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.

JEL-Codes: I24, J62, R23

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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 expan-

[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.

sion was in parts 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 kilometers 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 kilometers 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

[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).

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 (Lochner, 2011; Oreopoulos and Salvanes, 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. Acciari et al., 2022; Chetty et al., 2014; 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

[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 (Klein et al., 2019; Riphahn and Trübswetter, 2013).

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. 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.

[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).

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 Ger-

[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.

many 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

[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.

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 miss-measure 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 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.

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.

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

[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 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).

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

[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.

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:

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

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:

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

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 $\beta \times 100$, 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.

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 can not 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

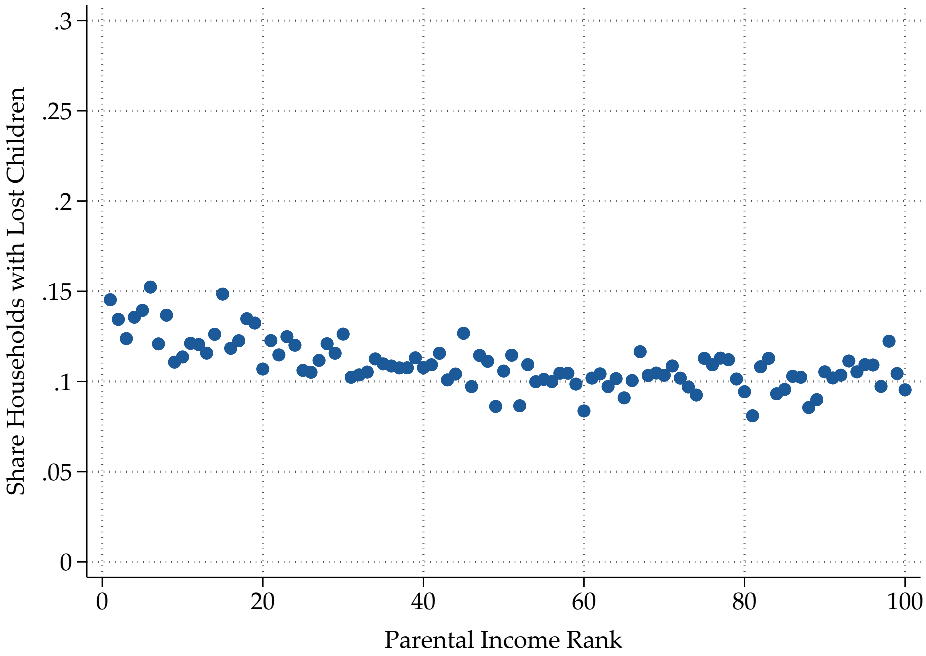
TABLE 3. Average Characteristics of Children by Age of Observation

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.

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 so-

FIGURE 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.

cial 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. Figure 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. Figure 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]

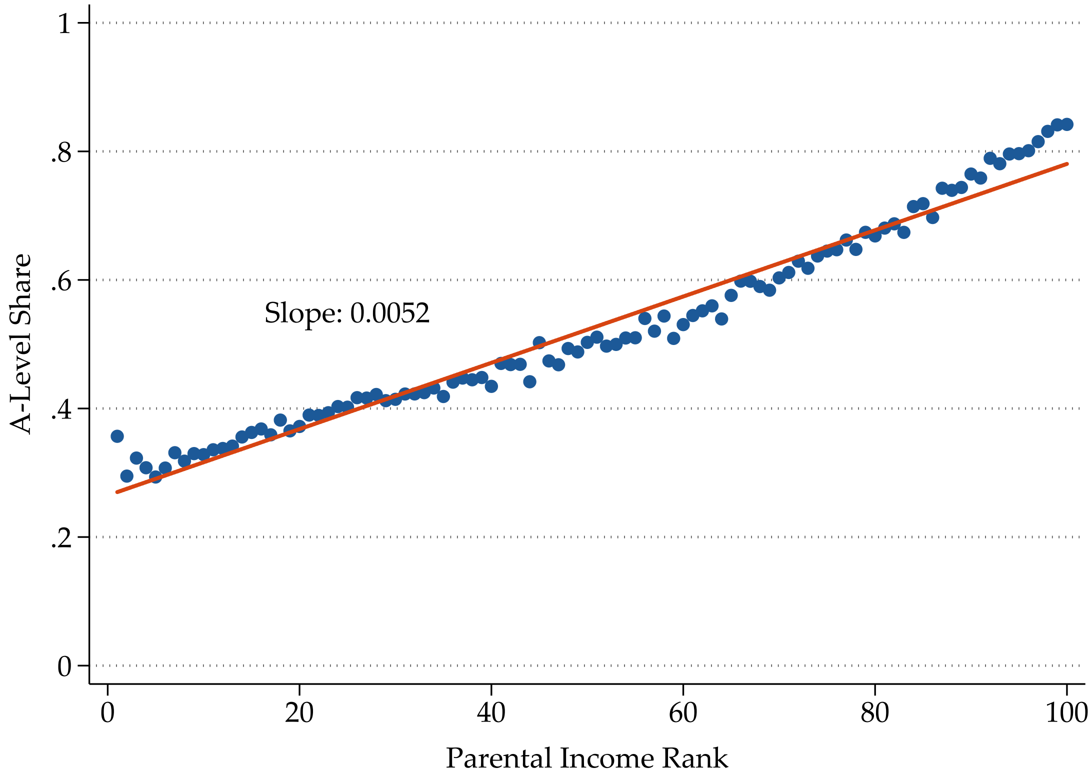
Do these estimates depict Germany as a country of high or low relative mobility? While a cross-country comparison of our results is not straightforward, as the German system of upper secondary education and university funding is unusual, we are aware of two US studies which report comparable mobility 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

[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.

FIGURE 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.

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]

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 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

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[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.

[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 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.

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† (0.057) 0.360†† (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† (0.039) 0.354†† (0.043)

Notes: This table shows estimates of intergenrational 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. † indicates that *child* family income is measured as the sum of individual labor earnings of the child and its cohabiting partner (excluding zero incomes), whereas †† indicates that child family income is measured as gross household income among all children are no longer cohabiting with their parents. The sample sizes underlying the German estimates range from 834 to 1041 individuals, depending on the specification. Robust standard errors in parentheses.

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

[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.

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).

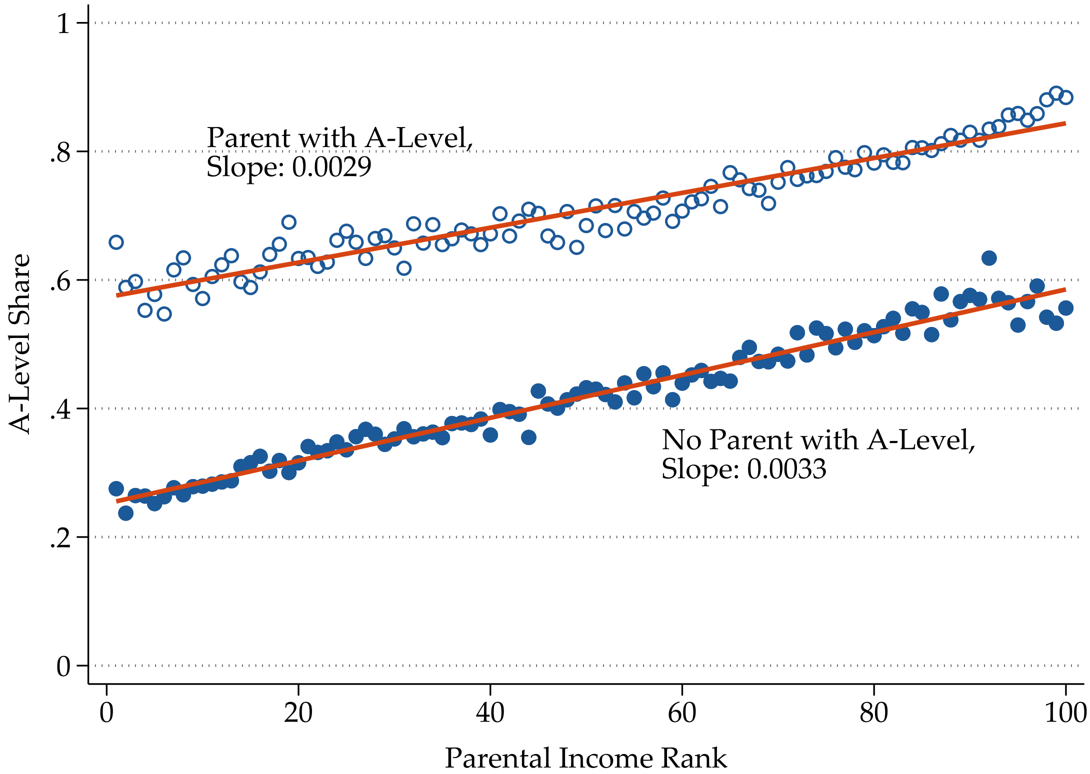
Table 5 reports mobility statistics separately for these groups. We document several interesting patterns. Most importantly, we find substantial differences by parental education. Figure 3 displays the A-Level share of children by parental income rank and the associated parental income gradient separately 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 posi-

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	8,640

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.

FIGURE 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.

tive 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.

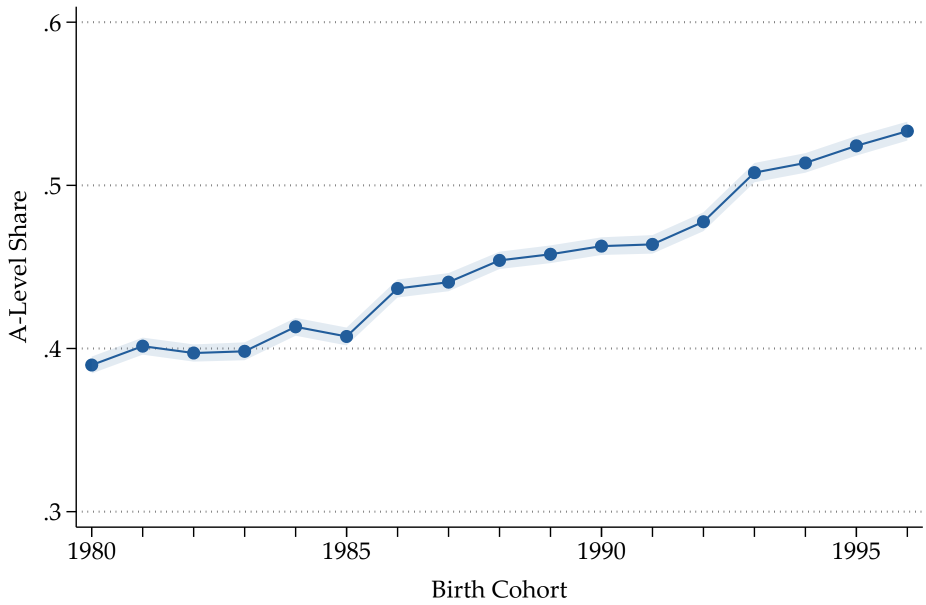
4.2 Time Trends

We next ask how social mobility has evolved over time. While our descriptive approach does not allow us to attribute changes in mobility 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 (Hadjar and Becker, 2006; Picht, 1964). 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. Figure 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

[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.

FIGURE 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.

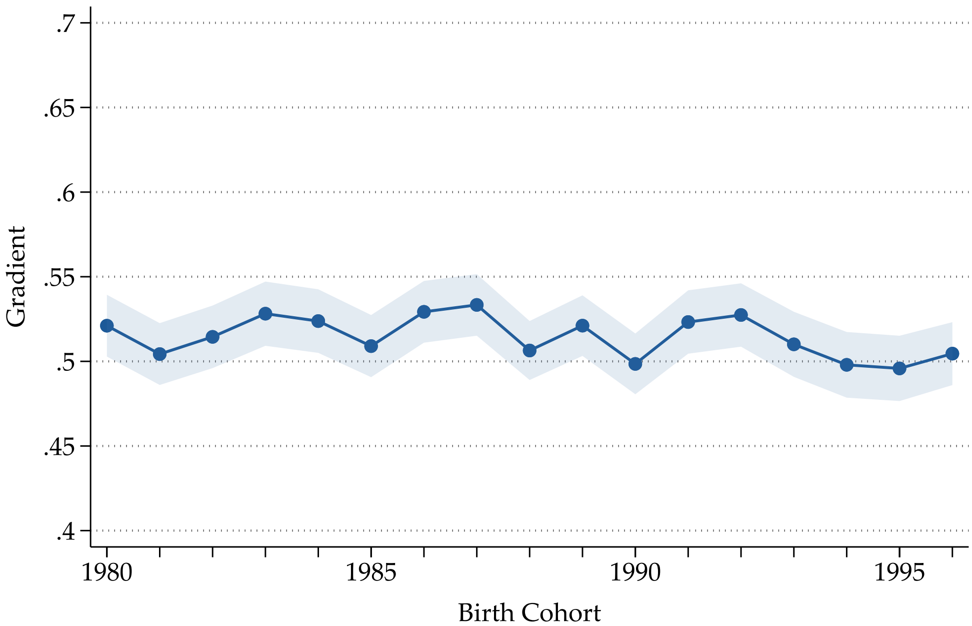
birth cohort to 53% for children born in 1996.[23] At the same time, income inequality increased only moderately,[24] and we do not find evidence that the expansion was accompanied by a decline in annually measured A-Level wage premia, as documented in Appendix Figure B.1. However, as the children under 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.

Figures 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

[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).

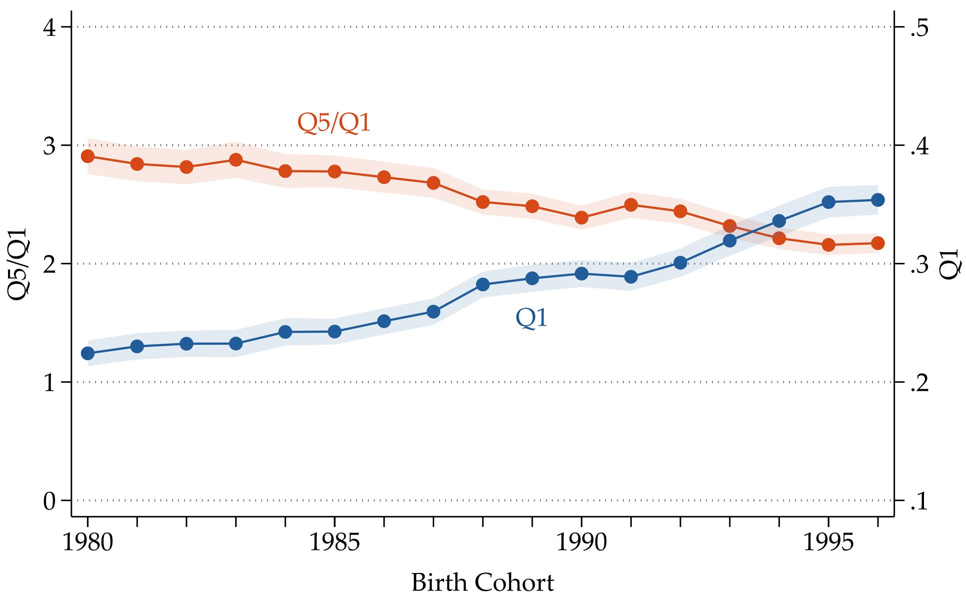
[24]While wage inequality rose in the 1990s and early 2000s when most children in our sample grew up, Fuchs-Schündeln et al. (2010) document that inequality in consumption and disposable income, the income concept used in this paper, increased only moderately.

FIGURE 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.

