Delivering Health at School and Educational Outcomes: Evidence from Brazil*

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Abstract

This paper investigates the educational impacts of a policy-driven change in health services available to public elementary school students in Brazil. We study a nationwide program designed to induce activities of primary health care professionals at schools —ranging from anthropometric measurement, nutritional and ophthalmological services to coordinated efforts to identify and fight endemic diseases— and to refer children to other professionals of the public health care network. Exploring variation in the timing of participation induced by rules that prioritized some municipalities first, we show that the program had negative impacts in retention and early withdrawal rates. An analysis of potential health mediators points to an important role for the components of the program associated with local endemic disease control. Our results contribute to the literature on the impacts of access to health services on human capital accumulation after early childhood, and suggest that programs that explore schools to target health-related conditions can be effective to improve educational outcomes.

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1 Introduction

Poor health conditions act as important constraints on the amount and productivity of time children spend accumulating human capital. In the last decades, widespread agreement on this fact led several local and national governments to adopt and expand school-based health programs (SBHP; see, WHO, 1999; World Bank, 2018; JPAL, 2020, for instance). A bet on intuitively promising features of such programs was already at the heart of the holistic approaches to early childhood development of *Head Start* and the *Abecedarian Project*, which considered health a crucial component of human capital, alongside cognitive and noncognitive skills. There is now a large evidence base on the long-run impacts of such programs and studies that point to health as a key mediator of these impacts.[1]

However, much less is known about policies that expand the set of health services available to students after early childhood, even in the short run. Since the modern evidence on the technology of human capital formation provides strong support for the existence of sensitive— or even critical— periods of investment (Heckman and Mosso, 2014; Bailey et al., 2020), filling this gap is important.

This paper studies the educational effects of a model SBHP targeting public school students in Brazil, created in 2007 and implemented from 2009 onward (*Health at School Program*, HSP). HSP can be considered a model SBHP for two reasons. First, its broad set of components —ranging from anthropometric measurement, nutritional and ophthalmological services to coordinated efforts to identify and fight endemic diseases— places it very close to the currently recommended optimal health package for school-age children (Bundy et al., 2018). Second, its main motivation, the under-explored synergies between services provided by the public education and public health systems, is in strong accordance with similar programs in the developed and developing world. The fast penetration of HSP, which had reached more than 90% of municipalities and 18 million students by 2014, leveraged the pre-existing structure of the *Family Health Program* (FHP), a national policy that greatly expanded the supply of primary care using family health teams since the 1990s. The main focal points of contact of FHP with the population are *households*, and HSP may be well viewed as the systematic inclusion of *schools* in FHP's set of focal points.

In order to study HSP's effects, we build a panel of municipalities with information on

[1] Bailey et al. (2021) evaluates long-run effects of the *Head Start* preschool centers expansion on human capital accumulation. Evidence on the support of health as a key mediator of these impacts can be found, for instance, in Ludwig and Miller (2007) and Carneiro and Ginja (2014). Anderson (2008) and García et al. (2020) study the long-run impacts of the *Abecedarian Project*. Notice also that the idea that early childhood interventions should explicitly target health-related conditions is not specific to the US policy context (see Rossin-Slater and Wüst, 2017, which studies preschools for poor children in Denmark, which have a strong health care component).

program participation and data on educational and health outcomes from 2007 to 2014. We focus on elementary school students in the public Brazilian K-12 system, from grades 1 to 5, because these grades were the main target of HSP in its first years. Like the FHP, the HSP was implemented decentrally and in a staggered fashion by municipalities using resources provided by the federal government. Hence, one major estimation challenge is that program participation was not exogenously assigned: unobserved factors affecting health care availability may be correlated with determinants of educational outcomes, compromising the validity of the parallel trends assumption. A second challenge is that different groups of municipalities might have been heterogeneously affected by HSP, likely threatening the validity of the constant treatment effects assumption that would allow one to identify clearly interpretable causal parameters with standard panel data methods[2].

We take advantage of one specific feature of our setting in order to address these identification concerns. Specifically, the timing of entry of municipalities was constrained by prioritization rules put in place by the federal government in the first years of program operation (from 2009 to 2012). A sub-set of such rules related to educational performance, as measured by a continuous indicator with a range from 0 to 10, called *Basic Education Development Index* ("Indíce de Desenvolvimento da Educação Básica", IDEB).[3] Essentially, these rules were set by the federal government in order to induce worst-performers in education to benefit from the services financed by HSP first. For instance, in 2009, municipalities with a 2005 IDEB below a cutoff of 2.69 were deemed prioritary. In 2010, in turn, municipalities with a 2007 IDEB below a cutoff of 3.1 were considered a priority. After another change in rules for 2011 and 2012, which used a cutoff of 4.5 in the 2009 IDEB to induce participation in municipalities with better educational outcomes, all rules were dropped from 2013 onward. We provide descriptive evidence that these changes closely match the pattern of entry of municipalities from different educational levels into HSP.

Our main empirical strategy leverages these changes in prioritization rules, combining three components, which can be considered as adaptations of typical strategies in fuzzy regression discontinuity designs (Carneiro and Ginja, 2014; Grembi et al., 2016) to the staggered adoption design generated by HSP. First, we explore the prioritization rules as sources of exogenous variation in participation through time in a dummy instrumental variable (IV) framework. Specifically, we define an indicator for being deemed prioritary according to IDEB in a given year and use it in the first stage to isolate effects of participation that are more likely to be exogenous to latent determinants of our main outcomes of interest. Second, we restrict our sample to municipalities

[2]See, Roth et al. (2022), for instance, for a comprehensive discussion of identification in staggered adoption designs

[3]We discuss the additional rules used for prioritization, and why we select this sub-set as our preferred instrument in detail in Section 2.

in windows around the cutoffs set by these rules and allow for window-specific time trends (window-by-year fixed effects) to flexibly accommodate for time patterns specific to the heterogeneous groups of municipalities that were sequentially targeted by the rules. Third, we control for linear time trends interacted with polynomials of different degrees on the relevant IDEBs, in an effort to net out remaining convergence patterns not captured by the set of window-specific time trends. We provide descriptive evidence that, jointly, the three components allow us to exploit variation in program participation over time induced by rules that are arguably exogenous to baseline characteristics of municipalities and to dynamic patterns in our main outcomes.

We start by asking whether HSP participation affected educational attainment in public elementary schools. The two outcomes we consider —retention and early withdrawal during the academic year— lead to or increase age-grade distortions, which are very common among Brazilian public school students (at 40% by the end of primary school) and highly predictive of dropout in later stages of education. Our results provide strong support for reductions in retention rates due to HSP. In our preferred specification, which combines all the components discussed above, we find a significant IV estimate of -1.35 percentage points, amounting to a reduction of roughly 11% from the baseline average rate of 12.4%. Since retention happens either due to low grades or lack of minimal attendance, this result indicates that at least one of these margins was influenced by HSP. We then consider changes in students' attachment to schooling using early withdrawal rates as a proxy. We document that HSP had significant effects close to -0.5 percentage point, or 16% from the baseline average rate of 3.4%.

In the analysis based on the empirical strategy described above, we present evidence that the instrument is well suited for causal identification. First, we show that being deemed prioritized at some point is not systematically correlated with baseline characteristics, if we compare municipalities in the narrow windows around the cutoffs set by the prioritization rules. Second, we compare the sensitivity of OLS and 2SLS estimates to the inclusion of window-specific time trends, finding stark contrasts. While the OLS estimates are largely attenuated by the inclusion of these trends, the 2SLS estimates are remarkably stable. This suggests that there are time-varying confounders at the window level that are systematically associated with participation but that are seemingly orthogonal to prioritization, which highlights the importance of our instrumental variable. Third, we use an event-study specification and graphically inspect the dynamic behavior of our main outcomes in the years before municipalities became prioritary. After incorporating the window-specific time trends and the time trends interacted with polynomials of IDEB we find suggestive evidence of common pre-trends. As an additional effort to put our results under further strain we perform a variety of robustness exercises. Overall, these exercises show that the qualitative conclusions on the HSP effects we find on educational outcomes are robust to alternative sample restrictions and panel time frames.

We then turn our attention to potential health mediators. Unfortunately, there is no systematic registry of all health services delivered by HSP for the whole period we analyse in this paper, even though descriptive evidence points to large increases in ophthalmological, anthropometrics, and nutritional services and collective activities on healthy habits promotion. However, we can provide a rich picture of one health mediator: the efforts toward the early detection of endemic diseases, observing local epidemiological indicators. We start by showing that the estimates of effects on the incidence of most endemic diseases on the average municipality are imprecisely estimated. Then, since the efforts toward endemic disease control were to be guided by information on local presence, we use proxies of exposure (baseline incidence) to investigate whether there were decreases where awareness of the problem was more salient to health professionals when the program was created. We find strong support for the latter hypothesis for all diseases.

A large strand of literature documents associations between school participation and poor health conditions (see World Bank, 2018, and references therein), most of which are targeted by the large set of HSP services.[4] Our findings are more directly related to the literature on the direct impacts of policy-driven improvements in access to health on human capital accumulation among school-age children. A number of observational and experimental studies have focused on isolated components of SBHP — such as, for instance, treatment for intestinal worms and soil-transmitted helminths (e.g., Miguel and Kremer, 2004; Baird et al., 2016) or vision screening and provision of eyeglasses (e.g., Ma et al., 2014; Glewwe et al., 2016; Nie et al., 2020) —, but there are little prior evidence policies bundling health investments into one comprehensive package and operating at scale. In this sense, in a recent review of educational interventions designed to improve learning and school participation in low- and middle-income countries, Snilstveit et al. (2015) argue that, despite being widely implemented, "*the effects of* [...] *school-based health programs are not clear because few studies have been conducted*" (p. 1).[5] As discussed above, this is particularly true for school-based interventions that affect children after early childhood (Abrahamsen et al., 2021; Lundborg et al., 2022).

Two exceptions in the literature are Abrahamsen et al. (2021) and Lovenheim et al. (2016). Abrahamsen et al. (2021) use variation from a 1999-reform in Norway that increased the availability of nurses across municipalities and cohorts to study longer-term effects of increasing the availability of health services in schools. The authors document reductions

[4]For thorough literature reviews on health and health-related conditions and their impacts on educational achievement, productivity, and labor allocation across sectors, see Glewwe and Miguel (2007) and Dupas and Miguel (2017), respectively, and references therein.

[5]In a similar vein, Abrahamsen et al. (2021) argue that "*despite recent work supporting that at later stages of childhood it is possible to ameliorate early disadvantage,* [...] *there is still scarce evidence about the effectiveness of interventions at school age*" (p. 1).

in teenage pregnancy and college attendance among girls that can be attributed to the policy change. Lovenheim et al. (2016) study the effects of providing basic preventative health services and contraception for low-income high school students through school-based health centers in the United States using within-state variation in the timing of entry across counties during the 1990s and 2000s. The authors find that the adoption of services equivalent to the average center had a negative effect of 5% on teen birth rates over time, but they report little evidence that they affected high school dropout rates. Both papers concentrate on the health mediator of early pregnancy. We complement this literature by studying primary school students, where this health mediator plays no role, and considering the implementation of SHBP at scale in a developing country context.

