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DO INITIAL ENDOWMENTS MATTER ONLY INITIALLY?
THE PERSISTENT EFFECT OF BIRTH WEIGHT ON SCHOOL ACHIEVEMENT

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PRELIMINARY DRAFT - COMMENTS WELCOME - DO NOT CITE

ABSTRACT. This paper investigates the causal relationship between birth weight and school achievement among children in grades 1 through 8. A 10% increase in birth weight improves performance in math by nearly 0.05 standard deviations in 1st grade. The causal link is identified by using a twins fixed effects estimator - we collected birth weight and basic demographic data on *all* twins born in Chile between 1992-2000 and match these twin pairs to administrative school records between 2002-2008. We exploit repeated observations on twin pairs to show that while OLS estimates predict a steady decline in the birth weight effect in later grades, twins fixed effects estimates predict a *persistent* effect that does not deteriorate as children advance through grade 8. The difference in the two estimates is likely due to the role of parental investments and other unobserved family characteristics. Using detailed data on parental investments, we find that while parental investments are correlated with birth weight, they do not differ between twins. There are no differences in school attendance by birth weight, suggesting that missing school perhaps due to health problems is likely not a channel via which test score differentials arise.

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"We came into the world like brother and brother; And now let's go hand in hand, not one before another." Shakespeare, Comedy of Errors

1. INTRODUCTION

Given the sizable medical literature associating birth weight with numerous cognitive, developmental and mortality related outcomes,[1] birth weight is considered the "primary measure of a baby's health in most analyses of infant health and welfare in economic research" (Almond, Chay, and Lee 2005). Academic research on birth weight has been bolstered by the immense policy and public health interest in this topic in both developing and developed countries. In 2002 UNICEF declared reducing the incidence of low birth weight a priority in South Asia; the World Bank allocated tens of millions of dollars in integrated nutrition programs in countries like Bangladesh and India where one of the stated goals was to significantly reduce incidence of low birth weight births. In the United States, many papers have noted the stated goal of increasing birth weight in programs such as Medicaid, the WIC program et cetera (Currie and Gruber 1996). It is no surprise then that numerous papers in economics have examined the role of maternal behavior and environmental factors in affecting birth weight (Grossman and Joyce 1990, Currie and Moretti 2007, Deschênes, Greenstone, and Guryan 2009, Almond and Mazumder 2008), while others have examined the link between birth weight and socioeconomic status, adult labor market outcomes, completed schooling, maternal complications et cetera (Currie and Hyson 1999, Behrman and Rosenzweig 2004, Black, Devereux, and Salvanes 2007, Royer 2009).

Since educational attainment and its link to the labor market has been studied extensively in the labor literature, a natural, intermediate outcome to examine is whether birth weight affects human capital accumulation. While there is some debate about short-run health impacts of birth weight (Almond, Chay, and Lee 2002), long-run impacts on labor market outcomes appear fairly well established. However, most of the literature on the impacts of birth weight has examined outcomes soon after birth or in adults. A recent line of research suggests that cognitive and non-cognitive ability is an important predictor of socioeconomic success, and that inequalities in these abilities open up early in the lives of children (Heckman 2008). Test scores and school achievement, while predominantly thought of as measuring cognitive ability, also reflect some effects of non cognitive ability and are influenced by birth weight (Heckman 2007). Hence, if cognitive

[1] A small sampling of papers examining the association between birth weight and cognitive development include: (Lewis and Bendersky 1989, Richards, Hardy, Kuh, and Wadsworth 2002, Hack, Klein, and Taylor 1995, Davies and Stewart 1975, Jefferis, Power, and Hertzman 2002)

and non cognitive ability during childhood predicts completed schooling and adult labor market success, it is important to ask: Does birth weight play a role in determining these abilities? If birth weight does play a role in the development of these abilities, do the effects show up early in life? Moreover, do these effects increase or decrease (or stay constant) during the child's formative years? Finally, do parental investments related to human capital accumulation respond to birth weight?

This paper examines whether birth weight plays a role in the accumulation of human capital by examining school achievement. As opposed to other studies that have looked at birth weight and completed schooling (Behrman and Rosenzweig 2004, Black, Devereux, and Salvanes 2007), by looking at performance on test scores in schools we are able to provide a more in-depth look at some of the mechanisms by which birth weight might affect ultimate educational attainment and performance in the labor market. This paper also examines *when* birth weight begins to have an impact on test outcomes, and (by virtue of being able to follow a child's performance in school over multiple years) whether this effect is a *persistent* one. One might imagine that initial differences in test scores due to birth weight differences might be wiped out (or exacerbated) by the responses of teachers and parents - hence, examining whether birth weight has a persistent effect throughout a child's schooling years is important in making sense of the results that find effects of birth weight on completed schooling and labor market outcomes.

As always, the challenge in estimating these objects of interest is the idea that allocation of birth weight is not random. Children with higher birth weight might have other, unobserved characteristics that affect their school performance. One way to deal with this problem of bias due to unobservables is to examine twins, who differ in birth weight, but are presumably similar along other observed and unobserved characteristics that affect that the outcome of interest. Using twins as a way to get around omitted variables bias has been quite popular in economics since Rosenzweig and Wolpin (1980). We use a large sample of twins from Chile to derive the causal impact of birth weight on test scores. By using twins in the context of birth weight, our paper is similar in methodology to some recent papers like Behrman and Rosenzweig (2004), Black, Devereux, and Salvanes (2007), Royer (2009), Oreopoulos, Stabile, and Walld (2008) and Almond, Chay, and Lee (2005). The novel addition to the estimation in this paper is that we have a *panel* of twins, hence, can address questions regarding the persistent effect of birth weight. By employing a correlated random effects strategy in the context of twins as in Ashenfelter and Krueger (1994), we are also able to address the impact of potentially unobserved family characteristics on test scores over time. Using the panel feature also enables us to modify a standard value added model used in the education literature to a twins-based value added model. The advantage of the twins value added model in this context is that it comes with fewer assumptions compared to both, a standard twins model and a standard value added model. Finally, for a subset of our data, we have detailed information on parental investments at the individual child level. We use this data to examine whether parental investments systematically vary by birth weight of the individual twin. This is a central assumption in twins based studies examining birth weight, and by directly testing it, we show the validity of our methods.

We find that birth weight plays a significant role in determining outcomes in test scores in school using a large data set on twins and tests scores from Chile. Moreover, the effect of birth weight on test scores begins early in the life of the child and is persistent throughout the schooling years (observed up to Grade 8) of the child. In Grade 1, a 10% increase in birth weight increases outcomes in math scores by 0.05 standard deviations. We see smaller increases in language test scores of around 0.038 SD. Low birth weight (less than 2500 grams) and very low birth weight (less than 1500 grams) children perform worse in math by approximately 0.1 and 0.2 SD respectively. For the most part, it appears that the effect of birth weight on test scores is fairly stable between grades 1 through 8. This implies a persistence effect of birth weight that is seemingly not undone (or exacerbated) by the behavioral responses of parents and teachers. We verify our findings using a nation wide test covering math, social science and language administered to all students in fourth grade. A 10% increase in birth weight increases math scores on this national test by 0.06 SD. 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).[2]

The twins fixed effects results are in contrast to the OLS results, which show a steady decline in the effect of birth weight on test scores. This is likely due to unobserved parental investments "making up" for the effect of low birth weight. Using data on parental investments we find that education related investments are indeed 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. A twins fixed effect on the other hand nets out this component of parental investment (the likely source of bias in the OLS estimates) and finds a persistent effect.

[2]We only cite a small sample of papers where interventions have resulted in increased test scores. There are certainly examples of interventions that have not led to significant increases in test scores as in Glewwe, Kremer, and Moulin (2009).

Our data allows us to test whether school absences might be a mechanism that drive our results. If lower birth weight children have to stay out of school for longer periods of time due to health reasons, then the relationship between birth weight and test scores might be a pure health phenomenon rather than some notion of birth weight affecting cognitive ability. However, using individual data on school attendance, we do not find any effect of birth weight on school absences.

This paper bridges a gap in the literature investigating the role of initial endowments, in particular birth weight. Most papers either examine early life outcomes or adult outcomes. By examining repeated educational performance outcomes for children between the ages of 6-14, we are able to provide a more complete picture of how birth weight might affect adult labor market outcomes. We are also one of the first papers to causally link birth weight to school test outcomes and examine its effect over time. While Black, Devereux, and Salvanes (2007) look at IQ at age 18 as an outcome in their analysis of the impact of birth weight, they do not have repeated observations on cognitive achievement. We are able to show that test scores differences due to birth weight differentials arise early, and stay that way as children progress through school.

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). Like Loughran, Datar, and Kilburn (2004) and others, we use birth weight as a summary measure of initial endowments. We find that parents investments are negatively correlated with birth weight; this behavior likely drives the difference between the OLS and twins fixed effects estimates. Additionally, this paper directly addresses an important assumption used in many twins based studies. Most twins papers that examine the role of birth weight, have to *assume* that parental investments are not related to individual birth weight; we directly test and verify that this is indeed the case - while parents in general invest more in lower birth weight babies, they do not differentiate based on birth weight between twins.

We are also able to address some of the concerns that arise when using twins estimators to derive the returns to education. A crucial question in this context, raised by Bound and Solon (1998), is: "[...] if monozygotic twins are perfectly identical, why do they ever display any schooling difference at all?"[3] That is to say, why should we believe that twins similar along every other characteristic, randomly end up with different years of completed schooling? While we do not have data on school dropouts, we do find that the

[3]A similar concern is voiced by Antonovics and Goldberger (2005): "We are left wondering just which contexts and policy interventions would ... [lead] some Minnesotan identical twins born between 1936 and 1955 to acquire nonidentical years of schooling."

heavier twin is less likely to ever repeat a grade. Hence, twins can differ in completed schooling attainment at a given age simply because the twin with less birth weight is more likely to fail a grade. While this might address Bound and Solon's (1998) question, it raises similar concerns with the use of twins in examining returns to education - if inherent ability does differ within twins (as shown in this paper using test scores) due to birth weight, then even using a twins estimator does not completely eliminate the ability bias.

