IOSR Journal Of Humanities And Social Science (IOSR-JHSS)
Volume 30, Issue 4, Series 4 (April, 2025) 19-30
e-ISSN: 2279-0837, p-ISSN: 2279-0845.
www.iosrjournals.org

Impact Of The Implementation Of The National Civic-Military Schools Program (PECIM) On Brazilian Educational Indicators

Ariane Cristina Oliveira Olimpio [1], Wellington Ribeiro Justo[2]
(PPGECON/ Federal University Of Pernambuco, Brazil)
(PPGECON, Federal University Of Pernambuco / PPGERU/Regional University Of Cariri, Brazil)

Abstract:
In the context of Brazil's persistent educational challenges, which include structural problems, school violence and a shortage of teaching resources, this study investigates the National Civic-Military Schools Program (PECIM). The initiative was driven by the remarkable performance of military schools, which stand out for their infrastructure and students' academic performance. The federal government, motivated by these indicators, decided to invest in PECIM, selecting public schools with low scores on the Basic Education Development Index (IDEB) and poor infrastructure. This study aims to evaluate the impact of PECIM on these schools, taking into account infrastructure indices and school performance rates. Using the Factor Analysis and Differences in Differences approach with multiple periods, as developed by Callaway and Sant'Anna (2021), the results indicate a positive evaluation of the policy. The factor analysis reveals that the six factors explored significantly explain 77.53% of the total variance of the data, demonstrating a strong correlation between the variables and heterogeneity in the covariances. Using the methodology of Callaway and Sant'Anna (2021), school performance rates showed a significant average treatment effect for the indicators analyzed: an increase in the pass rate and a reduction in the dropout and failure rates, corroborating the effectiveness of the policy even in the face of the challenges imposed by the COVID-19 pandemic. However, for a more comprehensive understanding of the positive impact on these schools, a longer period of exposure to the Program is necessary.
Background*: Brazil faces persistent educational challenges, including structural deficiencies, school violence, and a shortage of teaching resources. Amid these issues, the National Program for Civic-Military Schools (PECIM) emerged, inspired by the superior infrastructure and academic performance of military schools. Motivated by these results, the federal government invested in PECIM, targeting public schools with low scores in the Basic Education Development Index (IDEB) and inadequate infrastructure to improve educational indicators.*
Materials and Methods*: This study evaluates the impact of PECIM on selected schools by analyzing infrastructure indices and school performance rates. It employs Factor Analysis to identify key variables and the Differences-in-Differences with Multiple Periods (DDMP) approach, as developed by Callaway and Sant'Anna (2021), to assess treatment effects over time, using military schools as a control group.*
Results*: Factor analysis revealed six factors explaining 77.53% of data variance, indicating a strong correlation of variables and covariance heterogeneity. DDMP analysis demonstrated a significant average treatment effect, with increased approval rates and reduced dropout and failure rates, affirming the effectiveness of PECIM despite COVID-19 challenges.*
Conclusion: *Findings suggest a positive impact of PECIM on infrastructure and academic performance in targeted schools. However, a longer exposure period is necessary for a comprehensive evaluation of its sustained effects, highlighting the potential of this policy to address Brazil's educational challenges.*
Key Word: *Difference-in-Differences; Factor Analysis; Military Schools; PECIM; Impact Assessment.*

Date of Submission: 01-04-2025 Date of Acceptance: 11-04-2025

I. Introduction

Education is part of a set of institutions that are important for a country's socio-economic development and for the distribution of economic growth. In Brazil, the high level of social inequality underscores the importance of education in the social context, and thus the importance of public policies also arises with regard to the determinants of the school performance of Brazilian students, i.e. schooling, teacher experience and qualifications, school infrastructure, as well as learning (ALBERNAZ et al.,2002).

In the last five years, Brazil has seen the loss of 1.9 million students from primary to secondary school and has also faced problems with the precariousness of school infrastructure, failure rates, among others, according to the National Institute for Educational Studies and Research Anísio Teixeira (INEP). And it is through these perspectives and ideals that the civic-military schools (ECIM) emerged, in order to implement a new way of managing the educational, didactic-pedagogical and administrative areas of conventional public schools with the support of the military and later the introduction of the National Program of Civic-Military Schools (PECIM) in the ECIM of the MEC model.

According to Barbosa et al. (2021), civic-military schools can provide quality education, contributing to improvements in the family, school and social environment. The contribution of military bodies to public schools is a major contribution to basic education in terms of access, permanence and learning. The implementation of civic-military schools was conceived and designed on the great example of military schools, which have the best indicators in educational performance research rankings, a low dropout rate and a low failure rate.

The ECIM model aims to promote management excellence in the educational, didactic-pedagogical and administrative areas, based on the military school model. This will be achieved through actions linked to the development of behaviors, values and attitudes, with the aim of developing students and preparing them to exercise citizenship. Actions to achieve good didactic-pedagogical management will be focused on school supervision, pedagogical support, educational evaluation and the pedagogical proposal. The ECIM model will provide training for all the professionals involved in PECIM (BRASIL, 2019).

The criterion for choosing civic-military schools is that the IDEB score must be below average in order to be able to compare satisfactory post-implementation results. Schools that offer primary and/or secondary education are also eligible; - preferably with an enrollment of 501 to 1,000; schools that have the approval of the school community to apply the model (BRASIL, 2021).

At the start of implementation, the Ministry of Education (MEC) set 54 educational institutions to receive the pilot project in 2020, spread across 22 states and the Federal District, and over the course of the students, other schools have joined, with more than 100 schools now covered. The model was implemented in partnership with the Ministry of Defense and schools joined the program on a voluntary basis.

