The effects of large-scale nutrition Interventions on Early Childhood and Neonatal Outcomes: evidence from Brazil

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May 2023

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Abstract

This study exploits the introduction of a new prioritization criteria for food security interventions to estimate the marginal impact of such programs. Findings indicate that, in municipalities assigned to receive nutrition policies more intensely, the number of children receiving micronutrient supplements was higher. In addition, being prioritized was associated with a very small improvement in neonatal health, but no significant improvements in infant diarrhea morbidity. A heterogeneity analysis indicated that positive impacts in infant morbidity only exist for municipalities with higher supply of primary healthcare inputs.

Keywords: nutrition, food insecurity, early childhood development, neonatal health, impact evaluation, Brazil, Latin America

Contents

1 Introduction

In recent decades, increasing attention has been given to the role of the first years of a child's life for their future human capital accumulation, with economic research building considerable evidence on its importance. Interventions such as expanding caloric and nutritional intake, or reducing the incidence of parasitic infections, have been found to improve children's cognition (Aurino et al, 2023), as well as school attendance and grades (Kremer et al, 2004). Additionally, the longer-term effects of reducing food insecurity [1] and adverse health events, both in-utero and during childhood, include a decreased risk of metabolic diseases in adulthood and better economic outcomes (Hoynes et al, 2016).

These findings place investment in human capital accumulation during the first years of life as one of the main mechanisms that can be used to reduce health and income inequalities within and across countries, by attenuating the intergenerational transmission of poverty. For this reason, programs that foster nutritional adequacy during early childhood[2] have been considerably expanded, with a focus on initiatives that target children from low-income households at scale.

In particular, School Feeding programs and bio-fortification of food staples have emerged as some of the most common alternatives to secure a stable provision of macro[3] and micronutrients[4] to the largest possible number of children. Indeed, most countries offer their version of a school meal program, with similar interventions reaching approximately 418 million children globally (WFP, 2022).

In Brazil, large-scale biofortification programs have taken the form of mandatory iodization of salt, and the inclusion of iron and folic acid in flour. Similarly, Brazil's School Feeding initiative is guaranteed by the Constitution and is one of the largest in the world, covering an average of 41.5 million pupils each year (WFP, 2017).

In spite of helping ensure proper nutrition for school-aged children, School Feeding programs are not typically successful in targeting children below the age of six, mostly due to the low enrollment rates in primary schools. While some of its benefits could be extended to younger siblings through substitution effects [5], or through food sharing [6], policy interventions of this type that effectively manage to reach infants at scale are still relatively uncommon.

Given the relative importance of the antenatal period and of the first 24 months of life, and the fact that school feeding is unlikely to reverse damage stemming from undernourishment during that

[1] The lack of access to sufficient food, both in terms of caloric and nutritional requirements.

[2] Early Childhood is defined as children of up to the age of 8 years old. However, this study is focused on children 5 and under. That is, before the compulsory school starting age in Brazil.

[3] Defined as carbohydrates, fat and protein.

[4] Essential vitamins and minerals.

[5] Whereby households replace home provision of meals to school-aged children by school provision.

[6] For School Meal programs that offer take-home rations.

period, nutrition interventions that target these age groups are essential. In Brazil, this is especially important due to the growing child obesity rates, which can be aggravated by in-uterus deprivations, and to the recent wave of food insecurity that has been affecting the country. For this reason, complementary health and nutritional interventions targeting infants and pregnant people are increasingly gaining traction.

While these types of programs do exist worldwide, taking the form of Micronutrient Supplementation of Pregnant people and infants, or Behavior Change Communication to encourage breastfeeding, many constraints are often present to implementing them at a national level. Additionally, whenever these interventions are at scale in the Global South, their effectiveness is less often evaluated, as interest remains focused on the nutritional effects of social protection programs such as school meals and cash transfers.

For this reason, more evidence is still needed on the viability, costs, and determinants of success of supplementary nutrition interventions at large scale. In particular, in Brazil's case, the pre-existing reach and efficiency of its universal healthcare system has the potential of making the streamlining of such initiatives easier, thus constituting a viable pathway to improve the nutritional status of children that haven't reached the school age yet.

In this paper, I use a Regression Discontinuity Design, as well as a Differences-in-Differences approach, to estimate the marginal benefits of increasing the intensity of nutrition initiatives. While I cannot differentiate between them, their effects on various health outcomes, and the heterogeneities with respect to existing constraints, can help shed a light on which mechanisms might be at play.

This analysis contributes to understanding the current effectiveness of Brazil's complementary nutrition programs, as well as binding aspect that might be hindering the extraction of their full benefits. In addition, evidence on the effects of large-scale nutrition supplementation interventions in Brazil might prove useful to other Latin American countries looking to implement similar policies.

2 Conceptual Framework

A basic theoretical framework to understand individuals' demand for health, proposed by Grossman (1972), models well-being as a function of health investments that fade out with the passage of time. Because health depreciates as one becomes older, the investment in early periods becomes less important as the years go by. Furthermore, since the investments in early childhood and late one are perfect substitutes in this model, food insecurity as an infant could be completely offset by increasing nutritional intake during later stages of life.

In spite of the popularity of the Grossman model, the conclusion it arrives at when it comes to the impacts of early-life investments are in contrast to the stylized fact that this period has lasting effects for human capital accumulation. For this reason, as research investigating the impact of pre-natal[7] and early post-natal investments became more common, and the evidence on their persistence was solidified, the demand for theoretical frameworks that could represent these empirical relationships emerged. To fill this gap, Almond and Currie (2011b) suggest a modified version of the Grossman framework, in which the discount factor allows early childhood events to be more important than older-age ones, and in which investments in the two periods are not necessarily perfect substitutes.

3 Previous Literature

Evidence suggests that adverse shocks in-uterus and during the first five years of life, such as illnesses and exposure to radiation, negatively affect individuals' cognitive abilities (Almond et al, 2009), school performance (Almond, 2006), and increase the likelihood of metabolic disorders (Hoynes et al, 2016). Negative health events during that period of time have also been found to be long-lasting, as they lead to poor health status in the following phases (Currie et al, 2010) and hamper the capacity to invest in human capital, thus lowering educational attainment and future wages (Almond, 2006).

Potential measures that can be used to guarantee the necessary conditions for proper development during early childhood, or remediate the effects of adverse shocks, were also extensively studied. Social protection programs, which include but are not limited to food provision, have been shown to offer protective effects against ill conditions.

Cash transfers, while not specifically targeted towards food consumption, can improve the children's food security by increasing the family's disposable income and therefore have the potential of positively contributing to developmental aspects. Indeed, Currie and Cole (1993) find evidence that their receipt increases birth weight for a subset of the studied families, using instrumental variables for the participation in the Aid for Families with Dependent Children program.

In Brazil, a study using propensity score matching also indicates that receiving the Bolsa Familia Program, a conditional cash transfer for low-income households, is associated with lower food insecurity levels, and with improved nutritional status of beneficiary children (Baptistella, 2012). Other two propensity score matching studies indicate a correlation between being a Bolsa Familia beneficiary and having lower household food insecurity levels, as well as decreased probability of being overweight as a child (Baptistella, 2012) and diminished consumption of processed foods (Sperandio et al, 2017).

Near-cash Social Protection programs, which are generally thought to function similarly to cash

[7] Barker's "Fetal Origins Hypothesis" marked the start of increased interest in investigating the effects of in-uterus conditions on future health outcomes, as it proposed a shift from prior belief that the placenta fully protected fetuses from adverse shocks (Almond and Currie, 2011a).

transfers[8], are also shown to foster early childhood development. In the United States, Food Stamps are found to increase food consumption (Hoynes and Schanzenbach 2009), and to improve adult health outcomes by lowering the incidence of metabolic diseases in children below the age of five (Hoynes et al, 2016).

Likewise, Social Protection Programs that provide in-kind food transfers are meant not only to relieve short-term hunger, but also to improve health and educational outcomes through the availability of macro and micronutrients. School Meals in particular have the added benefit of promoting school attendance (WFP, 2009), generating synergies for human capital investments.

As expected, empirical evidence vastly confirms this, with findings from a randomized control trial in Ghana pointing to positive effects of school lunches in nutritional status, as well as improved cognition and educational outcomes (Aurino et al, 2023). Deworming, which is often implemented in schools in combination with the meal program, has been shown to decrease absenteeism at very low costs, with large positive externalities for untreated schools as well (Kremer et al, 2004).

In spite of the demonstrated impact on children's health, most Social Protection interventions are either not exclusively targeted towards nutritional goals, like cash-transfers, or do not aim to reach children in particular, such as food vouchers.

School Feeding Programs are one of the few safety net programs which have the improvement of children's nutritional status as one of their main objectives. However, individuals below the school starting age can usually only expect to be reached through spillover effects. Evidence from Burkina Faso confirms that younger siblings of school-aged children benefit from take home rations, but finds no indication that substitution effects[9] have a significant effect on children below the age of five (Kazianga et al, 2013). This prompts the question of what large-scale interventions can be used to address the nutritional needs of individuals during the crucial pre-school phase.

In Latin America and the Caribbean, the extension of school meals beyond primary education is relatively common, with 12 out of 16 countries offering universal access to preschoolers as well (WFP, 2017). Nevertheless, it is often the case that enrollment rates, at ages in which school is not compulsory yet, are very low.

In Brazil, many people in that age group are effectively excluded from entering pre-school, due to the limited number of facilities that exist in the country. According to the Childcare Need Index 2018-2020, only 37% of children below the age of 4 were enrolled in one as of 2018. Furthermore, these estimates are even lower among households of lower socio-economic status, with only 27.8% being matriculated in a pre-school. In spite of wider age scope[10] of Brazil's School Feeding Program

[8]As their value is usually lower than what the household would have spent on that good or service absent the voucher (Almond and Currie, 2011b).

[9]Whereby older siblings being fed by schools would increase food availability for preschoolers and infants.