This paper is subject to caveats similar to other recent papers that use twins estimation. For example, we do not observe zygosity of the twins, often considered critical in twins estimation. The paper by Black, Devereux, and Salvanes (2007) utilizes zygosity information on a subsample of their data to show that the effect of birth weight on labor market outcomes is similar for monozygotic and dizygotic twins. We attempt to deal with this issue by showing the robustness and stability of our results by various twin paris - same sex, boy-boy, boy-girl and girl-girl.[4] A similar analysis was conducted by Almond, Chay, and Lee (2005) who also do not observe zygosity of the twins. Moreover, generalizability of our findings is another issue as twins tend to be of lower birth weight and tend to have more health problems than non twins. We are cognizant of these shortcomings of this analysis and discuss the implications these shortcomings have for our overall results later in the paper. We also recognize that birth weight is largely a proxy for initial health conditions. Hence, while we think this paper picks up on the causal link between birth weight and test outcomes, if birth weight proxies for some other (unobservable) initial health measure that affects cognitive development, then we are also picking that up. In that sense, we think of birth weight as capturing initial health conditions.

The rest of this paper is as follows: section 2 discusses the methodology, section 3 explores some of the relevant medical literature, section 4 describes our unique data set, section 5 discusses results and section 6 concludes.

2. METHODOLOGY

We begin by specifying a production function for cognitive achievement similar to that in Todd and Wolpin (2007). We start with an education production function of the form:

$$T_{ijt} = T_t(X_{ij}(t), E_{ij0}, \Psi_j) \tag{1}$$

[4]Ivanovic et al (2006) show that the DZ-MZ ratio in Chile is 1.14, and that *within* same sex twins, MZ twins make up around 63%.

Where T_{ijt} is the achievement in school by student i born to mother j at time t. $X_{ij}(t)$ is the vector of all inputs applied until time t, and E_{ij0} is the child specific endowment at birth (birth weight is a proxy for this in this paper, and hence forth, we will use BW_{ij} to capture the notion of initial endowments), while Ψ_j is the mother (or family) specific endowment. The observed component of Ψ_j we will call F_j and the unobserved component, we will call μ_j. An estimable version of 1 is:

$$T_{ijt} = \lambda_t BW_{ij} + \alpha_{\mathbf{t}}\mathbf{F_j} + \omega_t \mu_j + \beta_1 X_{ijt} + \beta_2 X_{ijt-1} + \ldots + \beta_t X_{ij1} + \epsilon_{ijt} \tag{2}$$

Where T is the test outcome measured with error ϵ, and X's are educational inputs up to time t. Estimating 2 would require detailed input histories as well as data on family specific endowments in F_j and μ_j. In this exercise, we are interested in estimating λ_t. We do not have data on educational inputs, hence, the X's will form part of the error term in the estimating equation. In the absence of detailed input histories and family specific endowments, identifying λ_t will be problematic if lagged inputs (i.e. the X's) are correlated with birth weight, or if unobserved family specific characteristics affect test outcomes as well as birth weight (i.e. if BW_{ij} and unobserved components of μ_j are correlated). In order to get around these issues we employ different versions of a twins estimator.

2.1. **Twins Fixed Effects**

Before we write down the twins fixed effects estimator, it is useful to rewrite equation 2, with a new error term that captures all the unobservables:

$$T_{ijt} = \lambda_t BW_{ij} + \alpha_{\mathbf{t}}\mathbf{F_j} + \omega_t \mu_j + \underbrace{\beta_1 X_{ijt} + \beta_2 X_{ijt-1} + \ldots + \beta_t X_{ij1} + \epsilon_{ijt}}_{u_{ijt}} \tag{3}$$

A twins estimator is particularly useful in estimating λ_t from equation 3. As a twins fixed effects estimator essentially differences equation 3 within twins, it would difference out observable (the F_j's) and unobservable (μ_j) mother (or family) components, since these are shared within twin pairs. Calling the other twin i', a twins estimate of equation 3 results in:

$$T_{ijt} - T_{i'jt} = \lambda_t (BW_{ij} - BW_{i'j}) \tag{4}$$

$$+ \underbrace{\beta_1 (X_{ijt} - X_{i'jt}) + \ldots + \beta_t (X_{ij1} - X_{i'j1}) + \epsilon_{ijt} - \epsilon_{i'jt}}_{u_{ijt} - u_{i'jt}} \tag{5}$$

Consistent estimation of λ_t from equation 5 requires that parents make input decisions (observed and unobserved) that are not based on individual child specific endowments. Hence, in this version of a twins fixed effects estimate of λ_t, we assume that lagged inputs are essentially the same when it comes to twins - i.e., X_{ijt}=$X_{i'jt}$ for all t. Empirically we know whether twins go to the same school, and share the same class room, teacher et cetera. The assumption applies more for parental inputs - for example, we have to assume that parents spend equivalent time with their twin children, or that if do spend differential amounts of time, the decision to do so is not based on BW_{ij} and $BW_{i'j}$. Hence, our estimable version of equation 5 is essentially identical to the specification used by Almond, Chay, and Lee (2005) and Black, Devereux, and Salvanes (2007), with X_{ijt}=$X_{i'jt}$ for all t. Since we have multiple observations per twin pair (i.e. as they progress through elementary and middle school) we estimate equation 5 for each grade level that we have data for.

2.2. **Twins Correlated Random Effects**

An alternative way to proceed to tackle the issue of unobserved family characteristics, would be to project the family specific unobserved component on the child specific endowments of both twins and an error term (Chamberlain 1982, Ashenfelter and Krueger 1994, Card 1999):

$$\mu_j = \phi_1 BW_{ij} + \phi_2 BW_{i'j} + \delta \mathbf{F_j} + v_j \tag{6}$$

Equation 6 shows the general correlation between the unobserved family component and the observable components, and v_j is uncorrelated with BW's and the F's . Substituting equation 6 in equation 2, and suppressing the unobserved educational inputs, we obtain:

$$T_{ijt} \quad = \quad (\lambda_t + \phi_1 \omega_t) BW_{ij} + \omega_t \phi_2 BW_{i'j} + (\alpha_\mathbf{t} + \omega_\mathbf{t} \delta)\mathbf{F_j} + e_{ijt} \tag{7}$$

Where e_{ijt} contains the original error term u_{ijt} and v_j. If the correlation between the family effect and each twin's birth weight is the same, that is if $\phi_1 = \phi_2 = \phi$, then we can rewrite equation 7 as:

$$T_{ijt} \quad = \quad \lambda_t BW_{ij} + \omega_t \phi [BW_{ij} + BW_{i'j}] + (\alpha_\mathbf{t} + \omega_\mathbf{t} \delta)\mathbf{F_j} + e_{ijt} \tag{8}$$

ϕ captures the correlation between family characteristics and birth weight. If families in general provide more attention and investments towards the lower birth weight child, then we should expect ϕ to be negative.

ω_t captures the effect of this family specific unobservable component on test scores in each time period. The advantage of the correlated random effects approach is that we can trace out over time, the role played by the individual specific endowment (in this case BW_{ij}) as well as the role played by family level characteristics, captured in part by $\omega_t \phi$. The assumptions regarding equality of educational inputs within twin pairs remains in this estimation strategy as well. Equation 8 is symmetric for the other twin (i.e. if the outcome variable was $T_{i'jt}$) and can be estimated by OLS, although GLS might be preferred (Ashenfelter and Krueger 1994).

2.3. **Twins Value Added Model**

In the absence of data on history of parental inputs, the education literature often adopts a *value added model*, where lagged test scores are used as regressors. Lagged test scores are after all, a function of the lagged inputs themselves. Hence, in our case we exploit the panel nature of the data to partially relax some of the assumptions made while estimating 5 in the context of twins. Since we observe consecutive test outcomes for twin pairs, we can modify equation 2 into a twins based value added model.

We begin with the simplest expression for a value added model, using lagged test score as a regressor, but constraining its coefficient to 1:

$$T_{ijt} = (\lambda_t - \lambda_{t-1})BW_{ij} + T_{ijt-1} + (\alpha_{\mathbf{t}} - \alpha_{\mathbf{t-1}})\mathbf{F_j} + (\omega_t - \omega_{t-1})\mu_j + \eta_{ijt} \tag{9}$$

The above equation imposes that the impact of lagged test scores does not decay over time. This is a matter of much discussion in this literature, although the consensus appears to reject the idea that the coefficient on the lagged test score is 1.[5] Hence, researchers usually express lagged test scores with a coefficient that is less than 1. For our purposes, we denote the decay term by γ, resulting in a slightly different expression of equation 9:[6]

$$T_{ijt} = (\lambda_t - \gamma\lambda_{t-1})BW_{ij} + \gamma T_{ijt-1} + (\alpha_{\mathbf{t}} - \gamma\alpha_{\mathbf{t-1}})\mathbf{F_j} + (\omega_t - \gamma\omega_{t-1})\mu_j \tag{10}$$

$$+ \underbrace{\beta_1 X_{ijt} + (\beta_2 - \gamma\beta_1)X_{ijt-1} + \ldots + (\beta_t - \gamma\beta_{t-1})X_{ij1} + e_{ijt} - \gamma e_{ijt-1}}_{\nu_{ijt}} \tag{11}$$

[5] See Andrabi, Das, Khwaja, and Zajonc (2008) and Boozer and Rouse [??] for a discussion of the merits and demerits of assuming γ=1 in this context. Andrabi, Das, Khwaja, and Zajonc (2008) strongly reject the idea that γ=1.