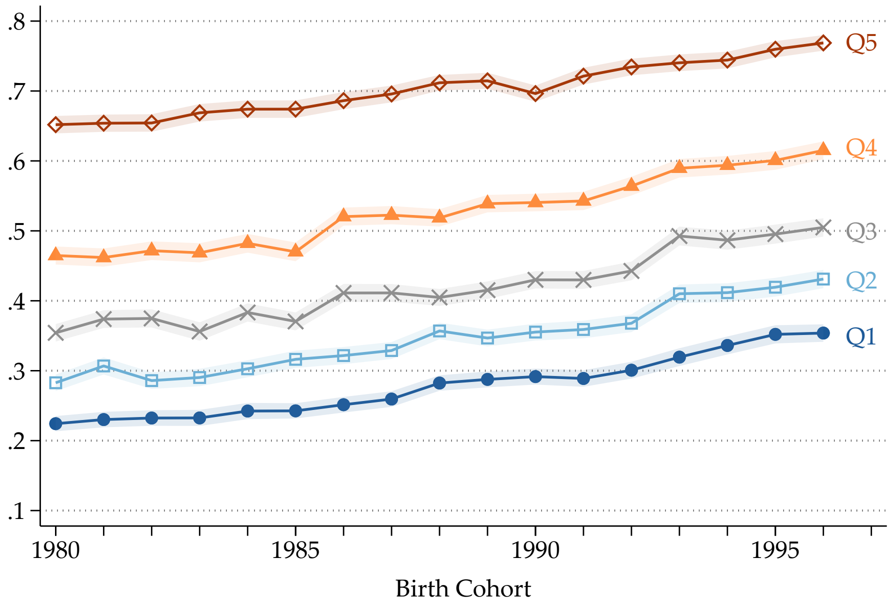
FIGURE 6. Quintile Measures by Cohort



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.

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.

FIGURE 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.

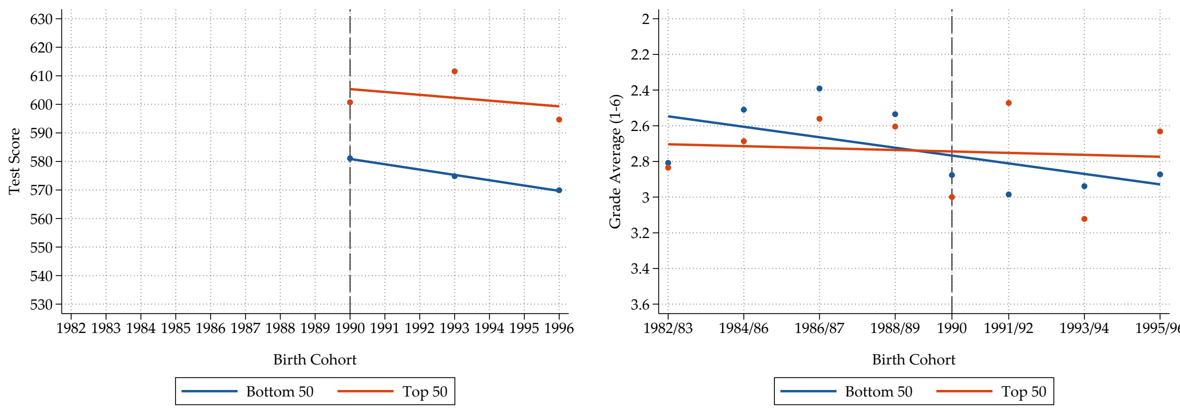
The connection between these findings is best summarized in Figure 7, which depicts the A-Level share by quintile across birth cohorts: The *Bildunsexpansion* took place uniformly across the income distribution, with increases of about 14 percentage points in the A-Level share in all parts of the distribution. 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 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. Pokropek et al., 2022; Rindermann, 2007). 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. Brunello and Rocco, 2013; Gneezy et al., 2019; Hanushek et al., 2022; Jensen and Rasmussen, 2011), we use grades and test scores in math to obtain an ability proxy which can be compared consistently across social groups.[25]

Figure 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.

FIGURE 8. Time Trend Math Grades and Test Scores



(A) Test Scores PISA

(B) Grade Average SOEP

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 1,000 15-year old students on Gymnasium and the Gymnasialzug of Gesamthochschulen per cohort, the SOEP sample covers 1,061 children in total. Additional information on the underlying data is disclosed in Appendix C.

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

[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.

parental income groups. First, we assume that test scores (and grades) have no trend for inframarginal students, such that the changes seen in Figure 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

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).

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 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. Acciari et al., 2022; Chetty et al., 2014; Chuard and Grassi, 2020; Corak, 2020; Deutscher and Mazumder, 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 (Bütikofer and Peri, 2021; Chetty and Hendren, 2018). 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 kilometers 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

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.

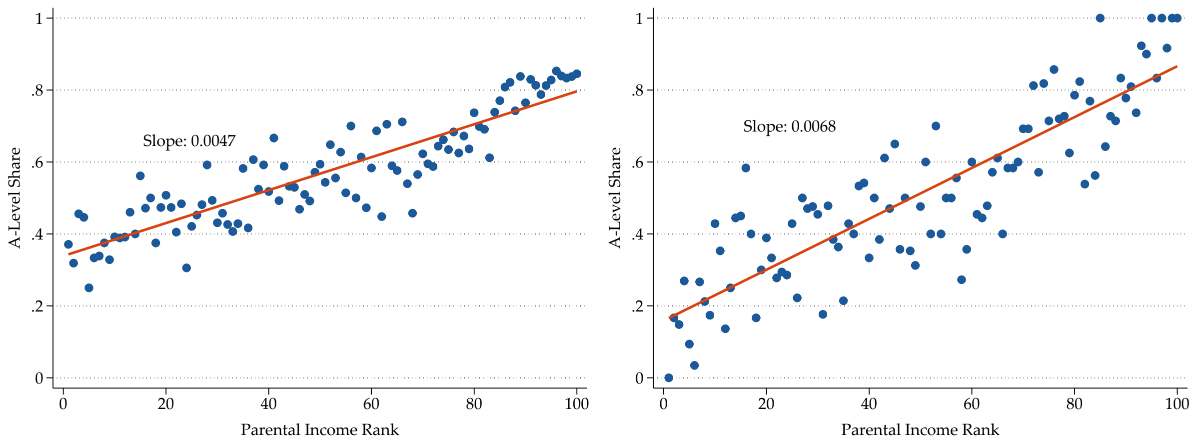
aforementioned characteristics of the state education systems displayed in the last two columns of the table. Our findings suggest that, while certainly important, the design of the tracking system cannot readily explain the pronounced differences in our mobility measures between states.

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 kilometers apart. Similarly, our estimates of absolute mobility differ by 8 percentage points between Nuremberg and Munich, two large cities in Bavaria.

FIGURE 9. Social Mobility in Hamburg and Leipzig



(A) Hamburg (B) 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.

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. Figure 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]

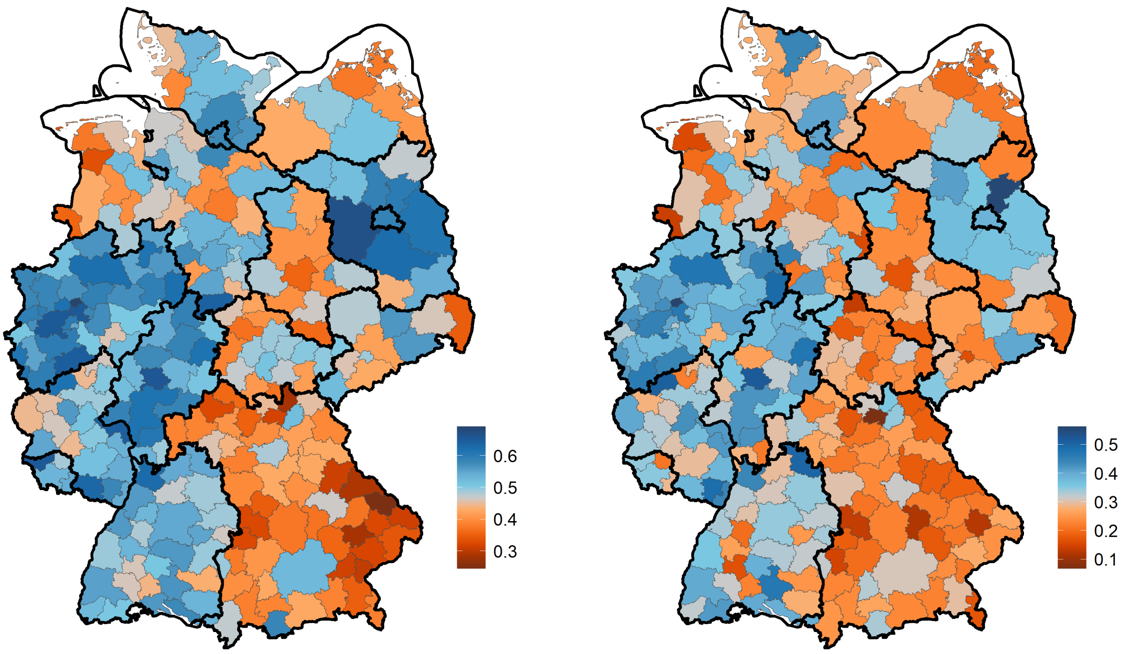
5.3 Local Labor Markets

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).

Regional Patterns in Absolute Mobility. We begin our local labor market-level analysis by studying regional variation in absolute mobility. Figure 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.

[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. (forthcoming).

FIGURE 10. A-Level Share and Q1 Measure by Local Labor Market



(A) A-Level Share

(B) Q1 Measure

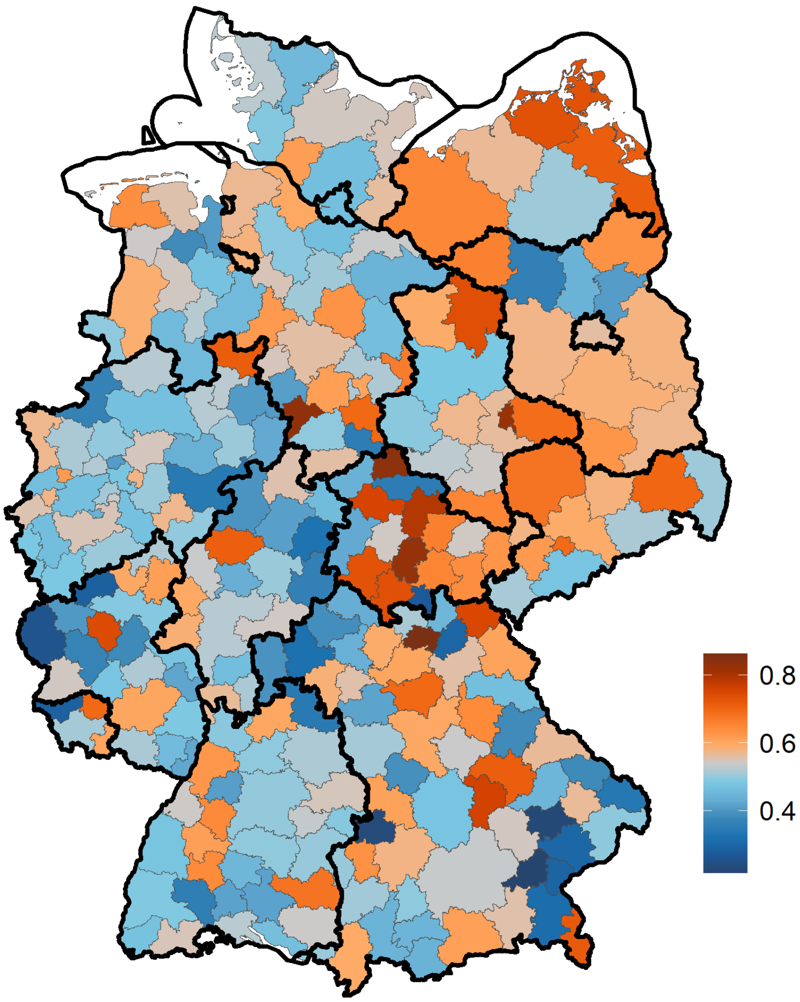
Notes: This figure presents heat maps of the A-Level share (Panel A) and the Q1 measure (Panel B) by LLM. Children are assigned to LLMs according to their current residence. The estimates are based on children aged 17-21 in the years 2011-2018 for which we have non-missing information on educational 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.

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. Figure 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

[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.

FIGURE 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.

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 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. Figure 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]

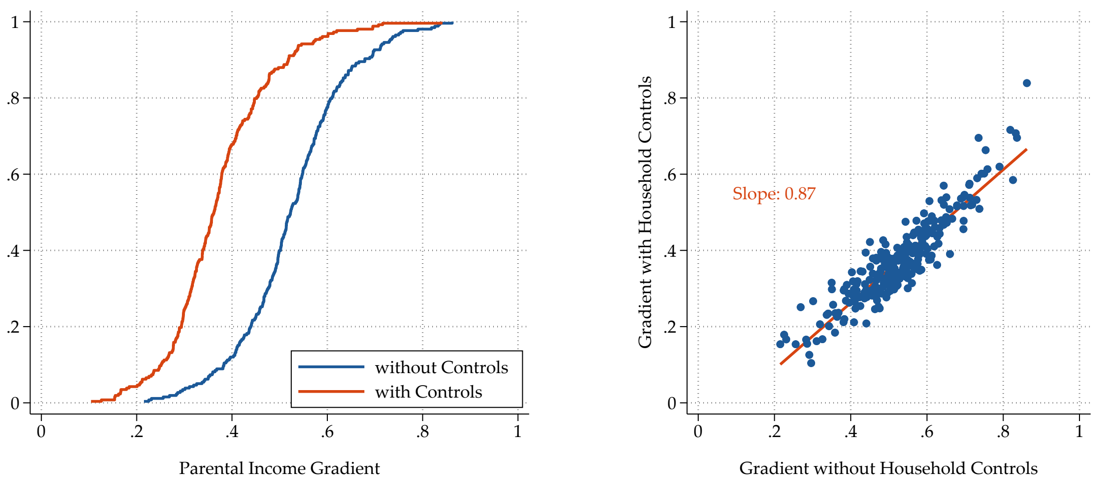
Predictors of Mobility. If sorting cannot account for most of the spatial variation in mobility, the question remains why some regions of Germany exhibit a higher degree

[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.

[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.

FIGURE 12. Sorting: Conditional and Unconditional Rank Gradients



(A) Cumulative Distribution Function

(B) Scatter Plot

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.

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.

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).

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A Additional Information on the Mikrozensus

The Microcensus (Mikrozensus, MZ) is the largest household survey in Europe. Conducted annually with a sampling fraction of 1% of all individuals who have the right of residence in Germany, it yields representative statistics on the German population. The MZ has been conducted in West Germany since 1957 and in the new federal states (East Germany) since 1991. It is planned and prepared by the Federal Statistical Office of Germany and carried out by the statistical offices of the 16 German states. The legal basis of the MZ is the Microcensus Law, which makes it compulsory for households to provide answers to the core items of the survey. The non-response rate is further minimized by repeated visits of interviewers to non-responding households and multiple possible ways for the sampled households to submit information.

FIGURE A.1. Illustration of the Microcensus Survey Design

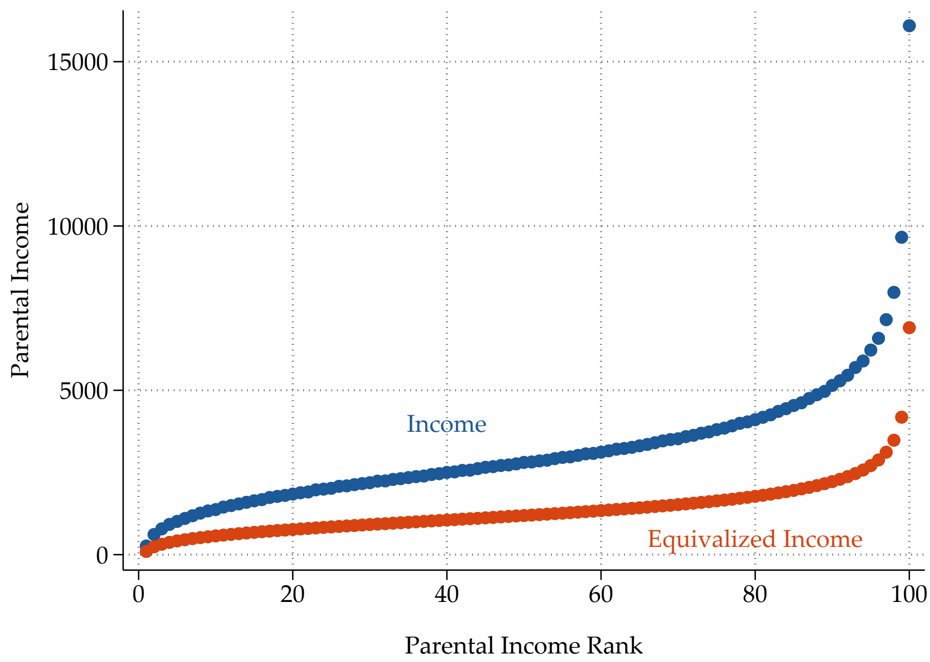
	Rotation Quarter							
Survey Wave	1	2	3	4	5	6	7	⋯
1	✓	✓	✓	✓	X	X	X	⋯
2	X	✓	✓	✓	✓	X	X	⋱
3	X	X	✓	✓	✓	✓	X	⋱
4	X	X	X	✓	✓	✓	✓	⋱
⋮	⋮	⋱	⋱	⋱	⋱	⋱	⋱	⋱

Since 1972, the MZ uses a single-stage stratified cluster sampling design. The primary sampling units typically consist of neighboring buildings (larger buildings are divided into smaller partitions). For the survey waves utilized in this paper, the target size for a cluster is 7–15 households. All households and residents in the sampled clusters are interviewed. The database used to assign households to clusters is created based on the most recent full census and updated annually using information on new construction activities. Since 1977, each cluster is assigned to a "rotation quarter" that remains in the survey for four years. Each year, a quarter is replaced by new clusters. The survey does not follow individuals who leave their cluster, but replaces them by the new residents. The MZ survey design results in data best described as a repeated survey with partial overlap of units, as sketched in Figure A.1.

