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Spillover effect on crime during the COVID-19 lockdowns in the Czech Republic

Bachelor's thesis

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Declaration of Authorship

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Prague, July 31, 2023

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Abstract

This thesis seeks to assess the impact of COVID-19 restrictions on crime spillovers within the context of the Czech Republic. To examine this effect, daily panel data are utilized, revealing that the implementation of COVID-19 measures, such as restriction of free movement, has a significant negative effect on all crime categories, including Violent crimes, Property crimes, Offenses – BESIP, and Other offenses. The Ordinary least squares regression with fixed effects is used as a baseline model. However, due to the presence of spatially lagged dependent variable, a Spatial lag model with fixed effects is adopted to address this issue. Moreover, the analysis includes a z-test, which surprisingly demonstrates a statistically significant increase in the spillover effect in Offenses – BESIP during the COVID-19 period in the Czech Republic.

JEL Classification	K11, K14, K19, K42, K49
Keywords	spatial regression, crime, COVID-19

Title	Spillover effect on crime during the COVID-19 lockdowns in the Czech Republic

Abstrakt

Tato práce zkoumá vliv opatření proti onemocnění COVID-19 na šíření kriminality v České republice. K tomuto účelu jsou využita denní panelová data. Získané výsledky ukazují, že implementace těchto opatření, jako je například omezení volného pohybu, má významně negativní dopad na všechny kategorie kriminality, včetně násilných trestných činů, majetkových trestných činů, přestupků v souvislosti s Oddělením pro bezpečnost silničního provozu a dalších přestupků. Jako základní model je aplikována regrese pomocí metody nejmenších čtverců s fixními efekty. Kvůli přítomnosti prostorové prodlevy závislé proměnné je k vyřešení této situace využit model s prostorovou prodlevou a fixními efekty. Následná analýza zahrnuje také z-test, který překvapivě ukázal statisticky významné zvýšení efektu šíření přestupků v souvislosti s Oddělením pro bezpečnost silničního provozu během období COVID-19 v České republice.

Klasifikace JEL	K11, K14, K19, K42, K49
Klíčová slova	prostorová regrese, kriminalita, COVID-19

Název práce	Spillover efekty kriminality během lockdownů při pandemii COVID-19 v České republice

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Acronyms

BESIP Road Safety Department (Bezpečnost silničního provozu)

OLS Ordinary least squares

SAR Spatial autoregressive

SEM Spatial error model

SLM Spatial Lagrange multiplier

FE Fixed effects

RE Random effects

PCR polymerase chain reaction

Chapter 1

Introduction

"A Pandemic Bright Spot: In Many Places, Less Crime"[1]

The COVID-19 pandemic, caused by the SARS-CoV-2 virus, is an unimaginable phenomenon that broke out at the end of 2019 in Wuhan, China. It resulted in dire worldwide consequences, for example, in economic decline (see Jackson *et al.* 2020), deterioration of social ties (Philpot *et al.* 2021), mental health issues (Vindegaard & Benros 2020), and, above all, in significant loss of human lives (Mathieu *et al.* 2020).

Moreover, the empirical evidence suggests that the pandemic had a side effect on crime[2] rates (Stickle & Felson 2020). Certain crime categories, such as property crimes (see Frith *et al.* 2022), and violent crimes (see Liu *et al.* 2022), declined during this period. On the other hand, there is some evidence of an increase, for example, in crime rates of domestic violence (Piquero *et al.* 2020). However, it is notable to say that the results vary across crime categories, countries, cities, etc.

Governments around the world tried to prevent the spread of the disease by employing state regulations, including lockdowns (Mathieu *et al.* 2020). These measures have brought about significant changes, such as in daily routines (de Palma *et al.* 2022). This had a side effect in the form of a change in criminal behavior, as suggested by routine activity theory. This work aims to address the specific challenges posed by these changes.

[1] New York Times, May 26, 2020. Source: `https://www.nytimes.com/2020/05/26/us/coronavirus-crime.html`

[2] Within the framework of this thesis, the term "crime" encompasses both criminal crime and offenses. The term "criminal crime" is defined in accordance under the Criminal code of the Czech Republic No. 40/2009 Coll., §13 (Trestní zákoník), while "offenses" is defined under the Act on Liability for Misdemeanors and Proceedings on Them of the Czech Republic No. 250/2016 Coll., §5 (Zákon o odpovědnosti za přestupky a řízení o nich).

Understanding the relationship between COVID-19 and criminality is crucial for developing effective strategies to mitigate its effects on society. In the context of this study, the focus is on the Czech Republic, a country that implemented lockdown measures to combat the virus. This thesis investigates the impact of these lockdown measures on crime spillovers with an emphasis on four crime categories: Violent crimes, Property crimes, Offenses – Road Safety Department (BESIP), and Other offenses. It is worth noting that there are relatively few studies that have examined the spatial analysis of crime during COVID-19 using fixed effects. This study aims to be the first of its kind in the Czech Republic, and potentially, throughout Central and Eastern Europe, to the best of the author's knowledge.

To analyze the effects, the daily panel data are utilized, chosen to capture the short-term impacts of the lockdown policy, considering its limited duration. Lockdown measures lasted in February in several districts and nearly a month and a half in March and April for the entire country (Slabá 2022). The data on criminality in the Czech Republic comes from the criminality map by the Police of the Czech Republic. The effect of lockdown on crime is estimated with a Fixed effects (FE) model using the Ordinary least squares (OLS) estimator and a Spatial autoregressive (SAR) model, specifically the Spatial lag model with fixed effects.

The purpose of this thesis is to answer the following hypothesis:

Hypothesis #1: During the lockdown, the restricted movement across districts had a negative spillover effect on crime in the Czech Republic.

Hypothesis #2: A drop in Property crimes is more substantial than a drop in Violent crimes due to COVID-19 restrictions.

Hypothesis #3: The Spatial lag model is more suitable than (OLS) model while working with crime data.

In this study can be found evidence that crime is spatially dependent, moreover, that crime is affected by COVID-19 measures, such as lockdowns. There has been found a significant decline in all crime rates across all categories, i.e. Violent crimes, Property crimes, Offenses – BESIP, and Other offenses. Moreover, the application of a z-test revealed a significant increase in spatial effects for Offenses – BESIP during the COVID-19 period.

Chapter 2

Literature review

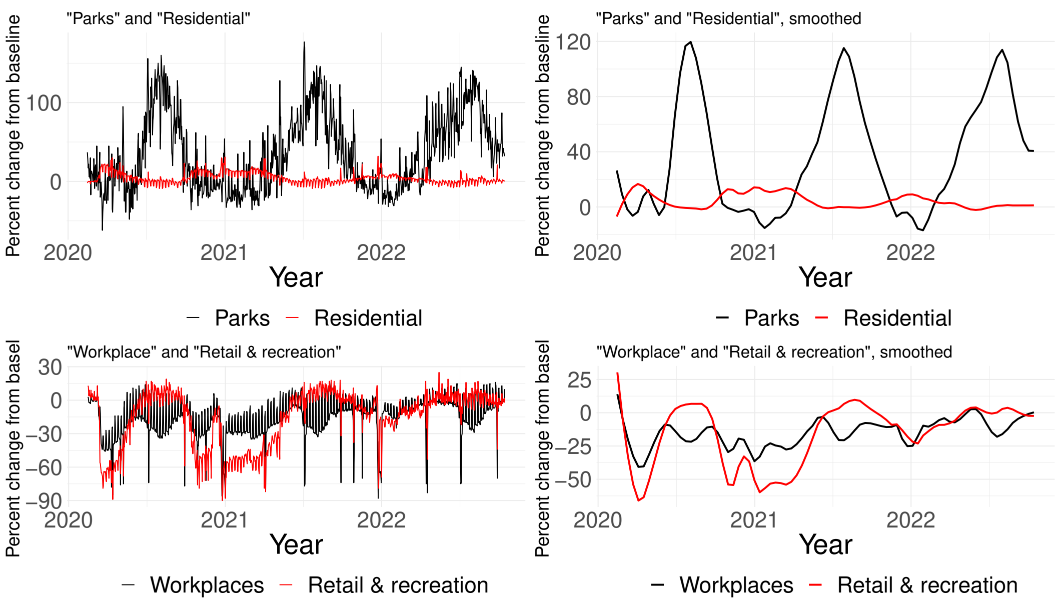
"Why are some people re-victimized frequently while others rarely are victims? Why do some places experience a lot of crime while other places experience almost none?" (Brantingham *et al.* 2017), those are examples of the main questions that criminology seeks to explain. They lead us to one of the basic hypotheses about crime that suggests crime is not random in time or space.

Numerous studies have examined the spatio-temporal analysis of crime and tried to find patterns of criminal behavior. For instance, the temporal analysis suggests that burglars tend to commit a crime at a time when a residential property is very likely to be empty, which is mostly while victims are at work. This hypothesis has been supported by studies conducted by Bates (1987) while investigating four communities in Chicago or by Nee & Taylor (2000). The spatial analysis, on the other hand, has identified the areas where criminal activity tends to be concentrated, commonly referred to as "Hot spots". According to Weisburd & Amram (2014), approximately 50% of all crime takes place in these places. Focusing police resources on these areas can lead to more effective and cost-efficient solutions to fight crime. The study of Townsley *et al.* (2015) tested between-region burglary and found that the closer the offender's home is to the victim's property, the higher chance is that he will commit a crime.

A paper conducted by Cohen & Felson (1979) first examined a theory called "routine activity theory". This theory states that an act will be committed when the three following aspects collide: the presence of probable perpetrators, the availability of feasible targets, and the lack of competent guardianship. When certain special events occur, such as the COVID-19 restrictions, that change daily routines, the collision of these factors may vary temporally and spatially.

During the COVID-19 pandemic, governments around the world implemented various regulations in an attempt to mitigate the spread of the SARS-CoV-2 virus (Cepaluni *et al.* 2022; Nivette *et al.* 2021). In the Czech Republic, the government imposed several measures including social distancing, quarantine for infected individuals and those returning from abroad, restrictions of free movement in the form of a lockdown, the closure of shops, services, and schools, the mandatory wearing of respiratory protection, etc. (Slabá 2022). According to de Palma *et al.* (2022), the COVID-19 restrictions influenced household lifestyles as well as the selection of travel routes, destinations, and departure times, among others. As can be seen in Figure 2.1, using Google Community Mobility Reports[1] in the Czech Republic, workplace, retail & recreation, mobility during the pandemic decreased, however, residential mobility and mobility in parks increased. The studies conducted by Engle *et al.* (2020) showed that regulations had a more significant effect on reducing mobility than the increase in infectious rates.

Figure 2.1: Mobility in selected categories during pandemic, daily



Source: Author's own research. Data obtained from Google LLC (2022).

[1]https://www.google.com/covid19/mobility/

Nivette *et al.* (2021) investigated the effect of stay-at-home restrictions on crime in 27 cities across 23 countries worldwide during the COVID-19 pandemic. They utilized daily crime data and applied random effects metaregression techniques to examine the relationship. Their findings revealed a significant negative effect of stay-at-home restrictions on crime, resulting in an average decline in overall criminality by 37%. Moreover, their research identified a correlation between urban mobility and the implementation of stay-at-home restrictions, shedding light on the interconnectedness of these factors. However, it is important to note that the study by Nivette *et al.* (2021) acknowledged certain limitations in their research. In particular, they highlighted the non-random sample of cities included in their analyses, which predominantly consisted of cities situated within Europe and the Americas: *"While the results presented here extend knowledge on the impact of COVID-19 restrictions on crime across international contexts, the study is not without limitations. We acknowledge that the sample of cities included in the analyses is non-random and dominated by cities situated within Europe and the Americas."*. Although their findings provide valuable insights into the impact of COVID-19 restrictions on crime across international contexts, the limited geographic representation in their study suggested the need for further research to encompass a more diverse range of cities worldwide.

