The Impact of the Green-Blue Municipality Program on Diseases Regarding Water and Air Quality in São Paulo State, Brazil

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Abstract:

This study evaluated the impact of the Green-Blue Municipality Program on the number of hospitalizations regarding air quality and number of disease cases due to contact with or consumption of contaminated water in the São Paulo State, Brazil from 2007 to 2015. For that purpose, the Propensity Score Matching and Difference-in-Differences approach were the strategies used for identification. The main results showed no significant reduction in the cases of diseases related to polluted water and air quality in municipalities in the São Paulo State. We find that environmental policy-makers at the state of São Paulo need to improve the program focus, making the economic benefits clearer and, consequently, contributing positively to the environmental and public health policy management.

Acknowledegment:

JEL Codes: C18, Q57

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Keywords: Impact Evaluation; Green-Blue Municipality Program; Public Policy.

JEL code: Q53; Q58; C21.

1. Introduction

With the development of urban areas, the socio-environmental issue is often left out of the agenda of municipal actions, aggravating ecological issues. Environmental public policies need to be implemented to develop better models of conservation planning and management. Moreover, they are necessary to fight current challenges in urban regions and end the idea that economic and political values overlap the environmental ones (Oliveira et al., 2013).

São Paulo is the most urbanized and populated state in Brazil with 645 municipalities, estimated population of 44,749,699 and a monthly nominal household income per capita of R$ 1,723[1] in 2016 (IBGE, 2017)[2].

Densely industrialized urban regions, such as those in São Paulo State, require considerable amounts of materials, energy and water. However, these materials are not usually performed sustainably, which generates waste that is not properly discarded, polluting the air and water.

[1] In real values of 2016 and US$ 528.67.
[2] Information from IBGE States, available at: http://www.ibge.gov.br/estadosat/.

Air and water contamination can generate highly damaging effects to the population health in the polluted areas (Giatti et al., 2004). Studies have shown a strong correlation between air pollution and respiratory diseases (Braga et al., 2001; Mazzoli-Rocha et al., 2008; Nardocci et al., 2013; Chagas et al., 2016; Freitas et al., 2016).

According to Braga et al. (2001), although combustion engines, steel and chemical industries were economic activities that emerged in the last century, their impacts on the environment and human health have not yet been considered. Air pollution has been a problem since the mid-20th century, especially in industrialized urban centers and with the presence of automobiles, such as the Metropolitan Region of São Paulo (MRSP). Nardocci et al. (2013) evidenced this relation in the city of Cubatão, an industrial pole of petrochemicals, steel and fertilizers of São Paulo State. Pollutants had a significant impact on the number of hospitalizations due to the respiratory diseases, mainly, on children under 5 years of age.

According to Freitas et al. (2016), the burning of fossil fuels, for example, generates pollutants such as coarse Particulate Matter (PM_{10}), sulfur trioxide (SO_3), carbon monoxide (CO), nitrogen oxides (NO_x) and ozone (O_3). For Braga et al. (2001), the burning of fossil fuels, such as gasoline and diesel, is more toxic than the burning of biomass fuels, such as ethanol. However, according to Mazzoli-Rocha et al. (2008), biomass burning is the main responsible for the accumulation of Total Suspended Particles (TSP) worldwide, causing high pollution levels, mainly in developing countries. São Paulo State is Brazil's largest producer of sugarcane. Until 2013, the practice of burning sugarcane straw in the field was common, which also contributed to increased air pollution.

Similarly, Chagas et al. (2016) studied the impacts of sugarcane production on health conditions of individuals in the plantation areas and in their vicinity using data from municipalities of São Paulo State. The authors found that sugarcane burning increased the number of hospitalizations due to respiratory diseases, because a large amount of toxic particles and gases released.

Therefore, mortality and morbidity rates related to respiratory and cardiovascular problems are important indicators of air pollution effects on human health. The increase in asthma attacks and pre-cordial pain, functional limitation, greater use of medications, number of visits to emergency room and hospital admissions indicate the main problems observed related to urban air pollution (Braga et al., 2001).

In addition, some Brazilian studies analyzed infections by diseases related to direct or indirect ingestion of contaminated water (Amaral et al., 2003; Giatti et al., 2004).

Amaral et al. (2003) point out that human consumption is one of the most important vehicles of water diseases, such as infectious diarrhea. Giatti et al. (2004) reported the conditions of basic sanitation in the city of Iporanga in São Paulo State, highlighting that pollution of rivers and streams by domestic sewage, along lack of sanitary knowledge by the population, increases contamination risks by intestinal parasitic diseases, such as schistosomiasis.

Due to impacts of pollution on health and well-being of individuals, public policies have the responsibility to mitigate negative externalities and control new emissions. Public policies can influence production systems and how people live, and are not only instruments for social development, but also as specific way of preservation of natural resources, ensuring life quality (Salheb et al., 2009).

Therefore, the objective of this study is to analyze the impacts of a regional public policy, the Green-Blue Municipality Program (GBMP)[3], on municipalities of São Paulo State, in Brazil from 2007 to 2015. Specifically, we evaluate the impact of participation in the GBMP on the number of diseases related to ingestion of contaminated water and associated to air pollution, such as respiratory diseases.

The municipalities participating in the GBMP, through of the certification of Green-Blue Municipality[4], receive economic benefits that are converted into incentives for executive, legislative and civil society for implementation of proposed directives by program. The compliance with the directives allows improvements in water management, sewage collection and air quality.

Then, our hypothesis is that the greater number of municipalities joining the GBMP reduces the number of hospitalizations and confirmed cases of respiratory diseases and illnesses related to ingestion or contact with contaminated water, reducing negative externalities related to water and air pollution.

The paper is divided into five sections, including this introduction. Section 2 presents a brief description of the GBMP; Section 3 shows the methodology applied in this study and a summary of the database and its sources; Section 4 presents the results estimated and the tests performed; and, finally, Section 5 contains the policy considerations about the results and the program.

[3] In Portuguese, the public policy is called "Programa Município Verde-Azul (PMVA)".
[4] In Portuguese, "Certificado de Município Verde-Azul".

2. Green-Blue Municipality Program

The GBMP was stablished in 2007 by the Secretariat of Environment of the São Paulo State (SMA)[5], and its main objective is to compose an agenda of shared environmental management actions and mutual accountability of municipalities in order to have control of environmental quality. Thus, there is improvement of sustainable development and an active participation of municipal population to implement the program. Specifically, the GBMP seeks to encourage more effective participation of municipalities in the state environmental policy through a plan of goals based on 10 directives that allows the integration of the municipal environmental agenda with the state policies, considered priorities by the SMA (2016). The GBMP directives are presented in Table 1.

Table 1
Directives of GBMP

Directives	Objectives
1. Sewage Treatment	To increase the rates of collection, transportation, treatment and appropriate disposal of urban sewage.
2. Water Management	To strengthen the municipal management on water quality, mainly in the public supply of water.
3. Solid Waste	To fortify the management of solid household waste and civil construction rubble; and to stimulate the programs/actions of selective collection and post-consumer responsibility.
4. Sustainable City	To increase the awareness and commitment to sustainable development practices as a means of vulnerabilities reduction, providing resilience and fostering well-being and security to citizens.
5. Biodiversity	To protect and/or recover/restore strategic areas for the maintenance of natural resources.
6. Urban Afforestation	To increase the management of the urban environment through the planning and the definition of priorities for urban afforestation.
7. Environmental Education	To implement environmental education at formal and informal level in three areas: training, professional qualification and community mobilization.
8. Air Quality	To implement activities and to participate in initiatives that contribute to the maintenance or improvement of air quality and control the excess of greenhouse gases emissions.
9. Environmental Structure	To stimulate the strengthening of the Secretariats/Departments/ Directorates of Environment.
10. Environmental Council	To stimulate the regular functioning of the Environment Municipal Councils.