[10]In Brazil, the school meal program extends to as individuals from age of six months onward.

when compared to other countries, the under supply of childcare services means that an important gap still exists in addressing nutrition policies to the years that are expected to be most cost-effective.

Complementary interventions, which are usually delivered independently from school meal programs, are thus one of the most common ways to reach ante-natal and early childhood populations and fill gaps left by larger initiatives.

Among the most important examples of complementary interventions are Micronutrient Supplementation programs, which usually consist of Iron-Folic Acid (IFA), Vitamin A or Multiple Micronutrients. They are used to decrease anemia and iron deficiency in those who are pregnant, as well as to reduce the frequency of low birth-weight (WHO, 2012) and of congenital defects in the neural tubes and the heart (Czeizel, 2011). As expected, a randomized control trial proved that the administration of Multiple micronutrient (MMN)[11] supplementation significantly reduced the incidence of preterm births and low birth weight (West et al, 2014).

Overall, in spite of the overwhelming evidence that providing micronutrients during those periods can be a very cost-effective way of improving childrens' future socio-economic status, there appears to exist little evidence on the effect of such practices at scale. Nutrition programs targeting the in-uterus and infancy periods in developing countries are fairly common, with various examples in Latin America. Nevertheless, their inter-sectoral and decentralized nature, particularly in Brazil, makes them harder to monitor when compared to School Meals (Oliveira et al, 2022).

Understanding the actual effects of such programs when implemented widely in developing countries is thus necessary. Undoubtedly, limitations in their execution at higher jurisdictional levels might lower their general effectiveness compared to lab-in-the-field experiments or randomized control trials. Nevertheless, because these interventions target the periods with the highest return to spending, and because they are quite inexpensive in nature (WFP, 2009), they are still potentially interesting even in the presence of large inefficiencies. Therefore, understanding the constraints and spillover effects is necessary to get a clear picture of how these programs compare to more traditional social protection measures, and how they might be used and adjusted to reach younger and more vulnerable populations.

4 Background

4.1 Food Insecurity and Children's Nutritional Status in Brazil

Over the past twenty years, food security has been a major concern for policy-makers in Brazil. Under the Zero Hunger program, launched in 2003, the country successfully achieved the Millenium Development Goal of decreasing the number of food insecure individuals by half (FAO, 2014). At

[11]Supplements containing fifteen different micronutrients, among which iron-folic acid.

the time, an intense investment to guarantee food security and proper nutrition was being undertaken, with a budget of approximately USD 35 billion allocated to those purposes in 2013 alone (FAO, 2014). As a result, between 2003 and 2013, the percentage of food secure households in Brazil increased by 12.3 percentage points, reaching a peak of 77.4 percent in 2013 (IBGE, 2018).

However, subsequent economic crises followed by large budget cuts during the next administrations led the scenario to quickly deteriorate and, by 2017, the percentage of food insecure households had gone back to pre-2003 levels (IBGE, 2018), with the COVID Pandemic years further complicating the situation.

In this scenario, discussions on the policies that should be put in place could secure appropriate levels of nutrition among young children have returned to the limelight. The 2021 SISVAN study further emphasizes the urgency of these discussions, revealing alarming statistics. On average, 11.72% of Brazilian children are below their appropriate height for their age, and that 4% of them are wasted[12]. In conjunction with increasing nutrition deficits, child obesity rates have also been surging, with 7.72% of the population under 5 being overweight (SISVAN, 2021[13]). These findings highlight the pressing need to address nutrition deficits through effective policy implementation.

Furthermore, despite the significant reduction in the budget allocated to nutrition programs, public expenditures on food policy in Brazil still remain sizable both in absolute and relative terms. For instance, in 2015, the federal government's transfers to municipalities for the School Feeding program amounted to approximately USD 1.130 billion (WFP, 2017). This presents an opportunity to evaluate the effectiveness of nutrition policies, given their substantial costs and potential importance in overcoming Brazil's current challenges.

4.2 Nutrition Programs in Brazil

The history of food security programs in Brazil dates back to the 20th century, with the establishment of the Social Security Food Service program (SAPS) in 1940, a policy which provided subsidized meals to the working class to ensure sufficient calorie intake and maintain productivity levels. In 1954, these efforts expanded beyond adult workers with the introduction of Brazil's first School Meal Campaign. This program, predominantly funded by external donors, aimed to enhance food security among school-aged populations.

However, it was in 1973 that the groundwork for the current model of food security programs was laid out. The first phase of the National Food Supply Program (PRONAN) was initiated, marking the beginning of a comprehensive national food security policy that targeted specific vulnerable groups, including pregnant individuals and young children.

[12] Below the appropriate weight for their age.

[13] Author's own calculations.

Furthermore, the second phase of PRONAN, initiated in 1976, introduced nutrient supplementation and emphasized the importance of synergies between food security programs and the strengthening of local agricultural value chains. During that time, various new programs were created.

Perhaps most importantly, Brazil's current National School Meals Program (PNAE) was initiated in 1979 and, from 1986, it expanded to children between the ages of 4 and 7. Currently, Brazil's School Feeding initiative, which covers the public school system and reaches children as young as 6 months old, benefits 41.5 million students (WFP, 2017). However, the coverage of children under the age of 4 is likely low, due to the restricted access to primary schools in the country.

During the second phase of the PRONAN, complementary programs aimed at improving nutrition during the in-uterus and infancy periods were also created. Among these, a large-scale food distribution program created in 1985[14]. Micronutrient supplementation strategies were also initiated, through the dissemination of iodized salt in 1975, and the expansion of Iron and Vitamin A provision during the seventies and eighties (Silva, 1995).

Nation-wide iterations of these micronutrient supplementation programs arose throughout the years. The National Program for Iron Supplementation (PNSF) was first implemented in 2005, targeting iron tablets to children between 6 and 24 months, as well as pregnant and postpartum individuals (Ministry of Health, 2013). Additionally, the National Program for Vitamin A Supplementation (PNSVA), which involves the administration of a megadose of Vitamin A to children aged 6 to 59 months, was established in 2005, and expanded to all Brazilian regions in 2012. Both initiatives are currently executed through primary care units.

In 2003, the start of the Zero Hunger Strategy marked another milestone for Brazil's food security policies. Within that framework, restaurants offering subsidized food were revived (Fagundes et al, 2022). Additionally, the newly created Food Acquisition Program (PAA) was conceived as a way to achieve a twofold objective through the direct acquisition of produce: strengthening local markets and distributing food to vulnerable populations. The integration of the PAA purchases with the School Feeding program helped to address both food security and sustainable agricultural development in local communities, leading other programs in the region to be modelled after these policies (WFP, 2017). Despite its success, between 2012 and 2019, the PAA faced severe budget cuts and was temporarily discontinued in 2021, when it was replaced by the Feed Brazil Program (PAB), only to be re-launched in 2023.

The Zero Hunger Strategy also pioneered the multi-sectoral approach of food security policies in Brazil, recognizing that addressing food security requires collaboration and coordination across various sectors, including agriculture, health, education, and social development.

An example of this is the Health in School Program (PSE), which was launched in 2007 as a joint effort between the Ministry of Education and the Ministry of Health. It has the objective

[14]Brazil's Food Supplementation Program (PSA).

of integrating the promotion of healthy activities within the educational environment. One of this program's components, the Nutrition in Primary Care and Food and Nutrition Surveillance of the Unified Health System (NutriSUS), was designed to provide micronutrient supplementation to children between 6 and 48 months. Its implementation, which started in 2014 and has reached more than 233 thousand people, hinges in the coordination with participating primary schools, who are responsible for adding a fortified power to children's meals (Ministry of Health, 2015).

The increasing complexity of food security programs, which not only involve different government levels, but also require managing action from different ministries, led to the creation of the National Food and Nutrition Security System (Sisan) in 2006. The Sisan aims at coordinating the different government levels involved in food security policies, as well as civil society, and it has been responsible for the creation of many of the monitoring structures over the years, including the Map of Food and Nutritional Insecurity (Mapa InSAN).

4.2.1 Targeting of Nutrition Programs through the MapaINSAN

The MapaINSAN was created in 2016 to provide a clear picture of food insecurity in Brazil and to help target nutrition interventions to the most vulnerable areas. Using the stunting rates for children under the age of 5, this report classified municipalities as "Food Secure" or "Food Insecure", with the latter group being considered the priority for initiatives aiming at improving access to nutrients and food. Since its creation, the MapaINSAN has been adopted as targeting criteria for a number of pre-existing nutrition policies.

The National Program for Vitamin A Supplementation (PNSVA) has been using the MapaINSAN to target particularly food insecure municipalities since 2018. In those areas, the Vitamin A supplementation is designed to reach 60% of all children, regardless of their socio-economic status. Conversely, in non-priority zones, only the beneficiaries of the National Conditional Cash Transfer program are eligible for the supplementation (Parana State Government, 2020). Within the context of micronutrient supplementation, the NutriSUS also targets its actions to Food Insecure Municipalities in the MapaINSAN, in addition to all municipalities in the Northern Region (CGAN, 2022)[15].

Other large scale programs, such as food acquisition programs like the PAA and PAB also use MapaINSAN classification to prioritize the most at risk areas for their purchasing schemes (CONAB, 2020) [16]. Food distribution has also been earmarked to give priority to insecure territories, and the Food Distribution Campaign (ADA), which was especially active during the COVID-19 Pandemic, also based its goals on the MapaINSAN.

Naturally, it is expected that some programs might use this targeting criteria to increase the service intensity in key areas, without necessarily establishing it as a formal criteria. For this reason,

[15] Source: https://www.cosemssc.org.br/wp-content/uploads/2022/03/webinario.pdf

[16] Source: https://www.conab.gov.br/images/arquivos/agricultura_familiar/Criterios_PAA2021.pdf

this study looks not only at policies that explicitly state using the MapaINSAN, but also at ones that might use it to make marginal decisions about service delivery. The choice of the programs is conditional on available data.

