Offline crime returns to pre-COVID levels, cyber doesn’t: Interrupted time-series analysis in Northern Ireland

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# Author contributions

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# Availability of data and materials

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# Competing interests

The authors declare that they have no competing interests.

# Abstract

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# Keywords

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

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# Abstract

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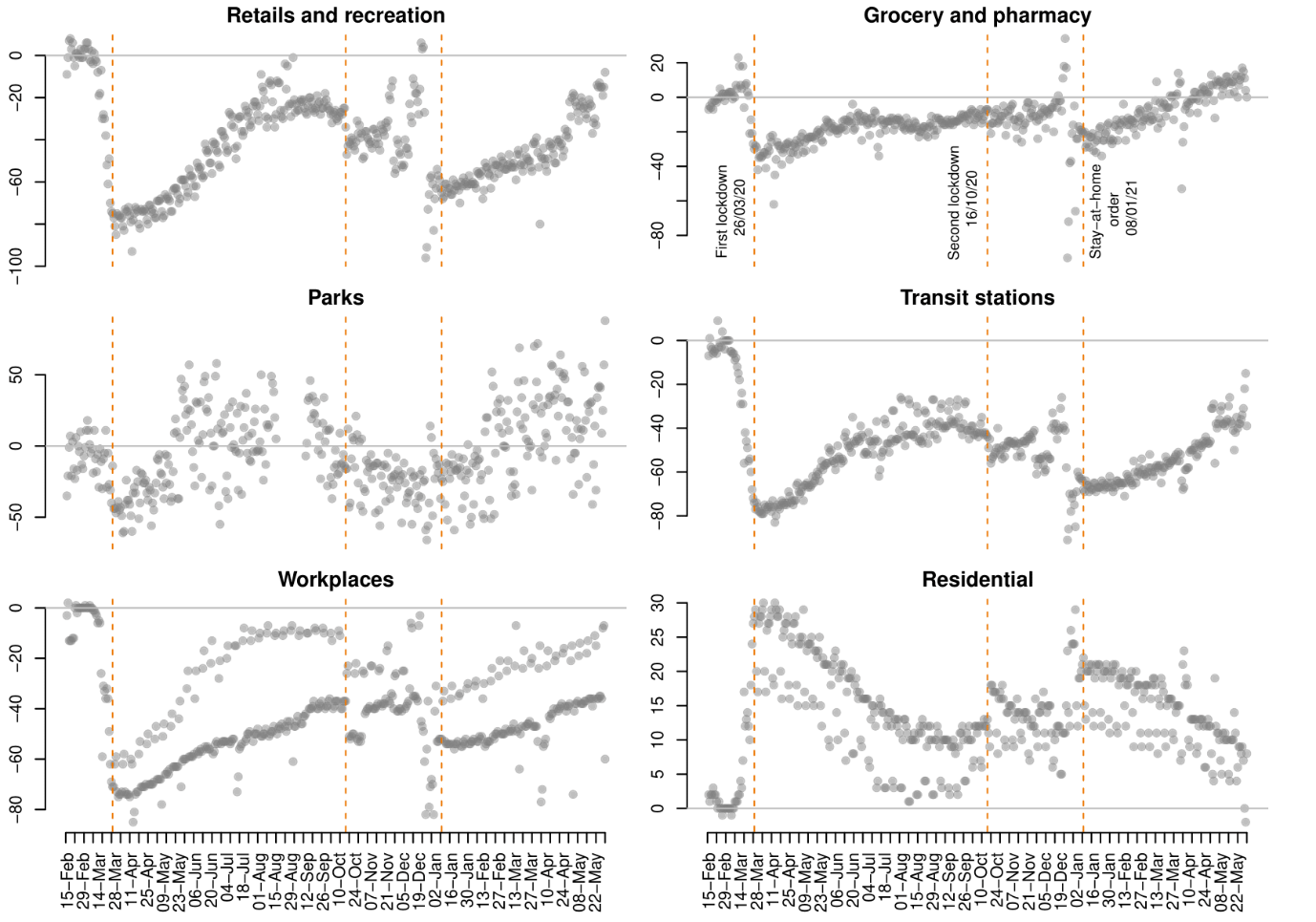
# 1. Introduction

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, 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 important social domains, including inequality (Abedi et al., 2021; Czymara et al., 2021), psychological wellbeing (Rajkumar, 2020), small and medium businesses (Bartik et al., 2020) and crime (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), Mexico (Estévez-Soto, 2021), China (Borrion et al., 2020) and 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 some forms of hacking (Buil-Gil et al., 2021), increased. After the first few months of COVID-19 pandemic, researchers noted that rates of traditional, offline crime started to bounce back to pre-COVID levels (Balmori de la Miyar et al., 2021; 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 offline and online crime, in Northern Ireland during COVID-19, and to investigate the short- and medium-term impact of the three COVID-19 lockdowns on crime. We 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).

# 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. 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 coronavirus 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, 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.*** *Percent change from baseline in mobility indicators 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 lockdown. Further restrictions, mostly related to the closure of cafes, hospitality, non-essential shops and gyms, were introduced on November 27th. The second COVID-19 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 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. 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 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 returned 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 on crime in Northern Ireland, as seen in other parts of the world (Nivette et al., 2021). More specifically, we will analyse changes in crime 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).