Due to data protection laws, we do only observe this panel structure in our data following wave 2011. In Section 4.2, we therefore cannot cluster standard errors at the level of time-constant primary sampling units. We instead cluster standard errors at the household level. As the number of households per cluster is low, the consequences for standard errors are negligible.

Sample Income Distribution and Ranks. Figure A.2 displays the sample distribution of equivalized monthly net household income and the corresponding percentile ranks in the 2011-2018 MZ data. We CPI adjust all household incomes in order to allow for meaningful aggregation of survey-years before computing ranks. Ties are broken by allocating households to the lower quantile. Our findings are insensitive to the choice of tie-breakers. Ranks are computed separately for each year within the sample of all households that have at least one co-resident child in the age range 17-21.

FIGURE A.2. Household Income by Percentile Rank



Notes: This figure plots equivalized net monthly household income (net of income of dependent children) by parental income rank in the 2011-2018 MZ data. Equivalization is based on the modified OECD scale. For comparison, the non-equivalized values are plotted as well. Both income measures are expressed in constant 2015 Euro.

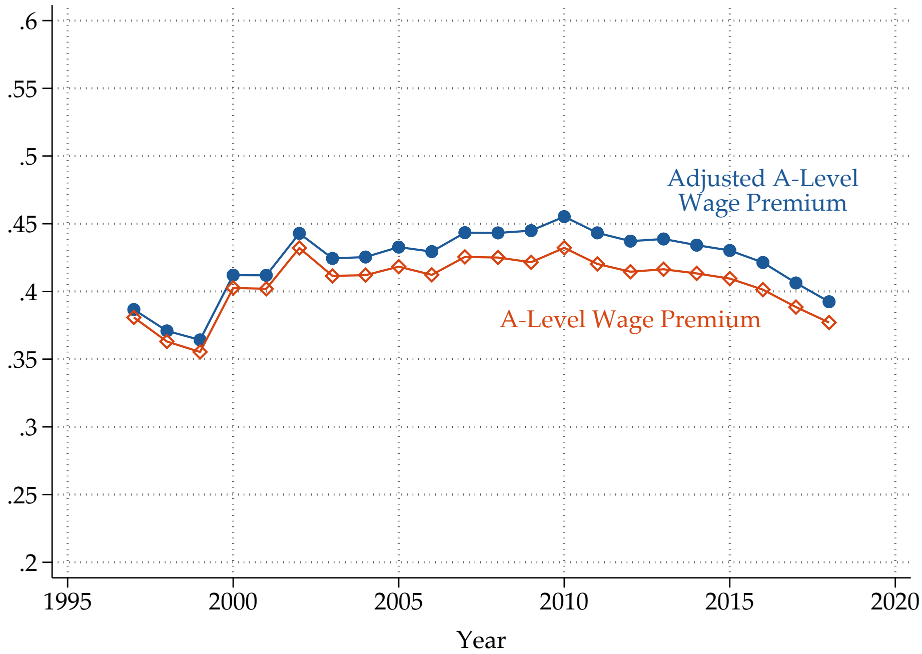
B Additional Figures and Tables

TABLE B.1. National Estimates for Different Age-Restrictions

Age	Gradient	Q1	Q5	Q5/Q1	A-Level Share	N
17-21	0.52 (0.004)	0.34 (0.003)	0.76 (0.003)	2.25 (0.021)	0.52	230,972
17-21 (Averaged)	0.52 (0.004)	0.34 (0.003)	0.77 (0.003)	2.26 (0.022)	0.52	230,972
17	0.53 (0.007)	0.30 (0.005)	0.73 (0.004)	2.46 (0.042)	0.49	53,324
18	0.51 (0.007)	0.35 (0.005)	0.77 (0.004)	2.18 (0.033)	0.54	51,278
19	0.51 (0.008)	0.35 (0.005)	0.77 (0.005)	2.19 (0.035)	0.53	46,747
20	0.51 (0.008)	0.35 (0.005)	0.77 (0.005)	2.19 (0.036)	0.53	42,396
21	0.52 (0.008)	0.34 (0.006)	0.77 (0.005)	2.24 (0.039)	0.52	37,227

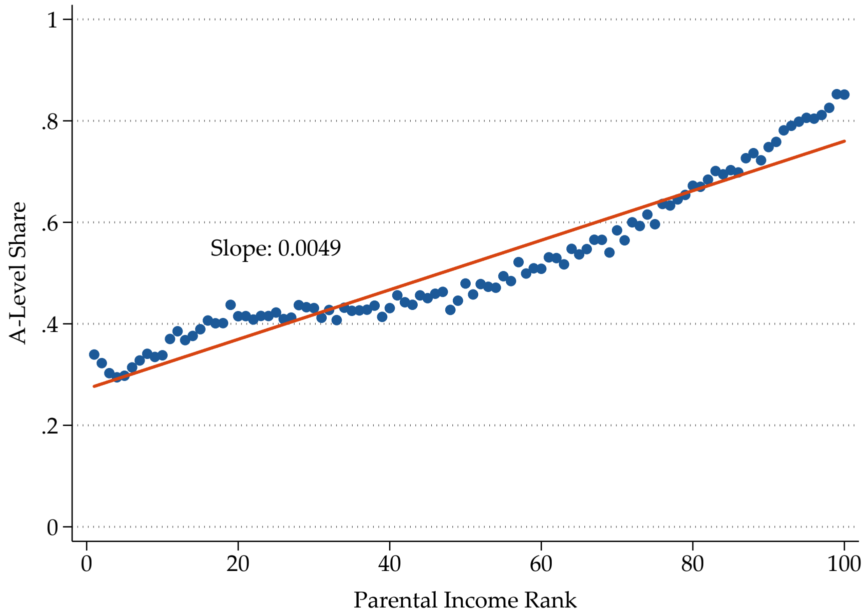
Notes: This table reports national mobility statistics for the MZ waves 2011-2018. The gradient measures the gap in the probability of obtaining an A-Level between children at the top and the bottom of the parental income distribution. Q1 and Q5 denote the share of children obtaining an A-Level in the first and fifth quintile of parental income; Q5/Q1 is the ratio between both measures. The first row corresponds to our primary sample. The second row replicates these estimates using multi-year averages of parental income before assigning ranks. The additional rows report estimates for samples containing only children of a given age at measurement, as indicated in the first column. The standard errors in parentheses are computed as described in Section 3.3.

FIGURE B.1. A-Level Wage Premium, Years 1997-2016

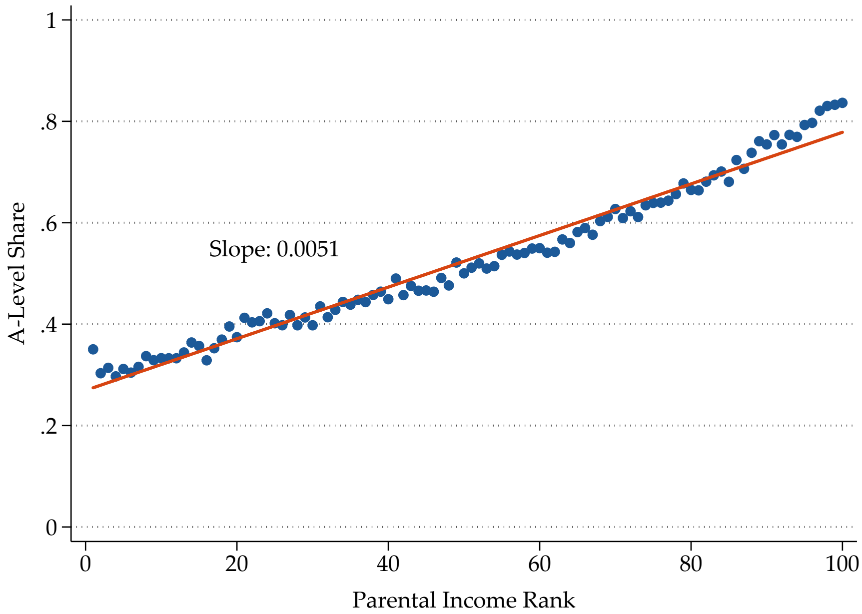


Notes: This figure shows the development of the A-Level wage premium for the years 1997-2016 as computed in the MZ. We compute the A-Level wage premium by regressing the log of net monthly personal income of full-time working employees aged 30-45 on an A-Level dummy. The adjusted A-Level wage premium is computed by additionally conditioning on a set of age indicators to indirectly account for job experience.

FIGURE B.2. National Estimates under Different Equivalization Schemes



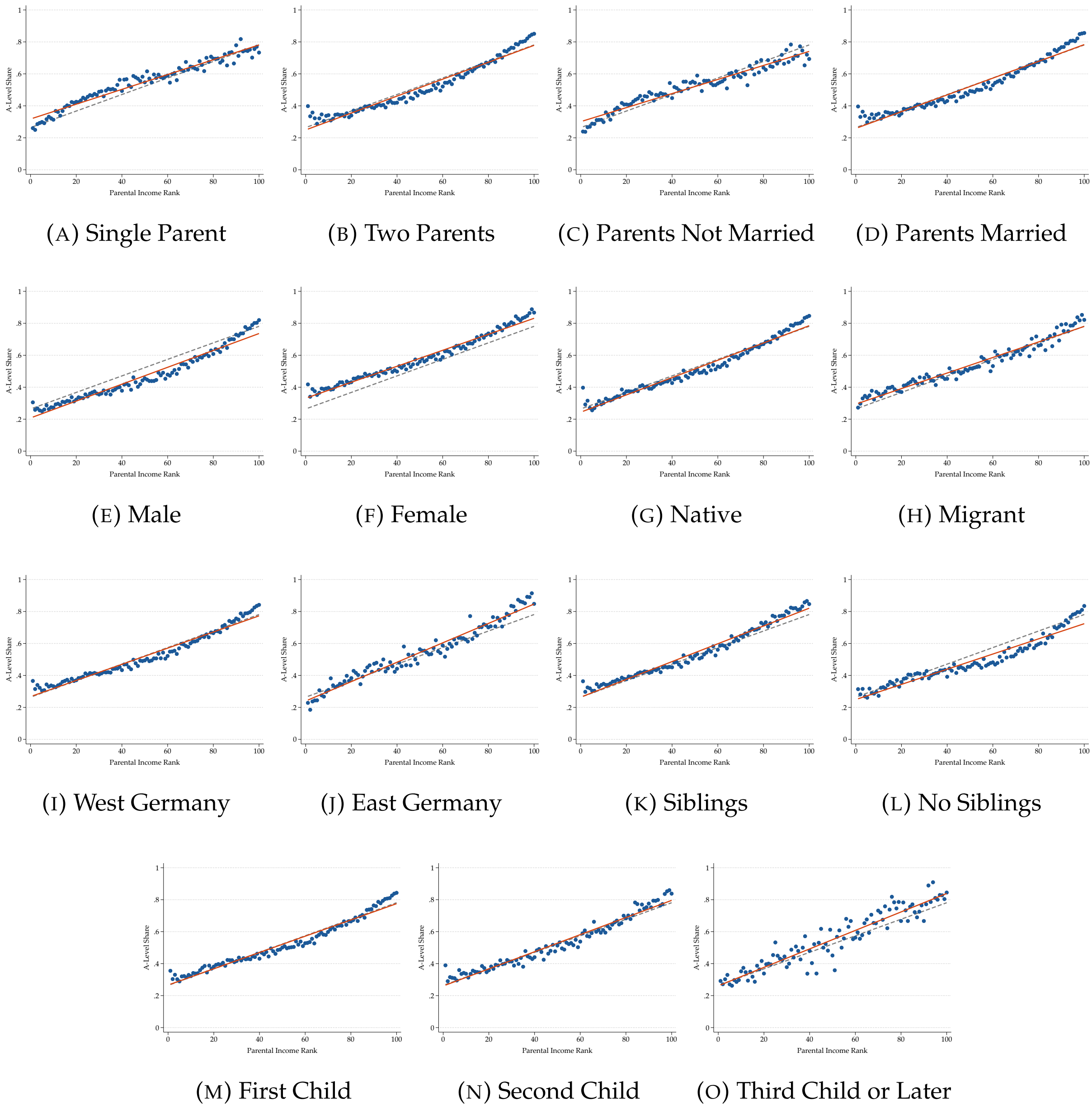
(A) No Adjustment



(B) Per Capita Adjustment

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 based on the MZ waves 2011-2018, as well as the best linear approximation to the empirical CEF. In Panel (A), parental income is not adjusted for household size, whereas in Panel (B) income is divided by the number of household members. The OLS slopes reported in the figure are estimated using the underlying micro data.

FIGURE B.3. Social Mobility for Subgroups



(A) Single Parent (B) Two Parents (C) Parents Not Married (D) Parents Married

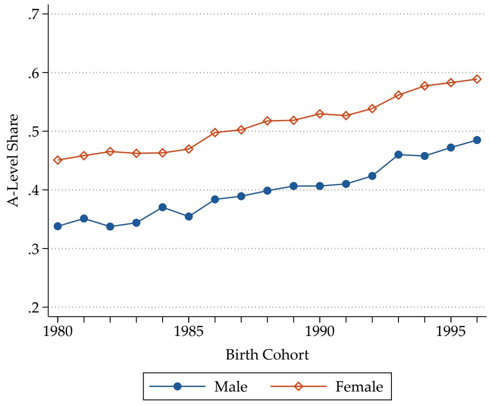
(E) Male (F) Female (G) Native (H) Migrant

(I) West Germany (J) East Germany (K) Siblings (L) No Siblings

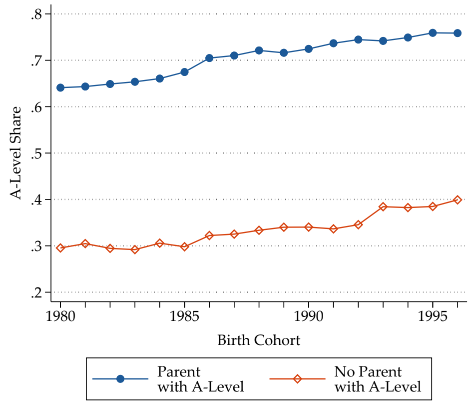
(M) First Child (N) Second Child (O) Third Child or Later

Notes: This figure shows for different population subgroups 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 based on the MZ waves 2011-2018, as well as the best linear approximation to the empirical CEF in orange. The dashed gray line plots the national gradient as a comparison. 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.