[6] We follow Todd and Wolpin (2007), and subtract γT_{ijt-1} on both sides from equation 2, collect the terms and rearrange.

Since the coefficient of interest in many education production function estimations is β_1, value added models typically assume that the effect of all inputs, endowments and unobserved characteristics decline geometrically: i.e. $\lambda_t = \gamma\lambda_{t-1}$, $\omega_t = \gamma\omega_{t-1}$, $\alpha_t = \gamma\alpha_{t-1}$ and $\beta_t = \gamma\beta_{t-1}$ for all t. We are interested in estimating $\lambda_t - \gamma\lambda_{t-1}$, and by employing a twins estimator embedded in a value added model, need fewer assumptions in estimating equation 11. While we certainly need that $\beta_t = \gamma\beta_{t-1}$ for all t, we can subtract equation 11 within twins to eliminate family level characteristics, both observed and unobserved.[7] Subtracting equation 11 within twin pairs, we obtain a twins value added estimator:

$$T_{ijt} = (\lambda_t - \gamma\lambda_{t-1})(BW_{ij} - BW_{i'j}) + \gamma(T_{ijt-1} - T_{i'jt-1}) + \tag{12}$$

$$+\beta_1(X_{ijt} - X_{i'jt}) + (\beta_2 - \gamma\beta_1)(X_{ijt-1} - X_{i'jt-1}) + \tag{13}$$

$$\ldots + (\beta_t - \gamma\beta_{t-1})(X_{ij1} - X_{i'jt-1}) + (e_{ijt} - \gamma e_{ijt-1}) - (e_{i'jt} - \gamma e_{i'jt-1}) \tag{14}$$

As mentioned earlier, we assume that $\beta_t = \gamma\beta_{t-1}$ for all t, and are left with:

$$T_{ijt} = (\lambda_t - \gamma\lambda_{t-1})(BW_{ij} - BW_{i'j}) + \gamma(T_{ijt-1} - T_{i'jt-1}) + \tag{15}$$

$$+ \underbrace{\beta_1(X_{ijt} - X_{i'jt}) + (e_{ijt} - \gamma e_{ijt-1}) - (e_{i'jt} - \gamma e_{i'jt-1})}_{p_{ijt}} \tag{16}$$

In other words, while the twins fixed effects model in section 2.1 assumed equality of inputs within twin pairs (i.e. $X_{ijt} = X_{i'jt}$ for all t), in a twins value added model, we assume that the impact of these inputs decline geometrically at rate γ and that this is true for all inputs. We also need that elements in p_{ijt} are not correlated with birth weight differentials within twins.

The downside of the value added specification is that we no longer recover λ_t, our initial parameter of interest. We can only recover the impact of birth weight on test scores net of a decay term. However, this is an economically relevant variable, which translates to how much birth weight adds to test scores in each period, net of its impact in the previous period. In the results section we provide estimates for λ_t as well as $\lambda_t - \gamma\lambda_{t-1}$ from the specifications discussed above.

[7] I.e. we do not need to assume $\omega_t = \gamma\omega_{t-1}$ and $\alpha_t = \gamma\alpha_{t-1}$

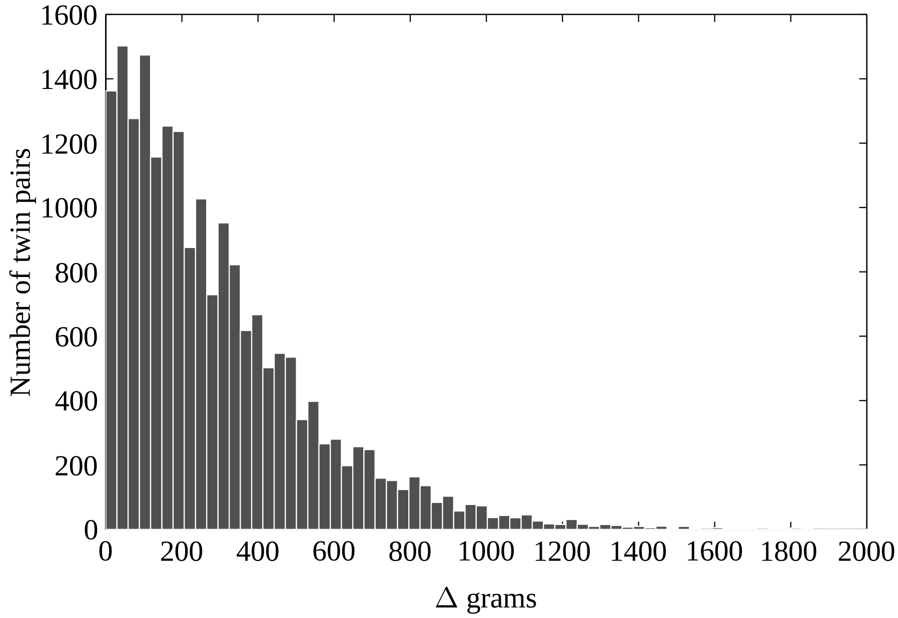
3. Relevant medical literature

This section provides some background from the medical literature on two topics important for this paper: why twins differ in birth weigh in the first place, and what some of the pathways between birth weight and cognitive development might be.

3.1. **Why do twins differ in birth weight?**

Figure 1 shows the distribution of birth weight differences within twins for our sample.

Figure 1. 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 2000. N=40169

Two recent papers using a twins estimator do an excellent job reviewing the medical literature regarding why differences in birth weight arise within twin pairs. Rather than reinvent the wheel, in this section we summarize the arguments made in Almond, Chay, and Lee (2005) and Black, Devereux, and Salvanes (2007). Figure 1 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).[8] The leading reason for

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

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 (a majority of MZ twins share a placenta), the placement of the umbilical chord affects nutritional intake. For more details and paper citations on the subject, we refer the reader to footnote 13 in Almond, Chay, and Lee (2005).

3.2. **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 (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.

4. Data

4.1. **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 the children born in the year 1992-2000. It provides data on the sex, birth weight, length, weeks of gestation and several demographics of the parents such as the age, education and occupational status. In addition, the dataset provides a variable describing the type of birth, be it a single birth, double (twins), triple (triplets), etc. While the data identifies whether a particular birth was a twin or not, it does not automatically provide an identifier for the sibling of the twin. The twin sibling is determined by matching the date, location (exact hospital), and type of birth. In addition, the demographics of both parents are used to determine each twins sibling. For details on the exact matching algorithm, please see the Data Appendix. Unfortunately. the data does *not* provide information on zygosity of the twins.

4.2. **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 kindly provided by the Ministry of Education of Chile (MINEDUC).

4.2.1. *RECH - Registro de Estudiantes de Chile.* 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.

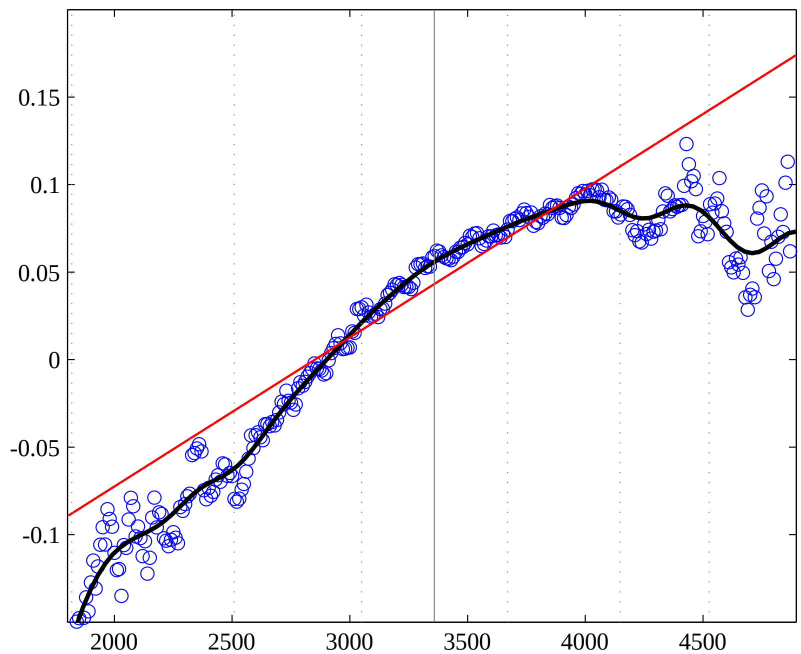
4.2.2. *SIMCE.* The SIMCE test covers three main subjects: Mathematics, Science and Language Arts and is administered to every student in grade 4 as well as 8 and 10 depending on the year. It is used to evaluate the progress of students regarding the national curriculum goals set out by MINEDUC. The 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.

5. RESULTS

5.1. **OLS Results**

Figure 2 shows the relationship between test scores in math and birth weight. The relationship is remarkably linear, with higher birth weight babies doing better in math.

FIGURE 2. Standardized math scores and Birth Weight



Note: This graph shows the relationship between birth weight and grade math scores for students born from 1992-2000 in Chile. The math 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 50 grams. The straight line represents the predicted values from a simple OLS regression. Vertical dashed bars represent the percentiles $\{1, 5, 25, 50, 75, 95, 99\}$. The mean is represented by a vertical solid bar. N=1,696,699.

Further exploration of this relationship via regressions confirms that this correlation is robust to the addition of various controls. The regressions estimated take the form:

$$T_{ijt} = \lambda_t BW_{ij} + F_j' \alpha_t + \epsilon_{ijt} \tag{17}$$

Where T_{ijt} is the normalized test score in a subject (math or language) obtained by student i, born to mother j in grade t. BW is the birth weight (log birth weight in all specifications) and F is a vector of parental characteristics like education, age and occupation.

