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ORIGINAL ARTICLE

Assessing the impact of a doctor in remote areas of Brazil

Joana Raquel Raposo dos Santos[1,2] · Hellen Geremias dos Santos[4] · Carlos Manuel Matias Dias[2,3] · Alexandre Dias Porto Chiavegatto Filho[1]

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Abstract

Objectives The More Doctors Program (MDP) is an ongoing Brazilian policy that aims to improve healthcare by providing physicians to the most vulnerable municipalities. We aimed to measure the impact of MDP in mortality and infant mortality rate, the proportion of live births with low weight, prenatal appointments, childbirths at first and fifth min Apgar, public health investment and immunization in Brazil.

Methods Municipal health indicators were collected before and after the intervention (2012 and 2015). Effects were measured by applying propensity score matching with difference-in-differences.

Results Our findings show that infant mortality presented the highest improvement during the period (a decrease in 11 infant deaths per 1000 live births, $p < 0.01$). A significant effect, albeit smaller, was also found for the age-standardized total mortality (a decrease in five deaths per 10,000 residents), proportion of children with Apgar score lower than 8 in the fifth min and children with low birth weight.

Conclusions MDP contributed to improve important health indicators, highlighting the importance of a doctor in remote areas of Brazil.

Keywords Propensity score · Public health · Mais médicos · Public policy

Introduction

Brazil has a historical shortage and uneven distribution of physicians. In 2013, the country had two physicians per 1000 inhabitants (Scheffer 2015) but the southeast presented over twice more physicians per capita than the north and northeast (2.7, 1.09 and 1.3, respectively). To address this problem, in 2013, the Brazilian government, with close support from the Pan American Health Organization (WHO/PAHO) (PAHO/WHO 2018), introduced the More Doctors Program (MDP).

The main objective of the program was to reduce inequalities in access to primary healthcare in Brazil. The MDP entailed a total of eight main objectives, such as increasing the number of physicians in rural and remote areas, improving medical training and investing in primary care infrastructure (Presidência da Republica 2013). To participate in the MDP, municipalities must be considered eligible according to local necessities, and areas within a pre-defined poverty threshold were considered priority (CONASS 2013; Presidência da Republica 2013).

According to the Brazilian Ministry of Health, in 2015, more than 4.000 municipalities received doctors from the

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✉ Joana Raquel Raposo dos Santos
joanasantos@usp.br

Hellen Geremias dos Santos
hellen.santos@fiocruz.br

Carlos Manuel Matias Dias
carlos.dias@insa.min-saude.pt

Alexandre Dias Porto Chiavegatto Filho
alexdiasporto@usp.br

1 School of Public Health, University of São Paulo, São Paulo, Brazil

2 Department of Epidemiology, National Health Institute Doctor Ricardo Jorge, Lisbon, Portugal

3 Public Health Research Center, National School of Public Health, NOVA University of Lisbon, Lisbon, Portugal

4 Cargos Chagas Institute, Oswaldo Cruz Foundation, Curitiba, Paraná, Brazil

MDP (DATASUS 2018). The provision of doctors to the most remote areas was the main priority of the program and gained public visibility due to the hiring of foreign physicians, mostly of Cuban origin, to work in remote areas. Until 2016, around 17.000 physicians had been allocated all over Brazil, with a balanced percentage of Cuban and Brazilian doctors (47% and 46%, respectively). (PAHO/WHO 2018).

The large costs associated with the program increased the pressure for independent measurements of its health impact (Ministerio Saude 2013). The impact of a program can be measured by determining if a potential change can be specifically attributed to the program (Josselin and Le Maux 2017). Assessing impact requires the existence of a counterfactual (Peixoto 2012) that can frequently be approximated by randomizing the intervention, which was not the case for the MDP.

