Health at Birth, Parental Investments and Academic Outcomes

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Abstract

This paper explores the relationship between health at birth, subsequent parental investments, and academic outcomes using administrative panel data from Chile. Parental investments are found to be compensatory with regard to initial health but not so among twins. Twins FE models estimate a persistent effect of birth weight on academic achievement while OLS and siblings FE models find this relationship declines over time. In the context of a model of human capital accumulation and endogenous parental investments these findings suggest that initial health shocks significantly affect academic outcomes but that parents partially offset their impact over the long run.
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1 Introduction

Recent empirical work has shown evidence that initial health endowments are important determinants of later life labor market and cognitive outcomes (Almond and Currie 2011b). However there is much less evidence on the relationship between initial health endowments and intermediate academic outcomes, or how investments in human capital adjust in response to these differences. This paper contributes to this literature by examining the relationship between health at birth, subsequent parental investments, and academic outcomes from childhood to early adolescence using administrative data covering the entire student population of Chile. This empirical evidence is important as it sheds light on the mechanisms through which initial health affects later life labor market outcomes (Black, Devereux, and Salvanes 2007).

We use administrative data from Chile to link vital records for all births in the country between 1992 and 2002 to the academic records from the entire schooling system between 2002 and 2012. This panel data set follows cohorts of students from first grade through high school and college entrance exams. The data set covers over four million students and includes over twenty million student-year observations. It allows for the estimation of models with rich heterogeneity as well as models with siblings and twins estimators which have been amply used in the literature to account for unobserved characteristics affecting both birth weight and the outcome of interest. A unique feature of this paper is that we have direct data on parental investments at the individual child level, from both parent and child reports. We use this data to examine whether parental investments systematically vary by birth weight, and in particular, whether parents differentially invest within twin pairs.

We find that birth weight is significantly affects academic outcomes throughout the schooling years. Our estimates that include twins fixed effects (the standard in this literature for estimating causal impacts) suggest that in first grade, a 10% increase in birth weight increases outcomes in math and language scores by 0.04-0.06 standard deviations. We find this result to be stable from first grade through to middle and high school, and even for college entrance exams. This implies a persistent effect of birth weight among twins that is seemingly not undone (or exacerbated) by the behavioral responses of parents and teachers. The effect of being born low birth weight (less than 2500 grams) or very low birth weight (less than 1500 grams) is greater, a decrease of around 0.1-0.2 standard deviations, suggesting non-linearities in the birth weight-academic outcomes relationship. To put the magnitude of our results in perspective, consider that recent examples of large-scale interventions in education in developing countries show increases in test scores between 0.17 SD to 0.47 SD (Duflo and Hanna 2005, Muralidharan and Sundararaman 2009, Banerjee, Cole, Duflo, and Linden 2007).

These results contrast with siblings fixed effects and OLS estimators which show a steady decline in the effect of birth weight on test scores. However, the decline is less among siblings who are closer together in age than among siblings who are further apart. Using detailed data on parental investments, we find that education-related investments are negatively correlated with birth weight; i.e. parents invest more via time spent reading, time spent helping out with home work etc, in children with lower birth weight. We find that within twins however, parental investments are *not* systematically correlated with birth weight, which is the assumption typically made when using twins fixed effects estimators.

We present a model of human capital accumulation and parental investments to rationalize the empirical results described above. This model suggests that over time, depending on parental preferences (whether parents compensate or reinforce initial conditions), test score differences within sibling or twin pairs will converge or diverge over time. To this fairly standard model of academic achievement, we add a dimension of public goods in parental investments within the household to explain the differences we observe when using twins and sibling fixed effects. The main intuitive insight of the model is that if there are public goods within the household with regards to parental investments, then test score differences will converge or diverge *less* over time, compared to a case with no public goods in investments. We argue that in the case of twins the role of public goods in investments could be large (if a parent reads to one twin, it is difficult to actively prohibit the other twin from listening in) implying that even if parents wish to invest differentially, they are unable to do so. Hence, the model would predict that over time, twins fixed effects estimates diverge or converge less than OLS and in this way the twins estimates bring us closer to the causal effect of birth weight over time. We emphasize that the time component is critical to our model and results as twins fixed effects and OLS differences at any given point in time (in cross sectional data) can be explained by things such as measurement error.

This paper bridges a gap in the literature investigating the lasting role of initial endowments, in particular initial health endowments. By examining repeated educational performance outcomes for children between the ages of 6-18, we are able to provide a more complete picture of how initial health and human capital accumulation might affect cognitive performance, which in turn is a potential mechanism for explaining adult labor market outcomes. Papers by Black, Devereux, and Salvanes (2007) and Oreopoulos, Stabile, and Walld (2008) look at long term cognitive outcomes in their analysis of the impact of birth weight using twins and sibling estimators. However these papers do not have repeated observations on cognitive achievement to study how the health endowment effect evolves over time. We study the dynamics of how these endowments affect school performance taking into account the role of parental investments, using and explaining the differences between both twins and sibling fixed effects strategies. A recent related paper by Figlio, Guryan, Karbownik, and Roth (2013) finds similar persistent effects of birth weight on test scores using data on twins from Florida in elementary school years. In contrast to the current study, Figlio, Guryan, Karbownik, and Roth (2013) do not consider the role of compensatory parental investments and conclude that initial health seems to have a persistent effect on adult outcomes. While our twins estimate suggest a similar conclusion, our results on parental investments in conjunction with a close examination of the OLS and siblings fixed effects models suggest that parental investments may have the ability to reduce initial health inequalities among the general population. This difference is important as it highlights that some of the inequalities at birth can potentially be undone through the efforts made by parents and possibly public policies aimed at investing in the health and human capital of children.

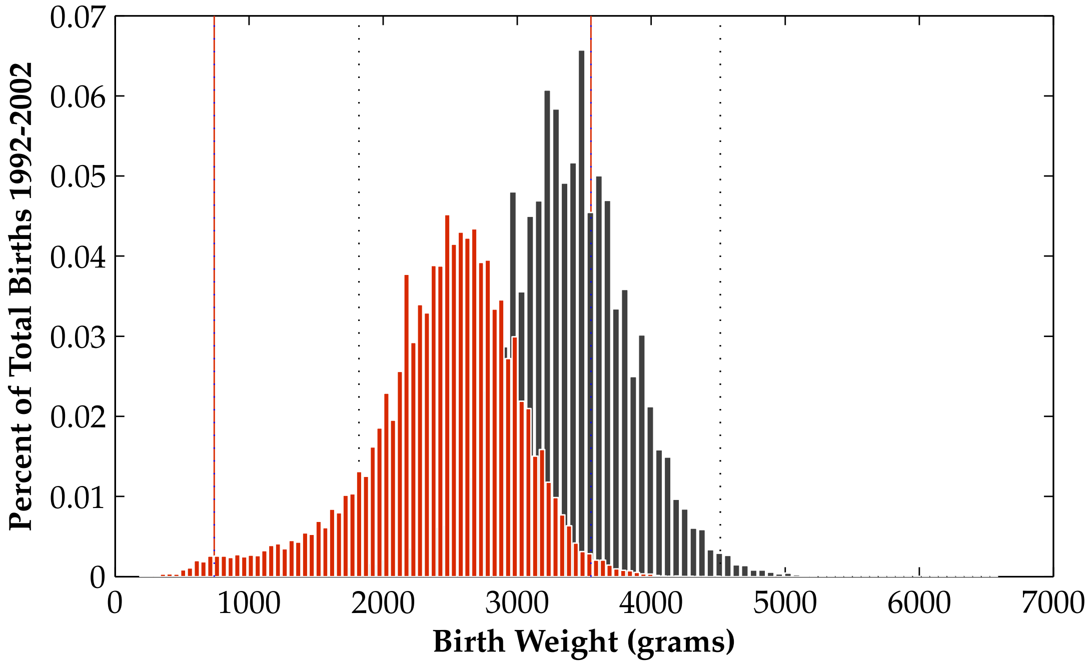
This paper also adds to the literature on parental investments and initial endowments (Aizer and Cunha 2010, Rosenzweig and Zhang 2009, Ashenfelter and Rouse 1998, Adhvaryu and Nyshadham 2012). Like Loughran, Datar, and Kilburn (2004) and others, we use birth weight as a summary measure of initial endowments. We find that parental investments are negatively correlated with birth weight which viewed through the lens of our model would explain the difference between the sibling fixed effects, OLS, and twins fixed effects estimates. Additionally, this paper partially addresses an important assumption used in many twins based studies. Most twins papers that examine the role of birth weight on long term outcomes, have to *assume* that parental investments are not related to individual birth weight. We find that while parents in general invest more in lower birth weight children, they do not differentiate based on birth weight within twins. Providing a framework and empirical evidence for understanding the differences between OLS and twin/sibling fixed effects estimates is a key contribution of this paper.

2 Medical Background

2.1 Birth Weight and Cognitive Development

Medical research suggests a few pathways by which birth weight and the incidence of low birth weight affects cognitive development. Hack, Klein, and Taylor (1995) suggest an association between brain damage and low birth weight, leading to poorer performance by low birth weight babies on tests. The extent of brain damage and lesions associated with low birth weight can be as severe as resulting in extreme forms of cerebral palsy. Another pathway that is highlighted in Lewis and Bendersky (1989) is that of intraventricular hemorrhage (IVH, or bleeding into the brain's ventricular system). However IVH is often thought to be due to shorter gestational periods, and therefore less likely to be the mechanism in the case of twins (Annibale and Hill 2008). Using detailed MRI data from very low birth weight and normal birth weight babies, Abernethy, Palaniappan, and Cooke (2002) suggest that learning disabilities might be related to the growth of certain key brain structures like the caudate nuclei (pertaining to learning and memory) and the hippocampus. Hence, it appears from our reading of a sampling of the medical literature that low birth weight is correlated with developmental problems of the brain, which might lead to lower to cognitive ability later in life. Figure 1 shows the distribution of birth weight for the population and for twins.

Figure 1: Distribution of Birth Weight

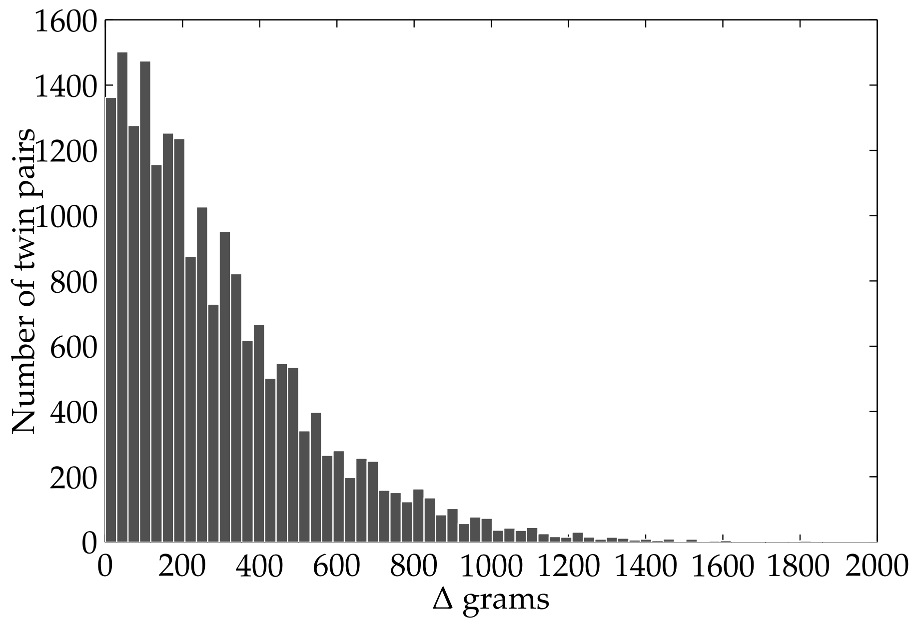


This histogram shows all live births in Chile between 1992 and 2002 and also only twin births. The two vertical lines indicate the 1st and 99th percentile of the distribution respectively.

