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Weather and population size effects on water and sewer treatment costs: Evidence from Brazil

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ABSTRACT

The provision of sanitation services generates investments, employment, and income; they contribute to human capital stock accumulation, and, therefore, to economic development. Recent studies suggest that climate change can increase sanitation costs, and it can be a constraint to emerging economies where institutional inefficiencies raise challenges to the universal supply of these services. We combined data of sanitation companies collected by the Brazilian government and the historical weather data from Xavier et al. (2015) generating a unique dataset between 1995 and 2016 to test the weather effects on sanitation costs. The results indicate that water treatment costs increase if the temperature rises, while sewer treatment costs decrease. We also found evidence that the migrating population from smaller to larger cities in Brazil can overload the sanitation infrastructure and increase the costs. Technical change estimates are -0.67% per year on average, indicating the non-sustainability of the sector in the long run.

1. Introduction

The economics literature has demonstrated a positive effect of human health on output growth. Better health levels are associated with higher individual earnings, labor productivity, and physical capital investments (Noronha et al., 2010). Despite basic sanitation being fundamental for enhancing productivity, there are still many countries with an insufficient supply of water and sewer treatment. The world still leaves untreated human waste of 4.2 billion people and the universal provision of safe water and sanitation by 2030 is at the risk of not being achieved (UNICEF and WHO, 2020). There is a wide variety of challenges associated with the expansion of sanitation services in low-income countries, such as improving the efficiency of sanitation services under high-density population areas and climate change events (UNICEF and WHO, 2020).

Several countries in Latin America, including Brazil, have the majority of their population without access to safely managed sanitation services (UNICEF and WHO, 2020). In Brazil, 35 million people do not have access to piped water, and 100 million people do not have proper sewer collection, which is about 16.5% and 47% of the Brazilian population, respectively (SNIS, 2019). The expansion of sanitation services in Brazil could improve life expectancy (Soares et al., 2003), reduce infant mortality (Gamper-Rabindran et al., 2010), and even reduce gender gaps in education (Zhang and Colin, 2010). In this sense, water-use efficiency and water productivity contribute positively to economic development through sustainable water management, infrastructure, and adequate sanitation. Additionally, resource-efficient technologies may create opportunities for employment, especially in water-dependent sectors under conditions of water scarcity (United Nations, 2016).

Since 2013, the National Plan for Basic Sanitation (PLANSAB) has had the goal to provide water and sewer for, respectively, 99% and 92% of Brazilian households until 2033 (BRASIL, 2013). However, the current trend indicates that institutional improvements should be developed to achieve these goals. Combining the results from SNIS (2019) and Saiani and Toneto (2010) the water treatment coverage grew by 0.65% per year, and sewer collection grew by 1.4% per year, on average, between 1990 and 2017; that is, the goals set in PLANSAB for water coverage could be reached only in 2044 and, for sewer, only in 2058. In this sense, productivity and efficiency improvements are indispensable to speed up the sanitation coverage expansion.

Previous results in the literature suggest that economies of scale, scope and density are driving sources for improving the productivity of water and sewer treatment, as well as the institutional framework and the quality of water in springs. On the other hand, there is mixed evidence about ownership effects on technical efficiency (Appendix A).

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Climate change can affect the efficiency of water and sewer treatment by extreme weather events like droughts, floods, storms, and sea-level rise increasing the pressure on sanitation infrastructure (Zouboulis and Tolkou, 2015). In Brazil, climate change could increase floods in the Southeast and South regions, deteriorating the quality of water springs (Tiezzi et al., 2019). Abbott et al. (2012) argued that the performance of sanitation companies in Australia has been affected by alterations in the hydrological balance of Australian streams as a consequence of climate change. Souza et al. (2007) claimed that climate uncertainty requires collective actions from the economic agents; however, the sanitation sector has institutional dissonances in Brazil that do not favor coordinated decisions for dealing with these challenges (Barbosa et al., 2016); (Sampaio and Sampaio, 2020).

The sanitation companies' productivity is also related to population size variations. Urbanization and migration set challenges to provide sanitation services efficiently (UNICEF and WHO, 2020). Small cities can face difficulty in using their sanitation facilities optimally; on the other hand, large cities can have their sanitation infrastructure pressured by population growth (e.g., (Tupper and Resende, 2004); (Filippini et al., 2008); (Abbott et al., 2012)). Estimations from the Brazilian Institute of Geography and Statistics (IBGE) indicate that the group of municipalities under 20,000 inhabitants is the one with a higher number of municipalities that had reduced its population in 2020 when compared to 2019. Otherwise, the group with a population between 100,000 and 1,000,000 inhabitants presented a higher proportion of municipalities with population growth. Municipalities with more than 1,000,000 inhabitants grew 0% to 1% between 2019 and 2020 (IBGE, 2020a).

Over the last three decades, Brazil has increased life expectancy, reduced child mortality and improved access to the public health system. On the other hand, the country faces relatively scarce access to basic sanitation services. Brazil has begun the 2020's with insufficient water and sewage treatment, the absence of an active regulatory agency and population dynamics indicating demographic concentration in medium and large cities. At the same time, changes in temperature and rainfall as a consequence of climate change can jeopardize the Brazilian sanitation expansion and sustainability. Therefore, it is essential to understand the cost-effects associated with these dynamics in order to universalize sanitation services and boost Brazilian economic development.

The objective of this paper is to estimate the effects of weather (atmospheric temperature and rainfall) and population size on Brazilian water and sewer treatment companies (WSTC). The results provide evidence for public policies that can boost the supply of water and sewage treatment services, contributing to foster a healthy environment, form human capital and promote insights to improve sanitation services in developing countries.

The rest of the paper is organized as follows: Section 2 presents the theoretical framework and the empirical model, discusses the construction of the dataset for empirical estimation and selected variables; Section 3 presents the results and discussion; Section 4 provides a conclusion.

2. Methodology

This study complements other recent studies on Brazilian water and sewage treatment, adopting an original empirical model at the firm-level that controls for different technologies and estimates the effects of atmospheric temperature, rainfall and population size on sanitation costs. Since our objective is to examine the cost efficiency of the sewer and treatment companies, we use a cost frontier approach that is represented by:

$$C_{it} = C^*_{it}\left(p_{it},\ y_{it}; \beta_i\right) \times A_{it} \tag{1}$$

where A_{it} is interpreted as either technical efficiency or TFP (Atkinson and Cornwell, 1994; Griffith et al., 2004; Amiti and Konings, 1981), among others). We keep the spirit of these formulations but depart from them in decomposing A_{it} into various components. More formally, we specify $\ln A_{it} = \mu_i + v_{it} + \eta(Z_i^\eta) + u(Z_{it}^u)$.

In doing so, we are decomposing technical efficiency (TFP) into a persistent (time-invariant) and a transient (time-varying) components, in addition to time-invariant firm effects and random noise. Logarithms of these efficiency components, i.e., $\eta(Z_i^\eta)$ and $u(Z_{it}^u)$, are interpreted as persistent and transient inefficiency, respectively.[1] In stochastic frontier (SF) models these components are assumed to be random (see, for example, p. Lai and Kumbhakar (2018), and the references cited in there).[2] Here we specify these inefficiencies as functions of exogenous variables Z_i^η and Z_{it}^u. $C^*_{it}(.)$ is the standard neoclassical cost function for which the arguments are input prices (p_{it}) and outputs (y_{it}). In our application C_{it} are the production costs of WSTC (water and sewer treatment company) i in year t; $\ln C^*\left(p_{it},\ y_{it}; \beta_i\right)$ is the cost frontier (translog); p_{it} is the vector of input prices; y_{it} is output; β_i and β_t are the parameters to be estimated; t is a trend variable that is introduced to allow for neutral technical change. Finally, μ_i are unobserved firm-effects, and v_{it} are random noise (productivity shocks).

