Offline crime may go back to pre-COVID levels, cyber won’t: Interrupted time-series analysis in Northern Ireland

Contributions should be fewer than 5,000 words, not including references, endnotes, figures or tables.

Ideas

Interrupted time series analysis + counterfactuals: https://ds4ps.org/pe4ps-textbook/docs/p-020-time-series.html#the-counterfactual

Focus in Northern Ireland

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# Abstract

Guideline does not specify wordcount

# Keywords

Coronavirus; Fraud; Counterfactuals; Temporal; Routine activities; Cyber-enabled

# 1. Introduction

The COVID-19 pandemic and the associated stay-at-home orders imposed by national and regional governments to control the spread of the virus caused unprecedented changes in the everyday lives of millions worldwide. Due to the quick spread and mortality of the virus (on 24th June 2021, the World Health Organization has recorded more than 179 million cases and almost 4 million deaths), many countries established and enforced lockdown and social distancing measures to control the virus, which had severe short- and medium-term effects on multiple social domains, including psychological wellbeing (Krendl and Perry, 2021; Rajkumar, 2020), inequality (Abedi et al., 2021; Czymara et al., 2021), the subsistence of small and medium businesses (Bartik et al., 2020) and crime rates (Nivette et al., 2021).

Many researchers and public organisations observed important decreases in some types of violent and property crime immediately after the first national and regional lockdowns in the United States (Abrams, 2021; Ashby, 2020; Mohler et al., 2020), the United Kingdom (Halford et al., 2020), Australia (Payne et al., 2021) and many other countries (Nivette et al., 2021). Simultaneously, others indicated that while street crimes decreased during the first months of the pandemic, other offences that occur in physical and digital places less affected by lockdown mobility restriction, such as domestic violence (Piquero et al., 2021), cyber-enabled fraud (Kemp et al., 2021), online hate speech (Stechemesser et al., 2020) and cyber-dependent crime (Buil-Gil et al., 2020), increased. After the first months of COVID pandemic, researchers noted that rates of traditional, offline crime started to bounce back to pre-COVID levels (Langton et al., 2021; Nix and Richards, 2021), but there is a lack of research about the medium-term impact, and the potential long-term impact, of stay-at-home orders on cyber-enabled and cyber-dependent crime. There is also a gap in research about the effect of the second and third UK lockdown periods on crime. More importantly, crime research has yet to understand whether the peak in cybercrime seen immediately after the first lockdown orders returned to pre-COVID levels after the ease of stay-at-home restrictions, or whether it remained well above pre-pandemic trends, thus indicating a potential long-term post-pandemic upward trend in cybercrime. Thus, the aim of this research is to analyse changes in crime, including both offline and online crime, in Northern Ireland during COVID-19 up until May 2021, and to investigate the short- and medium-term impact of each of the three COVID-19 lockdowns on crime. We will analyse this using interrupted time series (ITS) analysis and counterfactuals (McDowall et al., 2019).

The timeline of the COVID-19 pandemic in Northern Ireland was similar to that of other parts of the UK and Europe. The first case was detected in the town of Antrim on February 27th 2020, and the number of cases rose steeply throughout March. In order to control the spread of the virus, the UK Government announced the first COVID national lockdown on March 23rd, which came into force three days later on March 26th. All non-essential social and business activity was restricted for weeks, and non-essential shops, schools and universities, businesses, pubs and other venues were closed. The first lockdown was gradually eased during June and July 2020. Due to the steep rise in COVID infections during late September and early October 2020, the Northern Ireland Government announced a second lockdown on October 14th 2020, which officially began on October 16th. The second Northern Ireland lockdown was mostly lifted by the second week of December. This second lockdown involved the closure of schools, universities and the hospitality sector, but it did not involve a stay-at-home order as such and the social distancing restrictions were less strict than that of the first national lockdown. Just a few days later, on December 17th, a third lockdown was announced, which began on December 26th. Some mobility restrictions were hardened on 8th January 2021, when a stay-at-home order came into force due to the spread of a new variant of the virus. This last lockdown meant that people were only allowed to leave home for medical reasons, to buy food, exercise and go to work only in those cases in which work could not be done from home. Stay-at-home orders were progressively lifted during March and April 2021, following the increase in the proportions of persons vaccinated against COVID-19.

The remainder of this paper is organised as follows: Section 2 describes the main changes in routine activities seen during the COVID-19 pandemic, and how these affected rates of different types of crimes in different parts of the world. Section 3 introduces the main aims and research questions of this paper. Section 4 discusses the data and analytical strategy used in this paper. Section 5 presents the results of the analysis, and Section 6 presents the discussion and conclusions of the study.

