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NEONATAL HEALTH OF PARENTS AND COGNITIVE DEVELOPMENT OF CHILDREN

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Neonatal Health of Parents and Cognitive Development of Children*

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Abstract

This paper documents a strong relationship between birth endowments of parents and the cognitive development of their children. The association between maternal birth weight and child school test scores corresponds to 80 percent of the association between the child's own birth weight and test scores (both in univariate and multivariate settings). We find a strong relationship, even when controlling for family differences, by looking at birth weight variation between sisters and the test score outcomes of their children, and when controlling for parental education and economic resources. Child test scores are also strongly related to paternal birth weight. To assess external validity, we replicate recent results from the US on the relationship between child birth weight and test scores. Our intergenerational results suggest that inequality in birth endowments may be important for inequality in key outcomes of the next generation.

Keywords: Neonatal health, human capital formation, intergenerational dependency

JEL: I12, J13, J24

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1 Introduction

Today, it is a stylized fact that inequality in birth endowments is related to inequality in key socioeconomic outcomes later in life (Currie, 2011). For example, many studies have established a relationship between birth weight and measures of cognitive development (Almond & Currie, 2010), and this relationship exists between siblings and between twins, thereby holding family background fixed (Currie & Moretti, 2007; Black et al., 2007), and it also holds when the outcome is early school performance of children (Figlio et al., 2014).

This paper documents a strong relationship between the neonatal health of one generation (birth weights of parents) and the cognitive development of the next generation (early school performance of children) using Danish population data. The intergenerational literature has established a strong correlation across generations for a huge set of socioeconomic outcomes (Solon, 1999; Black & Devereux, 2011; Chetty et al., 2017; Boserup et al., 2017; Landersø & Heckman, 2017), and also in birth endowments (Currie & Moretti, 2007; Royer, 2009). As a result, it is natural to expect that differences in birth endowments within a generation are associated with differences in cognitive development of the next generation. On the other hand, we might not expect a strong association. Our data, as well as previous studies (e.g. Currie & Moretti, 2007), show that a one percent higher birth weight of the mother is associated with about a 0.2 percent higher birth weight of the child, suggesting that the link between a mother's birth weight and her child's test scores is 20 percent of the coefficient between the child's own birth weight and test scores. Since, in our data and also in Figlio et al. (2014), a one percent higher birth weight of the child is associated with higher test scores in elementary school of 0.3 percent of a standard deviation (SD percent), we might expect, from these (partial) estimates, a one percent higher birth weight of the mother to be associated with a 0.05 SD percent better test score of the child (i.e. $0.2 * 0.3 \approx 0.05$). This conjecture would be correct if neonatal health of children is a 'sufficient statistic' incorporating maternal neonatal health.

We find that maternal neonatal health plays a much larger role than suggested by the conjecture. A one percent higher maternal birth weight is associated with a 0.25 SD percent higher child test score. This is around five times larger than the conjecture, and it is 80 percent of the association between the child's own birth weight and test score. When running multivariate regressions that include birth weights of both the child and the mother, we find a coefficient on the mother equal to 0.2 SD percent and, again, close to 80 percent of the child coefficient, and non-parametric evidence reveals a strong association between maternal birth weight and child test scores, conditional on the birth weight of the child, throughout the child birth weight distribution.

A key question is whether the association between child test scores and maternal birth weight only reflects differences in the family backgrounds of mothers, with well-off families (grandparents) having both heavier children at birth (the mothers in our sample) and grandchildren doing better in school (the children in our sample). In the second part of the analysis, we address this issue by looking at a subsample of sisters with children of school age.[1] When including sibling fixed effects, we find across all specifications that the coefficient on maternal birth weight is in the range 0.1–0.15 SD percent and approximately half of the coefficient on the child's own birth weight, also after including a large number of covariates reflecting the economic resources of the parents measured just before the birth of the child.

These empirical results may reflect a large direct effect of maternal birth endowments on the cognitive development of the next generation. For example, it may be that moth-

[1] Using siblings to isolate within family variation is done both in the literature studying the role of neonatal health and in the intergenerational literature (e.g. Currie & Moretti, 2007 and Bingley & Cappellari, 2017). An alternative is to examine twins. We find a larger point estimate on maternal birth weight when looking at twin-mothers, but the sample is very small and gives imprecise estimates.

ers who are heavier at birth make larger early child investments without this being captured by the child's own birth weight, family background of the mothers (captured by the sibling fixed effects), and parental economic resources. We show theoretically that an alternative and more subtle explanation may be that child birth endowments alone matter for the cognitive development, but that the variation in child birth endowments related to parental birth endowments is more important for the cognitive development than the variation in child birth endowments unrelated to family background. We cannot distinguish empirically between these two explanations, but both interpretations of the empirical results point to the same overall conclusion that inequality in birth endowments of one generation is important for inequality in cognitive development of the next generation.

For a smaller subsample we also have information about the birth weight of the father. When repeating the first part of the analysis with birth weights of both mothers and fathers for this subsample, we find that the two birth weight coefficients are of nearly the same size across all specifications. For example, when running multivariate regressions with birth weights of both children and parents, we find a coefficient of around 0.2 SD percent for both parents and close to 80 percent of the child coefficient. Thus, the birth endowments of both parents are strong predictors of child school performance.

Our results are robust to model specification. For example we show that results are similar if the analyses focus on the implications of a low birth weight, defined conventionally as a birth weight below 2,500 grams (Almond et al., 2005). To further assess the generalizability of our findings, we make two additional analyses. First, we redo the first part of our analysis on another sample of births. This sample is smaller and has only survey information on maternal birth weight, but the survey population is representative of births, unlike the administrative data where mothers on average are younger due to availability of birth weight data for mothers. We find, in general, that the birth weight coefficients are slightly smaller for the survey sample, but that the relative size of the mother/child coefficients is more or less unchanged.

Second, we replicate recent evidence for the US by Figlio et al. (2014) on the relationship between the birth weight of an individual and school test performance in elementary school. Following their study, we measure this relationship across singletons as well as between siblings and between twins, and we provide both regression results and non-parametric results. For all specifications we find very similar results for Denmark. This suggests that our main results on the relationship between neonatal health of parents and cognitive development of children may also be relevant for the US and probably other countries. The very similar results for Denmark and the United States are also interesting because of the very different institutional settings, with Denmark having publicly provided universal health care (including pre-natal and post-natal care) and school system, with a very limited role of privately financed supplementary spending on health and schools.

The main findings in this paper complement previous studies demonstrating a long run impact of neonatal health on individual outcomes (Bharadwaj et al., 2017). Our results show that inequalities in endowments at birth persist into the next generation. Several studies have shown that endowments at birth are affected by external factors (Almond & Currie, 2011), for example, nutritional shocks (Almond & Mazumder, 2011), health shocks (Currie & Schwandt, 2013), stress (Black et al., 2016; Persson & Rossin-Slater, 2017) and environmental factors (Currie & Schwandt, 2016). Our findings indicate that such external factors, as well as health innovations and policies affecting birth endowments, may have significant effects on the next generation.

The rest of the paper proceeds as follows: Section 2 describes our data; Section 3 presents the main empirical results on the relationship between parental neonatal health and child school performance; Section 4 assesses the generalizability of the findings. Section 5 provides concluding remarks.

2 Data

2.1 Sources

The information on each individual is based on three data sources linked together through a unique personal identifier. The first data source is The Medical Birth Registry, which contains information on all births in Denmark for the period 1973 to 2014. The registry includes information on birth outcomes (birth weight, child height, gestational age), date of birth, parity, gender, and birth place, as well as personal identifiers for the child, the mother and the father. Information on births in hospitals is based on data from the hospital registry while information on home births comes from reports by the midwife.

The second data source is provided by the Danish Ministry of Education and contains information on test results for the National Tests in Danish public schools. Our dataset contains all tests for the period 2010 (the first year of the test) to 2015, giving more than three million test results. The data contains information on the raw test results (including test results for the three sub-areas of each test), the test date and time, a school identifier, the test subject and the child's grade.[2]

The third data source is administrative data from Statistics Denmark, which contains information on income, wealth excluding pension wealth, and education (degree completed). The income and wealth measures of Statistics Denmark are based on third-party

[2]Data from the National Tests in Danish Public schools is fairly new, but has been used for research before (e.g., Andersen et al., 2016; Sievertsen et al., 2016).

reports from employers, banks, financial intermediaries, etc. to the tax authorities who use it for tax assessment and selection for audit, and the data is therefore of a high quality (Kleven et al., 2011).

In Denmark, each individual is given a unique personal identifier at birth (the so-called CPR number) and this is registered together with the personal identifiers of the parents. We use the personal identifier from the Medical Birth Registry to obtain an exact link across the three datasets and across generations: for each child we first merge information from the birth registry with information on test outcomes and background characteristics using the personal identifier, and we then merge the child data to data on parental background (income, education, etc.) using the unique identifier from the Medical Birth Registry.

To complement the study based on administrative registers, we further use data from the Danish National Birth Cohort (DNBC), which is a nationwide survey of almost 100,000 pregnant women in Denmark between 1997 and 2004, where the mother was interviewed during pregnancy and at the beginning of the child's life. The survey contains self-reported information about the birth weight of the mothers, which enables us to assess our findings on a smaller, but more representative, sample of mothers and children.