We specify the cost function in (1) as

$$\ln C_{it} = \ \alpha_0 + \ln C^*_{it}\left(p_{it},\ y_{it}; \beta_i\right) + \beta_t\ t\ +\ \mu_i + v_{it} + \eta(Z_i^\eta) + u(Z_{it}^u) \tag{2}$$

where η_i and u_{it} are the persistent and transient inefficiency components and Z_i^η and Z_{it}^u are, respectively, the vectors of exogenous determinants of persistent and transient inefficiency.[3] Without the inefficiency (TFP) components, the model in (1) is a standard panel cost function. This is a testable hypothesis. Similarly, one can test whether cost efficiency is only persistent or only transient. For example, Atkinson and Cornwell (1994), considered a cost frontier specification in which $\ln A_{it} = \mu_i + v_{it}$, and they treated μ_i as inefficiency. Thus, their model is much more restrictive in the sense that they did not take into account persistent and transient inefficiency components.

The model in (1) can be estimated using a SF approach in which all the components in $\ln A_{it}$ are assumed to be random with some specific distributions on them.[4] In this paper we consider a non-stochastic frontier approach meaning that both the (in)efficiency components are non-stochastic (deterministic) functions. The advantage of this approach is that we do not need to make any distributional assumptions. That is, instead of assuming that the persistent and transient inefficiency are random (as done in SF models), we specify them as deterministic functions in terms of the means of $\eta(Z_i^\eta)$ and $u(Z_{it}^u)$, denoted by $g_\eta(Z_i^\eta)$ and $g_u(Z_{it}^u)$, respectively. The downside of this is that we cannot identify the constant terms in the persistent and transient inefficiency components and therefore, we can estimate relative (not absolute) efficiencies.[5] Relative efficiency estimates are not of any concern because we can estimate the marginal effects of Z_i^η and Z_{it}^u on (in)efficiency without knowing their absolute levels. This is because the marginal effects of Z_i^η and Z_{it}^u on the absolute and relative efficiency are the same. Our focus in this paper is on the marginal effects of Z_i^η and Z_{it}^u on cost. In percentage terms the marginal effects of Z_i^η and Z_{it}^u

[1] Technical inefficiency and efficiency are often used interchangeably used because efficiency is defined as $\exp(-\text{inefficiency}) \approx 1 -$ inefficiency.

[2] In a JDE paper back in the early 1980s, Pitt and Lung-Fei (1981), were the first to propose a panel SF model to estimate efficiency of Indonesian weaving firms. To investigate the sources of inefficiency they regressed the firm intercepts (obtained from the analysis of covariance) on firm characteristics because estimates of observation-specific (in)efficiency were not available in 1981. Things have changed since then.

[3] From now on, the time trend variable t will be included in $\ln C^*$.

[4] The typical distributions are: $\eta_i \ \sim N^+(0, \sigma_\eta^2(Z_i^\eta))$ and $u_{it} \ \sim N^+(0, \sigma_u^2(Z_{it}^u))$; $v_{it} \ \sim N(0, \sigma_v^2)$ and $\mu_i \sim N(0, \sigma_\mu^2)$, where N^+ refers to a half-normal distribution. See p. Lai and Kumbhakar (2018), for example.

[5] See Atkinson and Cornwell (1994). Lau and Yotopoulos (1971), also used the concept of relative efficiency in a cross-sectional model in which the deterministic part of $\ln A_i$, in our notation, is a function of farm size dummies.

on inefficiency and cost are the same (i.e., $\partial \ln C_{it}/\partial Z_i^\eta = \partial g_\eta(Z_i^\eta)/\partial Z_i^\eta$ and $\partial \ln C_{it}/\partial Z_{it}^u = \partial g_u(Z_{it}^u)/\partial Z_{it}^u$).

Using the deterministic functions $g_\eta(Z_i^\eta)$ and $g_u(Z_{it}^u)$ to represent persistent and transient inefficiencies, we rewrite the cost function in (2) as:

$$\ln C_{it} = g_\eta(Z_i^\eta) + g_u(Z_{it}^u) + \ln C_{it}^* \left(p_{it},\ y_{it}; \beta_i\right) + \alpha_i + v_{it} \tag{3}$$

where α_i are the firm effects, v_{it} are i.i.d. noise with zero mean. For fixed effects, we assume $\sum_i \alpha_i = 0$ for identification. Similarly for random effects, we assume $E(\alpha_i) = 0$ and α_i are uncorrelated with the variables in the cost function. This is unlikely to be the case in a production function where the arguments are inputs which are likely to be correlated with firm effects. However, in a cost function, the firm effects are unlikely to be correlated with the arguments of the cost function (input prices and outputs) which are exogenous to the firms. This is especially true when outputs are outside firms' control which is the case in our application.

It is worth mentioning that our model in (3) is very general and is the state-of-the-art in efficiency models. Many of the existing panel efficiency models can be derived from (3) as special cases. Of particular interest are models with either no persistent (transient) inefficiency or no inefficiency at all. To implement the model in (3) empirically we use the following steps. In Step 1 we assume $g_\eta(Z_i^\eta)$ and $g_u(Z_{it}^u)$ to be non-parametric. And use transformation to remove them from (3). For this, we take the expectation of every variable conditional on Z_i^η and Z_{it}^u and subtract these conditional means from (3) to obtain (4) below:

$$\ln \overline{C}_{it} = \ln \overline{C}_{it}^* \left(p_{it},\ y_{it}; \beta_i\right) + \alpha_i + v_{it} \tag{4}$$

where,
$\ln \overline{C}_{it} = \ln C_{it} - E(\ln C_{it}|Z)$ and $\ln \overline{C}_{it}^* \left(p_{it},\ y_{it}; \beta_i\right) = \ln C_{it}^* \left(p_{it},\ y_{it}; \beta_i\right) - E(\ln C_{it}^* \left(p_{it},\ y_{it}; \beta_i\right)|Z)$; and Z represents all the variables in both Z_i^η and Z_{it}^u variables. Note that in defining $\ln \overline{C}_{it}^* \left(p_{it},\ y_{it}; \beta_i\right)$, we do the above transformation on each and every variable in $\ln C_{it}^* \left(p_{it},\ y_{it}; \beta_i\right)$.

Step I - Since (4) looks like a standard panel model, we estimate the parameters and predict the values of α_i using the fixed effects (random effects) technique. Note that to do so, we do not need any distributional assumptions on the error terms. Also no functional forms are assumed on $g_\eta(Z_i^\eta)$ and $g_u(Z_{it}^u)$ which are eliminated from (4) using the transformation.

Step II - Using the estimated parameter in $\ln \overline{C}_{it}^*$, which are the same as those in $\ln C_{it}^*$, we rewrite (2) as:

$$\ln C_{it} - \ln C_{it}^* - \alpha_i \equiv r_{it} = \alpha_0 + g_\eta(Z_i^\eta) + g_u(Z_{it}^u) + v_{it} \tag{5}$$

where α_0 is the intercept term in $\ln C_{it}$ which is not identified in Step I. Since $g_\eta(Z_i^\eta)$ and $g_u(Z_{it}^u)$ are non-negative, we assume parametric function on them. For simplicity, we assume them to be Cobb–Douglas functions, i.e., $g_\eta(Z_i^\eta) = \prod_j (Z_{ji}^\eta)^{\theta_j}$ and $g_u(Z_{it}^u) = \prod_m (Z_{mit}^u)^{\theta_m}$. Then, Eq. (5) is estimated using non-linear least squares procedure. Note that we did not include constant terms in $g_\eta(Z_i^\eta)$ and $g_u(Z_{it}^u)$ to avoid identification problem on them.