2.2 Why do twins differ in birth weight?

Empirical estimation strategies that use twins fixed effects identify the relationship between birth weight and outcomes from the variation of birth weight between twins. This makes it important to understand why these differences arise. In this section we capitalize on the excellent reviews of the medical literature regarding why differences in birth weight arise within twin pairs provided in Almond, Chay, and Lee (2005) and Black, Devereux, and Salvanes (2007), and summarize their arguments. Figure 2 shows the density of birth weight differentials within twin pairs in our sample of twins. The average birth weight differential is around 175-200 grams. The main reason why birth weight differentials arise within twins is due to IUGR (intrauterine growth retardation).[1] The leading reason for differential fetal growth is nutritional intake - in the case where two placentae are present, nutritional differences can arise due to position in the womb. Among monozygotic twins (which most often share a placenta), the placement of the umbilical chord affects nutritional intake. For details and references on the subject, we refer the reader to footnote 13 in Almond, Chay, and Lee (2005). Figure 2 shows the distribution of birth weight differences within twins for our sample.

Figure 2: Histogram of Birth Weight Differentials among Twins



Note: This histogram shows the distribution of birth weight differentials among twins born in Chile between 1992 and 2002.

[1]The other common reason for low birth weight is gestational age, however, gestational age is identical for twins, hence, the birth weight differentials must arise from fetal growth factors.

3 Data

The data used in this paper is largely similar to the data used for the Chile specific analysis in Bharadwaj, Loken and Neilson (2013). While what follows is a brief summary, we refer the interested reader to the Online Appendix in Bharadwaj, Loken and Neilson (2013) for details on merge rates and attrition across the various data sets used.

3.1 Birth Data

The data on the birth weight and background information on parents come from a dataset provided by the Health Ministry of the government of Chile. This dataset includes information on all children born 1992-2002. It provides data on the sex, birth weight, length, weeks of gestation as well as demographic information on parents such as the age, education and occupational status. In addition, the dataset provides a variable describing the type of birth (single or multiple). Twins and siblings are identified by using a mother-specific ID made available for our purposes. Unfortunately. the data does not provide information on zygosity of the twins.

3.2 Education Data

The data on school achievement comes from the SIMCE and RECH database that consists of administrative data on the grades and test scores of every student in the country between 2002 and 2008. This database was provided by the Ministry of Education of Chile (MINEDUC).

3.2.1 RECH

The RECH is the Registro de Estudiantes de Chile (the student registry). This database consists of the grades by subject of each student in a given year and is a census of the entire student population. This database provides the information on the educational results of twins broken up by subjects and allows the construction of the ranking and level measures of academic success at the school/class/grade level.

3.2.2 SIMCE

The SIMCE test covers three main subjects: Mathematics, Science and Language Arts and is administered to every student in fourth grade as well as in eighth and tenth grade depending on the year. It is used to evaluate the progress of students regarding the national curriculum goals set out by MINEDUC. The test is constructed to be comparable across schools and time. This test is also accompanied by two surveys, one to parents and one to teachers. These surveys include questions about household income and other demographics. The education data sets were subsequently matched to the birth data using individual level identifiers. Since we observe grades for all students in a given class, we normalize the test scores of individual twins with respect their class. Hence, all test scores reported in this paper are normalized test scores.

3.2.3 PSU

The PSU or *Prueba de Selecion Universitaria* test is the college entrance exam and is the main criteria used in determining admission to the higher education system in Chile. The data included in this study covers both Mathematics and Language. The test is voluntary but required for most forms of financial aid and for the current years includes the majority of graduating seniors. The test is standardized each year. For more information on the PSU and college admissions in Chile see Hastings, Neilson, and Zimmerman (2013).

3.3 Parental Investments Data

Data on parental investments come from the aforementioned surveys that are conducted alongside the SIMCE national exams. These tests and surveys began to be used in Chile in 1988 as a way of providing information to parents on the quality of schools. This is important in the Chilean context as the education system is compromised of a large private and voucher school system. The tests and surveys are administered to all children in a given grade. Between 1988 to 2005, the test alternated between 4th, 8th and 10th grades. Since 2006, the test is administered to 4th grade every year and alternates between 8th and 10th grade every other year. The total number of children varies between 250,000 and 280,000 across approximately 8000 schools. The response rate to the test is generally over 95% (which is higher than average attendance), while the parent survey has a response rate above 80%. This survey is a large endeavor that requires visiting even the most remote schools in the northern and southern regions of the country and substantial efforts are made to evaluate all schools, both private and public.

The parent survey covers questions about the demographics of the household as well as the parents' opinion of the school and the teacher. In some years the survey covered specific questions regarding parental investments. These years are 2002 and 2007. In 2009, the latest year available, SIMCE surveyed not only the parents but also the students. This allowed students to give their opinions regarding their perceptions of school in many dimensions. One component of the survey asked about the help they received from their parents and how they perceived their parents' role in their education. We use this data in conjunction to the data on parental investments.

4 Economic Framework

The economic framework described in what follows shares some of the notions presented both in (Heckman 2007) and (Almond and Currie 2011a). Most importantly, history of investment, and not just current investment, is relevant for the level of human capital (test score). Endowments and investment enter in a non-linear way in the determination of the current level of human capital. Heckman, and Almond and Currie develop models that emphasize the differential impact of investment at different stages of development. An important aspect of this framework is that the trajectory of investments in human capital are endogenous and parental preferences and budget restrictions will imply certain allocation of parental investments. The way we endogenize this process in the evolution of cognitive ability does not allow for a more general specification but is flexible enough to capture the preferences of parents regarding allocation within the households, and not only between time or stages of development, in the same way that Almond and Currie proposed in their work. We begin by specifying a general production function for cognitive achievement similar to that in Todd and Wolpin (2007). We then specify the interhousehold allocation problem and parental investments when they are at least partially a public good. We derive some testable empirical implications of the model which we show are in line with the empirical evidence presented in the subsequent section.

4.1 Model of Human Capital Accumulation

We begin by defining the production function for test scores, investments and endowments in a similar way as in Conti, Heckman, Yi, and Zhang (2010):

$$T_{ijg} = T(X_{ijg}, \theta_{ijg}) \tag{1}$$

$$X_{ijg} = f(\theta_{ijg}, \theta_{i'jg'}) \tag{2}$$

$$\theta_{ijg} = f(\theta_{ij(g-1)}, X_{ij(g-1)}) \tag{3}$$

Where T_{ijg} is the achievement in school by student i born to mother j at grade g. X_{ijg} is the vector of all inputs applied in that grade, and θ_{ijg} is the child's cognitive endowment. In this framework, the cognitive endowment θ_{ijg} includes health endowments. Child i has a sibling (or twin) denoted by i'.

This framework allows us to study the effect of an initial shock e_{ij0} (for example being born low birth weight) on future school achievement. We assume that this initial shock only has a direct effect on the initial cognitive endowment θ_{ij0}. Therefore, the effect of a shock in period 0 on test scores at grade g is

$$\frac{dT_{ijg}}{de_{ij0}} = \frac{\partial T}{\partial X_{ijg}} \cdot \frac{\partial X_{ijg}}{\partial \theta_{ijg}} \cdot \frac{\partial \theta_{ijg}}{\partial \theta_{ij0}} \cdot \frac{\partial \theta_{ij0}}{\partial e_{ij0}} + \frac{\partial T}{\partial \theta_{ijg}} \cdot \frac{\partial \theta_{ijg}}{\partial \theta_{ij0}} \cdot \frac{\partial \theta_{ij0}}{\partial e_{ij0}} \tag{4}$$

$$\frac{dT_{i'jg'}}{de_{ij0}} = \frac{\partial T}{\partial X_{i'jg'}} \cdot \frac{\partial X_{i'jg'}}{\partial \theta_{ijg}} \cdot \frac{\partial \theta_{ijg}}{\partial \theta_{ij0}} \cdot \frac{\partial \theta_{ij0}}{\partial e_{ij0}} \tag{5}$$

We interpret the first term of equation (4) as a resource reallocation effect (this shows that an initial shock to one sibling affects the investments in the other sibling via the intra-household reallocation of resources), and the second term as a cognitive-biological effect. We take the cognitive-biological effect as negative (being born with deficiencies leads to poorer test scores). However, the sign of the resource reallocation effect is less clear without a deeper understanding of parental preferences. The reallocation effect will depend on whether parents want to equalize achievement across siblings (”compensating behavior”), or parents want to invest more on the child with higher returns (“reinforcing behavior”).[2] If parents compensate (lower endowment child gets greater investments), then the effect of the negative biological shock in equation (4) is muted by the positive sign on the reallocation component.

Twins effects in this context are used under the assumption that within twins differences “net out” the resource allocation component. In this case, imagine differencing equation (4) and (5); what we are left with if we assume lack of resource allocation behavior in the twins case is the just the biological effect of the shock. Herein lies the logic of interpreting differences in OLS and twins fixed effects in our setting: *if* we believe that twins fixed effects net out the resource allocation effect, then the difference between OLS and twins estimates is the component that is due to resource allocation. With some structure, we can discern important aspects about parental investment behavior by examining whether OLS is larger or smaller than twins estimates.

[2] A good discussion about parents’ strategic reactions and a survey of the empirical evidence supporting both hypothesis can be found in Almond and Mazumder (2013).

4.2 Model of Parental Investments

To gain a deeper insight into what factors affect the sign of the resource allocation term, we derive optimal parental inputs from a model where parents at each time t, maximize household utility that depends on the test scores of the two children in the house (T_{1jg} and $T_{2jg'}$). Child 1 is in grade g, and child 2 is in grade g'. Parents use the technology described in equations (1-3) for each child. We define the total investment constraint that parents face as T_E.[3] Formally,

$$\begin{aligned} \max_{X_{1jg}, X_{2jg'}} \quad & U(T_{1jg}, T_{2jg'}) \qquad (6) \\ \text{s.t.} \quad & \text{equations (1) through (3)} \\ & X_{1jg} + X_{2jg'} \leq T_E \end{aligned}$$

We follow Behrman, Pollak, and Taubman (1982) and use a CES functional form to describe the household's utility function:

$$U(T_{1jg}, T_{2jg'}) = \Big((T_{1jg})^{\rho} + (T_{2jg'})^{\rho}\Big)^{\frac{1}{\rho}} \qquad (7)$$

ρ in this case governs what Behrman, Pollak, and Taubman (1982) call "inequality aversion". This implies that depending on ρ parents either behave in ways that allocate more investments to the child with the higher returns, or they are "inequality averse" and invest in the child with lower returns in a bid to lower test score gaps. To see this more

[3] We provide a simple model of parental time allocation across educational and non-educational inputs in the Appendix. We can consider T_E as the optimal time allocation for educational activities as emerging from this utility maximization problem.

clearly, we also assume that test scores for each child i are produced according to the following technology:

$$T_{ijg} = \theta_{ijg}^{\gamma} X_{ijg}^{1-\gamma} \tag{8}$$

This implies that households maximize the following utility function

$$\max_{X_{1jg}, X_{2jg'}} \left(\theta_{1jg}^{\gamma\rho} (X_{1jg}^{1-\gamma})^{\rho} + \theta_{2jg'}^{\gamma\rho} (X_{2jg'}^{1-\gamma})^{\rho} \right)^{\frac{1}{\rho}} \tag{9}$$

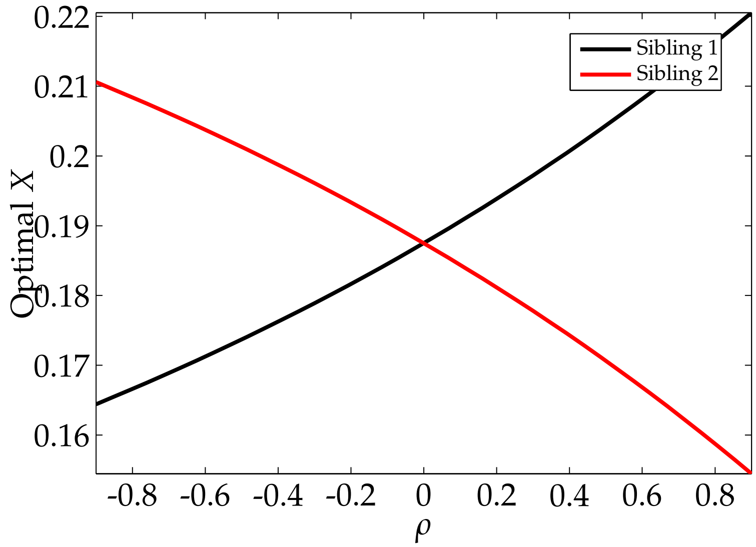
Equation (9) shows that each child's cognitive endowments act as loading factors in the CES utility function. Large positive ρ would suggest that the parents should invest more in the child with better endowments to raise their utility. However, parents may have aversion for inequality, captured by a small, or negative ρ. When $\rho \to -\infty$ households invest in order to equalize test scores across siblings. Hence, ρ is the fundamental parameter governing whether parents invest more in the child with lower endowments or whether they invest more in the child with better endowments.

