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Impact of social distancing due to the COVID-19 pandemic on property crimes in São
Paulo: a Bayesian spatiotemporal modelling case study

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Supervisor: Prof. Dr. Luiz Guilherme Dácar da Silva Scorzafave

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Resumo

Fukushima, Ian Shinji Ferreira. **Impacto do distanciamento social devido à pandemia de COVID-19 nos crimes contra propriedade em São Paulo: um estudo de caso espaço-temporal Bayesiano.** Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto, Universidade de São Paulo, Ribeirão Preto, 2021.

Com o objetivo de frear o número de infecções por COVID-19, vários países adotaram regulamentações de distanciamento social, incluindo o fechamento de estabelecimentos não essenciais e restrições de mobilidade. Este artigo estima o impacto dessas regulamentações sobre os crimes contra a propriedade no estado de São Paulo. O impacto é estimado usando um modelo espaço-temporal Bayesiano e é desagregado por microrregiões. A variabilidade espacial do impacto é usada para inferir quais variáveis observadas caracterizam os locais com maior probabilidade de terem sido impactados. Os resultados indicam que a maioria das microrregiões sofreu uma redução nos crimes contra a propriedade e que esses locais são caracterizados por índices de isolamento mais altos e menos recebimento de transferências emergenciais de dinheiro.

Palavras-Chave: Análise Bayesiana; Impacto Causal; Crime; COVID-19; Aproximações de Laplace Aninhadas e Integradas.

JEL: C33; C99; J19.

Abstract

Fukushima, Ian Shinji Ferreira. **Impact of social distancing due to the COVID-19 pandemic on property crimes in São Paulo: a Bayesian spatiotemporal modelling case study**. School of Economics, Business Administration and Accounting at Ribeirão Preto, University of São Paulo, Ribeirão Preto, 2021.

With the goal of stopping COVID-19 infections, several countries adopted social distancing regulations, including closure of non essential establishments and mobility restrictions. This paper estimates the impact of these regulations on property crime in the state of São Paulo. The impact is estimated using a Bayesian spatiotemporal model, and is disaggregated by microregions. The space variability of the impact is used to infer which observed variables characterize places with higher probability of impact. We found that most microregions experienced a decrease in property crime, and that these places are characterized by higher isolation indices and less receipt of emergency cash transfers.

Keywords: Bayesian analysis; Causal impact; Crime; COVID-19; Integrated Nested Laplace Approximations.

JEL: C33; C99; J19.

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1 Introduction

The spread of COVID-19 infections worldwide since the early months of 2020 motivated social distancing regulations in several countries, with the goal of stopping the disease by imposing mobility restrictions and quarantine. The impact on economic and social variables was great. Closure of establishments considered non essential led to unemployment (Blustein et al., 2020), and even mental health was affected due to the mobility restrictions (Pfefferbaum and North, 2020). People’s routine was greatly impacted, as time spent at home increased (Google, 2020).

Considering environmental criminological theory, it is expected that such changes in routine also impact the occurrences of property crimes: Routine Activity Theory (Cohen and Felson, 1979) asserts that crime occurrences depends on the convergence of potential victims and motivated offenders in the absence of capable guardians, and Crime Patterns Theory (Brantingham and Brantingham, 1993) highlights the importance of geography in determining this convergence, given that places with different uses attract different persons. These theories elucidate why it is expected that quarantine measures impact property crime, but do not determine the expected direction of the impact and how it can differ across locations. In fact, existing empirical works have investigated such impacts and found heterogeneous results across space and across crime types (Mohler et al., 2020; Campedelli et al., 2020). While causally inferring that quarantine impacted property crime occurrences is an interesting result, that agrees with environmental criminological theory and is of practical use for social police planners, it is important to consider the spatial variability of the impact and investigate what drives this variability.

This study aims to estimate the impact of social distancing during the COVID-19 pandemic on four different property crimes in the Brazilian state of São Paulo, where a statewide quarantine was declared by the government with restrictions to mobility and economic activities. To our knowledge, no such study has yet been performed in Brazil, and most published studies have focused on developed countries (Mohler et al., 2020; Campedelli et al., 2020; Ashby, 2020; Halford et al., 2020) with some exceptions that focused on underdeveloped countries (Balmori de la Miyar et al., 2021; Rashid, 2021). In general, results cannot be extrapolated spatially, hence the importance of studying multiple regions. Additionally, most existing works focus only on the temporal variability of crime (Halford et al., 2020) or separately estimate the impact for different spatial units (Mohler et al., 2020; Campedelli et al., 2020; Ashby, 2020). Considering the concerns raised in the last paragraph, we use Bayesian spatiotemporal models to estimate impact simultaneously for all São Paulo microregions.

More specifically, impact is defined as the difference between what we actually see when an intervention is in place and what would have been seen if no intervention was implemented. Since no experiment with random control was in place and since compara-

tive case frameworks (such as difference-in-differences) are unattainable (the quarantine measure was applied to the whole state of São Paulo, and other states with available crime data either imposed quarantine measures, or were affected by the COVID-19 pandemic), the chosen approach to impact estimation is the construction of a synthetic control using a methodology based on Brodersen et al. (2015), but extended to consider the spatial variability.

In Brodersen et al. (2015), causal impact is inferred by estimating a Bayesian state-space model for a target time-series that has undergone an intervention. The model is fitted using pre-intervention data. The Bayesian framework allows the simulation from a posterior predictive distribution for the post-intervention period, which is used to simulate a counterfactual for the post-intervention period. Samples from this distribution allows the computation of a posterior distribution of the impact by subtracting the sampled value (counterfactual) from the actual target time-series values in the post-intervention period. To allow for space varying impact we extend Brodersen et al. (2015) approach by using a Bayesian spatiotemporal model. This results in the simultaneous estimation of impact in different microregions and also takes advantage of the information present in the time-series of each microregion to borrow strength for the model as a whole. The strength of the results can be tested by comparing it with impact calculated for placebo periods, i.e., using pre-intervention periods as post-intervention.