Our results also relate to the growing literature on the equity effects of expanding access to primary health care among underprivileged populations (Bhalotra et al., 2019, see, for instance). Brazil reached near-universal enrollment in elementary education in the last decades, and one of the main features of the country's school system is the fact that public and private schools are very different in terms of student's income and quality indicators.[6] Policies targeted at public schools, such as HSP, end up reaching the bulk of vulnerable and under-served children in the population and may address widely documented public-private school gaps.

The remainder of the paper is organized as follows. Section 2 describes the institutional background and the program. Section 3 presents our data. Section 4 describes how we use prioritization rules put in place in the first years of the program as a source of exogenous variation in program participation over time to study its effects. Section 5 presents the main results on educational outcomes. Section 6 presents the results on endemic disease control. Section 7 concludes with a discussion of our findings.

2 Institutional Background

2.1 Access to Primary Health Care in Brazil: The Unified Health System and The Family Health Program

In 1988, Brazil established universal and egalitarian access to health care as a constitutional right. In the following years, infra-constitutional legislation introduced the Unified Health System (*Sistema Único de Saúde*, SUS). The system follows a social insurance model of health care financing designed to guarantee free universal health coverage. A vast literature documents that, over the last decades, SUS has successfully expanded access to health services throughout the country, improved health outcomes,

[6]For instance, in 2014, only 2%, 3% and 4% of high school students in families in the first, second and third income quintile were in private schools, respectively (Almeida et al., 2017). Also, retention and early withdrawal rates are substantially higher in public schools (Costa, 2013).

and reduced health inequalities (see, for instance Soares and Rocha, 2010; Bhalotra et al., 2019; Castro et al., 2019).

The new system was expanded along with a rapid scaling up of a network of primary care community services, led by the roll-out of the Brazilian *Family Health Program* ("Programa/Estratégia Saúde da Família", FHP). The main goal of the FHP was to shift the provision of health care from large public hospitals placed in main urban centers towards a decentralized model, with FHP teams placed in local communities, being responsible for the delivery of primary health care and the referral to other services. FHP teams are composed of at least one family doctor, one nurse, one nurse assistant, and four or more community health agents based in primary health care facilities. They are responsible for outpatient visits and periodic household visits to a predetermined number of families in specific catchment areas. FHP teams now often include dentists, dental technicians, and other professionals such as nutritionists, psychologists, social workers, physical education specialists, speech and hearing therapists, among others.

The main activities of FHP teams cover counseling on the prevention and detection of diseases in their early stages through continuous monitoring and screening of health conditions. The teams are also responsible for implementing large-scale health interventions, such as immunization campaigns or coordinated efforts against locally endemic diseases (Macinko and Harris, 2015; Soares and Rocha, 2010). FHP rolled out over the mid-1990s throughout the early 2000s and is currently the largest community-based primary care program in the world. It is present in nearly all municipalities and covers approximately 64.5% of the Brazilian population.[7]

2.2 The Health at School Program

2.2.1 Creation, Rollout and Health Services

In 2007, after the bulk of the FHP expansion across and within municipalities had occurred, the Ministry of Health (MS) and the Ministry of Education (ME) jointly launched the *Health at School Program* ("Programa Saúde na Escola", HSP henceforth, Brasil-DOU, 2007). HSP was designed to provide financial resources to municipalities in order to induce and standardize activities of health professionals from FHP teams at schools in their catchment area.

There are several reasons why a SHBP as HSP was considered a promising policy alternative, from both efficiency and equity standpoints. Some of these reasons are specific to the Brazilian setting, while some relate more generally to potentially beneficial effects of such programs (World Bank, 2018). First, Brazil has reached near-universal enrollment in primary and lower secondary education, and nearly all children in the

[7] Data from MS/SAPS/DESF as of December 2019.

country engage with the educational system at some point in their lives, enabling such programs to reach a significant part of the population. Second, one of the main features of the country's school system is that public and private schools are starkly segmented in terms of students' socioeconomic status and quality indicators. In educational systems that are highly segmented in terms of family income, the program targeting may provide direct transfers to poor households that would otherwise sub-invest in health products with high private returns (Dupas, 2011). Thus, targeting health interventions at public school students would reach under-served children while at the same time addressing widely documented public *versus* private school performance and quality gaps. Finally, the program emphasized the economies of scale brought about by providing health services in institutional settings like schools (MS/ME, 2011).

As in the FHP case, the HSP is financed by federal resources and implemented by municipalities decentrally. The HSP financial resources were given as an addition to, not as a replacement of, the municipalities' own public primary health care funding through FHP. Figure 1 describes the evolution of the average coverage of the FHP and HSP across municipalities. We observe that the expansion of the FHP had already reduced its pace, both across and within municipalities, at the time the HSP was launched. We also observe that entry into HSP occurred less continuously than entry into FHP. Participation in HSP grew from 20% in 2010 and 2011 to roughly 45% in 2012 to close to 90% in 2013 and 2014. Figure 2 plots this roll-out on a map by marking the year in which the program was adopted in a given municipality. We observe that early adopters tend to be in the Northern and Northeastern regions, in Brazil's most socioeconomically vulnerable states. We also see that the program was widespread in 2014, after the end of the prioritization rules. In fact, HSP gained substantial scale all over the country. According to data from the Ministry of Health, in 2014, HSP had reached 18 million students from public schools in Brazil, or around 40% of the total, nearly 80 thousand public schools, and involved 30 thousand FHP teams.[8]

The main principle of HSP is that schools should also be considered by FHP health professionals as focal points. The guidelines of the program indicate normative material to standardize practices and signal the expectation of the health authorities about municipality-level health outputs. The health services listed are:

- *ophthalmological*: (*a*) visual acuity screening in students (*Snellen* test) by health professionals and identification of students with visual problems;[9] (*b*) referral to basic health units for students with identified visual problems;

[8]Data from MS, as of 2015.

[9]*Snellen* tests use charts printed with eleven lines of block letters, where the first line consists of one very large letter and subsequent rows have letters that decrease in size. A person taking the test covers one eye from 20 feet away, and reads aloud the letters of each row, beginning at the top. In total, the test takes no more than 3-5 minutes *per* child.

- *anthropometric and nutritional*: (*a*) height and weight measurement; (*b*) classification of students into categories, such as undernourished or obese; (*c*) referral to basic health units for students with identified with growth or weight problems (*d*) provision of families with information on food habits that are adequate for children in each specific situation;
- *oral health*: (*a*) epidemiological screening of cavities or periodontal diseases; (*b*) collective educational activities on oral health; (*c*) supervised tooth-brushing; (*d*) fluoridation procedures; (*e*) distribution of personal oral health kits containing toothbrush, fluoride toothpaste and dental floss;
- *language development*: (*a*) screening by health professionals and identification of students with language development or hearing problems; (*b*) referral to phonoaudiologists for children with language development impairments (*c*) referral to basic health units for students with identified hearing problems, for wax removal or acquisition of hearing aid devices;
- *vaccination schedule updating*: (*a*) verification of the vaccination schedule; (*b*) referral to basic health units for students with poor immunization;
- *collective activities of health promotion*: (*a*) healthy habits seminars; (*b*) physical activities;
- *early detection of local endemic diseases*: (*a*) evaluations to identify signs of neglected health diseases, observing local epidemiological indicators (MS/ME, 2011).

Unfortunately, there is no systematic registry of students' use of school health services for the whole period we analyse in this paper. However, for 2014, information on the number of children aged 6 to 11 reached by the procedures grouped in each component listed above was collected at the school level and is available from the *Health System Information for Basic Attention* ("Sistema Informação em Saúde para a Atenção Básica", SISAB/Datasus).[10]

We collapse these data at the municipality level and present descriptive statistics in Table 1. Columns (1) and (2) present the total number of children reached by each group of health procedures for HSP and non-HSP municipalities, respectively. Columns (3) and (4) in Table 1 presents the average ratio between the total number of children covered and the total number of children enrolled in the public school system (multiplied by 1,000). Overall, the inspection of Table 1 leads to two conclusions. First, apart from oral health services, municipalities that did not participate in HSP had little or no access to services that were funded by the program. Given that this is the last year of our panel,

[10]Children in Brazil enter the grade 1 of the K-12 system with 6 years and, absent any retention, would end primary school in grade 5 with 10 years old. Thus, this is the best approximation we have for the underlying population of interest of this study.

this conclusion backs the qualitative evidence that, despite efforts to emphasize health promotion within schools, progress in this direction was "fraught by the inability to create integrating actions" before the HSP (de Sousa et al., 2017, p. 1782). Second, the most important HSP services were ophthalmological, anthropometrics and nutritional, and collective activities on healthy habits promotion.

Notice that the last component of HSP aimed to coordinate the identification of cases of locally endemic diseases using schools as focal points, while at the same time providing information to the population through schools. The identification of cases was considered part of the screening process of FHP professionals working inside schools, in close observance of local incidence indicators. Furthermore, one of the recommendations was that these professionals scheduled focused consultations to track endemic diseases at the basic health units. The information component, on the other hand, aimed to boost the early detection of endemic diseases by instructing school staff on symptoms. The set of diseases mobilizing most of the efforts at the local level should, according to the guidelines, follow the consideration of local epidemiological indicators. However, the federal government listed from the start the following set of diseases as targets for HSP: *Dengue* fever, viral hepatitis, schistosomiasis, leishmaniasis, and tuberculosis. Unfortunately, the SISAB/Datasus does not contain a systematic registry of procedures related to this domain. In Section 3, we discuss data on disease incidence we use to describe the effects of HSP on these potential health mediators.

2.2.2 Municipality Prioritization Rules

The timing of entry of municipalities into HSP was influenced by rules put in place by the federal government. The main motivating idea underlying these rules was to prioritize municipalities with low educational performance and high FHP capacity. Educational performance is officially measured in Brazil by a continuous indicator called *Basic Education Development Index* ("Indíce de Desenvolvimento da Educação Básica", IDEB henceforth), created in 2005 by the Ministry of Education. IDEB varies between 0 and 10, and is computed at the school-grade level (grades 5, 9, and 12) as well as at the municipality-grade level. The index combines student achievement scores from a bi-annual national standardized exam called *Prova Brasil* with student approval rates. FHP capacity, in turn, is measured by the Ministry of Health and defined in terms of population coverage. More precisely, coverage is officially approximated by the number of FHP teams multiplied by 3,000 and divided by the municipality's population.

Figure 3 presents a timeline describing how the prioritization rules evolved over time. The first set of rules, active for 2009, considered as prioritary municipalities with IDEB lower than 2.69, as measured in 2005 for grade 5, and with 100% of FHP population coverage as of November 2008. The first agreements and federal disbursements were made at the end of the 2008 academic year. In 2010-2011, the prioritization cutoffs moved to IDEB lower than 3.1, as measured in 2007 for grade 5, and at least 70% of the population covered by the FHP program as of August 2009. In 2012, the cutoffs moved again, and municipalities with IDEB lower than 4.5, as measured in 2009 for grade 9, and at least 70% of the population covered by the FHP program as of June 2010 became prioritary. All rules were then abandoned from 2013 onwards. The timeline depicted in Figure 3 matches the patterns of Figure 1, which shows that the evolution of the HSP coverage across municipalities moves discontinuously along the changes in prioritization rules.