Using the full sample of all students observed at some point in grade 4 between 2002-2008 and for whom we have birth information, Table 1 shows that the coefficient on log birth weight stays robust to the addition of various controls like year of birth, parental characteristics and school and classroom fixed effects when these variables are added sequentially. Table 2 estimates equation 17 for every grade with a full set of controls - birth year dummies, parental education dummies, parental age, father's occupation, sex of the child, municipality of birth dummies and classroom fixed effects. Table 2 is replicated for the sample with only twins (and not using the twins fixed effect) in Appendix Table 1.

OLS estimates of λ_t from Table 2 suggest that a 10% increase in birth weight raises test scores in 1st grade in math by 0.035 SD (column 1, panel A). However, by grade 8, a similar increase in birth weight appears to raise math scores by only 0.01 SD (these differences are statistically significant). In fact, there appears to be a steady decline in the impact of birth weight on math and language test scores as students move from grade 1 to grade 8. A simple explanation for this declining effect of birth weight in later grades could be attributed to responses by teachers and/or parents. However, any such claim cannot be made unless we first know the true impact of birth weight on test scores. As we discussed earlier, λ_t as obtained under OLS might not reflect the impact of birth weight on test scores even in grade 1. Moreover, due to lack of data, we are not able to control for lagged inputs, which are quite crucial in this context as per the empirical model. This is because parents who have higher birth weight children might have other unobserved characteristics that might affect both birth weight and test scores.

5.2. **Twins Fixed Effects Estimates**

To tackle the problem of unobserved characteristics and inputs, we modify equation 17 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. Tables 3-5 estimate equation 18 using log birth weight, a dummy variable for low birth weight and variable for very low birth weight as the independent variables of interest.

$$T_{ijt} = \lambda_t BW_{ij} + \mu_j + \epsilon_{ijt} \tag{18}$$

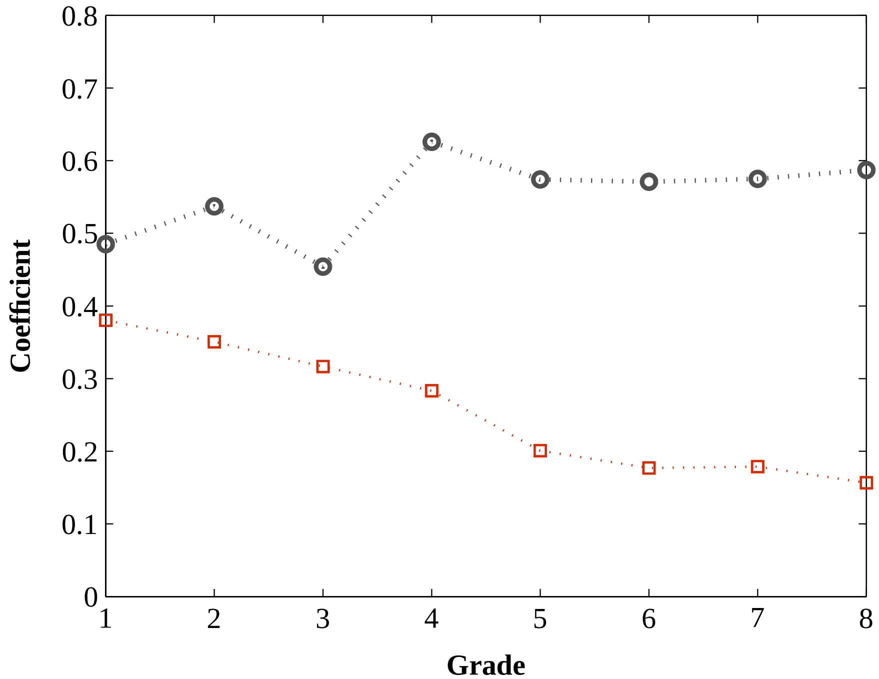
In table 3, we use log birth weight on the right hand side to uncover λ_t in grades 1 through 8. Statistical tests reveal that λ_8 and λ_1 as obtained under the fixed effects estimation are not different, suggesting that the twins estimates of the impact of birth weight on test scores do not appear to diminish over time.

Table 3 suggests that a 10% increase in birth weight (corresponding to a 250 gram increase) raises test scores in math by 0.048 SD in 1st grade. Scores in language are affected less; as mentioned above, the impact on both math and language are fairly constant between grades 1 through 8. In tables 4 and 5 we explore some non linear cuts of the data. Low birth weight is defined as being less than 2500 grams at birth and is associated with numerous developmental issues. We find 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. However, the most severely affected group appears to be babies who were born as very low birth weight (less than 1500 grams). As we can see in table 5, for this group, the effect is around 0.2 SD less in math; however, very low birth weight babies form a small fraction of the entire population (approximately 3%).

5.3. **Why do Twins FE and OLS estimates differ?**

Twins fixed effects and OLS estimates contrast in pattern that is worth exploring further. In particular, the fixed effects and OLS estimates are quite similar for grade 1, they appear to steadily diverge until grade 8.

FIGURE 3. OLS and Fixed Effects Estimates : Grades 1 to 8



Note: This graph shows how the coefficient on log birth weight changes as time children become older. The dotted line with square markers shows the coefficients estimated using OLS. The dotted line with circle markers shows the results for the fixed effects estimator presented above.

5.3.1. *The Role of Parental Investments.* As comparison between OLS and fixed effects estimates is of keen interest, we plot λ_t as obtained from OLS and fixed effects regressions above. The graph is telling in that while λ_t^{OLS} declines over the grades λ_t^{FE} stays constant through various grades. An explanation for this pattern follows the logic of unobserved family inputs that might affect test scores and be correlated with birth weight. Recall that under OLS, we estimate λ_t with bias:

$$\lambda_t^{OLS} = \lambda_t + Cov(BW_{ij}, \epsilon_{ijt}) \tag{19}$$

Where ϵ_{ijt} contains the unobserved parental inputs (the X_{ijt}'s from equation 2). The direction of bias is partially testable given the data we have on parental investments. Below, we show the correlations between birth weight and various types of parental investments like time spent reading with the child, time spent helping out with home work, posing math problems to the child etc.

Parental Investments and Birth Weight

Question	Coefficient on Birth Weight	t-stat
Read to Child	-.0000857	-3.25
Make Child Write Short Texts	-.0000624	-2.28
Study with Child	-.0000666	-2.68
Buy educational books	-.0000541	-2.00
Do Home Work with Child	-.0000421	-1.79
Pose Math Problems to Child	-.0000376	-1.74
Talk to Student	-.0000286	-1.75
Check Home Work	-.0000219	-1.06
Make Child do Errands	-.0000127	-0.52

Note: The exact survey question can be translated as follows: Normally in your household, how often are the following situations encouraged? (1=Never, 2=Almost Never , 3=Sometimes, 4= Often, 5=Very Often).
This survey was done in 2002 as part of a nation wide academic achievement test. Demographics used as controls are house hold income, fathers education, mothers education, and tuition paid for school. Over 290,000 children took part of the survey but regression results use between 180k-200k because not all children have reported the full set of demographics used in the regression.

In almost all such investments, the correlation between birth weight and investments appears to be negative and statistically significant. While OLS and FE estimates for grade 1 are quite similar, they become more dissimilar over time suggesting that parents (or teachers) react to the scores a child obtains and invest differentially, *reducing* the importance of birth weight in determining test scores later in life. One of the main reasons for conducting a twins fixed effects analysis is to get rid of such bias.

Turning to the fixed effects estimates, the fact that they stay constant suggests no differential investment within a twin pair.[9] If parents did invest differentially within twin pairs, then the fixed effects estimates of λ_t should also contain bias, and likely a negative bias term if parents of twins behave no differently from parents of singletons in terms of investments and birth weight. Hence, if the identifying assumption required in the fixed effects estimations were not held, then we'd expect λ_t to change over time (due to a bias term) and likely expect it to follow the pattern of the OLS estimates. The absence of any movement in the estimates suggests that twins fixed effects does indeed capture the true effect of birth weight on test scores. This idea is supported by Table 12: there appears to be no statistically significant relationship between parental investment and birth weight within twin pairs.

Alternatively, we can test for the negative correlation between family level inputs and birth weight by adopting the CRE framework mentioned in Section 2.2. Table 6 estimates equation 8 and shows the coefficients for λ_t and for $\omega_t \phi$. The estimates for λ_t are very similar to that in Table 3. The coefficient on log total birth weight of the twins gives us estimates of $\omega_t \phi$. The negative coefficient suggests the negative correlation between family inputs and birth weight. The pattern of results in the CRE model suggest that unobserved family characteristics are likely driving the OLS results to show a pattern of decrease over time.

5.3.2. *The Role of Measurement Error*. One possible explanation for why OLS estimates are smaller than the FE estimates could be measurement error. Classical measurement error in birth weight would typically drive the coefficient towards zero. Measurement error in twins fixed effects estimates is differenced out since twins are presumably weighed with similar error. However, we can rule out the role played by measurement error by observing the *pattern* of the OLS and fixed effects estimates. If classical measurement error were the only driver of OLS and FE differences we would expect OLS to be less than FE from grade 1 onwards, not a decreasing pattern in the OLS estimates. The fact that λ_1^{OLS} and λ_1^{FE} are quite similar leads us to believe that measurement error might not play a major role in explaining the OLS and FE differences.