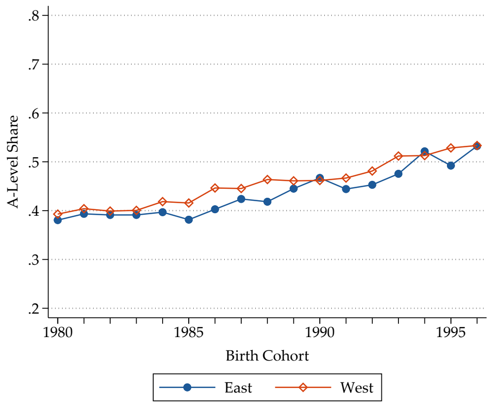
FIGURE B.4. Time Trend A-Level Share for Subgroups



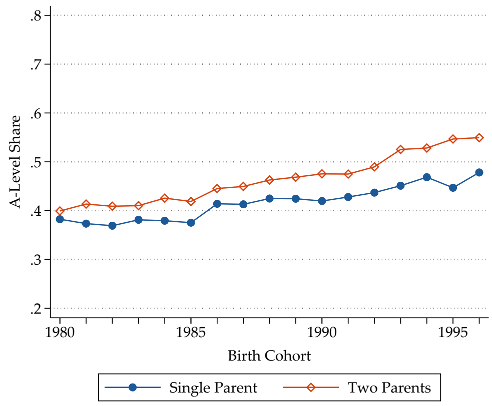
(A) Gender



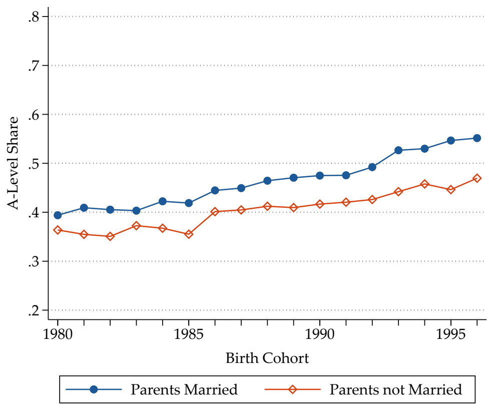
(B) Parental Education



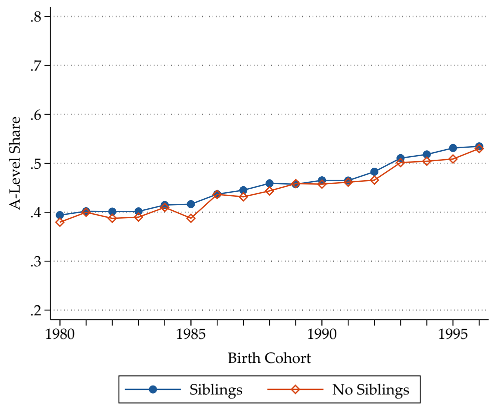
(C) Region



(D) Parenting Status



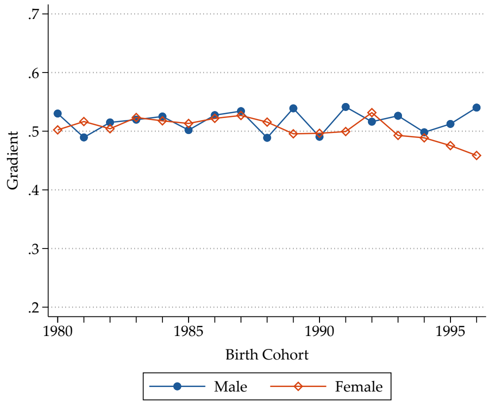
(E) Parental Marital Status



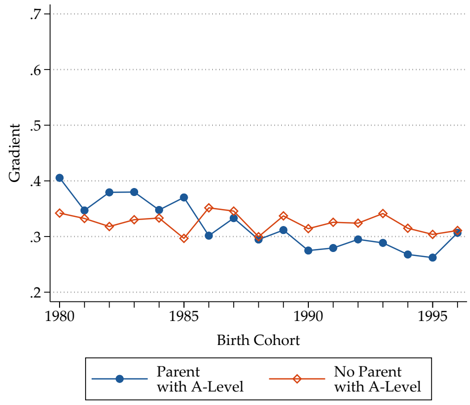
(F) Siblings

Notes: This figure shows the development of the A-Level share for different population subgroups for birth cohorts 1980-1996 in the MZ. The A-Level share is given 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.

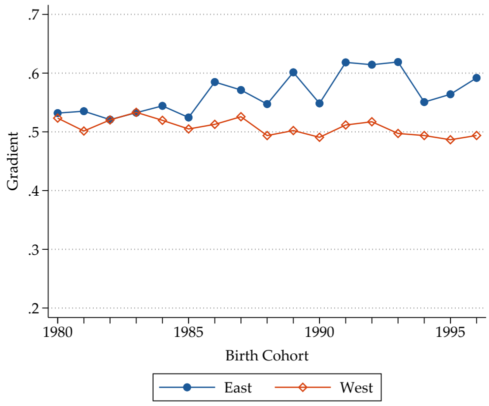
FIGURE B.5. Time Trend Parental Income Gradient for Subgroups



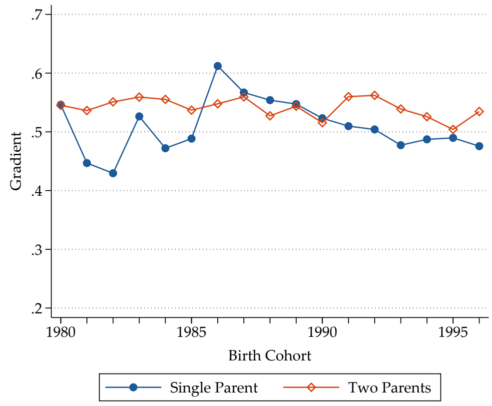
(A) Gender



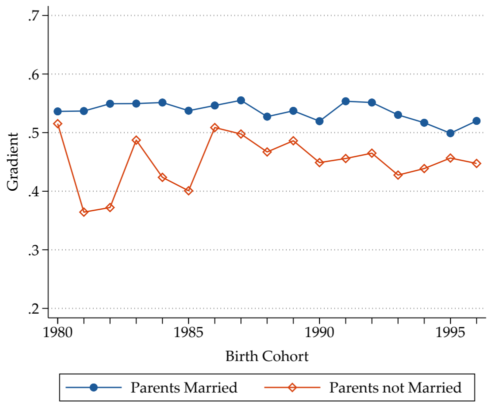
(B) Parental Education



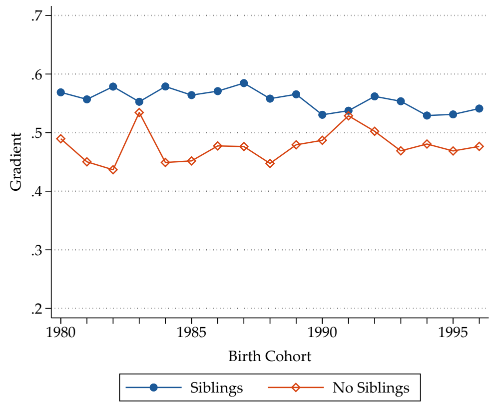
(C) Region



(D) Parenting Status



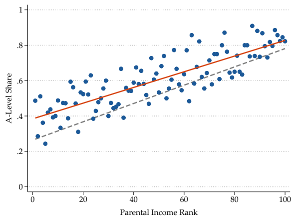
(E) Parental Marital Status



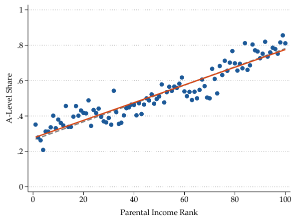
(F) Siblings

Notes: This figure shows the development of the parental income gradient for different population subgroups for birth cohorts 1980-1996 in the MZ. The parental income gradient per cohort is estimated as $100 \times \gamma_t$ in the following regression: $Y_{i,t} = \alpha + \beta_t C_t + \gamma_t C_t \times R_i + \varepsilon_{i,t}$, where C_t denotes a cohort and $C_t \times R_i$ the interaction between cohort and parental income rank.

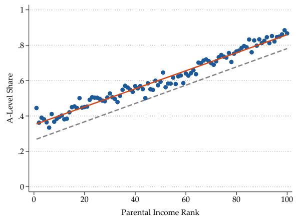
FIGURE B.6. Social Mobility at the State Level



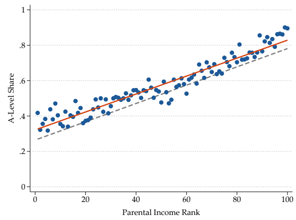
(A) Hamburg



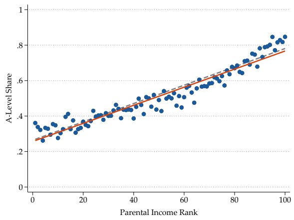
(B) Rhineland-Palatinate



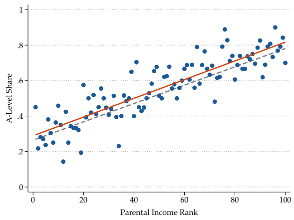
(C) North Rine-Westphalia



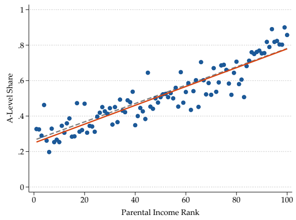
(D) Hesse



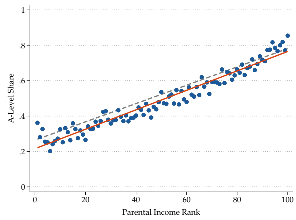
(E) Baden-Württemberg



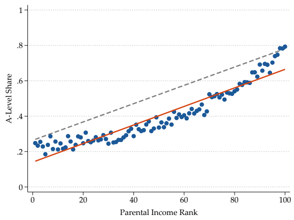
(F) Saarland



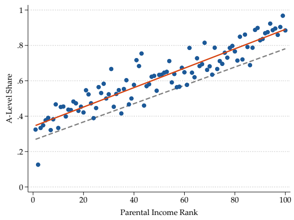
(G) Schleswig-Holstein



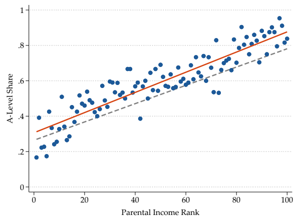
(H) Lower Saxony



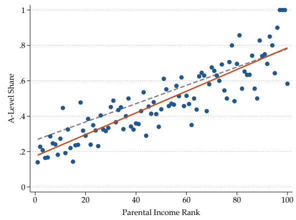
(I) Bavaria



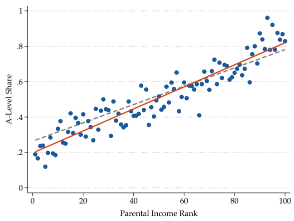
(J) Berlin



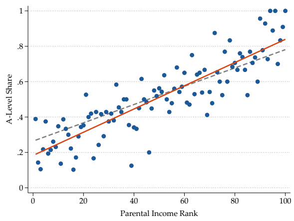
(K) Brandenburg



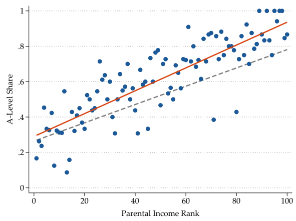
(L) Saxony-Anhalt



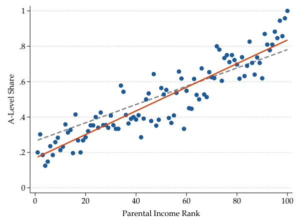
(M) Saxony



(N) Mecklenburg-Vorpommern



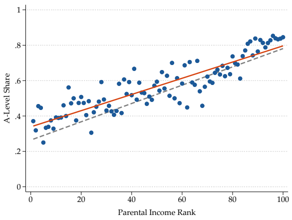
(O) Bremen



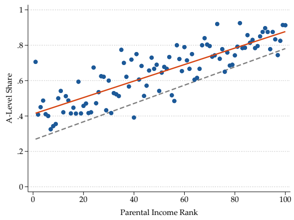
(P) Thuringia

Notes: This figure shows for each German state 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 based on the MZ waves 2011-2018, as well as the best linear approximation to the empirical CEF in orange. The dashed gray line plots the national gradient as a comparison.

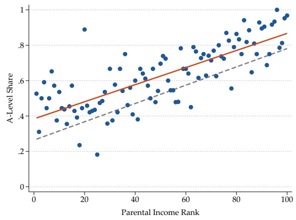
FIGURE B.7. Social Mobility for Cities



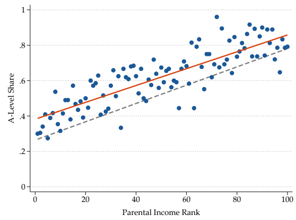
(A) Hamburg



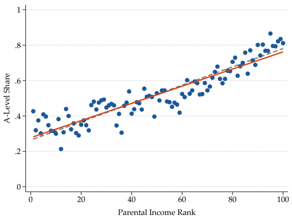
(B) Düsseldorf



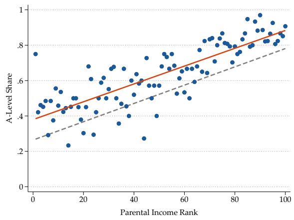
(C) Münster



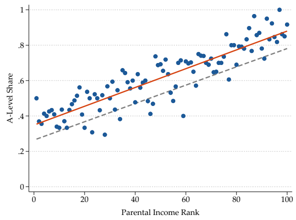
(D) Gelsenkirchen



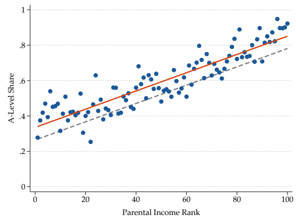
(E) Stuttgart



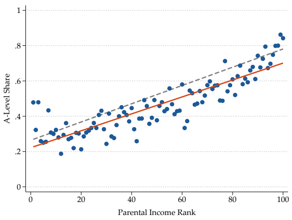
(F) Bonn



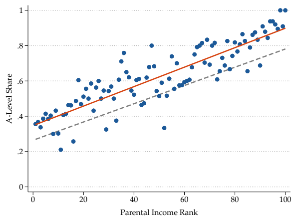
(G) Duisburg



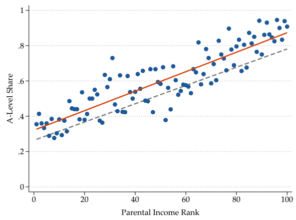
(H) Frankfurt



(I) Munich

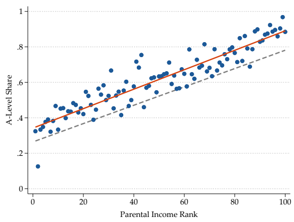


(J) Dortmund

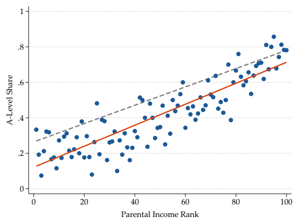


(K) Cologne

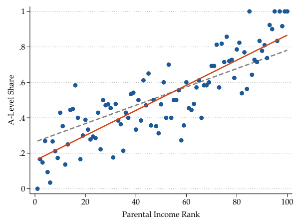
(L) Hanover



(M) Berlin



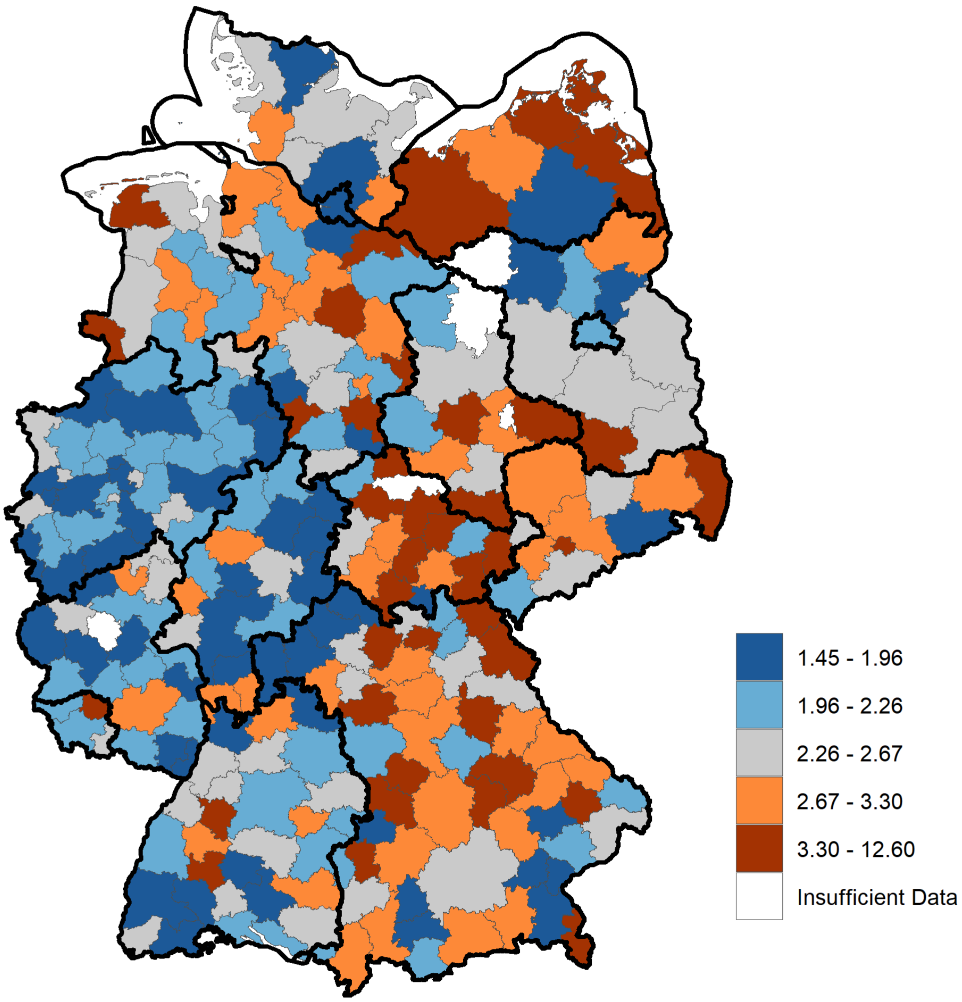
(N) Nuremberg



(O) Leipzig

Notes: This figure shows for the 15 largest (by population size in 2017) local labor markets in Germany 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 based on the MZ waves 2011-2018, as well as the best linear approximation to the empirical CEF in orange. The dashed gray line plots the national gradient as a comparison.