5 Empirical Strategy

This analysis aims to estimate the marginal effect on neonatal[17] and early childhood outcomes of being more intensely targeted by micronutrient supplementation programs. I exploit the fact that municipalities in which the levels of recorded child stunting in 2014 were 10.1% or higher are considered more food insecure than others, and therefore prioritized by programs after 2016.

In order to estimate the effect of being targeted more intensely, developing a counterfactual for the health and educational outcomes of intensely targeted municipalities, had they not been prioritized, is necessary. However, comparing the outcomes of municipalities that were prioritized to the ones that were not would not lead to causal estimates. The potential outcomes of these two groups are likely to be very different, since the targeting decision was based on initial levels of child stunting.

Indeed, absent the intensive provision of nutrition programs, vulnerable areas that were chosen as priority by the federal government would probably have had far worse outcomes than other municipalities. For this reason, a direct comparison of treated and untreated, where treatment stands for being targeted more intensely, would greatly bias the effects of intensifying the provision of such programs.

5.1 Differences-in-Differences

Given the lack of comparability between the two groups, a first possible strategy is to compare the evolution of the outcomes of interest for the two groups over time. Using a differences-in-differences approach allows us to filter out time-invariant differences in the potential outcomes of the municipalities, as it is plausible to believe that these inherent differences would remain constant over time. Furthermore, this design allows to control for time-varying trends that affect all municipalities in the same way.

The Differences-in-Differences estimator would thus allow us to estimate the effects of more intensive targeting of micronutrient supplementation. However, two assumptions are necessary for that to be the case. First, no factor other than the more intensive targeting should have affected the outcomes of interest of the two groups differently. In other words, absent treatment, the outcomes of treatment and control units would have continued to follow parallel trends, and any shocks that were

[17] The Neonatal period relates to newborn children under 28 days of age.

to happen in the post-treatment period would have been common ones. Second, the treatment effect prior to the publishing of the MapaINSAN must be zero. This implies that the federal government should not have used a preliminary version of the report to target nutrition policies.

I estimate the following model:

$$Y_{i,t} = \alpha_i + \lambda_t + \beta(1[t = 1] * T_{i,t}) + \epsilon_{i,t} \tag{1}$$

In the regression equation, α_i and λ_t are municipality and year fixed effects, respectively. The coefficient β gives the effect of the interaction between treatment status and post-treatment period[18]. That is, it represents the differences-in-differences estimate of the effect of intensively targeting a municipality on the outcomes of interest. In this specification, standard errors are clustered at the municipality level, because that is the level at which treatment is assigned.

5.2 Regression Discontinuity Design

I exploit the criteria used by the government to determine whether a municipality is ”Food Insecure” to estimate the effects of being targeted more intensively by the nutrition programs through regression discontinuity design (RDD). A municipality classification in the MapaINSAN is determined by more than 10.1% of children under 5 having been stunted in 2014.

Because a larger share of children was too short for their age in prioritized municipalities, absent treatment, they are likely to have overall worse child development outcomes when compared to the rest of the country. This indicates that comparing treated to non-treated would generate biased results of the marginal return to nutrition interventions. However, the potential outcomes of municipalities with very similar stunting rates in 2014 shouldn't differ systematically.

The underlying assumption for the Regression Discontinuity Design is that potential outcomes are not going to majorly change when approaching the discontinuity threshold from either side, thus allowing us to find causal estimates of the effect of prioritization. However, a necessary condition for this to be true is that reaching 10.1% of child stunting shouldn't abruptly change important variables other than the nutritional policies targeted through the MapaINSAN. Intuitively, this seems to hold, as that number is only an arbitrary trigger for a municipality prioritization, and it is not tied to any known changes in political or biological factors that might affect health or educational outcomes.

The federal government classified municipalities as ”Food Insecure” using stunting data available while the MapaINSAN report was being written. Nevertheless, stunting figures have been

[18] A household is considered not treated if the MapaINSAN classifies it as ”Food Secure”, thereby not being eligible for prioritization. On the other hand, if ”Food Insecure”, it is considered treated. Treatment is considered to start after MapaINSAN began to be used as a targeting mechanism. Since the MapaINSAN was published in late 2016, already with the objective of helping target future nutrition policies, I consider 2017 as the first treated year (t=1) and all years before that as pre-treatment (t=0).

updated after that, since additional children have been added to the 2014 database in later periods, as is common due to the long processing times of data on individual health check-ups. While adding information on new children doesn't dramatically shift the figures, it did cause a number of municipalities to fluctuate above and below the 10.1% threshold.

Considering that estimates of child stunting changed as data on children monitored in 2014 was processed and added to the 2014 database in later periods, we have to be mindful that processing time could differ systematically between municipalities depending on the quality and efficiency of their public health services. Another possible confounder is that municipalities with a higher number of children under 5 would get faster to a point in which adding a few new entries would not change the child stunting percentages as much. It is therefore clear the compliance status is very likely to be determined by underlying municipality characteristics.

However, since the preliminary data is a good indicator of final share of stunting in 2014, final stunting levels in 2014 being above the 10.1% cutoff increase the chances of having been prioritized by the MapaINSAN. For this reason, we can use a fuzzy regression discontinuity design (RDD) to estimate the effect of treatment on a subset of the municipalities. In this model, the final share of stunted children in 2014 (running variable) increases the chance that the municipality is prioritized for nutrition interventions (treatment).

The results estimate the local average treatment effect[19] of being more intensely targeted by nutrition interventions. That is, for municipalities whose final stunting rates in 2014 did not change to which side of the 10.1 cutoff they would end up, compared to where the preliminary data had originally assigned them. I estimate a global parametric RDD and two local specifications.

In all of these specifications, Y_i are the outcomes of interest, which include health status, as well as nutrition input provision. Similarly, S_i is the final share of stunted children in the municipality, and T_i is the treatment status, or whether a municipality was prioritized for nutrition programs.

5.2.1 Global Polynomial Regression

The parametric RDD allows the effect of treatment to differ after the cutoff point, using the following instrumental variable approach. The first stage is estimated using this equation:

$$T_i = \alpha + \delta C_i + h(S_i) + \epsilon_i \tag{2}$$

Here T_i=1 signals that a municipality was prioritized by the MapaINSAN. That is, that the municipality was treated with an increased intensity of complementary nutrition programs. The variable C_i being equal to 1 means that the municipality was above the 10.1 cutoff. On the other hand, $h(S_i)$ is a function of the percentage of stunted children in a given municipality, which in this case

[19]On municipalities whose stunting scores in 2014 were largely unaffected by the addition of new observations.

is a first order polynomial. I avoid using higher order polynomials due to the noisiness of their implicit weights (Imbens and Gelman, 2014), and because many different specifications are already included in the study.

The second stage is then estimated as follows:

$$Y_i = \gamma + \delta\hat{T}_i + h(S_i) + u_i \tag{3}$$

Here, δ gives us the local average treatment effect of being targeted more intensively by federal-level nutrition interventions. The same functional form specification is used in the first and second stage. Within the parametric specification, I use all available observations, independent of how far they are to the cut-off point, and do not include covariates.

5.2.2 Local Polynomial Regression

First, estimate the LATE using a continuity-based approach. This method still assumes a polynomial functional form. However, it only uses observations that are closer to the cut-off, determining the optimal bandwidth to be used by minimizing the mean square error. Following the approach described by Cattaneo et al (2023b), the continuity-based RDD is estimated using the rdrobust package, which calculates τ_T and τ_Y by fitting two different local linear polynomials at each side of the cutoff point, as the equations below suggest.

The first stage is estimated as such:

$$\tau_T \equiv \lim_{x \downarrow 10.1} \mathbb{E}[T_i | S_i = x] - \lim_{x \uparrow 10.1} \mathbb{E}[T_i | S_i = x] \tag{4}$$

Here τ_T represents the effect of having 10.1% or more child stunting on the probability of a municipality being prioritized for nutrition programs.

The reduced form effect, or the effect of child stunting levels on the outcomes of interest, regardless of prioritization, is given by τ_Y, which is estimated as follows:

$$\tau_Y \equiv \lim_{x \downarrow 10.1} \mathbb{E}[Y_i | S_i = x] - \lim_{x \uparrow 10.1} \mathbb{E}[Y_i | S_i = x] \tag{5}$$

Finally, the effect of treatment on the treated is calculated using the ratio of τ_T on τ_Y. Because the bandwidth needs to be small enough to have potential outcomes not be systematically different, the package selects a single bandwidth for the estimation of both τ_T on τ_Y, by minimizing mean-squared errors (Cattaneo et al, 2023a).

5.2.3 Local Randomization

The Local Randomization Framework allows us to estimate the regression discontinuity model without making initial assumptions about the functional form. This method considers that, by using a small enough bandwidth around the threshold, the treatment assignment is as good as random. We assume that, in that small bandwidth, treatment is independent of observed and unobserved characteristics, and thus of potential outcomes. The local-randomization fuzzy RD parameter is estimated as the ratio between the first stage and the reduced form estimates. The first stage is found in the following manner:

$$\theta_T \equiv \frac{1}{N_W}\mathbb{E}_{\mathbb{W}}\left[\frac{C_i T_i}{P_W(C_i = 1)}\right] - \mathbb{E}_{\mathbb{W}}\left[\frac{(1 - C_i)T_i}{1 - P_W(C_i = 1)}\right] \tag{6}$$

Here, $C_i = 1$ represents a municipality being above the cutoff, W is the window within which the randomization assumption is expected to hold, N_W is the number of observations within that neighborhood, and P_W and E_W are probabilities and expected values within each neighborhood of the threshold. The reduced form is estimated as follows:

$$\theta_Y \equiv \frac{1}{N_W}\mathbb{E}_{\mathbb{W}}\left[\frac{C_i Y_i}{P_W(C_i = 1)}\right] - \mathbb{E}_{\mathbb{W}}\left[\frac{(1 - C_i)Y_i}{1 - P_W(C_i = 1)}\right] \tag{7}$$

This model is estimated using the rdrandinf package. The bandwidth W is selected through a data-driven approach, which consists of choosing the largest neighborhood that allows pre-determined covariates, which are otherwise strongly related to the share of child stunting, to be completely unrelated to the running variable. This is done using the function rdwinselect. I use the municipality's GDP and the share of children under the age of five in the year of 2010 as my pre-determined covariates, which are both significant predictors of the final stunting levels in 2014.

