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Lockdown, does it work? Fighting the COVID-19 pandemic in the countryside of São Paulo, Brazil

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To my grandparents, who are no longer with us.

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Abstract

This work aims to evaluate the impact of social distancing policies adopted in the context of the COVID-19 pandemic in the countryside of the State of São Paulo, Brazil, in epidemiological and socioeconomic aspects. In particular, I look at the impact of lockdown policies, in which most establishments are forbidden to open and the circulation of citizens is restricted to strictly essential activities. With data at the municipal level, I identified 15 municipalities that adopted this type of policy between May and June 2021 in the Regional Health Departments (DRSs) of Araraquara, Barretos, Franca, and Ribeirão Preto. Next, a control group was built using propensity score matching to select municipalities in the same DRSs as the treated ones. Finally, the lockdown impact on social isolation, COVID-19 cases and deaths, and employment was estimated using a difference-in-differences model with two-way fixed effects in an event study design to temporally align policy adoption. The results suggest that lockdown increased social isolation one week after its adoption, decreased cases from two weeks on, reduced deaths from four weeks on, and did not impact employment significantly.

Keywords: COVID-19, lockdown, mortality, employment, Brazil

JEL codes: H12, I12, I18, J01, J20

Resumo

Este trabalho tem como objetivo avaliar o impacto de políticas de distanciamento social adotadas no contexto da pandemia da COVID-19 no interior do Estado de São Paulo, Brasil, em termos epidemiológicos e socioeconômicos. Mais especificamente, olha-se para o impacto de políticas de lockdown, nas quais proibi-se a abertura da maioria dos estabelecimentos e restringe-se a circulação dos cidadãos a atividades estritamente essenciais. Com dados a nível municipal, foram identificados 15 municípios que adotaram este tipo de política entre maio e junho de 2021 nos Departamentos Regionais de Saúde (DRSs) de Araraquara, Barretos, Franca e Ribeirão Preto. A seguir, construiu-se um grupo de controle utilizando *propensity score matching* para selecionar os municípios nos mesmos DRSs dos tratados. Por último, estimou-se o impacto da política sobre isolamento social, casos e óbitos de COVID-19 e emprego usando um modelo de diferenças-em-diferenças com efeitos fixos de dois níveis em um design de *event study* para alinhar temporalmente a adoção da política. Os resultados sugerem que o lockdown aumentou o isolamento social uma semana após a sua adoção, diminuiu os casos a partir de duas semanas, reduziu os óbitos a partir de quatro semanas e não impactou o emprego significativamente.

Palavras-chave: COVID-19, *lockdown*, mortalidade, emprego, Brasil

Códigos JEL: H12, I12, I18, J01, J20

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1. Introduction

1.1 Context

The fact that the COVID-19 pandemic was poorly controlled in Brazil is globally recognized. The lack of coordination between municipal and state policies, the absence of a national leadership in fighting the pandemic, and the negligent behavior of federal government representatives (especially the President of the Republic) regarding the severity of this global phenomenon resulted in an uncontrolled spread of the virus throughout the country (Castro et al. 2021; Ajzenman, Cavalcanti, and Da Mata 2020). These factors combined with a slow vaccination rate, the emergence of new variants of concern (VOCs) and the continuing uncoordinated measures to combat the pandemic resulted in a frightening scenario in Brazil for almost two years, which already has more than 21 million cases and 600 thousand deaths as a direct result of the pandemic according to the Ministry of Health[1].

One tool that became commonplace around the world throughout the pandemic to try to stem the growth in cases and deaths associated with COVID-19 were non-pharmaceutical interventions (NPIs) of social distancing, which attempt to decrease infection rates by reducing the social interactions of citizens. The most intense level of this type of restriction has come to be known as "lockdown", a situation in which all non-essential activities of the economy are suspended, and individuals' ability to move about is limited to strictly necessary activities. Debates about the effectiveness of this type of policy have been intense in both the public and academic arenas, given the potential trade-off between health and economic performance that

1. https://covid.saude.gov.br/. Access in 03/11/2021.

is faced when this type of measure is adopted.

1.2 Objectives and hypothesis

This work seeks to contribute to this debate about the impacts of social distancing measures, focusing geographically on municipalities in the State of São Paulo and on the period from February to June 2021, in which the second wave of the pandemic strongly affected the countryside of the state and many municipalities adopted lockdowns as a way to contain contamination rates. The central idea is to conduct an empirical econometric approach in order to evaluate the impact of these policies on epidemiological and socioeconomic variables, such as social isolation, cases, deaths, and employment. Natural hypotheses to be tested are as follows: the measures i) *increase* social isolation, ii) *decrease* cases, iii) *decrease* deaths, and iv) *increase* unemployment.

The importance of this type of analysis cannot be underestimated, especially in the Brazilian context that combined: i) slow pace of vaccination; ii) emergence of VOCs; and iii) debate about the effectiveness of NPIs, taking into account the hypothetical trade-off between economic performance and health. The policies that are intended to be analyzed were adopted during the second wave of the pandemic in Brazil, at which time new VOCs began circulating in the country and the number of cases and deaths jumped within a few weeks. Despite the relaxation of measures at the state level in São Paulo, cities in the countryside were forced to adopt stricter policies in order to decrease the number of infections and hospitalizations in a scenario of few vacancies available in hospitals.

Studies of this type contribute to the growing literature dedicated to analyzing the effect of NPIs and may be useful to inform future decisions in the context of contagious disease pandemics, such as COVID-19. An attempt will be made to understand whether the lockdowns were able to slow the rate of contamination and how they affected employment in the municipalities of interest.

1.3 Literature review

Although the COVID-19 pandemic began only two years ago, the number of published studies related to it is already extensive. This can be considered natural, given that this is a global event and that it has therefore incited efforts by many in the academic community to help solve it. In the field of economic sciences, one can simplistically divide the studies into three major groups.

The first focuses on developing predictive models of the trajectory of cases and deaths associated with the disease, in order to assist policy makers in their decision making through the knowledge of possible future scenarios – e.g. Zeroual et al. (2020) and Luo (2021). The second seeks to assess the impact of the pandemic on different variables such as employment and inequality – e.g. Alon et al. (2020), Beland, Brodeur, and Wright (2020), Blundell et al. (2020), and Fairlie, Couch, and Xu (2020). Finally, the studies in the third group aim to assess the impacts of measures to combat the pandemic on different variables such as cases, deaths, social isolation, and employment – e.g. Akim and Ayivodji (2020), Dave et al. (2020), Bargain and Aminjonov (2020), Kong and Prinz (2020), and Goolsbee and Syverson (2021).

Considering the theme of the present work, this last group is the one that interests me the most. I will therefore list some important works and results from this literature, highlighting points to which one should pay attention when conducting an analysis of the Brazilian case and drawing inspiration from the methodological point of view so that I can estimate the impacts of the policies of interest.

An important point to highlight is that, despite growing, the literature on the evaluation of NPIs in the context of the COVID-19 pandemic is still largely focused on developed regions such as the United States of America (USA) and the European Union. Nevertheless, it is known that the context of these countries is very different from those found in less developed countries (LDCs) such as Brazil. It is therefore important to expand the number of rigorous analyses that seek to identify the impact of social distancing measures in LDCs.

One factor that affects the effectiveness of NPIs is the level of civic capital in the country or region, as found by Barrios et al. (2021). Intuitively, the authors of the paper find that USA states with higher levels of civic capital have higher levels of social isolation and mask use, even when subjected to similar policies. Another element that appears to alter the impact of NPIs on variables such as cases, deaths, and social distancing is poverty level (Akim and Ayivodji 2020; Bargain and Aminjonov 2020; Wright et al. 2020; Brown and Ravallion 2020) – it is worth saying that this result is again intuitive, given that poor individuals are less likely to have both infrastructure and employment to stay home in isolation. Results like these are important to explicit the potential difference in the impact of NPIs when adopted in developed and less developed countries, keeping in mind that higher levels of civic capital and lower levels of poverty are positively correlated with development.

In addition to the aforementioned points, which motivated me to evaluate policies in LDCs, other results from the literature that one should keep in mind when evaluating results are cited below. Amuedo-Dorantes, Kaushal, and Muchow (2020) assess that the timing of policy adoption is relevant in determining its impact, i.e., it may be important to compare not only municipalities that adopted and did not adopt lockdown, but also municipalities that adopted early and those that adopted late – the authors suggest a metric to define this issue of policy adoption speed.

The results of Dave et al. (2020) reinforce this idea and show that the impacts of social distancing measures are heterogeneous across the units that adopt it, this heterogeneity is presented in a way that suggests that the earlier the adoption and the more populous the region subject to the policy, the greater its impact. Goolsbee and Syverson (2021), in turn, point to the possibility that policies are not necessarily the most relevant determinants of social distancing, and therefore of the trajectory of the pandemic. The results of this study point out that most of the behavior of individuals in this context is explained by fear of the pandemic as a whole, Goolsbee and Syverson's strategy for identifying this component is to add the number of deaths from the previous day as an explanatory variable in a regression that looks at a mobility variable. The authors conclude that too many deaths today increase fear tomorrow, and therefore increase voluntary social distancing tomorrow. These three studies are focused on municipalities or states in the USA and use techniques such as Differences-in-Differences (DiD) and fixed effects.

Furthermore, Fairlie, Couch, and Xu (2020) draw attention to the fact that the impacts of the pandemic and social distancing policies may also depend on the color of individuals' skin. Through a DiD model that interacts the treatment variable with skin color dummies and looking at data from the USA, the authors show that the gap between the employment level of whites relative to other minorities such as Latinos and blacks increased during the pandemic. One should be wary, therefore, to explore these heterogeneous effects of policies according to citizens' skin color when data with this degree of granularity is available.

When we look specifically at the studies in the literature that have focused on the Brazilian case, three works seem to be of special interest to this study. The first of these is that of Castro et al. (2021), in which an attempt is made to understand and explain how SARS-CoV-2 spread through Brazil. In a nutshell, the paper concludes that the combination of i) lack of coordination between municipal and state policies, ii) absence of the federal-level effort to combat the pandemic, and iii) low testing frequency, resulted in an uncontrolled spread of the virus, with no defined pattern, throughout Brazil. Not enough, the authors point to the danger of a second wave even more severe, in view of the emergence of new VOCs and the slow pace of vaccination in the country, something that unfortunately was confirmed over the first half of 2021.

The results found by Ajzenman, Cavalcanti, and Da Mata (2020), in turn, reinforce the idea that the actions of the federal power so far have not helped in controlling the pandemic, on the contrary. Through a model with a format similar to an ES, the authors show that the speeches and acts of President Jair Bolsonaro with content that disregard the severity of the pandemic resulted in a reduction of social isolation in municipalities in which the politician has majority support.

Focusing on municipalities in the State of São Paulo, Maia et al. (2021) use an instrumental variable approach (instrumenting isolation with rainfall data) to show that municipalities that had greater social distancing also had decreased cases of COVID-19 and did not suffer more economically, i.e., did not have higher unemployment. This result is remarkable because it contradicts the hypothetical trade-off between health and economics that many use to argue against social distancing policies.

Finally, I highlight two methodological articles written by Goodman-Bacon and Marcus (2020) and Sun and Abraham (2020). These papers point out potential problems in using conventional fixed effects and DiD models in this type of policy evaluation, recommending the use of models in the Event Study (ES) format. According to the studies, parallel trends before the intervention can give confidence in the ES estimators. Goodman-Bacon and Marcus (2020) still recommend using unit-specific trends. Some studies that adopt this type of approach that will serve as inspiration for the present work are Dave et al. (2020), Askitas, Tatsiramos, and Verheyden (2020), and Kong and Prinz (2020).

