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Impact of a Physical Activities Program on Expenses with Hospitalization for Diabetes in the State of Pernambuco – Brazil

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ABSTRACT

Background: The Health Gym Program (HGP) is the main program to promote health and physical activity in the public health system in Brazil. This intervention uses financial resources from the federal government and municipalities to encourage the population of Brazilian municipalities to adopt more active and healthy lifestyles.

Objective: To evaluate the impact of the Health Gym Program on hospital admissions for type II diabetes mellitus in the state of Pernambuco – Brazil.

Method: This is an impact assessment of public policies that used a panel of data from all 185 municipalities in Pernambuco from 2007 to 2018. The 130 municipalities that adopted the HGP from 2011 were designated as treaties while the others 55 that did not implement the program made up the control group. The empirical strategy used an econometric modeling that uses the difference-in-differences estimator weighted by the propensity score.

Results: Hospitalizations for diabetes represented, respectively, 1.47% and 1.00% of all hospitalizations performed in 2007 and 2018. The expenditure on these hospitalizations was US$ 899,687.34 in 2018 and corresponded to 0.59% of the cost of all hospitalizations. The municipalities that implemented the HGP spent an average of 19.74% less on hospitalizations for diabetes than the municipalities that did not, and this result was statistically significant at the 5% level.

Conclusion: The Health Gym Program impacted in reducing the expenses with hospitalizations for diabetes when comparing the municipalities that implemented and those that did not implement this intervention.

KEYWORDS: Health Impact Assessment. Health Politics. Health Expenditure. Diabetes. Health Promotion; Physical Activity; Primary Health Care.

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INTRODUCTION

Chronic non-communicable diseases (NCDs) are one of the biggest public health problems today since they cause a loss of quality of life, generate incapacities in the performance of some activities of daily living and premature deaths[1]. NCDs are responsible for 41 million deaths per year, which represents 72% of total deaths worldwide[2]. In Brazil, in 2018, CNCDs were responsible for 60.68% of deaths between 30 and 60 years of age [3].

Among the NCDs, type II diabetes mellitus is one of the main co-responsible of hospitalizations, given its higher prevalence among the adult and elderly population[4]. According to the Surveillance of Risk and Protection Factors for Chronic Diseases by Telephone Survey (2021), diabetes was one of the most prevalent pathologies in the country, since 9.1% of respondents reported having a medical diagnosis of this NCD[5].

In addition to the impact on quality of life, type II diabetes also impacts significantly health expenditures. This disease was responsible for 124,879 hospital admissions in Brazil in 2018, which resulted in an expense of US$ 23,918,479.68 for the Brazilian public health system[6].

Diabetes, like other NCDs, has multiple risk factors and is influenced by living conditions, social inequality, and especially lifestyle[7]. The main strategy to promote health and encourage the adoption of more active and healthy lifestyles in Brazil is the Health Gym Program (HGP). The HGP was created in 2011 and uses federal government resources to finance the construction and monthly cost of public spaces with infrastructure and personnel to develop health promotion actions in support of primary health care teams in Brazilian municipalities[8].

By 2018, the Brazilian Ministry of Health had already registered 2,538 HGP centers distributed in all Federation Units, of which 266 were in municipalities in Pernambuco[9]. The implementation of the HGP in the state of Pernambuco occurred before the other federative entities since this state already had similar physical activity programs, which were incorporated into the program even before the other states and municipalities started building the hubs[9].

One of the specific objectives of the HGP is to increase the population's level of physical activity, and the program is considered strategic for the national health system in Brazil, mainly because some evidence indicates that if the prevalence of physical inactivity were reduced by 50%, there would be savings of US$ 957.208.113,96 in health resources, due to the decrease in the number of hospitalizations for type II diabetes mellitus[10].In this sense, the program is an investment with the potential to improve the quality of life, articulate health promotion actions in the Primary Care network, and to reduce costs with the treatment of diabetes in Brazil [11].

Evidence points to the impact of HGP to increases the population's level of physical activity[12] and on spending on hospital admissions for cerebrovascular diseases[13]. On the other hand, the impact of this intervention on expenses with hospitalizations for type II diabetes, and the potential savings generated for the public health sector due to its implementation in the municipalities is not yet clarified. Therefore, this study aims to analyze the impact of the Academia da Saúde Program on hospital admission expenses for type II diabetes mellitus in the state of Pernambuco.

