Social fund and infant mortality: evidence from an anti-poverty policy in Northeast Brazil

Abstract

The Brazilian Northeast is a region characterized by high levels of poverty and inequality. These aspects hinder its prospects of economic development. A possible way to alleviate these problems is to improve the early-life conditions of the poor. In 2000, the Brazilian government launched the *Fundos Estaduais de Combate e Erradicação da Pobreza (FECEP)*, a social fund targeted at meeting the needs of the poor. The goal of this paper is to evaluate the effects of this intervention on poverty, infant mortality, and birth outcomes in the Brazilian Northeast region. Using a difference-in-differences approach robust to heterogenous treatment effects, we find that the program led to a significant reduction in poverty and infant mortality. Taken as a whole, these results provide consistent evidence that financing targeted public investments constitute an effective tool to reduce infant mortality and improve the living standards of vulnerable communities.

Keywords: social funds; infant health; infant mortality; poverty; Brazilian Northeast

JEL Classification: I1; I3; I38; I14; J13; J18.

Fundo social e mortalidade infantil: evidências de uma política de combate à pobreza no Nordeste do Brasil

Resumo

O Nordeste Brasileiro é uma região caracterizada por altos níveis de pobreza e desigualdade. Esses aspectos dificultam suas perspectivas de desenvolvimento econômico. Uma maneira possível de aliviar esses problemas é melhorar as condições de vida dos pobres. Em 2000, o governo brasileiro lançou os Fundos Estaduais de Combate e Erradicação da Pobreza (FECEP), um fundo social destinado a atender às necessidades dos pobres. O objetivo deste artigo é avaliar os efeitos dessa intervenção sobre a pobreza, mortalidade infantil e desfechos de natalidade na região Nordeste do Brasil. Usando uma abordagem de diferença em diferenças robusta para efeitos de tratamento heterogêneo, descobrimos que o programa levou a uma redução significativa da pobreza e da mortalidade infantil. Tomados como um todo, esses resultados fornecem evidências consistentes de que o financiamento de investimentos públicos direcionados constitui uma ferramenta eficaz para reduzir a mortalidade infantil e melhorar os padrões de vida das comunidades vulneráveis.

Palavras-chave: fundos sociais; saúde infantil; mortalidade infantil; pobreza; Nordeste Brasileiro

1. Introduction

The access to health is a right of every baby at birth yet many babies worldwide do not receive basic health services, contributing to the high rates of infant mortality in some regions. In 2015, approximately 5.9 million infants died before reaching 5 years of age, with one million dying in the first day of life, another million in the first week, and 2.8 million within the first month (Marinho et al., 2020). A series of recent studies emphasize that these high levels of infant mortality are heavily concentrated among the poor (Cutler, Deaton and Lleras-Muney (2006), Klasen (2008), Eudy (2009), Currie (2009), Pritchard and Keen (2016), Singh et al. (2017), Taylor-Robinson et al. (2019), Mohamoud, Kirby and Ehrenthal (2019) and Filho et al. (2021)). Poor socioeconomic conditions early in life adversely affect the health and development of infants. This is not surprising, since financial constraints limit the capacity of disadvantaged families to access to essential goods and services, such as food, housing, and sanitation (Aber et al., 1997).

As a result, many developing countries have implemented decentralized social financing policies, or the so-called social funds. Social funds channel resources for interventions aimed at reducing poverty and social exclusion (Paxson and Schady (2002), White (2002), Haan, Holland and Kanji (2002) and Abou-Ali et al. (2010)). In particular, the social fund is a mechanism for funding small and large-scale actions and programs in various sectors, with a focus on meeting the local and regional demands of vulnerable groups in the economy. These resources come typically from multilateral and bilateral donations as well as from taxes on luxury goods and services (Jorgensen and Van Domelen, 1999; Van Domelen, 2002; Djimeu, 2014). Key features of policies of this sorting include self-financing (the financing does not depend directly on the local government) and conditionalities (on the part of the policymaker and beneficiaries) (Fiszbein and Schady, 2009; Souza, Junior and Moreira (2017); Silva et al., 2021).

Despite the growing interest in the design of decentralized mechanisms of social funds, there is still little consistent empirical evidence on the extent to which these interventions translate into better infant health outcomes (Rawlings and Schady (2002), Newman et al. (2002), Chase & Sherbume-Benz (2001), Chase (2002), Pradhan and Rawlings (2002), Parajuli et al. (2012) and Djimeu (2014)). It is not obvious that this is the case. First, the resources obtained through the fund may be insufficient to meaningfully improve the living conditions of poor communities. Second, the implementation of these funds typically implies an increase in taxes on certain goods and this could have negative impacts on local economic activity. If this effect is large enough, the introduction of these programs could unintendedly lead to an increase poverty rates by increasing unemployment rates and reducing parental income. Finally, the presence of corruption and poor institutions may reduce the effectiveness of these programs (Pradhan and Rawlings, 2002; Rawlings; Sherburne-Benz and Van Domelen, 2004; Göksen et al., 2008).

This paper explores the effects of an anti-poverty fund reform that substantially increased the investment capacity of subnational regions by increasing tax rates on luxury consumption. We investigate the extent to which the introduction of the *Fundos Estaduais de Combate e Erradicação da Pobreza* (FECEP) in Northeast Brazil affected infant mortality. We also examine the effects of the FECEP on birth outcomes. The Brazilian Northeast region provides a compelling setting for at least two reasons. First, approximately 50 percent of the poor population resides in this region. Second, before the adoption of the FECEP, the Northeast region exhibited a high infant mortality rate. Therefore, we study the effects of an anti-poverty reform in a highly policy-relevant context.

To study the effects of the FECEP, we adopt an identification strategy that compares treated and untreated states before and after the program in a difference-in-differences framework. Since the timing of program adoption varies across areas, we use the doubly-robust estimator for multiple periods and potentially heterogeneous treatment effects developed by Callaway and Sant'Anna (2021). Using this empirical strategy, our analysis yields the following. We first show that the program led to significant improvements in poverty indicators in treated areas. We then document find a significant decline in infant mortality, especially for boys and preventable causes. On the other hand, we find no evidence of improvements in birth outcomes, including the prevalence of low birth weight and preterm births. A possible reason is that since the FECEP improved survival rates, potentially saving babies on the margin with poorer health outcomes, the null effects on birth outcomes may be the result of changes in the composition of births. Taken together, our findings suggest that anti-poverty funds constitute an important tool to alleviate poverty and improve health conditions early in life.

Our findings contribute to a fervent debate on the effects of policies targeting the poor on infant health (Gertler (2004), Fernald, Gertler and Neufeld (2008), Rasella et al. (2013) and Silva and Paes (2019)) and to the literature on the effects of social fund reforms on infant health (Newman et al. (2002), Chase & Sherbume-Benz (2001), Chase (2002), Pradhan and Rawlings (2002), Morrison et al. (2010), Parajuli et al. (2012), Djimeu (2014), Daoud et al. (2017) and Onwujekwe et al. (2019)). Our analysis adds to the literature by exploring a broader set of infant health outcomes that had not been analyzed to date. We provide detailed estimates of the effects on neonatal, post-neonatal and avoidable infant mortality, and document heterogeneous effects by gender and causes of death. Taking advantage of the recent advancements in the estimation of dynamic treatment effects and difference-in-differences, our analysis allows to document the effects of the social fund program in a more transparent way and provide a more precise examination of heterogeneous treatment effects.

To the best of our acknowledge, this paper is the first to examine the effects of the FECEP on infant health in Brazil. In previous work, Silva et al. (2021) estimates the effects of this reform on several poverty measures using the synthetic control method for the Ceara state and document significant reductions in the prevalence of poverty. Santos and Bueno (2021) estimate the effects of the FECEP on income inequality using the standard two-way fixed effects estimator, finding no evidence of an effect. They argue that this null result is most likely due to the pervasiveness of corruption and clientelism in some regions. However, these results are difficult to interpret given the limitations of the two-way fixed effects estimator in the presence of heterogeneous treatment effects (Callaway and Sant'Anna (2021)). Our findings suggest that the FECEP has been effective in improving the living conditions and health outcomes of poor children.

