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Abstract

This paper estimates the effects of birth weight on health and educational outcomes for Brazil using a twin fixed effect approach. The recent literature, mainly based on data from developed countries, has provided evidence that health at birth is a critical factor for outcomes related to health and to cognition. Using a matching of administrative records of birth and school enrollment we aim to provide this type of evidence for Brazil. The main finding is that birth weight matters. For instance, there is evidence that a 10% increase in weight is associated with a 0.6% increase in Apgar, a score for health at birth. In the educational dimension, the findings suggest that a 10% increase in birth weight is associated with a 6% increase in the chances of completing high school by the age of 17 and with a 3.6% decrease in the probability of repeating a grade. Furthermore, estimates provide evidence that parents tend to reinforce, rather than compensate, the negative effects of adverse initial health conditions. Larger effects are found for the infants with low birth weight, limited access to basic health care services, lower maternal education and enrolled at schools of lower socioeconomic status.

Keywords: health at birth, parental response, educational outcomes.

JEL Codes: I10, I14, I20

1 Introduction

Health at birth, mainly measured by birth weight, has been for a long time a primary concern in the literature on economic development, mainly because of the high prevalence of low birth weight infants in developing countries and the strong association between poor neonatal health and infant mortality (UNICEF; WHO, 2004; ALMOND; CHAY; LEE, 2005; OREOPOULOS et al., 2008). A growing body of economic and medical literature, however, has stressed that poor health at birth can have short-run and long-lasting effects on health, cognitive and non-cognitive development (BLACK; DEVEREUX; SALVANES, 2007; NILSSON, 2017; LARROQUE et al., 2001; SANZ-CORTES et al., 2014). Moreover, initial endowments and early life investments have been associated with the perpetuation of lower socioeconomic status (CURRIE, 2011; HECKMAN; MOSSO, 2014). Because of data availability, most of the studies assessing the enduring consequences of poor health at birth have provided evidence for developed countries. This paper contributes to the literature by presenting additional evidence of the effects of birth weight on health and educational outcomes for children in Brazil, a developing country.

The literature investigating the effects of birth weight on newborn health frequently uses the Apgar score, an index which, in order to evaluate health at birth, assesses five vital signs one and five minutes after birth, and survival in the first year of life. Several studies have confirmed the effects of birth weight on these outcomes (ALMOND; CHAY; LEE, 2005; BLACK; DEVEREUX; SALVANES, 2007; BHARADWAJ; LøKEN; NEILSON, 2013; CARRILLO; FERES, 2017). Particularly for Brazil, Carrillo e Feres (2017) estimate that a 1% increase in birth weight lead to a 1.6% reduction in infant mortality. The effect is much higher than the one estimated for developed countries[1], suggesting that poor health at birth may have severer impacts in developing contexts. Likewise, the estimated effects of birth weight on Apgar scores presented in this paper is twice larger than the effects found by Black, Devereux e Salvanes (2007) for Norway. In addition to direct impacts on children's well-being, poor health at birth is also associated with higher hospital costs, which are incurred by society as a whole (ALMOND; CHAY; LEE, 2005).

Moreover, it is well documented that the impacts of bad health at birth can last throughout schooling and adult life. Exploring a discontinuity design that assigns special medical care to very low birth weight newborns (less than 1500g), Bharadwaj, Løken e Neilson (2013) and Breining et al. (2015) found that early life health interventions have positive impacts on test scores in elementary school. Furthermore, Figlio et al. (2014) and Bharadwaj, Eberhard e Neilson (2018) present evidence that the gap in academical achievement, explained by birth weight differences between twins, is persistent and does not fade in higher grades. Also using twins weight differences, Black, Devereux e Salvanes (2007) show that low birth weight infants present worse long-run outcomes, such as lower high school completion rate and worse labor market outcomes, including earnings. Nilsson (2017) indicates that newborns with compromised health because of *in-utero* exposition to alcohol are associated with lower cognitive and non-cognitive ability as well as with worse labor market outcomes.

Most of the estimation of the impacts of health at birth consists of seeking to separate the effect of birth weight itself from parental characteristics and investments made during life. After all, maternal background characteristics and even genetic factors associated with the birth weight may also play a critical role in determining a child's health and educational outcomes. In order to address this omitted variable bias issue, a twin fixed effect (TFE) identification strategy has been widely used instead of the Ordinary Least Square (OLS) estimations. The OLS estimator confounds the direct effects of health at birth with parental investments, whereas looking at the variation within twins - by using the TFE identification strategy - captures the effect that can be

[1] Almond, Chay e Lee (2005) found that for the USA the increase in 1% in birth-weight is associated with a 0.51% decrease in infant mortality, while Black, Devereux e Salvanes (2007) provide evidence that this elasticity is -0.83 in Norway

attributed only to the health shock. Bharadwaj, Eberhard e Neilson (2018) presents a theoretical model that supports the notion that the differences between OLS and TFE estimators can be attributed to the role of parental investment.

Parental investment can be positively or negatively correlated with a child's initial adverse shock - e.g. being born with low birth weight. If the response of parents is positively correlated with the shock, their behavior is considered as reinforcing the effect of the initial adverse situation. On the other hand, if the response is negatively correlated with the shock, it is seen as a compensating behavior. Within families, parents reinforce or compensate a child's initial shock according to their degree of aversion to inequality among children. If parents allocate more resources to the infant with better health, they reinforce the effect of the initial shock, increasing the outcome gaps between children. In contrast, more parental investments in the lower birth weight newborn reveal a response that counters the initial shock, by attempting to mitigate or reduce the dissimilarity among the infants (ALMOND; MAZUMDER, 2013; BHARADWAJ; EBERHARD; NEILSON, 2018).

This paper uses two rich administrative records for birth (System of Information on Live-Born Infants-SINASC) and school attendance (School Census) so as to produce evidence of the effects of birth weight through life for Brazil. Using the date of birth, municipality of birth, gender and municipality of residence as a child identifier, 17% of all births in Brazil from 1999 to 2006 were successfully matched to the schooling records. Although the birth register data available is not restricted to the years between 1999 and 2006, these cohorts were chosen to ensure a minimal quality of birth records while observing children in at least half of the mandatory schooling years (6 years for the cohorts born in 2006). Regarding the variables of interest, the birth register provides information on birth weight and Apgar scores (measurement of newborn health) while repetition, dropout and age-grade distortion rates for ages 7 to 16 and high school completion are outcomes provided by school records.

The Apgar score is a measure of health at birth consolidated in the literature (ALMOND; CHAY; LEE, 2005; BLACK; DEVEREUX; SALVANES, 2007). It assesses five vital signs - heart rate, respiratory effort, reflex irritability, muscle tone and skin color - of a newborn and is a critical information, for example, in the decision to use resuscitation methods in certain circumstances (APGAR, 1953). Created in 1953, the Apgar measurement has been widely used in hospitals as part of neonatal care protocols (EHRENSTEIN, 2009). In the educational sphere, high school completion is an outcome frequently used in the literature as a measure of schooling accumulation (BLACK; DEVEREUX; SALVANES, 2007; NILSSON, 2017). Other educational outcomes, however, are not widely used, test score being the main educational outcome of interest in this literature. Despite the data availability of scores from large-scale assessment tests in Brazil, the data structure does not allow the linkage with birth records. Barros (2017) argues that in the absence of a measure of cognitive achievement, grade retention confounds the effect of low academic performance with lack of motivation and student engagement. On the other hand, there is no consensus in the literature about the impact of retention itself on academic and motivational results. While some have found evidence that repeating a grade improves future achievement (JACOB; LEFGREN, 2004; SCHWERDT; WEST; WINTERS, 2017), others argue that repetition is not associated with better achievement and may cause demotivation, increasing the chances of school dropout (EREN; DEPEW; BARNES, 2017; BARROS, 2017). Furthermore, these effects can be context-dependent: retention in a country or a region can have effects different from those identified in another one (IKEDA; GARCíA, 2014). Although providing a consolidated understanding of the positive or negative effects of repetition is beyond the scope of this paper, it is important to shed light on the relation between grade retention, dropout, and educational outcomes, especially for the Brazilian context.

According to PISA Key Findings Report (OECD, 2016), Brazil is the country with the second largest grade retention rate, only behind Colombia. Nevertheless, according to the

2017 School Census, 29.45%[2] of schools in Brazil organize the elementary school (1^{st} to 9^{th} grade) in cycles within which students have automatic grade promotion[3]. Concerning the profile of the students more vulnerable to repetition, PISA 2015 findings state that, across OECD countries, even after accounting for students' previous educational performance and self-reported motivation, socioeconomically disadvantaged students and males are more likely to have repeated a grade. Similarly, Soares et al. (2015) show that the following groups are more likely to drop out of school in Brazil: boys, students with a prior history of grade repetition, students with low academic achievement and little engagement in school activities.

Using the richness of the administrative data for Brazil, the main contribution of this paper is threefold: (i) to estimate the effects of birth weight on Apgar score and educational outcomes using a twin fixed effect identification strategy; (ii) to compare the OLS and TFE estimations, providing evidence on parental reinforcing behavior; (iii) to show that birth weight impacts are different across socioeconomic groups.

Regarding the first contribution, we estimate the effects of birth weight on short-run health outcomes, the Apgar scores, and on educational outcomes - the repetition, dropout, and age-grade distortion rates -, using Ordinary Least Squares (OLS) and twin fixed effect (TFE) estimators. As these are probably the first estimates of this type for Brazil, this paper contributes to the literature by focusing on a developing country and by providing evidence on Brazil's need of public policies that mitigate the effects of initial inequalities that can last through adulthood.

Following the theoretical framework proposed by Bharadwaj, Eberhard e Neilson (2018), under the assumption that parents can not fully differentiate investments within twins, the second contribution consists of empirical evidence suggesting that parents act reinforcing the effect of low weight at birth, particularly with respect to educational outcomes. Parental behavior reinforcing initial endowments was also found by Adhvaryu e Nyshadham (2016) in Tanzania, whereas Bharadwaj, Eberhard e Neilson (2018) find evidence of parental compensating behavior in Chile.

The third contribution is to provide evidence of differential impact across socioeconomic groups. The impacts of birth weight on the Apgar score, the grade retention rate and the age-grade distortion are much less relevant for children of highly educated mothers and for the ones attending schools with better socioeconomic status. The effects are either zero or smaller than the ones observed for children with a disadvantaged background. These results contrast remarkably with the evidence of stability in the effects of birth weight on educational outcomes across demographic and socioeconomic groups found by Figlio et al. (2014), Black, Devereux e Salvanes (2005), Bharadwaj, Eberhard e Neilson (2018).

The remaining of the paper is organized as follows. In Section 2, the main causes of low birth weight are discussed, especially in the context of a twin pregnancy. The medical channels that may justify differences in future development following birth weight differences are presented, along with details on the Apgar score and its computation. Section 3 introduces the two datasets used and presents the matching algorithm and the matching rates; it also displays the main descriptive statistics. Section 4 describes the theoretical framework and the empirical approach used. Section 5 shows the results and discusses the heterogeneous effects. Section 6 presents the final remarks.

[2] Own calculations.The share does not vary significantly across years, it is 30.6% in 2014 and 25.60% in 2009.

[3] States, municipalities and private schools can have their own rules for student promotion/retention. Even so, it is known that the most common way of organizing cycles are: 1^{st} to 3^{rd} grade, 4^{th} to 5^{th} grade and 6^{th} to 9^{th} grade. A school that organizes the 1^{st} to 9^{th} grade in cycles does not necessarily follows the aforementioned classification, nor does the school need to organize all grades in cycles. Whatever the cycle composition is, in case of insufficient achievement, the retention occurs in the last grade of the cycle.

2 Background: Health at Birth, Weight and Apgar Score

Birth weight is a central measure of health at birth, and the occurrence of low birth weight is highly correlated with adverse neonatal outcomes. Low birth weight is defined by the World Health Organization (WHO) as weight below 2500g at birth (UNICEF; WHO, 2004). Medical literature lists two causes for a baby's low birth weight: premature birth and intrauterine growth restriction (IUGR). Premature birth occurs before 37 weeks of gestation. Since much of a baby's weight is gained during late pregnancy, an early birth means less time in the mother's uterus to grow and gain weight. IUGR refers to a fetal growth rate fetus below the limits considered normal for the population. There are three sources of IUGR: (i) placental dysfunctions that include placental insufficiency and abnormal cord insertions, (ii) maternal health, including inadequate nutrition, smoking or drug use habits, (iii) fetal conditions such as anomalies and multiple pregnancy (UNICEF; WHO, 2004; KRAMER, 1987). Preterm birth and IUGR are situations that can occur together or separately, which means that not all babies born before 37 weeks is growth restricted and that a baby born at term (after 37 weeks) might present growth below its potential[4].

In a twin pregnancy, gestational length is the same for both babies, so that birth weight discordance [5] among twins arises solely due to differences in intrauterine growth. It is well established in medical literature that during gestation, twins have a growth curve different from singletons and that differences arise mainly in the third trimester of pregnancy (TOWNSEND; KHALIL, 2018; KIBEL et al., 2017). In addition to the differentiated growth curve, weight discordance and IUGR among twin siblings arise solely due to placental factors, since maternal health and fetal conditions (not considering situations of congenital anomalies) are held constant for twins (PAEPE et al., 2010; CAMBIASO et al., 2016; KIBEL et al., 2017).

Twin pregnancies are distinguished by whether the twins are identical (monozygotic) or fraternal (dizygotic) and by whether they share the same placenta (monochorionic) or have one placenta for each (dichorionic). Fraternal twins are always dichorionic (DC) meaning that each fetus has one placenta. According to Laventhal e Treadwell (2018), two-thirds of identical twins are monochorionic (MC). Chorionicity rather than zygosity is the key factor determining pregnancy characteristics and risks. MC pregnancies present a higher risk of stillbirth, growth restrictions and perinatal loss (TOWNSEND; KHALIL, 2018; LAVENTHAL; TREADWELL, 2018; DUBE; DODDS; ARMSON, 2002). For both types of twin pregnancies, the placental aberrant characteristics and type of cord insertion play an essential role in determining growth discordance among twins and also IUGR. Specifically for DC twins, Kibel et al. (2017) argues that the main cause of growth restriction is the non-central umbilical cord insertion rather than other placental pathologies.

Whatever may be the cause for a particular situation of low birthweight and IUGR, this condition is associated in medical literature with fetal and neonatal mortality, neonatal abnormal neurobehaviour, worse cognitive outcomes, and chronic diseases in later life (UNICEF; WHO, 2004; LARROQUE et al., 2001; SANZ-CORTES et al., 2014; CRUZ-MARTINEZ et al., 2009). The exact biological mechanisms explaining the worse short and long-term outcomes of growth-restricted babies are not yet clearly determined in medical literature. Nevertheless, there is

4 It is important to highlight that IUGR and "small for gestational age" (SGA), other definition frequently used in the medical literature, are different conditions. SGA is defined as a birth weight lower than the 10^{th} centile. However, a SGA baby can be, in fact, genetically and constitutionally small, though well-nourished and healthy, presenting no growth restrictions. Considering an average growth curve, being either SGA or born with less than 2500g is considered a proxy for having IUGR.

5 Discordant growth here does not necessarily refer to the selective fetus growth restriction (sFGR) but instead to any differences in birth weight among twins. sFGR is increasing risk factor in twins pregnancy, strongly correlated with the incidence of IUGR in a twin pregnancy. For a review of the definitions of selective growth restriction see Blickstein e Kalish (2003).

evidence that the structure and the functions of the brain in IUGR babies are different from the ones observed in non-restricted babies. Notably, medical research has found differences in the frontal area of the brain -which is related with instinctual behaviour, attention and impulsiveness (CRUZ-MARTINEZ et al., 2009)-; in brain stem, which is important for motor and sensory systems; as well as in the cerebellum, which plays a central role in motor control and in the performance of tasks such as memory, attention and language (SANZ-CORTES et al., 2014)

This paper uses birth weight discordance among dichorionic (DC) twins to estimate the impacts of birth weight on health and educational outcomes. The matching algorithm used to link birth records to school register requires the twins to be of opposite gender, hence creating a sample exclusively with DC twins (we present more details on the matching in section 3). Following the available medical literature, we assume that among twins weight differences arise only due to placental factors, e.g., the type of umbilical cord insertion, which an exogenous factor, not related with any intrinsic characteristics of the babies. Moreover, material characteristics are held constant when looking at variations within twins.

Another important measure of newborn health is the Apgar score. It was created in 1953 by Dr. Virginia Apgar and rates five vital signs: heart rate, respiratory effort, reflex irritability, muscle tone and skin color, in 0, 1 or 2 whether these signs are absent or present, compounding a final index that varies from 0 to 10, where 10 stands for perfect newborn health. Several factors including uterus health, maternal health, fetus position, the delivery type (e.g. use of forceps), induction of labor and anesthesia can influence the Apgar score of a baby(APGAR, 1953). Worldwide, the Apgar score measured one minute after birth is used as a critical variable to decide on the use of resuscitation methods, while the five minutes score serves to evaluate the effectiveness of the resuscitation. Low Apgar score (≤ 7) is associated with neonatal mortality as well as with worse cognitive outcomes later in life (EHRENSTEIN, 2009). In our sample, 20% of the infants present one minute Apgar below this cut-off, and 4% present low five minute Apgar.

3 Data

This section describes the data and provides details on the merge algorithm used to link birth records to school administrative data. We also discuss the quality of birth and school records, as well as the quality of the merge and potential differences across the universe (the totality of births registered), the set of individuals that could be potentially be matched, and the final sample.

3.1 Birth administrative records: SINASC

The System of Information on Live-Born Infants (SINASC - *Sistema de Informações de Nascidos Vivos*) was created in 1990 by the Health Ministry of Brazil aiming to collect information on births in all municipalities, so as to support the design of health policies. Prior to the creation of SINASC, the Civil Registration instituted in 1939 was the only source of birth information. However, due to the relatively high cost of registering a child[6], the absence of a pattern for the registration, sub-registration and late registration, Civil Registration has not been considered a reliable source of information on vital events, particularly for public policy purposes. In this context, SINASC was gradually implemented by the municipalities using a unified form, the Declaration of Live Born (DNV- *Declaração de Nascido Vivo)* to collect information directly from hospitals and from Civil Registration Offices for births occurring outside a hospital (BORGES; SILVA, 2015). The microdata are publicly available at the website of the Health Ministry, starting in the year of 1994, but since 1996 it has a similar structure,

[6] Only on 1997 did law n°.9.534 ensure costless Civil Registration.

which is the reason why the following analysis will focus on the period from 1996 onwards. Figure 1 shows the evolution over time of the total number of records (line and left-hand axis) in SINASC as well as an estimate of SINASC coverage (bar and right-hand axis)[7]. SINASC coverage increased between 1995 and 1999, reaching a stable level of around 95% of coverage after 2003. The observable increase in the number of births until 1999 can be explained by the improvement in coverage, rather than by the increase in births itself. It is known that since the 1970's Brazil is experiencing a reduction in fertility rates, leading to a gradual reduction in the number of births over time (SIMõES, 2016). The reduction in the total number of births after 1999 - when coverage surpassed 90% - is a result of a reduction in fertility rates.

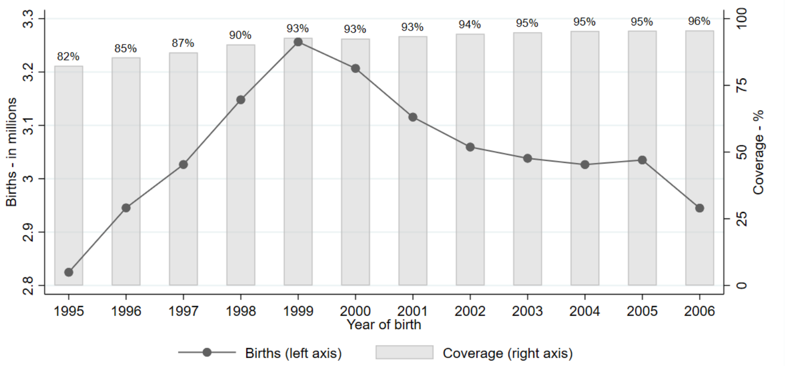


Figura 1 – SINASC estimated coverage and number of births registered 1996-2006

The information collected by the DNV changed over time with the inclusion of additional variables (e.g., mother's characteristics). Considering the most recent version of the form, the information collected includes mother's characteristics, gestation conditions and birth conditions. Mother's characteristics available in the public dataset are: age, education, marital status, number of previous births and municipality of residence. Gestation conditions include the number of prenatal visits, gestation length, and an indicator of the type of birth (single or multiple). Birth conditions include municipality and place of birth (home or hospital), date of birth, baby's gender and race, birth weight and Apgar score. Figure 2 depicts the share of missing information registered in a few key variables across years. Data quality improved significantly after 2000, as expressed by the reduction of missing values in these variables. Therefore, this paper will focus on the cohorts born between 1999 and 2006. Although the data quality is not so high for 1999, this cohort is of particular interest when linked with the educational record because students born in this year are eligible to complete high school in 2016, allowing the inclusion of high school completion as a relevant outcome.

In case of multiple births, SINASC data do not identify individuals who are the twins, neither provides information on the zygosity of the twins. However, in the dataset entries for twins are close to each other, displaying identical mother, gestational characteristics and date of birth. Using these facts, it is possible to create an algorithm that matches the twin siblings[8]. Out of all double pregnancies registered, 68% had both siblings identified using the algorithm.

[7] Coverage estimation from RIPSA- *Rede Interagencial de Informções para a Saúde*- available at <http://tabnet.datasus.gov.br/cgi/idb2012/a17.htm>.

[8] Unfortunately, the time of birth is available in SINASC only since 2006, so that this information was not used for matching the twin siblings. Births that occurred around midnight, for which the day of birth of each twin is different, were not captured by the algorithm. Expanding the algorithm to match lines with equal maternal and gestational characteristics within one day of difference in date of birth leads to few additional matched siblings, whereas most of them linked twins that already have a matched sibling born on the same day. In order to avoid matching wrong siblings, the most conservative algorithm was used, which means that neither the flexibilization of the day of birth, nor slight differences in maternal and gestational characteristics were allowed.

