Does low income in early childhood affect adolescent school attainment?

Evidence from the German Socio-Economic Panel

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Abstract

We examine the relationship between child outcomes, parental financial resources and parental background using data for Germany and focusing on the child outcome 'school type at age 14'. We also consider the relevance of the timing of the low income spell, and seek to capture adequately the heterogeneity among children. Our results shed light on how far existing evidence, mainly for the USA, is generalisable rather than country and institution specific.

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1. Introduction and Motivation

As the issue of child poverty has recently gained prominence among policy makers and researcher, the relationship between child outcomes, parental financial resources and parental background has come under renewed scrutiny. According to some observers the magnitude of the income effect should be large, whereas others argue that it should be small. We examine such opposing views using data for Germany and focusing on the child outcome 'school type at age 14'. Our investigation also considers the relevance of the timing of the low income spell, and seeks to capture adequately the heterogeneity among children. Our results will also shed light on how far existing evidence, mainly for the US (e.g. Blau (1999), Duncan et al. (1997, 1998) and Haveman and Wolfe (1995)), is generalisable rather than country and institution specific. @@ perhaps need to place some references strategically to suggest a friendly referee to editor@@

Parental financial resources are commonly believed to be strongly correlated with children's educational attainment. Such priors are often based on models of investment in human capital with credit constraints (e.g. Acemoglou and Pischke (2001) and Shea (2000)). Different perspectives focus more directly on the transmission mechanism linking income and child outcomes. Having more money might play several roles, ranging from increasing the ability to purchase goods which provide the child with a stimulating environment (such as books and educational toys), to being a measure of the stability of the parental environment. Poor children not only suffer from the lack of material goods but often are exposed to higher levels of stress. There is also evidence about the importance of the early years for determining long term developments (Currie (2000) surveys some results). Developmental progress in the early years may be hindered by the induced lack of the 'readiness to learn' with cumulative consequences. Hence it is also important to investigate the relevance of the timing of the low income spell. If the financial mechanism is the principal one operating in practice, the optimal policy response designed to improve child outcomes is simple redistribution, particularly during the early years: the poor child would, after the intervention, be similar to its non-poor peer in all relevant aspects.

An alternative story, however, focuses directly on parents in terms of parenting skills, their ability and educational background rather than on income directly. Accordingly, financial resources play no special role over and above their association with parental background. What matters is the value parents place on education and their active learning support, the quality of the home environment in short. The policy implication of this

alternative transmission mechanism is very different: direct income redistribution will not work, whereas resources directed at improving parenting skills and educational support will.

1.1 The German Case

We estimate the sizes of conditional income effects using educational choice data from West Germany taken from the German Socio-Economic Panel (GSOEP). The educational outcome measure that we have data for is 'school type at age 14'. The German system has three separate strands. The 'Gymnasium' leads to the qualification (after a total of 13 years of schooling) entitling the pupil to enter university. Pupils at 'Hauptschule' leave school at age 16 and typically proceed onto a vocational training track (the German system of formal three or four year apprenticeship coupled with regular school attendance at special training colleges). Finally, 'Realschule' also terminates formal schooling at age 16 but provides a more academically demanding schooling than Hauptschule. Pupils typically proceed to enter vocational training colleges, or move to a Gymnasium. Note that German schools do not charge fees, being publicly funded and typically well-resourced. Private schools are uncommon, and, unlike in countries such as the UK, the best schools are in the public sector.

In view of these separate institutions and educational paths, the school type chosen at age 14 has long-term consequences. In order to illustrate the importance of this school choice variable, Table 1 reports mean earnings of prime aged males in West Germany in 1994, conditional on the various school graduation qualifications. An income gradient is clearly visible, the mean premium for attending Gymnasium rather than Hauptschule being about 47%. Hence the variable 'school type at age 14' is a key measure of longer-term educational attainment. Since school choice and progress within the system is typically perceived to be meritocratic rather than depend on financial resources (ignoring the issue of opportunity costs), this system is a suitable testing ground to examine the role of money in determining educational attainment. Since career paths are mapped out at such an early age, the study of this specific German key child outcome variable offers the prospect of making a valuable addition to the existing evidence (largely based on US data), which is mainly focused on total years of education, test score outcomes, and the chances of high school graduation.

<Table 1 near here>

1.2 The unconditional income effect

We report in Table 2 a cross-tabulation of children's school type at age 14 and their contemporaneous household income (the data will be described extensively below) in order to provide a quantitative benchmark for our investigation. This appears to lend weight to the first view concerning income and child outcomes outlined above. The table shows a strong income gradient in education choice. Only 15 per cent of children attending Gymnasium come from the poorest fourth of the income distribution, whereas 46 per cent come from the richest fourth. This 31 per cent differential is substantial. Similarly, of all children in the poorest fourth of incomes, only 20 per cent attend Gymnasium, whereas 60 per cent of all children in the richest fourth do.

