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Counterfactual Analysis of Covid-19 Impacts on the Revenue of Subnational Entities and Social Isolation and Lockdown Policies.

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Abstract

The aim of this study is to estimate the counterfactual impacts of the Covid-19 pandemic on state revenue and mortality rates for UF in Brazil, considering the adoption of lockdown and social isolation policies. DiD models indicate that daily consumption of electricity was inversely associated with state mortality rates. The ArCo results showed that the greater the pandemic severity, the greater the impacts on collection, and the higher the rate of social isolation, the lower the counterfactual mortality rates. There is no significant evidence of a state lockdown policy or state mortality rate.

Keywords: Covid-19, Collection, Mortality Rate, Counterfactual Inference.

JEL: I18, C32, H27

SUMÁRIO

1 Introduction

The Covid-19 pandemic brought to the world, Brazil, and the Federative Units new behaviors, new policies, new research topics, and abruptly changed the choices of agents in the face of a new scenario with additional health risk. The speed of the spread of cases, combined with the acceleration of lethality in the sequence, generated impact of public policies that went from complete movement restrictions to socio-economic relief policies. The consequences of these policies and/or of the pandemic evolution generated chain effects in the markets and in the economy. The subnational entities have directly suffered this exogenous shock, the impacts translated as a drastic increase in uncertainty and, consequently, an increase in the individual agents' perception of risk. The generalized reduction in tax collection would reflect this behavior, causing subnational governments to adopt different policies to combat the rise in pandemic mortality rates. Within the range of the adopted policies, two were more widespread: the recommendation of social isolation, leaving to individual discretion the responsibility, benefits and costs of adhering to this policy; the adoption of legal decrees to restrict movement, or as it became known as the lockdown policy.

Several important questions arise about state revenue and mortality rates. Studies can, depending on the complexity, be directed at analyzing the trajectory of the facts as they occurred and can reach important conclusions, however, when dealing with an unexpected, abrupt, and sudden event, as was the Covid-19 pandemic event, it turned out to be a quasi-experimental event, The most relevant questions arise from the questions of what would have happened in a counterfactual context, that is, what would have happened to the same sub-national entity in terms of revenue and mortality rates if it had not had the pandemic intervention, or if it had not adopted a lockdown policy in the pandemic intervention, or if there had not been a large adherence to social isolation. The answers to these important questions lead us to counterfactual (or causal) inference, and in this context two panels were built: a tax collection panel, containing seasonally disaggregated monthly data on tax collection and commercial activity from January 2000 to June 2020, totaling 246 temporal observations per Federal Government, and a pandemic panel, containing daily data on mortality rates per 100,000/inhabitant and daily electricity consumption from Feb 22, 2020 to Aug 14, 2020, totaling 172 temporal observations per Federal Government. To each of these panels state information was added, in the form of dummy variables, to construct the counterfactual effects to be estimated: GDPs above the national median, high demographic density, adoption of lockdown[1] policy and high adherence to social isolation (for the tax collection panel it was still considered an indicator of pandemic severity).

The first step was to present the construction details of the study variables, as well as an exploratory breakdown of the data. Two temporal counterfactual inference approaches are put to the test to study the two panels given with Brazilian states: differences-in-differences (DiD) panel models and the recent high-dimensional artificial counterfactual (ArCo) panel models. The results of these two approaches converge when analyzing social isolation and lockdown policies, the evidence found indicates that high adherence to social isolation had negative counterfactual, statistically significant impact on revenue, while a higher social isolation rate is associated with a lower pandemic mortality

1 Although strictly speaking they do not have the same meaning, we will use without loss of generality, lockdown as a synonym for lockout.

rate in states. The adoption of lockdown policy did not show statistically significant effects on either collection or mortality rates in any estimated approach.

The paper presents in section 2 a brief review of the literature on different impacts of the Covid-19 pandemic in different areas, including the fiscal issue of revenue collection. In section 3 we detail all the models used in the study, with the description of the data and results being presented in section 4, the conclusions of the study in section 5, and a final section dedicated to the analysis of the implications in public policies of the results of the study and the application of the methods proposed here.

2 Literature

No other dated event has had the scope, the impact, the magnitude in such a sudden way as the Covid-19 pandemic. The Covid-19 pandemic marked recent world history not only by the high speed of spread and intensity of lethality, but also by the impacts on many different areas of knowledge. As soon as its impacts reached worldwide proportions, researchers from different fields of science accelerated efforts to identify the different effects of this new phenomenon in their respective research niches.

The numbers of cases, deaths from Covid-19, and recoveries began to be updated and tracked daily in most countries[2] and publications emerged already estimating its impacts on future deaths, as in the Roberton et al. (2020) study, which presents initial estimates of the indirect effects of the Covid-19 pandemic on maternal and infant mortality in low- and middle-income countries. Sumner et al. (2020) estimated the effects on global poverty and came to the worrying conclusion that, ceteris paribus, assuming a 5 percent contraction in per capita income, the world could witness a potential increase in the number of poor people, relative to 2018 figures, of more than 80 million for the $1.9/day poverty line, more than 130 million for the standard $3.2/day, and nearly 124 million for the upper $5.5/day line.

The economic effects studied were not limited to future poverty themes, but also to current effects on unemployment, as in the study by Fairlie et al. (2020), which shows how the pandemic impacted minority unemployment using microdata through April 2020. African Americans experienced an increase in unemployment to 16.6 percent, less than anticipated based on previous recessions. Other studies such as Coates et al. (2020) and Kurmannet al. (2020), show other different impacts on unemployment. Lockdown policies were also the target of research, such as the study by Ozili and Arun (2020), showed that the increased number of lockdown days, monetary policy decisions, and international travel restrictions severely affected the level of economic activities and the closing, opening, lower and higher stock prices of major stock market indices.

Although most of the impacts of the Covid-19 pandemic were negative, some studies report ecological and climatic benefits that the abrupt social slowdown caused, for example Wang and Su (2020), Mandaland Pal (2020), Norouzi et al. (2020), and Le Quéré et al. (2020), just to name a few examples. The impacts on financial markets, according to Baker et al. (2020) and Fernandes (2020),

2 The JHU University has created a pandemic information dashboard for a large group of countries available at: https://coronavirus.jhu.edu

have been unprecedented. Baker et al. (2020) show that no previous infectious disease outbreak, including the Spanish flu, impacted the North American stock market as vigorously as the Covid-19 pandemic. In fact, previous pandemics have left only slight traces on the US stock market. The evidence from this study suggests that government restrictions on commercial activity and voluntary social distancing have operated as powerful effects in a service-oriented world economy, which would be the main reasons why the U.S. stock market reacted as strongly to Covid-19 as it did to previous pandemics.

De Vito and Gomez's (2020) study investigated how the Covid-19 health crisis may affect the liquidity of listed companies in 26 countries. The results indicated that bridge loans are more cost-effective in avoiding a massive cash crisis. The studies by Garcin et al. (2020) used a nonparametric approach to estimate the time-variations of the density of daily price returns of various stock indices and, using various divergence statistics, were able to describe the chronology of the crisis as well as regional disparities. For example, a more limited Covid-19 impact on financial markets in China, a strong impact in the US, and a slow recovery in Europe. Zhang et al. (2020) show that the rapid spread of the coronavirus (Covid-19) had dramatic impacts on volatility and risk levels in financial markets around the world, causing investors to suffer significant losses in a very short period. Al-Awadhi et al. (2020) showed that both daily growth in total confirmed cases and total death cases caused by Covid-19 have significant negative effects on stock returns across companies on Chinese stock exchanges. Topcu and Gulal's (2020) study estimating the impacts of Covid-19 on emerging country stock markets reveals that the negative impact of the pandemic on emerging stock markets gradually dropped and started to decrease in mid-April. In terms of regional classification, the impact of the outbreak was greatest in Asian emerging markets, while emerging markets in Europe had less intensity.

2.1 Literature on Covid-19 Impacts on Fiscal Policy

During economic crises, state and local government budgets come under pressure. The stress arises due to contractions in revenues and collections and increases in spending requirements. The same is largely true for federal, state, and local governments; one recourse for this situation occurs when the federal government has the power to issue short- and long-term debt. State and local governments, in contrast, have restrictions of varying degrees of severity on their legal authority to issue debt in response to unexpected spending or revenue shocks (Poterba,1994; Clemens and Miran 2012).

We compare the likely impact of the pandemic on state government revenues to most common economic contractions. Unlike typical contractions, during which income declines more sharply than consumption (Canova, 1998) the Covid-19 lockdowns generated exceptionally large declines in consumption relative to income. This is largely because revenues were driven by stimulus, some of which are taxable and some of which are not. In addition, Covid-19 resulted in a dramatic decline in personal consumption expenditures on health care, restaurants, and lodging. In the short run the revenue strains were therefore particularly severe in states that rely to a significant degree on sales taxes, and on sales in exposed sectors. On the other hand, as in most recessions, property tax bases are unlikely to contract significantly during the recession itself, because property values are typically reassessed with substantial delays, according to Lutz, Molloy, and Shan (2011). At the Brazilian subnational level, states lost relative participation in the distribution of tax revenues and municipalities affirmed the position obtained in the 1988 constitutional order, according to Tristao (2003).

Studies with the response of governments to mitigate the perverse effects also began to emerge, such as the study by Casado et al. (2020), which provides a way to evaluate almost in real time fiscal measures to stimulate local economic activity. On the other hand, the impact on public finances was also the subject of a study by Clemens and Veuger (2020), who estimated a revenue shortfall of $106 billion projected for the year 2021. Even daily impacts on the economy have been estimated using electricity consumption data for Italy, as shown by Fezzi and Fanghella (2020).

The purpose of this brief review is not to exhaust all the numerous studies dealing with the impacts of the Covid-19 pandemic, but to bring examples from different areas of research, up to the topic of state revenue that will be treated as the main topic of this study.

3 Methodology

3.1 Introduction to Causal Inference and Differences-in-Differences Panel Data Models

The randomized experimental study, since the emergence of statistical hypothesis testing, has been consolidated as one of the main pillars of scientific development. In the clinical environment, controlled dosimetry and the identification of control and treatment groups allowed the identification of drug or treatment efficacy. In the social sciences context, the reproduction of this methodological tool has proved to be a great challenge. From the pioneering work of John Snow (1855), who sought to identify the causes of the cholera epidemic in London, to the first version of the differences-in-differences model presented by Ashenfelter and Card (1985), it took more than a hundred years. Facing the impossibility of a completely randomized experiment, statistics evolved to methods that allowed a pseudo randomization through quasi-experimental phenomena. The idea was to estimate counterfactual effects from the reconstruction of a pseudo treatment unit that would allow an estimate of the effects of an intervention to be obtained.

Thus, consider the notation presented by Carvalho et al. (2018);

1) Units: indexed by $i=1,\ldots,n$which can be individuals, states, countries, etc. The treatment occurs in one of these units and does not affect the others;

2) Variables: $z_{it}=(z_{it}^{1},\ldots,z_{it}^{qi})$ being $q_i > 1$ the total number of variables related to the treatment units;

3) Intervention: The intervention occurred only in the unit treated at the time $T_0 = \lambda_0 T$ with $\lambda_0 \in (0,1)$.

Suppose, without loss of generality, that the unit treated is the first (i=1). Consider further that $z_{1t}^{(0)}$ e $z_{1t}^{(1)}$ are the outcomes of the first unit with treatment and without treatment, respectively. Normally, we do not observe the two outcomes simultaneously. Instead, we observe:

$$z_{1t} = D_t z_{1t}^{(0)} + (1 + D_t) z_{1t}^{(1)} \tag{5}$$

Where D_t takes value 1 if the unit is currently in treatment t and 0 otherwise. The objective is to test the hypothesis that the effects of the intervention are statistically significant for

$t > T_0$. Interventions are considered in the following format:

$$y_t^{(1)} = \begin{cases} y_t^{(0)}, t = 1, \dots, T_0 \\ y_t^{(0)} + \delta_t, t = T_0, \dots, T \end{cases} \quad (6)$$

Where y_t represents the response variable of interest. Considering a panel data context, the effect δ_t can be estimated from fixed effect models, according to Angrist (2008):

$$y_{it} = \alpha_i + \lambda_t + \theta D_{int} + \phi D_{trat} + \delta(D_{int} \times D_{trat}) + z_{it}'\beta + \varepsilon_{it} \quad (7)$$

Where, D_{int} is the intervention dummy and D_{trat} the treatment dummy. The counterfactual effects of Differences-in-Differences (DiD) are obtained by the parameter $\delta\hat{}$. For Card and Krueger (1994) the main advantage of the DiD method is that it can control for the influences of outcome variables for unobservable characteristics that are fixed in time, this is an important advantage, because if these unobservable characteristics influence the decision to participate in treatment, what is called selection bias will occur. In other words, the DiD tool can take into account the association between the outcome variable, treatment participation, and the unobservable characteristics of individuals that are invariant over time, thus circumventing selection bias. The main hypotheses of this model are:

1) The regression model was correctly specified, with the inclusion of other independent control variables;

2) The error term is on average equal to zero: E (ε_{it}) = 0;

3) The error term is not correlated with other variables in the equation. This assumption, known as the parallel trend assumption;

4) The omitted variables are constant over time;

5) No cross-section dependency;

6) There is no endogeneity present in the model;

Several of these assumptions have been challenged by Bertrand et al. (2004), the key assumption of common trends which is called the parallel trend assumption. This assumption has no formal test in the literature and thus the validity of its counterfactual inferences depends directly on the belief in its validity in the estimated models.

3.2 High-dimensional Artificial Counterfactual Panel Data Models

A recent alternative to address the restrictive assumptions of DiD models, has been the emergence of synthetic or artificial counterfactual models. The synthetic control method (SCM) proposed by Abadie et al. (2010), Abadie et al. (2015), Abadie and Gardeazabal (2003) is a popular approach to estimate the impact of a treatment on a single unit in environments with many control units and with many pretreatments with results for all units. The idea is to construct a weighted average of the control units, known as a synthetic control, that corresponds to a treated unit that is statistically closest to a pretreated unit. The estimated impact is then the difference in post-treatment outcomes between the treated unit and the synthetic control. An important limitation of this approach is that while SCM minimizes the imbalance in pre-treatment outcomes, it generally fails to achieve the exact balance between treated and untreated post-intervention due to the curse of dimensionality, the resulting imbalance can lead to severe bias.

The first proposed solution to eliminate this bias was proposed by Hsiao, Ching, and Wan (2012), which considers a two-step method in which, in its first step, the counterfactual for a single treated variable of interest is constructed as a linear combination of a low-dimensional set of observed covariates from pre-selected elements of a group of pairs. The model is estimated by ordinary least squares using data from the pre-intervention period. Its theoretical results were derived under the assumption of correct specification of a linear panel data model with common factors and no covariates. The selection of the pairs included in the linear combination is done by information criteria.

The method proposed by Carvalho et al. (2018), high-dimensional artificial counterfactual panels (ArCo), generalizes the work of Hsiao, Ching, and Wan (2012) in important directions. First, by considering LASSO estimation in the first stage, we allow many covariates/pairs to be included, not requiring any pre-estimation selection that may bias the estimates. In addition, LASSO estimation is quite attractive when the sample size is small compared to the number of parameters to be estimated. Secondly the theoretical results are derived without strict assumptions about the generating process of the series, which is assumed to be unknown. Another major advantage of this method is that it is not necessary to estimate the true conditional expectation. This is a good feature of the ArCo methodology, since models are usually misspecified. Third, there is no balancing restriction between treated and untreated, that is, there is no restriction to analyze a single treated variable. It is still possible, for example, to measure the impact of interventions on several variables of the treated unit simultaneously. ArCo models also allow for testing at various points in time of the variable of interest. Fourth, the ArCo methodology can be applied when the intervention time is unknown, allowing the intervention time to be estimated endogenously. Consider the assumptions up to equation (6).

The ArCo methodology proposes $y_t^{(j)} = h\,(z_{1t}^{\,j}) \in R^q$, $j \in \{0,1\}$, h(.) being a measurable function of z_{1t} and $\{\delta_t\}_{t=T\_0}^{T}$ being a deterministic sequence. The function h(.) is a general function that allows interventions on the mean, variance, covariance and so on. The ArCo method focuses on the hypothesis:

$$H_0 : \Delta_T = \frac{1}{T-T_0+1} \sum_{t=T_0}^{T} \delta_t = 0 \tag{8}$$

Where Δ_T represents the average treatment effect during the treatment period. We did not observe $y_t^{(0)}$ for $t \geq T_0$, this will be the counterfactual value, that is, what would be the y_t in the absence of the intervention. In the first step of the ArCo method, let $z_{0t} = (z_{2t}', \ldots, z_{nt}')'$ and $Z_{0t} = (Z_{2t}', \ldots, Z_{nt}')'$ a collection of all untreated units up to an arbitrary lag $p \geq 0$. The size of Z_{0t} depends on the number of units, the number of lags, and the number of variables per unit. Now consider the following model for $y_t^{(0)}$:

$$y_t^{(0)} = \mathcal{M}_t + v_t \tag{9}$$

With the only chances of E $(\upsilon_t) = 0$ and M_t being a measurable mapping, not necessarily an explicit function, that is, it can take any functional form, such as decision trees, random forests, non-linear functions, panel data models, time functions with various dependency structures, etc. The first step in the ArCo model is to estimate equation (9) using the T_0- 1 observations, since for $t < T_0$ we have $y_t = y_t^{(0)}$. With the set $T_1 = T_0 - 1$ and $T_2 = T - T_0 + 1$, it is possible to estimate $\hat{M}_{t,T\_1} = \hat{M}_{t,T1} (Z_{0t})$ and use it to construct the counterfactual:

$$y_t^{(0)} = \begin{cases} y_t^{(0)}, t = 1, \dots, T_0 \\ \widehat{\mathcal{M}}_{t,T_1}, t = T_0, \dots, T \end{cases} \tag{10}$$

Finally, the ArCo estimator is defined as:

$$\widehat{\Delta}_T = \frac{1}{T - T_0 + 1} \sum_{t=T_0}^{T} \hat{\delta}_t \tag{11}$$

Where $\hat{\Delta}_T = y_t - y_t^{(0)}$.

The ArCo methodology is a two-stage estimation approach, the first stage being the estimation of M_t in the pre-intervention sample and in the second stage we estimate $\hat{\Delta}_T$ which is the average impact of the intervention.

As Carvalho et al. (2018) point out, when compared to DiD estimators, the advantages of the ArCo methodology are threefold. First, we do not need the number of treated units to grow. In fact, the laborious situation is when there is a single treated unit. The second and most important difference is that the ArCo methodology was developed for situations where the n-1 untreated units differ substantially from the treated one and cannot form a control group even after conditioning on a set of observables. Finally, the ArCo methodology works even without the assumption of parallel trends.

Although, the ArCo and SCM methods construct a counterfactual as a function of observed variables from a group of pairs, the two approaches have important differences. Just listing the main points listed by Carvalho et al. (2018), first, the SCM method relies on a convex combination of pairs to build the counterfactual which, as pointed out by Ferman and Pinto (2016), generates bias in the estimator. This is clearly evidenced in simulation experiments. The ArCo solution is a general, possibly nonlinear function. Even in the case of linearity, the method does not impose any restrictions on the parameters. For example, the constraint that the weights in the SCM methods are all positive is also a strong constraint. Furthermore, the weights in the SCM method are generally estimated using time averages of the observed variables for each pair. Therefore, all dynamics of the time series are removed and the weights are determined in a pure cross-section scenario. In some applications of the SCM method, the number of observations to estimate the weights is much smaller than the number of parameters to be determined. For example, Abadie and Gardeazabal (2003), the authors have 13 observations to estimate 16 parameters.

Furthermore, as highlighted in Carvalho et al. (2018), the SCM method is designed to evaluate the effects of the intervention on a single variable. To evaluate the effects on a vector of variables, the method must be applied multiple times. The ArCo methodology can be applied directly to a vector of variables of interest. Furthermore, there is no formal inferential procedure for hypothesis testing in the SCM method, while in the ArCo methodology, a simple and uniform standard valid test method can be applied. A final disadvantage of the SCM, highlighted in Ferman, Pinto, and Possebom (2016), the SCM method does not provide any guidance on the selection of variables used to construct the weights that will be used to create the counterfactual values.

For estimation purposes we will use generalized linear models with complex penalization, which combine different types of regularization methods l_1 (LASSO), l_2 (Ridge Regression) and the combination of these two (the elastic net), with a cyclic descending coordinate estimation algorithm, as presented by Friedman et al (2010). This formulation guarantees to estimate different temporal structures of the dynamics of the variables and units of the panels used for the study.

3.2.1 Estimating Unknown Intervention Time in ArCo Models

In many cases, it is reasonable to assume that the timing of intervention is unknown. For example, although some new policy was initiated at a known time, its effects may have been anticipated due to expectations. Or, the difference between the estimated values in the pre-intervention models are not yet statistically different from any observed time to some point post-intervention. In these cases, regardless of the source of uncertainty, it is necessary to estimate λ_0 by fitting the ArCo Estimator to be a function λ, $\hat{\Delta}_T(\lambda)$, as highlighted by Carvalho et al. (2018).