Step III - The relative persistent efficiency (RPE) and relative transient efficiency (RTE) are then obtained from $RPE = \exp(-\hat{g}_\eta)/\max\{\exp(-\hat{g}_\eta)\}$ and $RPE = \exp(-\hat{g}_u)/\max\{\exp(-\hat{g}_u)\}$, where $\hat{g}_\eta$ and $\hat{g}_u$ are obtained from Step II. Finally, we obtain the relative overall efficiency (ROE) from $ROE = RPE \times RTE$.

Since the WTSC can work with three types of firms: only water treatment (WA), only sewer (SE), and both water and sewer treatment (BO), we considered a fully-flexible translog (FFT) formulation on them (Triebs et al., 2016). This allows the cost function technology to be specific for a WSTC type and estimated in a single panel regression setting using all the data. By doing this, the degrees of freedom are increased when compared to estimations of each of these translog functions separately for WA, SE and BO type firms.

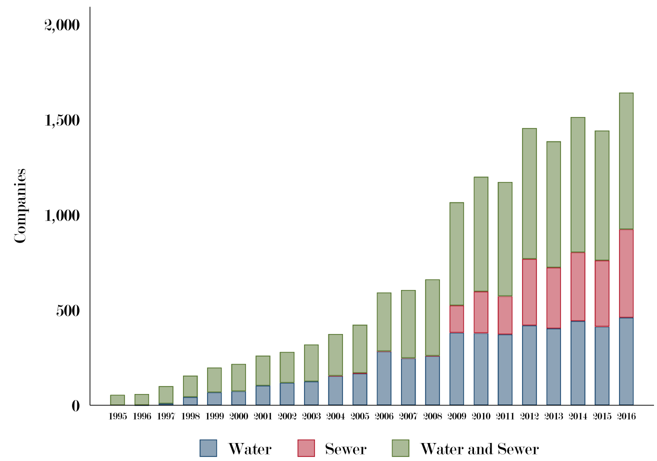

Fig. 1. Distribution of the SNIS data.

The FFT is represented by:

$$\ln C_{it} = WA * \ln C_{it}^{\text{WA}} \left(p_{it},\ y_{it}; \beta_i\right) + SE * \ln C_{it}^{\text{SE}} \left(p_{it},\ y_{it}; \gamma_i\right) + BO * \ln C_{it}^{\text{BO}} \left(p_{it},\ y_{it}; \delta_i\right) \tag{6}$$

where WA is a dummy variable that indicates the water-only companies (water-only = 1; 0 otherwise), SE indicates a sewer-only company (sewer-only = 1; 0 otherwise = 0) and BO indicates a both-type WTSC (water and sewer = 1; 0 otherwise). The cost functions with superscripts WA, SE and BO are different for three different types of firms with their own parameters and inefficiency components. Note that one can also estimate the cost function of each type separately. The advantage of using (6) is the degrees of freedom advantage since data on all types of companies are pooled together. We employed a translog functional form for each of the cost functions in (6). In addition, the cost functions were normalized by capital prices to impose homogeneity (in input prices) condition.

The model proposed by Triebs et al. (2016) allows us to test whether there is a single technology for all three types of firms, i.e., H_0 : $\beta_i = \gamma_i = \delta_i$, or their technologies are different. Imposing the same technology for all is likely to give wrong estimates of the parameters and efficiencies.

2.1. Data

Data on 1054 water and sewer treatment companies (WSTC) between 1995 and 2016 were drawn from the National Sanitation Information System, the (SNIS, 2019), as described in Section 3.1. From Xavier et al. (2015), whose database ranges from 1980 to 2016, we obtained the daily average temperature and rainfall by year. Both databases combined gave us a unique dataset from 1995 to 2016, providing a sample with 6,542 valid observations. Descriptive statistics for the variables used in both empirical models are provided in Table 1.

The National System of Sanitation Information - SNIS

Based in SNIS (2019), the companies' data are collected each year by voluntary participation. The information is validated, and new indicators are calculated from the primary data obtained in the questionnaires. Fig. 1 illustrates the distribution of companies according to their scope of production.

Table 2 describes the selected information in SNIS database to estimate the cost function. Regarding production factors, there is no information for human capital and, therefore, the information on the number of employees is the most detailed variable available. We estimated

Table 1
Descriptive statistics of the empirical model variables.

Variable	Description	Unit	Mean	SD
Frontier				
C	Total costs without taxes	1,000 R$	65,800.00	372,000.00
K	Water and sewer network extension	km	1,481.94	7,420.98
L	Number of employees	Employee	290.41	1,259.17
Y_w	Volume of treated water	1,000 m^3	25,671.65	154,140.70
Y_s	Volume of treated sewer	1,000 m^3	5,543.26	38,605.74
P_K	Capital price	R$/km	17,734.97	140,153.50
P_L	Labor price	R$/L	47,287.43	31,452.27
Efficiency				
Pop	Average population by municipality	*People*	180,964.60	714,897.30
Temp	Average daily temperature	°C	23.95	2.80
Rain	Average daily rainfall	mm	3.99	1.30

Notes: 1. All monetary values were deflated to 2018 levels using the consumer price index (IPCA). SD: Standard-Deviation.

Table 2
Description of selected variables from the SNIS database.

Variable	Cod.	Proxy for	Unit
Expenditure with labor force	FN010	Labor price (P_L)	R$
Total expenditure	FN015	Total Cost (C)	R$
Taxes	FN021	Total Cost (C)	R$
Network extension of water services	AG005	Capital Stock (K_w)	km
Network extension of sewer services	ES004	Capital Stock (K_s)	km
Number of employees	FN026	Labor force (L)	No. of employees
Total treated water	AG007	Output (y_w)	1,000 m^3
Total treated sewer	ES006	Output (y_s)	1,000 m^3

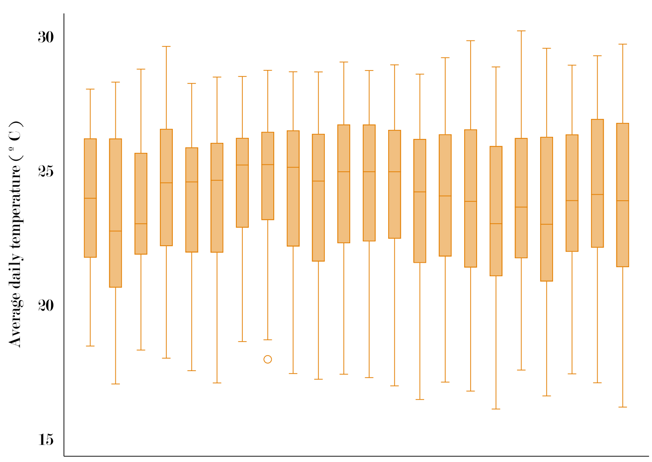

Fig. 2. Average daily temperature for each municipality between 1980 and 2016. *Source:* The authors, with data from Xavier et al. (2015).

