. Our definition subsumes all students on *Allgemeinbildende Schulen* enrolled in the *Gymnasiale Oberstufe* as well as students from specialized tracks like *Berufliches Gymnasium* or *Fachoberschule* which award an A-Level degree.

[10] The national average failure rate is approximately 3 percent on average for the years 2010–2020. For an overview of the share of children failing the final examination see https://www.kmk.org/dokumentation-statistik/statistik/schulstatistik/abiturnoten.html.

Table 1
Co-residence rate by child age.

Child age	15	16	17	18	19	20	21	22	23
Share living with parents	0.99	0.98	0.97	0.92	0.84	0.72	0.62	0.52	0.44

Notes: This table reports the fraction of individuals which live in the same household as at least one of their parents in the MZ waves 1997 to 2018 by age at observation.

Table 2
Monthly child-related expenditures of single child households.

Category	Total	Education	Health	Food	Culture	Mobility	Other
Top decile	1212	83	113	156	205	85	244
Bottom decile	424	28	11	104	47	29	65
Ratio	2.85	2.96	10.27	1.5	4.36	2.93	3.75

Notes: This table reports estimates of the monthly child-related expenditures in Euro of dual parent, single child households in the top and bottom decile of the German national income distribution for different expenditure categories. The data is reported in the 2018 Income and Consumption Survey (EVS) of the Federal Statistical Agency (Statistisches Bundesamt, 2021).

allows us to capture children that can reasonably be expected to obtain an A-Level degree but rotate out of the survey before they do so. Finally, including younger children disproportionately increases sample size, as younger children are more likely to live with their parents. Table 1 displays the share of children living with at least one parent by age of the child, calculated from our data. Virtually all children younger than 15 still co-reside with at least one parent. However, the share of children living with their parents is decreasing with child age, especially after the legal age of 18. While 92% of the 18 year olds are living with at least one of their parents, this fraction drops to 44% for individuals at the age of 23. In Section 3.3, we discuss how the co-residency and move-out patterns observed in the MZ data affect the interpretation of our results.

Measuring parental background. We measure parental background by a household's self-reported monthly net income, excluding the income of all dependent children. Our income measure covers all sources of income, including labor income, business profits and social security transfers. To account for differences in need and standard of living by household composition, we scale all household incomes by the modified OECD equivalence scale.[11] We then compute the households' percentile ranks in the sample distribution of equivalized household income, and assign each child the rank of their respective household, which we refer to as the parental income rank R_i.[12]

Parental income ranks are a conceptually attractive measure of family circumstances, as the relevance of financial resources and costly enrichment activities for different aspects of child development is widely recognized and there exists empirical evidence of significant disparities in child-related expenditures across the income distribution in Germany. Table 2 reports estimates of monthly child-related expenditures in different categories based on data of the 2018 Income and Consumption Survey (EVS) for dual parent households with single children in the top and bottom decile of the national income distribution. The estimates reveal substantial gaps in monthly expenditures on child-enrichment activities in categories such as education, health as well as culture and leisure activities, suggesting that parental income ranks are a suitable measure of parental background for the construction of mobility statistics in Germany.

The continuous measure of household income provided in the MZ data that we use to compute parental income ranks is not asked for directly in the survey but imputed by the Statistical Office. The survey respondents report their personal income in 24 predefined bins. The Statistical Office then transforms the personal binned income into a continuous variable, essentially randomizing individuals uniformly within each bin. In a second step, these values are summed up to a continuous measure of household income. We discuss potential implications of this procedure for the external validity of our mobility statistics in Section 3.3.

3.2. Mobility statistics

The central building block of all mobility statistics reported in this paper are estimates of the probability of children attaining an A-Level degree conditional on parental income rank $E[Y_i|R_i]$. Following the recent literature, we define two sets of mobility statistics with the aim of distinguishing between two mobility concepts: absolute and relative mobility. While measures of absolute mobility are informative about the level of opportunities for disadvantaged children, relative mobility measures seek to capture differences in opportunities between children of disadvantaged backgrounds relative to those of more advantaged backgrounds.

Absolute mobility. We measure absolute mobility by the probability of obtaining an A-Level degree for a child from the bottom quintile of the parental income distribution:

$$\text{Q1} = E(Y_i|R_i \leq 20). \tag{1}$$

We refer to this estimand as the Q1 measure. A high value of the $Q1$ measure implies high absolute mobility, as it indicates that a large share of disadvantaged children are eligible to enter the university system.

Relative mobility. We define two measures of relative mobility, both concerned with the difference in opportunities between children from low and high-income families. A simple non-parametric measure of relative mobility is the Q5/Q1 ratio:

$$\text{Q5/Q1} = \frac{E(Y_i|R_i > 80)}{E(Y_i|R_i \leq 20)}, \tag{2}$$

which captures the odds ratio of obtaining an A-Level degree for children from the top quintile relative to those in the bottom quintile of the parental income distribution. A high value of the $Q5/Q1$ ratio implies low relative mobility. For example, a ratio of $Q5/Q1 = 2$ means that children from the top quintile of the income distribution are twice as likely to obtain an A-Level degree as children from the bottom quintile of the income distribution.

Next to the $Q5/Q1$ ratio, we also estimate a parametric statistic of relative mobility. As demonstrated in the results section of this paper, the empirical conditional expectation function, $\widehat{E[Y_i|R_i]}$, of our outcome given the parental income rank is close to linear in various partitions of our data. As a consequence, we can approximate the respective conditional expectation function (CEF) by its best linear predictor, which is defined as

$$\theta_{LP} = \arg\min_{\theta} E[(Y_i - Z_i'\theta)^2],$$

with $Z_i = (1, R_i)'$ and $\theta = (\alpha, \beta)$. In practice, we estimate the model parameters by running an OLS regression of our outcome indicator on the parental income rank variable. The slope coefficient β measures the gap in the probability of obtaining an A-Level between children at the top and the bottom of the income distribution. We refer to the slope coefficient as the *parental income gradient* and report estimates of $\beta\times100$, which captures the gap in percentage points, for improved readability. While the Q5/Q1 ratio measures the relative outcome difference between children at the top and the bottom of the income distribution, the parental income gradient characterizes the absolute outcome difference and is therefore not sensitive to the baseline probability of obtaining an A-Level in the underlying population of interest.

[11] Figure B.2 demonstrates that the choice of the scaling factor is not influential for our results at the aggregate level. However, the empirical conditional expectation function of our A-Level indicator can be better approximated linearly when computing ranks based on equivalized incomes.

[12] In Appendix A we provide information on the sample income distributions and details on the construction of the rank variable.

Table 3
Average characteristics of children by age of observation.

Child age	Share female	Mean parental Inc. (Equiv.)	Parental Inc. rank	Share parents with A-Level
17	0.49	1367	50	0.33
18	0.48	1367	50	0.32
19	0.47	1367	50	0.32
20	0.44	1359	50	0.31
21	0.42	1360	50	0.31

Notes: This table reports average attributes of children in the MZ waves 1997 to 2018 that are observed in the same household as at least one of their parents by age of observation. The ranks are computed based upon the sample distribution of equivalized household income as described in Section 3.3.

Note that both of our measures of relative mobility are relative only in the sense that parental income is measured in ranks, whereas opportunities of children are measured with the A-Level degree, which is an absolute, rather than relative outcome.

3.3. Sample definition and limitations

We use the MZ survey waves from 1997 to 2018, for which a consistent definition of all relevant variables is available. For our national and regional estimates, we restrict our sample to the survey waves 2011–2018 (231,000 children) to produce recent mobility statistics and avoid ambiguities caused by a series of administrative reforms that changed county boundaries. The mobility statistics by birth cohort reported in Section 4.2 are computed based on the 1980–1996 birth cohorts (526,000 children).

Our primary sample contains all children aged 17–21 which are observed in the same single-family household as at least one of their parents. The age range is chosen to balance the following trade-off: For older children, our outcome is measured more precisely, i.e. we do not need to rely on upper-stage enrollment but are more likely to observe the completed degree. At the same time, the fraction of children in our sample that has already moved out of the parental household, and thus cannot be matched to their parents, increases with age, which guides our choice for the upper bound. The lower bound is chosen as children enrolled in the upper stage of an A-Level track are typically at least 17 years old. In the following, we discuss potential concerns regarding the external validity of our mobility estimates.

Sample selection. An immediate concern caused by the observed move-out patterns in the MZ data relates to the representativeness of our sample. If the observed move-out decisions were systematically related to both parental income and the educational attainment of children, the external validity of our estimates would be undermined as our statistics would not measure social mobility in the population of interest. While we acknowledge that dependencies of this type are generally plausible, we do not find evidence of sample selection in our data. Table 3 documents how time-constant characteristics of the children in our sample change with the age at observation. If move-out were to occur randomly, we should not see systematic changes in these statistics for older children for which the co-residency rate is lower. While move-out varies with social characteristics like gender, the average parental income and the associated income rank of children in the age range 17–21 are essentially constant. In addition, we can exploit the partial panel dimension of the MZ to investigate selection patterns more directly. Fig. 1 displays the share of observed move-outs of children by parental income rank for the subsample of households in our data that is observed in the survey in multiple years. It shows that move-outs occur near uniformly across the income distribution and are thus uncorrelated with parental income rank. Both exercises suggest that sample selection is not a major concern for our analysis. In addition, we demonstrate in the next section that choosing alternative age ranges barely affects our results.

