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

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# Abstract

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# Keywords

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

# 1. Introduction

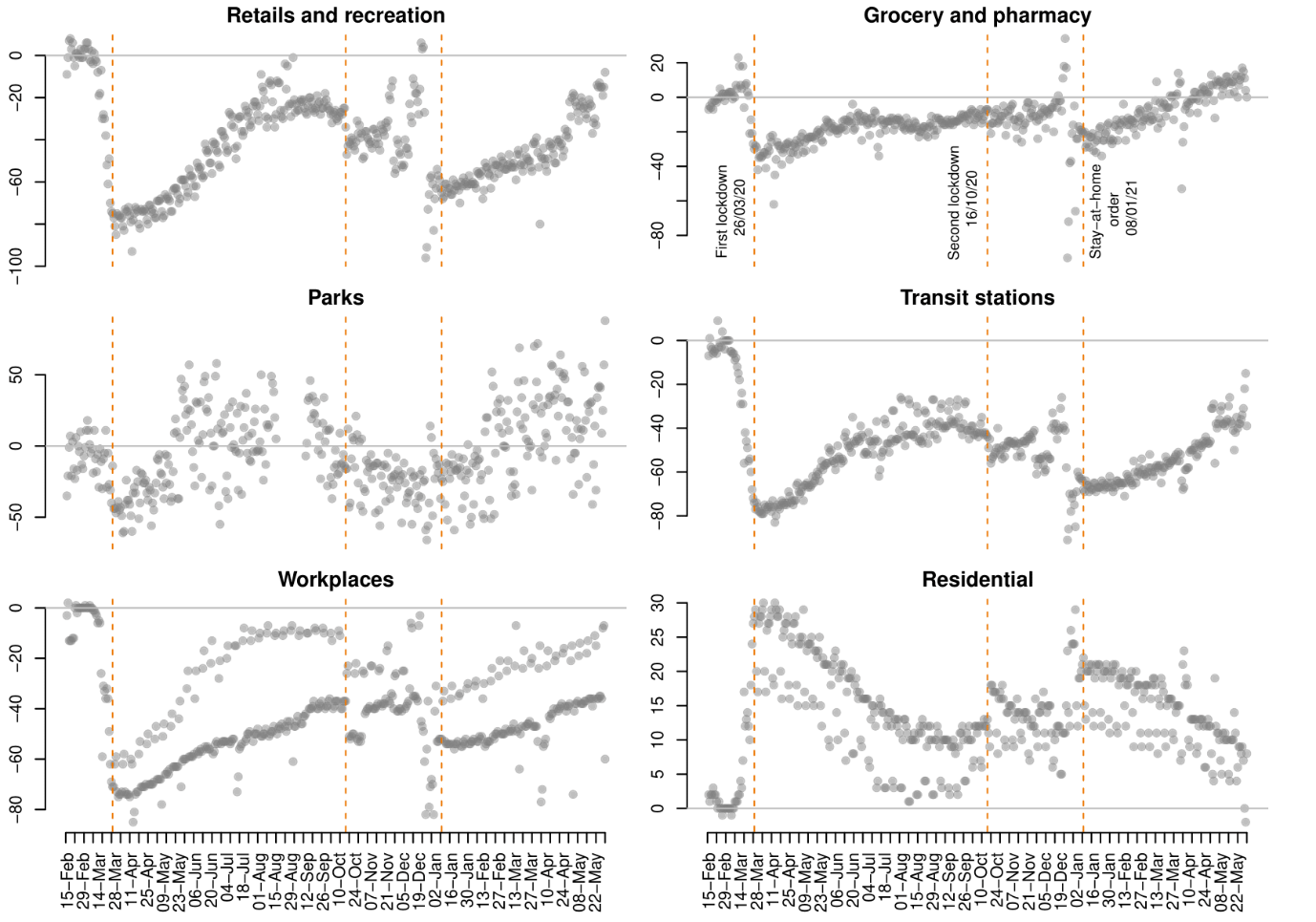
The COVID-19 pandemic and the associated stay-at-home orders imposed by national and regional governments to control the spread of the virus caused unprecedented changes in the everyday lives of millions worldwide. Due to the quick spread and mortality of the virus (on 29th June 2021, the World Health Organization had recorded more than 181 million cases and almost 4 million deaths), many countries established and enforced lockdown and social distancing measures aimed at containing COVID-19 infections, which had anomalous 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 restrictions, 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., 2021), increased. After the first few months of COVID pandemic, researchers noted that rates of traditional, offline crime started to bounce back to pre-COVID levels (Langton et al., 2021a; Nix and Richards, 2021), and some violent offences even surpassed crime rates seen before the pandemic (Kim and Phillips, 2021), but there is a lack of research about the medium- and long-term impact of lockdown orders on cyber-enabled and cyber-dependent 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 cybercrime rates remained well above pre-pandemic trends, thus indicating a potential long-term post-pandemic upward trend in cybercrime. There is also a gap in research about the effect of the first, second and third COVID-19 lockdowns on crime in Northern Ireland. 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 the three COVID-19 lockdowns on crime. We will analyse the effect of lockdowns on crime trends using interrupted time series (ITS) analysis based on segmented linear regressions and counterfactuals (McDowall et al., 2019).