METHOD

This study is an impact assessment of public policies, which used a panel of data from Pernambuco municipalities from 2007 to 2018. The quasi-experimental evaluation approach used multiple periods difference-in-differences (DID) method with fixed effects, and was weighted by the Propensity Score Matching (PSM) to estimate the impact of HGP on hospital admission expenses for type II diabetes in the state of Pernambuco[14,15].

The combination of Propensity Score Matching and Difference-in-Differences Regression, also called Double Difference Matching (DDM) method, makes the results of non-experimental studies more robust[14,15], since the DID method reduces potential selection biases by traits of the treated and controls, while the propensity score matching (PSM) minimizes biases related to the absence of common support and reduces biases arising from the distribution of observable traits[16,17,18,19].

Variables and Data Collection

The study used secondary public domain data from all 185 municipalities in Pernambuco from 2007 to 2018. The 130 municipalities that implemented the PAS were considered treated and the 55 that did not implement the program were designated as controls.

The outcome variable for this study is the natural logarithm of expenditure on hospital admissions for type II diabetes by the residence place of the individual. The conversion of the outcome variable into a logarithm is commonly used in econometrics, especially when the relationships between the dependent and independent variables are not linear [20].

The explanatory variables were selected according to the epidemiological models that indicate epidemiological, demographic, and socioeconomic characteristics associated with hospitalizations for chronic non-communicable diseases and diabetes in the Brazilian population[21,22,23,24].

The epidemiological variables used in this study were the percentage of primary care coverage and the rates of doctors and hospital beds (both per groups of 10,000 inhabitants) for each municipality, which were collected on the website of the Department of Informatics of the Unified Health System (DATASUS).

As for socioeconomic and demographic data, these were obtained from the website of the Brazilian Institute of Geography and Statistics (IBGE), the Ministry of Economy (Annual List of Social Information - RAIS), the Federation of Industries of the State of Rio de Janeiro (FIRJAN), the State Database (BDE), the Information System on Public Health Budgets (SIOPS) and the National Health Fund (FNS). Variables related to the number of graduates and those who dropped out of primary and secondary education collected from the website of the National Institute of Educational Studies and Research Anísio Teixeira (INEP).

The socioeconomic variables were expenditure on hospitalizations for diabetes (by patient's place of residence), the natural logarithm of annual expenditure on health in the municipalities of Pernambuco (from 2007 to 2018), Gross Domestic Product (GDP) per capita and the Index Municipal Development for Employment and Income (FIRJAN).

The demographic variables were: the general population by municipality, the proportion of the female and male population, the proportion of individuals over 40 years of age in the population, the approval and completion rates of elementary and secondary education, and the general Municipal Development Indexes. and related to education.

Data Analyzes

We adopted descriptive statistical procedures (frequencies, means, and standard deviations) to characterize the epidemiological, socioeconomic, demographic, and treated and control municipalities' profile before matching. To compare the means and standard deviations of the variables related to treated and control municipalities and the respective calculation of the effect size, Cohen's d measure was used.

Propensity Score Matching

The pairing uses a balanced score, which is obtained based on a regression model with a *logit* linkage function that uses a binary dependent variable that takes the value one, if the municipality implemented the HGP (treated), or zero, otherwise (control).

The probability of municipalities implementing the PAS was estimated using a model that considered a vector of characteristics from the period before exposure to the program [25,26] which is given by:

$$\mathbf{P\ (HGP_{\mathit{i},0}=1)=\emptyset(\beta X_{\mathit{i}},-1)} \qquad \textbf{(1)}$$

where $\emptyset$ is a *logit* cumulative distribution function and HGP_i is a dummy variable that takes the value 1 if the i-th municipality has implemented HGP (treated) and 0 if not treated, X_i,-1 is a vector of k explanatory variables weighted by the inverse of the treatment probability and β is a vector of parameters associated with these variables.