Furthermore, we benefit from the impact space variability to take one step further and investigate microregion characteristics related to the presence or absence of impact. One characteristic expected to be correlated with impact is how binding the quarantine measures were in each place, which can be approximated by an isolation index that measures people’s mobility. In Brazil, another social event of interest occurred during quarantine: a cash transfer program, the Emergency Aid Transfer (EAT), was implemented by the Brazilian federal government. The aid consisted of approximately 57% of the Brazilian minimum wage and covered more than 40% of the population in the researched period. Poverty rate dropped from 12% in 2019 to 8% during the pandemic in Brazil with concomitant declines in extreme poverty and inequality (Menezes-Filho et al., 2021). Given that these cash transfers were heterogeneous in space and that poverty and inequality are important crime correlates (Kelly, 2000; Pridemore, 2011; Neil Metz, 2018), it can also be an important correlate to the impact estimates.

The remainder of the work is divided in seven sections. Data sources and descriptive statistics and is presented at Section 2. In Section 3 the methodology used to infer causal impact is detailed. Section 4 presents the metrics and results of the model selection. Model evaluation and placebo test are made in Section 5. The final results of the impact estimation are in Section 6 while Section 7 characterizes the impacted places. Finally, Section 8 concludes with a discussion.

2 Data

Property crimes are a common type of crime in Brazil. This article focus on São Paulo, which is the most populous Brazilian state (the population was 41223683 according to the 2010 census, a larger population than in countries like Australia, Canada and the Netherlands) and one of the few to make publicly available the monthly count of police reports on the occurrence of different types of crimes. The analysis is done at the micro-regional level, where a microregion is a cluster of municipalities defined by the Brazilian Institute of Geography and Statistics with the aim of providing details of the territory and attributes of the country (Brazilian Institute of Geography and Statistics, 2017). São Paulo is made up of 645 municipalities grouped into 63 microregions. At this aggregation space variability is preserved and it is possible to test the hypotheses proposed in Section 1.

The study period ranges from January 2009 to May 2020. The first quarantine measure covering the whole state of São Paulo to contain COVID-19 infections was adopted on March 23, 2020 (São Paulo Government, 2020). Given that data frequency is monthly, the intervention period considered starts in March, 2020. This is more reasonable than using March in the model fit, since *a)* the model would capture changes in crime due to the quarantine measures and *b)* the first COVID-19 case in Brazil was confirmed in February 26, 2020 (Rodriguez-Morales et al., 2020), thus people’s daily routines had already changed in March. The remainder of this section presents data sources and relevant descriptive statistics.

2.1 Crime data

Four property crime categories are considered: theft, vehicle theft, robbery and vehicle robbery. We use the monthly number of crime occurrences reported to the police as a *proxy* to the number of actual crime occurrences. This practice is standard in empirical studies involving crime statistics, and, for brevity, from now on we will refer to the monthly number of reported crimes as the monthly number of crime occurrences. The monthly number of crime occurrences is made publicly available by the São Paulo state government through the São Paulo Department of Public Security.

Table 1 presents descriptive statistics of each considered crime type for both pre-intervention and post-intervention periods. It is noticeable that most crime types have a low first quartile (only theft is higher than 12), especially vehicle robbery, which is characterized by a high zero occurrence.

It is also noticeable that the mean for the post-intervention period is lower. Since the pre-intervention period is considerably longer, this summary statistic can be misleading. Figure 1 provides further evidence of the decrease by comparing the months of March to May 2019 with 2020. Overall, there was a reduction in crimes across the state, with greater

Table 1: Descriptive statistics: minimum, first quartile (Q_1), mean, standard deviation (sd), third quartile (Q_3), and maximum of each crime type, considering pre-intervention (Pre) and post-intervention (Post) data.

<i>Crime</i>	<i>Mean</i>	<i>sd</i>	<i>Minimum</i>	Q_1	Q_2	<i>Maximum</i>
Theft (Pre)	690.06	2275.68	2	135	509	26704
Theft (Post)	410.97	1500.02	4	70	281	16045
Vehicle Theft (Pre)	140.94	556.91	0	8	77	5573
Vehicle Theft (Post)	75.47	302.27	0	4	40	2913
Robbery (Pre)	359.06	1692.00	0	12	133	17699
Robbery (Post)	266.05	1413.02	0	6	61	13711
Vehicle Robbery (Pre)	99.66	517.19	0	1	25	6556
Vehicle Robbery (Post)	39.09	180.43	0	0	16	1832

absolute decreases in the eastern region, which is where property crime (and population) is concentrated.

2.2 Crime covariates

The methodology adopted for impact estimation allows the use of covariates, but, to ensure good estimates, these covariates must not be affected by the intervention (quarantine) (see the discussion in Brodersen et al. (2015)), and they must also vary in time. Considering that the data frequency is monthly, these restrictions pose a challenge to finding good crime covariates since they exclude the possibility of adding known crime correlates such as unemployment and illiteracy (Alves et al., 2018); while the first was highly affected by the quarantine measures, the latter lacks available data in the time frequency considered. Additionally, most socioeconomic variables are available either annually or once every decade.

With these limitations in mind, four crime covariates are considered: population, proportion of female population, proportion of young male population (aged between 15 and 34 years old), and urbanization rate. These are available on an annual basis from the São Paulo State Data Analysis System, and the population counts are projections based on census counts (made once every decade) and trends in fertility, mortality, and migration. The last census was in 2010, and the 2020 counts are projections made before the COVID-19 pandemic started; thus, it is assured that the population variables are not affected by the quarantine measures. The annual variables were linear interpolated to the monthly frequency.

Figure 2 shows the temporal evolution of these covariates. Visual inspection indicates that the young males proportion is the variable with the most potential to improve the quality of the impact estimates since it is characterized by some changes in trend direction and temporal variability. It is also noticeable that most microregions have an urbanization

Figure 1: Property crimes per 100,000 inhabitants in São Paulo microregions. A comparison between March-May 2019 and March-May 2020.

rate around 0.9, but some had it as low as 0.5 and experienced increases. Such temporal variation can also help the estimates.