The remainder of this paper is organised as follows: Section 2 describes the main changes in routine activities seen during the COVID-19 pandemic in Northern Ireland, and Section 3 describes how changes in routine activities during COVID-19 affected rates of different types of crimes in different parts of the world. Section 4 introduces the main aims and research questions of this paper. Section 5 discusses the data and analytical strategy used in this paper. Section 6 presents the results of the analysis, and Section 7 presents the discussion and conclusions of the study.

# 2. COVID-19 and changes in everyday life in Northern Ireland

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 of COVID-19 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. These measures had enormous effects on mobility trends, as can be seen in Figure 1, with almost immediate reductions in mobility in places dedicated to retail and recreation, grocery and pharmacy, transit stations and workplaces, and important increases in mobility in residential areas. The first lockdown was gradually eased during June and July 2020.



***Figure 1.*** *Mobility indicators percent change from baseline in Belfast (February 15th 2020 to May 31st 2021). Source: Google COVID-19 Community Mobility Reports (*[*https://www.google.com/covid19/mobility/index.html?hl=en*](https://www.google.com/covid19/mobility/index.html?hl=en)*)*

Due to the steep rise in COVID-19 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. 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. Although the measures associated with the second lockdown contributed to immediate changes in mobility, especially in places dedicated to retail and recreation and workplaces and residential areas (see Figure 1), the extent of these changes was very small compared to that of the first COVID-19 lockdown. Further restrictions, mostly related to the closure of cafes, hospitality, non-essential shops and gyms, were introduced on November 27th. The second Northern Ireland lockdown was mostly lifted by the second week of December.

Just a few days later, however, on December 17th, a third lockdown was announced, which began on December 26th. Entertainment and hospitality businesses and non-essential shops were closed, and a maximum of three household were allowed to meet up over Christmas. Some mobility restrictions were later 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 when work could not be done from home. As can be seen in Figure 1, some of these measures had impacts in mobility as evident as those of the first COVID-19 lockdown (some of the extreme changes in mobility seen during the last days of December are due to Christmas shopping and Christmas celebrations). Stay-at-home orders were progressively lifted during March and April 2021, following the increase in the proportion of persons vaccinated against COVID-19, and mobility trends return progressively to the pre-COVID baseline.

All these unprecedented changes in routine activities brought about by the COVID-19 lockdowns are expected to have short- and medium-term impacts in crime, as seen in other parts of the world (Nivette et al., 2021). More specifically, we will analyse changes in crime rates after the first lockdown (March 23rd 2020), second lockdown (October 16th 2020) and the stay-at-home order of the third lockdown (January 8th 2021) in Northern Ireland.

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

Crime is known to be dependent on illicit opportunity structures which vary according to changes in everyday routine activities. By the end of the 1970s, Cohen and Felson (1979) argued that property and violent crime was increasing in the United Stated mainly due to social changes that increased the availability of suitable crime targets and reduced the capacity of people to serve as guardians of these targets. Some of these changes were associated with the increase in female labour participation, the generalised access to holidays and the increase in ownership of valuable and movable goods. Based on this observation, Cohen and Felson (1979) proposed the Routine Activity Approach, which explains that crime will tend to grow when opportunities for offenders to converge with suitable targets in the absence of capable guardians increase. Since then, Routine Activity Approach has been applied to explain the effect of natural disasters on crime (Leitner et al., 2011), the impact of social changes related to joining the European Union on crime in Eastern European countries (Piatkowska et al., 2016), and to explain why crime increases during National Football League games in the US (Kalist and Lee, 2014), to mention just some examples. However, no event in recent history has affected everyday routine activities as much as COVID-19 and the associated lockdown orders. Researchers from all over the world have presented evidence that changes in routine activities associated with stay-at-home orders had severe impacts on crime rates.