For any ρ, the optimal allocations are

$$X_{1jg} = \frac{T_E}{1 + \left(\frac{\theta_{2jg'}}{\theta_{1jg}} \right)^{\frac{\gamma\rho}{(1-\gamma)\rho - 1}}} \left(\frac{\theta_{2jg'}}{\theta_{1jg}} \right)^{\frac{\gamma\rho}{(1-\gamma)\rho - 1}} \tag{10}$$

$$X_{2jg'} = \frac{T_E}{1 + \left(\frac{\theta_{2jg'}}{\theta_{1jg}} \right)^{\frac{\gamma\rho}{(1-\gamma)\rho - 1}}} \tag{11}$$

Figure 3: Optimal Investment Time X



Note: This figure displays optimal allocations, for different values of ρ at a specific point in time t. In this case we assume that sibling 1 has a higher cognitive endowment at time t.

Figure 3 displays optimal allocations, for different values of ρ at a specific point in time t. In this case we assume that sibling 1 has a higher cognitive endowment at time t. It is clear that when $\rho \geq 0$, parents in a way that would be considered "reinforcing"; they act in compensating ways when $\rho < 0$. We extend this framework to multiple time periods to study how test score gaps within siblings evolve over time.

According to the original description presented in equations (1) to (3), cognitive endowment evolves endogenously. We adopt a rather general structure for this evolution (investments and endowments can be imperfect substitutes or compliments) :

$$\theta_{ijg} = \beta_\theta \theta_{ij(g-1)} + \beta_X X_{ij(g-1)} + \beta_{X\theta} \theta_{ij(g-1)} X_{ij(g-1)} \tag{12}$$

β_θ captures depreciation of the cognitive endowment over time and is hence between 0 and 1; educational inputs increase the cognitive endowment through a cognitive accumulation production function implying that β_X is positive;[4] and finally $\beta_{X\theta}$ captures the complementarity of the investment. If $\beta_{X\theta} = 0$ cognitive endowment and parental investment are perfect substitutes. Our intuitive theoretical results are preserved without any specific assumption on the sign of $\beta_{X\theta}$, as long as $\beta_{X\theta}$ is small.[5]

4.3 Public Good Dimension of Parental Investment

Up to this point, we have described the household problem assuming that parents can completely differentiate the educational input dedicated to each child. However, parental investment may have a public good dimension, or spillover effects across siblings.

For instance, parents may read books to both children, or they may simultaneously help them with their homework. The fundamental assumption for our model with public goods is that when siblings are close in age, we expect the degree of spillover to be greater. Therefore, under certain conditions, it can be potentially difficult for parents to invest differentially across children. Twins are an extreme example of this issue, in the sense that they are of the same age and, if they attend the same school and classroom (85% of twins in our sample are observed in the exact same classroom for example), their homework and other educational needs are probably very similar. For these reasons, we conjecture that it might be difficult for parents to differentially invest across siblings when they are very close together in age.

To formalize public goods in parental investments, we use a loading function $\delta(1, 2)$ (taking values between 0 and 1) which is larger when sibling age difference is smaller. For

[4]We also explore a more general function , in which $X_{ij(g-1)}$ enters with an exponent, similar to a standard Ben-Porath human capital accumulation function. The main results are preserved.

[5]Our empirical application, however, has to make several simplifications to this rather general structure. We discuss these in the following section.

example, $\delta(1,2) = C^{(\text{Age difference in siblings})}$ where C is some constant between 0 and 1 would be a candidate loading function.[6] This loading function captures the degree of public good dimension of parental investment. If $\delta(1,2)$ is zero, parental investments have no public good dimension, and we return to the problem described in equation (6). The bigger $\delta(1,2)$ is, the more important is the public good dimension in the provision of parental investment. Thus, the effective parental investment in child 1, for example, $\hat{X}$ is described by

$$\hat{X}_{1jg} = X_{1jg} + \delta(1,2)X_{2jg'} \tag{13}$$

where X_{1jg} is the optimal parental investment, coming from the problem without public goods in parental investments (6). Note that as far as parents are concerned, a public good dimension in X increases the effective time endowment available for educational activities.

$$\hat{T}_E = \hat{X}_{1jg} + \hat{X}_{2jg} = (1 + \delta(1,2))(X_{1jg} + X_{2jg}) = (1 + \delta(1,2))T_E \tag{14}$$

We can derive time endowments from a "first stage" where parents decide between educational and non-educational inputs in the Appendix. Under certain conditions as expressed in the Appendix, we show that the total time allocation for educational inputs *reduces* as the public good dimension in educational investment increases. In the case of twins the total time allocation component does not matter for our overall results as the public good dimension simply results in equal investments across both twins.

We assume that parents are aware of the public good dimension and solve the follow-

[6] C=0.8 in our simulations.

ing within twin allocation problem:[7]

$$\max_{X_{1jg}, X_{2jg'}} \quad \left(\theta_{1jg}^{\gamma\rho}(\hat{X}_{1jg}^{1-\gamma})^{\rho} + \theta_{2jg'}^{\gamma\rho}(\hat{X}_{2jg'}^{1-\gamma})^{\rho}\right)^{\frac{1}{\rho}} \tag{15}$$

$$\text{s.t.} \quad \hat{X}_{1jg} = X_{1jg} + \delta(1,2)X_{2jg'}$$

$$\hat{X}_{2jg'} = X_{2jg'} + \delta(1,2)X_{1jg}$$

$$\hat{X}_{1jg} + \hat{X}_{2jg'} \leq \hat{T}_E$$

Defining $T_E^{**} = \frac{\hat{T}_E}{1+\delta(1,2)}$, the new optimal allocations are

$$X_{1jg} = \frac{T_E^{**}}{(1-\delta(1,2))\left[1+\left(\frac{\theta_{2jg'}}{\theta_{1jg}}\right)^{\frac{\gamma\rho}{(1-\gamma)\rho-1}}\right]}\left[\left(\frac{\theta_{2jg'}}{\theta_{1jg}}\right)^{\frac{\gamma\rho}{(1-\gamma)\rho-1}} - \delta(1,2)\right] \tag{16}$$

$$X_{2jg'} = \frac{T_E^{**}}{(1-\delta(1,2))\left[1+\left(\frac{\theta_{2jg'}}{\theta_{1jg}}\right)^{\frac{\gamma\rho}{(1-\gamma)\rho-1}}\right]}\left[1 - \delta(1,2)\left(\frac{\theta_{2jg'}}{\theta_{1jg}}\right)^{\frac{\gamma\rho}{(1-\gamma)\rho-1}}\right] \tag{17}$$

For the specific case of twins, where $\delta(1,2) = 1$, effective parental investment is equal across twins. This is because allocations are not defined for $\delta(1,2) = 1$ (i.e. the case with no age gap between siblings, which is the twins case), as in that case the problem has infinite solutions for X_{1jg} and $X_{2jg'}$. However, parents know that any feasible solution in this case implies equal *effective* parental investment among twins. Hence, for simplicity we assume that the solution for twins $X_{1jg} = X_{2jg'}$. In this case, parents may try to differentiate across twins, but the public good dimension of their investment counters any strategic behavior

[7]Parents solving for the effective parental investment or just the parental investment, but knowing the nature of the public good feature lead to the same solution.

(either mitigating or reinforcing). Consequently parents simply invest the same amount for each twin.

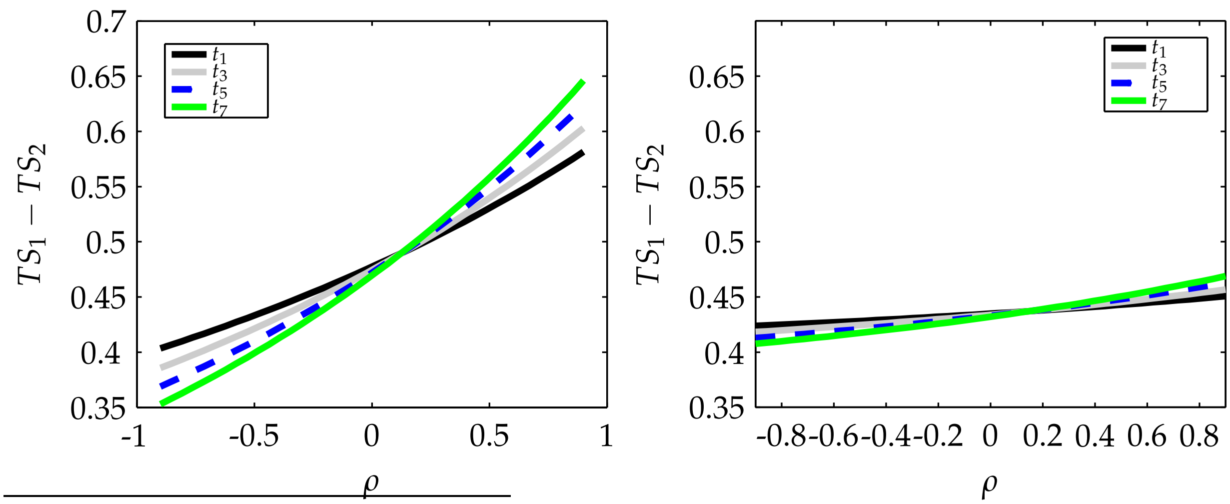
Test scores are a function of initial conditions and the history of educational inputs; hence, in the twins case, initial conditions differ, but educational inputs are the same for both children at any time. The history dependent feature of test scores implies that the relative importance of initial endowment diminishes over time. Therefore, the model implies a slight decrease in the test score gap.[8] Siblings offer additional insight about the underlying strategic behavior of parents. In this case, we are able to deduce the evolution of the test score gap between siblings, because $\delta(1,2) < 1$. Moreover, using variation across families in age differences, we can assess whether the public good dimension decreases with increasing age difference.

We can now graph the evolution of test scores using the structure on optimal parental investments, test score production and endowment evolution for different parameters values of ρ with and without the public good aspect.[9] Figure 4 displays the evolution of the gap in test scores (Test score child 1 - Test score child 2), over time, for both different values of ρ.

[8]The rate of convergency depends mainly on γ.

[9]Other parameters and details of how we create these graphs are presented in the Appendix.

Figure 4: Evolution of Test Scores and Public Good Parental Investment



Note: This figure displays how differences in achievement change over time under different assumptions about parental preferences ρ. The right panel assumes parental investment is a public good among twins and on the left panel there is no public good aspect to parental investments. It can be seen in this simulation that differences are muted and change less over time in the presence of public goods.