Basically, you determine $\Lambda = (\underline{\lambda}, \bar{\lambda})$ as a limit for λ_0 to avoid finite sample bias near the limits, and we define $\|.\|_p$ as the norm l_p, then the intervention time will be estimated as:

$$\hat{\lambda}_{0,\wp} = \underset{\lambda \in \Lambda}{arg\ max} \left\|\widehat{\Delta}_T(\lambda)\right\|_{\wp}$$

In this way, $\hat{\lambda}_{0,p}$ will be the value that maximizes the norm l_p of the ArCo estimator.

4. Results

4.1 Description, Treatment and Descriptive Statistics of the Data

The construction of the database used in this study considered the possibility of building two balanced panels for the Brazilian states considering the monthly collection dynamics in the first, and the daily pandemic dynamics in the second. This formulation allowed the implementation of the Dif--in-Dif panel models, in addition to the estimation of the panel data artificial counterfactual models. The construction of these panels therefore considered the availability in different sources of data information, of state information.

Table 1 - Data Description

State Revenue Study Panel		
Variable	Description	Source
Collection	Monthly state revenue data	CONFAZ - National Council of Treasury Policy
Commercial Activity	State retail sales volume index	IBGE - Table 3416
State Data	Population and population density data	IBGE - Cities and States Table
Statewide Pandemic Study Panel		
Variable	Description	Source
State Mortality	Daily data of deaths per 100,000 inhabitants	ARPEN Data - SRAG Brazilian Registry Offices Association
Electrical Energy Consumption	Daily consumption of state electricity	Electrical Energy Chamber of Commerce

Source: Own elaboration.

Table 1 describes the set of information available for openings at the sub-national entities level. The monthly data considered the beginning of the series in January 2000 to the last recent data made available by CONFAZ referring to the month of June 2020, making a total of 246 temporal observations per Federative Unit. The state volume index of retail sales (PMC), was used in the construction of the panel study of tax collection as a proxy of economic activity at the state level, present for all Brazilian states. In the construction of the statewide pandemic panel the number of deaths was adjusted to represent a rate per 100,000 inhabitants and thus allow estimation free of population scale effects. Daily electricity consumption data were used as a proxy for the level of daily economic activity at the state level. These daily data cover the period from February 22, 2020 to August 14, 2020, with a total of 172-time observations per Federal State.

The state tax collection data were seasonally adjusted using X-13ARIMA-SEATS (GÓMEZ; MARAVALL, 1996) considering the seasonal adjustment specifications of the Monthly Trade Survey (PMC). In this specification all calendar effects and moving holidays, such as Carnival, Easter and Corpus Christi, are considered, in addition to the stochastic seasonality hypothesis. The seasonally adjusted figures from the PMC itself were also used.

With the panels constructed for the pandemic and revenue counterfactual studies, the variables for estimating the Diff-in-Dif effects were constructed, as shown in Table 2:

Table 2 - Construction of the Diff-in-Dif Effects

STATE	I_iso	I_grave	I_Lockout	I_PIB	I_dens
RO	1	0	0	0	1
AC	1	1	0	0	0
AM	1	1	1	0	1
RR	0	1	0	0	1
PA	1	1	1	1	0
AP	1	1	1	0	0
TO	0	0	1	0	0
MA	1	0	1	0	0
PI	1	0	1	0	0
CE	1	1	1	1	1
RN	0	1	1	0	1
PB	0	0	0	0	1
PE	1	1	1	1	1
AL	1	1	0	0	1
SE	0	1	0	0	1
BA	0	0	0	1	0
MG	0	0	0	1	0
ES	0	1	0	0	1
RJ	1	1	1	1	1
SP	0	1	0	1	1
PR	0	0	1	1	0
SC	0	0	0	1	1
RS	1	0	0	1	1
MS	0	0	1	0	0
MT	0	0	0	1	0
GO	0	0	0	1	0
DF	1	0	0	1	1
Total (1):	13	13	12	13	15
Total (0):	14	14	15	14	12

Note: The variables I_GDP and I_dens were constructed using the IBGE data - Cities and States Table:

I_GDP: indicator of nominal GDP of the state above the Brazilian median;

I_dens: indicator of demographic density above the Brazilian median.

The variable I_grave was constructed considering the results of the number of deaths per 100,000 inhabitants on 08/14/2020, observed on 8/31/2020 after 15 days of reviews of their vintages:

I_grave: indicator of death rate per 100 inhabitants above of the Brazilian median.

The variable I_lockout was constructed from the official publications of the state or local governments enacting explicit restrictions on public movement, closure of establishments and areas in at least one city in the state:

I_lockout: Lockdown indicator in the UF.

The variable I_iso was constructed from the Social Isolation index developed by Inloco, using technology that maps the The geolocation of 60 million Brazilians.

The index represents the percentage of the population that is respecting the isolation recommendation:

I_iso: indicative of high adherence to social isolation, i.e., UF with index above the Brazilian median, considering the percentile 90 of the index from April to August by Federal Government. Details on this variable are provided in Appendix Table 2.

Source: Own elaboration.

From Table 2 we can see that thirteen states showed high adherence to recommendations for social isolation (RO, AC, AM, PA, AP, MA, PI, CE, PE, AL, RJ, RS, and DF), another thirteen Brazilian states were classified as severe pandemic condition (AC, AM, RR, PA, AP, CE, RN, PE, AL, SE, ES, RJ, and SP). Despite the pandemic severity, some states showed low adherence to social isolation, such as RR, RN, SE, ES, and SP. In twelve states extreme lockdown policies were verified (AM, PA, AP, TO, MA, PI, CE, RN, PE, RJ, PR, and MS), among these, seven states showed severe pandemic condition (AM, PA, AP, CE, RN, PE, and RJ). Among the states that used lockdown policies, four states showed low adherence to social isolation (TO, RN, PR, and MS), which shows, still in an exploratory way, that lockdown policies may not have effects on the regional pandemic.

For each study panel (Collection and Pandemic), given that they individually have distinct temporal dynamics, collection with monthly data and pandemic with daily data, the pandemic onset marking was distinct for each of these studies. The pandemic onset marking for the collection data occurs in the month of February 2020 for all states, while for the daily pandemic data, the regional pandemic onset marking occurs from the date of registration of the first Covid-19 death.

The combination within each study panel, of the pandemic onset dummies with the variables presented in Table 2, allows us to estimate the counterfactual effects for each of these variables in the context of panel data model. In Table 3 we present the results of descriptive statistics considering the pre-pandemic and pandemic periods of tax collection by Federal Government, considering in the comparison, the same period of 2019.

The results in the table show 3 a drop in the average tax collection for almost all the Brazilian states. On average, in percentage terms, tax collection fell 5.9%, with a median of 7.9%.3 of 5.9%, with a median of 7.9%. Among the 27 states, five showed an increase in the average collection in the pandemic period, in percentage terms: MT (12.12%), MS (8.63%), RR (1.68%), AM (1.57%), and PA (0.96%). When we consider the magnitude of the average collection drop, eight states stand out in percentage terms: CE (20.12%), AP (12.24%), RJ (9.8%), SE (9.79%), BA (9.79%), AL (9.55%), RN (9.3%) and PE (9.22%). There is also an increase in the variability of monthly collection in the pandemic period in all Brazilian states, indicating a heterogeneity of the impacts caused by the pandemic, and thus a significant increase in the respective coefficients of variation[3], from 0.04 (4%) on average, to 0.31 (31%). The value of minimum collection observed in the pandemic period was lower than that of the comparison period for all the states, but the value of maximum collection in the pandemic period was also higher for all the states when compared to the pre-pandemic period, indicating a strong recovery process even during the pandemic.

Table 4 presents contingency sub-tables of the average collection values considering the one-year horizon for the Diff-in-Dif effects to be estimated in the subsequent section. In all sub-tables, the pre-pandemic and pandemic periods and the different effects were considered. The exploratory results indicate a lower average value of collections for the states that adopted lockdown policies, however with a higher percentage reduction in the pandemic period from the states without lockdown policies. In terms of the magnitude of this reduction, the states without the adoption of this type of policy have an average reduction of 12% against 11% in states with lockdown policies.

Table 3 - Descriptive Statistics of the State Revenue

3 The percentage values and coefficients of variation and have been suppressed in the body of the document, but are available in Table 1 in the Appendix.

Pre-Pandemic Period - Feb/19 to Jun/19				
State	**Average**	**Standard Deviation**	**Minimum**	**Maximum**
AC	118.718.836	5.158.994	112.183.348	126.379.247
AL	382.763.013	14.715.722	358.533.112	399.889.500
AM	893.765.124	30.258.090	837.213.145	924.164.388
AP	108.525.059	9.524.292	98.254.478	124.227.344
BA	316.898.516	13.159.724	304.762.542	342.029.640
CE	1.268.607.493	195.779.012	1.154.429.405	1.659.341.608
DF	831.397.940	33.375.465	781.465.587	875.027.455
ES	1.100.205.868	38.276.588	1.039.408.797	1.151.339.846
GO	1.618.987.955	30.746.079	1.566.144.244	1.661.465.411
MA	700.339.769	10.423.302	683.168.572	712.678.381
MG	5.065.035.909	207.330.852	4.902.924.089	5.461.236.594
MS	951.107.584	28.960.048	925.896.395	1.007.821.225
MT	1.289.483.003	49.180.447	1.193.876.485	1.333.980.338
PA	1.254.469.014	20.365.520	1.222.777.930	1.283.159.830
PB	531.278.479	16.459.643	520.221.155	563.908.915
PE	1.574.603.331	14.260.261	1.555.223.789	1.595.001.879
PI	403.835.095	58.528.223	370.369.931	520.563.259
PR	3.166.321.838	124.875.423	2.928.379.055	3.283.532.729
RJ	3.778.213.948	170.760.613	3.517.872.384	4.029.731.761
RN	511.513.210	7.536.897	498.232.612	519.102.381
RO	460.699.961	17.908.043	425.930.941	475.537.152
RR	112.417.924	10.905.604	102.417.512	130.392.358
RS	3.243.057.391	44.331.689	3.194.431.122	3.310.832.943
SC	2.259.346.778	30.049.282	2.227.686.105	2.310.512.344
SE	316.898.516	13.159.724	304.762.542	342.029.640
SP	14.285.223.260	113.509.250	14.126.824.600	14.480.172.500
TO	270.006.497	2.866.144	265.598.780	273.510.374

Pandemic Period - Feb/20 to Jun/20				
State	**Average**	**Standard Deviation**	**Minimum**	**Maximum**
AC	109.629.719	35.244.266	2.422.956	236.679.573
AL	346.222.065	115.063.618	39.787.712	487.949.653
AM	907.835.174	253.161.189	107.403.471	1.147.625.532
AP	90.904.959	33.755.759	7.924.209	152.456.200
BA	285.872.278	94.104.732	29.079.511	466.062.373
CE	1.013.387.755	339.473.309	133.101.937	1.659.341.608
DF	790.269.364	229.330.160	111.820.637	927.703.651
ES	1.019.272.995	277.871.976	148.987.517	1.186.503.150
GO	1.527.685.647	521.912.294	159.901.431	3.801.654.704
MA	652.389.353	205.979.476	47.738.867	868.317.392
MG	4.638.169.079	1.409.095.708	627.408.247	5.911.600.362
MS	1.033.274.147	273.585.094	82.353.863	1.123.311.276
MT	1.445.877.552	396.832.788	114.724.064	1.963.284.757
PA	1.266.561.811	374.105.831	93.397.989	1.423.875.035
PB	488.810.145	154.569.576	54.564.453	604.026.441
PE	1.429.409.575	452.471.639	179.944.260	2.244.184.330
PI	373.560.448	128.779.839	32.887.344	577.171.411
PR	2.964.979.362	961.120.964	352.367.410	4.672.946.912
RJ	3.408.064.641	1.054.176.319	658.052.220	5.276.449.316
RN	463.894.723	147.337.786	52.648.467	549.003.521
RO	447.634.715	131.217.988	26.167.426	564.114.745
RR	114.307.254	30.555.323	6.786.233	148.880.307
RS	2.999.974.113	915.341.543	126.992.109	4.536.925.026
SC	2.081.635.333	606.025.609	226.542.180	2.402.363.655
SE	285.872.278	94.104.732	29.079.511	466.062.373
SP	13.043.716.280	3.949.209.732	2.562.458.125	17.502.688.200
TO	266.340.656	81.200.035	21.098.352	369.957.240

Note: The figures are seasonally adjusted.

Source: Own elaboration.

Tabela 4 - Tabelas Contingenciais de Valores Médios de Arrecadação dos Efeitos Dif-em-Dif - Jun/19 a Jun/20

	No Lockdown	**With Lockdown**	**Average**
Pre-pandemic	2.236.205.888	1.292.203.812	1.816.649.410
Pandemic	1.974.996.588	1.155.883.550	1.610.946.349
Average	2.135.740.773	1.239.772.942	1.737.532.848

	Low Insulation	**High Insulation**	**Average**
Pre-pandemic	2.382.823.098	1.206.923.900	1.816.649.410
Pandemic	2.118.550.552	1.064.295.669	1.610.946.349
Average	2.281.179.811	1.152.066.888	1.737.532.848

	Lower Gravity	**Higher Gravity**	**Average**
Pre-pandemic	1.586.154.927	2.064.874.238	1.816.649.410
Pandemic	1.428.319.442	1.807.621.479	1.610.946.349
Average	1.525.448.971	1.965.930.869	1.737.532.848

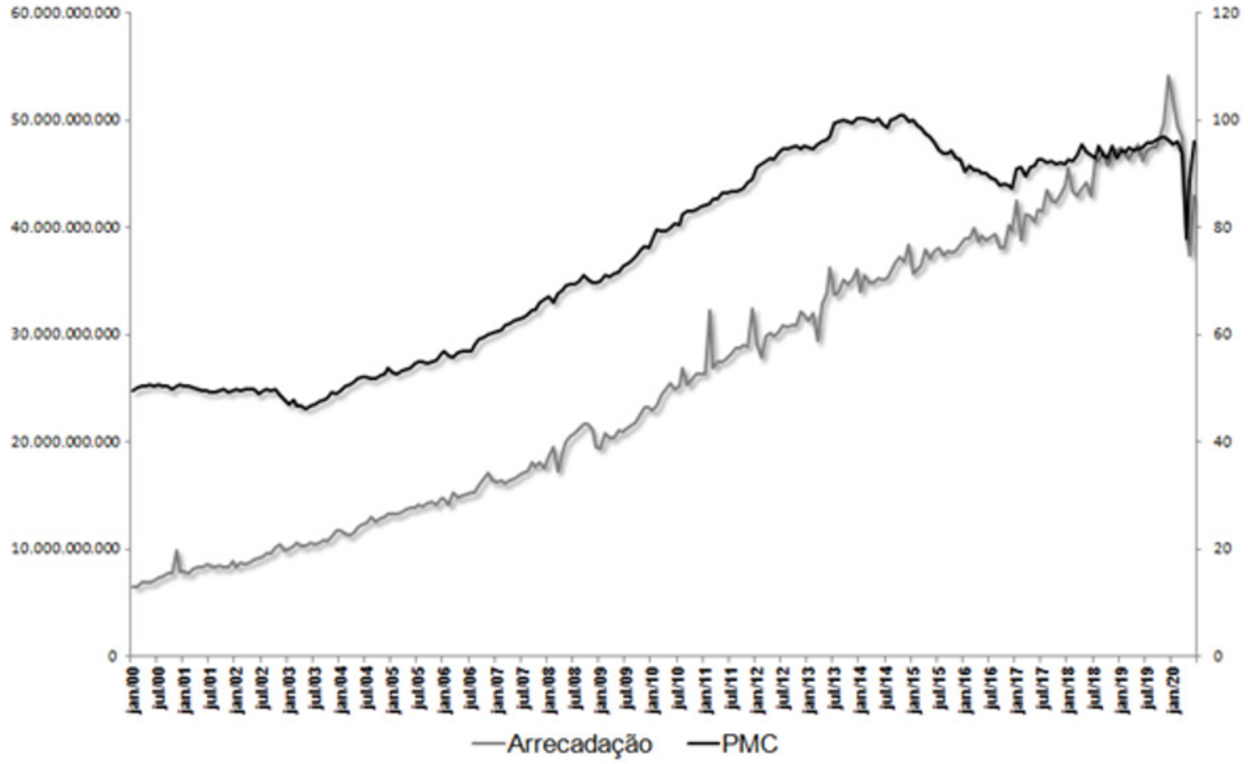
	Lowest GDP	**Largest GDP**	**Average**
Pre-pandemic	518.906.999	3.214.218.160	1.816.649.410
Pandemic	471.424.902	2.838.123.291	1.610.946.349
Average	500.644.654	3.069.566.288	1.737.532.848

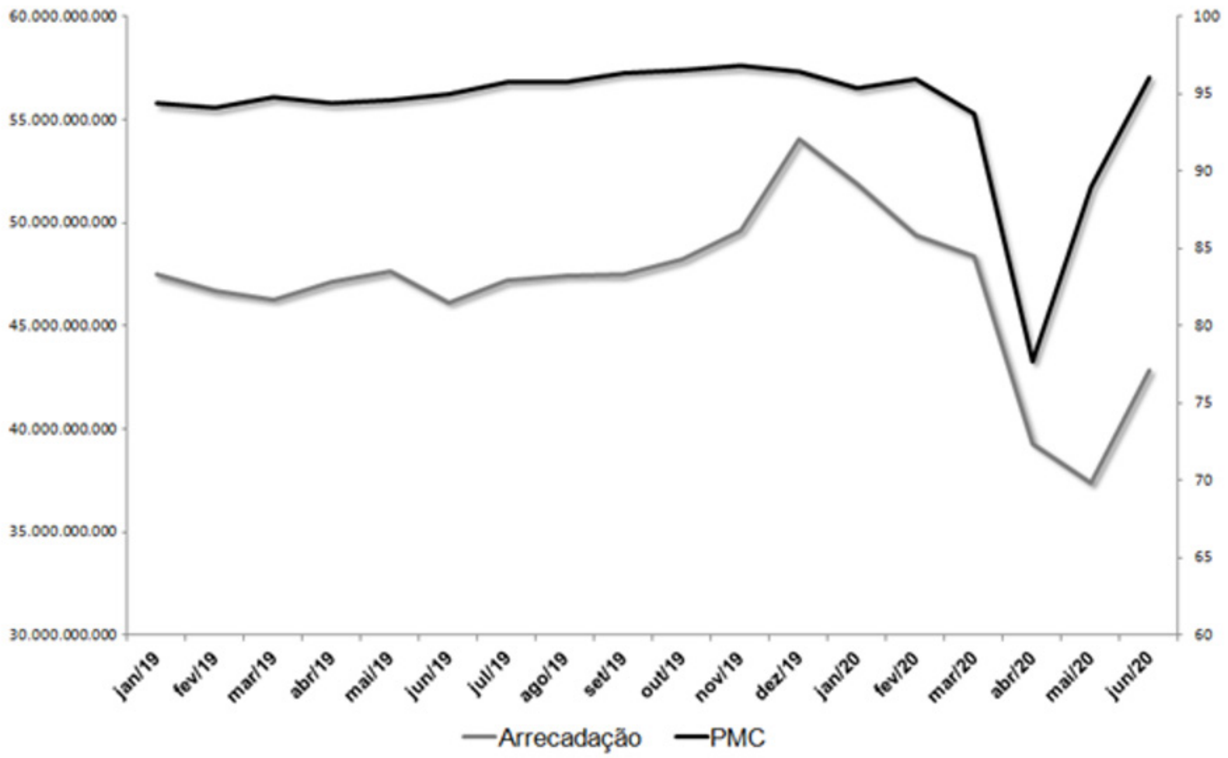
	Lower Densities	**Higher Densities**	**Average**
Pre-pandemic	1.345.633.604	2.193.462.055	1.816.649.410
Pandemic	1.221.270.418	1.922.687.094	1.610.946.349
Average	1.297.801.609	2.089.317.839	1.737.532.848

Fonte: Elaboração própria.

The high population adherence to isolation is associated, in an exploratory manner, with a lower average tax collection, but with a greater percentage reduction in the states with high isolation rates during the pandemic period. The states with the most severe pandemic suffered a greater percentage reduction in average tax collection in the pandemic period, however, in terms of overall tax collection, they are associated with the UFs with higher tax collection. In terms of GDP, the states above the national median showed a greater average reduction in tax collection, both in absolute and percentage terms, than the other UFs in the pandemic period. The results observed for the GDP sub--table are valid for demographic density. For a better understanding of the relationship between tax collection and commercial activity, we present the following Figure 1 we present graphs of the entire historical series of these variables, with an emphasis on the recent period from January 2019 onward, where it is possible to clearly identify the decline caused by the Covid-19 pandemic.