Notwithstanding the contrived changes to prioritization rules over time in terms of IDEB and FHP coverage, other rules added further nuance to municipality selection into HSP. First, municipalities that had at least one school participating in the *More Education Program* ("Programa Mais Educação", MEP) were considered prioritary for the HSP, but prioritization was restricted to affect the schools that participated in the program. MEP was created in 2007 by the Ministry of Education with the aim of extending public schools curriculum and increasing time spent in school with activities complementary to formal class hours.[11] Second, prioritization criteria made just a few municipalities prioritary in some states, so legislation also enabled the inclusion of the 20 worst-performing municipalities in each state, selected according to the ranking of IDEB, as measured in 2005 for grade 5, up to 3.8 (the national average) and as long as they met full FHP coverage.[12]

3 Data

Our analysis relies on a balanced municipality-by-year panel of data on health, educational, and control variables for the 2007 throughout 2014 period. It starts in 2007 because sufficiently detailed data on health and educational indicators are available only from that year onward. Since HSP was officially launched in December 2007, but the first federal disbursements were made available only at the end of the 2008 academic year, we consider 2009 as the first year of exposure to the program and the previous two years as our pre-program period. As discussed in Section 2, all prioritization rules were dropped from 2013 onward, and, in 2014, about 93% of the Brazilian municipalities participated in the program. We thus consider the two years of 2013 and 2014 as our final period as we expect entry to become increasingly endogenous following the end of the prioritization restrictions.[13]

[11] We observe that schools from 254 municipalities that would not be prioritary for HSP were allowed into the program because of MEP. We discuss the robustness of our main results to the exclusion of these municipalities

[12] Official lists indicate a total of 192 municipalities that became prioritary to HSP at different points in time because of state rankings.

[13] In our discussion of the robustness of the findings, we include exercises to show that the time frame restriction in our panel is immaterial for our main results.

3.1 HSP Participation and Prioritization Rules

Data related to HSP funding are obtained from the Ministry of Health and the System of Information on Public Health Budgets (*Sistema de Informações sobre Orçamentos Públicos em Saúde*, SIOPS). We use these data to compute participation in HSP as an indicator of positive transfer to a municipality in a given year.

We follow official documentation and federal legislation in *Diário Oficial da União* (DOU) to compute all prioritization indicators listed based on: (*i*) municipality IDEB, using data available from the Ministry of Education (Inep/MEC); (*ii*) FHP coverage in the relevant periods for prioritization, obtained from the Ministry of Health (CNES/MS); (*iii*) worst-performer municipalities, also using data available from the Ministry of Education (Inep/MEC); (*iv*) MEP prioritization, using the annual lists of municipalities that are explicitly mentioned as eligible to HSP in according to these criteria in DOU. Table A.1 presents descriptive statistics on these indicators, broken down by year.

Table A.1 summarizes the evolution of the number of municipalities and the respective share that adopted the program under each criterion. Notably, the criteria defined by the sharp rules of the program are not met by some of the listed municipalities, as shown in the last column of Table A.1. We further discuss prioritization and selection details in Section 4.

3.2 Educational Data

We use data on yearly educational outcomes at the municipality level by using data available from Inep/MEC and indicators available from the Observatory of the National Plan for Education (*Observatório do Plano Nacional da Educação*). Our analysis focuses on students from public schools enrolled in grades 1-5, which are 6 to 10 years old. Educational attainment is measured by (*i*) student retention rates, which describe the share of students from grades 1-5 that are not allowed to attend the subsequent grade as a result of insufficient grade achievement or lack of minimal daily attendance; and (*ii*) early withdrawal rates, which is the share of students from grades 1-5 that stop attending school at some point during the academic year.

3.3 Incidence of Endemic Diseases

One of the components of HSP aimed to coordinate the identification of cases of locally endemic diseases using schools as focal points. As explained in Section 2, the set of diseases should follow the consideration of local epidemiological indicators, but the federal government listed from the start the following diseases as targets for HSP: *Dengue* fever, viral hepatitis, schistosomiasis, leishmaniasis, and tuberculosis. For all these diseases, we can observe the number of cases of endemic diseases confirmed in a year for a given age group through epidemiological data available from the Information System for Notification Harm (*Sistema de Informação de Agravos de Notificação*, Datasus/SINAN). We use these data to construct an age-specific (5 to 9) number of confirmed cases for each neglected disease.

3.4 Auxiliary Data

We make use of additional variables at the municipality level that is auxiliary to our analysis. First, we obtain from the Ministry of Cidadania (former MDS/SAGI) the municipality coverage of the *Bolsa Família*, a conditional cash transfer program, and the main social assistance policy of Brazil. We also collect data on educational and health care resources: a dummy that indicates the presence of hospitals served by SUS (Ministry of Health/DAB), the number of public schools, and the total number of enrolled students (Inep/MEC) and children of primary school age (between 5-9 years old). We obtain data on population by age from IBGE and annual GDP from Ipeadata, enabling us to construct the municipality GDP per capita. Finally, we rely on the 2010 Demographic Census (IBGE) to construct municipality socioeconomic indicators – such as family income per capita, Gini Index, the share of the urban population, and access to water and sanitation – which are used in the characterization of a group of municipalities under different prioritization criteria for HSP.

3.5 Descriptive Statistics

Our initial sample contains all the 5,557 municipalities of Brazil over the eight years throughout the 2007-2014 period, which allows a window of two years of data before the first municipalities were enrolled in the HSP, and two years after the entry into the program became unrestricted.[14] Given the centrality of IDEB in our analysis, we drop the 583 municipalities that did not have information on these indicators for at least one of the years used in the prioritization criteria. [15] We refer to the remaining 4,974 municipalities and 39,792 observations as our full sample and discuss additional sample restrictions in Section 4. Table 2 presents the descriptive statistics of our main variables.

[14]Brazil had, as of 2014, 5,570 municipalities. We exclude from the panel the 13 municipalities that originated from splits of one municipality into two or more municipalities during the period of the panel data.

[15]We exclude these municipalities as they are not observed in the distribution of IDEB, which is used in our empirical strategy to define samples around prioritization cutoffs. These municipalities were likely not eligible for HSP because we do not observe any of them participating in the program in the years when the restrictions apply.

4 Empirical Framework

4.1 Conceptual Setup

In this paper, we assess whether the introduction of HSP is associated with changes in educational outcomes and potential health mediators. The following equation provides the conceptual setup for the analysis:

$$Y_{mt} = \alpha_m + \gamma_t + \tau \text{HSP}_{mt} + \mathbf{X}'_{mt}\mathbf{\Theta} + v_{mt} \tag{1}$$

where Y_{mt} is an educational or health outcome of interest for municipality m in year t. The variable HSP_{mt} indicates participation in the program, and α_m and γ_t are municipality and year fixed-effects, respectively. The fixed-effects α_m intend to absorb the confounding influence of initial conditions and persistent municipality characteristics that are not expected to vary within a short period of time, such as climate and local epidemiological features as well as local state capacity, access to public utility services and physical infrastructure. The fixed-effects γ_t control for common time trends, such as macroeconomic conditions and the political cycle. The term $\mathbf{X}_{mt}$ is a vector of relevant time-varying controls, which absorb the influence of observable demand-side and supply-side determinants of education and health — GDP per capita, the presence of hospitals, and the population coverage of the FHP, population coverage of the conditional cash transfer *Bolsa Família*, and the number of schools per 1,000 children of school age. Finally, v_{mt} is the error component.

Should participation in HSP be random (potentially, after conditioning on the fixed-effects and the time-varying controls) and the effects of HSP be constant across observational units, the OLS estimate of τ would capture the causal effects of HSP participation (Roth et al., 2022). However, even though participation was exogenously constrained for different groups of municipalities, we consider that OLS estimates of equation (1) could still be biased.

First, entry might be correlated with non-observable determinants of low educational performance, then potentially raising concerns about the parallel trends assumption. For instance, conditional on prioritization, participation in government programs is typically correlated with policy-making capacity and voters' preferences. Although arguably persistent within a short period of time, these variables are potentially correlated with entry into alternative government programs or with non-observable trends in determinants of educational outcomes. Second, non-observable convergence in educational outcomes could lead to overestimation of HSP effects, should selection be relatively more pervasive among the most vulnerable municipalities, and we know that the rules indeed prioritized and induced entry of low-performers first. Still, even if the parallel trends assumption holds, different groups of municipalities experienced a different evolution of their exposure to treatment as prioritization thresholds moved to include higher-performers over time, thus potentially violating the constant treatment effect hypothesis and compromising the interpretation of single two-way fixed-effects estimator (de Chaisemartin and D'Haultfœuille, 2020). Finally, as mentioned in Section 3, our analysis relies on administrative microdata sets, which are subject to measurement error. This is particularly worrisome with respect to FHP coverage, which is officially proxied by a formula based on the ratio of population size to the number of health teams, and for SINAN/Datasus data because of under-reporting of disease cases and changes in procedures coding over time.

4.2 Empirical Strategy

Our main empirical strategy combines three components to alleviate the concerns raised above. These components can be considered as adaptations of usual strategies in fuzzy regression discontinuity designs (Carneiro and Ginja, 2014; Grembi et al., 2016) to the staggered adoption design generated by HSP. We discuss in detail the reasoning underneath each component in what follows.

4.2.1 Instrumental Variable: IDEB Prioritization

As discussed in Section 2, the pace of the HSP roll-out across the country was influenced by prioritization rules regarding IDEB levels, FHP coverage, and participation in other programs (PME). Although all these rules could potentially offer useful variation in HSP participation, we consider that the prioritization rules based on IDEB provide the most transparent set of predictors associated with participation in the program. First, IDEB thresholds were indeed the main constraint to HSP adoption. Most of the municipalities that were prioritary because of IDEB were also prioritary through FHP, but the opposite does not hold.[16] Second, in principle, prioritization through FHP is potentially subject to manipulation by the municipality as this is the level at which health teams are hired, and the coverage is defined. The IDEB, in turn, is calculated by the federal government and the relevant value of the indicator refers to at least three years before the year when it is used to define prioritary municipalities.

In light of these facts, we propose the following instrumental variable approach to the estimation of (1):

$$Y_{mt} = \alpha_m + \gamma_{m,t} + \tau \text{HSP}_{mt} + \mathbf{X}'_{mt}\mathbf{\Theta} + v_{mt} \tag{2}$$

$$\text{HSP}_{mt} = \pi_m + \delta_{m,t} + \eta \text{Priorit}^{\text{IDEB}}_{mt} + \mathbf{X}'_{mt}\mathbf{\Pi} + \xi_{mt} \tag{3}$$

[16] For instance, in the 2010-2011 wave, only 18% of the municipalities that were prioritary through IDEB were constrained by FHP, while 76% of the municipalities that were prioritary through FHP were constrained by IDEB.

where $\text{Priorit}_{mt}^{\text{IDEB}}$ indicates whether municipality m is considered prioritary for HSP in year t according to IDEB cutoffs:

$$\text{Priorit}_{mt}^{\text{IDEB}} = \begin{cases} 0, & \text{for } t \leq 2008 \\ 1, & \text{for } t = 2009 \text{ if } \text{IDEB}_m^{5,2005} \leq 2.69 \\ 1, & \text{for } t = 2010, 2011 \text{ if } \text{IDEB}_m^{5,2007} \leq 3.1 \\ 1, & \text{for } t = 2012 \text{ if } \text{IDEB}_m^{9,2009} \leq 4.5 \\ 1, & \text{for } t \geqslant 2013 \\ 0, & \text{otherwise} \end{cases}$$

where m stands for municipality, and the superscript indicates the grade and year of the relevant IDEB used to set the cutoffs. In all specifications, the term $\mathbf{X}'_{mt}$ adds dummies that indicate whether the municipality is prioritary to HSP because of other criteria (FHP coverage, MEP, or state ranking) in order to specifically isolate the shift into treatment triggered by IDEB rules.