<Table 2 near here>

Our goal is to answer the question of whether the strong income gradient in these correlations persists once we have adequately controlled for parental background and their educational inputs. Our results suggest that the answer ranges from 'little' to a resounding 'no': the conditional income effect is about 0–8 per cent depending on income and the model estimated, i.e. substantially less the 31 per cent (unconditional) effect reported in Table 2. Moreover, the income effect depends on the income level in a non-linear way: we find that the income effect for children with below average income is non-existent. Only among children with higher childhood incomes do we observe a positive income effect, one that may compensating for the relative lack of parental educational qualifications. The timing of periods of low income versus high income receipts during childhood also matters. Despite the small magnitude, it is only income in early childhood (and not contemporaneous income) which plays a role in the determination of the educational choice at age 14. We also present evidence on the heterogeneity of the transmission mechanism linking income, parental background and child outcomes beyond the income dimension.

1.3 The International Context

Our results for Germany contribute to a growing body of existing evidence about the relationship between child outcomes, parental income and parental background. As most recent studies are confined to US data, our evidence for Germany suggests that the transmission mechanisms at work are not country or institution specific. Thus the existing

evidence is generalisable. We study the ordered categorical child outcome 'school type at age 14'. Most authors using US data have studied non-categorical models of child outcomes such as 'years of completed schooling' or cognitive scores. See Haveman and Wolfe (1995) for an extensive survey, Duncan *et al.* (1997), Duncan *et al.* (1998), and Blau (1999). Duncan *et al.* (1998) also study the outcome 'high school graduation'. They find, as we do, that income affects child outcomes non-linearly, and that early income is relatively more important than contemporaneous income. Some authors have studied other child outcomes. Currie and Coles (1993) and Levine and Zimmerman (2000) analysed the effect of the incidence of maternal welfare receipt on child birth weight and cognitive scores. By contrast, Cameron and Heckman (2000) examined on the probability of attending college. Consistent with our results, these studies agree on a substantially diminished income effect once parental background has been controlled for. The sizes of the income effect differ according to the childhood stage at which income is measured, the early years being found to be more important adolescence. Finally, income effects on outcomes such as physical health are typically lower than on achievement measures.

Some authors consider countries other than the USA. Ermisch and Francesconi (2000) analyse educational attainment in the UK, measured in terms of the probability of attaining A-levels. Their estimated reduced form equation excludes income, and hence their results do not permit a cross-national comparison of income effects. Büchel *et al.* (2001) considered child outcomes in Germany as measured by the 'school type at age 14' as we do. Much of their analysis, however, is confined to documenting facets of the high raw correlation between income and school choice (as illustrated by our Table 2).

The rest of this paper is organised as follows. In Section 2 we discuss the nature of the econometric model that we shall estimate. Section 3 contains a description of the data. In Section 4 we present our estimation results and use them to analyse the relative importance of the income effect and the parental background effect for choice of school type. Section 5 concludes.

2. The Econometric Model

We seek to estimate a reduced form model of a parent's child outcome demand function. Our interest is in the conditional income effect, i.e. the association between income and outcomes, controlling for the impact of other relevant factors. Consequently, as in any textbook demand function, the explanatory variables in the regression model should not include any variables

that are subject to the choice of the parent or the child. If they are included, then one cannot undertake conduct comparative static exercises such as the study of income effects (a point re-iterated by Blau, 1999). In these cases, based on assumption about the sequential timing of the decision, computing the income effect on the child outcome would also require taking into account the indirect effect via a first stage regression of theses decision variables on the income, background and demographic covariates.

Underpinning the empirical model is the concept of a child outcome production function, that relates output and inputs, such as income and the quantity and quality of parental involvement in the child's education. From this interpretation, higher income affords more readily quantifiable inputs such as books and educational toys, but also increases factors providing a more conducive learning environment, such as more space and less stress, and thus a greater readiness to learn. We do not attempt to distinguish between these interpretations – that would require a 'structural' model – rather we remain agnostic and let the data 'speak for themselves'.