Figure 1 – Monthly Collection Dynamics and Activity of the Retail Trade



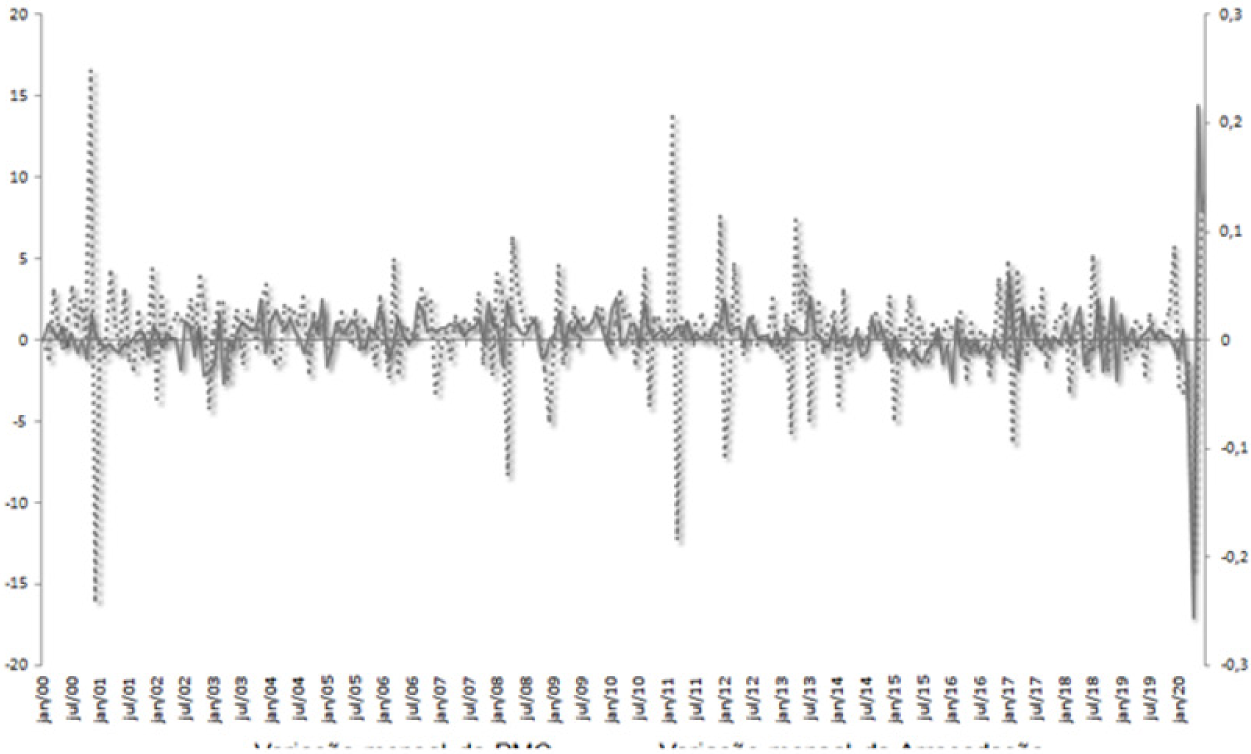


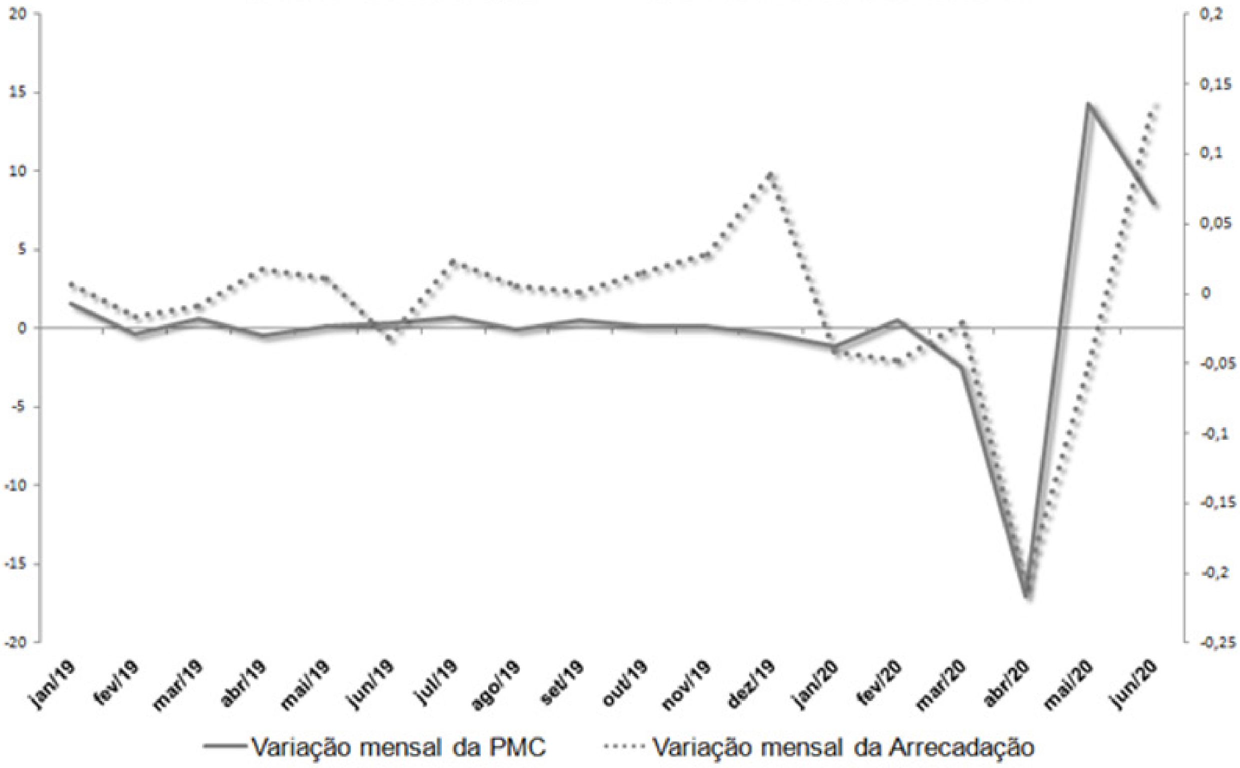
Source: CONFAZ, IBGE and own elaboration.

In figure 2 we present the first difference of the logarithm of these variables, also giving emphasis to the recent period post-January 2019. This graph allows us to identify more clearly the direct relationship of business activity and tax collection. Thus, these graphical indications reinforce the choice of this variable as a proxy for state[4] economic activity.

Figure 2 – Dynamics of the Monthly Variation of Revenues and Retail Trade.

4 As far as the researchers know, there is no other variable considering the time horizon and all the federative units for this panel study.





Source: CONFAZ, IBGE and own elaboration.

When we consider the epidemic panel, we present in Table 5 the usual descriptive statistics of the pandemic and the respective Diff-in-Dif effects to be estimated. The number of deaths per 100,000/inhab. needs to be weighted by the epidemic evolution in each state, and therefore consider the number of days since registration of first Covid-19 death. When we rank from the highest mortality rate to the lowest, and associate this with the effects, we can trace, in an exploratory manner, a grouping profile of the UFs. The first cut brings the states with a rate above 70 deaths per 100,000/ inhabitant, in this group there is a predominance of states with high adherence to social isolation, with adoption of Lockdown policy, high population density, and with GDP above the national median.

Tabele 5 - Pandemic State by Federal State

State	Number of Covid-19 Deaths per 100,000/ inhab.	Number of pandemic days	I_iso	I_Lockout	I_grave	I-GDP	I_dens
AM	90	140	1	1	1	0	1
CE	82	142	1	1	1	1	1
PA	71	136	1	1	1	1	0
RR	71	133	0	0	1	0	1
RJ	70	149	1	1	1	1	1
AP	67	133	1	1	1	0	0
PE	66	142	1	1	1	1	1
AC	56	130	1	0	1	0	0
ES	55	135	0	0	1	0	1
SE	44	135	0	0	1	0	1
SP	42	150	0	0	1	1	1
AL	41	137	1	0	1	0	1
RN	40	139	0	1	1	0	1
RO	39	137	1	0	0	0	1
MA	39	138	1	1	0	0	0
PB	36	136	0	0	0	0	1
DF	33	139	1	0	0	1	1
MT	32	134	0	0	0	1	0
PI	29	140	1	1	0	0	0
TO	21	122	0	1	0	0	0
BA	18	139	0	0	0	1	0
GO	14	140	0	0	0	1	0
PR	11	141	0	1	0	1	0
RS	11	141	1	0	0	1	1
SC	10	140	0	0	0	1	1
MG	9	138	0	0	0	1	0
MS	8	137	0	1	0	0	0

Note: The number of pandemic days is counted from the first Covid-19 death record.

Source: Own elaboration.

The second cut, has mortality between 40 and 69 deaths per 100 thousand/inhabitant, in this group half the states had high adherence to social isolation, with only two states with Lockdown policy, being most of them with high demographic density and lower GDPs. The third cut, has mortality between 20 and 39 deaths per 100 thousand/inhab, again has half of the states with high adherence, however with few states with Lockdown policy, mostly UFs with lower GDPs and half being of high population density. The last group has mortality up to 19 deaths per 100,000/inhab, mostly states with GDP above the national median, with low adherence to social isolation, low population density and with only two states with Lockdown policies. All these results will be subjected to counterfactual inference to have such perspectives validated. In Table 6 we present contingent sub-tables of the Diff--in-Dif effects to be estimated in the next section.

Table 6 - Contingency Tables of Average Number of Covid-19 Deaths per 100,000/inhab. of the Diff--in-Dif Effects - First 70 days pandemic.

	No Lockdown	**With Lockdown**	**Average**
Low Insulation	59	36	53
High Insulation	64	110	92
Average	61	85	72

	Lower Gravity	**Higher Gravity**	**Average**
Low Insulation	32	90	53
High Insulation	55	115	92
Average	40	105	72

	Lowest GDP	**Largest GDP**	**Average**
Low Insulation	69	36	53
High Insulation	87	97	92
Average	78	64	72

	Lower Densities	Higher Densities	Average
Low Insulation	29	76	53
High Insulation	89	94	92
Average	54	86	72

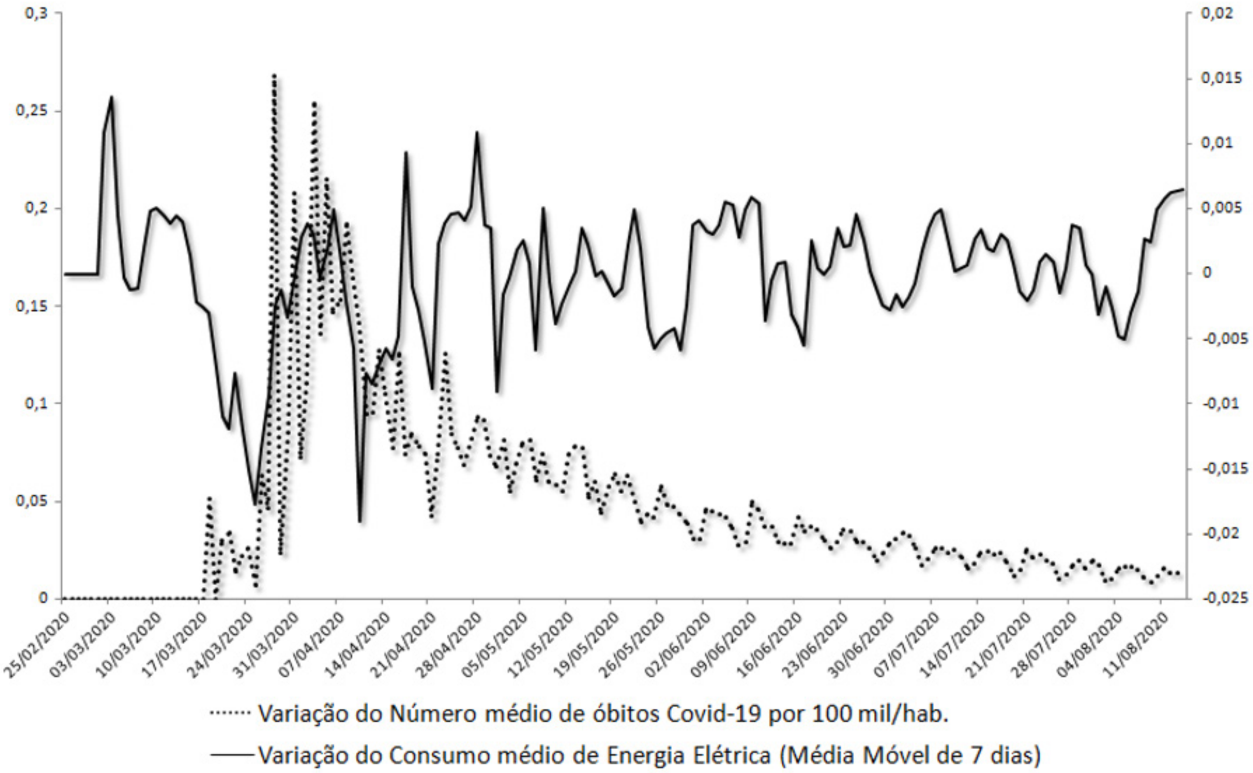
Source: Own elaboration.

The results in Table 6 were considered up to the 70th pandemic day so that it was possible to compare the average mortality rates by FSU with different pandemic developments. The result of the first sub-table indicates that the average mortality rate is higher for UFs with lockdown policies, and even higher for UFs with greater adherence to social isolation. When we consider pandemic severity, we observe that for states with low adherence to social isolation, the average mortality rate is almost three times higher for severe cases, and more than double for states with high adherence. Considering the distributions of GDP indicators, we observe that states with higher GDP and with low adherence have lower mean mortality rates compared to all other possibilities. Regarding the demographic density indicator, states with lower adherence to social isolation and low demographic density have lower average mortality rates. The general results of these sub-tables, indicate, in an exploratory manner, that the more severe the pandemic in the UF, the greater the adherence to social isolation, to the adoption of lockdown policies. Again, these results lack causal inference to elucidate these initial indications.

With the choice of electricity use as a proxy for the level of daily state economic activity, we present in Figure 3, the relationship of this variable with the pandemic evolution. The graph for the aggregated data for all Brazilian states needs to be analyzed with a 7-day moving average transformation of the original electricity consumption data to eliminate its daily seasonality. The graphical indication suggests that in many moments, there is a positive relationship between electricity consumption and pandemic evolution.

Both in the tax collection study panel and in the pandemic study panel by Federal Government, the use of control covariates for counterfactual inference is fundamental, both for Dif-in-Dif panel models and in artificial counterfactual temporal models. The indications of the descriptive statistics, although they may contribute to a previous identification of possible features of the phenomenon under study, cannot be used directly to evaluate public policies or the quasi-experimental events provided by the advent of the pandemic. Thus, in the next section we begin our counterfactual inference with difference-in-difference panel models.

Figure 3 – Daily Pandemic Dynamics and Electricity Consumption.



Source: CCEE, SRAG ARPEN and own elaboration.

4.2 Results of the Differences-in-Differences Panel Data Models

In this section we present the results of the Diff-in-Dif panel data models considering two scopes of studies:

a) Counterfactual study of estimated monthly state collections;

b) Counterfactual study of the estimated daily mortality rate.

An important property for using linear models that combine time series concerns stationarity. Neglecting this property means that any inferential results may be spurious and, therefore, not representing the reality of the phenomenon. This concern has evolved in the econometric literature to extend the traditional unit root tests to the panel data context. In this sense, one of the main motivations in adapting unit root tests for panels was the possibility of increasing the power of the test, a point in which tests for a single time series have long suffered. Among some possibilities of unit root tests for panel data, we use in this study the Fisher type test that combines the p-values of unit root tests using the four methods proposed by Choi (2001). The null hypothesis being tested by these methods is that all units in the panel contain a unit root. For a finite number of units, the alternative is that at least one unit is stationary. To counterfactual inference using difference-in-differences panel models, we present in Table 7 the results of unit root tests for all variables that will be used in the study.

Table 7 - Fisher Test for Stationarity of Panel Data

Test	Statistics	P-value
Collection	Pm = -4.5625	0.01
PMC	Pm = -7.3819	0.01
Var Collection	Pm = -33.787	0.01
Var PMC	Pm = -23.007	0.01
NR_OBITS100	Pm = -8.3726	0.01
Consumption_EE_MWh	Pm = -4.5062	0.01
Var NR_OBITS100	Pm = -10.705	0.01
Var Consumption_EE_MWh	Pm = -14.898	0.01

Note: 1) Var refers to the first difference of the logarithm of the variable, that is, its variation at the margin.
2) For the variables Collection and PMC, different tests were performed The conclusions are unchanged and we report the results for the 10th lag.
3) For the variables Number of deaths per 100,000/inhabitant and Consumption of different time lags were tested: 5, 10, 20 e 30. The conclusions are unchanged and we report the results for the 30th lag.
Source: Own elaboration.

The conclusions of the tests, even considering different lags, indicate stationary series at level, always rejecting the hypothesis of the presence of a unit root. Thus, we have evidence of stationarity that allows us to use traditional panel data estimation methods.

4.2.1 DiD Model Results for State Revenue

Starting from a narrower assumptions approach to more general models, we first estimate a pooling panel for the monthly tax collection of the sampled federal states, with the strong assumption that there is no individual heterogeneity, and that the parameters are constant over time. The results of this first model are detailed in Table 8 below.

The results of this model have global significance validated by the F-test with a portion of 74% of the variability of the states' tax collection, in the sample period, explained. Considering the estimated parameters, we observe that, if the hypotheses of this model are valid, we find that commercial activity has a positive average impact[5], statistically significant, of great magnitude on the monthly tax collection of the states. Considering the counterfactual effects variables, only three of the five Diff.-in--Diff effects were statistically significant. States that are not among the highest GDP, would have had higher (average) tax collection during the pandemic period, had they had the high GDP level. States that did not have the most severe Covid-19 pandemics, would have had higher revenue (on average) if

5 The presence of population aims to correct distortions that the population difference may cause in the estimated coefficients, alternatively panels with per capita tax collection were estimated; as the results did not change significantly, we chose to report the models with the estimated population parameter explicitly described.

they had faced a more severe pandemic, this is a counterintuitive result, and may be a result of the assumptions made in this model. The last statistically significant counterfactual effect is related to states with higher adherence to social isolation: states with low adherence would have a drop (on average) in collections if they had had high adherence to the social isolation policy. The counterfactual effect of lockdown was not found to be statistically significant. We emphasize that the hypotheses of this model are extremely strong and suggest caution with this evidence.

Table 8 - Diff-in-Dif Panel Data Model for State Revenue and the Covid-19 effects

Pooling Model - Estimated Parameters				
	Estimate	**Desv.Pad**	**t value**	**Pr(>|t|)**
(Intercept)	-1.5650e+09	4.4335e+07	-35.2991	< 2.2e-16 ***
PMC_Sales	1.8875e+07	5.2359e+05	36.0499	< 2.2e-16 ***
pop	1.8072e+02	1.6256e+00	111.1711	< 2.2e-16 ***
I_grave	-5.3478e+06	2.8437e+07	-0.1881	0.85083
I_GPD	-5.4803e+08	2.9784e+07	-18.4005	< 2.2e-16 ***
I_iso	-6.1535e+07	2.6230e+07	-2.3460	0.01901 *
I_Lockout	-1.1552e+08	2.7133e+07	-4.2574	2.097e-05 ***
I_density	1.6022e+08	2.7957e+07	5.7309	1.043e-08 ***
I_pan	-1.6800e+08	1.8886e+08	-0.8895	0.37376
I_pan_lock	-8.2539e+07	1.9030e+08	-0.4337	0.66450
I_pan_grave	3.2059e+08	1.9387e+08	1.6537	0.09824 .
I_pan_pib	1.0737e+09	1.6706e+08	6.4269	1.392e-10 ***
I_pan_iso	-3.0134e+08	1.7902e+08	-1.6833	0.09237 .
I_pan_den	1.3748e+08	1.9557e+08	0.7029	0.48212
NOTE				6642
R2				0.74999
Adjusted R2				0.7495
F-statistic				1529.43 with 13 and 6628 GL, p-value: < 2.22e-16

Note: 0 '***' 0,001 '**' 0,01 '*' 0,05 '.' 0,1 ' ' 1

Source: Own elaboration.

One way to relax such restrictions is to use fixed effects models, which assume that individual characteristics of the FHUs (individual heterogeneity) can be estimated for each state in the sample. This approach allows modeling differences in the individual behavior of the UF, the parameters still constant over time, but possibly varying from state to state. The first estimated fixed effect model, also known as LSDV (Least Square Dummy Variable), has its estimated results presented in Table 9.