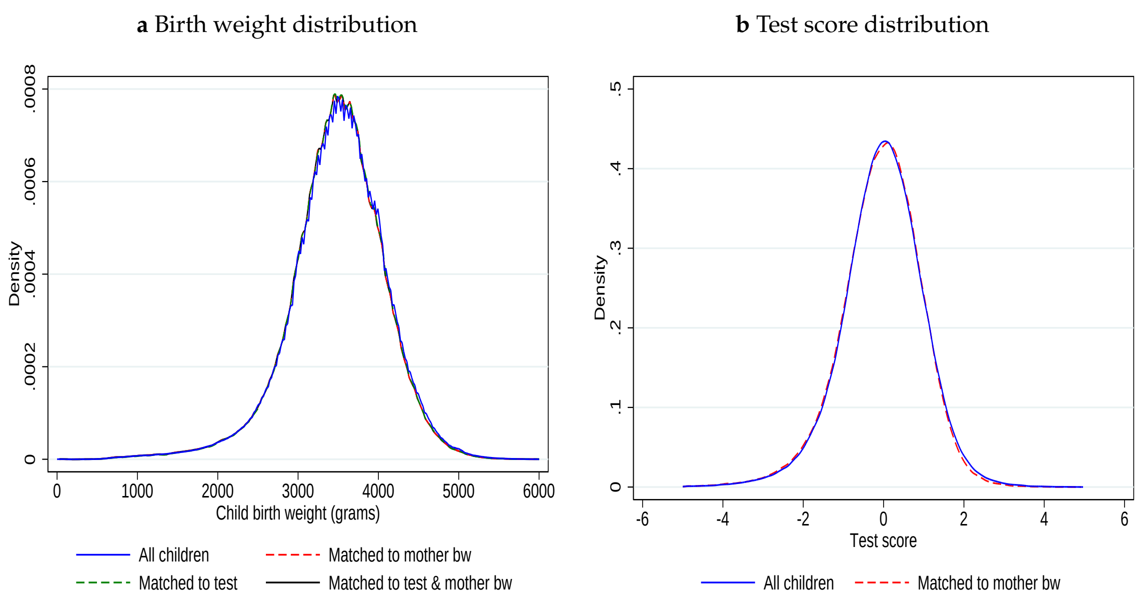
2.2 Sample selection

The point of departure for our sample selection is the 927,805 children born in Denmark from 1995 to 2007. The tests are only mandatory in public schools, which enables us to match 740,769 of the children to test results in primary school.[3] Our sample is reduced to 226,304 (31 percent of the matched child birth weight and child test score data) when we

[3] In 2007 public schools accounted for 81.4 percent of all students, boarding schools (Danish: "Efterskoler") account for 3.6 percent, private schools (Danish: "Friskoler og private grundskoler") for 12.9 percent and the remaining two percent are in schools for children with special needs and other schools (Danish: specialskoler, behandlingshjem, kommunale ungdomsskoler, etc.).

merge the child records to information on maternal birth weight. This reduction in sample size is caused by the fact that the mother has to be born in 1973 or later in order to be included in the Medical Birth Registry. The two sources of sample selection could lead to non-representative samples. However, as Figure 1 shows, the samples have remarkably similar birth weight distributions (Panel A) and test score distributions (Panel B). In addition, we replicate our main results on the smaller, but more representative DNBC survey sample in a robustness analysis in section 4.

Figure 1: Birth weight and test score distributions for each step of the sample selection



Notes: Based on all children born in Denmark from 1995 to 2007. The densities are estimated using an Epanechnikov kernel with the "optimal" bandwidth.

2.3 Variable definitions

Birth weight

Data accuracy in the Medical Birth Registry is very high as the information is provided directly from hospital records for births in hospitals, comprising about 99 percent of all births, and by midwives for all home births. Moreover, the birth outcomes (including birth weight) are recorded by health professionals (i.e. not self-reported). However, from 1973 to 1978, birth weight was recorded in 500-gram intervals, and from 1979 to 1989 birth weight was recorded in ten-gram intervals, and as of 1990, birth weight is recorded in one-gram units. For the births between 1973 and 1989 we use the midpoints of the bins. Although the attenuation bias in general should work against our results, we also assess the robustness of our results by using an indicator specification, where we estimate the impact of a low birth weight defined as a birth weight below 2,500 grams (Almond et al., 2005). Furthermore, we replicate our main findings using the continuous, self-reported, measure of maternal birth weight in the survey data from the DNBC.

Test scores and child variables

We use all tests from all subjects (Math, Reading, English, Geography, Biology, and Physics) across all grades (2,3,4,6, and 8) and follow previous studies by standardizing each test score to have a mean of zero and a unit standard deviation within each test year, test subject, and test grade cell.[4] We can, therefore, interpret the variable as deviations from the mean score for all children taking the test in the same grade and the same subject in the same year, measured in standard deviations. For each test we also create variables for the test grade (indicators), test year (indicators), and the subject of the test (indicators). For each child we create variables on year of birth (indicators), month of birth (indica-

[4]Not all subjects are tested every year. Reading is tested in grades 2, 4, 6, and 8. Mathematics is tested in grades 3 and 6. English is tested in grade 7, and Geography, Biology, and Physics are tested in grade 8. We show in appendix A3 that the results are very similar if we only focus on test scores in Mathematics or in Reading.

tors), gender, birth order (indicators), number of siblings (indicator) and an indicator for whether the child is a singleton.

Parental characteristics

Each child record is matched to information on parental disposable income (gross income minus taxes plus transfers), a self-employment indicator, highest completed education and age at child birth. We measure the parental characteristics in the calendar years two years prior to child birth. The advantage of this approach is that the variables are measured before the neonatal health of the child is observed. However, as these variables are measured at a relatively early stage of the parents' careers, they may not be perfectly representative of the parents' human and economic capital. Therefore, we also show results where parental variables are measured in the calendar year five years after child birth. While this approach more accurately captures parental resources, it is also likely to be endogenously affected by the child's neonatal health. Throughout the analyses, we include mother and father variables separately.

2.4 Summary Statistics

Table 1 provides variable means and standard deviations, as well as the median and the first and third quartile for a number of key variables. The average birth weight is 3,487 grams and five percent of the children have a low birth weight (birth weight below 2,500 grams). The mean is slightly higher than the 3,342 grams (for singletons) in the data from Florida used by Figlio et al. (2014), where 5.9 percent of the singletons have a low birth weight.

The mothers have a somewhat lower mean birth weight than their children who, on average, are born 27 years later. The difference in mean birth weight is primarily driven

Table 1: Summary statistics

	Mean	SD	P25	P50	P75
A. Child variables					
Birth weight, grams	3486.82	587.77	3160.00	3500.00	3860.00
Birth weight $<$2500g	0.05	0.21	0.00	0.00	0.00
2500 $\leq$ Birth weight $<$3000g	0.11	0.32	0.00	0.00	0.00
3000 $\leq$ Birth weight $<$3500g	0.32	0.46	0.00	0.00	1.00
Birth weight $\geq$ 3500g	0.52	0.50	0.00	1.00	1.00
Female	0.49	0.50	0.00	0.00	1.00
Singleton	0.97	0.18	1.00	1.00	1.00
Number of siblings	1.53	0.70	1.00	1.00	2.00
Test score observations	3.96	2.58	2.00	3.00	6.00
B. Mother variables					
Birth weight, grams	3295.42	538.59	2904.50	3249.50	3749.50
Birth weight $<$2500g	0.06	0.24	0.00	0.00	0.00
2500 $\leq$ Birth weight $<$3000g	0.20	0.40	0.00	0.00	0.00
3000 $\leq$ Birth weight $<$3500g	0.40	0.49	0.00	0.00	1.00
Birth weight $\geq$ 3500g	0.35	0.48	0.00	0.00	1.00
Age at child birth	26.81	3.56	24.00	27.00	29.00
Years of schooling	13.31	2.24	11.00	13.00	14.25
Annual net income (Thousand EUR)	17.18	8.40	12.19	17.43	21.70
C. Father variables					
Age at child birth	29.85	4.63	27.00	30.00	33.00
Years of schooling	13.51	2.29	11.00	14.00	14.50
Annual net income (Thousand EUR)	22.21	12.32	16.49	22.35	27.25
Individuals	226,304				
Observations	895,587				

Notes: The sample consists of all children born 1995-2007 matched to test results, child birth weight and mother birth weight. Only observations with non-missing parental date of birth and birth order are included. Parental characteristics are measured in the calendar year two years prior to child birth. Birth weight is measured in 500-gram intervals from 1973 to 1978 and in ten-gram intervals from 1979 to 1989. For individuals (mothers) born in these years we use the midpoint of the bin. Parental income are adjusted to the 2015 price level using the consumer price index. In the few cases where parental variables have missing values we assign the observation a random value drawn from the distribution of non-missing observations. We do not report the birth weight of the father as this information only exists for a subsample.

by the right tail, as a smaller share of mothers have a birth weight above 3,500 grams. Both parents have completed on average about 13 years of schooling.