In the left panel we can see that for high values of ρ, the solid black line representing period 1 is below the gray line representing period 3, which in turns is below the dashed blue line representing period 5, and so on. This sequence means that the gap is increasing over time. The original gap is positive because child 1 has higher initial cognitive endowment that child 2. This is the graphical representation of the effect of a reinforcing parental behavior on the dynamics of the gap in test scores. We observe the exactly opposite evolution when $\rho < 0$. In this case, the gap diminishes over time, as a reaction of the parents' compensating efforts. Note from this graph that the switch from divergence over time to convergence over time in test score gaps does not occur precisely around ρ=0. This means that just observing whether test scores diverge or converge over time is not enough to discern whether parents want to compensate or reinforce. However, combined with knowledge of the correlation between investments and endowments, we can make an informed guess of whether parents compensate or reinforce initial endowments.

The right panel of 4 shows the test score evolution in the presence of some public goods in parental investments ($\delta = 0.7$),[10] Y axis scales are purposely kept the same as in Figure 4 to show how the evolution in differences is muted with a higher δ. Hence, the public good dimension diminishes the ability of either the compensating behavior or the reinforcing behavior.

The implications of our model for the evolution of test scores over time can be summarized by a fairly intuitive proposition and two corollaries:

Proposition 1 *If compensating (reinforcing) parents can fully differentiate the educational inputs allocated to each child, the test score gap between siblings will decrease (increase) over time. If there is only partial parental investment differentiation, the test score gap may decrease (increase), but this decrease (increase) will be <u>less</u> than in the case of full differentiation.*

Proof 1

Please see Appendix A.

Corollary 1 *The public good dimension of parental investment implies partial differentiation across children. Thus, the compensating (reinforcing) behavior will take longer to reduce (increase) the test score gap, than in the absence of public good dimension.*

Proof 2

Please see Appendix A.

Corollary 2 *For twins, in the presence of public goods in parental investments, the test score gap will be quite stable*[11] *over time.*

[10] In our calibrations, $\delta = 0.7$ corresponds to an age difference of 1.5 years.

[11] If $\beta_\theta = 1$, and $\beta_{X\theta} = 0$ the test score gap will be exactly constant.

Proof 3

In this case the actual (effective) parental investment is equal across twins. Over time, the only change in test score gap comes from the evolution of the cognitive endowment. In particular, when $\beta_\theta < 1$, the depreciation of the initial endowment will imply a convergence of test scores over time.

5 Estimation

In what we have shown above, cognitive endowment and parental investments are a function of past inputs and endowments. Therefore, an alternative specification for equation (1) is

$$T_{ijg} = T(X_{ijg}, X_{ij(g-1)}, \ldots, X_{ij0}, \theta_{ij0}) \tag{18}$$

Hence, school achievement on grade g depends on the initial cognitive endowment and the whole history of educational inputs. In other words, test score is a cumulative function of past inputs, and endowment at birth θ_{ij0}. From here on, we call θ_{ij0} birth weight, which is our measured initial endowment. Such a production function is very similar to the one used by Todd and Wolpin (2007).

A linear, estimable version of (18) is:

$$T_{ijg} = \lambda_g \theta_{ij0} + \beta_1 X_{ijg} + \beta_2 X_{ijg-1} + \ldots + \beta_t X_{ij1} + \epsilon_{ijg} \tag{19}$$

Where T is the test outcome measured with error ϵ, and X is a vector of educational inputs up to grade g. In this exercise, we are interested in estimating λ_g and estimating (19) would require detailed parental input histories. We do not have data on the entire sequence of parental inputs, hence, the X's will form part of the error term in the estimating equation. As the model in the above section suggests, parental investments are likely correlated with birth weight and hence, in OLS, λ_g will be measured with bias, where the direction of bias is governed by the covariance between inputs and endowments, and as per the model in section 2, by the degree of parental inequality aversion. We estimate OLS for the entire sample in figures, but also focus on the sample that shares a common support with twins between 700-3000 grams (3000 grams represents the 90th percentile of the twin birth weight distribution). Since twins are significantly smaller than the rest of the population, valid comparisons for our purposes are only derived by focussing on singletons on the same birth weight support as twins.

5.1 Twins Fixed Effects

Before we write down the twins fixed effects estimator, it is useful to rewrite equation 19, with a new error term that captures all the unobservables:

$$T_{ijg} = \lambda_g \theta_{ij0} + \underbrace{\beta_1 X_{ijg} + \beta_2 X_{ijg-1} + \ldots + \beta_t X_{ij1} + \epsilon_{ijg}}_{u_{ijg}} \tag{20}$$

A twins estimator is particularly useful in estimating λ_g from equation (20). As a twins fixed effects estimator essentially differences equation (20) within twins, it would difference out observable and unobservable time invariant family level components (while we have not modeled these variables like parental education explicitly, we believe that they would play a role in the bias that exists in OLS) since these are shared within twin pairs.

Calling the other twin i', a twins estimate of equation (20) results in:

$$
\begin{aligned}
T_{ijg} - T_{i'jg} &= \lambda_g (BW_{ij} - BW_{i'j}) && (21)\\
&\quad + \underbrace{\beta_1 (X_{ijg} - X_{i'jg}) + \ldots + \beta_t (X_{ij1} - X_{i'j1}) + \epsilon_{ijg} - \epsilon_{i'jg}}_{u_{ijg} - u_{i'jg}} && (22)
\end{aligned}
$$

The model in the previous section would suggest that rather than *assuming* that parental investments are the same within twins, one way to think of why they might *effectively* be the same even when parents wish to invest differentially based on birth weight is due to public goods in the parental investment component. Under the conditions of our model in the previous section, *if* there are perfect spillovers within twins, then the effective parental investment is the same within twins and equation (22) will result in consistent estimation of λ_g. In what follows, we estimate equation (22) for first through eighth grade for math and language classroom grades, fourth, eighth and tenth SIMCE test scores in math and language and for the college entrance exam, also for math and language.

We wish to note an important caveat at this point. Twins fixed effects are useful in estimating λ_g only if there are no heterogenous returns to birth weight by parental investment. Empirically, this implies that we cannot have interaction terms between investments and birth weight in equation (19). While the model we presented in section 2 was quite general, the specific empirical application uses stricter functional form assumptions on the production of test scores and the evolution of the endowment. This is however essential to keep the empirical component tractable and meaningful, but we are aware that this is indeed a (perhaps drastic) simplification of reality.

5.2 Siblings Fixed Effects

A siblings fixed effects estimator is similar in spirit to the twins fixed effects estimator, with the difference that we expect a "greater" bias if we believe the lesser degree of public goods in parental investment within siblings as per the model in section 2 and proposition 1. For siblings (i and i') who are observed in grade g, we estimate a siblings fixed estimator of the form:

$$
\begin{aligned}
T_{ijg} - T_{i'jg} &= \lambda_g (BW_{ij} - BW_{i'j}) && (23)\\
&\quad + \underbrace{\beta_1 (X_{ijg} - X_{i'jg}) + \ldots + \beta_t (X_{ij1} - X_{i'j1}) + \epsilon_{ijt} - \epsilon_{i'jg}}_{u_{ijt} - u_{i'jg}} && (24)
\end{aligned}
$$

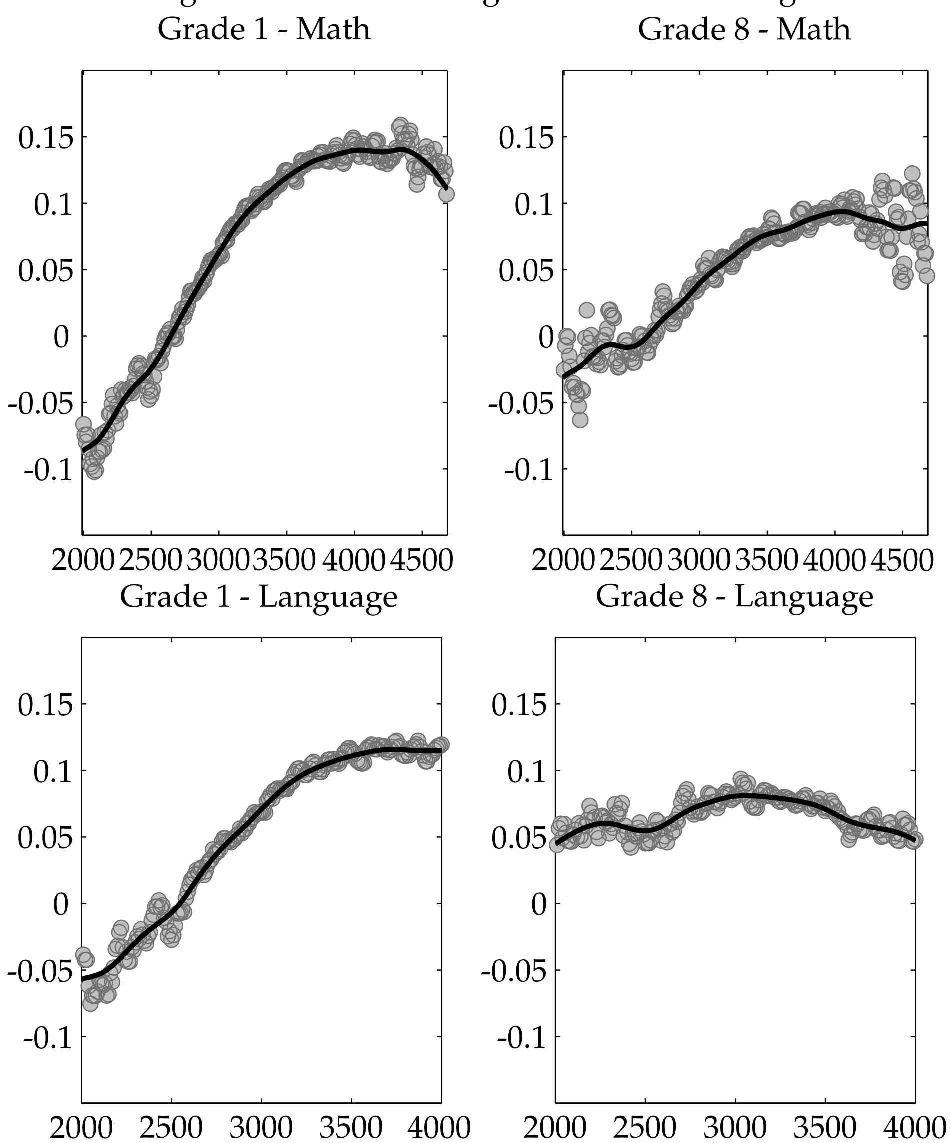
We estimate equation (24) for siblings varying in age difference from 1-5 years. Data limitations do not allow us to estimate this equation for very large age differences.

6 Results

6.1 Nonparametric and OLS Results

Figure 5 shows the relationship between academic achievement in math and language and birth weight in first and eighth grade. The relationship between birth weight and both math and language achievement is remarkably linear and upward sloping up until approximately 3300 grs (which is approximately the average birth weight) , with higher birth weight babies doing better in both measures.

Figure 5: Standardized grades and Birth Weight



Note: This graph shows the relationship between birth weight and achievement in math (top panel) and language arts (bottom panel) for students born from 1992-2002 in Chile. The grades have been standardized at the classroom level. The black solid line represents a local second order polynomial regression. The dots represent a moving average with a centered window width of 30 grams.