1.4 Methods and results

In summary, I identified 15 municipalities in the Regional Health Departments (DRSs) of Araraquara, Barretos, Franca and Ribeirão Preto that adopted lockdown between May and June 2021. Next, I used Propensity Score Matching (PSM) to assemble a control group using municipalities from the same DRSs cited above. Finally, I used a DiD model with two-way fixed effects (TWFE) in an ES design to align policy adoption in terms of time and estimate the daily municipal-level impact of the lockdown policy on social isolation, COVID-19 cases and deaths, and employment.

The results suggest that social distancing grows in the week after the policy, cases fall more strongly three weeks later, deaths fall more strongly five weeks later, and employment does not change significantly between the treatment and control groups. Thus, it appears that the lockdown policy is epidemiologically effective by reducing cases and deaths through increased social isolation and does not have significant employment costs.

This work is divided into three chapters other than this Introduction. Chapter 2 presents the data used and the methodology adopted, Chapter 3 presents the results obtained and a discussion of them, and Chapter 4 concludes with some final remarks.

2. Data and Methods

This chapter aims to present the data that will be used in the empirical estimates of this work and to explain the methodology that will be adopted in order to identify the effect of lockdown policies adopted in the countryside of the State of São Paulo during the second wave of the COVID-19 pandemic in Brazil. The chapter is divided into two sections. In the first one, the data that will be used are exposed and all their respective sources are specified, as well as some details of the creation or changes in some databases. Then, in the second section, the procedure that was carried out to divide the municipalities between treated and controls and the empirical model that will be used to estimate the impact of the policies of interest are described, namely, Propensity Score Matching (PSM) and Event Study (ES), respectively.

2.1 Data

As stated above, this work aims to evaluate the impact of social distancing policies in the context of the COVID-19 pandemic on epidemiological and socioeconomic variables. To this end, it is necessary to organize different databases in order to have sufficient information for the dependent, explanatory and control variables, enabling the estimation of the empirical model that will be explained in the second section of this chapter. Here, I present the data that will be used, their respective sources and the procedures that were applied to them in order to enable the creation of a consolidated panel with the necessary information for each municipality of interest in each day of the sample period.

The data on social distancing policies adopted from February to June 2021 were obtained through direct consultation of official bulletins of municipal governments and renowned news vehicles (Folha de S. Paulo, G1, UOL and others), in the latter case always verifying the accuracy of the news by reading the specific decree related to the established measure. More than 50 municipal decrees were consulted, through which it was possible to identify 15 municipalities that adopted policies according to the analysis interest. It is worth pointing out that it was sought policies that restricted the circulation of citizens of the municipality and closed most of the commercial establishments, allowing their operation only in the delivery mode. I refer to this type of policy as "lockdown".

Among the policies adopted between February and June, it was noted that most of them were enacted at the end of this interval. In view of this, I restricted the analysis to policies that were adopted between May and June 2021 in order to ensure that the municipalities analyzed were at a more similar moment of the pandemic in epidemiological and socioeconomic terms. Besides this temporal restriction, I also opted for a geographical restriction, reducing the sample to municipalities belonging to the neighboring Regional Health Departments (DRS) of Araraquara, Barretos, Franca, or Ribeirão Preto. This last choice has the objective of increasing the probability that the evaluated municipalities are similar in unobservable variables such as history, culture, and others, for being in the same region. More details of the policies and the main decrees collected can be seen in Table 2.1.

The data on social isolation, cases and deaths associated with COVID-19 were obtained through open data from the São Paulo State Government[1]. The social isolation index has a daily frequency and is made available by telecommunication service providers (Vivo, Oi, Claro, Tim) through a platform managed by the Brazilian Association of Telecommunication Resources (ABR Telecom). Intuitively, the value of the index should be interpreted as the percentage of inhabitants of the municipality who did not leave their homes on a given day[2]. The terms social isolation (or only isolation) and social distancing will be used interchangeably. The num-

1. https://www.saopaulo.sp.gov.br/planosp/simi/dados-abertos/. Access in 30/09/2021.
2. Normally the place that is considered the individual's residence is the place where the mobile phone spent the night. There is a range around the domicile in which the individual can move without considering that he or she has broken isolation, this prevents inaccurate location signals from being interpreted as breaking social distancing.

ber of cases and deaths associated with COVID-19, on the other hand, are made available by the Secretary of Health of the State of São Paulo. To avoid seasonality problems, I will often use the 7-day moving average of the data described above, which is calculated as a simple arithmetic average of the last 6 days and the current day, always considering 7 periods.

Table 2.1: Details of lockdown policies

Municipality	Start	End	Days	Major decrees	
				Number	Date
Altinópolis	25-05-2021	07-06-2021	14	66 68	22-05-2021 29-05-2021
Araraquara	20-06-2021	27-06-2021	8	12600	17-06-2021
Batatais	15-05-2021	31-05-2021	17	3988	13-05-2021
Bebedouro	20-05-2021	30-05-2021	11	14732	18-05-2021
Brodowski	25-05-2021	06-06-2021	13	4277	26-05-2021
Colômbia	21-05-2021	25-05-2021	5	2027	21-05-2021
Cristais Paulista	28-05-2021	10-06-2021	14	2918	25-05-2021
Franca	27-05-2021	10-06-2021	15	11271	24-05-2021
Itirapuã	27-05-2021	10-06-2021	15	1092	25-05-2021
Jardinópolis	03-06-2021	13-06-2021	11	6424	31-05-2021
Patrocínio Paulista	28-05-2021	10-06-2021	14	3442	26-05-2021
Restinga	27-05-2021	10-06-2021	15	363	25-05-2021
Ribeirão Preto	27-05-2021	02-06-2021	7	118 123	24-05-2021 31-05-2021
São José da Bela Vista	28-05-2021	10-06-2021	14	1947	25-05-2021
Taiúva	20-05-2021	30-05-2021	11	2803	19-05-2021

Notes: Lockdowns adopted in Araraquara (Februarry/March), Cajuru (April/May), Guará (April), and Ribeirão Preto (March) were excluded from the analysis to allow the policies analyzed to focus on a more similar period of the pandemic, between the months of May and June 2021.

Employment information at the municipal level was calculated using the unidentified microdata from the General Cadastre for Employed and Unemployed (CAGED) and the Annual Social Information Report (RAIS) made available by the Labor

Statistics Dissemination Program (PDET) of the Ministry of Labor[3]. The admissions and dismissals in each municipality were used to calculate the monthly aggregate and specific employment balance according to different information available in the base, such as economic activity, gender, and workers' skin color. Despite the availability of these more specific breakdowns, only aggregate employment data was used in the analysis.

Other data that were used are vaccination, GDP, poverty levels, population, elderly population, and area of the municipality. Vaccine data at the municipal level and with daily frequency were calculated using the information made available by the Information System of the National Immunization Program (SI-PNI) referring to the National Vaccination Campaign against COVID-19 of the Ministry of Health[4]. This database contains anonymized data of all vaccines applied in Brazil with various specifications. The municipal code of the vaccinated person's domicile address and the date of vaccine application were used to calculate the number of vaccines applied in each municipality on each day since the beginning of the immunization campaign against COVID-19. The database also allows one to differentiate whether the shot was a first dose, second dose, or a single dose vaccine.

The information about municipal GDP and value added (VA) by sector was made available by the Brazilian Institute of Geography and Statistics (IBGE) and refers to the year 2018[5]. The municipal data that were used as poverty proxies are related to the 2010 Census conducted by IBGE[6] and inform the percentage of individuals who live in permanent households and have monthly household income per capita below certain income ranges such as $\frac{1}{4}$ or $\frac{1}{2}$ of the minimum-wage. The population and elderly population estimates used, both at the municipal level, are made available by the Government of the State of São Paulo along with the data on cases and deaths and are calculated by the State System of Data Analysis Foundation (SEADE-SP). The municipal territorial area data were also obtained by the open data of the São

3. http://pdet.mte.gov.br/microdados-rais-e-caged. Access in 30/09/2021.
4. https://opendatasus.saude.gov.br/dataset/covid-19-vacinacao/resource/ef3bd0b8-b605-474b-9ae5-c97390c197a8?inner_span=True. Access in 19/07/2021.
5. https://www.ibge.gov.br/estatisticas/economicas/contas-nacionais/9088-produto-interno-bruto-dos-municipios.html?=&t=resultados. Access in 09/06/2021.
6. https://www.ibge.gov.br/estatisticas/multidominio/condicoes-de-vida-desigualdade-e-pobreza/9662-censo-demografico-2010.html?=&t=downloads. Access in 09/06/2021.

Paulo State Government.

2.2 Methods

The methodology adopted here can be divided into two main steps. The first, consists in the use of Propensity Score Matching (PSM) as a tool to construct a control group. The second, uses Differences-in-Differences (DiD) in an Event Study (ES) framework to align the different timing of lockdown adoption between the municipalities and estimate its causal effect on isolation, cases, deaths, and employment. This steps are further detailed below.

2.2.1 Propensity Score Matching

The data described above determines explicitly which municipalities adopted lockdown policies within the period and region of analysis, and with that, determines the composition of the treatment group. To evaluate the impact of this type of policy, however, one should find a control group to represent the counterfactual of the treated one. In other words, in order to identify the causal impact of lockdown policies over social distancing, cases, deaths, and employment, one should be able to estimate what would have happened in the municipalities that adopted the policy in case they had never adopted it. Unfortunately, as in most of the empirical causal research in social sciences, the data here does not give us the composition of this control group. Therefore, the main challenge ahead is to find a set of municipalities that did not adopt lockdown *and* have similar characteristics to the ones that adopted lockdown, convincing us that any differences between the variables of interest after the policy are caused by the lockdown itself.

The first steps taken in order to find this control group have already been mentioned above. The policies to be evaluated were restricted to the period between May and June of 2021, the idea here is to guarantee that the municipalities are all in a similar moment of the COVID-19 pandemic in epidemiological and socioeconomic terms. Additionally, the municipalities of interest were restricted to the DRSs of Araraquara, Barretos, Franca, and Ribeirão Preto in an effort to ensure that they are similar in unobservable variables such as habits, culture, and historical institutions in general, as they are neighbors. This second restriction already reduces the number of municipalities available to compose the control group in the analysis: only 88 of the 645 municipalities in the State of São Paulo are in the mentioned DRSs and did not adopted lockdown. Nevertheless, the challenge remains to identify within this pool of municipalities those that most closely resemble the 15 that have adopted lockdown between May and June 2021.

To create a control group choosing among these 88 municipalities that have not adopted lockdown and are in the DRSs of interest, I resorted to the method of PSM that makes use of a number of observable variables to select a set of municipalities that resembles the treated ones (Dehejia and Wahba 2002). In a nutshell, when estimating the PSM one knows which units are treated and which units are not. One can also select a range of observable variables that he or she considers relevant to characterize the municipalities, both treated and controls. With this information, one can estimate how this group of variables predicts the treatment status for each unit of analysis. For example, a municipality should be more likely to adopt a seawater quality control policy if they are close to the sea, relative to a municipality that is inland. Using these variables, therefore, the PSM estimates the probability that each municipality has adopted the policy (as if we did not know which ones did it) and selects a number of control municipalities for each treated one so that their probabilities of doing so are as close as possible within the results obtained. This ensures that the two groups are as similar as possible, within the available pool of units, in terms of the observable characteristics selected for the PSM.