FIGURE B.8. Q5/Q1 Ratio by Local Labor Market



Notes: This figure presents a heat map of the Q5/Q1 ratio 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 Q5/Q1 ratio is computed by dividing the share of children with an A-Level degree in the top 20% through the share of children with an A-Level degree in the bottom 20% of the parental income distribution. The colors indicate the quintile of the respective LLM point estimate in the distribution of estimates to account for outliers of the Q5/Q1 ratio induced by small denominators. 6 LLMs with less than three children in the top 20% of the parental income distribution without an A-Level degree are excluded from the analysis.

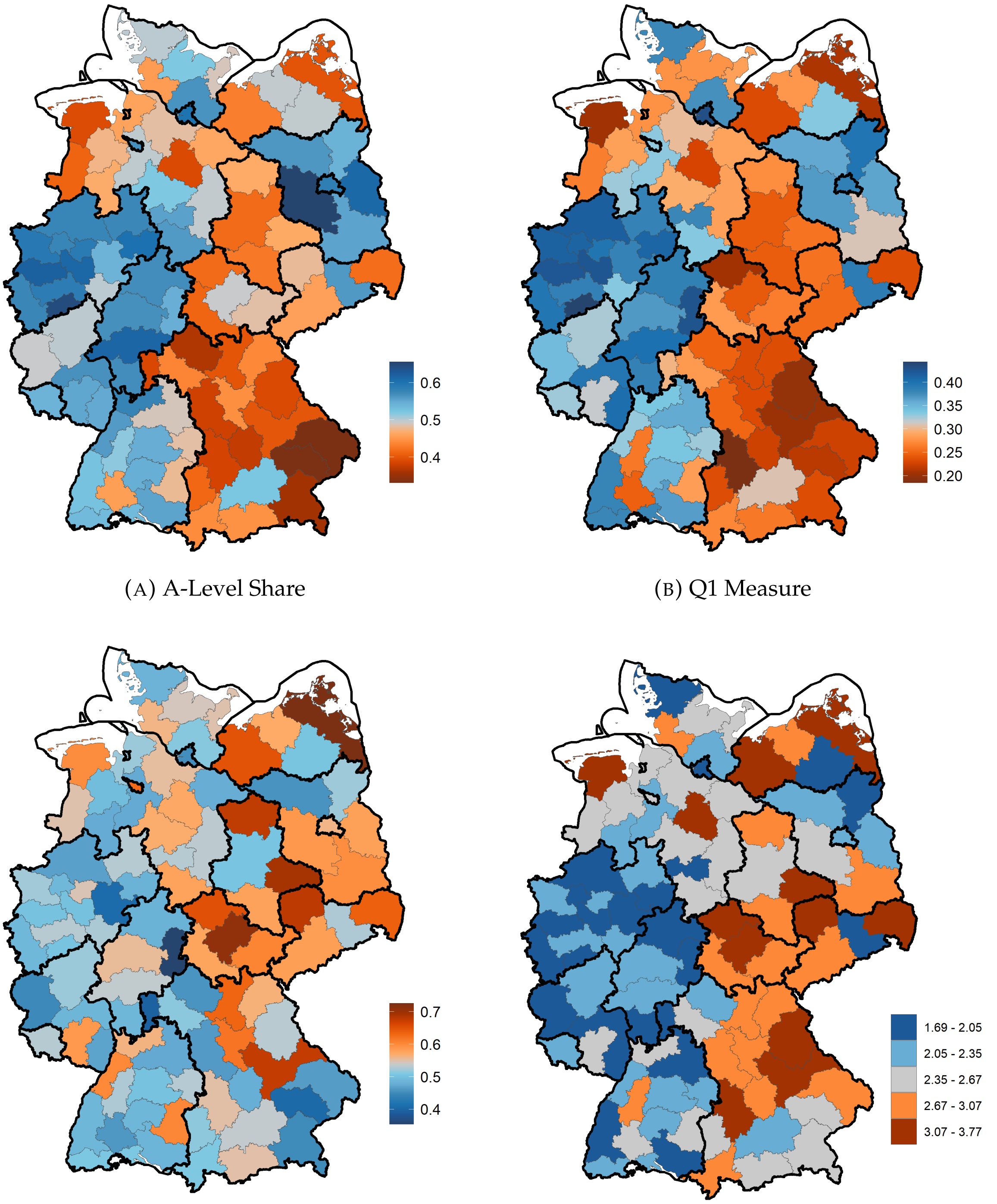
TABLE B.2. Correlation between Mobility Measures

Measure	Corr.	A-Level	Q1	Q5	Q5/Q1	Gradient
A-Level	ρ	1	-	-	-	-
	r	1	-	-	-	-
Q1	ρ	0.76	1	-	-	-
	r	0.78	1	-	-	-
Q5	ρ	0.70	0.44	1	-	-
	r	0.71	0.48	1	-	-
Q5/Q1	ρ	-0.40	-0.72	0.088	1	-
	r	-0.48	-0.84	-0.04	1	-
Gradient	ρ	-0.01	-0.45	0.45	0.65	1
	r	-0.07	-0.47	0.33	0.76	1

Notes: This table reports the pairwise correlations between estimates of different measures of social mobility across LLMs in Germany. ρ denotes the Pearson correlation coefficient, r denotes the Spearman rank correlation coefficient.

Table B.2 reports the correlations between our mobility measures. While the Q1 measure is well predicted by the unconditional A-Level share, there exists no systematic association between the A-Level share and the parental income gradient, highlighting that the gradient is not sensitive to the baseline probability of obtaining an A-Level degree. Finally, the correlation between the parental income gradient and the Q1 measure ranges below -0.5, demonstrating that a high level of absolute mobility in a given LLM does not always imply a high level of relative mobility.

FIGURE B.9. Mobility Estimates by Spatial Planning Region



(A) A-Level Share

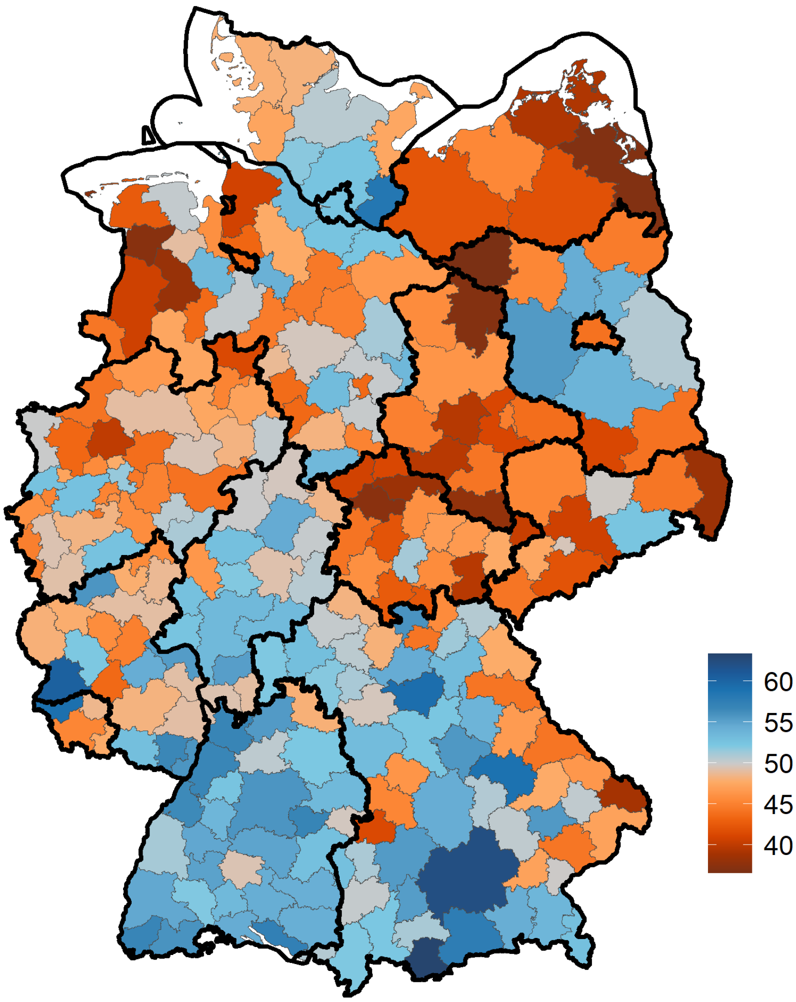
(B) Q1 Measure

(C) Gradient

(D) Q5/Q1 Ratio

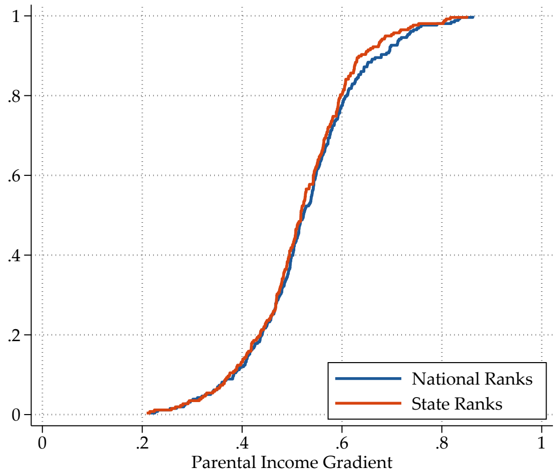
Notes: This figure presents heat maps of the A-Level share (Panel A), the Q1 measure (Panel B), the parental income gradient (Panel C) and the Q5/Q1 ratio (Panel D) for the 96 spatial planning regions of Germany. Spatial planning regions constitute a more comprehensive version of the LLMs discussed in Section 5, as they also represent aggregations of counties based on commuting flows. Children are assigned to spatial planning regions 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. In Panel (D), the colors indicate the quintile of the respective point estimate in the distribution of estimates to account for outliers of the Q5/Q1 ratio induced by small denominators.

FIGURE B.10. Mean Parental Income Rank by Local Labor Market

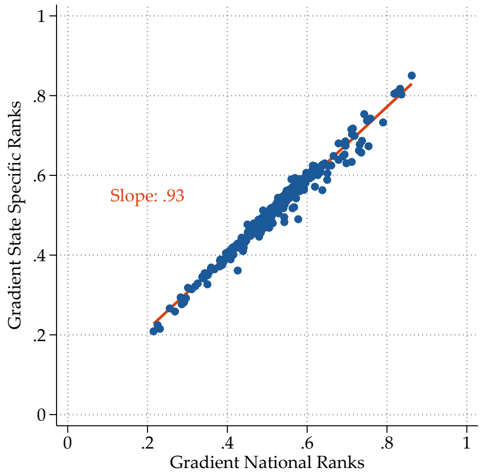


Notes: This figure presents a heat map of the mean parental income rank by LLM. Children are assigned to LLMs according to their current place of residence. The estimates are based on children aged 17-21 in the years 2011-2018 for which we have non-missing information on educational attainment and parental income. The mean parental income rank is computed as the local labor market specific averages of parenal income ranks in the national income distribution.

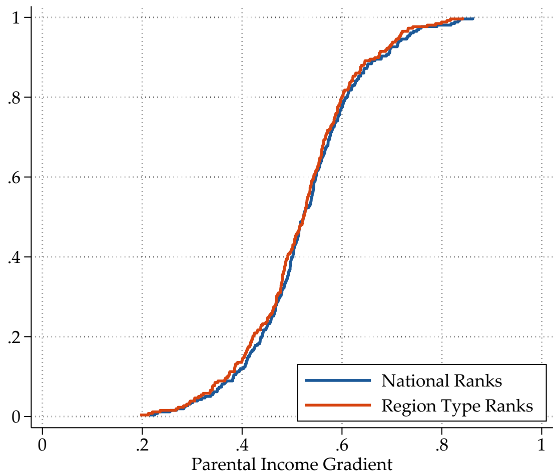
FIGURE B.11. Robustness to State and Region Specific Parental Income Ranks



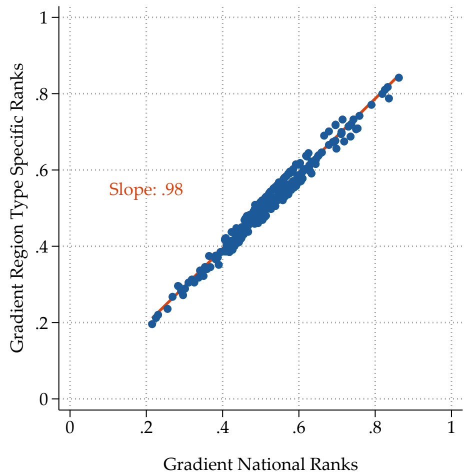
(A) CDFs



(B) Scatter Plot National/State



(C) CDFs



(D) Scatter Plot National/Region Type

Notes: This figure displays the sensitivity of our LLM-level estimates of the parental income gradient with respect to the reference income distribution. For this aim, the upper two panels compare gradients computed based on the national and the state-specific income distributions: Panel (A) displays the Cumulative Distribution Function (CDF) of both gradients, Panel (B) shows a scatter plot of the point estimates as well as their linear fit. The bottom two panels compare the gradients obtained by computing income ranks based on the national and the region-type-specific income distribution. The region types are defined by the Federal Institute for Building, Urban Affairs and Spatial Research (BBSR) and classify each county into either urban, suburban or rural. For LLMs comprising of counties of different types, we assign the most frequent category. Again, Panel (C) displays the Cumulative Distribution Function (CDF) of both gradients, whereas Panel (D) shows a scatter plot of the point estimates as well as their linear fit. The reported slope parameters of 0.93 and 0.98 correspond to the OLS slope estimates obtained by regressing the gradients computed by using the respective local ranks on the gradients computed by using national income ranks.

C Data Appendix SOEP and PISA

C.1 Data Appendix SOEP

The SOEP is a nationally representative household panel survey of the German population, established in 1984. In its more recent waves, it annually samples around 15,000 German households or 25,000 individuals each year (Goebel et al., 2019). Respondents provide information about a broad range of socio-economic variables such as income, education, employment status or biographical characteristics, as well as subjective measures like life satisfaction. Since 2000, participants turning 17 years old answer a youth questionnaire, where they are asked about their current situation in the education system, including school grades, and their aspirations and goals for the future.