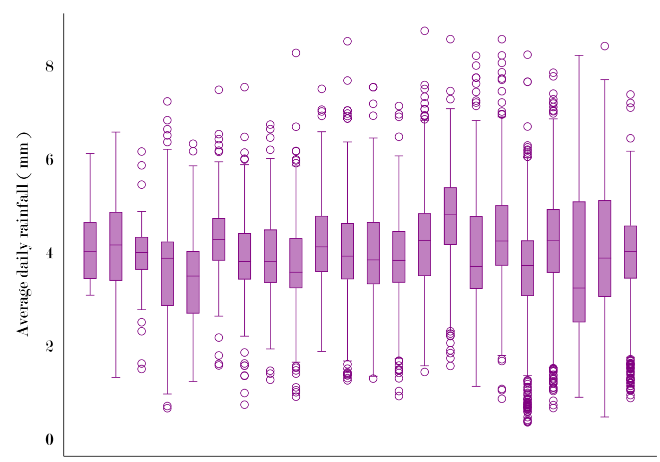

Fig. 3. Average daily rainfall for each municipality between 1980 and 2016. *Source:* The authors, with data from Xavier et al. (2015).

the capital price according to the methodology proposed by Souza et al. (2007). That is: $p_K = (C - p_L * L)/K$, where p_k is the capital price, C is the total cost, p_L is the labor price, L is the labor force, and K is the capital stock. Following Souza et al. (2007), we used the network extension of pipes for water and sewer as a proxy to capital stock, since other information about the companies' installed capacity is not available. That is, the capital stock for water treatment (K_w) and the capital stock for sewage treatment (K_s) is defined as $K\left(K_w, K_s\right) = K_w + K_s$.

Weather variables

Variations in temperature and rainfall can have different impacts on water and sewage treatment (Zouboulis and Tolkou, 2015). For example, while the marginal increase in rainfall can dilute pollutants in streams and thus facilitate water treatment, the dilution of activated sludge reduces the efficiency of sewage treatment. The marginal increase in temperature reduces the water quality in the springs while favoring the treatment of sewage by stimulating biological decomposition.[6]

To include temperature and rainfall data in the empirical model as determinants of inefficiency, we used the spatial data generated by Xavier et al. (2015), which contains daily data for the Brazilian territory between 1980 and 2013 (later updated for 2016). To merge the weather data in SNIS database, we considered the cities where each company is based and adopted the central-mark coordinates for these cities to obtain a representative value of temperature and rainfall for each firm, the unit of observation.[7] Figs. 2 and 3 present the distribution of temperature and rainfall by year for each municipality.

We considered the temperature and rainfall deviations from the historical average for each municipality, that is: $\phi^x_{it} = \frac{x_{it}}{\bar{x}_i}$, where ϕ is

[6] See also Tundisi and Tundisi (2011).

[7] It is noteworthy that the average temperature was calculated as the simple mean of maximum and minimum temperature.

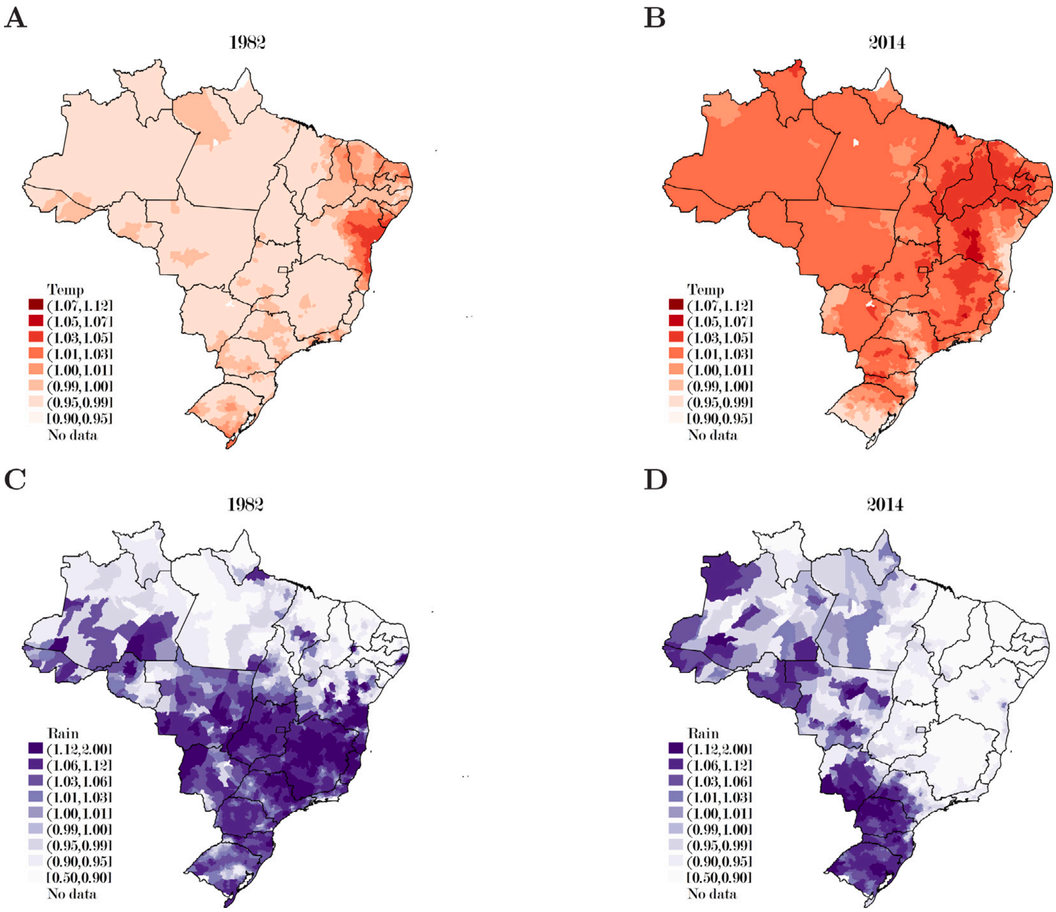

Fig. 4. Temperature trend (A, B) and rainfall trend (C, D) between 1980 and 2016 for Brazilian municipalities. Values of 5-years moving averages. *Source:* the authors using data from Xavier et al. (2015).

the deviation from the sample average between 1995 and 2016 for each climatic variable x (rainfall or temperature), x_t indicates the climatic variable for municipality i in year t and $\overline{x}$ represents the historical average for each climatic variable.

Fig. 4 presents the spatial visualization of trends for temperature and rainfall over country territory. We divided the average temperature (rainfall) for each municipality by their respective long-term average between 1980 and 2016. Then, we computed the 5-year moving averages to highlight each variable trend. In this sense, the values in Fig. 4-A and Fig. 4-C represent the average deviation between 1980 and 1984, while Fig. 4-B and Fig. 4-D represent the average deviation between 2012 and 2016.

Population

Since the expansion and maintenance of water and sewage networks are long-term investments, we obtained the average population estimates from 2001 to 2019 (IBGE, 2020b) for each municipality and, then, merged the population data in the SNIS database considering the cities where each company is based. In this sense, the average population size is a variable for density effects and represents a determinant of persistent inefficiency. According to Tupper and Resende (2004), the population size can be correlated with other sources of inefficiency, such as leaks and the number of connections per area. For empirical estimations, we adopted a relative population size index, that is, we constructed an index by dividing the average population for each municipality by the sample average, that is: $\rho_i = pop_i/pop_{average}$.