6 Data

6.1 Data Sources and Content

The main objective of this paper is to understand the effects of increasing the intensity of food security programs on the outcomes of newborns and infants, exploiting the creation of a new prioritization criteria for nutrition programs. For this reason, this empirical analysis required data on which municipalities were prioritized, the quantities of nutrition inputs delivered, and the health outcomes of newborns and infants.

To gather data on which municipalities were identified for prioritization, I use the 2016 Map of Food and Nutritional Insecurity (Mapa InSAN)[20], a study published by the Brazilian government to diagnose the food insecurity issue in the country and provide criteria to target nutrition programs to areas that are most at risk. The Mapa InSAN classifies municipalities as Food Insecure if more than 10.1% of its children are stunted, which leads that administrative division to be prioritized. The preliminary stunting figures used for that report came from the 2014 Food and Nutritional Surveillance System (SISVAN), a dataset containing yearly information on the percentage of children under the age of five that are below the appropriate height and weight for their age in each city.

Although, in principle, the 2014 SISVAN data should have offered an exact measure of the prioritized zones, this is not true in practice. The average stunting rate for a given year in the SISVAN is determined by averaging the reported information for all the children that have been monitored by the public health system during that period. However, while preliminary figures are available quickly, they are subject to change because of the long reporting and processing time.

For this reason, the estimated percentages of stunting and wasting for 2014 look different now than when the government's study was conducted. Essentially, as anthropometric measures for new children are added to the system, later figures are likely to better reflect true stunting than preliminary data released in 2014, which calculated municipality-wide stunting percentages based on a much smaller sample.

Treatment information is thus collected from the MapaINSAN, and it includes all municipalities that were above the 10.1% cutoff based on the preliminary data used by the government. On the other hand, my running variable is constructed using the most up to date information on stunting in 2014, which is extracted from the SISVAN 2014. This includes all the observations originally used for the prioritization in the Mapa InSAN, plus later entries.

Stunting rates in a given locality are thus used as the treatment assignment variable, as being above the 10.1% threshold is a good predictor for a municipality having been prioritized, considering the close connection between the preliminary stunting data and the final one. Overall, figure 1 indicates that the average share of stunted children is 12.1%, which is consistent with more than half of the sample being treated: indeed, 56% of municipalities are prioritized in food security programs.

The analysis also uses municipality-level data on the implementation of nutrition programs in Brazil. A first database [21] contains information on the number of children reached by the Vitamin A supplementation. It also details the infants benefitting from the powdered supplementation program (NutriSUS), as well as the pregnant people and children that received Iron supplements. This information was collected for the 2017-2022 period, except for the Vitamin A figures, which ware

[20]https://aplicacoes.mds.gov.br/sagirmps/portal-san/artigo.php?link=15

[21]https://sisaps.saude.gov.br/micronutrientes/

available from 2015 onward. Transfers from the federal government to municipalities for the implementation of the School Feeding program were also gathered for the years of 2016-2022, using the Transparency Portal of the Comptroller General of the Union[22]. Average values for the input variables are detailed in figure 1.

Finally, data on health outcomes was collected. The first database used consisted of the Information System on Live Births (SINASC), which contains all registered births in the Brazilian municipalities between the years of 2014 and 2018. It reports information on the weight, health status at birth (APGAR scores[23]), gestational age, gender at birth, cephalic presentation, number of previous pregnancies and presence of congenital anomalies. The birth defect dummy is constructed to indicate whether a newborn has any congenital health problems that fall into the International Statistical Classification of Diseases and Related Health Problems (ICD-10). The other neonatal variables are just municipality averages of the original individual-level figures.

A second source of information for the health outcomes are hospitalizations of children under the age of one due to diarrhea. Data on the number and days of hospitalizations, as well as expenditures, from 2010 to 2022, is collected from the Hospital Information System of the Unified Health System (SIH-SUS)[24]. I use it to construct incidence rates of diarrhea in those less than 12 months old. Measures of the intensity of the disease were also created based on the length of hospital stay and per capita expenditures with hospitalization. I use the 2011 "Basic Municipal Information Survey" (MUNIC) to collect pre-determined covariates at the municipality level.

The running variable describing treatment assignment, as well as the actual prioritization status, inputs and outcome variables were used to build a panel dataset. For the Differences-in-Differences model, all years before 2020 used, in order to avoid confounding effects from the Pandemic. For the Regression Discontinuity analysis, I selected the second year in which the prioritization was active: 2018. Figure 1 displays the descriptive statistics for all variables used in the analysis in 2018.

[22] https://portaldatransparencia.gov.br/transferencias

[23] Appearance (skin color), Pulse (heart rate), Grimace (reflex irritability), Activity (muscle tone), and Respiration.

[24] http://tabnet.datasus.gov.br/cgi/deftohtm.exe?sih/cnv/nibr.def

Figure 1: Descriptive Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Stunting Rates (Running Variable)	5,560	12.11785	6.597238	0	50.6
Prioritization in the MapaINSAN (Treatment Variable)	5,560	0.568429	0.49534	0	1
Goal of Iron Provision to Children	5,524	535.6722	2826.694	7	154343
Goal of Iron Provision to Pregnant people	5,524	269.1687	1576.159	2	87834
Goal of NutriSUS provision	1,032	291.8159	548.1915	1	13656
Goal of Vitamin A provision (younger than 1)	3,521	408.7089	1461.17	0	36419
Goal of Vitamin A provision (younger than 4)	3,521	1245.721	4948.223	3	169771
Transfers received for the School Feeding Program	5,455	508568.2	1939890	10	95900000
Any Birth Defects/ Congenital Anomalies	5,521	0.007872	0.011521	0	0.3333333
Newborn is male	5,524	0.513697	0.053918	0.176471	0.8181818
Cephalic Presentation	5,524	0.957855	0.042314	0.303798	1
Number of Pregnancies	5,524	1.241044	0.289033	0.222222	2.969697
Gestational Age	5,524	38.51801	0.37585	36.16667	41.4186
Birth weight	5,524	3196.962	85.06994	2691.429	3714.565
Days at the hospital by diarrhea case (below age of 1)	1,399	3.110562	1.970571	0	33
Expenditures by diarrhea case (below age of 1)	1,381	379.7625	328.3522	39.42857	7932
Share of diarrhea morbidity (below age of 1)	3,007	0.00455	0.010658	0	0.1765258
APGAR below 7 (5 minutes after birth)	5,388	0.010679	0.013172	0	0.3333333
Municipality GDP in 2011	5,570	12600.34	14758.83	2256	312220
Population in 2010	5,382	34398.84	203426	805	11300000
Number of Children	5,382	3011.337	15608.35	52	860893

7 Results

7.1 Differences-in-Differences

7.1.1 Testing the Parallel Trend Assumption

In order for the identification strategy to work, the trends affecting the outcomes of interest should have been the same prior to the onset of the MapaINSAN prioritization. I check whether this is true by plotting the pre-trends for the main set of variables included in the analysis.

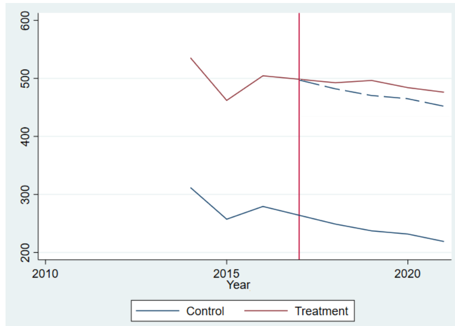

Figure 2: Pre-trends: Targeted beneficiaries - Vitamin A supplementation (below age of 1)

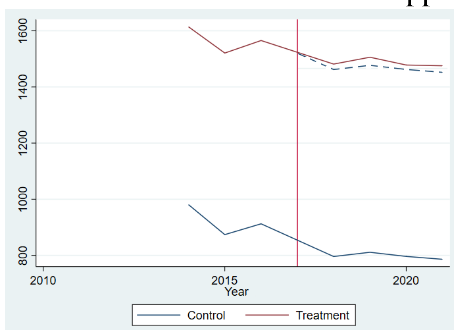

Figure 3: Pre-trends: Targeted beneficiaries - Vitamin A supplementation (between age of 1 and 4)

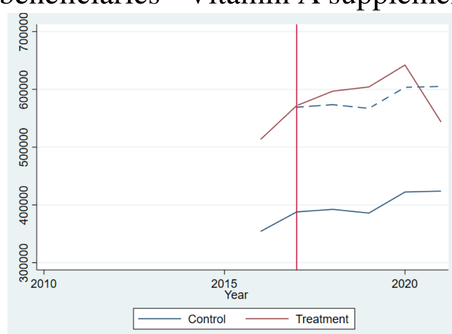

Figure 4: Pre-trends: Expenditures on School Feeding Programs

The graphs above suggest that, prior to 2017, the provision of these nutrition programs was following similar trends, with more food insecure municipalities already receiving considerably more attention by nutrition programs. After the publication of the MapaINSAN, it is possible to observe some deviation from the previous parallel trend, especially in the supply of Vitamin A to children below the age of one, as well as in the federal transfers for school meals. The only exception is the sharp downturn of School Feeding transfers that occurred during the first year of the Pandemic, affecting treated municipalities more strongly. I therefore restrict the sample for the analysis to years before 2020.