More formally, PSM uses a vector X_i of observable characteristics to estimate the probability of a unit being treated, $p_i = P(t_i = 1)$, conditioned on a binary variable t_i that defines the treatment status. This is done using a maximum likelihood model and the estimated probabilities are called propensity scores; commonly logit or probit models are used, to ensure that the score is between 0 and 1. After this estimation, it is possible to identify for each treated unit the untreated units with the closest propensity scores, known as nearest neighbors. The matching and control group construction, therefore, uses a vector of observable characteristics X_i

to calculate the propensity scores p_i conditioned on the binary treatment variable t_i to select a quantity k of nearest neighbors for each treated unit.

The idea is that if a municipality A has the same probability of adopting a policy as a municipality B, one can consider that the fact that A is in the treatment group and B is in the control group is random and that therefore any difference between these municipalities after the adoption of the policy must be caused by the policy itself. The main assumption behind this type of procedure is that the vector of observable characteristics X_i contains enough information to predict the outcome of the variable of interest, allowing one to identify both potential and concrete outcomes for the units of analysis, i.e., both when it is treated, $Y_i(t_i = 1)$, and untreated, $Y_i(t_i = 0)$, even though it is impossible to know one of these in fact.

In practical terms, the variables used here to estimate the PSM, components of the vector of observable characteristics X_i, were the following: daily cases of COVID-19, daily deaths by COVID-19, monthly employment balance, daily vaccinations, population, elderly population, VA by sector (agriculture, industry, services and administration), GDP per capita, and share of population in households with monthly per capita income below $\frac{1}{4}$ of the minimum wage[7]. This last variable is intended to serve as a proxy for poverty in the municipalities, the variables for cases, deaths, employment and vaccinations are per hundred thousand inhabitants and were used as an average for the period before the policy. In the main specification, the period considered for the calculation of these averages consists of one month from April 14 to May 14, 2021, given that the first municipality in the sample to adopt lockdown did so on May 15, 2021. The control group was constructed using the $k = 3$ nearest neighbors for each treated unit, with replacement – that is, a municipality can be a control for more than one treated.

The choices of the component variables of the vector X_i, the period before the policy considered to calculate the average of the variables with daily or monthly frequency and the parameter k that determines the number of neighbors were made by testing more than 60 different specifications for the PSM. The specification that

7. The social isolation variable was not used in the PSM because data is not available for all municipalities.

best respected parallel trends in the model to be estimated (this is better explained below) and seemed most intuitive was selected to compose the main results. The results were robust to other specifications, such as the one in Appendix A, in which the period from May 1 to May 14, 2021 was used as the pre-policy for averaging and $k = 5$ nearest neighbors for each treated unit were selected to make up the control group. The results of the PSM are discussed in details in the next chapter.

2.2.2 Event Study

Once the control group has been formed using the PSM framework described above, it is now necessary to determine what the identification strategy will be to determine the impact of lockdown policies on the variables of interest (Y), namely, social isolation, cases, deaths, and employment. To this end, I have resorted to the Difference-in-Differences (DiD) model, in which one compares the difference, between the treatment (T) and control groups (C), of the difference in the variable of interest before and after the intervention for each group (Equation 2.1).

$$\hat{\beta}_{DiD} = (Y^T_{post} - Y^T_{pre}) - (Y^C_{post} - Y^C_{pre}) \tag{2.1}$$

The idea here, as suggested before, is that the difference in the outcome of the control group before and after the policy represents what would have happened for the municipalities in the treatment group if they had not adopted the policy. The difference between the actual variation in the treatment group and the variation in the control group, thus, should give us the impact of the lockdown over the variable of interest Y. More formally, writing Equation 2.1 in terms of conditional expectations and adding zero by summing and subtracting the expected outcome for the treated if they had not adopted the policy, $E[Y^T_{t=0}|post]$, one can find Equation 2.2, where t is an indicator variable that identifies whether the municipality received or not received the treatment – have adopted or have not adopted the policy.

$$\begin{aligned}\hat{\beta}_{DiD} = &\left(\mathbb{E}\left[Y^T_{t=1} \mid post\right] - \mathbb{E}\left[Y^T_{t=0} \mid pre\right]\right) - \left(\mathbb{E}\left[Y^C_{t=0} \mid post\right] - \mathbb{E}\left[Y^C_{t=0} \mid pre\right]\right) \\ &+ \left(\mathbb{E}\left[Y^T_{t=0} \mid post\right] - \mathbb{E}\left[Y^T_{t=0} \mid post\right]\right)\end{aligned} \tag{2.2}$$

Rearranging Equation 2.2 one can find Equation 2.3, where we can finally see the structure of the DiD estimator. The first line displays exactly what we were looking for, that is, the difference in the outcome of the treated municipalities Y^T if they were treated ($t = 1$) and if they were not treated ($t = 0$) both *after* the policy adoption, in expectation terms. This is the so called Average Treatment Effect (ATT). The second line represents the difference in the variation of the variable Y before and after the policy between the treatment and the control groups when both of them do not receive the treatment, i.e., when none of them adopted the policy (Cunningham 2021).

$$\begin{aligned}\hat{\beta}_{DiD} &= \left(\mathbb{E}\left[Y^T_{t=1} \mid post\right] - \mathbb{E}\left[Y^T_{t=0} \mid post\right]\right) \\ &\quad + \left(\mathbb{E}\left[Y^T_{t=0} \mid post\right] - \mathbb{E}\left[Y^T_{t=0} \mid pre\right]\right) - \left(\mathbb{E}\left[Y^C_{t=0} \mid post\right] - \mathbb{E}\left[Y^C_{t=0} \mid pre\right]\right) \quad (2.3)\end{aligned}$$

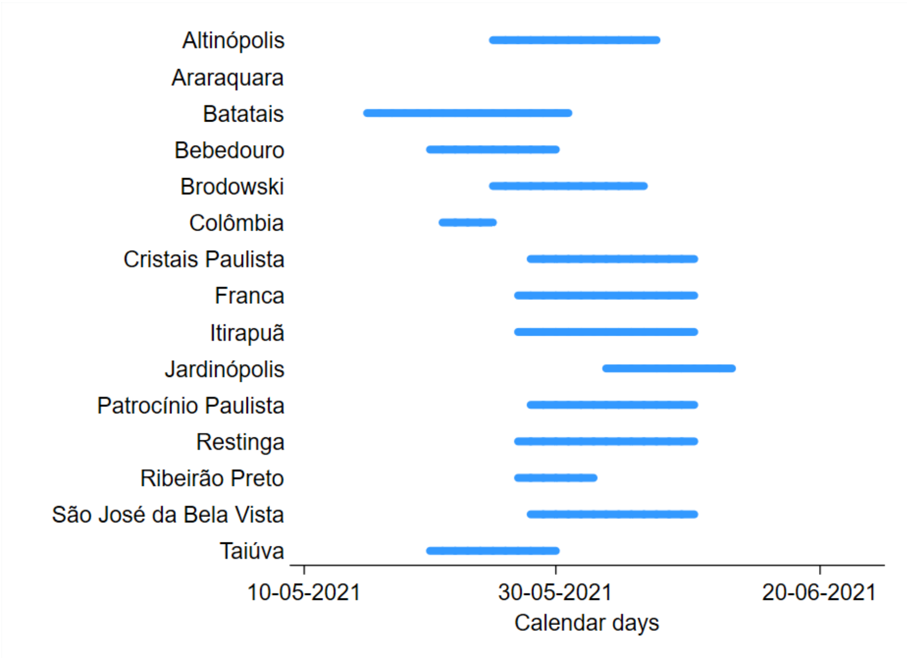
As argued above, by constructing a control group with the methods discussed, I hope to convince the reader that the this difference (second line of Equation 2.3) equals zero and that, consequently, the DiD estimator equals the ATT. This is the main assumption behind the DiD design, and is known as the "parallel trends" assumption. It is worth highlighting the intuition of this premise: the *trajectory* or *variation*, and not the level, of the variable Y would have been the same between the two groups if the treated municipalities had not adopted the policy.

One should also notice that we cannot observe the outcome of the treated municipalities after the policy in a scenario where they did not adopted the policy, i.e., we are not able to observe $\mathbb{E}\left[Y^T_{t=0} \mid post\right]$. This is why we have to consider the control group as the counterfactual of the treated municipalities. The best one can do to evaluate the validness of the parallel trends assumption is to check whether the trajectories of the variable of interest are similar between the groups before the intervention, and this will be discussed below.

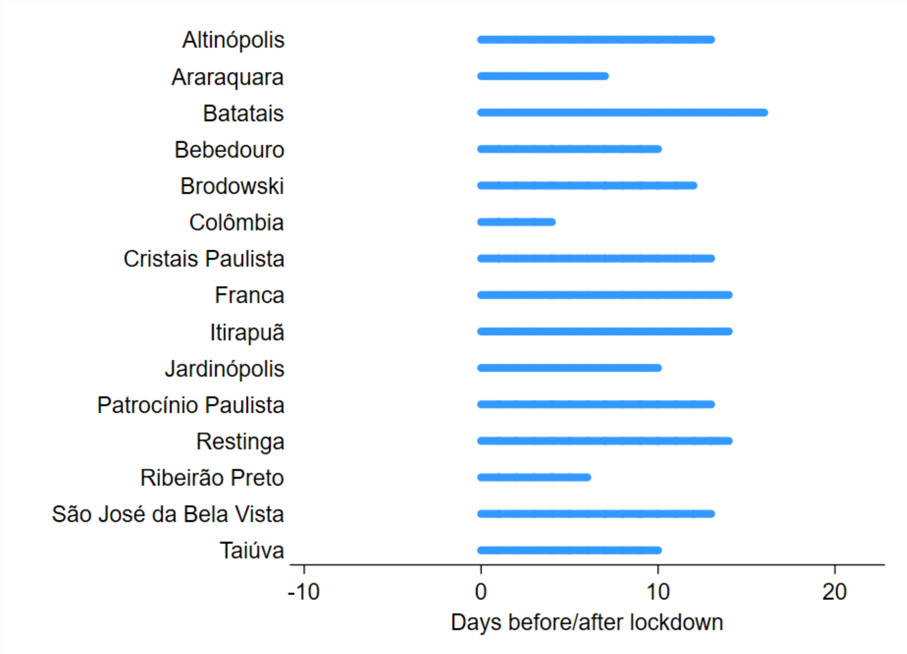
The DiD design discussed above is intuitive, especially when there is a specific adoption date for the intervention, a scenario in which the pre- and post-policy periods are easily defined. Nevertheless, this is not the most common case, since if one wants to analyze different units that have adopted a policy, it is likely that they have done so at different points in time. The careful reader should have realized that this is the case here: the lockdown policies to be studied were adopted at different moments in time by the treated municipalities, as shown in Table 2.1. This context in which units are subject to the intervention at different periods is also known as staggered adoption.

Figure 2.1: Event study illustration for lockdown policies

(a) Calendar time



(b) Time relative to policy



This is where the Event Study (ES) framework becomes handy. The idea here is to run a DiD analysis but looking for the time relative to the policy rather than the calendar time when thinking about the pre- and post-policy periods, forcing a temporal alignment between the treated units regarding the intervention. For example, if a municipality A adopted lockdown on May 20, 2021 and a municipality B did so on May 25, the pre- and post-policy periods are not aligned when we look at the calendar. However, if we think about policy-related days, we have that day 0 will be May 20 for municipality A and May 25 for municipality B, day 1, in turn, will be May 21 for A and May 26 for B, and so on. Figure 2.1 illustrates the temporal alignment that the ES design enables by showing the lockdown policy duration for each municipality and the differences when we look for calendar days and policy-related days.