Similar results can be seen in an article by Halford *et al.* (2020) which worked with daily recorded crime data in the UK to forecast the level of crime during the five-week period following the imposition of the lockdown, using an ARIMA model for time series. According to Halford *et al.* (2020), overall criminality fell by 41% within a week after the lockdown. Moreover, their study examined the mobility elasticity of crime using Google Community Mobility Reports, which allowed them to examine the relationship between crime rate change and a change in mobility.

Frith *et al.* (2022) focused on routine activity theory, the increase of households' protection, and burglary during COVID-19 restrictions in the UK, using Google Community Mobility Reports. Unlike the most current work, they used a spatio-temporal model. Like the results of Halford *et al.* (2020), they showed a significant decrease in crime due to COVID-19 policies.

In contrast to the three previous studies, Mohler *et al.* (2020) primarily worked with the daily number of calls for service in Indiana and Los Angeles. They investigated the effect of social distancing during COVID-19 on crime and they found it statistically significant. Analogously to Halford *et al.* (2020)

or Frith *et al.* (2022), they used Google mobility data due to the probability of possible delay of stay-at-home restrictions in some locations. They controlled for temporal effects as they included variables for seasonality, day of the week, and week of the month. The results indicated an impact of social distancing on specific types of crime.

Moreover, the results vary across countries, cities, and, most importantly, across crime categories. From the analysis conducted by Halford *et al.* (2020), it can be concluded that the decrease in property crimes was more significant than in violent crimes. Further, time also has a significant effect on crime. Studies by Piquero *et al.* (2020) showed some evidence of increased domestic violence in the first two weeks after stay-at-home orders were implemented in Dallas and Texas, however, a decrease after this period. Nonetheless, the effect of COVID-19 restrictions on criminality differs among studies. For example, while Nivette *et al.* (2021) reported an average decrease of 39% in crime associated with vehicle theft across cities, Mohler *et al.* (2020) observed an increase in Los Angeles. This diversity in results is consistent with a study by Ashby (2020), which identified an increase in crime in nine examined cities, with a significant increase in two of them, and a decrease in eight cities, with a significant decrease in three of them.

Table 2.1 represents the articles that used spatial effects of crime for the analysis using the Spatial autoregressive model (SAR). The majority of studies employed a Binary Contiguity matrix, and interestingly, all of them incorporated Fixed Effects (FE) in their analyses. Overall, the spatial autoregressive parameter demonstrates statistical significance across all crime categories.

Table 2.1: Articles on Spatial effects of crime using SAR

Author, Year	Country/City	Time period	Significant ρ - Crime categories	FE x RE	Matrix
Bhatia & Jason (2023)	Chicago	2014—2018	Violent, Nonviolent, Total crimes	FE	Binary Contiguity
Gökmen & Eralp (2023)	Turkiye	2014–2020	Domestic violence	FE	Binary Contiguity
Chancí *et al.* (2021)	Colombia/Bogotá	2010–2018	Violent crimes, Property crimes	FE	Distance-Based
Lauridsen *et al.* (2013)	EU-15	2000–2007	Total crimes	FE	Binary Contiguity
Puech (2004)	Brazil	1986–2002	Property crimes	FE	Binary Contiguity

Source: Author's own research.

Chapter 3

Data

This chapter focuses on selected data which are further described in more detail in individual subsections. Table 3.1 provides an overview of summary statistics of the data used in estimation, excluding the dummy variables.

Table 3.1: Summary statistics of data in the Czech Republic across all districts

Variable	Min	Mean	Median	Max	SD
Violent crimes	0	0.493	0	19	0.940
Property crimes	0	2.834	1	131	8.233
Offenses – BESIP	0	34.22	26	1923	48.938
Other offenses	0	8.011	6	214	11.143
COVID-19 infected (7 days)	0	163.9	0	44275	700.032
COVID-19 tests	0	107.8	0	30861	518.391

Notes: The data for the period from January 1, 2016 to November 30, 2022. Not recalculated per 100,000 citizens. # of observations is normalized to 194,502 and it is the same across all variables.

Variable	Min	Mean	Median	Max	SD
Violent crimes	0	0.44	0	19	0.881
Property crimes	0	2.304	1	98	6.346
Offenses – BESIP	0	29.5	23	530	34.175
Other offenses	0	7.879	6	145	10.489
COVID-19 infected (7 days)	0	401.5	112	44275	1048.563
COVID-19 tests	0	263.4	88	30861	783.75

Notes: The data for the period from March 1, 2020 to November 30, 2022. Not recalculated per 100,000 citizens. # of observations is normalized to 79,772 and it is the same across all variables.

Source: Author's own research.

3.1 Crime data

The daily panel data on criminality in the Czech Republic obtained on the Police of the Czech Republic website[1] are from January 1, 2016, to November 30, 2022. While the data are available from 2012, the period between 2012 and 2016 is deemed insufficient and unsuitable for further work. As new cases are added retroactively on a daily basis, the data has been fixed to date January 2, 2023, to ensure consistency. The database contains coordinates, date, category, subcategory, state, relevance, and ID of each criminal report. The geocoding software Nominatim[2] is used to assign the appropriate district to each set of coordinates. Subsequently, the data are then distributed to corresponding categories and subcategories according to Table 3.2. The number of crimes is normalized by population per 100,000 citizens. Given that cases often fall under multiple subcategories, duplicates are eliminated during the estimation process.

Table 3.2: Categories of crime data

Category	Subcategories
Violent crimes	Murder, Robbery, Extortion, Disorderly conduct, Fight, Intentional bodily harm, Restriction of personal freedom
Property crimes	Residential burglary, Non-residential burglary, Other property crime
Offenses – BESIP	Vehicular intoxication, Speeding, Other traffic offenses
Other offenses	Intoxication, Public-order, Against property

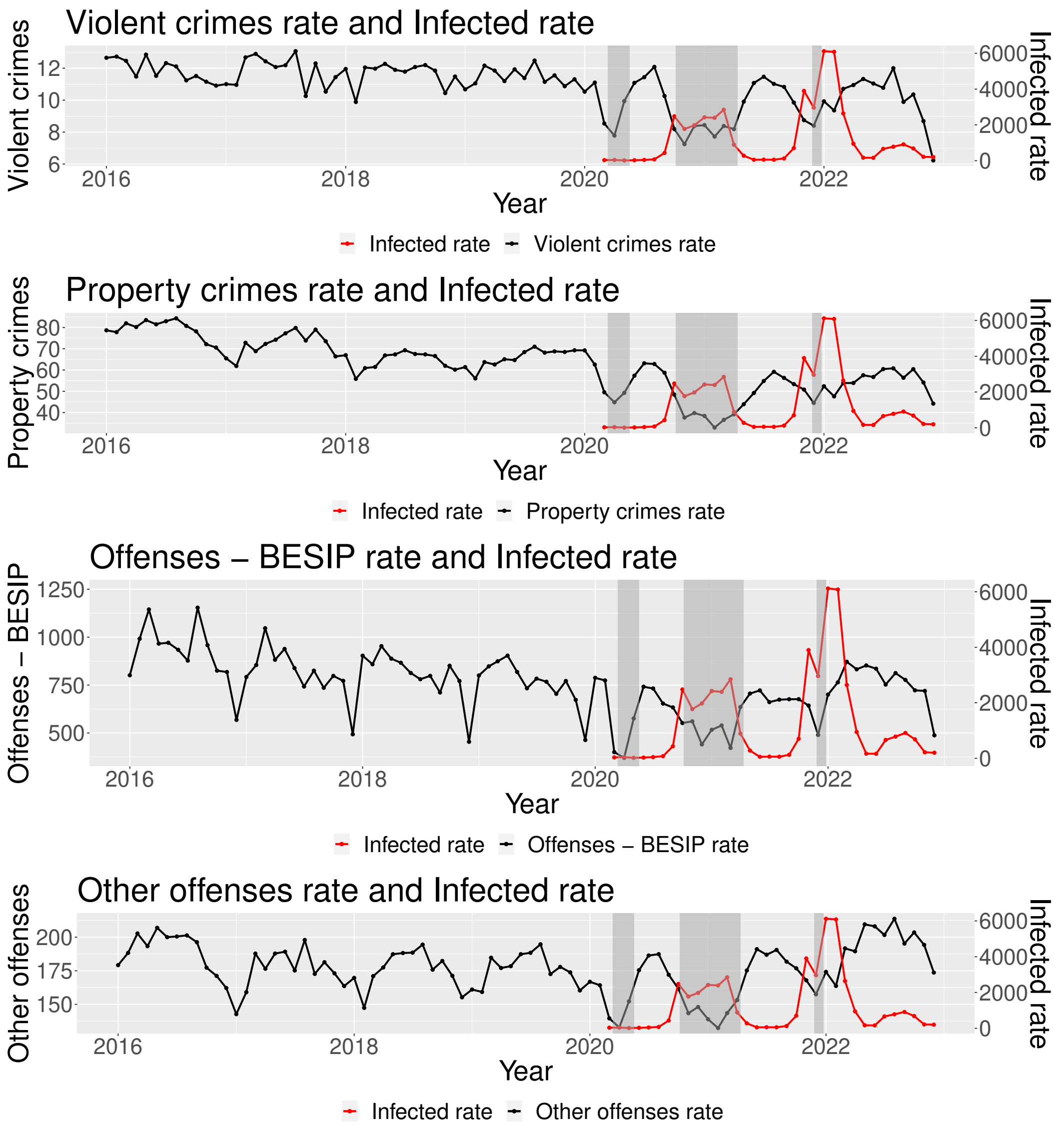
Source: Author's own research.

As can be seen in Figure 3.1, the most frequent crime category in the dataset is Offenses – BESIP, followed by Other offenses. Criminal crimes are not as prevalent as expected. Seasonality patterns can be observed across all crime categories, with the most noticeable pattern occurring around the turn of each year. Moreover, a decreasing trend is observed in Property crimes and Offenses – BESIP. Distinct fluctuations are evident in the data during the COVID-19 pandemic period. By comparing the crime rates on the first y-axis and the infected rate on the second y-axis, a relationship between the two variables becomes apparent. During the states of emergency associated with COVID-19, the infected rate increases while the crime rate decreases. Nevertheless, it is

[1]https://kriminalita.policie.cz/
[2]https://nominatim.openstreetmap.org/ui/search.html

important to highlight that the initial state of emergency, occurring between March 12, 2020, and May 17, 2020, did not exhibit a comparable magnitude of infection rates to the subsequent states of emergency. The scope of the data set is limited by the fixation of the date to January 2, 2023, and the potential for delayed reporting. Due to this rationale, December 2022 is included only in graphs, not in the estimation process.

Figure 3.1: Frequency of crime and COVID-19 in the Czech Republic, per 100,000 citizens, monthly



Source: Author's own research. Data obtained from Policie České republiky (2023) and Komenda *et al.* (2020). Dark gray zones indicate an active state of emergency.