5.4. **Twins based value added model**

Having established that λ_t is positive and significant across different grades using a simple twins estimate, we now turn our attention to a twins based value added model. A twins based value added model

[9] The only other explanation is a *perfectly compensatory* investment - in that parents invest just as much in the lower birth weight twin as they disinvest in the higher birth weight twin. Moreover the causal impact of these investments and disinvestments on test scores have to cancel each other out.

in this context estimates:

$$T_{ijt} = \rho_t BW_{ijt} + \gamma T_{ijt-1} + \eta_j + \epsilon_{ijt} \tag{20}$$

Where T_{ijt-1} is the lagged test outcome and η_j denotes the twin fixed effect. As mentioned in section 2, the coefficient on birth weight in this specification $\rho_t = \lambda_t - \gamma\lambda_{t-1}$. This is interpreted as the impact of birth weight on year t's test scores net of its impact on year $t-1$ along with a decay term denoted by γ. Table 6 estimates equation 20 for grade 2-8 (for grade 1 we do not have lagged test scores). The estimates of ρ_t appear stable over time for math. The twins value added model is useful if we were unwilling to believe in some of the assumptions of the simpler twins model. However, there are other assumptions needed to usefully interpret the twins value added model as mentioned in section 2.1. In sum we believe that both estimates reveal similar and related parameters about how birth weight affects performance in school.

5.5. **Heterogenous effects, Mechanisms and SIMCE test scores**

In table 8 we explore the impact of birth weight on test scores by the educational attainment of the mother. Panel A in table 8 replicates the estimation as in table 3 for mothers who have at least completed high school, while panel B in table 8 does the estimation for mother with less than high school. Comparing each grade, we do not observe a statistically significant difference across the coefficients on log birth weight. We also obtained birth weight effects by type of school attended (pubic, private, voucher), by location (urban, rural, Santiago, non-Santiago etc) but did not find statistically significant role for these interactions. Thus there appears to be a limited role for heterogenous effects in this case.

One mechanism we can explore in this paper is that of school absences. If lower birth weight leads to poorer overall health, which leads to school absences, it is likely that the mechanism driving the results on test score differentials comes from a pure health channel, rather than differences in cognitive development. Table 9, Panel A explores this channel. We find school attendance within twins to not be a function of birth weight (except in 1st grade). Hence, it appears that school absences is not one of the mechanisms driving our main results.

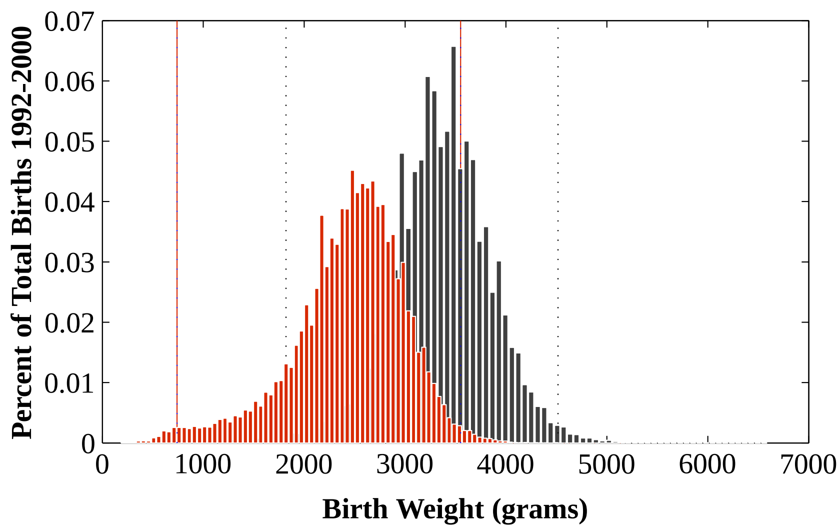
Finally, we explore 2 other outcomes as a function of birth weight - grade repetitions and scores on a nationalized exam administered for 4th and 8th graders in Chile (SIMCE). Panel B of table 9 suggests that apart from 1st grade, birth weight does not have an impact on grade repetitions. In 1st grade, a 10%

increase in birth weight decreases the probability of repeating a grade by 0.004 percentage points, or 8% lower than the average. However, grade repetition is a rare event in any case and birth weight does predict *ever* having to repeat a grade. Table 10 uses the same estimation strategy on a different set of test outcomes. As described in the data section, the SIMCE is a nationally administered exam in three subjects administered to 4th and 8th graders in Chile. Table 10 suggests similar effects of birth weight on test scores in math as seen in the classroom test scores, with slightly lower effect on language scores.

5.6. **Twins vs. Singletons and Zygosity**

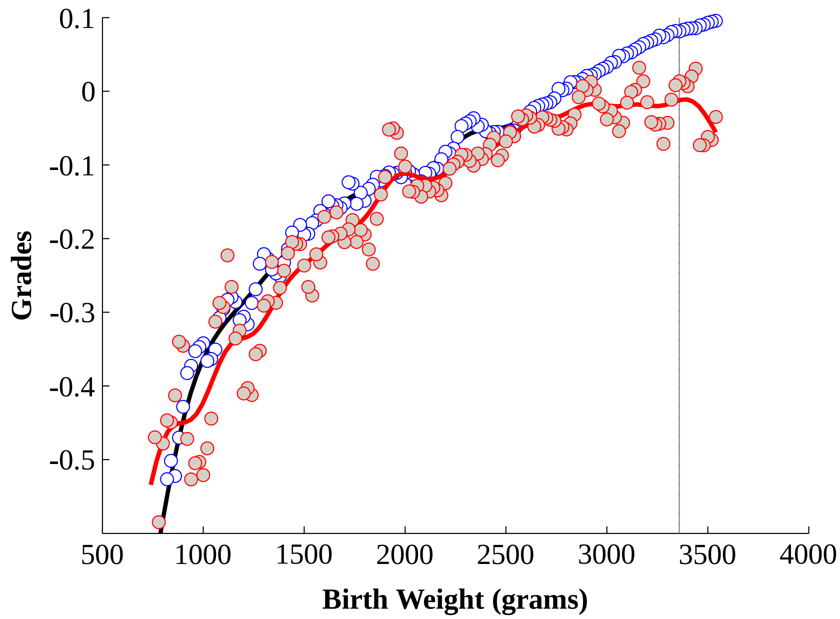
One common criticism of twins based studies is that twins are not representative of the population. Figure 4 shows this to be true. To partially address issue, we plot the relationship between test scores and birth weight among singletons who have similar support on the birth weight distribution as the twins. Figure 5 shows the relationship between birth weight and math grades for both single births and twins for the children born between the 1st and 99th percentile of the twins birth weight distribution.

FIGURE 4. Distribution of Birth Weight



Note: This histogram shows all live births in Chile between 1992 and 2001 and also only twin births. The two vertical lines indicate the 1st and 99th percentile of the distribution respectively. $\mu = 3347, \sigma = 514, N = 2,350,000$ and for twins $\mu = 2459, \sigma = 621, N = 40169$

FIGURE 5. Standardized math scores and Birth Weight



Note: This graph shows the relationship between birth weight and math scores for students born from 1992-2000 in Chile and by differentiating between the sample of twins and single births. The red line and dots correspond to twins and the blue to single births. The math grades have been standardized at the classroom level. The solid line represents a local linear order polynomial regression. The dots represent a moving average with a centered window width of 100 grams. Vertical dashed bar represent the mean of the whole sample. The x axis shows birth weight from the 1st percentile to the 99th percentile of the twins distribution.

Zygosity is an important factor in twins based studies. However, the vital statistics data we have does not allow us to separately identify monozygotic and dizygotic twin pairs. As mentioned earlier, the recent Black et al (2007) paper uses some zygosity information and shows no difference in birth weight effects across MZ and DZ twins. As a robustness check, Table 11 explores the basic set of coefficients for the effect of birth weight on math scores in each grade by type of twin pair. Our results are robust even when we use explicitly dizygotic twin pairs (boy-girl twin pairs). In Table 11, estimates for all types of twin pairs appear robust across grades and are similar in magnitude to the overall twin sample used in Table 3.

6. CONCLUSION

This paper is one of the first to examine the causal impact of birth weight on the process of human capital accumulation. By using a twins estimation strategy and taking differences in birth weight within twin pairs, we find that birth weight has a fairly sizable impact on test scores, specially for very low birth weight children where the effect on math scores can be as large as 0.2 SD less. Importantly, we find these effects to be persistent between grades 1 through 8. Using data on parental investments, we find that parental investments are negatively correlated with birth weight and likely drive the differences between OLS and twins fixed effects estimates. The same data also allows us to test a central assumption in many twins based papers analyzing the impact of birth weight: we find no differences in parental investments between twins.

We are certainly cognizant of the caveats that come with our chosen estimation strategy. Twins are very different from the general population. Similar to Black, Devereux, and Salvanes (2007) we find that the incidence of low birth weight among the twins population is much higher than in the overall population (44% as opposed to 15%). Moreover, we do not observe the zygosity of the twins, and it is possible that genetic differences within dizygotic twins could contaminate out results.

Despite these caveats, we believe this study contributes to the literature in three ways. First, we underscore the importance of initial health endowments as measured by birth weight in human capital formation. Second, by examining performance in school we add to the literature on birth weight and its effects, which so far has examined outcomes soon after birth or as adults. Finally, by being able to follow twin pairs over time in school, we are able to highlight the pattern of OLS and twins fixed effects, and show that parental investments are likely driving these differences. Hence, we address whether the effect of birth weight on school achievement is a temporary effect or a persistent one.

REFERENCES

ABERNETHY, L., M. PALANIAPPAN, AND R. COOKE (2002): "Quantitative magnetic resonance imaging of the brain in survivors of very low birth weight," *Archives of disease in childhood*, 87(4), 279.

AIZER, A., AND F. CUNHA (2010): "Child Endowments, Parental Investments and the Development of Human Capital," *Brown University Working Paper*.

ALMOND, D., K. CHAY, AND D. LEE (2002): "Does low birth weight matter? Evidence from the US population of twin births," *University of California, Berkeley, Center for Labor Economics Working Paper*, 53.

——— (2005): "The Costs of Low Birth Weight," *The Quarterly Journal of Economics*, 120(3), 1031–1083.