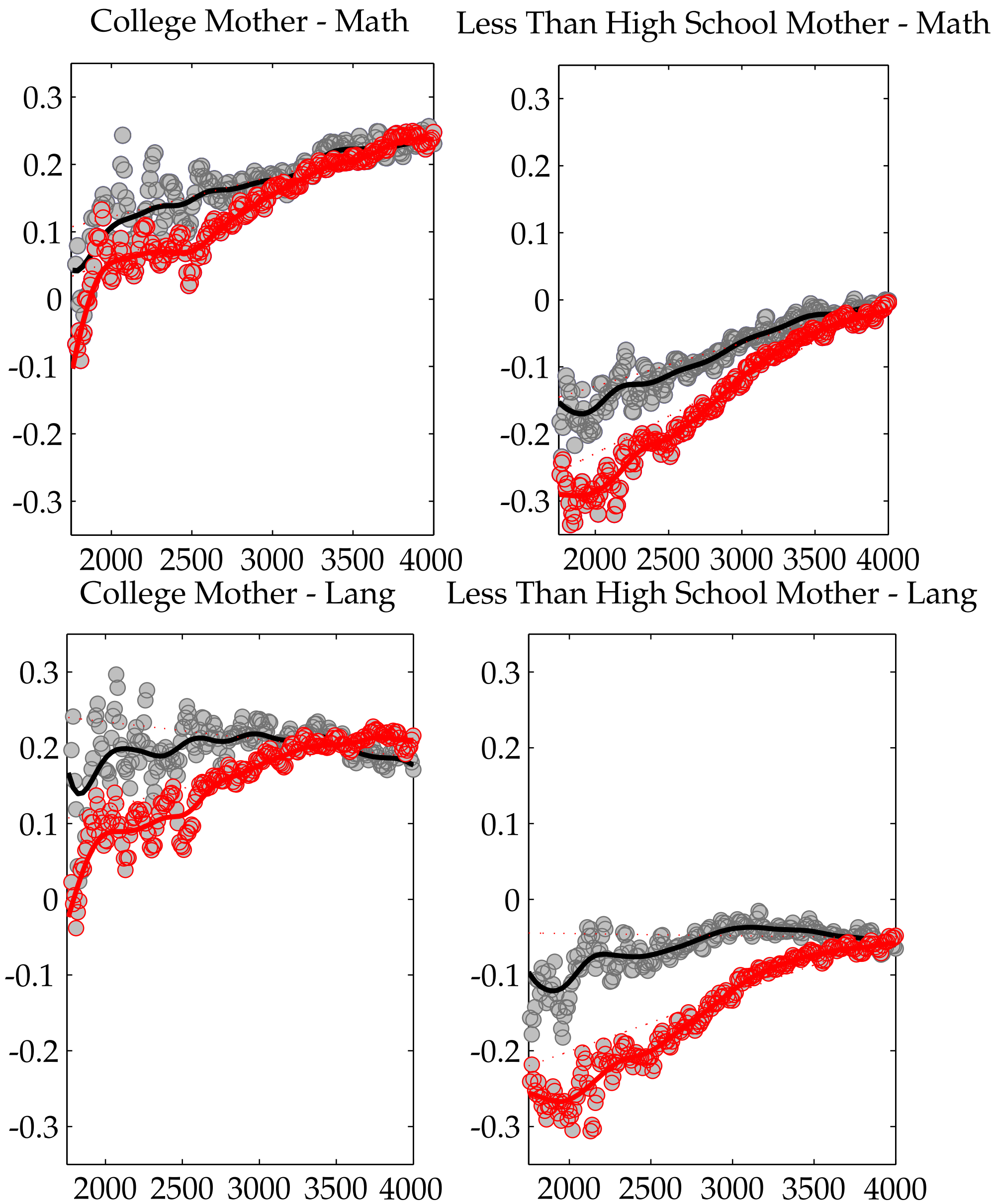
Further exploration of this relationship via regressions confirms that this correlation is robust to the addition of various controls. The regressions estimated in Table 1 shows the OLS coefficient for the birth weight effect at each grade on math grades for various samples of the data using a specification similar to that in equation (19), with the exception that we do not have controls for the history of parental inputs. Moreover, since twins are quite different from the rest of the population, we wanted to focus our attention to siblings and singletons with the same birth weight support which is between 0-3000 grams. As is evident from fire (5), most of the effects of birth weight on the outcome of interest is observed within this support. Row 1 shows λ_g estimated for the sample that shares the same birth weight support as the twins sample. In all OLS specifications, we control for gestational age, mother's education, mother's age at birth and sex of the child. The second row shows the same specifications but restricting the sample to just the twins sample.

Across all rows, the results appear fairly similar and the main pattern among the coefficients is the decline in the birth weight effect in later grades. In first grade, the effect of birth weight appears to be around 0.35-0.4 SD and by eighth grade the birth weight effect declines to 0.2 SD. Examining test scores in fourth, eighth and tenth grades we find similar results. The OLS regression coefficient declines over time in each case.

6.1.1 Heterogeneity

We also examine whether the OLS relationship between birth weight and math grades varies by observable characteristics of the mother. The following graphs show that students with mothers with college education preform better than those of mothers with lower education levels but that the positive relationship between birth weight and academic achievement is similar in both groups in 1st grade. It can also be seen that over time, this relationship diminishes in strength for both groups with lower birth weight children raising their relative performance. The results from this section show that the simple correlation between initial health endowment and academic outcomes is quite significant but that this relationship seems to weaken over time.

Figure 6: Standardized Math and Language grades and Birth Weight by Mothers Education



Note: This graph shows the relationship between birth weight and achievement in math (top panel) and language arts (bottom panel) for students born from 1992-2002 in Chile to mothers with college education and with less than high school education. The red circles and lines indicate first grade results and the darker colors represent eighth grade achievement. The grades have been standardized at the classroom level. The solid line represents a local second order polynomial regression. The dots represent a moving average with a centered window width of 30 grams.

6.2 Twins Fixed Effects Estimates

To tackle the problem of unobserved characteristics and inputs, we modify equation (19) by including a dummy for the mother - i.e. a twins fixed effect. As suggested earlier, under certain assumptions, a twins estimate does a good job of recovering the true λ_t. Table 2 estimates equation (22) using log birth weight and a dummy variable for low birth weight in separate regressions as the independent variables of interest. In table 2, statistical tests reveal that λ_8 and λ_1 as obtained under the fixed effects estimation are not different, suggesting that the twins estimates of the impact of birth weight on test scores do not appear to diminish over time.

Table 2 suggests that a 10% increase in birth weight (corresponding to a 250 gram increase) raises test scores in math by 0.046 SD in 1st grade and that this effect is largely persistent. This is in sharp contrast to the OLS estimates discussed earlier. Table 2 also shows that the impact of being born low birth weight is fairly severe on math grades - on average, being low birth weight reduces math scores by 0.1 SD.

6.2.1 Heterogeneity

We can also examine whether twins fixed effects results vary by observable characteristics of the mother. In Table 3 we show that examining twins fixed effects for mothers with high school and above is very similar to the effects obtained for mothers without a high school degree. To interpret this result in the context for our model, we require some ideas of whether more educated and less educated mothers have different preferences with regards to inequality aversion across their children. To the extent we think that inequality aversion does not vary across high and low educated mothers, this result is not all together surprising.

The next two rows in Table 3 examines the results by type of school and the socioeconomic background of the children at the school. The SIMCE survey categorizes schools into five SES brackets using household data on the parents of the students that attend each school. We take the two lowest levels and designate them as “Low SES”. Twins fixed effects results restricted to this school type shows largely similar results, although the birth weight effect seems to increase slightly over time. The next panel shows the results by private schools in Chile and the while the pattern over time is similar in that the effect remains the same, the levels are quite a bit larger. We interpret these results as evidence that there does appear to be some heterogeneity in the birth weight effect by school type and socioeconomic background.

6.3 Differences in Twins and OLS Estimates: The Role of Parental Investments

Twins fixed effects and OLS estimates contrast in patterns that are worth exploring further. In particular, while all estimation methods show a similar effect in grade 1, twins estimates stay persistent, while OLS estimates steadily decline over time (i.e. the effect of birth weight appears to lessen in later grades). Our model in Section 2 suggests that part of the reason for the differences in twins and OLS estimates is the role of parental investments.

Recall that under OLS, we estimate λ_t with bias:

$$\lambda_t^{OLS} = \lambda_t + Cov(BW_{ij}, \sum_{s=0}^{t-1} \beta_{s+1} X_{ijt-s} + \epsilon_{ijt}) \tag{25}$$

Where ϵ_{ijt} is the current shock to T and $\sum_{s=0}^{g-1} \beta_{s+1} X_{ijg-s}$ contains the complete history of unobserved parental inputs (the same X_{ijt}'s from equation (19). Given that OLS is smaller than twins fixed effects, we can conclude, if twins fixed effects are unbiased, that the direction of bias is negative. The results and the model would imply that parental investments and birth weight are negatively correlated. We can test this correlation in the data. We acknowledge that while we view these correlations as a partial explanation for why the differences in twins and OLS estimations arise, these results are by no means causal, and neither do we attempt to get at a causal relationship between the role of parental investments and test scores. We also recognize that OLS and twins fixed effects can vary for a host of reasons, but within the context of our model and the data, the role of parental inputs appears to be the most tractable.

Table 4 estimates the relationship between parental investments (as reported by parents and children in separate columns) and birth weight for a subset of the data (see the data section on why we only have this data for a subset of our overall sample). The investments (measured in grade 4) are on a scale of 1-5 where 5 denotes "very often" and 1 denotes "never". We aggregate these responses into a dummy variable that takes on the value of 1 if parents report "often" or "very often" and 0 if parents report "never", "not often" or "sometimes". Since there are a wide range of investment questions, we aggregate these into a single index and also perform factor analysis to get summary measures of investments. These factors appear to be easily interpretable (in the parent responses for example) into educational and non-educational inputs. Educational inputs for example include questions like, "How often do you read to your child", "Do you help your child with homework" etc, whereas non-educational inputs include questions like, "How often do you talk to your child", "How often do you write messages for your child", "How often do you run errands with your child". In the case of child responses about parental investments, the factors lump into what we can term as more straightforward educational inputs and "educational encouragement". "Educational encouragement" contains questions such as, "Parent congratulates me on good grades in school", "Parent challenges me to get better grades" etc. A detailed list of the investment questions and its correlation with birth weight appears in Table 5.

The broad results from Table 4 and 5 are quite obvious: OLS estimates reveal a negative relationship between investments and birth weight. In particular this appears to be true in the case of educational inputs. What is interesting is that both, parent and child responses to the questions reveal similar correlations. This is important as parents might be more likely to misreport how much they invest in their own children.

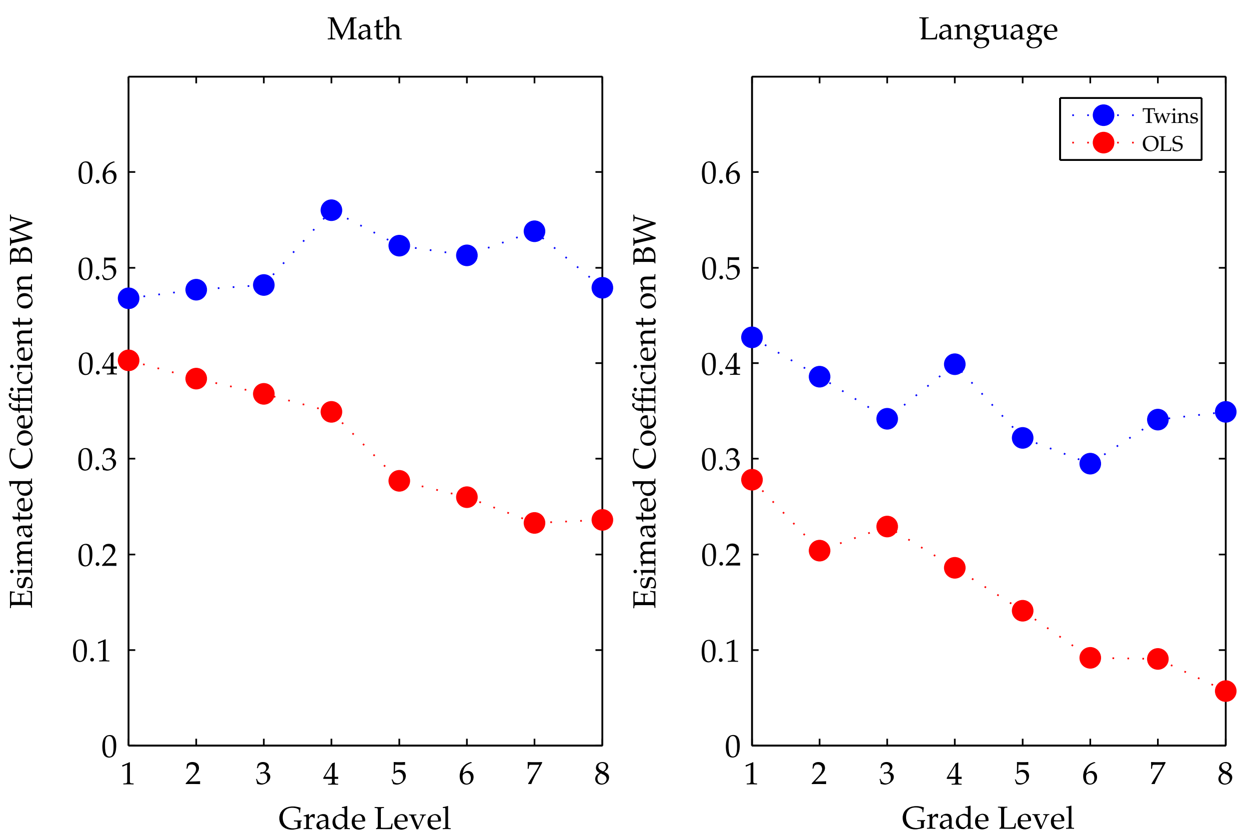
A crucial assumption for interpreting twins fixed effects as revealing the unbiased effect of birth weight on test scores is that parental investments are the same within twins. The model in section 2 suggested why this might be the case for twins due to public goods and spillovers in investments in households with twins. Given the data on parental investments, we can test within a twins fixed effects framework whether investments vary by birth weight. Table 6 shows that with a twins fixed effect there appears to be no significant correlation between birth weight and parental investments. Hence, in the context of our model and the data, it appears that twins fixed effects do indeed result in an unbiased coefficient of birth weight on test scores.