The high space variability of the total population masks the temporal evolution of this variable, but it is a linear increasing trend. The proportion of females in the population has some space and time variability with some changes in trend direction, but stays mostly between 0.48 and 0.52.

2.3 Impact correlates

Socioeconomic variables are used to explain the variability in the probability of a given place having experienced an impact on each crime type. There is a special interest in two

Figure 2: Monthly evolution of (a) population, (b) proportion of females in the population, (c) proportion of young males (aged between 15 and 34 years), and (d) urbanization rate. Each line is a different microregion.

variables: isolation index and the EAT.

The isolation index at the municipality level is measured daily by the technology company Inloco using geolocation data from smartphones¹. Higher index means greater isolation, which is a sign of adherence to quarantine. The index is available for 564 out of 645 São Paulo municipalities on all days of the post-intervention months. These daily measures were aggregated monthly using the index mean and spatially at the microregional level by the population-weighted average.

The EAT was a monetary aid provided by the Brazilian federal government to a wide range of the population, such as informal and autonomous workers, micro-entrepreneurs, and unemployed individuals. The first aid was given in April and consisted of approximately 57% of the Brazilian minimum wage. The variable is included as the per capita

¹InLoco developed a software that is integrated with multiple smartphone apps and that detects when the smartphone remains in the same location for a prolonged period of time. The company had access to over than 27% of the smartphones in February, 2020 (de Oliveira et al., 2020).

Table 2: Descriptive statistics: minimum, first quartile (Q_1), mean, standard deviation (sd), third quartile (Q_3), and maximum of impact covariates.

<i>Variable</i>	<i>Mean</i>	<i>sd</i>	<i>Minimum</i>	Q_1	Q_3	<i>Maximum</i>
Isolation index	0.416	0.038	0.234	0.392	0.442	0.507
Emergency aid per capita	98.382	74.082	0	0	154.4	258
Deaths per case	0.0546	0.0647	0	0	0.0833	0.4211
Demographic density	334.659	882.295	13.197	40.741	167.690	6196.347
GDP per capita	35.716	14.158	14.433	28.254	40.692	94.649
Illiteracy rate	0.060	0.017	0.032	0.046	0.072	0.105
MDMI	0.724	0.140	0.148	0.692	0.825	0.901

emergency monetary aid destined for a given microregion in a given month, in 2020 R\$ (Official Brazilian currency). The aid was 0 in March.

Other data considered are the monthly number of COVID-19 cases per capita and deaths per case, counted by the Brazilian Ministry of Health; the monthly microregion demographic density; the gross domestic product (GDP) per capita; in thousands of 2016 R\$; the 2010 illiteracy rate; and the Municipality Decentralized Management Index (MDMI), a monthly index calculated by the Brazilian Ministry of Citizenship to measure the quality of some municipalities public services. The index was aggregated at the microregion level using the population-weighted average. Table 2 presents descriptive statistics of the impact covariates.

3 Impact Estimation Method

Causal impact inference is a challenge that involves dealing with an unobservable quantity. If we define y_{1it} as the number of crime occurrences in place i and period t given that place i was under quarantine measures on time t , and, similarly, y_{0it} as the number of crime occurrences given that no quarantine measures were in effect, the causal impact at time t in place i is defined as

$$\Delta \equiv y_{1it} - y_{0it} \quad (3.1)$$

and directly calculating this quantity is unfeasible, given that for fixed i and t either y_{1it} or y_{0it} is unobservable (counterfactual).

In general, to overcome this problem, impact estimation is done in comparative cases framework, where some units are exposed to the event of interest (treated units) and others are not (control units) (Abadie et al., 2010). But quarantine measures were imposed simultaneously in the whole state of São Paulo, so in every time period t , either all places are considered treated units or all places are considered control units. Furthermore, in other Brazilian states where crime data is available, similar interventions also took place

at the same time. This precludes the use of methods such as differences-in-differences and discontinuous regression in their usual formats.

Some alternative methods to comparative cases framework are available for time-series data by taking advantage of the temporal structure of the target (possibly impacted) variable to make predictions which are used as a synthetic counterfactual. These alternatives include the use of structural time-series models (Harvey and Durbin, 1986) and autoregressive models (Lawton et al., 2005), and are common in the quantitative criminology literature (Ashby, 2020; Payne et al., 2021; Piquero et al., 2020). A more recent method for causal inference was developed in Brodersen et al. (2015), combining both structural time-series models and comparative cases frameworks in a fully Bayesian manner.

Brodersen et al.'s (2015) approach consists of constructing a synthetic counterfactual for a target time-series that has undergone an intervention by estimating a state-space model using time-series correlated to the target as covariates. The model is fitted using pre-intervention data, and its posterior predictive distribution is used to simulate a post-intervention period. Samples from this distribution allow the computation of a posterior distribution of the impact by subtracting the sampled value (counterfactual) from the actual target time-series values in the post-intervention period. The inclusion of covariates is limited to variables that are available for the post-intervention period and that were not affected by the intervention, because they are used to construct the synthetic counterfactual, which is an estimate of what would have happened without the intervention.

Since this research goal involves the estimation of the impact in different places (there is prior reason to believe that the impact is heterogeneous in space (Mohler et al., 2020; Ashby, 2020)) the methodology used for inference is based on the one presented in Brodersen et al. (2015), but extended to allow the simultaneous estimation of impact in different microregions. For each crime type, a choice is made between three Bayesian models: a hierarchical Poisson model, a hierarchical negative-binomial model, and a separate Poisson model.

A key issue in causal inference is to distinguish whether the relationship found is spurious or causal. The method differences-in-differences, for example, rests on the assumptions of common trend and unobservable effects constant over time, and from these assumptions returns confidence intervals for the impact. In Abadie et al. (2010) synthetic control method, the causality is tested in a type of placebo test: estimation is done for all units in the control group, and a hypothesis test is made comparing the actual estimated value and the placebo ones. The method described in Brodersen et al. (2015) rests on hypotheses more flexible than the difference-in-difference method by using structural time series to model the target, and the Bayesian framework results in probability distributions for the impact, which are directly interpretable. In addition to these distributions, to solidify that the found relationship is causal, the estimation can be made for placebos, as

in Abadie et al. (2010), but defining periods of time prior to the intervention as placebos. This approach is followed in Section 5, while the remainder of this section details the impact estimation method.