2.2. Empirical Model

The empirical model to be estimated in Step 1 is represented by Eq. (9) which combines cost functions of three types of WSTC via the dummy variables WA, SE and BO, i.e.

$$\ln \overline{C}_{it} = WA * \ln \overline{C}_{it}^{\mathrm{WA}} \left(p_{it},\ y_{it}; \beta_i\right) + SE * \ln \overline{C}_{it}^{\mathrm{SE}} \left(p_{it},\ y_{it}; \gamma_i\right) + BO * \ln \overline{C}_{it}^{\mathrm{BO}} \left(p_{it},\ y_{it}; \delta_i\right) \tag{7}$$

where,

$$\begin{aligned} \ln \overline{C}_{it}^{\mathrm{WA}} &= \ln \overline{C}_{it}^{\mathrm{WA}} \left(p_{it},\ y_{it}; \beta_i\right) + \alpha_i^{\mathrm{WA}} + \varepsilon_{it}^{\mathrm{WA}} \\ &= \beta_p \ln \overline{p}\ + \beta_{y_w} \ln \overline{y}_w + \beta_{\mathrm{pp}} \ln \overline{p}^2 +\ \beta_{y_w y_w} \ln \overline{y}_w^2 \\ &+\ \beta_{p y_w} \ln \overline{p} \ln \overline{y}_w + \beta_t\ \overline{t}\ + \alpha_i^{\mathrm{WA}} + \upsilon_{it}^{\mathrm{WA}} \end{aligned} \tag{8}$$

$$\begin{aligned} \ln \overline{C}_{it}^{\mathrm{SE}} &= \ln \overline{C}_{it}^{\mathrm{SE}} \left(p_{it},\ y_{it}; \gamma_i\right) + \alpha_i^{\mathrm{SE}} + \varepsilon_{it}^{\mathrm{SE}} \\ &= \gamma_p \ln \overline{p}\ + \gamma_{y_s} \ln \overline{y}_s + \gamma_{\mathrm{pp}} \ln \overline{p}^2 +\ \gamma_{y_s y_s} \ln \overline{y}_s^2 + \gamma_{p y_s} \ln \overline{p} \ln \overline{y}_s \\ &+ \gamma_t\ \overline{t}\ + \alpha_i^{\mathrm{SE}} + \upsilon_{it}^{\mathrm{SE}} \end{aligned} \tag{9}$$

and

$$\begin{aligned} \ln \overline{C}_{it}^{\mathrm{BO}} &= \ln \overline{C}_{it}^{\mathrm{BO}} \left(p_{it},\ \delta_i,\ y_{it}\right) + \alpha_i^{\mathrm{BO}} + \varepsilon_{it}^{\mathrm{BO}} \\ &= \delta_p \ln \overline{p}\ + \delta_{y_w} \ln \overline{y}_w + \delta_{y_s} \ln \overline{y}_s + \delta_{\mathrm{pp}} \ln \overline{p}^2 +\ \delta_{y_w y_w} \ln \overline{y}_w^2 +\ \delta_{y_s y_s} \ln \overline{y}_s^2 \\ &+ \delta_{p y_w} \ln \overline{p} \ln \overline{y}_w +\ \delta_{p y_s} \ln \overline{p} \ln \overline{y}_s + \delta_{y_w y_s} \ln \overline{y}_w \ln \overline{y}_s + \delta_t\ \overline{t}\ + \alpha_i^{\mathrm{BO}} + \upsilon_{it}^{\mathrm{BO}} \end{aligned} \tag{10}$$

Transformation of the variables with an 'overbar –' is discussed in Eq. (4). To estimate persistent and transient inefficiency, we follow steps II and III discussed in (5) and (6) specifically for WA, SE and BO. That is, we estimate:

$$r_{it} = \alpha_0 + (\phi_{11it}^{\theta_{11}} * \phi_{12it}^{\theta_{12}}) + (\phi_{21it}^{\theta_{21}} * \phi_{22it}^{\theta_{22}}) + (\phi_{31it}^{\theta_{31}} * \phi_{31it}^{\theta_{32}}) + \rho_{1i}^{\theta_4} + \rho_{2i}^{\theta_5} + \rho_{3i}^{\theta_6} + v_{it} \quad (11)$$

where ϕ_{11} is the temperature index for WA-type companies, ϕ_{12} is the rainfall index for WA-type companies, ϕ_{21} is the temperature index for SE-type, ϕ_{22} is the rainfall index for SE-type, ϕ_{31} is the temperature index for BO-type, ϕ_{32} is the rainfall index for BO-type; ρ_{1i}, ρ_{2i} and ρ_{3i} are the population index for WA, SE and BO-type, respectively. Finally, the θs are unknown parameters to be estimated. Note that we use weather variations as exogenous determinants of costs. Therefore, even they affect the efficiency levels and thus, the sector's performance, they do not depend directly on better managerial practices. Alternatively, managers cannot influence weather variations and thus they can be treated as exogenously given.

3. Results And discussion

Estimation results, defined in Step I, are presented in Table 3. Results from the cost frontier model, estimated jointly as proposed in Triebs et al. (2016), is presented in column I. Columns II, III and IV present the estimates for each technology separately. The result of the likelihood ratio test rejects the null hypothesis that the coefficients between the joint and separate estimates are equal (p-$value < 0.001$). Therefore, the model with fully flexible technology is appropriate to estimate the cost functions.

We also checked whether the theoretical properties such as monotonicity and concavity are satisfied by the estimated cost functions. Results show that only 0.20% of the sample have concavity violation in Model I. Therefore, there is no reason to impose constraints to satisfy concavity globally. Regarding technological change, the trajectory of productivity differs among production technologies. While the WA and BO have a positive trend over time (technical regress) ($\hat{\beta}_t = 0.0171^{****}$; $\hat{\delta}_t = 0.00546^{****}$), SE technology shows technical progress ($\hat{\gamma}_t = -0.0399^{****}$), that is, a downward cost trend, *ceteris paribus*. The weighted average indicates that the minimum cost for the industry raised at the rate of 0.672% per year. This result is lower than those obtained by Ferro et al. (2014), which was 2.4% per year. The evidence shows that the sanitation industry has a decreasing productivity over time, which jeopardizes its long-term competitiveness and reinforce the role of institutional reforms that allow public and private investments in the sector able to promote positive technical progress growth rate and, thus, productivity growth,[8].

Technical efficiency

After estimating the cost frontier, we proceed with Step III to estimate the relative persistent and transient efficiency (Table 4). The relative overall efficiency of 88.2% indicates that sector costs can be 11.8% higher than they would be if the sector were to operate at full efficiency. The efficiency level estimated is higher than that obtained by Ferro et al. (2014), who estimated an overall efficiency of 67.7%. Our model differs from that used by these authors since we consider two sources of inefficiency, and we also use a deterministic frontier approach. We report the distribution of ROE, RPE and RTE for each WSTC type in Fig. 5.

[8] Since the public investments (% GDP) were less than 4% in 2015 (Orair and Siqueira, 2018) an efficient regulatory environment is required to attract private investment to reduce the supply infrastructure deficit of sanitation services in the country.

Table 3
Cost function parameter estimates.

Coefficients	(I) FFT	(II) WA	(III) SE	(IV) BO
β_p	0.586****	0.622****		
	(61.38)	(58.08)		
β_{y_w}	0.225****	0.211****		
	(17.93)	(15.01)		
β_{pp}	0.0191***	0.0189**		
	(2.85)	(2.53)		
$\beta_{y_w y_w}$	0.0354****	0.0381****		
	(10.96)	(10.89)		
$\beta_{p y_w}$	0.00876*	0.0163***		
	(1.70)	(2.91)		
β_t	0.0171****	0.0000390		
	(12.00)	(0.72)		
γ_p	0.659****		0.657****	
	(52.31)		(37.47)	
γ_{y_s}	0.154****		0.162****	
	(9.86)		(7.87)	
γ_{pp}	0.0411****		0.0423****	
	(23.09)		(17.98)	
$\gamma_{y_s y_s}$	0.0272****		0.0229***	
	(4.33)		(2.84)	
$\gamma_{p y_s}$	−0.0307****		−0.0335****	
	(−5.10)		(−4.19)	
γ_t	−0.0399****		−0.00114****	
	(−5.90)		(−13.59)	
δ_p	0.569****			0.587****
	(34.08)			(41.88)
δ_{y_w}	0.518****			0.366****
	(47.50)			(33.00)
δ_{y_s}	0.0754****			0.0317****
	(8.98)			(4.34)
δ_{pp}	−0.00407			−0.00634
	(−0.43)			(−0.82)
$\delta_{y_w y_w}$	0.117****			0.0663****
	(23.95)			(14.19)
$\delta_{y_s y_s}$	0.0196****			0.0196****
	(7.79)			(9.85)
$\delta_{p y_w}$	0.0183***			0.0155***
	(2.93)			(3.02)
$\delta_{p y_s}$	−0.0286****			−0.0270****
	(−4.96)			(−5.74)
$\delta_{y_w y_s}$	−0.0313****			−0.0121****
	(−10.09)			(−4.63)
δ_t	0.00546****			−0.000371**
	(4.91)			(−1.97)
W	−22.68****			
	(−6.15)			
S	90.69****			
	(6.57)			
Constant (B)	−0.118****	−0.184****	−0.0228	−0.158***
	(−6.09)	(−6.42)	(−0.40)	(−2.95)
N	6542	2300	631	3611