Standard errors. The standard errors reported alongside our estimates in the results section of this paper abstract from the fact that we estimate the cutoffs defining the percentile ranks. For the parental income gradient as well as the Q1 and Q5 measure, we cluster standard errors at the level of the sampling district, the primary sampling unit of the MZ. For the Q5/Q1 ratio, we report plug-in standard errors based on a delta-method argument.[13]

4. National estimates

We begin our empirical analysis by characterizing social mobility at the national level. Fig. 2 shows the share of children with an A-Level degree by parental income rank in our data, as well as the best linear approximation to the empirical CEF. As can be seen, a linear model provides a reasonable approximation to the CEF, a regularity that we observe in essentially all considered partitions of our data. In the national data, we estimate the parental income gradient at $\beta \times 100 = 0.52$, implying a gap of roughly 50% in the probability of obtaining an A-Level degree between children from the top and the bottom of the income distribution.[14] Our measure of absolute mobility in the national data suggests that one third of children from the bottom quintile of the income distribution complete an A-Level degree, with Q1 estimated at 0.34. Both parametric and non-parametric mobility statistics imply that the odds ratio in the probability of obtaining an A-Level degree between children from the top quintile relative to the bottom quintile is greater than 2, with Q5/Q1 estimated at 2.25.[15]

Do these estimates depict Germany as a country of high or low relative mobility? While a cross-country comparison of our results is not straightforward, as the German system of upper secondary education and university funding is unusual, we are aware of two US studies which report comparable mobility statistics. Using data from the Census 2000, Hilger (2015) reports a parental income rank gradient of 3.6 percentage points in attending college for children aged 19–21. A higher point estimate is reported in Chetty et al. (2014), who estimate the rank gradient in college enrollment at 6.7 percentage points for children aged 18–21 based on tax registry data. Under the assumption that college enrollment conditional on having obtained an A-Level degree is weakly increasing in parental income rank, our estimate of 5.2 percentage points implies a college enrollment gradient that falls into the range of point estimates reported for the US. Abstracting from differences in the distributions of college quality and the selection of students of different parental backgrounds into colleges of different quality, our estimates suggest that educational mobility in Germany is similar to the US. We consider this finding noteworthy, as (after tax) income inequality is more pronounced in the US than in Germany, suggesting that one could expect steeper rank gradients in the US.[16]

[13] The MZ data allows for consistent identification of primary sampling units across waves following the 2011 survey. For the estimates in Section 4.2, where we also use prior waves, we instead cluster standard errors at the household level. For the delta method, we linearize the ratio of averages which yields the following approximation for the variance of the sampling distribution of the $\overline{Q5}/\overline{Q1}$ sample ratio: $V(\overline{Q5}/\overline{Q1}) \approx \frac{1}{(Q1)^2}\left(V(\overline{Q5}) + \left[\frac{Q5}{Q1}\right]^2 V(\overline{Q1}) - 2\frac{Q5}{Q1}Cov(\overline{Q5},\overline{Q1})\right)$.

[14] For the national estimates, we pool our data over the period 2011–2018 to ensure consistency with the regional estimates in Section 5, for which obtaining results before 2011 is difficult due to frequent reforms of local administrative boundaries.

[15] Appendix Table B.1 summarizes the estimates and shows that they are robust to variations in the age restriction defining our sample. Furthermore, results are unchanged when averaging parental income over several years before assigning the ranks, strongly suggesting that transitory income shocks in parental income do not bias our estimates.

[16] Rauh (2017), for example, finds a negative correlation between inequality and public education expenditures across countries. If public education expenditures benefit lower-income children more, one expects a steeper rank gradient in the US. Our results do not support this conclusion.

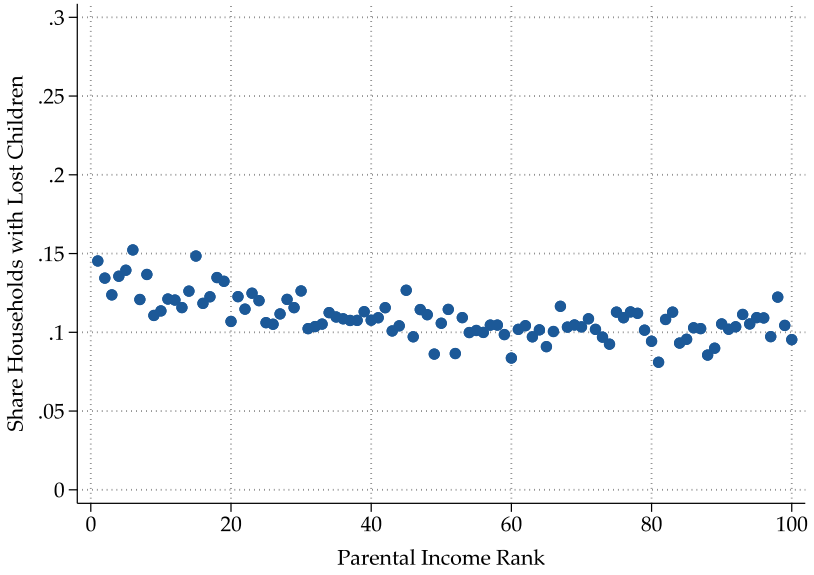


Fig. 1. Move-out frequency by parental income rank. *Notes:* This figure shows the relative frequency of move-outs of children aged 17–20 by parental income rank. It is computed based on a sample of 265,229 children in the years 2012–2018 where we observe the partial panel dimension of the MZ and can identify households surveyed for more than one wave. We define households with "lost children" as households which report a lower number of children aged 17–20 than in the previous year.

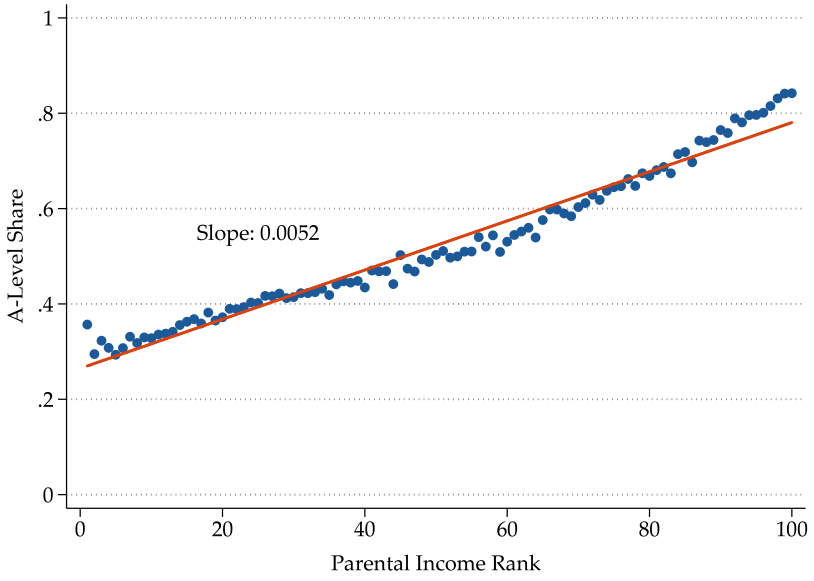


Fig. 2. Social mobility at the national level. *Notes:* This figure shows the fraction of children aged 17–21 that are either enrolled in the upper stage of an A-Level track or have already attained an A-Level degree by percentile rank of their parents in the national income distribution for the MZ waves 2011–2018. The income ranks are computed with respect to the national income distribution of households with children aged 17–21 in each survey year. The reported slope coefficient of 0.0052 (SE 0.004) is estimated by OLS using the underlying micro data.

The similar gradients between parental income and higher education in Germany and the US could imply two different things with respect to the transmission of income from parents to their children. On the one hand, intergenerational income mobility in Germany might be similarly low as in the US. On the other hand, the gradient between own and parental income in Germany could be less steep than the gradient between the A-level and parental income.[17]

To shed light on this question, we compute measures of intergenerational income mobility in the German Socio-economic Panel (SOEP), and compare them to the US and Denmark, two countries with recent available estimates and typically viewed at opposing ends of income mobility among high income countries. We use the studies by Chetty et al. (2014) and Helsø (2021) as comparisons. Both focus on child incomes early in the lifecycle around age 30. To ensure comparability, we restrict the income observation window to ages 29–33.[18] Parental income is measured as gross family income, child income either as

[17] Compare, for example, the insights from Landersø and Heckman (2017), who find that Denmark, a society that is characterized by high levels of income mobility, is similar to the US in terms of measures of educational social mobility.

[18] We can only cover around half of the cohorts included in the main analysis, since for the younger ones we do not observe earnings at age 29–33

Table 4
Intergenerational income mobility in the US, Denmark and Germany.

Child income	Parental income	Estimand	US	DK	DE
Individual labor earnings (excl. 0)	Gross family income	IGE	–	–	0.276 (0.052)
Gross family income	Gross family income	IGE	0.344 (0.000)	0.171 (0.004)	0.278[a] (0.057) 0.360[b] (0.080)
Individual labor earnings (excl. 0)	Gross family income	Rank-rank	0.282 (0.000)	0.223 (0.003)	0.341 (0.037)
Gross family income	Gross family income	Rank-rank	0.341 (0.000)	0.203 (0.003)	0.320[a] (0.039) 0.354[b] (0.043)

Notes: This table shows estimates of intergenerational elasticities (IGE) and rank-rank slopes of intergenerational income mobility in the US and Germany (DE). The US estimates are taken from Table I in Chetty et al. (2014), the estimates for Denmark from Table 1 in Helsø (2021). The German estimates are own calculations based on the SOEP. To ensure the highest possible degree of comparability between estimates, the German sample is restricted to children between 29–33 years old, and parental income is measured when children are 15–19 years olds. The sample sizes underlying the German estimates range from 834 to 1041 individuals, depending on the specification. Robust standard errors in parentheses.

[a] Indicates that *child* family income is measured as the sum of individual labor earnings of the child and its cohabiting partner (excluding zero incomes).