# 2. Rapid social changes and crime: The COVID-19 case

Changes in mobility

Changes in street crime

Changes in cyber

Increase in romance fraud suffered by young people in the UK (Buil-Gil and Zeng, 2021)

Reduction in successful deliveries of drugs bought in cryptomarkets (Bergeron et al., 2020)

# 3. The present study

# 4. Methodology

## 4.1 Data

In this article we analyse data recorded by the Police Service of Northern Ireland between April 2015 and May 2021. Crime data was accessed and downloaded from the crime open data portal of the police (<https://www.psni.police.uk/inside-psni/Statistics/police-recorded-crime-statistics/>). Historical crime data can also be downloaded from the Open Data Northern Ireland portal (<https://www.opendatani.gov.uk/dataset/police-recorded-crime-in-northern-ireland>). To the extent of our knowledge, the Police Service of Northern Ireland is the only police force in the UK that publishes open access crime data for both offline and online offences, thus allowing us to analyse our research questions. More specifically, we will analyse the following types of crime aggregated in months:

1. Violence and sexual crime: including violence with injury, violence without injury, sexual offences, and harassment.
2. Drug crimes, damage and public order: including possession of drugs, drug trafficking, public order and possession of weapons, and criminal damage (e.g., arson, forced entry into a property, graffiti).
3. Burglary: including residential and non-residential burglary.
4. Theft and robbery: including theft from person, bicycle theft, theft of or from vehicle, shoplifting, robbery, and all other theft.
5. Fraud and cybercrime: including online shopping fraud, advance fee fraud (when victims are asked to make upfront payments for goods or services that do not materialise; for example, fraud recovery scams, inheritance fraud, lender loan fraud, ‘419’ frauds or rental frauds), consumer fraud (for example, doorstep fraud, holiday fraud, electricity scam, bogus tradesmen fraud, ticket fraud or call centre fraud, but excluding online shopping fraud), investment and credit fraud (when criminals convince victims to invest in schemes or products that are worthless or criminals compromise personal information from banking or credit, for example Pyramid schemes, pension scams, hedge fund fraud, boiler room fraud, credit card fraud or mandate fraud), other fraud (for example, fraud by abuse of trust, corporate employee fraud, driving licence fraud, false accounting or business trading fraud), and cyber-enabled crime (crimes that can only take place online, such as hacking, denial of service attacks and computer viruses).

Thus, we will analyse a variety of crime types that may have affected in different ways by the mobility restrictions of the three COVID-19 lockdowns. Opportunities for violence offences and theft are found mostly in ‘public places’ and thus were likely to decrease during stay-at-home orders. While residential burglary opportunities may decrease due to the increase of ‘capable guardians’ at home, this may not be the case for non-residential burglaries. Some fraud types are clearly cyber-enabled, such as online shopping fraud, and thus their opportunities were likely to increase with the increased use of the internet, while other fraud categories may be committed online, be committed online but depend on offline events or be committed offline (for example, in the case of consumer fraud, call centre fraud may be committed through telephone, ticket fraud is cyber-enabled but depends on concerts and sport events that were cancelled during the pandemic, and doorstep fraud is fully offline). Cyber-dependent crimes can only take place online. Moreover, while some of these crime types are typically highly seasonal and tend to increase during summer and decrease in winter (e.g., bicycle theft, criminal damage, violence) others are less affected by seasonality (e.g., shoplifting, online shopping fraud, burglary, drug trafficking), which will also enable us to foreground potential disruptions in seasonal patterns.

## 4.2 Analytical approach

In order to analyse the immediate effect of each COVID-19 lockdown on crime, but also the medium-term changes in crime after each lockdown, we will utilise ITS analysis based on segmented linear regressions. The ITS model used here is given by:

where is the value of crime in a given month, represents time (in months) from 1 (to 74, , and correspond to the first, second and third lockdowns, respectively, and , and is the time (months) past since the first, second and third lockdowns, respectively. This is a simple approach that can be used to analyse the effect of lockdowns on crime. In order to compare the observed crime trends with the expected changes in crime if COVID-19 had not happened, we will calculate the ‘counterfactuals’ (i.e., the linear trend that crime had followed if lockdown restriction had not taken place). We will predict the ‘counterfactuals’ from:

With a very few examples (e.g., Fei et al., 2020; Humphreys et al., 2013; Martin et al., 2018; Steinbach et al., 2015), this approach has been rarely applied in crime research, but its application is widespread in epidemiology, economics, education and other fields. We present tables with the model results and illustrate these with visualisations in the following section. While this a simple approach that enable obtaining direct results to address our questions, it is not free of limitations. One of the main assumptions of the ordinary least squares (OLS) estimation used here is that error terms are independent from one another, but this may be highly problematic in time-series analysis when the score of (crime values) at one point in time is correlated with the scores at another points (i.e., there may be ‘serial autocorrelation’). This assumption often does not hold in temporal crime analysis. Moreover, the segmented linear regression proposed here does not account for the seasonality that define the trends of some crime types, and thus our coefficient estimates may be affected by seasonal patterns (e.g., the second lockdown began in October 2020, after summer, when crime may decrease due to seasonal crime variation) beyond stay-at-home orders.