3.2 COVID-19 data

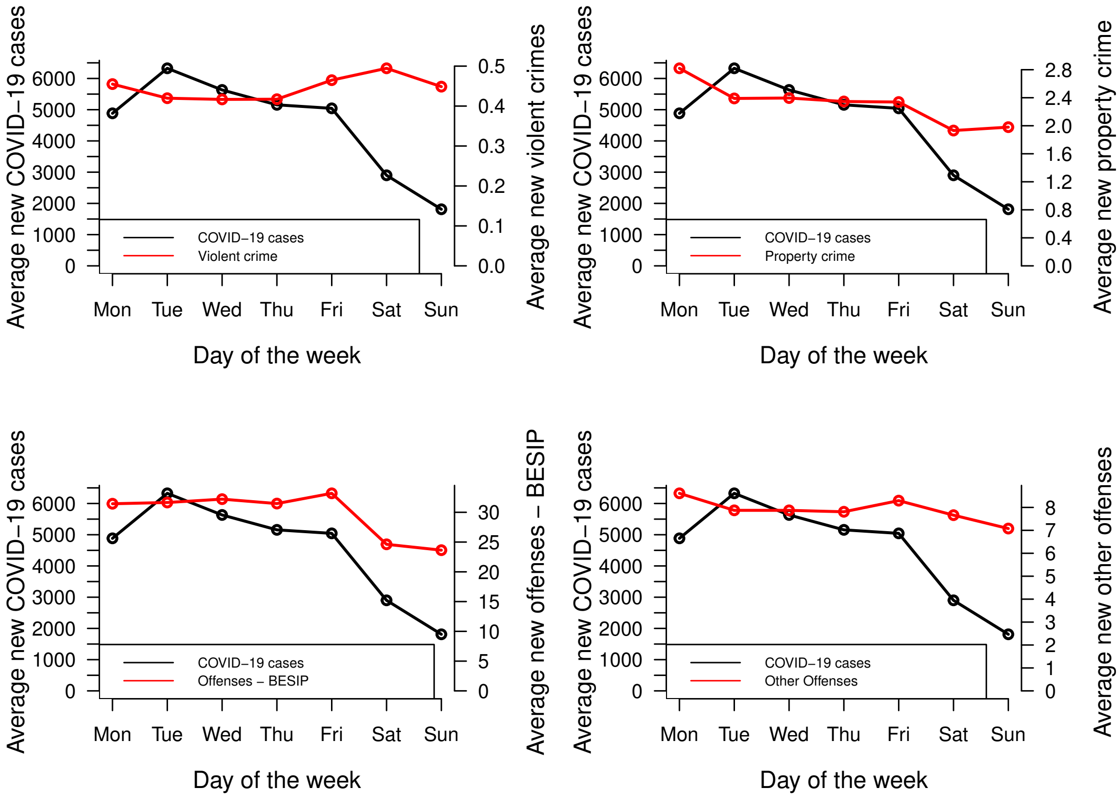
The Ministry of Health of the Czech Republic regularly updates the database regarding the COVID-19 pandemic on their websites[3] with the help of Komenda *et al.* (2020).

3.2.1 COVID-19 – infected

The daily panel data used in the model contain various factors such as day, district, 7 and 14-day incidence rates, and incidence rate per 100,000 citizens. The district's incidence rates per 100,000 citizens were recalculated using the district's population data from the Czech Statistical Office to ensure consistency with calculations of crime rates. Figure 3.2 depicts an average number of active cases every day of the week using data from March 1, 2020, to November 30, 2022, in comparison with the average number of crimes in the same period. The data reveals that a higher number of COVID-19 cases is typically reported on weekdays compared to weekends, and a similar pattern can be observed in the case of crime. A plausible explanation for both phenomena is the fact that most individuals are at work during the weekday. For example, as suggested by Bates (1987), burglars tend to operate when residential areas are unoccupied, resulting in an increase in property crimes during workdays. Furthermore, a greater presence of police officers during weekdays leads to heightened enforcement of traffic regulations and to increase in offenses related to traffic violations (BESIP). Notably, violent crimes exhibit a relatively consistent frequency throughout the week. On average, the highest number of new COVID-19 cases are confirmed on Tuesdays, while the lowest number is reported on Sundays.

[3]https://onemocneni-aktualne.mzcr.cz/api/v2/covid-19

Figure 3.2: Average new COVID-19 cases and Average new crimes, daily

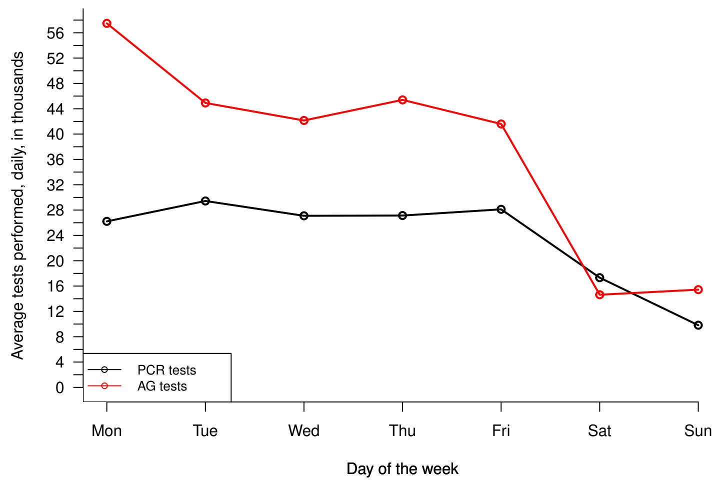


Source: Author's own research. Data for the period from March 1, 2020, to November 30, 2022. Data obtained from Policie České republiky (2023) and Komenda *et al.* (2020).

3.2.2 COVID-19 – tests performed

The second dataset regarding COVID-19 used in this study is the panel data containing incremental and cumulative daily numbers of polymerase chain reaction (PCR) tests conducted in the Czech Republic. These data are organized based on the regional and district divisions within the country. The dataset spans from August 1, 2020, to November 30, 2022, covering a substantial period relevant to the study. These data allow a deeper insight into the whole pandemic, as an increase in the number of tests corresponds to greater identification of infected individuals and consequently contributes to a reduction in mobility. Similar to incidence data, the data regarding the number of tests performed were recalculated to 100,000 citizens. The trend of new COVID-19 cases confirmation is directly proportional to the number of PCR tests and relatively proportional to the number of antigen (AG) tests performed, as can be seen in Figure 3.3.

Figure 3.3: Average tests performed, daily, in thousands



Source: Author's own research. Data for the period from June 1, 2020, to November 30, 2022. Data obtained from Komenda *et al.* (2020).

3.3 Other data

The yearly data for the **Population** of districts are collected by Czech Statistical Office[4] (Český statistický úřad). These data are used to calculate crime rates and to recalculate COVID-19 incidence rates per 100,000 citizens.

State restrictions are extracted from the article by Slabá (2022). These restrictions include the implementation of states of emergency, restrictions of free movement, the closure of educational institutions, as well as the closure and limitations of shops and services. Notably, an additional state of emergency was declared in 2022, nevertheless, its rationale was attributed to the substantial increase in immigrant arrivals, which was triggered by the ongoing conflict in Ukraine. Primary documentation for this information can be found in Resolution No. 147 of March 2, 2022, and Resolution No. 256 of March 30, 2022.

Restrictions of free movement between districts are obtained from the Resolutions of the Government. Specifically, Resolution No. 121 of February 11, 2021, and Resolution No. 134 of February 14, 2021, for the Cheb, Sokolov, and Trutnov districts, and Resolution No. 216 of February 26, 2021,

[4]https://www.czso.cz/csu/czso/pocet-obyvatel-v-obcich-k-112022

Resolution No. 299 of March 18, 2021, and Resolution No. 315 of March 26, 2021, for all districts in the Czech Republic. An overview of the selected measures can be found in Appendix A in Table A.1.

School holidays are determined annually by the Ministry of Education, Youth, and Sports through its official website[5]. These holidays encompass half term holidays, spring holidays, Easter holidays, summer holidays, autumn holidays, and Christmas holidays. It is important to note that these holidays do not adhere to a fixed date and exhibit slight variations from year to year. Half term holidays typically span 1-2 days around the transition between January and February. Spring break, lasting for one week, occurs during the months of February and March, with the order of occurrence varying among districts. The Easter holidays consistently span from Thursday to Monday during the Easter period. The summer holidays extend for a duration of two months, encompassing July and August. Autumn holidays generally last 1-2 days and are predominantly scheduled towards the end of October. Finally, the last holiday of the year is the Christmas holidays, commencing from approximately December 23rd and continuing until the second working day after New Year's Day.

Public Holidays are designated and regulated under the Public Holidays Act No. 245/2000 Coll., specifically in § 1, which addresses public holidays, and § 2, which pertains to other holidays. From 2016 to 2022, the number of annual public holidays remained constant at 13, with the potential consideration of January 1 as two distinct public holidays, resulting in a total count of 14. A detailed overview of the specific public holidays observed within this timeframe is provided in Appendix A, specifically in Table A.2.

A spatial weights matrix is constructed in R using a map of Czechia from package RCzechia. If two districts share the same border, the fact is represented in the matrix by number $\frac{1}{\textbf{\# of neighbors}}$, otherwise, if they are not adjacent, by "0". On the diagonal, the matrix has only "0" (it is considered that the district is not adjacent to itself). This row-standardized spatial weights matrix is also called the Binary Contiguity matrix.

[5]https://www.msmt.cz/

Chapter 4

Methodology

In order to find the connection between lockdown and criminality, the following steps need to be proceeded. First, the Ordinary least squares (OLS) model is introduced and used as a baseline model. Second, Moran's I test and SLM test will show which model is most efficient for dealing with crime spillovers across districts. Third, R package splm can be employed for the estimation of Spatial Panel Data Models using fixed effects. Finally, z-test can be used to determine the impact of the COVID-19 pandemic on spatial effects in the context of crime. These procedures are elaborated upon in the subsections below.

4.1 Ordinary Least Squares Model

Following Wooldridge (2015), the Ordinary least squares (OLS) model is a linear regression model which utilizes the OLS method to estimate the unknown parameters by minimizing the sum of squared residuals. The general form is:

$$\mathrm{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + u$$

In the context of this study, OLS was utilized to test for spatial autocorrelation, spatial error dependence, and for spatially lagged dependent variable. Moreover, the FE model using OLS was used to supplement the SAR model results.

4.2 Spatial panel data models

When working with spatial panel data, the following general model with a spatially lagged dependent variable should be considered (see, for example, Anselin 2003; Millo *et al.* 2012; Elhorst 2010):

$$y_{i,t} = \rho W y_{i,t} + x_{i,t}\beta + \mu_i + \epsilon_{i,t}$$

where i, $i \in (1, ..., N)$ is the index of cross-sectional dimension, t, $t \in (1, ..., T)$ denotes the time dimension, y represents the dependent variable, W is a spatial weights matrix of order N, ρ is the spatial parameter, $x_{i,t}$ denotes a matrix of observations on the independent variables with dimensions $(NT \times k)$, β is the corresponding parameter for independent variables, μ_i stands for a spatial-specific effect, and $\epsilon_{i,t}$ is independent and identically distributed error term such that $\epsilon_{i,t} \sim (0, \sigma_\epsilon^2)$.

In order to estimate the spatial panel model, the FE or the Random effects (RE) model can be used. In the FE model for each spatial unit, there is a dummy variable. On the other hand, the RE model considers the spatial-specific effect μ_i as an independent and identically distributed random variable with $\sim (0, \sigma_\mu^2)$. Moreover, it should be noted that μ_i and $\epsilon_{i,t}$ are assumed to be independent.

In this paper, the RE model is not used. This decision is based on the presumption that fixed effects are expected to be present across districts, rather than random effects. Furthermore, prior research within the field has not utilized random effects, as indicated in Table 2.1 in Chapter 2. By not incorporating random effects, the presence of unobserved individual-specific or time-specific effects is not assumed. Instead, the focus is primarily on the fixed effects and other factors that are considered in the research.

The estimates can be obtained by maximizing the log-likelihood function that looks for FE spatial lag model as follow:

$$LogL = \frac{-NT}{2} log(2\pi\sigma_\epsilon^2) + T log\,|I - \rho W| - \frac{NT}{2\sigma_\epsilon^2} e'e$$

where I is an identity matrix of order N.