# 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) observed that property and violent crime was growing in the United Stated mainly due to series of social changes that increased the availability of suitable targets and reduced the ability 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 of crime, which argues that crime increases when (and where) there are more opportunities for offenders to converge with suitable targets in the absence of capable guardians. Since then, Routine Activity Approach has been applied to explain the effect of natural disasters on crime (Leitner et al., 2011), the impact of rapid structural and political changes related to joining the European Union on crime in Eastern Europe (Piatkowska et al., 2016), and changes in crime during US National Football League games (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 measures. 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.

After the first COVID-19 lockdown was announced in many countries in March 2020, several researchers noted immediate changes in crime. Mohler et al. (2020) analysed calls for police services in Los Angeles and Indianapolis between January and April 2020 and observed that burglary and robbery reports decreased immediately after the first stay-at-home order, but such reduction was more evident in Los Angeles than Indianapolis. Both cities saw important decreases in traffic stops and increases in calls related to domestic violence. Also using Los Angeles crime data, Campedelli et al. (2020a) observed a significant decrease in robbery, shoplifting, theft and battery during March and April 2020, but no significant changes were seen for burglary, homicide, vehicle theft or assault. Ashby (2020) analysed crime data recorded in sixteen large US cities between January and May 2020 and noted a reduction in residential burglary and motor vehicle theft in some cities after the first stay-at-home orders, though such change did not happen in other cities. There was little variation in non-residential burglary and serious assault. In the UK, Halford et al. (2020) analysed changes in crime in Lancashire during March 2020, and noted that, by the week of March 23rd, there was a large decrease in shoplifting, theft, theft from vehicle, domestic abuse, assault and residential and non-residential burglary. Similar results were found in other countries, including Sweden, where assault, pickpocketing and burglary decreased, but robbery and drug crime did not experience changes (Gerell et al., 2020), and Australia, where all property crime, except fraud, decreased after March 2020 (Payne et al., 2021). Nivette et al. (2021) recorded crime data from 27 cities across 23 countries and concluded that stay-at-home orders contributed to a considerable drop in urban crime in most cases. The immediate effect of stay-at-home orders on crime varied across geographic areas in each city (Campedelli et al., 2020b; Payne et al., 2021; Langton et al., 2021b).

Some researchers noted, however, that while many types of offline crime were decreasing, there were signs that the changes in routine activities brought about by the first COVID-19 lockdown had increased opportunities for online crime. Using data about cyber-enabled fraud and cyber-dependent crime recorded by Action Fraud, the UK National Fraud and Cybercrime Reporting Centre, between May 2019 and May 2020, Buil-Gil et al. (2021) observed significant increases in some forms of hacking and online shopping fraud after the first stay-at-home orders. Lallie et al. (2021) searched for cyber-attacks reported globally through online search engines and observed an increase in cybersecurity incidents such as phishing, malware and cyber-enabled fraud after February 2020. Kemp et al. (2021) analysed reports of fraud and cybercrime made to the UK Action Fraud and observed a large increase in cyber-dependent crime (i.e., hacking, denial of service attacks and malware), online shopping fraud and dating fraud after the first COVID-19 lockdown, while those forms of fraud associated with offline events, such as doorstep fraud and ticket fraud, decreased. As argued by these researchers, the first stay-at-home orders contributed to an immediate spike in internet use for entertainment, including online gaming, streaming content and watching TV, teleworking, socialising with family and friends through videocalls, buying products and services, and meeting new people, thus increasing the amount of valuable crime targets in online environments. Other forms of crime enabled by the internet also increased, for example, Stechemesser et al. (2020) recorded Tweets with anti-Chinese racist content between January and April 2020 and observed a spike in online hate speech during March 2020. Interestingly, while it is likely that more people tried to acquire drugs through online dark markets during the early stages of the pandemic, Bergeron et al. (2020) observed a decrease in successful deliveries of drug packages, which was explained by the impact of stay-at-home order on supply chains.

All this body of literature contributes to understanding the effect of large-scale, rapid social changes on offline and online crime. However, crime research is not only interested in the short-term impact of the COVID-19 lockdown on crime, but it also aims to understand the effect of stay-at-home orders on medium- and long-term crime trends. Langton et al. (2021a) showed that, after the first COVID-19 lockdown in the UK, crime started to bounce back to pre-COVID levels. Similar results were found by Balmori de la Miyar et al. (2021) using data recorded in Mexico. Nix and Richards (2021) observed that domestic violence calls for police services in six police jurisdictions in the US returned to pre-COVID levels when lockdown restrictions were lifted.

Existent research appears to indicate that the quick changes in offline crime seen immediately after the first COVID-19 lockdown were temporary, and crime trends progressively returned to pre-COVID levels after social distancing restrictions are relaxed. Nonetheless, while some of the changes in offline routine activities brought about by stay-at-home orders may indeed be temporary (e.g., bars and restaurants reopen, employees return to work from the office, sport events and concerts are organised, travelling is allowed), some of the changes in online everyday practices may not be restricted to the pandemic and may have long-term effects on cybercrime. Online shopping is a clear example, since internet sales were well above pre-COVID levels even after May 2021 (Office for National Statistics, 2021). There is also an expected long-term post-pandemic upward use of online gaming, social media, teleworking, online food delivery, online conference platforms and online dating (Nurse et al., 2021; Ofcom, 2021). Thus, it is plausible that the upward trend seen in cybercrime since March 2020 may not return to levels recorded before the pandemic. For instance, Buil-Gil and Zeng (2021) observed that reports of cyber-enabled romance fraud in the UK continued growing nine months after the first COVID-19 lockdown. This research uses crime data recorded in Northern Ireland between April 2015 and May 2021 to analyse the effect of the first, second and third COVID-19 lockdowns on short- and medium-term trends in crime, both offline and online.