The child outcome that we focus on is the type of school chosen at age 14. This outcome is therefore a categorical variable. Moreover, school type is naturally ordered from lowest (Hauptschule) to highest (Gymnasium): the ordering is associated with a progressively more challenging academic education and increasingly better career prospects. Let the school type at age 14 of child j in family i be denoted by x_{ji}. The covariates included in the regression are variables summarising the demographic structure of the family, Z_{ji}, income covariates Y_{ji}, and parental educational qualifications E_i. Suppose that there is a latent index describing school type on some underlying continuum

$$x_{ji}^* = x_{ji} + e_{ji} \tag{1}$$

where the observable index is

$$x_{ji} = b_1'Z_{ji} + b_2'Y_{ji} + b_3'E_i \,. \tag{2}$$

Assuming that the disturbance term (e_{ji}) has a logistic distribution, we estimate the following probabilities:

$$\begin{aligned} \Pr(\text{school type = Hauptschule}) &= \Lambda(-x_{ji}) \\ \Pr(\text{school type = Realschule}) &= \Lambda(\kappa_1 - x_{ji}) \\ \Pr(\text{school type = Gymnasium}) &= 1 - \Lambda(\kappa_2 - x_{ji}) \end{aligned} \tag{3}$$

where the ancillary parameters satisfy $1 < k_1 < k_2$ and $\Lambda(.)$ denotes the cumulative logistic distribution function. Hence we estimate an ordered logit model.

The income effect (derived from estimates of b_2) may be biased upwards by the presence of an unobserved family specific or child effect, α_{ji}, such as ability, so that the true latent index is given by $x_{ji}^* = a_{ji} + x_{ji} + e_{ji}$. The commonly-used estimation strategy of using variations in outcomes amongst siblings to difference out any family-specific effect ($a_{ji} = a_i$) is not feasible in our case because the sample size and sibling variation are too small. Instead, we have also estimated a random effects model.[1] It turned out, however, that we could not reject the hypothesis that that the variance of the Normally distributed random effect was not statistically significantly different from zero.[2] The results from this model are therefore not reported here. Another type of heterogeneity is at work if income effects for poor and rich children differ. We investigate this potential non-linearity in income below using a spline model.

In order to facilitate the interpretation of the estimates of the model's β parameters and the 'income effect' in particular, we have computed marginal effects[3] for each of the covariates.

3. The Data

We base our analysis on the German Socio-Economic Panel (GSOEP)[4], using data from the first wave in 1984 through to the 1997 interview wave. As in the rest of the paper the measure of income used is household net (post-tax post-benefit) income, assumed to be shared equally amongst household members – but not equivalised, as we wish to examine the effects of differences in money income. Differences in household composition are controlled for directly.

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[1] The presence of child or family specific effects poses substantial problems for categorical dependent variable models. As Arellano and Honoré (2000) observe: 'Since little is know about how to deal with fixed effects other than the ones discussed above, it is often appealing to make assumptions on the distribution of the individual effects' (p.70).

[2] Fixed effects are more general since the fixed effect (such as ability) can be correlated with income. In this case, and given the likely positive correlation between the two, our estimates of the income coefficient need to be interpreted as upper bounds. This does not cause major problems since the estimated income effects are small, so the true effect would be even smaller.

[3] The marginal effects are calculated as $\partial[\text{Prob(school type} = i)]/\partial X_j$ for each continuous regressor X_j and for each dummy variable are calculated as the difference Prob(school type = i| dummy = 1) – Prob(school type = i| dummy = 0). In both cases all other covariates are evaluated at their sample mean. Note that the marginal effects sum to zero across school types. The marginal effects of dummy variables such as the parental educational categories are, of course, reported relative to the reference category. However, the marginal effects of switching between different educational categories are easily quantified since these marginal effects are transitive.

[4] See http://www.diw-berlin.de/ soep/ soepe.htm and Burkhauser et al. (2000) for details.

Our unit of analysis is the child. We have divided childhood into three stages, roughly corresponding to key developmental and schooling stages: the 'early years' (when aged 0–5 years), the 'middle years' (ages 6–10), and the 'contemporaneous years' (age 11+). For each child, we have averaged household income during these periods. We use measures of income from each of the three stages of childhood in our analysis because since we wish to study the importance of the timing of periods of low income. Table 3 shows that the income levels at different childhood stages are not highly correlated, the reason being that income mobility in Germany is relatively high.[5]

<Table 3 near here>

In order to maximise sample size, we selected the sample according to the following rule: a child must have at least one income observation in all three childhood stages. (Hence, a child in the sample is not necessarily born in 1984 and present in every single wave.) The sample selection rule yields a sample of 520 children. About one half (51 per cent) of these were present in the panel for 14 years. A further 24 per cent were present 13 years, and 19 per cent were present 12 years. Some 3 per cent were present for 11 years and 2 per cent for 10 years.

The third key explanatory variable in the ordered logit regressions is the highest educational qualification attained by the child's mother and father. For each, we defined five categories, in ascending order of value: no qualification, Hauptschule or Realschule (grouped to increase cell size), more advanced school leaving qualifications such as graduation from Gymnasium, apprenticeship, and finally university degree (or equivalent). Table 4 shows the proportion of children whose parents fall into the various categories.