ALMOND, D., AND B. MAZUMDER (2008): "The effects of maternal fasting during Ramadan on birth and adult outcomes," *Working Paper Series*.

ANDRABI, T., J. DAS, A. KHWAJA, AND T. ZAJONC (2008): "Do value-added estimates add value? accounting for learning dynamics," *Harvard University*.

ANNIBALE, D., AND J. HILL (2008): "Periventricular Hemorrhage–Intraventricular Hemorrhage," *URL: www. emedicine. com/ped/topic*, 2595.

ANTONOVICS, K., AND A. GOLDBERGER (2005): "Does increasing women's schooling raise the schooling of the next generation? Comment," *American Economic Review*, pp. 1738–1744.

ASHENFELTER, O., AND A. KRUEGER (1994): "Estimates of the economic return to schooling from a new sample of twins," *The American Economic Review*, pp. 1157–1173.

ASHENFELTER, O., AND C. ROUSE (1998): "Income, Schooling, and Ability: Evidence from A New Sample of Identical Twins," *Quarterly Journal of Economics*, 113(1), 253–284.

BANERJEE, A., S. COLE, E. DUFLO, AND L. LINDEN (2007): "Remedying Education: Evidence from Two Randomized Experiments in India*," *The Quarterly Journal of Economics*, 122(3), 1235–1264.

BEHRMAN, J., AND M. ROSENZWEIG (2004): "Returns to birthweight," *Review of Economics and Statistics*, 86(2), 586–601.

BLACK, S., P. DEVEREUX, AND K. SALVANES (2007): "From the Cradle to the Labor Market? The Effect of Birth Weight on Adult Outcomes*," *The Quarterly Journal of Economics*, 122(1), 409–439.

BOUND, J., AND G. SOLON (1998): "Double trouble: on the value of twins-based estimation of the return to schooling," *NBER working paper*.

CARD, D. (1999): "The causal effect of education on earnings," *Handbook of labor economics*, 3, 1801–1863.

CHAMBERLAIN, G. (1982): "Multivariate regression models for panel data," *Journal of Econometrics*, 18(1), 5–46.

CURRIE, J., AND J. GRUBER (1996): "Saving babies: The efficacy and cost of recent changes in the Medicaid eligibility of pregnant women," *Journal of Political Economy*, 104(6), 1263–1296.

CURRIE, J., AND R. HYSON (1999): "Is the impact of health shocks cushioned by socioeconomic status? The case of low birthweight," *American Economic Review*, 89(2), 245–250.

CURRIE, J., AND E. MORETTI (2007): "Biology as destiny? Short-and long-run determinants of intergenerational transmission of birth weight," *Journal of Labor Economics*, 25(2).

DAVIES, P., AND A. STEWART (1975): "Low-birth-weight infants: neurological sequelae and later intelligence," *British Medical Bulletin*, 31(1), 85.

DESCHÊNES, O., M. GREENSTONE, AND J. GURYAN (2009): "Climate Change and Birth Weight," *American Economic Review*, 99(2), 211–217.

DUFLO, E., AND R. HANNA (2005): "Monitoring works: getting teachers to come to school," *NBER Working Paper*.

GLEWWE, P., M. KREMER, AND S. MOULIN (2009): "Many children left behind? Textbooks and test scores in Kenya," *American Economic Journal: Applied Economics*, 1(1), 112–135.

GROSSMAN, M., AND T. JOYCE (1990): "Unobservables, pregnancy resolutions, and birth weight production functions in New York City," *Journal of Political Economy*, pp. 983–1007.

HACK, M., N. KLEIN, AND H. TAYLOR (1995): "Long-term developmental outcomes of low birth weight infants," *The future of children*, 5(1), 176–196.

HECKMAN, J. (2007): "The economics, technology, and neuroscience of human capability formation," *Proceedings of the National Academy of Sciences*, 104(33), 13250.

——— (2008): "Schools, skills, and synapses," *Economic inquiry*, 46(3), 289.

IVANOVIC, D., E. LLOP, J. ALVEAR, H. PEREZ, N. DIAZ, B. LEYTON, A. ALMAGIA, C. LARRAIN, J. ALVAREZ, Y. HERRERA, ET AL. (2006): "Chilean School-Age Children Twin Registry: Planning, Sampling and Implications," *Twin Research and Human Genetics*, 9(6), 743–746.

JEFFERIS, B., C. POWER, AND C. HERTZMAN (2002): "Birth weight, childhood socioeconomic environment, and cognitive development in the 1958 British birth cohort study," *British Medical Journal*, 325(7359), 305.

LEWIS, M., AND M. BENDERSKY (1989): "Cognitive and motor differences among low birth weight infants: Impact of intraventricular hemorrhage, medical risk, and social class," *Pediatrics*, 83(2), 187.

LOUGHRAN, D., A. DATAR, AND M. KILBURN (2004): "The Interactive Effect of Birth Weight and Parental Investment on Child Test Scores," *RAND Labor and Population Working Paper WR-168*.

MURALIDHARAN, K., AND V. SUNDARARAMAN (2009): "Teacher performance pay: Experimental evidence from India," *Working Paper*.

OREOPOULOS, P., M. STABILE, AND R. WALLD (2008): "Short, Medium, and Long Term Consequences of Poor Infant Health: An Analysis Using Siblings and Twins," *Journal of Human Resources*, 43, 88–138.

RICHARDS, M., R. HARDY, D. KUH, AND M. WADSWORTH (2002): "Birthweight, postnatal growth and cognitive function in a national UK birth cohort," *International Journal of Epidemiology*, 31(2), 342.

ROSENZWEIG, M., AND K. WOLPIN (1980): "Testing the Quantity-Quality Fertility Model: The Use of Twins as a Natural Experiment," *Econometrica*, 48(1), 227–240.

ROSENZWEIG, M., AND J. ZHANG (2009): "Do Population Control Policies Induce More Human Capital Investment? Twins, Birth Weight and China's One-Child Policy," *Review of Economic Studies*, 76(3), 1149–1174.

ROYER, H. (2009): "Separated at girth: Estimating the long-run and intergenerational Effects of Birthweight using Twins," *American Economic Journal - Applied Economics*.

TODD, P., AND K. WOLPIN (2007): "The production of cognitive achievement in children: Home, school, and racial test score gaps," *Journal of Human capital*, 1(1), 91–136.

7. DATA APPENDIX

This section is a work in progress. More details furnished upon request.

Summary Statistics

Sample Characteristics		
Number of twin pairs	16322	
Twin Pairs with valid school observations	16038	
Twin Paris observed in same classroom	14537	
Number of school observations per twin pair	5.95	
Grades covered by the education data	1-8	
Years education data available	2002-2008	
Birth Characteristics	*Mean*	*Std Deviation*
Years covered by Vital Stats data	1992-2000	
Birth weight	2517.69	477.52
Birth length	45.93	2.78
Gestational age	36.38	2.04
Incidence of Low Birth Weight (overall)	44%	

TABLE 1: Log Birth Weight and Test Scores - Ordinary Least Squares

	Math Scores			
VARIABLES	(1)	(2)	(3)	(4)
Log Birth Weight	0.232***	0.239***	0.249***	0.245***
	(0.005)	(0.005)	(0.005)	(0.005)
Dummy for Female		0.617***	0.704***	0.260
		(0.002)	(0.004)	(0.805)
Father's Age			0.002***	0.001***
			(0.000)	(0.000)
Mother's Age			0.002***	0.002***
			(0.000)	(0.000)
Constant	3.456***	3.481***	3.762***	3.214***
	(0.041)	(0.041)	(0.041)	(0.039)
Other variables		1+ Birth year dummies	2 + Parental Education + Father's Education	3 + Classroom fixed effects
Observations	1,074,359	1,074,359	1,074,355	1,074,355
R-squared	0.002	0.005	0.073	0.049

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Math scores from Grade 4 used in these regressions

TABLE 2: OLS Estimates: Birth Weight and School Achievement in Grades 1-8 (Full Sample)

	Grade in School							
	1	2	3	4	5	6	7	8
Panel A - Math								
Log Birth Weight	0.39115**	0.34672**	0.31224**	0.30411**	0.25286**	0.23681**	0.20912**	0.20246**
	[0.00526]	[0.00475]	[0.00470]	[0.00471]	[0.00495]	[0.00542]	[0.00602]	[0.00711]
Constant	-3.35889**	-2.96446**	-2.82782**	-2.30342**	-1.90178**	-1.79274**	-1.59755**	-1.56291**
	[0.10157]	[0.04372]	[0.03885]	[0.03812]	[0.03999]	[0.04375]	[0.04858]	[0.05740]
Observations	1,382,367	1,636,921	1,640,103	1,645,311	1,492,721	1,246,889	1,017,163	738,976
R-Squared	0.03116	0.0293	0.02675	0.02347	0.02214	0.02012	0.01718	0.01383
Panel B - Language								
Log Birth Weight	0.31822**	0.26006**	0.19912**	0.18394**	0.12549**	0.10707**	0.07995**	0.07344**
	[0.00520]	[0.00470]	[0.00465]	[0.00467]	[0.00487]	[0.00535]	[0.00593]	[0.00699]
Constant	-2.69448**	-2.32794**	-1.91831**	-1.25328**	-0.78948**	-0.66994**	-0.47801**	-0.43039**
	[0.09387]	[0.04308]	[0.03842]	[0.03772]	[0.03935]	[0.04318]	[0.04785]	[0.05642]
Observations	1,373,986	1,628,204	1,630,970	1,636,313	1,483,728	1,239,806	1,011,726	735,085
R-Squared	0.03719	0.0411	0.04418	0.0436	0.05368	0.05499	0.05564	0.05254

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Notes: All regressions include the following controls: dummies for year of birth, father and mother's age, father and mother's education, father's occupation and employment status, sex of the child, municipality of birth dummies and classroom fixed effects.