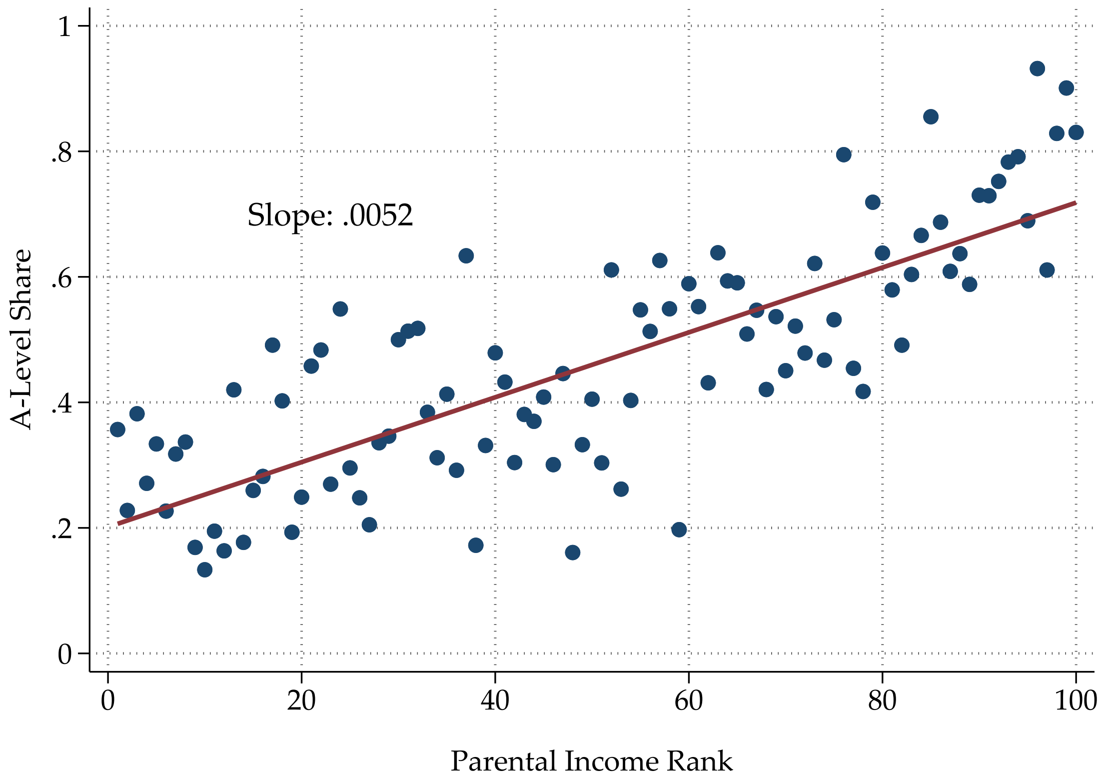
Measuring the A-Level degree. In a first step, we replicate our definition of an A-Level degree from the MZ in the SOEP. Because the SOEP follows children even after moving out of the parental household and collects annual information on educational attainment, we choose a cutoff age of 21.[32] At this age, our A-Level dummy turns one if a child has obtained, or is on track to obtain, a degree that is equivalent to an A-Level. Using this definition, Figure C.1 shows that we exactly replicate the parental income gradient of 0.52 from the MZ also in the SOEP, albeit with less precision.

For the remaining analyses, we simply assign an A-Level degree to each respondent who reports having obtained such a degree—again including both *Allgemeine Hochschulreife* and *Fachhochschulreife*—but exclude students enrolled in an A-Level track at age 21.

Measuring Ability. Among the educational information in the youth questionnaire, respondents are asked about their last school grade in the subjects of mathematics, German, and the first foreign language. Within the A-Level track, these grades provide a proxy for ability that is broadly comparable among children. We focus on math grades, as they are less likely to be confounded proxies for ability than grades in German, where migration history and command of the German language may result in

[32] To the extent that moving out of the parental household leads to panel attrition of some individuals, a small bias is also extant in the SOEP.

FIGURE C.1. Social Mobility in the SOEP



Notes: This figure shows for the birth cohorts 1980-1896 the fraction of children aged 21 in the German Socio-economic Panel (SOEP) that have already attained an A-Level degree by percentile rank of their parents in the national income distribution. The income ranks are computed with respect to the national distribution of equivalized net household income among households with children in birth cohorts 1980-1996. The reported slope coefficient of 0.0052 is estimated by OLS using the underlying micro data.

worse grades even for talented students. As the SOEP does not cover track enrollment in secondary school in sufficient detail, we make the assumption that all students that had obtained an A-Level degree by age 21 were previously enrolled in an A-Level track at age 17.

Building an Intergenerational Sample. To create an intergenerational sample, we link all children of SOEP respondents that are born during the years 1980-1996 to their parents. In our further sample restrictions, we aim to make our sample as comparable as possible to the data used in Chetty et al. (2014). For this reason, incomes of children are measured as the average over the five-year interval when children are between 29 and 33 years old. Parental information is measured in the five-year interval when children are between 15 and 19 years old.

C.2 Data Appendix PISA

The PISA international student achievement test is conducted by the OECD since the year 2000. PISA assesses achievement in mathematics, science, and reading in a representative cross-section of 15-year-old students, independent of grade level or educational track attended.

To create comprehensive measures of competencies, students complete a broad array of tasks of varying difficulty in assessments that last for up to two hours. PISA achievements in math, science, and reading were standardized to a mean of 500 test-score points and a standard deviation of 100 test-score points for OECD-country students in wave 2000 (and rescaled on the same metric again in 2003 in math and in 2006 in science). PISA test scores are provided as a distribution of five different plausible values. In our analysis, we take the average of all five plausible values. We use the PISA student weights throughout to obtain unbiased parameter estimates.

Measuring Educational Attainment. As PISA test scores are elicited at age 15 before children enter the 2-3 last years of higher secondary schools when different A-Level tracks open up, we focus exclusively on children attending *Gymnasium*, the highest secondary school track and the main avenue to obtaining an A-Level. In our analysis, we thus assume that all children enrolled in *Gymnasium* at age 15 will eventually obtain an A-Level degree. Within *Gymnasium*, PISA test scores provide an excellent proxy for ability and are well comparable among children.

Measuring Parental Income. Since 2006, PISA administers a separate parental questionnaire in selected countries, including Germany. In this questionnaire, parents report gross annual household income in six bands. To derive a continuous measure of income from the banded data, we fit a Singh-Maddala distribution in each wave. Parental income ranks are then computed based on this continuous income measure among all children of each wave.

C.3 Adjustment of Ability Trends

In this section, we first describe the calculations behind the results in Table 6 and then describe our second approach for predicting changes in grades for inframarginal students.

Assuming Constant Grades/Test Scores for Inframarginal Students. The trends in Figure 8 pool the grades of both inframarginal and marginal students. As a first way to obtain an estimate for the grades of marginal students, we assume that grades for inframarginal students have not changed.

Since the A-Level share among children at the top of the income distribution was initially already much higher than among children at the bottom of the distribution, and because the absolute increase in the A-Level share was approximately the same in all parts of the parental income distribution, the share of marginal children among all children obtaining an A-Level degree at the end of the *Bildungsexpansion* is strongly decreasing in parental income rank. For this reason, grade trends among marginal children may look quite different from the patterns in Figure 8.

To obtain the grade trend among marginal children in the SOEP, we make use of the following equation

$$\text{Grade}_{1996} = \frac{\text{A-Level}_{1980}}{\text{A-Level}_{1996}}\text{Grade}_{1980} + \frac{\Delta\text{A-Level}}{\text{A-Level}_{1996}}\text{Grade}^{M}_{1996}, \tag{3}$$

where we denote the average grade at the end of the educational expansion in 1996 as Grade_{1996}. It equals the weighted average of the inframarginal students (whose grade we denote by Grade_{1980}) and the marginal students (whose grade we denote by Grade^{M}_{1996}). Note that we define $\Delta\text{A-Level} = \text{A-Level}_{1996} - \text{A-Level}_{1980}$, i.e. the weights add up to one.

Rewriting, we can express the grade among marginal children as follows:

$$\text{Grade}^{M}_{1996} = \frac{\text{Grade}_{1996} * \text{A-Level}_{1996} - \text{Grade}_{1980} * \text{A-Level}_{1980}}{\Delta\text{A-Level}} \tag{4}$$

The same calculation can be analogously applied to obtain the average PISA test scores among marginal children. We do this analysis separately for above- and below-median-income children and thereby obtain grades and test scores of marginal students from both income groups.

Adjusting for Grade/Test Score Trends among Inframarginal Children. Equation 4 assumes that the grades of inframarginal children do not change during the educational expansion. While this assumption is a natural starting point, we now explore how our implications about the relative grades of marginal students with high- and low-parental income change if relax this assumption. We therefore incorporate a potential grade trend in the analysis. To achieve this, we predict test scores of inframarginal children based on observables by estimating the following Probit model

$$\begin{aligned} P(\text{A-Level} = 1) = \beta_0 &+ \beta_1 \,\text{Education Mother} + \beta_2 \,\text{Education Father} \\ &+ \beta_3 \,\text{Occupation Mother} + \beta_4 \,\text{Occupation Father} \\ &+ \beta_5 \,\text{Migrant} + \beta_6 \,\text{Gender} + \varepsilon, \end{aligned}$$

among all children of the initial birth cohorts (1982-1984 in the SOEP, 1990 in PISA). Hence, we model the likelihood of attaining an A-level degree as a function of parental education and occupation, migration status and gender.[33] We then predict among all birth cohorts the probability for each child to graduate with an A-Level degree, and classify all children above the 75th percentile in this probability as "inframarginal". These are typically children where both parents hold a college degree, or where parents have prestigious occupations. The intuition behind this exercise is that children from these backgrounds would have been very likely to attain an A-Level degree also in absence of the educational expansion.

Table C.1 shows that grades and test scores for children who are inframarginal according to this definition slightly deteriorated. In the SOEP, this decline in our ability proxies happened mainly among low SES children. In the PISA, the decline is more pronounced for children with above-median parental income.

[33] While migration status and gender (2 categories each), and parental education (ISCED 1-6) are defined consistently in both SOEP and PISA, the coding of parental occupation differs slightly between both data sets (6 categories in PISA, 10 categories in the SOEP).

Table C.1. Math Grades and Test Scores of Inframarginal Children

	SOEP		PISA	
	Bottom 50	Top 50	Bottom 50	Top 50
1982	2.3	2.6	-	-
1990	3.2	2.6	585	622
1996	3.0	2.5	583	614

Notes: This table shows the average math grades in the German Socio-Economic Panel (SOEP) and the average PISA math test scores for inframarginal children in birth cohorts 1982, 1990 and 1996, separately for children below and above median parental income. See the text for a definition of inframarginal children. 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).

To estimate the grades of marginal students, we now account for these changes in grades among inframarginal children, we can compute the average grade among marginal children according to the following formula:

$$\text{Grade}_{1996} = \frac{\text{A-Level}_{1980}}{\text{A-Level}_{1996}}\text{Grade}^{I}_{1991} + \frac{\Delta\text{A-Level}}{\text{A-Level}_{1996}}\text{Grade}^{M}_{1996}, \tag{5}$$

which is essentially the same as (3) with the only difference that Grade^{I}_{1996} replaces Grade_{1980}. Hence, for the inframarginal students we do not assume that their grades equal the grades of 1980 but take the probit model predictions as stated in Table C.1. Rearranging, we get:

$$\text{Grade}^{M}_{1996} = \frac{\text{Grade}_{1996} * \text{A-Level}_{1996} - \text{Grade}^{I}_{1996} * \text{A-Level}_{1980}}{\Delta\text{A-Level}}. \tag{6}$$

As for the first approach, we do this analysis separately for above- and below-median-income children and thereby obtain grades and test scores of marginal students from both income groups. The results in Table C.2 show that adjusting for grade trends among inframarginal children does slightly alter the conclusions regarding the ability of marginal children. While the grades of marginal children did not differ substantially (or significantly) between children below and above median parental income if we consider cohorts from 1980-1996, there are differences for the time period 1982-1990: among those cohorts, marginal students with lower parental income outperform marginal students with higher parental income.

TABLE C.2. Math Grades and Test Scores of Marginal Children - Adjusted for Changes among Inframarginal Children

	SOEP			PISA		
	Bottom 50	Top 50	Δ	Bottom 50	Top 50	Δ
1982-1990	2.2	2.5	0.31 SD	-	-	-
1990-1996	4.0	2.9	0.99 SD	554	601	0.68 SD
1982-1996	2.7	2.7	0.04 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 6 and take into account the differential development in grades among inframarginal children. 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 72 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).

D Regional Predictors of Mobility

Regional Indicators. We construct a comprehensive database of 73 regional indicators for this analysis, with information on labor market participation, economic conditions, infrastructure, demographics, local educational institutions and social characteristics.

Table D.1 displays all 73 regional indicators we use as predictors in the Random Forest algorithm. In a first step, we retrieve data from the Federal Institute for Building, Urban Affairs and Spatial Research (BBSR), which maintains the INKAR database of regional indicators (`https://www.inkar.de/`). These data are collected from various government bodies in Germany, including the German Statistical Office (Destatis) and the Institute for Employment Research (IAB). We select all indicators which we suppose to be potentially relevant for social mobility and are not collinear: for example, we do not include the general unemployment rate and the unemployment rates among males and females at the same time. In a second step, we add data from Destatis publications with information on the share of Gymnasium students among all secondary school students, the share of A-Level degrees obtained on vocational schools and compute the distance of the geographical center of each LLM to the next college based on data from the website of the Hochschulrektorenkonferenz (HRK; `https://www.hochschulkompass.de/hochschulen/downloads.html`). In a third step, we compute additional regional statistics on the LLM level using the MZ data, like the Gini coefficient in household income, the local A-Level wage premium or the ISEI (an international index of social status). We construct our final variables by averaging the local indicators over the years 2011-2018 at the LLM level.

Prediction Exercise. To study the association between local characteristics and intergenerational mobility, prior literature has typically relied on correlation coefficients or estimated multiple linear models (Chetty et al., 2014; Corak, 2020). Both approaches have disadvantages. As socio-economic characteristics are highly correlated at the regional level, correlation coefficients are often spurious. While this remedy is overcome in a multiple linear OLS regression, these models are prone to overfitting in high-dimensional data sets (Babyak, 2004), resulting in diminished external validity. One way to address this it to reduce dimensionality of the covariates via variable selection.

Belloni and Chernozhukov (2013) suggest to preselect covariates via Lasso before estimating a multiple linear model.[34] This approach is for example applied by Finkelstein et al. (2016) to explain geographical variation in health care utilization in the US.

We take a similar two-step approach, but preselect variables using a Random Forest variable importance measure instead of a Lasso regression. This is because we find that a linear Lasso model fits our data poorly: To compare the out-of-sample performance of this algorithm against an implementation of a Lasso and an Elastic Net regression with α =0.5, we split our data in a training and test data set (75-25 split). The Random Forest algorithm predicts 39% of the variation in the test sample (R^2 = 0.39), whereas the predictive power of Lasso (R^2 = 0.15) and Elastic Net (R^2 = 0.17) is lower. The results for Lasso and Elastic Net are based on λ chosen by 5-fold cross-validation. For the Random Forest, we fit 1000 trees and randomly select $73/3 \approx 24$ variables for each split.

Before constructing the Random Forest, we standardize all 73 indicators to have mean 0 and standard deviation 1. Once the Random Forest is fitted, we can rank covariates according to their predictive power and thereby obtain a measure of variable importance. We choose the implementation proposed by Strobl et al. (2008), which computes a conditional permutation importance measure that accounts for the dependence structure between the predictors, using the `party` `R` package (`http://CRAN.R-project.org/package=party`).

Most Informative Predictors. The set of the 15 most informative predictors is displayed in Table D.2, ranked by a measure of variable importance computed by the Random Forest.[35] The last column displays the sign of the bivariate correlation between each variable and the parental income gradient. A positive sign implies that the indicator predicts low mobility (a high gradient). For example, LLMs with a high prevalence of school dropouts are associated with low relative mobility. Overall, our selection procedure highlights social characteristics, the local organization of the education system and labor market conditions. These correlational findings are consistent

[34] An alternative approach to deal with model uncertainty is model averaging. See Kourtellos et al. (2016) for an application in the context of social mobility.

[35] The exact ranking of predictors varies for different implementations of the Random Forest algorithm. We are therefore cautious not to over-interpret the ranking between single predictors.

with causal studies that emphasize the importance of local characteristics for child and adolescent outcomes (Chetty and Hendren, 2018; Damm and Dustmann, 2014).