It is important to realize that these parental investments are positively correlated with test scores.[12] While the model might suggest that controlling for parental inputs will make the OLS estimates closer to twins estimates, we do not find this to be true. We believe this

[12]Correlations between school performance and parental investments (using the parental responses) suggest that moving from "Never" to "Often" in terms of studying with the child, is correlated with an increase in test scores of 0.04 SD (these correlations are available upon request).

is due to the fact that ultimately we only observe a small subset of various investments that parents engage in. Moreover, we certainly do not believe that the *entire* difference between OLS and twins are due to parental investments. There could be other biases at play, such as the role of schools or teachers that could mitigate or exacerbate the role of initial endowments.

Figure 7: OLS and Fixed Effects Estimates for Twins: Math and Language



Note: This graph shows how the coefficient on log birth weight changes as children become older using different estimation strategies. These coefficients are from Tables 2, 7 and 8.

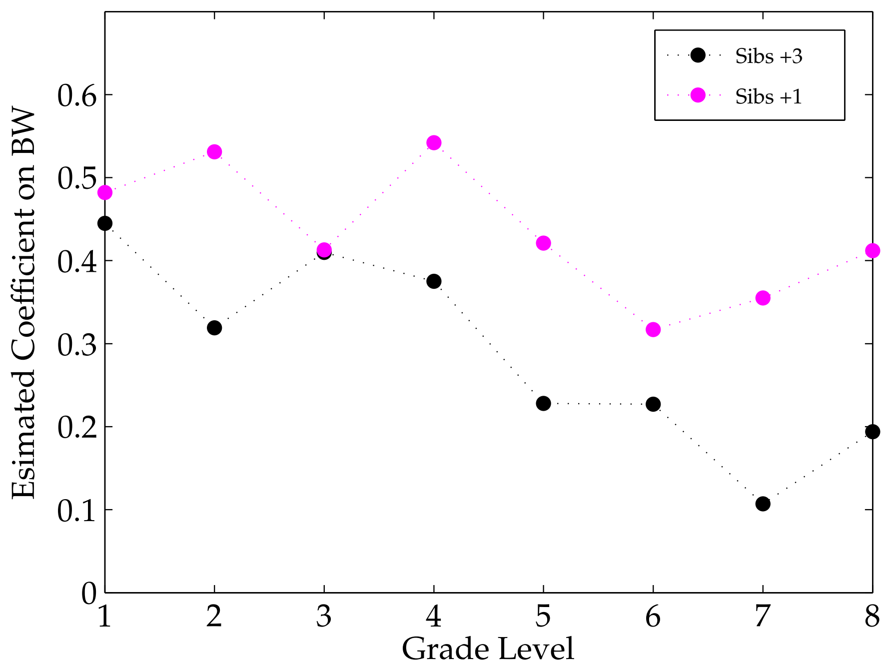
6.4 Siblings Fixed Effects Estimates

Siblings fixed effects in our case are useful to validate the ”degree” of public goods argument in Section 2. Proposition 1 suggests that over time, in the presence of public goods, test scores should converge less than without public goods or spillovers. Siblings can provide a validation check on this idea by tracking test scores differences within siblings who are close together in age and siblings far apart in age. Table 7 estimates equation (24) for two types of sibling groups - those who are 1 year apart and those between 3 and 4 years apart. The results across grades suggest that siblings 1 year apart show patterns quite similar to twins whereas siblings 3-4 years apart show patterns similar to OLS, in that the test score differences over time show declines.

Siblings fixed effects, while validating our idea of public goods within the household for parental investments, also show in a more general setting the importance of health at birth in determining school performance. Since twins form a small portion of the overall population, it is useful to show that the basic patterns appear to hold using other methods.

Figure 8: OLS and Fixed Effects Estimates for Twins: Math and Language

Math



Note: This graph shows how the coefficient on log birth weight changes as children become older using different estimation strategies. These coefficients are from Tables 2, 7 and 8.

6.5 Other School Achievement Variables

While mathematics grades in school is the main subject we have focussed on, the data allows us to examine the effects of birth weight on language grades as well as nationalized tests such as SIMCE and the PSU. Table 8 shows our main estimates using OLS, twins and sibling fixed effects strategies for language scores between grades 1 and 8. The patterns for language mirror the patterns seen in math. While twins fixed effects estimates show a stable coefficient across each grade, OLS and larger sibling differences show a steady decline. Estimates for siblings 1 year apart are quite close to the twins estimates.

Table 9 uses the SIMCE and PSU as the main dependent variable. In each case we have examined both math and language scores. The main difference here is that we are able to examine the birth weight effect upto grade 10 and even up to grade 12 (PSU). Hence, we find that the birth weight effect in the case of twins appears to last throughout the schooling period. The OLS counterpart in these tables show some decline in the effect, but the define is less than what is seen using classroom level grades. Moreover, we are unable to estimate sibling fixed effects models in the case of SIMCE and PSU given the timing of the tests and the data availability. We view these results as supportive of our overall findings, but ultimately given that the tests are only administered in 4th, 8th and 10th grade, we do not view these results as the core of the paper which is focussed on understanding the dynamics of the birth weight effect over time.

7 Conclusion

This paper examines the relationship between health at birth, subsequent parental investments and academic outcomes from childhood to adolescence using administrative data from Chile, a middle income OECD member country. Using data on all births in the country from 1992 to 2002 merged with schooling records for the entire education system we construct a panel following children from birth to high school graduation. We find a declining correlation between initial health measured by birth weight and academic outcomes as children progress through school. In contrast, siblings and twins fixed effects estimators show a more persistent relationship between initial health and academic outcomes throughout schooling years. In particular twins fixed effects models show strikingly persistent effects throughout 1st to 8th grade academic results with a 10% increase in birth weight is associated with nearly 0.05 standard deviations higher performance in math. Similar results are found for national tests taken in fourth, eighth and tenth grade as well as for the national college entrance exam after high school graduation. In addition, we find evidence that parental investments are larger for children of lower birth weight across families with similar observable characteristics suggesting a compensatory relationship between initial health and investments. We find suggestive evidence that this differential parental investment is decreasing in the age difference among siblings and is virtually absent among twins.

We present a simple model of human capital accumulation and extend existing models of intra household allocations to include a dimension of parental investment spillovers. This model is able to rationalize three empirical features found in the data : 1) the observed behavior of parental investments, 2) declining correlation between birth weight and academic achievement in the population and 3) persistent twins estimates. This framework interprets the different empirical results through the lens of a simple human capital accumulation model that implies varying degrees of bias in estimates of the relationship between initial health and later academic outcomes depending on the relationship between parental investments and endowments and how these accumulate over time. Thus this model rationalizes both the observed behavior of parental investments and the different OLS, siblings and twins estimates of the relationship between initial health and academic achievement in school as well as its evolution over time.

We conclude that within the context of our model, because parents do not differentially invest among twins, these fixed effects models effectively identify the structural relationship between initial conditions at birth measured by birth weight and later academic outcomes described in the model presented. However, given the evidence presented shows parental investments are compensatory in this context, twins estimates overestimate the empirical relationship in the general population and suggest that differential parental investments seem to mitigate to some extent initial differences in endowments and this becomes more relevant over time as parents have more time to adjust. This result helps put prior empirical work using twins estimators into context with regard to the general population. It also highlights that some of the inequalities at birth can potentially be undone through the efforts made by parents and possibly public policies aimed at investing in the health and human capital of children. A deeper understanding of how parents invest and precisely what types of investments matter more would be a fruitful topic for future research in this area.

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A Appendix: Model

A.1 Deciding Between Educational and Non-Educational Inputs

In order to better understand what happens to effective time endowments in the case with and without public goods in parental investments, we consider a problem where education is not the only activity in the household, and other competing activities may be also important for raising a child. The second part of the problem is related to the possibility that parents can strategically use investment time to reinforce the difference between siblings, for efficiency motives, or compensate the less endowed child, for inequality aversion motives. In our model, we explore the implications of both cases.

We start assuming that parents allocate time among different activities to raise their children. Specifically, parents can allocate time between educational activities T_E or non educational activities T_{NE}. We can think of the parents' problem as

$$\begin{aligned} \max_{T_E, T_{NE}} \quad & V(T_E, T_{NE}) \\ \text{s.t.} \quad & T_E + T_{NE} \leq T \end{aligned} \tag{26}$$

Where V is the utility coming from educational and non educational activities[13]. T is

[13] An alternative formulation consists on assuming that parents maximize the production of "children quality", that uses time in both educational and non educational inputs. Thus, the allocation of time is related

the total time allocated to raise the children in the household. Note that, if there are more than on child in the household, parents use the aggregate educational and non educational times, and utilities to make the allocation decision.

We denote T_E^* and T_{NE}^* the optimal allocation of time, coming from the solution of the maximization problem in equation (26). Note that the optimal allocation depends on the marginal utilities associated with the educational and non-educational activities. In the main text, for expositional ease, we refer to T_E^* as T_E.

A.2 Allocations in the presence of public goods

$$\begin{aligned} \max_{T_E, T_{NE}} \quad & V(T_E, T_{NE}) \\ \text{s.t.} \quad & T_E + T_{NE} \leq T \end{aligned} \tag{27}$$

If T_E^* and T_{NE}^* are the optimal allocation, they satisfied the first order conditions:

$$\begin{aligned} \frac{\partial V(T_E^*, T_{NE}^*)}{\partial T_E} &= \lambda \\ \frac{\partial V(T_E^*, T_{NE}^*)}{\partial T_{NE}} &= \lambda \\ \text{combined:} \quad \frac{\partial V(T_E^*, T_{NE}^*)}{\partial T_E} &= \frac{\partial V(T_E^*, T_{NE}^*)}{\partial T_{NE}} \end{aligned} \tag{28}$$

to the marginal productivity, in opposite to the marginal utility associated with the formulation presented in the main text.