3 Relationship between neonatal health of parents and school performance of children

This section presents the main empirical results. First, we study the relationship between maternal birth weight and child test score in the sample. Second, we consider the same relationship for the subsample of mothers having sisters in the sample, enabling us to study how the within family variation in birth weights of mothers relates to differences in the test scores of their children. Third, we discuss two potential mechanisms underlying the association between maternal birth weight and child test scores. Finally, we redo the first part of the analysis for a subsample where we also have information about the birth weight of the father.

3.1 Maternal birth weight and child test scores

Previous studies have looked at the association between birth weight and school test scores of an individual as well as the intergenerational correlation in birth weight between the child and the mother. We first replicate previous findings using our data. The first row in Table 2 reports the result from estimating a simple linear relationship between the (normalized) test score and the natural logarithm of birth weight in grams for all individuals in our sample. We pool test scores across all grades and, to be conservative, we cluster standard errors at the grandmother level.[5] The OLS estimate is 0.28 and is precisely esti-

[5]To be precise, we cluster standard errors at the grandmother level on the mother side. This is a natural choice later in the analysis where we study within-sister variation of mothers using sibling-fixed effect models. For consistency, we also cluster standard errors at the grandmother level in this part of the analysis. Standard errors are slightly smaller if we cluster standard errors at the mother level or at the child level.

mated with a 95 percent confidence interval of (0.26, 0.30). The point estimate means that a one percent increase in birth weight is associated with a 0.3 percent of a standard deviation (SD percent) increase in test scores. This is in line with the recent evidence for the US in Figlio et al. (2014); column 1 of panels A and B in their Table 2 reports a coefficient of 0.29 for both singletons and twins. The second row in Table 2 reports the result from regressing the logarithm of the child's birth weight on the logarithm of the mother's birth weight. The OLS estimate is 0.18, implying that a 1 percent increase in the birth weight of the mother is associated with a 0.18 percent increase in the birth weight of the child. This estimate is very close to the findings for the US in Currie & Moretti (2007); column 1, row 3 of their Table 2 reports a coefficient of 0.20.[6]

By combining the above estimates of the association between birth weight and school test scores and the intergenerational association in birth weights, resembling the existing evidence in the literature, we may form a conjecture about the association between the test scores of the child and the birth weight of the mother. Intuitively, a one percent higher birth weight of the mother gives a 0.18 percentage increase in the birth weight of the child multiplied by a 0.30 higher test score per percentage increase in child birth weight, which is equal to approximately 0.05 percent of a standard deviation better child test scores, as described in row 3 of Table 2. This conjecture would be correct if neonatal health of children is a 'sufficient statistic' incorporating maternal neonatal health. However, if we run a regression of child test scores on birth weight of the mother, we obtain a much stronger association with an estimated coefficient of 0.25 as shown in row 4. This is around five times the conjecture and this difference is not a coincidence, as revealed by the high statistical precision of the coefficient in both the regression and the conjecture. The association

[6] Currie & Moretti (2007) survey previous studies of the inter-generational correlation in birth weight. Our results are also in the same ballpark as Royer (2009) who estimates, for a female twin sample, that a one-gram higher birth weight of the mother is associated with a 0.18 gram higher birth weight of the child (Table 3, panel B, column 1). We find an association of 0.21 (see Appendix Table A.1, second row).

between maternal birth weight and test score is more than 80 percent of the association between the child's own birth weight and test score.[7]

Table 2: Relationships between child test score (y), child birth weight (w_g), and maternal birth weight (w_{g-1})

	Method	Relationship	Point-estimate($\hat{\beta}$)	Conf. int.
1.	regression:	$testscore = \alpha + \beta log(bw_g) + u$	0.280***	[0.258,0.303]
2.	regression:	$log(bw_g) = \alpha + \beta log(bw_{g-1}) + u$	0.183***	[0.177,0.189]
3.	conjecture:	$testscore = \alpha + \beta log(bw_{g-1}) + u$	0.051***	[0.047,0.056]
4.	regression:	$testscore = \alpha + \beta log(bw_{g-1}) + u$	0.245***	[0.220,0.271]

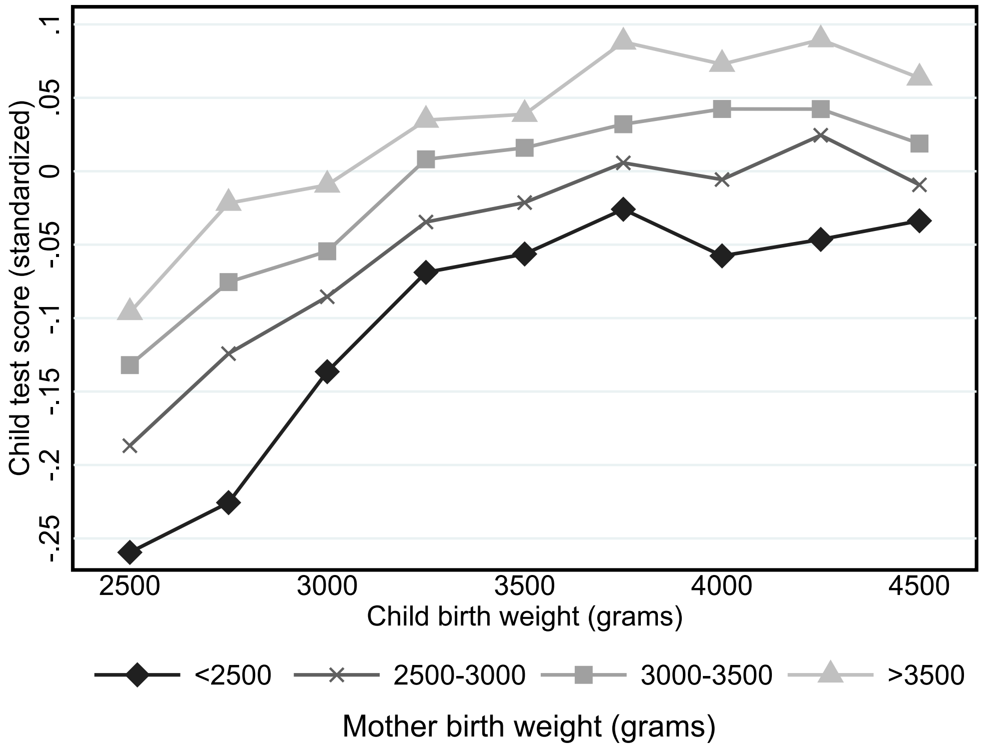
Notes: The point estimate of the conjecture in row 3 is obtained by multiplying the point estimates from rows 1 and 2. Point estimates, standard errors (SE) and confidence intervals are for the beta coefficient. The confidence interval indicates the point-estimate $\pm$ 1.96 times the standard error. Standard errors are clustered on the grandmother level. Standard errors for the conjecture are computed by means of bootstrapping with 500 replications. Asterisks indicate significance at the following levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Next, we explore the association between test scores and birth weight of the mother conditional on the birth weight of the child. Figure 2 provides non-parametric evidence. Each point in the graph shows the mean child test score for 250-gram bins of child birth weight, divided into four sub-groups depending on the birth weight of the mother. As expected, the test score is steadily increasing in the birth weight of the child. More interesting is the horizontal variation showing a steady increase in child test scores at higher birth weight of the mother for each level of child birth weight. The figure reveals an almost parallel shift upwards in the relationship between test score and child birth weight when we move between the groups of parental birth weights.

To quantify the importance of the mother's birth weight in a single number, we estimate the relative importance of maternal birth weight when both child birth weight and

[7]We obtain similar results (see Appendix Table A.1) if we estimate the regressions with birth weights in levels instead of employing a logarithmic transformation of birth weight as most commonly done.

Figure 2: Relationship between child test score, child birth weight, and maternal birth weight



Notes: Each dot shows the mean child test score for a child with the birth weight indicated on the x-axis (in 250-gram bins) for four groups of maternal birth weights.

maternal birth weight are included in a regression. Column (1) in Table 3 displays the results from simple regressions of child test scores on the birth weights of the two generations. Panel A provides point estimates from estimating specifications where birth weight is included in logs. The coefficients in the third specification are somewhat smaller than the results from the univariate regressions in the first and second specifications, reflecting the inter-generational correlation in birth weight. More importantly, if we compare the mother coefficient to the child coefficient, then it is again 80 percent. Thus, the conclusion from the univariate regressions carry over to a multiple regression setting.

In panel B of Table 3 we provide estimates from regressions where birth weight is included in terms of an indicator variable that equals one if an individual is born with low birth weight, defined as a birth weight below 2,500 grams. In that case, the mother coefficient is around two-thirds of the child coefficient in both the univariate and multivariate regressions.

In column (2) of Table 3, we add basic covariates for child and mother characteristics. These covariates include child gender, child and mother birth order (indicators), number of siblings for both the child and the mother (indicators), child and mother birth year (indicators), child and mother birth month (indicators), test year (indicators), test subject (indicators), test grade (indicators), child origin (indicator for non-western). In total, we estimate 119 additional parameters compared to the model in column (1). The point estimates on the birth weight of the child go up a little in the log specification, while the coefficients on maternal birth weight decrease a bit, but the mother coefficient is at least 50 percent of the child coefficient across all specifications (log and indicator, univariate and multivariate).