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)

# 4. The present study

# 5. Methodology

## 5.1 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.

## 5.2 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 a 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.

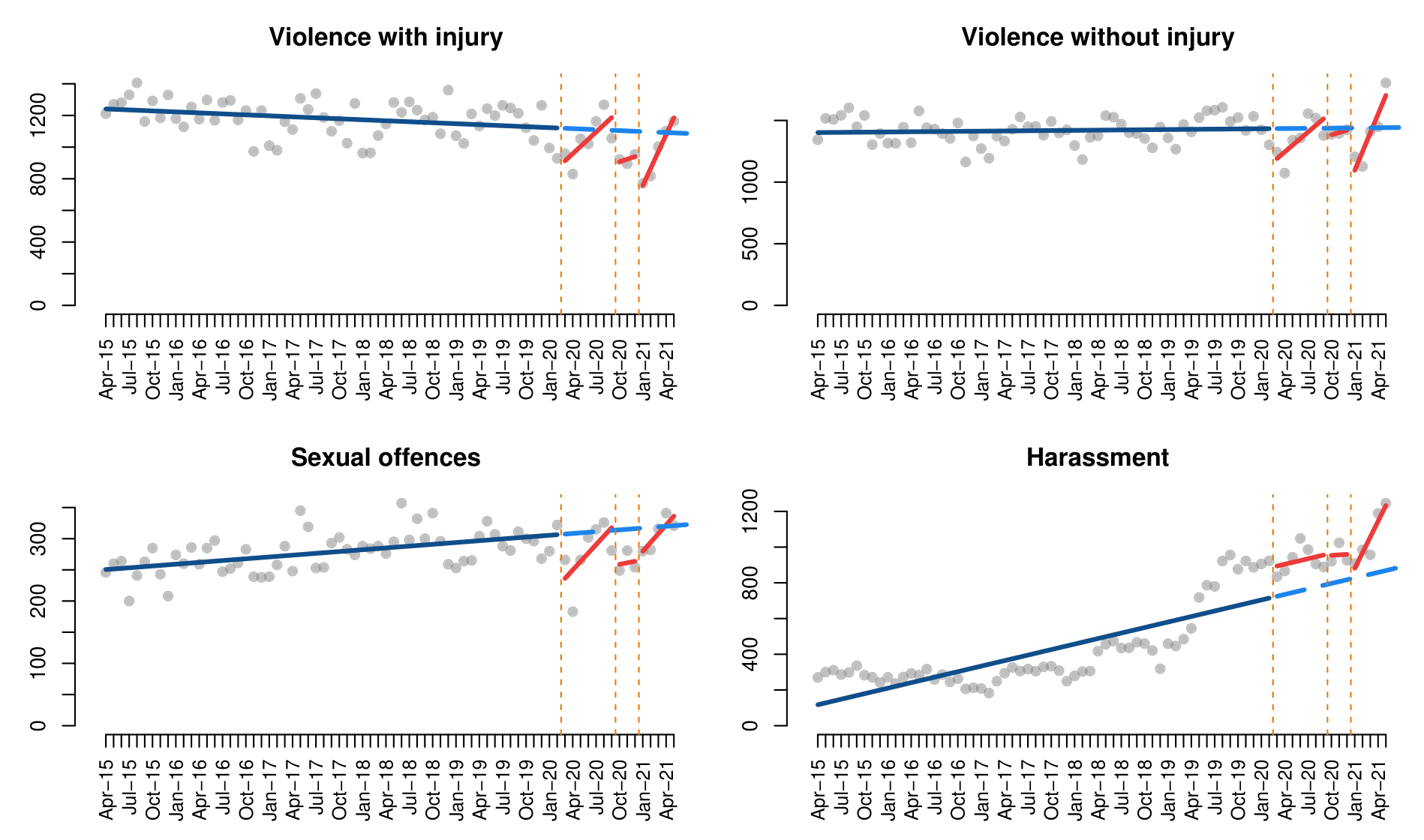
The analysis has been conducted in R software (R Core Team, 2021) with the assistant of the ‘forecast’ package (Hyndman et al., 2020), and all data and codes are available from a Github repository (ADD URL).