[b] Indicates that child family income is measured as gross household income among all children are no longer cohabiting with their parents.

individual labor earnings or as gross family income.[19] Our analysis is then limited in sample size with around 800 to 1000 linked parent–child pairs. Somewhat reassuringly, as shown in Appendix Figure C.1, the gradient between obtaining an A-Level degree and parental income rank in the SOEP is estimated at 0.52, which is the same number we obtain in our main estimates based on the MZ.

Table 4 shows the results for estimated income mobility. We consider both, rank-rank coefficients and the IGE. The estimates based on the SOEP suggest that income persistence in Germany and the US is similar.[20] Remarkably, the estimates for Germany are outside the confidence bands of the reported numbers for Denmark. As such, we find no evidence that Germany should be considered as having high levels of income mobility, as observed in the Scandinavian countries. If anything, the estimates suggest similar magnitudes as for the US comparing similar age cohorts.[21] In light of the strong sample size limitations encountered in the German Socio-Economic Panel, we now shift the focus back to the examination of social mobility patterns within the MZ data. This offers the most robust and reliable assessment of social mobility in Germany.

4.1. Subgroup estimates

A natural question to ask is whether the national estimates mask meaningful differences in mobility measures across subpopulations. We focus on selected subgroups typically emphasized in the analysis of social mobility. Next to parental income, parental education is the second main measure of socio-economic background in the literature. We are therefore interested in the change of our mobility measures when conditioning on A-level degrees in the parental household. As intergenerational transmission mechanisms are further dependent on the family structure, we split by gender, parenting status (i.e. whether the child grew up with one or both parents in the household), the number of siblings, and the birth order. Our measurement approach is in particular suited to study how mobility varies between men and women, as our outcome measure is not affected by differential labor market participation, which complicates the analysis of gender differences in intergenerational income mobility. Specific to Germany, we want to additionally distinguish mobility between the eastern and western part of the country, which still differ widely in many socio-economic characteristics 30 years after the reunification. Finally, we focus on migration status, since we know that mobility patterns can differ substantially between migrants and natives (e.g. Abramitzky et al., 2021).

Table 5 reports mobility statistics separately for these groups. We document several interesting patterns. Most importantly, we find substantial differences by parental education. Fig. 3 displays the A-Level share of children by parental income rank and the associated parental income gradient separately for children from households where no parent has an A-Level degree and for children from households where at least one parent has an A-Level degree. The A-Level share among children of parents without an A-Level degree at the top of the income distribution is comparable to the A-Level share among children with at least one A-Level educated parent at the bottom of the income distribution. Roughly speaking, the empirical distribution for children of A-Level educated parents is shifted upwards by approximately 30 percentage points, uniformly across ranks. The conditional rank gradients are attenuated due to the positive correlation between parental education and income ranks, with point estimates of approximately 0.3 in both groups. The intergenerational correlation in A-Level attainment in our data is 0.54. This finding highlights that the interpretability advantages of income-only based measures of parental background come at the cost of missing observable attributes of households that could be used to characterize social mobility more comprehensively.

The estimates reported in Table 5 reveal a few more interesting discrepancies. At the bottom of the income distribution, females and children with migration background are approximately 11 and 4 percentage points more likely to obtain an A-Level degree than their respective male and native counterparts. While the gender-gap is close to constant across the income distribution, the difference between migrant and native children vanishes in the top quintile. Moreover, we document larger income rank gradients for children of married and cohabiting couples, as well as for natives and children living in East Germany. The East-West gap in parental income gradients is 0.1, implying a 10 percentage points larger top-bottom gap in the probability of attaining an A-Level degree in East Germany as compared to West Germany. We investigate such regional patterns in more detail in Section 5.

4.2. Time trends

We next ask how social mobility has evolved over time. While our descriptive approach does not allow us to attribute changes in mobility

yet. More information on sample restrictions and some descriptive evidence is disclosed in Appendix C.1.

[19] The reason why we use two different child income definitions is as follows. More than 20% of the children in our linked parent–child sample are still living in the parental household at the age of 29–33. We address this with two alternative approaches. First, we drop all cohabiting children from our sample. Second, we compute child family income as the sum of individual labor earnings of the child and its cohabiting partner, missing out on non-labor income since this is only measured at the household level. The first approach has the advantage to account for other sources of income than labor income, the second one the advantage to avoid sample selection.

[20] The association between individual earnings rank and parental income is actually higher in Germany, while the comparison of the association between child and parent family income depends on the way we measure family income of children.

[21] Our analysis updates previous work by Bratberg et al. (2017) with the SOEP, which focuses on cohorts around 20 years older (birth years 1956–1976). Their study finds income mobility in Germany to be more comparable to Scandinavia, suggesting a decline in income mobility compared to the birth cohorts preceding our sample. Closer investigation of these trends has to be left for future research, however, as it would require different data sources and much larger sample sizes than currently available.

Table 5
Mobility statistics for subgroups.

		Gradient	Q1	Q5	Q5/Q1	A-Level	N
Parental education	No A-Level	0.33 (0.006)	0.28 (0.003)	0.55 (0.006)	1.94 (0.028)	0.39	145,892
	A-Level	0.29 (0.007)	0.61 (0.007)	0.84 (0.003)	1.36 (0.016)	0.75	85,080
Parenting status	Single parent	0.50 (0.010)	0.34 (0.004)	0.72 (0.009)	2.13 (0.037)	0.47	50,622
	Two parents	0.54 (0.005)	0.34 (0.004)	0.76 (0.003)	2.26 (0.027)	0.54	179,715
Parents married	Not married	0.46 (0.010)	0.33 (0.004)	0.69 (0.008)	2.12 (0.037)	0.47	51,018
	Married	0.54 (0.005)	0.35 (0.004)	0.77 (0.003)	2.22 (0.025)	0.54	172,999
Gender	Male	0.53 (0.006)	0.29 (0.004)	0.72 (0.004)	2.49 (0.033)	0.47	123,649
	Female	0.50 (0.006)	0.40 (0.004)	0.81 (0.003)	2.02 (0.023)	0.58	107,323
Migration status	Native	0.55 (0.005)	0.32 (0.004)	0.76 (0.003)	2.35 (0.028)	0.54	164,018
	Migrant	0.47 (0.009)	0.36 (0.004)	0.75 (0.007)	2.11 (0.032)	0.48	60,908
Region	West	0.50 (0.005)	0.34 (0.003)	0.76 (0.003)	2.19 (0.022)	0.52	201,684
	East	0.60 (0.011)	0.31 (0.007)	0.80 (0.007)	2.61 (0.062)	0.51	29,288
Siblings	Yes	0.55 (0.005)	0.35 (0.003)	0.79 (0.003)	2.29 (0.024)	0.52	156,960
	No	0.49 (0.007)	0.32 (0.005)	0.72 (0.004)	2.27 (0.039)	0.52	74,012
Birth order	1st child	0.51 (0.005)	0.34 (0.003)	0.76 (0.003)	2.22 (0.023)	0.53	165,336
	2nd child	0.52 (0.008)	0.34 (0.005)	0.77 (0.005)	2.27 (0.036)	0.51	56,996
	Later child	0.57 (0.021)	0.31 (0.009)	0.78 (0.017)	2.48 (0.092)	0.45	8640

Notes: This table reports mobility statistics for selected groups of children observed in the MZ survey waves 2011–2018. The gradient measures the gap in the probability of obtaining an A-Level between children at the top and the bottom of the parental income distribution. Q1 and Q5 denote the share of children obtaining an A-Level in the first and fifth quintile of parental income; Q5/Q1 is the ratio between both measures. Migration background subsumes all individuals who immigrated to Germany after 1949, as well as all foreigners born in Germany and all individuals born in Germany with at least one parent who immigrated after 1949 or was born in Germany as a foreigner. The standard errors reported in parentheses below each point estimate are computed as described in Section 3.3.

measures to specific policies, our measurement strategy enables us to provide novel evidence on the evolution of social mobility in Germany for relatively recent birth cohorts. The period we study is particularly interesting, as it covers the second half of the arguably most significant educational reform in post-war Germany, the *Bildungsexpansion*, a large-scale policy of expanding upper secondary and higher education that, starting in the early 1970s, increased the A-Level share from around 20% to approximately 50% for the birth cohorts since the mid 1990s. This expansion was a policy response to a heated public debate on social mobility (Dahrendorf, 1966) and the increasing importance of education for economic growth at the time (Picht, 1964; Hadjar and Becker, 2006). We ask whether the large-scale expansion of upper-secondary education in Germany was accompanied by changes in social mobility as defined by our mobility measures.

To this end, we focus on a sample of 526,000 children born between 1980–1996.[22] At the time of writing, the children of the respective birth cohorts are 25–40 years old and constitute a significant part of the German working population. Including relatively young cohorts in our analysis is feasible, as, in contrast to traditional measures that rely on the labor market incomes of children, our education-based measure of opportunities does not suffer from life-cycle biases. Fig. 4 depicts the evolution of the A-Level share among 17–21 year old children in the MZ data for the birth cohorts under consideration. Our data covers roughly the second half of the expansion, with an observed increase in the A-Level share of 14 percentage points from 39% for the 1980 birth cohort to 53% for children born in 1996.[23] At the same time, income inequality increased only moderately,[24] and we do not find evidence that the expansion was accompanied by a decline in annually measured A-Level wage premia, as documented in Appendix Figure B.1. However, as the children under consideration have only partially entered the labor market even today, we note that with the currently available data it is not possible to rule out that the A-Level premium may eventually differ for these cohorts. Furthermore, the counterfactual development of the A-Level wage premium in absence of the *Bildungsexpansion* is inherently unobserved.

[22] We restrict our attention to these cohorts to rule out that our estimates are affected by differences in the distribution of age at measurement. For the considered cohorts, the share of 17, 18-, 19-, 20- and 21-year-olds in our data is constant.