<Table 4 near here>

Table 5 reports the sample means of the covariates used in our regressions.

<Table 5 near here>

[5] Similar correlations are reported by Duncan *et al.* (1998) for the USA. For detailed studies of income mobility in the USA and Germany, see e.g. Burkhauser *et al.* (1998) and Schluter and Trede (2001).

4. Estimation

4.1 The models defined

We distinguish several models in order to examine potentially different facets of the transmission mechanism. The dependent variable is 'school type at age 14'. All models include regressors for income, parental background, and households demographics. The income variables are defined for each of the three childhood stages (early, middle, and contemporaneous). The parental background variables are defined in terms of the highest educational qualification attained, naturally ordered from 'none' to 'university degree'. General family controls include variables such as the age of the parents at the birth of the child, the number of children in the family when the child is aged 14, and a dummy variable summarising whether the child belongs to a guest-worker family. These covariates are common to all models.[6]

We also investigate the effect of maternal labour supply decisions.[7] Since this decision also depends on income, computing the income effect on the child outcome thus also requires taking into account the indirect effect via a first stage regression of this variate on income, background and demographic covariates. Family breakdowns are major shocks in a child's life. We therefore investigate three avenues. Model 1 focuses on the timing of the shock, and also looks at the event of the mother finding another partner. Rather than focusing on the shock variable, Model 2 includes a variable measuring the duration of lone parenthood. Model 3 includes an indicator variable of whether the child ever lived in a lone parent household.

After dropping the insignificant labour supply and family breakdown variables, we then proceed to address in Model 4 the issue arising from the correlation between family income and parental educational attainment. The appearance of both covariates in the child outcome equation, as in Models 1-3, reduces the background effect. On the other hand, income should appear in the outcome equation in its own right, since it is an input in the production of the child outcome. We have therefore estimated a standard first-stage equation

[6] We also incorporated interaction terms which turned out to be insignificant and had therefore been excluded from our reported regressions.

[7] Blau (1999) has argued that parental wage rates are also legitimate regressors in models of this kind since they reflect the opportunity cost of parents' time, relevant to choices about how much time to devote to their child's education. As it happens, the coefficient estimates on parental wage rate variables were not statistically significant when these variables were included as regressors, and therefore we have not reported the estimates of these models.

to predict household income, the residuals of which were then used as regressors in the second-stage outcome equation. Note that the income coefficient will remain unchanged by this procedure, whilst the background coefficient will in the presence of a positive correlation will rise. This is our Model 4. All following models use the residuals from the first-stage regression.

Models 1-4 are based on income contributing linearly to the child outcome index of equation (2). However, this may be an excessively strong simplification in that the effect of changes in income may differ for children in low income families compared to children in rich families. In order to investigate this possibility, Model 5 allows for non-linear effects using splines. In view of the our finding of heterogeneity in the income dimension, we also consider heterogeneity more generally by estimating the regressions separately for different income groups.

4.2 Estimation Results

The estimates of the ordered logit model are reported in Table 6.[8] Before interpreting the coefficients in terms of the marginal effects on child outcomes, we focus first on the coefficients directly. The income coefficients exhibit the same pattern across Models 1-3. The coefficients for early childhood income are approximately twice as large as for middle and contemporaneous income, suggesting that the timing of low income periods is crucial. However, the latter two coefficients are not statistically significant. The other Models therefore focus only on early childhood income. Duncan *et al.* (1998) reported similar results for the USA concerning the importance of the timing of income receipt for the case where the child outcome variables were 'years of education' and 'high school completion'.

The parental background covariates make large and statistically significant contributions. The relative magnitude of income and parental background effect will be discussed extensively in Section 4.4.

The general household demographic variables are insignificant with the exception of the number of children in the family at age 14. The maternal labour supply decision, captured by Models 1-3, does not play a role in determining the child outcome except during child ages 6-10. None of the family breakdown variables – whether in terms of the shock's

[8] We also estimated a binary logit model that focused exclusively on whether the child attends Gymnasium or not (i.e. collapsing categories used in the ordered logit model). The estimates imply similar marginal effects of income on outcome, and so are not reported here.

incidence or duration – is significant at conventional levels. Interestingly, these variables also fail to be significant in studies of child outcomes in the US (Duncan et al., 1998).

Given these preliminary results we have dropped the insignificant income, family breakdown and maternal labour supply covariates from Model 4 onwards. Recall that these models include the residuals from a first-stage income regression, rather than the income covariate directly. As expected, using the residuals strenghens the parental background effects.