# 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 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 the impact of the COVID-19 lockdowns on both crime types. More specifically, we will analyse the following types of crime aggregated in months:

1. Violence and sexual crime: including violence with and without injury, sexual offences, and robbery.
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/from vehicle, and shoplifting.
5. Fraud and cybercrime: including investment and advance fee fraud (when victims are asked to make upfront payments for goods, services, schemes or products that do not materialise; for example, fraud recovery scams, inheritance fraud, lender loan fraud, ‘419’ frauds, rental frauds, Pyramid schemes, pension scams or boiler room fraud), consumer fraud offline (for example, doorstep fraud and consumer non-investment fraud), consumer fraud online (for example, online shopping fraud, computer software service fraud and consumer phone fraud), other types of fraud (for example, fraud by abuse of trust, corporate employee fraud, credit card fraud, charity 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 analyse a variety of crime types that could be affected in different ways by the mobility restrictions of the three COVID-19 lockdowns. For example, opportunities for violence offences and theft are found mostly in ‘public places’ and thus were likely to decrease during stay-at-home orders and return to normal levels after each lockdown (Balmori de la Miyar et al., 2021). While residential burglary opportunities were likely to decrease during lockdown due to the increase of ‘capable guardians’ at home, this may not be the case for non-residential burglaries (Felson et al., 2020). Some fraud types are clearly cyber-enabled, such as online shopping fraud, and thus their opportunities were likely to increase with the increased of internet use both during and after lockdown, while other fraud categories may be include both offline and online incidents (for example, investment and advance free fraud Pyramid schemes or ‘419’ frauds which can be enabled by the internet in some cases but not always). Cyber-dependent crimes can only take place online.

## 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 utilise ITS analysis based on segmented linear regressions. The ITS segmented linear 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. 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 few exceptions (e.g., Humphreys et al., 2013; Steinbach et al., 2015), this approach has been rarely applied in crime research, but its application is widespread in epidemiology, economics and other fields. We present the model results using tables and visualisations.

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 value) at one point in time is correlated with the scores at another points (i.e., there may be ‘serial autocorrelation’). Moreover, the segmented linear regression 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 beyond stay-at-home orders (e.g., the second lockdown began in October 2020, after summer, when crime could decrease due to seasonal crime variation). 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 multivariate ARIMA error model with the best goodness-of-fit for each crime type. This algorithm seeks a data-driven selection of the components (order of the auto regressive model), (order of differencing) and (order of moving average), and , and (the seasonal components), of the model, thus finding the model that adjust best to the data in each case. We evaluated the models selected using the Durbin-Watson and Ljung-Box tests to assess the autocorrelation of the residuals, and the KPSS test to assess the stationarity of fitted values. In some cases, the components of the model were adjusted manually to ensure that model assumptions were met. 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) and all data and codes are available from a Github repository (anonymised repository: <https://anonymous.4open.science/r/covid_crime_NI-Anonymise/>).

# 5. Results

This section presents the results of the ITS analysis based on segmented linear regressions. The results of the multivariate ARIMA errors are presented in the Appendix as a sensitivity check.