4.2.1 Moran's I test

Moran's I test is commonly employed to examine spatial autocorrelation, which investigates the presence of similarity among neighboring locations, specifically in the case of this study, among neighboring districts. In R, the spdep library can be utilized for conducting this analysis. The spdep library, developed by Bivand & Wong (2018), builds upon the work of Cliff and Ord (1981). The formula for the Moran's I test, proposed by Anselin (2003) based on the work of Cliff and Ord (1981), can be expressed as follows:

$$I = \frac{N}{S_0} \cdot \frac{e'We}{e'e}$$

where e is a vector of OLS residuals, $S_0 = \sum_i \sum_j w_{ij}$, a standardization factor equivalent to the sum of weights for the nonzero cross-products.

4.2.2 SLM test

SLM test is used to check for spatial error dependence and for spatially lagged dependent variable, in other words, if the SAR model or Spatial error model (SEM) can be utilized. Following Anselin (2003), the test for spatial error dependence is calculated using this formula:

$$LM_{err} = \frac{d_{err}^2}{T} = \frac{(\frac{e'We}{\frac{e'e}{N}})^2}{tr(W^2+W'W)} \sim \chi^2(1)$$

And for spatially lagged dependent variable:

$$LM_{lag} = \frac{d_{lag}^2}{D} = \frac{(\frac{e'Wy}{\frac{e'e}{N}})^2}{\frac{(WX\beta)'(I-X(X'X)^{-1}X')(WX\beta)}{\sigma_\epsilon^2}+tr(W^2+W'W)} \sim \chi^2(1)$$

where e is a vector of OLS residuals. Several parameters are introduced as in the presentation by Anselin (2017).

However, in LM_{err} the null hypothesis is rejected if the lag model is present, on the other hand, in LM_{lag} the null hypothesis is rejected if the error model is present. Therefore, using robust forms of those tests, these problems can be avoided because of an asymptotic adjustment. The robust version takes the form:

$$LM_{err}^* = \frac{(d_{err}-\frac{T}{D}d_{lag})^2}{T(1-TD)} \sim \chi^2(1)$$
$$\mathrm{LM}_{lag}^* = \frac{(d_{lag}-d_{err})^2}{D-T} \sim \chi^2(1)$$

The objective of employing this test is to assess the suitability of utilizing the SAR model. This is crucial as the primary objective of this study is to address how the dependent variable $\mathrm{y}_{i,t}$ ($\mathrm{crime}_{d,i}$) spreads across space. In other words, it examines whether there is a spatial dependence in the data and how it affects the dependent variable. This particular question cannot be effectively addressed through the application of the SEM, as it answers how the spatial dependence in the error term affects the estimated coefficients and model performance.

4.3 Z-test

In order to examine the significance of the difference between the two regression coefficients, a z-test can be utilized. The interest of this thesis is in the difference in regression coefficients between the two periods. The first period corresponds to the duration of the COVID-19 pandemic, specifically spanning from March 1, 2020, to November 30, 2022. The second period encompasses the entire time frame from January 1, 2016, to November 30, 2022. The purpose of this test is to determine the impact of the COVID-19 pandemic on spatial effects in the context of crime. Following Paternoster *et al.* (1998), the z-test can be expressed as:

$$z = \frac{\rho_1 - \rho_2}{\sqrt{SE(\rho_1) + SE(\rho_2)}}$$

where ρ_1 is the spatial parameter for the COVID-19 period and ρ_2 is the spatial parameter for the whole period. Additionally, in accordance with the specifications presented by Paternoster *et al.* (1998), the estimate of the standard deviation of the sampling distribution in this formula is unbiased.

4.4 Model description

The following Spatial panel data model is estimated:

$$\begin{aligned}\text{Crime}_{d,i} = {} & \rho \cdot W \cdot \text{Crime}_{d,i} + \beta_1 \cdot \text{Infected}_{d,i} + \beta_2 \cdot \text{Tests}_{d,i} \\ & + \beta_3 \cdot \text{Infected} \cdot \text{Tests}_{d,i} + \beta_4 \cdot \text{Lockdown}_{d,i} + \beta_5 \cdot \text{Controls}_d \\ & + \beta_6 \cdot \text{Public\_holiday}_d + \beta_7 \cdot \text{School\_holiday}_d \\ & + \beta_{10} \cdot \text{Time\_fixed\_effects}_d + u_{d,i}\end{aligned}$$

where the dependent variable is $\text{Crime}_{d,i}$, representing the crime rate of a specific category in a given district for 100,000 citizens. W is a row-standardized spatial weights matrix for districts wherein the sum of values in each row equals one. The variables $\text{Infected}_{d,i}$ and $\text{Tests}_{d,i}$ represent the rates of people infected with COVID-19 and tests performed, respectively, both recalculated per 100,000 citizens in the district. $\text{Lockdown}_{d,i}$ is a dummy variable that equals “1” during restrictions of free movement between districts and “0” on the contrary. Controls_d encompasses a set of variables, namely: $\text{State\_of\_emergency}_{d,i}$, Schools_d, Shops_services_d, and $\text{Restriction\_of\_free\_movement}_d$. In each model, one of those variables is employed. The binary variable $\text{State\_of\_emergency}_{d,i}$ takes the value of “1” when a state of emergency is active due to the COVID-19 pandemic and “0” otherwise. Two dummy variables, Schools_d and Shops_services_d, are used to indicate whether schools, shops, and services were closed due to COVID-19. They equal "1" when closures are in effect and "0" contrarily. In contrast to variable Lockdown$_{d,i}$, Restriction_of_free_movement$_d$ is a more comprehensive variable, encompassing measures such as night curfews and limitations on movement beyond a certain distance from one's residence without valid justification. Two additional dummy variables, School_holiday$_{d,i}$, and Public_holiday$_d$, indicate the presence of any holidays in the district for schools or the general public, respectively. They equal "1" when holidays occur and "0" in another way. The model incorporates time-fixed effects, referred to as Time_fixed_effects$_d$ which includes a year, a month, and a weekday. The inclusion of these particular time-fixed effects is motivated by the observed seasonality in the data during weekdays. It is important to note that the same model was estimated using OLS but without the inclusion of $\rho \cdot W \cdot \text{Crime}_{d,i}$ term. Indexes of variables are d which stands for day and i representing district. For a more detailed description of the data, please refer to Chapter 3.

A significant proportion of crime values are equal to zero. For Property crimes, the ratio of zero values in the dataset is 30.58%, while for violent crimes is 67.17%. However, when considering the objective of identifying crime spillover in the Czech Republic, the utilization of alternative models such as Poisson regression may not be necessary, as was the case of Ranson (2014). Ranson focused on crime, weather, and climate change, demonstrated the suitability of Poisson regression when dealing with a high proportion of zero values in the dependent variable. However, the number of zero values in this research does not reach the levels observed in Ranson (2014), making a Spatial lag model with fixed effects a more suitable choice. This modeling approach allows to effectively capture the spatial dependence and explore the dynamics of crime spillover across districts within the Czech Republic, aligning closely with research objectives.

Chapter 5

Limitations of empirical methods

In this thesis, several limitations should be considered:

1. The crime data obtained from the Police of the Czech Republic website may encounter issues with particular subcategories of property crimes due to the possibility of delayed reports. For instance, during the district closure, people were not required to travel to their vacation homes, therefore, only after the end of the lockdown, they discovered that their property had been burglarized. Hence, the crime reports of those cases may be delayed. Moreover, the data do not consider that the act depicted as a crime did not happen or is not a crime based on information obtained during criminal proceedings or from the conclusion of the public prosecutor.

2. The available data pertaining to PCR testing for COVID-19 in the Czech Republic lacks the information from the initial period of PCR testing at the district level, specifically from January 27, 2020. Instead, the data encompass only the period starting from August 1, 2020. Before this date, there is a risk of incompleteness of these individual data. Therefore, the Ministry of Health relies only on aggregated data in that period, which, however, do not allow more complex analytical calculations.

3. Another potential factor that could impact the research is weather conditions. The fluctuation in temperature has been found to be associated not only with the transmission of COVID-19 but also with variations in crime rates. As stated by Mecenas et al. (2020), the spread of COVID-19 tends to worsen in climates with higher temperatures and humidity levels. Additionally, Mišák (2022), examined data from the Czech Re-

public and revealed an association between rising temperatures and an escalation in assault, theft, and sexual crime rates. Consequently, these findings imply that changes in weather patterns may potentially act as a confounding variable in the study, complicating the determination of the precise factors influencing the observed crime rates during the COVID-19 pandemic. However, it is important to acknowledge that this research focuses primarily on the interaction between COVID-19 restrictions and crime trends and further investigation would be required to disentangle the connection between weather conditions, COVID-19, and crime rates.

4. According to a study by Ceccato and Haining (2004), that focused on crime between Sweden and Denmark after building the Oresund Bridge, cross-border crime can have a significant impact on certain crime categories in border regions. However, this bachelor's thesis works only with the capital city of Prague and 76 districts in the Czech Republic but does not include foreign districts. Consequently, this indicates an absence of cross-border crime manifestation in the obtained results.

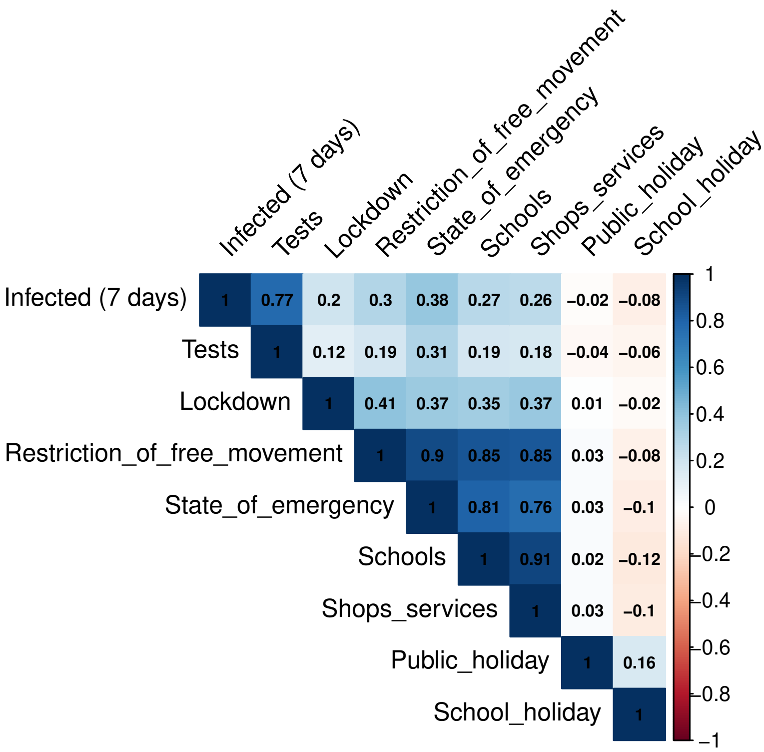
Despite the presence of limitations and difficulties, the data and methodology used in this study should be sufficient for an estimation relationship between crime and the COVID-19 lockdown in Czechia.