In order to account for both these threats to the validity of our results, we also estimate multivariate linear regressions with Auto Regressive Integrated Moving Average (ARIMA) errors as a sensitivity check. This approach is used to account for the potential serial autocorrelation and seasonality of crime time series. We apply a variation of the Hyndman-Khandakar algorithm (Hyndman and Khandakar, 2008) to select the model with the best goodness-of-fit based on an data-driven selection of the components (order of the auto regressive model), (order of differencing) and (order of moving average) of the model, thus finding the model that adjust best to the data in each case. We will use the results of the multivariate models with ARIMA errors as a sensitivity check on our results. The results of the models with ARIMA errors are presented in the Appendix, showing remarkably similar results to that of the ITS analysis, but we also note a few important differences that will be described in detail in the next section.

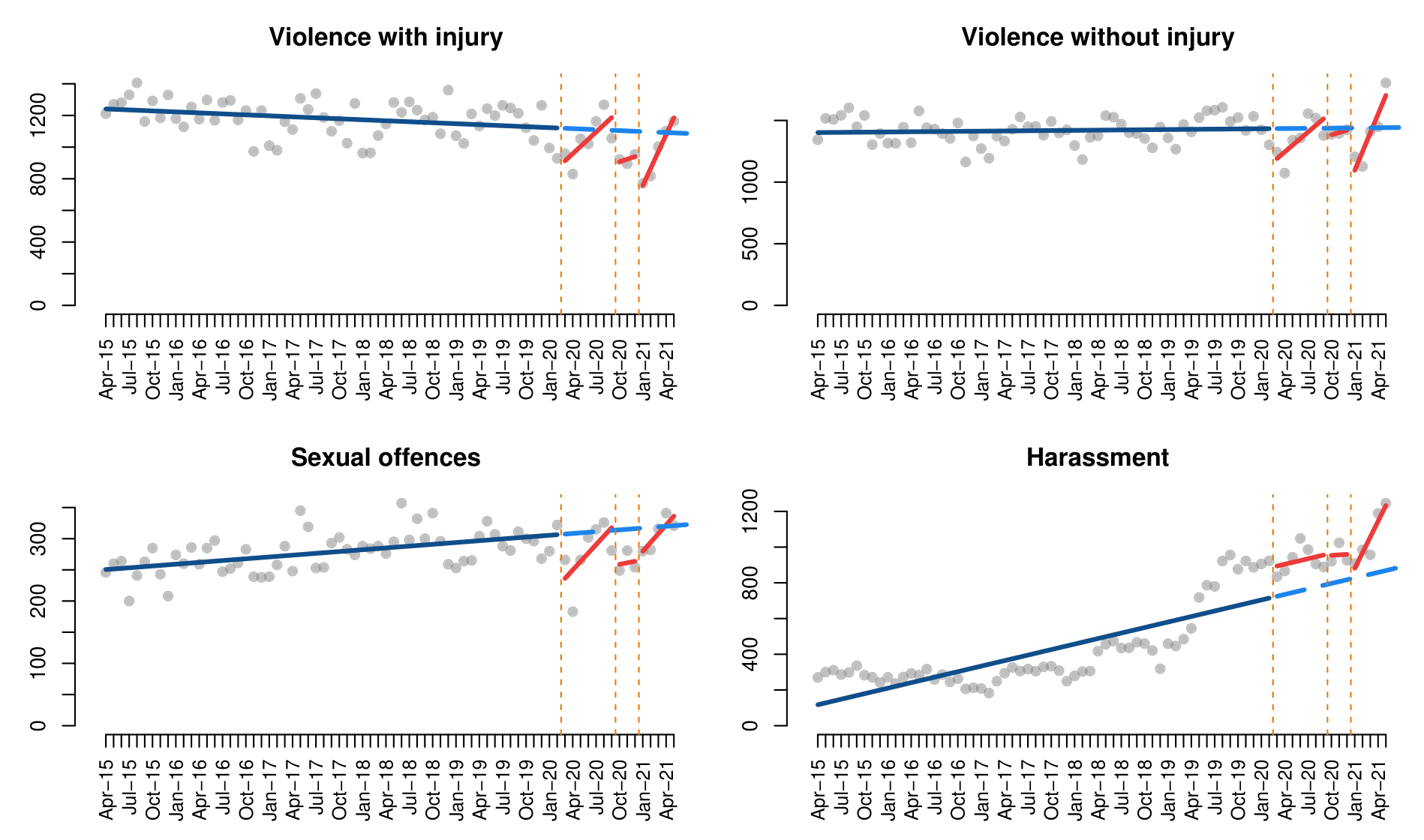
The analysis has been conducted in R software (R Core Team, 2021) with the assistant of the ‘forecast’ package (Hyndman et al., 2020), and all data and codes are available from a Github repository (ADD URL).