A conceptual framework was proposed by Rubin in 1974 to overcome this constraint (Rubin 1974). Rubin's causal model (Holland 1986; Shadish 2010) lies on the following assumptions (1) each individual i has a potential outcome Y_i^1 associated with participating in the treatment ($Zi = 1$) and a potential outcome Y_i^0 if not participating ($Zi = 0$) with the effect being the difference between the outcome with and without treatment, for the same individual; and (2) simulating randomization in observational studies is possible, under particular assumptions, through the assignment of a *propensity score* which is the conditional probability of being assigned a particular treatment given a vector of observed covariates. (Rosenbaum and Rubin 1983). As a result, one is able to measure the average treatment effect on the treated (ATT), i.e., the difference between the expected values of the potential outcomes of treated individuals (Leite 2017). An important assumption of this framework is ignorability, or "no hidden bias," meaning that the assignment of the treatment can be assumed to be random based on all observable characteristics of the observations under study (Stuart 2010). Although with different objectives, several studies have been carried out under this conceptual framework (Filho et al. 2012; Gebel and Voßemer 2014; Jonk et al. 2015), all of these three studies employed a propensity score matching approach to measure the effect of a program in health indicators, when the study design was not experimental and random allocation was not possible. Our study used a similar technique to assess the effect of the MDP. Our analysis applied a similar technique to assess the effect of the MDP, followed by a difference-in-differences (DiD) approach, a statistical technique used to estimate effects of a policy before and after the intervention between treatment and control groups (Josselin and Le Maux 2017). In short, a major strength of combining these approaches is that under these assumptions, it is possible to estimate the impact of a program on a population even without a randomized experiment. By matching units that were similar before the program, the PSM reduces the treatment assignment bias and mimics randomization.

Before the program, some municipalities in Brazil did not have a doctor. It is expected that one doctor contributes more to improve health outcomes in these areas than in places that already have a few doctors. The objective of this study is then to measure the impact of the More Doctors Program in 2015 in these municipalities for the following health outcomes: crude and age standardized mortality rate, infant mortality rate, percentage of live births with low weight, percentage of pregnancies with least seven prenatal appointments, percentage of newborns with first min Apgar less than 8 and percentage of newborns with fifth min Apgar less than 8, per capita public health investment and immunization rate in municipalities of Brazil.

Methods

We analyzed the municipalities of Brazil that did not have a physician in 2012, the year before the start of MDP ($n = 395$). For this purpose, the ratio of physicians per capita was estimated, with data collected from DATASUS (DATASUS 2018). Covariates were collected from IBGE, TSE (Electoral Superior Court) and Ministry of Health (MOH) (Electronic supplement 1). Information on the provision of physicians for each municipality and cycle of allocation was provided by the Ministry of Health (Federal 2018). Rates and proportions for the outcomes of interest for each municipality were estimated: crude and age standardized mortality, infant mortality rate (IMR), the proportion of births with at least seven antenatal visits, proportion of births with low weight (under 2.5 kg), the proportion of births with Apgar score below eight at first (Apgar 1) and fifth min (Apgar 5) and the rate of mortality due to undetermined causes. Variables were measured before the intervention to avoid endogeneity.

To build the propensity score, we used a set of covariates (Electronic supplement 1) related to sociodemographic and health access characteristics of municipalities as long as they are conceptualized to be prior to the MDP. Nonetheless, covariates with zero variance were removed (Garrido et al. 2014) but correlated variables were kept. We used these variables to identify comparable municipalities with and without the intervention (i.e., participating or not in the MDP) using propensity matching approach. A logistic regression was performed to estimate the propensity score. We then inspected the common support area visually, and treated municipalities were matched to similar controls on the propensity score with a caliper of 0.1 standard deviation from the PS (with replacement) (Austin 2011a, b).

We then analyzed the health outcomes from the two group of municipalities in two time points, in the year immediately before the program started in 2012 (when not available, data were collected from 2010, the year of the last census), and then after the beginning of the program (2015—the most recent data available). We applied a difference-in-differences analysis (Gebel and Voßemer 2014) which consists of a double subtraction between the outcomes before and after the intervention and between the intervention and control groups (Jonk et al. 2015; Katchova 2017).