The probability that the municipality will be treated, given the set of features X, is called the propensity score, $\hat{P}(X) = P(HGP_{i},0=1 \mid X_{i},-1)$. To calculate the propensity score, variables were selected that described the characteristics of the municipalities that potentially explain their adherence to implementing the HGP. Matching was performed using Kernel algorithms, with 50 bootstrap repetitions[19].

Differences-in-Differences Regression

To minimize eventual selection biases due to unobservable characteristics of the treated and controls, we estimated a differences-in-differences regression model[25]. This estimator is widely used in public policy impact assessments and can be described according to equation 2 below:

$$\mathbf{DD = E\ [(Y_i^{t1} - Y_i^{t0}) - (Y_j^{t1} - Y_j^{t0})]} \qquad \textbf{(2)}$$

This equation considers a variable t = 0 as the period before the implementation of a policy or program, and t = 1 as the period after; Y_i as the outcome variable for a treated municipality i, and Y_j as the outcome variable for a control municipality j.

Considering δ_i as the difference-in-differences estimator value calculated in equation (2) above, we can represent the DID method in this study using the generic equation:

$$\boldsymbol{Y_{it}= \alpha_i+\beta_{1i}\mathrm{HGP}_{it}+\beta_{2i}P\acute{o}s\mathrm{HGP}_{it} + \delta_i(\mathrm{HGP}*\mathrm{T})_{it}+ \epsilon_{it}} \qquad \textbf{(3)}$$

where δ_i HGP_{it} is a dummy variable that takes the value 1 if the municipality has centers of the Health Gym Program implemented from 2011 and 0 otherwise, T_{it} is a dummy variable equal to 1 for periods after the program and 0 if otherwise, αi is the vertical intercept, $\beta 1$ and $\beta 2$ are parameters, and ϵit is the error term.

Double Difference Matching

Aiming to increase the robustness of the evaluation results, blocks of paired municipalities framed in the area of common support between treaties and controls were used to weight a differences-in-differences regression model[25]. In this way, it was possible to estimate the impact of the treatment on the municipalities paired with a common support "C". Thus, the DDM_i estimate for each treated municipality i in the time periods (t = 0; 1) was calculated by the equation:

$$\mathbf{DDM = E\ [(Y^1_{i1} - Y^1_{i0})\ \Sigma_{j\epsilon c}\ W_{ij} - (Y^0_{j1} - Y^0_{j0})]} \qquad \textbf{(4)}$$

where W_{ij} is the weight given to control municipality *j*, paired to treatment municipality *i*. In this case, a weight of 1 was assigned to the treated municipalities and for the controls, the weight was calculated by:

$$\mathbf{\hat{P}(X)/1-\hat{P}(X)} \qquad \textbf{(5)}$$

Considering that the adhesion of municipalities to the HGP took place in different years between 2011 and 2018, the model described in equation (4) was increased by fixed effects of year and municipalities. In addition, Wooldridge test was performed to verify the serial self-correction of the regression residuals and the Wald test verified the presence of group heteroscedasticity in the regression residuals in panel models.

All analyzes were performed using the Stata statistical package, version 16.0. This study used secondary data in the public domain, therefore, there was no need to review the project by the research ethics committee.

RESULTS

The results are presented in three sections. The first describes the epidemiological, socioeconomic, and demographic characteristics of the municipalities that make up the treated and control groups. The second part presents the graphical analysis and the balancing test, which were used to verify the fulfillment of the assumptions and quality of the Propensity Score Matching. The third section presents the impact of HGP on hospital admission expenses for type II diabetes using the Double Difference Matching (DDM) method.

Epidemiological, Socioeconomic, and demographic characteristics of the municipalities

In the state of Pernambuco, there were 513,776 hospitalizations for all causes in 2007 and in 2018 there were 549,719 occurrences. Of the total hospitalizations in 2007, 7,594 were due to diabetes (1.47% of all hospitalizations - 59.6% among women) and in 2018 there were 5,494 hospitalizations due to diabetes (1% - 51.3% among women).

Hospitalizations for diabetes demanded a total expense of US$ 1,153,958.40 in 2007 (0.8% of the expense with all hospitalizations) and US$ 899,687.34 (0.59%) in 2018. Table 1 presents the epidemiological, socioeconomic, and demographic characteristics of the municipalities of Pernambuco.