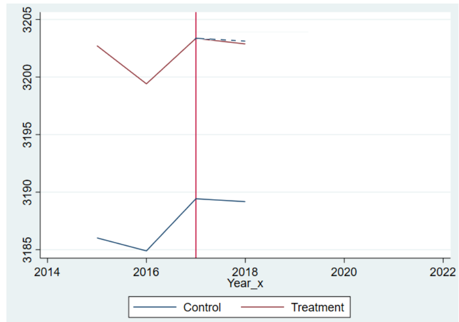

Figure 5: Pre-trends: Weight at birth

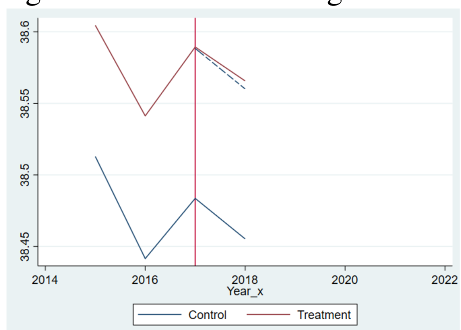

Figure 6: Pre-trends: Duration pregnancy (weeks)

Figure 7: Pre-trends: Share of Diarrhea Morbidity in children under 1

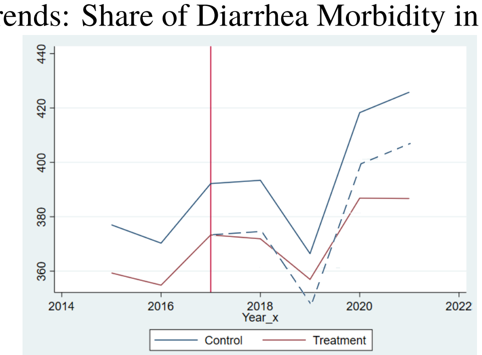

Figure 8: Pre-trends: Expenditures by case of Diarrhea in children under 1

Similarly, health outcomes before 2017 also appeared to be following similar trends, except for diarrhea morbidity during and after 2020. Deviations from the pre-trends after the onset of the MapaINSAN targeting mechanisms, however, are less clear. This is expected, as the provision of nutrition programs is directly tied to targeting mechanisms, whereas impacts that might result from this marginal increase in intensity are not anticipated to be as large.

7.1.2 Differences-in-Differences Results

Panel 1 in Figure 9 reports the results for the Differences-in-Differences estimation. The figures suggest that being in a prioritized municipality after the onset of the prioritization is connected to significant, albeit very small, improvements in newborn's health. It is associated with increases in newborns' weight by 6.9 grams, significant at the 1% level. Similarly, there is a statistically significant increase in gestational age: newborns in treated municipalities have gestational ages that are 0.06 weeks longer than their counterparts, which is equivalent to a bit less than half a day. The incidence of birth defects in such municipalities is also 0.0008 percentage points lower.

We cannot reject the null that being in a targeted municipality after 2016 has no effect on the probability of having a normal APGAR score 5 minutes after birth. This indicates that no visible effects on newborns' health status appear to exist. Such a result is expected, since the effects on a child's weight and gestational age are very small, and APGAR scores reflect more visible measures of a newborn's well-being.

On the other hand, impacts on infant morbidity do not have such clear effects. Being in a prioritized municipality after the release of the MapaINSAN targeting metric appears to be connected to a minimal, but significant, increase in the incidence of diarrhea in children below the age of 1. While unexpected, this could be explained if the MapaINSAN were being used to target more intensive efforts to treat diarrhea in at-risk municipalities. This could then lead to an increase in the number of reported cases, if the incidence of diarrhea had been subject to under-notification in previous periods. Reassuringly, cases of gastrointestinal disease appear to be somewhat less serious in intensively targeted areas, with the average expenditure per hospital stay decreasing in 11.6 reais, but no significant changes in the length of stay.

Figure 9: Results - Health Outcomes

	Health Outcomes						
	Neonatal Health				Diarrhea		
	Weight	APGAR below 7 (at 5 minutes)	Any Anomaly	Weeks of Pregnancy	% Children under 1 affected by diarrhea	Days in hospital by case (below 1)	Expenditure by case (below 1)
Mean:	3196.962	0.0106791	0.0078718	38.51801	0.0045498	3.110562	379.7625
Panel 1: DiD							
Targeted X After 2016	6.899368	0.0001205	-0.0008108	0.0632345	0.0004742	0.0143399	-11.65791
S.E	(1.527048)***	(.0002877)	(.0001931)***	(.006592)***	(.0000459)**	(.0440684)	(6.805172)*
Number observations	27,640	26,954	27,636	27,640	29,900	14,458	14,287
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel 2: Regression Discontinuity							
Global RDD							
Above Food Insecurity Threshold	13.03383	0.0003783	-0.0001703	0.0905	0.0006	-0.1153896	-24.52304
S.E	(4.653497)***	(.0007324)	(.0006315)	(.0203499)***	(.000739)	(.1950)	(32.753)
Number observations	5,524	5,388	5,521	5,524	3,007	1,399	1,381
Local RDD							
Continuity-based: Above Food Insecurity Threshold	37.089	0.00477	-0.00136	0.09727	-0.00342	-5.2538	-531.15
S.E	(48.801)	(.00818)	(.0048)	(.17687)	(.00699)	(5.7438)	(712.51)
Number observations	1691	1483	1814	2026	1248	502	592
Power Calculation	0.113	0.16	0.15	0.167	0.086	0.054	0.058
Local Randomization:							
Above Food Insecurity	4.59	0	-0.001	0.031	0	-0.884	-168.723
p-value	0.692	0.98	0.66	0.598	0.918	0.194	0.648
Number observations	214	208	214	214	100	57	56

In this table the effect on birthweight is measured in grams, and the expenditure is measured in Brazilian Reais.

7.2 Regression Discontinuity Design

7.2.1 Density at the cutoff

For several reasons, it seems unlikely that the municipalities would have had any success in manipulating their classification in the 2016 MapaINSAN. First, that was the first iteration of the food insecurity map, and the first time such measures were systematically being used for prioritizing recipients of nutrition programs. This means that the assignment rule for receiving nutrition programs more intensively was not known in advance, and there was no expectation that stunting levels would have been used to target provision. Second, the SISVAN data on stunting used in the 2016 MapaINSAN was from 2014, meaning that municipalities would have to have manipulated the stunting levels two years prior to the release of the report. Third, the SISVAN does not seem particularly amenable to manipulation by municipality-level policy-makers, since it is constructed using data directly reported by physicians to the national public health system. This means it is not subject to approval or validation by municipality authorities.

Figure 10 indicates that no sign of bunching around the threshold has been found, reiterating that there appears to be no major cause for concern that policy-makers are able to manipulate the running variable. Formally, we fail to reject the null hypothesis, meaning that there appear to be no indications that the density is different below and above the cutoff. The p-values for the binomial manipulation test are reported in Figure 14 (Annex 1).

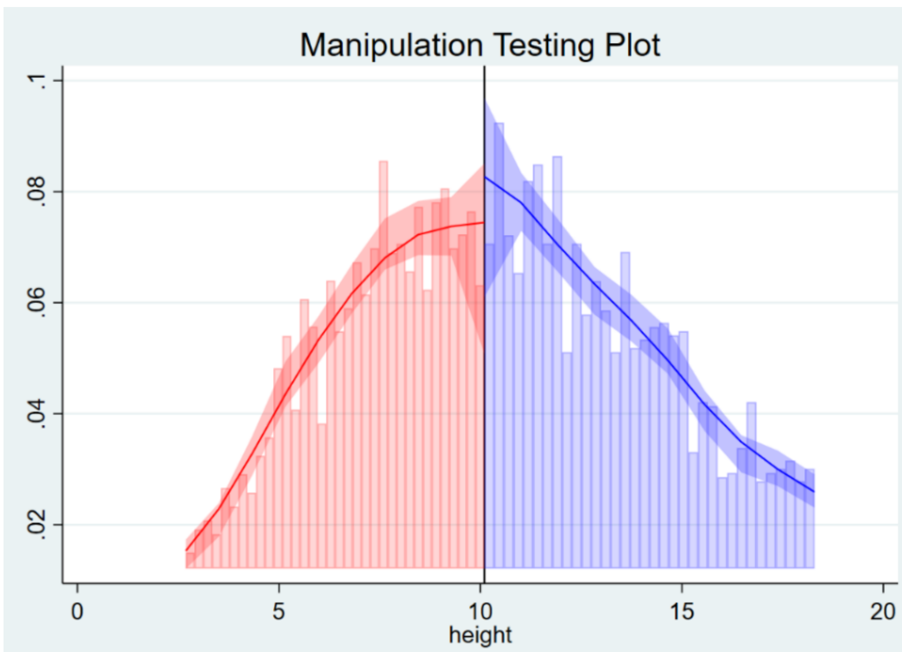

Figure 10: Manipulation Test: Density plot

7.2.2 First-stage

In order for the fuzzy regression discontinuity design to work, the share of stunted children being above 10.1% must be a valid instrument for the prioritization. This implies that two conditions need to be fulfilled. First, the existence of a first-stage is necessary. That is, conditionally on the stunting rate, there must be a relationship between being above the 10.1 threshold and being intensely targeted for nutrition programs. Second, the only way through which being above the 10.1 threshold should affect health outcomes is through the prioritization of the municipality for these policies. This is assumed to be satisfied within small bandwidths around the cutoff, in which the share of stunting is very similar, thus requiring weaker assumptions than a true Instrumental Variable approach.

However, it is necessary to probe the relationship between being eligible for prioritization (having more than 10.1% of stunted children), and actual prioritization. Figure 11 shows that the probability of a municipality being prioritized by nutrition programs jumps from approximately 0.2 to approximately 0.8 at the cutoff. From the image below, it is possible to identify that, although the probability of prioritization jumps discontinuously at the cutoff point, non-compliance[25] is happening on both sides: there are municipalities with higher levels of stunting in 2014 that were not prioritized, and municipalities with lower levels of stunting that were.