3.1 Bayesian Spatiotemporal Poisson Model for Impact Estimation

Let $I = \{1, 2, \dots, n\}$ index place, and $\mathcal{T} = \{1, 2, \dots, T, t_s, \dots, t_f\}$ index time. Define t_s as the period when the intervention started and y_{it} as the number of occurrences of a given crime in an arbitrary place $i \in I$ and time $t \in \mathcal{T}$. We suppose that y_{it} follows a Poisson distribution with a stochastic intensity for which the intensity function is a Gaussian random field, defining a Cox process. More specifically, we suppose the following model:

$$\begin{aligned} y_{it} &\sim \text{Poisson}(\lambda_{it}) \\ \log(\lambda_{it}) &= \eta_{it} \\ \eta_{it} &= b_i + \boldsymbol{\beta} \mathbf{x}_{it} + \gamma_t + \delta_{it} + \epsilon_{it} \end{aligned} \tag{3.2}$$

where b_i is a spatial random effect, $\mathbf{x}_{it}$ is a $k \times 1$ vector of covariates, $\boldsymbol{\beta}$ is a $k \times 1$ vector of fixed effects, γ_t is a seasonal temporal random effect, and δ_{it} and ϵ_{it} are spatiotemporal random effects. The goal is to use pre-intervention data $(y_{i,1:T}, \mathbf{x}_{i,1:T})$ to fit the model and obtain a predictive posterior distribution to the post-intervention period, $y_{i,t_s:t_f}$. This predictive posterior distribution is used as a counterfactual to estimate the impact of quarantine on crime, which is given by the difference between the actual observed values and the predicted values.

The use of the posterior as a counterfactual requires that the covariates included in the model are not affected by the quarantine measure. Violation of this hypothesis would interfere with impact estimation, since the intervention itself would be indirectly included in the counterfactual.

3.1.1 Hierarchical Model

A hierarchical model is considered by assuming that the random effects in Equation 3.2 are governed by distributions with the same hyperparameters. This allows, for each crime category, the simultaneous estimation of the impact for all microregions in one model, and also allows the inclusion of spatial dependence between the occurrences. More specifically, the random effects are defined as follows:

The strictly spatial random effect b_i is modelled as an unstructured random effect:

$$b_i \sim \text{Normal}(0, \sigma_b^2) \tag{3.3}$$

where σ_b is a precision hyperparameters.

The strictly temporal random effect γ_t is modeled as a seasonal component with periodicity 12, and probability density given by

$$\pi(\gamma_t|\tau_\gamma) \propto \tau_\gamma^{\frac{T-12+1}{2}} \exp \left[-\frac{\tau_\gamma}{2} \sum_{t=1}^{T-11} \left(\sum_{k=0}^{11} \gamma_{t+k} \right)^2 \right] \quad (3.4)$$

where τ_γ is a precision hyperparameter.

The spatiotemporal random effects are formulated as a interaction between a spatial and a temporal parameter, as proposed by Knorr-Held (2000). More specifically, ϵ_{it} is the interaction between space and time unstructured random effects such that

$$\epsilon_{it} \sim \text{Normal}(0, \sigma_\epsilon^2) \quad (3.5)$$

while δ_{it} is the interaction between b_i and a temporal structured component modelled as a random walk of order 1. Thus, $\delta = \{\delta_{1,1}, \delta_{1,2}, \dots, \delta_{n,T}\}$ follows a multivariate normal distribution with mean $\mathbf{0}$ and precision matrix given by

$$\tau_\delta I_n \otimes R_\delta \quad (3.6)$$

where I_n is the identity matrix of order n , τ_δ is a precision hyperparameter and R_δ is a $T \times T$ matrix given by

$$R_\delta = \begin{bmatrix} 1 & -1 & & & \\ -1 & 2 & -1 & & \\ & -1 & 2 & -1 & \\ & & \ddots & \ddots & \ddots \\ & & & -1 & 2 & -1 \\ & & & & -1 & 1 \end{bmatrix} \quad (3.7)$$

To finish specifying the hierarchical structure, non-informative priors are assigned to the hyperparameters. Defining the hyperparameters in terms of precision of the normal distributions, a $\text{loggamma}(1, 5 \times 10^{-5})$ is used as a prior for all the hyperparameters. The fixed effects β are estimated as in a pooled model, and normal priors with mean 0 and precision 0.001 are assigned for each $\beta \in \beta$.

3.1.2 Negative-binomial Model

Even though the Cox process is very flexible in terms of capturing underdispersion and overdispersion when compared to a Poisson process without random effects, it is possible to include a structure specifically for capturing dispersion, by supposing that y_{it} follows a negative-binomial distribution; i.e., its probability density is given by

$$\pi(y_{it}) = \frac{\Gamma(y_{it} + n)}{\Gamma(n)\Gamma(y_{it} + 1)} p^n (1 - p)^y, \quad (3.8)$$

where Γ is the gamma function, n is a dispersion parameter to be estimated, and the mean is given by

$$\lambda_{it} = n \frac{1 - p}{p}, \quad (3.9)$$

which is modeled as in Equation 3.2.

3.1.3 Separate Model

The hierarchical model is adequate if there is inter regional dependence in crime occurrences. If the events are independent, a separate model is more suitable. The separate model still assumes that y_{it} follows a Cox process as in Equation 3.2, but the random effect b_i is defined as a fixed effect (intercept), and the seasonality γ_t and hyperparameters are no longer shared between regions.