Finally, taking into account what was discussed above, the empirical models to be estimated in this work are presented below. Equation 2.4 refers to the estimates of the daily impact of lockdown on the variables of social isolation, COVID-19 cases, and COVID-19 deaths. Equation 2.5 refers to the estimates of the monthly impact of lockdown on the employment variable. All variables are analyzed at the municipal level, the variables of cases, deaths and employment are considered relative to 100,000 inhabitants, the variables of social isolation, cases and deaths are used as 7-day moving averages to avoid seasonality. All linear regressions were estimated with weighted least squares, where the weight is the municipality's population.

$$Y_{i,t} = \sum_{\substack{d=-7 \\ d\neq -1}}^{50} \beta_d \times \mathbb{1}_d(d = t - t_i^*) + \delta_t + \gamma_i + \delta_t \times \gamma_i + \varepsilon_t \tag{2.4}$$

$$E_{i,t} = \sum_{\substack{m=-3 \\ m\neq -1}}^{3} \beta_m \times \mathbb{1}_m(m = t - t_i^*) + \delta_t + \gamma_i + \delta_t \times \gamma_i + \varepsilon_t \tag{2.5}$$

In Equation 2.4, the subscripts i and t index each municipality and date of the year, respectively – this subscript t denoting time should not be confused with the above binary treatment variable used to explain the DiD model. Further on, Y is the dependent variable – isolation, cases or deaths –; t_i^* is the date of lockdown adoption in municipality i; $\mathbb{1}_d(d = t - t_i^*)$ are 57 indicator variables that are triggered on day d; δ_t are date of the year fixed effects; γ_i are municipal fixed effects; $\delta_t \times \gamma_i$ are municipal-specific trends; and ε_t is a robust error term.

The use of units and time fixed effects is known as two-way fixed effects (TWFE) and it captures any aggregate variation by day of the year – such as WHO announcements and presidential speeches – or municipal-specific characteristics that are constant over time. The municipal-specific trends controls for any trend in the municipalities before or after the policy adoption. This type of analysis is more robust than a standard DiD model and the parallel trends before the intervention give us confidence in the estimated results (Dave et al. 2020; Sun and Abraham 2020; Goodman-Bacon and Marcus 2020).

Considering the geographic constraint of the municipalities being in the same DRSs, the temporal constraint of the policies being adopted at a similar time of the pandemic, the use of the PSM to create the control group with several relevant control variables, the TWFE, and the municipal-specific trends, I assume that the β_d coefficients identify the daily impact of the lockdown policy on the dependent variable Y. The interpretation of these coefficients can be performed as explained below.

The $\mathbb{1}_d(d = t - t_i^*)$ variables equal 1 on day d and 0 on the other days for the treated municipalities, for the control they always equal 0[8]. The dummy variable for the day immediately before the policy ($d = -1$) is omitted to serve as a baseline against the other daily dummies. Therefore, each β_d represents the difference on day d in the variable Y between the treated and control municipalities relative to the day before the policy adoption. Intuitively, β_d with $d \in \{z \in \mathbb{Z}; -7 \leq z \leq -2\}$ allows us to identify parallel trends, given that it represents the difference in the trajectory between the treatment and control groups *before* the policy, which should be zero. On the other hand, β_d with $d \in \{z \in \mathbb{Z}; 0 \leq z \leq 50\}$ gives us the daily impact of the lockdown policy since the adoption day ($d = 0$) until 7 weeks, plus 1

8. An example to facilitate the interpretation of the indicator function is developed here. If a municipality A adopted lockdown on May 20, we have $t_A^* = 20\text{-}05\text{-}2021$ and d will be defined for every t as the day relative to the policy, i.e., in the day before the policy, we have $d = t - t_A^* = 19\text{-}05\text{-}2021 - 20\text{-}05\text{-}2021 = -1$. This logic is analogous for the other days of the year.

day, after ($d = 50$).

The interpretation of Equation 2.5 is analogous, with the only difference being that the frequency of the employment variable is monthly, as is the definition of all other time-related variables.

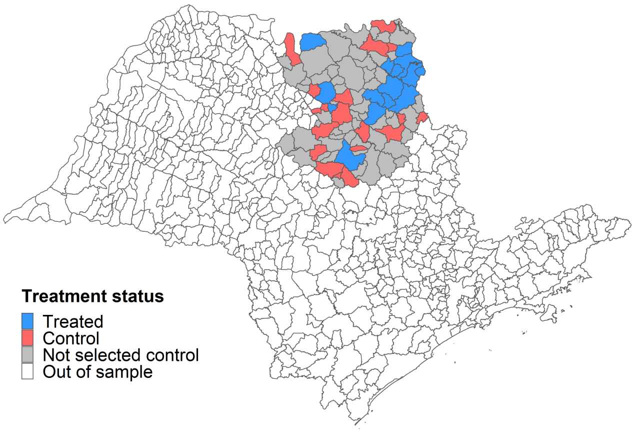
3. Results and Discussion

In this chapter, I present and discuss the main results obtained using the data and methodology exposed above. First, the PSM results are reported, explaining the components of the control group, geographically illustrating the composition of the sample, and demonstrating a balance in observable variables between the treatment and control groups through a test of means. Next, the main results of this work are presented, namely, the results of the estimates from the ES regressions that identify the daily impact of the lockdown policies on social isolation, cases, deaths, and employment. The evaluation of the fulfillment of the parallel trends hypothesis of DiD models and the robustness of these results are also discussed in detail.

3.1 Propensity Score Matching results

The estimation of the PSM according to the parameters specified in Chapter 2 resulted in the selection of 18 municipalities in the DRSs of Araraquara, Barretos, Franca, and Ribeirão Preto to compose the control group. It is worth remembering that, although the number of nearest neighbors in terms of propensity score is equal to $k = 3$, replacement was allowed and, therefore, some municipalities are controls for more than one treated unit. An illustration of the geographic distribution of the municipalities comprising the sample according to their PSM eligibility and treatment status is presented in Figure 3.1, as well as the names of the municipalities in each group are detailed in its notes.

Figure 3.1: Municipalities by treatment status



Notes: The treatment group is composed by the following municipalities: Altinópolis, Araraquara, Batatais, Bebedouro, Brodowski, Colômbia, Cristais Paulista, Franca, Itirapuã, Jardinópolis, Patrocínio Paulista, Restinga, Ribeirão Preto, São José da Bela Vista, Taiúva. The control group is composed by the following municipalities: Aramina, Boa Esperança do Sul, Guaraci, Igarapava, Ituverava, Itápolis, Jaborandi, Jaboticabal, Jeriquara, Monte Azul Paulista, Morro Agudo, Motuca, Santa Cruz da Esperança, Santa Rita do Passa Quatro, Serra Azul, Serrana, Tabatinga, Vista Alegre do Alto, Tabatinga, Vista Alegre do Alto. All municipalities that are not "Out of sample" are in the Regional Health Departments of Araraquara, Barretos, Franca or Ribeirão Preto.

Given the definition of the control and treated municipalities, one can test whether the two groups are indeed balanced in terms of observable variables. Considering that the objective of the PSM was to select a control group that is similar to the treated one in the provided variables, one should find no differences in the means of these variables between the two groups. The results of a mean test for a set of variables is presented in Table 3.1. Here, the means for the treated and control group and its differences are presented both before and after the PSM.

In summary, the last column of Table 3.1 shows that, although some variables were significantly different between the control and treatment groups before the PSM – such as population, elderly population, and VA for some sectors –, one cannot reject the null hypothesis that the each difference between the group means is statistically equal to 0 at conventional significance levels such as 1% and 5% after the matching. Therefore, it can be said that the PSM was successful, since the treatment and control groups are statistically equal in relevant variables such as population, elderly population, GDP per capita, poverty, and cases, deaths, vaccines, and employment per 100,000 inhabitants before the policy. These results gives us confidence to proceed to the regression analysis.

Table 3.1: Mean test before/after propensity score matching

Variable	Unmatched / Matched	Mean Treated	Mean Control	Diff.	Mean test t	Mean test p-value
Cases per 100k inhabitants	U	34.668	38.15	-15.1	-0.48	0.629
	M		42.532	-34.2	-0.9	0.375
Deaths per 100k inhabitants	U	0.938	1.384	-60.3	-1.75	0.083*
	M		0.671	36	1.09	0.284
Employment per 100k inhabitants	U	720.72	159.09	34.1	1.81	0.074*
	M		84.069	38.6	1.07	0.293
Daily vaccines per 100k inhabitants	U	443.35	449.51	-5.2	-0.16	0.875
	M		397.63	38.4	1.14	0.264
Population	U	100000	27615	55	3.18	0.002***
	M		28606	54.3	1.5	0.145
Elderly population	U	16701	4346.7	56.6	3.26	0.002***
	M		4739.7	54.8	1.51	0.142
VA Agriculture	U	84997	65595	37.4	1.24	0.219
	M		91565	-12.7	-0.34	0.734
VA Industry	U	580000	280000	36.1	1.71	0.091*
	M		160000	50.3	1.48	0.149
VA Services	U	2700000	450000	50.3	3.01	0.003***
	M		470000	50.2	1.37	0.181
VA Administration	U	420000	120000	54.1	3.13	0.002***
	M		120000	52.9	1.46	0.155
GDP per capita	U	32187	33783	-8	-0.24	0.809
	M		27626	22.9	1.1	0.28
Pop. with income under $\frac{1}{4}$ mw (%)	U	5.615	4.840	31.8	1.34	0.183
	M		5.4729	5.8	0.15	0.88
Inhabitants/km^2	U	1.608	1.238	14.5	0.56	0.576
	M		2.718	-43.6	-0.89	0.379

Notes: The value added (VA) data by sector and GDP per capita are from 2018. The data on share of population with income under $\frac{1}{4}$ of a minimum-wage (mw) are from the 2010 Census. For the variables that are not constant over time, an average was calculated for the period before the policy, from April 14 to May 14, 2021.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

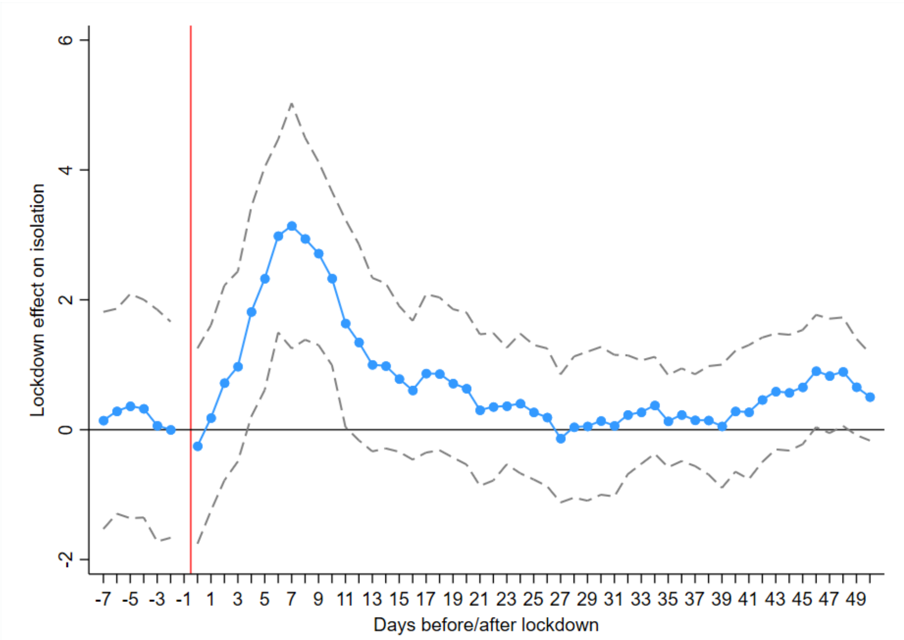
3.2 Event Study results

Using the treatment and control groups described above, the empirical equations presented in Chapter 2 were estimated for the dependent variables of interest, namely, social isolation, cases, deaths, and employment. The estimates were done both to identify the daily impact of lockdown policies and by aggregating this effect in weeks after the policy adoption. The daily impact of the policy is presented in graphs that plot the coefficients of interest of the regression and its confidence intervals at the 95% level.