Table 9 - Diff-in-Dif Panel Data Model for State Revenue and the Covid-19 effects

Fixed Effects Model (LSDV) - Estimated Parameters				
	Estimate	**Desv.Pad**	**t value**	**Pr(>|t|)**
PMC_Sales	1.882e+07	4.583e+05	41.073	< 2e-16 ***
pop	7.315e+00	4.309e+01	0.170	0.865201
I_grave	7.367e+09	1.672e+09	4.407	1.06e-05 ***
I_GPD	8.057e+09	1.917e+09	4.203	2.67e-05 ***
I_iso	6.970e+08	1.957e+08	3.562	0.000370 ***
I_Lockout	-1.019e+09	8.876e+07	-11.485	< 2e-16 ***
I_density	-8.611e+09	1.611e+09	-5.345	9.36e-08 ***
I_pan	-1.669e+08	1.627e+08	-1.026	0.304937
I_pan_lock	-8.242e+07	1.639e+08	-0.503	0.615047
I_pan_grave	3.205e+08	1.669e+08	1.920	0.054960 .
I_pan_gpd	1.073e+09	1.439e+08	7.461	9.67e-14 ***
I_pan_iso	-3.018e+08	1.542e+08	-1.957	0.050342 .
I_pan_den	1.374e+08	1.684e+08	0.816	0.414468
factor(sg_uf)AC	-9.242e+09	1.820e+09	-5.078	3.93e-07 ***
factor(sg_uf)AL	-5.838e+08	1.391e+08	-4.196	2.75e-05 ***
factor(sg_uf)AM	5.588e+08	1.733e+08	3.224	0.001272 **
factor(sg_uf)AP	-8.226e+09	1.889e+09	-4.356	1.35e-05 ***
factor(sg_uf)BA	-9.344e+09	1.279e+09	-7.305	3.11e-13 ***
factor(sg_uf)CE	-7.287e+09	1.837e+09	-3.967	7.36e-05 ***
factor(sg_uf)DF	-1.194e+09	3.676e+08	-3.247	0.001171 **
factor(sg_uf)ES	4.262e+08	1.273e+08	3.348	0.000818 ***
factor(sg_uf)GO	-8.576e+09	1.617e+09	-5.304	1.17e-07 ***
factor(sg_uf)MA	-6.422e+08	1.171e+08	-5.484	4.32e-08 ***
factor(sg_uf)MG	-7.029e+09	1.009e+09	-6.966	3.57e-12 ***
factor(sg_uf)MS	1.848e+08	8.952e+07	2.064	0.039071 *
factor(sg_uf)MT	-8.867e+09	1.769e+09	-5.012	5.54e-07 ***
factor(sg_uf)PA	-1.597e+10	3.469e+09	-4.603	4.24e-06 ***

factor(sg_uf)PB	7.584e+09	1.783e+09	4.253	2.14e-05 ***
factor(sg_uf)PE	-7.129e+09	1.819e+09	-3.919	8.97e-05 ***
factor(sg_uf)PI	-8.777e+08	1.498e+08	-5.859	4.88e-09 ***
factor(sg_uf)PR	-6.965e+09	1.494e+09	-4.661	3.22e-06 ***
factor(sg_uf)RJ	-5.813e+09	1.488e+09	-3.907	9.42e-05 ***
factor(sg_uf)RN	1.162e+09	8.876e+07	13.097	< 2e-16 ***
factor(sg_uf)RO	6.957e+09	1.506e+09	4.621	3.90e-06 ***
factor(sg_uf)RR	6.961e+09	1.616e+09	4.832	3.96e-06 ***
factor(sg_uf)RS	-1.054e+09	3.565e+08	-3.136	0.001682 **
factor(sg_uf)SC	-1.001e+09	3.591e+08	-3.201	0.001191 **
factor(sg_uf)SE	-8.151e+08	1.321e+08	-5.989	4.98e-09 ***
factor(sg_uf)SP	-7.983e+09	1.237e+09	-3.992	9.62e-05 ***
factor(sg_uf)TO	1.925e+08	8.987e+07	2.071	0.039981 *
NOTE				6642
R2				0.8526
Adjusted R2				0.8518
F-statistic				1124 with 34 and 6608 GL, p-value: < 2.22e-16

Note: 0 ‘***’ 0,001 ‘**’ 0,01 ‘*’ 0,05 ‘.’ 0,1 ‘ ’ 1

Source: Own elaboration.

The results of the LSDV model, as well as the Pooling model, have global significance confirmed by the F test, however with a higher percentage of variance explained in the concept of R2, of 85%. The results of the parameters estimated in the Pooling model are still valid in the LSDV model, with the exception of the population covariate, since part of the adjustments proposed by the inclusion of this variable are captured in the individual heterogeneity parameters. The causal effects estimated by Diff.-in-Diff, also held in relation to the model without individual heterogeneity, having the same signs and interpretations. Individual heterogeneity in this model is assumed to be an intrinsic characteristic of the UF, not given by a random shock (Random Effects Models), being estimated by individual intercept parameters. The results of the Table 9 present evidence that individual heterogeneity is present, in a statistically significant way, for all Brazilian states.

Another fixed effects estimation approach, known as Within, extracts the time average of the variables from their respective countries and then re-estimates the panel. The results of this method are detailed in Table 10.

Table 10 - Diff-in-Dif Panel Data Model for State Revenue and the Covid-19 effects

Fixed Effects Model (Within) - Estimated Parameters				
	Estimate	**Desv.Pad**	**t value**	**Pr(>|t|)**
PMC_Sales	18824291	458319	41.0725	< 2.2e-16 ***
I_pan	-166876696	162650639	-1.0260	0.30494
I_pan_lock	-82417546	163882571	-0.5029	0.61505
I_pan_grave	320462375	166948386	1.9195	0.05496 .
I_pan_gpd	1073443562	143868757	7.4613	9.669e-14 ***
I_pan_iso	-301767421	144167379	-2.0932	0.03645 *
I_pan_den	137448923	168420210	0.8161	0.41447
NOTE				6642
R2				0.21767
Adjusted R2				0.21376
F-statistic				262.65 with 7 and 6608 GL, p-value: < 2.22e-16

Note: 0 '***' 0,001 '**' 0,01 '*' 0,05 '.' 0,1 ' ' 1

Source: Own elaboration.

Note that for this model time-constant variables have null parameters, given the first time-average extraction step. The overall results hold for the LSDV version, with overall significance, the same statistically significant counterfactual effects. All the results presented are valid only on condition that the model assumptions are active. Failure of the assumptions leads to incorrect inferences and/or estimates, so we submit the estimated models to a battery of various tests that make their conclusions more reliable, and thus we present the results of all these tests in Table 11.

Table 11 - Tests on Panel Data Models

Test	Statistics	Degrees of Freedom	P-value
F-test for individual effects	F = 116.48	gl1 = 20, gl2 = 6608	< 2.2e-16
Breusch-Pagan student	BP = 764.38	gl = 12	< 2.2e-16
Breusch-Godfrey/Wooldridge test for serial correlation in panel models	chisq = 6315.9	gl = 246	< 2.2e-16
Pesaran Test for Cross-Sectional Dependency in Panels	z = 75.192	-	< 2.2e-16
Fisher's test for stationarity of the panel residual	Pm = -6.7966	-	0.01
Wooldridge test for unobservable individual effects	z = 1.8955	-	0.05803

Source: Own elaboration.

The first test puts the hypothesis of the Pooling model to the test, that is, the existence or not of individual heterogeneity. The p-value points to the existence of statistically significant individual effects, rejecting the null hypothesis of the test. Thus, the evidence from fixed effects models should be viewed with greater certainty and, therefore, the other tests will be applied to the Within model, given its parsimony in terms of estimated parameters, resulting in a greater degree of freedom, an important characteristic in inference in linear models. The Breusch-Pagan test in the following does not reject the hypothesis of heteroscedasticity, that is, the variance is not constant and, therefore, inferences using the t-test on estimated parameters are compromised. The Breusch-Godfrey/Wooldridge test presents statistical evidence of the presence of serial autocorrelation, which has similar effects as heteroscedasticity on parameter inference, again compromising t-test inference. Cross-sectional dependence presents itself in panels with long time series. The Pesaran test is used for this type of dependence, where the null hypothesis is that the residuals across individuals are uncorrelated, thus we have evidence that there is a dependence structure between the residuals of the FHUs in the sample. The Fisher test for stationarity of the residuals ensures a good fit of the linear panel data model. Finally, the Wooldridge test for unobservable individual effects is at the threshold (p-value of 0.058) for rejecting the null hypothesis of absence of these unobservable individual effects.

Heteroscedasticity and serial autocorrelation are recurrent problems in Diff-in-Dif models. A common practice in these circumstances is to employ a consistent estimator of the covariance matrix to formulate asymptotically valid hypothesis tests. Given the evidence of heteroscedasticity and serial autocorrelation in the Within model we re-estimated this model considering the correction proposed by Cribari-Neto (2004) to the widely employed HC4 estimator presented by Arellano (2003,1987). This estimator is consistent both in the presence of heteroscedasticity and serial autocorrelation of errors besides considering the context of small cross-section samples and possible leverage points. The results of the Within model robust to breaking heteroscedasticity and serial autocorrelation are presented in Table 12.

Table 12 - Diff-in-Dif Panel Data Model for State Revenue and the Covid-19 effects

Fixed Effects Model (Within+Het.Auto.Corr.) - Estimated Parameters				
	Estimate	**Desv.Pad**	**t value**	**Pr(>|t|)**
PMC_Vendas	18824291	6453252	2.9170	0.003546 **
I_pan	-166876696	261506471	-0.6381	0.523407
I_pan_lock	-82417546	239601546	-0.3440	0.730874
I_pan_grave	320462375	420633067	0.7619	0.446172
I_pan_pib	1073443562	358424948	2.9949	0.002756 **
I_pan_iso	-301767421	155002391	-1.9469	0.051681 .
I_pan_den	137448923	229617721	0.5986	0.549461

Note: 0 '***' 0,001 '**' 0,01 '*' 0,05 '.' 0,1 ' ' 1

Source: Own elaboration.

The correction for heteroscedasticity and serial autocorrelation significantly changes the standard deviation of the estimated parameters and thus also all inference from the t-tests. The new results only three variables are statistically significant: the volume of trade sales, with a positive parameter, indicating that each one point change in the PMC index, generates (on average) eighteen million Brazilian Reais in revenue, already free of seasonal effects; The counterfactual effects of adherence to the policy of social isolation in the pandemic, with a negative parameter, that is, states that did not have high adherence to social isolation, would have had a drop (on average) of a little more than three hundred million (considering the estimated standard deviation, the average impacts would be between 146 million and 456 million), in relation to the states that had high adherence to social isolation. The states which are not in the group of the largest state GDPs would have had an average increase in revenue of a little more than one billion Reais, had they had a GDP among the largest in Brazil.

4.2.2 Results of DiD Models for Mortality Rate

Following the same modeling steps as in section 4.2.1, we present in this section the results of causal inference for the mortality rates of the FSUs. According to the results in Table 8 the variables in this panel (mortality rates and electricity consumption) are also stationary in the panel data context and therefore we initially estimated the Pooling model of more restricted assumptions about individual heterogeneity, and its results are presented in Table 13.

Table 13 - Dif- in-Dif Panel Data Model for Number of Deaths per 100,000/inhabitant and State Characteristics

Pooling Model - Estimated Parameters				
	Estimate	**Desv.Pad**	**t value**	**Pr(>|t|)**
(Intercept)	7.0277e+00	2.6570e+00	2.6449	0.0081980 **
Consumption_EE_ MWh	3.5343e-05	9.4917e-06	3.7236	0.0001988 ***
I_GPD	-8.5225e+00	2.7126e+00	-3.1418	0.0016896 **
I_iso	-8.9520e+00	2.6112e+00	-3.4283	0.0006126 ***
I_Lockout	-1.2293e+01	1.8661e+00	-6.5875	4.971e-11 ***
I_density	-8.4938e+00	2.6747e+00	-3.1756	0.0015049 **
I_pan	2.5916e+01	2.7642e+00	9.3754	< 2.2e-16 ***
I_pan_lock	3.7456e+01	2.1568e+00	17.3664	< 2.2e-16 ***
I_pan_GPD	-7.6100e+00	2.8479e+00	-2.6722	0.0075624 **
I_pan_iso	2.2424e+01	2.8482e+00	7.8732	4.274e-15 ***
I_pan_den	1.4058e+01	2.8517e+00	4.9295	8.531e-07 ***
NOTE				4644
R2				0.44589
Adjusted R2				0.44015
F-statistic				77.6167 with and 10GL4633, p-value: < 2.22e-16

Note: 0 '***' 0,001 '**' 0,01 '*' 0,05 '.' 0,1 ' ' 1

Source: Own elaboration.

The results of the pooling model for mortality rate shows overall significance by the F-test with 45% of the variability in the mortality rate explained in the R-concept2.

If the assumptions of this model are valid, electricity consumption, used as a proxy for daily economic activity level, has a positive parameter, from which it follows that increases in activity level are associated with average increases in mortality rate. Among the causal effects, states with no lock-down policy and low adherence to social isolation policy would have (on average) higher death rates if they had adopted such a policy or had high adherence to social isolation. This same interpretation is valid for states with lower population density. Being among the largest GDPs in Brazil, would have, on average, a negative counterfactual effect, i.e., the group with the lowest GDP, would have had a lower mortality rate, had their GDP level been higher. Again, the counterintuitive results of this model should be read with caution, given the restriction of its hypotheses. These results, again, need further relaxation of its hypotheses and validation of panel data tests to ensure these inferences. Considering fixed effects models, the LSDV approach was estimated and its results are presented in Table 14.

Table 14 - Dif- in-Dif Panel Data Model for Number of Deaths per 100,000/inhabitant and State Characteristics

Fixed Effects Model (LSDV) - Estimated Parameters				
	Estimate	**Desv.Pad**	**t value**	**Pr(>|t|)**
Consumption_ EE_MWh	4.519e-04	6.315e-05 7.155	9.67e-13 ***	
I_GPD	-1.598e+02	2.360e+01	-6.774	1.41e-11 ***
I_iso	8.441e+01	1.856e+01	4.548	5.55e-06 ***
I_Lockout	-7.172e+00	3.412e+00	-2.102	0.035592 *
I_density	-3.775e+00	3.608e+00	-1.046	0.295508
I_pan	2.641e+01	2.662e+00	9.921	< 2e-16 ***
I_pan_lock	1.052e+00	5.208e+00	0.202	0.839914
I_pan_gpd	-4.397e+00	2.796e+00	-1.572	0.115918
I_pan_iso	2.048e+01	2.744e+00	7.462	1.02e-13 ***
I_pan_den	1.658e+01	2.768e+00	5.991	2.25e-09 ***
factor(UF)AC	-7.913e+01	1.874e+01	-4.222	2.47e-05 ***
factor(UF)AL	-1.040e+02	1.883e+01	-5.521	3.55e-08 ***
factor(UF)AM	-6.384e+01	1.922e+01	-3.322	0.000901 ***
factor(UF)AP	-6.520e+01	1.895e+01	-3.440	0.000587 ***
factor(UF)BA	1.224e+02	1.873e+01	6.536	6.99e-11 ***
factor(UF)CE	8.817e+01	6.659e+00	13.241	< 2e-16 ***
factor(UF)DF	4.951e+01	5.878e+00	8.422	< 2e-16 ***
factor(UF)ES	-1.300e+00	4.182e+00	-0.311	0.755952
factor(UF)GO	1.315e+02	2.037e+01	6.459	1.17e-10 ***
factor(UF)MA	-9.477e+01	1.968e+01	-4.815	1.52e-06 ***
factor(UF)MG	7.532e+01	1.350e+01	5.581	2.53e-08 ***
factor(UF)MS	-1.492e+01	4.016e+00	-3.717	0.000204 ***
factor(UF)MT	1.557e+02	2.169e+01	7.177	8.25e-13 ***
factor(UF)PA	7.753e+01	7.867e+00	9.855	< 2e-16 ***
factor(UF)PB	-9.167e+00	3.986e+00	-2.300	0.021513 *
factor(UF)PE	7.038e+01	6.369e+00	11.051	< 2e-16 ***
factor(UF)PI	-9.712e+01	1.895e+01	-5.125	3.10e-07 ***
factor(UF)PR	1.178e+02	1.844e+01	6.388	1.84e-10 ***

factor(UF)RJ	3.838e+01	5.968e+00	6.431	1.40e-10 ***
factor(UF)RN	-6.351e+01	1.055e+01	-3.611	0.000599 ***
factor(UF)RO	-1.052e+02	1.870e+01	-5.627	1.95e-08 ***
factor(UF)RR	2.519e+01	4.027e+00	6.255	4.33e-10 ***
factor(UF)RS	1.099e+02	1.654e+01	6.644	4.75e-10 ***
factor(UF)SC	1.079e+02	1.923e+01	5.613	2.11e-08 ***
factor(UF)SE	-9.433e+01	1.811e+01	-5.208	3.05e-07 ***
factor(UF)SP	3.929e+01	5.657e+00	6.921	1.89e-10 ***
factor(UF)TO	-9.005e+01	1.991e+01	-4.522	1.61e-07 ***
NOTE				4644
R2				0.5669
Adjusted R2				0.5639
F-statistic				188.6 with 32 and 4612 GL, p-value: < 2.22e-16

Note: 0 '***' 0,001 '**' 0,01 '*' 0,05 '.' 0,1 ' ' 1

Source: Own elaboration.

The results of the LSDV model present global significance by the F test with an increase of R2, reaching 57%, which may be occurring by the reduction of degrees of freedom due to the increase in the number of estimated parameters, characteristic of this model. The electricity consumption remained statistically significant and positive, maintaining its interpetration from the pooling model. Among the four[6] Dif-in-Dif effects estimated in this model, we can observe that only the effects of adherence to social isolation policy and demographic density were statistically significant, i.e., states that did not have high adherence to social isolation would have had (on average) higher mortality rates if their population had adhered to this policy, while states with low demographic density would have had (on average) higher mortality rates if they had higher demographic density. Again, the counterintuitive result of the I_pan_iso effect may be related to the assumptions of this model, and will be better described in the next steps of the study.

When we analyze the individual heterogeneity estimated by the LSDV model's intercept parameters we observe that all the FSUs have significant parameters, except for the State of Espírito Santo. The large number of statistically significant parameters in this model suggests a high cost of degrees of freedom already highlighted above, recommending the estimation of the Within fixed effect model. The results of this model are detailed in Table 15.

6 Note that in the panel data models with mortality rate we do not consider the Diff-in-Diff effect of pandemic severity per FU considered in the models with revenue panel, since severity, now as mortality rate, is the response variable of the model.

Table 15 - Dif-em-Dif Panel Data Model for Number of Deaths per 100,000/inhabitant and State Characteristics

Fixed Effects Model (Within) - Estimated Parameters				
	Estimate	**Desv.Pad**	**t value**	**Pr(>|t|)**
Consumption_EE_ MWh	4.5187e-04	6.3152e-05	7.1552	9.673e-13 ***
I_pan	2.6408e+01	2.6620e+00	9.9206	< 2.2e-16 ***
I_pan_lock	1.052e+00	5.208e+00	0.202	0.839914
I_pan_gpd	-4.3971e+00	2.7963e+00	-1.5724	0.1159
I_pan_iso	2.0475e+01	2.7441e+00	7.4616	1.016e-13 ***
I_pan_den	1.6581e+01	2.7679e+00	5.9907	2.249e-09 ***
NOTE				4644
R2				0.18656
Adjusted R2				0.1811
F-statistic				211,554 with 5 and 4612 GL, p-value: < 2.22e-16

Note: 0 '***' 0,001 '**' 0,01 '*' 0,05 '.' 0,1 ' ' 1

Source: Own elaboration.

The Within model showed overall significance by the F-test and with R2, of 18%. The statistically significant parameters remain the same, with the same signs and interpretations. These inferential results need to be tested against assumptions about variance, unobserved individual effects, etc. The results of these tests are presented in Table 16.

Table 16 - Tests on Panel Data Models

Test	**Statistics**	**Degrees of Freedom**	**P-value**
F-test for individual effects	F = 20.245	gl1 = 21, gl2 = 4612	< 2.2e-16
Breusch-Pagan student	BP = 1025.2	gl = 10	< 2.2e-16
Breusch-Godfrey/Wooldridge test for serial correlation in panel models	chisq = 4500.4	gl = 172	< 2.2e-16
Pesaran Test for Cross-Sectional Dependency in Panels	z = 198.74	-	< 2.2e-16
Fisher's test for stationarity of the panel residual	Pm = -6.9967	-	0.01
Wooldridge test for unobservable individual effects	z = 2.7444	-	0.006063

Fonte: Elaboração própria.

The F-test for individual effects concludes for the presence of individual heterogeneity, suggesting the use of fixed effects models. As in the monthly revenue panel models, the Breusch-Pagan and Breusch-Godfrey/Wooldridge tests present evidence of heteroscedasticity and serial autocorrelation, compromising the t-test inferences presented in the estimated models. Although the residuals are stationary by the Fisher-type test, we have the indication of the presence of cross-section dependence by the Pesaran test. The Wooldridge test does not reject the hypothesis of unobservable individual effects, these unobservable individual effects can have several origins, but perhaps the most relevant is the possibility of endogeneity between mortality rate and electricity consumption as a proxy for daily economic activity, where a higher mortality rate can reduce economic activity, as well as a higher level of economic activity can suggest a higher incidence of the number of cases and ultimately increasing the mortality rate, however this issue will be better detailed in the sequence of the study. Given this evidence, the Within model was estimated with the same correction as the HC4 estimator commented in the previous section. The results are shown in Table 17.

Table 17 - Dif- in-Dif Panel Data Model for Number of Deaths per 100,000/inhabitant and State Characteristics

Fixed Effects Model (Within+Het.Auto.Corr.) - Estimated Parameters				
	Estimate	**Desv.Pad**	**t value**	**Pr(>|t|)**
Consumption_EE_ MWh	0.00045187	0.00020202	2.2368	0.02535 *
I_pan	26.40819890	5.94871728	4.4393	9.236e-06 ***
I_pan_lock	1.0520e+00	4.4589e+00	0.2359	0.8134946
I_pan_gpd	-4.39706543	7.63732143	-0.5757	0.56482
I_pan_iso	20.47524110	7.25676182	2.8215	0.00480 **
I_pan_den	16.58146673	6.99635416	2.3700	0.01783 *
I_pan_den	137448923	229617721	0.5986	0.549461

Note: 0 '***' 0,001 '**' 0,01 '*' 0,05 '.' 0,1 ' ' 1

Source: Own elaboration.