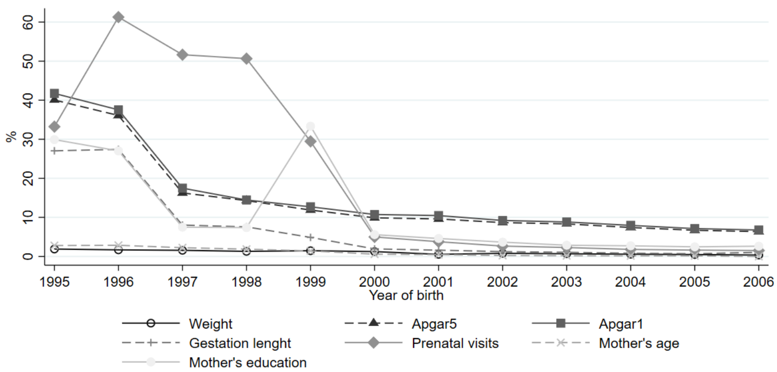


Figura 2 – Number of births registered in SINASC 1996-2006

In short, SINASC data provide information on health at birth - measured by birth weight and Apgar at 1 and 5 minutes -, in addition to prenatal, gestational and maternal characters. As discussed in Section 2 Apgar scores are a measure of health at birth that can be affected by birth weight as well as by birth circumstances. In order to explain how birth weight impacts on Apgar scores, the measurements at 1 and 5 minutes will be outcome variables. Yet these scores will also be treated as explanatory variables when educational outcomes are analyzed.

3.2 School enrollment records: School Census

The School Census is an administrative record created by INEP (Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira), a department of the Brazilian Ministry of Education. Prior to 2007, the data was collected at school level, aggregating information of students and teachers. Since 2007 it encompasses four interconnected datasets at school, class, student and teacher levels. Schools report the information to INEP every year, in the last week of May.

The School Census does not use the civil IDs/registers available in Brazil as identifiers, neither are these fields mandatory for students' registration. Instead, the Census uses a student code created by INEP for this purpose. Using the student code, it is possible to link each of the Census's cross sections creating a panel of students from 2007 to 2017. The panel contains information on school and grade of enrollment in each year, in addition to individual characteristics like gender, date and municipality of birth, municipality of residence, etc.

Despite the increasing quality of the registers of the School Census, inconsistencies[9] can happen when the student moves to a new school that does the registration under a new ID (student code). It is possible to clean these duplicates to some extent, by adding identifiers other than the student code, such as students' and parents' names. However, for confidentiality reasons, public datasets do not contain names, nor the non-mandatory IDs (when the school filled it in), making the process of cleaning the duplicates of individuals unfeasible without additional information. Section 3.3 discuss how SINASC information can be used to clean some of these duplicated registers.

[9] Another kind of inconsistency is that there are students enrolled at different schools and even in different grades in regular education at the same Census' cross-section. This probably happens when a student changes schools and the previous school keeps reporting the student. Furthermore, the previous school could not have approved the student for the subsequent grade but the student changes to a new school that promotes the student. This fact explains how the same student code can be at different grades in a given year. For data cleaning purposes, if a student appears in a given year t of the School Census in a new school but also in the school he/she was enrolled in t-*1*, the information of the new school is considered as correct. That happens with less than 1% of students per year.

Figure 3 compares the estimated total number of students born in each year according to school register (dark grey line) with the amount of births in SINASC, correcting the observable number of births in Figure 1 by the estimated coverage also depicted in Figure 1 (light grey line). Considering that school coverage in Brazil is high[10] and that some mortality occurs, the number of registered students is expected to be smaller than the number of infants born in each year (schools registers include only Brazilian natives). However, as can be seen in Figure 3, the panel of students contains a higher number of students registered than births, confirming the existence of duplicates.

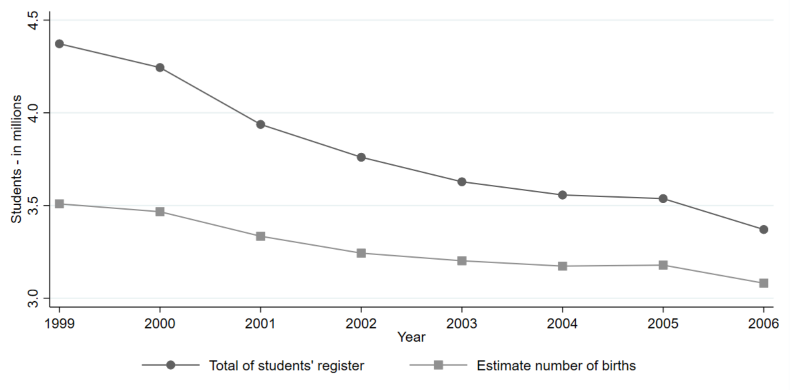


Figura 3 – Number of students registered in School Census from 2007 to 2017 according to year of birth- cohorts 1996-2006

Even taking into account these inconsistencies, the panel of students created using the School Census from 2007 to 2017 (using student code) is a reliable source of information of grade promotion, repetition, and age-grade distortion rates. To create promotion/repetition rates by year, it is sufficient to observe the student in two subsequent years. For age-grade distortion rates, only grade and age are needed, which are both mandatory and reliable information. In contrast, the panel does not provide a reasonable estimate for dropout rates. The aforementioned inconsistencies can lead to a misestimation of school dropout since the absence of a student code in a given year might mean either data inconsistency or dropout[11]. Therefore, the outcome variables obtained from the School Census panel are:

- *Repetition at a specific year/age*: grade repetition occurs at year t (age g) when a student is enrolled in year t (age g) at the same grade k of enrolment at year $t-1$ (age $g-1$). Also, a variable of grade repetition overall is considered: it assumes value 1 when at least one of the specific year/age repetition variables is 1, and zero otherwise.

- *Dropout at a specific year/age*: a dropout occurs at year t (age g) when the student does not appear in the School Census in year t (age g) and the last register occurred in year $t-i$ (age $g-i$), $i >= 1$, at grade k, $k < 12$ ($k = 12$ implies high school completion), and in the next register in year $t+n$ (age $g+n$), $n >= 1$, the student is enrolled in grade $k+1$ (assuming grade promotion before dropping out) or k (assuming the student was

[10] 97.7% of the population of 6 to 14 years old is at school and 84.3% of the population of 15 to 17 years old. See <http://www.observatoriodopne.org.br/metas-pne/2-ensino-fundamental> and <http://www.observatoriodopne.org.br/metas-pne/3-ensino-medio> for more details.

[11] It is important to notice that, in order to clean duplicates when computing official promotion, repetition and dropout rates, INEP uses the available additional confidential identifiers and a dataset sent by schools at the end of the academic year containing student's final situation. Both sets of information are not publicly available. For more information see: <http://download.inep.gov.br/informacoes_estatisticas/indicadores_educacionais/2007_2016/nota_tecnica_taxas_transicao_2007_2016.pdf>.

not promoted before dropping out). A variable of overall dropout assumes value 1 when at least one of the specific year/age dropout variables is 1.

- *Age-grade distortion at specific year/age*: considering grade k and the adequate age d for that grade, age-grade distortion occurs when the student enrolled at year t (age g) at grade k is $d+2$ years old or more. Adequate age for 1$^{\text{st}}$ graders is 6 years, for 2$^{\text{nd}}$ grades 7 years, and so on, until 17 years for the 12$^{\text{th}}$ grade. Overall age-grade distortion assumes value 1 when the student is older than the adequate age at any grade. Age-grade distortion is an accumulative variable: once a student is older than expected in grade k, this will persist through the following grades.

- *Non-cumulative age-grade distortion at specific year/age*: the non-accumulative age-grade distortion assumes values 1 at year t (age g) if it is the first year(age) in which the student became older than the adequate for the current grade. This variable assumes value 1 at every new event (repetition or return to school after dropout) that creates an additional year of distortion.

- *High-school completion*: students born in 1999 and 2000 are able to complete high school in 2016 or 2017, since they will be 18 and 17 years old in 2017, respectively. For these two specific cohorts, high school completion assumes value 1, for students born in 1999, if the student is enrolled in grade 12 in 2016 or 2017 (17 or 18 years old); for those born in 2000, the variable takes value 1 if the student is enrolled in the 12$^{\text{th}}$ grade in 2017 (17 years old). Due to the cohort composition, this variable has the smallest sample size.

Section 3.4 presents descriptive statistics of these outcomes for the overall population as well as to the final merged sample.

3.3 Merge algorithm

Data from SINASC and School Census are merged using the date of birth, municipality of birth, gender and municipality of residence, which are variables present in both administrative registers. The first three variables are more precise, since are mandatory information in the two datasets and are not affected by migration. Hence, the merge is implemented in two rounds, the first of which considers the date of birth, municipality of birth and gender as identifiers. The second round adds municipality of residence for the observations that were not matched. The municipality of residence is used as ID only when it is constant over time in the School Census, showing that the student has not moved to a new city of residence. SINASC data from 1999 to 2006 are merged with a panel of students created using the School Census from 2007 to 2017.

Assuming that SINASC can be under-reported and is less likely to have duplicated entries compared to the School Census, the merge algorithm searches in the panel of students only the uniquely identified births. Therefore, the algorithm has five steps. The first step selects the uniquely identified births in SINASC according to round 1 and round 2 criteria. Next, the second step performs a merge using round 1 criteria assuming that more than one student in the School Census is associated with each entry in SINASC, either because SINASC is under-reported (and so the entry is in truth not uniquely identified) or because the panel of students has duplicates.

The third step uses the successfully merged observations in round 1 to eliminate the duplicates of the panel of students. The SINASC identifiers are a source of additional information that allows to distinguish between two situations in the School Census. In the first kind of situation, two or more students' codes with consistent educational information are matched to the same individual in SINASC. Having consistent information over time means that each student code appears in several years of the School Census with a logical and consistent sequence

of grades and schools. These cases can happen due to SINASC underreporting, so that it is assumed that the students are not uniquely identified and thus they are not considered in the final sample. The second kind of situation is the identification of duplicates in the panel of students. As in the first case, a unique individual from SINASC is linked to more than one student code. However, these codes seem to refer to the same individual, since the data are fragments that, put together, form a consistent educational history. Therefore, student codes that always appear in alternate years or that appear once simultaneously in a maximum of two schools in the same year are considered to refer to the same individual (i.e. student codes alternates in all years except for a specific year, in which the two codes are registered in a school)[12].

The fourth step performs a new merge using round 2 IDs for those observations in the panel of students that were not matched in round 1. The fifth and last step cleans the duplicates of round 2. Steps four and five use the same procedures and hypotheses of steps two and three. A combination of successfully merged observations in round 1 and round 2 generates the final merged dataset.

Table 1 shows the number of observations in SINASC from 1999 to 2006 and how many of them are uniquely identified by either of the criteria (round 1 or round 2). Almost 30% of all entries in SINASC[13] are births uniquely identified using the date of birth, municipality of birth, gender and municipality of residence. When merging the birth information with the panel of students using these IDs, 59% of the students uniquely identified are successfully matched, resulting in a sample of more than 4 million students[14]. The share of uniquely identified students matched is considered satisfactory compared to other studies[15]. Only 6.2% of matched twin siblings are uniquely identified because the identification of twins requires that siblings to be of opposite genders (one boy and one girl), so that they can be differentiated from each other in the School Census. Hence, out of the total of uniquely identified twin siblings matched, 39.9% are merged with the panel of students.

Tabela 1 – SINASC and Scholle Census Total, Uniquely identified and matched registers total and by samples- 1999 to 2006

Sample	Total	Uniquely identified		Matched			
		Nbr.	% of total	Nbr.	% of total	% of uniquely id	% of matched
SINASC							
Total	24,682,893	7,274,976	29.5%	4,306,170	17.4%	59.2%	100.0%
Singleton	24,157,717	7,197,043	29.8%	4,268,643	17.7%	59.3%	99.1%
Twins	453,915	53,495	11.8%	29,114	6.4%	54.4%	0.7%
Twins siblings matched	293,634	18,280	6.2%	7,286	2.5%	39.9%	0.2%
Missing	71,261	24,438	34%	8,413	11.8%	34.4%	0.2%
School Census							
Total	30,407,578	10,108,545	-	4,899,676	-		
After duplicates corrections	26,724,257	8,884,080	33.2%	4,306,170	16.1%	48%	

The second panel of Table 1 shows the merge results from the perspective of the School Census, including an estimate for the share of duplicated entries. In the first line, where the totals

12 As for the case of a student code enrolled at different schools in the same year, only the new school is considered; if both schools are different from the previous, the higher grade is considered.

13 Out of those, 54,5% or 16.1% of total observations are uniquely identified according to round 1 criteria.

14 69.1% of students were matched using criteria from round 1 (the date of birth, municipality of birth, gender).

15 For instance, Figlio et al. (2014) use students' name, date of birth and social security number to match birth records with scholar records in Florida, U.S., and successfully match 79.6% of the registers.

are displayed, one can see that out of more than 30 million registers, around 10 million were uniquely identified. A total of, 4,899,676 records were successfully matched to birth records (not necessarily are uniquely identified). However, part of these records (12%) were duplicated entries of the same individual. After the duplicate cleaning process, these matched records were reduced to 4,306,170 observations. Assuming that the share of duplicated registers (12%) can be applied to the totality of the Census, the second line of the panel "School Census" in Table 1 presents an estimate of the totals without duplicates. Correcting the duplicates, the totals in School Census and SINASC became much similar, not considering the estimations of underreporting in SINASC so far. Among all the matched records, most of them (99%) are from singletons (similar to the proportion of this group on the population, and 0.2% are twins with siblings matched. Although 0.2% percent is a smaller percentage of the total matched sample, it represents more than 7 thousand students, a considerably large sample.

Figure 4 and Figure 5 represent the geographical coverage of the matched sample. Figure 4 shows the percentage of births from 1999 to 2006 that are in the matched sample, according to the municipality of residence of the mother. In general, the municipalities located in the Brazilian regions known as Midwest and South have a greater share of birth of residents in the final sample. Administrative region North and a considerable part of the coast have more municipalities with a lower percentage of births in the final sample.

The place of of birth, however, might not coincide with the municipality of the school where the student is registered. Thus, Figure 5 presents the average of the percentage of students matched over the total number of students registered in schools in each municipality from 2007 to 2017. Two important facts can be seen in Figure 5. First, the percentages are, on average, lower than when considering the municipality of birth. This is because the numerator in the percentage is the number of registers matched after cleaning duplicates and the denominator is the total number of registers, regardless of duplicates. That said, one can see that the pattern of regions is very close to the geographical coverage of births: a bigger share of students in the Midwest and South regions are part of the sample, while a smaller share of students in the North and Coast is in the final sample.

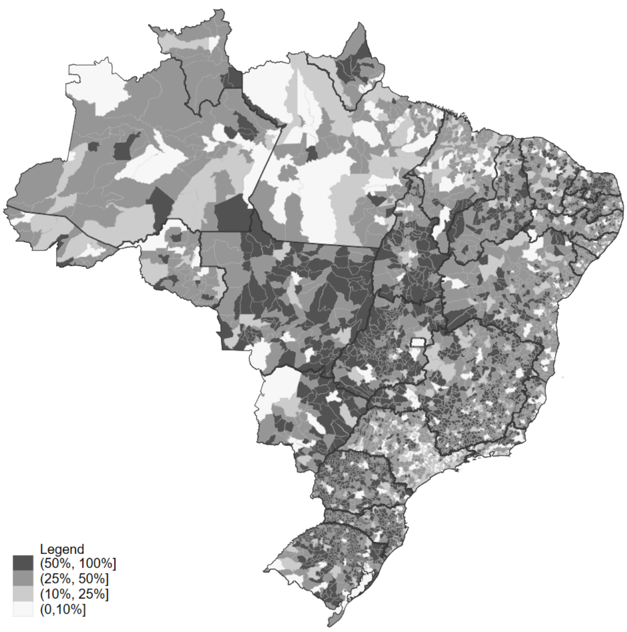


Figura 4 – Percentage of birth records for residents from 1999 to 2006 in the final sample

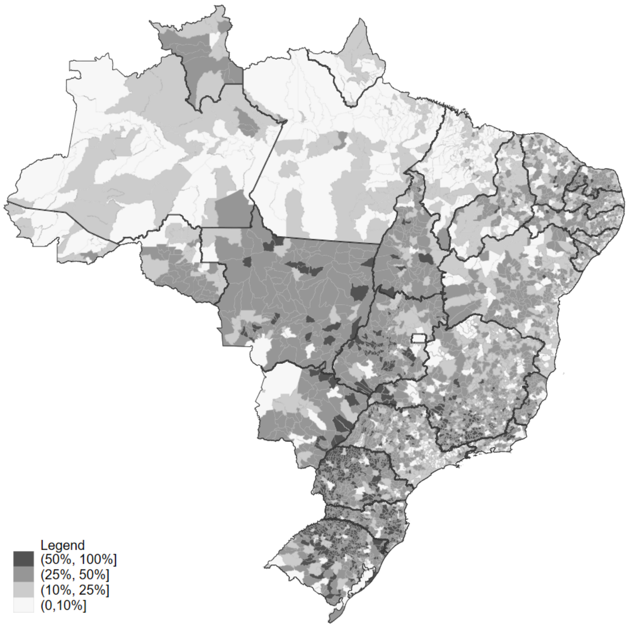


Figura 5 – Average percentage of students in the final sample (2007 to 2017)

3.4 Population versus Sample Characteristics

Table 2 presents the descriptive statistics of key variables from SINASC for the population and the matched sample overall and divided by birth weight below 3500g, twins and twins with sibling matched. The cut-off of 3500g was chosen to generate a sample with common support to the twin sample, as 95% of the twins in the sample weigh less than this threshold. The average birth weight is 3185 grams for the population and 3251 grams for the full matched sample, or 2% higher than the population average. This difference, yet small, should be explained by two channels. The first is the smaller proportion of twins, which are lighter than singletons, in the matched sample compared to the population. The second and more important channel is related to neonatal and infant mortality. The lighter the baby, the higher are the chances of mortality during the first year of life, generating a sample of children that survived the first year of life, on average, heavier than the average of the totality of newborns (CARRILLO; FERES, 2017; OREOPOULOS et al., 2008; BLACK; DEVEREUX; SALVANES, 2007; UNICEF; WHO, 2004). Despite the small difference in means, Figure 6 shows that the distributions of birth-weight for the population, for the population of singletons, for the full matched sample and for matched singletons are quite similar.

It is known that twins are lighter than singletons (FIGLIO et al., 2014; ALMOND; CHAY; LEE, 2005; BLACK; DEVEREUX; SALVANES, 2007), which can be confirmed by the averages in Table 2 and by the left-shifted weight distribution for twins in Figure 6. Matched twins and twin siblings have a similar birth weight, with a difference of 75 grams. Looking at matched twin siblings, the main sample of interest, they are on average 678 grams (or 21%) lighter than the average of the population (and 744 grams or 23% lighter, relative to the full matched sample). The birth weight distribution of the sample with matched twin siblings is right-shifted compared to the distribution for all twin births (Figure 6). Again, neonatal and infant mortality partially justifies the differences in the birth weight distribution between the sample of twin siblings and the population of twins. However, other fact plays a more import role and justify the greater differences for twins compared to singletons. The sample of matched siblings has exclusively dichorionic twins, who have on average a higher birth weight than monochorionic twins, (TOWNSEND; KHALIL, 2018; PAEPE et al., 2010) who are part of the population.

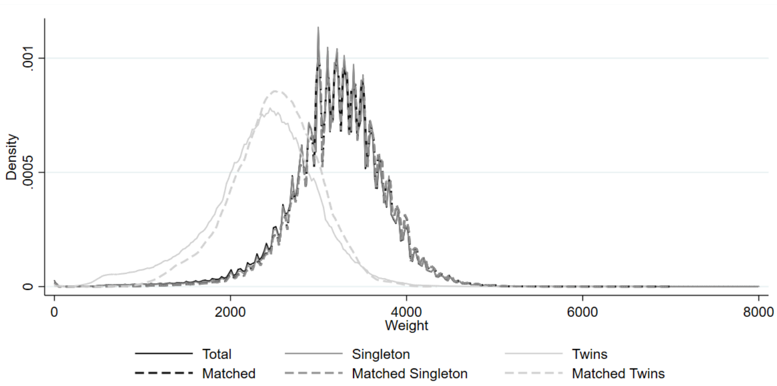


Figura 6 – SINASC weight distribution total observations and matched sample 1996-2006

Apgar scores display a pattern similar to birth weight: the full matched sample has slightly higher scores than the population and twins are the group with the lowest average Apgar score. All reasons that explain the differences in birth weight across groups are valid for the Apgar scores.

Almost the totality of registered births in Brazil occurred at hospitals (97%) and this percentage does not vary considerably across samples. Cesarean sections represent 40% of all births, reaching 65% in the sample of twins siblings matched. Although twin delivery represents an increased risk factor for mothers' and babies' lives (LAVENTHAL; TREADWELL, 2018), the rates of cesarean sections in both cases are high compared to an ideal rate of 10% to 15% that is being recommended by WHO since 1985 (WHO, 2015). On average, half the pregnant women have 7 or more prenatal visits, and one third have 4 to 6 visits, for the population and in the matched samples. These numbers are not high considering that the WHO recommendations until 2016 suggested a minimum number of 4 visits, while the current recommendation suggests 8 or more visits (WHO, 2016). Preterm birth (less than 37 weeks) occurs in 27% of the twin births and in 6% of births for the overall population. This fact is in accordance with the medical literature, since twin pregnancy increases the chances of preterm birth (LAVENTHAL; TREADWELL, 2018; TOWNSEND; KHALIL, 2018).

The educational characteristics indicate a sub-representation of highly-educated mothers in the matched sample, 35% of the matched babies have mothers with incomplete high school or higher education whereas this proportion is of 45% on the population. The remaining soci-oeconomic characteristics show that the sample of twins with matched siblings is considerably different from the population and from the full matched sample. Mothers of twins are older on average (28 years old versus 25) for the population and in full sample, in conformity with other studies (LAVENTHAL; TREADWELL, 2018; FIGLIO et al., 2014) and a higher proportion of such mothers are married.

All these facts evidence that there are differences in the characteristics of the population, if compared to the full matched sample as well as to the twins samples. Notwithstanding, when reducing the analysis to the twin sample aiming to eliminate confounding factors of the effects of birth weight on future outcomes, one should have in mind that the gains in internal validity bring some loss of external validity, due to the particular characteristics of twins.