# 6. Results



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

## 6.1 Violence and sexual crime



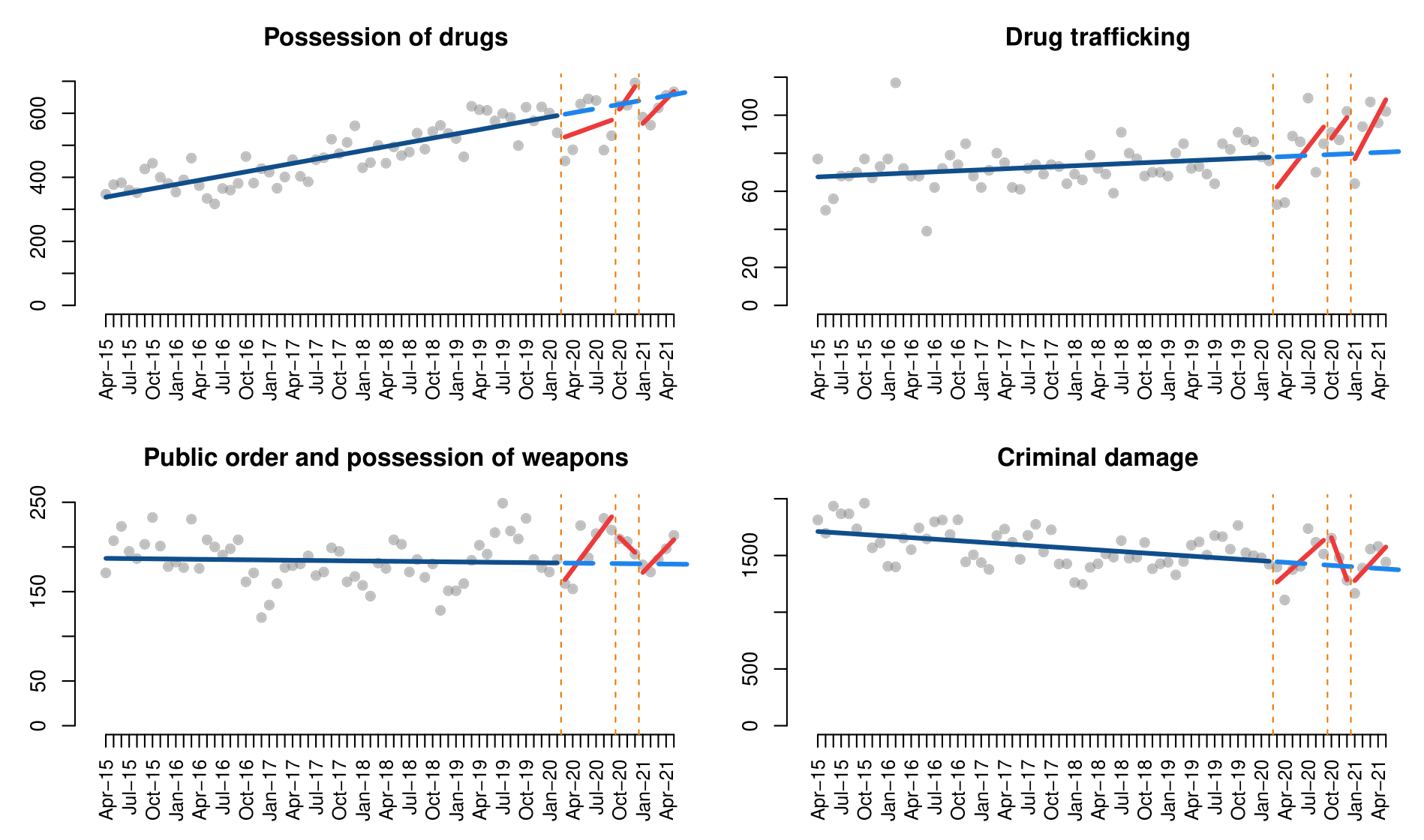
***Figure 2.*** *Interrupted time series analysis of violent and sexual crimes*