Source: SMA (2016).

[5] In Portuguese, “Secretaria do Meio Ambiente do Estado de São Paulo (SMA)”.

Based on the analysis and evaluation of municipal performance in relation to the proposed directives, the Environmental Assessment Index (EAI)[6] is constructed for each municipality that adheres to the GBMP. The EAI is calculated as follows:

$$EAI = \sum PI_i - PL, \tag{1}$$

where: PI_i is the Performance Indicator for each Environmental Directive (i) in the GBMP. This indicator varies on a scale from 0 to 10 and the score is attributed according to the actions proposed and it is adjusted by the weight of each directive; $\sum PI_i$ refers to the sum of each Performance Indicators, which the maximum value is 100 (one hundred) points; PL consists of any type of pendency and/or environmental liabilities of the municipality. This value ranges from 0 to 30, according to the liabilities established by the Environmental System of the São Paulo State.

According to the results of EAI, the SMA annually publishes the Environmental Ranking of the municipalities of the São Paulo State for the knowledge of municipalities and population in general. The first ranking developed had the certification of 44 municipalities in 2008, and in 2014, this number increased to 130, demonstrating the increase of the adhesion to the GBMP. Fig. 1 shows the evolution of municipalities that joined the program.

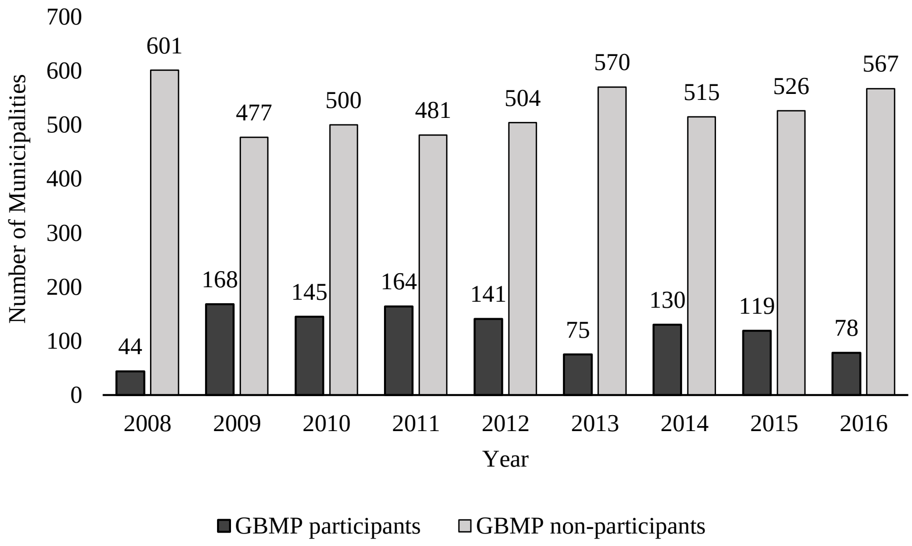

Fig. 1. Evolution of the participating and non-participating municipalities in the GBMP from 2008 to 2016.
Source: SMA (2016).

[6] For more information about the GBMP and the construction of EAI see the GBMP Manual 2016, available in: <http://arquivos.ambiente.sp.gov.br/municipioverdeazul/2011/11/PMVA-MANUAL.pdf>.

The certificate "Green-Blue Municipality" is granted only to municipalities that achieve score equal to or greater than 80 points in EAI. The major advantages of this certification is the resources received from the State Fund for Pollution Prevention and Control (FECOP)[7] and the priority in state funds related to environmental investments (Oliveira et al., 2013).

3. Methodology

In the public policies evaluation, the ideal to estimate the effect of an intervention (treatment) is to compare a same group of agents participating and non-participating in the program (public policy). However, it is not possible to have the same group, at a given moment of time, in these two contexts simultaneously (Duflo et al., 2007). Thus, the main challenge of evaluating the impacts of a policy is to create a counterfactual scenario (Ravallion, 2008).

In addition, a simple comparison between participating and non-participating agents of the program is not adequate, because it can generate selection bias, since entities have distinct characteristics that may affect their participation in the program evaluated (Duflo et al., 2007; Chabé-Ferret; Subervie, 2013). Therefore, the control group should be statistically identical to the one assisted by the program, differing only from the fact that it does not receive the benefit (Caliendo; Kopeinig, 2008; Khandker et al., 2009).

The main method that eliminates the selection bias and creates very similar groups, both with regard to observable and unobservable characteristics, is the randomization process (Heinrich et al., 2010). In this method, treatment and control groups are randomly selected in a well-defined subset of agents (Ravallion, 2008). Thus, a simple difference of averages between participants and non-participants of the program would result in the average effect of the program:

$$ATE = E(Y_i^T \mid P_i = 1) - E(Y_i^C \mid P_i = 0), \tag{2}$$

where, ATE is the Average Treatment Effect; Y_i^T is the potential result for the treated group and Y_i^C for the control group; P_i is a binary variable, if $P_i = 1$, the municipality receives the treatment and if $P_i = 0$ does not receive.

[7] In Portuguese "Fundo Estadual de Prevenção e Controle da Poluição (FECOP)".

Although randomization is a "gold-standard" method to determine the treatment causality, this type of experiment can suffer from political and financial viability problems, because they are expensive and difficult to control (Ravallion, 2008). Thus, current studies are performed with "quasi-experimental" techniques that evaluate the average treatment effect on the treated. Among them, we can highlight the Propensity Score Matching (PSM) and the Difference-in-Differences (DID) techniques, which will be detailed below.

3.1. Propensity Score Matching

The PSM method comprises the selection of a control group comparable to the treatment group by estimating a probability model (Logit/Probit). The Logit/Probit model evaluates probabilities of participating in the treatment and the matching of groups using observable characteristics. The propensity score, developed by Rosenbaum and Rubin (1983), is defined as the conditional probability of receiving a treatment, given a vector of pre-treatment observable characteristics, so:

$$p(X) = \Pr(T = 1|X) = E(T|X), \tag{3}$$

where, T indicates the treatment position (1 if it participates in the GBMP and 0 if it does not participate) and X is a characteristic vector. Thus, it is possible to calculate the Average Treatment Effect on the Treated (ATT), which is given by:

$$ATT = E_{P(X)|T=1}\{E[Y_{1i}|T_i = 1, p(X_i)] - E[Y_{0i}|T_i = 0, p(X_i)]|T_i = 1\}. \tag{4}$$

To calculate the ATT, two hypotheses must be satisfied. The combination of these hypotheses is known as strong ignorability condition (Rosenbaum; Rubin, 1983):

- Hypothesis 1 - Conditional Independence: $Y_i(1), Y_i(0) \perp T_i | X_i$, that is, unobserved factors do not affect the participation;
- Hypothesis 2 - Common Support: for some $c > 0, c < p(x) < 1 - c$. Therefore, the treatment observations have "near-by" comparison observations on the distribution of propensity scores.

Since the main objective of PSM is only the classification of the sample, the binary outcome models that evaluate the probabilities may not be crucial (Caliendo; Kopeinig, 2008).

The next step in estimating the propensity score is the matching procedure, which can be performed by different methods. In this study, following methods[8] are used: 1) Nearest Neighbor Matching; 2) Nearest Neighbor with caliper; 3) Mahalanobis technique (Covariate Matching); and 4) Non-Parametric Kernel regression.