Tabela 2 – SINASC - Average values of variables for Total, Matched Sample, Matched Singletons and Matched Twins siblings (1999 to 2006)

Variables	Total			Full Matched Sample			Sample weight <=3500g			Matched Twins			Matched Twins siblings		
	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD
Weight	24,490,950	3,185	553	4,261,319	3,251	511	3,065,297	3,024	388	22,729	2,582	600	7,237	2,507	489
Apgar 1 minute	22,547,534	8.09	1.41	3,836,756	8.10	1.35	2,752,662	8.10	1.36	20,127	7.73	1.61	6,672	7.81	1.47
Apgar 5 minute	22,392,457	9.18	1.15	3,798,692	9.25	1.16	2,727,878	9.24	1.16	19,872	8.93	1.36	6,645	9.03	1.14
Race															
White	21,473,712	0.53	0.50	4,007,322	0.54	0.50	2,859,171	0.55	0.50	20,969	0.53	0.50	6,730	0.58	0.49
Non white	21,473,712	0.47	0.50	4,007,322	0.46	0.50	2,859,171	0.45	0.50	20,969	0.47	0.50	6,730	0.42	0.49
Pregnancy type															
Singleton	24,611,632	0.98	0.13	4,294,681	0.99	0.08	3,060,506	0.99	0.09	22,962	0.00	0.00	7,286	0.00	0.00
Twins	24,611,632	0.02	0.13	4,294,681	0.01	0.08	3,060,506	0.01	0.09	22,962	1.00	0.00	7,286	1.00	0.00
Birth type															
Caesarean	24,577,814	0.40	0.49	4,289,745	0.35	0.48	3,058,421	0.34	0.47	22,839	0.56	0.50	7,280	0.65	0.48
Vaginal	24,577,814	0.60	0.49	4,289,745	0.65	0.48	3,058,421	0.66	0.47	22,839	0.44	0.50	7,280	0.35	0.48
Birth place															
Hospital	24,673,764	0.97	0.18	4,304,640	0.95	0.22	3,064,316	0.95	0.21	22,950	0.95	0.22	7,281	0.96	0.19
Home or other place	24,673,764	0.03	0.18	4,304,640	0.05	0.22	3,064,316	0.05	0.21	22,950	0.05	0.22	7,281	0.04	0.19
Prenatal visits															
None	23,147,428	0.04	0.19	4,073,301	0.04	0.19	2,907,700	0.04	0.19	21,555	0.04	0.21	6,950	0.03	0.17
1 to 3	23,147,428	0.10	0.30	4,073,301	0.11	0.31	2,907,700	0.11	0.32	21,555	0.11	0.32	6,950	0.09	0.29
4 to 6	23,147,428	0.34	0.47	4,073,301	0.38	0.49	2,907,700	0.38	0.49	21,555	0.37	0.48	6,950	0.36	0.48
7 or more	23,147,428	0.52	0.50	4,073,301	0.47	0.50	2,907,700	0.47	0.50	21,555	0.47	0.50	6,950	0.52	0.50
Pregnancy length															
Less than 36 weeks	24,265,933	0.06	0.24	4,245,678	0.05	0.21	3,027,637	0.06	0.24	22,324	0.26	0.44	7,156	0.27	0.44
37 to 41 weeks	24,265,933	0.92	0.28	4,245,678	0.92	0.27	3,027,637	0.91	0.28	22,324	0.71	0.45	7,156	0.72	0.45
42 or more weeks	24,265,933	0.02	0.15	4,245,678	0.03	0.17	3,027,637	0.03	0.16	22,324	0.03	0.16	7,156	0.01	0.12
Mother Age	24,580,093	24.9	6.35	4,284,685	24.6	6.38	3,051,662	24.3	6.39	22,815	27.3	6.48	7,276	28.0	6.33
Nbr. of live children	21,569,141	1.34	1.63	3,842,415	1.46	1.78	2,726,358	1.38	1.73	20,820	1.96	2.12	6,750	1.89	2.07
Mother education															
None	22,841,507	0.04	0.19	3,989,793	0.06	0.23	2,847,628	0.05	0.23	21,107	0.08	0.27	6,816	0.07	0.25
Incomplete elementary school	22,841,507	0.51	0.50	3,989,793	0.59	0.49	2,847,628	0.59	0.49	21,107	0.59	0.49	6,816	0.56	0.50
Incomplete high school	22,841,507	0.32	0.47	3,989,793	0.26	0.44	2,847,628	0.26	0.44	21,107	0.22	0.42	6,816	0.25	0.43
Complete high school or more	22,841,507	0.12	0.33	3,989,793	0.09	0.29	2,847,628	0.09	0.29	21,107	0.11	0.31	6,816	0.12	0.33
Mother marital status															
Single	22,095,956	0.46	0.50	3,898,636	0.44	0.50	2,781,608	0.44	0.50	20,710	0.39	0.49	6,672	0.35	0.48
Married	22,095,956	0.53	0.50	3,898,636	0.55	0.50	2,781,608	0.55	0.50	20,710	0.60	0.49	6,672	0.63	0.48
Divorced or Widow	22,095,956	0.01	0.10	3,898,636	0.01	0.10	2,781,608	0.01	0.10	20,710	0.01	0.12	6,672	0.02	0.12
Mother occupation															
Outside the household	16,099,207	0.32	0.47	2,931,605	0.37	0.48	2,102,741	0.36	0.48	15,074	0.41	0.49	4,996	0.42	0.49
Housewife	16,099,207	0.68	0.47	2,931,605	0.63	0.48	2,102,741	0.64	0.48	15,074	0.59	0.49	4,996	0.58	0.49

The last descriptive statistics presented come from the School Census. In fact, the existence of duplicated registers in this dataset complicates the computation of retention, dropout, age grade distortion and high school competition rates for all students. The panel of students, which ignores the existence of duplicated registers, does not generate reliable statistics. To overcome this issue, the rates are computed only for the merged sample (which accounts for duplicate cleaning) and official rates published by INEP are used to compare the population rates with the ones obtained in the sample.

Using INEP rates, published each year by grades, it is possible to recover the overall rate (repetition, dropout, and age-grade distortion) in each year. However, official rates consider all students' cohorts enrolled at a school in a given year, while the rates computed using the sample consider only students born from 1999 to 2006. Thus, looking at the School Census cross-section for example, in 2008, the oldest students present in the sample are enrolled in grade 4, or in lower grades[16]. For 2009, the sample comprises students at grade 5, or lower grades, and so on. Therefore, the overall official rates for each year were recovered taking into account the grades found in the sample. Even so, the official rate may be composed of older students and will be higher than the rates obtained using the sample. For more recent years, the sample cohorts comprise a greater part of the student population, so that the divergences between official and estimated rates tend to be smaller. Figure 7 confirms these facts. The divergence between official and estimates rates are expected, not actually a problem. Furthermore, they confirm that the rates computed using the sample are reliable, especially when presented by age (as in the estimations). Unfortunately, the official rates are not presented by age and the best comparison possible is the one carried out.

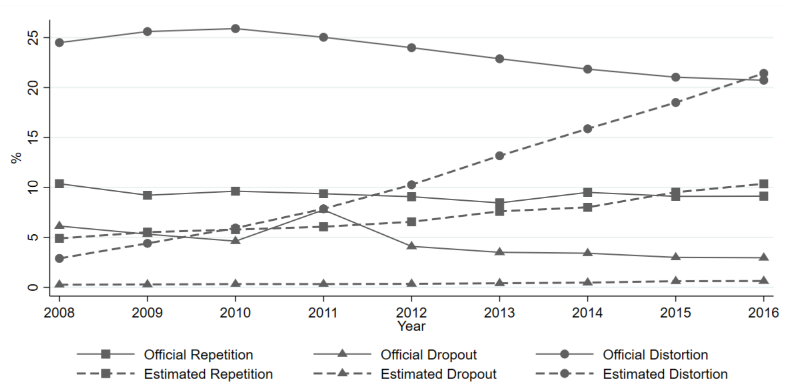


Figura 7 – Retention, dropout and age-grade distortion rates- using official and estimated rates- 2008-2016

Table 3 presents the mean rates in each sample considered. The twin sample presents some outcomes slightly higher than the other samples. For the full sample, for the sample with birth weight less than 3500g and for the one with twins with a matched sibling, 38% of the students have repeated a grade, whereas this figure is 43% in the sample of twins. The chances of repeating a grade and dropping out of school increase with age and around 40% of 16-17 year old students have completed high school.

[16] They entered school at the age of 6 in 2005.

Tabela 3 – School Census - Average values of Retention, dropout age-grade distortion and high school completion rates overall and by age

	Full Matched Sample			Sample weight <=3500g			Twins Matched			Twins siblings Matched		
Variables	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD
Repetition	4,306,170	0.38	0.49	3,065,297	0.38	0.48	26,038	0.43	0.49	7,286	0.37	0.48
At age 7	2,922,873	0.03	0.17	2,093,452	0.03	0.17	17,227	0.04	0.19	5,161	0.03	0.16
At age 8	3,660,725	0.07	0.25	2,613,115	0.07	0.25	21,828	0.08	0.28	6,340	0.07	0.26
At age 9	4,198,111	0.09	0.28	2,989,137	0.09	0.28	25,259	0.11	0.31	7,156	0.10	0.29
At age 10	4,233,455	0.09	0.29	3,013,882	0.09	0.29	25,515	0.11	0.32	7,199	0.10	0.30
At age 11	4,237,038	0.08	0.27	3,016,415	0.08	0.27	25,566	0.10	0.30	7,209	0.09	0.28
At age 12	3,678,977	0.09	0.28	2,618,076	0.08	0.28	22,614	0.10	0.30	6,096	0.09	0.28
At age 13	3,105,652	0.11	0.31	2,208,832	0.10	0.31	19,198	0.12	0.32	5,052	0.10	0.30
At age 14	2,529,068	0.12	0.33	1,793,974	0.12	0.33	15,927	0.13	0.34	4,084	0.11	0.31
At age 15	1,912,295	0.13	0.33	1,351,163	0.13	0.33	12,187	0.14	0.34	3,090	0.12	0.32
At age 16	1,289,661	0.13	0.34	907,990	0.13	0.33	8,226	0.14	0.35	2,116	0.13	0.33
Dropout	4,306,170	0.03	0.18	3,065,297	0.03	0.18	26,038	0.04	0.19	7,286	0.03	0.16
At age 7	3,215,996	0.00	0.05	2,304,046	0.00	0.05	18,958	0.00	0.05	5,599	0.00	0.04
At age 8	3,782,770	0.00	0.07	2,699,957	0.00	0.07	22,605	0.01	0.07	6,480	0.00	0.05
At age 9	4,278,069	0.00	0.07	3,045,595	0.00	0.07	25,839	0.01	0.07	7,258	0.00	0.05
At age 10	4,293,839	0.00	0.06	3,056,716	0.00	0.06	25,940	0.00	0.07	7,273	0.00	0.05
At age 11	3,738,686	0.00	0.06	2,660,391	0.00	0.06	23,046	0.00	0.07	6,186	0.00	0.05
At age 12	3,167,563	0.00	0.07	2,252,724	0.00	0.07	19,674	0.01	0.08	5,151	0.00	0.06
At age 13	2,604,368	0.01	0.07	1,847,140	0.01	0.07	16,436	0.01	0.08	4,193	0.01	0.08
At age 14	2,047,621	0.01	0.08	1,445,678	0.01	0.08	13,049	0.01	0.09	3,244	0.01	0.09
At age 15	1,477,733	0.01	0.09	1,039,496	0.01	0.09	9,462	0.01	0.09	2,349	0.01	0.08
At age 16	925,822	0.01	0.11	645,744	0.01	0.11	6,011	0.01	0.12	1,513	0.02	0.12
Age-grade distortion	4,306,170	0.29	0.45	3,065,297	0.29	0.45	26,038	0.34	0.47	7,286	0.29	0.45
At age 7	3,666,499	0.02	0.15	2,617,330	0.02	0.15	21,913	0.03	0.17	6,346	0.02	0.14
At age 8	4,177,148	0.03	0.16	2,974,593	0.03	0.16	25,165	0.03	0.18	7,133	0.03	0.16
At age 9	4,203,564	0.07	0.25	2,992,967	0.07	0.26	25,376	0.09	0.29	7,167	0.08	0.26
At age 10	4,215,511	0.12	0.33	3,001,594	0.13	0.33	25,430	0.16	0.37	7,188	0.14	0.35
At age 11	4,217,722	0.16	0.36	3,002,795	0.16	0.36	25,433	0.20	0.40	7,165	0.18	0.38
At age 12	3,662,548	0.18	0.39	2,606,303	0.19	0.39	22,516	0.23	0.42	6,060	0.21	0.40
At age 13	3,094,648	0.24	0.42	2,201,001	0.24	0.42	19,127	0.29	0.45	5,030	0.26	0.44
At age 14	2,521,942	0.27	0.45	1,788,881	0.27	0.45	15,908	0.32	0.47	4,075	0.29	0.45
At age 15	1,907,024	0.29	0.45	1,347,545	0.29	0.45	12,157	0.34	0.47	3,079	0.31	0.46
At age 16	1,287,720	0.27	0.44	906,749	0.27	0.45	8,216	0.32	0.47	2,112	0.29	0.46
Non-cumulative age grade distortion	4,306,170	0.29	0.45	3,065,297	0.29	0.45	26,038	0.34	0.47	7,286	0.29	0.45
At age 7	3,666,499	0.02	0.15	2,617,330	0.02	0.15	21,913	0.03	0.17	6,346	0.02	0.14
At age 8	4,164,643	0.02	0.15	2,965,468	0.02	0.15	25,073	0.03	0.17	7,109	0.02	0.15
At age 9	4,128,750	0.05	0.22	2,938,309	0.05	0.22	24,845	0.07	0.26	7,036	0.06	0.23
At age 10	4,006,440	0.08	0.27	2,850,001	0.08	0.27	23,824	0.10	0.31	6,798	0.09	0.29
At age 11	3,849,038	0.08	0.26	2,736,089	0.08	0.27	22,612	0.10	0.30	6,476	0.09	0.28
At age 12	3,233,686	0.08	0.27	2,297,083	0.08	0.27	19,234	0.10	0.30	5,258	0.09	0.28
At age 13	2,657,814	0.11	0.31	1,886,831	0.11	0.31	15,757	0.13	0.34	4,218	0.11	0.32
At age 14	2,521,942	0.27	0.45	1,788,881	0.27	0.45	15,908	0.32	0.47	4,075	0.29	0.45
At age 15	1,583,636	0.14	0.35	1,117,394	0.14	0.35	9,659	0.17	0.38	2,484	0.14	0.35
At age 16	1,071,126	0.12	0.33	752,809	0.12	0.33	6,559	0.15	0.36	1,722	0.13	0.34
High School completion	979,610	0.41	0.49	682,175	0.41	0.49	6,388	0.35	0.48	1,570	0.39	0.49

4 Conceptual Framework

This section describes the economic framework underlying the channels through which birthweight can affect short-run outcomes such as the Apgar score, as well as mid-run educational outcomes like grade retention, school dropout, and high school completion. The economic framework presents the sources of bias when using the Ordinary Least Square (OLS) estimates and shows how a twin fixed effect (TFE) estimator addresses these biases. The section dealing with the empirical framework presents the OLS and TFE models used.

4.1 Economic Framework

The economic framework presented next is an application of the model proposed by Bharadwaj, Eberhard e Neilson (2018). The model considers the following general production function for a child outcome (T_{ijg}), parental investments (X_{ijg}) and infant endowments (θ_{ijg}) for a child i born to mother j at age (g) who has a sibling denoted by i':

$$T_{ijg} = T(X_{ijg}, \theta_{ijg}) \tag{1}$$
$$X_{ijg} = f(\theta_{ijg}, \theta_{i\prime jg}) \tag{2}$$
$$\theta_{ijg} = f(\theta_{ij(g-1)}, X_{ij(g-1)}) \tag{3}$$

The child outcome (health or educational outcome) is a function of parental investments (X_ijg) and current endowment (θ_{ijg}). The intra-household allocation decision of parental investment depends on each child's endowments ($\theta_{ijg}, \theta_{i'jg}$) and has the characteristics of a public good, as it is subsequently discussed. Finally, children's endowments are a function of previous endowments ($\theta_{ij(g-1)}$) and of past investments ($X_{ij(g-1)}$).

An initial shock e_{ij0}, such as being born low birthweight, can only have a direct effect on the initial endowment and will affect future outcomes only through the effect it has on initial endowment. Therefore, the effects of the shock on the child and his or her sibling are:

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

$$\frac{dT_{i\prime jg}}{de_{ij0}} = \frac{\partial T}{\partial X_{i\prime jg}} \cdot \frac{\partial X_{i\prime jg}}{\partial \theta_{ijg}} \cdot \frac{\partial \theta_{ijg}}{\partial \theta_{ij0}} \cdot \frac{\partial \theta_{ij0}}{\partial e_{ij0}} \tag{5}$$

The first term in both Equation 4 and Equation 5 is the intra-household resource reallocation as a response to the initial shock. The second term is a biological effect of the shock e_{ij0} that affects only the child that suffered it through θ_{ij0}.

The biological effect is assumed to be negative. As discussed in Section 2, being born with a low birth weight is associated with changes in the brain structure that have a negative impact on short and long-run outcomes. The sign of the resource reallocation effect, however, depends on parental preferences and on the way parents react to the initial shock. If parents have a preference for equalizing children's outcomes by investing more in the child who suffered the negative shock, this *compensating behavior* will have a positive sign as it may reduce, or even cancel out, the effects of the shock. On the other hand, parents can have preferences by investing more in the child with a higher return, so that this *reinforcing behavior* will have a negative sign, amplifying the effects of the initial shock.

In the absence of information that captures all the investment parents have made in each child, the coefficient associated with the initial shock (birthweight, for example) in an OLS estimation that captures the biological and resource allocation effects. Assuming that parents' investment has the features a public good, the TFE estimator nets-out the resource allocation effect, allowing to isolate the biological effects.

The idea behind the public good dimension of parental investment is that when children are close in age, and in the most extreme case twins, parental investments have a spillover effect. Hence, parents cannot fully differentiate in which child to invest. When parents can only partially differentiate, the reinforcing or compensating effect is attenuated and will thus take longer to have greater effects. When no differentiation is possible, the difference between siblings' outcomes will be considerably stable over time.

Assuming that parents cannot invest differently in each twin and that hence the TFE estimator nets-out the resource reallocation effects, the difference in magnitude between OLS and TFE coefficients can be interpreted as evidence of reinforcing or compensating parental behavior. For outcomes measuring positive achievements, e.g. high school completion, if OLS estimates are larger with respect to TFE, parents may be reinforcing the differences among children, whereas smaller OLS estimates can be seen to reveal a compensating behavior.

More details on the model are presented by Bharadwaj, Eberhard e Neilson (2018), who also demonstrate the public good dimension of parental investment and discuss the model's limitations more thoroughly. The main limitation important for this application is that parental investments are the only source of investment in children, ignoring, for instance, investments by medical services or by teachers, which can both differ across siblings. Despite these limitations, the model is useful to shed light on the channels through which birth weight can affect future outcomes and on the way TFE estimations address the biases present in OLS estimations.

4.2 Empirical Framework

Following Bharadwaj, Eberhard e Neilson (2018), the outcome (Equation 1) can be written in an alternative representation, as a function of past parental investment and endowments. Thus:

$$T_{ijg} = T(X_{ijg}, X_{ij(g-1)}, \cdots, X_{ij0}, \theta_{ij0}) \tag{6}$$

And a liner version for estimations purposes, Equation 6 is:

$$T_{ijg} = \lambda_g \theta_{ij0} + \beta_1 X_{ijg} + \beta_2 X_{ij(g-1)} + \cdots + \beta_t X_{ij0} + e_{ijg} \tag{7}$$

Where the outcome of infant i, born from mother g at age g (T_ijg) is explained by the initial endowment at birth θ_{ij0}, by the complete history of parental investments, the vector X, and by an error term e_{ijg}. Moreover, the parental investments vector includes choices made even before birth such as the mother's decisions related to her health (smoking or drug use) and prenatal visits. Birth weight is the endowment at birth θ_{ij0} and θ_g is the parameter of interest.

In the absence of measurements for the complete history of parental investment $X = (X_{ijg}, X_{ij(g-1)}, \cdots, X_{ij0})$, parental characteristics can be used as controls, partially capturing the effects of investments. Hence, the outcome T_{ijg} is expressed as:

$$T_{ijg} = \lambda_g BW_{ij} + X'_{ij}\beta + e_{ijg} \tag{8}$$

Parental observable characteristics, such as mother's education, age, and marital status are thus considered as part of vector X. However, the parental investment itself is unobservable and will be in the error term e_{ijg}. According to the Equation 2, parents' inputs that directly affect the outcome are a response to children's current endowments that is itself dependent on initial endowment (Equation 3). In this particular case, these facts imply that parental investment choices are correlated with the birth weight (the initial endowment). Therefore, OLS estimations of Equation 8 generate biased estimates of λ_g, the parameter of interest. The bias is given by the relation between birth weight and X as follows:

$$\lambda_g^{OLS} = \lambda_g + \frac{Cov(BW_{ij}, X)}{Var(BW_{ij})} \tag{9}$$

The direction of the bias in the OLS estimates depends on whether parents act in order to equalize or reinforce differences between children. The twin fixed effect estimator used by Bharadwaj, Eberhard e Neilson (2018), Figlio et al. (2014), Black, Devereux e Salvanes (2007), Almond, Chay e Lee (2005) among others, can address this potential bias by using the variation in birth weight among twins and the fact that parental investment does not vary among twins. Taking the differences of Equation 8 with respect to the twin sibling $i\prime$ generates:

$$T_{ijg} - T_{i\prime jg} = \lambda_g(BW_{ij} - BW_{i\prime j}) + \underbrace{(X'_{ij} - X'_{i\prime j})\beta + (e_{ijg} - e_{i\prime jg})}_{\varepsilon_{ijg} - \varepsilon_{i\prime jg}} \tag{10}$$

The part of vector X that refers to the parental characteristics is necessarily the same for twins. Furthermore, as it is discussed in Section 2 the only source of variation in birth weight among twins is associated to placental characteristics, mainly the position of cord insertion that caused differences in nutritional intake (disregarding anomalies). Regarding to parental investments, the aforementioned model assumes that it has a public good dimension, so that parents cannot completely differentiate investment across twins. The weaker hypothesis needed for the estimation of an unbiased λ_g is that parental investment is necessarily the same (has perfect spillover) when parents wish to differentiate investment *based on birth weight*.