TABLE 3: Twins Estimates: Log Birth Weight and School Achievement in Grades 1-8

Dependent Variable:	Grade in School							
Standardized Test Scores	1	2	3	4	5	6	7	8
Panel A - Math								
Log Birth Weight	0.485	0.537	0.454	0.626	0.574	0.571	0.575	0.587
	[0.061]***	[0.056]***	[0.057]***	[0.057]***	[0.061]***	[0.068]***	[0.078]***	[0.095]***
Constant	-3.915	-4.264	-3.562	-4.879	-4.394	-4.329	-4.367	-4.487
	[0.475]***	[0.437]***	[0.444]***	[0.443]***	[0.474]***	[0.535]***	[0.608]***	[0.742]***
Number of Twin Pairs	7853	8864	8455	8216	7230	5815	4654	3381
Panel B - Language								
Log Birth Weight	0.398	0.41	0.287	0.296	0.267	0.221	0.325	0.192
	[0.058]***	[0.055]***	[0.054]***	[0.053]***	[0.055]***	[0.061]***	[0.072]***	[0.088]**
Constant	-3.23	-3.249	-2.221	-2.265	-1.95	-1.548	-2.365	-1.339
	[0.451]***	[0.428]***	[0.422]***	[0.415]***	[0.427]***	[0.475]***	[0.560]***	[0.686]*
Number of Twin Pairs	7835	8845	8439	8201	7210	5805	4651	3379

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Notes: Twins fixed effects employed in all regressions. Regressions run only on twin pairs that are in the same class for each grade. Test scores range from 1-7.

TABLE 4: Twins Estimates: Low Birth Weight and School Achievement in Grades 1-8

Dependent Variable: Standardized Test Scores	Grade in School							
	1	2	3	4	5	6	7	8
Panel A - Math								
Low Birth Weight (1 if <2500 gm, 0 otherwise)	-0.085	-0.091	-0.061	-0.117	-0.126	-0.11	-0.131	-0.113
	[0.019]***	[0.017]***	[0.017]***	[0.017]***	[0.019]***	[0.021]***	[0.024]***	[0.029]***
Constant	-0.091	-0.032	0.011	0.063	0.149	0.184	0.188	0.155
	[0.010]***	[0.009]***	[0.009]	[0.009]***	[0.009]***	[0.011]***	[0.012]***	[0.014]***
Number of Twin Pairs	7853	8864	8455	8216	7230	5815	4654	3381
Panel B - Language								
Low Birth Weight (1 if <2500 gm, 0 otherwise)	-0.078	-0.067	-0.048	-0.058	-0.054	-0.041	-0.081	-0.061
	[0.018]***	[0.017]***	[0.016]***	[0.016]***	[0.017]***	[0.019]**	[0.022]***	[0.027]**
Constant	-0.086	-0.016	0.039	0.071	0.16	0.199	0.212	0.192
	[0.009]***	[0.008]*	[0.008]***	[0.008]***	[0.008]***	[0.009]***	[0.011]***	[0.013]***
Number of Twin Pairs	7835	8845	8439	8201	7210	5805	4651	3379

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Notes: Twins fixed effects employed in all regressions. Regressions run only on twin pairs that are in the same class for each grade. Test scores range from 1-7.

TABLE 5: Twins Estimates: Very Low Birth Weight and School Achievement in Grades 1-8

Dependent Variable: Standardized Test Scores	Grade in School							
	1	2	3	4	5	6	7	8
Panel A - Math								
Very Low Birth Weight (1 if <1500 gm, 0 otherwise)	-0.144	-0.098	-0.168	-0.225	-0.234	-0.227	-0.284	-0.315
	[0.060]**	[0.058]*	[0.060]***	[0.062]***	[0.066]***	[0.075]***	[0.085]***	[0.107]***
Constant	-0.124	-0.069	-0.011	0.018	0.1	0.142	0.138	0.112
	[0.005]***	[0.005]***	[0.005]**	[0.005]***	[0.005]***	[0.006]***	[0.006]***	[0.008]***
Number of Twin Pairs	7853	8864	8455	8216	7230	5815	4654	3381
Panel B - Language								
Very Low Birth Weight (1 if <1500 gm, 0 otherwise)	-0.138	-0.096	-0.066	-0.051	-0.113	-0.133	-0.149	-0.163
	[0.056]**	[0.057]*	[0.057]	[0.058]	[0.059]*	[0.066]**	[0.079]*	[0.099]*
Constant	-0.116	-0.043	0.02	0.047	0.139	0.184	0.18	0.169
	[0.005]***	[0.004]***	[0.004]***	[0.004]***	[0.004]***	[0.005]***	[0.006]***	[0.007]***
Number of Twin Pairs	7835	8845	8439	8201	7210	5805	4651	3379

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
Notes: Twins fixed effects employed in all regressions. Regressions run only on twin pairs that are in the same class for each grade. Test scores range from 1-7.

TABLE 6: CRE Estimates: Birth Weight and School Achievement in Grades 1-8 (Twins Sample)

Dependent Variable: Standardized Test Scores	Grade in School							
	1	2	3	4	5	6	7	8
Panel A - Math								
Log Birth Weight	0.539	0.534	0.452	0.54	0.53	0.568	0.526	0.559
	[0.088]***	[0.082]***	[0.081]***	[0.080]***	[0.084]***	[0.093]***	[0.103]***	[0.121]***
Log Sum of Birth Weight	-0.201	-0.242	-0.183	-0.318	-0.396	-0.476	-0.465	-0.535
	[0.095]**	[0.089]***	[0.089]**	[0.088]***	[0.092]***	[0.103]***	[0.112]***	[0.134]***
Constant	-2.565	-2.627	-2.39	-1.533	-0.723	-0.42	-0.168	0.265
	[0.624]***	[0.307]***	[0.294]***	[0.295]***	[0.310]**	[0.351]	[0.387]	[0.482]
Observations	20360	23955	23479	23200	20727	17081	13864	9976
R-Squared	0.06	0.06	0.06	0.05	0.05	0.05	0.06	0.07
Panel B - Language								
Log Birth Weight	0.456	0.463	0.36	0.349	0.362	0.298	0.351	0.34
	[0.087]***	[0.082]***	[0.080]***	[0.079]***	[0.083]***	[0.090]***	[0.101]***	[0.119]***
Log Sum of Birth Weight	-0.193	-0.252	-0.13	-0.224	-0.309	-0.334	-0.371	-0.484
	[0.094]**	[0.089]***	[0.088]	[0.086]***	[0.091]***	[0.099]***	[0.111]***	[0.132]***
Constant	-1.865	-2.08	-2.176	-0.752	-0.068	0.568	0.509	1.548
	[0.619]***	[0.307]***	[0.295]***	[0.290]***	[0.304]	[0.335]*	[0.377]	[0.471]***
Observations	20204	23775	23314	23054	20561	16963	13791	9920
R-Squared	0.07	0.07	0.07	0.07	0.08	0.08	0.08	0.1

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Notes: All regressions include the following controls: dummies for year of birth, father and mother's age, father and mother's education, father's occupation and employment status, sex of the child, municipality of birth dummies

TABLE 7: Twins Based Value Added Model: Birth Weight, Lags of Test Scores and School Achievement in Grades 1-8

Dependent Variable:	Grade in School							
Standardized Test Scores	1	2	3	4	5	6	7	8
Panel A - Math								
Log Birth Weight	0.4	0.336	0.158	0.317	0.231	0.188	0.201	0.262
	[0.055]***	[0.054]***	[0.051]***	[0.049]***	[0.051]***	[0.055]***	[0.062]***	[0.073]***
Test score in previous grade		0.511	0.616	0.634	0.597	0.636	0.65	0.671
		[0.011]***	[0.010]***	[0.010]***	[0.010]***	[0.011]***	[0.012]***	[0.013]***
Constant	2.606	-2.658	-1.255	-2.467	-1.732	-1.415	-1.523	-2.049
	[0.430]***	[0.424]***	[0.400]***	[0.387]***	[0.397]***	[0.431]***	[0.488]***	[0.572]***
Number of Twin Pairs	8344	7396	7171	6933	6800	5709	4478	3338
Panel B - Language								
Log Birth Weight	0.362	0.232	0.053	0.077	0.104	0.04	0.144	-0.008
	[0.057]***	[0.051]***	[0.047]	[0.046]*	[0.046]**	[0.050]	[0.059]**	[0.070]
Test score in previous grade		0.585	0.629	0.621	0.568	0.603	0.617	0.636
		[0.011]***	[0.010]***	[0.010]***	[0.010]***	[0.011]***	[0.013]***	[0.014]***
Constant	2.814	-1.821	-0.411	-0.576	-0.715	-0.238	-1.056	0.1
	[0.446]***	[0.398]***	[0.370]	[0.362]	[0.363]**	[0.388]	[0.461]**	[0.549]
Number of Twin Pairs	8326	7373	7151	6917	6776	5692	4468	3336

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Notes: Twins fixed effects employed in all regressions. Regressions run only on twin pairs that are in the same class for each grade. Test scores range from 1-7.