# 5. Results



***Figure 1.*** *Interrupted time series analysis of all crime*

## 5.1 Violence and sexual crime



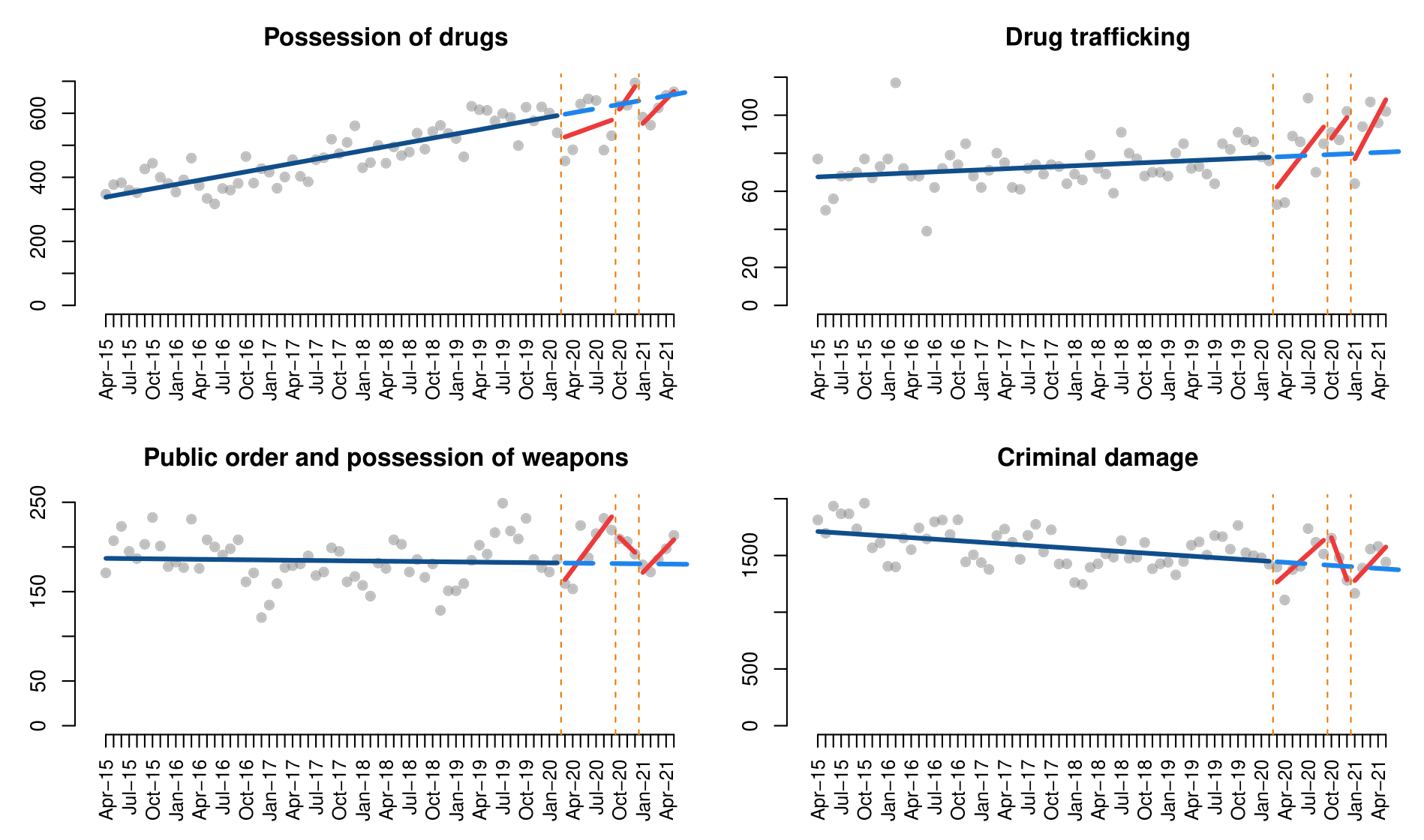
***Figure 2.*** *Interrupted time series analysis of violent and sexual crimes*

***Table 1.*** *Interrupted time series models of violent and sexual crimes*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Violence with injury | Violence without injury | Sexual offences | Harassment |
| (Intercept) | 1243.3\*\*\* | 1401.2\*\*\* | 249.5\*\*\* | 107.0\*\* |
| Time | -2.1\* | 0.5 | 1.0\*\*\* | 10.3\*\*\* |
| First lockdown | -253.5\*\* | -297.1\*\* | -83.7\*\* | 169.3 |
| Time since first lockdown | 47.7\* | 53.4\* | 12.6\* | -0.0 |
| Second lockdown | -215.5 | -73.0 | -56.9 | 164.3 |
| Time since second lockdown | 18.6 | 18.5 | 1.5 | -7.3 |
| Third lockdown | -450.0\*\*\* | -496.3\*\*\* | -50.4 | -24.2 |
| Time since third lockdown | 109.1\*\* | 151.8\*\*\* | 13.13 | 77.7+ |
| Adjusted R2 | 0.42 | 0.24 | 0.28 | 0.82 |