Equation 10 is estimated via TFE using the natural logarithm of birth weight and dummies for twins and controlling only by child gender (which is necessarily different between twins in the sample considered). In order to compare the TFE estimates with the OLS estimates, Equation 8 is also estimated using the natural logarithm of birth weight, gender, and race as child individual controls. Vector X includes: mother's age, education, marital status, occupation, number of prenatal visits, dummies for Brazilian macro-region and for birth cohorts. Except for the Apgar, all other outcomes are binary variables and thus the OLS estimations are in fact a Linear Probability Model (LMP).

Two concerns with the TFE approach should be emphasized. The first one regards the fact that both twins should be observed in school registers to be part of the sample. Biases can be raised if the reasons why one twin is not in school registers is correlated with birth weight. For instance, due to neonatal mortality of the lower birthweight child. This source of selection is more likely to happen with the lighter twin not being part of the sample. Supposing that the lightest twins are not in the sample, and so their respective twin pairs, this would lead to an underestimation of the coefficients λ_g. A similar effect can also happen to the OLS estimations. However, this bias is not of major concern if one considers that the sample of interest relies on babies that survived.

The second concern is the fact that because of the matching strategy the sample of twins has only fraternal and not identical twins. One can argue that the estimated effects can be the

expression of genetic characteristics through birth weight rather than to birth weight itself. This argument is minimized firstly by referring to medical literature and secondly by considering similar papers that could test for zygotic characteristics. According to medical literature, the main cause for birth weight differences even between identical twins is the position of the umbilical cord. Boys are more likely to be heavier than girls and this is the reason why gender is an important variable to account for, but it is difficult to believe that other genetic characteristics that determine a baby's weight play an important role in determining future outcomes. Considering similar research, Black, Devereux e Salvanes (2007) has access to zygosity information and found no differences in the effects estimated using the full twin sample and the monozygotic sample for high school completion, the probability of full-time work and adult earnings. Figlio et al. (2014) do not have access to zygosity information but test differences in effects of birth weight in test scores considering a same-sex sample, which has a larger share of monozygotic twins. They found no differences in estimations using the full and gender-restricted samples. Because of all these facts, it is not likely that genetic differences are the main driver of the results.

5 Results

5.1 Main results

The OLS and TFE estimates of effects of birth weight on Apgar score, repetition rate, dropout, age-grade distortion and high school completion are shown as follows. The estimates are obtained using: (i) full matched sample, (ii) the sample with birth weight less than 3500 grams, (iii) the twins sample and (iv) sample with matched twin siblings. The TFE estimator is implemented only in the last sample (matched twin siblings), which is also used for the OLS estimations in order to make results comparable across samples. The OLS and TFE regressions include a set of control variables that are omitted from the tables presented. The results tables include an auxiliary estimate of the percentage change in the outcome of interest as a response to a 10% increase in birth weight, displaying the stars for the statistical significance of the coefficient.

Table 4 shows the results for the one and five minute Apgar scores and for high school completion. The OLS estimate using the full sample for Apgar at 1 minute of life indicates that a 10% increase in birth weight is associated with a Apgar increase of 0.067 (in a scale of 0 to 10). The average Apgar at 1 minute for the full sample is 8.10, implying the estimated 0.8% increase. The coefficient for birth weight increases by a factor of 2 using the sample with less than 3500g, and by a factor of 2.5 for the twin sample and for the sample of matched twins siblings. All the three alternative samples select babies with potentially poor health outcomes compared to the full sample since the weight cut-off and twin pregnancy imply increased health vulnerability. Hence, the overall increase in the coefficient is justified by the selection of more vulnerable babies. The sample of matched twin siblings is a subsample of the matched twins sample, with potentially less confounding factors. Therefore, the OLS coefficient in the twin siblings sample is expected to be more similar, and more comparable, to the TFE estimate rather than the OLS coefficient in the twins sample.

The TFE estimated for the one minute Agpar implies that a 10% increase in birth weight raises the Apgar by 0.083, or by 1.1% over the average Agpar. The coefficient point estimate obtained by TFE is smaller than the OLS estimates, in line with what Black, Devereux e Salvanes (2007), Almond, Chay e Lee (2005) found for Apgar at 5 minutes.

The estimates for Apgar at 5 minute follow the same pattern observed for the results for Apgar at 1 minute, but are smaller in magnitude. The five minute Apgar measurement incorporates the newborn's response to the resuscitation methods, or to other interventions applied when needed, being less sensitive to weight only. Other birth conditions that include

the hospital and even the medical team also play a crucial role in the determination of the five minute Apgar. The OLS and TFE coefficients estimated using the twins sample can be compared to the results found by Black, Devereux e Salvanes (2007) for Norway. The OLS point estimate for the twin sample in Norway is 1.46 (standard deviation 0.06) and the twin fixed effect point estimate is 0.35 (standard deviation 0.07)[17], while for Brazil these estimates are respectively 1.14 (or 1.15 for the whole twins sample) and 0.526.

According to the economic framework presented in Section 4 both estimates suggest that immediate neonatal care acts as a compensating component, equalizing health differences among twins. Especially for the most vulnerable and fragile babies, actions taken immediately after birth are essential to save the infant's life. Consequently, the compensating behavior in this context is not surprising given that it is a matter of saving a baby's life. Nevertheless, the TFE estimate for Brazil is higher than for Norway, while the OLS estimate for Brazil is smaller. The two OLS estimates use a different set of controls and the estimates for Brazil that use a set of controls as similar as possible to Black, Devereux e Salvanes (2007) generate a coefficient of 1.09 in the twin siblings sample[18]. Anyhow, the differences in socioeconomic context between Brazil and Norway play a more important role in explaining the differences in magnitude[19].

The probability of high school completion is the first educational outcome analyzed. Although, from the perspective of a life cycle sequence, it is the last educational outcome considered in this research, its results are displayed first because it is also comparable to Black, Devereux e Salvanes (2007). Birth weight is positively associated with the probability of high school completion at age 17 or 18, feasible and adequate ages to finish high school in Brazil. The OLS estimates are all close in magnitude implying that a 10% increase in birth weight is associated with a 0.8 to 1.3 percentage points increase in the probability of completing high school before 18 years old (similarly to Black, Devereux e Salvanes (2007)). Even though the effect on percentage point might seem small, it represents a rise in the chances of completing high school from 2% to 3.1% depending on the sample considered. The TFE estimate, by its turn, reveals that the magnitude of birth weigh impact is twice bigger, a 10% increase in birth weight raises the chances of finishing high school by 2.3 percentage points or 6%.

In contrast to the relation found for the Apgar scores (in which parents behave compensating the effect of low birth weight), the TFE coefficient for high school completion is greater in magnitude than the OLS, suggesting that parents act reinforcing the effect of low birth weight on educational outcomes. The educational outcomes presented next add evidence to this finding. Retention rates, school dropout, and age-grade distortion are variables negatively associated with birth weight, meaning that the higher the weight, the lower are the chances to have these adverse outcomes. The biological effect of the initial shock (being born low birthweight) has a positive sign, raising the chances of the adverse outcome. Therefore, if the module of TFE coefficient is greater than the module of the OLS, parents are reducing the positive effect of raising the birth weight and *reinforcing* the effect of the initial shock. Contrarily, if the module of the TFE is smaller than OLS, parents have a *compensating* behavior, mitigating the effect of the initial shock and reducing the chances of the adverse outcome as the birth weight increases.

Table 5 displays the results for the probability of repeating a grade at any time and by age. The first fact to be noted is that the OLS and TFE coefficients are negative, confirming the fact that the higher the birth weight, the lower the chances of repeating a grade at any

[17] Black, Devereux e Salvanes (2007) have a larger sample with more than 20,000 twins.

[18] The controls used by Black, Devereux e Salvanes (2007) are: year and month of birth dummies, indicators for mother's education and age, sex of the child and birth order. Birth order is not available in Brazilian registers, but all other variables are a subset of the controls used in the OLS estimates. The OLS coefficient using the subset of controls for the twins sample is 1.11 (standard error 0.052) and 1.09 (standard error 0.071) for the matched twin siblings.

[19] For instance, while 88% of the mothers in Brazil have less than 12 years of education (incomplete high school or less) the average education of mothers in Norway is 11.25 years of schooling.

age. The TFE coefficient suggests that a 10% increase in birth weight reduces the chances of repeating a grade in 1.3 percentage point or in 3.5% for an average repetition rate of 37% (one-third of students have repeated a grade at least once). The overall chance, however, hides differences across ages that can also be associated with the organization of grades in cycles and with policies of automatic promotion within a cycle. Unfortunately, the School Census does not inform the cycles' structures within schools. At ages of 7 and 8 students attend the 2^{nd} and 3^{rd} grade, respectively. The non-significative TFE effect for these grades are explained by the fact that repetition rates are lower in first grades (3% and 7%, respectively). At the age of 9, when students who have not repeated before are in grade 4, the repetition rate is 9.5%, and the effect of birth weight is to reduce the chances of grade retention in 10.4%. For students 11, 12 and 13 years old the effects are also considered to be high, reaching a reduction of -11.6% in the probability of repeating a grade as a response to a 10% increase in birth weight. For ages 14 to 16, when students with no previous repetitions are in the 9^{th} grade or 1^{st} and 2^{nd} grade of high school the effects are statistically zero.

When the TFE coefficients of birth weight are statistically different from zero, they are always bigger in module in comparison to the OLS coefficient for all samples. The increase in birth weight has a smaller effect of reducing the chances of grade retention when parents' behavior is accounted for (OLS estimate). Parents seem to choose to invest in the child with the higher return.

The estimates for school dropout are presented in Table 6. It is worth to highlight that dropout rates are not as accurate as the other outcomes due to data limitations. Anyhow, this outcome shows important results. The OLS estimates for the full sample and for the sample with less than 3500g are negative and statistically significant. The effect for dropout at any age indicates a 2.8% decrease in the chances of dropping out of school in response to a 10% increase in birth weight. For the twins sample, either OLS or TFE estimates give small coefficients, which are statistically equal to zero. The twins sample contains a larger share of siblings than the full sample, while the sample of matched twin siblings necessarily contains only siblings. The composition of these samples can explain the differences in the results obtained since it is less likely to have parents allowing just one child to drop out of school. Repeating a grade is an event that occurs independently of parents approval, whereas it is less likely to believe that parents will allow just one of the twin siblings to drop out of school. The absence of variation among twins explains the null results for the twins samples.

For the age-grade distortion, Table 7 and Table 8 show that the OLS coefficient indicates a 3.9% decrease in the probability of being older than the adequate for a grade, when birth weight increases by 10%. The overall effect, however, is non-significant when estimated using TFE. This fact is driven by the absence of effect in early life, since the TFE is significant and larger in magnitude than the OLS mainly after the age of 9. As for the retention grade, the coefficients evidence a reinforcing behavior on the part of parents.

Tabela 4 – OLS and TFE Estimates: Apgar 1 and 5 Minute

	(1)	(2)	(3)
Variables	Apgar 1 minute	Apgar 5 minute	High school completion
OLS-Full sample			
Ln weight	0.671***	0.577***	0.115***
	(0.00550)	(0.00470)	(0.00287)
Beta: % of the mean	0.8%***	0.6%***	2.8%***
Observations	3,811,466	3,774,567	948,081
R-squared	0.031	0.035	0.151
OLS-Sample weight <=3500g			
Ln weight	1.218***	0.966***	0.127***
	(0.00798)	(0.00689)	(0.00400)
Beta: % of the mean	1.5%***	1.0%***	3.1%***
Observations	2,742,273	2,718,066	673,258
R-squared	0.041	0.043	0.152
OLS-Twins sample			
Ln weight	1.615***	1.149***	0.0869***
	(0.0528)	(0.0521)	(0.0228)
Beta: % of the mean	2.1%***	1.3%***	2.5%***
Observations	22,221	21,870	6,132
R-squared	0.082	0.073	0.145
OLS-Twins siblings matched sample			
Ln weight	1.621***	1.146***	0.0778
	(0.0925)	(0.0704)	(0.0574)
Beta: % of the mean	2.1%***	1.3%***	2.0%
Observations	6,652	6,625	1,544
R-squared	0.064	0.066	0.174
TFE-Twins siblings matched sample			
Ln weight	0.831***	0.526***	0.233**
	(0.169)	(0.0980)	(0.0970)
Beta: % of the mean	1.1%***	0.6%***	6.0%**
Observations	6,638	6,612	1,544
R-squared	0.772	0.827	0.782

*** p<0.01, ** p<0.05, * p<0.1.The beta as % of the mean is computed using the mean of the outcome variable for the sample considered.

All OLS estimates include as controls: student gender and race, mother age, education, marital status and occupation, number of prenatal visits, dummies for Brazilian macro-region and for birth cohorts. Robust standard errors of the OLS estimates are in parentheses.

The TFE estimate includes as controls: student gender and fixed effect dummies for twins. Clustered standard errors at twins level of the TFE estimates are in parentheses.

Tabela 5 – OLS and TFE Estimates: Repetition rate- overall and by age

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Retention	At age 7	At age 8	At age 9	At age 10	At age 11	At age 12	At age 13	At age 14	At age 15	At age 16
OLS-Full sample											
Ln weight	-0.102***	-0.00619***	-0.0290***	-0.0450***	-0.0484***	-0.0422***	-0.0354***	-0.0261***	-0.0273***	-0.0286***	-0.0274***
	(0.00133)	(0.000625)	(0.000816)	(0.000862)	(0.000877)	(0.000831)	(0.000918)	(0.00109)	(0.00128)	(0.00149)	(0.00184)
Beta: % of the mean	-2.7%***	-2.1%***	-4.3%***	-5.2%***	-5.4%***	-5.3%***	-4.2%***	-2.5%***	-2.2%***	-2.3%***	-2.1%***
Observations	4,237,826	2,892,322	3,614,735	4,132,864	4,167,054	4,170,334	3,615,102	3,047,057	2,476,420	1,868,233	1,256,021
R-squared	0.165	0.015	0.034	0.038	0.042	0.043	0.042	0.043	0.043	0.040	0.027
OLS-Sample weight <=3500g											
Ln weight	-0.108***	-0.00613***	-0.0296***	-0.0469***	-0.0511***	-0.0446***	-0.0382***	-0.0277***	-0.0286***	-0.0293***	-0.0250***
	(0.00182)	(0.000850)	(0.00112)	(0.00119)	(0.00121)	(0.00114)	(0.00126)	(0.00148)	(0.00174)	(0.00204)	(0.00252)
Beta: % of the mean	-2.8%***	-2.0%***	-4.4%***	-5.4%***	-5.7%***	-5.6%***	-4.5%***	-2.6%***	-2.4%***	-2.3%***	-1.9%***
Observations	3,047,615	2,086,013	2,602,646	2,972,294	2,996,681	2,999,105	2,600,745	2,192,240	1,778,240	1,336,922	895,883
R-squared	0.166	0.015	0.035	0.038	0.042	0.044	0.043	0.044	0.044	0.040	0.027
OLS-Twins sample											
Ln weight	-0.0558***	0.00571	-0.0105	-0.0364***	-0.0477***	-0.0242***	-0.0364***	-0.00585	-0.00727	0.00327	-0.0296*
	(0.0116)	(0.00567)	(0.00758)	(0.00804)	(0.00794)	(0.00730)	(0.00830)	(0.00885)	(0.0104)	(0.0121)	(0.0157)
Beta: % of the mean	-1.3%***	1.5%	-1.3%	-3.3%***	-4.2%***	-2.5%***	-3.7%***	-0.5%	-0.6%	0.2%	-2.1%*
Observations	25,499	16,998	21,447	24,736	24,987	25,039	22,105	18,732	15,507	11,832	7,955
R-squared	0.178	0.020	0.044	0.049	0.052	0.053	0.052	0.048	0.050	0.045	0.036
OLS-Twins siblings matched sample											
Ln weight	-0.0939***	0.0111	-0.0164	-0.0386**	-0.0657***	-0.0659***	-0.00526	-0.0153	-0.0104	-0.0368	-0.0577
	(0.0262)	(0.0116)	(0.0167)	(0.0171)	(0.0181)	(0.0169)	(0.0169)	(0.0191)	(0.0232)	(0.0282)	(0.0373)
Beta: % of the mean	-2.5%***	4.2%	-2.3%	-4.0%**	-6.5%***	-7.5%***	-0.6%	-1.5%	-1.0%	-3.1%	-4.5%
Observations	7,223	5,125	6,286	7,093	7,136	7,146	6,036	4,999	4,036	3,051	2,083
R-squared	0.187	0.017	0.052	0.052	0.071	0.067	0.063	0.058	0.058	0.052	0.052
TFE-Twins siblings matched sample											
Ln weight	-0.130***	-0.0185	-0.0373	-0.0993***	-0.000817	-0.102***	-0.0994**	-0.101**	0.0525	0.0222	-0.107
	(0.0490)	(0.0173)	(0.0268)	(0.0345)	(0.0385)	(0.0382)	(0.0405)	(0.0484)	(0.0507)	(0.0597)	(0.0863)
Beta: % of the mean	-3.5%***	-6.9%	-5.3%	-10.4%***	-0.1%	-11.6%***	-11.6%**	-10.1%**	5.0%	1.9%	-8.4%
Observations	7,226	5,006	6,190	7,020	7,070	7,084	5,964	4,924	3,962	2,948	1,924
R-squared	0.766	0.864	0.794	0.728	0.665	0.675	0.622	0.627	0.617	0.643	0.607

*** p<0.01, ** p<0.05, * p<0.1. The beta as % of the mean is computed using the mean of the outcome variable for the sample considered.
All OLS estimates include as controls: student gender and race, mother age, education, marital status and occupation, number of prenatal visits, dummies for Brazilian macro-region and for birth cohorts.
Robust standard errors of OLS estimates are in parentheses
The TFE estimate includes as controls: student gender, and fixed effect dummies for twins. Clustered standard errors at twins level of the TFE estimates are in parentheses

Tabela 6 – OLS and TFE Estimates: Dropout rate- overall and by age

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Dropout	At age 7	At age 8	At age 9	At age 10	At age 11	At age 12	At age 13	At age 14	At age 15	At age 16
OLS-Full sample											
Ln weight	-0.00874***	-0.000658***	-0.00175***	-0.00221***	-0.00184***	-0.00169***	-0.000878***	-0.00103***	-0.00106***	-0.000993**	-0.000792
	(0.000530)	(0.000179)	(0.000219)	(0.000216)	(0.000201)	(0.000217)	(0.000240)	(0.000284)	(0.000348)	(0.000454)	(0.000704)
Beta: % of the mean	-2.8%***	-2.7%***	-3.9%***	-4.9%***	-4.6%***	-4.2%***	-2.0%***	-2.0%***	-1.7%***	-1.3%**	-0.7%
Observations	4,237,826	3,181,170	3,734,127	4,210,510	4,225,857	3,673,407	3,107,420	2,549,783	1,999,608	1,438,311	896,432
R-squared	0.021	0.001	0.003	0.003	0.003	0.003	0.002	0.002	0.002	0.002	0.002
OLS-Sample weight <=3500g											
Ln weight	-0.00955***	-0.000868***	-0.00166***	-0.00253***	-0.00189***	-0.00200***	-0.00102***	-0.00131***	-0.000360	-0.00108*	-0.000312
	(0.000723)	(0.000249)	(0.000303)	(0.000303)	(0.000280)	(0.000302)	(0.000325)	(0.000384)	(0.000480)	(0.000619)	(0.000969)
Beta: % of the mean	-3.0%***	-3.6%***	-3.7%***	-5.5%***	-4.7%***	-5.0%***	-2.3%***	-2.5%***	-0.6%	-1.4%*	-0.3%
Observations	3,047,615	2,295,742	2,688,920	3,028,129	3,039,134	2,642,763	2,235,808	1,830,934	1,430,299	1,025,434	637,409
R-squared	0.021	0.001	0.003	0.003	0.003	0.003	0.002	0.002	0.002	0.002	0.002
OLS-Twins sample											
Ln weight	0.00176	-0.000193	0.00123	-0.00172	-0.000224	-0.00106	0.00139	0.00281	0.00325	0.000138	0.00385
	(0.00486)	(0.00170)	(0.00212)	(0.00180)	(0.00181)	(0.00189)	(0.00243)	(0.00255)	(0.00258)	(0.00373)	(0.00613)
Beta: % of the mean	0.5%	-0.7%	2.4%	-3.4%	-0.4%	-2.3%	2.2%	4.0%	4.4%	0.2%	2.8%
Observations	25,499	18,690	22,198	25,307	25,405	22,523	19,191	15,997	12,661	9,135	5,772
R-squared	0.026	0.003	0.005	0.007	0.004	0.004	0.005	0.004	0.003	0.007	0.005
OLS-Twins siblings matched sample											
Ln weight	-0.0182**	-0.00602*	0.00222	-0.000796	-0.00209	-0.00239	-0.00361	-0.00412	0.00196	-0.00597	-0.0263
	(0.00899)	(0.00359)	(0.00249)	(0.00254)	(0.00281)	(0.00266)	(0.00381)	(0.00604)	(0.00747)	(0.0101)	(0.0193)
Beta: % of the mean	-7.3%**	-41.9%*	8.4%	-2.7%	-7.2%	-11.3%	-11.5%	-6.3%	2.5%	-8.2%	-17.9%
Observations	7,223	5,562	6,426	7,195	7,210	6,125	5,098	4,144	3,204	2,315	1,488
R-squared	0.029	0.007	0.008	0.014	0.003	0.007	0.011	0.011	0.007	0.024	0.018
TFE-Twins siblings matched sample											
Ln weight	-0.0148	-0.000723	-0.0142**	0.00126	-0.00377	-0.00413	-0.00595	0.00545	-0.000687	0.00979	-0.00628
	(0.0183)	(0.00466)	(0.00577)	(0.00448)	(0.00709)	(0.00675)	(0.00909)	(0.0126)	(0.0153)	(0.0210)	(0.0303)
Beta: % of the mean	-5.9%	-5.0%	-53.7%**	4.3%	-13.0%	-19.5%	-19.0%	8.4%	-0.9%	13.4%	-4.3%
Observations	7,226	5,502	6,400	7,172	7,200	6,122	5,100	4,142	3,204	2,292	1,454
R-squared	0.625	0.624	0.688	0.699	0.599	0.576	0.625	0.535	0.617	0.686	0.542