Note: 95% t-statistics in parenthesis. * p < 0.1, ** p < 0.05, *** p < 0.01, **** p < 0.001.
Source: the authors.

The efficiency gap closure (11.8 percentage points) corresponds to an annual reduction of R$ 7.78 million per company at the sample average. For the 1054 companies present in the sample, the accumulated cost reduction corresponds to R$ 8.20 billion per year. To obtain these values from a sectoral perspective, the investment projected by PLANSAB between 2014 and 2033 for scenarios 1 and 2 are, respectively, R$ 445 billion and R$ 326 billion, already deflated to 2018 prices (BRASIL, 2013). That is, the average annual investment projected by PLANSAB varies between R$ 16 billion and R$ 22 billion per year. In this sense, the efficiency gap closure corresponds to up to 51% of the budget in order to achieve the sanitation goals of the Brazilian government.

One interesting aspect of our model is that we can identify companies that are on the top (bottom) of the efficiency distribution because estimates of efficiency are observation-specific. This information can be useful to the regulators in providing incentives to the top performers.

Table 4
Weather and population size effects.

Variables	Constant	WA	SE	BO
Coefficient (α_0):	−6.003****			
	(0.00326)			
Persistent Inefficiency				
ρ		−0.00569***	−0.00378	0.00587***
		(0.00218)	(0.00355)	(0.00211)
Transient Inefficiency				
ϕ_{temp}		1.004****	−1.857****	−0.261
		(0.238)	(0.505)	(0.185)
ϕ_{rain}		0.0271	0.0518	−0.0161
		(0.0242)	(0.0421)	(0.0187)
N	6542	2300	631	3611

Note: 95% t-statistics in parenthesis. * p < 0.1, ** p < 0.05, *** p < 0.01, **** p < 0.001.
Source: the authors.

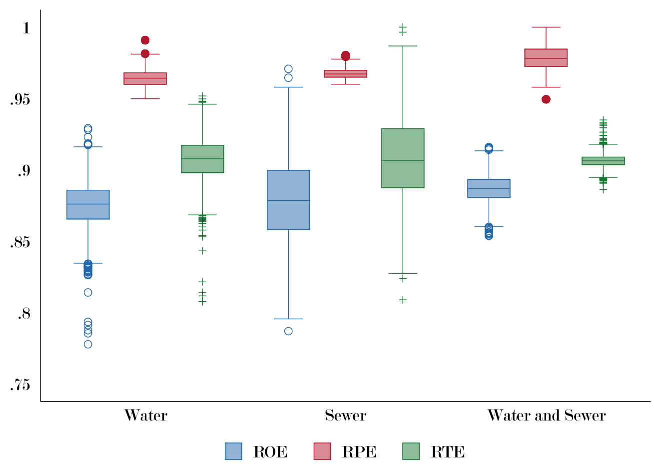

Fig. 5. Box-plot of ROE, RPE and RTE by each WSTC type.
Source: The authors.

It is important to note that since the technology of WA, SE and BO are assumed to be different, we cannot simply compare all the firms' efficiencies. However, we can compare the efficiency of companies within each type.

Population size effects

The population size variable shows significant and opposite effects for WA and BO types. The marginal effect suggests that an population size increase reduces the costs for water-only companies, while it increases the costs for BO types. Since population size for BO are 8 times higher than to WA, these results suggests that population size increasing in larger cities can put pressure in sanitation's infrastructure.

To investigate these opposite effects, we tested: (i) the relationship between the water connections density[9] (T) and $\ln(\rho^*)$; (ii) the relationship between leakages[10] (L) and the $\ln(\rho)$. We found that T and $\ln(\rho)$ have a positive relationship; that is, more populated cities have lower costs due to economies of density (Tupper and Resende, 2004). However, we also found that L and $\ln(\rho)$ have a positive relationship; that is, more populated cities have larger leakages (Tupper and Resende, 2004). Therefore, WSTCs in high populated cities can improve efficiency by appropriate maintenance to avoid leakages. The population concentration in medium and large cities should reduce the efficiency in small cities and overload the infrastructure in the largest cities and, therefore, has cost-increasing effects.

Weather effects

The temperature shows significant and mixed effects for the water and sewage treatment. A marginal increase in average temperature reduces the costs of sewage treatment but increases the water treatment costs. On the other hand, the temperature coefficient was not significant for BO-type companies. It might occur as a consequence of these opposite effects. However, considering only the significant effects, it is possible to estimate the effect of increasing the average temperature by 1-percent on costs for all WSTC types using the marginal effects for each WA and SE type weighted by the mix of products, generating the Temperature Effect Index (TEI).[11]. In this sense, the overall temperature effects on BO-types will depend on their mix of products. For this sample, we estimated an average TEI of 0.1650%[12]. So the spatial analysis of TEI is useful for identifying regional patterns (Fig. 6).

It is noteworthy that in the Center-West and North regions, the rising temperature has been increasing the costs in several micro-regions. The Center-West and North regions are covered by the Cerrado and Amazon biomes, which are environmental and ecological hotspots; that is, they have been endangered with accelerated changes in land use due to anthropic actions (Strassburg et al., 2017). On the other hand, the average TEI can be cost-saving in some micro-regions due to the presence of sewer-only companies or higher shares of sewer treatment in the sample. A comparison between Figs. 6 and 7 illustrates the negative relationship for sewer treatment and TEI. Therefore, the expansion of sewer services could reduce the cost-increasing effect of rising temperature on water treatment.

It is possible to estimate a proportion of water and sewer treatment that could mitigate the temperature effect, that is, a break-even point in BO-type companies. In Table 4, we see that the coefficient estimated to temperature is 1.85 times higher in sewage treatment than in water treatment at the sample average.[13] Thus, the proportion of water and sewer that can balance the climate effect is 65% for water treatment and 35% for sewage treatment.[14] Considering only the municipalities that have the entire population served with water and sewage treatment (N = 608), water treatment represents 75.32% (±1.1976%, 95% confidence interval) of the production mix. Therefore, those municipalities have a production mix above the break-even point, suggesting that the rising temperature increases the overall sanitation costs in some Brazilian municipalities, even if they achieved full sanitation coverage for their population.

Up to this point, we found that rising temperature has overall cost-increasing effects. Considering the historical data (Xavier et al., 2015), we estimated trends for temperature in Brazilian municipalities using fixed and random effects and found ($g = 0.078\%$)[15]. In this sense, the rising temperature trend might increase sanitation costs, making it increasingly difficult for the poorest households to access this service. Additionally to this result, according to the latest Intergovernmental Panel on Climate Change (IPCC) Report – August 2021 – climate changes will increase in all regions, and estimations indicate the global warming level of 1.5 °C in the next decades (IPCC, 2021). Therefore, this might be an additional constraint for Brazil to reach the target to supply sanitation services for the total population until 2033.