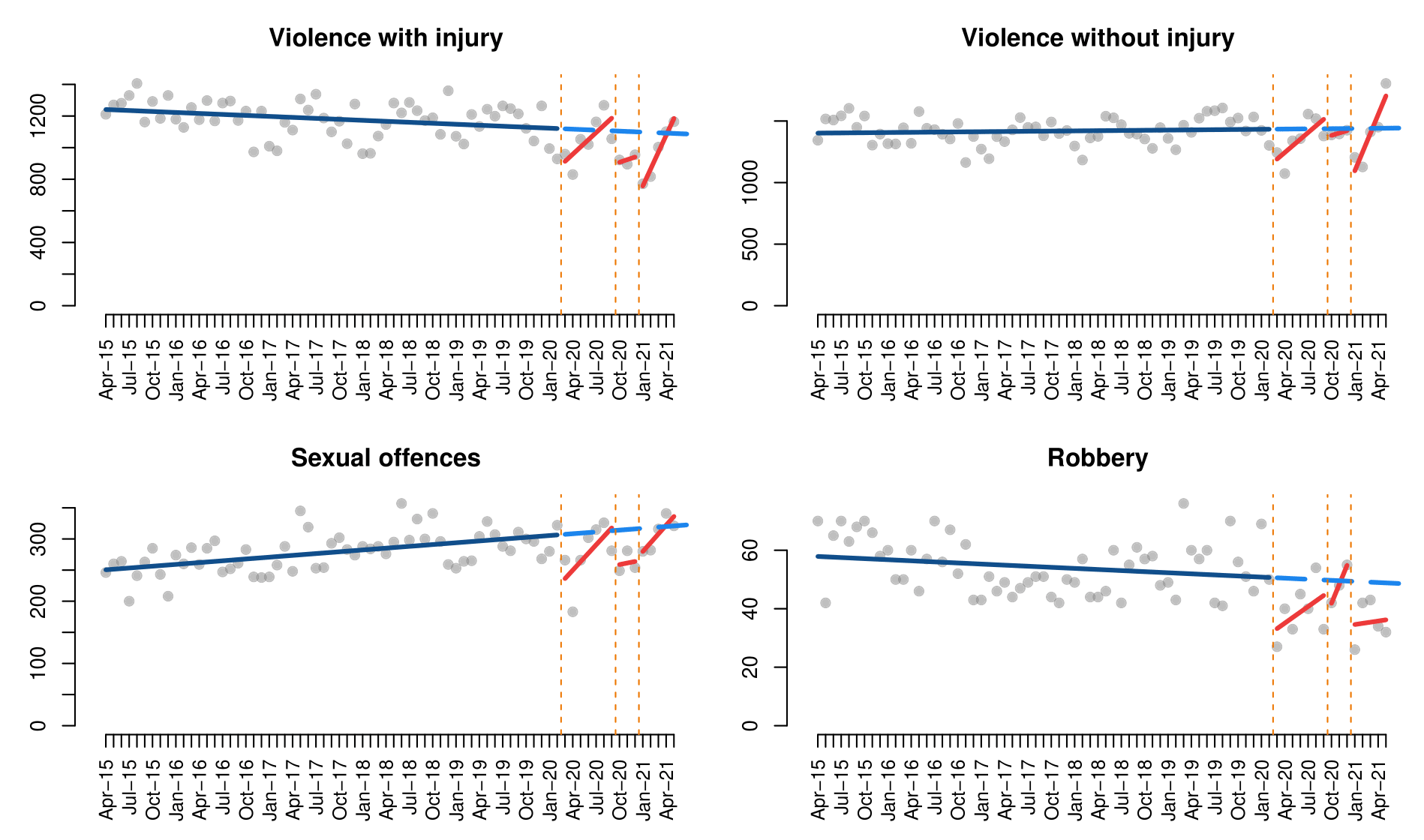
Overall, as shown in Figure 2, crime suffered an important decrease after the first and third lockdowns in Northern Ireland, while the effect of the second lockdown was less evident. Crime records progressively returned to pre-COVID levels after the first and third lockdown. However, as described above in the literature review, this is likely to mask huge differences between crime types, and may be affected by seasonal patterns that affect some offences more than others. The following subsections analyse crime trends for each crime type.



***Figure 2.*** *Interrupted time series analysis of all crime*

## 5.1 Violence and sexual crime

The results of the ITS analysis of violence and sexual offences, including violence with injury, violence without injury, sexual crimes and robbery, show that crime levels decreased immediately after each COVID-19 lockdown, and rapidly returned to pre-COVID levels after each lockdown (Figure 3). The results of the ITS models, presented in Table 1, further reinforce this finding, showing that: (a) the decrease in crime resulting from the first lockdown was statistically significant in all four cases; (b) the increase in crime after the first lockdown is statistically significant in the case of violence with and without injury and sex crime, but not robbery; and (c) violent crime with and without injury significantly decreased immediately after the third lockdown, and returned to pre-COVID levels during the following months as lockdown restrictions were lifted. The results of the multivariate models with ARIMA errors show remarkably similar results (see Appendix), but they also indicate that, in the case of robbery, the effects of the second lockdown (negative), time since second lockdown (positive), and third lockdown (negative) on crime were likely to be statistically significant.