Table 1 - Descriptive statistics of the epidemiological, socioeconomic and demographic variables of the municipalities. Pernambuco, 2007 to 2018.

HGP	Coef.	z	[95% Conf.	Interval]
Epidemiological				
Hospital bed/municipality	0.001 (0.001)	0.97	-0.001	0.004
% coverage PHC teams	-1.122** (0.531)	-2.11**	-2.163	-0.082
Physician / inhabitant	693.981* (258.139)	-2.98*	-1.378	-0.2846
Socioeconomics				
per capita GDP	-0,000 (-0,000)	-0.30	-0,000	-0,000
Total Health Care spends(log)	0.651 (0.248)	2.63	0.166	1.137
Demografic				
Population (log)	-0.831** (0.279)	-2.98**	-1.378	-0.2846
high school pass rate	-0.006 (0.012)	-0.50	-0.029	0.017
pass rate in elementary school	-0.021 (0.034)	-0.64	-0.089	0.045
failure rate in elementary school	-0.065 (0.043)	-1.52	-0.149	0.019
High school dropout rate	-0.014 (0.0108)	-1.34	-0.036	0.007
Outlier	0.537 (0.238)	2.26	0.071	1.003
Consant	-0.614 (3.936)	-0.16	-8.328	7.100

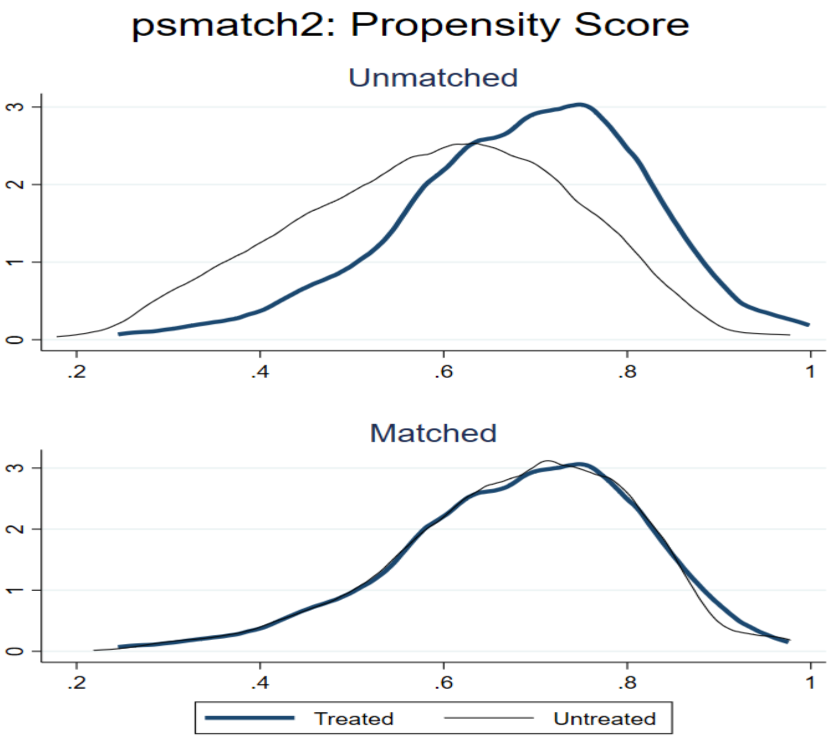
Source: Prepared by the authors.
Note 1: Table prepared by the author based on data from SIH, SIOPS, and IBGE
Note 2: (*) values in US Dólars

Propensity Score Matching

The propensity score matching model included the same epidemiological, socioeconomic, and demographic variables that made up the DID and DDM model (difference-in-differences weighted by propensity score). One of the main objectives of the PSM is to make the treated and control groups similar, considering their observable characteristics, as shown in Figure 1, which describes the sample distribution before and after matching.

Figure 1 shows that before matching the groups of treated and control municipalities had very different observable characteristics, with a greater concentration of the latter in the left tail of the distribution, while the treated groups were concentrated in the right tail and in the upper portion. However, after matching the common support area between treated and controls (in the center of the distribution) was expanded, reducing the differences in the estimated probability distribution, and making the two groups similar. It indicates that the proposed model is adequate to evaluate the impact of the HGP on hospital admission expenses for Type II Diabetes Mellitus in the state of Pernambuco.