The results of the ES analysis to identify the daily impact of the lockdown policy on social isolation are presented in Figure 3.2. First, one should see that, intuitively, the impact of the policy in the 7 days before its adoption is null. As discussed in Chapter 2, the non-significance of these coefficients before the policy adoption gives us confidence that the parallel trends assumption is being respected. Secondly, observing the trajectory of the impact, which is heterogeneous in terms of time, one can see that the social isolation significantly increased in the treatment group from days 4 to 11 after the policy, reaching its highest point one week, 7 days, after the lockdown.

It is worth highlighting that the plotted coefficients gives us the difference between the treatment and control groups relative to the day before the policy. Therefore, Figure 3.2 shows us that 7 days after the policy adoption social distancing increased approximately 3% in the treatment group compared to the control one relative to the day before the lockdown. This effect, however, does not persist from day 12 onward, being statistically not different from 0 at the 5% level. The short-term feature of this effect might be caused by the short duration of the policies, which ranges from 5 o 17 days in the treatment group, as shown in Table 2.1.

Figure 3.2: Lockdown effect on social isolation



Notes: The regression used to elaborate this graph contains one indicator variable for each day from 1 week before the lockdown adoption until 7 weeks later and was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as a 7-day moving average. The estimate controls for municipality and day fixed effects and municipal-specific trends. Robust standard errors were used to construct the 95% confidence interval represented by the dashed lines. The number of observations equals 499 and the R-squared equals 0.98. In this case, because social isolation data is scarce, there is only one municipality in the control group and 5 in the treatment one.

Additionally, Table 3.2 confirms that the effects of the policy were positive on the social distancing in the treatment group, as the coefficient for weeks 1 to 3 are positive in all specifications. In the three columns, the impact in the first week after the lockdown is significant at the 10% level. It is easy to see why the 5% significance does not hold when we aggregate the results by week: Figure 3.2 shows us that the impact of the policy in the days immediately after the policy adoption (days 0 to 3) were not statistically different from 0 at the 5% level.

Unfortunately, the data on social isolation is scarce and these results should be interpreted with caution. The control group here is composed by only one municipality (Jaboticabal) and the treatment group by five (Araraquara, Batatais, Bebedouro, Franca, and Ribeirão Preto). This only happens for this dependent variable.

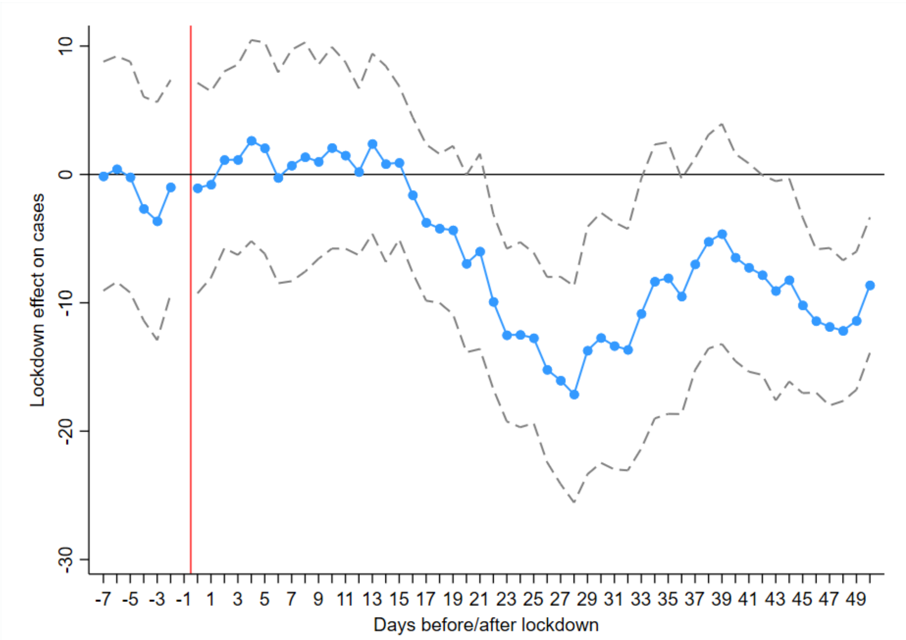
Table 3.2: Lockdown effect on social isolation, by week

Independent variables	Dependent variable: Social isolation (1)	(2)	(3)
Week 1	1.715***	1.869**	1.796*
	(0.508)	(0.667)	(0.847)
Week 2	3.057***	1.819**	1.614
	(0.498)	(0.695)	(1.023)
Week 3	0.043	0.364	0.016
	(0.533)	(0.637)	(1.203)
Week 4	-0.497	0.152	-0.320
	(0.566)	(0.607)	(1.392)
Week 5	-0.511	-0.417	-1.274
	(0.550)	(0.676)	(1.795)
Week 6	-0.764	-0.123	-1.380
	(0.547)	(0.650)	(2.038)
Week 7	-0.697	0.398	-1.446
	(0.507)	(0.639)	(2.309)
Constant	40.939***	40.702***	41.360***
	(0.234)	(0.558)	(1.303)
R-squared	0.096	0.967	0.974
Observations	354	348	348
Municipal FE		X	X
Date FE		X	X
Municipal-specific trends			X

Notes: Robust standard errors are in parenthesis. The regression was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as a 7-day moving average. In this case, because social isolation data is scarce, there are only one municipality in the control group and 5 in the treatment one.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The results of the ES analysis for COVID-19 cases are presented in Figure 3.3, and the interpretation of the results is analogous to the one developed above for social distancing. Again, one can see that the parallel trends assumption is respected, given that the coefficients for the days prior to the policy are statistically null at the 5% level. Looking for the daily impact of the lockdown on the 7-day moving average of COVID-19 cases per 100,000 inhabitants in the treatment group, it is easy to see that there is a drop in the cases trajectory starting two weeks after the policy adoption. From 15 days onward after the lockdown, all the coefficients are negative and from days 22 to 33, and 42 to 50, they are also statistically different from 0 at the 5% level. Four weeks after the lockdown, on day 28, for example, there was approximately -17 COVID-19 cases per 100,000 inhabitants in the treatment group compared to the control one relative to the day before the policy adoption, when the average was approximately 38. The lockdown, therefore, four weeks after its adoption, reduced the cases in the treatment group in nearly 45% compared to the control group relative to the average in the day before the policy[1].

Figure 3.3: Lockdown effect on cases



Notes: The regression used to elaborate this graph contains one indicator variable for each day from 1 week before the lockdown adoption until 7 weeks later and was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as a 7-day moving average and per 100,000 inhabitants. The estimate controls for municipality and day fixed effects and municipal-specific trends. Robust standard errors were used to construct the 95% confidence interval represented by the dashed lines. The number of observations equals 2,924 and the R-squared equals 0.66.

These results are quite intuitive when combined with those found for the social isolation variable. If social isolation rose one week after the lockdown was adopted, it is perfectly believable that cases would begin to fall two weeks after the policy, since there must be a time lag between the increase in isolation and the decrease in cases. Additionally, one should note that the cases in the treatment group remains

1. This type of estimate was calculated simply dividing the coefficient of the respective day by the constant of the regression.

in a lower level compared to the control one even after the policy is over. The weekly impact of the policy is presented in Table 3.3. The Column (3) confirms the results obtained before by showing negative coefficients from week 3 onward after the policy. Nevertheless, these coefficients are not significantly different from zero at conventional levels, this may happen because the aggregation of the impact by week might hide the heterogeneous impact of the policy for each day in the 7-day intervals.

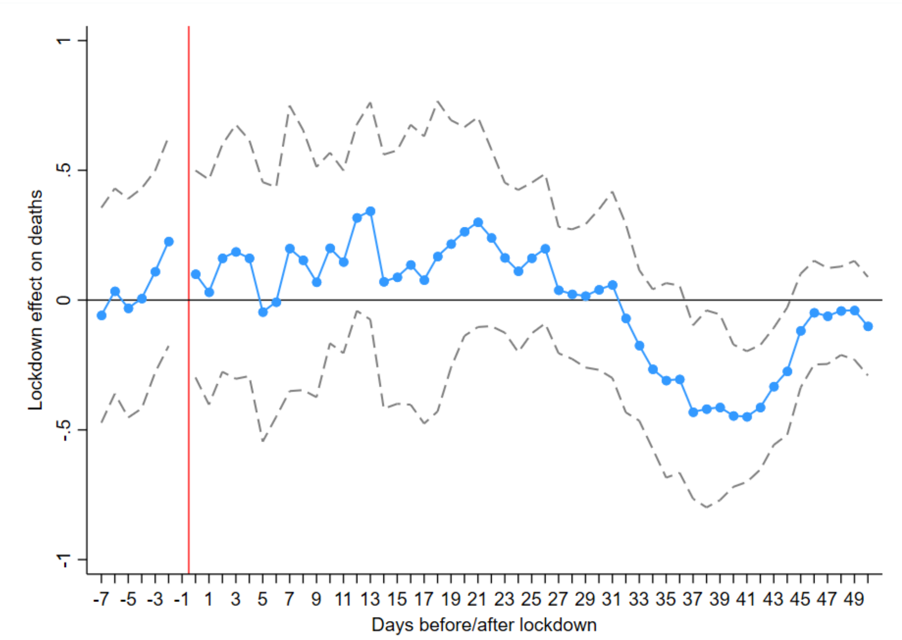
Table 3.3: Lockdown effect on cases per 100k inhabitants, by week

Independent variables	Dependent variable: Cases (1)	(2)	(3)
Week 1	5.006	0.033	0.421
	(2.747)	(6.141)	(3.765)
Week 2	5.558*	1.469	2.114
	(2.450)	(6.136)	(4.567)
Week 3	5.431**	-1.679	-1.837
	(1.886)	(6.103)	(5.434)
Week 4	1.460	-8.467	-9.579
	(1.467)	(6.104)	(6.818)
Week 5	1.596	-4.328	-6.033
	(1.982)	(6.282)	(8.064)
Week 6	-1.423	2.670	-0.146
	(1.260)	(6.272)	(9.525)
Week 7	-6.388***	2.877	-1.787
	(1.309)	(6.129)	(10.762)
Constant	34.867***	36.529***	37.453***
	(0.898)	(4.091)	(4.519)
R-squared	0.024	0.441	0.651
Observations	2472	2472	2472
Municipal FE		X	X
Date FE		X	X
Municipal-specific trends			X

Notes: Robust standard errors are in parenthesis. The regression was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as a 7-day moving average and per 100,000 inhabitants.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The daily impact of the lockdown policy on the 7-day moving average of COVID-19 related deaths per 100,000 inhabitants is presented in Figure 3.4. Again, one can say that the parallel trends are respected, given that the coefficients for the days before the policy are statistically not different from zero at the 5% level. One month after the lockdown, in turn, the deaths begin to drop in the treatment group and this difference is significantly different from zero at 5% between days 37 and 46, that is, in the sixth to seventh week after the policy adoption. In the 41st day after the lockdown, the 7-day moving average of deaths per 100,000 inhabitants in the treatment group was approximately -0.45 lower than in the control group relative to the day before the policy adoption, when the average was close to 1. The lockdown, thus, 6 weeks after its adoption, reduced the cases in the treatment group nearly 42% compared to the control group relative to the average in the day before the policy. This effect, however, does not seem to be maintained over time, since from day 45 the difference seems to be zero again.