When parents know the public good dimension of parental investment, they realize that their effort T_E effectively converts into $\hat{T}_E = (1 + \delta(i, i'))T_E$. Therefore, they solve the problem

$$\begin{aligned} \max_{\hat{T}_E, T_{NE}} \quad & V(\hat{T}_E, T_{NE}) \\ \text{s.t.} \quad & \frac{\hat{T}_E}{1 + \delta(i, i')} + T_{NE} \leq T \end{aligned} \tag{29}$$

In a similar way than in the absence of public good, we combined the first order equations to obtain

$$\frac{\partial V(T_E^{**}, T_{NE}^{**})}{\partial T_E}(1 + \delta(i, i')) = \frac{\partial V(T_E^{**}, T_{NE}^{**})}{\partial T_{NE}} \tag{30}$$

where $T_E^{**}(1 + \delta(i, i') = \hat{T}_E^{*}$.

Proposition: *If V is a Leontief utility function, the optimal allocation for educational activities when there is a degree of public good dimension in parental investments is smaller than in the case without public goods.*

Proof 1

Let's denote T_E^{*} and T_{NE}^{*} the optimal allocations in the absence of public good dimension on parental investment, and T_E^{**} and T_{NE}^{**} the optimal allocations when public good dimension on parental investment is present. Finally, $\hat{T}$ represents the effective time, when the public good dimension feature is present.

V is a Leontief production function, expressed as

$$V(T_E, T_{NE}) = \min\{a_1 T_E, a_2 T_{NE}\}$$

It is well known that the solution for the optimal allocation for the Leontief utility function is that

$$T_E^* = \frac{a_2}{a_1 + a_2} T \quad \wedge \quad T_{NE}^* = \frac{a_1}{a_1 + a_2} T \tag{31}$$

The public good dimension of parental investment effectively increases the parameter a_1 from its original value to $a_1(1 + \delta(i, i'))$. Therefore, the new optimal allocations are

$$T_E^{**} = \frac{a_2}{a_1(1 + \delta(i, i')) + a_2} T \quad \wedge \quad T_{NE}^* = \frac{a_1(1 + \delta(i, i'))}{a_1 + a_2} T \tag{32}$$

Comparing the allocation assigned to educational activities in (31) with the one displayed in (32), it is easy to see that the public good dimension of parental investment induce a decrease in the time assigned to educational activities.

A.3 Proof of Proposition 1 from Section 4

If compensating (reinforcing) parents can fully differentiate the educational inputs allocated to each child, the test score gap between siblings will decrease (increase) over time. If there is only partial parental investment differentiation, the test score gap may decrease (increase), but this decrease (increase) will be less than in the case of full differentiation.

Proof 2

For the case of fully differentiation, equations (10) and (11) indicate that, for given cognitive endowments θ_{1jg} and $\theta_{2jg'}$, the allocation for child 1 is just a factor of allocation for child 2.

In particular, the factor is

$$C(\gamma, \rho, \theta_{1jg}, \theta_{2jg'}) = \left(\frac{\theta_{2jg'}}{\theta_{1jg}} \right)^{\frac{\gamma\rho}{(1-\gamma)\rho-1}}$$

Without loss of generality, let's assume that child 1 has a higher cognitive endowment that child 2. Thus, $\frac{\theta_{2jg'}}{\theta_{1jg}} < 1$.

Additionally, if $\rho < 0$, or when parents present a compensating behavior, the exponent $\frac{\gamma\rho}{(1-\gamma)\rho-1} > 0$, because numerator and denominator are both negative. We conclude that $C(\gamma, \rho, \theta_{1jg}, \theta_{2jg'}) < 1$, and therefore, the parental investment allocation for child 2 is bigger than for child 1, which is consistent with the compensating behavior.

Note that, if $\rho > 0$, $\frac{\gamma\rho}{(1-\gamma)\rho-1} < 0$, and therefore $C(\gamma, \rho, \theta_{1jg}, \theta_{2jg'}) > 1$.

If child 2 has lower cognitive endowment that child 1, he or she will receive higher educational inputs. Equation (12) captures the evolution of cognitive endowments, and it shows that higher values of educational inputs for child 2 will reduce the gap between the cognitive endowments[14]. As $\theta_{2jg'} \longrightarrow \theta_{1jg}$, the factor $C(\gamma, \rho, \theta_{1jg}, \theta_{2jg'}) \longrightarrow 1$, producing the convergency of cognitive endowments, optimal educational inputs and test scores.

In the case of partial differentiation, we can assume without loss of generality that the actual parental investment received by the children is a weighted average of the optimal

[14] In order to rule out a *overshooting* behavior from the parents, and to make the evolution of cognitive endowment a relatively persistent process, we assume a specific region for the parameters β_X, $\beta_{X\theta}$, and T.

parental investment expressed in equations (10) y (11). In other words,

$$\begin{aligned}\tilde{X}_{1jg} &= \alpha_1 X^*_{1jg} + (1-\alpha_1) X^*_{2jg'} \\ \tilde{X}_{2jg} &= \alpha_2 X^*_{1jg} + (1-\alpha_2) X^*_{2jg'}\end{aligned}$$

where the tilde represents the actual educational input received by each child.

Partial differentiation implies that α_1 and α_2 are in the interval (0,1). From the previous discussion, we know that if child 2 has a lower endowment, $X_{1jg} < X_{2jg'}$, and therefore

$$X^*_{1jg} < \tilde{X}_{1jg} < X^*_{2jg'} \quad \wedge \quad X^*_{1jg} < \tilde{X}_{2jg'} < X^*_{2jg'}$$

It is easy to conclude that the compensating effort in the partial differentiation case will reduce less the gap in the cognitive endowment dimension than in the case of full differentiation. This is because $X^*_{1jg} < \tilde{X}_{1jg}$, or the high endowed child receives more parental investment in the partial differentiation case, and $\tilde{X}_{2jg'} < X^*_{2jg'}$ implies that the low endowed child receives less parental investment in the partial differentiation case.

Corollary 2 *The public good dimension of parental investment implies partial differentiation across children. Thus, the compensating (reinforcing) behavior will take longer to reduce (increase) the test score gap, than in the absence of public good dimension.*

Proof 3

According to our model, the public good dimension feature of parental investment implies that the optimal allocation for child 1 (denoted by double stars) satisfies

$$
\begin{aligned}
\hat{X}^*_{1jg} &= X^{**}_{1jg} + \delta(1,2) X^{**}_{2jg'} \\
&= \frac{T_E^{**}}{(1-\delta(1,2))\left[1+\left(\frac{\theta_{2jg'}}{\theta_{1jg}}\right)^{\frac{\gamma\rho}{(1-\gamma)\rho-1}}\right]}\left[\left(\left(\frac{\theta_{2jg'}}{\theta_{1jg}}\right)^{\frac{\gamma\rho}{(1-\gamma)\rho-1}} - \delta(1,2)\right) + \delta(1,2)\left(1-\delta(1,2)\left(\frac{\theta_{2jg'}}{\theta_{1jg}}\right)^{\frac{\gamma\rho}{(1-\gamma)\rho-1}}\right)\right] \\
&= \frac{T_E^{**}}{(1-\delta(1,2))\left[1+\left(\frac{\theta_{2jg'}}{\theta_{1jg}}\right)^{\frac{\gamma\rho}{(1-\gamma)\rho-1}}\right]}\left[(1-\delta(1,2)^2)\left(\frac{\theta_{2jg'}}{\theta_{1jg}}\right)^{\frac{\gamma\rho}{(1-\gamma)\rho-1}}\right] \\
&= \frac{T_E^{**}}{\left[1+\left(\frac{\theta_{2jg'}}{\theta_{1jg}}\right)^{\frac{\gamma\rho}{(1-\gamma)\rho-1}}\right]}\left[(1+\delta(1,2))\left(\frac{\theta_{2jg'}}{\theta_{1jg}}\right)^{\frac{\gamma\rho}{(1-\gamma)\rho-1}}\right] \quad \text{but} \quad T_E^{**} = \frac{\hat{T}_E^*}{1+\delta(1,2)} \\
&= \frac{\hat{T}_E{}^*}{\left[1+\left(\frac{\theta_{2jg'}}{\theta_{1jg}}\right)^{\frac{\gamma\rho}{(1-\gamma)\rho-1}}\right]}\left(\frac{\theta_{2jg'}}{\theta_{1jg}}\right)^{\frac{\gamma\rho}{(1-\gamma)\rho-1}}
\end{aligned}
$$

Which is exactly the same expression than in the original case, but with $\hat{T}_E^*$ instead of T_E^*. Furthermore, because $\hat{T}_E^* < T_E^*$, it is easy to show that there is α_1 such that $\hat{X}^*_{1jg}$ can be written as

$$\hat{X}^*_{1jg} = \alpha_1 X^*_{1jg} + (1-\alpha_1) X^*_{2jg'}$$

Similarly for $\hat{X}^*_{2jg'}$.

Therefore, the public good dimension is a particular case of partial differentiation, and the results of the proposition can be apply for this case.

A.4 Simulation Details

All the figures in the main text where constructed using the solutions simulated in Matlab 7.12.

The solutions for the optimal allocations are presented in equations (10) and (11). We simulate the solutions with the following parameters:

Optimal Allocation Parameters	
ρ	40 equidistant points in the interval $[-0.9, 0.9]$
γ	0.8
θ_{1j1}	3.0
θ_{2j1}	2.0
T_E	0.375
Evolution of Endowments	
β_X	0.3
β_θ	1.0
$\beta_{X\theta}$	0.01
Public Good Parameters	
$\delta(i, i')$	$\delta^{(\text{age difference})}$
δ	0.8
Age Difference	1.5

Starting with the initial values of θ presented in the table above, and the solution for optimal allocation of parental investment X^*, we constructed the evolution of θ over time for each child.

Once we have the sequence of optimal X and the implied θ, we calculate the test scores, using the equation

$$T_{ijg} = \theta_{ijg}^{\gamma} \cdot X_{ijg}^{(1-\gamma)}$$

TABLE 1: Birth Weight and Test Scores - OLS Estimates

	Grade							
Standardized Math Scores	1	2	3	4	5	6	7	8
OLS: Sample uses same birth weight support as twins (0-3000 grams)								
Log Birth Weight	0.403	0.384	0.368	0.349	0.277	0.260	0.233	0.236
	(0.00958)***	(0.00896)***	(0.00891)***	(0.00880)***	(0.00904)***	(0.00965)***	(0.0103)***	(0.0117)***
Observations	485,991	552,931	581,559	591,286	557,175	491,201	431,634	357,937
OLS: Twins sample								
Log Birth Weight	0.357	0.298	0.329	0.333	0.277	0.282	0.244	0.202
	(0.0322)***	(0.0308)***	(0.0335)***	(0.0321)***	(0.0322)***	(0.0352)***	(0.0380)***	(0.0465)***
Observations	30,353	31,586	31,212	30,849	28,478	24,919	21,755	17,874

Robust standard errors in par
*** p<0.01, ** p<0.05, * p<

Note: All estimates control for gestational age, mother's age and education and sex of the child. The dependent variable is standarized classroom grades in math.

TABLE 2: Birth Weight and Test Scores - Twins Fixed Effect Estimates

	Grade							
Standardized Math Scores	1	2	3	4	5	6	7	8
Log Birth Weight	0.468	0.477	0.482	0.560	0.523	0.513	0.538	0.479
	(0.0410)***	(0.0408)***	(0.0410)***	(0.0415)***	(0.0432)***	(0.0477)***	(0.0524)***	(0.0590)***
Low Birth Weight	-0.0777	-0.0815	-0.0861	-0.104	-0.109	-0.0902	-0.108	-0.103
	(0.0134)***	(0.0133)***	(0.0134)***	(0.0136)***	(0.0140)***	(0.0154)***	(0.0169)***	(0.0189)***
Observations	30,353	31,586	31,212	30,849	28,478	24,919	21,755	17,874
Number of Twin Pairs	15,740	16,496	16,350	16,187	14,961	13,160	11,572	9,564

Robust standard errors in par
*** p<0.01, ** p<0.05, * p<

Notes: All estimates control for sex of the child.