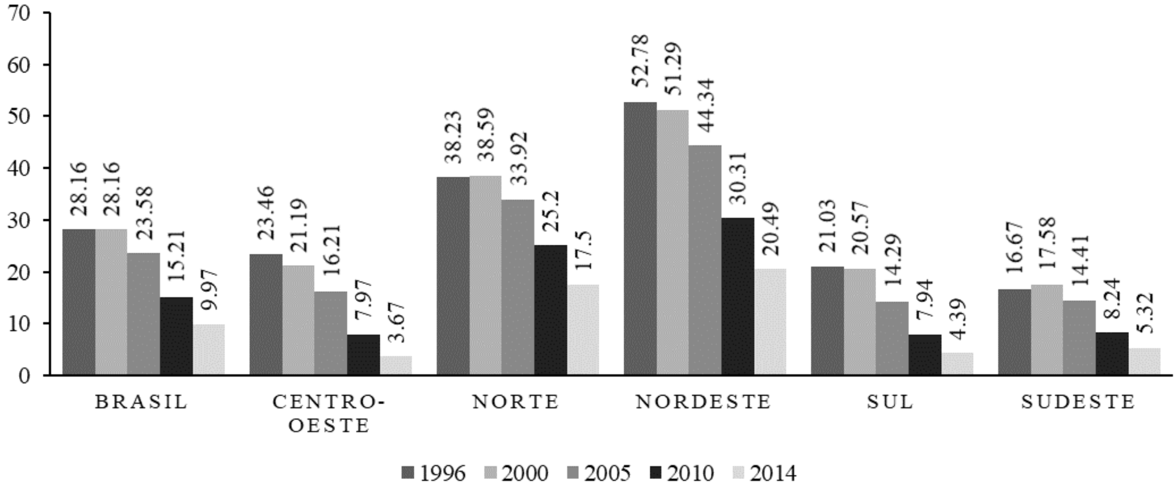
The rest of the paper is organized as follows. Section 2 provides background information on the FECEP. Section 3 describes the data and empirical strategy. Section 4 presents the results and Section 5 concludes.

2. Social Funds in Northeast Brazil

In the beginning of the 1990s, the poverty and infant mortality rates were strikingly high in Brazil. The poor macroeconomic performance and adverse social conditions prevailing during this period led people demand policies to combat poverty, especially in the Northeast region (Sousa and Filho, 2018).

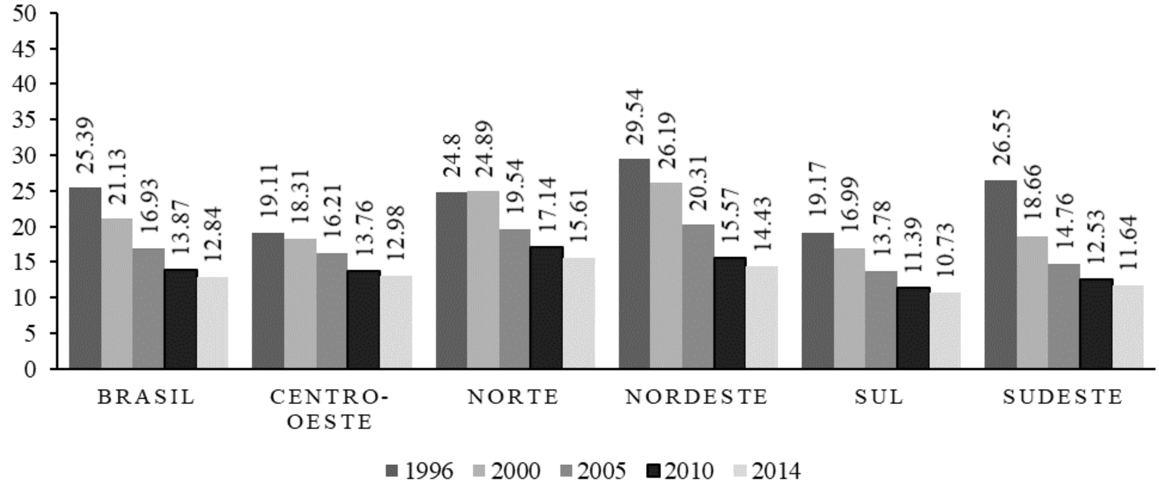
The Northeast had the highest levels of poverty and infant mortality in the country in 1996 and 2000, a period marked by an intense political debate on poverty alleviation strategies. In 2000, this region registered a proportion of poor households of 51.29%, which is approximately twice the corresponding national poverty rate of 26.16%. In addition, the Northeast region exhibited an infant mortality rate of 26.19 per thousand live births, which is also substantially higher when compared to other regions (Figures 1 e 2). These worrying levels of poverty and infant mortality, along with pressures from the international community, led the government to identify and evaluate alternatives to address these social issues. This motivated the constitution of a social fund to combat poverty (Melo, 2005).

Figure 1 – Evolution of the proportion of poor households in Brazilian regions (1996 – 2014)



Notes: Elaborated by the authors, with data from the *Pesquisa Nacional por Amostra de Domicílios* (PNAD).

Figure 2 – Evolution of infant mortality rate in Brazilian regions (1996-2014)



Notes: Elaborated by the authors, with data from the *Sistema de Informação sobre Mortalidade* (SIM) and the *Sistema de Informação de Nascidos Vivos* (SINASC).

In 2000, the government launched the FECEP social fund.[1] This program was implemented across states gradually over time as a mechanism for financing actions aimed at eradicating poverty. To achieve this goal, financial resources are allocated mandatorily to nutrition, housing, education and health dimensions. Although the FCEPs were designed to last a decade, Constitutional Amendment No. 67, of December 22, 2010, extended this public policy indefinitely (Souza, Junior and Moreira, 2017; Silva et al., 2021).

[1]This resto f this section is based primarily on an analysis of newspapers, official documents from the government, transparency portals, and other publicly available reports. We also build on previous studies on the FECEP (Silva et al. (2021), Alencar and Simplício (2021), Santos and Bueno (2021), Oliveira et al. (2020), Souza, Junior and Moreira (2017) and Melo (2005)).

To finance the FCEP, the legislation authorized subnational governments to implement an additional tax of up to 2% in the ICMS rate — Tax on the Circulation of Goods and Services — on superfluous products and services (cigarettes, alcoholic beverages, air vehicles, boats, jewelry, among others) or in the tax that replaces it, the provision of art. 158, item IV, of the Federal Constitution. The resources obtained from this tax change are then used to finance actions to fight poverty. In addition, FCEPs can also receive resources from donations, aids, grants, and income from investments in the financial system (Souza, Junior and Moreira, 2017; Santos and Bueno, 2021).

Table 1 – Foundation legislation of FECEP in Brazil

FU	States	Year	Foundation legislation/regulation	Tax rate
BA	Bahia	2002	Lei nº 7.988/2001.	2%
SE	Sergipe	2003	Lei nº 4.731/2002.	2%
RJ	Rio de Janeiro	2003	Lei nº 4056/2002.	1%
CE	Ceará	2003	Lei nº 37/2003; Decreto nº 29.910/2009	2%
PE	Pernambuco	2003	Lei nº 12.523/2003.	2%
GO	Goiás	2003	Lei nº 14.469/2003; Decreto nº 5.832/2003	2%
MT	Mato Grosso	2003	Lei nº 144/2003.	2%
RN	Rio Grande do Norte	2004	Lei de nº 261/2003.	2%
AL	Alagoas	2005	Lei de nº 6.558/2004.	2% e 1%
MA	Maranhão	2005	Lei nº 8.205/2004; Lei nº 10.329/2015	2%
PB	Paraíba	2005	Lei nº 7.611/2004; Decreto nº 25.879/2005	2%
ES	Espírito Santo	2005	Lei nº 336/2005.	2%
PI	Piauí	2006	Lei nº 5.622/2006; Decreto nº 12.554/2007	2%
MS	Mato Grosso do Sul	2007	Lei nº 3.337/2006.	2%
DF	Distrito Federal	2008	Lei nº 4.220/2008.	2%
MG	Minas Gerais	2012	Lei nº 19.978/2011.	2%
PR	Paraná	2016	Lei nº 18.573/2015.	2%
RS	Rio Grande do Sul	2016	Lei nº 14.742/2015.	2%
RO	Rondônia	2016	Lei nº 842/2015.	2%
TO	Tocantins	2016	Lei nº 3.015/2015.	2%
SP	São Paulo	2016	Lei nº 16.006/2015.	2%
AM	Amazonas	2017	Lei nº 3.584/2010; Lei nº 4.457/2017.	1,6%,1,9% e 2%.