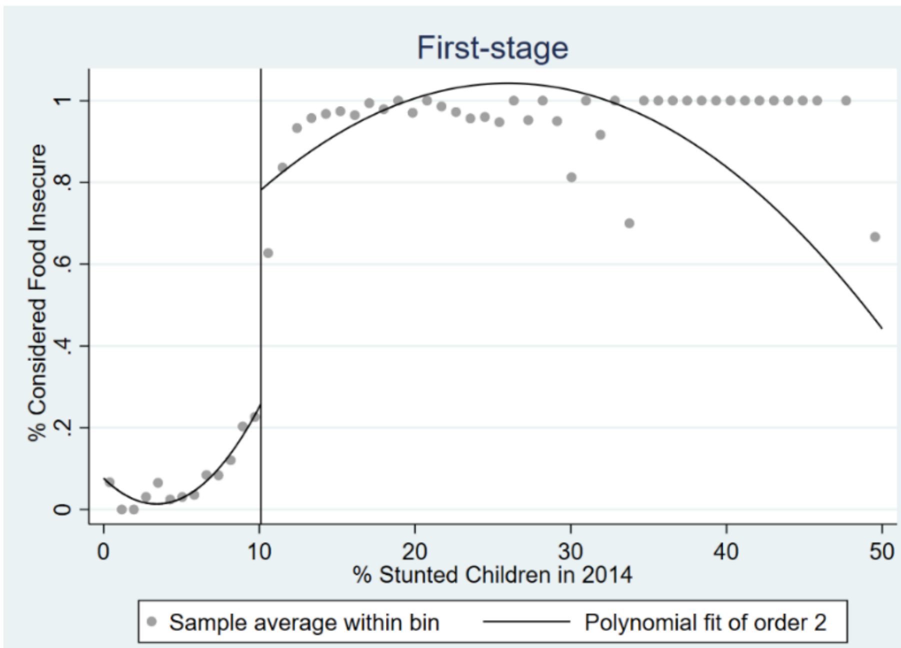

Figure 11: RD Plot: First Stage

The first stage is also tested in a formal manner, both globally and locally. The results below indicate a strong first-stage. Taking into account all observations, such as in regression 2, being above the 10.1% threshold of stunted children increases the probability that a municipality is prioritized by 69.9 percentage points, at the 1% significance level[26]. On the other hand, the first-stage

[25]Although the decision of prioritization was made solely by looking at stunting levels, non-compliance is happening due to municipalities official levels of stunting in 2014 changing with the addition of new children to the database. The addition of new children would lead to important changes in the recorded share of stunted children if a municipality falls under certain circumstances. That is, if it has a small population of children under the age of five, or particularly slow or error-prone reporting systems. Non-compliance is thus tied to municipalities' characteristics just as much as it would be if complying were a municipality's choice.

[26]The F-statistic is also high, at 5082.

discontinuity is considerably smaller in the neighborhood of the threshold. Following regression 4 and 6, I estimate that the local jump in probability of being prioritized is 13.7 and 13.1 percentage points, significant at the 5 and 10% levels, respectively. It is clear from these estimates, however, that under the Local Randomization method having more than 10% of stunted children is a weak instrument for prioritization.

	Global RDD	Local RDD	
		Continuity-based	Local Randomization
Effect of being above the threshold:	0.6992018	0.1368	0.131*
S.E	(.0112846)***	(.05875)**	0.078 (p-value)
F-stat	5082.89	217.22	6.9
Observations	5,560	1295	214

Figure 12: RD Regressions: First Stage

7.2.3 Health Outcomes

In Figure 9, Panel 2 reports the parametric RDD estimates of the effects of prioritization for nutrition programs on health outcomes. The first four columns contain the coefficients related to neonatal health status, whereas the last three are related to infant health. Under the parametric regression discontinuity design, prioritization is found to be associated with an increase in birth weight of about 13 grams. The size of the effect is a bit higher than what had been found using a differences-in-differences approach. Conversely, non-parametric RDD specifications find insignificant effects on weight, in spite of the point estimates being similar in magnitude to those of the DiD and global parametric RDD.

The RDD estimates further corroborate the findings from the differences-in-differences model, as the effects on the probability of having an APGAR score out of normality is not significant and very close to zero. The effects on gestational age are also similar in magnitude in the three RDD models, closely resembling what was found in the previous section, but only the global parametric estimates are significant.

Nonetheless, some results also deviate from the initial DiD findings: despite the negative sign, the effect of being prioritized for nutrition programs is not associated with a significantly lower probability of the occurrence of birth defects. Furthermore, discrepancies between the differences-in-differences results and the regression discontinuity ones increase for early childhood health outcomes. The initially positive association between being in a prioritized municipality and the share of children affected by diarrhea in 2018 become statistically insignificant when units with very similar levels of stunting are being compared. Moreover, while the DiD results seemed to suggest that the gravity of diarrhea cases was potentially smaller in prioritized municipalities, due to the lower expenditures by case, the RDD estimates are negative, but not statistically different from zero.

An additional heterogeneity analysis, presented in Figure 25 of the Annex, indicates how the LATE differs in municipalities that have a higher number of primary healthcare workers. The effects on neonatal outcomes remain mostly unchanged, both in magnitudes and significance levels: municipalities with more access to primary healthcare inputs do not appear to be affected differently. Conversely, the effects on infant health outcomes change slightly. Like in the model without interactions, the pure effect of being above the prioritization threshold does not seem to affect the diarrhea-related morbidity. However, the effect of prioritization in municipalities with better access to primary care appears to be different. In prioritized municipalities, icreasing the number of primary health workers by 10 decreases expenditures with a given diarrhea case by almost 4 reais.

7.2.4 Power Calculations

Power calculations indicate that the local regressions discontinuity designs lack the power to detect statistically significant effects. As a consequence, the absence of significance of their estimates is not enough to claim that the supplementary nutrition programs have no effect on health outcomes. Overall, it is not possible to rule out that prioritization for supplementary nutrition programs could have small but positive impacts on newborn and infant status, as suggested by the results from the differences-in-differences and the global regression discontinuity models.

7.2.5 Robustness and Falsification Checks

Falsification Checks

A first analysis requires that predetermined covariates, other than the ones used to find the bandwidth in the local randomization method, are balanced above and below the threshold, regardless of prioritization status. These variables should not change abruptly at the cutoff, because they are unaffected by prioritization that happened in later years. I check whether this holds for municipality characteristics in 2011 that are likely to be correlated to health outcomes, such as the presence in the municipality of public primary healthcare clinics, emergency rooms, and sewage systems, as well as the percentage of infants under the age of 1 that died in 2011. Results, reported in Figure 19 (Annex I), indicate that there are no major differences in pre-determined covariates above and below the cutoff.

A second investigation consists of analyzing discontinuities at the threshold for outcome variables that are known to not be affected by the supply of nutrition programs. I check for discontinuities in the gender of newborns, fetal position, as well as the number of pregnancies. Estimates reported in figure 23 (Annex I) suggest that there are no discontinuities at the cutoff in outcomes that are not expected to be affected by the provision of nutrition programs.

Robustness Check: Placebo Cutoffs

In order to understand whether the RDD estimates are capturing spurious effects, I test whether the reduced form relationships continue to be significant using placebo cutoffs. The identification strategy assumes a discontinuous jump in the intensity of provision of nutrition interventions, as well as in the health outcomes, when municipalities cross the 10.1% stunting rate threshold and thus increases its probability of prioritization. Finding discontinuities in health outcomes anywhere else would cast a doubt on the findings, because no other cutoffs are being used to target such programs.

This is investigated by running the reduced form regressions using cutoffs that, unlike 10.1, are not actually related to any targeting mechanism. In order to avoid contamination from treatment effects, placebo cutoffs above 10.1 are evaluated using treated municipalities only (Cattaneo et al, 2023a). Similarly, the analysis for those below 10.1 uses only untreated municipalities. I use the continuity-based RDD specification, and consider placebo cutoffs between 6.1 and 14.1% of stunting. The estimates, reported in Annex I, indicate no treatment effect other than the one from the true cutoff, providing reassuring evidence on the identification strategy.

7.3 Mechanisms

While marginal increases in the intensity of targeting is shown to have positive impacts for both neonatal and early childhood health outcomes, more insight is needed on what mechanisms are possibly driving these effects. I look at the supply of federal government programs to understand which of them might be intensified following the determination of municipalities to be prioritized. Naturally, State-level programs could also be using the MapaINSAN to prioritize municipalities that are expected to be more food insecure.

The increased difficulty in having a complete list of all nutrition programs at lower jurisdictional levels, as well as the scarce availability of data on their execution, led me to only look at the provision of the main federal-level programs, with special focus on the ones that explicitly stated that the MapaINSAN was used to prioritize their actions. To a lesser extent, monitoring data on federal-level nutrition programs was also imperfect, limiting the scope for my investigation of what programs might be driving the effects[27]. This implies that the mechanisms highlighted in the section are likely to only account for a fraction of the estimated effects on the health outcomes of infants and newborns.