[23] The *Bildungsexpansion* featured a parallel increase of tertiary education and did not decrease the share of A-Level graduates taking up university studies. In the years 2002–2015, where most of our birth cohorts graduate, it fluctuated around 70% (https://www.datenportalbmbf.de/portal/de/Tabelle-2.5.74.html).

[24] While wage inequality rose in the 1990s and early 2000s when most children in our sample grew up, Fuchs-Schündeln et al. (2010) document that inequality in consumption and disposable income, the income concept used in this paper, increased only moderately.

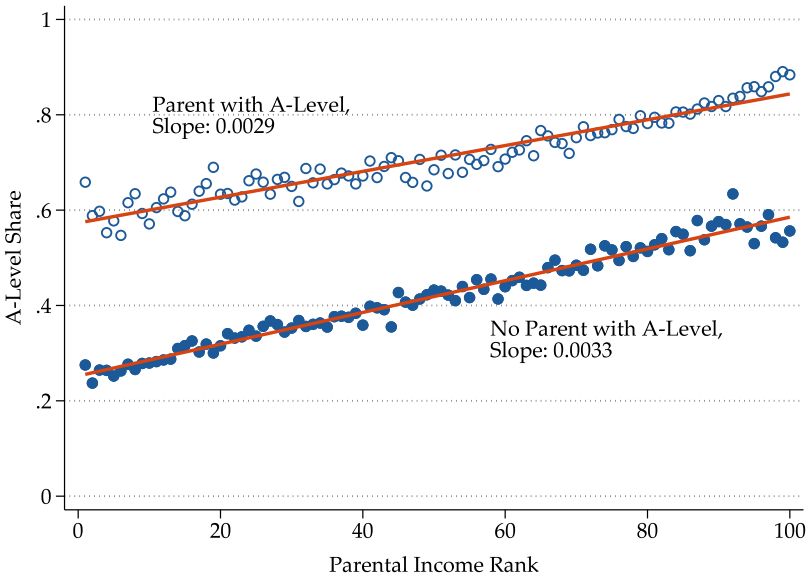


Fig. 3. Differences by parental education. *Notes:* This figure shows the fraction of children aged 17–21 observed in the MZ survey waves 2011–2018 that are either enrolled in the upper stage of an A-Level track or have already attained an A-Level degree by parental income rank, separately for children of parents who have not obtained an A-Level degree and children of parents where at least one of the parents has obtained an A-Level degree. The ranks are computed based upon the sample distribution of equivalized household income as described in Section 3.3. The reported estimates of the parental income gradient are based on the underlying micro data. Standard errors are reported in the first panel of Table 5.

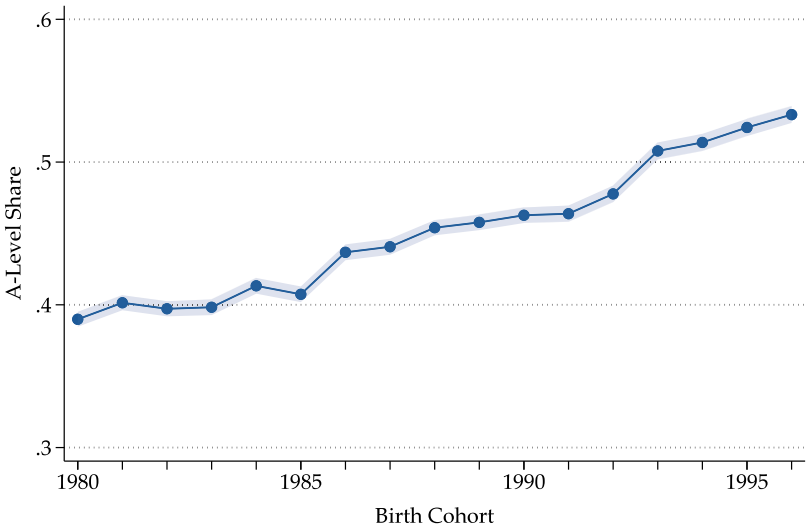


Fig. 4. A-Level share by cohort. *Notes:* This figure shows the fraction of children born between 1980 and 1996 and observed at ages 17–21 that are either enrolled in the upper stage of an A-Level track or attained an A-Level degree in the MZ data. The shaded area displays pointwise 95% confidence intervals based on standard errors as described in Section 3.3.

Figs. 5 and 6 display estimates of our mobility measures for the same cohorts. While the odds ratio captured by the Q5/Q1 ratio decreased by approximately one third, from around 3 for the 1980 birth cohort to slightly above 2 for the 1996 cohort, the parental income gradient has remained constant at around 0.52, the point estimate that we report at the national level based on more recent data. At the same time, absolute mobility as measured by the Q1 measure increased substantially, from approximately 0.22 in 1980 to 0.35 in 1996. The same overall pattern emerges when estimating mobility trends for the subgroups studied in Section 4.1 as reported in Figures B.4 and B.5 in the Appendix.

The connection between these findings is best summarized in Fig. 7, which depicts the A-Level share by quintile across birth cohorts: The *Bildunsexpansion* took place uniformly across the income distribution, with increases of about 14 percentage points in the A-Level share in all parts of the distribution. Did the *Bildunsexpansion* achieve its goal of fostering social mobility in Germany? While the expansion unquestionably increased absolute mobility as we measure it, the time trend in relative mobility is less straightforward to interpret. On the one hand, the attenuation of the Q5/Q1 ratio caused by the uniform increases in A-Level shares could suggest an increase in relative mobility according to a proportional notion of the concept. On the other hand, a less optimistic angle to interpret the same development is to consider the inverse odds ratio, that is the ratio between the probability *not* to obtain an A-Level for children in both quintiles. In the birth cohort 1980, children in Q1 were 2.2 times more likely not to obtain an A-Level degree than children in Q5. For children born in 1996, this inverse odds ratio has increased to 2.8, meaning that the relative gap in not obtaining an A-Level has actually widened. In contrast, the unaltered top-bottom gap in the probability of attaining an A-Level captured by the parental income gradient emphasizes stagnation in absolute differences. As the parental income gradient is insensitive to

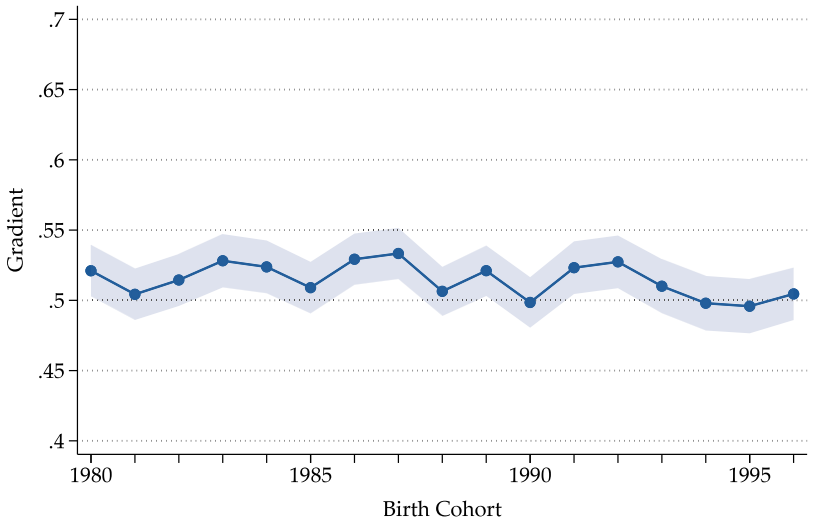


Fig. 5. Parental income gradient by cohort. *Notes:* This figure shows for children aged 17–21 the evolution of the parental income gradient by birth cohort. The shaded area displays pointwise 95% confidence intervals based on standard errors as described in Section 3.3.

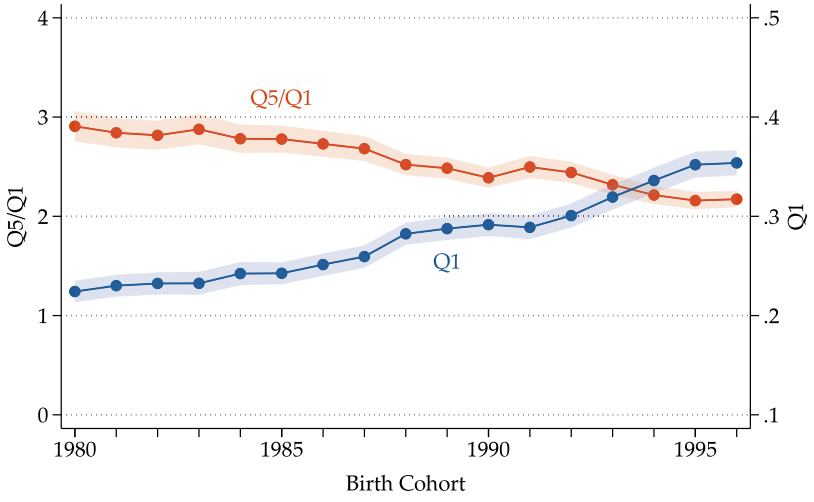


Fig. 6. Quintile measures by cohort. *Notes:* This figure shows for children aged 17–21 the evolution of the quintile based measures of social mobility by birth cohort. While the left axis corresponds to the Q5/Q1 ratio, the right axis corresponds to the Q1 measure. The shaded areas display pointwise 95% confidence intervals based on standard errors as described in Section 3.3.

the chosen reference point, we tend to interpret the evidence primarily as a stagnation of relative mobility. However, as both absolute and relative disparities often form the normative basis for interventions, all readings can be justified.