A natural question to ask is whether the relationship between the neonatal health of one generation and the cognitive development of the next generation is simply reflecting measures traditionally used to assess intergenerational mobility, especially educational attainment and income, or whether parental neonatal health has predictive power on child development beyond these measures. Column (3) reports the results from including an extensive set of controls for parental resources in the previous regressions. For each parent we include eight indicators for the highest educational level completed two years prior to child birth, and we include 100 indicators for the percentile rank in the income distribution by child birth year. Appendix Figure A.1 shows that these measures are strongly correlated with the school performance of the child and also correlated with the birth weight of the mother. When going from the results in column (2) to column (3), that now includes more than 200 explanatory variables, the birth weight coefficients fall considerably, but the mother coefficient is still sizable and between 1/3 and 1/2 of the child coefficient across the different types of specifications.

The additional parental variables are measured prior to child birth to avoid endogeneity. At this relatively early stage of the parents' careers, measures of human and economic capital may not be good at capturing the relevant levels of parental resources (Haider & Solon, 2006). In Appendix Table A.2, we replicate column (3) Table 3 and show that we obtain very similar results when we measure parental income five years after child birth. We also show that the results are very similar if we weight observations so that each family has the same weight instead of each child having the same weight, and when we include only reading test scores or only mathematics test scores in the regressions.

3.2 Within family variation in maternal neonatal health

A key question is whether the association between child test scores and maternal birth weight only reflects differences in family background of mothers. To address this question, we consider the subsample of mothers who have sisters in the sample. More precisely, we consider the subsample of children, where we observe at least two mothers having the same mother (two children with the same grandmother, but different mothers). This reduces the sample by a factor ten. Statistical significance is still evaluated based on standard errors clustered at the grandmother level.

By relating differences in birth weight between mothers who are siblings to differences in test scores of their children, we may study the effect of within family variation in neonatal health on child school performance. Table 4 shows the results from this analysis. First, we redo the regressions with basic controls in column (2) of Table 3 for this subsample of children. By comparing column (1) in Table 4 to column (2) in Table 3, we see that the birth weight coefficients in general are a bit smaller, but very close to the coefficients in the full sample. In column (2) we add fixed effects, such that we only consider variation in mother birth weight between siblings. Across the panels, the birth weight point-estimates decrease somewhat compared to column (1) but are still quantitatively important and significant.

In column (3) of Table 4 we further add the full set of controls for parental education and income. This has almost no impact on the point estimates and increases precision slightly. We find across all log specifications with sibling fixed effects that the coefficient on maternal birth weight is in the range 0.1–0.15 SD percent and approximately half of the coefficient on the child's own birth weight, also when including the large number of covariates reflecting the economic resources of the parents.

Results based on siblings may be subject to sibling-specific unobserved factors. This is not the case for results based on twins, but they may be subject to other concerns, as discussed by Almond & Mazumder (2013). Unfortunately, we have only a few twin-mothers with children of school age. We report results with twin-fixed effects in Appendix Table A.3, which shows larger point estimates for maternal birth weight in the twin sample than the sibling sample, but the twin sample is too small to obtain significant coefficients.

Table 3: Child test score regressed on child birth weight and maternal birth weight: controlling for parental resources

	(1)	(2)	(3)
A. Log-specification			
1. Mother birth weight			
Log mother birth weight	0.245***	0.200***	0.101***
	(0.013)	(0.012)	(0.012)
2. Child birth weight			
Log child birth weight	0.280***	0.293***	0.206***
	(0.012)	(0.012)	(0.011)
3. Child and mother birth weight			
Log mother birth weight	0.200***	0.151***	0.066***
	(0.013)	(0.013)	(0.012)
Log child birth weight	0.250***	0.266***	0.195***
	(0.012)	(0.012)	(0.011)
B. Indicator specification			
1. Mother birth weight			
Mother birth weight <2500g	-0.110***	-0.084***	-0.037***
	(0.010)	(0.009)	(0.008)
2. Child birth weight			
Child birth weight <2500g	-0.162***	-0.146***	-0.098***
	(0.010)	(0.010)	(0.009)
3. Child and mother birth weight			
Mother birth weight <2500g	-0.105***	-0.079***	-0.034***
	(0.010)	(0.009)	(0.008)
Child birth weight <2500g	-0.157***	-0.142***	-0.097***
	(0.010)	(0.010)	(0.009)
Clusters	127,663	127,663	127,663
Observations	895,587	895,587	895,587
Basic controls (119 controls)		Yes	Yes
Parental resources (219 controls)			Yes

Notes: The dependent variable is standardized child test score. Basic controls include: Child gender, mother and child sibsize (indicators), mother and child birth order (indicators), mother and child birth year (indicators), mother and child birth month (indicators), test year (indicators), test grade (indicators) and test subject (indicators). Parental resources include: parental education (indicators for the level), parental income percentile (indicators), and an indicator for self-employment. All parental controls are included separately for mother and father. All parent variables are measured in the calendar year two years prior to child birth. Standard errors clustered on the grandmother level in parenthesis. Asterisks indicate significance at the following levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 4: Child test score regressed on child birth weight and maternal birth weight: Within family variation in birth weight

	(1)	(2)	(3)
A. Log specification			
1. Mother birth weight			
Log mother birth weight	0.185***	0.127**	0.125**
	(0.030)	(0.053)	(0.052)
2. Child birth weight			
Log child birth weight	0.288***	0.223***	0.212***
	(0.030)	(0.036)	(0.035)
3. Child and mother birth weight			
Log mother birth weight	0.141***	0.106**	0.105**
	(0.031)	(0.054)	(0.052)
Log child birth weight	0.261***	0.219***	0.207***
	(0.031)	(0.037)	(0.036)
B. Indicator specification			
1. Mother birth weight			
Mother birth weight <2500g	-0.102***	-0.076**	-0.071**
	(0.021)	(0.033)	(0.032)
2. Child birth weight			
Child birth weight <2500g	-0.115***	-0.083***	-0.071**
	(0.029)	(0.032)	(0.031)
3. Child and mother birth weight			
Mother birth weight <2500g	-0.098***	-0.075***	-0.070**
	(0.021)	(0.033)	(0.032)
Child birth weight <2500g	-0.107***	-0.082***	-0.070**
	(0.029)	(0.031)	(0.031)
Clusters	10,997	10,997	10,997
Observations	101,199	101,199	101,199
Basic controls (119 controls)	Yes	Yes	Yes
Mother sibling FE (10,997 grandmothers)		Yes	Yes
Parental resources (219 controls)			Yes

Notes: Based on all cousins in the sample, who took the same test (same subject and grade, but not necessarily in the same year). The dependent variable is standardized child test score. Basic controls include: Child gender, mother and child sibsize (indicators), mother and child birth order (indicators), mother and child birth year (indicators), mother and child birth month (indicator), test year (indicators), test grade (indicators) and test subject (indicators). Parental resources include: parental education (indicators for the level), parental income percentile (indicators), and an indicator for self-employment. All parental controls are included separately for mother and father. All parent variables are measured in the calendar year two years prior to child birth. Standard errors clustered on the grandmother level in parenthesis. Asterisks indicate significance at the following levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

3.3 Mechanisms behind the association between maternal birth weight and child school performance?

An obvious potential explanation behind the association between maternal birth weight and child school test scores is that maternal birth weight is associated with other characteristics of the mothers, that are important for child school performances and not fully captured by the child's own birth endowment, family background of the mothers (captured by mother sibling fixed effects) and educational and economic resources of both parents. This could for example be behavioral characteristics, such as time investments of the mother during early childhood. This can, however, only be an explanation if the investment behavior of the mother is related to her own birth weight, and its effect on child school performance is not captured by the other controls.

Below we demonstrate an alternative and more subtle potential explanation. It may arise because variation in child birth weight related to maternal birth weight is more important for child cognitive development than the variation in child birth weight unrelated to maternal birth weight. To see this formally, consider the following two relationships:

$$w_g = \gamma_w w_{g-1} + \gamma_\varepsilon \varepsilon, \tag{1}$$

$$y_g = \alpha_w w_{g-1} + \alpha_\varepsilon \varepsilon + \sigma, \tag{2}$$

where y_g is the test score result of an individual in generation g having birth weight w_g and with maternal birth weight w_{g-1}, and where γ_w,γ_ε, α_w and α_ε are parameters, while ε and σ are stochastic terms.[8] The first equation is a simple linear projection of child birth

[8] It is possible to normalize γ_ε to one, but we have chosen this symmetric specification of the relationships because it is helpful for the interpretation of the result below. Note also that the equations may represent transformed variables, e.g., the logarithmic values of birth weights.

weight on parental birth weight, which provides a definitoric decomposition of the variation in child birth weight into variation related to parental birth weight (first term) and variation orthogonal to parental birth weight (second term). The second equation states that variation in child test scores is associated with variation in child birth weight—but allowing for separate effects of the two underlying components of child birth weight—as well as variation unrelated to child birth weight (σ).