Chapter 6

Results

The findings presented in this chapter summarize and interpret the regression results that investigate the relationship between crime and the COVID-19 pandemic in the Czech Republic, using the methods described in Chapter 4. The findings focus on four crime categories – Violent crimes, Property crimes, Offenses – BESIP, and Other offenses. The same econometric approaches, namely the FE model using the OLS estimator and the Spatial lag model with fixed effects, were applied to all crime categories. The analysis employs four distinct models. In Model (1), the variable "Restriction_of_free_movement" is incorporated as a control. Model (2) includes the variable "State_of_emergency", while Model (3) takes into account the variable "Schools", and Model (4) considers the variable "Shops_services". The correlation table of each independent variable is presented in Figure 6.1. It is observed that the COVID-19-related dummy variables exhibit notable correlations among themselves. Moreover, the same pattern can be seen among the number of infected cases and tests performed. However, it can be argued that the issue of multicollinearity is not present in the "Infected" and "Tests" due to the absence of "Tests" data from March 1, 2020, to July 31, 2020. When correlations are examined solely from August 1, 2020, onwards, the obtained correlation value of 0.686 is smaller than the value presented in the correlation table. Additionally, during the initial pandemic period, starting from March 1, 2020, the number of infected cases was relatively low despite the remarkable number of tests being conducted. To mitigate the issue of multicollinearity arising from these correlated variables, the analysis employs four separate models.

Figure 6.1: Correlation table



Source: Author's own research.

6.0.1 Tests

Table 6.1 presents the results of Moran's I test applied to OLS residuals. With the exception of Other offenses, the p-values for all crime categories are statistically significant, leading to the rejection of the null hypothesis. This indicates a spatial autocorrelation, suggesting that similar high and low values within the dataset are more spatially clustered. In other words, regions with high crime rates tend to be surrounded by other regions with high crime rates, and vice versa. However, in the case of Other offenses, the p-value does not provide substantial evidence to support the rejection of the null hypothesis. Therefore, definitive conclusions cannot be drawn for this specific category. The results of Moran's I test may be influenced by the heterogeneity of crime data, as it encompasses various subcategories with different spatial patterns. This is evident in cases such as the Other offenses category which includes all offenses that did not fit into other categories. Another possibility is the scarcity of crime data, like for Violent crimes, as their occurrence is less common. Consequently, the category Other offenses represents the least important category among all. The findings are consistent with the study conducted by Chancí *et al.* (2021), which identified spatial autocorrelation in certain subcategories of criminal crimes.

Table 6.1: Results of Moran's I test

Violent crimes	0.015
(p-value)	(<0.001)
Property crimes	0.008
(p-value)	(<0.001)
BESIP	0.064
(p-value)	(<0.001)
Other offenses	−0.013
(p-value)	(1)

Source: Author's own research. Based on regression with modified variable "Lockdown" without the period from March 27, 2021, to April 11, 2021 and with all control variables.

Table 6.2 contains the results of SLM tests to check for spatial error dependence and spatially lagged dependent variable applied on OLS regression. Their robust form can be found in Appendix A in Table A.3. The obtained results demonstrate consistency in terms of the classical SLM tests, with all crime categories exhibiting p-values below 0.05. This indicates that OLS estimation is insufficient for these models which confirms hypothesis #3. The robust SLM tests do not reveal any new information while implementing spatial models as there is not possible to reject any null hypothesis. However, it remains unclear which specific model, either SAR or SEM, would be more appropriate for this analysis as their results are not one-sided. In this study, the SAR model was used, as it can answer the main research question, which is how dependent variable "crime" spreads across space.

Table 6.2: Results of SLM tests

	LMlag	LMerr
Violent crimes	25.393	25.544
(p-value)	(<0.001)	(<0.001)
Property crimes	95.276	99.343
(p-value)	(<0.001)	(<0.001)
Offenses – BESIP	1854.547	1829.048
(p-value)	(<0.001)	(<0.001)
Other offenses	72.073	72.575
(p-value)	(<0.001)	(<0.001)

Source: Author's own research. Based on regression with modified variable "Lockdown" without the period from March 27, 2021 to April 11, 2021 and with all control variables.

6.0.2 Main results

The results of the estimated effect of COVID-19 are summarized in Figure 6.2, and Figure A.1 graphically and in Table 6.3, Table 6.5, Table 6.7, Table 6.9 numerically for OLS and in Table 6.4, Table 6.6, Table 6.8, and Table 6.10 for SAR, respectively. These results suggest that the COVID-19 pandemic had a negative impact on crime rates.

Each table provides the results of fixed effects regressions conducted for a specific crime category using four different models with different control variables, either for the Spatial lag model or the Fixed effects (FE) model using the OLS estimator.

Table 6.3 and Table 6.4 presents the specific outcomes of Violent crimes. All SAR regressions reveal that the spatial parameter ρ is positive and statistically significant. The estimated values are 0.017 for all models, indicating the presence of spatial dependence in the data. The variable "Lockdown" suggests that the implementation of lockdown measures has a detrimental impact on Violent crimes. However, the coefficient for this variable is not statistically significant in all four models. Conversely, the variable "Restriction_of_free_movement" is statistically significant at a 99% confidence level and exhibits a negative effect in the model (1). This variable encompasses limitations on movement between districts, including the enforcement of nighttime curfews. The estimation results demonstrate that "Restriction_of_free_movement" represents a more stringent constraint compared to simply restricting movement between districts as it is in the case of "Lockdown". "Infected" exhibits a negative and statistically significant effect across all models. On the other hand, "Tests" is statistically insignificant with varying directional changes. Moreover, the interaction between variables "Infected" and "Tests" exhibits statistical insignificance at a 95% confidence level across all models as well. Despite these discrepancies, the joint effect of both variables remains, on average, negative. Variables "State_of_emergency", "Schools", "Shops_services" have all negative and statistically significant effects. Nevertheless, considering all variables linked to the pandemic, the overall impact of COVID-19 is negative. R^2 is low with a value around 0.008 for OLS and 0.057 for SAR. In contrast to the findings of Campedelli *et al.* (2021) and Ashby (2020), which did not observe significant effects on specific subcategories of violent crimes, this present study aligns more closely with the works of Halford *et al.* (2020) and Nivette *et al.* (2021) due to the evidence indicating a significant decrease in violent crimes due to the impact of COVID-19.

Table 6.3: Results of Violent crimes using FE model with OLS estimator

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Infected (7 days)	-0.00004^{***}	-0.00003^{***}	-0.00004^{***}	-0.00004^{***}
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Tests	0.00006	0.00002	-0.000005	-0.00001
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Infected (7 days) * Tests	0.00000001	0.000000003	0.00000002	0.00000002^{**}
	(0.00000001)	(0.00000001)	(0.00000001)	(0.00000001)
Lockdown	-0.004	-0.008	-0.015	-0.014
	(0.013)	(0.013)	(0.013)	(0.013)
Restriction_of_free_movement	-0.069^{***}			
	(0.007)			
State_of_emergency		-0.077^{***}		
		(0.006)		
Schools			-0.070^{***}	
			(0.006)	
Shops_services				-0.076^{***}
				(0.006)
Public_holiday	0.020^{**}	0.020^{**}	0.018^{**}	0.019^{**}
	(0.008)	(0.008)	(0.008)	(0.008)
School_holiday	0.016^{***}	0.014^{**}	0.015^{***}	0.017^{***}
	(0.005)	(0.005)	(0.005)	(0.005)
N - # of observations	194,502	194,502	194,502	194,502
Y, M, W	Y	Y	Y	Y
R^2	0.008	0.008	0.008	0.008

Notes: For each column, an individual regression was made. *** significant at the 1%; ** 5%; * 10%. Variables Infected, Tests, and dependent variable are recalculated per 100,000 citizens. The rest are dummy variables. *Source:* Author's own research.

Table 6.4: Results of Violent crimes using Spatial lag model with fixed effects

	(1) SAR	(2) SAR	(3) SAR	(4) SAR
Infected (7 days)	−0.00004***	−0.00003***	−0.00004***	−0.00004***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Tests	0.000005	0.00002	−0.000005	−0.00001
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Infected (7 days) * Tests	0.00000001	0.000000003	0.00000002	0.00000002*
	(0.00000001)	(0.00000001)	(0.00000001)	(0.00000001)
Lockdown	−0.004	−0.008	−0.014	−0.014
	(0.013)	(0.013)	(0.013)	(0.013)
Restriction_of_free_movement	−0.067***			
	(0.007)			
State_of_emergency		−0.075***		
		(0.007)		
Schools			−0.069***	
			(0.006)	
Shops_services				−0.075***
				(0.006)
Public_holiday	0.019**	0.020**	0.018**	0.019**
	(0.008)	(0.008)	(0.008)	(0.008)
School_holiday	0.016***	0.014**	0.015***	0.017***
	(0.005)	(0.005)	(0.005)	(0.005)
N - # of observations	194,502	194,502	194,502	194,502
Y, M, W	Y	Y	Y	Y
ρ (SAR coefficient)	0.017***	0.017***	0.017***	0.017***
	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.043	0.043	0.043	0.043

Notes: For each column, an individual regression was made. *** significant at the 1%; ** 5%; * 10%. Variables Infected, Tests, and dependent variable are recalculated per 100,000 citizens. The rest are dummy variables. *Source:* Author's own research.

The results of Property crimes depicted in Table 6.5 and Table 6.6 exhibit resemblances to the findings related to Violent crimes. The difference is in the variables "Public_holiday" and "School_holiday" which exhibit negative effects across all models. Moreover, variables "Infected" and "Tests" exhibit contrary effects and significance than in Violent crimes. The variable "Infected" is significant only in models (2) and (3) and the interaction variable is only in model (4). The impacts observed are generally more pronounced than those observed for Violent crimes. These results serve to validate the initial hypothesis #2 and align with the findings of Halford *et al.* (2020). Additionally, the investigation conducted by Mohler *et al.* (2020) and Frith *et al.* (2022), among other relevant studies, demonstrates a significant decrease in certain subcategories of property crimes during the COVID-19 period. These findings align consistently with the results obtained in this study. The spatial parameter ρ is statistically significant and positive with values 0.021 for models (1) and (2), 0.019 for (3), and 0.020 for model (4). R^2 is higher with a value around 0.057 for OLS and 0.339 for SAR.

Table 6.5: Results of Property crimes using FE model with OLS estimator

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Infected (7 days)	0.00003	0.00005**	0.00005**	0.00002
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Tests	−0.0002***	−0.0001***	−0.0003***	−0.0003***
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Infected (7 days) * Tests	0.00000003	0.000000003	0.00000003	0.00000006***
	(0.00000002)	(0.00000002)	(0.00000002)	(0.00000002)
Lockdown	−0.022	−0.061**	−0.058**	−0.073***
	(0.027)	(0.026)	(0.026)	(0.026)
Restriction_of_free_movement	−0.275***			
	(0.013)			
State_of_emergency		−0.259***		
		(0.013)		
Schools			−0.295***	
			(0.012)	
Shops_services				−0.279***
				(0.013)
Public_holiday	−0.392***	−0.390***	−0.396***	−0.394***
	(0.016)	(0.016)	(0.016)	(0.016)
School_holiday	−0.031***	−0.040***	−0.037***	−0.028**
	(0.011)	(0.011)	(0.011)	(0.011)
N - # of observations	194,502	194,502	194,502	194,502
Y, M, W	Y	Y	Y	Y
R^2	0.057	0.057	0.058	0.057

Notes: For each column, an individual regression was made. *** significant at the 1%; ** 5%; * 10%. Variables Infected, Tests, and dependent variable are recalculated per 100,000 citizens. The rest are dummy variables. *Source:* Author's own research.