Figure 3.4: Lockdown effect on deaths



Notes: The regression used to elaborate this graph contains one indicator variable for each day from 1 week before the lockdown adoption until 7 weeks later and was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as a 7-day moving average and per 100,000 inhabitants. The estimate controls for municipality and day fixed effects and municipal-specific trends. Robust standard errors were used to construct the 95% confidence interval represented by the dashed lines. The number of observations equals 2,924 and the R-squared equals 0.58.

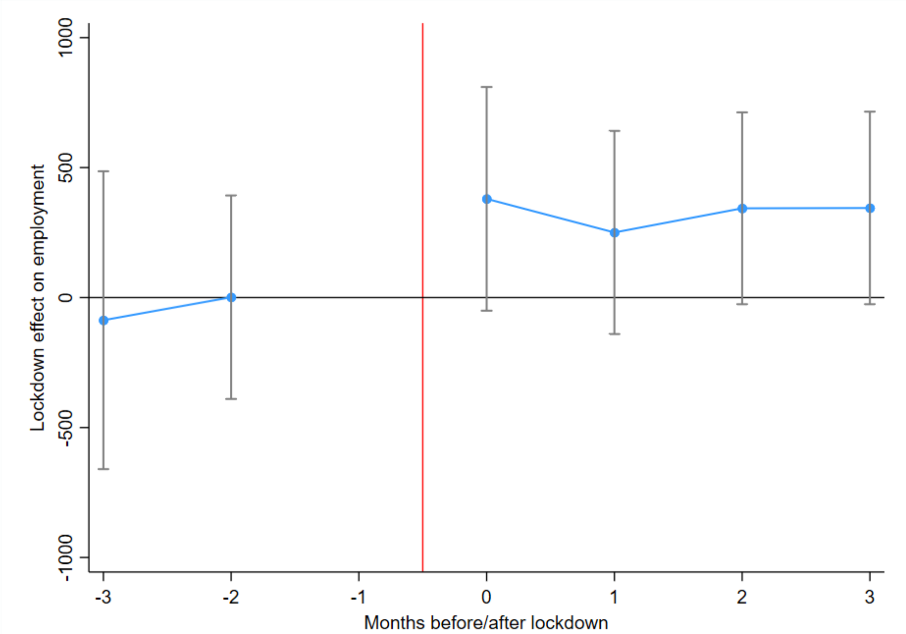
Table 3.4: Lockdown effect on deaths per 100k inhabitants, by week

Independent variables	Dependent variable: Deaths (1)	(2)	(3)
Week 1	0.784***	-0.020	-0.057
	(0.104)	(0.169)	(0.166)
Week 2	0.520***	0.141	0.048
	(0.095)	(0.178)	(0.218)
Week 3	0.903***	0.192	0.029
	(0.159)	(0.183)	(0.283)
Week 4	0.632***	0.284	0.003
	(0.097)	(0.166)	(0.338)
Week 5	0.239**	0.090	-0.206
	(0.084)	(0.173)	(0.411)
Week 6	-0.188***	-0.224	-0.515
	(0.055)	(0.173)	(0.489)
Week 7	-0.184***	0.074	-0.208
	(0.046)	(0.170)	(0.566)
Constant	0.922***	1.128***	1.265***
	(0.038)	(0.108)	(0.224)
R-squared	0.154	0.456	0.569
Observations	2472	2472	2472
Municipal FE		X	X
Date FE		X	X
Municipal-specific trends			X

Notes: Robust standard errors are in parenthesis. The regression was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as a 7-day moving average and per 100,000 inhabitants.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.4, in the specification with all the controls, Column (3), confirms the results discussed above for the deaths variable. The coefficients for weeks 5, 6 and 7 are all negatives. These are not significant at the conventional levels probably because the days of greater impact are divided between weeks 6 and 7 that also contain days with no significant impact, as shown in Figure 3.4. Again, these results are notably intuitive if combined with the ones previously presented. The lockdown increased the social distancing 1 week after its adoption, decreased the cases 2 weeks after, especially on week 4, and the deaths started to drop after week 4, reaching its lowest point in the treatment group on weeks 6 and 7, within 14 days after the minimum number of daily cases. The time intervals between the impacts of the variables of interest add up and this will be discussed further below.

Figure 3.5: Lockdown effect on employment



Notes: The regression used to elaborate this graph contains one indicator variable for each month from 1 month before the lockdown adoption until 4 months later and was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as per 100,000 inhabitants. The estimate controls for municipality and day fixed effects. Robust standard errors were used to construct the 95% confidence interval represented by the dashed lines. The number of observations equals 229 and the R-squared equals 0.13.

Finally, the monthly impact of the lockdown policy on employment per 100,000 inhabitants is presented in Figure 3.5. One should be aware that the estimates for this variable contain a considerably smaller number of observations, given that its frequency is lower. The coefficients for the months -3 and -2 before the policy are close to and statistically not different from 0 at the 5% level. Although these are only two months, it gives us some confidence in the existence of parallel trends. After the policy, in turn, the coefficients are positive, but not significant at the conventional levels. In other words, this results suggest that the lockdown did not significantly affect the employment in the treated municipalities compared to the control ones relative to the month before the policy. Table 3.5 confirms these results by presenting positive coefficients for almost all the months after the policy and no significance for all of them at the 5% significance level. These findings are further discussed below.

Table 3.5: Lockdown effect on employment per 100k inhabitants, by month

Independent variables	Dependent variable: Employment (1)	(2)	(3)
Month 1	241.603	398.307	277.082
	(200.595)	(216.512)	(293.385)
Month 2	129.299	274.046	42.049
	(120.929)	(203.106)	(366.294)
Month 3	241.537*	367.578	7.864
	(105.635)	(196.225)	(494.867)
Month 4	181.882*	365.685	-206.110
	(76.896)	(201.599)	(697.903)
Constant	142.495**	75.294	212.714
	(53.035)	(81.346)	(184.429)
R-squared	0.022	0.134	0.346
Observations	229	229	229
Municipal FE		X	X
Date FE		X	X
Municipal-specific trends			X

Notes: Robust standard errors are in parenthesis. The regression was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as per 100,000 inhabitants.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.3 Discussion and Robustness

The results presented above, in sum, point to an effectiveness of lockdown policies in epidemiological terms, which seem to decrease cases and deaths by increasing social isolation with their respective time lags. Furthermore, the results show that the policies did not have an economic cost in terms of increased unemployment in the municipalities that adopted them. Thus, it seems that the supposed trade-off between economics and health often raised in the debate about methods of fighting the pandemic in Brazil is not necessarily true. This is in line with the results obtained by Maia et al. (2021) and shows how social isolation policies could have been used more widely in the country to combat the COVID-19 pandemic, despite the resistance of the President of the Republic (Ajzenman, Cavalcanti, and Da Mata 2020; Castro et al. 2021).

Additionally, the results obtained add to the vast literature that points to the positive impact of lockdown policies, such as Dave et al. (2020), despite the expectation of a lower or null impact of this type of policy in less developed countries due to poverty (Akim and Ayivodji 2020; Bargain and Aminjonov 2020; Wright et al. 2020; Brown and Ravallion 2020) and lower levels of civic capital (Barrios et al. 2021).

With regard to the robustness of the estimates made, some procedures are proposed to convince the reader that the results found are not the work of chance. First, one should think about whether the results make sense in terms of time lags. Assuming that the lockdown policy has an effect on epidemiological variables through social isolation, it would not make sense that cases would have dropped before social isolation increased. It would make even less sense if deaths had dropped before a drop in cases a few days earlier, if that happened the explanation would likely be related to a new treatment method rather than a social distancing policy.

However, the results presented follow a time logic that is in line with what is known about the progression of COVID-19 in the human body. The medical literature points to the fact that, on average, the progression of the COVID-19 virus occurs as follows: symptoms take about 5 days from the date of infection to manifest themselves, and deaths usually occur within 18 to 28 days, that is, between 2.5 and 4 weeks after infection (Wang et al. 2020; Guan et al. 2020; Huang et al. 2020; Zhou et al. 2020; Yang et al. 2020).

Recalling the timing of the results found here, we have that social isolation increased significantly in the week after the policy was adopted. This makes sense, if we consider that there are a few days of adjustment to the policy, in which citizens realize that there is indeed enforcement and the measures must be respected. The cases, in turn, began to fall from 15 days after the adoption of the policy, in other words, one week after the largest increase in social isolation. Considering what was stated above, that the average delay for the manifestation of the symptoms is 5 days, it is intuitive to think that the reporting of cases fell after a week of the increase in social isolation, and not immediately after. Between this increase in isolation and the fall in cases, some cases that were contracted before were being tested with this 5 day lag, because this is the time it took for the patients to have the symptoms. The largest drop in cases happened 4 weeks after the adoption of the policy, this persistence of the reduction is also intuitive, because besides the decrease in social interactions, the lower number of cases implies a slowdown of the transmission rate in the municipality.

Finally, the results for deaths pointed to the onset of the decline one month after the lockdown began and with the greatest impact, in absolute terms, occurring 40 days after the policy. In other words, the onset of the decline in deaths occurred within 3 to 4 weeks after the onset of the increase in social distancing and the greatest decline occurred within 2 weeks after the greatest decrease in cases. Again, this is in agreement with the aforementioned medical literature, which points to an average time between 2.5 and 4 weeks between infection and deaths.

Therefore, the results presented above make sense in terms of time lags and this gives us confidence in their credibility. To ensure their robustness, however, two more tests were performed. The first of these is presented in Appendix A, in which I estimated the same equations as in the figures and tables for the impact of lockdown on the variables of interest, but now using a different specification for the PSM, with a greater number of nearest neighbors to compose the control group and changing the pre-policy period used to calculate the averages of the variables with daily or monthly frequency. One can see that the results obtained with this different control group are very similar to those presented above, increasing our confidence in them.

The second robustness test, on the other hand, is presented in Appendix B and consists of a placebo test. In this, I estimated the placebo effect of a non-existent lockdown policy for the same treatment and control groups used in the main analysis. The idea here is to estimate the same models used to construct the graphs discussed above, but now as if the lockdown policy in the treated municipalities had been adopted 1 year earlier. Intuitively, the results found should not persist in a scenario in which there was no policy. That is, this test suggests robustness of the results when the placebo effect of the policy at a hypothetical adoption date is zero. This is exactly what is found in the test and one can see this in more detail in Figures B.1 to B.4. Consequently, this test also suggests the robustness of the results here obtained.

4. Conclusion

The present work focused on the effectiveness of non-pharmacological interventions (NPIs) of social distancing in the context of fighting the COVID-19 pandemic in the countryside of São Paulo, Brazil, during its second wave, which occurred in the first half of 2021. I focused on policies that became known as lockdown, in which all establishments are closed and the circulation of individuals in the city is restricted in order to decrease the rate of virus transmission via reduced social interactions. More specifically, this study analyzed policies adopted in the North and Northeastern regions of the State of São Paulo, by municipalities belonging to the Regional Health Departments (DRSs) of Araraquara, Barretos, Franca, and Ribeirão Preto.