TABLE 3: Birth Weight and Test Scores - Heterogeneity: Twins Estimates

	Grade							
Standardized Math Scores	1	2	3	4	5	6	7	8
All coefficients reported are on log birth weight using twin fixed effects								
Mother with high school and above	0.476 (0.0477)***	0.520 (0.0473)***	0.536 (0.0476)***	0.613 (0.0484)***	0.541 (0.0503)***	0.514 (0.0555)***	0.563 (0.0616)***	0.465 (0.0697)***
Mothers with less than high school	0.436 (0.0809)***	0.339 (0.0812)***	0.302 (0.0820)***	0.397 (0.0815)***	0.456 (0.0854)***	0.497 (0.0935)***	0.478 (0.101)***	0.517 (0.112)***
Mother Employed	0.482 (0.0784)***	0.604 (0.0802)***	0.572 (0.0805)***	0.531 (0.0837)***	0.472 (0.0899)***	0.454 (0.0976)***	0.555 (0.108)***	0.343 (0.123)***
Mother Unemployed	0.459 (0.0477)***	0.421 (0.0470)***	0.445 (0.0475)***	0.569 (0.0476)***	0.539 (0.0491)***	0.532 (0.0546)***	0.533 (0.0599)***	0.523 (0.0672)***
Santiago	0.486 (0.0643)***	0.513 (0.0639)***	0.443 (0.0630)***	0.544 (0.0644)***	0.505 (0.0671)***	0.549 (0.0740)***	0.497 (0.0835)***	0.404 (0.0941)***
Non-Santiago	0.454 (0.0531)***	0.450 (0.0529)***	0.514 (0.0540)***	0.572 (0.0541)***	0.535 (0.0566)***	0.484 (0.0624)***	0.565 (0.0672)***	0.531 (0.0756)***
Private schools	0.319 (0.191)*	0.804 (0.194)***	0.813 (0.182)***	0.748 (0.179)***	0.751 (0.187)***	0.743 (0.195)***	0.790 (0.205)***	0.713 (0.254)***
Poor Schools	0.432 (0.0562)***	0.329 (0.0573)***	0.339 (0.0590)***	0.504 (0.0599)***	0.465 (0.0634)***	0.483 (0.0721)***	0.515 (0.0790)***	0.506 (0.0878)***

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All estimates control for sex of the child. School categories are based on a 2010 categorization of schools in Chile. Hence, a school's classification as of 2010 is assumed to be the same between 2002-2008.

Table 4: Parental Investments and Birth Weight - OLS Estimates

	Parent report of Investments				Child's report of parental investments		
	Standardized Investment 2002	Standardized Investment 2007	PCA: Non-Educational Investments	PCA: Educational Investments	Standardized Investment 2009	PCA: Educational Investments	PCA: Educational Encouragement
OLS: Full Sample							
Log Birth Weight	-0.0128	-0.0588	0.0240	-0.100	-0.0460	-0.0367	0.00766
	(0.0146)	(0.0165)***	(0.0147)	(0.0145)***	(0.0105)***	(0.0119)***	(0.0119)
Observations	192,833	169,234	193,017	193,017	377,853	295,137	295,137
OLS: Sample uses same birth weight support as twins							
Log Birth Weight	-0.00989	-0.0813	0.0703	-0.121	-0.0736	-0.0507	0.0146
	(0.0276)	(0.0347)**	(0.0277)**	(0.0275)***	(0.0210)***	(0.0298)*	(0.0313)
Observations	58,806	48,010	60,027	60,027	105,893	48,635	48,635
OLS: Twins Sample							
Log Birth Weight	-0.180	-0.0936	-0.0799	-0.309	0.0338	0.00455	-0.0784
	(0.117)	(0.101)	(0.119)	(0.116)***	(0.0848)	(0.132)	(0.131)
Observations	2,833	2,617	2,900	2,900	2,583	2,583	2,583

Robust standard errors in
*** p<0.01, ** p<0.05, *

Notes: All regressions control for gestational age, mother's age and education and sex of the child. "Standardized" investments use all investment related questions to create a single composite measure. "PCA" denotes measures obtained from Pricipal Components Analysis. Details of this procedure are available upon request. "PCA" components for parental responses are computed over their responses to the 2002 survey, and child responses are obly available from 2009. All investment meausres are asked of children in grade 4.

Table 5: Parental Investments and Birth Weight - OLS Estimates Details

Common support sample							
Details on Investments (Parent Responses)	Review Homework	Help with Homework	Study with Child	Read to Child	Give math problems	Talk to Child	Run errands with child
Log Birth Weight	-0.0348	-0.0520	-0.0450	0.00463	-0.00913	0.00674	-0.0151
	(0.0129)***	(0.0144)***	(0.0148)***	(0.0110)	(0.0149)	(0.00999)	(0.0141)
Observations	45,106	45,106	45,106	45,106	45,106	45,106	45,106
Mean of dependent variable	0.777	0.679	0.634	0.322	0.643	0.882	0.708
Details on Investments (Child Responses)	Parent explains things	Parent helps study	Parent helps with chores	Parent knows grades in school	Parent congratulates me on good performance	Parent challenges me to get good grades	Parent willing to help
Log Birth Weight	-0.0376	-0.0447	-0.0344	0.00767	-0.00572	-0.0180	0.00518
	(0.0112)***	(0.0117)***	(0.0119)***	(0.0106)	(0.00915)	(0.0120)	(0.0116)
Observations	79,839	79,762	78,676	78,759	68,489	73,551	78,486
Mean of dependent variable	0.555	0.500	0.484	0.752	0.835	0.408	0.618
Twins sample							
Details on Investments (Parent Responses)	Review Homework	Help with Homework	Study with Child	Read to Child	Give math problems	Talk to Child	Run errands with child
Log Birth Weight	-0.104	-0.162	-0.110	-0.0834	0.0242	0.0112	-0.0125
	(0.0518)**	(0.0561)***	(0.0573)*	(0.0305)***	(0.0575)	(0.0380)	(0.0538)
Observations	2,900	2,900	2,900	2,900	2,900	2,900	2,900
Mean of dependent variable	0.744	0.665	0.633	0.367	0.637	0.885	0.719
Details on Investments (Child Responses)	Parent explains things	Parent helps study	Parent helps with chores	Parent knows grades in school	Parent congratulates me on good performance	Parent challenges me to get good grades	Parent willing to help
Log Birth Weight	0.0173	0.00570	-0.0222	-0.0386	0.0243	0.00229	0.0356
	(0.0420)	(0.0433)	(0.0437)	(0.0376)	(0.0360)	(0.0438)	(0.0426)
Observations	5,652	5,641	5,548	5,583	4,857	5,206	5,540
Mean of dependent variable	0.543	0.486	0.467	0.737	0.824	0.405	0.615

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All regressions control for gestational age, mother's age and education and sex of the child.

Table 6: Parental Investments and Birth Weight - Fixed Effects Estimates

	Parent report of Investments				Child's report of parental investments		
Overall measures	Investment 2002	Investment 2007	PCA: Non-Educational Investments	PCA: Educational Investments	Standardized Investment	PCA: Educational Investments	PCA: Educational Encouragement
Log Birth Weight	0.109	0.120	0.105	-0.0186	-0.0397	0.0998	0.299
	(0.0835)	(0.0907)	(0.0882)	(0.101)	(0.146)	(0.238)	(0.263)
Observations	2,833	2,617	2,900	2,900	5,701	2,583	2,583
Details on Investments (Parent Responses)	Review Homework	Help with Homework	Study with Child	Read to Child	Give math problems	Talk to Child	Run errands with child
Log Birth Weight	0.0502	-0.0699	0.0382	0.0249	0.0499	-0.00482	0.0449
	(0.0466)	(0.0490)	(0.0495)	(0.0270)	(0.0488)	(0.0355)	(0.0430)
Observations	2,900	2,900	2,900	8,541	2,900	2,900	2,900
Details on Investments (Child Responses)	Parent explains things	Parent helps study	Parent helps with chores	Parent knows grades in school	Parent congratulates me on good performance	Parent challenges me to get good grades	Parent willing to help
Log Birth Weight	0.0622	-0.0795	-0.0144	-0.107	0.0285	-0.0604	0.0893
	(0.0764)	(0.0785)	(0.0850)	(0.0727)	(0.0713)	(0.0847)	(0.0812)
Observations	5,652	5,641	5,548	5,583	4,857	5,206	5,540
Mean of dependent var	0.543	0.486	0.467	0.737	0.824	0.405	0.615

Robust standard errors in
*** p<0.01, ** p<0.05, *
Notes: all regressions control for sex of the child.

TABLE 7: Birth Weight and Test Scores - Sibling Fixed Effect Estimates

	Grade							
Standardized Math scores	1	2	3	4	5	6	7	8
Siblings 1 year apart								
Log Birth Weight	0.482	0.531	0.413	0.542	0.421	0.317	0.355	0.412
	(0.122)***	(0.102)***	(0.101)***	(0.0967)***	(0.102)***	(0.111)***	(0.125)***	(0.138)***
Observations	2383	2659	2796	3052	2967	2607	2265	1775
Siblings 3-4 years apart								
Log Birth Weight	0.445	0.319	0.410	0.375	0.228	0.227	0.107	0.194
	(0.0747)***	(0.0719)***	(0.0720)***	(0.0707)***	(0.0728)***	(0.0855)***	(0.0983)	(0.139)
Observations	6434	7062	7215	7388	6647	5293	3989	2494

Robust standard errors in paren
*** p<0.01, ** p<0.05, * p<0.

Note: Sample uses siblings on common birth weight support as twins (0-3000 grams). All regressions control for gestational age, mother's age and education and sex of the child.

TABLE 8: Birth Weight and Language Test Scores

	Grade							
Standardized Language Scores	1	2	3	4	5	6	7	8
Twins FE	0.427	0.386	0.342	0.399	0.322	0.295	0.341	0.349
	(0.0394)***	(0.0392)***	(0.0391)***	(0.0391)***	(0.0400)***	(0.0435)***	(0.0491)***	(0.0553)***
OLS (Twins Sample)	0.278	0.204	0.229	0.186	0.141	0.0918	0.0906	0.0569
	(0.0316)***	(0.0315)***	(0.0306)***	(0.0326)***	(0.0321)***	(0.0353)***	(0.0378)**	(0.0478)
Siblings 1 year apart (FE)	0.218	0.473	0.193	0.338	0.236	0.0307	0.160	0.272
	(0.119)*	(0.0990)***	(0.0968)**	(0.0948)***	(0.0970)**	(0.107)	(0.118)	(0.135)**
Siblings 3-4 years apart (FE)	0.362	0.327	0.282	0.194	0.170	0.155	0.0616	-0.110
	(0.0730)***	(0.0690)***	(0.0696)***	(0.0692)***	(0.0713)**	(0.0839)*	(0.0954)	(0.139)

Robust standard errors in paren
*** p<0.01, ** p<0.05, * p<0.

Notes: All estimates control for sex of the child. OLS and Sibling estimates contain other controls, see notes under Table 1 & 7.

Table 9: SIMCE and PSU test scores

VARIABLES	4th grade	SIMCE 8th Grade	10th Grade	College Entrance
All estimates are the coefficient on log birth wei				
Math				
Twins FE	0.601	0.578	0.432	0.465
	(0.0503)***	(0.0975)***	(0.102)***	(0.109)***
OLS (Twins Sample)	0.308	0.306	0.178	0.329
	(0.0291)***	(0.0598)***	(0.0634)***	(0.0770)***
Observations	22790	6180	5416	5052
Language				
Twins FE	0.397	0.338	0.327	0.281
	(0.0531)***	(0.101)***	(0.112)***	(0.109)***
OLS (Twins Sample)	0.115	0.102	0.121	0.142
	(0.0292)***	(0.0607)*	(0.0662)*	(0.0763)*
Observations	22,790	6,180	5,416	5,052

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: All estimates control for sex of the child. OLS estimates contain other controls, see notes under Table 1.