The current government ended the civic-military schools program in July 2023 and one of the arguments is that the purpose of the Armed Forces has been diverted. While almost all governors have proposed continuing and expanding the program, the state of Paraná and the Federal District have been among them. The main results already observed are: 85,292 students served; 4,219 teachers involved; 43 certified schools that implemented the program's management model in the 1st cycle, in 2020, with the methodology established by the Brazilian Institute of Information in Science and Technology (IBICT) and the University of Brasilia (UNB), according to the Civic-Military Schools guidelines.

The relevant factors and characteristics of Military Schools lead to the core of the following structured work to evaluate the impact of civic-military schools on student performance and on transfers of resources for school infrastructure, with the aim of verifying that the implementation of this educational model has added to the beneficiary schools, in order to be able to contribute in the future to public policy decisions.

Recent studies highlight the importance of investments in school infrastructure to improve educational outcomes, as in Jackson et al. (2016), a central objective of PECIM in Brazil.

The study uses the method of differences in differences with multiple periods by Callaway and Sant'Anna (2021) to evaluate the impact on schools where PECIM was implemented. The years chosen were from 2018 to 2022, in which the years 2020, 2021 and 2022 belong to the years in which these schools were already inserted or joined. Thus, using the method of differences in differences with multiple periods, the years before and after implementation were used for the study, with the Military Schools being used as a control variable in the methodology implemented. The variables chosen were infrastructure and school performance rates, as the program has a short exposure time for treatment in the chosen methodology. The aim is to identify whether the transfer from the Federal Government to the schools that implemented PECIM actually had any impact.

This paper is structured in four parts, including this introduction. The second part of the paper will discuss military schools, followed by civic-military schools, the fourth part of the paper refers to the methodology used, and finally, the results and final considerations.

II. Military Schools And Their Characteristics

Cabral (2018) points out that militarization has expanded considerably in previous years. There were 93 schools in 18 states of the Federation, with the response to this expansion focused on the issue of violence and an indicator of improved performance, given that, among the state schools in these 18 states, 9 of them obtained first place in the National High School Exam (ENEM).

Cabral (2018) points out that militarization has expanded considerably in previous years. There were 93 schools present in 18 states of the Federation, with the response to this expansion focused on the issue of violence and an indicator of improved performance, given that, among the state schools, of these 18 states, 9 of them obtained first place in the National High School Exam (ENEM). In the social context, the demands and rigid discipline are seen as something positive by the more conservative population, who consider it "political correctness" to combat vulnerabilities.

Military schools are funded by the Ministry of Education, the Ministry of Defense and the military police. Teachers' salaries exceed 10,000 reais, and the schools have infrastructure with different laboratories, such as chemistry and robotics, sports courts and swimming pools. The result of this investment is in the infrastructure of these schools, the appreciation of educators, and the return on this investment can be seen in the performance of medals, IDEB, among others. The elementary school index for military schools has an IDEB score of 6.5, compared to 4.1 for state schools.

According to Schlosser (2020), the initial motivation behind the creation of these schools was related to concerns about school safety, one of the main objectives being the preventive nature of safety for students and teachers. However, the same author points out that the consequence of this militarization in schools leads to an improvement in student learning and performance rates, since the presence, for example, of police officers in the school would have a direct impact on combating student violence and indiscipline.

There are authors who disagree with this point of view, for example, for Pellanda (2019) in an interview with Matouka for the Jornal Educação Integrada, the demand for military schools is more related to a need for improvement and quality in Brazilian schools than for militarized schools. She argues that, with better infrastructure in schools, it is possible to reduce classroom crowding, increase teachers' salaries and invest in the qualification of these teachers, to lead to an improvement in educational quality.

III. The National Program For Civic-Military Schools (Pecim) And The Debate On Civic-Military Schools

PECIM arose from the need to improve the teaching-learning process, given the high level of learning and quality of the military schools of the Army, the Police and the Military Fire Brigades throughout Brazil. It has been set up as a school management model of excellence for basic education, and is being implemented in cooperation with the states, municipalities and the Federal District. Each school receives an investment of around one million reais per school per year to be invested in infrastructure upgrades and other improvements.

The program targeted schools with different social vulnerabilities in order to have a positive impact through new educational, didactic-pedagogical and administrative management. It was necessary to adjust some needs and simplify the Civic-Military School Guidelines. In the first year, it managed to achieve success in its implementation, with positive results for the schools belonging to the Program, even in the face of difficulties caused by the Covid-19 pandemic (BRASIL, 2021).

According to Ordinance No. 1071, which regulates the implementation of PECIM, schools will be selected based on the following criteria: socially vulnerable students; below-average performance in the IDEB; preferably with an enrollment of 501 to 1,000; offering the final years of regular basic education and/or regular high school; offering a morning and/or afternoon shift; approval of the school community to implement the model, through public consultation in person or electronically.

The program is part of a set of actions to stimulate and strengthen ECIMs, with the aim of improving the school environment, school management, pedagogical practices in the school and the academic performance of its students, in collaboration with the states, municipalities and the Federal District. The civic-military school and its values should lie in civility, excellence and dedication (BRASIL, 2021)

The region with the most civic-military schools in 2022 was the North, followed by the South. In all, there are 196 civic-military schools. The national model is applicable to any public school, whether state or municipal, seeking to maintain its individuality and, at the same time, innovating aspects of management implemented in military schools, without claiming to be a new teaching modality in Brazilian education, but with the obligation to have its own school management model (MINISTÉRIO DA EDUCAÇÃO, 2022).

The proposal of civic-military schools is based on proposing a system that is based on the pillars of behavior, values and attitudes, in order to improve coexistence at school and then also prepare for coexistence outside the school environment, not annulling individualities, but disciplining to make this coexistence a responsibility towards the other. In an educational environment of practice and evolution, PECIM has strategic objectives, some of which are: quality of education; equal access, permanence and learning; encouraging entry and ensuring the permanence and training of students; contributing to the training of teachers and professionals in basic education; and catching schools with IDEB lower than the municipal, state or national average (MINISTÉRIO DA EDUCAÇÃO, 2022).