Covariate balance before and after the propensity matching approach was assessed by the number of covariates with standard mean difference less than 25%, as previously used in the literature (Stuart et al. 2013; Leite 2017; Austin 2009). Assessment of PS balance was measured by taking into account whether the number of balanced covariates improved after matching and later checked with p value of t test to verify if groups after matching were different from each other. The package *matching* for *R* was used for the analyses (Sekhon 2018).

Results

Our sample was composed of 395 municipalities that did not have a physician in 2012. From these, 194 did not receive a physician and 201 did until May 2014 (corresponding to the fifth cycle of the program). Of the municipalities without a physician, 31% were in the south, 27% in the northeast, 26% in the southeast, 10% in the north and 7% in the center-west region.

The distribution of the results of the propensity scores for the two groups (with and without MDP) is shown in Fig. 1. It is possible to identify an interesting overlap of treated and untreated municipalities, which allows for pairwise comparisons. Figure 2 presents the distribution of propensity score before and after matching, for all municipalities and according to having, or not, received the MDP. The complete numerical distribution of the covariates for the two groups before and after matching, as well as their standardized means difference (in %), is presented in Electronic Supplement 2. We obtained 163 pairs within this caliper width, and municipalities that were not within this exact caliper width of distance from another municipality with opposite treatment were dropped from further analyzes.

Electronic Supplement 2 shows that before matching, out of 97 covariates, 86 presented a SMD of less than 25%, and 75 had a significant t test p value. After matching, 94

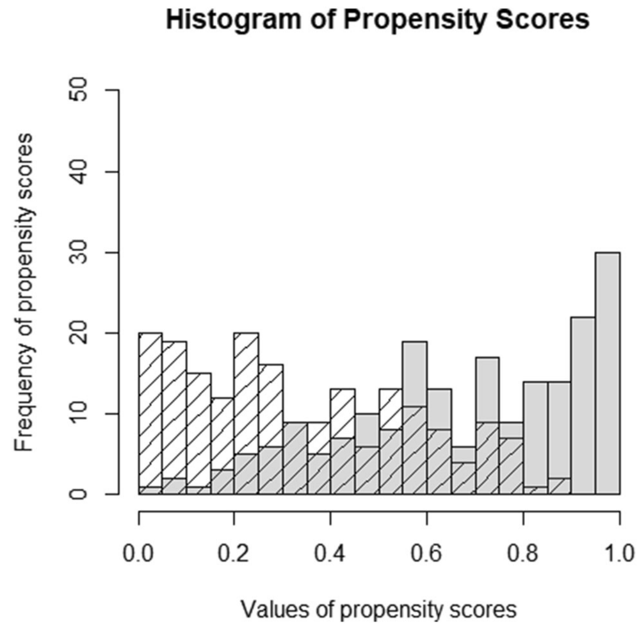

Fig. 1 Propensity score values distribution for treated and untreated Brazilian municipalities, 2012. Shaded bars correspond to municipalities without the More Doctors Program and gray to municipalities with the More Doctors Program

presented a SMD of less than 25%, and 92 covariates increased their t test p value, indicating better balance between treated and untreated.

Table 1 presents the effect of the program on health outcomes after differences-in-differences. There was a significant effect in the age-standardized mortality rate, with a decrease in five deaths per 10,000 inhabitants between 2012 and 2015 ($p = 0.01$), a decrease in the IMR ($p < 0.01$) of 11 deaths per 1000 live births, a decrease in the proportion of newborns with low birth weight and with Apgar at fifth min lower than 8 ($p < 0.01$) and in the proportion of children with low birth weight ($p = 0.01$). However, for the last two outcomes, the decrease was very small.

Discussion

We found that the MDP improved some health indicators in municipalities that joined the program when compared to those that did not after 2 years of participation. Propensity score matching was successful in improving the balance for most of the covariates. After matching, 97.9% were considered to be well-balanced between the two groups (intervention and control), meaning that the intervention and control municipalities, matched to measure the impact of the program, were very similar at baseline.