*** p<0.01, ** p<0.05, * p<0.1. The beta as % of the mean is computed using the mean of the outcome variable for the sample considered.
All OLS estimates include as controls: student gender and race, mother age, education, marital status and occupation, number of prenatal visits, dummies for Brazilian macro-region and for birth cohorts. Robust standard errors of OLS estimates are in parentheses
The TFE estimate includes as controls: student gender and fixed effect dummies for twins. Clustered standard errors at twins level of the TFE estimates are in parentheses

Tabela 7 – OLS and TFE Estimates: Age-grade distortion - overall and by age

Variables	(1) Grade distortion	(2) At age 7	(3) At age 8	(4) At age 9	(5) At age 10	(6) At age 11	(7) At age 12	(8) At age 13	(9) At age 14	(10) At age 15	(11) At age 16
OLS-Full sample											
Ln weight	-0.112***	-0.00893***	-0.0193***	-0.0518***	-0.0858***	-0.101***	-0.117***	-0.123***	-0.128***	-0.130***	-0.137***
	(0.00126)	(0.000480)	(0.000525)	(0.000796)	(0.00101)	(0.00110)	(0.00125)	(0.00146)	(0.00168)	(0.00197)	(0.00238)
Beta: % of the mean	-3.9%***	-4.0%***	-7.3%***	-7.6%***	-7.0%***	-6.5%***	-6.4%***	-5.3%***	-4.7%***	-4.5%***	-5.1%***
Observations	4,237,826	3,620,156	4,111,932	4,137,557	4,149,244	4,151,293	3,598,968	3,036,238	2,469,434	1,863,110	1,254,123
R-squared	0.161	0.031	0.013	0.042	0.070	0.088	0.104	0.125	0.130	0.127	0.113
OLS-Sample weight <=3500g											
Ln weight	-0.117***	-0.00851***	-0.0212***	-0.0545***	-0.0908***	-0.106***	-0.125***	-0.133***	-0.138***	-0.141***	-0.149***
	(0.00173)	(0.000656)	(0.000741)	(0.00111)	(0.00141)	(0.00152)	(0.00175)	(0.00203)	(0.00234)	(0.00275)	(0.00334)
Beta: % of the mean	-4.0%***	-3.8%***	-7.8%***	-7.8%***	-7.2%***	-6.7%***	-6.7%***	-5.7%***	-5.1%***	-4.9%***	-5.5%***
Observations	3,047,615	2,606,772	2,957,747	2,975,898	2,984,438	2,985,544	2,589,084	2,184,481	1,773,235	1,333,385	894,647
R-squared	0.162	0.032	0.014	0.043	0.071	0.089	0.106	0.126	0.131	0.128	0.115
OLS-Twins sample											
Ln weight	-0.0565***	-0.00732	-0.0132***	-0.0402***	-0.0771***	-0.0770***	-0.0938***	-0.0939***	-0.0913***	-0.0959***	-0.101***
	(0.0110)	(0.00490)	(0.00486)	(0.00745)	(0.00929)	(0.00989)	(0.0111)	(0.0126)	(0.0142)	(0.0164)	(0.0200)
Beta: % of the mean	-1.7%***	-2.6%	-4.2%***	-4.5%***	-4.8%***	-3.9%***	-4.1%***	-3.3%***	-2.9%***	-2.8%***	-3.1%***
Observations	25,499	21,532	24,646	24,858	24,901	24,912	22,016	18,668	15,491	11,803	7,944
R-squared	0.177	0.039	0.016	0.053	0.091	0.108	0.123	0.141	0.145	0.146	0.128
OLS-Twins siblings matched sample											
Ln weight	-0.0729***	0.00859	-0.0156	-0.0281*	-0.0774***	-0.0868***	-0.0786***	-0.0921***	-0.0983***	-0.122***	-0.127***
	(0.0239)	(0.00795)	(0.0100)	(0.0153)	(0.0202)	(0.0218)	(0.0249)	(0.0285)	(0.0328)	(0.0380)	(0.0475)
Beta: % of the mean	-2.6%***	4.4%	-5.8%	-3.8%*	-5.5%***	-4.9%***	-3.8%***	-3.6%***	-3.4%***	-4.0%***	-4.3%***
Observations	7,223	6,294	7,070	7,104	7,125	7,102	6,000	4,978	4,029	3,042	2,079
R-squared	0.191	0.054	0.029	0.074	0.107	0.130	0.143	0.161	0.165	0.167	0.154
TFE-Twins siblings matched sample											
Ln weight	-0.0621	-0.00343	-0.0160	-0.0922***	-0.0920**	-0.101**	-0.115**	-0.156***	-0.139**	-0.137*	-0.191**
	(0.0461)	(0.0105)	(0.0122)	(0.0273)	(0.0376)	(0.0420)	(0.0488)	(0.0565)	(0.0630)	(0.0743)	(0.0841)
Beta: % of the mean	-2.2%	-1.8%	-5.9%	-12.3%***	-6.6%**	-5.7%**	-5.6%**	-6.1%***	-4.9%**	-4.5%*	-6.5%**
Observations	7,226	6,200	6,986	7,030	7,058	7,018	5,906	4,892	3,944	2,932	1,906
R-squared	0.768	0.915	0.879	0.786	0.743	0.746	0.750	0.753	0.751	0.763	0.771

*** p<0.01, ** p<0.05, * p<0.1.The beta as % of the mean is computed using the mean of the outcome variable for the sample considered.
All OLS estimates include as controls: student gender and race, mother age, education, marital status and occupation, number of prenatal visits, dummies for Brazilian macro-region and for birth cohorts.
Robust standard errors of OLS estimates are in parentheses
The TFE estimate includes as controls: student gender and fixed effect dummies for twins. Clustered standard errors at twins level of the TFE estimates are in parentheses

Tabela 8 – OLS and TFE Estimates: Non-Cumulative Age-grade distortion- overall and by age

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Grade distortion	At age 7	At age 8	At age 9	At age 10	At age 11	At age 12	At age 13	At age 14	At age 15	At age 16
OLS-Full sample											
Ln weight	-0.112***	-0.00893***	-0.0162***	-0.0397***	-0.0570***	-0.0550***	-0.0564***	-0.0552***	-0.0598***	-0.0645***	-0.0681***
	(0.00126)	(0.000480)	(0.000494)	(0.000703)	(0.000864)	(0.000864)	(0.000951)	(0.00120)	(0.00146)	(0.00173)	(0.00201)
Beta: % of the mean	-3.9%***	-4.0%***	-6.9%***	-7.7%***	-7.3%***	-7.3%***	-7.5%***	-5.1%***	-4.5%***	-4.5%***	-5.6%***
Observations	4,237,826	3,620,156	4,099,743	4,064,553	3,946,072	3,792,059	3,181,908	2,611,982	2,080,575	1,550,304	1,045,212
R-squared	0.161	0.031	0.012	0.037	0.051	0.062	0.070	0.084	0.091	0.089	0.075
OLS-Sample weight <=3500g											
Ln weight	-0.117***	-0.00851***	-0.0179***	-0.0411***	-0.0602***	-0.0572***	-0.0600***	-0.0575***	-0.0632***	-0.0659***	-0.0698***
	(0.00173)	(0.000656)	(0.000695)	(0.000979)	(0.00120)	(0.00120)	(0.00133)	(0.00166)	(0.00201)	(0.00240)	(0.00281)
Beta: % of the mean	-4.0%***	-3.8%***	-7.4%***	-7.8%***	-7.6%***	-7.5%***	-7.9%***	-5.3%***	-4.7%***	-4.6%***	-5.6%***
Observations	3,047,615	2,606,772	2,948,679	2,921,605	2,834,207	2,720,982	2,282,624	1,873,432	1,489,358	1,106,283	743,220
R-squared	0.162	0.032	0.012	0.038	0.052	0.063	0.071	0.086	0.092	0.090	0.077
OLS-Twins sample											
Ln weight	-0.0565***	-0.00732	-0.00761*	-0.0324***	-0.0610***	-0.0388***	-0.0572***	-0.0397***	-0.0437***	-0.0289*	-0.0601***
	(0.0110)	(0.00490)	(0.00443)	(0.00670)	(0.00804)	(0.00785)	(0.00873)	(0.0105)	(0.0126)	(0.0150)	(0.0180)
Beta: % of the mean	-1.7%***	-2.6%	-2.7%*	-4.6%***	-5.9%***	-4.0%***	-5.8%***	-3.0%***	-2.8%***	-1.7%*	-4.0%***
Observations	25,499	21,532	24,555	24,334	23,346	22,180	18,839	15,414	12,551	9,408	6,360
R-squared	0.177	0.039	0.015	0.051	0.073	0.078	0.090	0.101	0.112	0.113	0.096
OLS-Twins siblings matched sample											
Ln weight	-0.0729***	0.00859	-0.0117	-0.0174	-0.0655***	-0.0716***	-0.0140	-0.0358	-0.0328	-0.0665**	-0.0827**
	(0.0239)	(0.00795)	(0.00906)	(0.0134)	(0.0179)	(0.0178)	(0.0181)	(0.0223)	(0.0268)	(0.0332)	(0.0413)
Beta: % of the mean	-2.6%***	4.4%	-4.9%	-3.0%	-7.3%***	-8.1%***	-1.7%	-3.2%	-2.6%	-4.8%**	-6.2%**
Observations	7,223	6,294	7,046	6,973	6,739	6,418	5,204	4,177	3,297	2,454	1,695
R-squared	0.191	0.054	0.028	0.068	0.083	0.096	0.102	0.115	0.127	0.127	0.122
TFE-Twins siblings matched sample											
Ln weight	-0.0621	-0.00343	-0.0162	-0.0795***	-0.0524	-0.105***	-0.0662	-0.101*	-0.0436	-0.0991	-0.133
	(0.0461)	(0.0105)	(0.0116)	(0.0265)	(0.0356)	(0.0382)	(0.0407)	(0.0523)	(0.0541)	(0.0675)	(0.0807)
Beta: % of the mean	-2.2%	-1.8%	-6.9%	-13.8%***	-5.8%	-11.9%***	-7.8%	-8.9%*	-3.5%	-7.1%	-9.9%
Observations	7,226	6,200	6,954	6,856	6,492	5,954	4,696	3,712	2,866	2,076	1,402
R-squared	0.768	0.915	0.883	0.750	0.699	0.711	0.689	0.692	0.690	0.732	0.685

*** p<0.01, ** p<0.05, * p<0.1. The beta as % of the mean is computed using the mean of the outcome variable for the sample considered.
All OLS estimates include as controls: student gender and race, mother age, education, marital status and occupation, number of prenatal visits, dummies for Brazilian macro-region and for birth cohorts. Robust standard errors of OLS estimates are in parentheses
The TFE estimate includes as controls: student gender and fixed effect dummies for twins. Clustered standard errors at twins level of the TFE estimates are in parentheses

5.2 Heterogeneous effects

In order to understand whether the previous findings changes are in conformity with socioeconomic conditions and with the profile of access to health services, this section presents estimates of the TFE model by subsamples of interest. High school completion is the only educational outcome that is not part of this exercise due to the reduced sample size. For the Apgar score, only the heterogeneity related to birth weight, maternal characteristics and health conditions are presented. For all heterogeneous, the sample is broken into two groups, so as to keep subsamples with equal sizes, approximately half of the total of observations.

The first heterogeneity divides the sample according to low birth weight. There is evidence in the literature that the lower the weight, the higher the effects would be (FIGLIO et al., 2014; BLACK; DEVEREUX; SALVANES, 2007). To test for this, the sample is divided into two subgroups, one with birth weight lower or equal to 2500g and other with weight above 2500g.

Based on the importance of the access to health services to explain birth outcomes, the second kind of heterogeneity divides births according to a proxy for the quality of public health services in the mother's municipality of residence at the time of the birth. In the mid-1900s a community-based health program (Programa Saúde da Família) has been created in Brazil and since then has provided basic health care by means of community-based professional teams [20]. The health teams are responsible for a well-defined population of 3000 to 4500 people and are based in basic health care units, being also responsible for household visits. Among other information, the Brazilian Ministry of Health provides, since 1998, data on the number of children aged 1 year old or less registered by these teams, the number of babies aged 4 months or less registered, as well as the number of medical appointments for children 1 year old or less. These three variables are used to create a measure of the access to public health care in each municipality on a monthly basis.

Using SINASC records, for each municipality/month the number of live children aged 4 months or less and 1 year or less is computed as the sum of births in the 4 months or 12 months previous to a given month (each month is included as the last month of its sum). Then, these sums are assumed to be the total population of children aged 4 months and 1 year or less. Based on the data of the community-based health services, three variables are created for each municipality/month: the share of children aged 4 months or less registered, the share of children aged 1 year or less registered and the number of medical appointments by children. A child born in month t is exposed to the share of children aged 4 months or less registered of the months $t, t+1, t+2, t+3$ and to the variables for children aged 1 year or less of the months $t, t+1, ..., t+11$. Thus, for each municipality-month, the coverage variable associated with a month of birth is the mean of the months in which the child has been exposed to health coverage. Finally, for each variable of average coverage share, the municipality is evaluated as being above or below the median for Brazil in each month. If the municipality/month is below the median in two or more variables, it is considered to have low health coverage. If the municipality/month is above the median in two or more variables, it is considered to have high health coverage.

The third type of heterogeneity regards the socioeconomic level of schools. In 2014, INEP has launched a socioeconomic status index (SES index) for schools using the socioeconomic questionnaires from two large-scale tests[21]. The index scale provides seven levels of socioeconomic status for students. The schools were classified into these same levels according to the average profile of students. In the sample of matched twin siblings, an average SES index is created considering the average SES of all schools a student has ever attended. A cut-off to separate

[20] See Rocha e Soares (2010) for evidence of the positive impact of the program on reducing mortality especially at an early ages.

[21] The tests are Prova Brasil, taken by students of 5th and 9th grade and ENEM, an exam for the admission in higher education. The index combines students' answers through Item Response Theory using the questionnaires of 2011 and 2013. For more information see INEP (2014).

the students into low and high school average SES has been selected considering the median of the average distribution and the original socioeconomic levels created by INEP. Hence, a school with low SES corresponds to INEP's levels I to III, meaning that the average student has parents with incomplete elementary education or (less schooling) and household income of to 1.5 minimum wages[22]. The high SES schools are those where the majority of students have parents with incomplete middle school or higher schooling and household income of more than 1.5 minimum wages.

The last two heterogeneities refer to mothers' characteristics. The students were divided into two groups of low and high maternal education using the information on educational level at the time of the birth. Mothers with incomplete elementary schooling (or less) are the low-education group, while mothers with at least incomplete high school or higher education are the group of high education. Finally, the last heterogeneity considers the number of live children the mother had already had at the time of the birth. Mothers are split in two groups: in one the twins are the first children, while in the other they have at least one older sibling.

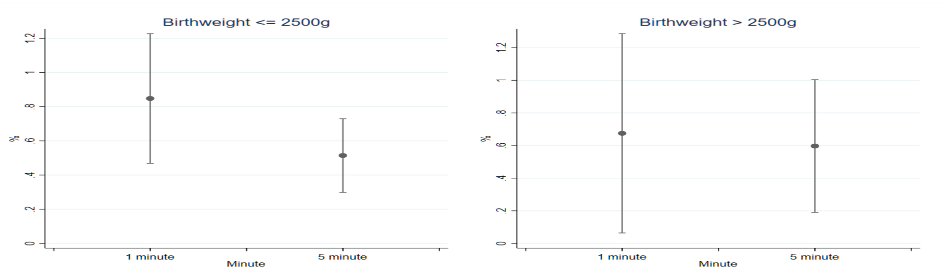
The results for these heterogeneities are presented in a sequence of graphs where the left-hand line refers to the group associated to 'low' characteristics, while the right-hand represents the 'high' profile. For the Apgar score, the dots are the estimated coefficients and the ranges are the 95% confidence interval. For the educational variables, the connected line refers to the coefficient and the shaded area to the 95% confidence interval. Appendix 6 show the complete regressions tables.

For the Apgar score, Figure 8(a) shows that the effect of birth weight at one minute is higher for those born with low weight than for the babies weighing more than 2500g. The coefficient for the lighter babies is 0.84, showing that this group is responsible for most of the effect found in the full sample. For the Apgar at 5 minutes, the coefficient is not different across the weight ranges, confirming the fact that the weight itself is less relevant to explain the Apgar at 5 minutes, when medical intervention plays an important role in newborn health. The variance is higher in the sample relative to a weight larger than 2500g due to the relatively small sample size.

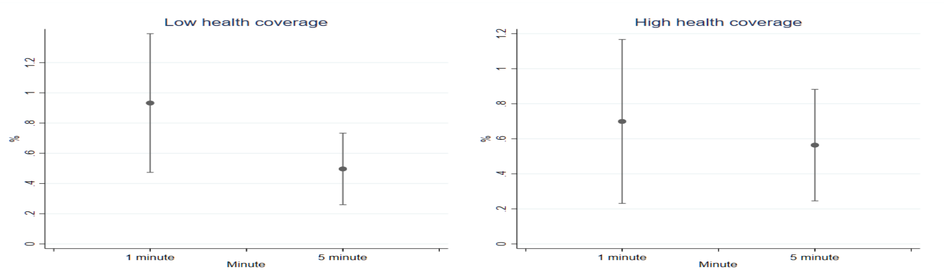
The health coverage variable is associated with the basic health care received at community level rather than to the hospital care received right after birth. The higher the measurement of health coverage, the higher are the chances that the mother had received adequate health care prior to birth, potentially including prenatal care. The effect of birth weight on 1 minute Apgar is 30% higher in regions with low basic health coverage compared to the regions with high coverage (Figure 8(b)). The possible differences in prenatal supply can explain the higher effect in municipalities with lower health coverage. The five minute Apgar, which is more sensitive to the immediate post-birth care, exhibits no relevant differences across health coverage situation.

There are no differences in the effect of birth weight o the five and one minute Apgar, according to maternal education groups (Figure 8(c)). The last heterogeneity is in line with the well-known fact in the medical literature that the first pregnancy is associated to a higher risk, so that the first child (or children in this particular case of twin pregnancy) exhibits worse neonatal outcomes. Effects of birth weight on Apgar score are higher for first children.

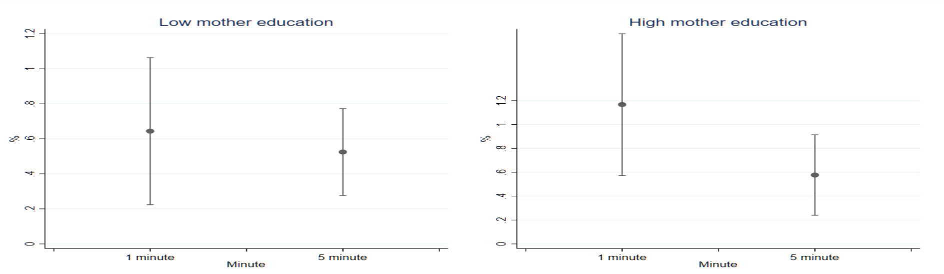
[22] Between 2011 and 2013 the minimum wage augmented from R$545 to R$678. Considering the mean minimum wage in the period of R$615, this would correspond to a monthly income of US$175, approximately.



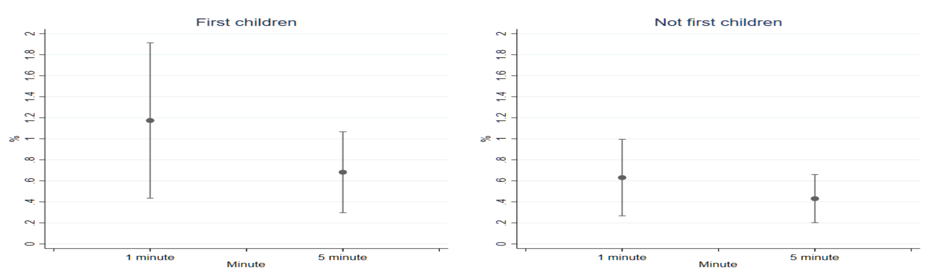
(a) Birth weight



(b) Quality of Health Services



(c) Mother's education



(d) Number of children

Figura 8 – TFE Heterogeneity for Apgar

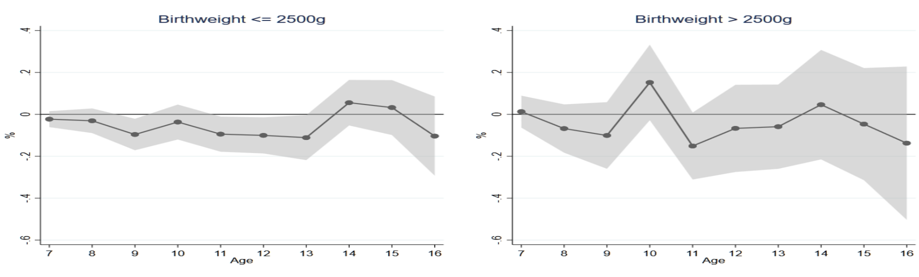
Except for the school dropout outcome - TFE coefficients are small and statistically zero with no differentiation of results across socioeconomic and health quality groups (see Figure 10) - all educational outcomes have similar effects overall and across groups.

Students born weighing less than 2500g are driving the overall effect of increasing birth weight on the probability of grade repetition or age-grade distortion. The point estimates for the non-low birthweight group are not only smaller in magnitude than the low birthweight group, but also non-significant. Indeed, at the age of 12 a 10% increase in birth weight reduces the chances of repeating a grade in 12.1% for the low birthweight group and in 7.3% (non-significant) for the non-low birthweight group (see Figure 9(a)). Bharadwaj, Eberhard e Neilson (2018) and Figlio et al. (2014) found similar results using test score as an outcome.