Notes: Elaborated by the authors, based on Silva et al. (2021). The states of Acre, Amapá, Pará, Roraima e Santa Catarina did not constitute FECEP, therefore they were not listed.

The FCEP primarily finance actions and projects for families in conditions of extreme poverty. The financial resources of this social mechanism are allocated in two dimensions: i) social assistance to the population below the poverty line[2]; and ii) programs intended to help families escape from poverty. The FCEPs are managed by bodies with executive management,

[2] A person who lives on less than US$ 1.90 a day in 2019 is considered extremely poor. Those who live on less than US$ 5.50 a day are considered poor. However, in Brazil, those who live on up to half and up to a quarter of the minimum wage, respectively, are also considered poor and extremely poor.

an advisory board, and social participation. Furthermore, its resources can only be used for provided purposes in the founding legislation, it cannot be relocated or transferred. The use of the resources for staff remuneration and social charges is also forbidden. These legal restrictions ensure that resources will be allocated to actions aimed at combating and eradicating poverty.

The foundational and regulatory legislation of the FECEP are presented in Table 1. Table 1 also provides information about the ICMS rate defined in each state. In the Northeast, all states implemented FECEP until 2006, with emphasis on Bahia, Sergipe, Ceará and Pernambuco, the predecessors, followed by Rio Grande do Norte, Alagoas, Maranhão and Paraíba. However, in Piauí, the constitution and implementation of policy resources took place late, only in 2006 and 2009, respectively. The rapid adoption of the social financing mechanism by the Northeastern states highlights the need for revenues to fight poverty. Furthermore, practically all states stipulated an additional 2% ICMS rate to compose the social fund, except for the state of Alagoas, where rates of 1% and 2% are adopted, depending on the luxury goods and services sold.

The money collected with FECEP is used to finance programs of social assistance, nutrition and food security, family agriculture, solidarity economy, literacy, professional qualification, social housing and basic sanitation for the poor population. Bahia is the state that raised the most financial resources. From 2002 to 2009, the FECEP raised R$1.9 billion and invested R$1.8 billion in Bahia. Despite having collected less expressive amounts of money than Bahia, the other states have increased the amounts raised over the years. Considering all the Northeastern states with exception of Bahia, in 2005, the FECEP raised an amount of R$ 276.2 million. In 2015, this value increased to approximately R$ 1 billion, a significant improvement.

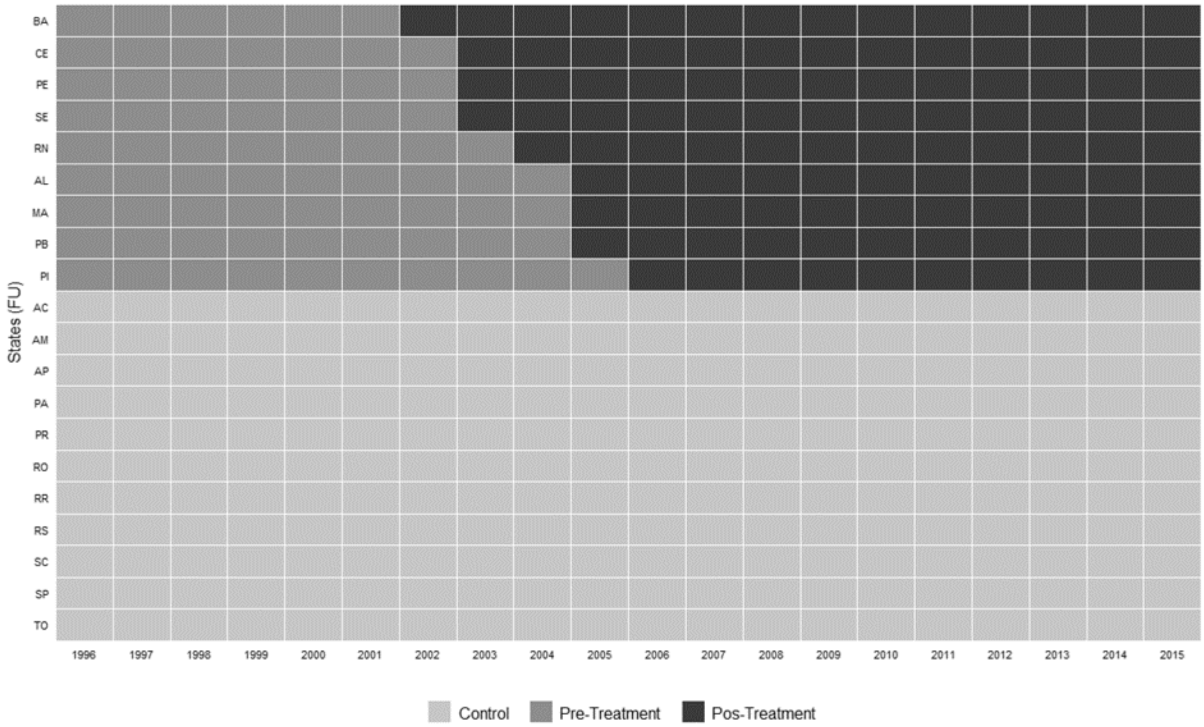
3. Data and Research Design

Our empirical approach requires data characterizing infant mortality, health at birth, and poverty across Northeast states over the 1996-2015 period. We estimate the effects of FECEP on these outcomes using difference-in-differences approach exploiting variation in the timing of FECEP adoption across states. To overcome the potential biases due to heterogeneous treatment effects, we follow the statistical approach developed by Callaway and Sant’Anna (2021). This approach allows one to identify the causal effects of an intervention when the units are treated at different moments in time and whose treatment status remain unchanged afterward. In what follows, we provide an overview of the data sources and present the empirical strategy in detail.

3.1 Data

To evaluate the effects of the FECEP on infant mortality, we use data from the Brazil’s Ministry of Health trough the National System of Mortality Records (SIM, for its acronym in Portuguese). The SIM offers detailed information on each death in the entire Brazilian territory, including information on cause, date, and geographical location. From the SIM, we compile count of deaths by age and sex for the 1996-2015 period. We then construct a state-by-year panel dataset of infant mortality. While mortality records are subject to measurement error due to sub-notification, our empirical approach controls for state and time fixed effects. Hence, it accounts for any measurement error in infant mortality that is time-invariant and common to all states.

Figure 3 – Control and treatment groups of the FECEP impact assessment in the Northeast



Notes: The treatment and control states were defined according to the foundational legislation of the State Funds to Combat and Eradicate Poverty (FECEP) in Brazil (Table 1).

We look at the infant mortality rate stratified by the age at death (neonatal and post-neonatal), whether it is avoidable, and baby's gender.[3]The main outcome of interest is the mortality rate of individuals under a year of life. The infant mortality rate is calculated as the number of infant deaths divided by the number of live births, multiplied by 1000. A detailed description of the variables used in this paper can be found in the online appendix[4] Table A.1. The Northeast states where the FECEP was implemented compose the treatment group, whereas the rest of states that do not adopt the program between 2000 and 2015 represent the control group (Figure 3). We exclude the states of Rio de Janeiro, Goiás, Mato Grosso, Mato Grosso do Sul, Espírito Santo, Minas Gerais e Distrito Federal, which also implemented the program during the study period.[5] There are 9 treated states and 11 untreated ones.

Data on births come from the National System of Information on Birth Records (SI-NASC). To examine the effects of the FECEP on birth outcomes, we collect information on the following outcomes: total number of births, fraction of low birth weight, fraction preterm births, and fraction of births with low APGAR scores.[6] It is important to note that information

[3]The infant mortality corresponds to the deaths of infants under a year of age. Neonatal deaths correspond deaths within the first 27 days of life, whereas post-neonatal deaths correspond to those deaths between 28 and 364 days of life. Avoidable infant deaths are those deaths occurring between 0 and 4 years of life.
[4] Access to the online appendix: <https://bityli.com/dMDpOD>.
[5]Given the heterogeneity between states and regions, we focus on states within the Northeast region. The length of the study period is chosen so that it adequately balances the size of the control group (Silva et al., 2021).
[6] The APGAR score is s a clinical test that is given to the newborn in which five parameters are assessed. These include muscle tone, respiratory effort, heart rate, reflexes, and skin color. The test provides a total score between 0 and 10, where a higher score means "healthier". We use the APGAR score computed within the first 5 minutes of life.

on maternal characteristics is not available for the entire study period, making unfeasible its use in our analysis.