\*\*\*p-value<0.001, \*\*p-value<0.01, \*p-value<0.05, +p-value<0.1

## 5.2 Drug crimes, damage and public order



***Figure 3.*** *Interrupted time series analysis of drug crimes, damage and public order*

***Table 2.*** *Interrupted time series models of drug crimes, damage and public order*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Possession of drugs | Drug trafficking | Public order and possession of weapons | Criminal damage |
| (Intercept) | 333.8\*\*\* | 67.4\*\*\* | 187.3\*\*\* | 1715.9\*\*\* |
| Time | 4.4\*\*\* | 0.2\* | -0.1 | -4.5\*\*\* |
| First lockdown | -75.5+ | -21.0\* | -30.5 | -245.2+ |
| Time since first lockdown | 4.4 | 5.1\* | 11.8\* | 66.1\* |
| Second lockdown | -46.4 | 3.2 | 37.8 | 426.3+ |
| Time since second lockdown | 31.1 | 5.3 | -8.4 | -181.5+ |
| Third lockdown | -93.7+ | -10.5 | -19.0 | -200.1 |
| Time since third lockdown | 20.7 | 7.6\* | 9.3 | 78.8+ |
| Adjusted R2 | 0.76 | 0.29 | 0.05 | 0.28 |

\*\*\*p-value<0.001, \*\*p-value<0.01, \*p-value<0.05, +p-value<0.1

## 5.2 Burglary



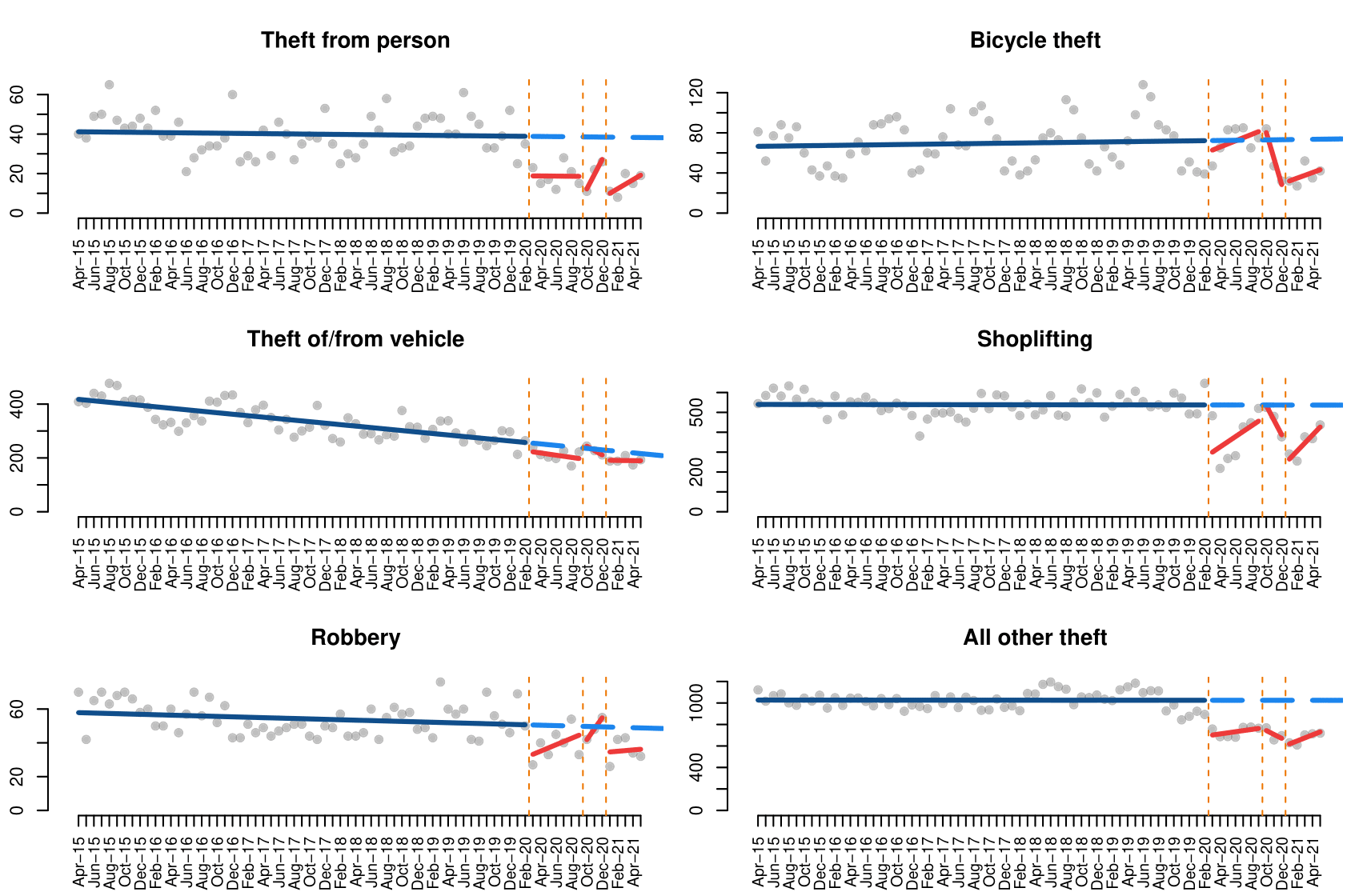
***Figure 4.*** *Interrupted time series analysis of burglary*