The results of the correction for heteroscedasticity and autocorrelation do not alter the number of statistically significant parameters. For each increase of 10,000 Megawatt-hours[7], there was, in the sample period, an average increase of 5 new deaths per 100,000 inhabitants, or still, for each increase of 100,000 Megawatt-hours, there were 45 new deaths per 100,000 inhabitants. Among the significant Dif-em-Dif effects, states with low population density would have a higher death rate (on average) of 17 deaths per 100,000 population if they had high population density. The Dif-em-Dif effect associa-

7 To give you a reference of the size of this impact, one megawatt-hour (Mwh) is equal to 1,000 kilowatt-hours (Kwh). It is equal to 1,000 kilowatts of electricity used continuously for one hour. It is equivalent to the amount of electricity used by about 330 households for one hour.

ted with lockdown policy was not shown to be statistically significant in any model. The Diff-in-Diff effect associated with social isolation policy, with a positive parameter, translates as: states with low adherence to social isolation would have, on average, a mortality rate of 20 more deaths per 100,000 inhabitants if they had high adherence. This counterintuitive result is closely related to the hypothesis of unobservable individual effects verified in the Wooldridge test, that is, the possible presence of endogeneity between mortality rate and adherence to social isolation, where we may have a higher adherence to social isolation policy due to a higher mortality rate. Another possible effect well known in the literature of panel models in Dif-em-Dif, which can explain the presence of unobservable individual effects, are the lagged effects of the response variable, i.e., the dynamics between the mortality rate of previous periods in the estimated Dif-em-Dif effect, where an increase in the mortality rate in one period, would induce greater adherence in the next period.

4.2.3 Counterfactual Conclusions of Dif-in-Dif Models

The results presented in the last two sections present evidence both dynamics of the level of economic activity, with its proxies, for monthly tax revenue and for the Covid-19 daily death rate by state, and the testing of several counterfactual effects. The results highlight the importance of commercial activity for Brazilian states' monthly tax collection, in the best-fit model, this impact averaging 18 million for each unit of the sales volume index, this impact being 11 to 24 million on average, already considering seasonality. Among the counterfactual effects estimated in the tax collection panel, we have evidence that Brazilian states with higher GDPs performed better during the pandemic, since UF outside the group with the highest GDPs would have an average increase of a little over a billion in tax collection if they had higher GDPs. The effect associated with the social isolation policy was statistically significant with a negative sign, i.e., we have evidence that states with high adherence to this policy had considerable revenue losses, since states with low adherence to social isolation would have had an average revenue reduction of between 146 and 456 million Reais, in the counterfactual context.

Regarding the mortality panel of Brazilian states, we have evidence that the level of economic activity, measured by electricity consumption, has a positive impact on the mortality rate during the sample period, the increase of 10,000 Megawatt-hours, generated an average increase of 5 new deaths per 100,000 inhabitants. Another result of these mortality rate panel models reveal that the pandemic has a strong population density component, with an estimated counterfactual effect of 17 more deaths (on average) relative to low population density states. A counterintuitive result related to the Diff-in--Dif effect of social isolation policy throws caution on the inferences obtained using DiD models. The best-fit model results indicate that states with low adherence would have on average, 20 more deaths (on average) in the death rate if they had high adherence to social isolation. This result, along with Wooldridge's test of unobservable individual effects, suggests the nature of other dynamics in this panel: endogeneity and/or lagged effects of the death rate on adherence to the social isolation policy.

In summary, monthly state revenue showed statistically significant decreasing effects in states with high adherence to lockdown, while the death rate showed a strong demographic component, however in none of the panels did the counterfactual effect of states that adopted the lockdown policy prove statistically significant, i.e., there is no evidence of an impact on revenue, or on death rates. All these results, counterfactual inferences, depend directly on the assumptions of the Differences-in-Differences panel data models. In this sense, a central assumption is that the states are different from each other, but in a constant manner, this translates into there being no trends present in the individual heterogeneity component, i.e. the trends are necessarily parallel, which in many situations is an extremely restrictive assumption. The Pesaran test for cross-section dependence and the Wooldridge test for unobservable individual effects, in addition to the persistent presence of heteroscedasticity and serial autocorrelation, are indications that the assumptions of the Dif-in-Dif models and their inferences may be failing according to Bertrand et al (2004). Another sensitive issue concerns the lagged effects of interventions, such as lockdown or social isolation policies, where the effects may occur slowly, creating an autocorrelation structure and requiring GMM techniques, such as Arellano and Bond (1991), for their estimation, in a literature not yet consolidated for Diff-in-Dif effects. If the distribution of the response variable is changing over time, and even introducing temporal dynamics in panel data models, the need for parallel trends remains present and with it all its inference difficulties. The problem of endogeneity can also generate biased and inconsistent estimates, in this case aggravating and making the assumptions of parallel trends even more restrictive.

An alternative to all these causal inference issues in panel data models is the High-Dimensional Artificial Counterfactual (ArCo) panel models presented by Carvalho et al. (2018). The ArCo approach encompasses the PF method proposed by Hsiao et al.(2012) and can be seen as a generalization of the Synthetic Control approach on the same lines discussed by Doudchenko and Imbens (2016) and Ferman and Pinto (2016). The ArCo method is more suitable than the Difference-in-Differences (DiD) estimators, even for comparative case studies when there is a single treated unit and no similar control group is available, even after the inclusion of many control variables, or presence of endogeneity. In addition, the ArCo approach relaxes the strict parallel trend constraint of DiD methods. Recently, Gobillon and Magnac (2016) generalize DiD estimators considering a correct specification linear panel model found with strictly exogenous regressors and interacting fixed effects represented as a series of common factors with heterogeneous loadings. Their theoretical results rely on double asymptotics when T and n go to infinity. The authors allow that the common confounding factors have nonlinear deterministic trends. The ArCo method differs from Gobillon and Magnac (2016) in several directions:

1) The model is not considered to be specified correctly and there is no need to estimate the common factors. The consistent estimation of factors necessitates that both the time series and the cross-section dimensions diverge at infinity and can be severely biased in small samples;

2) The ArCo methodology requires only the divergence of the time series dimension. Moreover, the regressors need not be strictly exogenous, which is an unrealistic assumption in most applications with aggregate data. Heterogeneous nonlinear trends are also allowed, but there is no need to estimate them (either explicitly or by means of common factors);

3) Finally, as in the DiD case, ArCo also does not require the number of treated units to grow or have a reliable control group (after covariate conditioning).

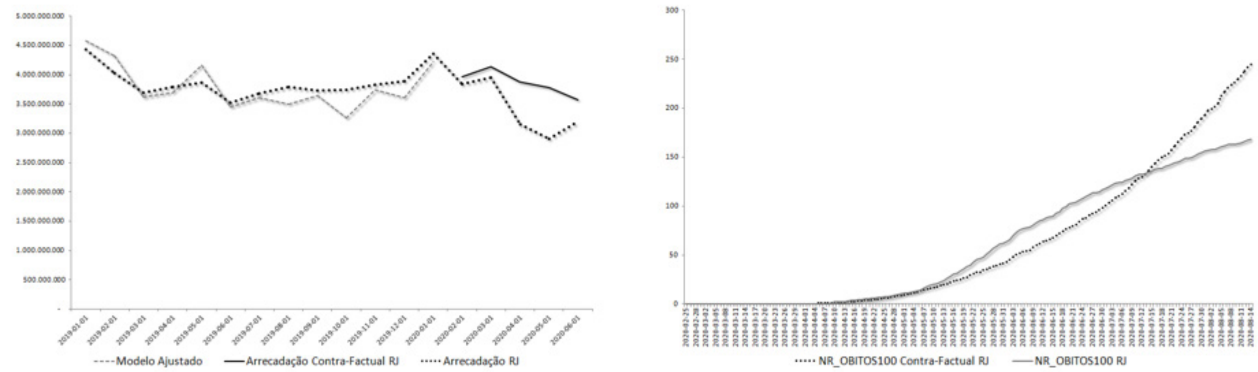
Given all these issues we present in the next section the ArCo results for estimating counterfactual behavior in the collection and mortality rate panels.

4.3 Results from Artificial Counterfactual Panel Data Models

We present in this section the results of the artificial counterfactual panel data (ArCo) models for the panels of state revenue and mortality rates. The intervention point for the monthly collection study was exogenously set as February 2020. For the mortality rates panel, the intervention date was estimated endogenously as presented in section 3.2.1, in view of the different pandemic evolution velocities by UF, and represents the moment at which, there is a statistically significant difference between the observed and counterfactually estimated mortality rates.

Initially we present case[8] studies to elucidate the results obtained and how they will be treated. In the Figure we4 present the results of[9] the ArCo model for RJ.

Figure 4 – Case Study: RJ



Source: Own elaboration.

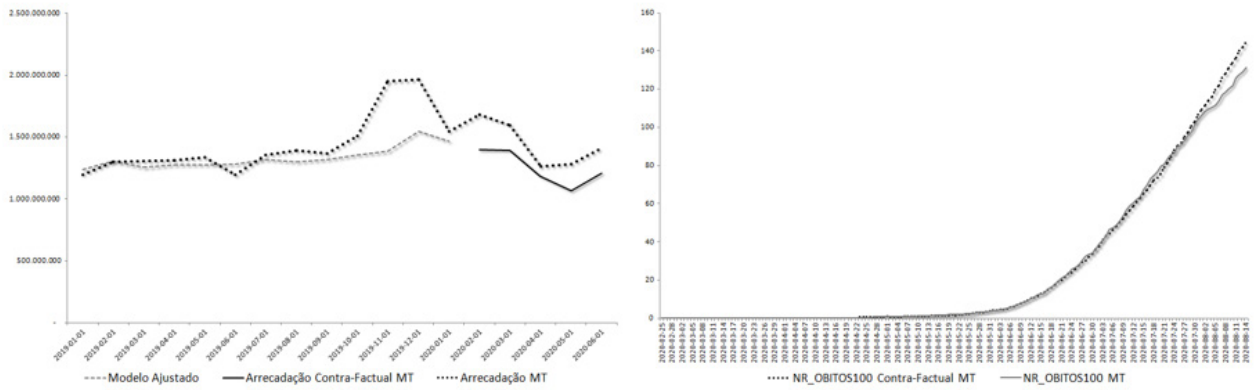
The case of RJ reflects the counterfactual behavior of the tax collection, starting with the February 2020 intervention, above the observed tax collection, that is, in a counterfactual context without pandemic, using the best estimate of a counterfactual RJ, RJ's tax collection would have been significantly higher, revealing that for RJ the pandemic brought severe losses in tax collection. The behavior of the mortality rate was until July 12th , it was above the counterfactual mortality rate, and in this stretch the pandemic was more severe than it would be in the counterfactual context, however from this date on, the mortality rate remained below the RJ-Counterfactual rate, that is, from July 12th on, the pandemic became less severe for RJ, if it followed its counterfactual growth.

Next, we present in Figure 5 the results for the MT case, which is the counterpoint to the RJ case. We can graphically observe that the tax collection observed in the pandemic period was above that of MT-Counterfactual as of the intervention, and in this case, MT would have had a lower impact of the pandemic on tax collection. In terms of mortality rate, we did not observe for MT, almost during the entire sample period, a difference between the observed and counterfactual rates, only after July 31, the rates of the MT-Counterfactual started to take off, indicating a less severe pandemic for this state.

8 The remaining case studies are presented in the Appendix.

9 When we consider the number of estimated parameters for all models: estimation model, counterfactual fit model, it has become impractical to report these models given the page limitation. Such results can be requested at any time from the authors.

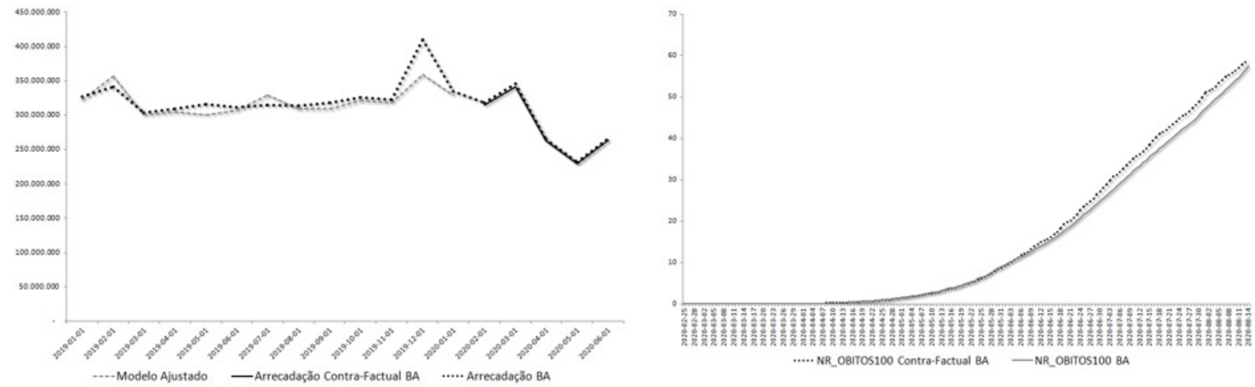
Figure 5 – Case Study: MT



Source: Own elaboration.

In the case study of Bahia, presented in Figure 6, we see from the Arc estimates that the collection was not, statistically, higher or lower than it would have been in a counterfactual context, and in terms of pandemic severity, the counterfactual values were slightly above the values observed as of June 11, indicating that the pandemic in this state was also slightly less severe.

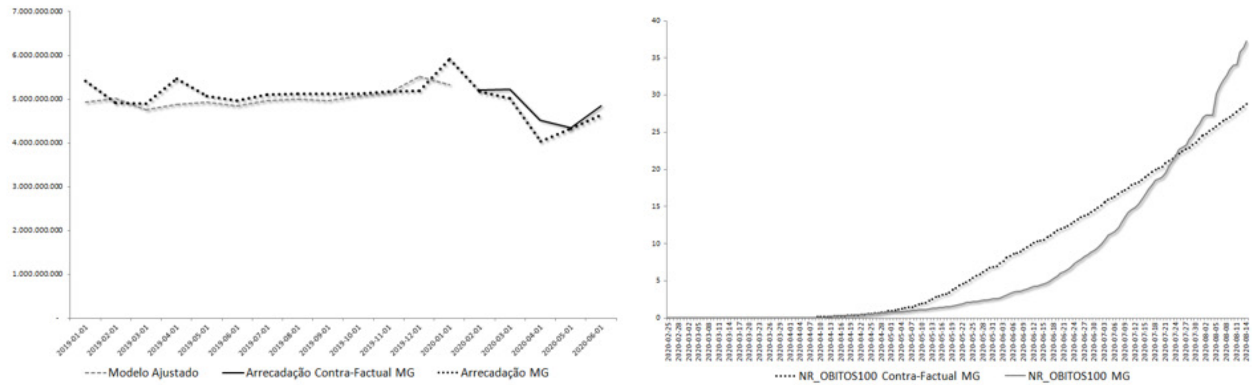
Figure 6 – Case Study: BA



Source: Own elaboration.

There are several possible combinations of revenue impacts and pandemic severity, and each state will present its own peculiarity during the sample period. The detailing of each state, by itself, would be the subject of a study of its own. However, we emphasize the case studies of MG and SP, because they are the two Brazilian states with the highest absolute collection, as detailed in Table 3. We can observe in Figure 7 that the state of MG, like RJ, has revenue values above MG-Counterfactual revenue, which can be translated into another state with a large negative impact on revenue. From the pandemic point of view, the state of MG was most of the sample period below the counterfactual value, however, from July 24, we observed an acceleration of the mortality rate above its counterfactual value, indicating that the pandemic became more severe from that date on.

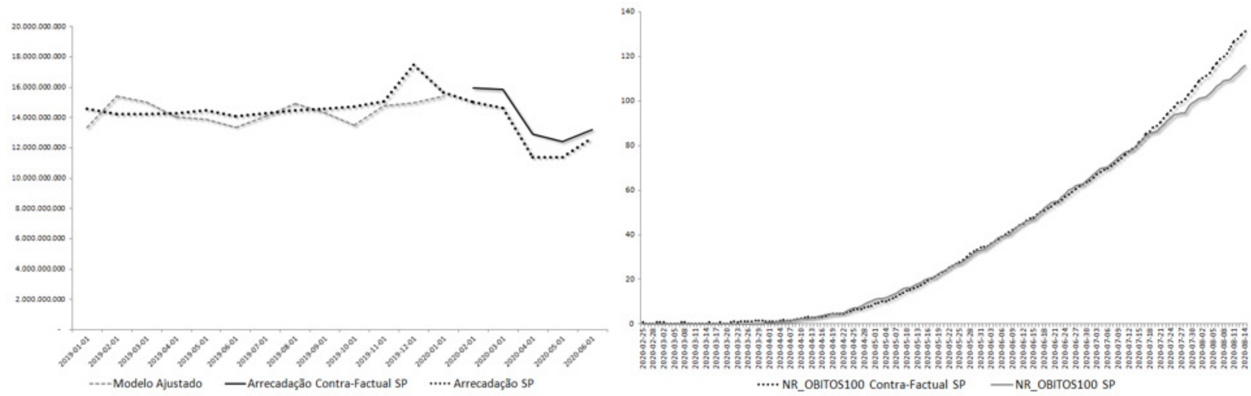
Figure 7 – Case Study: MG



Source: Own elaboration.

We present in Figure 8 the case study of SP, like MG and RJ, had collection values below what they would be in a counterfactual context, and given its representativeness in terms of national collection, its impact of the pandemic in terms of collection was the greatest. In terms of mortality rate, the state of SP, was for most of the sample period, very close between the observed and counterfactual mortality rates, the detachment occurs after July 18, when the rate values of SP-Counterfactual accelerates, and therefore, from this date on, we see a lower severity of the pandemic.

Figure 8 – Case Study: SP



Source: Own elaboration.

The results presented in these case studies show the heterogeneity of the pandemic impacts on state revenues and the different pandemic evolutions by Federal Government. To get an idea of this impact in counterfactual terms, we will use two measures: Counterfactual Difference (CSD) and the Percentage Counterfactual Difference (PCD). The first measure is the difference between the counterfactual variable and its observed value, while the second considers this difference in modulo, divided by the observed value, allowing us to have a percentage idea of the counterfactual difference. While the mean DCFP allows us to have a measure of total impact, without discriminating whether the counterfactual was above or below the observed value, the mean DCF provides the idea of counterfactual state predominance. We present in Table 18 and 19 the results of these measures for the 27 UF, ranked from highest average DCF of collections to lowest.

Table 18 - Covid-19 Estimated Counterfactual Pandemic Impacts by Federal Government

UF	I_iso	I_lock-down	Average Counterfeit Collection - pandemic period	Average revenue - pandemic period	Average Collection Feb/2019 to Jun/2019	Number of Counterfactual Deaths per 100 thousand/inhab. - Feb/20 to Jun/20 (Average)	Number of Deaths per 100 thousand/inhab. - Feb/20 to Jun/20 (Average)	Number of Counterfactual Deaths per 100,000/ inhab. (Average)	Number of Deaths per 100 thousand/inhab. (Average)	Average DCF Collection
SP	0	0	14.083.004.476	13.043.716.280	14.285.223.260	17,69	17,62	37,97	36,66	1.039.288.196
RJ	1	1	3.862.599.233	3.408.064.641	3.778.213.948	23,29	30,54	61,17	60,43	454.534.592
MG	0	0	4.823.427.609	4.638.169.079	5.065.035.909	3,49	1,70	8,24	6,97	185.258.530
CE	1	1	1.075.034.627	1.013.387.755	1.268.607.493	34,73	35,42	77,97	68,00	61.646.872
DF	1	0	846.771.113	790.269.364	831.397.940	7,80	6,99	32,57	26,55	56.501.749
MA	1	1	680.025.842	652.389.353	700.339.769	14,08	14,22	29,08	30,91	27.636.489
ES	0	0	1.045.954.533	1.019.272.995	1.100.205.868	17,00	17,32	42,57	42,85	26.681.538
AL	1	0	360.726.969	346.222.065	382.763.013	14,61	14,21	34,93	33,04	14.504.904
PI	1	1	382.974.294	373.560.448	403.835.095	4,31	6,90	14,50	23,67	9.413.846
AP	1	1	96.880.118	90.904.959	108.525.059	26,63	25,71	62,15	51,69	5.975.159
RN	0	1	468.331.822	463.894.723	511.513.210	8,07	10,63	23,76	32,13	4.437.099
BA	0	0	282.431.402	285.872.278	316.898.516	5,27	5,02	15,42	14,45	-3.440.876
SE	0	0	282.431.402	285.872.278	316.898.516	8,84	9,27	32,17	34,75	-3.440.876
TO	0	1	258.849.905	266.340.656	270.006.497	5,12	5,26	14,18	14,93	-7.490.752
PB	0	0	476.617.518	488.810.145	531.278.479	10,86	10,41	28,28	28,32	-12.192.627
AC	1	0	97.090.969	109.629.719	118.718.836	16,71	18,37	44,20	42,01	-12.538.751
RR	0	0	98.255.633	114.307.254	112.417.924	12,65	20,58	33,27	54,66	-16.051.621
RO	1	0	429.499.992	447.634.715	460.699.961	10,19	11,33	26,07	30,82	-18.134.723
PE	1	1	1.390.580.295	1.429.409.575	1.574.603.331	36,72	28,16	71,75	54,33	-38.829.280
AM	1	1	861.810.572	907.835.174	893.765.124	46,58	45,52	82,06	73,60	-46.024.602
RS	1	0	2.937.456.125	2.999.974.113	3.243.057.391	3,21	2,30	8,64	8,69	-62.517.988
PA	1	1	1.179.434.964	1.266.561.811	1.254.469.014	24,18	30,93	59,59	56,51	-87.126.847
SC	0	0	1.959.003.523	2.081.635.333	2.259.346.778	2,72	2,22	11,03	8,10	-122.631.810
MS	0	1	900.654.874	1.033.274.147	951.107.584	1,01	0,99	4,00	6,28	-132.619.272
MT	0	0	1.252.394.123	1.445.877.552	1.289.483.003	4,14	4,15	25,80	25,18	-193.483.429
GO	0	0	1.282.694.014	1.527.685.647	1.618.987.955	2,08	2,36	10,11	11,50	-244.991.633
PR	0	1	2.576.657.594	2.964.979.362	3.166.321.838	2,07	2,27	9,66	8,85	-388.321.768

Source: Own elaboration.