***Figure 3.*** *Interrupted time series analysis of violent and sexual crimes*

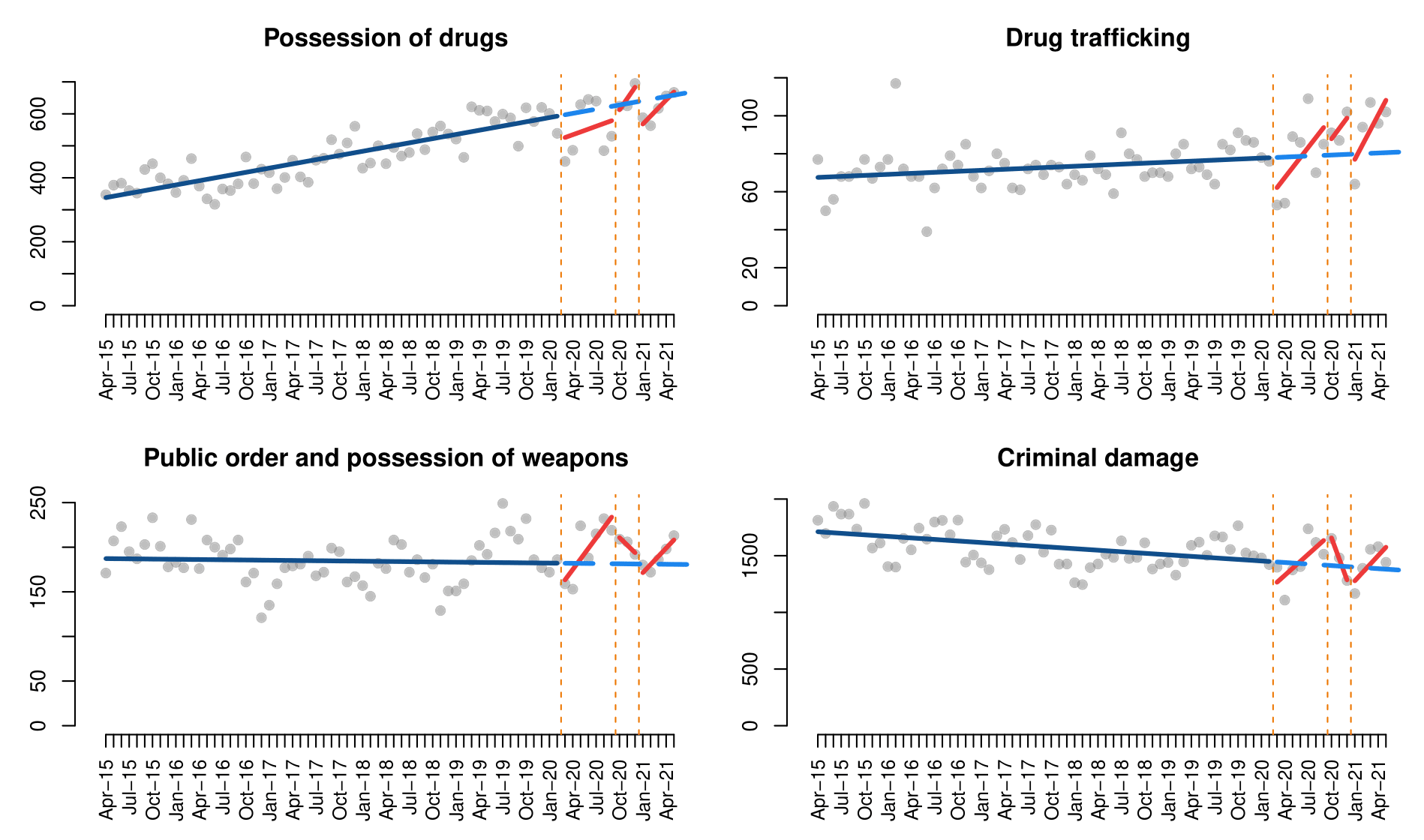
***Table 1.*** *Interrupted time series models of violent and sexual crimes*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Violence with injury | Violence without injury | Sexual offences | Robbery |
| (Intercept) | 1243.3\*\*\* | 1401.2\*\*\* | 249.5\*\*\* | 58.0\*\*\* |
| Time | -2.1\* | 0.5 | 1.0\*\*\* | -0.1+ |
| First lockdown | -253.5\*\* | -297.1\*\* | -83.7\*\* | -19.4\* |
| Time since first lockdown | 47.7\* | 53.4\* | 12.6\* | 2.0 |
| Second lockdown | -215.5 | -73.0 | -56.9 | -14.5 |
| Time since second lockdown | 18.6 | 18.5 | 1.5 | 6.6 |
| Third lockdown | -450.0\*\*\* | -496.3\*\*\* | -50.4 | -15.3 |
| Time since third lockdown | 109.1\*\* | 151.8\*\*\* | 13.13 | 0.5 |
| Adjusted R2 | 0.42 | 0.24 | 0.28 | 0.32 |

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

## 5.2 Drug crimes, damage and public order

Drug-related crimes and public order/criminal damage offences show remarkably different trends. One the one hand, drug crimes show a similar pattern to that of violence offences, with crime levels decreasing immediately after each COVID-19 lockdown and returning progressively to pre-COVID levels during the following months. On the other hand, ITS analysis of public order and criminal damage shows that crime decreased immediate after the first and third lockdowns, and it then returned to the overall linear trendline, but the observed effect of the second lockdown was different to those seen above, showing a decrease in crime after October 2020. This can be seen both in Figure 4 and Table 2. However, as can be observed in Figure 4, the trends of public order and criminal damage during the pandemic follow remarkably similar patterns to pre-COVID trends, with increases in crime during summer and lower crime levels in winter. Thus, we need to be cautious when trying to establish links between COVID-19 lockdowns and crime, since changes in crime may simply be driven by crime seasonality. It can also be highlighted that drug trafficking offences are clearly larger during COVID-19 than before.



***Figure 4.*** *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 | 0.06 | 0.28 |

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

The results of the segmented linear models (Table 2) are very similar to that of the multivariate ARIMA error regressions (Appendix), but there are some notable differences regarding the statistical significance of some temporal variables. For instance, the ARIMA error model shows that the negative effect of the first lockdown on crime was also statistically significant in the case of public order and possession of weapon offences, the effect of time since the second and third lockdowns is also significant in the case of possession of drug crimes (while the negative effect of the third lockdown on possession of drugs may not be significant), and the negative effect of the third lockdown on criminal damage may be statistically significant.

## 5.3 Burglary

The effect of COVID-19 on burglary trends was clearly different depending on whether the crime happened in a household or non-residential building. While residential burglary decreased after March 2020 and remained well below pre-COVID levels since then, non-residential burglary was not affected in any significant way by the COVID-19 lockdowns (Figure 5). None of the lockdowns had significant effects on non-residential burglary records in Northern Ireland. In the case of residential burglary, the segmented linear model results indicate that crime decreased immediately after the first and third lockdowns, and these changes were statistically significant (Table 3), but the ARIMA error model indicates that only the effect of the first lockdown was statistically significant (Appendix).