To estimate the effects of the FECEP on poverty, we construct a state-by-year panel dataset on poverty using data from the *Pesquisa Nacional por Amostra de Domicílio* (PNAD). We define the fractions of poor and extremely poor families as those with per capita income below 50 and 25% the minimum wage respectively. These income thresholds correspond to the poverty lines commonly used by the Brazilian government.

Finally, to evaluate the robustness of our results, we obtain data on several state characteristics from the Census conducted in 2000, on the onset of the FECEP. We refer to these covariates as “basic characteristics of the economy” (Table A.1). These characteristics are time-invariant and determine subsequent economic conditions, but they are not themselves affected by the FECEP. The empirical strategy we employ in this study uses these covariates only in the re-intervention period (Callaway and Sant’Anna (2021)). Table 2 presents summary statistics of these covariates.

Table 2 – Descriptive statistics of the pre-treatment period covariates

Covariates	**Control Group**		**Treatment Group**	
	Mean	**Stand. deviation**	**Mean**	**Stand. deviation**
Population	6.830.271,00	10.700.000,00	5.305.373,00	3.656.505,00
% Rural Population	23.03	9.26	30.96	5.28
% Female population	49.77	0.82	51.00	0.44
% Black population	4.54	1.32	6.58	3.04
% Indigenous population	1.69	2.55	0.31	0.16
Territorial area (km²)	424.687,20	497.360,90	171.934,70	18.520,90

Notes: In the econometric model, population and land area (km²) were included in the form of natural logarithm.

3.2 Summary Statistics

Appendix Table B.1 shows summary statistics for all variables, splitting the sample between treated and control states. The mean infant mortality rate is 18.54 deaths per 1000 live births, with standard deviation of 5.6. There exists a sizable difference in this figure when comparing the pre- and post-intervention periods. During the pre-FECEP period, the infant mortality was 26.3, whereas it falls to 18.5 after the FECEP was implemented. This reduction was more pronounced for treated states, yielding a difference-in-differences of approximately -1.6 infant deaths per 1000 live births. This admittedly raw estimate differs somewhat from the difference-in-differences we formally estimate below, most likely because the raw figure does not account for heterogeneity in treatment effects over time.

Appendix Table B.1 also reveals a similar pattern for post-neonatal and avoidable mortality. However, there is no evidence that the policy led to improvements in neonatal mortality. In fact, the control group appears to have experienced a more rapid decline in the neonatal mortality rate compared to the treatment group.

Appendix Figures C.1 and C.2 shows the way how the mortality outcomes evolved over time across treated and untreated states. These figures also illustrate key features of these data. First, prior to the FECEP, treated and untreated states were experiencing similar trends in terms of these outcomes. Second, following the establishment of the FECEP, the gap between both groups declines gradually over time. This occurred for all the mortality outcomes, except the neonatal mortality rate. In fact, the neonatal mortality rate exhibits similar trends across treated and untreated states both before and after the implementation of the FECEP. These improvements in child mortality outcomes are likely the result of the FECEP, consistent with the evidence we shall show below that the program improvements the living conditions of the areas adopting it.

Looking at specific causes of deaths, the figures indicate that child deaths from endocrine, infectious, and respiratory causes declined the most in treated areas after the introduction of the FECEP. Put differently, there are significant differences in the trajectory of these causes of deaths before and after the FECEP. On the other hand, we do not observe a clear pattern for birth outcomes (see Appendix Figure C.3).

There are also noticeable differences in the dynamics of poverty. Prior to the FECEP, the fraction of poor families was 76.2 and 50.63% for treated and untreated states respectively, a difference of approximately 25 percentage points. Analogously, the fraction of families facing extreme poverty was 51 and 25% for treated and untreated states. Following the adoption of the FECEP, both poverty outcomes exhibit a declining trend that is more pronounced for treated states, with the gap between both groups declining from 25 to 15-19 percentage points. Appendix Figure C.4 documents this dynamic visually.

3.3 Empirical Strategy

To identify the effects of the FECEP, we employ a difference-in-differences model. As shown in Figure 3, the implementation of the FECEP occurred gradually and permanently across states, which potentially introduces a bias in the standard difference-in-differences estimator. [7] To address this issue, we use the method developed by Callaway and Sant'Anna (2021), which estimates the effects of policy in a flexible manner and eliminates any bias due to heterogeneous dynamic treatment effects.

The model assumes that there are T periods such that $t = 1, 2, \ldots, T$ and D_t is an indicator variable that equals to one when a state adopts the FECEP in year *t* and zero otherwise. Let G_g take the value one When a state is treated for the first time and zero otherwise. Let *C* take the value one for never-treated states and zero otherwise.

The generalized propensity score is given by $P_g(X) = P\left(G_g = 1 \,\middle|\, X,\, G_g + C = 1\right)$, corresponding to the probability that a state is treated conditional on the set of covariates (*X*) and on belonging to the treatment (*g*) or control (*C*) group. By invoking the common trends assumption, the vector of covariates (*X*) becomes a constant. The propensity score is estimated for each cohort *g* of treated states. This cohort-specificity produces greater flexibility in identifying control and treated states that are similar in terms of observable characteristics. The outcome in each period is estimated as follows:

$$Y_t = D_t Y_t(1) + (1 - D_t) Y_t(0) \tag{3.1}$$

Where $Y_t(1)$ e $Y_t(0)$ are the potential outcomes with and wihout treatment.

Unlike the standard difference-in-differences estimator, the parameter of interest here is the average treatment effect for group g, denoted by $ATT(g,t)$. Under the assumption that treated and untreated states would have followed similar trends, the estimated *ATT* for group *g* can be expressed as follows:

$$ATT(g,t) = \mathbb{E}[Y_t(g) - Y_t(0) \mid G = g] \tag{3.2}$$

[7] A body of recent research has documented that the standard difference-in-differences estimator yields biased estimates of the effect of policy in the presence of heterogeneous dynamic treatment effects (Callaway and Sant'Anna (2021), Athey and Imbens (2021), Goodman-Bacon (2021) and Sun and Abraham (2021).

Considering a balanced panel of states, the $ATT(g,t)$ can be written in a semi-parametric way as denoted by equation (3.3). The standard errors are then computed using bootstrap procedure, adjusting for autocorrelation and clustering:

$$ATT(g,t) = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}[G_g]} - \frac{\frac{p_g(X)C}{1-p_g(X)}}{\mathbb{E}\left[\frac{p_g(X)C}{1-p_g(X)}\right]}\right)\left(Y_t - Y_{g-1}\right)\right] \tag{3.3}$$

This estimator accounts for state and year fixed effects, eliminating biases due to time-invariant factors (Callaway and Sant'Anna (2021)). Hence, it accounts for initial and persistent conditions as well as for national-level factors affecting all states similarly (Carrillo and Feres (2019)).

To obtain an overall ATT, Callaway and Sant'Anna (2021) propose several ways to aggregate the $ATT\ (g,t)$. In the context of the FECEP, we must consider the differences in the timing of adoption across states. States that adopted the FECEP earlier could experience earlier the gains from the intervention. Hence, an unweighted aggregation likely would attribute greater weights to states that adopt the FECEP recently (Teixeira and Venter, 2021). In this case, Callaway and Sant'Anna (2021) suggest aggregating the $ATT(g,t)$ as follows:

$$\tilde{\theta}_S(g) = \frac{1}{T-g+1}\sum_{t=2}^{T} 1\,\{t \geq g\}ATT(g,t) \tag{3.4}$$

$$\theta_S = \sum_{g=2}^{T} \tilde{\theta}_S(g)P(G = g) \tag{3.5}$$

Where the equation (3.4) represents the specific treatment effect specific for each state, whereas equation (3.5) offers the overall treatment effect.