After the matching procedure, balancing tests are performed, ensuring the comparison of comparable groups. Rosenbaum and Rubin (1983) state that the standardized bias cannot exceed 20% and the p-values should not be greater than 10% of statistical significance. In addition, it may also be useful for balancing check (after matching) the likelihood ratio test to verify the joint significance of all regressors and pseudo R^2 analysis (Leuven; Sianesi, 2015; Caliendo; Kopeinig, 2008)[9].

These tests assume the null hypothesis that the covariate average of the analyzed groups are statistically equal (Heinrich et al., 2010). If, after this procedure, the matched sample is not balanced, a new specification of covariates must be carried out during the estimation of a new vector of propensity scores (Heinrich et al., 2010).

3.2. Difference-in-Differences

The panel data allows to evaluate the impact of a program by the DID method. This model calculates the effect of treatment of treated and untreated units in time periods, before and after the intervention (Ravallion, 2008). Thus, two differences are realized: between periods and between treatment and control groups. One advantage of this technique is the control of unobserved characteristics that are constant over time (Arima et al., 2014).

According to Li et al. (2017), the DID model is well accepted by the literature and is one of the best methods to analyze quasi-natural experiments along with PSM methods. This type of model is commonly used to evaluate the effects of shocks, such as natural disasters, economic crises and public policies.

[8] Further details on these matching techniques can be found in Santos et al. (2016).
[9] For this purpose, it can be used a Q-Q plot (Quantile-Quantile) (Ho et al., 2007) and the Hotelling test (Lee, 2013) of the propensity scores of the control and treatment units.

The hypothesis assumed by the DID is a common trend, which there is a parallel tendency over time of the control and treatment groups in the absence of treatment (Angrist; Pischke, 2009). Thus, it can be assumed that changes between the two groups between the analyzed periods are due only to the treatment (Arima et al., 2014).

The PSM and DID techniques can be combined, controlling observable and unobservable characteristics (Khandker et al., 2009; Arima et al., 2014); thus, the average effect of certification on certified municipalities i can be expressed as:

$$DID = \left(Y_{i,t}^{T} - Y_{i,t-1}^{T}\right) - \sum_{j \in c} \omega_{(i,j)} \left(Y_{i,t}^{C} - Y_{i,t-1}^{C}\right), \quad (5)$$

where, $\omega_{(i,j)}$ = is the weight (using PSM or covariate matching), given the j-th municipality of the control paired with the i-th municipality; t = is the treatment period (2009, 2010, 2011, 2012, 2013, 2014 e 2015); $t-1$ = is the initial reference period (2007); T = indicates the group of treated municipalities, that is, participants of the GBMP; C = indicates the group of control municipalities, not participants of the GBMP.

3.3. Data

According to the Epidemiological Surveillance Center "Prof. Alexandre Vranjac" - CVE (2017)[10] and with Martins et al. (2017), the main diseases cataloged with water transmission (Waterborne Diseases - WD) are: Botulism; Cholera; Diarrhea; Leptospirosis; Typhoid fever; Hepatitis A; Rotavirus; and Schistosomiasis. The number of confirmed cases for each of these diseases and for each municipality of the São Paulo State were obtained from the Department of Information Technology of SUS (Datasus) and CVE. However, the lack of data, limit the analysis to only four types of diseases transmitted by consumption or contact with contaminated water: Leptospirosis; Typhoid fever; Hepatitis A; and Schistosomiasis.

Data on waterborne diseases were aggregated into a single variable. If i represents the municipality, t is the year, and j the type of disease, and $NCC_{i,t,j}$ is the number of confirmed cases of the disease j in the municipality i in year t. Then, the aggregation of the number of confirmed cases of waterborne diseases in the municipality i in year t is given by $WD_{i,t}$:

[10] In Portuguese “Centro de Vigilância Epidemiológica “Prof. Alexandre Vranjac” (CVE)”.

$$WD_{i,t} = \sum_{j=1}^{n} NCC_{i,t,j}. \quad (6)$$

Data on the number of hospitalizations due to Airborne Diseases ($AD_{i,t}$) in each municipality i in year t were obtained from Datasus (2017) and consider the Chapter X classified as "Respiratory system diseases J00-J99"[11]. Therefore, the aggregation of Airborne and Waterborne Diseases ($AWD_{i,t}$) is given by the expression:

$$AWD_{i,t} = AD_{i,t} + WD_{i,t}. \quad (7)$$

Fig. 2 reports the number of disease cases related to air and water pollution in São Paulo State from 2006 to 2015[12].

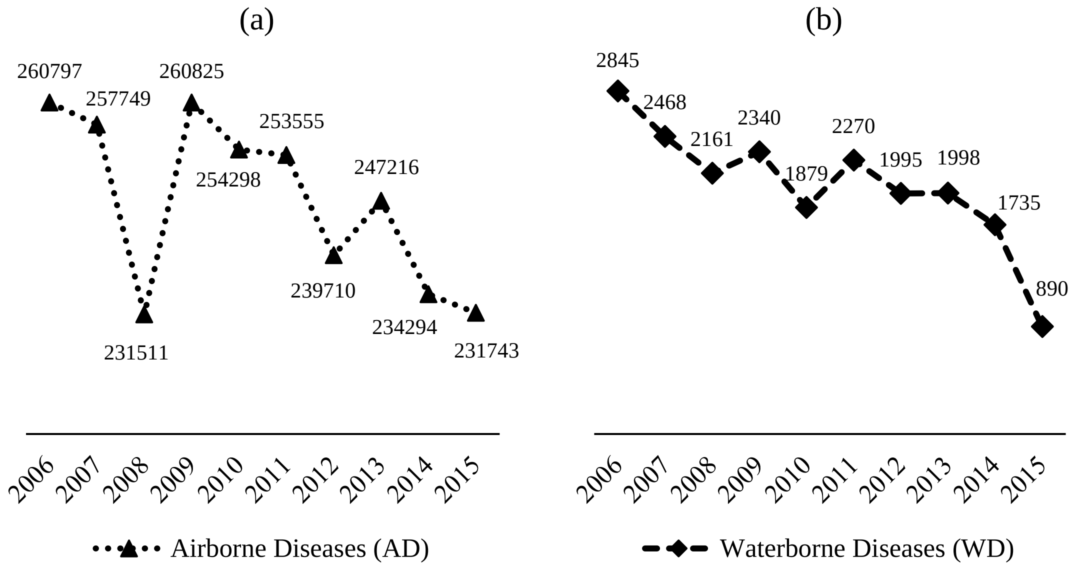

Fig. 2. Number of reported cases of diseases related to air pollution and water pollution in the São Paulo State between 2006 and 2015.
Source: Prepared by the authors based on data from Datasus (2017) and CVE (2017).

In Fig. 2a, the notifications of diseases related to air pollution occur in greater number than the cases associated with water pollution. This may reflect the high urbanization degree in São Paulo State and the industrial concentration of the region.

[11] The list of diseases related to air pollution considered in this analysis is available at: <http://www.datasus.gov.br/cid10/V2008/WebHelp/j00_j99.htm>.
[12] The data on airborne and waterborne diseases take into account the municipality of residence of the individual hospitalized. This procedure eliminates the problem related to pollution exposure in one municipality and hospitalization in another municipality, as in many cases people need to be hospitalized in a different municipality in Brazil due to lack of specialized hospitals in the municipality of residence.

Nonetheless, the number of reported cases on respiratory diseases declined from approximately 261,000 in 2006 to roughly 232,000 in 2015. The number of airborne diseases reduced expressively between 2007 and 2008. According to CETESB (2009), air quality changes due to the distribution and intensity of vehicles and industrial emissions. This is possibly attributed to the crisis in 2008 that resulted in lower economic activity, less traffic and industrial activity as well as less pollution, decreasing the number of hospitalizations.