***Figure 5.*** *Interrupted time series analysis of burglary*

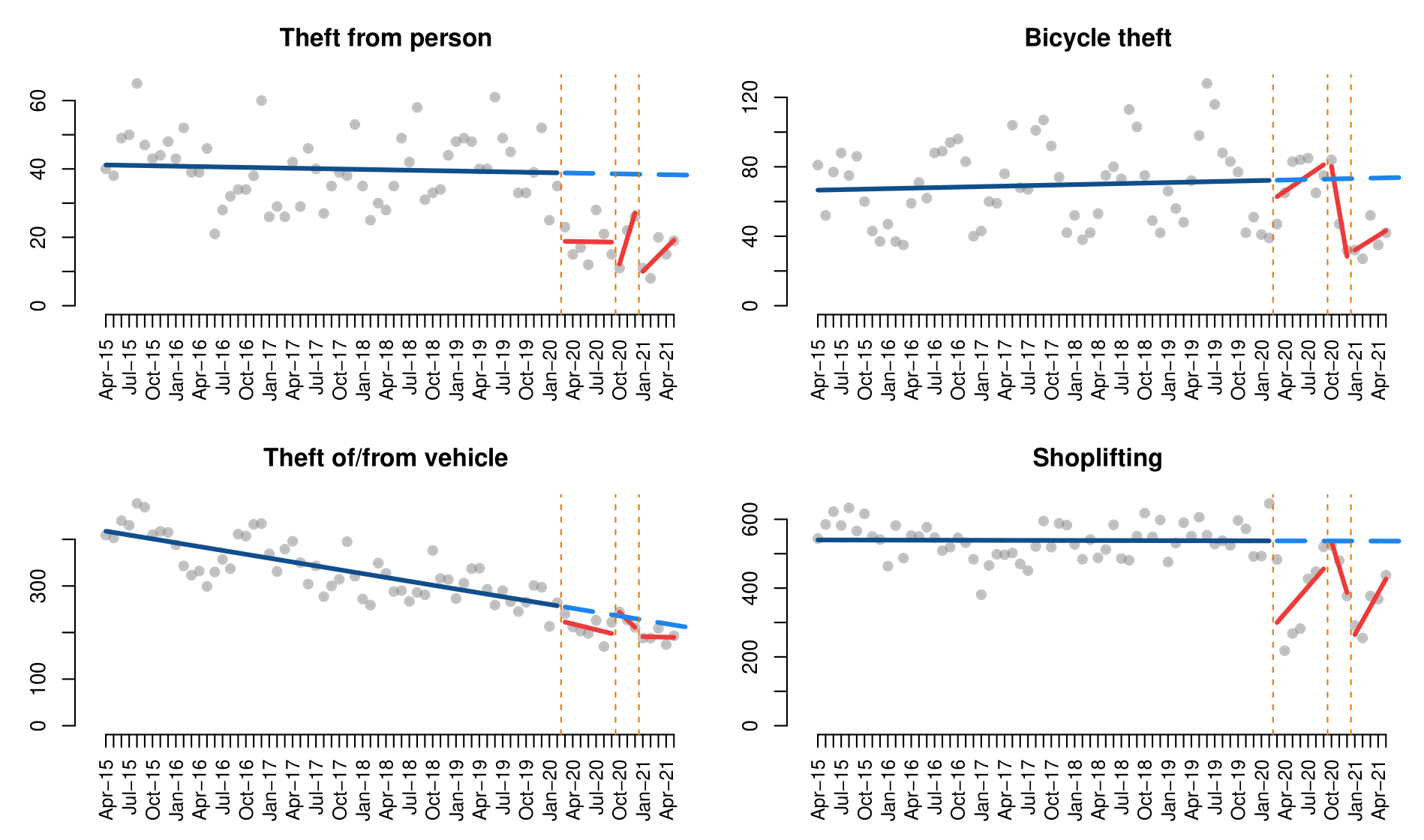
***Table 3.*** *Interrupted time series models of burglary*

|  |  |  |
| --- | --- | --- |
|  | 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 | 0.63 | 0.84 |

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

## 5.4 Theft

We distinguish four types of theft: theft from person, bicycle theft, theft of/from motor vehicle, and shoplifting. As can be seen in Figure 6, there are important differences across these types of theft. First, reports of theft from person decreased immediately after each COVID-19 lockdown, and started to return to pre-COVID levels progressively after lockdown restrictions were lifted in each case. While the ITS model in Table 4 indicates that the drops in crime observed after each lockdown were statistically significant, the results of the multivariate model with ARIMA errors show that these changes may not be statistically significant (Appendix). Second, the changes in bicycle theft during the pandemic appear to follow pre-COVID seasonal patterns, with large increases in crime during summer and fewer crimes recorded in winter. However, the decrease in bicycle theft seen immediately after the third lockdown provoked the lowest level in crime registered since April 2015, and as such this decrease is statistically significant both in the segmented linear model (Table 4) and the multivariate ARIMA error model (Appendix). Third, the trend of theft of/from vehicle during the pandemic follows the steady decreasing trend seen before COVID-19, and none of the changes observed since March 2020 are statistically significant (the ARIMA error model indicates that the decrease in crime after the third lockdown may be statistically significant). And fourth, we observe that shoplifting experienced an extensive decrease after the first and third lockdowns, and it started to bounce back to pre-COVID levels after these stay-at-home orders. Model results also show that, in this case, there was a decrease in crime records instead of an increase during the months following the second lockdown, and this does not appear to be attributed to pre-COVID seasonal trends. All these changes are statistically significant both in the ITS and multivariate ARIMA error models.