Although equation (3.5) summarizes the effects of the program into a single parameter, it is possible that the effects of the program are heterogeneous over time. It is inherently interesting to understand the timing and shape of the effects. One could expect the program affect mortality outcomes gradually over time as the actions promoted could take time to be realized. To explore this possibility, we compute the $ATT(g,t)$ for each year since the introduction of the FECEP as follows:

$$\tilde{\theta}_D(e) = \sum_{g=2}^{T}\sum_{t=2}^{T} 1\{t-g+1=e\}ATT(g,t)P(G=g\,|t-g+1=e) \tag{3.6}$$

Where (e) denotes the event-time, or the years of exposure since the adoption of the FECEP. The overall ATT for each period is then calculated:

$$\theta_D = \frac{1}{T-1}\sum_{e=1}^{T-1} \tilde{\theta}_D(e) \tag{3.7}$$

Equation (3.7) captures the dynamic of the treatment effects. A major difference between $\theta_D$and θ_S is the weight: θ_D puts greater weights on states with greater exposure to the policy (Teixeira and Venter, 2021). An advantage of the event-study estimates is that they allow one to visually judge the common trends assumption. If this assumption is violated, one would expect to observe significant effects in the years prior to FECEP. On the other hand, if treated and control areas begin to diverge only after the FECEP, then it would provide strong evidence that both groups would have experienced similar trends in the absence of the program (Carrillo and Feres, 2019).

To evaluate the robustness of our baseline results, we perform a series of exercise and alternative estimators. First, we perform the test of *Cramér-von-Mises* (CvM) as suggested by Callaway and Sant'Anna (2021) to formally test for differences in trends prior to the FECEP. This test is particularly adequate for groups with heterogenous treatment dates. A failure to reject the null hypothesis would provide evidence consistent with the identification assumption. To perform this test conditional on covariates, we consider a set of basic covariates for the pre-treatment period. Given the reduced sample of states, we choose these covariates carefully and parsimoniously to avoid spurious results. Second, we use an alternative control group to explore the extent to which the results are the product of which states are used as control. As a robustness check, we consider both never-treated and not-yet-treated states as control groups. Third, we also estimate outcome regression models to obtain overall $ATT(g,t)$ analogous to doubly robust method.[8]

Although two-way fixed effects regressions are not robust to heterogeneity in treatment effects across periods, Sun and Abraham (2021) provide an alternative dynamic estimator that is robust these issues under the common trends assumption.[9] In practice, this estimator is a particular case of the one developed by Callaway and Sant'Anna (2021) but uses an fixed-effects estimator. Without covariates, it should yield estimates similar to equation (3.7) in so far the time indicators are fully saturated and two cross-sectional units are omitted to avoid perfect collinearity issues. By comparing different estimators, we can examine the extent to which our results are driven by a specific way to estimate the parameter of interest. In theory, these methods should yield very similar results (Baker, Larcker and Wang, 2021).

4. Results

This section presents the main findings from the paper, divided into two parts. The first part estimates of the effects of the FECEP on poverty outcomes. In the second part, we examine the effects of the program on infant health outcomes and explore the robustness of these estimates.

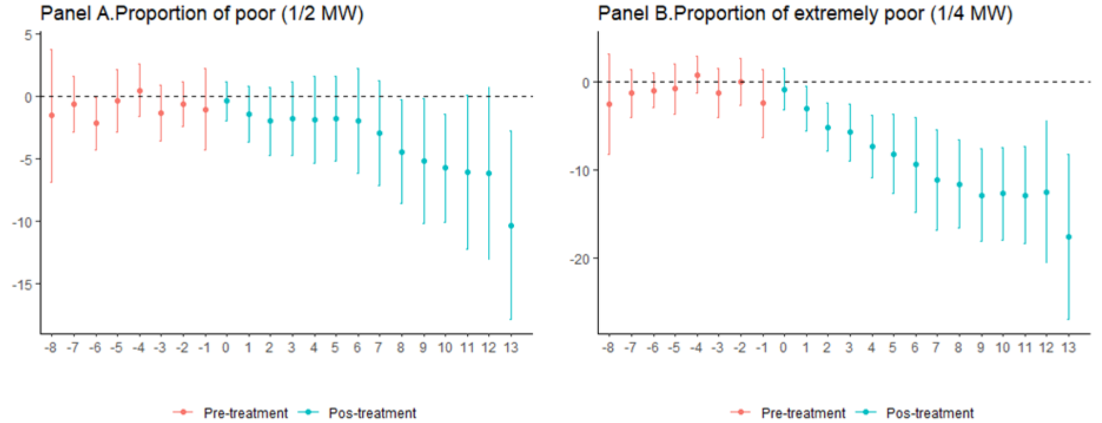
4.1 Effects on Poverty Outcomes

Since the basic goal of the FECEP is to reduce poverty, we begin our empirical analysis by examining the effects of the program on poverty. Figure 4 shows the results from estimating the event-study specification for the proportion of poor and extremely poor families. The red and blue lines correspond to 95 percent confidence intervals for the pre- and post-intervention periods respectively. For inference, we use standard errors clustered at the state level.

The results show clearly the absence of an effect prior to introduction of the FECEP. Treated and untreated appears to be similar trends during the pre-treatment period. The estimated coefficients are very small in magnitude and fluctuate randomly around zero. This provides evidence in favor of the identification assumption that treated and untreated states would have experienced similar trends in the absence of the FECEP. During the post-intervention period, there is an immediate and statistically significant decline in the poverty outcomes. Notably, the magnitude of this decline is increasing over time. Moreover, the effects are the largest for the fraction of families in extreme poverty.

[8]Callaway and Sant'Anna (2021) provide estimates of the $ATT(g,t)$ using inverse probability weighting (IPW), outcome regression and double robust estimator. All these alternative methods yield similar results.
[9] This procedure is discussed in detail in Sun and Abraham (2021).

Figure 4 – Effect of FECEP in the Northeast on poverty and extreme poverty



Notes: The horizontal axis indicates the duration of treatment exposure. The duration of exposure equal to zero (0) provides the mean effect of the constitution of FECEP in the Northeast among the groups in the period in which they implement the antipoverty policy for the first time. Exposure duration equal to (-1) corresponds to the pre-treatment period (before FECEP) and exposure duration equal to (1) denotes the first period after policy implementation (after FECEP). The bars of the event study graphs represent the 95% confidence interval, where robust standard errors are clustered at the state level.

Table 3 - Effect of FECEP in the Northeast on poverty and extreme poverty

	(1)
Panel A. Proportion of poor (1/2 SM)	
Group effect	-2.932*
	(1.253)
Dynamic effect	-3.688*
	(1.295)
Pre-FECEP mean	62.20
Panel B. Proportion of extremely poor (1/4 SM)	
Group effect	-8.426*
	(1.400)
Dynamic effect	-9.352*
	(1.345)
Pre-FECEP mean	37.35
CvM Test	
Panel A. Proportion of poor (1/2 SM)	1007.395
Panel B. Proportion of extremely poor (1/4 SM)	2147.852
Observations	400

Notes: *Significant for p-value < 0.05. The table reports the group and dynamic treatment effect parameters estimated by the doubly robust method under the assumption of unconditional parallel trends and with a control group composed of never treated states. Robust standard errors (reported in parentheses) are grouped at the state level.