IV. Methodology And Data

The variables used to calculate the impact assessment in this work were infrastructure variables and performance rates provided through INEP microdata. According to INEP (2023), school performance rates are guidelines published annually by the Institute, using data collected by the Basic Education School Census, and are essential for verifying and monitoring schools. The performance rates are part of the IDEB calculation and were used in the research, divided into:

- Pass: Pupil has satisfactory attendance and grades.
- Fail: Pupils do not have satisfactory attendance and/or grades.
- Dropout: Pupil no longer attends classes.

The pass rate refers to the percentage of students who, at the end of the school year, have met the minimum criteria for completing the stage of education. The failure rate, on the other hand, refers to the percentage of students who, at the end of the school year, did not meet the minimum criteria for completing the stage of education. For the dropout rate, it indicates the percentage of students who stopped attending classes after the reference date of the School Census. In cases where there is no concrete information on enrollment, they will be considered as having no information. And the sum of all these rates will always result in 100% of enrollments. Primary, secondary and integrated secondary school enrollments are part of the calculation of yield rates. For transfer students, the information for performance data will be placed under "admitted after" in the calculation of performance rates.

For microdata, INEP gathers data sets with information from the Institute's surveys, exams and assessments, making it possible to obtain a vast panorama of reliable information on Brazilian education. The school infrastructure microdata has a range of information, such as: filtered water, drinking water, artesanal well; types of sewage; types of energy; types of waste collection; sports courts, swimming pools, parks; computer, copier, printer; tablet, internet; food; security; teaching materials; among others.

Factor Analysis

Hair et al. (2005) argue that, due to the abundance of data often collected in empirical research, it is necessary to use dimensionality reduction methods to improve the interpretation of the results. One such method is factor analysis, which can be used to identify patterns or potential relationships between numerous variables. Factor analysis can also be used to determine whether data can be condensed or summarized into a smaller group of factors**.**

Factor analysis is a statistical method that consists of five steps: (1) Analysis and adjustment of the correlation matrix: the first step is to check whether the correlation matrix is suitable for factor analysis. This can be done using goodness-of-fit tests; (2) Extracting the number of factors: the second step is to identify the number of factors that best represent the data. This can be done using extraction methods such as exploratory factor analysis (EFA) or confirmatory factor analysis (CFA); (3) Rotating the factors: the third step is to rotate the factors to make them more interpretable. This can be done using rotation methods such as orthogonal rotation or oblique rotation; (4) Interpreting the factors: the fourth step is to interpret the factors. This can be done by identifying the variables that carry the most weight in each factor and (5) Validating the factor analysis: the fifth step is to validate the factor analysis. This can be done using validation methods such as confirmatory factor analysis.

Two well-known tests in factor analysis, the first is the Kaiser-Meyer-Olkin (KMO) statistical test, used to calculate whether the sample is best suited to the application of factor analysis, given by the equation:

$$KMO_j = \frac{\sum_{i \neq j} r_{ij}^2}{\sum_{i \neq j} r_{i,j}^2 + \sum_{i \neq j} u}$$

Where R = [r_ij] is the correlation matrix, U = [u_ij] is the partial covariance matrix, and ∑ is the sum. KMO values range from 0 to 1, KMO values are interpreted as:

Between 0.8 and 1, they indicate that the sampling is sufficient;

Less than or equal to 5 means that the sampling is insufficient and corrective action should be taken;

Close to 0 indicates that there are generalized correlations, i.e. bad for the factor analysis model.

KMO values vary from author to author; some, such as Hair et al. (2005), say that values between 0.5 and 1.0 are acceptable enough. The KMO together with the second test, Bartlett's test of sphericity, indicate that the factor analysis is adequate.

Kaiser (1974) then classified the values in the results as:

Table 1: Kaiser-Meyer-Olkin (KMO) test values, according to Kaiser (1974)

0,00 - 0,49	Unacceptable
0,50 - 0,59	Bad
0,60 - 0,69	Fair
0,70 - 0,79	Average
0,80 - 0,89	Good
0,90 - 1,00	Very good

Source: own elaboration based on Kaiser (1974).

Bartlett's test was used to check whether the correlation matrix of the data is suitable for factor analysis. According to Field et al. (2012), if the correlation matrix resembles an identity matrix, it means that the variables are weakly correlated with each other. If the correlation matrix is an identity matrix, it means that the variables are completely independent. The null hypothesis of the test is that the variables are not correlated in the population. The test statistic is given by:

$$T = \frac{(N-k)ln\ s_p^2 - \sum_{i=1}^{k}(N_i - 1)ln\ s_i^2}{1 + \left(\frac{1}{3(k-1)}\right)\left(\frac{\sum_{i=1}^{k} 1}{(N_i - 1)}\right) - \left(\frac{1}{N-k}\right)}$$

Let s_i^2 be the variance of the ith group, N the total sample size, N_i the sample size of the ith group, s_p^2 the grouped variance, given by the weighted average of the group variances, and k the number of groups/factors. In this case, k groups were considered and divided, representing the original set of observed variables. These groups are:

Table 2: Breakdown of factors from factor analysis

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
School resource by group	Infrastructure	Physical	Technological	Human	Teaching level	Accessibility

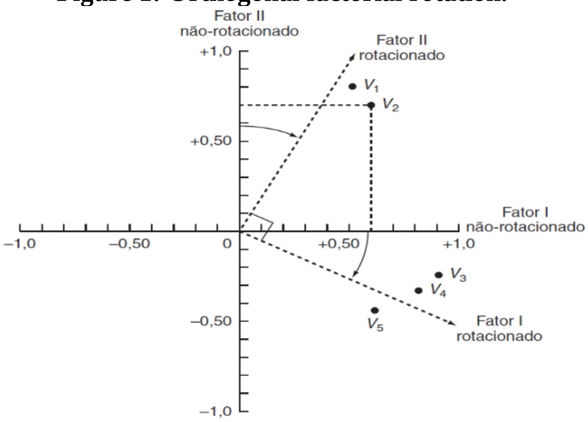
Source: Own elaboration.