	Goal of Input Provision					
	Vitamin A		Iron Supplementation		NutriSUS	School Feeding Transfers
	Age < 1	Age < 4	Children	Pregnant Women	Children	All children above the age of 6 months
Mean:	408.7089	1245.721	535.6722	269.1687	291.8159	508568.2
DiD						
Targeted X After 2016	165.7761	479.7255	200.7147	111.2477	-	36913.29
S.E	(34.38215)***	(132.5639)***	(41.87626)***	(25.53603)***	-	(10246.28)***
Number	17,454	17,454	16,508	16,508	-	21,242
Global RDD						
Above Food Insecurity Threshold	398.6942	1242.348	483.82	254.482	196.15	-327.888
S.E	(102.4592)***	(352.5564)***	(184.4984)***	(103.2171)***	(69.09404)***	(27996.11)
Number observations	3,521	3,521	5,524	5,524	1,032	5,316
Local RDD						
Continuity-based: Above Food Insecurity Threshold	1675.1	4336.1	2142.7	1144	573.71	240000
S.E	(880.59)*	(2357.2)*	(1128.7)*	(598.27)*	(593.35)	(260000)
Number observations	1394	1394	2165	2165	443	2,266
Power Calculation	0.072	0.076	0.083	0.085	0.057	0.083
Local Randomization: Above Food Insecurity Threshold	646.675*	1762.027	603.995*	323.687*	-47.451	-78400
p-value	0.104	0.108	0.066	0.066	0.632	0.468
Number observations	135	135	214	214	38	39

Figure 13: Effect of prioritization on the intensity of provision of nutrition-related inputs
In this table, all the effects are measured in the number of children or women targeted, except for the effects on School Feeding Transfers, which are measured in Brazilian Reais.

[27]For instance, I could not find municipality-level data on the execution of both the PAA, and food distribution.

The table above presents estimates of the effect of being prioritized for nutrition programs on the intensity with which nutrition inputs are provided. The Differences-in-Differences estimates and the Second-stage of Fuzzy RDD indicate that prioritization through the MapaINSAN significantly increased the provision of several federal-level nutrition programs.

After the publication of the MapaINSAN, being considered a priority municipality for nutrition programs appears to have led it to be more intensely targeted by the federal government. Indeed, prioritization was associated with an average increase of 165 on the number of infants reached by Vitamin A supplementation. It was also associated with having an additional 479 children below the age of 4 being targeted by the program. Similarly, the regression discontinuity estimates indicate a jump in the goal of Vitamin A supplementation. These findings are significant at the 1% level, and are corroborated by local RDD estimates indicating effects in the same direction, albeit with lower significance levels and higher magnitudes[28].

For the Iron Supplementation, estimates indicate that prioritization is associated with a higher number of children and pregnant women being targeted: respectively, 200 and 111 additional individuals. The global RDD regression points to similar results, but, again, with larger magnitudes. The effects remain positive and significant in local non-parametric models.

On the other hand, monitoring data is not available before 2017 for the other Multiple micronutrient supplementation program (NutriSUS), limiting the scope of estimation to RDD only. Estimates of its effect are significant in the global RDD regression, with LATE estimates indicating that, in complier municipalities close to the cutoff, 196 more children were targeted. Local estimates are not significant.

Perhaps more surprisingly, the differences-in-differences results suggest that universal school feeding program is also positively affected by the targeting, albeit to a small degree: being in a prioritized municipality is significantly associated with increases the resources received by roughly 36,000 reais[29]. The RDD regressions do not confirm a positive relationship between prioritization status and the amount transfers received for school feeding.

These transfers are regulated by the number of school-aged children in the municipalities, so the MapaINSAN is not expected to influence its targeting. Nevertheless, the small positive effect captured by the Differences-in-Differences model could be due to the delayed execution of the transfers from federal government to municipalities. It is common for the federal government to accumulate considerable debts with the municipalities, and plausible that food insecure ones would be prioritized whenever budget is available to pay it back, in spite of no public guidelines existing in that regard. However, even if that were partially the case, the fact that these effects were not captured by

[28] which likely reflect the more localized nature of these estimates.

[29] 1 USD is roughly equal to 5 reais.

the RDD indicates that it is unlikely that this would have major effects on children's health outcomes.

7.4 Internal Validity

The combination of a fuzzy regression discontinuity design (RDD) and differences-in-differences (DiD) provides a strong basis for assessing the effects of a municipality being prioritized by nutrition interventions.

Upon visual inspection of figures 1-8, it appears that the parallel trend assumption of the DiD holds during the pre-treatment period. However, the assumption that shocks would impact both treated and untreated variables equally seems somewhat questionable. By limiting the analysis to years prior to 2020, this strong assumption is somewhat mitigated, since it is likely that the major concerns would have been tied to food insecure municipalities being more affected by shocks from the Pandemic[30]. Nevertheless, the Regression Discontinuity estimates can help provide confidence that the stronger assumptions of the DiD model are not creating biased estimates.

On the other hand, the credibility of the RDD design is reinforced by a few key factors. First, the manipulation of stunting levels is highly unlikely due to the absence of prior knowledge regarding the assignment rule and to the way stunting data is reported. Moreover, formal tests provide no empirical evidence of municipalities sorting themselves into treatment.

Furthermore, the results from Placebo Outcome tests indicate that the 10.1 cutoff is the only one associated with discontinuous jumps in input provision and outcomes. This finding supports the conclusion that any effects observed in the model are indeed attributable to the MapaINSAN.

The instrument also appears to be sufficiently strong, since the F-statistic is only below 10 in the local randomization model, leading to the conclusion that the resulting estimates are unlikely to be biased. Because the RDD model is evaluated in a close neighborhood around the cutoff, it is also reasonable to believe that the exclusion restriction would be satisfied, as the potential outcomes of comparison groups would be very similar.

7.5 External Validity

The RDD design approximates the effect of prioritization for a sub-sample of municipalities that are very close to the cutoff point. However, observations close to the threshold can be significantly different from others, so local findings do not necessarily generalize. In the case of this analysis, the average stunting levels around the threshold are expected to be approximately 10.1%, which is below the mean levels of stunting for Brazil in 2014[31].

[30] Figures 4, 7 and 8 indicate that, indeed, 2020 might have affected treated and control areas in a different way.

[31] According to SISVAN 2014, the aggregated level of stunting in that year was around 13.41 for Brazil; and the average figure for the municipalities in our sample is around 12.

It is important to note that nutrition programs are typically intended to target municipalities that are more food insecure. Consequently, these estimates may have limited usefulness as they do not grant a comprehensive understanding of the effects on the entire population, but rather of the marginal effects in a sub-group of municipalities with lower stunting levels than average. Additionally, the use of a fuzzy instrumental variable means that we can only provide Local Average Treatment Effects, leading the effects to only be informative for the sub-population of compliers.

While the fuzzy RDD alone does not appear to be particularly useful for policy-making, combining it with the differences-in-differences estimates, which calculate the effects for the entire sample and is thus not subject to the limitations described in this section, allows one to get a better picture of nutrition programs' impacts.

8 Conclusion

Overall, MapaINSAN's prioritization criteria appears to be used to target the provision of nutrition-related programs more intensively to vulnerable areas. My estimates from the differences-in-differences model indicate that being prioritized by the MapaINSAN is significantly associated with a large increase in the number of children receiving Vitamin A doses. The RDD findings also support the significance of these results. Similarly, the number of children reached by Iron Supplementation was also increased at statistically significant levels in all models.

I also find minor, but significant effects in newborns' health outcomes. Prioritization is associated with being a few grams heavier at birth, and with a very small increase in gestational age. No consistent effects are found in health outcomes of older children. However, results from a heterogeneity analysis point to the existence of binding constraints for the improvement of infant morbidity through micronutrient supplementation. Namely, these actions appear to only be associated with lower disease burden if coupled with improved access to primary health care inputs. Intuitively, this makes sense, since both the Iron and the Vitamin A programs are implemented by primary healthcare facilities.

The combination of large effects in the provision of nutrition inputs with minimal positive effects in health outcomes suggests that the marginal effects of these programs is very small. Nevertheless, this could be partially due to the fact that the models only estimate the effect of increasing the intensity of micronutrient provision through prioritization of the most vulnerable regions, rather than expanding the program to previously uncovered areas.

One of the main limitations of this study is that we cannot exactly pinpoint which programs had an effect on the health outcomes, as I did not have data on the execution of all federal and state-level programs that might be using this prioritization criteria to some degree. Nevertheless, these effects can confidently be attributed to the MapaINSAN, either through a direct influence on the targeting criteria, or by informally streamlining the supply of nutritional inputs to more insecure municipalities.

A second limitation stems from the differences between the preliminary stunting data, used by the federal government when constructing the MapaINSAN, and the final stunting rates for 2014 that were available in the SISVAN portal in 2023. This constraint forced the use of fuzzy regression discontinuity, restricting the generalizability even further by estimating the local average treatment effects (LATE) in the bandwidth only. The possibility of comparing these estimates to the DiD ones, as well as the fact that the effects are generally similar in magnitude, eases this concern considerably.

Similarly, because of the weak statistical power of the local non-parametric RDD specifications, their estimates are more useful to check whether the magnitudes and direction of the effect reported by the DiD and the global parametric RDD seem to hold, and should not be interpreted alone.

Altogether, the particularly significant results for newborns indicate that there are still benefits to be reaped by increasing the food security of pregnant people. However, the mechanism through which the food and nutrition security of pregnant women cannot be directly attributed to iron supplements, as in-kind food provision or income increases from the Food Acquisition (PAA) and Food distribution (ADA) programs could be the driving forces behind this change.

These results are useful for Brazil's context, given that under the past administration many nutrition programs have been discontinued or scaled-down, and that major efforts are being made to determine which policies should be reintroduced or expanded. For this reason, understanding the magnitude of benefits that can be obtained by expanding and intensifying food security policies is useful to determine the course of action.

These results only apply to Brazil's current portfolio of nutrition-related policies, given both its implementation constraints and strengths. Notwithstanding, they might still be useful for other Latin American countries looking to expand the provision of their own programs. In particular, understanding the determinants of success might help other middle-income countries decide whether they have the appropriate conditions to guarantee that their own version of large-scale nutrition programs will reach the desired outcomes.

In order to obtain a comprehensive understanding of the effects of prioritizing nutrition programs, it is recommended that future work includes an analysis of its impact on other diseases that commonly affect infants, such as pneumonia and anemia. In addition, heterogeneity analysis using primary and nursery school enrollment would help further investigate the impacts of NutriSUS and the extent to which lack of access to these educational services is binding. Furthermore, expanding the analysis to estimate health impacts on older age groups, as well as the effects for local producers' livelihoods would contribute to a more thorough understanding of all the dimensions affected by such policies.