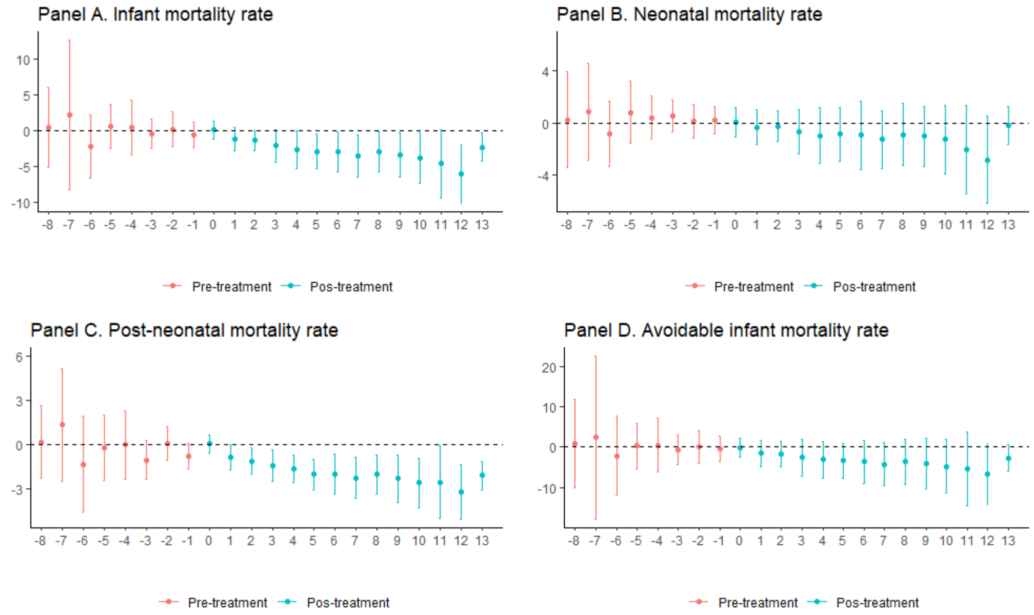
Table 3 summarizes the overall effect of the FECEP on these outcomes. Consistent with the graphical evidence, there is a significant improvement in the poverty outcomes of treated states. Panel A reveals that the introduction of the FECEP led to a decline of 3-3.6 percentage points in the fraction of poor families. Relative to the pre-FECEP mean, this represents an effect of 4.8 to 5.8 percent. Panel B documents a decline of approximately 9 percentage points in the fraction of families in extreme poverty. This effect is substantial in magnitude. It represents as much as a 28 percent reduction relative to the pre-FECEP mean.

As a further check of the plausibility of the common trends assumption, we perform the *Cramér-von-Mises* (CvM) test. As shown in Table 3, we cannot reject the null hypothesis that there are no pretrends effects. Assessing the effect of the FECEP for the Ceara state, Silva et al. (2021) find a decline of 9 and 12 percentage points in the proportions of poor and extremely poor families. Our results are very similar in magnitude to these previous findings and confirm that the policy has been effective in improving the living conditions of vulnerable communities.

4.2 Effects on Infant Health

Having documented a strong and robust "first-stage", we now explore the effects of the FECEP on infant health. Figure 5 presents event-study estimates for infant mortality. As one can infer from the figure, treated and untreated areas experienced similar trends before program adoption. By contrast, there is a clear decline in the post-neonatal mortality as well as infant deaths due to avoidable causes. On the other hand, the program does not appear to have affected neonatal mortality.

Figure 5 - Effect of FECEP in the Northeast on infant mortality



Notes: The horizontal axis indicates the duration of treatment exposure. The duration of exposure equal to zero (0) provides the mean effect of the constitution of FECEP in the Northeast among the groups in the period in which they implement the antipoverty policy for the first time. Exposure duration equal to (-1) corresponds to the pre-treatment period (before FECEP) and exposure duration equal to (1) denotes the first period after policy implementation (after FECEP). The bars of the event study graphs represent the 95% confidence interval, where robust standard errors are clustered at the state level.

Table 4 shows the average effect of the FECEP on these outcomes. Consistent with the graphical evidence, column (1) shows that the program led to improvements in the post-neonatal and avoidable infant mortality. Columns (2) and (3) explore heterogeneity by gender and show that the effects tend to be larger for boys. The point estimates from the dynamic estimator indicates that the infant mortality rate declined by 2.8, the post-neonatal mortality by 1.8, and the avoidable infant mortality by 3.4. Relative to the pre-FECEP means, these results represent a decline of 12, 19, and 12 percent respectively. The results from estimating the group estimator also suggest a significant decline in infant mortality, but the magnitude of the results is slightly smaller. On the other hand, we do not observe statistically significant improvements in neonatal mortality, though the sign of the coefficient is consistent with what one would expect. Importantly, the CvM cannot reject the null hypothesis that treated and untreated areas have similar trends during the pre-intervention period. This provides further support for the plausibility of the identifying assumption.

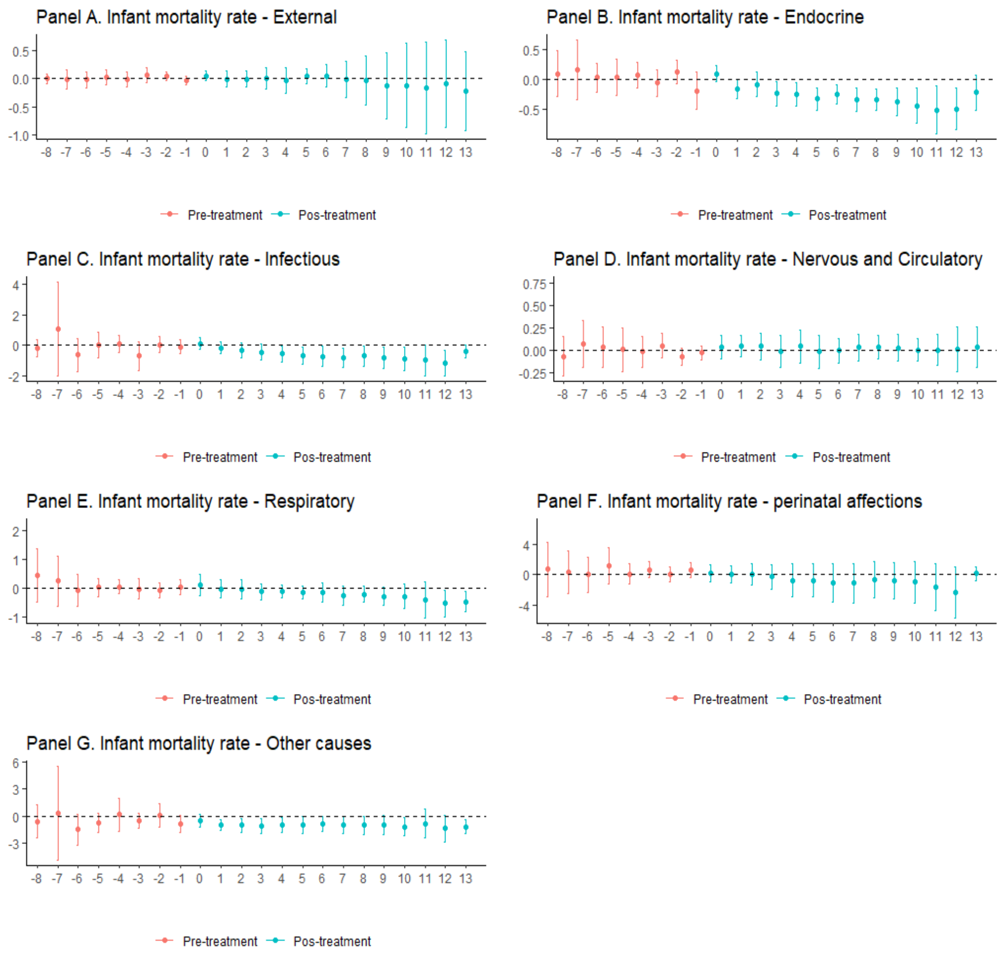
Table 4 - Effect of FECEP in the Northeast on infant mortality

	General (1)	Male (2)	Female (3)
Panel A. Infant Mortality Rate			
Group effect	-2.514*	-3.125*	-1.863*
	(0.850)	(0.941)	(0.872)
Dynamic effect	-2.821*	-3.537*	-2.058*
	(1.055)	(1.338)	(0.833)
Pre-FECEP *mean*	24.14	26.78	21.37
Panel B. Neonatal Mortality Rate			
Group effect	-0.798	-0.939	-0.644
	(0.526)	(0.641)	(0.590)
Dynamic effect	-0.948	-1.167	-0.710
	(0.766)	(0.875)	(0.693)
Pre-FECEP mean	14.11	15.88	12.25
Panel C. Post-neonatal Mortality Rate			
Group effect	-1.717*	-2.186*	-1.219*
	(0.447)	(0.500)	(0.412)
Dynamic effect	-1.874*	-2.370*	-1.348*
	(0.419)	(0.502)	(0.385)
Pre-FECEP mean	10.04	10.90	9.12
Panel D. Avoidable Mortality Rate			
Group effect	-3.099*	-3.707*	-2.450*
	(1.062)	(1.149)	(1.085)
Dynamic effect	-3.420*	-4.156*	-2.634*
	(1.122)	(1.426)	(0.947)
Pre-FECEP mean	28.68	31.55	25.66
CvM Test			
Panel A. Infant Mortality Rate	3839.8	5026.1	3214.6
Panel B. Neonatal Mortality Rate	1481.5*	1458.7*	1245.9*
Panel C. Post-neonatal Mortality Rate	1027.8	1410.9	824.21
Panel D. Avoidable Mortality Rate	4760.9	5838.5	4232.7*
Observations	400	400	400

Notes: *Significant for p-value < 0.05. The table reports the group and dynamic treatment effect parameters estimated by the doubly robust method under the assumption of unconditional parallel trends and with a control group composed of never treated states. Robust standard errors (reported in parentheses) are grouped at the state level.