3.2 Bayesian Inference

For each crime category, three models are estimated: the hierarchical model as defined in Section 3.1.1, the hierarchical model with negative-binomial distribution (Section 3.1.2), and the separate model (Section 3.1.3). For the separate model, when a region presents occurrences of zeros, a zero-inflation parameter is added. Since all models defined are latent Gaussian models, inference can be made with Integrated Nested Laplace Approximations (INLA) (Rue et al., 2009)². Models are compared according to their predictive performance in Section 4.

Suppose y_{it} is the number of occurrences of an arbitrary crime category in an arbitrary region i and arbitrary time t . Suppose that t_{post} is an arbitrary post-intervention period. The counterfactual for $y_{it_{post}}$ is the distribution of the linear predictor obtained from the fit of the best-performing model given the pre-intervention information $(\mathbf{x}_{1:n,1:T}, y_{i,1:T})$, and the post-intervention information $x_{1:n,t_s:t_f}$, i.e., the distribution of $E[\hat{y}_{it_{post}} | \mathbf{x}_{1:n,1:t_f}, y_{i,1:T}]$.

The choice of the linear predictor as the counterfactual is based on the result that the best predictor for $y_{it_{post}}$ is the conditional mean, when best is defined as least average squared error (Hastie et al., 2017). For brevity, from now on the linear predictor will be denoted by

$$\hat{y}_{it_{post}}^* \equiv E[\hat{y}_{it_{post}} | \mathbf{x}_{1:n,1:t_f}, y_{i,1:T}]. \quad (3.10)$$

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²Details of the INLA approach are omitted here to preserve space and can be found in Bakka et al. (2018).

From the linear predictor distribution, the impact distribution, $\Delta_{it_{post}}$, is obtained by subtracting $\hat{y}_{it_{post}}^*$ from the actual observed $y_{it_{post}}$:

$$\Delta_{it_{post}} \equiv y_{it_{post}} - \hat{y}_{it_{post}}^* . \quad (3.11)$$

Another distribution of interest derived from the linear predictor distribution is the relative impact distribution, $\Delta_{it_{post}}^R$, which is given by

$$\Delta_{it_{post}}^R \equiv \frac{\Delta_{it_{post}}}{\hat{y}_{it_{post}}^*} = \frac{y_{it_{post}} - \hat{y}_{it_{post}}^*}{\hat{y}_{it_{post}}^*} \quad (3.12)$$

and is especially useful for comparing the magnitude of the effect between regions.

4 Model Selection

The construction of a good synthetic counterfactual depends on the predictive power of the model when no intervention is in place. The leave-one-out cross-validation (LOO-CV) is suitable for evaluating such power (Vehtari et al., 2017). In the Bayesian framework, LOO-CV is done by calculating the conditional predictive ordinate (CPO), which is defined as

$$CPO_{it} = p(y_{it}|X, \mathbf{y}_{-it}) \quad (4.1)$$

where $\mathbf{y}$ is the dependent variable vector, X are explanatory variables, $y_{it} \in \mathbf{y}$ and $\mathbf{y}_{-it} = \mathbf{y} \setminus \{y_{it}\}$. Efficient calculation of the CPOs is made in the INLA framework as described in Ferkingstad et al. (2017), eliminating the need to re-estimate the models for each observation in $\mathbf{y}$.

To summarize the LOO-CV results in a single measure, the expected log pointwise predictive density (ELPD) is used. It is defined as

$$\begin{aligned} ELPD_{it} &= \log(CPO_{it}) \\ ELPD &= \sum_{it} ELPD_{it} \end{aligned} \quad (4.2)$$

Models with lower ELPD are chosen. Table 3 presents these measures, and, to compare metrics, two commonly used information criteria used in Bayesian model selection: the widely applicable information criterion (Watanabe, 2013) and the deviance information criterion (Spiegelhalter et al., 2002).

Table 3: Model Comparison - widely applicable information criterion (WAIC), deviance information criterion (DIC), and expected log pointwise predictive density (ELPD) for each model.

Crime	Model	WAIC	DIC	ELPD
Theft	Neg. Binomial	76540.95	77276.93	41250.37
	Poisson	76272.85	76912.12	41223.24
	Separate	76287.5	76811.08	40916.59
Vehicle Theft	Neg. Binomial	57417.71	57201.51	28871.75
	Poisson	55680.1	55569.86	28887.55
	Separate	55668.19	55607.04	28872.98
Robbery	Neg. Binomial	61159.55	60884.9	31013.41
	Poisson	59782.98	59613.01	31045.03
	Separate	59582.67	59679.5	31243.48
Vehicle Robbery	Neg. Binomial	40260.77	39707.54	20672.89
	Poisson	39106.03	39042.71	20094.11
	Separate	39627.72	39578.2	20521.87

5 Model Criticism

In this section, two model evaluations will be made. *a)* To evaluate the adequacy of the models, the Adjusted Probability Integral Transform (PIT) (Dawid, 1984; Czado et al., 2009) will be presented, and, *b)* as a sanity check, the selected models will be fit using intervention periods in which no statewide intervention was in effect to check if the model detects impact when it is not expected to.

a) PIT:

The PIT is based on the posterior distribution of the dependent variable. Following the notation used in Section 4, its definition is

$$PIT_{it} = p(y_{it}^* \leq y_i | \mathbf{y}_{-it}) + 0.5 \times p(y_{it}^* = y_{it} | \mathbf{y}_{-it}) , \quad (5.1)$$

and it follows a uniform distribution if the model is the true model. PIT histograms are shown in Figure 3. The vehicle robbery selected model PIT histogram is the one that most deviates from a uniform shape, and indicates an overdispersed and skewed model (Czado et al., 2009). This shape is due to the high presence of zeros in the variable.

b) Testing on different intervention periods

For each crime type, its respective selected model will be fit considering nine different post-intervention periods, called Test Periods from now on and defined in Table 4. The interest here is to check if the models capture impacts when it is not expected to. Since there are 63 microregions and 3 post-intervention months, each model estimates 189 im-

Figure 3: PIT histograms for (a) theft selected model, (b) vehicle theft selected model, (c) robbery selected model, and (d) vehicle robbery selected model.

pact distributions, as shown in Equation 3.11. The analysis will be made by counting, for each model and Test Period, the number of impact distributions with at least 95% probability of a 10% increase or 10% reduction. To minimize the high relative impact that low absolute changes have when the number of observed crimes is low, if a 10% relative impact implies a number of occurrences less than two, then two is used as a threshold instead of 10%.