***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

## 6.2 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

## 6.3 Burglary



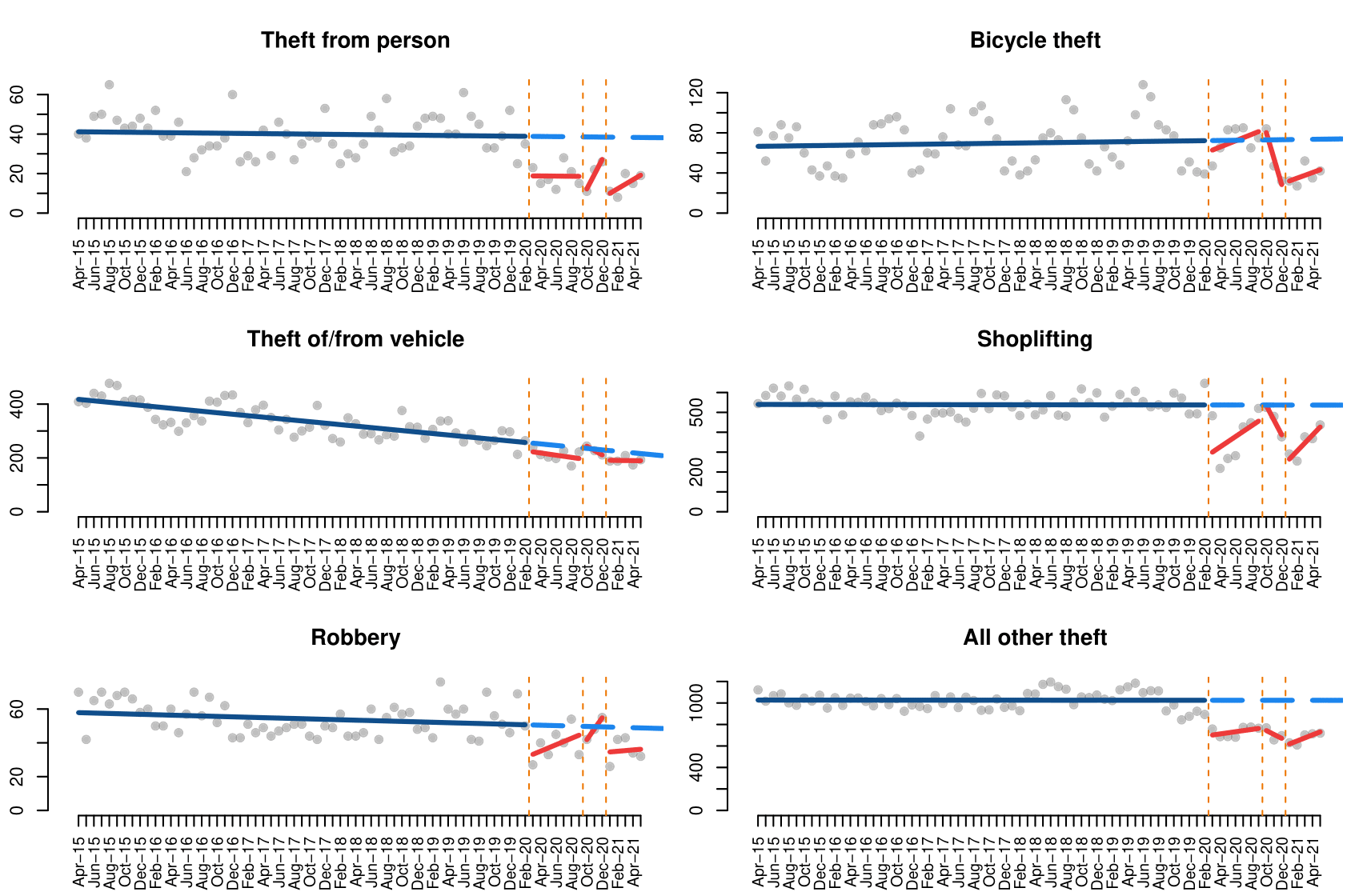
***Figure 4.*** *Interrupted time series analysis of burglary*