Trends in ability and selection patterns by parental income. An interesting question concerns the selection of students who were marginal with respect to the *Bildungsexpansion* policy — meaning they would not have entered the A-level track without this education expansion. If marginal students from low income families are more talented than marginal children from high income families, this could suggest that the school system itself discriminates against children from disadvantaged backgrounds at the costs of overall efficiency of the system and that the *Bildungsexpansion* was partially a remedy in that respect.

We turn to an additional data source to obtain measures of ability for the cohorts in question. The well-known Programme for International Student Assessment (PISA) administered by the OECD provides test scores at age 15. It is generally accepted as a measure which displays a high correlation with e.g. IQ tests and other skill assessments (e.g. Rindermann, 2007; Pokropek et al., 2022). It only covers the more recent birth cohorts 1990–1996 considered in our paper because parental income is only collected since the 2006 PISA wave. To complement this, we employ the German Socio-Economic Panel (SOEP), which has annually collected school grades at age 17 for the birth cohorts 1982–1996. While the SOEP does not offer test-score data, it contains information about grades. Following the literature in the economics of education (e.g. Hanushek et al., 2022; Gneezy et al., 2019; Jensen and Rasmussen, 2011; Brunello and Rocco, 2013), we use grades and test scores in math to obtain an ability proxy which can be compared consistently across social groups.[25]

Fig. 8 shows time trends of averaged grades (Panel B) and test scores (Panel A) for students attending the highest school track. The red line refers to above- and the blue line to below-median parental income.[26] Both measures suggest a slight deterioration of test scores and grades over time for both parental income groups.

The interesting question is about the differences in test scores and grades for marginal students from high versus low parental income.

[25] We obtain similar but slightly noisier results when averaging over all available grade and test score information. In the SOEP, this additionally includes grades in German and the first foreign language, in PISA test scores for German and "Science".

[26] The sample sizes do not permit finer parental income splits, unfortunately.

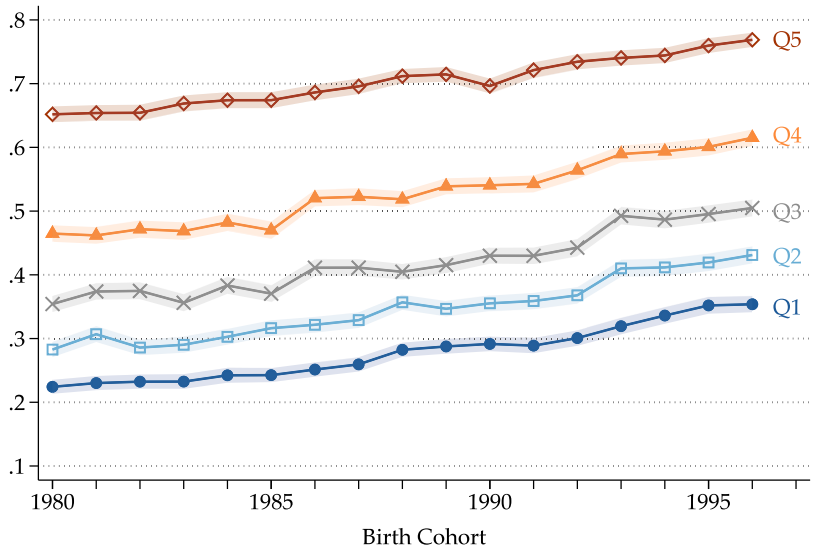
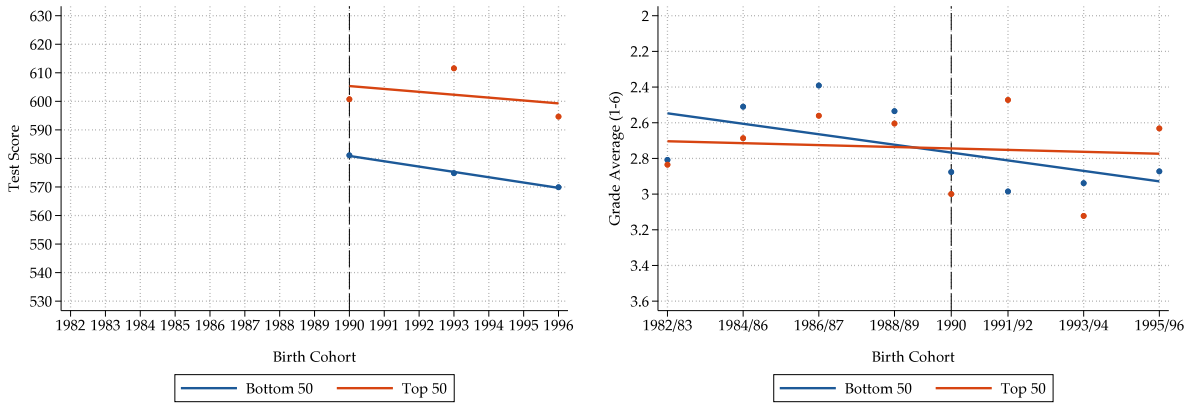


Fig. 7. A-Level share by cohort quintile. *Notes:* This figure shows the share of children born between 1980 and 1996 who obtained an A-Level degree by birth cohort and quintile of the parental income distribution in the MZ data. The shaded area displays pointwise 95% confidence intervals based on standard errors as described in Section 3.3.



(A) Test Scores PISA (B) Grade Average SOEP

Fig. 8. Time trend math grades and test scores. *Notes:* The figure shows averages math grades in the German Socio-Economic Panel (SOEP) in Panel (A), and average math test scores in the PISA-I data in Panel (B) by birth cohort. Math performance increases in PISA test scores, and decreases in SOEP grades, which range from 6 (worst) to 1 (best). The lines show the corresponding linear OLS fits. The PISA-I sample includes around 1000 15-year old students on gymnasium and the gymnasialzug of gesamthochschulen per cohort, the SOEP sample covers 1061 children in total. Additional information on the underlying data is disclosed in Appendix C.

Marginal here refers to these students who only entered the highest track because of the educational expansion and the increase in the number of students in the highest track. Since "being marginal" is, naturally, an unobservable state, we present two different ways to make assumptions that enable us to learn about ability differences between marginal students of both parental income groups. First, we assume that test scores (and grades) have no trend for inframarginal students, such that the changes seen in Fig. 8 can be attributed to entering marginal students. Appendix C.3 shows how, under this assumption, the ability for marginal students from both parental income groups can be inferred in a straightforward way by accounting for the increase of students in each group. In a second approach, we conduct a prediction exercise based on observables of children and parents to classify students as inframarginal. Then we consider how grades/test scores changed over time for students with those observables and impose these trends on inframarginal students. This procedure is described and results are shown in C.3. Although the assumptions behind the two approaches are rather different, they yield consistent results.

Table 6 shows the results of the first exercise. According to the PISA data, marginal children among birth cohorts 1990 to 1996 from the bottom half of the income distribution displayed lower test scores than marginal children from the top 50%. The difference of 21 test points corresponds to 31% of a standard deviation. For the same birth cohorts, the grade averages obtained in the SOEP data also suggest higher ability among marginal children from the upper half of the income distribution. This pattern is also there for older birth cohorts. Results are similar for the second approach. In Appendix C.3, we report that for the early birth cohorts (82–90) there is a small advantage for lower income students. However, for later cohorts (90–96) this reverses and the evidence suggest more favorable test scores and grades for high income students.

Summing up, over the whole period considered (birth cohorts 1982 to 1996), there is no evidence that marginal students with below-median parental income perform better than marginal students with above-median parental income. There is some evidence, however, that among the more recent cohorts (1990–1996) test scores and grades for

Table 6
Math grades and test scores of marginal children.

	SOEP			PISA		
	Bottom 50	Top 50	Δ	Bottom 50	Top 50	Δ
1982–1990	2.9	2.5	0.45 SD	–	–	–
1990–1996	3.5	2.6	0.84 SD	552	573	0.31 SD
1982–1996	3.1	2.6	0.54 SD	–	–	–

Notes: This table shows the average math grades in the German Socio-Economic Panel (SOEP) and the average PISA math test scores among "marginal" children in birth cohorts 1982, 1990 and 1996, separately for children below and above median parental income. The grades are computed using Equation 4 in Appendix C.3, which also contains more details about the calculation. The third column expresses the differences between both groups in terms of the standard deviations, which is 1.06 for math grades in the SOEP, and 69 points for PISA test scores. Due to the small sample size of the SOEP, three year averages around the actual birth cohort are used to compute grade averages (1982: 1982–1984, 1990: 1989–1991, 1996: 1994–1996).

marginal students from higher parental income backgrounds are better compared to lower parental income backgrounds.

5. Regional estimates

An interesting regularity documented in the recent empirical literature on social mobility is that there exists substantial geographic variation in social mobility measures within politically homogeneous entities, suggesting that regional comparisons can be used to gain a better understanding of the causes of social mobility (e.g. Chetty et al., 2014; Acciari et al., 2022; Corak, 2020; Deutscher and Mazumder, 2020; Chuard and Grassi, 2020). This idea is appealing, as attributing cross-country discrepancies in social mobility to differences in single characteristics or policies is difficult to justify. Complementary to well-designed evaluations of political reforms that rely on variation across time (e.g. Bertrand et al., 2021), within-country geographic variation can be helpful in understanding the causal mechanisms fostering or impeding social mobility by identifying exposure effects (Chetty and Hendren, 2018; Bütikofer and Peri, 2021). Moreover, pronounced regional differences can suggest mechanisms that warrant investigation.

The regional analysis conducted in this section is motivated by these considerations. In a first step, we present evidence of meaningful geographic variation in our mobility measures across regions in Germany. In a second step, we then ask what we can learn from the observed differences. We structure our regional analysis by disaggregating our data in a stepwise fashion, lending credence to our parametric mobility statistics while taking into account the political and economic landscape of Germany.