4.2.2 Sample Restriction and Window-Specific Nonlinear Time Trends

While using the instrumental variable described above should help isolate exogenous variation that induces participation, we take further steps to balance prioritary *versus* non-prioritary municipalities both in terms of observable and non-observable characteristics and to contemplate the potential concern of heterogeneity in treatment effects.

First, our preferred specifications are based on fitting regression models (2) and (3) on a restricted sample of municipalities, which lie close to the cutoffs induced by the IDEB prioritization rules discussed in detail above. More specifically, in our main analytical sample, we include only municipalities that laid at a minimal distance of 0.1 points of one of the three cutoffs that appear in the definition of $\text{Priorit}_{mt}^{\text{IDEB}}$ presented above.[17] This restricted sample contains 950 municipalities, corresponding to 7,600 observations in our panel.[18] Second, in order to assess the evolution of outcomes across similar groups of prioritary and non-prioritary municipalities within windows, irrespective of

[17]Thus, for each wave there is a designated window around the cutoff: the first window includes municipalities for which $\text{IDEB}_m^{5,2005}$ ranged between 2.59 and 2.79 in 2005, the second municipalities for which $\text{IDEB}_m^{5,2007}$ ranged between 3.0 and 3.2 in 2007, and the third municipalities for which $\text{IDEB}_m^{9,2009}$ ranged between 4.4 and 4.6 in 2009. Formally, this means defining a restricted sample of municipalities under the following conditions: $\mathbb{1}(2.59 \leqslant IDEB_m^{5,2005} \leqslant 2.79 \mid 3.0 \leqslant IDEB_m^{5,2007} \leqslant 3.2 \mid 4.4 \leqslant IDEB_m^{9,2009} \leqslant 4.6)$.

[18]Notably, we observe similar sub-sample sizes across windows, thus covering different parts of the IDEB distribution — there are 294, 277 and 379 municipalities that appear exclusively in the windows generated by the 2008-09, 2010-11, and 2012 waves, respectively. It is also worth noting that we observe 78 municipalities that appear simultaneously in the first two windows. Given that the official rules do not make it clear whether municipalities lose their prioritization status, we drop these 78 municipalities from our restricted sample. We show that the results remain robust to the inclusion of these observations.

specific trends across windows, we include interaction terms between year fixed effects and window indicators. We refer to those terms as window-specific nonlinear time trends, which enable us to assess the evolution of outcomes across similar groups of prioritary and non-prioritary municipalities within windows, flexibly and irrespective of specific trends across windows. In this case, our IV induces variation in program participation along different points of the distribution of educational performance, irrespective of the potentially confounding influence of trends steaming from different groups of municipalities.[19]

Table 3 compares our restricted sample of 950 municipalities to the full sample of 4,974 municipalities described in Section 3. Columns (1) and (2) present means and standard deviations of the covariates listed in rows using the full sample and the restricted sample, respectively. Column (3) presents t-tests associated with the null hypothesis that means in the two samples are different. Considering public education characteristics at baseline, we find that municipalities in the restricted sample have slightly higher rates of retention and early withdrawal rates. This is consistent with the fact that they are selected around cutoffs of the relevant IDEBs for prioritization. We also find evidence of small differences in public health characteristics, as municipalities in the restricted sample tend to have slightly higher FHP coverage rates and are more likely to have a public hospital. Finally, when looking at covariates from the 2000 census, we find evidence of negative selection in terms of observables with respect to income, urbanization and access to services related to water provision, sewage and garbage removal. Given these selection patterns, in our main results, we provide evidence that including more municipalities in our restricted sample — i.e., enlarging the window width — has little effect on our main results.

4.2.3 Time Trends on IDEB Polynomials

While the sample restriction and the inclusion of window-specific time trends should minimize concerns about systematic time-varying confounders, we incorporate one final component to our main empirical strategy and put our results under further strain. Specifically, given that $\text{IDEB}_m^{5,2005}$, $\text{IDEB}_m^{5,2007}$ and $\text{IDEB}_m^{9,2009}$ are continuous variables that determine the instrument $\text{Priorit}_{mt}^{\text{IDEB}}$), we include as controls in the regression linear time trends interacted with polynomials of different degrees on these three different indicators. This step can be considered as an effort to net out remaining convergence patterns not captured by the set of window-specific time trends, which would be particularly worrisome if non-observable determinants of convergence in educational outcomes led to overestimation of HSP effects.

[19] More formally, in equation 2, we add the terms $\gamma_t \times \mathbb{1}(2.59 \leqslant IDEB_m^{5,2005} \leqslant 2.79)$, $\gamma_t \times \mathbb{1}(3.0 \leqslant IDEB_m^{5,2007} \leqslant 3.2)$, and $\gamma_t \times \mathbb{1}(4.4 \leqslant IDEB_m^{9,2009} \leqslant 4.6)$ and analogously for δ_t in equation 3.

4.3 Inference

We compute standard errors clustered at the municipality level to allow for common variation in unobservables at the unit which HSP prioritization and participation are defined and vary over time. We also compute standard errors clustered at the more aggregate level of health regions, which allow for serial correlation and persistence in health shocks within groups of municipalities. In Brazil, health regions are contiguous groups of municipalities within states with similar epidemiological characteristics, and that constitutes the level at which municipalities and the state might coordinate the referral to high-complexity services, some allocation of resources, and epidemiological surveillance.

4.4 First-Stage and Identification

Figure 4 graphically illustrates the identifying variation in our main empirical strategy. The upper graphs are histograms of the relevant IDEBs and highlight the restricted sample with shaded vertical stripes denoting the windows of width 0.1 around the cutoffs used for prioritization. The cutoffs (dashed red lines) illustrate that the expansion of the program incorporated municipalities pertaining to various points of the distribution of the indicators. The middle graphs describe how the share of municipalities participating in HSP changed over time, for prioritary and non-prioritary municipalities, and for each relevant IDEB cutoff. Each figure plots binned scatter plots of the probability of switching from a null to a positive HSP transfer in each window. We observe substantial variation in the share of selected municipalities across prioritization cutoffs. Finally, the bottom figures plot the percent of municipalities participating in the program over time, restricting the sample to observations that are contained in the shaded areas and, breaking down municipalities into prioritary and non-prioritary. These figures show that the prioritization rules strongly affected the timing of entry of groups of municipalities into HSP during the program's roll-out.

Table 4 presents first-stage estimates. Column (1) considers a specification only with municipality fixed-effects, time fixed-effects and the baseline set of controls. Column (2) adds dummies that indicate whether the municipality is prioritary to HSP because of other criteria (FHP coverage, MEP, or state ranking). Importantly, the coefficient associated with the instrument $\text{Priorit}_{mt}^{\text{IDEB}}$ remains qualitatively unchanged, suggesting that the variation steaming from the sub-set of prioritization rules that relate to the IDEB is largely orthogonal to the variation that stems from other prioritization margins. The following columns sequentially incorporate all the components of the empirical strategy. Column (3) includes the window-specific time trends. Finally, columns (4), (5) and (6) include linear time trends interacted with polynomials on the IDEB indicator, with little sign of effects on the first-stage point estimates associated with $\text{Priorit}_{mt}^{\text{IDEB}}$. We observe robust and highly significant coefficients across all specifications. The coefficient on the instrument shows that being deemed prioritary in a given year increases the likelihood of participation, on average, in roughly 33 percentage points. Notice, finally, that partial F-statistics are bounded below by 280, suggesting that our first-stage is strong. Overall, these results suggest that our main instrument is relevant in equation (3) and shifts the probability of participation in HSP for the average municipality in our main analytical sample.

The exclusion restriction is valid if, conditional on fixed-effects and time-varying controls, the IV is uncorrelated with any other latent determinant of educational performance. Although not directly testable, we put this assumption under strain in different ways in our restricted sample. First, we test whether observable characteristics of prioritary and non-prioritary municipalities are well-balanced within windows. Column (4) of Table 3 presents point estimates and standard errors of OLS specifications in which the covariates displayed in rows are regressed on a dummy indicating IDEB prioritization, conditional on window fixed-effects. The inclusion of these window fixed-effects aims to mimic our preferred specifications and to net out variation arising from differences in baseline covariates across groups of municipalities defined around cutoffs that are far apart from each other. We find consistent evidence of balance with respect to nearly all characteristics. The only exception is access to adequate sewage, which is expected to remain stable in levels over the period of analysis.

The importance of the components of our empirical strategy is also illustrated in Figure 5. We use the following event-study specification and graphically inspect the dynamic behavior of our main outcomes in the years before municipalities become prioritary for our main analytical sample:

$$Y_{mt} = \alpha_m + \gamma_t + \sum_{i=1}^{6} \beta_{pre,i} \times \text{Priorit}^{\text{IDEB}}_{mt+i} + \mathbf{X}'_{mt}\mathbf{\Theta} + v_{mt} \tag{4}$$

We observe that only after incorporating the window-specific time trends and the time trends interacted with polynomials of IDEB we find suggestive evidence of common trends.

Overall, the results from Table 3 and Figure 5 suggests that the three components from our empirical strategy allow us to exploit variation in program participation over time induced by rules that are arguably exogenous to baseline characteristics of municipalities and to dynamic patterns in our main outcomes.

5 HSP Effects on Education

5.1 Main Results

We start by discussing the effects of HSP on educational outcomes. Table 5 considers retention rates (Panel A) and the rate of students that withdrew from school early (Panel B), respectively, and presents OLS, reduced form (RF) and IV estimates for each dependent variable. As in Table 4, which presents our first-stage results, estimates are from specifications that sequentially combine the components discussed in Section 4.

Column (1) presents estimates from specifications that include municipality, year fixed effects, and the baseline set of controls discussed in Section 4. In particular, we control for dummies for all other rules used to prioritize municipalities (FHP coverage, MEP, or state rankings), in order to specifically isolate the shift into treatment triggered by the sub-set of IDEB prioritization rules. In this specification, the OLS estimates show that HSP participation is strongly and significantly associated with reductions in retention rates. Additionally, the estimates from the RF specification and the IV specification suggest that this association is strongly linked to being prioritized according to the IDEB rule. In column (2), we add to this specification the window-specific trends in order to net out specific time patterns in outcomes across groups of municipalities sequentially targeted by the prioritization rules. Interestingly, the association described by the OLS estimate in column (1) is completely attenuated in this specification, but the RF and IV estimates are mostly unchanged. This suggests that there are time-varying confounders at the window level that are systematically associated with participation but that are seemingly orthogonal to prioritization and highlights the importance of the use of our instrumental variables strategy.

Columns (3), (4) and (5) incorporate the last component of our empirical strategy, sequentially including a linear time trend interacted with a polynomial of first, second and third degrees on the relevant IDEBs used to prioritize municipalities. The IV estimates are remarkably similar and column (5), which is our preferred specification, suggests that HSP participation led to an effect of -1.352 percentage points in retention rates, which corresponds to roughly 11% of the baseline average of 12.4%.