***Table 3.*** *Interrupted time series models of burglary*

|  |  |  |
| --- | --- | --- |
|  | Residential burglary | Non-residential burglary |
| (Intercept) | 465.2\*\*\* | 248.9\*\*\* |
| Time | -1.7\*\*\* | -2.6\*\*\* |
| First lockdown | -98.3\* | 4.4 |
| Time since first lockdown | 2.9 | -1.8 |
| Second lockdown | -11.5 | 18.1 |
| Time since second lockdown | -15.3 | -3.9 |
| Third lockdown | -124.1\* | -7.4 |
| Time since third lockdown | 2.7 | 2.0 |
| Adjusted R2 | 0.62 | 0.83 |

\*\*\*p-value<0.001, \*\*p-value<0.01, \*p-value<0.05, +p-value<0.1

## 5.4 Theft and robbery



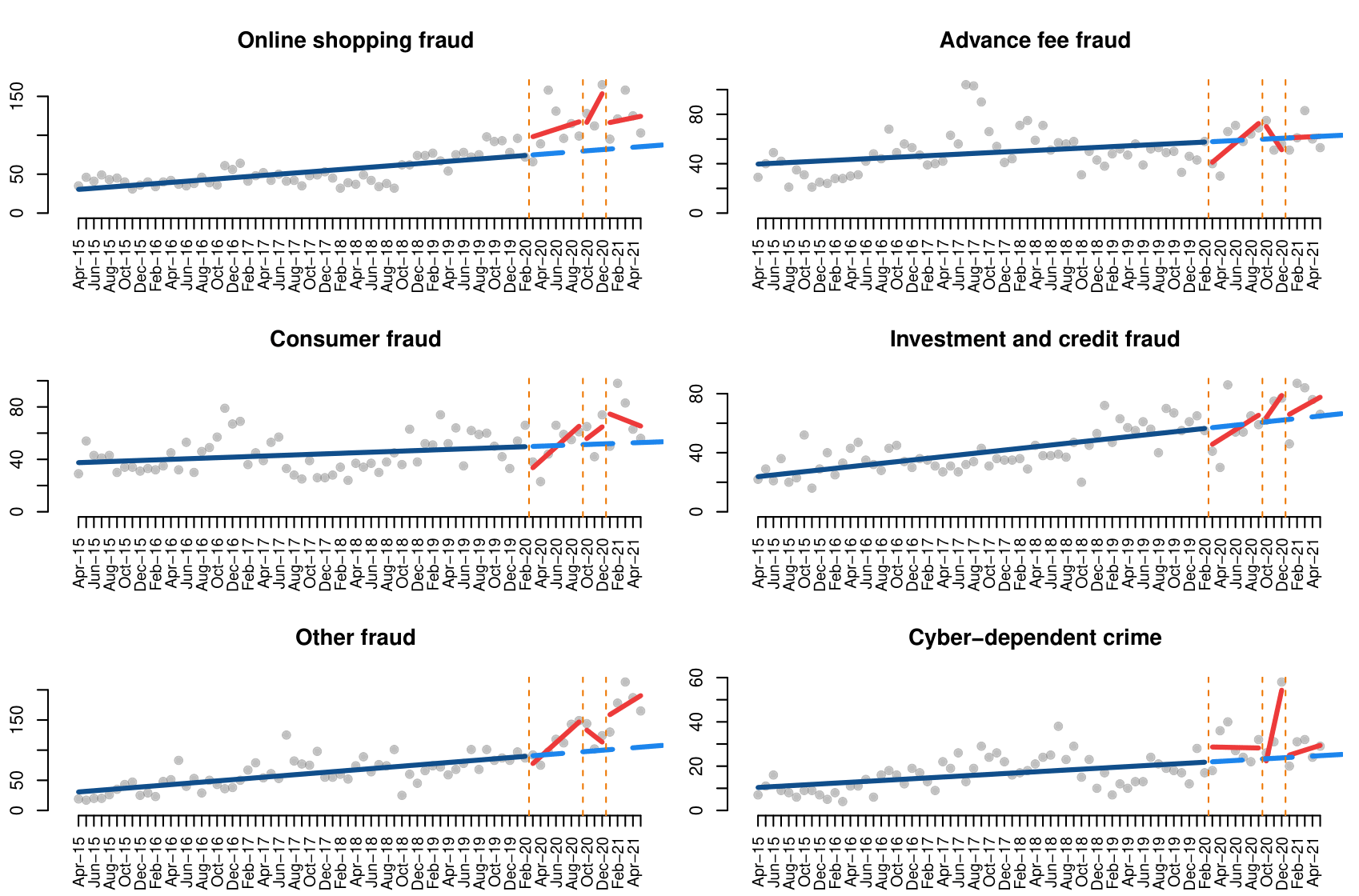
***Figure 5.*** *Interrupted time series analysis of theft and robbery*