According to Fig. 2b, notifications of diseases related to ingestion or contact with contaminated water showed a significant reduction in the period, from approximately 3,000 cases in 2006 to about 900 cases in 2015. Larger cities are affected by air and water pollution, whereas medium and small cities are more vulnerable to water pollution, mainly due to the lack of adequate sanitation, excessive use of agrochemicals in crops and prolonged drought, such as the period of dry weather in 2015 in São Paulo State.

Information on municipalities certified by the GBMP was obtained from the Environmental System of the São Paulo State (SAP)[13]. From this information, a dummy variable was created, 1 for municipalities certified by GBMP and 0 for non-certified municipalities. São Paulo State is comprised of 645 municipalities and the spatial distribution of the certificated municipalities by GBMP between 2008 and 2015 can be seen in Fig. 3.

To select the variables that will compose the logit models in this study, we researched in the literature which variables would be correlated with pollution and consequent impact on population health. The literature on air and water pollution diseases shows different relationships between economic activity, increased pollution and effects on human health (Oliveira et al., 2011; Yanagi et al., 2012; Nardocci et al., 2013; Haberman et al., 2014).

[13] In Portuguese, “Sistema Ambiental Paulista (SAP)”.

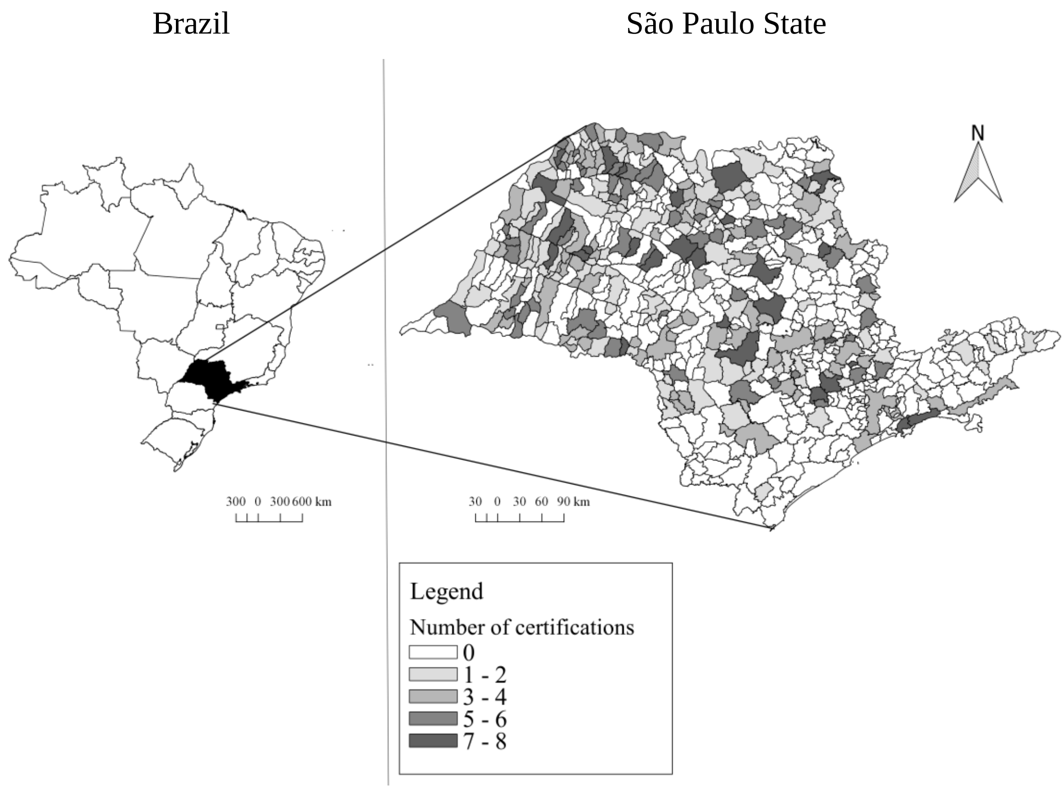

Fig. 3. Spatial distribution of the certificated municipalities by GBMP in São Paulo State between 2008 and 2015
Source: Prepared by the authors based on data from SAP (2016).

According to Habermann et al. (2014), accelerated economic growth and urbanization contribute to increased number of vehicles, a major source of air pollutant emissions, resulting in adverse health effects, such as greater number of hospitalizations, mortality and reduction of life expectancy.

In addition, Oliveira et al. (2011) argue that the long-term exposure to Particulate Matter (PM), if found in massive quantities in the atmosphere, is related to a reduction in life expectancy and the increase in risk of mortality by cardiopulmonary diseases. In urban areas, SO_2 emissions, the main inorganic component of $PM_{2.5}$, are very high, contributing even more to the formation of sulfuric acid (H_2SO_4), which has inflammatory effects on humans and animals, mainly in the lungs, aggravating health problems.

The main emitting sources of PM into the atmosphere are the combustion of fossil fuels and the burning of biomass, such as sugarcane. Thus, São Paulo State constitutes an important source of PM emissions, since it has many industries and an expressive fleet of vehicles, mainly in the metropolitan regions (Oliveira et al., 2011). Yanagi et al. (2012) verified that PM influenced the incidence of some types of cancer (skin, lung, thyroid, larynx and bladder) and increased deaths.

For Habermann et al. (2014), in the city of São Paulo, the regions with lower levels of economic development have small levels of vehicular traffic, presenting lower rates of air pollution. However, individuals with higher income live in areas with greater vehicular traffic and, therefore, more air pollution.

Hence, variables that measure economic growth, urbanization, industrialization and municipal fleet are relevant to the decision to participate in a program to control the emission of pollutants. Based on these arguments, we selected economic and control variables for the composition of the Logit model, such as the Gross Domestic Product (GDP), the Human Development Index (HDI) and the urban population for each municipality in the two years of analysis. We also considered industry and agriculture participation in the added value, because it is assumed that pollution levels are higher in more industrialized cities and with greater agriculture activities.

The choice of variables on "concessionaires" is justified by the possible differences in service quality of provision among the water companies. Fleet variables (automobiles, trucks, motorcycles and micro-buses) were selected because of their collaboration in increasing respiratory diseases due to pollutant emissions of vehicles. The choice of the urbanization degree is because an elevated urbanization level can generate greater pollution and a significant impact on diseases related to water and air quality. Table 2 shows the summary of the selected variables.

Table 2
Variables description (to be continued)

Variable	Description	Source
daa	Aggregation of the number of hospitalizations due to respiratory diseases and cases of waterborne diseases for the years from 2007 to 2015.	Datasus (2017) and CVE (2017)
treat	Dummy: municipalities certified by Green-Blue Municipality Program (GBMP). The variable assumes value 1 for the municipality certified by GBMP and 0 if not certified, from 2009 to 2015.	SAP (2016)
gdp	Gross Domestic Product 2009 from 2014. The value is in *Reais* (R$) of 2015.	SEADE (2017)
popurban	Municipal urban population from 2009 to 2015.	
part_ind_av	Share of the added value of the industrial sector in relation to the total added value in the municipality from 2009 to 2014. The added value is characterized as the value that the activity adds to the goods and services consumed in its production process.	
part_agro_av	Share of the added value of the agricultural sector in relation to the total added value in the municipality from 2009 to 2014.	
aut	Fleet of automobiles in the municipality from 2009 to 2015.	
buses	Fleet of buses in the municipality from 2009 to 2015.	
trucks	Truck fleet in the municipality from 2009 to 2015.	
motorcycle	Motorcycle fleet in the municipality from 2009 to 2015.	