Panel B in Table 6 follows the same sequence of specifications, focusing on the relationship between HSP participation and early withdrawal. The patterns are remarkably similar to those observed for retention rates. In particular, including window-by-year fixed effects greatly attenuates the OLS estimate. The coefficient of -0.528 in column (5) corresponds to 15.5% of the baseline average and suggests that HSP led to a substantial reduction in early withdrawal rates as well.

5.2 Robustness Exercises

For reasons discussed in Section 4, in our main specifications, we focused on a restricted sample of 950 municipalities lying at windows around at most 0.1 points to the IDEB cutoffs used for prioritization. Figure 6 shows that changing the window width mainly affects the precision of the point estimates, but not their magnitude. Once again, we sequentially consider retention rates (Panel A) and the rate of students that withdrew from school early (Panel B) as our dependent variables. For each window width, indicated in the x-axis, the five estimates and confidence intervals plotted in the $y-$axis are from the same five specifications in Table 5.[20]

Table 6 presents additional robustness exercises. As in Table 5, we consider retention rates (Panel A) and the rate of students that withdrew from school early (Panel B), respectively, concentrating on IV estimates for each dependent variable. For ease of comparison, column (1) replicates our preferred specification, which appears in column (5) of Table 5. In column (2), we show that our results are robust to including a linear time trend interacted with the baseline dependent variable. Second, in columns (3), (4) and (5) we show that our results are robust to restricting the time frame of our panel, particularly to excluding the year where the program was created (2007), the year in which HSP adoption is more likely to be endogenously determined (2014), and both years altogether. In column (6), we drop the municipalities that became eligible for HSP because of MEP and find little evidence of changes in the main results.[21] Finally, column (7) includes the municipalities that appeared in more than one window induced by the prioritization rules and suggests that this sample restriction played little role in determining the main results.

6 Discussion of Mechanisms

As mentioned in Section 2, HSP activities included the detection and control of specific neglected diseases that are endemic in certain regions of Brazil. We focus on *Dengue* fever, viral hepatitis, schistosomiasis, leishmaniasis, and tuberculosis, which were considered from the start as targets for health professionals working under the HSP. We compute disease incidence as the logarithm of the number of notified cases of children aged 5 to 9

[20]The main results, which we discussed above, are highlighted in each graph by a vertical shaded stripe.

[21]This could be justified by the fact that only the schools participating in MEP were eligible for HSP, and that participation in MEP is expected to be simultaneously correlated both with educational outcomes and participation in HSP. As mentioned in Section 2, MEP aimed at extending public schools' curriculum and increasing time spent in school with activities complementary to formal class hours. Although the existing evaluations of MEP indicate that it has not had significant impacts on educational outcomes, in principle, we should expect a confounding influence of participation in MEP as it should be correlated both with educational outcomes and participation in HSP.

per 1,000 children, for each of the neglected diseases covered by HSP.[22] We use again our most complete 2SLS specification to assess the effects of HSP on these outcomes, which corresponds to the one in column (5) of Table 5.

Table 7 presents the results. In the first row, we report 2SLS estimates of HSP direct effects.[23] In the bottom rows, we add an interaction term between HSP and the indicator of endemicity in the municipality computed at the baseline (2007), to investigate whether there were decreases where awareness of the problem was more salient to health professionals when the program was created. This interaction term is instrumented by the interaction between our IV and the indicator of endemicity. For all diseases, except for schistosomiasis, we use as a proxy of endemicity the disease incidence as measured at the baseline. For schistosomiasis, we rely on the official definition for baseline years provided by PCE/Datasus, which classifies whether the municipality is endemic or not.

In general, the point estimates on endemic disease incidence presented in the first row tend to be imprecisely estimated and provide little information on HSP effects on the average municipality. The only exception is the point estimate in column (3), which provides some support for reductions in the incidence of viral hepatitis (p-value = 0.176). In contrast, we observe negative and robust coefficients for all interaction terms shown in the bottom rows, while point estimates for direct HSP effects are generally non-significant. This indicates that most effects are accruing from municipalities that are hit the most by diseases.

7 Conclusion

This paper investigates the educational impacts of a policy-driven change in health services available to public elementary school students in Brazil. We study a nationwide program designed to induce activities of primary health care professionals at schools —ranging from anthropometric measurement, nutritional and ophthalmological services to coordinated efforts to identify and fight endemic diseases— and to refer children to other professionals of the public health care network. Exploring variation in the timing of participation induced by rules that prioritized some municipalities first, we show that the program had negative impacts in retention and early withdrawal rates. An analysis of potential health mediators points to an important role for the components of the program associated with local endemic disease control. From a public policy

[22] Since there are a lot of observations for which the number of notified cases is zero, we add 0.01 to the quantity inside the logarithm in order to avoid sample selection and keep the results as interpretable as possible.

[23] It is important to recall that the indicators on disease incidence capture both access to screening services, which potentially increases with exposure to HSP, and health conditions, expected to improve (i.e., prevalence is expected to decrease) because of early detection and treatment. The results from Table 7 provide us with the effects of the HSP only on the resultant outcome.

perspective, our results indicate that programs that operate through the decentralization of basic health care provision can explore schools as ideal *loci* for prevention, treatment of diseases, and targeting of other health-related conditions. This is a promising policy alternative that has beneficial effects on educational trajectories.

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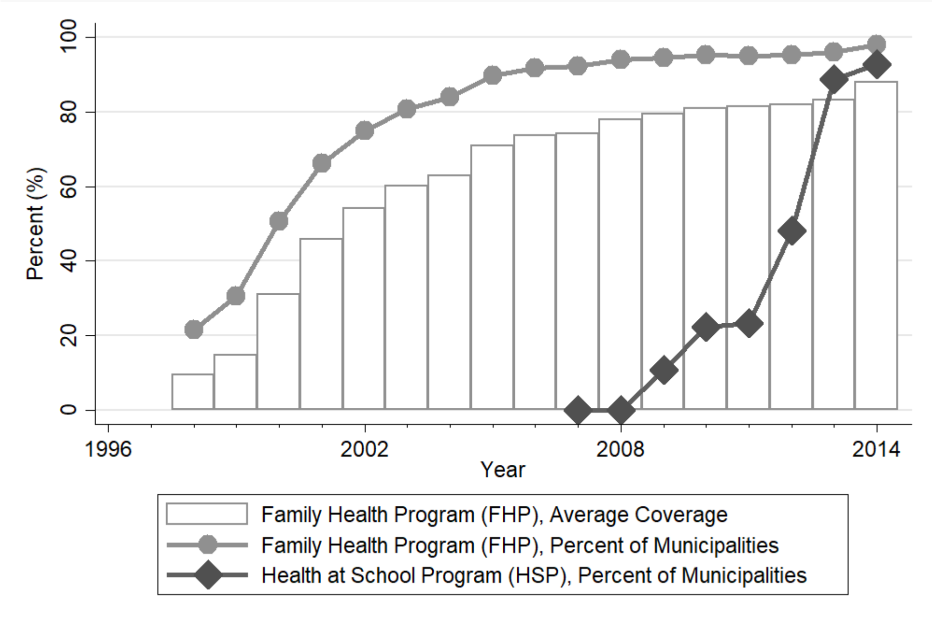
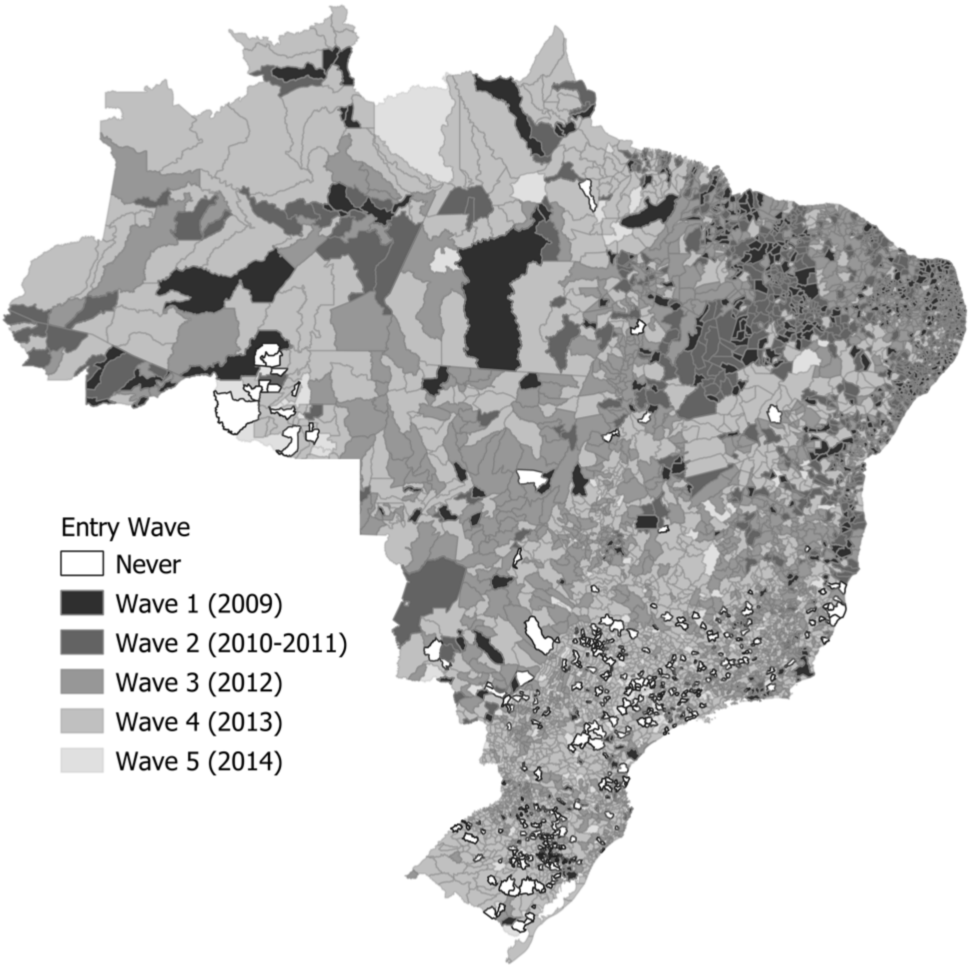
Figure 1: Expansion of *Family Health Program* and *Health at School Program* (1996-2014)



[BACK TO TEXT]

Notes: Data from the Ministry of Health (MS/DAB, Datasus and *Sistema de Informações sobre Orçamentos Públicos em Saúde*, SIOPS). This figure describes the roll-out of the *Family Health Program* (FHP) across and within municipalities in Brazil between 1996 and 2014 and the expansion of the Health in School Program (HSP) between 2007 (creation) and 2014. The evolution of the average coverage of the FHP is presented in bars and the cumulative adoption of the FHP and HSP across municipalities are presented in lines connected by circles and diamonds, respectively.