[9] We used the variable AG021 from SNIS (2019). The density of connections (T) is: $T = AG024 * K^{-1}$.

[10] We estimated Leaks (L) as the difference between the volume of water measured in the WTSC (AG012) and the volume measured obtained by the costumers (AG008). That is: $L = (AG012 - AG008) * K^{-1}$.

[11] See Appendix B.

[12] A simple t-test rejects average the hypothesis of $TEI = 0$ (p-value<0.01)

[13] See Table 9. The comparison of estimated coefficient for ϕ_{WA} and ϕ_{SE} is: $\frac{1.857302}{1.003624} \approx 1.8506$.

[14] Let x be the mix of water. So, $(x) * (1.003624) + (1 - x) * (-1.857302) = 0 \Rightarrow x = 64.92\%$.

[15] See Appendix C. At this rate, the Brazilian average temperature can increase by 1 °C in 53 years, which is comparable to IPCC (2021) - see page 29, fig.(a).

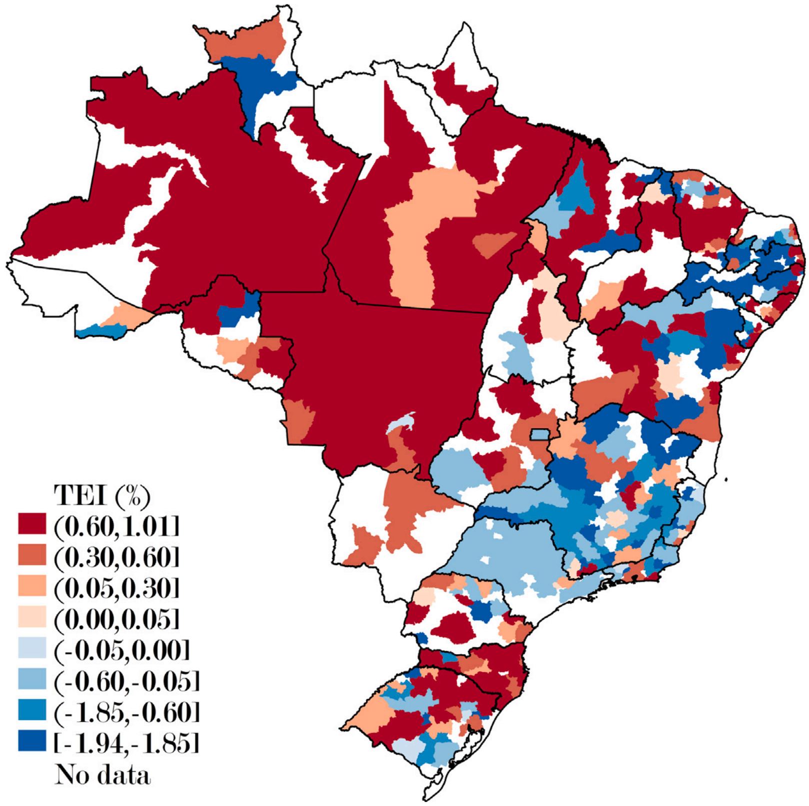

Fig. 6. Spatial distribution of the average TEI by micro-regions over Brazilian territory.
Source: The authors, with data from Xavier et al. (2015).

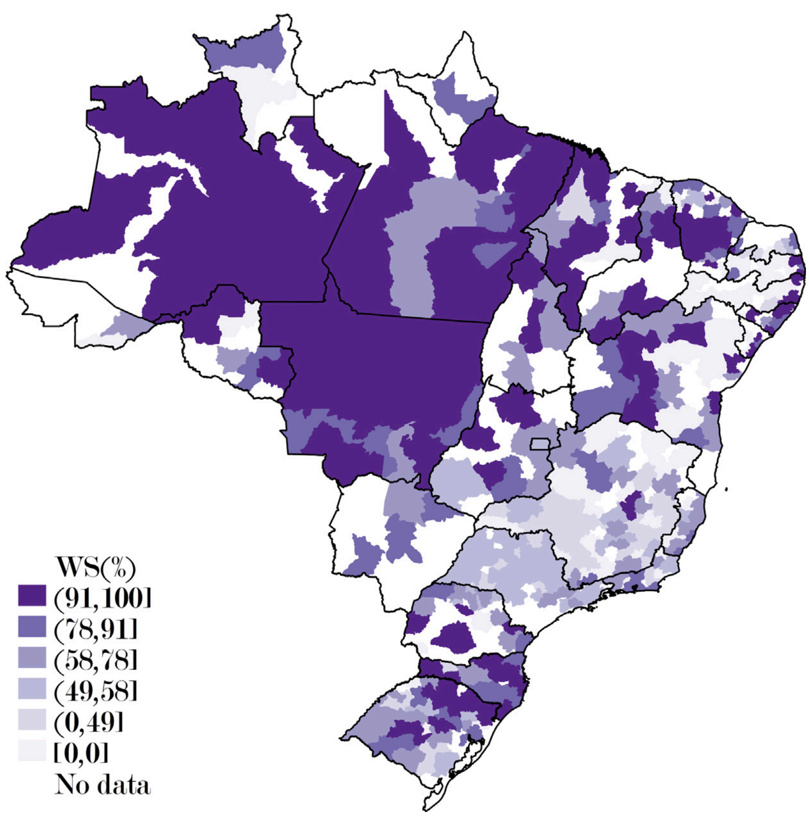

Fig. 7. Average share of water in production mix.
Source: The authors.

4. Conclusions

The main objective of this paper was to access the effects of atmospheric temperature, rainfall, and population size on sanitation costs. Our findings provide evidence that the rising temperature has cost-increasing effects on water treatment and cost-decreasing effects on sewer treatment. In this sense, the overall effect depends on the mix of products. Therefore, it is possible to mitigate negative weather effects on water treatment by combining water and sewer treatment in optimal shares. In this paper, we estimated shares of 65% for water and 35% for sewer treatment as the break-even point for a mix of products. Furthermore, we found that Brazilian municipalities that provide sanitation services for the entire population have a mix of production above the estimated break-even point, suggesting that some municipalities can have overall cost-increasing effects for rising temperature considering the current technology.

Although population growth can increase efficiency and productivity by exploiting economies of density, it is associated with a proportionally higher increase in leaks. In this perspective, access to funding and new investments will be decisive for providing water and sewer treatment to the entire population.

Future research may contribute by seeking sources of allocative inefficiency, which would allow us to identify and measure possible efficiency improvements from regulatory features. Furthermore, the inclusion of variables that capture the effect of forest cover and riparian forests is also encouraged since it could estimate their economic impacts as a consequence of improving water quality and mitigating adverse climatic effects.

Finally, the downward trend of productivity suggests demand for institutional reforms, with the risk of continuing to postpone the expansion of sanitation services and, consequently, constrain economic and social development. Therefore, an effective regulatory agency and environmental policies can decrease the sector's vulnerability in the face of potential demographic and climatic changes that make these services less affordable for Brazilian households.

CRediT authorship contribution statement

André F. Danelon: Concept, Design, Analysis, Writing or revision of the manuscript. **Humberto F.S. Spolador:** Concept, Design, Analysis, Writing or revision of the manuscript. **Subal C. Kumbhakar:** Concept, Design, Analysis, Writing or revision of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

See Table 5.

Table 5
Selected literature review for efficiency analysis in sanitation sector.