(end)

Variable	Description	Source
micro-buses	Fleet of micro-buses in the municipality from 2009 to 2015.	SEADE (2017)
urb	Share of the urban population in relation to the total population of the municipality from 2009 to 2015.	
hdi	Firjan Municipal Development Index from 2009 to 2013.	FIRJAN (2015)
c_dae	Dummy: Department of Water and Sewage* from 2009 to 2015. The value 1 indicates that the DAE is the concessionary company and the value 0 if not.	CETESB (2017)
c_ch	Dummy: City Hall from 2009 to 2015. The value 1 indicates that the prefecture is the concessionaire and the value 0 if not.	
c_saae	Dummy*:* Autonomous Water and Sewage Service[†] (SAAE) from 2009 to 2015. The value 1 indicates that the SAAE is the concessionary company and the value 0 if not.	
c_sae	Dummy*:* Secretariat of Water and Sewage[€] (SAE) from 2009 to 2015. The value 1 indicates that the SAE is the concessionaire and the value 0 if not.	
c_sabesp	Dummy*:* São Paulo State Basic Sanitation Company** (SABESP) from 2009 to 2015. The value 1 indicates that SABESP is the concessionaire and value 0 if not.	
c_other	Dummy*:* Other concessionaires from 2009 to 2015. The value 1 indicates that other concessionaires act in the municipality and the value 0 if not.	

Note: * In Portuguese "Departamento de Água e Esgoto (DAE)". [†] In Portuguese "Serviço Autônomo de Água e Esgoto (SAAE)". [€] In Portuguese "Secretaria de Água e Esgoto (SAE)". ** In Portuguese Companhia de Saneamento Básico do Estado de São Paulo (SABESP)".
Source: Prepared by the authors.

4. Results

The analysis of possible impact of GBMP requires to find a control group with similar economic and social characteristics to the treated group, differing only from the fact of not receiving the benefit. Tables A.1 and A.2 presented in Appendix A show the characteristics that may influence the probability of joining the program, therefore, it is possible to identify the comparable municipalities among those that did not join the program (Rosenbaum; Rubin, 1983).

Since the program impact analysis will be carried out year by year, the baseline used to the pre-match group mean test also changed year by year. Additionally, the t-student test was adopted with 10% of statistical significance.

In general, 13 variables capture the differences between groups (lngdp, popurban, hdi, c_sae, c_sabesp, part_ind_av, part_agro_av, aut, bus, trucks, motorcycles, micro-buses and urb), considering different years (Tables A.1 and A.2).

The second analysis step of the GBMP effect on the number of notifications of diseases related to water and air quality was the estimation of a Logit probability model of the municipality, certificated or not by the program. The results of this model can be seen in Table 3.

Table 3
Logit Model Results

Variables	2009	2010	2011	2012	2013	2014	2015
ln_gdp	0.0033	0.0001	0.2211	-0.0204	0.0522	-0.1608	-0.0283
	(0.1396)	(0.1384)	(0.1406)	(0.1230)	(0.1756)	(0.1399)	(0.1328)
hdi	1.7930	1.0648	4.3662**	3.8728*	7.3120**	5.8728**	9.1789***
	(1.5849)	(1.7954)	(2.0416)	(2.2512)	(3.1505)	(2.5067)	(2.8203)
popurban	-0.000032***	-0.0000282***	-0.0000278**	-0.0000107**	-0.000031***	-0.0000335***	-0.0000192***
	(0.0000109)	(9.27e-06)	(0.0000125)	(5.10e-06)	(0.0000116)	(0.0000106)	(6.90e-06)
c_dae	-0.0287	0.0071	-0.2779	-0.4603	0.6462	0.1495	-0.7383
	(0.5312)	(0.5728)	(0.5127)	(0.5171)	(0.6770)	(0.5451)	(0.5559)
c_pm	0.4013	0.3169	0.0540	-0.3483	0.3732	-0.0927	-0.6977
	(0.4658)	(0.4923)	(0.4526)	(0.4073)	(0.6166)	(0.4643)	(0.4308)
c_saae	0.2247	0.5674	0.0877	-0.4104	0.6448	-0.0678	-0.5825
	(0.5670)	(0.5490)	(0.5285)	(0.4826)	(0.6181)	(0.5176)	(0.4886)
c_sae	0.7017	1.1118*	1.1689**	0.6699	0.6641	-0.1143	-1.0930
	(0.6205)	(0.6060)	(0.5770)	(0.5416)	(0.7831)	(0.6559)	(0.8231)
c_sabesp	0.9470**	0.7060	0.4062	-0.2113	0.6186	0.1418	-0.4399
	(0.4294)	(0.4431)	(0.4182)	(0.3474)	(0.5336)	(0.4080)	(0.3635)
part_ind_av	-0.0042	-0.0052	-0.0194**	-0.0165*	-0.0120	-0.0074	-0.0148
	(0.0094)	(0.0097)	(0.0096)	(0.0089)	(0.0114)	(0.0097)	(0.0101)
part_agr_av	0.0173**	0.0133	0.0222**	0.0033	0.0185	-0.0050	-0.0015
	(0.0078)	(0.0081)	(0.0091)	(0.0093)	(0.0120)	(0.0096)	(0.0111)
aut	0.000045	0.0001**	0.000048	-0.0001	0.0001	0.0000457	0.0000395*
	(0.0012179)	(0.0000305)	(0.0000407)	(0.0000324)	(0.000035)	(0.0000293)	(0.000024)
buses	-0.0007	-0.0025*	-0.0019*	-0.0011	-0.0011	-0.0024**	-0.0017*
	(0.0012)	(0.0015)	(0.0011)	(0.0008)	(0.0010)	(0.0010)	(0.0009)
trucks	0.0001	-0.0003	-0.0003	0.0000404	0.0002	0.0002	0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
motorcycles	0.0000993***	0.0001**	0.0000385	0.0000221	0.0001**	0.0001**	0.0000418
	(0.000037)	(0.0000331)	(0.0000257)	(0.0000241)	(0.0000294)	(0.0000308)	(0.0000283)
micro-buses	0.0001	0.0001	0.0002	0.0005**	-0.0000255	0.0001	-0.0000139
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
urb	0.0263***	0.0251***	0.0260***	0.0157*	0.0318*	0.0318***	0.0164
	(0.0083)	(0.0085)	(0.0098)	(0.0093)	(0.0190)	(0.0119)	(0.0123)
constant	-5.4707***	-4.7181**	-9.4798***	-4.9398**	-11.6755***	-6.4592***	-8.8860***
	(1.9206)	(1.8320)	(2.1284)	(2.0096)	(3.2773)	(2.2902)	(2.5543)
N	645	645	645	645	645	645	645
Pseudo R^2	0.0654	0.0688	0.0907	0.0855	0.0935	0.1123	0.1260
Wald	41.65***	49.48***	61.16***	42.10***	31.29**	52.59***	64.01***

Note: Asterisks denote statistical significance at 1% (***), 5% (**), or 10% (*) level. Error Deviation between parenthesis.
Source: Prepared by the authors.

In total, 645 municipalities of São Paulo State were used in logit analysis. The null hypothesis that all coefficients are equal to zero was rejected at the significance level of 5%, showing a robustness of the model considering the coefficients together. The statistically significant coefficients were: hdi, popurban, c_sabesp, c_sae, urb, aut, buses, motorcycles, micro-buses, part_agro_av and part_ind_av.