***Table 4.*** *Interrupted time series models of theft and robbery*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Theft from person | Bicycle theft | Theft of/ from vehicle | Shoplifting | Robbery | All other theft |
| (Intercept) | 41.2\*\*\* | 66.5\*\*\* | 420.3\*\*\* | 540.0\*\*\* | 58.0\*\*\* | 1026.8\*\*\* |
| Time | -0.0 | 0.1 | -2.7\*\*\* | -0.0 | -0.1+ | -0.0 |
| First lockdown | -20.0\* | -12.5 | -30.9 | -263.6\*\*\* | -19.4\* | -333.9\*\*\* |
| Time since first lockdown | 0.0 | 3.0 | -1.3 | 26.1\* | 2.0 | 10.3 |
| Second lockdown | -33.9\* | 33.5 | 22.1 | 71.7 | -14.5 | -245.0\* |
| Time since second lockdown | 7.5 | -26.1 | -13.7 | -74.0+ | 6.6 | -36.5 |
| Third lockdown | -30.8\*\* | -44.0+ | -38.3 | -312.7\*\*\* | -15.3 | -434.7\*\*\* |
| Time since third lockdown | 2.3 | 2.7 | 2.4 | 40.5\* | 0.5 | 28.2 |
| Adjusted R2 | 0.46 | 0.09 | 0.76 | 0.57 | 0.31 | 0.74 |

\*\*\*p-value<0.001, \*\*p-value<0.01, \*p-value<0.05, +p-value<0.1

## 5.5 Fraud and cybercrime



***Figure 6.*** *Interrupted time series analysis of fraud and cybercrime*

***Table 5.*** *Interrupted time series model of fraud and cybercrime*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Online shopping fraud | Advance fee fraud | Consumer fraud | Investment and credit fraud | Other fraud | Cyber-dependent crime |
| (Intercept) | 29.7\*\*\* | 39.4\*\*\* | 37.3\*\*\* | 23.2\*\*\* | 29.6\*\*\* | 16.4\*\*\* |
| Time | 0.8\*\*\* | 0.3\* | 0.2+ | 0.6\*\*\* | 1.0\*\*\* | 0.2\*\* |
| First lockdown | 21.0 | -21.7 | -21.4+ | -14.0 | -23.4 | 8.8 |
| Time since first lockdown | 2.4 | 4.9 | 5.1+ | 2.7 | 10.5\*\* | -0.8 |
| Second lockdown | 18.7 | 20.0 | 0.2 | -4.0 | 46.5 | -6.5 |
| Time since second lockdown | 17.7 | -9.8 | 4.3 | 6.9 | -11.0 | 13.2\*\* |
| Third lockdown | 32.8+ | 0.1 | 25.1 | 1.0 | 51.0\* | 0.4 |
| Time since third lockdown | 1.2 | -0.0 | -2.5 | 2.3 | 6.9 | 1.6 |
| Adjusted R2 | 0.76 | 0.10 | 0.23 | 0.59 | 0.79 | 0.45 |

\*\*\*p-value<0.001, \*\*p-value<0.01, \*p-value<0.05, +p-value<0.1

# 6. Discussion and conclusions

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# Appendix

***Table A1.*** *Multivariate linear regressions with ARIMA errors (coefficients and 95% Confidence Intervals)*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Violence with injury | Violence without injury | Sexual offences | Harassment | Possession of drugs | Drug trafficking |
| First lockdown | **-313.7** [-408.2, -219.1] | **-157.2** [-255.0, -59.4] | **-64.0** [-93.4, -34.7] | **-98.2** [-163.9, -32.5] | **-53.3** [-103.0, -3.5] | **-16.6** [-27.7, -5.4] |
| Time since first lockdown | **45.6** [24.7, 66.5] | **24.9** [3.2, 46.6] | **11.8** [5.6, 18.0] | 9.2 [-15.7, 34.0] | 9.1 [-1.8, 20.1] | **5.3** [2.9, 7.7] |
| Second lockdown | **-290.1** [-459.5, -120.6] | -53.1 [-183.7, 77.5] | -27.5 [-74.3, 19.3] | -6.0 [-183.3, 171.3] | -17.6 [-105.5, 70.2] | 9.7 [-8.6, 28.0] |
| Time since second lockdown | 16.5 [-61.7, 94.7] | 27.4 [-25.8, 80.6] | -2.0 [-22.1, 18.1] | 3.0 [-40.0, 46.0] | **40.5** [5.4, 75.5] | 6.4 [-2.0, 14.7] |
| Third lockdown | **-530.9** [-647.7, -414.1] | **-453.0** [-578.6, -327.4] | -21.8 [-58.9, 15.4] | -99.5 [-303.5, 104.5] | -12.0 [-86.7, 62.7] | -6.6 [-20.3, 7.1] |
| Time since third lockdown | **107.0** [72.0, 142.0] | **152.8** [117.2, 188.3] | **12.1** [2.1, 22.0] | **84.5** [54.1, 114.9] | **21.9** [4.9, 38.8] | **8.5** [4.5, 12.5] |
| Model | (0, 0, 0) | (0, 0, 2) | (0, 1, 2) | (0, 1, 0) | (1, 1, 2) | (0, 0, 1) |