We proceed to interpret the coefficient estimates of Model 4 in terms of marginal effects, reported in Table 7, confining our attention to the probability of the child attending Gymnasium. We discuss the magnitude of the income effects in Section 4.4. The clearest role in determining the child outcome is played by parental background. The higher the parental educational attainment, the higher is the chance of the child attending Gymnasium. For instance, compared to the child with a father with no qualification, the child of a father with a university degree has a 60 per cent higher chance of attending Gymnasium. By transitivity of the marginal effects, we can also compare other educational categories. Unsurprisingly, this parental background effect is reduced when the reference category increases in educational attainment, but it remains substantial: there is a 40 per cent difference in the outcome probability between children with fathers having passed apprenticeships and the ones having university degrees. Similar comments apply to the effect of maternal educational background. These calculations focus only on one parent in isolation. However, the marginal effect of both parents having low educational attainment will be even more substantial; this is particularly since many parents in the low income group have major educational deficits.

The variables controlling for general demographic background have marginal effects of the expected signs but are insignificant, except for the number of children at child age 14. The more children there are, the smaller is the probability of attending Gymnasium.

<Table 6 near here>

<Table 7 near here>

4.3 Non-linear Income Effects and Heterogeneity

Models 1 – 4 are based on the assumption that the transmission mechanism linking child outcomes, income and parental background is the same for every child, irrespective of

whether the child is rich or poor. We relax this strong assumption by permitting income to vary non-linearly in equation (2). Model 5 captures this potential non-linearity using splines with knot points located at income deciles. Table 8 reports the coefficient estimates as well as the marginal effect of significant covariates on the probability of the child attending Gymnasium.

Table 8 does suggest that income effects are non-linear. The income coefficients for lower incomes are, in fact, not significantly different from zero. More precisely, the only significant income effects are located in the 5^{th}, 6^{th} and the 9^{th} income decile group. As it turns out, the latter group consists of an above average proportion of children whose fathers have obtained an apprenticeship. The income effect for this group then compensates for the parental educational shortcoming relative to university degrees.[9] Hence, it is not surprising that for this group the marginal effect on the probability of the child attending Gymnasium exceeds the estimated linear income effect of Model 4 by a factor 6. The marginal effects of the parental background covariates, however, are similar to those of Table 7.

Heterogeneity might also play a role beyond the income non-linearity. In order to investigate this possibility, we have split the sample in the income dimension (which has already exhibited heterogeneity), and ran separate regressions for income groups below and above the mean. The results are reported in Table 8.

As expected from the results of Model 5, the income effect below the mean is zero whereas above it positive but reduced. However, the parental background covariates now also exhibit a different pattern. For incomes above the mean, the paternal background effects are in effect zero, whereas the maternal background effects play the clearest role. We also note that the fit of the model, compared to the preceding ones, has substantially improved.

For children with early incomes below the mean, the significance of the parental effects is reversed: maternal effects are, in effect, zero whilst paternal background covariates are significant. Compared to the marginal effect of the homogeneity model reported in Table 7, the marginal effect of the father with university degrees has increased substantially whilst the other paternal marginal effects remain roughly unchanged.

< Table 8 here >

[9] The strong parental background effect can also be loosely interpreted as a 'social class' effect. The specific income effect then offers the interpretation of well-off parents with no university degrees to permit their children to move up into this 'social class'.

4.4 The Magnitude of the Conditional Income Effect on Prob(school type = Gymnasium)

We proceed to discuss the magnitude of the income effects, having now controlled for parental educational background. For the sake of brevity, we focus only on the predicted probabilities of the child attending Gymnasium. As a benchmark for judging the magnitude of income effects[10], recall that the unconditional effect, reported in Table 2, was 31 per cent when moving from the 25th to the 75th percentile of the income distribution. We provide two low income – rich comparisons. First, we examine the change in the outcome probability were early childhood income reduced or increased by one standard deviation from the level of mean income. As it turns out, the income change thus generated is substantial, as the resulting income position is outside the 25th percentile to 75th percentile range. We therefore also look at income changes which place the child at 25th and 75th percentiles of the income distribution.

The results are reported in Table 9. If early childhood income is set at its sample mean value, then the predicted probability of attending Gymnasium is 0.31. We consider first the implications of the linear income Model 4. Changing early childhood income from the mean up and down by one standard deviation results in a difference in the outcome probability of 15 percentage points (39 per cent minus 24 per cent). Comparing children with incomes at the 25th and 75th income deciles halves the difference in the outcome probability: the implied income effect is 8 percentage points (34 per cent minus 26 per cent). Controlling for parental educational background in the linear income Model 4 yields an income effect of 8 per cent which lies substantially below the benchmark value of 31 per cent for the unconditional correlations as reported in Table 2. The magnitude of the conditional income effect is reduced further once we take into account income non- linearities and heterogeneity. In particular, all regressions reported in Table 8 suggest that the income effect on the probability of the child attending Gymnasium for children with below average income is zero. A positive income effect is only observed for high incomes. This implies that a re-distribution of income sufficient to move the child from the 25% quantile to the 75% quantile will have no effect on the probability of the child attending Gymnasium.