Pereira et al. (2019) argue that the R factor is given by correlation coefficients between variables. Therefore, it is important that the variables are correlated with each other for the factor analysis to be carried out. Another method used in factor analysis literature is the Kaiser-Guttman criterion (Guttman, 1954; Kaiser, 1960). This criterion uses the eigenvalue of each factor to determine the number of factors to be extracted. In the case of this study, the number of factors was determined after testing with various numbers of factors. The Kaiser-Guttman criterion was used to choose six factors, as the eigenvalues of these factors were greater than 1.0 (λi>1).

According to Hair et al. (2005), because this model does not always provide factors that can be easily interpreted, factor rotation is used in order to simplify the process of manipulation or adjustments to synthesize a simpler and more meaningful factor solution.

The method chosen was varimax factor rotation, also known as orthogonal factor rotation, because it is the most widely used in research, and the aim is to reduce the number of original variables. It is used to simplify the columns in a factor matrix. The varimax criterion minimizes the number of variable loadings in a factor. Loadings close to +1 or -1 indicate a clear positive or negative association, and loadings close to 0 indicate a lack of association between the variable and the factor (Hair et al. 2005). The exploratory factor analysis was conducted following modern practices, according to Fabrigar & Wegener (2016), with Varimax rotation to maximize the interpretability of the factors. Figure 1 shows how varimax (orthogonal) rotation works.

Figure 1: Orthogonal factorial rotation.



Source: Hair et al. (2009).

Therefore, the purpose of factor analysis is to synthesize the information in several original variables into a new, but now smaller, set of new variables. The overview of the results focuses on common factors that provide insights into variations and data reduction. The next section discusses the database and more information about the data chosen for this research. In this study, the factors found by factor analysis will enter the models as control variables.

Differences in differences with multiple periods and variation over time

The purpose of this study is to evaluate the effectiveness of the National Civic-Military Schools Program, based on the hypothesis that the control group can provide an average trajectory of the outcome variable for the groups that did not join the program, given the investment that these schools received from the Federal Government. According to Hargreaves and Shirley (2022), well-being in schools is important for students, as it is directly linked to learning. As a result, there is a lower drop-out rate and greater motivation in the environment.

The Differences in Differences methodology, also known as “Diff-in-Diff”, is the most widely used empirical method for obtaining answers on impact evaluation. According to Fogel (2012), it is normally used when there is information on the outcome variable before and after the implementation of a program and/or a given period of intervention exposure. There are other models for impact evaluation, using statistics and econometrics, some of which are: Differences in Differences, Matching, Instrumental Variables, Randomization Method, Discontinuous Regression, among others. The aim of this work is to apply one of the impact assessment methods to evaluate the effect of the program mentioned in the paragraph above.

In this work, the difference-in-differences estimator with multiple periods (DDMT) by Callaway and Sant'Anna (2020) will be used to assess the impact of an intervention. The DDMT is an approach widely used in impact evaluation that compares the evolution of the variable of interest in a treatment group with the evolution of the same variable in a control group. The main advantage of DDMT is that it makes it possible to control for the effects of unobserved factors that may affect the variable of interest.

Callaway and Sant'Anna's DDMT extends the traditional difference-in-differences method to the case of multiple periods and variations in treatment time. The method also addresses the issue of violating the assumption of parallel trends, which can occur when the treatment group and the control group have different trajectories before the intervention.

To control for the effects of unobserved factors, we used a linear regression model with fixed effects for each treatment and control group. The model also includes controls for observed covariates that may affect the variable of interest.

Rotch, Sant'Anna, Bilinski, et al. (2023) present a breakthrough in the field of difference-in-differences econometrics. The study explores the “canonical” assumptions of the method, with an emphasis on multiple periods and variation in treatment time, potential violations of parallel trends and alternative structures for inference.

In the canonical model, there are two periods and two groups: a treatment group, which receives treatment from the second period onwards, and a control group, which does not receive treatment in any period. The fundamental assumption of the model is that, in the absence of treatment, the trajectories of the variables of interest in the two groups would be parallel. Furthermore, it is assumed that the treatment has no causal effect prior to its implementation.

To estimate the average treatment effect on treatment (ATT), the study uses a two-way fixed effects regression (TWFE). TWFE is a robust technique that can deal with violations of the parallel trends assumption.

In the model, difference-in-differences with multiple periods and variation in treatment timing applies to situations where there are more than two periods and the treatment units have different timing. Gardner (2021) demonstrates various alternative approaches to difference-in-differences regression that are robust to heterogeneity across groups and periods, where treatment is staggered.

Callaway and Sant'Anna (2020) present a difference-in-differences methodology with multiple periods (DDMT) that allows for the estimation of heterogeneous and dynamic treatment effects. The DDMT is divided into three stages: (1) Identification: disaggregated treatment effects are identified using a linear regression model with fixed effects for each treatment and control group; (2) Aggregation: the disaggregated treatment effects are grouped to form causal measures; (3) Estimation and inference: treatment effects are estimated and inferred using a bootstrap procedure.

DDMT is a robust technique that can handle violations of the parallel trends assumption and arbitrary heterogeneity. Furthermore, DDMT avoids interpretation issues with TWFE results, which can be biased when treatment effects are heterogeneous or dynamic.