Figure 6 and Table 5 look at different causes of deaths. The event-study figures document a significant decline in the infant mortality rate due to endocrine, infectious, and respiratory causes. While there appears to have a few significant pre-FECEP coefficients, these effects are not of the right order of magnitude to explain the pattern during the post-intervention period. Table 5 summarizes the magnitude of these effects. The program led to an average decline in the infant mortality rate of 0.28 (44 percent), 0.59 (22 percent), and 0.20 (12 percent) due to endocrine, infectious, and respiratory causes respectively. These results are important as these causes of death are concentrated among infants from poorer socioeconomic conditions. For the "other causes" category, we observe an average decline of about 1 or 15 percent relative to the pre-FECEPE mean. This category includes all other causes of death, including those related to conditions originating in the prenatal period.

Figure 6 – Effect of FECEP in the Northeast on infant mortality by cause of death



Notes: The horizontal axis indicates the duration of treatment exposure. The duration of exposure equal to zero (0) provides the mean effect of the constitution of FECEP in the Northeast among the groups in the period in which they implement the antipoverty policy for the first time. Exposure duration equal to (-1) corresponds to the pre-treatment period (before FECEP) and exposure duration equal to (1) denotes the first period after policy implementation (after FECEP). The bars of the event study graphs represent the 95% confidence interval, where robust standard errors are clustered at the state level.

Table 5 – Effect of FECEP in the Northeast on infant mortality by cause of death

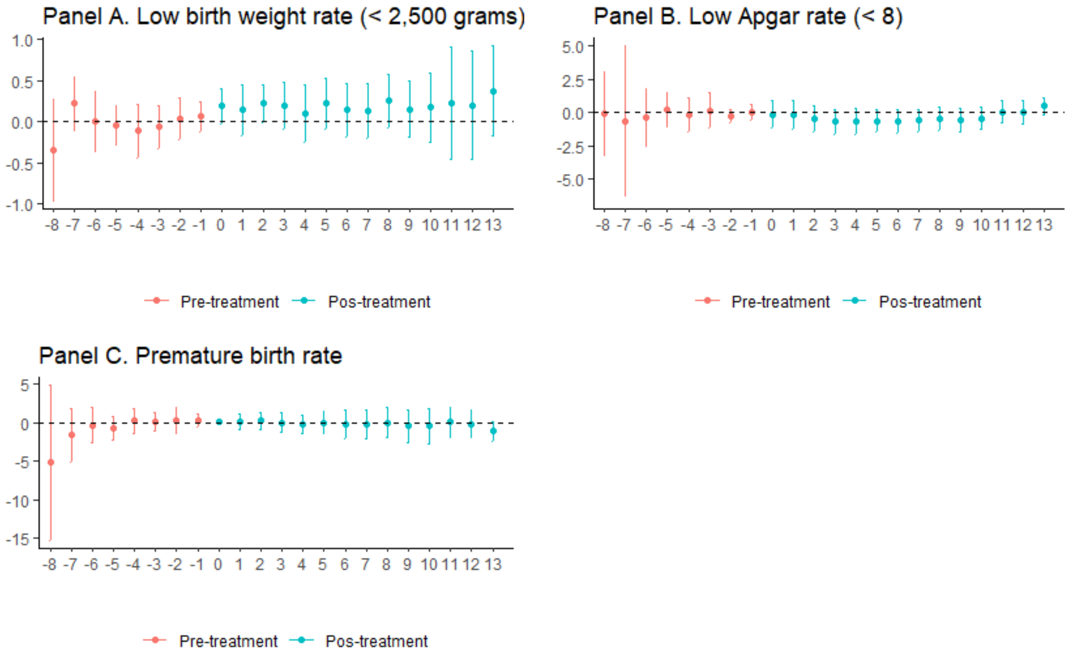
	Infant mortality rate by cause of death						
	Panel A	Panel B.	Panel C.	Panel D.	Panel E.	Panel F.	Panel G.
	External	Endocrine	Infectious	Nervous and Circulatory	Respiratory	Perinatal conditions	Other causes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Group Effect	-0.027	-0.259*	-0.553*	0.026	-0.148*	-0.578	-0.976*
	(0.133)	(0.069)	(0.188)	(0.038)	(0.064)	(0.555)	(0.374)
Dynamic Effect	-0.047	-0.282*	-0.598*	0.023	-0.205*	-0.696	-1.017*
	(0.161)	(0.069)	(0.212)	(0.037)	(0.094)	(0.861)	(0.352)
Pre-FECEP mean	0.35	0.64	2.72	0.44	1.67	11.67	6.57
Observations	400	400	400	400	400	400	400

Notes: *Significant for p-value < 0.05. The table reports the group and dynamic treatment effect parameters estimated by the doubly robust method under the assumption of unconditional parallel trends and with a control group composed of never treated states. Robust standard errors (reported in parentheses) are grouped at the state level.

Thus far, the results show that the introduction of the FECEP led to gains in infant mortality. This suggests that the anti-poverty fund program is an effective tool to improve infant welfare in poor areas. These findings also provide additional justification for decentralization programs to combat poverty and reduce health inequalities across regions (Jorgensen and Van Domelen (1999); Van Domelen (2002); Newman et al. (2002); Djimeu (2014) and Carrillo and Feres (2019)). Moreover, these results have potential long-run effects on well-being given the large body of evidence suggesting improved conditions early life has positive effects on the accumulation of human capital and labor market outcomes in adulthood (Black, Devereux and Salvanes (2007), Currie (2009), Almond and Mazumder (2011), Figlio et al. (2014), Almond, Currie and Duque (2018) and Miller and Wherry (2019)).

To uncover more detail on the effects of FECEP on infant health, we explore changes in birth outcomes: low birth weight, low APGAR scores, and preterm births. These outcomes have been shown to be associated with improved living conditions (Larson (2007), Nagahawatte and Goldenberg (2008), Braveman et al. (2010), Almond and Mazumder (2011), Aizer and Currie (2014) and Branco, Bermúdez and Lima (2017)). For example, poorer living conditions could lead to an inadequate nutrition during the pre- and post-natal periods, and this could directly affect infant health before and after birth. Examining birth outcome is important from a policy perspective because a major goal of the anti-poverty fund is to improve nutrition among the poor (Silva et al., 2021).

Figure 7 – Effect of FECEP in the Northeast on birth outcomes



Notes: The horizontal axis indicates the duration of treatment exposure. The duration of exposure equal to zero (0) provides the mean effect of the constitution of FECEP in the Northeast among the groups in the period in which they implement the antipoverty policy for the first time. Exposure duration equal to (-1) corresponds to the pre-treatment period (before FECEP) and exposure duration equal to (1) denotes the first period after policy implementation (after FECEP). The bars of the event study graphs represent the 95% confidence interval, where robust standard errors are clustered at the state level.

Figure 7 presents event-study results for the aforementioned birth outcomes. There is no evidence that the program led to gains in this dimension. In fact, there appears to have an increase in the prevalence of birth weight following the introduction of the program. In principle, this seems counterintuitive. However, it is important to highlight that the program had positive effects on survival chances, saving fetuses with poorer health status on the margin of survival. This introduces a change in the composition of births by increasing the share of babies with poorer health outcomes (Vanderlei et al. (2010) and Vilanova (2019)).

Although we do not observe significant effects on low birth weight or preterm births, we do observe a marginally significant effect on low APAGAR score rate. Indeed, column (2) of Table 6 suggests a decline in this outcome of 0.53 percentage points. This represents a decline of about 9 percent relative to the pre-program mean.