<Table 9 here>

[10] We compute income effects by setting all covariates other than income at their sample means.

5. Conclusion

Does low income in early childhood affect adolescent school attainment in Germany? Any affirmative answer naively based on the observed large unconditional income effect is untenable. Although we have found that early childhood income is the only income period that matters for the choice of school type at age 14, we have also found that the income effect conditional on parental education is small. In fact, the income effect for children with below average income found to be zero once non-linear income effects are allowed for in the estimated model. The observed large unconditional income effect is therefore a misleading estimate of the true size of the impact of income during childhood. These findings have profound implications for the design of policies aimed at widening access to Gymnasiums for children on low incomes, since merely redistributing resources will have little effect.

In contrast to the small income effects, parental educational background exhibits the most substantive association with the child outcome: children whose fathers have obtained university degrees rather than no formal qualification are 60% more likely to attend Gymnasium. The educational premium relative to fathers with apprenticeships is still a substantial 40%. Heterogeneity also appears to affect the transmission mechanism. Our split regressions suggest that for children with above average income, the educational background of the mother is more important than that of the father. For children with below average income, the parental roles are reversed. This is consistent with our observation that children in the upper income group have parents who both have attained higher educational levels.

These results for Germany are consistent with a growing body of evidence, mainly based on US data. This consistency suggests that, despite cross-national institutional differences in education, welfare provision and the precise educational outcome studied, the transmission mechanisms linking parental background, family income during the period of early childhood, and the child's educational outcomes are similar: Conditional income effects are substantively small and early income is more important than contemporaneous income. Some authors have also found, as we do, evidence for income non-linearities and heterogeneity. One difference between Germany and the US relates to the income non-linearity. Duncan et al. (1998) find that the income effect is larger for children on very low incomes than for children on higher incomes (the threshold is set at $20,000). By contrast, we find that the income effect is zero for all but a high income group. As it turns out, this group consists of an above average proportion of children whose fathers have not attended university, thus permitting the child to change 'social class'.

What are the specific implications of our findings for Germany? Low income *per se* appears to be no barrier to attendance at the school type with the best career prospects, *viz.* the Gymnasium. However, more worrisome is the strong parental background effect. The lower that parental educational attainment is, the lower are the child's chances of attending Gymnasium. This is the mechanism which gives rise to the poverty effect in the form of large unconditional raw correlations. Many poor parents have relatively low educational qualifications.

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Tables

Table 1. The "Gymnasium premium": mean and standard deviation of earnings in 1994 of male full time earners aged between 26 and 59. N= 3025.

School leaving qualification	Mean	S.D.
Other qualification	49709	17380
Hauptschule	57179	27585
Realschule	61241	45853
Technical training college (Fachhochschule)	82303	39108
Gymnasium	84265	44479

Table 2. School type at age 14 and contemporaneous income quartile group, row percentages (column percentages in parentheses)

School type	Quartile group of household income of child at age 14				
	1	2	3	4	Total
Hauptschule	30	32	24	14	100
	(46)	(49)	(38)	(22)	(39)
Realschule	30	25	29	16	100
	(34)	(29)	(33)	(18)	(28)
Gymnasium	15	17	22	46	100
	(20)	(22)	(30)	(60)	(33)
Total	25	25	25	25	100
	(100)	(100)	(100	(100	(100)

Table 3. Correlations between household income of child during the three childhood stages[a]

Corr(early childhood income, middle childhood income)	0.77
Corr(early childhood income, contemporaneous income)	0.61
Corr(middle childhood income, contemporaneous income)	0.79

[a]: Early childhood is ages 0–5 years; middle childhood is ages 6–10; contemporaneous refers to ages 11-14.

Table 4. Parental educational qualifications (column percentages)

Highest educational qualification	Father	Mother
No qualifications	7	12
Haupt- or Realschule	7	15
Other	12	12
Apprenticeship	60	56
University	13	5

Table 5 Summary statistics.