In empirical studies, researchers typically consider a difference-in-differences framework with variation in treatment timing and heterogeneous treatment effects. In this context, the causal parameter of interest is:

Yit = $\varphi_i + \varphi_t + \beta^{TWFE} + D_{i,t} + \epsilon_{i,t}$

However, there is no predictability that the variable β^TWFE establishes a causal relationship in the interaction of the parameters, leading to future problems. To address this, dynamic variations are also considered, given by:

$$Y_{i,t} = \varphi_i + \varphi_t + \gamma_k^{-K} D_{i,t}^{<-K} + \sum_{k=-K}^{-2} \gamma_k^{lead} D_{i,t}^{k} + \sum_{k=0}^{L} \gamma_k^{lags} D_{i,t}^{k} + \gamma_k^{L+} + \epsilon_{i,t}$$

The Callaway and Sant'Anna (2020) model uses an indicator, D_(i,t)^k, to identify the treatment group i in period t, k periods after the start of the treatment. The issue with TWFE is that it can be biased when there is heterogeneity in treatment effects. To address this problem, Callaway and Sant'Anna propose using a difference-in-differences model with multiple periods. This model is more robust to heterogeneity and allows for the estimation of dynamic treatment effects.

In this study, therefore, the DDMT model is followed for the period between 2018 and 2022, with treatment occurring from 2020 onward. Thus, there are schools exposed to the treatment for three years, two years, and one year. The control group consists of military schools.

The Difference-in-Differences with Multiple Periods approach by Callaway & Sant'Anna (2021) was chosen for its robustness to treatment heterogeneity, overcoming limitations of the traditional TWFE as noted by de Chaisemartin & D'Haultfœuille (2020) and Goodman-Bacon (2021).

Callaway and Sant'Anna (2020) consider a random sample:

$$\{ (Y_{i,1}, Y_{i,2}, Y_{i,3}, \ldots . Y_{i,\tau} D_{i,1}, D_{i,2}, D_{i,3}, \ldots . D_{i,\tau}, X_i \})_{i=1}^{n}$$

Where, D_(i,t)=1 if unit i is treated at time 3; D_(i,t)=2 if unit i is treated at time 4; D_(i,t)=3 if unit i is treated at time 5, and 0 for times prior to treatment. And, G_(i,g)=1 if i is the first group treated at time g, and 0 otherwise. C = 1 for the comparison group that was not treated.

With a limited treatment expectation:

E $[\, Y_t(g) \big| \, X, G_g = 1 \big] = E\,[Y_t(0)|X, G_g = 1]$

For all g ϵ G , t ϵ 1,2,... τ. When δ=0, the parameter of interest then focuses on the average treatment effect for the group of units first treated at time g, in time (year) t:

ATT (g,t) = E $[Y_t(g) - Y_t(0) \; \big| G_g = 1 \big]$

he first hypothesis of the study is given by: conditional parallel trends based on a 'never-treated' group, for each t ≥ g. With this, an additional group, C, is added. Resulting in:

E $[Y_t(0) - Y_{t-1}(0)|\, X, G_g = 1] = E\,[Y_t\,(0) - Y_{t-1}(0)\;|X, C = 1]$

The second hypothesis of the test focuses on parallel trends for groups not yet treated, for each (s,t) ∈ {2,...τ} × {2,...τ}, g ∈ G such that t ≥ g and s ≥ t:

E $[Y_t(0) - Y_{t-1}(0)|\, X, G_g = 1] = E\,[Y_t\,(0) - Y_{t-1}(0)\;|X, D_s = 0,\; G_g = 0$

Thus, assuming an incorporation and grouping of these identification hypotheses into the ATT, to be fully preserved, and considering that the covariates do not have significant importance in identifying the differences-in-differences, and that it fits the 'never-treated' group as the comparison group, we have:

$$ATT_{unc}^{nev}(g,t) = E\big[Y_t - Y_{g-1}\big|G_g = 1\big] - E\big[Y_t - Y_{g-1}\big|C = 1\big]$$

For “not yet treated” groups as a comparison group, therefore:

$$ATT_{unc}^{ny}(g,t) = E\big[Y_t - Y_{g-1}\big|G_g = 1\big] - EY_t - Y_{g-1}|D_t = 0, G_g = 0]$$

In which the principle of analogy and inference are used for some mean comparisons. For Callaway and Sant’Anna (2020), with an important role of covariates, the 'never-treated' groups are used as a comparison group, and it is possible to employ three estimation methods: Outcome Regression (OR), Inverse Probability Weighting (IPW), and Doubly Robust (AIPW). The estimation of the AIPW method for the 'never-treated' group is given by:

$$ATT_{dr}^{new}(g,t) = E\left[\left(\frac{G_g}{E[G_g]} - \frac{\dfrac{p_g(X)C}{1-p_g(X)}}{E[\dfrac{p_g(X)C}{1-p_g(X)}}\right)(Y_t - Y_{g-1} - m_{g,t}^{nev}(X))\right]$$

Where $m_{g,t}^{nev}(X) = E\big[Y_t - Y_{g-1}\big|X, C = 1\big]$ is the generalized propensity uniformly bounded to 1:

$p_{g,t}(X) = P(G_g = 1|X, G_g + (1 - D_t)(1 - G_g = 1) \leq 1 - \epsilon$

And, the AIPW estimate for the “not yet treated” group, still following the authors, is possible to obtain through the AIPW/DR estimate if this group is used as a comparison group, thus:

$$ATT_{dr}^{ny}(g,t) = E\left[\left(\frac{G_g}{E[G_g]} - \frac{\frac{p_g(X)(1-D_t)}{1-p_g,t(X)}}{E\left[\frac{p_g(X)(1-D_t)}{1-p_g,t(X)}\right]}\right)(Y_t - Y_{g-1} - m_{g,t}^{nY}(X))\right]$$

Where $m_{g,t}^{ny}(X) = E\left[Y_t - Y_{g-1} \middle| X, D_t = 0, G_g = 0\right]$.