In general, the results indicate that the HDI, agricultural participation in the added value, variables on “concessionaires” (SAE or SABESP), number of automobiles, motorcycles and micro-buses and the urbanization degree have a positive relation with the probability of participation in the program. However, urban population, number of buses in the municipality and industry participation in the added value have a negative impact, i.e., the higher the value of these variables, the lower the probability of the municipality to participate in the program.

Fig. 4 shows the probability distribution of participating in GBMP for each of the groups (participants and non-participants) before the matching procedure. There is no overlap between the two groups. Thus, the treatment and control groups are not statistically comparable in terms of observable characteristics; therefore, matching is necessary.

As described in the methodology section, propensity scores are created by pairing the treatment group with the control group. Afterward, it is possible to perform balancing tests to verify if the differences of the observable characteristics that existed between the two groups before the pairing are statistically non-significant, making them similar (balanced).

The balancing statistics (standardized bias and t-students) for all algorithms considered are presented in Appendix B of this study. For all years, most of the covariates used for the construction of the propensity scores were balanced at the significance level of 5%; therefore, there is no need for a new estimation of the Logit model from the more parsimonious models (Heinrich et al., 2010).

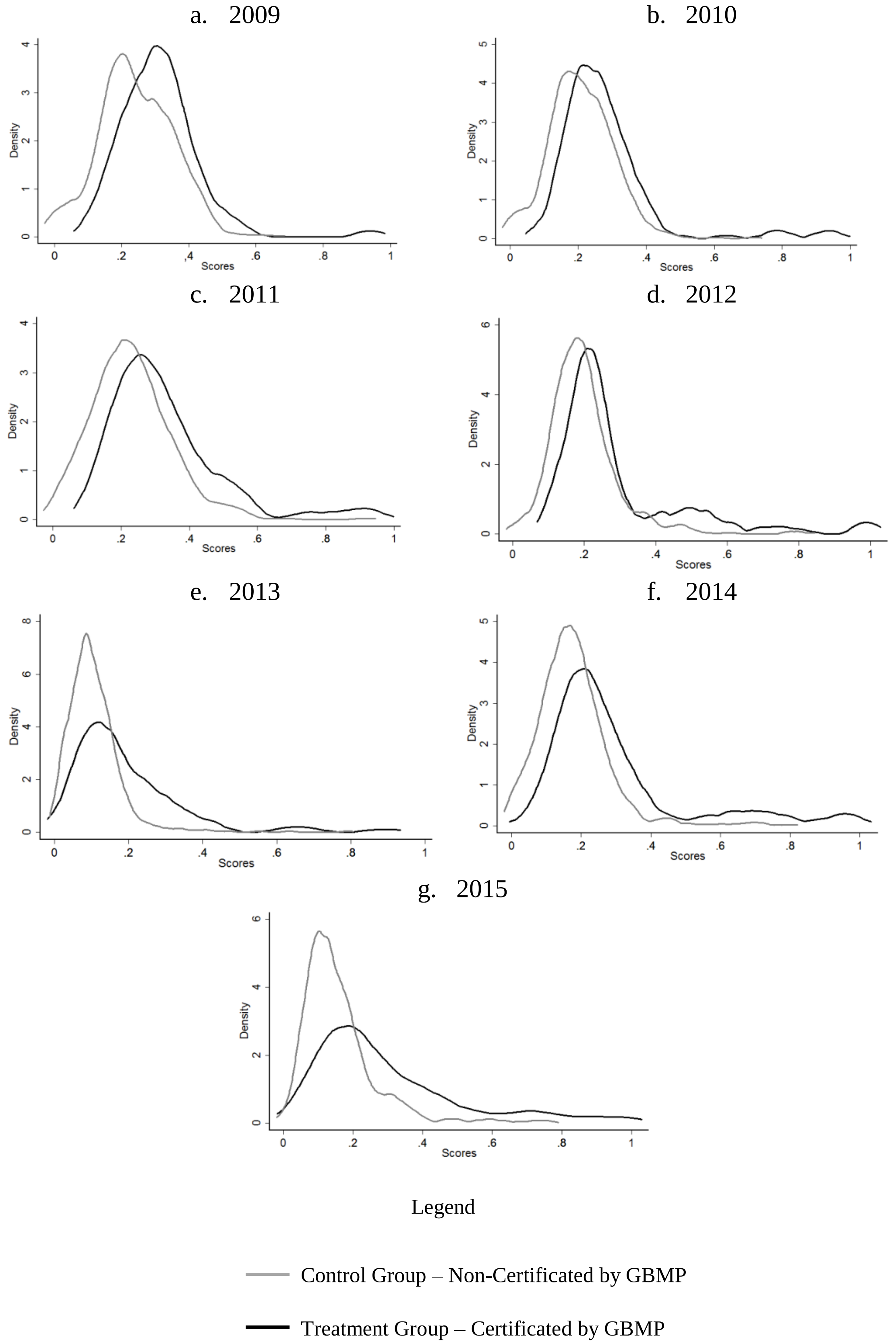

Fig. 4. Distribution of probability of participating in GBMP before pairing.
Source: Prepared by the authors using the STATA v.13 software.

The estimated impact of GBMP on the number of cases of diseases related to water and air quality is shown in Table 4. In general, the results indicate for all years considering the DID estimator without the paired sample (Naive estimator) and all matching techniques, no statistically significant reduction in the number of cases of diseases related to air and water quality in municipalities certified by GBMP in Sao Paulo State, except for the result for nearest neighbor with the caliper technique for 2015. In this case, this result can show long-run effect of GBMP.

Table 4
GBMP certification effect on the number of notifications of water and air diseases in the period of 2009-2015

Pairing Techniques	2009 - 2007	2010 - 2007	2011 - 2007	2012 - 2007	2013 - 2007	2014 - 2007	2015 - 2007
No Matching (Naive Estimator)	10.537 (14.343)	-1.812 (16.516)	7.904 (16.112)	-14.614 (25.057)	11.878 (26.282)	15.802 (29.510)	1.166 (33.534)
Nearest neighbor without caliper	-2.668 (10.966)	-18.381 (12.682)	-8.074 (18.910)	-18.474 (15.741)	13.148 (45.614)	-8.725 (14.103)	-39.184 (20.345)
Nearest neighbor with caliper†	-1.775 (11.981)	-6.937 (11.642)	0.120 (15.624)	0.182 (13.297)	-6.854 (20.823)	-4.788 (22.065)	-35.492*** (17.063)
Kernel€	-0.761 (12.476)	-7.078 (12.703)	11.261 (16.757)	-18.227 (14.348)	-10.666 (21.478)	-5.199 (21.883)	-40.667 (25.898)
Matching covariate	4.440 (12.528)	21.848 (28.651)	21.182 (16.099)	-0.638 (40.115)	-20.52 (32.36)	0.153 (21.474)	-6.15 (25.808)

Note: † the caliper size is defined as a ¼ of the standard deviation of the propensity score (Rosenbaum; Rubin, 1983); € optimum bandwidth is calculated according to the Silverman (1986) rule. Error Deviation between parenthesis.

This result suggests that, even after eight years of existence of public policy, no substantial positive externalities have been verified for the Unified Health System (SUS)[14], that is, a significant reduction in the number of cases of diseases associated with air and water pollution released into the environment.

Our result seems to be in line with Gehrsitz (2017), who investigated the effect of low pollution areas in Germany on air quality and the impact on children's health. Although the results indicate that the adoption of more restrictive low emission areas contributed to reducing pollution levels, the author argues that this reduction has not been sufficient to have effect on improving the health of children.