	Mean	S.D.
Income variables		
Average income, child aged 0-5	53150.5	20268.2
Average income, child aged 6-11	63336.5	25305.2
Average income, child aged 11+	72756	31068.3
Father's highest educational qualification:		
Haupt- or Realschule	0.0712	0.2573
Other	0.1250	0.3310
Apprenticeship	0.6019	0.4900
University	0.1288	0.3354
Mother's highest educational qualification:		
Haupt- or Realschule	0.1500	0.3574
Other	0.1154	0.3198
Apprenticeship	0.5692	0.4957
University	0.0500	0.2182
Household demographics:		
Child's sex is female	0.4923	0.5004
Father's age at child's birth	30.6962	6.3111
Mother's age at child's birth	26.9231	5.2906
Number of children	2.0269	1.0121
Guestworker household	0.3288	0.4702
Mother's labour supply:		
Years of work during child age 0-5	0.3269	0.8695
Years of work during child age 6-10	0.6538	1.4370
Years of work during child age 11+	0.6827	1.3100
Family breakdown and re-partnering:		
Ever in lone parent household	0.1077	0.3103
Breakdown during child ages 0-5	0.0231	0.1503
Breakdown during child ages 6-10	0.0481	0.2141
Breakdown during child ages 11+	0.0308	0.1729
Years of lone parenthood	0.5269	1.7501
Re-partnering during child ages 0-5	0.0038	0.0620
Re-partnering during child ages 5-10	0.0192	0.1375
Re-partnering during child ages 11+	0.0173	0.1305

Table 6: School type at age 14 (ordered logit model estimates).

Covariate	Model 1	Model 2	Model 3	Model 4
Income variables [$\times 10^{-6}$]				
Average income, child aged 0-5	16.0918	14.2426	13.7338	16.7696
	(7.2105)	(7.0362)	(7.0522)	(5.1878)
Average income, child aged 6-11	1.8001	4.8686	4.6983	
	(8.3458)	(7.9691)	(8.1089)	
Average income, child aged 11+	6.4975	4.0252	5.7475	
	(5.5629)	(5.4087)	(5.4647)	
Father's highest educational qualification: [ref. Cat.: 'none']				
Haupt- or Realschule	.0938	.0868	.1194	.1175
	(.5645)	(.5625)	(.562)	(.5609)
Other	.6009	.6466	.6413	.631
	(.4559)	(.4547)	(.4546)	(.4543)
Apprenticeship	.9961	1.0287	.9899	1.0065
	(.4474)	(.4484)	(.4478)	(.4445)
University	2.3343	2.3389	2.2876	2.7824
	(.5672)	(.5661)	(.5649)	(.5481)
Mother's highest educational qualification: [ref. Cat.: 'none']				
Haupt- or Realschule	.7166	.7485	.7416	.709
	(.4283)	(.4255)	(.4258)	(.4219)
Other	1.0119	.9846	.9923	.9897
	(.4074)	(.4069)	(.4067)	(.404)
Apprenticeship	.8057	.8084	.8125	.9534
	(.3842)	(.3839)	(.3836)	(.3818)
University	1.8707	1.8894	1.8666	2.1636
	(.6807)	(.6764)	(.6807)	(.6559)
Household demographics:				
Child's sex is female	.1396	.1333	.1403	.1276
	(.1777)	(.1757)	(.1754)	(.1737)
Father's age at child's birth	.0012	.0011	.0035	.0191
	(.0224)	(.0218)	(.0218)	(.0212)
Mother's age at child's birth	-.0164	-.0179	-.0195	-.0102
	(.0271)	(.0267)	(.0267)	(.0264)
Number of children	-.2198	-.2143	-.2224	-.1685
	(.1018)	(.1015)	(.1008)	(.0952)
Guestworker household	-.0621	-.094	-.0556	-.3061
	(.296)	(.2941)	(.2935)	(.2835)
Mother's labour supply:				
Years of work during child age 0-5	-.0557	-.0297	-.046	
	(.1526)	(.151)	(.1512)	
Years of work during child age 6-10	-.2404	-.2323	-.2172	
	(.1154)	(.1135)	(.1136)	
Years of work during child age 11+	.1562	.1483	.1233	
	(.0997)	(.097)	(.0969)	
Family breakdown and re-partnering:				
Ever in lone parent household			-.153	-.2899
			(.3054)	(.2832)
Breakdown during child ages 0-5	-.0905			
	(.6842)			
Breakdown during child ages 6-10	-.3906			
	(.4876)			

Breakdown during child ages 11+	.0325			
	(.5231)			
Years of lone parenthood		-.0908		
		(.0554)		
Re-partnering during child ages 0-5				
Re-partnering during child ages 5-10	.6524			
	(.7673)			
Re-partnering during child ages 11+	-1.0345			
	(.7867)			
Ancillary parameters:				
κ_1	1.6178	1.5054	1.6148	1.1674
	(.8924)	(.8929)	(.8893)	(.8592)
κ_2	3.1228	3.0081	3.111	2.6346
	(.8995)	(.8995)	(.8963)	(.8645)
Pseudo R^2	.1366	.1356	.1334	.1232
Log likelihood	-490.57	-491.144	-492.398	-498.191

Notes: Standard errors in parentheses.