The goal was to evaluate the impact of the policies both in epidemiological and socioeconomic terms, looking therefore at social isolation, COVID-19 cases and deaths, and employment. Some hypotheses raised about the impact of the policy were: i) *increase* in social isolation, ii) *decrease* in cases, iii) *decrease* in deaths, and iv) *increase* in unemployment.

To perform the analysis outlined above, I used different sources of municipal-level data in a Differences-in-Differences model with two-way fixed effects in an Event Study design. To construct the control group to be used in these estimates, I resorted to the Propensity Score Matching (PSM) method to select municipalities within the same set of DRSs as the treated ones.

The results obtained add to the literature evaluating NPIs suggesting a positive impact of the policy in epidemiological terms. Social isolation increases in the week after the lockdown, cases drop from two weeks later and deaths drop from one month later, all results are significant when evaluating the daily impact of the policy. Surprisingly, employment levels in treated municipalities are not reduced when compared to controls in the months after the lockdown, contradicting the idea that there is a trade-off between economics and health in this type of policy. In summary, of the four hypotheses listed above, the first three are confirmed and the last one is rejected.

The findings make sense in terms of the time lags of the impacts taking into consideration the results in the medical literature regarding the progression of the COVID-19 virus. Furthermore, the findings are also robust to different PSM specifications and placebo tests (Appendices A and B).

This work can serve as a basis and inspiration for some further research, such as the ideas are cited below. It might be interesting to evaluate the lockdown impact using microdata that allow to identify whether the effects vary according to the citizens' skin color or educational level. Additionally, municipal fixed effects might not be completely sufficient to control for ideological differences between municipalities, since this procedure is similar to demeaning and the mean of deaths, for example, is often close to zero in some municipalities, in this case, it may be useful to control the estimates by the vote share in each municipality for President Jair Bolsonaro, given his stance against COVID-19 prevention measures (Ajzenman, Cavalcanti, and Da Mata 2020). Finally, one can assess the heterogeneity of impact according to the timing of lockdown adoption by comparing early and late adopters.

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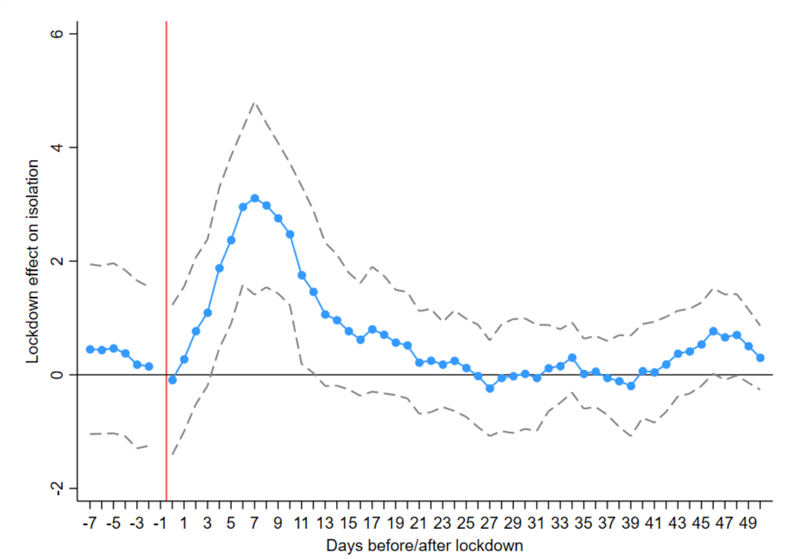
Appendix A. Different control group

The results in this Appendix were obtained through a different specification of the PSM, in which the period from May 1 to May 14, 2021 was used as the pre-policy for averaging the non-constant variables and $k = 5$ nearest neighbors for each treated unit were selected to make up the control group, with replacement. The control group is composed by the 30 following municipalities: Barrinha, Boa Esperança do Sul, Borborema, Buritizal, Cássia dos Coqueiros, Dourado, Guaraci, Guatapará, Igarapava, Ituverava, Itápolis, Jaboticabal, Jeriquara, Monte Azul Paulista, Motuca, Olímpia, Pitangueiras, Ribeirão Bonito, Ribeirão Corrente, Santa Cruz da Esperança, Santa Lúcia, Santa Rita do Passa Quatro, Serra Azul, Serrana, São Simão, Tabatinga, Taiaçu, Taquaritinga, Trabiju, Vista Alegre do Alto.

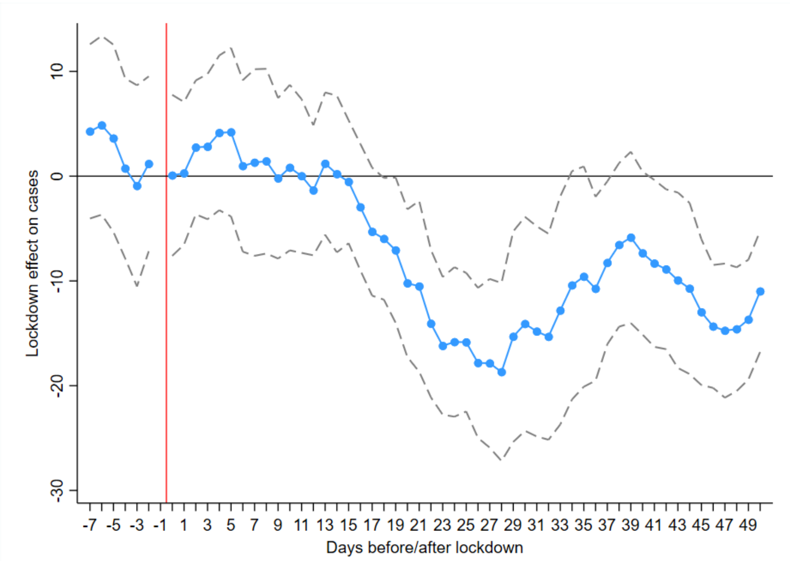
Just for the estimates in Figure A.1 and Table A.1, because social isolation data is scarce, there are only 3 municipalities in the control group (Jaboticabal, Olímpia, and Taquaritinga) and 5 in the treatment one (Araraquara, Batatais, Bebedouro, Franca, and Ribeirão Preto).

Figure A.1: Lockdown effect on social isolation



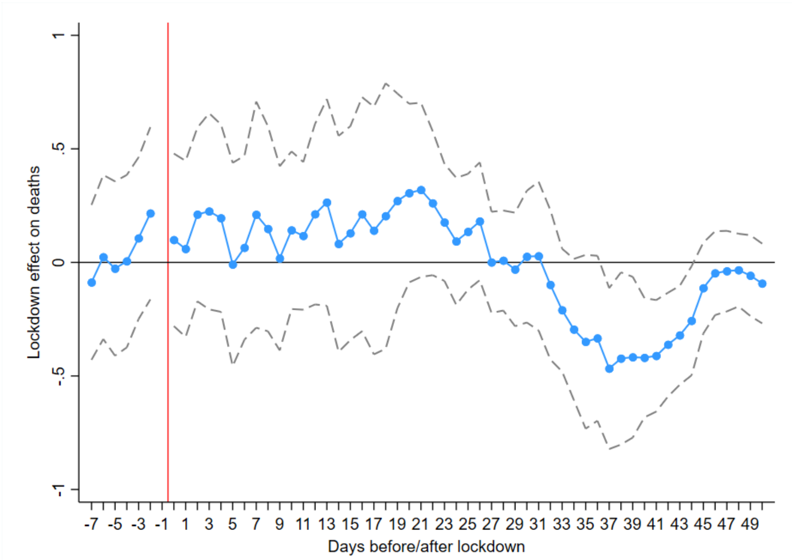
Notes: The regression used to elaborate this graph contains one indicator variable for each day from 1 week before the lockdown adoption until 7 weeks later and was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as a 7-day moving average. The estimate controls for municipality and day fixed effects and municipal-specific trends. Robust standard errors were used to construct the 95% confidence interval represented by the dashed lines. The number of observations equals 687 and the R-squared equals 0.98. In this case, because social isolation data is scarce, there are only 3 units in the control group and 5 in the treatment one.

Figure A.2: Lockdown effect on cases



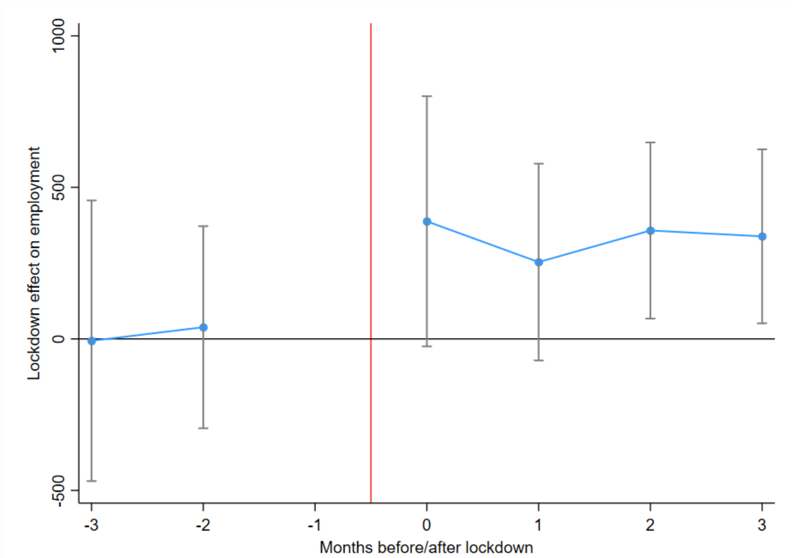
Notes: The regression used to elaborate this graph contains one indicator variable for each day from 1 week before the lockdown adoption until 7 weeks later and was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as a 7-day moving average and per 100,000 inhabitants. The estimate controls for municipality and day fixed effects and municipal-specific trends. Robust standard errors were used to construct the 95% confidence interval represented by the dashed lines. The number of observations equals 4,052 and the R-squared equals 0.64.

Figure A.3: Lockdown effect on deaths



Notes: The regression used to elaborate this graph contains one indicator variable for each day from 1 week before the lockdown adoption until 7 weeks later and was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as a 7-day moving average and per 100,000 inhabitants. The estimate controls for municipality and day fixed effects and municipal-specific trends. Robust standard errors were used to construct the 95% confidence interval represented by the dashed lines. The number of observations equals 4,052 and the R-squared equals 0.56.

Figure A.4: Lockdown effect on employment



Notes: The regression used to elaborate this graph contains one indicator variable for each month from 1 month before the lockdown adoption until 4 months later and was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as per 100,000 inhabitants. The estimate controls for municipality and day fixed effects. Robust standard errors were used to construct the 95% confidence interval represented by the dashed lines. The number of observations equals 313 and the R-squared equals 0.14.