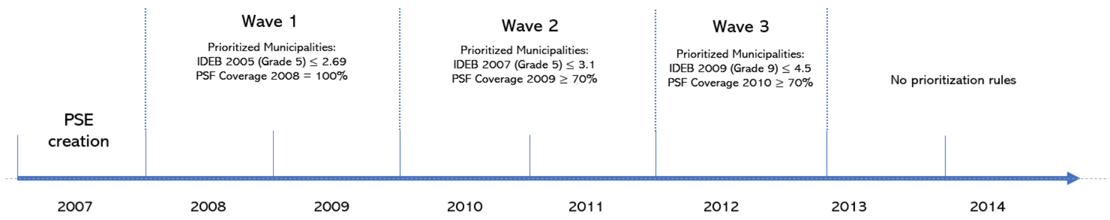
Figure 2: Geographical Variation in Expansion



[BACK TO TEXT]

Notes: This figure marks the year in which HSP was adopted in a given municipality. Participation in the program is defined by a dummy that indicates whether the municipality has received any HSP-related transfers from the federal government in a given year.

Figure 3: Prioritization Rules of *Health at School Program*



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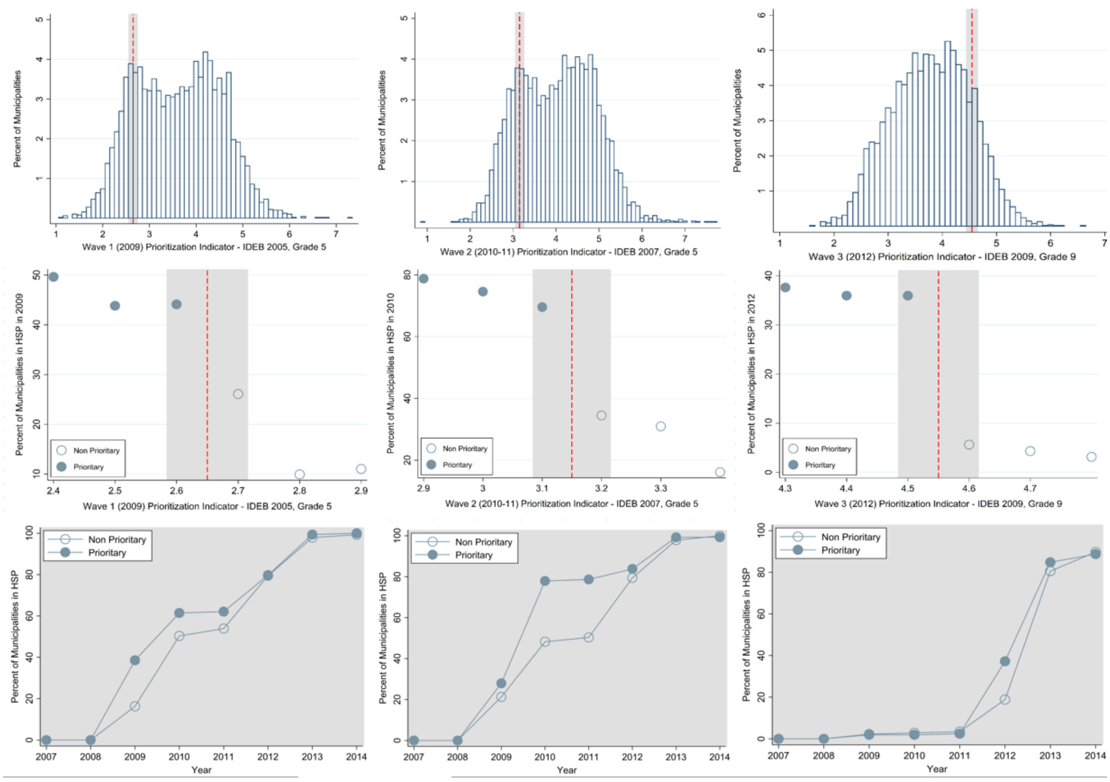
Notes: This timeline sums up the evolution of prioritization rules for municipality entry into HSP according to federal regulation (Brasil-DOU, 2008, 2009, 2010).

Table 1: Descriptives on HSP Components

	Total Number of Children Reached		Average (Number of Children Reached/ Number of Students Enrolled)*1000	
	HSP Municipalities	Non-HSP Municipalities	HSP Municipalities	Non-HSP Municipalities
	(1)	(2)	(3)	(4)
Ophtalmological	876,739	5259	117	8.7
Anthropometrics and Nutritional	1,564,003	12,824	210.9	22
Language Development and Hearing	24,187	0	3.9	0
Oral Health	3,225,019	143,731	593.6	407.9
Vaccination Schedule Updating	79,792	40	8.1	0
Health Promotion Collective Activities	1,539,108	15,770	265.6	33.7
Number of Children Enrolled	11,128,392	937,360		

Notes: This table documents the scale of HSP health services targeting students in public primary schools in 2014. Columns (1) and (2) show the total number or children reached by the procedures indicated in rows, for municipalities in and out of the program, respectively. Columns (3) and (4) display the average municipality-level ratio between the number of children reached by each procedure in rows and the number of students enrolled in public schools (in grades 1 to 5), again, for municipalities in and out of the program, respectively. [BACK TO TEXT]

Figure 4: Identifying Variation: IDEB Prioritization Cutoffs and Participation, per Wave of Entry



[BACK TO TEXT]

Notes: The upper figures are histograms of IDEB, the educational criterion used to define prioritized municipalities for the waves of entry in the first years of the HSP (see Figure 3). The shaded areas signal the sample of municipalities for our preferred estimates, which restrict the panel to municipalities that lie at a distance of 0.1 point (the minimal distance) from the binding cutoffs of the IDEB prioritization criteria in at least one entry wave (2.69 grade 5 IDEB in 2005 for the 2009 wave, 3.1 grade 5 IDEB in 2007 for the 2010/2011 wave and 4.5 grade 9 IDEB in 2009 for the 2012 wave of enters). The middle figures zoom into the shaded areas in the histograms and plot the proportion of entrants for each value of the IDEB score per wave around the cutoffs. The bottom figures restrict the sample to observations that are contained in the shaded areas and break down municipalities in prioritary and non-prioritary, indicating earlier entry of the former group.

Table 2: Descriptive Statistics at the Baseline

	Obs.	Mean	Stand Dev	Min	Max	Source of Data	Year
Educational Outcomes (per 100 children enrolled in the public educational system)							
Retention rates (grades 1 to 5)	4,974.00	12.02	7.34	0.00	51.90	INEP/MEC	2007
Early Withdrawal Rates (grades 1 to 5)	4,974.00	3.10	3.83	0.00	30.10	INEP/MEC	2007
Health Outcomes							
Confirmed cases of Dengue fever (SINAN, age group)	4,974.00	5.70	54.84	0.00	2,053.00	Datasus/SINAN	2007
Confirmed cases of schistosomiasis (SINAN, age group)	4,974.00	0.36	2.70	0.00	72.00	Datasus/SINAN	2007
Confirmed cases of viral hepatitis (SINAN, age group)	4,974.00	0.96	5.40	0.00	165.00	Datasus/SINAN	2007
Confirmed cases of leishmaniasis (SINAN, age group)	4,974.00	0.30	2.07	0.00	62.00	Datasus/SINAN	2007
Confirmed cases of tuberculosis (SINAN, age group)	4,974.00	0.14	1.60	0.00	65.00	Datasus/SINAN	2007
Program Participation Variables							
Municipality is prioritary according to the IDEB criterion	4,974.00	0.43	0.50	0.00	1.00	PSE/DAB	2007
Indicator of a interruptions in positive Federal transfer to PSE	4,974.00	0.03	0.18	0.00	1.00	PSE/DAB	2007
Indicator of a positive Federal transfer to PSE (absorbing, staggered)	4,974.00	0.37	0.48	0.00	1.00	PSE/DAB	2007
Eligible by PSF	4,974.00	0.58	0.49	0.00	1.00	PSE/DAB	2007
Eligible by PME Participation	4,974.00	0.26	0.44	0.00	1.00	PSE/DAB	2007
Eligible by State Rule	4,974.00	0.26	0.44	0.00	1.00	PSE/DAB	2007
Controls							
Children of Primary School Age (between 5-9 years old)	4,974.00	0.02	0.02	0.00	0.21	IBGE	2007
Dummy for FHP	4,974.00	73.03	33.29	0.00	100.00	Datasus/DAB	2007
Dummy for Hospital	4,974.00	0.72	0.45	0.00	1.00	Datasus	2007
Log (per capita GDP)	4,974.00	8.83	0.71	7.36	12.39	IBGE	2007
PBF (per capita)	4,974.00	0.09	0.05	0.00	1.41	MDS	2007

Notes: This table presents summary statistics for all variables used in the analysis, for our full sample, averaged across municipalities at the baseline year (listed in the last column).

Table 3: Sample Selection and Sample Balance at Baseline

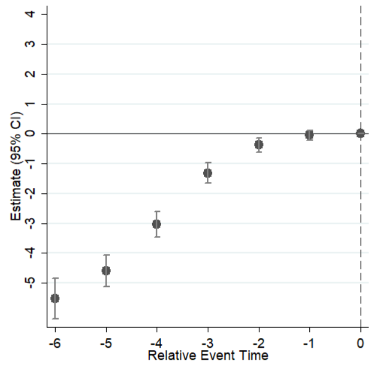
	Main Analytical Sample (N=950) — Selection			Balance
	Mean, 2007 Full	Mean, 2007 Restricted	t-statistic (1)=(2)	Within Window Prioritized Diff.-in Means
	(1)	(2)	(3)	(4)
Public Education Characteristics (2007)				
Retention Rates	12.016	12.922	6.909	-0.129
	(7.34)	(7.39)	–	(0.565)
Early Withdrawal Rates	3.102	3.546	6.924	0.192
	(3.83)	(3.96)	–	(0.16)
Primary Schools,	0.025	0.025	4.582	0.001
per 5-9 years old children	(0.02)	(0.02)	–	(0.002)
Public Health Characteristics (2007)				
FHP coverage, %	73.029	74.471	2.114	2.074
	(33.29)	(32.14)	–	(4.982)
Dummy of Hospital	0.717	0.729	2.126	0.078
	(0.45)	(0.44)	–	(0.059)
Other Covariates (2000)				
Log HH Income	6.995	6.927	-6.362	0.030
	(0.7)	(0.7)	–	(0.077)
Gini Coefficient (0-1)	0.533	0.535	-0.437	0.007
	(0.06)	(0.06)	–	(0.008)
Urbanization Rate, %	62.061	60.779	-4.334	-1.991
	(21.97)	(21.98)	–	(2.69)
Piped Water, %	58.735	57.013	-4.549	-3.904
	(22.97)	(23.01)	–	(2.615)
Adequate Sewage, %	23.673	19.555	-3.507	-12.647
	(29.10)	(26.24)	–	(4.219)***
Garbage Removal, %	54.036	51.371	-5.477	-3.999
	(26.350)	(26.360)	–	(2.800)

Notes: This table investigates sample selection and balance in our main analytical sample ("restricted"). For comparisons with the full sample of municipalities, columns 1 and 2 present means and standard deviations of municipalities in the full sample and in the restricted sample. Column 3 present the t-test from a comparison of the variables in rows in the full and in the restricted sample. Finally, column 4 presents the coefficient of a dummy defining whether a municipalities was ever prioritized for HSP absorbing the three window fixed effects.