***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

## 6.4 Theft and robbery



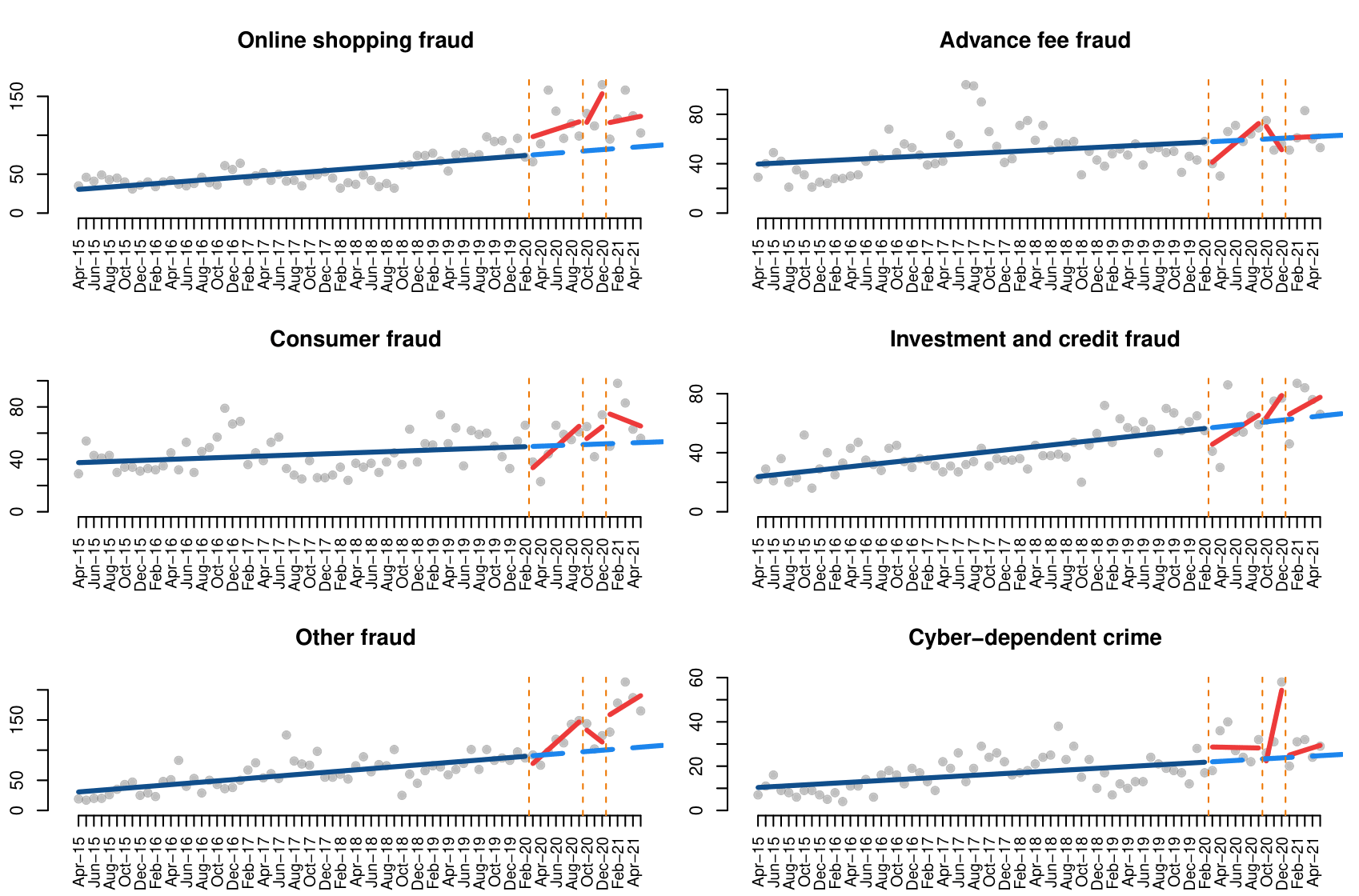
***Figure 5.*** *Interrupted time series analysis of theft and robbery*

***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

## 6.5 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

# 7. 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 components | (0, 0, 0) | (0, 0, 2) | (0, 1, 2) | (0, 1, 0) | (1, 1, 2) | (0, 0, 1) |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | 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 components | (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 components | (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 components | (1, 1, 1) | (0, 0, 2) | (0, 1, 1) | (0, 1, 1) | (0, 1, 1) |