Table 6.6: Results of Property crimes using Spatial lag model with fixed effects

	(1) SAR	(2) SAR	(3) SAR	(4) SAR
Infected (7 days)	0.00003	0.00005^{**}	0.00005^{**}	0.00002
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Tests	-0.0002^{***}	-0.0001^{***}	-0.0002^{***}	-0.0003^{***}
	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Infected (7 days) * Tests	0.00000003	0.000000002	0.00000003	0.00000006^{***}
	(0.00000002)	(0.00000002)	(0.00000002)	(0.00000002)
Lockdown	−0.022	-0.060^{**}	-0.057^{**}	-0.072^{***}
	(0.027)	(0.026)	(0.026)	(0.026)
Restriction_of_free_movement	-0.269^{***}			
	(0.013)			
State_of_emergency		-0.253^{***}		
		(0.013)		
Schools			-0.290^{***}	
			(0.012)	
Shops_services				-0.273^{***}
				(0.013)
Public_holiday	-0.383^{***}	-0.381^{***}	-0.389^{***}	-0.386^{***}
	(0.016)	(0.016)	(0.016)	(0.016)
School_holiday	-0.031^{***}	-0.039^{***}	-0.036^{***}	-0.027^{**}
	(0.011)	(0.011)	(0.011)	(0.011)
N - # of observations	194,502	194,502	194,502	194,502
Y, M, W	Y	Y	Y	Y
ρ (SAR coefficient)	0.021^{***}	0.021^{***}	0.019^{***}	0.020^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.339	0.339	0.340	0.339

Notes: For each column, an individual regression was made. *** significant at the 1%; ** 5%; * 10%. Variables Infected, Tests, and dependent variable are recalculated per 100,000 citizens. The rest are dummy variables. *Source:* Author's own research.

Offenses – BESIP in Table 6.7 and Table 6.8 exhibits similarities with findings from other categories. All COVID-19-related dummy variables within this crime category also reveal a negative effect on crime. In contrast to criminal crimes, the variables within the offenses categories demonstrate an increased frequency of significance. Similarly to Property crimes, the variable "Infected" is positive. The spatial parameter ρ is statistically significant and positive with values 0.352 for (1) and (3), 0.351 for (2), and 0.353 for (4). R^2 attains values around 0.172 for OLS and 0.352 for SAR. Comparable findings could be seen in the study conducted by Mohler *et al.* (2020), wherein a reduction in traffic stops was observed, likely attributed to both the decline in overall traffic volume and the mandatory decrease in social interactions. Table 6.9 and Table 6.10 subsequently present the results of Other offenses. Within this crime category, the spatial parameter ρ is statistically significant and positive, with values of 0.050 for both (1), (2), and 0.051 for (3) and (4). In the context of OLS and SAR models, the coefficient of determination, R^2, exhibits values approximately at 0.051 and 0.261, respectively.

Table 6.7: Results of Offenses – BESIP using FE model with OLS estimator

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Infected (7 days)	0.001***	0.002***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Tests	0.0005	0.002***	−0.0005	−0.002***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Infected (7 days) * Tests	−0.000002***	−0.000003***	−0.000002***	−0.000001***
	(0.0000002)	(0.0000002)	(0.0000002)	(0.0000002)
Lockdown	−5.152***	−6.372***	−6.543***	−6.379***
	(0.262)	(0.257)	(0.254)	(0.254)
Restriction_of_free_movement	−7.161***			
	(0.132)			
State_of_emergency		−6.385***		
		(0.130)		
Schools			−6.731***	
			(0.123)	
Shops_services				−7.530***
				(0.125)
Public_holiday	−3.309***	−3.266***	−3.428***	−3.374***
	(0.159)	(0.159)	(0.159)	(0.159)
School_holiday	−2.636***	−2.851***	−2.760***	−2.539***
	(0.110)	(0.110)	(0.110)	(0.110)
N - # of observations	194,502	194,502	194,502	194,502
Y, M, W	Y	Y	Y	Y
R^2	0.172	0.170	0.172	0.175

Notes: For each column, an individual regression was made. *** significant at the 1%; ** 5%; * 10%. Variables Infected, Tests, and dependent variable are recalculated per 100,000 citizens. The rest are dummy variables. *Source:* Author's own research.

Table 6.8: Results of Offenses – BESIP using Spatial lag model with fixed effects

	(1) SAR	(2) SAR	(3) SAR	(4) SAR
Infected (7 days)	0.001***	0.001***	0.001***	0.0009***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Tests	0.0001	0.001***	−0.0007**	−0.001***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Infected (7 days) * Tests	−0.000002***	−0.000002***	−0.000001***	−0.000001***
	(0.0000002)	(0.0000002)	(0.0000002)	(0.0000002)
Lockdown	−4.229***	−5.182***	−5.317***	−5.209***
	(0.258)	(0.254)	(0.251)	(0.251)
Restriction_of_free_movement	−5.658***			
	(0.132)			
State_of_emergency		−5.003***		
		(0.130)		
Schools			−5.346***	
			(0.123)	
Shops_services				−6.021***
				(0.125)
Public_holiday	−2.604***	−2.558***	−2.699***	−2.672***
	(0.157)	(0.157)	(0.157)	(0.157)
School_holiday	−2.183***	−2.343***	−2.282***	−2.116***
	(0.108)	(0.108)	(0.108)	(0.108)
N - # of observations	194,502	194,502	194,502	194,502
Y, M, W	Y	Y	Y	Y
ρ (SAR coefficient)	0.201***	0.205***	0.201***	0.197***
	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.352	0.351	0.352	0.353

Notes: For each column, an individual regression was made. *** significant at the 1%; ** 5%; * 10%. Variables Infected, Tests, and dependent variable are recalculated per 100,000 citizens. The rest are dummy variables. *Source:* Author's own research.

Table 6.9: Results of Other offenses using FE model with OLS estimator

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Infected (7 days)	-0.0003^{***}	-0.0003^{***}	-0.0003^{***}	-0.0003^{***}
	(0.00005)	(0.00005)	(0.00005)	(0.00005)
Tests	0.0006^{***}	0.0008^{***}	0.0005^{***}	0.0005^{***}
	(0.00008)	(0.00008)	(0.00008)	(0.00008)
Infected (7 days) * Tests	-0.0000002^{***}	-0.0000002^{***}	-0.0000001^{***}	-0.00000008
	(0.00000005)	(0.00000005)	(0.00000005)	(0.00000005)
Lockdown	-0.052	-0.144^{**}	-0.151^{***}	-0.155^{***}
	(0.059)	(0.058)	(0.057)	(0.057)
Restriction_of_free_movement	-0.664^{***}			
	(0.030)			
State_of_emergency		-0.634^{***}		
		(0.029)		
Schools			-0.689^{***}	
			(0.028)	
Shops_services				-0.723^{***}
				(0.028)
Public_holiday	-0.725^{***}	-0.720^{***}	-0.737^{***}	-0.731^{***}
	(0.036)	(0.036)	(0.036)	(0.036)
School_holiday	-0.125^{***}	-0.146^{***}	-0.138^{***}	-0.116^{***}
	(0.025)	(0.025)	(0.025)	(0.025)
N - # of observations	194,502	194,502	194,502	194,502
Y, M, W	Y	Y	Y	Y
R^2	0.050	0.050	0.051	0.051

Notes: For each column, an individual regression was made. *** significant at the 1%; ** 5%; * 10%. Variables Infected, Tests, and dependent variable are recalculated per 100,000 citizens. The rest are dummy variables. *Source:* Author's own research.

Table 6.10: Results of Other offenses using Spatial lag model with fixed effects

	(1) SAR	(2) SAR	(3) SAR	(4) SAR
Infected (7 days)	-0.0003^{***}	-0.0003^{***}	-0.0003^{***}	-0.0003^{***}
	(0.00005)	(0.00005)	(0.00005)	(0.00005)
Tests	0.0006^{***}	0.0008^{***}	0.0005^{***}	0.0004^{***}
	(0.00008)	(0.00008)	(0.00008)	(0.00008)
Infected (7 days) * Tests	-0.0000001^{***}	-0.0000002^{***}	-0.0000001^{**}	-0.00000007
	(0.00000005)	(0.00000005)	(0.00000005)	(0.00000005)
Lockdown	-0.051	-0.137^{**}	-0.145^{**}	-0.149^{***}
	(0.059)	(0.058)	(0.057)	(0.057)
Restriction_of_free_movement	-0.629^{***}			
	(0.030)			
State_of_emergency		-0.601^{***}		
		(0.029)		
Schools			-0.653^{***}	
			(0.028)	
Shops_services				-0.685^{***}
				(0.028)
Public_holiday	-0.685^{***}	-0.680^{***}	-0.697^{***}	-0.692^{***}
	(0.036)	(0.036)	(0.036)	(0.036)
School_holiday	-0.121^{***}	-0.141^{***}	-0.133^{***}	-0.113^{***}
	(0.025)	(0.025)	(0.025)	(0.025)
N - # of observations	194,502	194,502	194,502	194,502
Y, M, W	Y	Y	Y	Y
ρ (SAR coefficient)	0.052^{***}	0.052^{***}	0.051^{***}	0.050^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.261	0.261	0.261	0.262

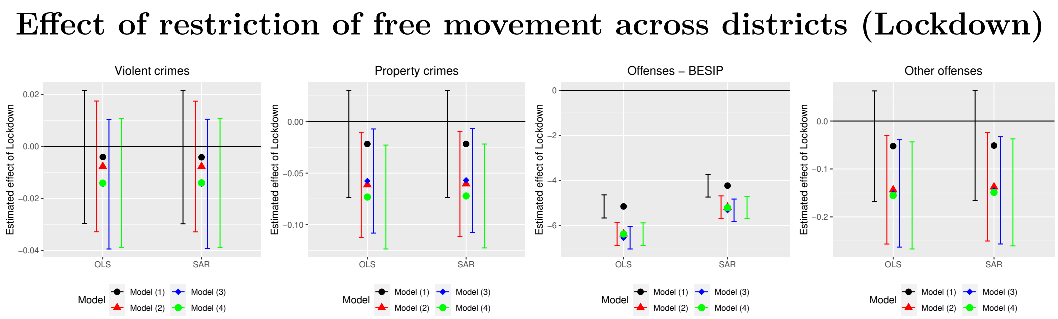
Notes: For each column, an individual regression was made. *** significant at the 1%; ** 5%; * 10%. Variables Infected, Tests, and dependent variable are recalculated per 100,000 citizens. The rest are dummy variables. *Source:* Author's own research.

Figure 6.2 shows a comparison of selected variables between each crime category for all models. Additional variables can be found in Appendix A, specifically in Figure A.1. Notably, the variable "Lockdown" exhibits a consistently negative relationship with crime rates across all crime categories and all models. This relationship is statistically significant for Property crimes and all offenses. The magnitude of the coefficient reflects the number of crimes in individual categories. However, observable patterns emerge in the case of Property crimes and Other offenses. Within model (1), this particular variable lacks significance due to its incorporation of the variable "Restriction_of_free_movement". Thus, it confirms that more general restrictions have a greater effect.