Table 6 – Effect of FECEP in the Northeast on birth outcomes

	Health rates at birth		
	Panel A.	Panel B.	Panel C.
	Low weight at birth (< 2500 g)	Low Apgar (< 8)	Premature births
	(1)	(2)	(3)
Group Effect	0.181	-0.537*	-0.107
	(0.104)	(0.143)	(0.473)
Dynamic Effect	0.195	-0.364	-0.163
	(0.109)	(0.310)	(0.464)
Pre-FECEP mean	6.89	5.93	5.24
Observations	400	400	400

Notes: *Significant for p-value < 0.05. The table reports the group and dynamic treatment effect parameters estimated by the doubly robust method under the assumption of unconditional parallel trends and with a control group composed of never treated states. Robust standard errors (reported in parentheses) are grouped at the state level.

4.3 Robustness check

In this section, we present a variety of additional exercises designed to evaluate the validity of the empirical strategy, focusing on infant mortality. Table 7 displays these results. For ease of comparison, column (1) repeats the baseline. In our main analysis, we perform the CvM conditional on covariates. As a robustness check, we perform the same test without including covariates other than the basic fixed effects. As one can infer, we cannot reject the null hypothesis of no pre-trends at the 5 percent for infant mortality, pos-neonatal mortality and avoidable infant mortality. What is different now is that we cannot reject the null hypothesis for neonatal mortality when we include additional covariates in the model.

In column (2), we present results for infant mortality based on an estimation sample that includes all never-treated and yet-treated states as comparison groups. The point estimates and standard errors remain very similar to the baseline.

Since the State of Bahia was the only one treated in 2002, our basic sample includes only a covariate (log population) because the doubly-robust estimator does not allow to include a number of covariates greater than the number of treated units. Column (3) documents that the results from the between-group and dynamic estimators remain similar to the baseline estimates. Column (4) repeats the same exercise but using a less restrictive comparison group. The results are hardly impacted by this change.

Before exploring the robustness of our results to the inclusion of other covariates, we first estimate the model using a basic two-way fixed effects regression to show that the coefficient estimates are very similar to the doubly-robust estimator. Despite the potential for bias in the two-way fixed effects estimator, the point estimates are comparable to that obtained via the doubly-robust estimator (column 5). We now use the two-way fixed effects to examine the sensitivity of our results to the inclusion of additional covariates – recall that this is not possible using the doubly-robust estimator. The inclusion of additional covariates tends to yield coefficients that are larger in magnitude, except for post-neonatal mortality, which is now statistically insignificant. By contrast, we now observe statistically meaningful effects for neonatal mortality. We reach the same conclusions when we use all never-treated and not yet-treated states in the comparison group (column 7).

Table 7 – Robustness analysis for infant mortality results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Infant Mortality								
Group effect	-2.514*	-2.489*	-2.454*	-2.428*	-2.514*	-2.945*	-2.674*	
	(0.850)	(0.780)	(0.713)	(0.717)	(0.804)	(1.091)	(1.052)	
Dynamic effect	-2.821*	-2.798*	-2.782*	-2.758*	-2.821*	-3.611*	-3.363*	-2.638*
	(1.055)	(0.927)	(0.875)	(0.904)	(1.011)	(1.484)	(1.323)	(0.732)
Pre-FECEP mean	24.14	24.14	24.14	24.14	24.14	24.14	24.14	24.14
Panel B. Neonatal Mortality								
Group effect	-0.798	-0.793	-0.771	-0.762	-0.798	-2.180*	-2.156*	
	(0.526)	(0.518)	(0.535)	(0.488)	(0.537)	(0.853)	(0.842)	
Dynamic effect	-0.948	-0.943	-0.942	-0.933	-0.948	-2.679*	-2.660*	-0.875
	(0.766)	(0.834)	(0.807)	(0.750)	(0.804)	(1.048)	(0.985)	(0.589)
Pre-FECEP mean	14.11	14.11	14.11	14.11	14.11	14.11	14.11	14.11
Panel C. Post-neonatal Mortality								
Group effect	-1.717*	-1.697*	-1.683*	-1.666*	-1.717*	-0.765	-0.518	
	(0.447)	(0.423)	(0.381)	(0.415)	(0.390)	(0.442)	(0.478)	
Dynamic effect	-1.874*	-1.855*	-1.840*	-1.825*	-1.874*	-0.932	-0.703	-1.762*
	(0.419)	(0.436)	(0.403)	(0.391)	(0.443)	(0.721)	(0.679)	(0.393)
Pre-FECEP mean	10.04	10.04	10.04	10.04	10.04	10.04	10.04	10.04
Panel D. Preventable Infant Mortality								
Group effect	-3.099*	-3.069*	-3.030*	-2.999*	´-3.099*	-3.847*	-3.404*	
	(1.062)	(0.886)	(0.830)	(0.838)	(0.951)	(1.412)	(1.303)	
Dynamic effect	-3.420*	-3.392*	-3.393*	-3.364*	-3.420*	-4.621*	-4.219*	-3.238*
	(1.122)	(1.048)	(0.879)	(0.978)	(1.111)	(1.745)	(1.640)	(0.824)
Pre-FECEP mean	28.68	28.68	28.68	28.68	28.68	28.68	28.68	28.68
Observations	400	400	400	400	400	400	400	400
Control group								
Never treated	*Sim*	*Não*	*Sim*	*Não*	*Sim*	*Sim*	*Não*	*Sim*
Not yet treated	*Não*	*Sim*	*Não*	*Sim*	*Não*	*Não*	*Sim*	*Não*
Estimation method								
Doubly robust	*Sim*	*Sim*	*Sim*	*Sim*	*Não*	*Não*	*Não*	*Não*
Result Regression	*Não*	*Não*	*Não*	*Não*	*Sim*	*Sim*	*Sim*	*Não*
Fixed Effect Regression	*Não*	*Não*	*Não*	*Não*	*Não*	*Não*	*Não*	*Sim*
Pre-treatment covariates								
Basic characteristics	*Não*	*Não*	*Não*	*Não*	*Não*	*Sim*	*Sim*	*Não*
Population logarithm	*Não*	*Não*	*Sim*	*Sim*	*Não*	*Não*	*Não*	*Não*
Cramer-von Mises Test								
A. Infant Mortality	3839.9		1866.4		3839.9	1339.2		
B. Neonatal Mortality	1481.6*		756.5*		1481.6*	310.1		
C. Post-neonatal Mortality	1027.9		560.6		1027.9	546.7		
D. Preventable Infant Mortality	4761.0		2289.3		4761.0	1805.5		

Notes: *Significant for p-value < 0.05. Robust standard errors (reported in parentheses) are grouped at the state level.

A potential concern with our results is that they could be confounded with other coinciding shocks affecting infant health, including the *Bolsa Familia* conditional cash transfer program (BFP) and the Family Health program (FHP). The inclusion of pre-program state characteristics help mitigate these concerns (Carrillo and Feres, 2019; Branco; Bermúdez and Lima, 2017). As an additional cheque, we now use the difference-in-difference estimator proposed by Sun and Abraham (2021) for heterogenous treatment effects and multiple periods[10]. These results are displayed in column (8). The point estimates are extremely similar to those

[10] The method developed by Sun and Abraham (2021) has a series of disadvantages compared to Callaway and Sant'Anna (2021): sensitivity to the use of covariates; absence of formal tests for pretreatment effects; stronger assumptions.

reported in column 1. Overall, we find that the FECEP led to a robust decline in infant mortality.

5. Final remarks

This paper has provided evidence on the effects of anti-poverty fund on infant health in Northeast Brazil. We first corroborate that the program reduced the prevalence of poverty as measured by the fraction of families below the poverty line. We then document that the program also led to significant improvements in infant mortality, especially from avoidable causes and those occurring during the post-neonatal period. The effects tend to be larger for boys, consistent with the literature suggesting that male babies are more sensitive to events and circumstances surrounding the birth.

These findings could stimulate and help design similar interventions in other contexts. As documented in this study, anti-poverty funds constitute an important tool to improve welfare by reducing inequalities during the first years of life.

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Online Appendix

Access to the **online appendix**: <https://bityli.com/dMDpOD>.

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