Regression Estimates. In a second step, we regress the gradient on these 15 indicators selected by the algorithm. All right-hand side variables are standardized so that the coefficients report the association between a one standard deviation change in the covariate and an absolute change in the gradient. The results are reported in Table D.3. The signs of the coefficients mostly match those from the bivariate correlations in Table D.2. For example, a one standard deviation increase in the school dropout rate is associated with a 3.9 percentage point higher parental income gradient.[36] This association becomes stronger when adding state indicators. A high gradient also aligns with a high number of teenage pregnancies, a high unemployment rate and a large share of households with access to broadband Internet. A negative association with the parental income gradient arises for the share of married individuals, the distance to the next college, the median income for individuals with a recognized vocational qualification, the share of children aged 0-2 in childcare and for the share of children on a vocational A-Level track. Due to the limited sample size of 258 local labor markets, we lack the power to precisely estimate most coefficients. Exceptions are the school dropout rate, broadband availability, the share of married individuals and the share of children on a vocational A-Level track.

[36]The school dropout rate refers to the share of secondary school students leaving school without the lowest possible certificate (*Hauptschulabschluss*. Although the A-Level share ceteris paribus decreases in the school dropout rate, there exists no direct mechanical relationship between the two. For example, any student dropping out of the two higher secondary school tracks (which enroll the vast majority of students) after grade 9 will automatically be awarded a *Hauptschulabschluss*, and thus not fall under the given definition of a school drop out.

TABLE D.1. List of Regional Indicators

Category	Variable	Source
Labor Market	Unemployment Rate	INKAR
	Share Long Term Unemployed	INKAR
	Share Female Employees	INKAR
	Share Part Time Employees	INKAR
	Share without Vocational Qualification	INKAR
	Share Marginal Employment	INKAR
	Share Employed in Manufacturing Sector	INKAR
	Apprenticeship Positions	INKAR
	Apprentices	INKAR
	Vocational School Students	INKAR
	Employees with Academic Degree	INKAR
	Commuting Balance	INKAR
	Hours Worked	INKAR
	A-Level Wage Premium	MZ
Education	Students (before Tertiary Education)	INKAR
	Students (Tertiary Education)	INKAR
	Students (Universities of Applied Sciences)	INKAR
	School Dropout Rate	INKAR
	Highly Qualified Persons	INKAR
	Share Children 0-2 in Childcare	INKAR
	Share Children 3-5 in Childcare	INKAR
	Share Students Enrolled in Gymnasium	INKAR
	Share Secondary School Students Enrolled in Gymnasium	Destatis
	Distance to Next College	HRK
	Distance to Next Elementary School	INKAR
	Share on Vocational A-Level Track	MZ
	Share A-Level Degree from Vocational Schools	Destatis
	Mean Parental Education	MZ
Income	Median Household Income	INKAR
	Median Household Income with Vocational Qualification	INKAR
	Gender Wage Gap	INKAR
	Child Poverty	INKAR
	Mean Household Income	INKAR
	Gini Household Income	MZ
	Expected Rank Difference Parental Income	MZ
	Mean Parental Income	MZ
	Gini Parental Income	MZ
	Ratio p85/p50 (Household Income)	MZ
	Ratio p50/p15 (Household Income)	MZ

Economy	GDP per Capita	INKAR
	Municipal Tax Revenues per Capita	INKAR
	Municipal Debt per Capita	INKAR
	Business Creation	INKAR
Housing	Construction Land Prices	INKAR
	New Apartments	INKAR
	Building Permits	INKAR
	Living Area	INKAR
	Share Apartment Buildings	INKAR
	Rent Prices	INKAR
Infrastructure	Physician Density	INKAR
	Broad Band Availability	INKAR
	Passenger Car Density	INKAR
	Hospital Beds	INKAR
Demographics	Average Age	INKAR
	Share Female	INKAR
	Share Foreigners	INKAR
	Share Asylum Seekers	INKAR
	Total Net Migration	INKAR
	Births Net of Deaths	INKAR
	Fertility Rate	INKAR
	Teenage Pregnancies	INKAR
	Life Expectancy	INKAR
	Child Mortality	INKAR
	Population Density	INKAR
	Share Single Parents	MZ
	Share Married	MZ
	Share Divorced	MZ
Social	Voter Turnout	INKAR
	Vote Share CDU	INKAR
	Vote Share SPD	INKAR
	Share Social Assistance	INKAR
	Mean ISEI	MZ
	Gini ISEI	MZ

Notes: This table displays all regional indicators considered for our analysis. The third column reports the data source, which is either the INKAR database, the Statistical Office of Germany (Destatis), the Hochschulrektorenkonferenz (HRK) or the Mikrozensus (MZ).

TABLE D.2. The 15 Most Informative Predictors of Relative Mobility

Variable	Importance Measure	ρ
School Dropout Rate	0.85	$+$
Share Married	0.60	$-$
Teenage Pregnancies	0.42	$+$
Students	0.39	$-$
Median Income Vocational Qualification	0.18	$-$
Broadband Availability	0.17	$+$
Distance to Next College	0.15	$-$
Unemployment Rate	0.14	$+$
Gender Wage Gap	0.14	$+$
Share without Vocational Qualification	0.13	$-$
Gini Parental Income	0.08	$-$
Share Marginal Employment	0.07	$-$
Share Children 0-2 in Childcare	0.07	$+$
Share Social Assistance	0.07	$+$
Share on Vocational A-Level Track	0.07	$-$

Notes: This table lists the optimal predictive set of 15 regional indicators for the local labor market parental income gradient estimates, as chosen by a Random Forest based measure of variable importance (second column, displayed in multiples of 1000). The last column shows the sign of the Pearson correlation coefficient between each variable and the parental income gradient. A positive correlation implies that an indicator is predictive for low relative mobility (a high gradient).

TABLE D.3. Social Mobility and Regional Characteristics

	(1)	(2)	(3)	(4)	(5)
School Dropout Rate	0.0391	0.0371	0.0393	0.0554	0.0539
	(0.0110)	(0.0110)	(0.0091)	(0.0162)	(0.0162)
Share Married	-0.0225	-0.0286	-0.0225	-0.0243	-0.0278
	(0.0089)	(0.0089)	(0.0065)	(0.0108)	(0.0109)
Teenage Pregnancies	0.0169	0.0123	0.0211	0.0160	0.0115
	(0.0226)	(0.0231)	(0.0155)	(0.0252)	(0.0266)
Students	-0.0143	-0.0166	-0.0055	-0.0214	-0.0246
	(0.0131)	(0.0128)	(0.0093)	(0.0164)	(0.0165)
Median Income Vocational Qualification	-0.0179	-0.0194	-0.0025	-0.0234	-0.0224
	(0.0129)	(0.0129)	(0.0114)	(0.0167)	(0.0177)
Broadband Availability	0.0260	0.0274	0.0194	0.0231	0.0261
	(0.0100)	(0.0100)	(0.0085)	(0.0105)	(0.0109)
Distance to Next College	-0.0048	-0.0059	-0.0051	-0.0025	-0.0045
	(0.0072)	(0.0077)	(0.0070)	(0.0072)	(0.0076)
Unemployment Rate	0.0368	0.0295	0.0124	0.0537	0.0476
	(0.0365)	(0.0365)	(0.0236)	(0.0464)	(0.0470)
Gender Wage Gap	-0.0029	-0.0041	0.0048	0.0156	0.0124
	(0.0142)	(0.0144)	(0.0126)	(0.0174)	(0.0177)
Share without Vocational Qualification	0.0057	0.0085	-0.0035	0.0132	0.0108
	(0.0171)	(0.0173)	(0.0127)	(0.0217)	(0.0220)
Gini Parental Income	-0.0171	-0.0108	-0.0236	0.0051	0.0117
	(0.0147)	(0.0150)	(0.0110)	(0.0200)	(0.0209)
Share Marginal Employment	-0.0086	-0.0162	-0.0183	-0.0222	-0.0250
	(0.0138)	(0.0142)	(0.0121)	(0.0152)	(0.0154)
Share Children 0-2 in Childcare	-0.0398	-0.0420	-0.0526	-0.0246	-0.0259
	(0.0192)	(0.0189)	(0.0182)	(0.0234)	(0.0236)
Share Social Assistance	-0.0607	-0.0429	-0.0406	-0.0969	-0.0782
	(0.0343)	(0.0361)	(0.0231)	(0.0450)	(0.0498)
Share on Vocational A-Level Track	-0.0165	-0.0171	-0.0133	-0.0213	-0.0224
	(0.0092)	(0.0092)	(0.0079)	(0.0100)	(0.0100)
Additional Controls	-	✓	✓	-	✓
State Indicators	-	-	-	✓	✓
Weighted	-	-	✓	-	-
N	258	258	258	252	252
R^2	0.256	0.273	0.253	0.296	0.305

Notes: Each column of this table reports coefficients from a linear regression with robust standard errors reported in parentheses. The dependent variable in all columns is the parental income gradient. The independent variables (as selected by the Random Forest, compare Table D.2) are standardized to have mean 0 and standard deviation 1. Columns (3) and (4) contain state dummies, for which we have to drop five LLMs crossing state borders and the LLM of Berlin. In columns (2) and (4), we additionally control for population, population density and the region type (rural, urban or mixed) to test whether coefficients of the regional indicators are affected by structural differences in mobility between more rural or urban LLMs. In column (3) we weight the regression with the number of observations per LLM.

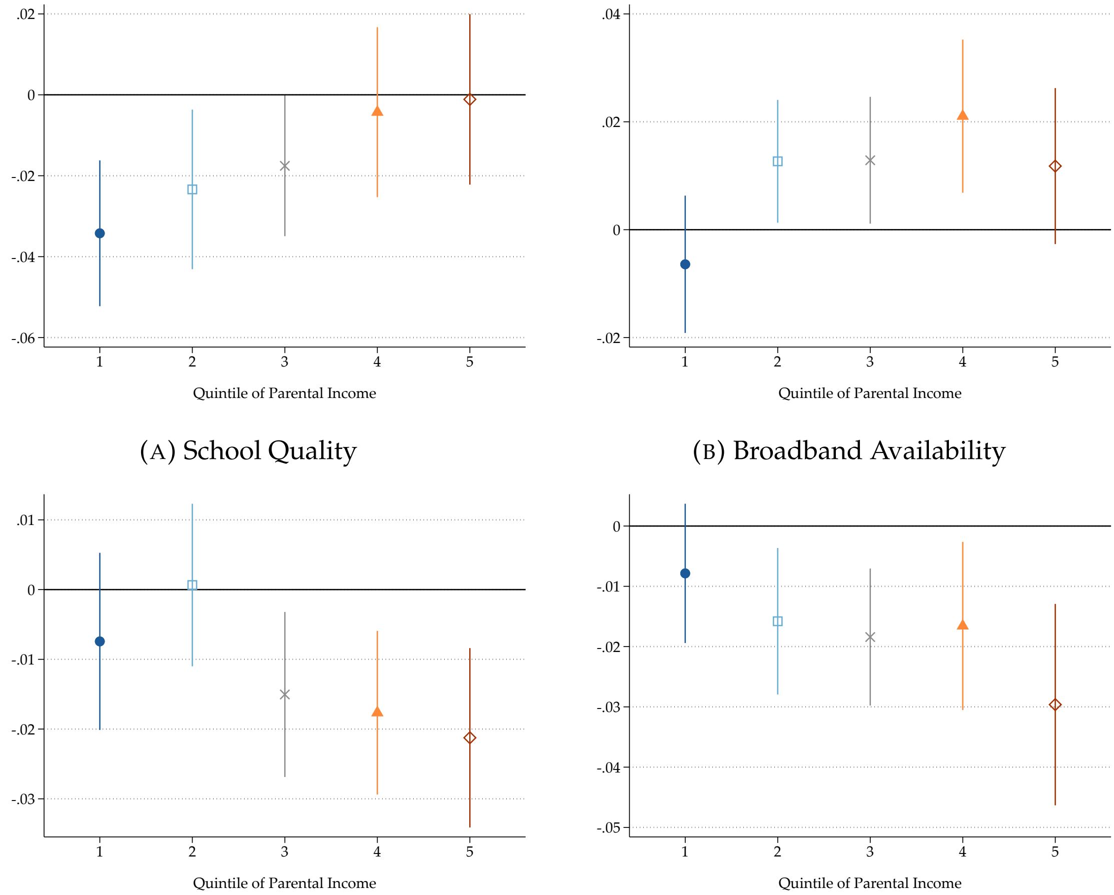
Graphical Evidence. To understand the relationship between relative mobility and the indicators with the largest t-statistics in more detail, we separately regress the A-Level share in each quintile of the parental income distribution on each indicator and plot the estimates in Figure D.1. These plots reveal whether, for example, a positive relationship between the parental income gradient and an indicator is driven by a lower A-Level share of children from low-income households or by a higher A-Level share of children from high-income households.

We start with the school dropout rate. In the US context, Chetty et al. (2014) interpret the school dropout rate, adjusted by parental income, as an indicator of school quality and find a strong negative correlation with relative mobility. In close analogy, we regress the dropout rate on mean parental income, the Gini coefficient of parental income, the share of parents holding an A-Level degree and the unemployment rate and take the residuals to obtain a measure of school quality which is adjusted for parental income and labor market conditions. This indicator is still highly correlated with mobility. As depicted in Figure D.1, Panel (A), low school quality (a high value of the indicator) is associated with a lower probability to obtain an A-Level degree for children from low income households but does not seem to affect children in the top two quintiles of the parental income distribution. While this would be consistent with the idea that school quality is crucial for improving opportunities for children from low socio-economic background, further information is needed to test this hypothesis in detail.[37]

Panel (B) sheds light on the negative connection between broadband availability and mobility. While broadband access is associated with a higher A-Level share on average, this is not true for children in Q1, for whom the relationship becomes negative. We can only speculate about the reasons. Broadband access is highly correlated with factors pointing to dynamic and prosperous labor markets, which exhibit above

[37]Most importantly, it remains open if the adjusted school drop out rate is indeed an appropriate proxy for school quality. In the US, Rothstein (2019) studies how closely the transmission of parental income to educational attainment and achievement (test scores) are correlated with income mobility at the commuting zone level. He finds income-income transmission to be closely connected to income-educational attainment transmission but not to income-educational achievement transmission. Rothstein (2019) therefore finds little evidence that differences in the quality of secondary schooling are a key mechanism driving variation in intergenerational mobility. However, the distinct features of the German secondary schooling system could lead to very different patterns in our data. Unfortunately, there exist no comparable data on student test scores in Germany, preventing us from investigating this issue further.

FIGURE D.1. Predicting the A-Level Share by Parental Income Quintile



(A) School Quality

(B) Broadband Availability

(C) Share Married

(D) Share on Vocational A-Level Track

Notes: Each panel of this figure reports coefficients from five separate linear OLS regressions with robust standards errors and 95% confidence bands. The dependent variable is the share of children which obtained an A-Level in the respective quintile of the parental income distribution. The independent variable is the adjusted school dropout rate (school quality index) in Panel (A), the share of broadband connections per 100 inhabitants in Panel (B), the share of married individuals in Panel (C) and the share of students on a vocational (rather than general education) A-Level track (Panel D). In addition, all regression include a set of state indicators and control for population, population density and the region type (rural, urban or mixed). We exclude 6 LLMs with insufficient observations for estimating Q5 from the sample. Due to the inclusion of state indicators, we have to further drop five LLMs crossing state borders and the LLM of Berlin from the sample, leaving us with 246 observations. All regressors are standardized to have mean 0 and standard deviation 1.

average inequality. For that reason, broadband availability may proxy urban areas in which all but children from the bottom of the income distribution profit from a dynamic and rewarding economic environment. However, broadband availability could also causally influence social mobility. For the US, Dettling et al. (2018) document that increased broadband availability fosters access to college and find the effect to be concentrated among students with parents from high socio-economic status. Similarly, Sanchis-Guarner et al. (2021) report a causal (positive) impact of broadband access on student test scores in England but find comparatively lower effects for students eligible for free school meals. Our results would be in line with these findings.

The opposite pattern emerges for the share of married individuals in Panel (C): this statistic is related to higher mobility but a lower A-Level share of children from high-income families. Finally, Panel (D) reports the association between the quintile measures and the share of children on a vocational, rather than general interest, A-Level track. There is reason to believe that the availability of such vocational tracks may dampen the influence of parental background on the opportunities of children. Children in these tracks have typically obtained a degree from the medium track (Realschule) and now attend a specialized vocational school to obtain an A-Level degree on top. In that setting, vocational schools may especially foster the opportunities of children from low-income households initially "misallocated" to the medium instead of the high track. Dustmann et al. (2017) show that vocational schools have the potential to fully offset adverse effects of early age tracking on long-term labor market outcomes, but cannot observe parental background.