Table 19 - Estimated Counterfactual Pandemic Impacts of Covid-19 by UF- Counterfactual Difference.

UF	I_iso	I_lockdown	Average DCF Collection	Average DCFP Collection	Average DCF of Nr. Deaths per 100,000/ inhab.	Average DCFP of Nr. Deaths per 100,000/ inhab.	Average Collection Feb/2019 to Jun/2019	Number of Deaths
SP	0	0	1.039.288.196	0,0815	-1,2286	3,7248	14.285.223.260	26.625
RJ	1	1	454.534.592	0,1448	-0,7407	0,1588	3.778.213.948	14.514
MG	0	0	185.258.530	0,0422	-1,2650	0,4668	5.065.035.909	3.945
CE	1	1	61.646.872	0,0948	-9,8995	0,2981	1.268.607.493	8.127
DF	1	0	56.501.749	0,0890	-6,0045	0,1167	831.397.940	1.936
MA	1	1	27.636.489	0,0611	1,8361	0,2348	700.339.769	3.241
ES	0	0	26.681.538	0,1191	0,3041	0,0737	1.100.205.868	2.850
AL	1	0	14.504.904	0,0422	-1,8702	0,1424	382.763.013	1.733
PI	1	1	9.413.846	0,0739	9,1650	0,2131	403.835.095	1.582
AP	1	1	5.975.159	0,0946	-10,4585	0,1212	108.525.059	612
RN	0	1	4.437.099	0,0393	8,3633	0,1524	511.513.210	2.042
BA	0	0	-3.440.876	0,0117	-0,9635	0,0973	316.898.516	4.273
SE	0	0	-3.440.876	0,0117	2,5939	0,1031	316.898.516	1.685
TO	0	1	-7.490.752	0,0524	0,7643	0,0626	270.006.497	500
PB	0	0	-12.192.627	0,0478	0,0372	0,0739	531.278.479	2.114
AC	1	0	-12.538.751	0,1150	-2,1686	0,0893	118.718.836	576
RR	0	0	-16.051.621	0,1395	21,3955	0,3659	112.417.924	565
RO	1	0	-18.134.723	0,0416	4,7485	0,1283	460.699.961	1.001
PE	1	1	-38.829.280	0,0557	-17,4170	0,2321	1.574.603.331	7.114
AM	1	1	-46.024.602	0,0829	-8,4517	0,1274	893.765.124	3.457
RS	1	0	-62.517.988	0,0405	0,0478	0,1923	3.243.057.391	2.632
PA	1	1	-87.126.847	0,0701	-3,0688	0,3355	1.254.469.014	5.927
SC	0	0	-122.631.810	0,0570	-2,9255	0,2449	2.259.346.778	1.743
MS	0	1	-132.619.272	0,1286	2,2859	0,1382	951.107.584	591
MT	0	0	-193.483.429	0,1319	-0,5965	0,1084	1.289.483.003	2.286
GO	0	0	-244.991.633	0,1581	1,3879	0,1148	1.618.987.955	2.287
PR	0	1	-388.321.768	0,1329	-0,8059	0,0838	3.166.321.838	2.613

Note: The number of deaths by Federal Government refers to the latest Covid-19 pandemic panel date: 08/14/2020 - Total: 106,571 (second vintage). | Source: Own elaboration.

The results in Table 18 and 19 summarize the counterfactual impacts of the Covid-19 pandemic on state tax revenues in addition to the counterfactual pandemic evolutions by State. The results in Table 19 show that for 11 states (SP, RJ, MG, CE, DF, MA, ES, AL, PI, AP, and RN), the tax collection DCF was positive, indicating that the observed tax collection values were, for most of the sample period, above their respective counterfactual values. For these states, the loss of revenues due to the Covid-19 pandemic went beyond the simple drop in observed values, a fact that was common to the great majority of all Brazilian states as presented in Table 18. For these states, the Covid-19 impact on tax collection can be considered more severe in the sense that even the states, which without the pandemic context would have had declines in their tax collection, observed tax collection declines beyond what would be their natural tax collection decline. For the other states where the DCF was negative, the interpretation is reversed, i.e., for these states, the eventual drop in revenues was below what would be their natural drop in revenues under Covid-19 conditions.

When considering the largest positive Counterfactual Differences, we have the sequence of the states of SP, RJ and MG, which are respectively the three largest national tax collections. For these states, the impact of the pandemic on tax collection can be considered severe. On the other hand, in terms of the mortality rate DCF, they show negative values (in the 11th, 14th and 10th positions, respectively). That is, for these states the pandemic, in counterfactual terms, was severe, however they were not among the most severe pandemics in relation to other subnational entities, despite SP and RJ having the highest absolute numbers of national deaths (26.625 and 14,514 on 08/14), as shown in Table 19. When we analyze the mean DCF of the mortality rate of the states with positive collection DFC, in most cases, they show negative mortality DFC, which indicates the observed mortality rate was (albeit slightly for some states) above the counterfactual mortality rate, i.e., the Covid-19 pandemic was individually severe. The largest positive collection DCF refers to the state of SP. According to the data in Table 18, SP observed an average collection drop of 1. 241 billion Reais in the pandemic period, when estimated counterfactual indicates a value (on average) of 1.039 billion Reais higher than this observed value, i.e., in a non-pandemic context, we would expect a significantly higher collection value of more than 200 million Reais.

The largest negative tax collection DCF was observed for the state of PR, from Table 18 , PR had an average drop of just over two hundred million Brazilian Reais, this drop should have been larger, by about 388 million Brazilian Reais, according to the PR-Counterfactual. When we consider the DCF of the PR mortality rate, we have a negative value and thus have evidence of an individually severe Covid-19 pandemic, however we note that PR was not among the most severe regional pandemics. When we compare it to PE, for example, we observe that this state had the highest negative DCF of death rate, which indicates that this state suffered the most severe individual pandemic, the death rate, was far above the number that would be its PE-Counterfactual, nonetheless, Nevertheless, this state had a negative tax collection, which on the other hand indicates that its tax collection did not reduce, as it would naturally fall, which according to Table 18 and 19, represented a reduction of 9.22%, equivalent to 145 million Reals, when counterfactually, there should be a reduction (on average) of 38 million Reals above this value. Another highlight of Table 19 shows the state of RR with the highest positive mortality rate, which indicates that the number of deaths per 100,000 inhabitants should be much higher than the observed mortality rate, with a total number of 564 registered deaths.

When we consider the positive ADC of revenues in Table 19, we have the set of states that suffered the greatest pandemic impacts, on the other hand, when we observe in this same table, the set of states that had a negative ADC we have the set of states that suffered more severe pandemics. Thus, we have a first group formed by states with positive CSF of revenues and negative CSF of mortality: SP, RJ, MG, CE, DF, AL and AP, these states had a great impact on revenues and suffered more severe pandemics than their respective counterfactuals. A second group is formed by states with positive tax revenues and positive mortality rates: ES, PI, MA and RN, these states had a large tax revenue impact, but suffered less severe pandemics than their respective counterfactuals. The third group is formed by states in which we observed negative tax and mortality NCDs: BA, AC, PE, AM, PA, SC, MT and PR. In these states, we observed a lower impact on tax collection in the pandemic period concomitant with more severe pandemics considering their respective counterfactuals. The last group is formed by states with negative collection DFC and positive mortality DFC: SE, TO, PB, RR, RO, RS, MS and GO, in these states had lower impacts on revenue and less severe pandemics, considering their respective counterfactual values.

In absolute terms, the highest impacts of revenue (DCFP) were observed in GO (15%) and RJ (14%), as the DCF of positive revenue in RJ, we have evidence that this state has faced the greatest negative impact of counterfactual revenue, while the state of GO, with DCF of negative revenue, indicates that it was the state with the lowest negative impact of counterfactual revenue. In terms of pandemic, the largest absolute impacts were observed in SP and MG, with negative BCD, indicating a great counterfactual pandemic severity in these states, while the state of RR, with impact of 36%, and with BCD of positive mortality, indicating that this state has experienced a lower counterfactual pandemic severity. Considering the total tax collection impact, we observe that the sum of DFC shows a positive value, indicating that in general there was a great tax collection impact in the country. Considering in the same way the whole mortality DFC, we observe a negative value, indicating that the pandemic was severe in general in the country.

To obtain final evidence of the impacts of the pandemic on tax revenues, as well as to diagnose the effects of social isolation and lockdown policies on state pandemics, two panels were estimated: Fixed-effects panel with the states' collection FCD having the mortality FCD as a covariate in addition to testing the effects of social isolation and lockdown considering only the pandemic period (February to June 2020); Fixed-effects panel with the average mortality FCD per FU for the pandemic months (February to June 2020) having the respective isolation rate and lockdown indicator as covariates. The results of these two panel estimates are presented in Tables 20 and 21 respectively.

Table 20 - Panel Data Model for State Revenue and Covid-19 effects

Fixed Effects Model (LSDV) - Estimated Parameters				
	Estimate	**Desv.Pad**	**t value**	**Pr(>|t|)**
DCFObits	-90343	54091	-1.671	0.09706 .
I_iso	39353870	21423725	1.836	0.06829 .
I_lockdown	-7466091	60046747	-0.124	0.90128
factor(UF)AC	50392044	85174463	0.592	0.55536
factor(UF)AL	77106320	84927612	0.908	0.36599
factor(UF)AM	23937433	104004458	0.230	0.81841
factor(UF)AP	75958276	104002575	0.730	0.46679
factor(UF)BA	-3479525	60048642	-0.058	0.95390
factor(UF)CE	104666982	108343305	0.966	0.33621
factor(UF)DF	119038244	84917603	1.402	0.16389
factor(UF)ES	26736733	60051963	0.445	0.65706
factor(UF)GO	-244946268	60049849	-4.079	8.78e-05 ***
factor(UF)MA	97786680	104026473	0.940	0.34935
factor(UF)MG	184975632	60216406	3.072	0.00270 **
factor(UF)MS	-125156043	84918230	-1.474	0.14349
factor(UF)MT	-193477577	60045520	-3.222	0.00169 **
factor(UF)PA	-15937872	105708160	-0.151	0.88044
factor(UF)PB	-12260144	60055197	-0.204	0.83863
factor(UF)PE	29949093	105854903	0.283	0.77779
factor(UF)PI	79954209	104350239	0.766	0.44525
factor(UF)PR	-380823790	84917164	-4.485	1.86e-05 ***
factor(UF)RJ	525806996	105955626	4.963	2.67e-06 ***
factor(UF)RN	12310671	85138475	0.145	0.88530
factor(UF)RO	44709470	85077892	0.526	0.60032
factor(UF)RR	-14795879	63328951	-0.234	0.81572
factor(UF)RS	-103920411	90016741	-0.115	0.90823
factor(UF)SC	-122710721	60058766	-2.043	0.04352 *
factor(UF)SE	-3370319	60056095	-0.056	0.95535
factor(UF)SP	1039294371	60045528	17.308	< 2e-16 ***

factor(UF)TO	41709561	84076812	0.496	0.62059
NOTE				135
R2				0.8095
Adjusted R2				0.7592
F-statistic				16.09 with 28 and 106 GL, p-value: < 2.22e-16
Breusch-Pagan studentized: BP = 3.673, GL = 3, P-value = 0.299				
Breusch-Godfrey/Wooldridge test: chisq = 3.992, GL = 4, p-value = 0.407				

Note: 0 '***' 0,001 '**' 0,01 '*' 0,05 '.' 0,1 ' ' 1

Source: Own elaboration.

The results in table 20 show overall statistical significance reported by the F-test with low P-value, with adjusted R^2 of 75%. The mortality DFC parameter proved statistically significant at 10% with a negative sign, i.e., the more severe the pandemic, the greater the impact on collections in counterfactual terms. Each increase in the negative difference (i.e., the more severe the pandemic, since the observed values are, in this case, above the counterfactual) counterfactual of one death, generates on average an increase of 90 thousand Reais in the counterfactual difference in tax collection. Since the positive DCF represents that the counterfactual tax collection values are above the observed values, we have evidence that the more severe the pandemic, the greater the impact on tax collection. In this same sense, it was also shown statistically significant variable I_iso, showing the great impact of social isolation on the tax collection DCF, states with high adherence to social isolation, had an average impact 39 million Brazilian Reais higher in relation to states with lower adherence, as positive DCF, we have the evidence of great impact on tax collection of the states. On the other hand, there is no statistically significant evidence of lockdown effects on collection DCF. All inferences are valid, for the absence of heteroscedasticity and serial autocorrelation verified by the Breusch-Pagan and Breusch-Godfrey/Wooldridge tests respectively. We present in Table 21 the results regarding pandemic severity.

Table 21 - Panel Data Model for Counterfactual Mortality by Federal Government

Fixed Effects Model (LSDV) - Estimated Parameters				
	Estimate	**Desv.Pad**	**t value**	**Pr(>|t|)**
Taxa_iso	0.76656	0.42691	1.795	0.074670 .
I_lockdown	0.13121	1.92691	0.068	0.945839
factor(UF)AC	2.19634	2.72506	0.806	0.422042
factor(UF)AL	0.44388	2.72506	0.163	0.870913
factor(UF)AM	-0.24850	3.33751	-0.074	0.940787
factor(UF)AP	-0.13633	3.33751	-0.041	0.967494

factor(UF)BA	-0.20563	1.92691	-0.107	0.915215
factor(UF)CE	1.50447	3.47379	0.433	0.665820
factor(UF)DF	0.09847	2.72506	0.036	0.971243
factor(UF)ES	0.29367	1.92691	0.152	0.879156
factor(UF)GO	0.24136	1.92691	0.125	0.900553
factor(UF)MA	0.75259	3.33751	0.225	0.822024
factor(UF)MG	-1.50516	1.92691	-0.781	0.436452
factor(UF)MS	-0.14643	2.72506	-0.054	0.957245
factor(UF)MT	0.03114	1.92691	0.016	0.987137
factor(UF)PA	6.27946	3.33751	1.881	0.062624 .
factor(UF)PB	-0.35922	1.92691	-0.186	0.852464
factor(UF)PE	-6.54619	3.33751	-1.961	0.052430 .
factor(UF)PI	2.82851	3.33751	0.847	0.398612
factor(UF)PR	0.03845	2.72506	0.014	0.988769
factor(UF)RJ	6.72335	3.33751	2.014	0.046467 *
factor(UF)RN	2.03680	2.72506	0.747	0.456442
factor(UF)RO	1.73558	2.72506	0.637	0.525554
factor(UF)RR	6.68120	1.92691	3.467	0.000758 ***
factor(UF)RS	-0.40791	1.90581	-0.214	0.830843
factor(UF)SC	-0.41985	1.92691	-0.218	0.827933
factor(UF)SE	0.37540	1.92691	0.195	0.845903
factor(UF)SP	0.03286	1.92691	0.017	0.986428
factor(UF)TO	1.56728	2.58229	0.606	0.544914
OBS				135
R2				0.8095
R2 ajustado				0.7592
Estatística F				16.09 com 28 e 106 GL, p-valor: < 2,22e-16
Breusch-Pagan studentizado: BP = 3.671, GL = 3, P-valor = 0.299				
Teste Breusch-Godfrey/Wooldridge: chisq = 3.991, GL = 4, p-value = 0.407				

Nota: 0 '***' 0,001 '**' 0,01 '*' 0,05 '.' 0,1 ' ' 1

Fonte: Elaboração própria.

The results in Table 21 have statistically significant overall validity by F-test with low P-value, with adjusted R2 of 25%. The isolation rate proved to be statistically significant, with a positive value, which translates as: each unit increase in the social isolation rate has an average impact of 0.77 on the FCD mortality, as in the positive case of this difference represents a lower pandemic severity, we have evidence that a higher isolation rate is associated with a less severe pandemic in counterfactual terms, i.e., the number of deaths per 100,000/inhabitant counterfactual greater than the number of deaths per 100,000/inhabitant observed. On the other hand, the lockdown policy was not shown to be statistically significant, i.e., the adoption of this policy has no effect on the counterfactual difference, either positively or negatively. All these inferences prove valid, due to the absence of heteroscedasticity and serial autocorrelation verified by the Breusch-Pagan and Breusch-Godfrey/Wooldridge tests, respectively.

5. Conclusion

In this paper we investigate how the Covid-19 pandemic affected the tax collection of subnational entities. The proposal of this study had as its main line of investigation the counterfactual inference of both the tax collection of the states and their respective pandemic dynamics. For this purpose, we built two study panels, the first with seasonally adjusted data on tax collection and commercial activity, with monthly dynamics by Federal Government and the second panel containing data on mortality per 100 thousand inhabitants and electricity consumption, with daily dynamics by Federal Government. The sample period comprised the period from January 2000 to June 2020 for the tax collection panel, making a sample of 246 temporal observations, while the pandemic panel comprised the period from 02/22/20 to 08/14/20, making a sample of 172 temporal observations.

The first step was to construct a set of indicator variables considering the characteristics of the UFs such as GDP and demographic density, as well as the adoption of lockdown policies, adherence to social isolation, and pandemic severity. A thorough exploratory analysis details the relationship between the variables used in the study. The study used two causal inference approaches: differences-in-differences (DiD) panel data models and the artificial counterfactual (ArCo) panel models.

The general conclusions of the estimated DiD models infer that increased trade activity has a large impact on state revenue (an increase of one unit of trade sales volume generates an average increase of 18 million in revenue). Among the estimated counterfactual effects, high adherence to social isolation policies and states with higher GDPs showed statistically significant effects. Thus, states with high adherence to social isolation policies had a negative revenue impact, on average, of 300 million, and this impact could be 146 to 456 million, relative to states without high adherence, counterfactually. The states with GDP below the national median would have an average increase of almost one billion Reais in tax collection during the pandemic, if they were from the set of UF with the highest GDPs. The counterfactual effects of adopting lockdown policies were not statistically significant in the Dif-in-Dif panel of tax collection. Regarding the panel with daily pandemic data, evidence was found that an increase of 10,000 Megawatt-hours, generated an increase (on average) of 5 deaths in the mortality rate per 100,000/inhabitant. Two counterfactual effects were found to be statistically significant, population density and high adherence to social isolation policies. Thus, states with high population density had (on average) 17 more deaths per 100,000/inhab, if they did not have this population density, which highlights the important demographic characteristic of the pandemic. Again, the counterfactual effects associated with the lockdown policy were not statistically significant. The results of the best fit model indicate that states with low adherence would have on average, 20 more deaths (on average) in the death rate if they had high adherence to social isolation. This counterintuitive result reveals the possibility of endogeneity between mortality rate and social isolation adherence across states, one of the weaknesses of the Diff-in-Dif Panel models. Therefore all these DiD inferences are sensitive to a set of assumptions, among these, the assumption that states are different from each other, but in a constant manner, stands out, this translates into no trends present in the individual heterogeneity component, that is, the trends are necessarily parallel, which in many situations is an extremely restrictive assumption, as an alternative to these (and other) weaknesses of DiD models were estimated the models for artificial counterfactual panels (ArCo).