Table A.1: Lockdown effect on social isolation, by week

Independent variables	Dependent variable: Social isolation (1)	(2)	(3)
Week 1	1.761	0.682	0.790
	(2.695)	(6.273)	(3.853)
Week 2	2.312	0.446	0.457
	(2.391)	(6.261)	(4.647)
Week 3	2.185	-4.021	-4.835
	(1.810)	(6.248)	(5.549)
Week 4	-1.785	-10.734	-12.570
	(1.368)	(6.257)	(6.936)
Week 5	-1.649	-4.998	-7.331
	(1.910)	(6.380)	(8.232)
Week 6	-4.669***	2.623	-0.564
	(1.144)	(6.308)	(9.638)
Week 7	-9.634***	1.214	-3.224
	(1.198)	(6.226)	(10.938)
Constant	38.113***	38.262***	39.287***
	(0.726)	(3.550)	(3.904)
R-squared	0.019	0.472	0.625
Observations	3600	3600	3600
Municipal FE		X	X
Date FE		X	X
Municipal-specific trends			X

Notes: Robust standard errors are in parenthesis. The regression was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as a 7-day moving average. In this case, because social isolation data is scarce, there are only one municipality in the control group and 5 in the treatment one.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.2: Lockdown effect on cases per 100k inhabitants, by week

Independent variables	Dependent variable: Cases (1)	(2)	(3)
Week 1	1.761	0.682	0.790
	(2.695)	(6.273)	(3.853)
Week 2	2.312	0.446	0.457
	(2.391)	(6.261)	(4.647)
Week 3	2.185	-4.021	-4.835
	(1.810)	(6.248)	(5.549)
Week 4	-1.785	-10.734	-12.570
	(1.368)	(6.257)	(6.936)
Week 5	-1.649	-4.998	-7.331
	(1.910)	(6.380)	(8.232)
Week 6	-4.669***	2.623	-0.564
	(1.144)	(6.308)	(9.638)
Week 7	-9.634***	1.214	-3.224
	(1.198)	(6.226)	(10.938)
Constant	38.113***	38.262***	39.287***
	(0.726)	(3.550)	(3.904)
R-squared	0.019	0.472	0.625
Observations	3600	3600	3600
Municipal FE		X	X
Date FE		X	X
Municipal-specific trends			X

Notes: Robust standard errors are in parenthesis. The regression was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as a 7-day moving average and per 100,000 inhabitants.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.3: Lockdown effect on deaths per 100k inhabitants, by week

Independent variables	Dependent variable: Deaths (1)	(2)	(3)
Week 1	0.753***	0.029	0.006
	(0.100)	(0.162)	(0.163)
Week 2	0.489***	0.091	0.032
	(0.091)	(0.170)	(0.210)
Week 3	0.872***	0.217	0.110
	(0.157)	(0.175)	(0.273)
Week 4	0.601***	0.217	0.014
	(0.093)	(0.158)	(0.325)
Week 5	0.208**	-0.015	-0.225
	(0.079)	(0.164)	(0.393)
Week 6	-0.219***	-0.291	-0.492
	(0.047)	(0.166)	(0.471)
Week 7	-0.215***	-0.014	-0.202
	(0.038)	(0.160)	(0.543)
Constant	0.952***	1.134***	1.214***
	(0.026)	(0.087)	(0.183)
R-squared	0.150	0.466	0.554
Observations	3600	3600	3600
Municipal FE		X	X
Date FE		X	X
Municipal-specific trends			X

Notes: Robust standard errors are in parenthesis. The regression was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as a 7-day moving average and per 100,000 inhabitants.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.4: Lockdown effect on employment per 100k inhabitants, by month

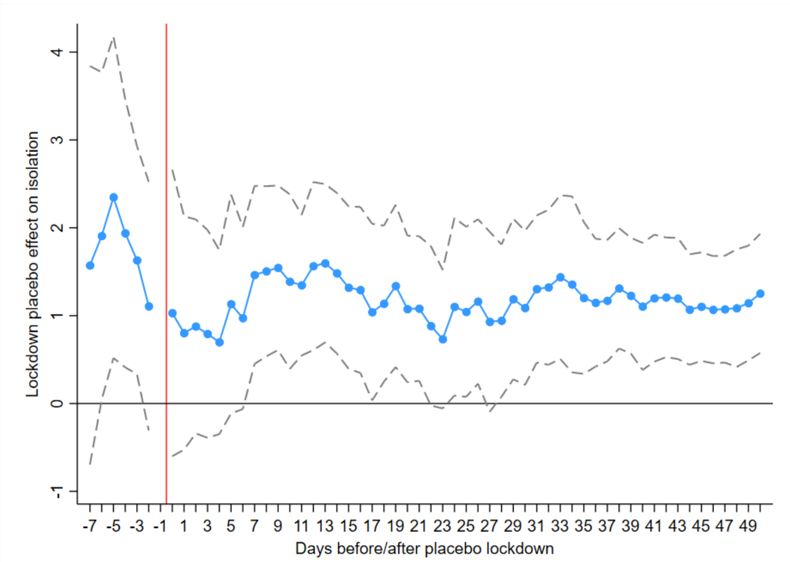
Independent variables	Dependent variable: Employment (1)	(2)	(3)
Month 1	247.313	380.623	346.185
	(197.795)	(202.387)	(270.503)
Month 2	135.009	244.431	174.742
	(116.878)	(163.354)	(297.311)
Month 3	247.248*	348.087*	231.278
	(101.074)	(149.300)	(387.965)
Month 4	187.593**	328.112*	101.130
	(70.722)	(152.535)	(538.982)
Constant	136.785**	89.056	131.434
	(43.815)	(62.110)	(131.150)
R-squared	0.024	0.142	0.357
Observations	313	313	313
Municipal FE		X	X
Date FE		X	X
Municipal-specific trends			X

Notes: Robust standard errors are in parenthesis. The regression was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as per 100,000 inhabitants.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix B. Placebo lockdown

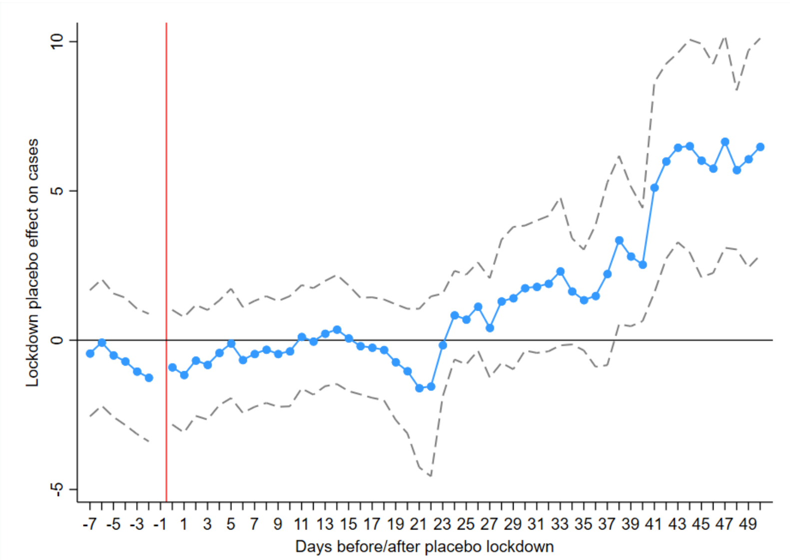
The results in this Appendix were obtained through a placebo test, as if the lockdown policies were adopted one year before its actual adoption. The control and treatment groups are the same of the main analysis.

Figure B.1: Placebo lockdown effect on social isolation



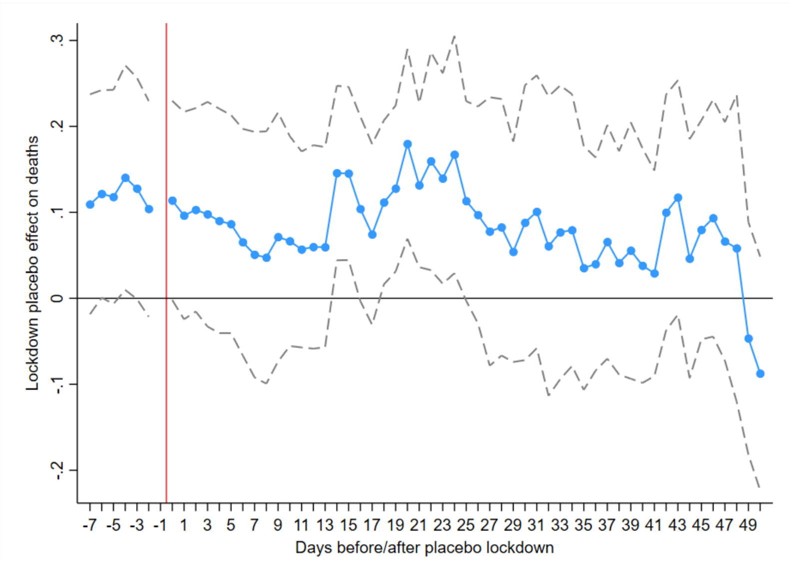
Notes: The regression used to elaborate this graph contains one indicator variable for each day from 1 week before the placebo lockdown adoption (1 year before the real adoption) until 7 weeks later and was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as a 7-day moving average. The estimate controls for municipality and day fixed effects and municipal-specific trends. Robust standard errors were used to construct the 95% confidence interval represented by the dashed lines. In this case, because social isolation data is scarce, there are only one municipality in the control group and 5 in the treatment one.

Figure B.2: Placebo lockdown effect on cases



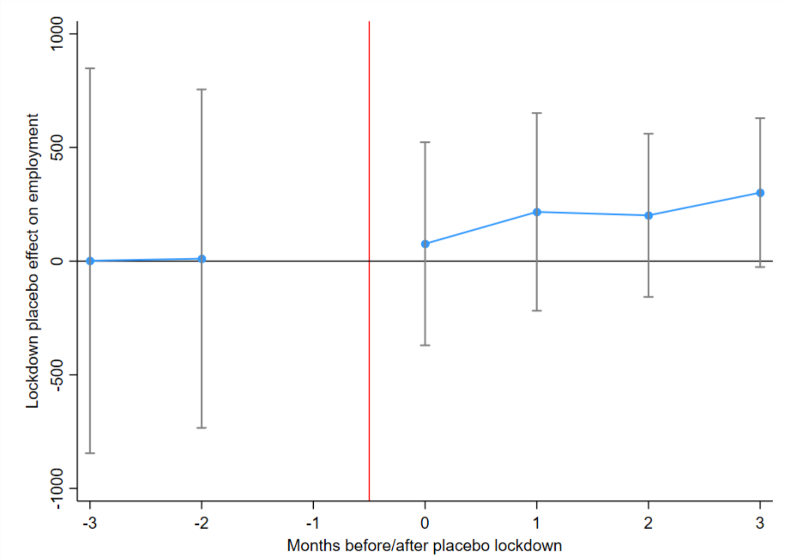
Notes: The regression used to elaborate this graph contains one indicator variable for each day from 1 week before the placebo lockdown adoption (1 year before the real adoption) until 7 weeks later and was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as a 7-day moving average and per 100,000 inhabitants. The estimate controls for municipality and day fixed effects and municipal-specific trends. Robust standard errors were used to construct the 95% confidence interval represented by the dashed lines.

Figure B.3: Placebo lockdown effect on deaths



Notes: The regression used to elaborate this graph contains one indicator variable for each day from 1 week before the placebo lockdown adoption (1 year before the real adoption) until 7 weeks later and was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as a 7-day moving average and per 100,000 inhabitants. The estimate controls for municipality and day fixed effects and municipal-specific trends. Robust standard errors were used to construct the 95% confidence interval represented by the dashed lines.

Figure B.4: Placebo lockdown effect on employment



Notes: The regression used to elaborate this graph contains one indicator variable for each month from 1 month before the placebo lockdown adoption (1 year before the real adoption) until 4 months later and was estimated with weighted least squares, where the weight is the municipality's population. The dependent variable is calculated as per 100,000 inhabitants. The estimate controls for municipality and day fixed effects. Robust standard errors were used to construct the 95% confidence interval represented by the dashed lines.

Appendix C. Data and Code

The data and code used in this project are publicly available in the following repository: https://github.com/angelokisilmarino/bachelor_thesis.