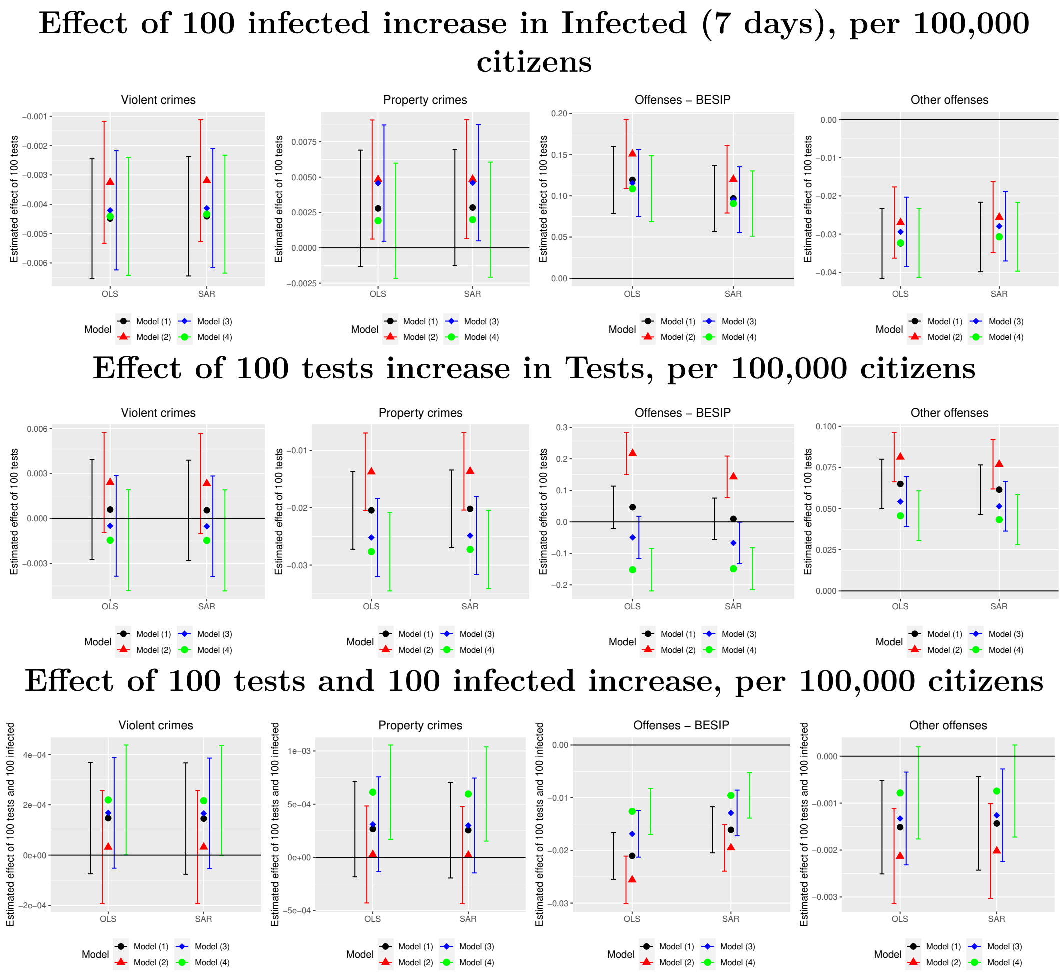
Consequently, the variable "Infected", representing the number of individuals infected with COVID-19 per 100,000 citizens in the last 7 days, demonstrates a contradictory pattern across the crime categories with the variable

"Tests". The potential justification for the negative effect observed in Violent crimes emerges from the mandatory reduction of social interaction, which limited opportunities for individuals to encounter one another, thus reducing the likelihood of violence. Conversely, in the context of Property crimes, the observed positive effect can possibly be attributed to factors such as reduced visits to vacation homes and an increase in abandoned vehicles, thereby creating more favorable conditions for theft. In addition, in Offenses – BESIP can be seen a significant positive effect, whereas in Other offenses a significant negative. The variable "Tests" demonstrates a positive and statistically significant association with Other offenses and with model (2) in Offenses – BESIP. On the contrary, in the case of Property crimes and models (2) and (3) of Offenses – BESIP, the variable "Tests" either lacks statistical significance or exhibits a significant negative effect, respectively. Moreover, when exploring the interaction between these variables, it is mostly significant and negative for offenses, with the exception of Property crimes in the model (4). Overall, the results indicate that a higher prevalence of COVID-19 infections and tests performed is associated with a decrease in crime incidents as the joint effect of both factors is negative. This suggests a possible indirect effect of the pandemic on crime rates, potentially influenced by factors such as reduced mobility, increased public health measures, or changes in social behavior. Furthermore, the decline in crime rates generally could be partially attributed to the possibility that crimes committed during a state of emergency might be considered as an aggravating circumstance[1], leading to the imposition of more severe penalties upon a convicted offender.

Figure 6.2: Effects of variables



[1]Criminal code of the Czech Republic No. 40/2009 Coll., § 42



Note: Vertical lines denote 95% confidence interval. *Source:* Author's own research.

Figure A.2 in Appendix A presents a bubble plot illustrating the mean residuals for each crime category across the districts of the Czech Republic for all models. Each district is represented by a bubble, where the size and color of the bubble indicate the magnitude of the residual associated with that specific district. The accompanying legend provides the values of the residuals for each district. The distribution of residuals appears to be relatively evenly distributed throughout the Czech Republic without a clear spatial pattern. Moreover, the pattern seems to be similar for all models. For Violent crimes, the residuals range from −0.049 to 0.035 across all models, while for Property crimes, the range is between −0.192 and 0.190. The residuals for BESIP show a wider range, varying from −7.845 to 5.307, and finally, for Other offenses, the range is from −0.653 to 0.367. These deviations from the expected values for each crime category correspond to the respective crime rates.

Table 6.11 presents the results of the z-test. Table 6.11 displays the outcomes of the z-test. While a majority of the coefficients demonstrate a negative trend, their lack of statistical significance implies that the spatial effects (ρ) remain unchanged between the COVID-19 period and the overall period. In other words, the spatial effect is consistent across both time frames. However, a notable exception is observed in the case of the Offenses – BESIP category, wherein the coefficient exhibits a positive and statistically significant association across all models. This finding suggests that the spatial effects pertaining to the Offenses – BESIP category are higher during the COVID-19 period compared to the overall period. An inference can be drawn that this observed increase in spatial effects during the COVID-19 period may be attributed to a rise in offenses that are specifically associated with the pandemic. Examples of such offenses may include illegal crossing of district borders or other violations that are influenced by unique circumstances and restrictions imposed during the pandemic. However, this finding is inconsistent with the original hypothesis #1. Nevertheless, it is essential to conduct further empirical investigations and adopt comprehensive analytical approaches to understand the precise reasons behind the elevated spatial effects of the Offenses – BESIP during the COVID-19 period and to focus on individual subcategories. By doing so, a deeper understanding of the interplay between the pandemic and criminal activity in this category can be obtained, thereby contributing to more informed policy responses and interventions.

Table 6.11: Results of z-test

	(1)	(2)	(3)	(4)
Violent crimes	−0.919	−0.975	−0.928	−0.989
(p-value)	(0.358)	(0.330)	(0.353)	(0.323)
Property crimes	−0.001	−0.033	−0.104	−0.120
(p-value)	(0.999)	(0.973)	(0.917)	(0.904)
BESIP	3.601	2.398	4.613	4.505
(p-value)	(<0.001)	(0.017)	(<0.001)	(<0.001)
Other offenses	−0.871	−1.166	−0.813	−0.735
(p-value)	(0.384)	(0.244)	(0.416)	(0.462)

Source: Author's own research.

Chapter 7

Conclusion

The findings presented in this thesis indicate that the implementation of COVID-19 restrictions, coupled with the number of infected individuals and tests conducted, has had a negative impact on crime. Specifically, during the crisis period, there was a decrease in crime across all examined categories – Violent crimes, Property crimes, Offenses – BESIP, and Other offenses. Moreover, the results obtained from the SAR model demonstrate the spatial dependence of crime in the 76 districts and Prague of the Czech Republic.

From this study, several policy implications can be concluded. First, this study suggests that the implementation of measures targeted at reducing mobility within a specific district could potentially result in a subsequent decrease in crime in the same district. Second, due to a decline in crime rates across all examined categories, law enforcement agencies could consider reallocating their resources to address other urgent issues during the pandemic, such as ensuring public health compliance and providing assistance, particularly in healthcare facilities. Third, despite the overall decrease in crime, certain districts might still encounter elevated crime rates. Hence, law enforcement agencies should closely and strategically monitor crime hotspots to achieve an effective distribution of resources.

However, it is important to acknowledge the limitations of this study. These include data limitations, other factors affecting crime, and cross-border crime. A detailed description can be found in Chapter 5. Despite these limitations, several contributions can be concluded from this study. The spatial autocorrelation was observed in all crime categories except Other offenses as indicated by the Moran's I test. Therefore, when working with crime data, it is advisable to employ the Spatial lag model rather than OLS. Additionally, the suitability of using the SAR model was demonstrated by the SLM test. By utilizing daily crime data, the regression results indicated a negative impact of COVID-19 on crime, particularly in Central Europe, with a specific emphasis on the Czech Republic. The state of emergency exhibits statistical significance and a negative impact across all crime categories. In addition, the findings suggest that the closure of schools, shops, and services had a negative significant effect on crime rates. Restriction of free movement between districts is found to have a negative and statistically significant impact on all crime categories except for Violent crimes. On the other hand, a broader variable, which encompasses various measures such as nighttime curfews, demonstrates a consistent and significant negative impact across all crime categories, while showing a pattern emerging in the case of Property crimes and Other offenses. Interestingly, when examining these models, the variable "Lockdown" lacks any statistical significance. Thus, it can be confirmed that more generalized restrictions have a more pronounced influence on crime rates. Subsequently, the z-test unexpectedly showed that COVID-19 and the associated restrictions lead to an increase in the spillover effect in Offenses – BESIP in the Czech Republic.

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Appendix A

Tables and graphs

A.1 State restrictions

Table A.1: State restrictions – COVID-19

Restriction	**Time period**
Lockdown	February 12, 2021 – February 28, 2021 for districts Cheb, Sokolov, Trutnov; March 27, 2021 – April 11, 2021 for all districts;
Restriction_of_free_movement	March 16, 2020 – May 17, 2020 October 22, 2020 – April 11, 2021
State_of_emergency	March 12, 2020 – May 17, 2020 October 5, 2020 – April 11, 2021 November 26, 2021 – December 25, 2021
Schools	March 13, 2020 – June 7, 2020 October 12, 2020 – May 23, 2021
Shops_services	March 14, 2020 – May 24, 2020 October 22, 2020 – December 2, 2020 December 18, 2020 – May 30, 2021

Source: Author's own research

A.2 Public Holidays

Table A.2: Public Holidays

Date	**Public Holiday**
January 1	New Year's Day, Restoration Day of the Independent Czech State
Not a fixed date	Good Friday
Not a fixed date	Easter Monday
May 1	Labour Day
May 8	Victory Day
July 5	Saints Cyril and Methodius Day
July 6	Jan Hus Day
September 28	Statehood Day
October 28	Independent Czechoslovak State Day
November 17	Struggle for Freedom and Democracy Day
December 24	Christmas Eve
December 25	The First Christmas Day
December 26	The Second Christmas Day

Source: Author's own research.