Theoretically, we may now distinguish between a relationship between test scores and variation in birth weight related and unrelated, respectively, to maternal birth weight according to

$$\left.\frac{\partial y}{\partial w_g}\right|_{\partial w_{g-1}} \equiv \frac{\partial y/\partial w_{g-1}}{\partial w_g/\partial w_{g-1}} = \frac{\alpha_w}{\gamma_w}, \quad \left.\frac{\partial y}{\partial w_g}\right|_{\partial \varepsilon} \equiv \frac{\partial y/\partial \varepsilon}{\partial w_g/\partial \varepsilon} = \frac{\alpha_\varepsilon}{\gamma_\varepsilon}. \tag{3}$$

If the sources of variation in child birth weight are equally important, $\alpha_w/\alpha_\varepsilon = \gamma_w/\gamma_\varepsilon$, then we would not need to make any decomposition as one extra gram of birth weight would lead to the same change in test score independent of the underlying source. On the other hand, if $\alpha_w/\alpha_\varepsilon > \gamma_w/\gamma_\varepsilon$ then variation in birth weight related to parental birth weight is more strongly related to child test scores than variation unrelated to parental birth weight and vice versa.

An OLS regression of child test score on child birth weight alone gives

$$\hat{\beta}_{\text{OLS}} = \frac{cov(y, w_g)}{var(w_g)} = \Omega\frac{\boldsymbol{\alpha_w}}{\boldsymbol{\gamma_w}} + (1-\Omega)\,\frac{\alpha_\varepsilon}{\gamma_\varepsilon}, \text{ where } \Omega \equiv \frac{\gamma_w^2 var(w_{g-1})}{\gamma_w^2 var(w_{g-1}) + \gamma_\varepsilon^2 var(\varepsilon)}, \tag{4}$$

showing that the estimate is a weighted average of the two underlying sources of variation. Adding parental birth weight in the regression has explanatory power if the underlying source of variation in child birth weight matters, $\alpha_w/\alpha_\varepsilon \neq \gamma_w/\gamma_\varepsilon$, which is seen by isolating w_{g-1} in eq. (1) and substituting the result into (2). This gives

$$y = \underbrace{\frac{\alpha_\varepsilon}{\gamma_\varepsilon}}_{\beta_0} w_g + \underbrace{\gamma_w \left(\frac{\alpha_w}{\gamma_w} - \frac{\alpha_\varepsilon}{\gamma_\varepsilon}\right)}_{\beta_1} w_{g-1} + \sigma. \tag{5}$$

This equation shows that in a multivariate regression including both birth weights, a positive coefficient on parental birth weight ($\beta_1 > 0$) may reflect that the family component in birth weight is more important than the component unrelated to parental birth weight, i.e. $\alpha_w/\gamma_w > \alpha_\varepsilon/\gamma_\varepsilon$. This result demonstrates that it is possible to have a causal relationship from child birth weight to child cognitive development without any direct impact of parents, but where parental birth weight becomes significant in the regression because of its relationship with child birth weight, although child birth weight in itself also enters the regression.[9]

We cannot distinguish empirically between the two potential explanations underlying the strong association between maternal birth weight and child school performance, but in both explanations of this finding the conclusion is that inequality in birth endowments play an important role for inequality in key outcomes of the next generation.

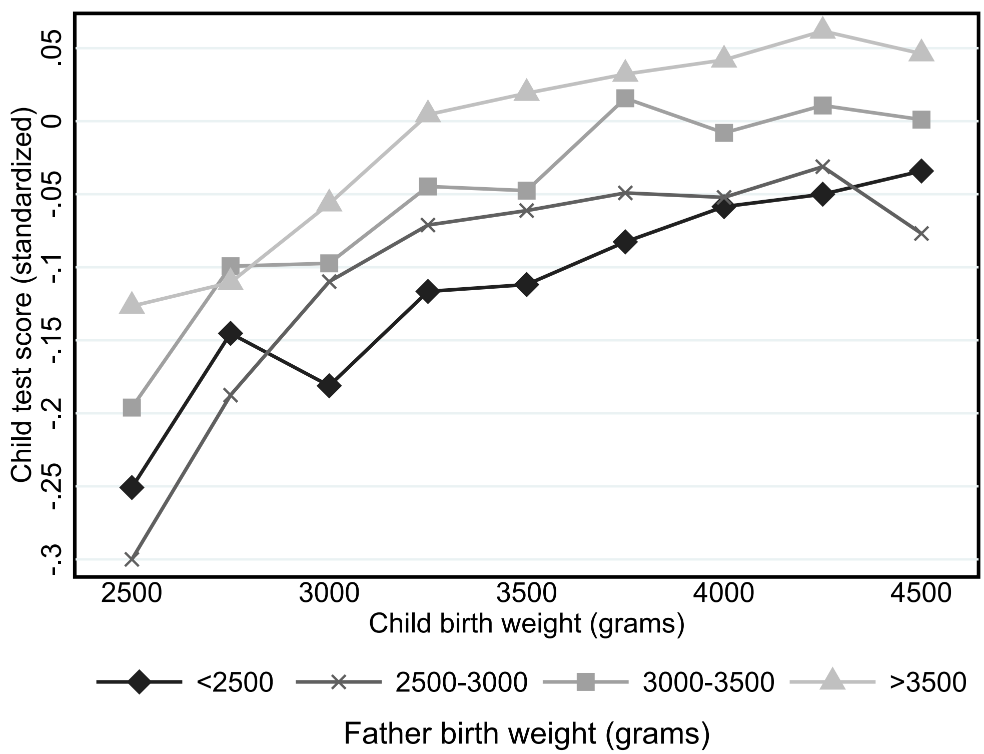
3.4 Including birth weight information of the father

So far, the empirical analysis has only looked at the relationship between maternal birth weight and child school performance. Our data allows us to include information about the neonatal health of the (biological) fathers. This requires, however, that we restrict the sample to all children with fathers born in 1973 or later in order to have birth weight

[9] In principle, it would be possible to measure the relative importance of the two underlying sources of variation in child birth weight (α_w/γ_w vs. $\alpha_\varepsilon/\gamma_\varepsilon$) in predicting test scores, but identification would require that we excluded the first type of explanation behind the association between maternal birth weight and child test scores.

information. This reduces the number of observations by more than a half and implies that fathers in the sample are younger than in the full sample. Figure 3 mimics Figure 2, but is based on the birth weight of the father instead of the mother. The lines are slightly more volatile, likely due to the smaller sample, but the overall picture is very similar. Having a father with a higher birth weight shifts the whole relationship between child test scores and child birth weight upwards.

Figure 3: Relationship between child test score, child birth weight, and birth weight of the father



Notes: Each dot shows the mean child test score for a child with the birth weight indicated on the x-axis (in 250-gram bins) for four birth weight groups of fathers.

Table 5: Child test score regressed on child birth weight, maternal birth weight and paternal birth weight

	(1)	(2)	(3)	(4)
A. Log specification				
1. Without child birth weight				
Log mother birth weight	0.235***		0.229***	0.091***
	(0.017)		(0.017)	(0.015)
Log father birth weight		0.241***	0.235***	0.091***
		(0.018)	(0.018)	(0.016)
2. With child birth weight				
Log mother birth weight	0.188***		0.186***	0.057***
	(0.018)		(0.017)	(0.015)
Log father birth weight		0.214***	0.212***	0.074***
		(0.018)	(0.018)	(0.016)
Log child birth weight	0.250***	0.261***	0.233***	0.186***
	(0.016)	(0.015)	(0.016)	(0.015)
B. Indicator specification				
1. Without child birth weight				
Mother birth weight <2500g	-0.103***		-0.102***	-0.034***
	(0.013)		(0.013)	(0.011)
Father birth weight <2500g		-0.091***	-0.091***	-0.025**
		(0.014)	(0.014)	(0.013)
2. With child birth weight				
Mother birth weight <2500g	-0.097***		-0.097***	-0.031***
	(0.012)		(0.012)	(0.011)
Father birth weight <2500g		-0.090***	-0.089***	-0.025*
		(0.014)	(0.014)	(0.013)
Child birth weight <2500g	-0.153***	-0.157***	-0.152***	-0.086***
	(0.013)	(0.013)	(0.013)	(0.013)
Clusters	82,818	82,818	82,818	82,818
Observations	470,601	470,601	470,601	470,601
Basic controls (119 controls)				Yes
Parental resources (281 controls)				Yes

Notes: Based on the subsample where information about paternal birth weight exists (all fathers born in 1973 or later). The dependent variable is standardized child test score. Basic controls include: Child gender, father, mother and child sibsize (indicators), father, mother and child birth order (indicators), father, mother and child birth year (indicators), father, mother and child birth month (indicators), test year (indicators), test grade (indicators) and test subject (indicators). Parental resources include: parental education (indicators for the level), parental income percentile (indicators), and an indicator for self-employment. All parental controls are included separately for mother and father. All parent variables are measured in the calendar year two years prior to child birth. Standard errors clustered on the grandmother level in parenthesis. Asterisks indicate significance at the following levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 5 shows estimates from regressing child test scores on the birth weight of the child and birth weights of both parents. Columns (1) and (2), specifications A1 and B1 show the results for the univariate regressions of child test scores on mother and father birth weight, respectively. The point estimates on the birth weights of the two parents are remarkably similar in magnitude, also when we include the child's own birth weight in specifications A2 and B2. In column (3) we include the birth weights of both parents in the regressions. The point estimates are again very similar, and they are also similar in size to the specifications where they are included separately. Finally, in column (4) we add the full set of controls. In this specification we also control for father birth year (indicators), birth month (indicators), birth order (indicators) and siblings (indicators). As in the previous specifications, the point estimates on the parental birth weights decrease considerably, but each of them is still more than one-fourth of the child coefficient. Again, the birth weights of the two parents are close to equally important in predicting child test scores.