However, unlike our results, the work of Li et al. (2017) found significant outcomes for a similar analysis developed in China. Li et al. (2017) studied the effects of the Environmental Non-Governmental Organizations (ENGOs). The ENGOs policies comprises a set of environmental issues, such as environmental education, biodiversity, energy conservation, water and air pollution, and projects of dams and hydropower. In

[14] In Portuguese “Sistema Único de Saúde (SUS)”.

China, a central ENGO called Institute of Public and Environmental Affairs (IPEA) constructs yearly a “pollution map” and calculates the “Pollution Information Transparency Index” (PITI) to evaluate eight categories of environmental policies in China. After the calculation of PITI, cities with a better pollution control are ranked on a PITI list. The study used the method of DID and the PSM-DID model to check robustness.

For the DID model, the study of Li et al. (2017) showed a significantly negative impact of ENGOs on pollution emissions in the cities on the PITI list, demonstrating a reduction of the pollution if compared with the non-PITI list cities. However, the cities with ENGOs were chosen to receive an environmental management due to serious pollution, which can be source of bias in the DID model (in this case the model could not guarantee that the enter in PITI list is random). Therefore, the authors used the PSM-DID model with kernel matching method to test robustness of the DID results. The results of the PSM-DID model show that the ENGOs have a negative impact on the pollution level in the municipalities with this type of environmental policy management.

The non-corroboration of the initial hypothesis of this study can be explained by some reasons. First, due to the short time of GBMP implementation, significant changes in conducting the municipal environmental policy have not yet been observed. Second, there is little publicity of GBMP to the population, resulting in low visibility of the program, which discourages a greater number of adhesions by mayors. Third, there is a large set of policies required for the entry and possible certification in the GBMP. In contrast, there is an incomplete system of economic benefits for municipalities that join the program. Hence, from the municipal management viewpoint, the benefits may not offset the costs incurred to achieve GBMP certification. Forth, the effects of GBMP on the number of cases of diseases related to air and water quality are underestimated due to the lack of municipal information on waterborne diseases, such as Diarrhea and Rotavirus. For Diarrhea, a possible explanation would be the self-medication and the consequent absence of demand for the Unified Health System (SUS) by the individuals, since the population considers it a disease with low severity.

According to Li et al. (2017), in China there is a “political tournament”, which stimulates the desire for accelerated GDP growth in local governments, resulting in several environmental problems. In Brazil, mayors are elected every four years; thus, the “political tournament” is a key factor that can affect adherence to GBMP. The change of political management (mayors) can influence adhesion to the GBMP and possible certification. Non-certification in one year may discourage voluntary membership in the next year, avoiding progress of public policy and consequently generating no significant effect on individual's health in each municipality. This is the fifth reason for no-effective results of GBMP.

In Brazil, GBMP discloses the list with all municipalities that joined to the program, but environmental information on municipalities that were not running for a GBMP certificate is not publicized, contributing to the perpetuation of environmental standards of each non-participating municipality. Similarly, Li et al., (2017) pointed that, in China, local governments do not publicize environmental information on cities with less pollution control because of a consciousness that "local shame should not be made public".

However, a result that calls attention is the significant impact for 2015 considering the nearest neighbor with the caliper technique. In this case, municipalities certified by GBMP have approximately 35 cases of diseases less than non-certified municipalities do. This suggests that the program is beginning to have an effect on human health. Nevertheless, future studies should investigate if there will be major and significant effects of certification on cases of diseases in the coming years.

5. Conclusions

This study evaluated the impact of GBMP on the number of cases of diseases regarding air and water quality between 2007 and 2015 in the municipalities of São Paulo State.

The identification strategy used combined the methods of PSM and DID. After the matching and tests related with the pairing procedure, the control and treated group were balanced. The results of DID-matching indicate that the GBMP had no effect on the number of hospitalizations due to airborne and waterborne diseases.

Some potential causes for this result can be highlighted. The brief time of program implementation, the little publicity and the need of better definition of benefits associated with participation in the program are the first reasons that we identify in our analysis. In addition, the lack of information on disease numbers, the Brazilian political tournament and non-release environmental data of all municipalities of state can contribute to non-significant GBMP results.

Therefore, program improvement is suggested through a clearer system of benefits and more economically efficient, making it attractive for adhesion of local public management. In addition, a better focus of the program, with well-defined goals, can aid implementation, conduction and its success.

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Appendix A. Pre-match group mean test

Table A.1. Pre-match group mean test for municipalities Certificated versus Non-Certificated by GBMP from 2009 to 2015 (Difference+)

Variable	2009	2010	2011	2012	2013	2014	2015
lngdp	0.1585	0.0412	-0.1999	-0.3457**	-0.5477***	-0.5425***	-0.8272***
	(0.1464)	(0.1588)	(0.1533)	(0.1614)	(0.2077)	(0.1663)	(0.1698)
popurban	28,304	-75,859.8*	-71,843.9*	-88,600.2**	-16,229.7	-11,725.6	-2,2511.1
	(39,872.5)	(42,378.5)	(40,879)	(43,295.5)	(56,341.2)	(45,297.1)	(46,975.2)
hdi	-0.0094	-0.0074	-0.0199***	-0.0214***	-0.0351***	-0.0352***	-0.0449***
	(0.0069)	(0.0070)	(0.0061)	(0.0062)	(0.0092)	(0.0073)	(0.0075)
c_dae	0.0226	0.0220	0.0161	0.0056	-0.0169	-0.0148	0.0090
	(0.0247)	(0.0255)	(0.0244)	(0.0241)	(0.0303)	(0.0242)	(0.0236)
c_ch	0.0339	0.0363	0.0388	0.0355	0.0368	0.0422	0.0564
	(0.0345)	(0.0363)	(0.0349)	(0.0357)	(0.0457)	(0.0377)	(0.0395)
c_saae	0.0173	-0.0109	-0.0088	0.0028	-0.0355	-0.0187	-0.0224
	(0.0214)	(0.0225)	(0.0216)	(0.0225)	(0.0296)	(0.0237)	(0.0250)
c_sae	-0.0123	-0.0271	-0.0442***	-0.0381**	-0.0102	0.0003	0.0100
	(0.0159)	(0.0171)	(0.0163)	(0.0173)	(0.0213)	(0.0170)	(0.0158)
c_sabesp	-0.0782*	-0.0273	0.0228	0.0505	0.0751	0.0766	0.0976*
	(0.0445)	(0.0469)	(0.0449)	(0.0473)	(0.0610)	(0.0487)	(0.0501)
part_ind_av	2.1747*	2.3860	2.3705*	0.9688	-0.2289	-1.3358	-1.9568
	(1.3188)	(1.5114)	(1.4239)	(1.4823)	(1.7933)	(1.3899)	(1.4318)
part_agro_av	-3.3051**	-2.4671	-2.0599	1.8039	1.3135	3.6301***	4.5797***
	(1.4378)	(1.5315)	(1.3957)	(1.3926)	(1.7408)	(1.3540)	(1.3919)
aut	8,637.5	-34,355**	-33,328.2*	-45,878.9**	-10,493.5	-8,370.9	-12,508.5
	(16,090.5)	(17,432.3)	(17,177.8)	(18,478.5)	(24,614.2)	(20,412.0)	(21,675.6)
bus	86.8	-260.5*	-257.6*	-317.2**	-57.4	-25.7	-63.3
	(140.3)	(148.9)	(148.2)	(156.9)	(203.8)	(170.2)	(177.1)
trucks	290.3	-1,075.3*	-1,076.2**	-1,602.3***	-697.1	-600.0	-830.4
	(555.5)	(570.1)	(537.9)	(549.4)	(708.4)	(587.4)	(625.8)
motorcycles	670.7	-6,991**	-7,323**	-10,838.0***	-5,229.9	-4,924.8	-6,557.2
	(2,761.2)	(3,124.9)	(3,199.8)	(3,497.5)	(4,711.4)	(3,944.6)	(4,238.3)
micro-buses	1,179.1	-5,327.2**	-5,504**	-7,970.9**	-1,999.9	-1,704.3	-2,448.7
	(2,375.8)	(2,681.2)	(2,780.6)	(3,089.8)	(4,253.4)	(3,666.0)	(4,002.9)
urb	-1.3699	-1.8589	-2.9093**	-3.6094***	-4.4253***	-4.8648***	-4.7443***
	(1.2865)	(1.3462)	(1.2772)	(1.3333)	(1.7075)	1(.3485)	(1.3821)

Note: + Mean difference of control and treatment group.