A.3 Robust SLM tests

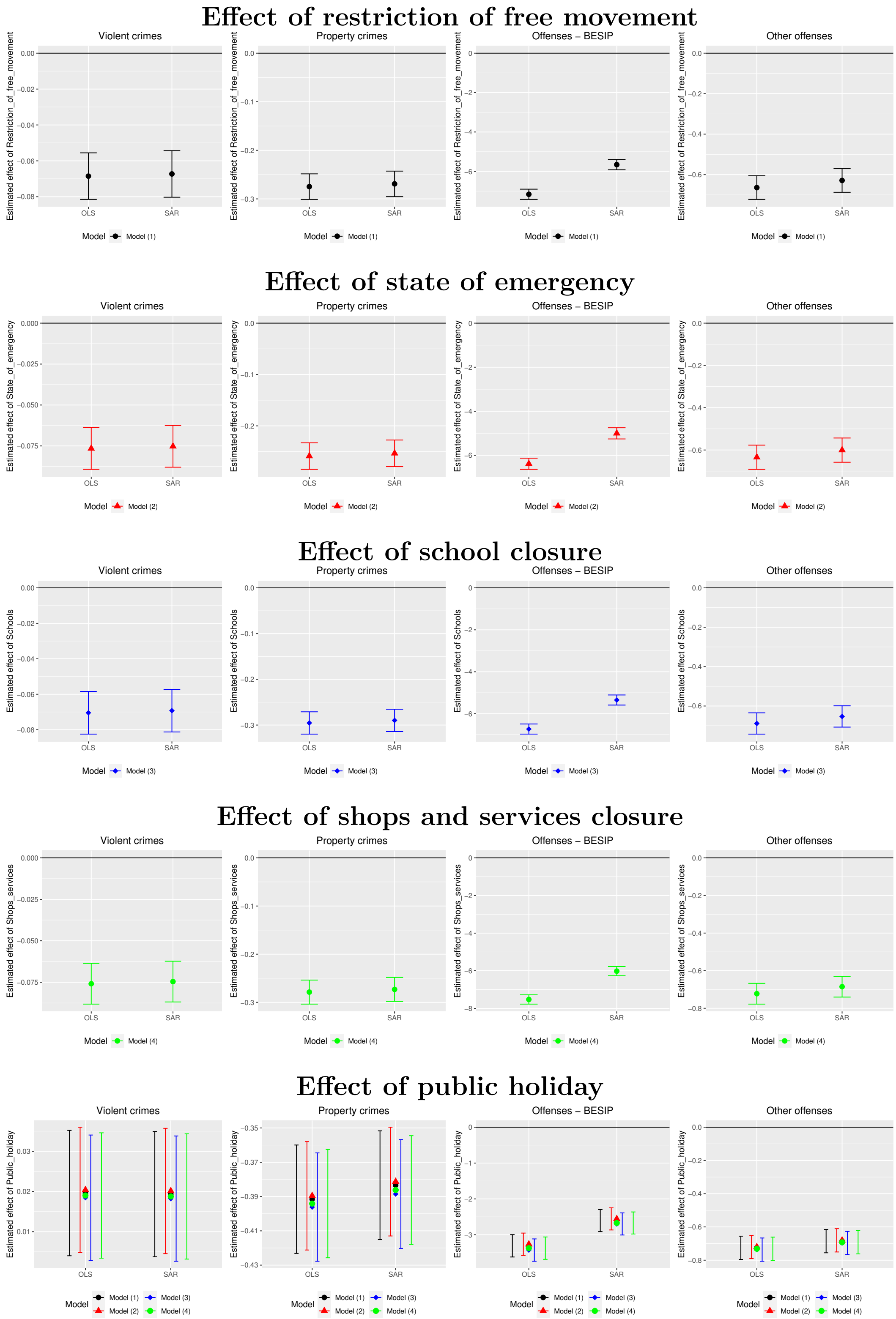
Table A.3: Results of Robust SLM tests

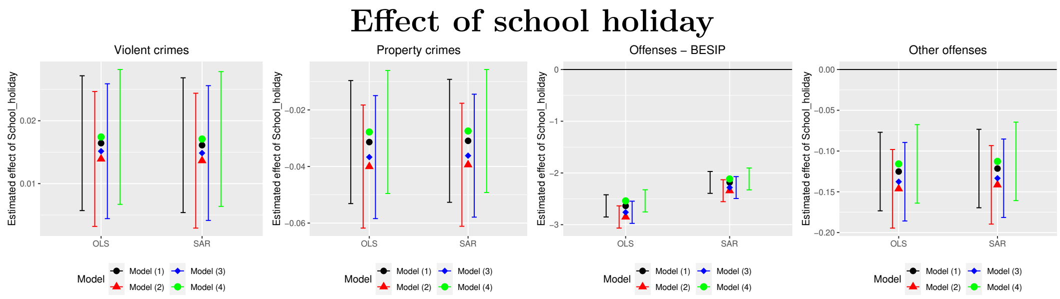
	LMlag	LMerr
Violent crimes	−0.684	−0.533
(p-value)	(1)	(1)
Property crimes	−17.847	−13.780
(p-value)	(1)	(1)
Offenses – BESIP	−3.883	−29.383
(p-value)	(1)	(1)
Other offenses	0.695	1.197
(p-value)	(0.405)	(0.274)

Source: Author's own research. Based on regression with modified variable "Lockdown" without the period from March 27, 2021 to April 11, 2021.

A.4 Results by variables

Figure A.1: Effects of variables

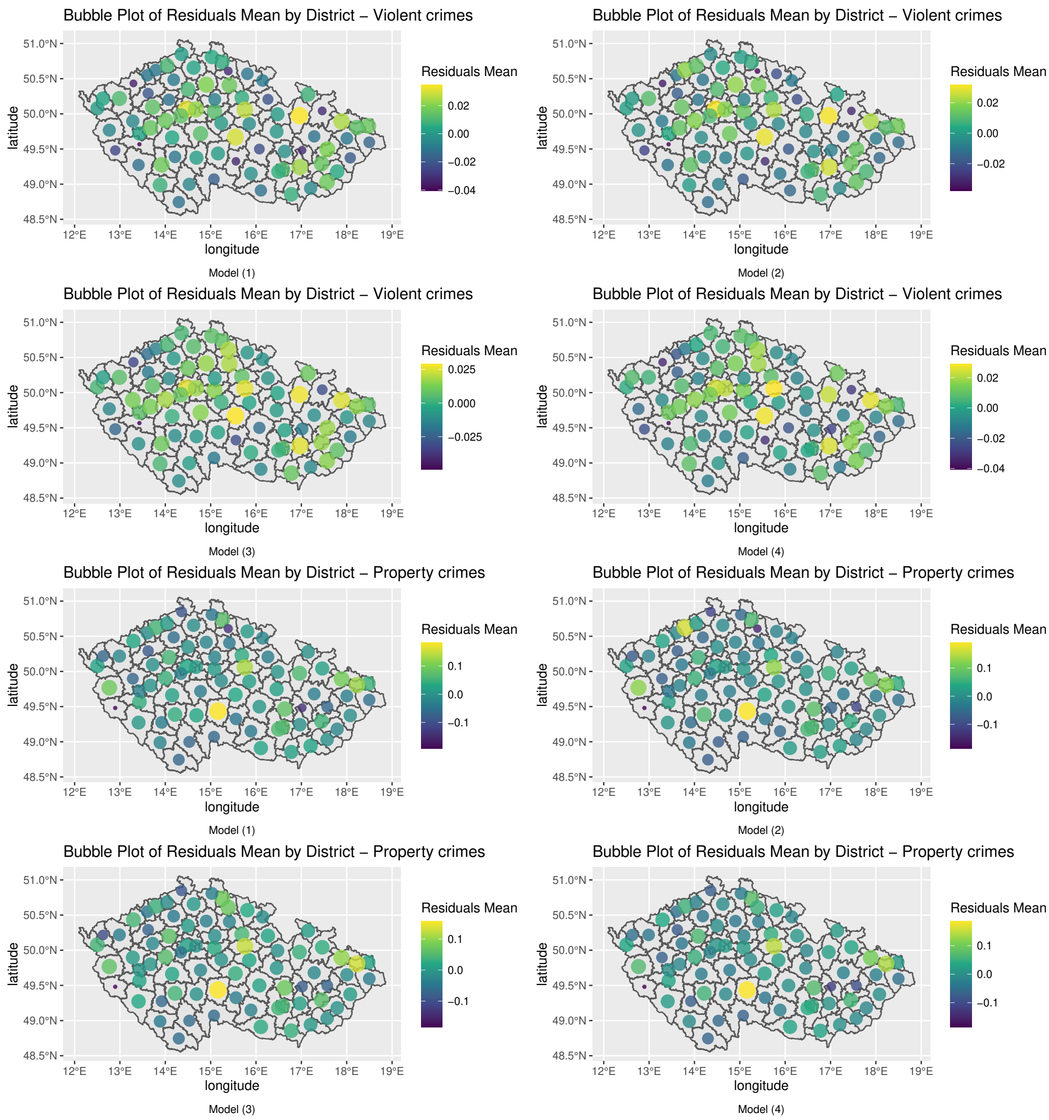


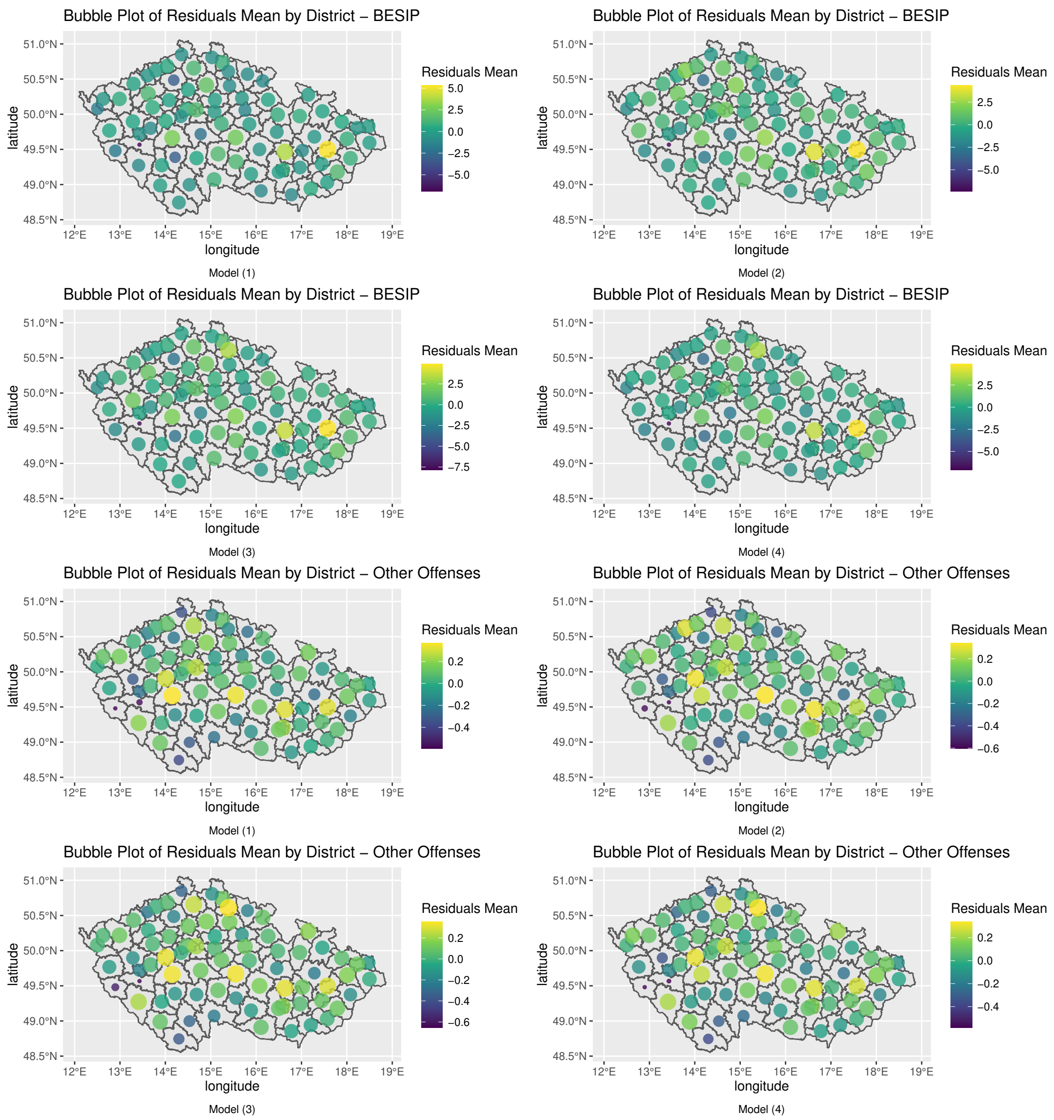


Source: Author's own research.

A.5 Bubble Plot of Residuals

Figure A.2: Bubble Plot of Residuals Mean by District in absolute value





Source: Author's own research.