Thus, the authors discuss the importance of the difference-in-differences with multiple periods (DDMT) methodology in economic research. In summary, DDMT is a technique that can be used to estimate the effect of an intervention on a variable of interest when there are more than two periods and the intervention can be applied at different times. An important aspect of DDMT is its flexibility with data. DDMT allows the data to adjust their behavior before and during the treatment. This is significant because, in practice, it is unlikely that the data will follow a perfectly parallel trajectory before and after the treatment. Finally, DDMT is a versatile technique that can be applied in a variety of contexts.

V. Results

The purpose of the Factor Analysis tests is to synthesize the information contained in the research database with the least possible loss of information and to enhance the reliability of the study. Hair et al. (2005) argue that these information summaries benefit researchers in impact analysis, where variables identified as highly correlated and belonging to the same factor group may exhibit similar profiles across different time periods in multivariate variance analysis or discriminant analysis.

To determine whether the factor analysis method is applicable and suitable for the purposes of this study, two statistical tests were used: the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity. The results of these two tests can be observed below:

Table 3: KMO and Bartlett test for data adequacy

Kaiser-Meyer-Olkin Measure of Sampling Adequacy	
KMO	0,7753
Barlet test of sphericity	
Chi-square	183,062
P-value	0,000

Source: prepared by the author.

The researcher has freedom regarding the selection of factor extraction; for this factor analysis, due to the abundance of data, it was divided into six factors. The factor analysis extracted six factors that explain 77.53% of the total variance in the data. This indicates that there is a good correlation between the variables, for which factor analysis is suitable for the study. Bartlett's test showed a p-value of 0.00, meaning that the covariance of the variables is heterogeneous.

These factors can be interpreted as follows:

• Factor 1: School Infrastructure. This factor consists of variables that measure the school's physical infrastructure, including potable water, electricity, sewage, waste management, and water treatment.

• Factor 2: Physical School Resources. This factor comprises variables that measure physical resources, including classrooms, restrooms, libraries, kitchens, and cafeterias.

• Factor 3: Technological School Resources. This factor consists of variables that measure technological resources, including computers, audio and video equipment, and educational software.

• Factor 4: Human School Resources. This factor comprises variables that measure human resources, including teachers, staff, and administrators.

• Factor 5: School Education Level. This factor consists of variables that measure the type of education offered, such as regular education, adult education (EJA), elementary school, high school, and technical education.

• Factor 6: School Accessibility. This factor includes variables that assess accessibility for individuals with physical disabilities.

Examples of how to interpret the factor analysis results:

I) A school with high values in Factor 1 is likely to have good school infrastructure, including potable water, electricity, sewage, waste management, and water treatment.

II) A school with high values in Factor 2 is likely to have abundant physical resources, including classrooms, restrooms, libraries, kitchens, and cafeterias.

III) A school with high values in Factor 3 is likely to have abundant technological resources, including computers, audio and video equipment, and educational software.

IV) A school with high values in Factor 4 is likely to have abundant human resources, including teachers, staff, and administrators.
V) A school with high values in Factor 5 is likely to have a high level of education.
VI) A school with high values in Factor 6 is likely to have good accessibility, including access for individuals with physical disabilities.

The results of the factor analysis can be used to identify areas for improvement in schools. For example, if a school has low values in Factor 1, it indicates that the school may need to improve its infrastructure. If a school has low values in Factor 3, it suggests that the school may need to enhance its technological resources.

To ensure the robustness of these results, the following procedures were carried out:
i. The choice of the number of factors was determined after testing various numbers of factors, with six being selected based on the Kaiser-Guttman criterion.
ii. Different rotation methods were also used. Rotation is a statistical procedure employed to improve the interpretability of the factors.
iii. The convergent and discriminant validity of the factors was also verified. Convergent validity is the extent to which variables theoretically expected to load onto the same factor actually do so. Additionally, the correlation matrix of the rotated common factors using the Varimax method is given by:

Table 4 Varimax model result.

Factors	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
Factor 1	1					
Factor 2	0.10	1				
Factor 4	0.11	0.14	1			
Factor 5	0.13	0.11	0.15	1		
Factor 6	0.11	0.16	0.18	0.12	1	
Factor 7	0.13	0.20	0.19	0.11	0.14	1

Source: prepared by the author.

The rotated factor correlation matrix shows that all factors are independent of each other, as their correlations are equal to 0. This means that each factor explains a unique set of variables, and there is no overlap between factors. A possible interpretation of these results is that you are dealing with a set of heterogeneous variables, i.e., variables that measure different aspects of a phenomenon.

Therefore, regarding the research sample, it is possible to observe positive results concerning the impact and effectiveness of the PECIM program in public schools in Brazil. Both in the infrastructure of these schools and in maintaining the presence of students, as evidenced through the differences-in-differences method with multiple periods in approval rates. However, more research is still needed to add to and achieve a range of also positive results, so that, in fact, absolute results regarding the program can be obtained, given that the exposure time of these schools to the program occurred over a short period, since the program ended in 2023, although some states still try to maintain it.

Regarding the results of the Callaway and Sant'Anna test (2021), one of the flexible methods in the economic literature that makes it possible to verify heterogeneous effects for different groups of treated units in several distinct time periods. This time can be either known as the calendar time or also the time related to adherence to the program. In this methodology, military schools are considered the control group.

The first objective of the study was to estimate the impact for each combination of groups of schools with the same year of inclusion in the evaluated program. The research period used was from 2018 to 2022, with treatment occurring from 2020 to 2022.