Our study found that the highest effect of the MDP was in decreasing the infant mortality rate in 11 deaths per 1000

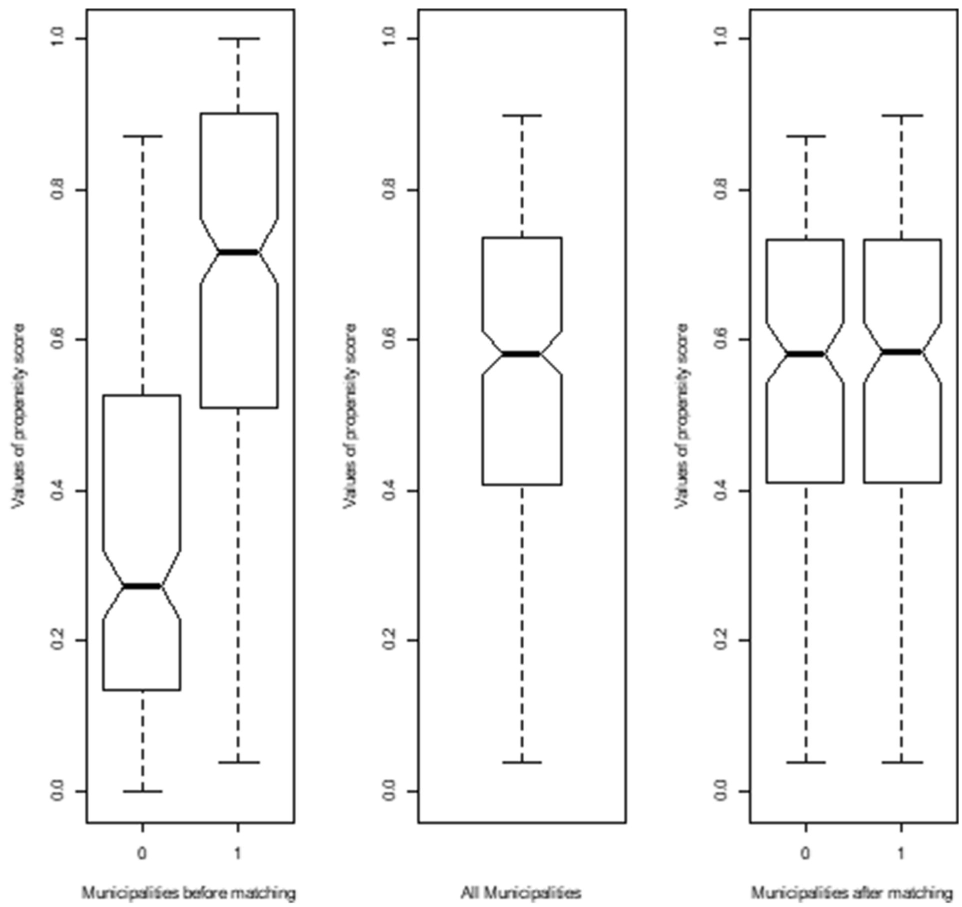

Fig. 2 Boxplot of propensity scores distribution before and after matching for Brazilian municipalities, 2012. Boxplot in the left corresponds to propensity scores before matching and according to municipalities that received the More Doctors Program (1) or not the More Doctors Program (0); boxplot in the middle corresponds to propensity scores after matching in all municipalities, and the boxplot in the right corresponds to propensity scores distribution according to municipalities that received (1) or not (0) the Program, after matching

live births. A previous study examined the effects of the MDP in infant health and found an increase in the number of prenatal visits (Carrilllo and Feres 2017). However, no significant effect was found for infant mortality between treated and untreated areas. This study differs from ours due to the fact that our sample is comprised of 395

Table 1 Estimated effects of the More Doctors Program for health outcomes after difference-in-differences propensity score matching, Brazil, 2012–2015