Figure 4 shows histograms with such counts. Although the models find impacts in the Test Periods, they are distributed between positive and negative impacts while in the quarantine period the impacts are almost all negatives. Given the multitude of time periods and microregions considered in the models, it is expected that, in some months and in some regions, actual interventions not included in the model specification happened, and are being captured as impacts. But it is notable that the number of detected impacts is far greater in quarantine periods.

To further explore these results, Figure 5 shows boxplots of the logarithm of the absolute value of the mean estimated impact for the distributions counted in Figure 4. In general, the mean estimated impact for the Test Periods is smaller than for the quarantine

Table 4: Test Periods Definitions

Intervention period	
Placebo 1	Dec 2017 - Feb 2018
Placebo 2	Mar 2018 - May 2018
Placebo 3	Jun 2018 - Aug 2018
Placebo 4	Sep 2018 - Nov 2018
Placebo 5	Dec 2018 - Feb 2019
Placebo 6	Mar 2019 - May 2019
Placebo 7	Jun 2019 - Aug 2019
Placebo 8	Sep 2019 - Nov 2019
Placebo 9	Dec 2019 - Feb 2020
Quarantine	Mar 2020 - May 2020

Figure 4: Number of impact distributions with probability $\geq 95\%$ of a 10% positive (white fill) or negative (gray fill) impact, considering models for “Placebo” and the actual intervention period. (a) theft, (b) vehicle theft, (c) robbery, (d) vehicle robbery.

period. This part of the model criticism already points to the result that the quarantine measures implied an overall decrease in the number of crimes reported in São Paulo.

Figure 5: Logarithm of the absolute value of the mean of the impact distributions with probability $\geq 95\%$ of a 10% positive or negative impact, considering models for “Placebos” and the actual intervention period. (a) theft, (b) vehicle theft, (c) robbery, (d) vehicle robbery.

6 Estimated Impact

The final products of the selected models are 756 (4 crime types, 3 post-intervention months, and 63 microregions) impact distributions, as defined in Equations 3.10, 3.11, and 3.12. Plots for all the impact distributions are presented in Appendix A. In this section, the distributions are summarized by the inferred posterior probability of a given relative impact. Every time the relative impact in question implies an absolute impact less than two, an absolute impact of two is considered instead.

To also see the temporal evolution of the impact, ie., to summarize the estimated impact distributions in each month, boxplots of the probability of 50%, 25%, and 10% reduction are shown in Figures 6, 7, 8, and 9. Points with transparent fill are the actual probabilities used to form each box, and points with black fill are inferred probabilities that far exceeds the 75th percentile or are far below the 25th percentile.

The probability of a reduction as high as 50% is low ($\leq 90\%$) for most microregions for every crime type. However considering a 25% reduction there are far more microregions with a probability $\geq 90\%$, especially for theft in April and May. For the other crime types, the distributions of a 25% reduction in April and May appear to be bimodals with peaks in very low and very high probabilities.

Considering a more parsimonious reduction of 10%, the probabilities are very high and homogeneous for theft and robbery in April and May. The number of microregions with a high probability of a 10% reduction in vehicle theft is also high in April, but it greatly decreases in May. For vehicle robbery, the distributions are still bimodals.

Figure 6: Boxplot of the probability that a microregion experienced a (a) 50% reduction, (b) 25% reduction, (c) 10% reduction, and (d) 10% increase in theft due to quarantine measures in a given month.

To quantify the “high” and “lows”, Table 5 shows the number of microregions with a probability greater than or equal to 95%, 90%, and 80% of having experienced a 10% reduction in a given crime due to the quarantine in any given month. It is notable that 56, 47, and 50 microregions have a probability greater than 95% of having experienced a reduction in theft, vehicle theft and robbery, respectively. This corresponds to 88.88%, 74.60%, and 79.37% of the microregions. Although the impact did not cover the entire state, it was quite broad.

Table 5: Number of microregions with high probability of having experienced a 10% reduction in a given crime.

Probability	Theft	Vehicle Theft	Robbery	Vehicle Robbery
0.95	56	47	50	20
0.90	59	53	56	22
0.80	60	59	58	27

Figure 7: Boxplot of the probability that a microregion experienced a (a) 50% reduction, (b) 25% reduction, (c) 10% reduction, and (d) 10% increase in vehicle theft due to quarantine measures in a given month.

Figure 8: Boxplot of the probability that a microregion experienced a (a) 50% reduction, (b) 25% reduction, (c) 10% reduction, and (d) 10% increase in robbery due to quarantine measures in a given month.

Even though the reduction impact was spatially wide for several crime types, there is a high probability that some regions experienced an increase in some crime types. Figures 7 and 8 show that this is the case for vehicle theft in May and for robbery in March. For vehicle robbery, there is only one microregion with a high probability of increase³; and for theft there is none.

³The result for vehicle robbery may seem inconsistent with the joint probability results, which shows more microregions with high probabilities of an increase, but it is not since these increases happened in places with low number of monthly vehicle robberies, and, thus, the 10% relative increase implies a number of occurrences less than two.

Figure 9: Boxplot of the probability that a microregion experienced a (a) 50% reduction, (b) 25% reduction, (c) 10% reduction, and (d) 10% increase in vehicle robbery due to quarantine measures in a given month.

To see the spatial distribution of the impact, the posterior distributions are summarized by its mean value in Figure 10. The maps give an indication of where the impact was higher in absolute numbers: the eastern region of the state. It is also possible to see how the impact increased from March to April, and remained strong in March.

Figure 10: Impact maps - mean value of the impact distributions.