The results of the ArCo models allowed, individually per state, to build their respective counterfactual collection, as well as their counterfactual pandemic. With these results it was possible to observe the behavior of the panels starting from an intervention date (exogenously fixed as the month of February 2020 for the revenue panel and endogenously estimated for the pandemic panel, given the different Covid-19 regional evolutions). The results revealed that the impacts were heterogeneous across states, collections such as those of SP and RJ, turned out to be below their counterfactual values, i.e., for these states, collections would have been higher in a counterfactual context, and therefore suffered large impacts on collections. Other states, such as PR and GO, had counterfactual revenues below their observed values, i.e., revenues in these states would have been lower in the counterfactual context, and therefore suffered smaller impacts in terms of revenues. There were also states such as BA and RN, in which there is almost no distinction between the observed values of collection and their counterfactuals, and thus the collection followed its natural course. In a similar analysis, we verified in this study, states like PI and RN, where the number of deaths per 100 thousand/inhabitant was below their respective counterfactual values, and therefore faced less severe pandemics, while states like PE and AP, we observed counterfactual values of the mortality rate far below their respective observed values, and therefore the pandemic severity was high. We also have cases in which the values of mortality rates, counterfactual and observed, showed virtually no difference, for example, the states of SP, RJ, BA and PR, i.e., for these states, the pandemic followed its natural course.

To scale the impacts of Covid-19 as of the intervention date, we constructed two measures of the difference between counterfactual and observed values of state revenue and mortality rate: the mean Counterfactual Difference (CVD), as the simple difference, and the mean Percentage Counterfactual Difference (PCDF), which considers the absolute value of this difference divided by the observed value, measuring absolute impacts. When we considered the DCF (positive or negative) for revenue and mortality rate, it was possible to identify four groups of states. The first group was formed with states with positive collection DCF and negative mortality DCF: SP, RJ, MG, CE, DF, AL and AP, these states had a large collection impact and suffered more severe pandemics than their respective counterfactuals. The second group, formed with states with positive taxable income and negative mortality rate: ES, PI, MA and RN, these states had a large taxable income impact, but suffered less severe pandemics than their respective counterfactuals. The third group, made up of states with negative taxable income and negative mortality rate: BA, AC, PE, AM, PA, SC, MT and PR, in these states, we observed a lower impact on taxable income in the pandemic period concomitant with more severe pandemics considering their respective counterfactuals. And finally, a group of states formed by DCF of negative revenue and DCF of positive mortality rate: SE, TO, PB, RR, RO, RS, MS and GO, in these states had lower impacts on revenue and less severe pandemics, considering their respective counterfactual values.

To elucidate the key questions of the study, two final monthly panels were estimated for the pandemic period considering the measures of counterfactual pandemic impact (DCF). The first fixed-effects panel showed evidence that the higher the pandemic severity, the greater were the impacts on revenue, as well as, the greater the adherence to social isolation policy the greater were the negative impacts on revenue, however there was no statistically significant evidence of revenue impacts from the adoption of lockdown policies. The second fixed effects panel showed evidence that the higher the social isolation rates, the less severe were the regional pandemics, however the adoption of lockdown policies did not show statistical significance. The causal inferential results of the ArCo and Diff-in-Dif methods converge with respect to the two main policies to combat Covid-19. A large adherence to social isolation policies showed evidence of large impacts on revenue and on the state mortality rate, on the other hand, there was no statistical evidence of effects of the adoption of lockdown policies, even though they did not show effects on state revenue, other variables not listed in the study, such as unemployment rate, bankruptcies, and other undiagnosed pathologies may have had a large elevation due to the adoption of the lockdown policy. The study concludes that Covid-19 impacts on tax revenues were heterogeneous, as well as providing evidence that regional pandemics were heterogeneous, with states experiencing greater and lesser impacts on tax revenues, as well as facing more severe pandemics than other states. The voluntary policy of adherence to social isolation was effective in reducing the mortality rate with costs in tax revenues of the subnational entities, but no effects were observed with deliberative policies of subnational governments. Thus, this study contributes to the literature as a pioneering study of the counterfactual impacts of the Covid-19 pandemic on state tax revenues.

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6. Appendix

Table 1 - Percentage Variations in Collection and Coefficients of Variation in Pandemic Comparison.

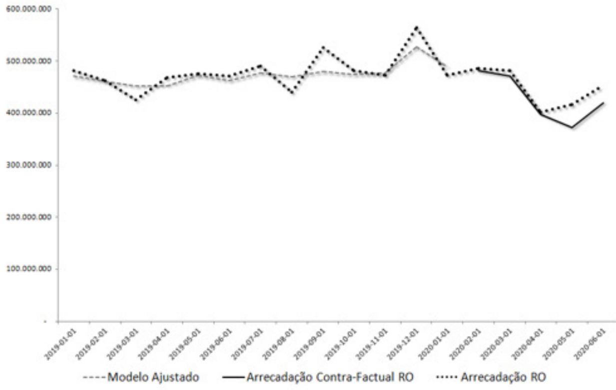
UF	Percent Variation between Pre-Pandemic and Pandemic Average	Coef. Variation Pre-Pandemic	Coef. Variation Pandemic
AC	-7,66	0,04	0,32
AL	-9,55	0,04	0,33
AM	1,57	0,03	0,28
AP	-16,24	0,09	0,37
BA	-9,79	0,04	0,33
CE	-20,12	0,15	0,33
DF	-4,95	0,04	0,29
ES	-7,36	0,03	0,27
GO	-5,64	0,02	0,34
MA	-6,85	0,01	0,32
MG	-8,43	0,04	0,30
MS	8,64	0,03	0,26
MT	12,13	0,04	0,27
PA	0,96	0,02	0,30
PB	-7,99	0,03	0,32
PE	-9,22	0,01	0,32
PI	-7,50	0,14	0,34
PR	-6,36	0,04	0,32
RJ	-9,80	0,05	0,31
RN	-9,31	0,01	0,32
RO	-2,84	0,04	0,29
RR	1,68	0,10	0,27
RS	-7,50	0,01	0,31
SC	-7,87	0,01	0,29
SE	-9,79	0,04	0,33
SP	-8,69	0,01	0,30
TO	-1,36	0,01	0,30
Average	-5,92	0,04	0,31
Median	-7,50	0,04	0,31

Source: Own elaboration.

Table 2 - Construction of Social Isolation Variables by Federal Government

UF	IIS_3004	IIS_3005	IIS_3006	IIS_3007	IIS_1508	IIS Percentil 90	I_Iso
RO	36,27	51,34	42,11	38,79	41,12	47,65	1
AC	39,78	54,50	42,67	40,57	43,28	50,01	1
AM	44,19	50,74	40,56	39,07	40,67	48,12	1
RR	37,19	49,84	38,72	37,04	38,63	45,39	0
PA	45,26	49,96	38,26	36,87	40,38	48,08	1
AP	42,92	56,05	42,17	38,42	40,69	50,80	1
TO	34,04	46,03	33,88	34,50	38,07	42,85	0
MA	44,20	48,75	37,32	37,12	38,96	46,93	1
PI	42,48	51,81	40,32	39,41	45,60	49,33	1
CE	44,68	52,94	41,06	39,39	40,85	49,64	1
RN	41,00	49,01	39,16	36,88	38,40	45,81	0
PB	41,86	50,27	39,24	37,38	38,56	46,91	0
PE	46,10	53,55	39,66	37,20	39,87	50,57	1
AL	42,35	53,52	39,40	37,34	39,22	49,05	1
SE	40,08	48,99	38,21	39,98	38,74	45,43	0
BA	38,66	50,08	39,92	38,57	40,31	46,17	0
MG	37,40	47,37	38,22	35,79	39,11	44,07	0
ES	38,14	50,81	38,82	39,69	38,28	46,36	0
RJ	44,38	51,00	40,91	39,05	39,25	48,35	1
SP	40,14	49,78	38,82	36,61	39,44	45,92	0
PR	35,58	47,74	39,11	36,02	43,92	46,21	0
SC	36,42	48,55	43,20	37,54	41,41	46,41	0
RS	38,01	52,17	45,87	37,37	42,06	49,65	1
MS	31,93	46,20	37,24	36,72	39,27	43,43	0
MT	33,81	46,76	40,78	37,09	38,96	44,37	0
GO	43,23	44,54	37,10	35,90	37,30	44,02	0
DF	49,77	49,49	41,04	38,55	39,49	49,66	1
Average	40,37	50,07	39,77	37,74	40,07	47,08	
Median	40,14	49,96	39,40	37,37	39,44	46,91	
Standard Deviation	4,28	2,71	2,33	1,46	1,90	2,28	
CV	0,11	0,05	0,06	0,04	0,05	0,05	