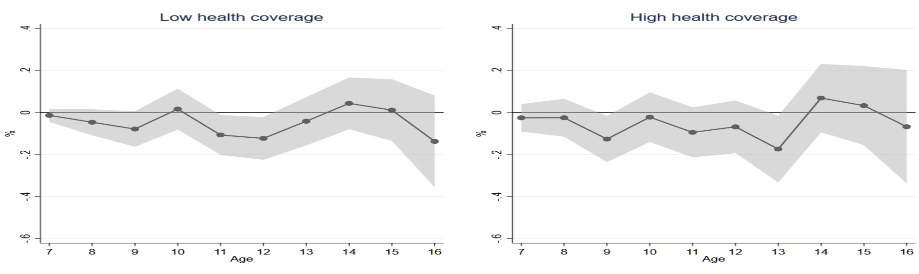
Primary health care coverage seems to be a relevant mechanism through which the impacts of being born low birthweight can be mitigated. For age-grade distortion, the coefficients associated to municipalities with low health coverage are higher in magnitude than the high coverage municipalities, as well as consistently different from zero. Particularly after the age of 12, the effects on age grade distortion in low health coverage areas are bigger (in module) than in high health coverage cities (see Figure 11(b)). Further investigation is needed to better understand the role of health services in these results. WHO e UNICEF (2009) suggest that home visits during the neonatal period are a strategy to increase children survival. The visits are important as they give parents orientation regarding early recognition of health problems, hygiene, breastfeeding and problems related to growth.

The SES level of a school can be associated with the educational environment the student has accessed or even with the student's own socioeconomic status. In both cases, attending a low SES school is indicative of being in a more vulnerable condition. Subgroups of low SES and low maternal education have similar trends, always displaying a greater sensitiveness to an increase in birth weight compared to the groups that have attended high SES schools or have more educated mothers. One can see in Figure 12(c) and 12(d) that the non-cumulative age-grade distortion is not statistically different from zero for the group with high SES and high mother education. On the other hand, the coefficient reaches a value of -0.208 at the age of 13 for the group of low mother's education, implying a reduction of 12.8% in the chances to have age-grade distortion when birth weight increases 10%. Further information and research are needed to understand the mechanisms underpinning the absence of effects in the student with a higher socioeconomic background. Even so, there is evidence that students with low socioeconomic background suffer stronger consequences of the initial adverse health conditions. This finding points to a peculiarity of the Brazilian scenario relative to the ones found by Bharadwaj, Eberhard e Neilson (2018) in Chile, by Figlio et al. (2014) in the USA, andby Black, Devereux e Salvanes (2007) in Norway, where the effects of birth weight on educational outcomes are quite stable across socioeconomic backgrounds.

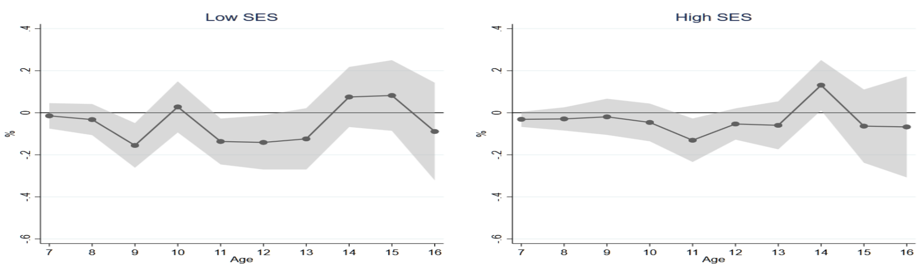
Regarding the fact of being the first child, the educational outcomes show evidence of a quality-quantity trade-off. Most of the effects obtained come from twins that are not the first to be born.



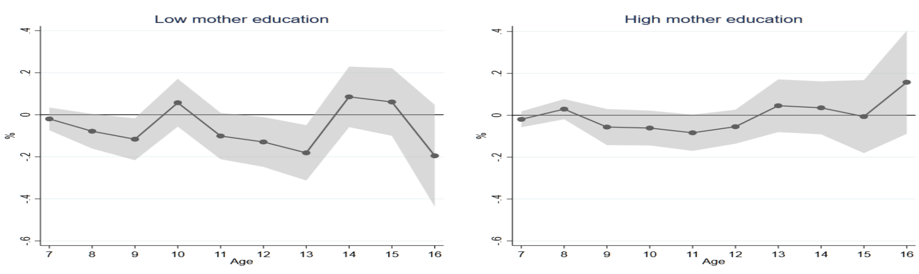
(a) Birth weight



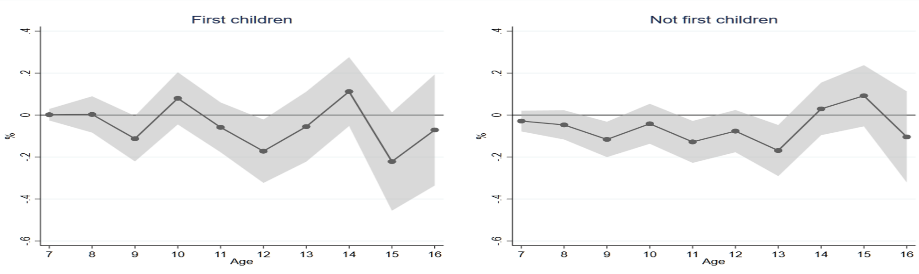
(b) Quality of Health Services



(c) Socioeconomic Status of School

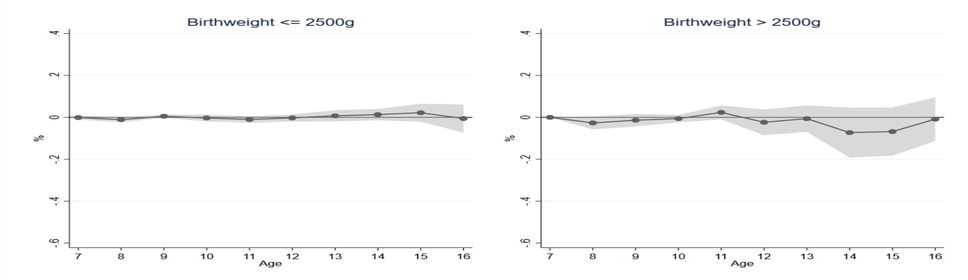


(d) Mother's education

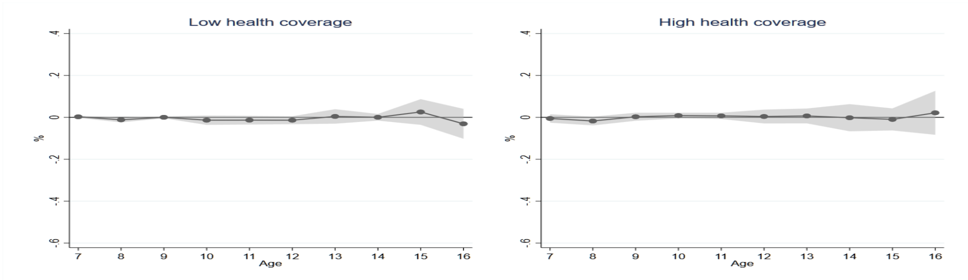


(e) Number of children

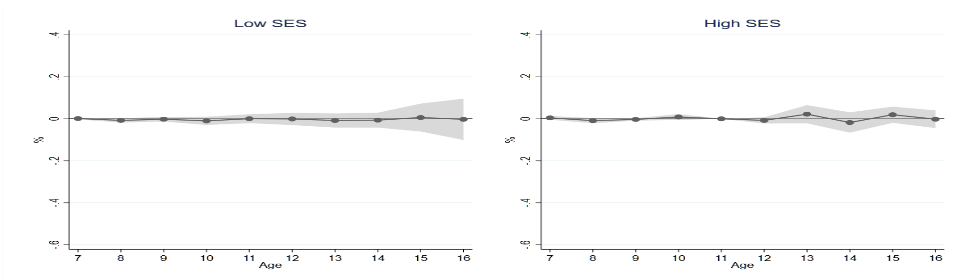
Figura 9 – TFE Heterogeneity for Retention Rates



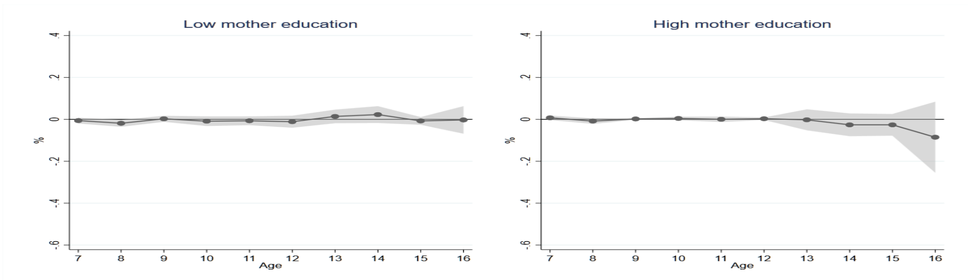
(a) Birth weight



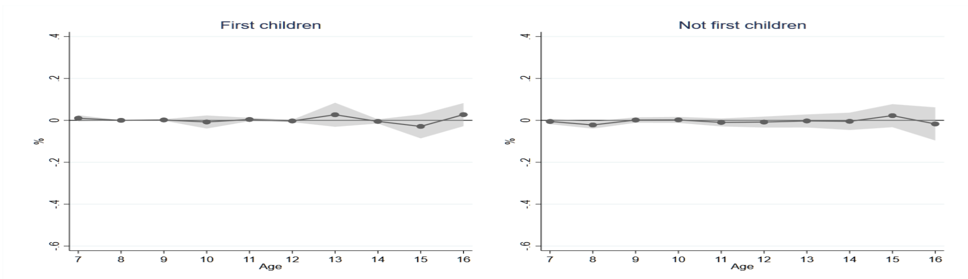
(b) Quality of Health Services



(c) Socioeconomic Status of School

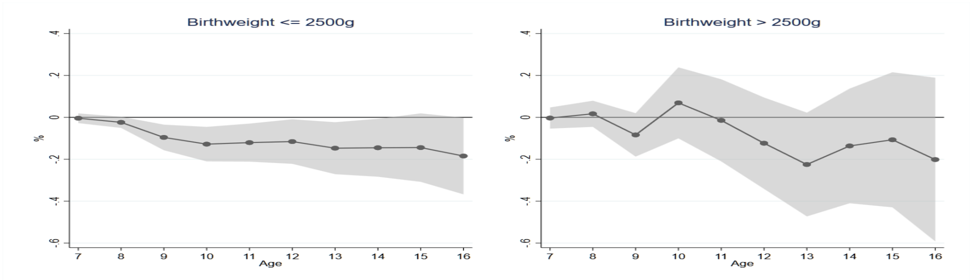


(d) Mother schooling

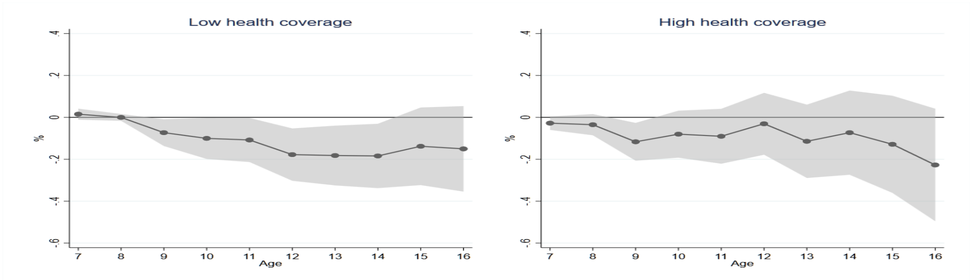


(e) Number of children

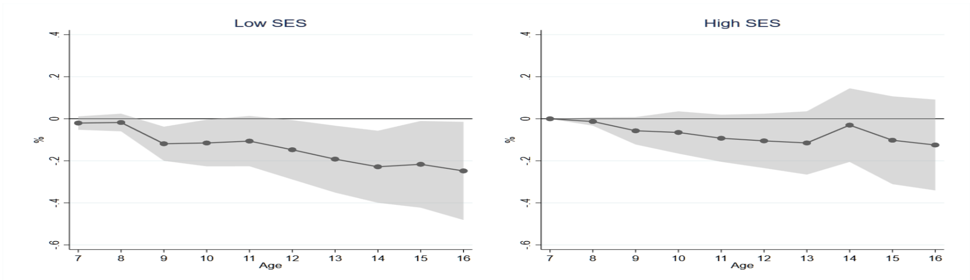
Figura 10 – TFE Heterogeneity for Dropout Rates



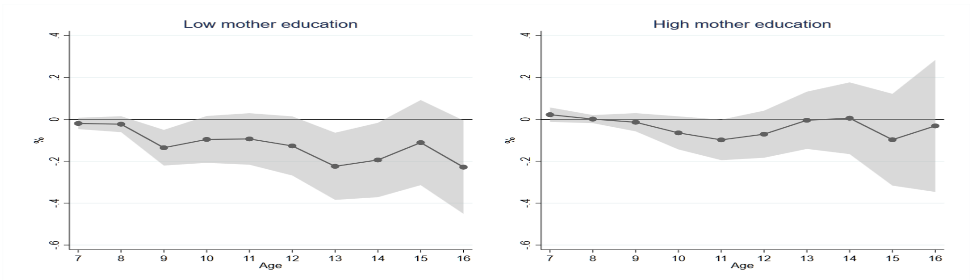
(a) Birth weight



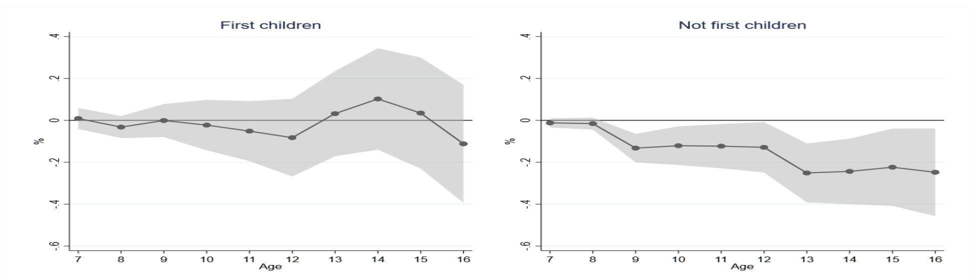
(b) Quality of Health Services



(c) Socioeconomic Status of School

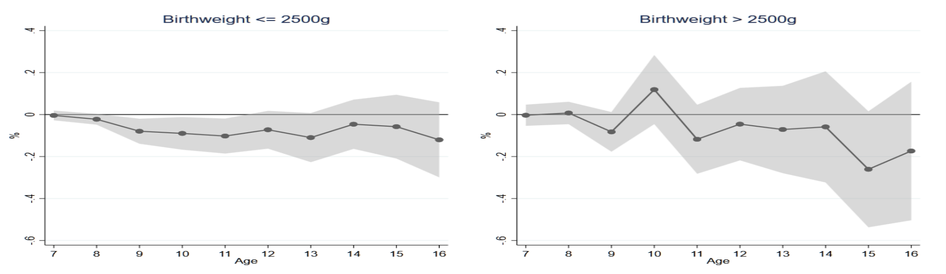


(d) Mother schooling

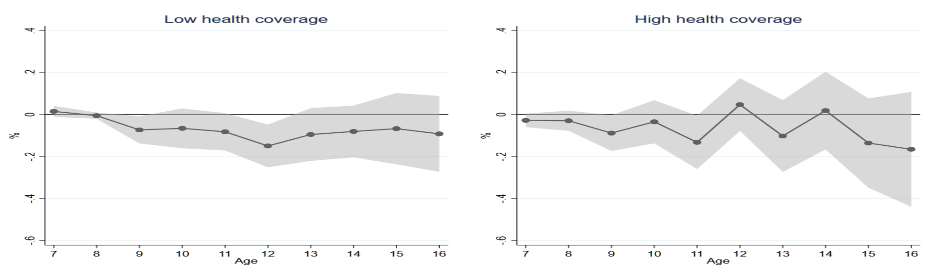


(e) Number of children

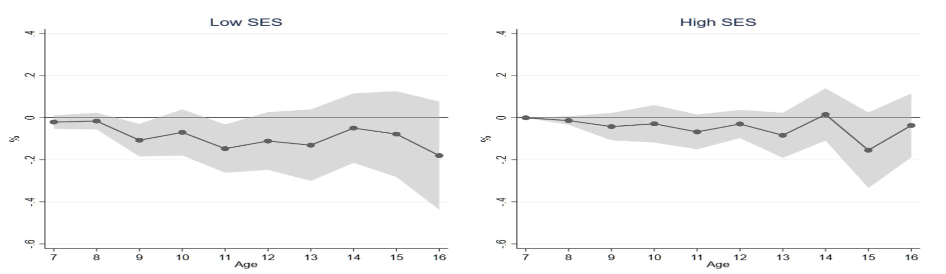
Figura 11 – TFE Heterogeneity for Age-Grade Distortion



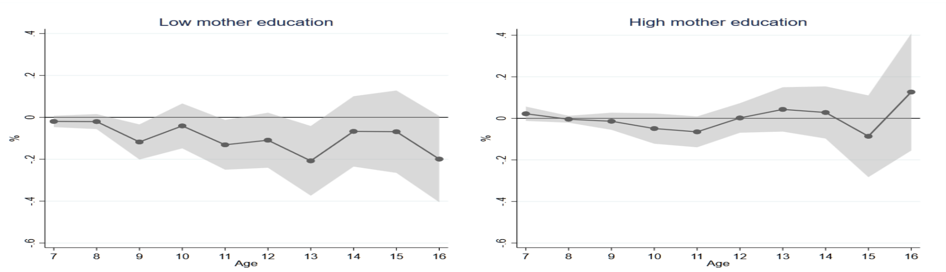
(a) Birth weight



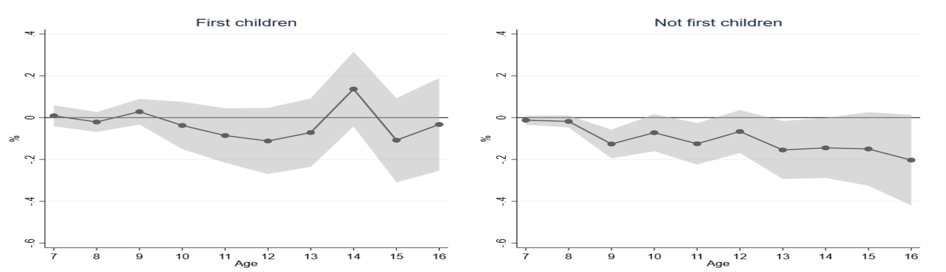
(b) Quality of Health Services



(c) Socioeconomic Status of School



(d) Mother schooling



(e) Number of children

Figura 12 – TFE Heterogeneity for Non-cumulative Age-Grade Distortion

6 Final Remarks

This paper presents the first estimations for Brazil of the effects of birth weight on health and educational outcomes, using a twin fixed effects approach. Administrative records related to birth and school enrollment were linked using the date of birth, municipality of birth, gender and municipality of residence. The main finding is that birth weight does matter: it has effects on infants' health and on educational outcomes. For the Apgar score, we found evidence that a 10% increase in weight is associated with a 0.6% increase in Apgar. While the percentage impact can be considered small, the coefficient is 1.5 times larger than the one found for Norway, meaning that a poor initial endowment may have stronger effects in Brazil.

For the educational outcomes, the findings suggest that a 10% increase in birth weight is associated with a 6% increase in the chances of completing high school by the age of 17 and with a 3.6% decrease in the probability of repeating a grade. We also found effects of birth weight in the reduction of the probability of being older than the expected for a grade after 9 years of age, but found no effects for school dropout. Furthermore, the differences in the magnitude of the OLS and TFE estimates reveal that parents act in a way that reinforces, rather than compensates, the negative effects of an adverse initial health condition. When heterogeneous effects are considered, we learn that most of the overall effects found are accentuated for those with low birth weight, less access to basic health care services, low educated mothers and education at schools of lower socioeconomic status.

The evidence that children born in municipalities with worse supply of a community-based health program and that children with lower socioeconomic background are more sensitive to birth weight justify the implementation of public policies, in the fields of health and education, targeting the most vulnerable groups. For instance, Duncan e Sojourner (2013) show that the Infant Health and Development Program (IHDP) has much larger impacts among low-income than high-income children[23].Similar public policies can be designed in Brazil, aimed at boosting early development of low-birthweight infants, especially those born of in a disadvantaged socioeconomic context.

The focus on maternal care, prenatal care and *in-utero* development can ensure more equal initial conditions for children, giving them fairer opportunities in life. After all, most of the parental background (education, wealth) closely associated with a child's development is not easily malleable by means of public policies. However, this does not seem to be the case of health at birth and immediate neonatal care, which are sensitive to health interventions and responsive to improvements in the environment to which the mother is exposed. Further research is needed to investigate the potential effects of interventions that seek to reduce pre-birth gaps in Brazil.

[23] The IHDP delivered a center-based curriculum targeting diverse groups of low birthweight children aged one to two years old.