4 Robustness

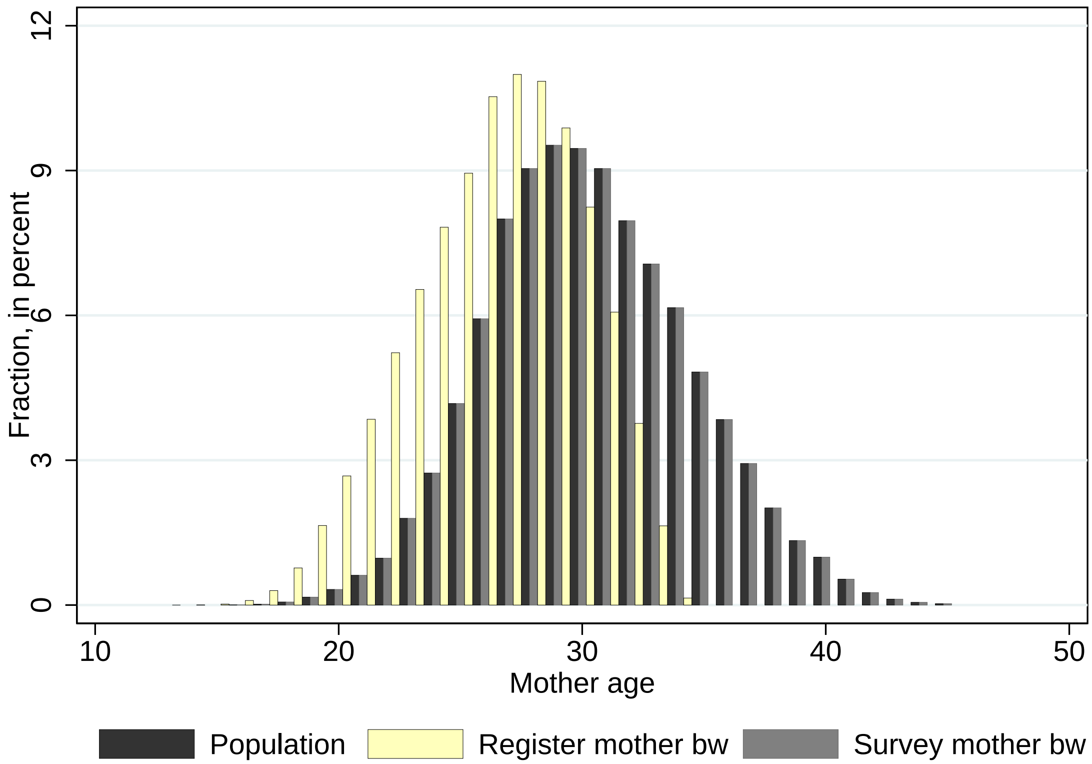
In this section, we provide two tests of the generalizability of our findings. First, we address the issue that our sample is limited to relatively young mothers, because information on birth weight is only available from 1973. Second, we replicate recent US results on the relationship between child test scores and child birth weight.

4.1 Replication of results with more representative survey data

To assess whether the estimated relationships are affected by the fact that we only observe birth weight for mothers born after 1973, we replicate results from section 3.1 on survey data from the Danish National Birth Cohort (DNBC). The DNBC is a nationwide cohort study based on a sample of women who were pregnant between 1996 and 2002. The survey contains self-reported information about the mothers' own birth weight. While the self-reported birth weights likely contain some measurement errors, they provide us with birth weights for a sample of 39,128 mothers, with an age distribution that is more similar to the overall population than the sample based on the birth registry (see Figure 4).

In Table 6 we show regression results for the relationship between child test scores and maternal birth weight using the survey sample. The results are comparable to Table 3. In general, the coefficients are somewhat lower in the survey sample, although the differences are not so large when we include all the covariates in column (3), e.g. 0.086 in the first specification, which should be compared to 0.101 in Table 3. More importantly, if we compare the relative size of the coefficient on the birth weight of the mother to the birth weight of the child, then it is reasonably stable across the two samples, in particular in the log specification. For example, in the univariate regressions the mother coefficient is about 90 percent of the child coefficient in both samples, in the multivariate regressions without additional controls it is about 80% in both cases, and when including the full set of controls it is about 30 percent in both cases. This suggests that our findings are not limited to the specific sample of mothers and children, where the mother is born in 1973 or later.

Figure 4: Mother age distribution by sample



Notes: The histograms show the distribution of mothers' age at child birth for the overall population (black bars) of children born in the period 1995 to 2007, for the children that are matched to mother birth weight from the birth registry (yellow bars) and for children with survey birth weight information on mothers' birth weight (grey bars).

Table 6: Regression of child test score on mother birth weight based on DNBC survey data

	(1)	(2)	(3)
A. Log-specification			
1. Mother birth weight			
Log mother birth weight	0.200***	0.174***	0.086***
	(0.022)	(0.021)	(0.019)
2. Child birth weight			
Log child birth weight	0.222***	0.280***	0.187***
	(0.022)	(0.023)	(0.021)
C. Both child and mother birth weight			
Log mother birth weight	0.166***	0.130***	0.055***
	(0.022)	(0.022)	(0.020)
Log child birth weight	0.191***	0.252***	0.175***
	(0.022)	(0.023)	(0.021)
B. Indicator specification			
1. Mother birth weight			
Mother birth weight $<$2500g	-0.121***	-0.104***	-0.039**
	(0.017)	(0.017)	(0.015)
2. Child birth weight			
Child birth weight $<$2500g	-0.142***	-0.136***	-0.075***
	(0.021)	(0.021)	(0.019)
3. Both child and mother birth weight			
Mother birth weight $<$2500g	-0.119***	-0.102***	-0.038**
	(0.017)	(0.017)	(0.015)
Child birth weight $<$2500g	-0.136***	-0.131***	-0.073***
	(0.021)	(0.021)	(0.019)
Clusters	30,510	30,510	30,510
Observations	368,372	368,372	368,372
Basic controls (119 controls)		Yes	Yes
Parental resources (219 controls)			Yes

Notes: The dependent variable is standardized child test score. Basic controls include: Child gender, mother and child sibsize (indicators), mother and child birth order (indicators), mother and child birth year (indicators), mother and child birth month (indicators), test year (indicators), test grade (indicators) and test subject (indicators). Parental resources include: parental education (indicators for the level), parental income percentile (indicators), and an indicator for self-employment. All parental controls are included separately for mother and father. All parent variables are measured in the calendar two years prior to the child birth. Standard errors clustered on the grandmother level in parenthesis. Asterisks indicate significance at the following levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

4.2 Replicating recent US results on the relationship between child birth weight and test score

In this subsection we replicate recent US evidence by Figlio et al. (2014) on the relationship between variation in birth weight of children and their test score results early in school. Their sample consists of all children born in Florida between 1992 and 2002. Following their study, we consider variation in the birth weights of singletons as well as fixed effect models based on siblings and twins. To resemble their analysis as closely as possible, we restrict the sample to test score results for only math and reading. Appendix A5 provides non-parametric results on the relationship between test score and birth weight, while Table 7 reports the results from estimating a linear relationship between test score and log birth weight, individually, for singletons, siblings and twins.

Columns (1) and (2) of Table 7 report results from OLS regressions where column (2) includes similar control variables as in Figlio et al. (2014). The coefficient for singletons in column (1) is, as expected, close to the coefficient in the first row of Table 2. Figlio et al. (2014) do not report results without controls, but when we include controls we obtain a coefficient of 0.306 for singletons, which should be compared to a coefficient of 0.285 reported in their Table 2. The corresponding coefficient for siblings is 0.304 in our case, which is not far from the 0.277 in their Table 2. The twin coefficient is 0.212, which is somewhat lower than their estimate of 0.285. In line with their study, we find that the sibling coefficient falls while the twin coefficient increases when including twin/sibling fixed effects. The sibling coefficient becomes a little lower in our case (0.205 vs. 0.238), while the twin coefficient becomes nearly identical across the two countries (0.454 vs. 0.443).

Appendix A5 provides non-parametric evidence on the relationship between birth weight and test scores for twins. These results are also very similar to the findings in

Table 7: Child test score regressed on child birth weight.