Figure 1– Distribution of treatment probability for treated and controls - Before and after matching



Source: Prepared by the authors

The model's robustness test showed that the matching met the balancing property, indicating that there were no statistical similarities between the matching variables. Furthermore, Rubin's B (20.6) and Rubin's R (1.16) statistics demonstrated that the treated and control groups are sufficiently balanced.

In the analysis of the difference-in-differences method paired by the propensity score, presented in table 2, it is observed that the presence of HGP caused a reduction of 19.74% in expenses with hospitalizations for type II diabetes mellitus when comparing treated and control municipalities. It should be noted that the impact of HGP on hospital admissions for DM betes was statistically significant, at least at a 10% level, except for 2018.

Table 2 - Impact of HGP on hospital admission expenses for type II diabetes using the Double Difference Matching (DDM) method. Pernambuco, 2007 to 2018.

Costs whith diabetes (natural logarithm)	Coef.	Std. Err.	[95% Conf.	Interval]
HGP	-0.1974** (0.077)	.081	-0.326	-0.004
PSM	1.133 (1.146)	1.146	-1.119	3.413
Epidemiological				
Hospital bed/municipality	-0.001** (0.001)	.001	-0.002	-0.000

% coverage PHC teams	0.393 (0.300)	.300	-0.198	0.985
Physician / inhabitant	-14.650 (176.831)	176.831	-363.528	334.226
Socioeconomics				
per capita GDP	0.000 (0.000)	.000	-0.000	-0.000
Total Health Care spends (log)	-0.073 (0.0474)	.0474	-0.166	0.020
Demografic				
Population (log)	-2.076 (1.330)	1.330	-4.696	0.555
high school pass rate	0.003 (0.006)	.006	-0.009	0.015
pass rate in elementary school	-0.022 (0.019)	.019	-0.061	0.016
failure rate in elementary school	-0.027 (0.024)	.024	-0.075	0.020
High school dropout rate	0.006 (0.005)	.005	-0.003	0.015
Outlier	-8.171*** (0.140)	.140	-8.449	-7.894
Year (After implementation)				
2012	-0.450*** (0.166)	0.166***	-0.827	-0.171
2013	-0.599*** (0.153)	0.153***	-0.901	-0.297
2014	-0.554*** (0.138)	0.138***	-0.826	-0.281
2015	-0.214* (0.124)	0.124*	-0.458	0.030
2016	-0.288** (0.119)	0.119**	-0.522	-0.053
2017	0.049* (0.101)	0.101*	-0.150	0.249
2018	0.162 (0.010)	0.010	-0.034	0.358
Constant	30.304** (14.094)	14.094**	2.497	58.111

Source: Own elaboration, using STATA software.

Note 1: Significance levels at 5% (*) and 10% (**). Matching performed by Kernel algorithm with 50 bootstrap repetitions.

DISCUSSION

Hospitalizations for type II diabetes mellitus correspond to 1.47% of the total hospitalizations in the state of Pernambuco in 2007 and 1.00% in 2018. These hospitalizations generated an expense equivalent to 0.80% and 0.59% of the total health expenditure with hospitalization in the state in the respective years. Thus, it denotes a decline in the absolute number of hospitalizations and in the expenses they entailed between 2007 and 2018. These findings corroborate the study by Gerhardt et al. (2016), who evaluated the temporal trend of hospitalization for DM in the state of Paraná (Brazil) and found that there was a reduction in hospitalizations for diabetes mellitus over 12 years (2001 to 2013)[27].

Regarding hospitalization expenses, there was a higher expenditure on DM in females in 2007 and 2018, a result that confirms what was exposed in the study by Santos et al. and elderly people living in the state of Ceará, Brazil, in the period 2001-2012 and identified that 58.4% of hospitalizations for diabetes mellitus occurred among women[28].

In line with the relative decrease in the number of hospitalizations between 2007 and 2018, there is a percentage reduction in spending on hospitalizations for DM in relation to all causes of hospitalization. In addition, there is greater total health care spending, which may be related to the potential of primary care to prevent and control diseases and, consequently, reduce the frequency and expense of hospitalizations, since health promotion and disease prevention at this level of care can mitigate diabetes complications that lead to hospitalization[27].