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Appendix A

Tabela 9 – TFE Apgar - By birth weight

Variable	(1) Apgar 1st minute	(2) Apgar 5th minute
Low birthweight		
Ln weight	0.848***	0.514***
	(0.193)	(0.110)
Gender-Female	0.0158	0.0257
	(0.0335)	(0.0217)
Observations	4,204	4,198
R-squared	0.760	0.810
Without low birthweight		
Ln weight	0.675**	0.597***
	(0.311)	(0.207)
Gender-Female	0.0571	0.0239
	(0.0366)	(0.0252)
Observations	2,434	2,414
R-squared	0.790	0.851

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 10 – TFE Apgar - By Quality of Health Services

VARIABLES	(1) Apgar 1st minute	(2) Apgar 5th minute
Low health quality		
Ln weight	0.933***	0.496***
	(0.234)	(0.121)
Gender-Female	0.0518	0.0128
	(0.0329)	(0.0215)
Observations	3,742	3,750
R-squared	0.768	0.809
High health quality		
Ln weight	0.699***	0.564***
	(0.239)	(0.162)
Gender-Female	0.00691	0.0401
	(0.0386)	(0.0258)
Observations	2,896	2,862
R-squared	0.777	0.846

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 11 – TFE Apgar - By Mother schooling

Variables	(1) Apgar 1st minute	(2) Apgar 5th minute
Low mother education		
Ln weight	1.174***	0.524***
	(0.214)	(0.127)
Gender-Female	0.0305	0.0241
	(0.0332)	(0.0224)
Observations	3,904	3,886
R-squared	0.771	0.829
High mother education		
Ln weight	1.167***	0.577***
	(0.303)	(0.172)
Gender-Female	0.0535	0.0391
	(0.0423)	(0.0270)
Observations	2,372	2,366
R-squared	0.759	0.807

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 12 – TFE Apgar - Number of Children

Variables	(1) Apgar 1st minute	(2) Apgar 5th minute
First children		
Ln weight	1.174***	0.682***
	(0.377)	(0.196)
Gender-Female	0.0423	0.0277
	(0.0520)	(0.0308)
Observations	1,634	1,632
R-squared	0.774	0.844
Has other children		
Ln weight	0.631***	0.431***
	(0.186)	(0.117)
Gender-Female	0.0254	0.0209
	(0.0291)	(0.0208)
Observations	4,598	4,578
R-squared	0.776	0.820

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 13 – TFE Redo - By birth weight

Variable	(1) Retention	(2) At age 7	(3) At age 8	(4) At age 9	(5) At age 10	(6) At age 11	(7) At age 12	(8) At age 13	(9) At age 14	(10) At age 15	(11) At age 16
Without low birthweight											
Ln weight	-1.04e-05	0.0130	-0.0678	-0.101	0.152*	-0.151*	-0.0669	-0.0588	0.0462	-0.0465	-0.138
	(0.119)	(0.0388)	(0.0587)	(0.0810)	(0.0918)	(0.0815)	(0.106)	(0.102)	(0.133)	(0.136)	(0.186)
Gender-Female	-0.140***	-0.00729	-0.0298***	-0.0480***	-0.0290***	-0.0525***	-0.0723***	-0.0589***	-0.0800***	-0.0640***	-0.0698***
	(0.0130)	(0.00459)	(0.00709)	(0.00836)	(0.00941)	(0.00873)	(0.0111)	(0.0115)	(0.0140)	(0.0167)	(0.0222)
Observations	2,622	1,836	2,280	2,548	2,570	2,574	2,182	1,812	1,456	1,080	714
R-squared	0.769	0.849	0.786	0.738	0.644	0.678	0.618	0.667	0.627	0.655	0.642
Low birthweight											
Ln weight	-0.150***	-0.0229	-0.0306	-0.0962**	-0.0366	-0.0945**	-0.100**	-0.111**	0.0557	0.0325	-0.104
	(0.0539)	(0.0193)	(0.0300)	(0.0383)	(0.0425)	(0.0427)	(0.0440)	(0.0547)	(0.0554)	(0.0667)	(0.0961)
Gender-Female	-0.130***	-0.00178	-0.0261***	-0.0371***	-0.0588***	-0.0559***	-0.0538***	-0.0666***	-0.0723***	-0.0744***	-0.0810***
	(0.0101)	(0.00313)	(0.00535)	(0.00705)	(0.00785)	(0.00727)	(0.00800)	(0.00994)	(0.0116)	(0.0134)	(0.0172)
Observations	4,604	3,170	3,910	4,472	4,500	4,510	3,782	3,112	2,506	1,868	1,210
R-squared	0.764	0.874	0.798	0.722	0.674	0.672	0.625	0.605	0.611	0.636	0.586

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 14 – TFE Redo - Quality of Health Service

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variable	Retention	At age 7	At age 8	At age 9	At age 10	At age 11	At age 12	At age 13	At age 14	At age 15	At age 16
Low health quality											
Ln weight	-0.107	-0.0133	-0.0462	-0.0785*	0.0166	-0.107**	-0.123**	-0.0413	0.0438	0.0118	-0.138
	(0.0662)	(0.0159)	(0.0317)	(0.0431)	(0.0497)	(0.0485)	(0.0519)	(0.0587)	(0.0628)	(0.0748)	(0.111)
Gender-Female	-0.131***	0.000166	-0.0211***	-0.0388***	-0.0396***	-0.0440***	-0.0527***	-0.0532***	-0.0579***	-0.0748***	-0.0794***
	(0.0106)	(0.00264)	(0.00534)	(0.00695)	(0.00734)	(0.00664)	(0.00800)	(0.00906)	(0.0110)	(0.0127)	(0.0182)
Observations	3,984	2,782	3,456	3,902	3,920	3,912	3,298	2,728	2,208	1,646	1,094
R-squared	0.760	0.905	0.781	0.728	0.684	0.675	0.608	0.638	0.652	0.657	0.575
High health quality											
Ln weight	-0.159**	-0.0249	-0.0247	-0.126**	-0.0218	-0.0944	-0.0678	-0.174**	0.0691	0.0331	-0.0674
	(0.0729)	(0.0334)	(0.0461)	(0.0560)	(0.0604)	(0.0607)	(0.0639)	(0.0810)	(0.0831)	(0.0959)	(0.138)
Gender-Female	-0.137***	-0.00911*	-0.0354***	-0.0439***	-0.0586***	-0.0674***	-0.0709***	-0.0765***	-0.0968***	-0.0649***	-0.0740***
	(0.0121)	(0.00481)	(0.00693)	(0.00851)	(0.0100)	(0.00938)	(0.0107)	(0.0127)	(0.0147)	(0.0171)	(0.0206)
Observations	3,242	2,224	2,734	3,118	3,150	3,172	2,666	2,196	1,754	1,302	830
R-squared	0.766	0.829	0.804	0.727	0.646	0.671	0.629	0.615	0.584	0.627	0.640

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 15 – TFE Redo - Socioeconomic Status of School

Variable	(1) Retention	(2) At age 7	(3) At age 8	(4) At age 9	(5) At age 10	(6) At age 11	(7) At age 12	(8) At age 13	(9) At age 14	(10) At age 15	(11) At age 16
Low school socioeconomic level											
Ln weight	-0.108	-0.0146	-0.0324	-0.155***	0.0279	-0.137**	-0.141**	-0.124*	0.0750	0.0822	-0.0891
	(0.0706)	(0.0309)	(0.0377)	(0.0541)	(0.0619)	(0.0556)	(0.0657)	(0.0744)	(0.0727)	(0.0856)	(0.118)
Gender-Female	-0.152***	-0.00515	-0.0336***	-0.0490***	-0.0573***	-0.0693***	-0.0744***	-0.0756***	-0.0889***	-0.0709***	-0.0800***
	(0.0113)	(0.00434)	(0.00612)	(0.00818)	(0.00916)	(0.00811)	(0.00987)	(0.0111)	(0.0131)	(0.0147)	(0.0185)
Observations	3,892	2,658	3,294	3,758	3,800	3,808	3,268	2,748	2,226	1,626	1,038
R-squared	0.762	0.840	0.789	0.723	0.664	0.691	0.622	0.625	0.614	0.647	0.633
High school socioeconomic level											
Ln weight	-0.104	-0.0312*	-0.0293	-0.0192	-0.0459	-0.131**	-0.0534	-0.0597	0.131**	-0.0635	-0.0674
	(0.0718)	(0.0184)	(0.0281)	(0.0438)	(0.0457)	(0.0527)	(0.0379)	(0.0581)	(0.0610)	(0.0887)	(0.122)
Gender-Female	-0.103***	-0.00320	-0.0182***	-0.0248***	-0.0363***	-0.0261***	-0.0278***	-0.0370***	-0.0368***	-0.0614***	-0.0624***
	(0.0118)	(0.00279)	(0.00568)	(0.00703)	(0.00761)	(0.00714)	(0.00740)	(0.00944)	(0.0110)	(0.0140)	(0.0195)
Observations	2,690	1,914	2,352	2,658	2,670	2,670	2,262	1,858	1,510	1,166	806
R-squared	0.766	0.905	0.794	0.741	0.644	0.621	0.618	0.615	0.651	0.660	0.579

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 16 – TFE Redo - Mother Schooling

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variable	Retention	At age 7	At age 8	At age 9	At age 10	At age 11	At age 12	At age 13	At age 14	At age 15	At age 16
Low mother education											
Ln weight	-0.155**	-0.0196	-0.0784*	-0.116**	0.0573	-0.101*	-0.129**	-0.181***	0.0852	0.0610	-0.195
	(0.0688)	(0.0275)	(0.0420)	(0.0508)	(0.0579)	(0.0562)	(0.0604)	(0.0670)	(0.0733)	(0.0820)	(0.123)
Gender-Female	-0.150***	-0.00712*	-0.0342***	-0.0498***	-0.0521***	-0.0694***	-0.0830***	-0.0847***	-0.0910***	-0.0900***	-0.0928***
	(0.0111)	(0.00396)	(0.00635)	(0.00796)	(0.00889)	(0.00837)	(0.00957)	(0.0107)	(0.0124)	(0.0150)	(0.0191)
Observations	4,256	2,874	3,708	4,112	4,138	4,160	3,598	3,010	2,416	1,798	1,094
R-squared	0.752	0.853	0.797	0.729	0.671	0.675	0.621	0.635	0.611	0.632	0.620
High mother education											
Ln weight	-0.0655	-0.0193	0.0292	-0.0564	-0.0609	-0.0836*	-0.0546	0.0456	0.0356	-0.00632	0.158
	(0.0734)	(0.0193)	(0.0245)	(0.0439)	(0.0424)	(0.0440)	(0.0414)	(0.0641)	(0.0643)	(0.0887)	(0.125)
Gender-Female	-0.0949***	0.000226	-0.0169***	-0.0242***	-0.0339***	-0.0260***	-0.0216***	-0.0337***	-0.0413***	-0.0470***	-0.0504**
	(0.0116)	(0.00322)	(0.00511)	(0.00677)	(0.00740)	(0.00619)	(0.00745)	(0.00998)	(0.0128)	(0.0141)	(0.0205)
Observations	2,516	2,006	2,318	2,464	2,482	2,472	1,952	1,520	1,172	814	532
R-squared	0.735	0.892	0.742	0.687	0.624	0.616	0.594	0.586	0.641	0.664	0.548

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 17 – TFE Redo - Number of Children

Variable	(1) Retention	(2) At age 7	(3) At age 8	(4) At age 9	(5) At age 10	(6) At age 11	(7) At age 12	(8) At age 13	(9) At age 14	(10) At age 15	(11) At age 16
First children											
Ln weight	-0.108	0.00171	0.00305	-0.113**	0.0797	-0.0585	-0.172**	-0.0551	0.112	-0.222*	-0.0710
	(0.0884)	(0.0140)	(0.0441)	(0.0552)	(0.0633)	(0.0604)	(0.0769)	(0.0848)	(0.0834)	(0.119)	(0.134)
Gender-Female	-0.111***	-0.00153	-0.0200***	-0.0292***	-0.0212**	-0.0415***	-0.0359***	-0.0399***	-0.0791***	-0.0836***	-0.0590**
	(0.0144)	(0.00431)	(0.00736)	(0.00879)	(0.00962)	(0.00857)	(0.0110)	(0.0135)	(0.0171)	(0.0189)	(0.0249)
Observations	1,696	1,260	1,492	1,662	1,670	1,672	1,366	1,114	884	644	422
R-squared	0.766	0.884	0.737	0.703	0.657	0.706	0.614	0.561	0.566	0.690	0.510
Has other children											
Ln weight	-0.166***	-0.0285	-0.0469	-0.116***	-0.0415	-0.128**	-0.0764	-0.169***	0.0294	0.0921	-0.104
	(0.0623)	(0.0252)	(0.0355)	(0.0429)	(0.0486)	(0.0509)	(0.0513)	(0.0620)	(0.0638)	(0.0742)	(0.110)
Gender-Female	-0.144***	-0.00541	-0.0321***	-0.0488***	-0.0566***	-0.0592***	-0.0675***	-0.0779***	-0.0793***	-0.0688***	-0.0746***
	(0.0101)	(0.00335)	(0.00556)	(0.00695)	(0.00776)	(0.00730)	(0.00830)	(0.00943)	(0.0110)	(0.0131)	(0.0169)
Observations	5,008	3,416	4,274	4,860	4,896	4,908	4,156	3,434	2,758	2,068	1,334
R-squared	0.756	0.859	0.801	0.734	0.664	0.666	0.619	0.634	0.620	0.618	0.632

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 18 – TFE Dropout - By birth weight

Variables	(1) Dropout	(2) At age 7	(3) At age 8	(4) At age 9	(5) At age 10	(6) At age 11	(7) At age 12	(8) At age 13	(9) At age 14	(10) At age 15	(11) At age 16
Low birthweight											
Ln weight	0.00146	-0.000865	-0.0112*	0.00539	-0.00295	-0.0101	-0.00284	0.00728	0.0132	0.0221	-0.00559
	(0.0192)	(0.00537)	(0.00605)	(0.00422)	(0.00817)	(0.00774)	(0.00861)	(0.0137)	(0.0136)	(0.0219)	(0.0341)
Gender-Female	-0.0117***	-4.37e-05	-0.00157	0.000278	-0.000154	-0.00206	-0.00386**	-0.00575*	0.00163	-0.00450	-0.00672
	(0.00415)	(0.00129)	(0.00132)	(0.000974)	(0.00152)	(0.00189)	(0.00174)	(0.00323)	(0.00338)	(0.00298)	(0.00738)
Observations	4,604	3,490	4,052	4,566	4,586	3,894	3,230	2,624	2,038	1,446	930
R-squared	0.619	0.624	0.625	0.749	0.624	0.499	0.666	0.548	0.564	0.749	0.560
Without low birthweight											
Ln weight	-0.103**	0	-0.0265*	-0.0137	-0.00592	0.0236	-0.0235	-0.00618	-0.0727	-0.0678	-0.00873
	(0.0517)	(0)	(0.0159)	(0.0151)	(0.00906)	(0.0169)	(0.0314)	(0.0321)	(0.0607)	(0.0585)	(0.0529)
Gender-Female	-0.0139***	0	-0.00408**	-0.00493**	-0.00167	0.000596	-0.00275	-0.00410	0.00188	0.00359	-0.00784
	(0.00497)	(0)	(0.00205)	(0.00204)	(0.00168)	(0.00140)	(0.00272)	(0.00353)	(0.00386)	(0.00458)	(0.00898)
Observations	2,622	2,012	2,348	2,606	2,614	2,228	1,870	1,518	1,166	846	524
R-squared	0.641		0.751	0.626	0.500	0.750	0.500	0.499	0.700	0.502	0.496

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 19 – TFE Dropout - Quality of Health Service

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Dropout	At age 7	At age 8	At age 9	At age 10	At age 11	At age 12	At age 13	At age 14	At age 15	At age 16
Low health quality											
Ln weight	-0.0281	0.00275	-0.0118*	0.000222	-0.0135	-0.0134	-0.0136	0.00443	0.000314	0.0257	-0.0308
	(0.0219)	(0.00262)	(0.00621)	(0.00238)	(0.0114)	(0.0106)	(0.00961)	(0.0176)	(0.00804)	(0.0312)	(0.0363)
Gender-Female	-0.0108***	0.000767	-0.00275**	-0.000495	-0.00211*	-0.00236	-0.00273*	-0.00503	0.00227	-0.000461	-0.0114
	(0.00391)	(0.00111)	(0.00137)	(0.000775)	(0.00124)	(0.00177)	(0.00159)	(0.00355)	(0.00214)	(0.00392)	(0.00797)
Observations	3,984	3,066	3,558	3,964	3,968	3,376	2,818	2,302	1,774	1,282	806
R-squared	0.638	0.700	0.667	0.833	0.611	0.501	0.502	0.553	0.749	0.609	0.579
High health quality											
Ln weight	0.00245	-0.00528	-0.0174*	0.00286	0.00843	0.00705	0.00406	0.00676	-0.00174	-0.00979	0.0216
	(0.0310)	(0.0103)	(0.0106)	(0.00977)	(0.00684)	(0.00761)	(0.0168)	(0.0181)	(0.0330)	(0.0267)	(0.0533)
Gender-Female	-0.0141***	-0.00104	-0.00214	-0.00301	0.000949	0.000279	-0.00423	-0.00519*	0.00134	-0.00225	-0.00248
	(0.00521)	(0.00113)	(0.00181)	(0.00191)	(0.00200)	(0.00195)	(0.00258)	(0.00315)	(0.00510)	(0.00304)	(0.00849)
Observations	3,242	2,436	2,842	3,208	3,232	2,746	2,282	1,840	1,430	1,010	648
R-squared	0.614	0.500	0.700	0.590	0.590	0.624	0.653	0.499	0.554	0.784	0.493

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 20 – TFE Dropout - Socioeconomic Status of School

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Dropout	At age 7	At age 8	At age 9	At age 10	At age 11	At age 12	At age 13	At age 14	At age 15	At age 16
Low school socioeconomic level											
Ln weight	-0.00928	0.00120	-0.00758	-0.00202	-0.00975	0.000580	-0.000694	-0.00804	-0.00634	0.00602	-0.00248
	(0.0270)	(0.00206)	(0.00522)	(0.00562)	(0.00996)	(0.0109)	(0.0149)	(0.0172)	(0.0181)	(0.0338)	(0.0501)
Gender-Female	-0.0137***	0.000733	-0.00209	-0.00216	-0.000922	-0.000572	-0.00494**	-0.00545	0.00310	-0.00294	-0.00520
	(0.00476)	(0.00121)	(0.00150)	(0.00155)	(0.00168)	(0.00212)	(0.00227)	(0.00336)	(0.00392)	(0.00416)	(0.00814)
Observations	3,892	2,934	3,412	3,852	3,876	3,354	2,848	2,330	1,806	1,274	782
R-squared	0.646	0.500	0.772	0.714	0.653	0.590	0.591	0.553	0.563	0.711	0.564
High school socioeconomic level											
Ln weight	0.00405	0.00452	-0.00872	-0.00292	0.00862	0	-0.00758	0.0220	-0.0176	0.0196	-0.00196
	(0.0218)	(0.00454)	(0.00629)	(0.00293)	(0.00714)	(0)	(0.00759)	(0.0220)	(0.0246)	(0.0196)	(0.0214)
Gender-Female	-0.00653*	-0.000805	-0.00201	0.000631	-0.00263**	0	0.000732	-0.00422	-0.000833	-0.00144	-8.97e-05
	(0.00371)	(0.000805)	(0.00142)	(0.000631)	(0.00133)	(0)	(0.000732)	(0.00387)	(0.00264)	(0.00145)	(0.00697)
Observations	2,690	2,056	2,394	2,680	2,688	2,290	1,896	1,556	1,204	892	594
R-squared	0.530	0.501	0.501	0.500	0.501		0.501	0.499	0.665	0.503	0.497

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 21 – TFE Dropout - Mother Schooling

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Dropout	At age 7	At age 8	At age 9	At age 10	At age 11	At age 12	At age 13	At age 14	At age 15	At age 16
Low mother education											
Ln weight	-0.0210	-0.00579	-0.0187**	0.00269	-0.00880	-0.00688	-0.0112	0.0139	0.0228	-0.00750	-0.00280
	(0.0256)	(0.00706)	(0.00861)	(0.00730)	(0.0118)	(0.0107)	(0.0146)	(0.0165)	(0.0205)	(0.00935)	(0.0334)
Gender-Female	-0.0127***	0.000980	-0.00344**	-0.00273*	-0.000856	-0.000839	-0.00493**	-0.00339	0.00283	0.00118	-0.0124
	(0.00466)	(0.00114)	(0.00153)	(0.00153)	(0.00190)	(0.00203)	(0.00229)	(0.00323)	(0.00327)	(0.00331)	(0.00817)
Observations	4,256	3,246	3,856	4,220	4,240	3,710	3,140	2,542	1,986	1,384	812
R-squared	0.624	0.666	0.682	0.722	0.557	0.499	0.633	0.550	0.569	0.721	0.496
High mother education											
Ln weight	-0.0125	0.00740	-0.00823	0.00192	0.00428	0.000320	0.00306	-0.00223	-0.0261	-0.0262	-0.0854
	(0.0205)	(0.00539)	(0.00679)	(0.00193)	(0.00429)	(0.00658)	(0.00308)	(0.0256)	(0.0276)	(0.0263)	(0.0859)
Gender-Female	-0.0124***	-0.00159	-0.00117	-0.000722	-0.000625	-0.00200	-0.00115	-0.0116***	0.00116	-0.00444	0.00835
	(0.00385)	(0.00112)	(0.00170)	(0.000722)	(0.000625)	(0.00143)	(0.00115)	(0.00449)	(0.00368)	(0.00443)	(0.0118)
Observations	2,516	2,128	2,376	2,500	2,506	1,992	1,562	1,214	852	570	324
R-squared	0.602	0.501	0.700	0.500	0.833	0.501	0.500	0.503	0.699	0.503	0.501

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 22 – TFE Dropout - Number of Children

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Dropout	At age 7	At age 8	At age 9	At age 10	At age 11	At age 12	At age 13	At age 14	At age 15	At age 16
First children											
Ln weight	0.0125	0.0102	0	0.00184	-0.00779	0.00416	-0.00287	0.0268	-0.00501	-0.0289	0.0274
	(0.0247)	(0.00744)	(0)	(0.00186)	(0.0159)	(0.00419)	(0.00292)	(0.0292)	(0.00511)	(0.0290)	(0.0278)
Gender-Female	-0.00662	-0.00257	0	-0.00112	-0.00146	0.00160	-0.00187	-0.00552	0.00276	-0.00502	0.00790
	(0.00533)	(0.00182)	(0)	(0.00112)	(0.00243)	(0.00160)	(0.00187)	(0.00622)	(0.00276)	(0.00501)	(0.00791)
Observations	1,696	1,360	1,534	1,686	1,694	1,386	1,136	910	678	474	284
R-squared	0.610	0.750		0.500	0.642	0.501	0.501	0.498	0.833	0.504	0.503
Has other children											
Ln weight	-0.0349	-0.00537	-0.0220**	0.00156	0.00222	-0.00987	-0.00815	-0.00283	-0.00469	0.0225	-0.0171
	(0.0242)	(0.00652)	(0.00887)	(0.00670)	(0.00737)	(0.00975)	(0.0133)	(0.0159)	(0.0211)	(0.0280)	(0.0402)
Gender-Female	-0.0143***	0.00135	-0.00373**	-0.00154	-0.000702	-0.00184	-0.00428**	-0.00495*	0.00157	-0.000359	-0.0122
	(0.00414)	(0.000819)	(0.00165)	(0.00128)	(0.00143)	(0.00180)	(0.00201)	(0.00277)	(0.00335)	(0.00322)	(0.00765)
Observations	5,008	3,776	4,418	4,966	4,984	4,276	3,574	2,894	2,272	1,622	1,046
R-squared	0.625	0.501	0.643	0.721	0.582	0.590	0.633	0.498	0.597	0.698	0.543