***Figure 6.*** *Interrupted time series analysis of theft and robbery*

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

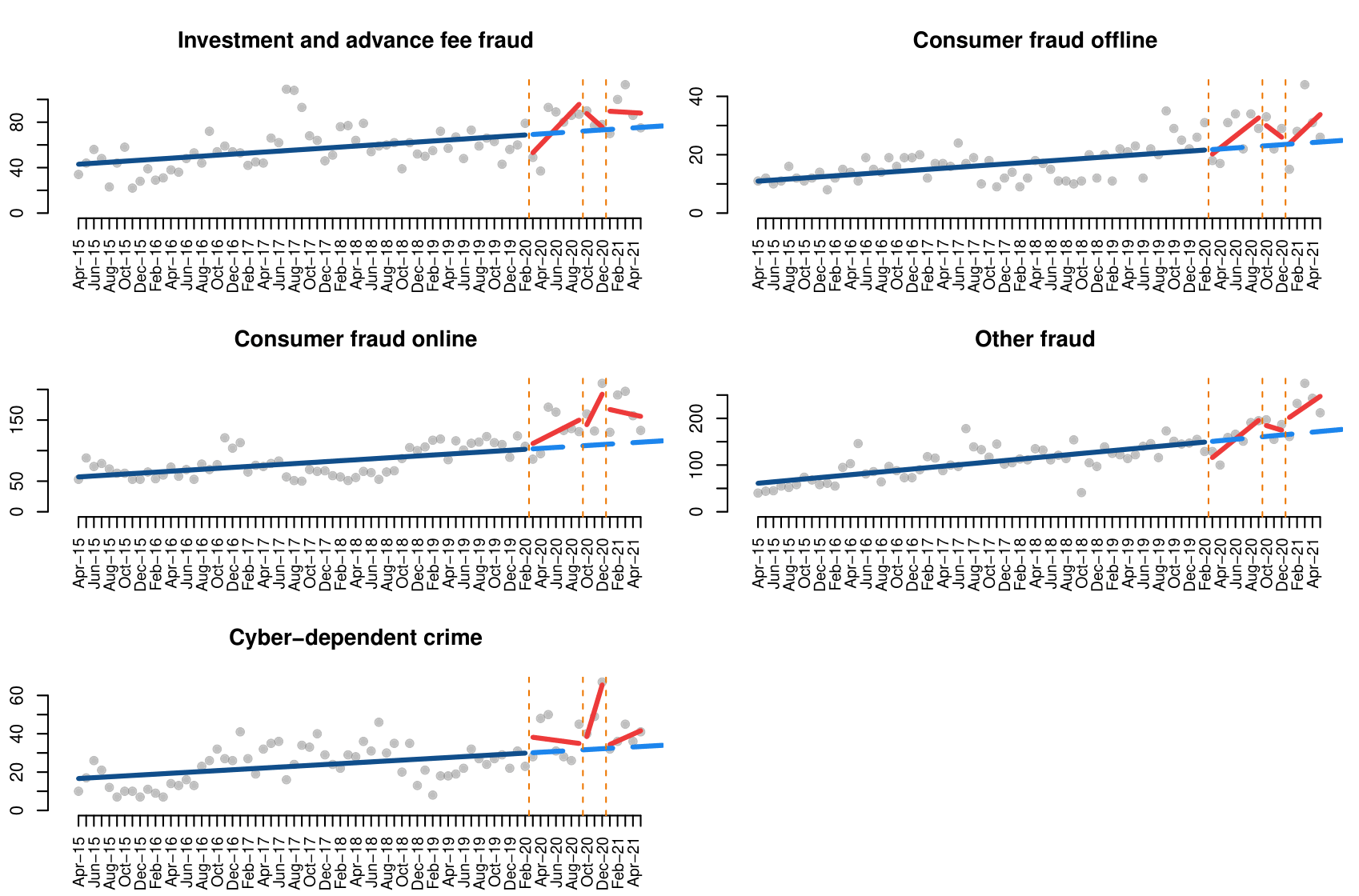
|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Theft from person | Bicycle theft | Theft of/ from vehicle | Shoplifting |
| (Intercept) | 41.2\*\*\* | 66.5\*\*\* | 420.3\*\*\* | 540.0\*\*\* |
| Time | -0.0 | 0.1 | -2.7\*\*\* | -0.0 |
| First lockdown | -20.0\* | -12.5 | -30.9 | -263.6\*\*\* |
| Time since first lockdown | 0.0 | 3.0 | -1.3 | 26.1\* |
| Second lockdown | -33.9\* | 33.5 | 22.1 | 71.7 |
| Time since second lockdown | 7.5 | -26.1 | -13.7 | -74.0+ |
| Third lockdown | -30.8\*\* | -44.0+ | -38.3 | -312.7\*\*\* |
| Time since third lockdown | 2.3 | 2.7 | 2.4 | 40.5\* |
| Adjusted R2 | 0.47 | 0.09 | 0.76 | 0.57 |

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

## 5.5 Fraud and cybercrime

We also analyse changes in fraud and cybercrime during COVID-19. At first sight, in Figure 7, we observe a remarkable increase in crime across all types of fraud, cyber-enabled and not, and cyber-dependent crime since March 2020. In all these cases there is also a steady increase in crime since 2015, which is observed in the statistically significant effect of time on crime trends in the ITS model results (Table 5). There are, however, important differences across crime types, and a more nuanced analysis of the model results is needed.