Our evidence shows that, relative to children from the top quintile, children from the bottom quintile are more likely to obtain an A-Level in local labor markets with a high prevalence of such schools. In addition, we find that at the national level the parental income rank is more predictive for the probability of attending the general high track (Gymnasium) at the age of 13-14 than of obtaining an A-Level degree later on (gradient of 0.55 versus 0.52), again suggesting that vocational schools may mediate the influence of parental background.

Summary of Results. The key insight from this exercise is that the Random Forest algorithm is able to find meaningful variation in our data at the regional level, corresponding to existing theories of determinants of mobility. For example, as in our data, the school dropout rate is among the most significant negative correlates of relative mobility in the US data analyzed by Chetty et al. (2014). Similarly, characteristics of the vocational education system, an evergreen in the debate on social mobility in Germany, feature prominently in this list. In light of this evidence, it seems unlikely that the regional variation between LLMs is mainly driven by sampling error. We also repeat the prediction exercise for the 129 largest and 129 smallest LLMs in Table D.4.

While this analysis displays some interesting differences between rural and urban areas, the recurring themes are the same.

At the same time, our results do not necessarily imply that mobility differences originate from regional policy-variant parameters like the local school infrastructure, childcare availability or local employment conditions. Some of the predictors in Table D.2, like the school dropout rate or the share of married individuals, could likewise point to the persistence of cultural norms or the existence of deep-rooted transmission parameters which are hard to capture with a contemporaneous set of regional indicators. For other outcomes of interest, research has shown that regional differences in Germany can reach far back into the past (e.g. Becker et al., 2020; Cantoni et al., 2019). We lack the statistical power for a detailed discrimination of these factors and exogenous variation to identify the causal determinants of mobility at the local level. We hope that future work will be able to build on our analysis and shed more light on these issues.

TABLE D.4. The 15 Most Informative Predictors by LLM Size

Variable	Importance Measure	ρ
Panel (A): 129 Largest Local Labor Markets		
School Dropout Rate	0.42	$+$
Gini Parental Income	0.23	$-$
Share Married	0.16	$-$
Share without Vocational Qualification	0.10	$-$
Students	0.09	$-$
Physician Density	0.09	$+$
Teenage Pregnancies	0.06	$+$
Mean Parental Income	0.06	$-$
Share Marginal Employment	0.06	$-$
Students (Universities of Applied Sciences)	0.05	$+$
Median Income Vocational Qualification	0.05	$-$
Distance to next Elementary School	0.03	$-$
Share Children 3-5 in Childcare	0.03	$+$
Child Mortality	0.03	$-$
Ratio p50/p15	0.03	$-$
Panel (B): 129 Smallest Local Labor Markets		
School Dropout Rate	0.75	$+$
Unemployment Rate	0.45	$+$
Child Poverty	0.40	$+$
Students	0.40	$-$
Share Married	0.33	$-$
Teenage Pregnancies	0.33	$+$
Median Income Vocational Qualification	0.19	$-$
Gender Wage Gap	0.19	$+$
Share Social Assistance	0.18	$+$
Total Net Migration	0.12	$-$
Highly Qualified Persons	0.10	$+$
Broadband Availability	0.10	$+$
Share on Vocational A-Level Track	0.08	$-$
Building Permits	0.08	$-$
Share Apartment Buildings	0.07	$+$

Notes: This table lists the 15 most predictive indicators for explaining variation in the parental income gradient between local labor markets in Germany, separately for the 129 largest (Panel [A]) and the 129 smallest (Panel [B]) local labor markets. See the text for the details on the implementation via a Random Forest variable importance measure. The second column displays the measure of variable importance (in multiples of 1000). The last column shows the sign of the Pearson correlation coefficient between each variable and the parental income gradient. A positive correlation implies that an indicator is predictive for low relative mobility (a high gradient).

E Robustness of Regional Estimates

A concern with the point estimates that we report in Section 5 of the paper is that the heterogeneity we document and depict in the maps could be driven by sampling variation. In order to address this concern in a principled way, we adopt an empirical Bayes (EB) perspective, i.e. we interpret our baseline estimates for each region j as noisy signals of parameters drawn from a distribution in the following hierarchical model:

$$\begin{aligned} \hat{\theta}_j|\theta_j, \sigma_j &\sim N(\theta_j, \sigma_j^2) \\ \theta_j|\sigma_j &\sim G(\theta) \qquad j = 1, ..., J. \end{aligned}$$

The first level of the hierarchy is justified (approximately) by a central limit theorem applying to our estimators of the mobility parameters. The second level of the hierarchy describes the cross-sectional distribution of the respective mobility measure across regions.

Measuring Overdispersion. In this framework, we first ask how much overdispersion we observe in our estimates, i.e. how much excess variation we observe in our estimates beyond what one would expect given the associated sampling uncertainty.[38] To that end we compute

$$\hat{\sigma}_\theta^2 = \frac{1}{J} \sum_{j=1}^{J} \left[\left(\hat{\theta}_j - \hat{\mu}_\theta\right)^2 - \hat{s}_j^2 \right],$$

an estimate of the variance of G, where $\hat{\mu}_\theta = J^{-1} \sum_{j=1}^{J} \hat{\theta}_j$ and $\hat{s}_j^2$ denotes the estimated variance of $\hat{\theta}_j$. Based on this measure of overdispersion, we report "reliability ratios" ($RR_{\hat{\theta}}$; see also Deutscher and Mazumder (2020)) that capture the share of excess variance in $\hat{\theta}$ via

$$RR_{\hat{\theta}} = \frac{\hat{\sigma}_\theta^2}{\hat{s}_\theta^2},$$

where $\hat{s}_\theta^2$ denotes the sample variance of $\hat{\theta}$. Table E.1 reports the results of this exercise.

[38] We thank an anonymous referee for suggesting an exercise along these lines.

TABLE E.1. Reliability Ratios of Mobility Measures

	A-Level	Q1	Q5	Q5/Q1	Gradient
States	0.92	0.89	0.86	0.94	0.78
Spatial Planning Regions	0.96	0.83	0.82	0.98	0.60
Local Labor Markets	0.93	0.69	0.66	0.71	0.51

Notes: This table reports the "reliability ratios" defined in Appendix E for our mobility measures estimated on different geographical aggregations. There are 16 states, 96 Spatial Planning Regions and 258 Local Labor Markets.

We conclude that, while sampling variation is certainly important, a substantial share of the regional variation that we document does indeed capture regional differences. As expected, our reliability ratios tend to decrease towards more fine-grained regional disaggregations, reflecting the fact that estimation uncertainty increases.

Empirical Bayes Confidence Intervals. In order to provide further transparency regarding the uncertainty associated with the ensemble of our local labor market-level parental income gradient estimates, we report empirical Bayes confidence intervals. Constructed around MSE-optimal linear shrinkage estimates, these intervals allow us to report sets of confidence intervals with coverage guarantees for the ensemble of projection coefficients, yielding visual summaries of the uncertainty associated with our local labor market-level estimates.

Specifically, we linearly shrink the original point estimates of the projection coefficients towards the respective state averages in proportion to the estimated signal-to-noise ratio

$$\hat{\theta}_j^* = \left(\frac{\hat{\sigma}_\theta^2}{\hat{\sigma}_\theta^2 + \hat{s}_j^2}\right)\hat{\theta}_j + \left(\frac{\hat{s}_j^2}{\hat{\sigma}_\theta^2 + \hat{s}_j^2}\right)\hat{\mu}_{s(j)},$$

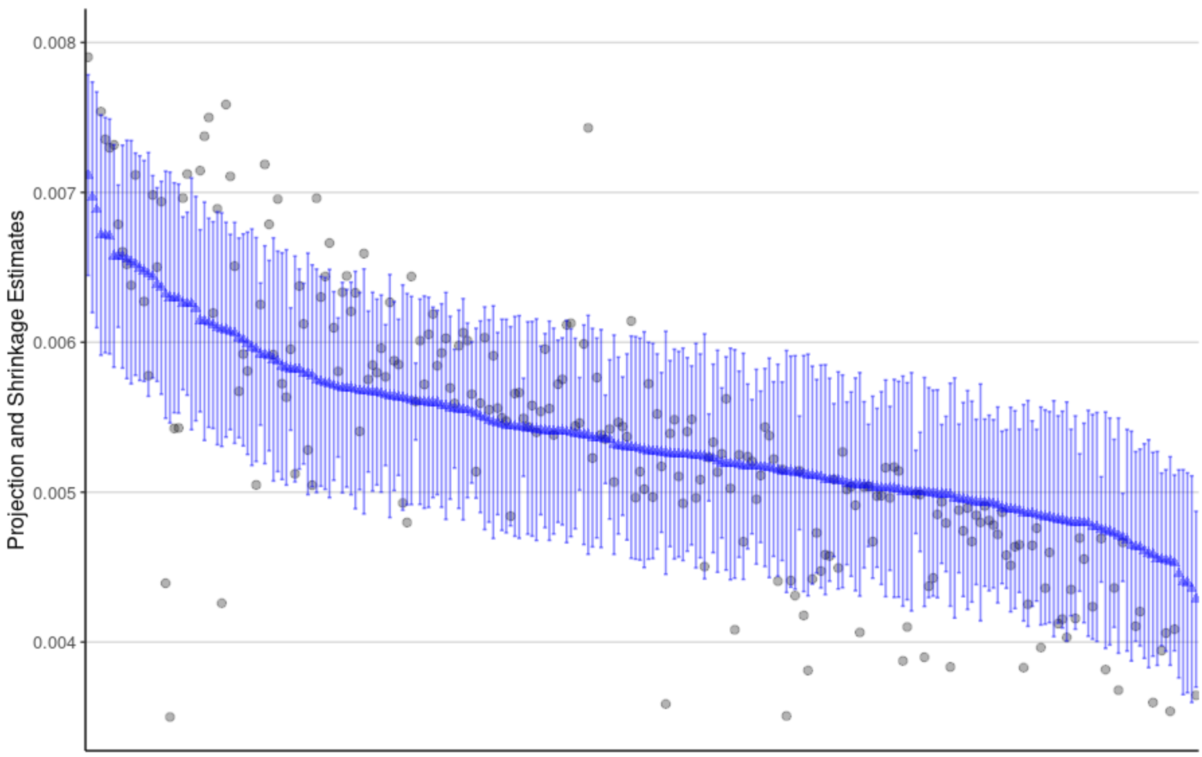
where $\hat{\mu}_{s(j)}$ denotes the (variance-weighted) state-average gradient estimate, and report intervals with ensemble coverage guarantees under two sets of assumptions on the mixing distribution G.

We first construct parametric empirical Bayes confidence intervals under the assumption that the sampling distribution of θ_j is conditionally normal

$$\begin{aligned}\hat{\theta}_j|\theta_j, X_j, \sigma_j &\sim N(\theta_j, \sigma_j^2)\\ \theta_j|X_j, \sigma_j &\sim N(\mu_\theta, \sigma_\theta^2) \qquad j = 1, ..., J,\end{aligned}$$

where X_j contains state-indicator variables. If G is correctly specified, the resulting parametric empirical Bayes confidence intervals (EBCIs) will cover $(1-\alpha)$ percent of the true effect parameters under repeated sampling of the data and the parameters (Morris, 1983). The results are depicted in Figure E.1.

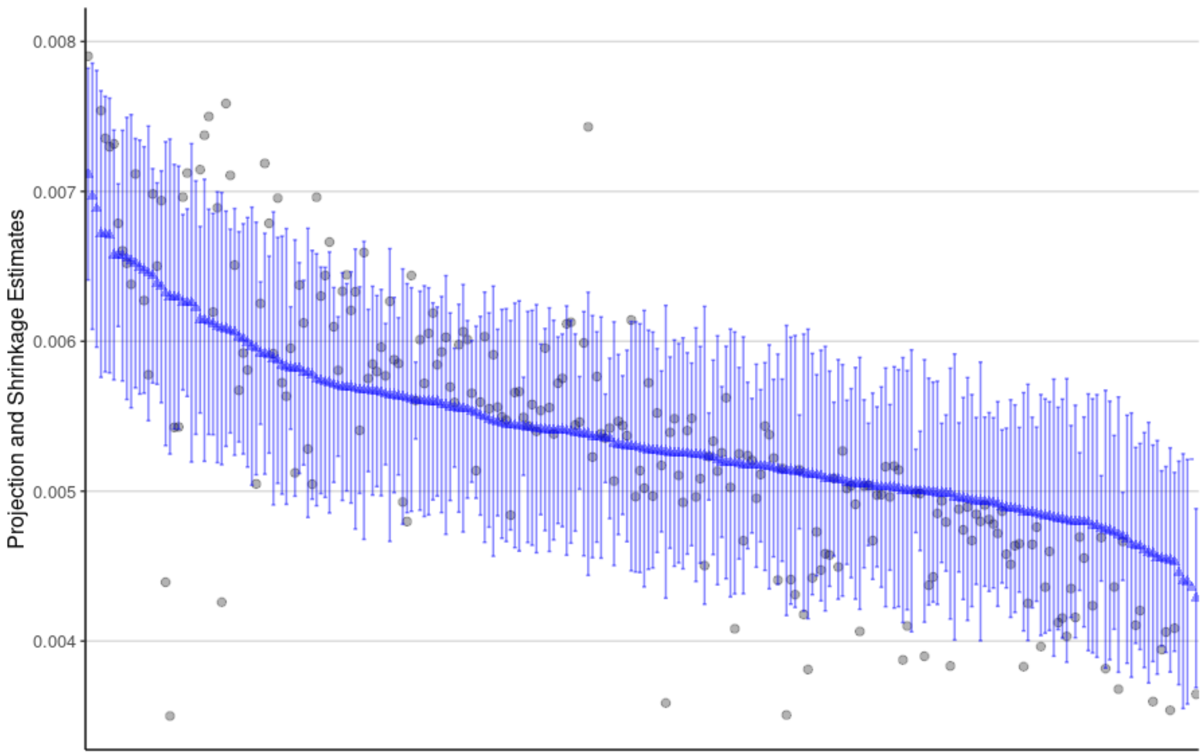
FIGURE E.1. Shrinkage Estimates and Parametric EB Confidence Intervals



Notes: This figure depicts the original point estimates of the projection coefficients (gray dots), as well as the MSE-optimal linear shrinkage estimates (blue triangles) and corresponding 90% parametric empirical Bayes confidence intervals by local labor market. Under repeated sampling of the parameters and data, 90% of the intervals contain the true projection coefficients with high probability.

In order to relax the normality assumption underlying the interval ensemble depicted in E.1, we further report robust empirical Bayes confidence intervals (Armstrong et al., 2022),[39] which provide coverage guarantees under the substantially weaker assumption that the conditional second moment and the kurtosis of the projection error $\varepsilon_j = \theta_j - X_j'\delta$ do not depend on (X_j, σ_j).[40] Next to relaxing the parametric restriction, these intervals also provide a frequentist coverage guarantee: If the parameters are treated as fixed, at least a fraction $(1-\alpha)$ of the robust EBCIs will contain their respective parameters with high probability. The results are depicted in Figure E.2.

FIGURE E.2. Shrinkage Estimates and Robust EB Confidence Intervals



Notes: This figure depicts the original point estimates of the projection coefficients (gray dots), as well as the MSE-optimal linear shrinkage estimates (blue triangles) and corresponding 90% robust empirical Bayes confidence intervals by local labor market. Under mild conditions, at least a fraction $(1-\alpha)$ of the robust EBCIs will contain their respective parameters with high probability.

[39]We implement the procedure using the `ebci` `R` package of Armstrong et al. (2022) which estimates the hyperparameters of the model (using weights $w_j = \hat{s}_j^{-2}$) via our baseline estimates.

[40]Conditional moment independence assumptions of this type are common in the literature and were also employed in Chetty and Hendren (2018) (cf. Remark 3.1 in Armstrong et al., 2022).

The procedures allow us to substantially tighten the confidence intervals relative to those associated with our baseline estimates. At the same time, Figure E.2 shows that the linear shrinkage estimates and confidence sets still display substantial heterogeneity, mitigating concerns that sampling variation is driving our results.

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