Paper	Method	Sample	Results
Lambert et al. (1993)	DEA	238 public e 33 private companies, United States, 1989	There are no differences for economies of scale between public and private companies. Inefficiency as a result of capital overuse.
Bhattacharyya et al. (1995)	SFA	190 public e 31 private companies, United States, 1992.	Private companies are less efficient.
Cubbin and Tzanidakis (1998)	DEA	29 companies, England and Wales, 1992/93	Regression Analysis and DEA provide reliable efficiency measurements.
Fabbri and Fraquelli (2000)	RA	173 companies, Italy, 1991	Companies have economies of scale and density
Garcia and Thomas (2001)	RA	55 companies, France, 1995–1997	Companies have economies of scale and density
Mizutani and Urakami (2001)	RA	112 companies, Japan, 1994	Companies have economies of scale and density
Anwandter and Ozuna (2002)	DEA	110 companies, Mexico, 1995	Regulatory agency not had effect on efficiency levels in the absence of competitive reforms
Estache and Kouassi (2002)	RA	21 companies, Africa, 1995–1997	Private companies are more efficient than public companies
Estache and Rossi (2002)	SFA	50 companies, Asia, 1995	There are no differences on efficiency level between private and public companies
Bottasso and Conti (2003)	SFA	10 BO companies, 12 WA companies WA, England and Wales, 1995–2001	Efficiency gaps have closing along the time. Technical and structural requirements determine efficiency level.
Estache and Trujillo (2003)	TI	4 provinces, Argentina, 1992–2001	Growing Total Factor Productivity after privatization
Tupper and Resende (2004)	DEA	20 companies, Brazil, 1996–2000	Evidence for economies of density
Woodbury and Dollery (2004)	DEA, MI	73 companies, Australia, 1999–2000	Technical inefficiency is larger than scale inefficiency. Water quality indicators should be included in analysis.
Aubert and Reynaud (2005)	SFA	211 companies, United States, 1998–2000.	Efficiency level is partially explained by regulatory framework.
Fraquelli and Moiso (2005)	SFA	18 regions, Italy, 1975–2005	Inefficiency is partially explained by heterogeneity in sanitation network
Erbetta and Cave (2006)	DEA	10 companies, England and Wales, 1993–2005	Changes in regulatory mark promote improvements on efficiency levels. Environmental variables affect the estimated efficiency.

(continued on next page)

Table 5 (*continued*).

Paper	Method	Sample	Results
Garcia and Thomas (2001)	DEA	24 companies, Spain, 1999.	Evidence for economies of density. There are no differences of efficiency level related to ownership
Motta and Moreira (2006)	DEA	79 BO companies and 25 WA companies, Brazil, 1998–2002	Ownership does not affect productivity gains. Regional companies benefit from higher economies of scale
Souza et al. (2007)	SFA	149 public e 15 private companies, Brazil, 2002.	There are no differences on efficiency level between private and public companies. Environmental variables are determinant to the efficiency level
Garcia et al. (2007)	RA	233 companies, United States, 1997–2000	Evidence for economies of scale and density
Saal et al. (2007)	SFA	10 companies, England and Wales, 1985–2000	Privatization enhanced technical change. Oversized companies can have diseconomies of scale (productivity reduction)
Filippini et al. (2008)	SFA	52 companies, Slovenia, 1997–2003	Efficiency measurements are affected by methodology. Diseconomies of scale in oversized companies.
Picazo-Tadeo et al. (2008)	DEA	40 companies, Spain, 2001	Water quality affect the efficiency level
Sabbioni (2008)	SFA	1163 observations, Brazil, 2000–2004	Economies of scale are the main source for cost reductions
Renzetti and Dupont (2009)	DEA	64 Companies, Canada, 1996	Ground elevation, population density and households with private access to water are determinant to the efficiency level
Byners et al. (2009)	MA	52 companies, Australia, 2000–2004.	Hydrological scarcity reduces technical efficiency. Evidence for economies of scale
Carvalho and Marques (2011)	DEA	66 companies, Portugal, 2002–2008	There are no differences between public and private companies. Residential customers, hydrological source, seasonality of water demand and density of customers have mixed effects on efficiency level.
Romano and Guerrini (2011)	DEA	43 companies, Italia, 2007	Ownership, size and localization affects the efficiency level
Abbott et al. (2012)	DEA Malmquist	6 municipalities, Australia, 1995/96 - 2007/08	Productivity gains in large urban centers.
Ferro et al. (2014)	SFA	127 companies, Brazil, 2003–2010	Regional and micro-regional companies have lower costs than local companies. Private companies are more efficient. There are no differences of costs among regions. Costs presents a positive growth trend.
Marques et al. (2014)	DEA	1,144 companies, Japan, 2004–2007	Technical efficiency has been stagnated along the time
Price et al. (2017)	SFA	944 companies, Canada, 2011	Quality of water in springs, measured as turbidity, is a determinant of efficiency level,
Molinos-Senante and Maziotis (2019)	DEA, SFA	23 companies, Chile, 2007–2015	Productivity and efficiency levels estimates can be different when estimated by SFA or DEA models

Source: the authors based on (Walter et al., 2009) and (Worthington, 2014).; DEA – *Data Envelopment Analysis*; IM – Malmquist Index; TI – Tornqvist Index, RA – Regression Analysis; SFA – *Stochastic Frontier Analysis*.

Appendix B

The temperature effect index (TEI) is constructed using the mix of products, the proportion of capital allocated to water and sewage treatment, the marginal effect of temperature for each WSTC from Eq. (12):

$$TEI = \frac{K_{it}^{\mathrm{WA}}}{K_{it}} * \hat{\tau}_1 + \frac{K_{it}^{\mathrm{SE}}}{K_{it}} * \hat{\tau}_2 \tag{12}$$

where,

TEI is the temperature effect index;

$K_{it} = K_{it}^{\mathrm{WA}} + K_{it}^{\mathrm{SE}}$;

K_{it}^{WA} is the network extension to water treatment services;

K_{it}^{SE} is the network extension to sewer treatment services.

$\hat{\tau}_1$ is the average marginal effect of temperature on costs to water-only companies in percentage terms $(\ln C_{it}/\partial \phi_{11it})$;

$\hat{\tau}_2$ is the average marginal effect of temperature on costs to sewer-only companies in percentage terms $(\ln C_{it}/\partial \phi_{21it})$;

Appendix C

We tested the hypothesis of a positive trend for average temperature over time considering Eq. (13):

Table 6
Average growth rate of temperature between 1980 and 2016.

Coefficient	Dependent variable: $\ln(\phi_{\mathrm{it}}^{\mathrm{temp}})$
g	0.000777****
	[0.000768,0.000786]
Constant	1.609****
	[1.591,1.627]
N	209380

Note: 95% confidence interval in brackets. * p < 0.1, ** p < 0.05, *** p < 0.01, **** p < 0.001.
Source: the authors.

$$\ln\left(\phi_{it}^{\mathrm{temp}}\right) = \ln(\phi_{i0}^{\mathrm{temp}}) + gt + \varepsilon_{it} \tag{13}$$

where $\phi_{it}^{\mathrm{temp}}$ is the temperature deviation from its historical average in the municipality i in the year t; and g is the average growth rate to be estimated.

The Hausman test indicated the random-effects model to be appropriate for the data (p-value = 0.9998). The estimated growth rate between 1980 and 2017 period was 0.078% per year, and the econometric results are provided in Table 6. At the average growth rate, the average daily temperature might increase around 2 °C in 100 years, which is compatible with the estimates presented by the IPCC (2019) in scenarios with low mitigation of greenhouse gas emissions.

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