5.1. States

A natural starting point for our regional analysis are the 16 federal states of Germany. By constitutional law, the responsibility for the design and implementation of the education system falls under the jurisdiction of the German states and not under the jurisdiction of the federal government. As a consequence, the states have considerable discretion in the design of their education systems, leading to distinctions in the rigor of the tracking system, the capacities of each track, the types of schools and curricula and other important features of the education system.

In particular, states differ with respect to the duration of primary school after which all children are allocated into the different tracks, the number of tracks (2 or 3) and the importance of teacher recommendations for admitted track choices. While in all states teachers recommend a track for each child at the end of primary school, track recommendations are binding only in some states. These parameters of the state education systems and their suspected consequences for social mobility are often at the center of the public debate on educational mobility in Germany.

Table 7 reports our mobility estimates for the 16 states, sorted by the point estimate of the parental income gradient in ascending order. We document significant and economically meaningful differences in both absolute and relative mobility measures between states. For example, the top-bottom gap in the probability of attaining an A-Level degree is approximately 20 percentage points larger in Bremen than in Hamburg, two city states in north-west Germany approximately 100 km apart. Similarly, the share of children obtaining an A-Level degree from the bottom quintile of the parental income distribution is 10 percentage points larger in Baden-Württemberg than in Bavaria, the two southernmost states of Germany. The estimated differences between states do not result from differences in the shape of the empirical CEFs, as we find that the linearity assumption underlying our parametric mobility estimates is supported by the data (compare Figure B.6). The table also reiterates the east–west gap documented in Section 4.1: except for Bremen, the least mobile states are all located in East Germany.

While we find that the differences in our measure of absolute mobility can be well explained by differences in the states' A-Level shares, that is the relative capacity of the highest track, there is no clear pattern in our estimates with respect to the aforementioned characteristics of the state education systems displayed in the last two columns of the table. Our findings suggest that, while certainly important, the design of the tracking system cannot readily explain the pronounced differences in our mobility measures between states.

5.2. Cities

A similar picture emerges when we restrict our analysis to urban regions of Germany. Table 8 reports our mobility estimates for the 15 largest labor markets of Germany, consisting of cities and their catchment areas as defined by commuting flows.

Compared to the national average, the largest urban regions of Germany show lower levels of relative, but higher levels of absolute social mobility. At the same time, the table shows that the regional differences observed at the state-level can also be found within states. For example, the top-bottom gap is approximately 8 percentage points larger in Cologne than in Düsseldorf, two large cities in North Rhine-Westphalia located approximately 40 km apart. Similarly, our estimates of absolute mobility differ by 8 percentage points between Nuremberg and Munich, two large cities in Bavaria.

The most striking discrepancy between cities in our data is observed for Hamburg and Leipzig, with a difference of approximately 20 percentage points in the estimated top-bottom gap, as well as 15 percentage points in our estimate of the Q1 measure. Fig. 9 displays our raw data for the two cities. Similar to the previously considered partitions of our data, we show in Figure B.7 that the empirical CEFs are well approximated by a linear function. Overall, our city-level findings suggest that the relative opportunities of children can differ meaningfully across politically similar and geographically close regions of Germany.[27]

5.3. Local labor markets

We finally disaggregate our data once more to the level of local labor markets (LLMs). The 258 LLMs in Germany represent aggregations of counties based on commuting flows, comparable to the commuting zones in the US. Except for five local labor markets (Bremen, Bremerhaven, Hamburg, Mannheim and Ulm), all counties aggregated into LLMs belong to a single state. The median number of children in our sample (observations) per LLM is 552 (mean: 895). The lowest number of observations across all LLMs is 100 (LLM Sonneberg) and the largest number of observations is 8159 (LLM Stuttgart).

[27] What cannot be inferred from Table 8 is the individual rank of each city. To obtain valid inference on rankings in terms of the parental income gradient or other mobility statistics, it is necessary to apply the methods developed in Mogstad et al. (2024).

Table 7
Social mobility at the state level.

State	Gradient	Q1	Q5	Q5/Q1	A-Level share	Tracks	Binding Rec.
Hamburg	0.45 (0.033)	0.43 (0.023)	0.80 (0.017)	1.86 (0.109)	0.60	2	No
Rhineland-Palatinate	0.50 (0.019)	0.36 (0.013)	0.76 (0.011)	2.12 (0.086)	0.53	2	No
North Rhine-Westphalia	0.51 (0.009)	0.41 (0.006)	0.82 (0.005)	2.02 (0.032)	0.59	3	Ref
Hesse	0.52 (0.015)	0.39 (0.011)	0.81 (0.007)	2.07 (0.061)	0.59	3	Ref
Baden-Württemberg	0.52 (0.011)	0.34 (0.008)	0.76 (0.006)	2.24 (0.056)	0.53	3	Ref
Saarland	0.53 (0.040)	0.33 (0.024)	0.74 (0.025)	2.28 (0.186)	0.54	2	Ref
Schleswig-Holstein	0.53 (0.023)	0.32 (0.015)	0.76 (0.014)	2.34 (0.117)	0.52	2	No
Lower Saxony	0.54 (0.013)	0.29 (0.008)	0.73 (0.009)	2.52 (0.077)	0.48	3	Ref
Bavaria	0.54 (0.011)	0.24 (0.007)	0.67 (0.006)	2.75 (0.084)	0.42	3	Yes
Berlin	0.56 (0.021)	0.39 (0.013)	0.85 (0.011)	2.20 (0.082)	0.59	2	No
Brandenburg	0.57 (0.027)	0.35 (0.019)	0.84 (0.014)	2.37 (0.134)	0.60	2	Ref
Saxony-Anhalt	0.58 (0.034)	0.25 (0.017)	0.72 (0.026)	2.88 (0.227)	0.43	2	Ref
Saxony	0.61 (0.025)	0.28 (0.014)	0.78 (0.016)	2.83 (0.156)	0.48	2	Yes
Mecklenburg-Vorpommern	0.63 (0.041)	0.25 (0.020)	0.76 (0.028)	3.00 (0.256)	0.45	2	No
Bremen	0.64 (0.044)	0.32 (0.025)	0.86 (0.026)	2.65 (0.220)	0.55	2	No
Thuringia	0.65 (0.032)	0.25 (0.017)	0.76 (0.023)	3.07 (0.234)	0.46	2	Yes

Notes: This table reports mobility statistics for each federal state of Germany based on all children observed in the MZ waves 2011–2018. The gradient measures the gap in the probability of obtaining an A-Level between children at the top and the bottom of the parental income distribution. Q1 and Q5 denote the share of children obtaining an A-Level in the first and fifth quintile of parental income; Q5/Q1 is the ratio between both measures. The standard errors reported in parentheses below each point estimate are computed as described in Section 3.3. The classification of the state education systems is based on the description of educational reforms in Helbig and Nikolai (2015). In the last column, "Ref" indicates that teacher recommendations were reformed during the time period relevant for our analysis.

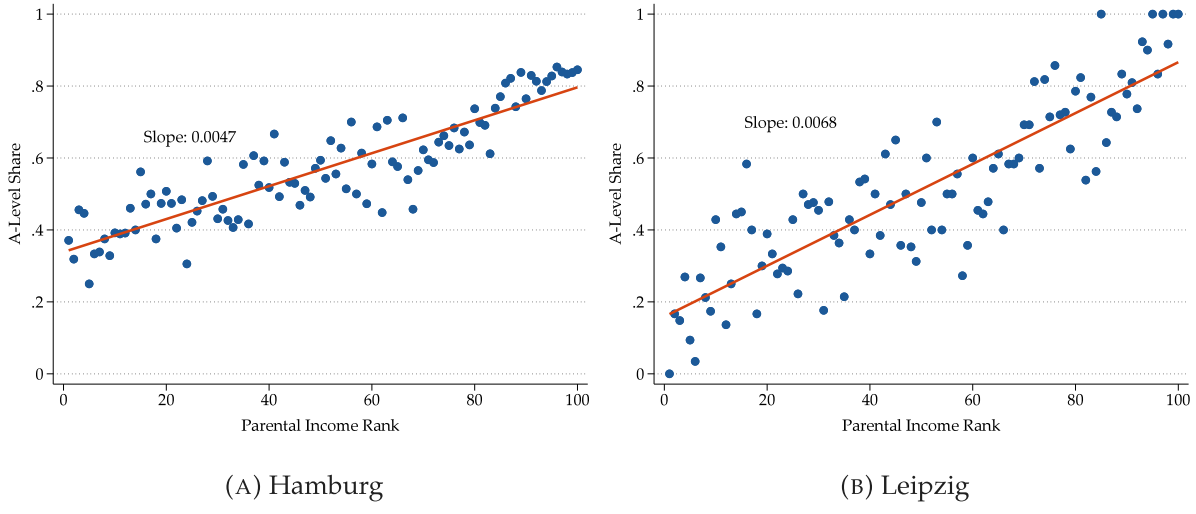


Fig. 9. social mobility in Hamburg and Leipzig. *Notes:* This figure shows the fraction of children aged 17–21 observed in the MZ survey waves 2011–2018 that are either enrolled in the upper stage of an A-Level track or have already attained an A-Level degree in Hamburg (Panel A) and Leipzig (Panel B). The reported slope coefficients are estimated by OLS using the underlying micro data. Standard errors are reported in Table 8.

Table 8
Social mobility in the 15 largest urban labor markets.