	(1)	(2)	(3)
A. Singletons			
Log child birth weight	0.324***	0.306***	
	(0.013)	(0.012)	
Observations	662,969	662,969	
B. Siblings (singletons only)			
Log child birth weight	0.319***	0.304***	0.205***
	(0.015)	(0.014)	(0.019)
Observations	488,358	488,358	488,358
C. Twins			
Log child birth weight	0.145***	0.212***	0.454***
	(0.049)	(0.046)	(0.089)
Observations	20,997	20,997	20,997
Controls (55 controls)		Yes	Yes
Sibling/twin FE			Yes

Notes: The sample is based on all children born between 1995 and 2007 and matched to test scores, child birth weight, mother birth weight, as well as parental birth date and birth order. Only tests in math and reading are included. This table splits the children into singletons (panel A), siblings (panel A) and twins (panel C). The dependent variable is standardized child test score. Controls included are child birth month and year (indicators), child birth order and number of siblings (indicators), maternal age at child birth (indicators), maternal education (indicators), maternal origin and maternal marital status. Standard errors clustered on the mother level in parenthesis. Asterisks indicate significance at the following levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Figlio et al. (2014). For example, we find that the heavier twin performs significantly better on average in school tests, and the difference is reasonably stable across school grades at a level of about 5 percent of a standard deviation to the lighter twin, as in Figlio et al. (2014).

The very similar results for Denmark and Florida suggest that our main results on the relationship between neonatal health of parents and cognitive development of children may also be relevant for the US, and probably for other countries. It is also interesting that the relationship between neonatal health and test scores within a population is so similar across two countries with such different institutional settings.

5 Concluding remarks

Our results show that the birth weight of children is not a sufficient statistic incorporating relevant information about parental neonatal health when predicting key child outcomes. Inequality in birth endowments of parents is a strong predictor of the cognitive development of their children, conditional on the children's own birth endowments, and this also applies when looking at within-family variation and controlling for a large set of variables capturing parental economic resources. These intergenerational findings suggest that neonatal health may be even more important than suggested by existing findings that look at the relationship between differences across individuals in neonatal health and differences in later outcomes of the same individuals. Many studies have found evidence of causal effects on birth endowments from a number of external factors, such as nutritional shocks, health shocks, stress and environmental factors (e.g. Almond & Mazumder, 2011; Currie & Schwandt, 2013; Black et al., 2016; Persson & Rossin-Slater, 2017; Currie & Schwandt, 2016). Our findings indicate that such external factors, and potentially policy choices that affect birth endowments, may have important effects that persist into the next generation.

Our analysis of the relationship between parental endowments and child outcomes are limited by data availability. At some point in the future, with additional information from new cohorts, it will be possible to strengthen our results in different ways. For example, we do not have a large enough sample to examine within-twin variation in the birth weight of mothers or to look at within family variation in paternal birth endowments. Data for additional cohorts will, at some point, make this possible. In addition, data for additional cohorts will make it possible to study a more representative sample of the population, although the survey data findings in section 4.1 indicate that the main results will be unchanged.

The well-known empirical relationship between child birth weight and child test score begs the question: what are the underlying mechanisms generating this association? Simiiarily, our empirical findings beg the question: why do birth weights of parents predict child cognitive development even when controlling for the child's own birth endowment, family background of mothers (i.e. mother sibling fixed effects) and educational and economic resources of the parents? As described in Section 3.3, one potential explanation is that parental birth endowments are associated with other characteristics of the mothers that are important for child school performances and not fully captured by the controls. Another potential explanation is that the family component in child birth weight is more strongly related to child cognitive development than the variation in child birth weight unrelated to family background. It is difficult to distinguish empirically between these two explanations. An example of the first type of explanation is that mothers who are heavier at birth not only get heavier children themselves, but also invest more in their children in early childhood without this being fully captured by the observable background characteristics of the parents. Such an explanation would relate to recent studies surveyed in Almond et al. (2017) examining the importance of parental investment in early childhood. Unfortunately, our data does not allow us to test hypotheses along this line, which we leave for future research.

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A Appendix (intended for online publication)

A1 Table 2 with birth weights in levels

The table below shows the results when we redo Table 2, but use birth weights in levels in the regressions instead of using the more common logarithmic transformation of birth weight.

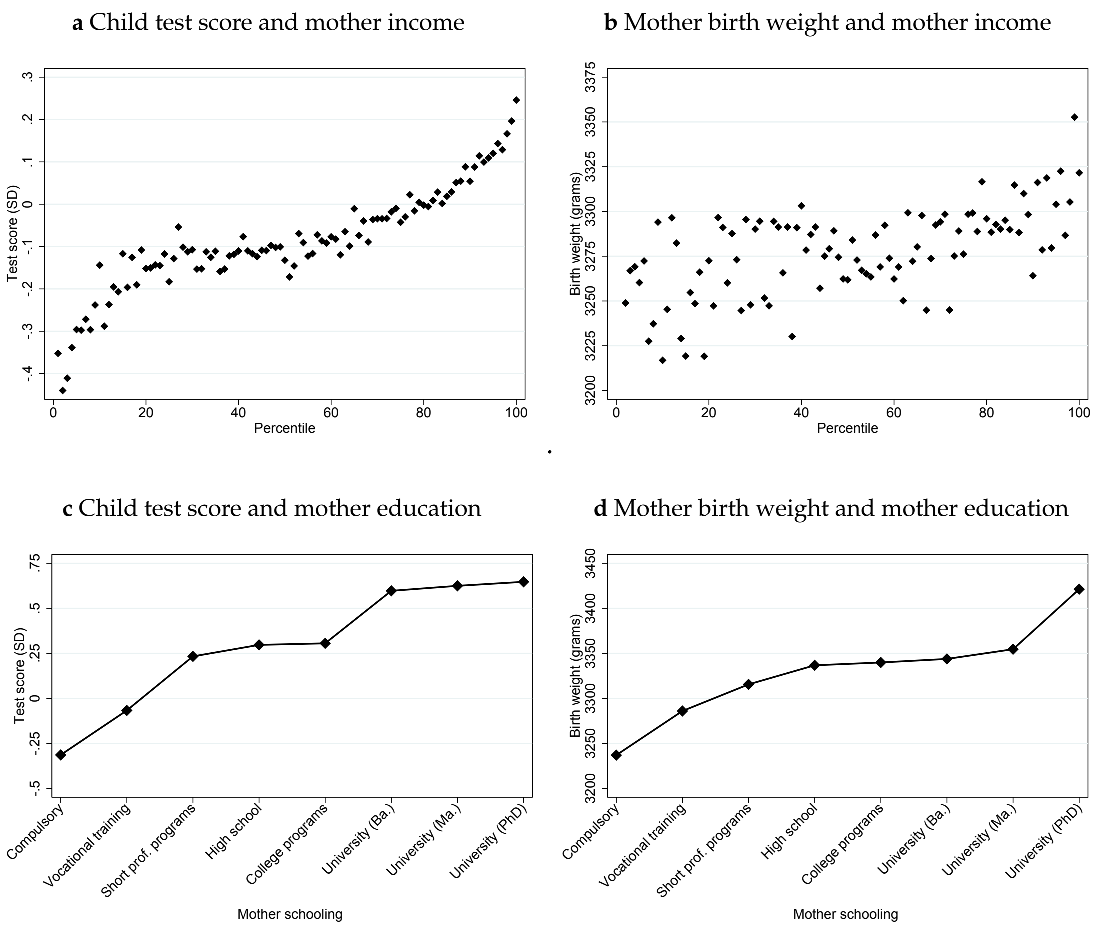
Table A.1: Relationships between child test score (y), child birth weight (w_g), and maternal birth weight (w_{g-1}): birth weight measured in levels (kg.).

	Method	Relationship	Point-estimate($\hat{\beta}$)	Conf. int.
1.	regression:	$testscore = \alpha + \beta bw_g + u$	0.092***	[0.085,0.099]
2.	regression:	$bw_g = \alpha + \beta bw_{g-1} + u$	0.213***	[0.207,0.218]
3.	conjecture:	$testscore = \alpha + \beta bw_{g-1} + u$	0.020***	[0.018,0.021]
4.	regression:	$testscore = \alpha + \beta bw_{g-1} + u$	0.082***	[0.073,0.090]

Notes: The point estimate of the conjecture in row 3 is obtained by multiplying the point estimates from rows 1 and 2. Point estimates, standard errors (SE) and confidence intervals are for the beta coefficient. The confidence interval indicates the point-estimate $\pm$ 1.96 times the standard error. Standard errors are clustered on the grandmother level. Standard errors for the conjecture are computed by means of bootstrapping with 500 replications. Asterisks indicate significance at the following levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

A2 Relationship between mother income/education and child test score/mother birth weight

Figure A.1: Mother resources, mother birth weight and child testscores



Notes: Vocational and academic high schools are collapsed. Mother variables (income and education) are measured in the calendar year two years prior to child birth.