Compliance with the assumptions and quality of the Propensity Score Matching

The variables used in the PSM model are in line with findings in the literature that report the influence of schooling, income, population, and health care network structure on hospital admissions for diabetes mellitus[22,27]. DM is more prevalent in age groups over 50 years old, and is strongly related to the illiteracy rate and income, as inequality in income distribution impacts access to resources and infrastructure, and in line with low schooling, influences the quality of self-care, knowledge, and control of risk factors[22,29,30].

The matching contributed to the construction of the final HGP impact assessment model, as the combination of this method with the difference-in-difference method minimizes selection biases by characteristics of the treated and controls, given that the matching attenuates the observable characteristics related to the absence of common support, while DID seeks to reduce unobservable characteristics[31].

The graphical analysis of the PSM indicates that the assumption of the common support of the Propensity Score Matching was met. It allows us to infer that municipalities with the same propensity score had a positive (and similar) probability of being treated or being a control[32], because although the distribution of the values of the vector of observable characteristics of the municipalities that implemented and that did not implement the HGP was slightly different before the pairing, this method managed to minimize these differences and form comparable groups[33].

Also noteworthy is the assessment of the quality of the matching, which was attested through the balancing test, which verified statistical similarities between the matching variables and the reduction of standardized bias before and after, both at the level of 5%[14,15].In this sense, the observable characteristics of the treated and control municipalities were satisfactorily balanced, given that Rubin's B and R statistics (20.6 and 1.16, respectively) were within the limits established in the literature ($B < 25$ and $0.5 < R < 2$, respectively) to test the balance quality[34].

Impact of the HGP on hospital admission expenses for type II diabetes

The model estimated using the DDM method pointed out that the municipalities that implemented the HGP spend 19.74% less on hospital admissions for diabetes than those who do did not implemented. Other studies have already observed that the presence of HGP in the state of Pernambuco reduced the mortality rate from systemic arterial hypertension[16] and the expenses of hospital admissions for cerebrovascular diseases[8].

Evidence shows that the HGP was effective in increasing the population's physical activity level[12]. This behavior has the potential to decrease the risk of developing diabetes[6,35,36], control body weight and blood glucose levels, which are important risk factors for diabetes[37].In this sense, the impact of the HGP on reducing expenses with DM hospitalizations can be related to the fact that most Brazilian municipalities adopt physical activity as the main intervention of the program[38].

Another potential explanation for the impact of the HGP in reducing expenses with hospitalizations for DM is the development of health promotion activities focused on encouraging the adoption of healthy eating habits, which are the guiding principles of the program[39,40].

CONCLUSIONS

This study aimed to assess the impact of the Health Gym Program on reducing diabetes hospital admissions for type II diabetes mellitus in Pernambuco. For that, we used the differences-in-differences technique weighted by propensity score matching, aiming to reduce the distribution biases of observable and unobservable characteristics, in order to estimate the impact of the treatment on the municipalities matched by a common support.

The variables included in the econometric models are aligned with those described in epidemiological studies that point to factors associated with hospital admissions for DM, reinforcing the theoretical plausibility of the proposed model to explain the impact of HGP.

The DDM Model showed that the municipalities that implemented the HGP spent an average of 19.74% less on hospital admissions for type II diabetes mellitus than municipalities that did not implement this program, and that this impact proved to be statistically significant over the years evaluated.

As a limitation of this study, we highlight the impossibility of using variables at the individual-level, and the non-inclusion of variables that may interfere with the choice to join the HGP, such as the political party of the municipal mayors. However, the use of propensity score matching reduces this problem and minimizes the possibility of selection bias due to observable characteristics of the treated and control groups[41]. In addition, it is also noteworthy that the use of the difference-in-differences estimator minimizes potential biases caused by possible omissions of observable characteristics[14,31,42].

The results of this study show the importance of expanding the Health Gym Program. This intervention is important to the promotion of physical activity on primary health care and also a strategy that impacts on expenses resulting from hospitalizations for diabetes, benefiting not only the population but also the management, since it allows the reduction of expenses with hospitalizations in the municipalities.

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