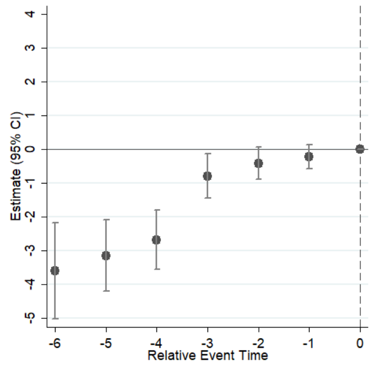
*, ** and *** indicate p-values lower than 0.1, 0.5 and 0.10 using standard errors robust to heteroscedasticity. [BACK TO TEXT]

Figure 5: Event-Study for Identification of Pre-Trends on IDEB Prioritization Rules

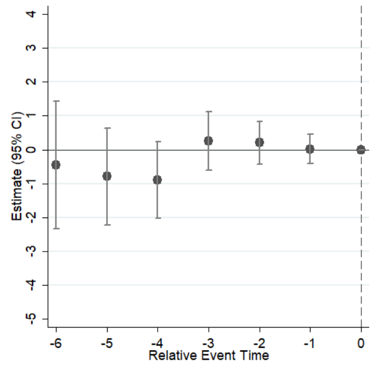
Panel A. Municipality-Level Retention Rate



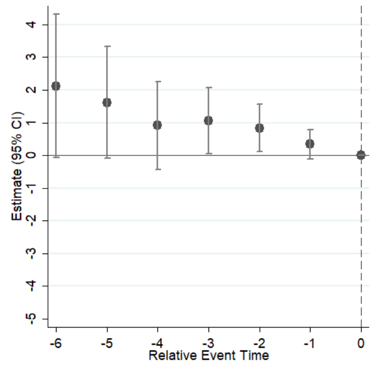
(a) Full Sample



(b) Restricts Sample

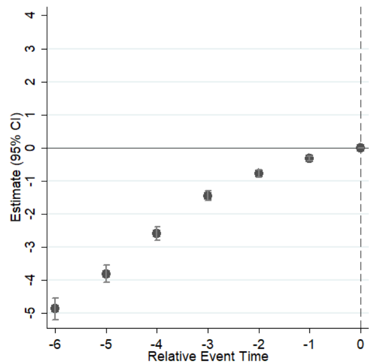


(c) Adds Window-Specific Nonlinear Time Trends

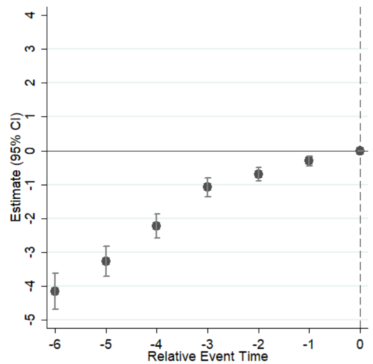


(d) Adds Linear Trends Interacted with IDEBs

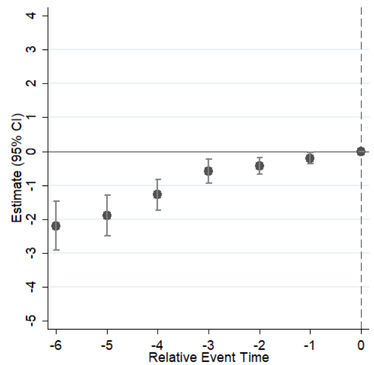
Panel B. Municipality-Level Early Withdrawal Rate



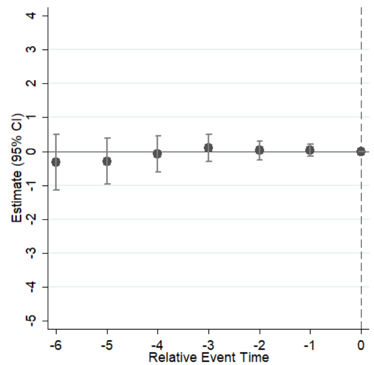
(e) Full Sample



(f) Restricts Sample



(g) Adds Window-Specific Nonlinear Time Trends



(h) Adds Linear Trends Interacted with IDEBs

[BACK TO TEXT]

Notes: These figures plots pre-trends in outcomes using specification 4, sequentially incorporating the components of the empirical strategy discussed in detail in 4.

Table 4: First Stage — Main Instrument, Other Prioritization Margins and *Health at School Program* Participation

	(1)	(2)	(3)	(4)	(5)	(6)
Instrument						
HSP prioritary (IDEB)	0.417	0.392	0.333	0.336	0.335	0.334
(*s.e.*, clust. Mun.)	(0.019)***	(0.018)***	(0.020)***	(0.020)***	(0.020)***	(0.020)***
{*s.e.*, clust. Health Region}	{0.021}***	{0.020}***	{0.022}***	{0.022}***	{0.022}***	{0.022}***
Kleibergeen Papp F-Statistic	480.6	459.2	284.6	288.9	286.4	284.3
Other HSP Prioritization Margins						
FHP		0.291	0.258	0.258	0.258	0.258
(*s.e.*, clust. Mun.)		(0.018)***	(0.018)***	(0.018)***	(0.018)***	(0.018)***
{*s.e.*, clust. Health Region}		{0.023}***	{0.024}***	{0.024}***	{0.024}***	{0.024}***
MEP		0.328	0.390	0.394	0.394	0.397
(*s.e.*, clust. Mun.)		(0.083)***	(0.077)***	(0.077)***	(0.077)***	(0.076)***
{*s.e.*, clust. Health Region}		{0.088}***	{0.080}***	{0.079}***	{0.079}***	{0.079}***
State Rankings		0.074	0.043	0.043	0.042	0.044
(*s.e.*, clust. Mun.)		(0.062)	(0.066)	(0.067)	(0.067)	(0.067)
{*s.e.*, clust. Health Region}		{0.064}	{0.068}	{0.068}	{0.068}	{0.069}
Sample	Restricted	Restricted	Restricted	Restricted	Restricted	Restricted
Window Bandwidth	0.1	0.1	0.1	0.1	0.1	0.1
Observations	7,600	7,600	7,600	7,600	7,600	7,600
Municipalities	950	950	950	950	950	950
Health Regions	346	346	346	346	346	
Municipality Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes				
Window-by-Year Fixed Effects			Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
HFP, MEP, State Rankings		Yes	Yes	Yes	Yes	Yes
Linear time trend interacted with IDEB polynomial...						
... of 1st order				Yes	Yes	Yes
... of 2nd order					Yes	Yes
... of 3rd order						Yes

Notes: The unit of observation is a municipality in forming a balanced panel over seven years (2007-2014). The table presents estimates of the first-stage association between the HSP prioritization rules and program participation for municipalities lying at a distance of 0.1 IDEB points from the relevant thresholds. Column 1 includes our benchmark controls, municipality and year fixed effects. Column 2 adds estimates for all prioritization margins (HFP, MEP and rankings within states). Column 3 interacts the year fixed effects with indicators of windows of entry. Column 4, 5 and 6 add to this specification a linear, quadratic and cubic polynomial in each of the IDEB levels relevant for prioritization, respectively. The benchmark controls are: the municipality coverage of the Brazilian's conditional cash transfer program (*Family Stipend*); a dummy indicating if the municipality has a hospital; yearly average income in logarithm; number of primary schools *per* children aged 5-9 in the municipality.

*, ** and *** indicate *p*-values lower than 0.1, 0.5 and 0.10 using standard errors clustered at the municipality level (in parentheses) or *p*-values lower than 0.1, 0.5 and 0.10 using standard errors clustered at the health region level (in squared brackets). [BACK TO TEXT]

Table 5: *Health at School Program* and Educational Outcomes (Grades 1-5)

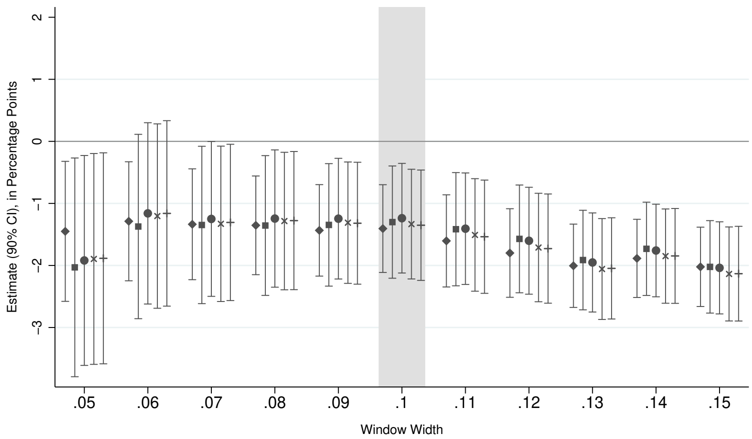
	(1)	(2)	(3)	(4)	(5)
	Panel A. Municipality-Level Retention Rate (Mean 2007 = 12.4%)				
OLS: HSP	-0.531	-0.037	0.016	0.017	0.014
(*s.e.*, clust. Municipality)	$(0.171)^{***}$	(0.180)	(0.177)	(0.177)	(0.177)
{*s.e.*, clust. Health Region}	$\{0.183\}^{***}$	{0.171}	{0.170}	{0.172}	{0.171}
RF: HSP prioritary (IDEB)	-0.551	-0.434	-0.417	-0.447	-0.451
(*s.e.*, clust. Municipality)	$(0.164)^{***}$	$(0.191)^{**}$	$(0.190)^{**}$	$(0.190)^{**}$	$(0.191)^{**}$
{*s.e.*, clust. Health Region}	$\{0.166\}^{***}$	$\{0.184\}^{**}$	$\{0.181\}^{**}$	$\{0.180\}^{**}$	$\{0.181\}^{**}$
IV: HSP	-1.406	-1.301	-1.238	-1.334	-1.352
(*s.e.*, clust. Municipality)	$(0.425)^{***}$	$(0.579)^{**}$	$(0.571)^{**}$	$(0.574)^{**}$	$(0.578)^{**}$
{*s.e.*, clust. Health Region}	$\{0.431\}^{***}$	$\{0.552\}^{**}$	$\{0.539\}^{**}$	$\{0.539\}^{**}$	$\{0.542\}^{**}$
	Panel B. Municipality-Level Early Withdrawal Rate (Mean 2007 = 3.4%)				
OLS: HSP	-0.504	-0.179	-0.144	-0.145	-0.157
(*s.e.*, clust. Municipality)	$(0.063)^{***}$	$(0.064)^{***}$	$(0.064)^{**}$	$(0.064)^{**}$	$(0.064)^{**}$
{*s.e.*, clust. Health Region}	$\{0.068\}^{***}$	$\{0.063\}^{***}$	$\{0.064\}^{**}$	$\{0.064\}^{**}$	$\{0.064\}^{**}$
RF: HSP prioritary (IDEB)	-0.267	-0.125	-0.150	-0.170	-0.176
(*s.e.*, clust. Municipality)	$(0.067)^{***}$	$(0.072)^{*}$	$(0.072)^{**}$	$(0.072)^{**}$	$(0.073)^{**}$
{*s.e.*, clust. Health Region}	$\{0.061\}^{***}$	$\{0.063\}^{**}$	$\{0.064\}^{**}$	$\{0.065\}^{***}$	$\{0.066\}^{***}$
IV: HSP	-0.682	-0.375	-0.447	-0.508	-0.528
(*s.e.*, clust. Municipality)	$(0.172)^{***}$	$(0.216)^{*}$	$(0.213)^{**}$	$(0.215)^{**}$	$(0.218)^{**}$
{*s.e.*, clust. Health Region}	$\{0.158\}^{***}$	$\{0.189\}^{**}$	$\{0.190\}^{**}$	$\{0.195\}^{***}$	$\{0.198\}^{***}$
Sample	Restricted	Restricted	Restricted	Restricted	Restricted
Window Width	0.1	0.1	0.1	0.1	0.1
Observations	7,600	7,600	7,600	7,600	7,600
Municipalities	950	950	950	950	950
Health Regions	346	346	346	346	346
Municipality Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes				
Window-by-Year Fixed Effects		Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
HFP, MEP, State Rankings	Yes	Yes	Yes	Yes	Yes
Linear time trend interacted with IDEB polynomial...					
... of 1st order			Yes	Yes	Yes
... of 2nd order				Yes	Yes
... of 3rd order					Yes