The asterisks denote statistical significance at 1% (***), 5% (**), or 10% (*) level. Error Deviation Difference between parenthesis.

Source: Prepared by the authors.

Appendix B. Balancing statistics between Certificated and Non-Certificated by GBMP

Table B.1. Balancing statistics between Certificated and Non-Certificated by GBMP in 2009 a 2011 (Bias %)

	2009				2010				2011			
	Nearest neighbor without caliper	Nearest neighbor with caliper	Kernel	Covariate matching	Nearest neighbor without caliper	Nearest neighbor with caliper	Kernel	Covariate matching	Nearest neighbor without caliper	Nearest neighbor with caliper	Kernel	Covariate matching
ln_gdp	0.8	0.2	1.7	11.6	-0.5	2.6	2.8	7.2	19.0	5.5	4.3	12.5
hdi	-3.4	1.1	2.1	7.3	-5.1	0.2	0.9	5.7	7.4	4.4	4.7	11.7
popurban	-0.2	-0.5	0.7	7.2	-0.1	0.2	0.1	13.2	11.7	10.3	8.4	13.1
c_dae	-9.0	-2.8	-1.3	0.0	0.0	0.5	-2.0	0.0	-2.3	-1.7	0.5	0.0
c_pm	0.0	-3.5	-4.0	0.0	-9.6	-3.8	-4.0	0.0	-3.3	0.4	0.1	0.0
c_saae	-7.8	-2.2	-2.5	0.0	-5.9	-2.2	-0.7	0.0	-2.5	-0.6	1.3	0.0
c_sae	-9.7	-1.5	-1.2	0.0	-7.2	4.7	5.4	0.0	3.0	1.7	2.0	0.0
c_sabesp	6.1	3.3	3.6	0.0	11.6	1.7	1.0	0.0	-3.7	0.3	-0.8	-1.2
part_ind_av	-1.7	-2.8	-1.6	6.0	-3.6	0.0	0.3	-1.4	15.8	1.8	3.3	-4.2
part_agro_av	-0.1	0.9	0.0	-2.6	7.4	-0.9	-1.0	-0.8	-15.9	-1.9	-1.7	-0.3
aut	0.6	0.7	0.5	4.3**	0.0	0.2	0.1	13.5	11.8	10.3	8.1	13.4
bus	0.5	0.9	0.6	3.7**	0.4	0.3	0.2	12.7	11.0	10.5	7.4	12.5
trucks	0.8	0.8	0.8	5.4**	0.0	0.9	0.6	13.9	12.3	10.3	7.0	14.7
motorcycles	1.2	0.5	0.9	7.6*	-0.1	0.6	0.4	15.1	12.5	10.0	8.1	15.4
micro-buses	0.5	0.7	0.5	4.3**	-0.1	0.2	0.1	13.4	11.6	10.3	7.9	13.4
urb	-1.6	0.5	1.4	1.5	-4.7	-0.2	0.2	0.4	9.3	0.3	0.7	0.3

Note: The asterisks denote statistical significance at 1% (***), 5% (**), or 10% (*) level.
Source: Elaboration of the authors based on the results of the Logit model.

Table B.2. Balancing statistics between Certificated and Non-Certificated by GBMP in 2012 a 2015 (Bias %)

	2012				2013				2014				2015			
	Nearest neighbor without caliper	Nearest neighbor with caliper	Kernel	Covariate matching	Nearest neighbor without caliper	Nearest neighbor with caliper	Kernel	Covariate matching	Nearest neighbor without caliper	Nearest neighb or with caliper	Kernel	Covariate matching	Nearest neighbor without caliper	Nearest neighbor with caliper	Kernel	Covariate matching
ln_gdp	13.0	15.8	15.1	11.1	-23.7	-6.8	-6.4	17.7	3.7	3.3	3.4	17.1	2.5	1.5	1.8	18.4
hdi	12.9	11.5	9.8	13.3	-6.5	-0.9	-1.4	15.4	-0.3	2.6	2.2	13.9	-1.4	0.9	1.5	20.5*
popurban	2.2*	1.7	1.9	13.4	-3.2	-1.6	-0.5	5.3	3.5	1.1	1.6	7.4*	1.1	0.8	0.6	8.3*
c_dae	-2.9	0.4	-0.5	-2.8	-5.2	3.8	2.5	0.0	-6.3	0.8	1.6	0.0	3.9	6.4	5.4	0.0
c_pm	0.0	-1.8	-1.6	0.0	0.0	2.2	2.5	0.0	-6.5	-1.1	-1.7	-2.1	0.0	-1.4	-2.2	0.0
c_saae	0.0	3.5	3.1	0.0	5.1	0.0	1.4	0.0	3.2	1.7	1.9	0.0	10.2	1.1	2.8	0.0
c_sae	-7.1	1.1	1.1	0.0	7.3	3.3	4.9	0.0	-13.9	1.0	0.7	0.0	-6.0	0.1	0.4	0.0
c_sabesp	2.9	-8.1	-10.1	1.4	0.0	-4.4	-5.9	0.0	8.1	2.3	2.5	-1.5	-8.8	-2.4	-3.0	-5.0
part_ind_av	5.0	5.3	5.4	-3.6	2.9	1.4	1.3	4.6	2.9	-0.2	0.8	6.0	0.1	-0.9	1.1	4.7
part_agro_av	-9.9	-7.0	-6.4	-0.7	25.6	8.0	8.1	-6.3	-5.4	0.1	-0.1	-6.5	7.9	0.4	0.3	-5.2
aut	2.0	1.0	1.1	15.5	-2.7	-1.7	-0.4	6.2	3.1	1.0	1.4	7.8*	1.5	0.9	0.7	8.5*
bus	1.8	1.7	1.4	13.7	-3.8	-3.0	0.0	4.8	2.0	0.6	0.9	5.7	1.4	0.6	0.4	6.5
trucks	4.0*	1.7	2.0	18.0	-7.0	-3.5	-0.9	9.1	3.9	2.0	2.4	11.4*	1.6	0.5	0.4	13.1*
motorcycles	3.5	1.4	2.1	17.7	-5.7	-1.6	0.3	10.3	5.3	1.6	2.1	13.5**	1.6	1.6	1.0	14.8**
micro-buses	2.1	1.2	1.2	15.9	-2.5	-1.4	0.5	6.6	3.0	1.3	1.6	8.3*	1.5	1.0	0.7	8.9*
urb	-5.9	1.7	1.6	1.6	-9.7	2.0	1.5	13.1	-0.3	-2.0	-1.7	5.3	-5.3	-0.8	-0.9	3.7

Note: The asterisks denote statistical significance at 1% (***), 5% (**), or 10% (*) level.
Source: Elaboration of the authors based on the results of the Logit model.