7 Characterizing Impacted Places

To characterize impacted places, a beta regression is fitted with the probability that a microregion has experienced a 10% decline in a given crime type due to quarantine measures as a dependent variable. One regression is fitted for each crime type. Explanatory variables included in the regressions are those presented in Table 2 and discussed in Section 2.3. Besides socioeconomic variables, there is also the inclusion of variables closely related to the quarantine measures: an social isolation index and the EAT provided by the federal government for a portion of the population during quarantine. The remainder of this section presents the beta regression formulation and its results.

7.1 Bayesian beta regression model

To specify the beta regression, suppose z_{it} is the probability of a 10% reduction in an arbitrary crime in region i and month t . Suppose that z_{it} follows a beta distribution, i.e., $z_{it} \sim \text{Beta}(a_{it}, b_{it})$, and, based on Ferrari and Cribari-Neto (2004), the parameterization

$$\begin{aligned}\mu_{it} &= \frac{a_{it}}{a_{it} + b_{it}} \\ \phi_{it} &= a_{it} + b_{it}\end{aligned}\tag{7.1}$$

is used. It implies $E[z_{it}] = \mu_{it}$ and $\text{var}(z_{it}) = \mu_{it}(1 - \mu_{it})/(1 + \phi_{it})$ and is convenient for regression since a linear predictor can be linked to the mean μ_{it} . Moreover, a logit-link is used, and the linear predictor is defined as

$$\eta_{it} = b_0 + b_i + \beta \mathbf{x}_{it}\tag{7.2}$$

where b_i is a unstructured random effects with the same definition as in Section 3, b_0 and β are fixed effects, and $\mathbf{x}_{it}$ is a covariate vector with the explanatory variables and dummies for March and April. The control for month is important especially because the quarantine started in late March, making the impact lower in this month, and the EAT began in April, so it is zero for all microregions in March. Thus, and not adding month dummies would make the EAT fixed effect capture this time variability in the estimated probability of impact.

Non-informative priors $\text{loggamma}(1, 5 \times 10^{-5})$ are assigned to the random effects hyperparameters, normal priors with mean 0 and precision 0.001 are assigned to the fixed effects, and a $\text{loggamma}(1, 0.1)$ prior is assigned to $\exp(\phi)$.

7.2 Results

Although causal inference is made, the fixed effects estimates indicates the characteristics present in places with higher probability of having experienced an impact on crimes. Table 6 presents the probability of a given fixed effect being less than zero for each crime type. This is a good summary for characterizing places with higher probability of impact.

For theft, places with higher probability of having experienced a reduction are the ones where the social distancing measures were more binding, i.e., places with higher isolation indices. Other probable characteristics are lower EAT and higher MDMI, GDP per capita and deaths per case. The results for vehicle theft also indicate high probability (greater than 0.85) that the GDP per capita fixed effect is lower than zero, but the 60% credible interval for the other socioeconomic related fixed effect contains zero.

Regarding GDP per capita for robbery and vehicle robbery, the results indicate the opposite of that obtained for theft and vehicle theft. The fixed effect related to the variable for robbery and vehicle robbery have a probability of 0.827 and 0.878 of being less than

Table 6: Summary of the beta regressions results - Probability that a given fixed effect is less than zero. Dependent variables are the probability of a 10% reduction in a given crime.

	<i>Dependent Variable:</i>			
	Theft	Vehicle Theft	Robbery	Vehicle Robbery
Intercept	0.498	0.138	0.003	0.409
Isolation Index	0.000	0.602	0.573	0.152
EAT	0.984	0.844	0.988	0.952
MDMI	0.156	0.518	0.693	0.554
GDP per capita	0.091	0.131	0.827	0.878
Deaths/cases	0.058	0.478	0.209	0.905
Demog. Dens.	0.595	0.210	0.498	0.551
March	0.969	0.927	0.999	0.988
April	0.991	0.195	0.949	0.962

zero, respectively. There is also a high probability (greater than 0.95) that the EAT fixed effect is less than zero for robbery and vehicle robbery and a high probability (greater than 0.8) that the isolation index fixed effect is greater than zero for vehicle robbery.

8 Discussion

The results suggests that the overall impact of social distance measures on property crime was a reduction in the number of reported cases in São Paulo, but this result was not homogeneous across the state; some microregions had a high estimated probability of having experienced an increase in some property crimes. Estimating such causal effects is important as a description of what occurred during this historical period and contributes to the criminological theory literature as empirical evidence for the importance of people’s routine in determining crime occurrences.

The space variability of the observed impact was explored by estimating a beta regression with a target variable of the estimated probability that a microregion experienced a 10% decrease in a given crime for each considered crime, with the goal of relating characteristics of the microregions to the probability of having experienced a reduction in that crime type. We found that higher isolation is linked to higher probability of reduction in theft and vehicle robbery, which is backed up by Routine Activity Theory and Crime Pattern Theory (Cohen and Felson, 1979; Brantingham and Brantingham, 1993), given that the crime types considered are highly dependent on the convergence of motivated offenders and potential victims in time and space, and this convergence is usually determined by the use of spaces, which changed due to the quarantine measures.

However for theft, vehicle theft, robbery, and vehicle robbery there is an indication

that higher EAT is related to places that have lower probability of reduction. Considering the economics of crime (Becker, 1968; Ehrlich, 1973), this result could go either way: every individual is a potential offender, and a crime is committed if the utility participating in the illegal activity plus the (des)utility of being caught, weighted by the probability of being caught, is greater than the utility of not committing the crime. In the quarantine context, it is arguable that the EAT led to an increase in the utility of not committing a crime for those who have benefited from it but, at the same time, increased the utility of committing a crime given the higher volume of available goods.

Another aspect of the EAT variable is that it is related to the socioeconomic aspects of a region; only individuals considered vulnerable in the pandemic were eligible to receive it. Since the socioeconomic variables included in the models are not current, the EAT fixed effect can be capturing socioeconomic differences between microregions that are not otherwise controlled for in the regressions.