Source: Own elaboration.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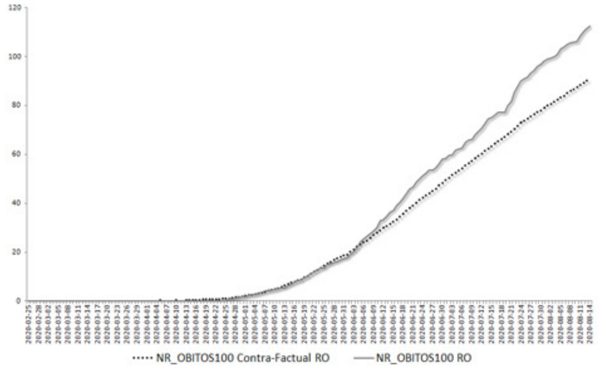
Arrecadação RO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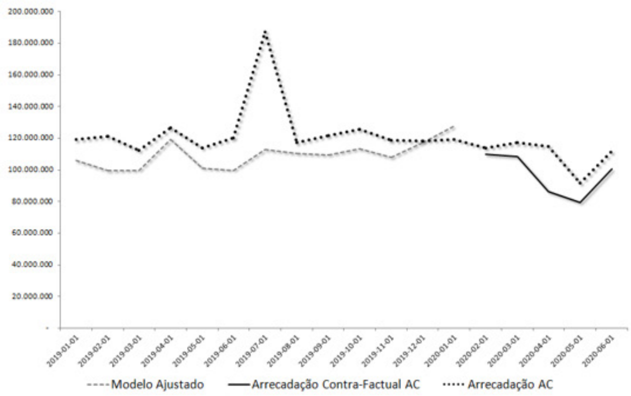
NR_OBITOS100 RO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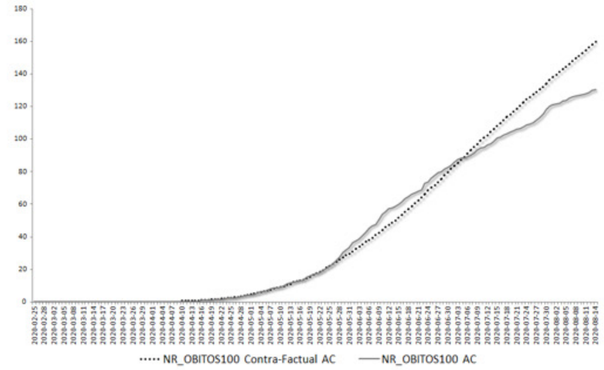
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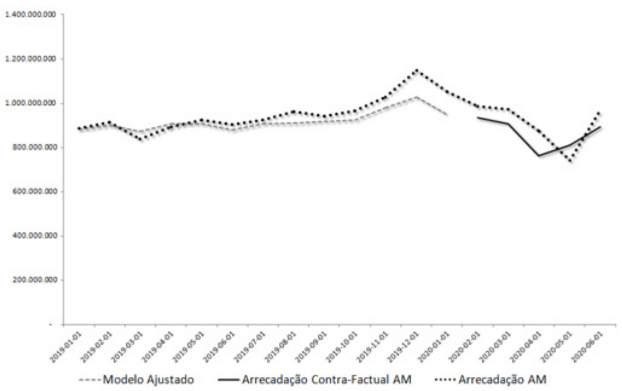
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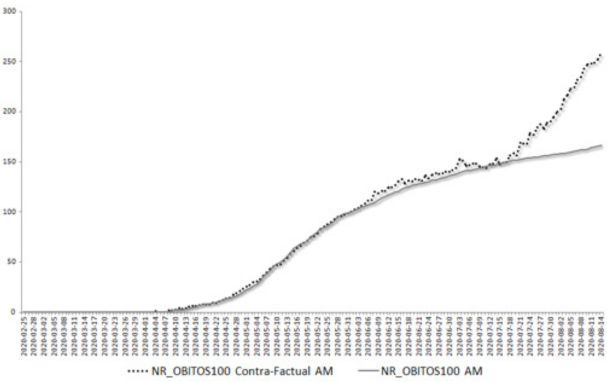
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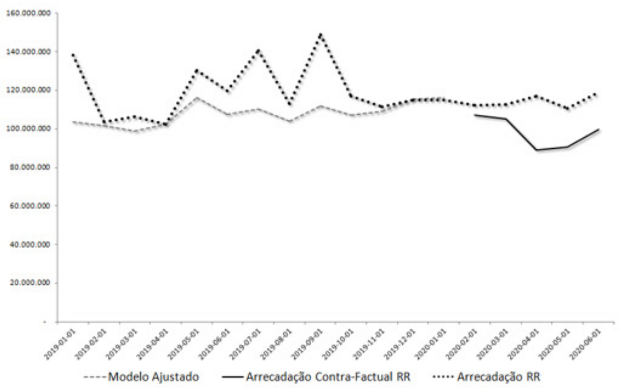
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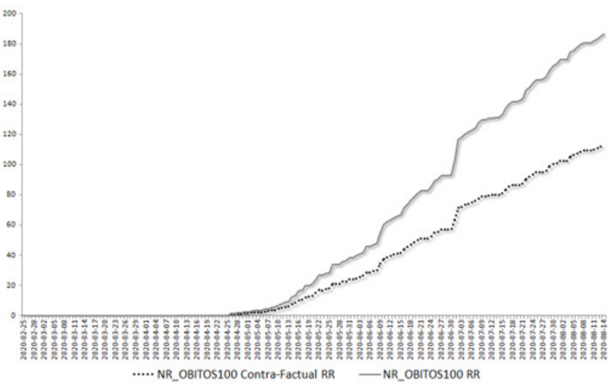
Arrecadação RR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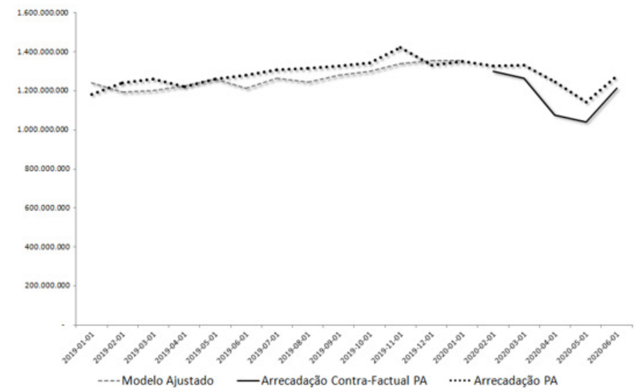
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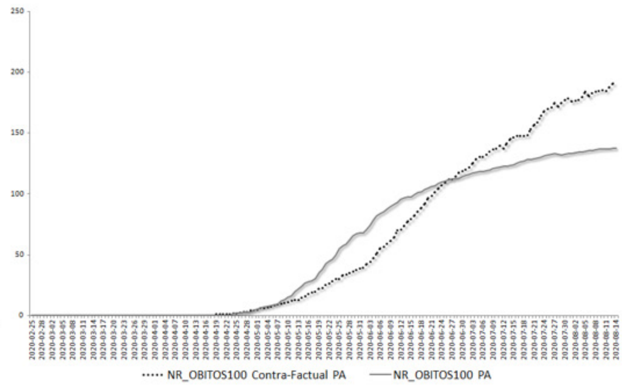
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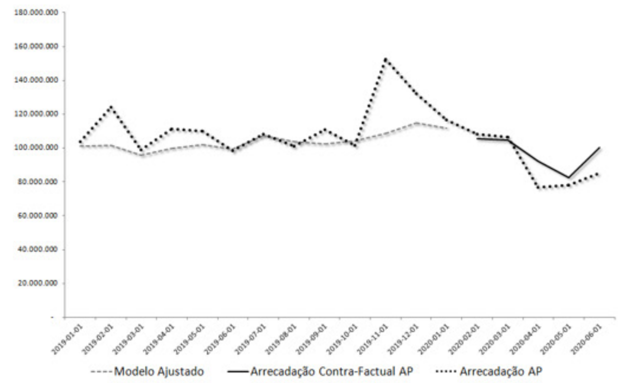
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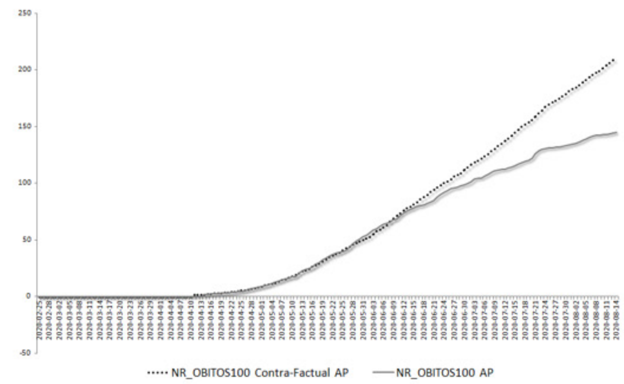
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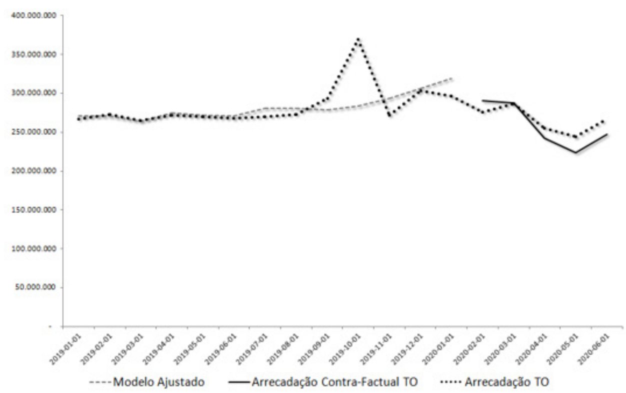
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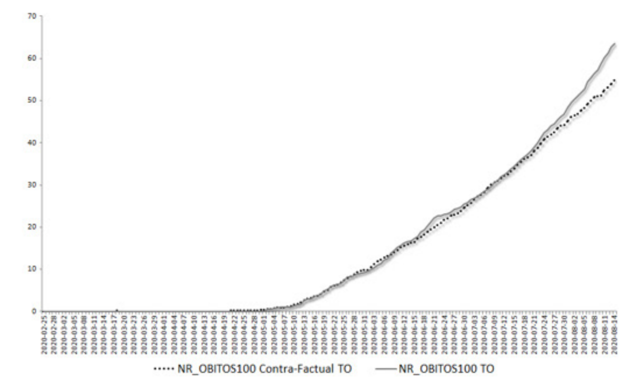
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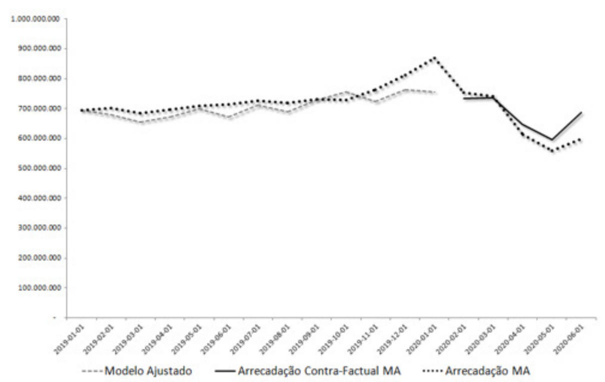
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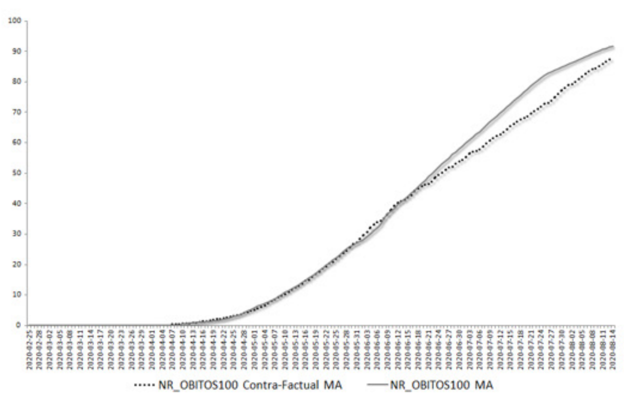
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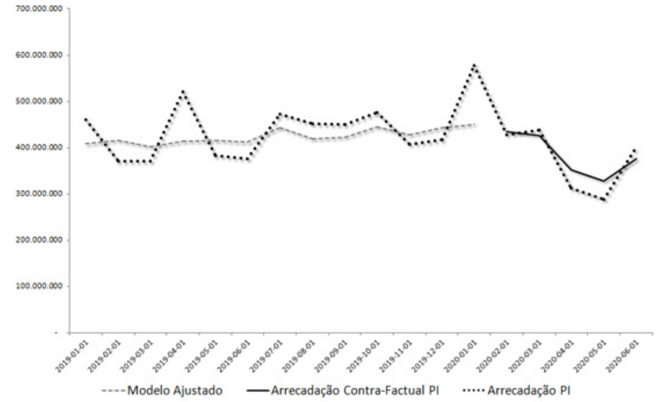
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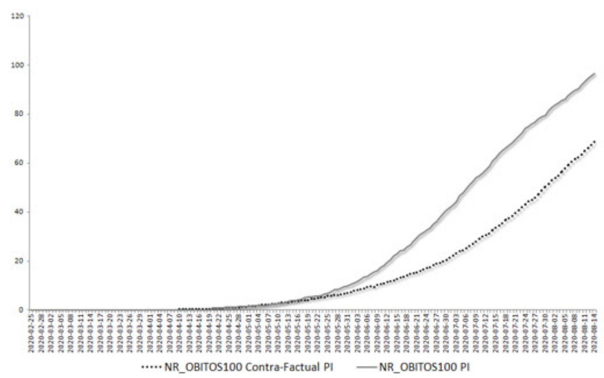
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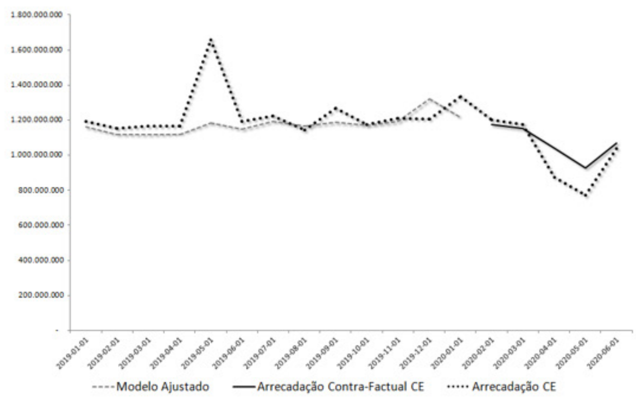
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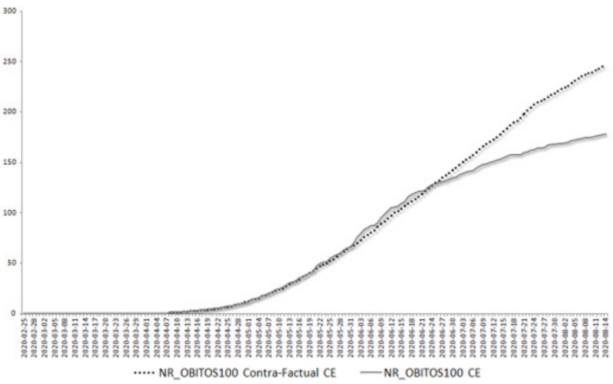
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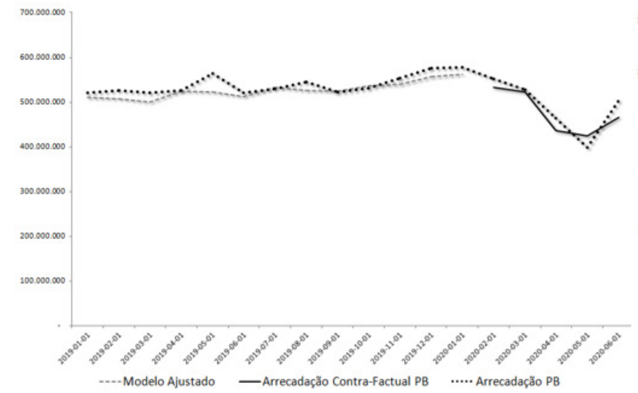
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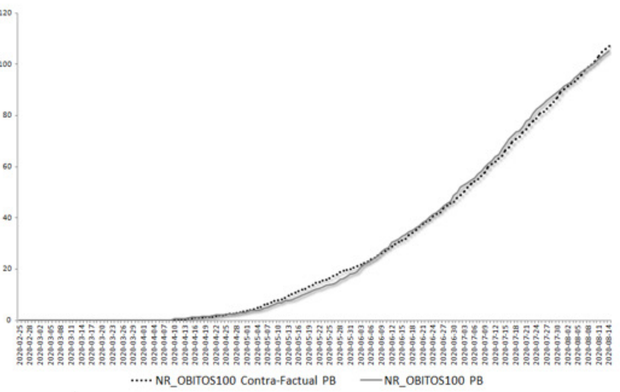
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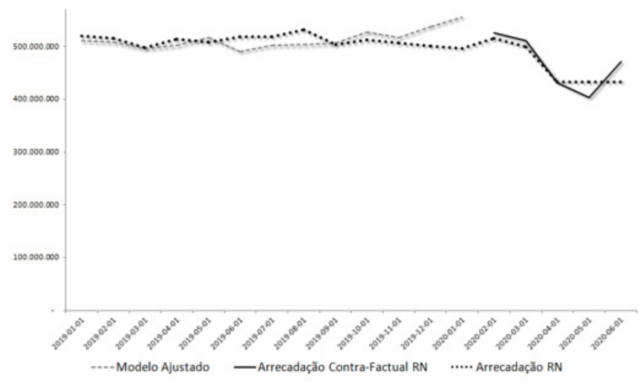
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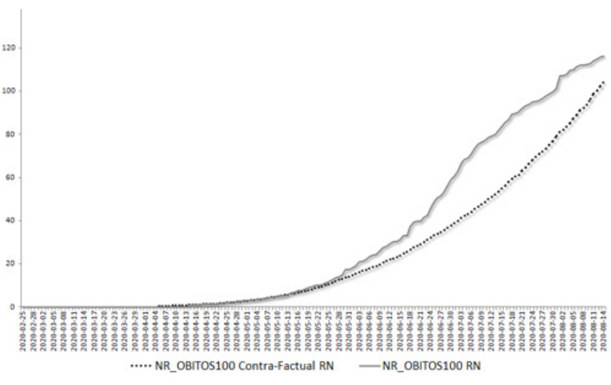
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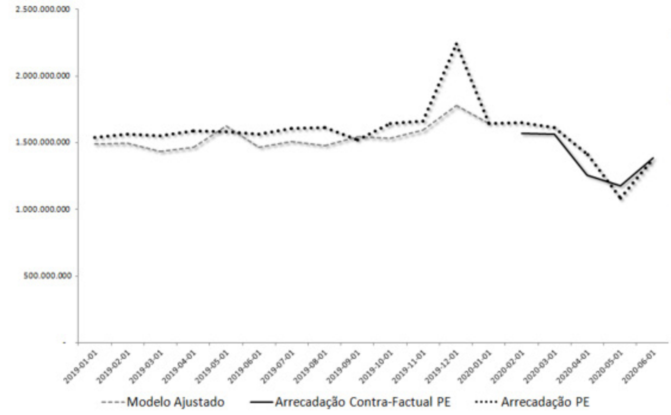
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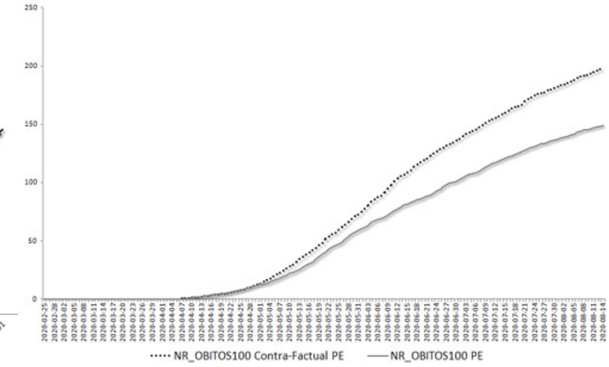
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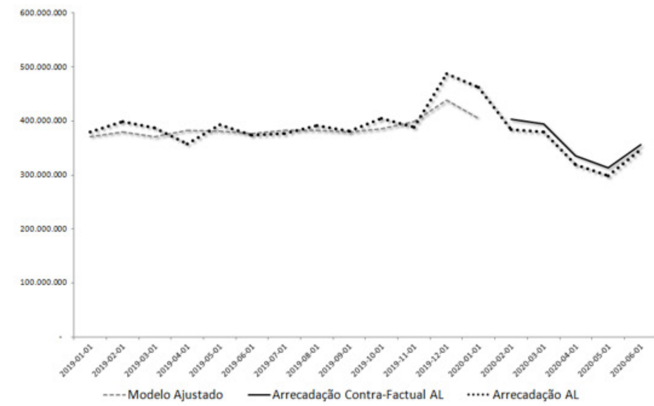
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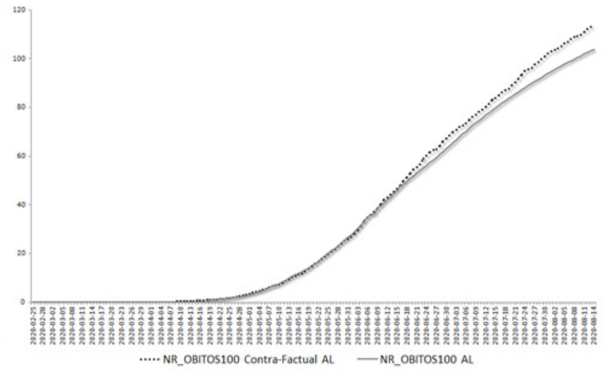
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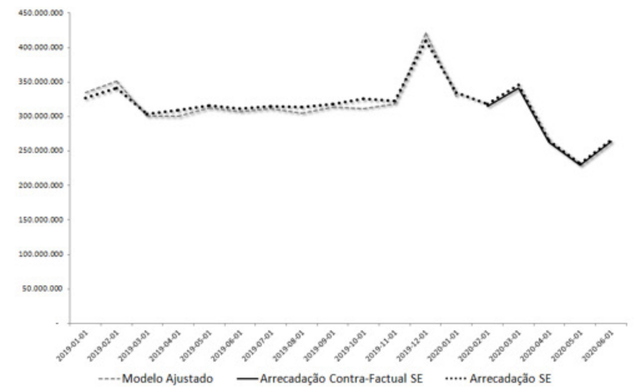
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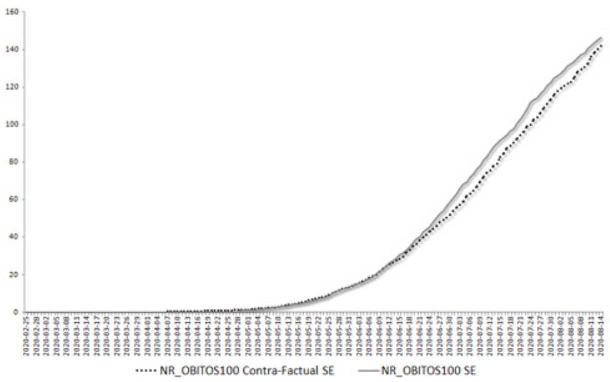
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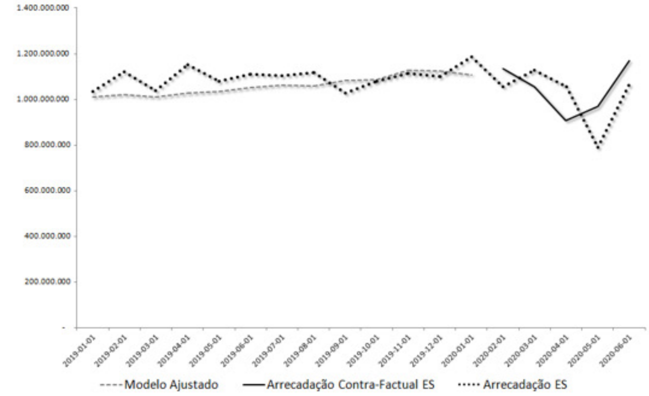
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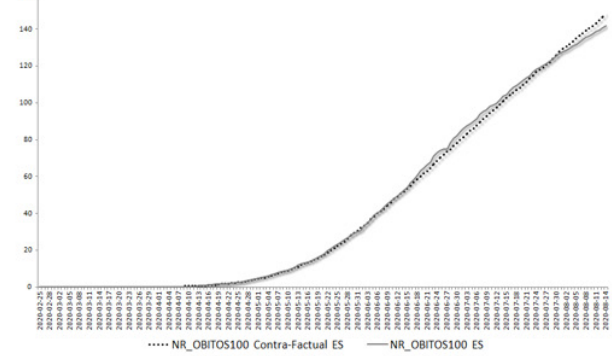
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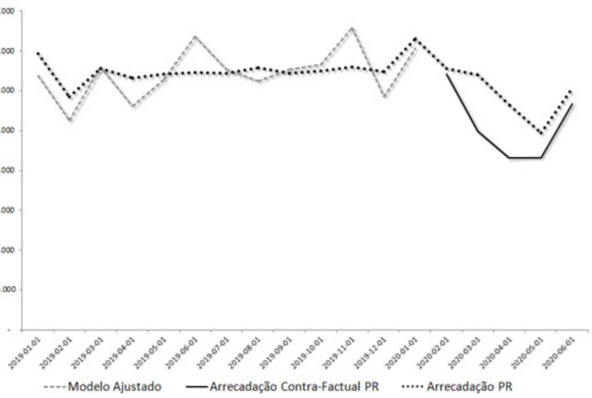
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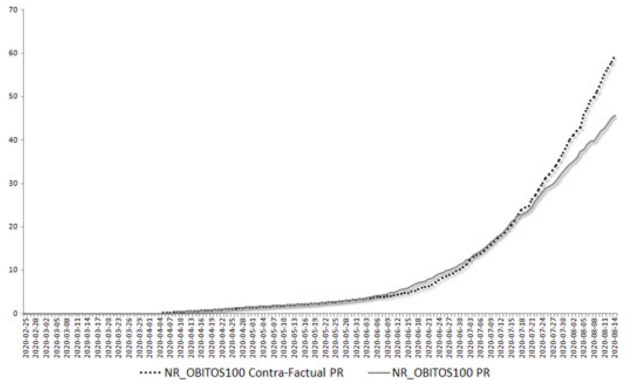
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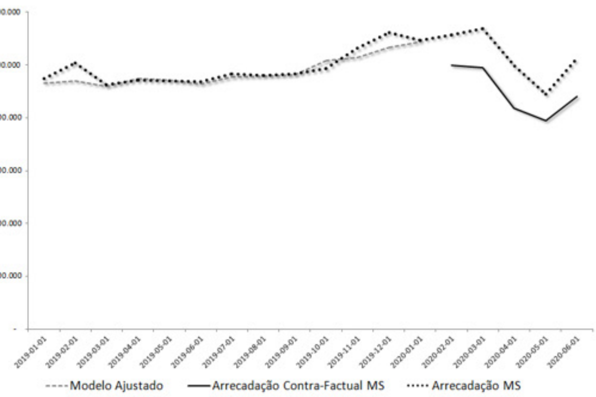
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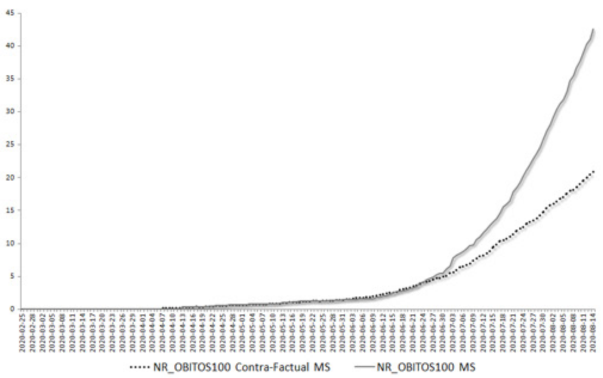
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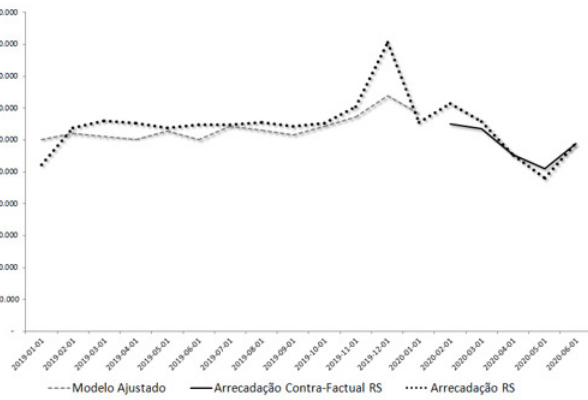
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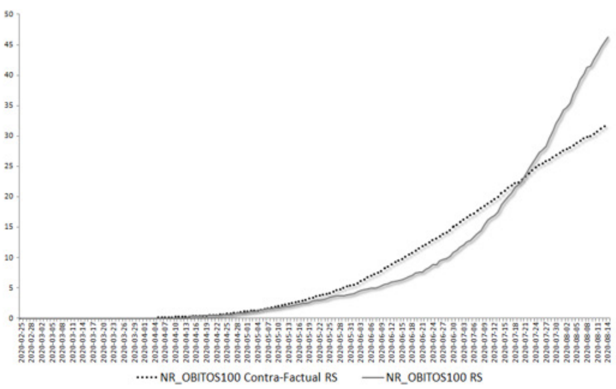
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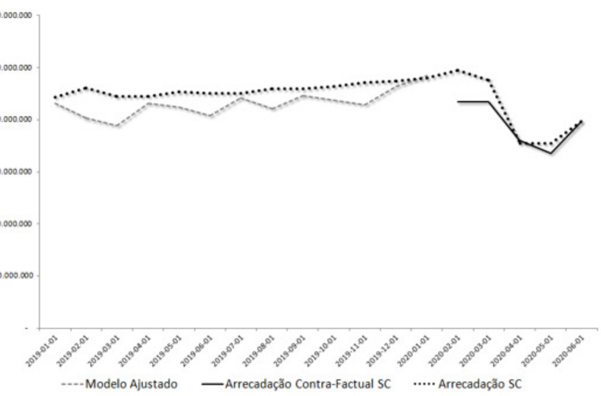
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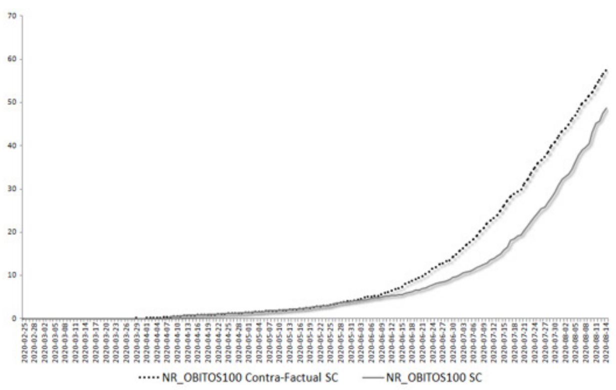
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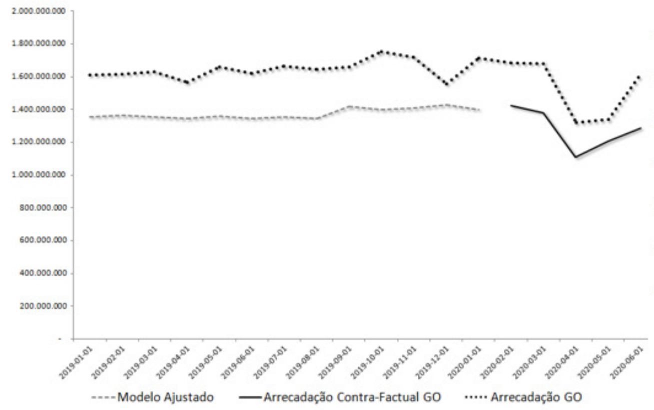

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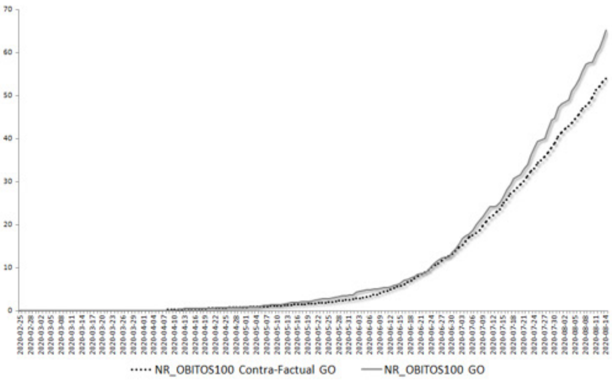

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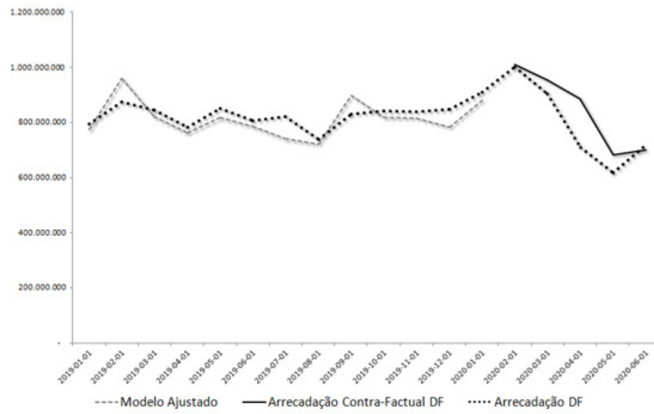

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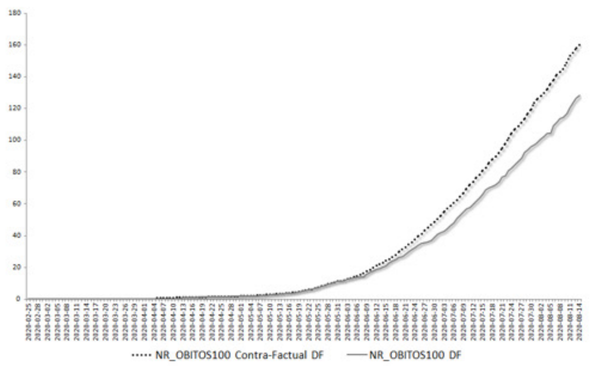

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