Health outcome	Effect estimates		*P* value (*t* test)
	Effect estimates after centering and scaling	Effect estimates in absolute values	
Crude mortality rate	− 0.119	− 0.255	0.344
Age-standardized mortality rate	− 0.284	− 0.511	0.01*
Infant mortality rate	− 0.399	− 11.871	0.001*
Percentage of live births with low weight	− 0.307	− 0.023	0.01*
Percentage of live births with at least seven prenatal appointments	− 0.009	− 0.001	0.944
Public health investment per capita	0.056	0.284	0.626
Percentage of childbirths with first min Apgar less than 8	0.036	0.004	0.800
Percentage of childbirths with fifth min Apgar less than 8	− 0.307	− 0.012	0.01*
Immunization rate	0.170	7.553	0.260
Mortality rate by undetermined causes	0.046	76.541	0.744

*Significant *p* value

municipalities purposively selected to include only municipalities that before treatment had no physician. We used this approach because the introduction of one physician can have a different effect for municipalities that did not previously have a physician, in relation to those that previously already had a few. We also included a wider range of control variables, such as hospital and ambulatory care access.

There is some previous evidence for the association between the presence of a physician density and IMR (Farahani et al. 2009; Anand and Bärnighausen 2004). One study, from Shi et al. (2004) found the supply of primary care physicians, especially of family doctors, was significantly associated with lower infant mortality and reduced rates of low birth weight. Another study, performed from 2005 to 2012 in municipalities in Brazil, also found a negative relationship between density of primary care physicians and infant mortality (Russo et al. 2019).

It is well-established that physicians play an important role in disease prevention especially for maternal and child health (Cutler et al. 2011), which are easier and less expensive to prevent. Although our analyses were not able to assess the pathway through which the IMR drop occurred, a recent study (Liebert and Mäder 2016) found that physicians can prevent diseases by providing essential information to the community. In particular, a doctor can influence neonatal and post-natal deaths by providing information to mothers regarding sanitary practices that prevent infants' deaths, such as poor nutrition, smoking, low birth weight, infectious and sexually transmitted diseases. (Shi et al. 2004) In the case of our study, these are likely to have an immediate and direct effect in the evolution of pregnancy and the health of the newborn.

We also found a significant improvement in other maternal and child health indicators, namely a decrease in the proportion of children with Apgar less than 8 on the fifth min and the proportion of newborns with low birth weight, though the magnitude of these effects was very small (0.01 and 0.02, respectively). Another study from Bladimir and Feres (Carrilllo and Feres 2017) found that although the program increased the number of physicians in treated areas and the number of prenatal care visits by 10%, the effects in low birth weight had coefficients of very small magnitude, finding a significant improvement only in areas with high social spending in education.

Regarding the decrease in age-standardized mortality rate, previous studies using different methodologies also found a significant decrease in the mortality rate of municipalities that joined the MDP (Bastos et al. 2015). Bastos et al. found a decrease in 0.538 deaths per 1000 inhabitants, and dos Santos (2018), a decrease in 0.235 for the group of municipalities among the 20% poverty risk.

Other outcomes such as the proportion of pregnant women with at least seven antenatal visits, public health investment in health in the municipality, proportion of newborns with Apgar lower than 8 in the first min, immunization coverage and mortality rate due to undetermined causes were not statistically significant. This is line with both studies mentioned before, namely for pregnant women with antenatal care visits (dos Santos 2018) and immunization (Carrilllo and Feres 2017).

This study has a few limitations. Data for the allocation of doctors were given by the MoH, and the original data presented some duplicates regarding the allocation of doctors according to cycles. This information was necessary to identify municipalities with and without the MDP, and although we performed the necessary corrections, there might still be residual bias. Another limitation is the fact that 2015 is very close to the start date of the program, so effects may still be very small at this point. Finally, although we included a large number of covariates to assess the propensity score (a total of 97), there may be still some remaining bias regarding unobserved variables.

Our study found that the MDP contributed to improve important health indicators in Brazilian municipalities, especially infant mortality. Other indicators such as age-standardized mortality and the percentage of children with low birth weight also improved, but to a lesser extent. These results highlight the importance of a doctor in bringing health to communities in remote areas of Brazil.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval We confirm that this work is original and has not been published, nor is it currently under consideration for publication elsewhere.

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