In the results of Table 3, as well as the next three tables, the authors' methods were used to conduct implications about the impact of the program over multiple periods, using the dropout rate for elementary and secondary education as the dependent variable, against regional control groups, using the ATT(g,t)s of interest to simultaneously test their confidence about the treated groups. The ATT(g,t) parameter is very useful for better understanding the heterogeneity of the treatment effect and is also used to synthesize treatment effects between groups and times since treatment. Consequently, the obtained result was as follows:

Table 5: Estimativas para os impactos sobre a taxa de abandono

	OLS	AE	AE	AE	FE	FE	FE
Dependent Variable: Elementary School Dropout Rate							
ATT	-0,60*	-0.50*	-0.61*	-0,60*	-0,10	-0,20**	-0,19***
Controls	Yes	No	Yes	Yes	No	Yes	Yes

Regional Controls	Yes	No	No	Yes	No	No	Sim
Dependent Variable: High School Dropout Rate							
ATT	-1,42	-1,80*	-1,19*	-1,49*	-1,08	-3,02	-3,48*
Controls	Yes	No	Yes	Yes	No	Yes	Yes
Regional Controls	Yes	No	No	Yes	No	No	Yes

Source: prepared by the author.

The main and important parameters are the average treatment effect on the treated groups (ATT) in a given period. It is a parameter that helps to understand the heterogeneity of the treatment effect. The average treatment effects on the group's time are also natural building blocks for more aggregated treatment effect parameters, such as overall treatment effects or event-study-type estimates. Two ATT models were estimated, divided into the bidirectional fixed-effects regression (TWFE) through the EA in Table 1, and the EF in the Callaway and Sant’Anna model.

The main focus of the study is on the average treatment effect in the EF group; when significant, it shows the effect of the policy. If the sign is negative, there is a decrease in the policy on the dependent variable, as shown in the results regarding dropout rates for both elementary and secondary education, presented in Table 1. That is, for results such as the dropout rate, it is expected to yield negative results both for dropout rates and for failure rates, as also shown in the following table.

Table 6: Estimates for the impacts on the failure rate

	OLS	AE	AE	AE	FE	FE	FE
Dependent Variable: Elementary School Failure Rate							
ATT	0,03	-0,51***	-0,04***	-0,03***	-0,13**	-0,23**	-0,29***
Controls	Yes	No	Yes	Yes	No	Yes	Yes
Regional Controls	Yes	No	No	Yes	No	No	Yes
Dependent Variable: High School Failure Rate							
ATT	-0,19	-0,95**	-0,22	-0,19***	-0,07	-0,79**	-0,11***
Controls	Yes	No	Yes	Yes	No	Yes	Yes
Regional Controls	Yes	No	No	Yes	No	No	Yes

Source: prepared by the author.

Table 7: Estimates for the impacts on the approval rate

	OLS	AE	AE	AE	FE	FE	FE
Dependent Variable: Elementary School Approval Rate							
ATT	0,55	0,22***	0,55*	0,56*	0,15	0,41**	0,49***
Controls	Sim	Não	Sim	Sim	Não	Sim	Sim
Regional Controls	Sim	Não	Não	Sim	Não	Não	Sim
Dependent Variable: High School Pass Rate							
ATT	1,21	2,76*	1,17¨***	1,21**	0,55	3,83***	3,59**
Controls	Sim	Não	Sim	Sim	Não	Sim	Sim
Regional Controls	Sim	Não	Não	Sim	Não	Não	Sim

Source: prepared by the author.

For variables with positive characteristics, such as the approval rate, it is expected that the result throughout the treatment will be positive. That is, the approval rates for elementary and secondary education are significant, resulting in a positive outcome of the policy implemented in the civic-military schools, as the positive sign increases the dependent variable.

The positive results of PECIM in approval and dropout rates corroborate international evidence on educational policies, as found by Dee & Jacob (2011), although the pandemic imposed additional challenges, as pointed out by Hanushek & Woessmann (2020).

VI. Conclusion

The study identified, through the impact assessment methodology using factor analysis and the differences-in-differences approach with multiple periods by Callaway and Sant'Anna (2021), whether the investments received from the Federal Government in public schools that adhered to the National Program of Civic-Military Schools (PECIM) had impacts on the education and infrastructure of these schools and whether there was a significant relationship with such investments. The years during which the schools received investments are divided into 2020, 2021, and 2022.

The results, using the Factor Analysis method with division into six factors, showed that the data used in the study are reliable and appropriate. The factors of school infrastructure, physical resources, technological resources, human resources, accessibility, and level of education of these schools have good correlations, and each of these factors explains a set of variables.

For the aggregated results over multiple time periods, the most important result from the Callaway and Sant'Anna (2021) model lies in the average treatment effect on the treated groups given by EF, as shown in Tables 3 to 5. The results were significant because the variables followed the trends, with approval rates showing positive results and failure rates showing negative results, thus demonstrating the effect of the policy.

Based on the results of this research, it is possible to observe that the PECIM program proved efficient and had an impact on the schools that implemented it. However, the exposure time was very short; a longer time window would have been ideal, as the study focused on infrastructure and performance rates due to the COVID-19 pandemic, to achieve realistic results.

The study aims to contribute to future decisions regarding public policies, especially for states that decided to maintain civic-military schools, as well as for future researchers who wish to evaluate the impact of the schools that remained under PECIM, or for researchers interested in using the methodology of Callaway and Sant'Anna (2021) in upcoming studies, given that there is very little research in the economic literature that has utilized this method.

Some suggestions for future studies include additional studies with a longer exposure time to evaluate the impacts of the program more comprehensively, and assessments of the program's impacts on other variables beyond infrastructure and performance rates.

References

[1] Albernaz, Â.; Ferreira, F.H.G.; Franco, C. (2002). Qualidade E Equidade No Ensino Fundamental Brasileiro. Pesquisa E Planejamento Econômico, 32(3), Dezembro.