TABLE 8: Birth Weight and Math Scores in Grades 1-8, by Mother's Education level

Dependent Variable: Standardized Test Scores	Grade in School							
	1	2	3	4	5	6	7	8
Panel A - High School and Over								
Log Birth Weight	0.547	0.595	0.53	0.707	0.594	0.527	0.55	0.551
	[0.072]***	[0.065]***	[0.066]***	[0.066]***	[0.070]***	[0.078]***	[0.091]***	[0.111]***
Constant	-4.307	-4.634	-4.076	-5.438	-4.482	-3.926	-4.105	-4.136
	[0.559]***	[0.506]***	[0.516]***	[0.517]***	[0.544]***	[0.613]***	[0.712]***	[0.865]***
Number of Twin Pairs	5762	6559	6255	6061	5322	4292	3375	2460
Panel B - Middle school and lower								
Log Birth Weight	0.367	0.404	0.282	0.406	0.52	0.701	0.661	0.702
	[0.115]***	[0.111]***	[0.111]**	[0.110]***	[0.123]***	[0.140]***	[0.149]***	[0.185]***
Constant	-3.249	-3.475	-2.443	-3.361	-4.164	-5.506	-5.194	-5.573
	[0.901]***	[0.866]***	[0.868]***	[0.859]***	[0.963]***	[1.095]***	[1.169]***	[1.444]***
Number of Twin Pairs	2101	2314	2206	2158	1915	1529	1285	923

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Notes: Twins fixed effects employed in all regressions. Regressions run only on twin pairs that are in the same class for each grade. Test scores range from 1-7.

TABLE 9: Twins Estimates: Birth Weight, Grade Repetition and Attendance in Grades 1-8

	Grade in School							
	1	2	3	4	5	6	7	8
Panel A - Attendance (%)								
Log Birth Weight	0.557	0.37	-0.158	0.256	0.012	0.186	0.16	0.285
	[0.305]*	[0.251]	[0.278]	[0.209]	[0.239]	[0.277]	[0.353]	[0.423]
Constant	89.831	91.865	96.351	93.319	95.056	93.797	94.28	93.107
	[2.380]***	[1.960]***	[2.171]***	[1.637]***	[1.866]***	[2.162]***	[2.756]***	[3.308]***
Number of Twin Pairs	8246	9157	8679	8479	7536	6087	4690	3478
Panel B - Grade repetition								
Log Birth Weight	-0.036	-0.026	0.003	0.005	0.001	0	-0.017	-0.01
	[0.018]**	[0.016]	[0.013]	[0.013]	[0.014]	[0.013]	[0.016]	[0.013]
Constant	0.329	0.245	-0.002	-0.018	0.02	0.024	0.155	0.089
	[0.137]**	[0.126]*	[0.100]	[0.098]	[0.108]	[0.105]	[0.123]	[0.102]
Number of Twin Pairs	8246	9155	8676	8473	7533	6083	4690	3476

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Notes: Twins fixed effects employed in all regressions. Regressions run only on twin pairs that are in the same class for each grade.

TABLE 10: Twins Estimates: Log Birth Weight and Performance on Grade 4 and Grade 8 National Exam

Test scores standardized at the national level	Math		Language	
	Grade 4	Grade 8	Grade 4	Grade 8
Log Birth Weight	0.661	0.565	0.349	0.185
	[0.063]***	[0.157]***	[0.066]***	[0.161]
Constant	-5.245	-4.479	-2.795	-1.498
	[0.494]***	[1.225]***	[0.513]***	[1.256]
Number of Twin Pairs	8406	1743	8406	1743
R-squared	0.01	0.01	0.01	0.01

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

TABLE 11: Twins Estimates: Log Birth Weight and Math Achievement in Grades 1-8 by types of Twin Pairs

Dependent Variable:	Grade in School							
Standardized Test Scores	1	2	3	4	5	6	7	8
Panel A - Same sex twin pairs								
Log Birth Weight	0.446	0.533	0.502	0.632	0.559	0.615	0.551	0.546
	[0.065]***	[0.060]***	[0.061]***	[0.060]***	[0.064]***	[0.071]***	[0.081]***	[0.097]***
Constant	-3.618	-4.242	-3.952	-4.932	-4.274	-4.675	-4.169	-4.167
	[0.507]***	[0.468]***	[0.473]***	[0.469]***	[0.498]***	[0.554]***	[0.634]***	[0.762]***
Number of Same Sex Twin Pairs	5908	6726	6434	6279	5505	4480	3599	2617
Panel B - Boy-Girl Twin Pairs								
Log Birth Weight	0.595	0.547	0.308	0.608	0.62	0.434	0.657	0.729
	[0.145]***	[0.134]***	[0.138]**	[0.139]***	[0.151]***	[0.178]**	[0.201]***	[0.255]***
Constant	-4.77	-4.326	-2.374	-4.721	-4.752	-3.241	-5.022	-5.598
	[1.136]***	[1.047]***	[1.084]**	[1.091]***	[1.183]***	[1.394]**	[1.576]***	[2.002]***
Number of Twin Pairs	1945	2138	2021	1937	1725	1335	1055	764
Panel C - Boy-Boy Twin Pairs								
Log Birth Weight	0.362	0.407	0.431	0.558	0.467	0.641	0.59	0.527
	[0.104]***	[0.094]***	[0.096]***	[0.096]***	[0.102]***	[0.115]***	[0.136]***	[0.161]***
Constant	-2.965	-3.217	-3.361	-4.328	-3.56	-4.895	-4.485	-4.002
	[0.809]***	[0.732]***	[0.753]***	[0.754]***	[0.795]***	[0.904]***	[1.065]***	[1.260]***
Number of Twin Pairs	2568	2932	2774	2699	2339	1871	1496	1094
Panel D - Girl-Girl Twin Pairs								
Log Birth Weight	0.509	0.625	0.553	0.686	0.629	0.597	0.523	0.559
	[0.083]***	[0.078]***	[0.078]***	[0.076]***	[0.081]***	[0.089]***	[0.100]***	[0.122]***
Constant	-4.101	-4.993	-4.376	-5.374	-4.814	-4.521	-3.955	-4.281
	[0.647]***	[0.608]***	[0.605]***	[0.594]***	[0.635]***	[0.697]***	[0.780]***	[0.949]***
Number of Twin Pairs	3340	3794	3660	3580	3166	2609	2103	1523

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Notes: Twins fixed effects employed in all regressions. Regressions run only on twin pairs that are in the same class for each grade. Test scores range from 1-7.

Table 12: Parental Investments and Birth Weight

	Hire a Tutor (1=yes, 0=no)		Education related spending (categorical variable from 1-14)		Non-education related spending (categorical variable from 1-14)	
	OLS	Twins-FE	OLS	Twins-FE	OLS	Twins-FE
Log Birth Weight	-0.004	-0.007	0.432	-0.054	-0.189	-0.009
	[0.011]	[0.016]	[0.272]	[0.135]	[0.099]*	[0.083]
Constant	0.065	0.113	-0.126	3.538	5.772	3.811
	[0.086]	[0.135]	[2.118]	[1.050]***	[0.774]***	[0.727]***
Number of Twin Pairs	4819	4819	1634	1634	6412	6412
R-squared	0	0	0	0	0.17	0.06

Dependent variables have responses ranging from 1-5. 1 is Never and 5 is Most Often	Does homework with child		Revises homework with child		Talks to child	
	OLS	Twins-FE	OLS	Twins-FE	OLS	Twins-FE
Log Birth Weight	-0.22	-0.065	-0.14	0.076	0.028	0.053
	[0.090]**	[0.086]	[0.079]*	[0.090]	[0.061]	[0.066]
Constant	5.709	4.527	5.27	3.619	4.328	4.11
	[0.700]***	[0.674]***	[0.615]***	[0.698]***	[0.475]***	[0.512]***
Number of Twin Pairs	1613	1613	1603	1603	1624	1624

Dependent variables have responses ranging from 1-5. 1 is Never and 5 is Most Often	Reads stories to child		Provides incentives for reading		Plays games with child	
	OLS	Twins-FE	OLS	Twins-FE	OLS	Twins-FE
Log Birth Weight	-0.13	0.039	-0.035	0.009	-0.012	0.085
	[0.101]	[0.098]	[0.092]	[0.099]	[0.100]	[0.095]
Constant	4.024	2.728	4.048	3.686	3.684	2.905
	[0.789]***	[0.764]***	[0.716]***	[0.772]***	[0.782]***	[0.737]***
Number of Twin Pairs	1604	1604	1612	1612	1603	1603

Robust standard errors in brackets
Note: Education spending data only available for 2002

APPENDIX TABLE 1: OLS Estimates: Birth Weight and School Achievement in Grades 1-8 (Twins Sample)

Dependent Variable:	Grade in School							
Standardized Test Scores	1	2	3	4	5	6	7	8
Panel A - Math								
Log Birth Weight	0.365	0.326	0.295	0.269	0.195	0.166	0.136	0.116
	[0.033]***	[0.030]***	[0.030]***	[0.031]***	[0.033]***	[0.037]***	[0.041]***	[0.050]**
Constant	-2.899	-3.054	-2.722	-2.125	-1.471	-1.327	-1.063	-0.819
	[0.603]***	[0.262]***	[0.244]***	[0.244]***	[0.256]***	[0.287]***	[0.319]***	[0.392]**
Observations	20360	23955	23479	23200	20727	17081	13864	9976
R-Squared	0.06	0.06	0.06	0.05	0.05	0.05	0.06	0.07
Panel B - Language								
Log Birth Weight	0.289	0.245	0.248	0.158	0.101	0.016	0.039	-0.061
	[0.032]***	[0.030]***	[0.030]***	[0.031]***	[0.032]***	[0.036]	[0.040]	[0.049]
Constant	-2.185	-2.526	-2.411	-1.168	-0.65	-0.067	-0.205	0.57
	[0.597]***	[0.265]***	[0.244]***	[0.241]***	[0.252]***	[0.277]	[0.311]	[0.384]
Observations	20204	23775	23314	23054	20561	16963	13791	9920
R-Squared	0.07	0.07	0.07	0.07	0.08	0.08	0.08	0.1

Standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Notes: All regressions include the following controls: dummies for year of birth, father and mother's age, father and mother's education, father's occupation and employment status, sex of the child, municipality of birth dummies