City	State	Gradient	Q1	Q5	Q5/Q1	A-Level share
Hamburg	HH/SH	0.47 (0.025)	0.41 (0.018)	0.79 (0.012)	1.94 (0.090)	0.58
Düsseldorf	NW	0.47 (0.029)	0.45 (0.023)	0.84 (0.014)	1.87 (0.100)	0.65
Münster	NW	0.47 (0.041)	0.47 (0.030)	0.84 (0.021)	1.78 (0.120)	0.62
Gelsenkirchen	NW	0.50 (0.035)	0.40 (0.018)	0.81 (0.029)	2.01 (0.116)	0.57
Stuttgart	BW	0.50 (0.024)	0.34 (0.017)	0.75 (0.012)	2.19 (0.114)	0.55
Bonn	NW	0.50 (0.039)	0.44 (0.030)	0.86 (0.016)	1.94 (0.135)	0.65
Duisburg	NW	0.51 (0.033)	0.42 (0.022)	0.84 (0.017)	2.02 (0.113)	0.58
Frankfurt	HE	0.52 (0.025)	0.42 (0.019)	0.83 (0.011)	1.97 (0.093)	0.62
Munich	BY	0.54 (0.025)	0.31 (0.021)	0.71 (0.011)	2.32 (0.162)	0.53
Dortmund	NW	0.55 (0.033)	0.40 (0.022)	0.86 (0.017)	2.16 (0.125)	0.59
Cologne	NW	0.55 (0.027)	0.38 (0.019)	0.85 (0.014)	2.25 (0.120)	0.60
Hanover	NI	0.56 (0.036)	0.30 (0.022)	0.76 (0.021)	2.51 (0.195)	0.53
Berlin	BE	0.56 (0.021)	0.39 (0.013)	0.85 (0.011)	2.20 (0.082)	0.59
Nuremberg	BY	0.60 (0.035)	0.23 (0.022)	0.70 (0.023)	3.01 (0.297)	0.43
Leipzig	SN	0.68 (0.044)	0.26 (0.026)	0.80 (0.028)	3.11 (0.335)	0.48

Notes: This table reports mobility statistics for the 15 largest urban local labor markets in Germany, as measured by their total population in 2017, based on the MZ waves 2011–2018. The gradient measures the gap in the probability of obtaining an A-Level between children at the top and the bottom of the parental income distribution. Q1 and Q5 denote the share of children obtaining an A-Level in the first and fifth quintile of parental income; Q5/Q1 is the ratio between both measures. The local labor markets are sorted, in ascending order, by the point estimate of the parental income gradient. Standard errors are computed as described in Section 3.3. The point estimates for the city-states can differ from those reported in Table 7, as the urban labor markets typically also include surrounding towns and villages.

Regional patterns in absolute mobility. We begin our local labor market-level analysis by studying regional variation in absolute mobility. Fig. 10 shows the A-Level Share (Panel A) and our estimate of the Q1 measure (Panel B) in each of the 258 LLMs. Red areas correspond to regions with low, and blue areas to regions with high values of the respective statistic. For both statistics, state-level clusters are clearly visible. Panel (A) shows that the A-Level share is uniformly higher in the local labor markets of states with high average A-Level capacities, such as North Rhine-Westphalia or Hesse. Comparing the two panels demonstrates that, unsurprisingly, our measure of absolute mobility is closely linked to the local A-Level share ($\rho = 0.76$). Consequently, we observe lower levels of absolute mobility in regions with low A-Level shares, such as Bavaria.

Overall, there exists substantial variation in absolute mobility. In some regions, less than 15% of children from the bottom quintile of the national income distribution obtain an A-Level degree, whereas in other regions this number exceeds 50%. We find that 44% of the variation in the Q1 measure and 57% of the variation in the A-Level share can be attributed to state level differences.

Regional patterns in relative mobility. While the variation in absolute mobility can be well explained by state A-Level shares, regional patterns in relative mobility are less obvious. Fig. 11 presents a heat map of our estimates of the parental income gradient.[28] Blue areas represent regions of high mobility (low gradients), whereas red areas indicate low mobility. In some rural labor markets, the parental income gradient is estimated below 0.3, whereas in the least mobile areas the gradient exceeds 0.8. While LLMs in the East exhibit lower mobility on average, clusters of high and low mobility are spread out across all of Germany. In contrast to our estimates of absolute mobility, some of the observed clusters extend beyond state borders. The LLMs with the highest gradient (Lichtenfels) and the lowest gradient (Mühldorf) are both located in Bavaria. Indeed, we find that only 13% of the variation across LLMs can be explained by state level differences.

Robustness of regional estimates. While disaggregating our data to the LLM level allows us to ask several interesting questions, it makes it harder to distinguish meaningful variation from sampling error, as our mobility estimates are based on fewer observations. In Appendix E, we employ empirical Bayes methods to address this concern in a principled manner. Reassuringly, we find evidence of substantial overdispersion. Moreover, the main patterns described above also become evident when computing mobility statistics at the level of spatial planning regions, a higher-level aggregation of LLMs. The median number of observations per spatial planning region is 1741 (mean: 2406). Figure B.9 displays heat maps of our mobility statistics for all 96 spatial planning regions of Germany. By construction, dispersion in mobility estimates is more muted as we move to a higher level of aggregation. Yet, we still find substantial variation in mobility estimates and clusters of high and low relative mobility crossing state borders (Panel C). Moreover, it is again the case that state level differences explain more of the variation in absolute than relative mobility (72% vs. 37%).

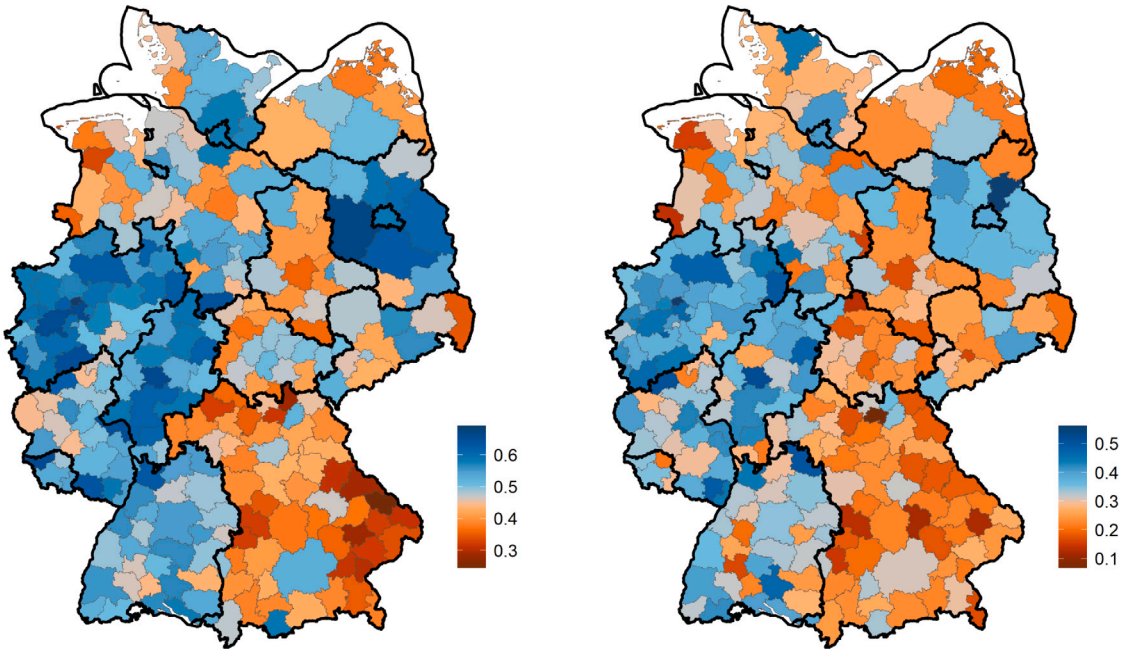
Furthermore, while average parental income ranks naturally vary across Germany (Figure B.10), we show in Figure B.11 that mobility estimates for local labor markets remain virtually unchanged when computing parental income ranks not with respect to the national income distribution but with respect to the income distribution in the respective state or region type.

Sorting. What can we learn from the estimated regional differences across local labor markets? A first insight relates to the debate on the potential of place-based mobility policies. An active literature argues that places shape economic outcomes and that place-based policies can be an effective and cost-efficient tool to improve outcomes by amending local conditions (Kline and Moretti, 2014; Neumark and Simpson, 2015). In the context of educational policies and social mobility, it is often argued that the government should allocate additional resources to the local public school systems of socially immobile regions to enhance mobility. However, such a policy is unlikely to achieve its objective if social mobility in the respective regions is low for reasons other than the quality of local schools. For example, if a region exhibits a high degree of inequality in parental educational attainment, the patterns we document in Section 4.1 would likely result in low levels of relative mobility as measured by the parental income gradient.

Such systematic sorting mechanisms are at the center of the academic debate regarding the interpretation of the regional differences in estimated mobility measures within countries.[29] The German census

[28] The corresponding heat map for the Q5/Q1 ratio is displayed in Figure B.8 in the Appendix. The correlations between our mobility measures are reported in Appendix Table B.2.

[29] For example, Rothbaum (2016) and Gallagher et al. (2018) suggest that in the US a substantial share of the geographic variation in the intergenerational mobility measures reported in Chetty et al. (2014) can be explained by differences in household characteristics across commuting zones. In Chetty et al. (2014), this was not tested directly, whereas in later work, Chetty and Hendren (2018) draw on a movers design to overcome this problem. By comparing outcomes of children who move across commuting zones, they can separate place effects from sorting patterns. Compared to our approach, the movers design utilizes only a subset of children, but has the advantage that it can control for a large share of potential sorting on (unobserved) household characteristics not captured by our set of variables.