This approach for characterizing impacted places has several limitations. First, the target variable is not straightforward to interpret since it is an estimated probability and not a deterministic indicator of impacted or not impacted. Second, no causal inference is being made in the beta regression and, thus, the estimated fixed effects posterior distributions are only indicators of how the explanatory variables are related to the target. Finally, socioeconomic variables considered important crime determinants by criminological theory, such as inequality (Pridemore, 2011; Neil Metz, 2018), are omitted due to a lack of current data.

The causal impact estimation approach is a novelty and also has limitations. It relies on the hypothesis that the spatial and temporal random effects added in the model are enough to control for unobserved effects. This hypothesis is not directly tested, and, to circumvent this and test the method strength, the number of microregions the method detects in periods where no quarantine measures were in place was examined.

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Appendix A Impact posterior distributions

The estimated impact distributions are plotted in this appendix. They are presented for every microregion, crime and every post-intervention month. The microregions are referenced by a unique ID. These IDs are mapped in Figure 11.

Figure 11: São Paulo map with microregions IDs.

ID	Microregion name	ID	Microregion name	ID	Microregion name
1	Jales	22	Avaré	43	Tatuí
2	Fernandópolis	23	Botucatu	44	Capão Bonito
3	Votuporanga	24	Araraquara	45	Piedade
4	São José do Rio Preto	25	São Carlos	46	Sorocaba
5	Catanduva	26	Rio Claro	47	Jundiaí
6	Auriflama	27	Limeira	48	Bragança Paulista
7	Nhandeara	28	Piracicaba	49	Campos do Jordão
8	Novo Horizonte	29	Pirassununga	50	São José dos Campos
9	Barretos	30	São João da Boa Vista	51	Guaratinguetá
10	São Joaquim da Barra	31	Mogi Mirim	52	Bananal
11	Ituverava	32	Campinas	53	Paraibuna/Paraitinga
12	Franca	33	Amparo	54	Caraguatatuba
13	Jaboticabal	34	Dracena	55	Registro
14	Ribeirão Preto	35	Adamantina	56	Itanhaém
15	Batatais	36	Presidente Prudente	57	Osasco
16	Andradina	37	Tupã	58	Franco da Rocha
17	Araçatuba	38	Marília	59	Guarulhos
18	Birigui	39	Assis	60	Itapeberica da Serra
19	Lins	40	Ourinhos	61	São Paulo
20	Bauru	41	Itapeva	62	Mogi das Cruzes
21	Jaú	42	Itapetininga	63	Santos

Theft March/2020

Figure 12: Posterior distribution for the impact of the quarantine on theft in March 2020, for every São Paulo microregion. Plot title indicates the microregion ID, which is mapped in Figure 11. 95% centered mass of the distributions are shaded in gray. Vertical black line indicates the 0 on the x-axis.

Theft April/2020

Figure 13: Posterior distribution for the impact of the quarantine on theft in April 2020, for every São Paulo microregion. Plot title indicates the microregion ID, which is mapped in Figure 11. 95% centered mass of the distributions are shaded in gray. Vertical black line indicates the 0 on the x-axis.

Theft May/2020

Figure 14: Posterior distribution for the impact of the quarantine on theft in May 2020, for every São Paulo microregion. Plot title indicates the microregion ID, which is mapped in Figure 11. 95% centered mass of the distributions are shaded in gray. Vertical black line indicates the 0 on the x-axis.

Vehicle Theft March/2020

Figure 15: Posterior distribution for the impact of the quarantine on vehicle theft in March 2020, for every São Paulo microregion. Plot title indicates the microregion ID, which is mapped in Figure 11. 95% centered mass of the distributions are shaded in gray. Vertical black line indicates the 0 on the x-axis.

Vehicle Theft April/2020

Figure 16: Posterior distribution for the impact of the quarantine on vehicle theft in April 2020, for every São Paulo microregion. Plot title indicates the microregion ID, which is mapped in Figure 11. 95% centered mass of the distributions are shaded in gray. Vertical black line indicates the 0 on the x-axis.

Vehicle Theft May/2020

Figure 17: Posterior distribution for the impact of the quarantine on vehicle theft in May 2020, for every São Paulo microregion. Plot title indicates the microregion ID, which is mapped in Figure 11. 95% centered mass of the distributions are shaded in gray. Vertical black line indicates the 0 on the x-axis.

Robbery March/2020

Figure 18: Posterior distribution for the impact of the quarantine on robbery in March 2020, for every São Paulo microregion. Plot title indicates the microregion ID, which is mapped in Figure 11. 95% centered mass of the distributions are shaded in gray. Vertical black line indicates the 0 on the x-axis.

Robbery April/2020

Figure 19: Posterior distribution for the impact of the quarantine on robbery in April 2020, for every São Paulo microregion. Plot title indicates the microregion ID, which is mapped in Figure 11. 95% centered mass of the distributions are shaded in gray. Vertical black line indicates the 0 on the x-axis.

Robbery May/2020

Figure 20: Posterior distribution for the impact of the quarantine on robbery in May 2020, for every São Paulo microregion. Plot title indicates the microregion ID, which is mapped in Figure 11. 95% centered mass of the distributions are shaded in gray. Vertical black line indicates the 0 on the x-axis.

Vehicle Robbery March/2020

Figure 21: Posterior distribution for the impact of the quarantine on vehicle robbery in March 2020, for every São Paulo microregion. Plot title indicates the microregion ID, which is mapped in Figure 11. 95% centered mass of the distributions are shaded in gray. Vertical black line indicates the 0 on the x-axis.

Vehicle Robbery April/2020

Figure 22: Posterior distribution for the impact of the quarantine on vehicle robbery in April 2020, for every São Paulo microregion. Plot title indicates the microregion ID, which is mapped in Figure 11. 95% centered mass of the distributions are shaded in gray. Vertical black line indicates the 0 on the x-axis.

Vehicle Robbery May/2020

Figure 23: Posterior distribution for the impact of the quarantine on vehicle robbery in May 2020, for every São Paulo microregion. Plot title indicates the microregion ID, which is mapped in Figure 11. 95% centered mass of the distributions are shaded in gray. Vertical black line indicates the 0 on the x-axis.