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10 Annex I

Manipulation test

P-values of binomial tests. (H0: prob = .5)

Window Length / 2	<c	>=c	P>|T|
0.060	17	13	0.5847
0.120	46	42	0.7493
0.180	61	60	1.0000
0.240	83	94	0.4524
0.300	112	129	0.3027
0.360	133	159	0.1433
0.420	163	187	0.2189
0.480	184	217	0.1099
0.540	204	238	0.1164
0.600	232	263	0.1775

Figure 14: Manipulation Test: p-values

Falsification Tests: Pre-determined covariates

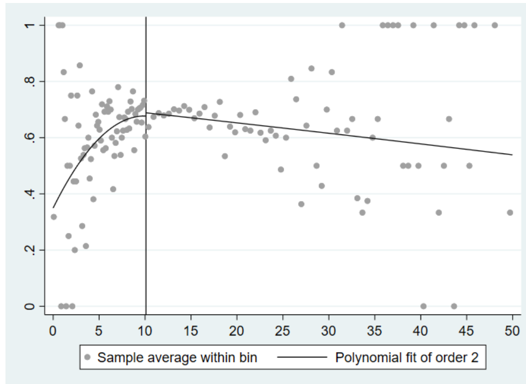

Figure 15: Pre-determined covariates: emergency rooms in 2011

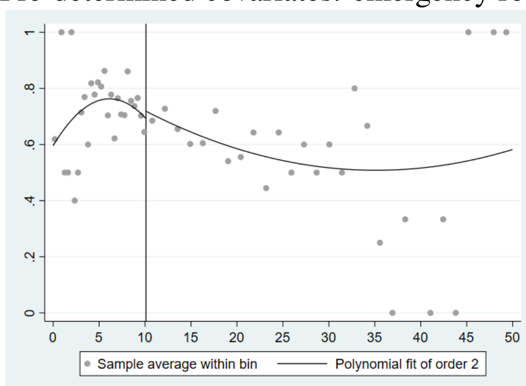

Figure 16: Pre-determined covariates: sewage systems in 2011

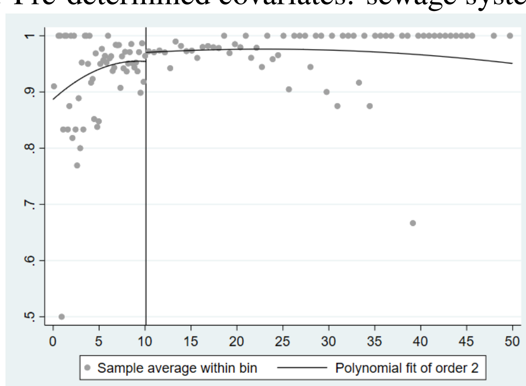

Figure 17: Pre-determined covariates: primary health clinics in 2011

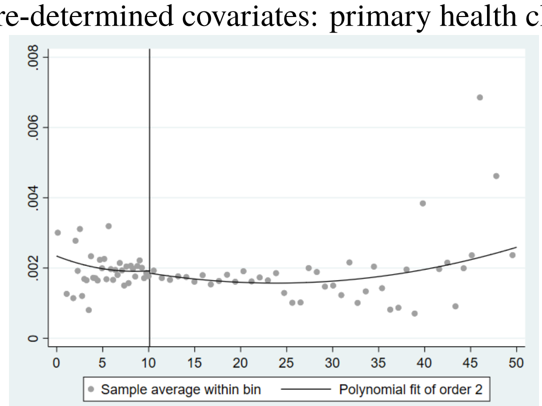

Figure 18: Pre-determined covariates: % deaths under age of 1 in 2011

	Global RDD	Local RDD	
		Continuity-based	Local Randomization
Sewage in 2011			
Differences in Means	-0.0551742	0.09224	0.08
p-value	0.139	0.309	0.628
Observations	1,556	508	67
Emergency Room in 2011			
Differences in Means	-0.0318855	-0.04906	0
p-value	0.124	0.182	0.97
Observations	5,518	3014	213
Primary Healthcare clinics in 2011			
Differences in Means	0.0080662	0.02874	0.039
p-value	0.336	0.109	0.328
Observations	5,524	2077	214
Mortality rate children under age of 1 in 2011			
Differences in Means	-0.0001321	0.000049	0
p-value	0.269	0.847	0.926
Observations	2,327	951	89

Figure 19: Pre-determined covariates: formal balance test

Falsification Tests: Placebo Outcomes

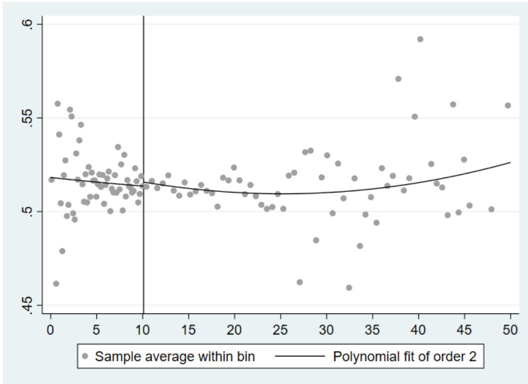

Figure 20: Placebo Outcomes: % Male Newborns in 2018

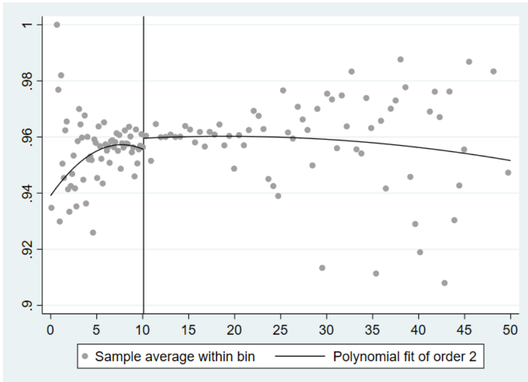

Figure 21: Placebo Outcomes: % Cephalic Presentation in 2018

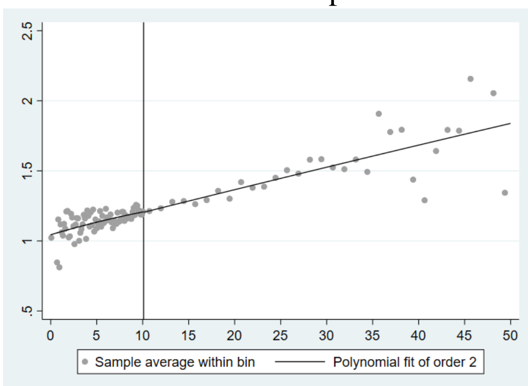

Figure 22: Placebo Outcomes: Number of Pregnancies in 2018

	Global RDD	Local RDD	
		Continuity-based	Local Randomization
% Male Newborn			
Differences in Means	0.000392	0.00128	0.001
p-value	0.868	0.774	0.924
Observations	5,524	2264	214
% Cephalic Presentation			
Differences in Means	0.000635	0.0014	0.001
p-value	0.73	0.684	0.85
Observations	5,524	2264	214
Number of previous pregnancies			
Differences in Means	-0.00667	-0.00949	0.014
p-value	0.57	0.651	0.662
Observations	5,524	2214	214

Figure 23: Placebo Outcomes: formal balance test

Falsification Tests: Placebo Cutoffs

	Goal of Input Provision						Health Outcomes	
	Vitamin A		Iron Supplementation		NutriSUS	School Feeding	Weight	Week of Pregnancy
Alternative Cutoff Points (% of Stunted Children)	Age < 1	Age < 4	Children	Pregnant	Children			
6.1								
p-value	0.216	0.264	0.295	0.291	0.202	0.358	0.697	0.751
7.1								
p-value	0.302	0.312	0.498	0.524	0.598	0.917	0.624	0.195
8.1								
p-value	0.766	0.689	0.461	0.47	0.116	0.878	0.874	0.851
9.1								
p-value	0.929	0.367	0.782	0.743	0.171	0.679	0.467	0.7
10.1								
p-value	0.006	0.004	0.004	0.004	0.421	0.004	0	0.034
11.1								
p-value	0.113	0.663	0.839	0.834	0.219	0.696	0.403	0.108
12.1								
p-value	0.423	0.783	0.494	0.526	0.16	0.275	0.317	0.97
13.1								
p-value	0.498	0.377	0.277	0.279	0.582	0.218	0.729	0.347
14.1								
p-value	0.647	0.848	0.188	0.138	0.692	0.308	0.159	0.67

Figure 24: Placebo Outcomes: formal balance test

Here, p-values under 0.1 indicate a discontinuous jump of the outcome at the cutoff. These jumps should only be seen at the real cutoff point (10.1), and any that appear in placebo ones undermine the results of the study.

	Health Outcomes						
	Neonatal Health				Diarrhea		
	Weight	APGAR below 7 (at 5 minutes)	Any Anomaly	Weeks of Pregnancy	% Children under 1 affected by diarrhea	Days in hospital by case (below 1)	Expenditure by case (below 1)
Mean:	3196.962	0.0106791	0.0078718	38.51801	0.0045498	3.110562	379.7625
Global RDD							
Above Food Insecurity Threshold	13.43401	0.0001105	-0.0002092	0.0900259	0.0005467	0.0284461	-8.051304
S.E	(4.960308)***	(.0007806)	(.0006763)	(.0217005)***	(.0008013)	(.2069158)	(34.99544)
Above X Share of health workers	-0.0154	0.00000266	0.00000141	-0.0001582	0.00000222	-0.0028118	-0.3739208
S.E	(.0324138)	(0.00000504)	(0.00000442)	(0001418)	(0.00000438)	(.0008398)***	(.1410354)***
Number observations	5,313	5,177	5,310	5,313	2,922	1,367	1,349

Figure 25: Heterogeneity analysis: Primary care workers in the municipality

Controls for the number of primary health workers in a municipality in 2014. Uses robust standard errors.