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| --- | --- | --- | --- | --- | --- | --- |
|  | Public order and possession of weapons | Criminal damage | Residential burglary | Non-residential burglary | Theft from person | Bicycle theft |
| First lockdown | **-33.4** [-57.6, -9.2] | **-241.2** [-397.3, -85.1] | **-72.4** [-125.0, -19.7] | 1.2 [-20.0, 22.4] | **-19.1** [-28.2, -10.0] | -4.8 [-24.0, 14.4] |
| Time since first lockdown | **11.2** [5.9, 16.5] | **52.8** [16.2, 89.4] | -5.9 [-17.7, 5.9] | -0.6 [-7.0, 5.7] | -0.5 [-2.4, 1.5] | 2.0 [-2.5, 6.5] |
| Second lockdown | **41.4** [5.4, 77.3] | **369.4** [93.2, 645.7] | -50.9 [-129.8, 28.0] | 17.8 [-28.7, 64.3] | **-34.6** [-49.0, -20.3] | **41.9** [11.1, 72.7] |
| Time since second lockdown | -11.5 [-26.8, 3.7] | **-186.0** [-277.8, -94.3] | -10.7 [-39.7, 18.4] | -3.7 [-16.0, 8.7] | **7.1** [0.7, 13.6] | **-27.5** [-40.5, -14.5] |
| Third lockdown | -17.9 [-48.3, 12.6] | **-295.4** [-570.2, -20.6] | **-153.4** [-229.1, -77.6] | -10.0 [-62.6, 42.7] | **-31.8** [-42.6, -20.9] | **-40.9** [-68.6, -13.3] |
| Time since third lockdown | 8.4 [-0.1, 16.9] | **73.5** [23.9, 123.2] | -0.1 [-18.6, 18.3] | 2.5 [-5.4, 10.5] | 2.2 [-1.0, 5.3] | 3.3 [-4.4, 11.0] |
| Model | (1, 0, 0) | (0, 1, 1) | (0, 1, 3) | (1, 1, 0) | (1, 0, 0) | (1, 0, 1) |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Theft of/ from vehicle | Shoplifting | Robbery | All other theft | Online shopping fraud |
| First lockdown | -34.0 [-74.8, 6.8] | **-247.5** [-305.5, -189.6] | **-23.0** [-31.0, -15.0] | **-217.0** [-286.6, -147.4] | 13.2 [-4.3, 30.7] |
| Time since first lockdown | -4.3 [-13.8, 5.1] | **23.9** [11.4, 36.4] | **1.9** [0.1, 3.7] | -6.4 [-22.0, 9.2] | 1.2 [-2.5, 4.9] |
| Second lockdown | -19.1 [-87.9, 49.8] | 47.5 [-42.5, 137.4] | **-19.0** [-33.2, -4.7] | **-269.7** [-371.4, -168.0] | 19.8 [-8.3, 48.0] |
| Time since second lockdown | -13.1 [-37.5, 11.4] | -68.7 [-108.5, -28.9] | 6.5 [-0.1, 13.1] | -26.4 [-64.5, 11.7] | **17.2** [6.6, 27.9] |
| Third lockdown | **-80.5** [-145.2, -15.8] | **-305.6** [-374.5, -236.7] | **-20.1** [-29.9, -10.3] | **-432.4** [-524.7, -340.1] | 14.1 [-8.5, 36.7] |
| Time since third lockdown | 0.7 [-13.2, 14.6] | **38.7** [18.7, 58.7] | 0.4 [-2.5, 3.3] | **26.7** [3.3, 50.1] | 2.8 [-2.8, 8.3] |
| Model | (1, 1, 1) | (1, 0, 0) | (0, 0, 0) | (1, 0, 2) | (0, 1, 2) |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Advance fee fraud | Consumer fraud | Investment and credit fraud | Other fraud | Cyber-dependent crime |
| First lockdown | **-18.9** [-33.9, -3.9] | **-29.1** [-43.6, -14.6] | **-17.9** [-27.8, -8.0] | **-22.4** [-39.2, -5.5] | **11.4** [3.6, 19.3] |
| Time since first lockdown | **5.6** [2.2, 9.0] | **7.5** [4.3, 10.8] | **2.7** [0.6, 4.8] | **10.4** [6.8, 13.9] | -0.1 [-1.9, 1.7] |
| Second lockdown | **33.0** [9.0, 57.1] | 15.5 [-4.9, 35.8] | -8.0 [-25.1, 9.1] | **46.8** [17.5, 76.2] | -0.6 [-14.4, 13.2] |
| Time since second lockdown | -8.8 [-17.7, 0.1] | 3.8 [-5.0, 12.6] | 6.9 [-0.5, 14.3] | -11.1 [-23.9, 1.7] | **13.5** [8.5, 18.6] |
| Third lockdown | 4.9 [-17.6, 27.3] | **21.4** [1.5, 41.3] | -3.2 [-16.3, 9.8] | **50.7** [28.4, 72.9] | 6.5 [-6.4, 19.5] |
| Time since third lockdown | 0.7 [-4.5, 5.9] | -0.3 [-5.9, 5.3] | 2.3 [-1.0, 5.7] | **6.8** [1.0, 12.6] | 1.8 [-0.7, 4.4] |
| Model | (1, 1, 1) | (0, 0, 2) | (0, 1, 1) | (0, 1, 1) | (0, 1, 1) |