Notes: The unit of observation is a municipality in forming a balanced panel observed over eight years (2007-2014). This table presents estimates of the association between the HSP program and municipality-level retention (Panel A) and early withdrawal (Panel B) rates among public school students enrolled in grades 1 through 5. Point estimates, and standard errors are in percentage-point units. Each panel presents: (i) ordinary least squares (OLS) estimates of specification (1), a two-way (municipality and time) linear fixed effects model with a binary treatment indicating that the municipality received a transfer from the federal government in a given year; (ii) reduced form (RF) estimates from a two-way (municipality and time) linear fixed effects model with a binary treatment indicating that the municipality was prioritized to receive a transfer from the federal government in a given year and (iii) two-stage least squares (IV) estimates based on specifications (2) and (3), using a time-varying prioritization rule as instrument for entry into the program in the first stage. Column 1 includes our benchmark controls, municipality and year fixed effects, and controls for all prioritization margins (HFP, MEP and rankings within states). Column 2 interacts the year fixed effects with indicators of windows of entry. Column 3, 4 and 5 add to this specification a linear, quadratic and cubic polynomial in each of the IDEB levels relevant for prioritization, respectively. The benchmark controls are: the municipality coverage of the Brazilian's conditional cash transfer program (*Family Stipend*); a dummy indicating if the municipality has a hospital; yearly average income in logarithm; number of primary schools *per* children aged 5-9 in the municipality.

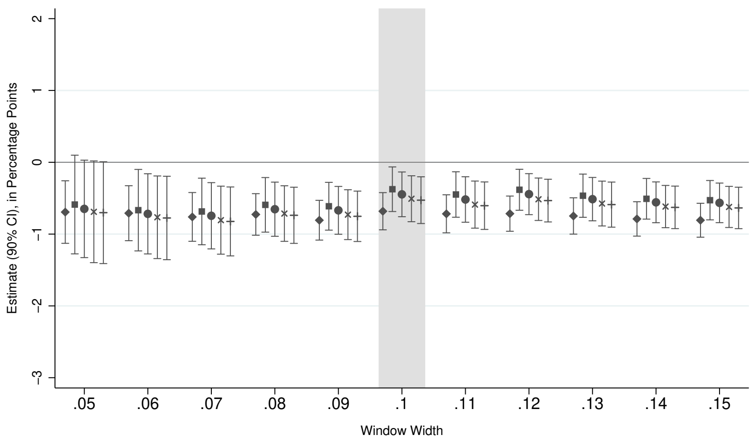
*, ** and *** indicate p-values lower than 0.1, 0.5 and 0.10 using standard errors clustered at the municipality level (in parentheses). [BACK TO TEXT]

Figure 6: *Health at School Program* and Educational Outcomes (Grades 1-5) — Robustness of Main Estimates to Window Width

Panel A. Municipality-Level Retention Rate



Panel B. Municipality-Level Early Withdrawal Rate



[BACK TO TEXT]

Notes: This figure tests the robustness of the estimates in Table 5 (presented in the shaded areas) to varying the window width. For each bandwidth, the five estimates and confidence intervals are from the same specifications in the table.

Table 6: *Health at School Program* and Educational Outcomes (Grades 1-5) — Other Robustness Exercises

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. Municipality-Level Retention Rate						
IV: HSP	−1.352	−1.292	−1.421	−1.100	−1.259	−1.686	−1.210
(*s.e.*, clust. Mun.)	(0.578)**	(0.576)**	(0.594)**	(0.581)*	(0.596)**	(0.666)**	(0.596)**
{*s.e.*, clust. Health Region}	{0.542}**	{0.542}**	{0.561}**	{0.556}**	{0.567}**	{0.617}***	{0.540}**
	Panel B. Municipality-Level Early Withdrawal Rate						
IV: HSP	−0.528	−0.488	−0.382	−0.487	−0.383	−0.537	−0.522
(*s.e.*, clust. Mun.)	(0.218)**	(0.217)**	(0.218)*	(0.228)**	(0.224)*	(0.253)**	(0.218)**
{*s.e.*, clust. Health Region}	{0.198}***	{0.195}***	{0.201}*	{0.208}**	{0.208}*	{0.231}**	{0.207}**
Sample	Restricted	Restricted	Restricted	Restricted	Restricted	Restricted	Restricted
Window Width	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Observations	7,600	7,600	6,650	6,650	5,700	4,504	8,320
Municipalities	950	950	950	950	950	563	1,040
Health Regions	346	346	346	346	346	181	352
Municipality Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Window-by-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HFP, MEP, State Rankings	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trend interacted with IDEB polynomial...							
... of 1st order	Yes	Yes	Yes	Yes	Yes	Yes	Yes
... of 2nd order	Yes	Yes	Yes	Yes	Yes	Yes	Yes
... of 3rd order	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robustness Exercise	Benchmark Table 5 Column (5)	Linear Trends Baseline Dep. Var.	Drops 2007	Drops 2014	Drops 2007 and 2014	Drops MEP Priorit.	Includes Cross. Muns.

Notes: The unit of observation is a municipality in forming a balanced panel observed over eight years (2007-2014). This table presents robustness checks for the IV estimates presented in Table 5. Point estimates, and standard errors are in percentage-point units.

*, ** and *** indicate *p*-values lower than 0.1, 0.5 and 0.10 using standard errors clustered at the municipality level (in parentheses). [BACK TO TEXT]

Table 7: *Health at School* and Endemic Disease Incidence (Notified Cases, Ages 5-9)

	Dengue Fever	*Schistosomiasis*	Viral *Hepatitis*	*Leishmaniasis*	*Tuberculosis*
	(1)	(2)	(3)	(4)	(5)
IV: HSP	0.209	-0.062	-0.326	0.038	-0.069
(*s.e.*, clust. Municipality)	(0.358)	(0.120)	(0.236)	(0.180)	(0.091)
{*s.e.*, clust. Health Region}	{0.340}	{0.110}	{0.241}	{0.189}	{0.086}
IV: HSP	0.309	0.075	-0.069	-0.002	-0.011
(*s.e.*, clust. Municipality)	(0.356)	(0.042)*	(0.090)	(0.059)	(0.024)
{*s.e.*, clust. Health Region}	{0.141}	{0.041}*	{0.097}	{0.059}	{0.022}
IV: HSP $\times$ Baseline Dengue Fever	-0.079				
(*s.e.*, clust. Municipality)	(0.025)***				
{*s.e.*, clust. Health Region}	{0.026}***				
IV: HSP $\times$ Baseline Endemic *Schistosomiasis* (Dummy)		-0.719			
(*s.e.*, clust. Municipality)		(0.125)***			
{*s.e.*, clust. Health Region}		{0.156}***			
IV: HSP $\times$ Baseline *Hepatitis*			-0.512		
(*s.e.*, clust. Municipality)			(0.130)***		
{*s.e.*, clust. Health Region}			{0.129}***		
IV: HSP $\times$ Baseline *Leishmaniasis*				-0.217	
(*s.e.*, clust. Municipality)				(0.122)*	
{*s.e.*, clust. Health Region}				{0.119}*	
IV: HSP $\times$ Baseline *Tuberculosis*					-2.183
(*s.e.*, clust. Municipality)					(0.382)***
{*s.e.*, clust. Health Region}					{0.379}***
Average Rate at Baseline (per 1000 children 5 to 9)	1.19	0.16	0.26	0.12	0.01
SD of Rate at Baseline (per 1000 children 5 to 9)	3.5	1.07	1.02	0.73	0.89
Sample	Restricted	Restricted	Restricted	Restricted	Restricted
Window Bandwidth	0.1	0.1	0.1	0.1	0.1
Number of Observations	7,600	7,600	7,600	7,600	7,600
Number of Municipalities	950	950	950	950	950
Number of Health Regions	346	346	346	346	346
Municipality Fixed Effects	Yes	Yes	Yes	Yes	Yes
Window-by-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
HFP, MEP, State Rankings	Yes	Yes	Yes	Yes	Yes
Linear time trend interacted with IDEB polynomial...					
... of 1st order	Yes	Yes	Yes	Yes	Yes

Notes: The unit of observation is a municipality in forming a balanced panel over seven years (2007-2014). In Panel A, we report IV estimates of HSP direct effects on notified cases. In Panel B, we add an interaction term between HSP and a the incidence of the respective disease in the municipality computed at the baseline (2007). The endogenous interaction term is instrumented by the interaction between our IV and the indicator of endemicity. Dependent variables consist of disease incidence computed as the municipality yearly number of notified cases of children aged 5 to 9 per 1,000 for each of the neglected diseases covered by HSP, transformed by using the inverse hyperbolic sine function to smooth the influence of outliers and gain direct interpretation in terms of percentage changes. In all columns we use our most complete IV specification, the same as reported in column 5 of Tables 5 and 6.

*, ** and *** indicate p-values lower than 0.1, 0.5 and 0.10 using standard errors clustered at the municipality level (in parentheses). [BACK TO TEXT]

Appendices

Appendix A Supplementary Figures and Tables

Table A.1: Prioritization Criteria and Participation in HSP

	Prioritization Status by Group of Rules											
	Prioritization by IDEB		Prioritization by HFP		Prioritization by IDEB and HFP		Prioritization by MEP		Prioritization by State Rankings		Eligible	
	Count	% in HSP	Count	% in HSP	Count	% in HSP	Count	% in HSP	Count	% in HSP	Count	% in HSP
2007	0	0,0%	0	0,0%	0	0,0%	0	0,0%	0		0	
2008	0	0,0%	0	0,0%	0	0,0%	0	0,0%	0		0	
2009	891	44,3%	2366	21,6%	537	68,7%	60	86,7%	98		695	
2010	1027	74,4%	3583	30,2%	835	90,2%	67	82,1%	143		1045	
2011	1027	75,2%	3583	31,2%	835	91,1%	67	82,1%	158		1060	
2012	4225	57,5%	3650	63,0%	3169	72,0%	138	37,0%	0		3307	
2013	4974	89,7%	4974	89,7%	4974	89,7%	4974	89,7%	4974		4974	
2014	4974	93,6%	4974	93,6%	4974	93,6%	4974	93,6%	4974		4974	

Notes: Data related to the implementation of the HSP are obtained from the Ministry of Health and the System of Information on Public Health Budgets (SIOPS). Participation in the program is defined by a dummy that indicates whether the municipality has received any HSP-related transfers from the federal government in a given year. We follow official documentation and federal legislation to compute eligibility to the program as an indicator based on municipality IDEB and FHP coverage, respectively obtained from the Ministry of Education (Inep/MEC) and the Ministry of Health (CNES/MS).