A3 Sensitivity analysis: Variants of column (3) of Table 3

Table A.2: Child test score regressed on child birth weight and maternal birth weight

	Year 5 (1)	Weighted (2)	Reading (3)	Mathematics (4)
A. Log-specification				
1. Mother birth weight				
Log mother birth weight	0.098***	0.097***	0.088***	0.113***
	(0.012)	(0.012)	(0.012)	(0.013)
2. Child birth weight				
Log child birth weight	0.203***	0.212***	0.192***	0.299***
	(0.011)	(0.012)	(0.012)	(0.013)
3. Child and mother birth weight				
Log mother birth weight	0.063***	0.059***	0.055***	0.060***
	(0.012)	(0.012)	(0.013)	(0.014)
Log child birth weight	0.192***	0.202***	0.183***	0.289***
	(0.011)	(0.012)	(0.012)	(0.013)
B. Indicator specification				
1. Mother birth weight				
Mother birth weight <2500g	-0.035***	-0.032***	-0.034***	-0.033***
	(0.008)	(0.009)	(0.009)	(0.010)
2. Child birth weight				
Child birth weight <2500g	-0.097***	-0.106***	-0.092***	-0.150***
	(0.009)	(0.010)	(0.010)	(0.011)
3. Child and mother birth weight				
Mother birth weight <2500g	-0.032***	-0.028***	-0.031***	-0.028***
	(0.008)	(0.009)	(0.009)	(0.010)
Child birth weight <2500g	-0.096***	-0.105***	-0.091***	-0.148***
	(0.009)	(0.010)	(0.010)	(0.011)
Clusters	127,663	127,663	126,927	109,160
Observations	895,587	895,587	443,240	241,454
Basic controls (119 controls)	Yes	Yes	Yes	Yes
Parental resources (219 controls)	Yes	Yes	Yes	Yes

Notes: The table shows four variations of column (3) of Table 3. Column (1) shows the results from a specification where parental income is measured five years after child birth (compared to two years prior to child birth in the table in the main text). Column (2) shows the results from a specification where observations are weighted such that all families have the same weight instead of all children having the same weight. Columns (3) and (4) show the results from regressions where only tests in respectively reading and mathematics are included. The dependent variable is standardized child test score. Basic controls include: Child gender, mother and child sibsize (indicators), mother and child birth order (indicators), mother and child birth year (indicators), mother and child birth month (indicators), test year (indicators), test grade (indicators) and test subject (indicators). Parental resources include: parental education (indicators for the level), parental income percentile (indicators), and an indicator for self-employment. All parental controls are included separately for mother and father. All parent variables are measured in the calendar year two years prior to child birth. Standard errors clustered on the grandmother level in parenthesis. Asterisks indicate significance at the following levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

A4 Mother twin FE results

Table A.3: Child test score regressed on child birth weight and maternal birth weight: Within family variation in birth weight

	(1)	(2)
A. Log specification		
1. Mother birth weight		
Log mother birth weight	0.122	0.211
	(0.100)	(0.201)
2. Child birth weight		
Log child birth weight	0.223	-0.024
	(0.151)	(0.170)
3. Child and mother birth weight		
Log mother birth weight	0.112	0.211
	(0.102)	(0.202)
Log child birth weight	0.210	-0.027
	(0.153)	(0.169)
B. Indicator specification		
1. Mother birth weight		
Mother birth weight $<$2500g	-0.113**	-0.113
	(0.054)	(0.080)
2. Child birth weight		
Child birth weight $<$2500g	-0.235**	0.065
	(0.117)	(0.120)
3. Child and mother birth weight		
Mother birth weight $<$2500g	-0.110**	-0.112
	(0.053)	(0.080)
Child birth weight $<$2500g	-0.224*	0.058
	(0.116)	(0.119)
Clusters	432	432
Observations	5519	5519
Basic controls (76 controls)	Yes	Yes
Mother twin FE		Yes

Notes: The sample consists of all cousins matched to test scores, with mothers who are twins, with non-missing birth weight. The dependent variable is standardized child test score. Basic controls include: Child gender, mother and child sibsize (indicators), mother and child birth order (indicators), mother and child birth year (indicators), mother and child birth month (indicators), test year (indicators), test grade (indicators) and test subject (indicators). Asterisks indicate significance at the following levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

A5 Child twin figures replicating Figlio et al. (2014)

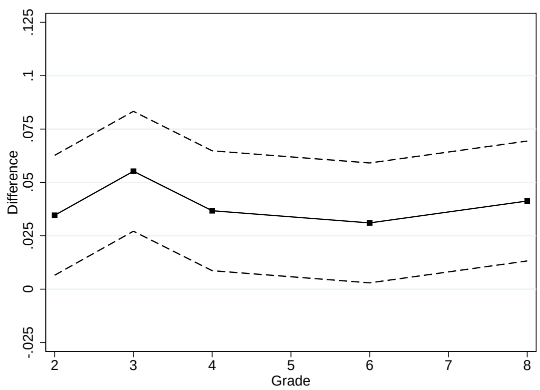
Here, we provide non-parametric evidence along the line of Figlio et al. (2014) to complement the results in section 4.2. Figures a and c are based on all twins born in Denmark between 1995 and 2007 where school test information exists for both twins. This data resembles most closely Figlio et al. (2014). Figures b and d are based on the subsample where we have information of maternal birth weight (i.e. a sample restriction equivalent to the main analysis where we study the role of parental birth weight).

Figures a and b correspond to Figure 3 in Figlio et al. (2014) and plot differences between the mean test score of the heavier and lighter twin of each twin pair in each grade. The graphs show that heavier twins do better in tests across all school grades. Figure a is very similar to Figure 3 in Figlio et al. (2014) and each point estimate is significant. We obtain a very similar relationship in Figure b, where we look at the restricted sample, although each point estimate in isolation is insignificant due to the small sample size.

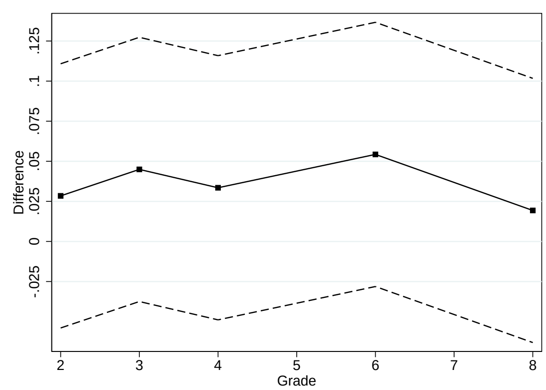
The nonparametric plot in figure c shows the relationship between birth weight and school performance from two regressions. The gray dots are the coefficients from a regression of test scores pooled across grades and test subjects (math, reading) on 100 gram-wide birth weight bin dummy variables, and the black dots are the coefficients from a similar regression where we include twin fixed effects. The two curves are similar and reveal an increasing concave relationship that resembles Figure 5 in Figlio et al. (2014). For the subsample in Figure d the relationship is noisier, but very similar to Figure c in the middle birth weight range where most of the observations are.

Figure A.2: With-in twin relationship between birth weight and test score

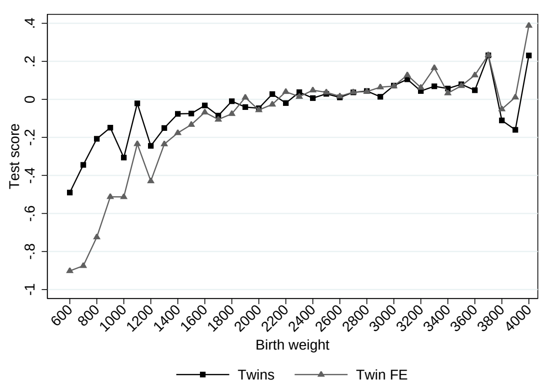
a By Grade: Children born 1995-2007 matched to tests.



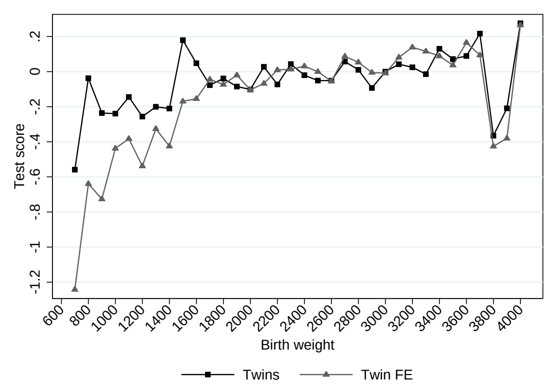
b By Grade: Children born 1995-2007 matched to tests and mother birth weight.



c By birth weight: Children born 1995-2007 matched to tests.



d By birth weight: Children born 1995-2007 matched to tests an mother birth weight.



Notes: Figures a and c are based on all twins born in Denmark between 1995 and 2007 where school test information exists for both twins. Figures b and d are based on the subsample where we have information of maternal birth weight (i.e. a sample restriction equivalent to the main analysis). Figures a and b correspond to Figure 3 in Figlio et al. (2014) and plot differences between the mean test score of heavier and lighter twin of each twin pair in each grade. The dashed curves are 95 percent confidence bands. Figures c and d show coefficients from OLS (black curve) and twin fixed effects (gray curve) models. In these graphs, we only include test score results from math and reading in order to resemble Figlio et al. (2014) as closely as possible. The reference category in Figure c is a birth weight of 500 grams. The reference category in Figure d is a birth weight of 600 grams.