[2] Barbosa, S.C., Et Al. (2021). The Current Scenario Of Education In Brazil And The Implementation Of The Civic-Military Education Model. Revista Gênero E Interdisciplinaridade, 2(03). DOI: 10.51249/Gei02.03.2021.413. Disponível Em: Https://Www.Periodicojs.Com.Br/Index.Php/Gei/Article/View/413.. Acesso Em: Julho De 2022.

[3] Brasil. (2019). Decreto Nº 10.004, De 5 De Setembro De 2019a. Disponível Em: Http://Www.Planalto.Gov.Br/Ccivil_03/_Ato2019-2022/2019/Decreto/D10004.Htm.. Acesso Em: Setembro De 2024.

[4] Brasil. Instituto Nacional De Estudos E Pesquisas Educacionais Anísio Teixeira (2020). Brasil No Pisa 2018. Brasília: Instituto Nacional De Estudos E Pesquisas Educacionais Anísio Teixeira.

[5] Cabral, Jefferson Fernando Ribeiro (2018). A Militarização Da Escola: Um Debate A Ser Enfrentado. Dissertação De Mestrado, Universidade De Taubaté, Taubaté. Disponível Em: Https://Mpemdh.Unitau.Br/Wp-Content/Uploads/2016/Dissertacoes/Mdh/Jefferson-Fernando-Ribeiro-Cabral.Pdf.. Acesso Em: 5 Nov. 2024.

[6] Callaway, B.; Sant'Anna, P.H.C. (2021). Difference-In-Differences With Multiple Time Periods. Journal Of Econometrics, 225(2), 200–230.

[7] Callaway, B.; Goodman-Bacon, A.; Sant'Anna, P.H.C. (2021). Difference-In-Differences With A Continuous Treatment. Arxiv Preprint Arxiv:2107.02637.

[8] Dee, T.S.; Jacob, B.A. (2011). O Impacto Do No Child Left Behind No Desempenho Dos Alunos. Journal Of Policy Analysis And Management, 30(3), 418–446.

[9] Fabrigar, L.R.; Wegener, D.T. (2016). Análise Fatorial Exploratória: Uso Atual, Desenvolvimentos Metodológicos E Recomendações. Multivariate Behavioral Research, 51(1), 1–5. DOI: Https://Doi.Org/10.1080/00273171.2015.1113562..

[10] Fogel, M., Et Al. (2012). Avaliação Econômica De Projetos Sociais. Fundação Itaú Social, São Paulo.

[11] Goodman-Bacon, A. (2021). Diferença Em Diferenças Com Variação No Tempo De Tratamento. Journal Of Econometrics, 225(2), 254–277. DOI: Https://Doi.Org/10.1016/J.Jeconom.2021.03.014..

[12] Hair, J.F., Et Al. (2009). Análise Multivariada De Dados. Bookman Editora.

[13] Hanushek, E.A.; Woessmann, L. (2020). Os Impactos Econômicos Das Perdas De Aprendizagem. Educational Researcher, 49(9), 682–689. DOI: Https://Doi.Org/10.3102/0013189X20984168.

[14] Hargreaves, A.; Shirley, D. (2022). Well-Being In Schools: Three Forces That Will Uplift Your Students In A Volatile World. ASCD.

[15] Jackson, C.K.; Johnson, R.C.; Persico, C. (2016). Os Efeitos Dos Gastos Escolares Nos Resultados Educacionais E Econômicos: Evidências Das Reformas Financeiras Escolares. Quarterly Journal Of Economics, 131(1), 157–218.

[16] Junior, Fontoura, Et Al. (2022). Avaliação Do Impacto Da Implantação Da Universidade Federal Do Pampa Sobre Os Indicadores Da Educação Básica No Município De Bagé.

[17] Kaiser, H.F. (1974). An Index Of Factorial Simplicity. Psychometrika. DOI: Http://Dx.Doi.Org/10.1007/BF02291575..

[18] KMO And Bartlett's Test Of Sphericity | Analysis INN. (2020). Disponível Em: Https://Www.Analysisinn.Com/Post/Kmo-And-Bartlett-S-Test-Of-Sphericity/.. Acesso Em: 10 Nov. 2023.

[19] Lockheed, M.; Hanushek, E. (1994). Concepts Of Educational Efficiency And Effectiveness. World Bank.

[20] Ministério Da Educação (MEC). (2019). Educação Básica. Pisa 2018 Revela Baixo Desempenho Escolar Em Leitura, Matemática E Ciências No Brasil. Disponível Em: Http://Portal.Mec.Gov.Br/Ultimas-Noticias/211-218175739/83191-Pisa-2018-Revela-Baixo-Desempenho-Escolar-Em-Leitura-Matematica-E-Ciencias-No-Brasil.. Acesso Em: Outubro De 2022.

[21] Ministério Da Educação (MEC). (2021). Programa Nacional Das Escolas Cívico-Militares: Diretrizes Das Escolas Cívico-Militares. Disponível Em: Https://Www.Gov.Br/Mec/Pt-Br/Media/Acesso_Informacacao/Pdf/10DIRETRIZESPECIMVERSO_Observaes_14072021convertido2.Pdf.. Acesso Em: Setembro De 2024.

[22] Pereira, A.S., Et Al. (2019). Apostila Análise Fatorial. Passo Fundo.

[23] Roth, J., Et Al. (2023). What's Trending In Difference-In-Differences? A Synthesis Of The Recent Econometrics Literature. Journal Of Econometrics.

[24] Schlosser, J. (2020). Estudo Sobre O Desempenho Escolar Nos Colégios Militares. Dissertação De Mestrado — Universidade Tecnológica Federal Do Paraná, Foz Do Iguaçu.

[25] De Chaisemartin, C.; D'Haultfœuille, X. (2020). Estimadores De Efeitos Fixos Bidirecionais Com Efeitos De Tratamento Heterogêneos. American Economic Review, 110(9), 2964–2996. DOI: Https://Doi.Org/10.1257/Aer.20181169.