(A) A-Level Share (B) Q1 Measure

Fig. 10. A-Level share and Q1 measure by local labor market. *Notes:* This figure presents heat maps of the A-Level share (Panel A) and the Q1 measure (Panel B) by LLM. Children are assigned to LLMs according to their current residence. The estimates are based on children aged 17–21 in the years 2011–2018 for which we have non-missing information on educational attainment and parental income. The A-Level share is defined as the fraction of children aged 17–21 that are either enrolled in the upper stage of an A-Level track or have already attained an A-Level degree. The Q1 measure reports this same share for children in the bottom 20% of the parental income distribution.

data allows us to directly test whether regional differences are muted once we account for household characteristics. We do so by computing conditional rank gradients, which we then compare to our parental income gradient. The set of conditioning variables we use for this exercise includes age and gender of the child, migration background, age and marital status of the parents, the number of siblings, a dummy for single parents and the highest parental education level in four categories. Fig. 12, Panel (A) plots the marginal distributions of conditional and unconditional rank gradients. It shows that the CDF of the unconditional gradient first order stochastically dominates the CDF of the conditional gradient, which is expected given the patterns documented in Table 5. At the same time, the variance of the distribution of conditional rank gradients is approximately the same as the variance of the unconditional gradient. Moreover, as reported in Panel (B) we find that, despite the predictive power of the included household attributes, the relative ordering of gradients is largely unaffected by conditioning, which suggests that regional sorting of households cannot explain the regional variation in relative social mobility as we measure it. Conditional and unconditional gradients are strongly correlated, with a Pearson correlation of 0.91 and a Spearman rank correlation of 0.89. The same pattern emerges when repeating this analysis for higher levels of regional aggregation.[30,31]

Predictors of mobility. If sorting cannot account for most of the spatial variation in mobility, the question remains why some regions of Germany exhibit a higher degree of social mobility than others. Similar to previous studies which document geographic variation in intergenerational mobility, we are not able to test existing theories of intergenerational transmission processes which could explain these patterns conclusively in our data. To nevertheless learn from our estimates, we conduct a prediction exercise to characterize mobile regions in more detail. In Appendix D, we describe the methodology underlying the prediction exercise and present the results, with Appendix Table D.2 displaying the 15 most informative predictors of mobility differences between local labor markets. Overall, our selection procedure highlights social characteristics, the local organization of the education system and labor market conditions. These correlational findings are consistent with causal studies that emphasize the importance of local characteristics for child and adolescent outcomes (Chetty and Hendren, 2018; Damm and Dustmann, 2014).

6. Conclusion

This paper provides novel empirical evidence on the level, evolution and geography of social mobility in Germany. Our measurement strategy allows for the use of large-scale census data and characterizes mobility using robust statistical measures of the association between the educational attainment of a child and its parents' relative position in the national income distribution. We find that on average a 10 percentile increase in parental income rank is associated with a 5.2 percentage point increase in the probability to obtain an A-Level degree, implying a top-bottom gap of approximately 50 percentage points. This gap remained stable for the 1980–1996 birth cohorts, despite a concurrent massive roll-out of higher secondary education. An expansion in access to higher education alone may therefore not be sufficient to reduce the opportunity gap between children from high and low income households. At the same time, we find that absolute mobility increased substantially.

[30] At the level of spatial planning regions, the Pearson correlation is 0.90 and the Spearman rank correlation 0.86. At the state level, the Pearson correlation amounts to 0.91 and the Spearman rank correlation to 0.84.

[31] Note that, while this finding suggests that sorting does not play a major role, the same pattern would emerge if our regional estimates were dominated by sampling error, in the sense that the between local labor market variation in gradients was negligible relative to the estimation uncertainty. We address this concern in Appendix E.

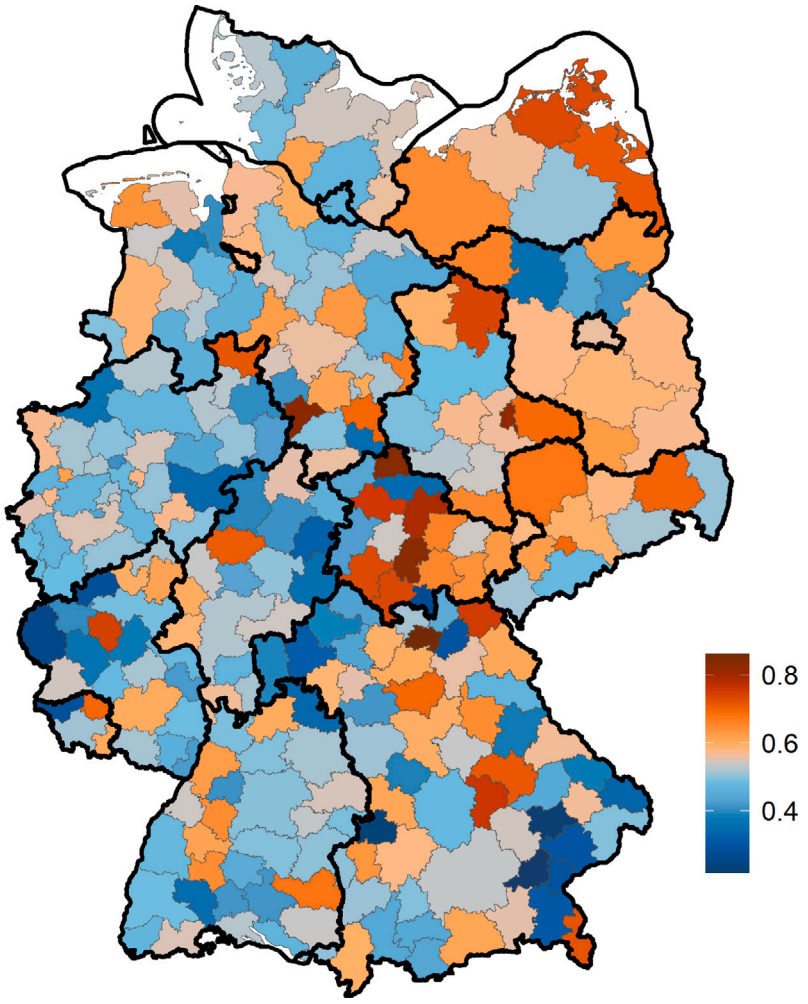
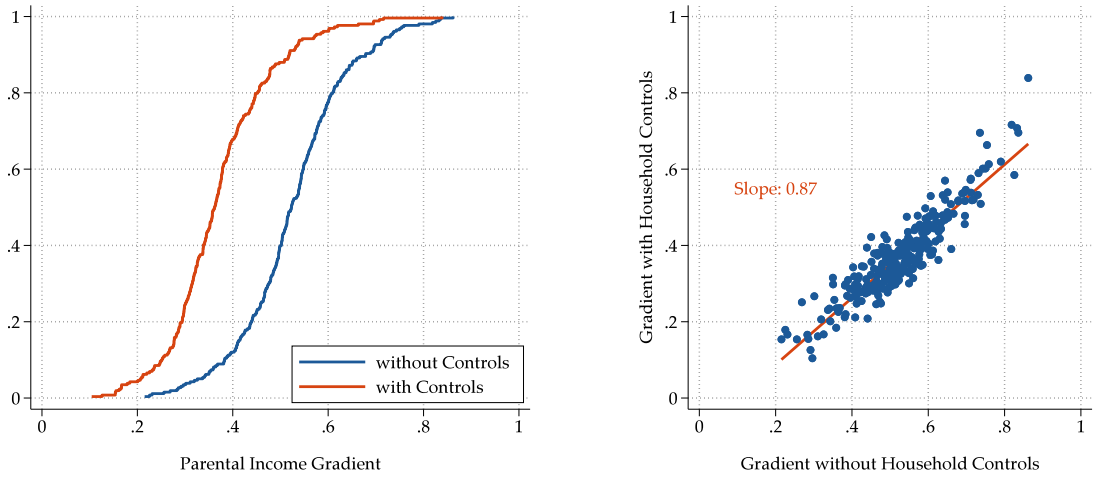


Fig. 11. Parental income gradient by local labor market. *Notes:* This figure presents a heat map of the parental income gradient by LLM. Children are assigned to LLMs according to their current place of residence. The estimates are based on children aged 17–21 in the years 2011–2018 for which we have non-missing information on educational attainment and parental income. The parental income gradient is obtained as the slope coefficient of a regression of the A-Level dummy on a constant and the parental income rank, multiplied by 100.



(A) Cumulative Distribution Function (B) Scatter Plot

Fig. 12. Sorting: Conditional and unconditional rank gradients. *Notes:* This figure compare unconditional and conditional estimates of the parental income gradient by local labor market. The conditioning variables include age and gender of the child, migration background, age and marital status of the parents, the number of siblings, a dummy for single parents and the highest parental education level in four categories. Panel (A) plots the Cumulative Distribution Function (CDF) of the conditional and unconditional parental income gradients, Panel (B) shows a scatter plot of the point estimates as well as their linear fit.

We further document variation in mobility measures across regions and show that household characteristics cannot account for these differences. As such, our findings are consistent with place-based rather than sorting-type explanations of geographic dispersion in mobility measures. Obtaining an optimal set of mobility predictors based on our disaggregated estimates, we find that social characteristics, the local organization of the education system and labor market conditions best predict mobility at the regional level. More research is needed to understand whether these correlations reflect structural relationships.

The measurement approach described in this paper provides a timely and feasible way to monitor the development of social mobility in Germany for recent cohorts. This framework may also prove useful in other countries where the highest secondary school degree is crucial for future career options. Education systems with secondary school degrees of comparable importance to the Abitur in Germany include Italy (Maturità), Austria (Matura) and the UK (A-Level).

Declaration of competing interest

We have received research funding for this project from the Joachim Herz Foundation. None of the authors have relevant or material financial interests in the research described in this paper. There are no conflict of interests.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jpubeco.2024.105074.

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