Table 7: Marginal effects on school type at age 14 (Model 4).

Covariate	Marginal effects		
	Hauptschule	Realschule	Gymnasium
Income variables [$\times 10^{-6}$]:			
Average income for child ages 0-5	-3.8	.2	3.6
Father's highest educational qualification:			
Haupt- or Realschule	-.026	.001	.025
Other	-.13	-.015	.145
Apprenticeship	-.229	.026	.204
University	-.382	-.215	.597
Mother's highest educational qualification:			
Haupt- or Realschule	-.145	-.018	.163
Other	-.19	-.042	.232
Apprenticeship	-.216	.02	.196
University	-.304	-.187	.491
Household demographics:			
Father's age at child's birth [$\times 10^{-3}$]	-4.3	.23	4.1
Mother's age at child's birth [$\times 10^{-3}$]	2.3	-.12	-2.2
Number of children	.038	-.002	-.036

Table 8: School type at age 14 (ordered logit model estimates).

Covariate	Model 5		Early income > mean		Early income < mean	
	Coefficients (S.E.)	Marginal Effects	Coefficients (S.E.)	Marginal Effects	Coefficients (S.E.)	Marginal Effects
Early income variables, child aged 0-5 [$\times 10^{-6}$]						
income > mean			43.3846 (11.6621)	10		
income < mean					5.1088 (15.0063)	
Spline model with knot points at:						
Income decile 1	-14.0565 (40.6475)					
Income decile 2	46.484 (92.8758)					
Income decile 3	-48.3657 (119.4326)					
Income decile 4	-101.03 (159.4694)					
Income decile 5	476.5048 (170.2937)	100				
Income decile 6	-289.131 (117.795)	-61				
Income decile 7	184.7031 (185.5462)					
Income decile 8	-97.1221 (95.2994)					
Income decile 9	105.3813 (52.1254)	22				
Income decile 10	22.9649 (16.6961)					
Father's highest educational qualification: [ref. Cat.: 'none']						
Haupt- or Realschule	.1304 (.5682)		.091 (1.2163)		-.1492 (.7218)	
Other	.6652 (.4639)		-1.097 (1.0864)		1.0804 (.5349)	.22
Apprenticeship	1.0771 (.4532)	.216	-.1018 (1.0744)		1.1917 (.5339)	.188
University	2.7458 (.5574)	.592	1.5954 (1.1599)		3.663 (.8884)	.714
Mother's highest Educational qualification: [ref. Cat.: 'none']						
Haupt- or Realschule	.7086 (.4297)		3.6087 (1.4366)	.634	.6435 (.5134)	
Other	1.144 (.412)	.269	4.4776 (1.506)	.673	.6458 (.4775)	
Apprenticeship	.997 (.3883)	.203	4.488 (1.4703)	.739	.5537 (.4528)	
University	2.3376 (.6913)	.521	6.0631 (1.6325)	.723	.5459 (1.4074)	
Household demographics:						

Child's sex is female	.1219	.2565	.1657	
	(.1753)	(.2846)	(.2328)	
Father's age at child's birth	.0237	-.0464	.0479	
	(.0216)	(.0353)	(.0286)	
Mother's age at child's birth	-.0196	.044	-.0418	
	(.0268)	(.0441)	(.0352)	
Number of children	-.1782	-.1124	-.2655	-.045
	(.0974)	(.164)	(.1254)	
Guestworker household	-.3237	-.6401	-.0953	
	(.2849)	(.6183)	(.3429)	
Ancillary parameters:				
κ_1	1.6889	3.3129	1.0544	
	(1.3502)	(2.0542)	(1.0471)	
κ_2	3.1902	4.8102	2.6285	
	(1.3548)	(2.062)	(1.0561)	
Pseudo R^2	.136	.2077	.0856	
Log likelihood	-490.91	-196.726	-282.008	

Notes. All models use residuals from first stage income regression. "Marginal effects" refer to the marginal effects on Pr{school type = Gymnasium} and are only reported for statistically significant covariates.

Table 9. Income effects on Prob(school type = Gymnasium), by early childhood income levels and model.

Early childhood income value	Prob(school type = Gymnasium)	
	Model 4	Model 5
Mean	0.31	0.31
Mean – 1 std. dev.	0.24	0.31
Mean + 1 std. dev.	0.39	0.31
25th percentile	0.26	0.31
75th percentile	0.34	0.31