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 23 – TFE Age grade distortion - By birth weight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Grade distortion	At age 7	At age 8	At age 9	At age 10	At age 11	At age 12	At age 13	At age 14	At age 15	At age 16
Low birthweight											
Ln weight	-0.0646	-0.00413	-0.0238*	-0.0958***	-0.128***	-0.121***	-0.116**	-0.147**	-0.145**	-0.144*	-0.185**
	(0.0509)	(0.0118)	(0.0136)	(0.0311)	(0.0420)	(0.0463)	(0.0542)	(0.0632)	(0.0704)	(0.0833)	(0.0931)
Gender-Female	-0.126***	-0.00431**	-0.0107***	-0.0344***	-0.0726***	-0.0879***	-0.107***	-0.141***	-0.152***	-0.139***	-0.119***
	(0.00944)	(0.00200)	(0.00268)	(0.00572)	(0.00783)	(0.00845)	(0.00964)	(0.0113)	(0.0133)	(0.0153)	(0.0183)
Observations	4,604	3,910	4,446	4,476	4,488	4,478	3,746	3,100	2,500	1,872	1,208
R-squared	0.765	0.923	0.865	0.767	0.747	0.751	0.753	0.760	0.748	0.761	0.774
Without low birthweight											
Ln weight	-0.0595	-0.00322	0.0170	-0.0837	0.0692	-0.0143	-0.123	-0.225*	-0.136	-0.107	-0.202
	(0.111)	(0.0257)	(0.0318)	(0.0528)	(0.0864)	(0.0999)	(0.111)	(0.126)	(0.139)	(0.164)	(0.199)
Gender-Female	-0.119***	-0.00183	-0.00352	-0.0271***	-0.0474***	-0.0751***	-0.0985***	-0.123***	-0.128***	-0.134***	-0.136***
	(0.0120)	(0.00273)	(0.00243)	(0.00627)	(0.00944)	(0.0108)	(0.0125)	(0.0148)	(0.0165)	(0.0193)	(0.0237)
Observations	2,622	2,290	2,540	2,554	2,570	2,540	2,160	1,792	1,444	1,060	698
R-squared	0.773	0.905	0.903	0.819	0.736	0.735	0.744	0.742	0.757	0.767	0.765

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 24 – TFE Age grade distortion - Quality of Health Service

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Grade distortion	At age 7	At age 8	At age 9	At age 10	At age 11	At age 12	At age 13	At age 14	At age 15	At age 16
Low health quality											
Ln weight	-0.0640	0.0151	-0.000248	-0.0730**	-0.100**	-0.108**	-0.178***	-0.182**	-0.184**	-0.138	-0.150
	(0.0592)	(0.0135)	(0.00826)	(0.0326)	(0.0500)	(0.0536)	(0.0637)	(0.0727)	(0.0783)	(0.0943)	(0.104)
Gender-Female	-0.113***	6.63e-05	-0.00259	-0.0278***	-0.0577***	-0.0738***	-0.0918***	-0.114***	-0.120***	-0.123***	-0.110***
	(0.00956)	(0.00166)	(0.00178)	(0.00543)	(0.00778)	(0.00822)	(0.00949)	(0.0112)	(0.0128)	(0.0151)	(0.0185)
Observations	3,984	3,458	3,874	3,902	3,896	3,882	3,286	2,724	2,220	1,642	1,088
R-squared	0.765	0.933	0.912	0.783	0.749	0.756	0.756	0.755	0.767	0.772	0.764
High health quality											
Ln weight	-0.0574	-0.0277*	-0.0350	-0.117**	-0.0802	-0.0903	-0.0306	-0.114	-0.0730	-0.129	-0.227*
	(0.0729)	(0.0164)	(0.0258)	(0.0460)	(0.0572)	(0.0668)	(0.0753)	(0.0892)	(0.102)	(0.118)	(0.137)
Gender-Female	-0.136***	-0.00772**	-0.0148***	-0.0365***	-0.0708***	-0.0953***	-0.119***	-0.159***	-0.172***	-0.155***	-0.144***
	(0.0116)	(0.00303)	(0.00371)	(0.00686)	(0.00952)	(0.0108)	(0.0124)	(0.0146)	(0.0170)	(0.0192)	(0.0228)
Observations	3,242	2,742	3,112	3,128	3,162	3,136	2,620	2,168	1,724	1,290	818
R-squared	0.766	0.901	0.857	0.787	0.736	0.734	0.740	0.745	0.730	0.750	0.773

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 25 – TFE Age grade distortion - Socioeconomic Status of School

Variables	(1) Grade distortion	(2) At age 7	(3) At age 8	(4) At age 9	(5) At age 10	(6) At age 11	(7) At age 12	(8) At age 13	(9) At age 14	(10) At age 15	(11) At age 16
Low school socioeconomic level											
Ln weight	-0.0738	-0.0205	-0.0177	-0.119***	-0.115**	-0.106*	-0.147**	-0.192**	-0.228***	-0.217**	-0.248**
	(0.0662)	(0.0162)	(0.0214)	(0.0413)	(0.0566)	(0.0610)	(0.0720)	(0.0810)	(0.0873)	(0.105)	(0.119)
Gender-Female	-0.148***	-0.00696***	-0.0141***	-0.0390***	-0.0760***	-0.102***	-0.132***	-0.173***	-0.179***	-0.161***	-0.157***
	(0.0106)	(0.00262)	(0.00308)	(0.00657)	(0.00889)	(0.00968)	(0.0113)	(0.0132)	(0.0150)	(0.0174)	(0.0206)
Observations	3,892	3,294	3,734	3,768	3,790	3,774	3,220	2,720	2,206	1,620	1,030
R-squared	0.770	0.915	0.858	0.784	0.747	0.748	0.737	0.744	0.741	0.750	0.778
High school socioeconomic level											
Ln weight	-0.0226	-0.000103	-0.0130	-0.0571*	-0.0651	-0.0927	-0.105	-0.115	-0.0302	-0.102	-0.125
	(0.0661)	(0.000184)	(0.0101)	(0.0333)	(0.0512)	(0.0571)	(0.0659)	(0.0767)	(0.0891)	(0.106)	(0.110)
Gender-Female	-0.0894***	-0.000854	-0.00203	-0.0181***	-0.0415***	-0.0528***	-0.0594***	-0.0740***	-0.0792***	-0.0913***	-0.0755***
	(0.0105)	(0.000855)	(0.00186)	(0.00514)	(0.00816)	(0.00893)	(0.00966)	(0.0115)	(0.0134)	(0.0156)	(0.0184)
Observations	2,690	2,352	2,642	2,652	2,668	2,642	2,254	1,852	1,514	1,158	798
R-squared	0.759	0.978	0.916	0.779	0.706	0.717	0.757	0.762	0.759	0.776	0.773

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 26 – TFE Age grade distortion - Mother Schooling

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Grade distortion	At age 7	At age 8	At age 9	At age 10	At age 11	At age 12	At age 13	At age 14	At age 15	At age 16
Low mother education											
Ln weight	-0.0698	-0.0195	-0.0232	-0.135***	-0.0958*	-0.0936	-0.127*	-0.224***	-0.194**	-0.111	-0.228**
	(0.0677)	(0.0138)	(0.0193)	(0.0434)	(0.0569)	(0.0627)	(0.0719)	(0.0816)	(0.0904)	(0.103)	(0.113)
Gender-Female	-0.145***	-0.00570**	-0.0103***	-0.0426***	-0.0766***	-0.103***	-0.129***	-0.171***	-0.172***	-0.156***	-0.148***
	(0.0105)	(0.00247)	(0.00295)	(0.00660)	(0.00896)	(0.00970)	(0.0110)	(0.0127)	(0.0143)	(0.0163)	(0.0197)
Observations	4,256	3,716	4,098	4,132	4,138	4,126	3,556	2,988	2,406	1,782	1,080
R-squared	0.762	0.909	0.874	0.785	0.745	0.747	0.745	0.744	0.743	0.758	0.784
High mother education											
Ln weight	-0.00797	0.0222	0.00119	-0.0139	-0.0646	-0.0980**	-0.0709	-0.00445	0.00535	-0.0972	-0.0315
	(0.0607)	(0.0175)	(0.00979)	(0.0221)	(0.0402)	(0.0493)	(0.0572)	(0.0695)	(0.0871)	(0.111)	(0.160)
Gender-Female	-0.0758***	4.51e-05	-0.00404*	-0.0152***	-0.0374***	-0.0481***	-0.0593***	-0.0661***	-0.0901***	-0.107***	-0.0694***
	(0.0102)	(0.00187)	(0.00212)	(0.00452)	(0.00735)	(0.00827)	(0.00952)	(0.0118)	(0.0149)	(0.0184)	(0.0230)
Observations	2,516	2,322	2,446	2,454	2,468	2,444	1,944	1,518	1,174	816	528
R-squared	0.705	0.921	0.886	0.747	0.665	0.663	0.699	0.720	0.725	0.727	0.719

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 27 – TFE Age grade distortion - Number of Children

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Grade distortion	At age 7	At age 8	At age 9	At age 10	At age 11	At age 12	At age 13	At age 14	At age 15	At age 16
First children											
Ln weight	0.0455	0.00884	-0.0321	-0.000953	-0.0227	-0.0514	-0.0826	0.0322	0.102	0.0348	-0.112
	(0.0835)	(0.0255)	(0.0268)	(0.0401)	(0.0614)	(0.0729)	(0.0944)	(0.103)	(0.123)	(0.135)	(0.143)
Gender-Female	-0.0986***	0.000316	-0.0132***	-0.0349***	-0.0452***	-0.0671***	-0.0851***	-0.101***	-0.127***	-0.128***	-0.109***
	(0.0130)	(0.00280)	(0.00425)	(0.00742)	(0.00971)	(0.0114)	(0.0135)	(0.0161)	(0.0205)	(0.0218)	(0.0253)
Observations	1,696	1,486	1,656	1,662	1,668	1,656	1,342	1,100	884	636	418
R-squared	0.752	0.944	0.807	0.712	0.725	0.727	0.743	0.740	0.725	0.778	0.787
Has other children											
Ln weight	-0.128**	-0.0122	-0.0156	-0.132***	-0.121**	-0.123**	-0.129**	-0.251***	-0.244***	-0.224**	-0.248**
	(0.0590)	(0.0111)	(0.0145)	(0.0347)	(0.0471)	(0.0539)	(0.0613)	(0.0718)	(0.0797)	(0.0940)	(0.107)
Gender-Female	-0.134***	-0.00337*	-0.00607***	-0.0318***	-0.0660***	-0.0889***	-0.111***	-0.149***	-0.152***	-0.148***	-0.132***
	(0.00946)	(0.00194)	(0.00220)	(0.00543)	(0.00778)	(0.00850)	(0.00975)	(0.0113)	(0.0129)	(0.0150)	(0.0185)
Observations	5,008	4,286	4,836	4,868	4,886	4,870	4,126	3,422	2,742	2,064	1,320
R-squared	0.763	0.919	0.900	0.799	0.744	0.748	0.744	0.750	0.747	0.750	0.758

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 28 – TFE Non-cumulative Age grade distortion - By birth weight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Grade distortion	At age 7	At age 8	At age 9	At age 10	At age 11	At age 12	At age 13	At age 14	At age 15	At age 16
Low birthweight											
Ln weight	-0.0646	-0.00413	-0.0224*	-0.0794***	-0.0897**	-0.102**	-0.0723	-0.110*	-0.0461	-0.0576	-0.120
	(0.0509)	(0.0118)	(0.0131)	(0.0304)	(0.0396)	(0.0425)	(0.0459)	(0.0596)	(0.0597)	(0.0774)	(0.0909)
Gender-Female	-0.126***	-0.00431**	-0.00927***	-0.0261***	-0.0526***	-0.0519***	-0.0575***	-0.0831***	-0.0948***	-0.0794***	-0.0655***
	(0.00944)	(0.00200)	(0.00256)	(0.00543)	(0.00716)	(0.00699)	(0.00742)	(0.00988)	(0.0121)	(0.0139)	(0.0162)
Observations	4,604	3,910	4,432	4,368	4,126	3,780	2,930	2,324	1,790	1,304	872
R-squared	0.765	0.923	0.866	0.730	0.716	0.721	0.690	0.690	0.692	0.720	0.674
Without low birthweight											
Ln weight	-0.0595	-0.00322	0.00749	-0.0825*	0.119	-0.118	-0.0456	-0.0711	-0.0586	-0.261*	-0.174
	(0.111)	(0.0257)	(0.0272)	(0.0481)	(0.0839)	(0.0837)	(0.0879)	(0.106)	(0.135)	(0.141)	(0.168)
Gender-Female	-0.119***	-0.00183	-0.00220	-0.0245***	-0.0326***	-0.0543***	-0.0499***	-0.0739***	-0.0684***	-0.0935***	-0.0757***
	(0.0120)	(0.00273)	(0.00202)	(0.00603)	(0.00859)	(0.00866)	(0.00977)	(0.0126)	(0.0142)	(0.0164)	(0.0222)
Observations	2,622	2,290	2,522	2,488	2,366	2,174	1,766	1,388	1,076	772	530
R-squared	0.773	0.905	0.916	0.787	0.660	0.685	0.686	0.697	0.688	0.755	0.700

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 29 – TFE Non-cumulative Age grade distortion - Quality of Health Service

Variables	(1) Grade distortion	(2) At age 7	(3) At age 8	(4) At age 9	(5) At age 10	(6) At age 11	(7) At age 12	(8) At age 13	(9) At age 14	(10) At age 15	(11) At age 16
Low health quality											
Ln weight	-0.0640	0.0151	-0.00519	-0.0730**	-0.0657	-0.0821*	-0.150***	-0.0950	-0.0804	-0.0671	-0.0919
	(0.0592)	(0.0135)	(0.00761)	(0.0331)	(0.0483)	(0.0453)	(0.0519)	(0.0641)	(0.0629)	(0.0865)	(0.0919)
Gender-Female	-0.113***	6.63e-05	-0.00178	-0.0266***	-0.0403***	-0.0424***	-0.0462***	-0.0656***	-0.0667***	-0.0738***	-0.0551***
	(0.00956)	(0.00166)	(0.00169)	(0.00537)	(0.00703)	(0.00609)	(0.00704)	(0.00902)	(0.0104)	(0.0131)	(0.0155)
Observations	3,984	3,458	3,862	3,838	3,622	3,350	2,708	2,186	1,706	1,240	832
R-squared	0.765	0.933	0.914	0.740	0.709	0.719	0.666	0.678	0.727	0.731	0.643
High health quality											
Ln weight	-0.0574	-0.0277*	-0.0294	-0.0882**	-0.0344	-0.132**	0.0475	-0.102	0.0191	-0.136	-0.165
	(0.0729)	(0.0164)	(0.0245)	(0.0434)	(0.0524)	(0.0648)	(0.0639)	(0.0871)	(0.0944)	(0.108)	(0.139)
Gender-Female	-0.136***	-0.00772**	-0.0128***	-0.0241***	-0.0523***	-0.0657***	-0.0666***	-0.0995***	-0.111***	-0.0996***	-0.0880***
	(0.0116)	(0.00303)	(0.00342)	(0.00629)	(0.00880)	(0.00954)	(0.0102)	(0.0137)	(0.0169)	(0.0179)	(0.0222)
Observations	3,242	2,742	3,092	3,018	2,870	2,604	1,988	1,526	1,160	836	570
R-squared	0.766	0.901	0.862	0.759	0.688	0.702	0.702	0.700	0.655	0.732	0.713

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 30 – TFE Non-cumulative Age grade distortion - Socioeconomic Status of School

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Grade distortion	At age 7	At age 8	At age 9	At age 10	At age 11	At age 12	At age 13	At age 14	At age 15	At age 16
Low school socioeconomic level											
Ln weight	-0.0738	-0.0205	-0.0158	-0.107***	-0.0694	-0.147**	-0.111	-0.130	-0.0492	-0.0776	-0.180
	(0.0662)	(0.0162)	(0.0202)	(0.0396)	(0.0559)	(0.0585)	(0.0701)	(0.0867)	(0.0842)	(0.104)	(0.131)
Gender-Female	-0.148***	-0.00696***	-0.0114***	-0.0280***	-0.0562***	-0.0631***	-0.0680***	-0.115***	-0.110***	-0.0956***	-0.0857***
	(0.0106)	(0.00262)	(0.00283)	(0.00625)	(0.00822)	(0.00822)	(0.00953)	(0.0125)	(0.0148)	(0.0161)	(0.0202)
Observations	3,892	3,294	3,710	3,666	3,418	3,098	2,426	1,910	1,472	1,032	700
R-squared	0.770	0.915	0.856	0.763	0.705	0.718	0.679	0.698	0.704	0.747	0.717
High school socioeconomic level											
Ln weight	-0.0226	-0.000103	-0.0133	-0.0421	-0.0286	-0.0672	-0.0295	-0.0833	0.0156	-0.154*	-0.0364
	(0.0661)	(0.000184)	(0.0103)	(0.0332)	(0.0455)	(0.0422)	(0.0341)	(0.0546)	(0.0634)	(0.0914)	(0.0772)
Gender-Female	-0.0894***	-0.000854	-0.00204	-0.0169***	-0.0309***	-0.0294***	-0.0235***	-0.0375***	-0.0393***	-0.0611***	-0.0353***
	(0.0105)	(0.000855)	(0.00186)	(0.00491)	(0.00731)	(0.00628)	(0.00582)	(0.00857)	(0.00964)	(0.0134)	(0.0129)
Observations	2,690	2,352	2,640	2,614	2,546	2,380	1,966	1,582	1,252	956	656
R-squared	0.759	0.978	0.911	0.717	0.635	0.662	0.709	0.642	0.658	0.703	0.628

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 31 – TFE Non-cumulative Age grade distortion - Mother Schooling

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables	Grade distortion	At age 7	At age 8	At age 9	At age 10	At age 11	At age 12	At age 13	At age 14	At age 15	At age 16
Low mother education											
Ln weight	-0.0698	-0.0195	-0.0203	-0.118***	-0.0408	-0.131**	-0.109	-0.208**	-0.0670	-0.0685	-0.199*
	(0.0677)	(0.0138)	(0.0183)	(0.0427)	(0.0546)	(0.0606)	(0.0669)	(0.0847)	(0.0855)	(0.100)	(0.105)
Gender-Female	-0.145***	-0.00570**	-0.00824***	-0.0357***	-0.0558***	-0.0709***	-0.0776***	-0.117***	-0.110***	-0.116***	-0.0940***
	(0.0105)	(0.00247)	(0.00270)	(0.00638)	(0.00837)	(0.00850)	(0.00946)	(0.0124)	(0.0141)	(0.0162)	(0.0195)
Observations	4,256	3,716	4,076	3,992	3,670	3,274	2,574	2,040	1,540	1,126	718
R-squared	0.762	0.909	0.883	0.751	0.711	0.723	0.695	0.697	0.690	0.741	0.723
High mother education											
Ln weight	-0.00797	0.0222	-0.00423	-0.0139	-0.0491	-0.0649*	0.00205	0.0431	0.0284	-0.0862	0.127
	(0.0607)	(0.0175)	(0.00841)	(0.0210)	(0.0372)	(0.0378)	(0.0362)	(0.0543)	(0.0639)	(0.1000)	(0.143)
Gender-Female	-0.0758***	4.51e-05	-0.00346*	-0.0113***	-0.0236***	-0.0245***	-0.0244***	-0.0331***	-0.0431***	-0.0519***	-0.0248
	(0.0102)	(0.00187)	(0.00204)	(0.00418)	(0.00644)	(0.00586)	(0.00615)	(0.00855)	(0.0115)	(0.0147)	(0.0166)
Observations	2,516	2,322	2,436	2,426	2,404	2,296	1,794	1,374	1,042	710	464
R-squared	0.705	0.921	0.863	0.649	0.618	0.579	0.623	0.642	0.691	0.602	0.612

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tabela 32 – TFE Non-cumulative Age grade distortion - Number of Children

Variables	(1) Grade distortion	(2) At age 7	(3) At age 8	(4) At age 9	(5) At age 10	(6) At age 11	(7) At age 12	(8) At age 13	(9) At age 14	(10) At age 15	(11) At age 16
First children											
Ln weight	0.0455	0.00884	-0.0209	0.0284	-0.0373	-0.0856	-0.112	-0.0714	0.137	-0.108	-0.0326
	(0.0835)	(0.0255)	(0.0243)	(0.0312)	(0.0577)	(0.0664)	(0.0804)	(0.0832)	(0.0909)	(0.102)	(0.112)
Gender-Female	-0.0986***	0.000316	-0.0117***	-0.0211***	-0.0240***	-0.0467***	-0.0305***	-0.0494***	-0.0749***	-0.0718***	-0.0547***
	(0.0130)	(0.00280)	(0.00396)	(0.00619)	(0.00832)	(0.00923)	(0.00970)	(0.0120)	(0.0176)	(0.0171)	(0.0209)
Observations	1,696	1,486	1,650	1,626	1,586	1,514	1,154	902	698	500	336
R-squared	0.752	0.944	0.786	0.672	0.675	0.678	0.625	0.634	0.602	0.770	0.563
Has other children											
Ln weight	-0.128**	-0.0122	-0.0181	-0.126***	-0.0720	-0.125**	-0.0664	-0.155**	-0.145**	-0.150*	-0.203*
	(0.0590)	(0.0111)	(0.0145)	(0.0350)	(0.0451)	(0.0506)	(0.0524)	(0.0707)	(0.0732)	(0.0896)	(0.110)
Gender-Female	-0.134***	-0.00337*	-0.00579***	-0.0284***	-0.0501***	-0.0579***	-0.0633***	-0.0950***	-0.0926***	-0.0971***	-0.0713***
	(0.00946)	(0.00194)	(0.00212)	(0.00531)	(0.00722)	(0.00711)	(0.00781)	(0.0102)	(0.0118)	(0.0137)	(0.0173)
Observations	5,008	4,286	4,816	4,736	4,446	4,022	3,178	2,522	1,938	1,404	952
R-squared	0.763	0.919	0.899	0.759	0.699	0.715	0.693	0.691	0.689	0.718	0.708

Note: Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1