In the case of investment and advance fee fraud, which can be cyber-enabled in some cases but not others, crime decreased immediately after the first lockdown, but there was an increase in crime records immediately after the second and third lockdown orders. While none of these associations is statistically significant according to the results of the segmented linear model (Table 5), the results of the multivariate ARIMA error model (Appendix) show that the immediate positive effect of the first and second lockdown may be statistically significant. There was also a steady increase in investment and advance fee fraud after the first lockdown. Regarding consumer fraud offline, the results of the ITS model show that the only temporal variable that may be statistically significant in explaining crime trends is the time since the first lockdown (Table 5), with a slight increase in crime during the months following March 2020. This is, however, not reflected in the results of the multivariate ARIMA error model (Appendix), which nonetheless shows that the negative effect of the first lockdown, time since second lockdown and third lockdown on offline consumer fraud may be statistically significant. In the case of consumer fraud online, we see a steep increase in crime records during the COVID-19 pandemic, and while the results of the ITS model (Table 5) show that the only statistically significant temporal variable was the immediate effect of the third lockdown, the multivariate ARIMA error model show that the time since the first lockdown and the second lockdown were also likely to have statistically significant positive effects on online consumer fraud. The multivariate ARIMA error model results also show that the first lockdown could have a negative effect on records of online consumer fraud. Regarding other frauds, which may be cyber-enabled or committed fully offline, we observe that the first lockdown could provoke a decrease in crime which was then followed by an increase in crime records, though this is not observed in the results of the ARIMA error model. The ARIMA error model shows, however, that other frauds increased significantly since the third lockdown. Finally, with regards to cyber-dependent crime, we also see large peaks in crime records during COVID-19, but the only temporal variables with statistically significant effects are the time since the second lockdown, according to the ITS model (Table 5), or the time since the second lockdown and the first lockdown, according to the ARIMA error model (Appendix).



***Figure 7.*** *Interrupted time series analysis of fraud and cybercrime*

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

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Investment and advance fee fraud | Consumer fraud offline | Consumer fraud online | Other fraud | Cyber-dependent crime |
| (Intercept) | 42.6\*\*\* | 10.8\*\*\* | 56.2\*\*\* | 59.5\*\*\* | 16.4\*\*\* |
| Time | 0.4\*\*\* | 0.2\*\*\* | 0.8\*\*\* | 1.5\*\*\* | 0.2\*\* |
| First lockdown | -22.8 | -3.5 | 3.0 | -46.5\* | 8.8 |
| Time since first lockdown | 6.7\* | 1.9+ | 5.6 | 11.8\* | -0.8 |
| Second lockdown | 21.8 | 9.1 | 9.8 | 29.8 | -6.5 |
| Time since second lockdown | -6.4 | -2.2 | 24.2 | -6.5 | 13.2\*\* |
| Third lockdown | 16.7 | -2.1 | 60.1\* | 26.3 | 0.4 |
| Time since third lockdown | -0.8 | 2.3 | -3.6 | 7.9 | 1.6 |
| Adjusted R2 | 0.36 | 0.49 | 0.67 | 0.74 | 0.45 |

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

# 6. Discussion and conclusions

The COVID-19 pandemic and the associated lockdown orders were associated with rapid, unprecedented changes in everyday routine activities, which had direct effects on opportunities for crime (Nivette et al., 2021). Immediately after the first stay-at-home orders came into force in many countries in March 2020, many researchers noted that various forms of property and violent crime suffered an important decrease due to the reduced opportunities for offenders to converge with targets in physical settings (Abrams, 2021; Ashby, 2020; Halford et al., 2020). Crime trends, however, varied across geographic areas (Campedelli et al., 2020b; Payne et al., 2021) and crime targets (Felson et al., 2020). Simultaneously, others highlighted that some cyber-enabled and cyber-dependent crimes were increasing due the growth in internet use for work and leisure (Kemp et al., 2021; Lallie et al., 2021; Stechemesser et al., 2020). After the first months of pandemic, some of the social distancing restrictions were relaxed and rates of offline crime began to bounce back to pre-COVID trends (Balmori de la Miyar et al., 2021; Langton et al., 2021a; Nix and Richards, 2021), but there is a gap in research about the long-term effects of each COVID-19 lockdown on offline crime. This research analysed crime data recorded in Northern Ireland between April 2015 and May 2021 to analyse the short-, medium- and long-term effects of each lockdown on various forms of offline and online crime. We applied ITS segmented linear model to analyse our data, and used multivariate ARIMA error models as a sensitivity check on our analysis.

We

Discuss seasonality for some crime types

Violence larger than before covid

Shoplifting – open shops

Negative effect online consumer fraud – businesses closed

While the findings presented in this article are first-of-its-kind and contribute to the criminological literature about the effect of rapid social changes on crime (offline and online), these are not free of limitations. The main threat to the validity of our findings is related to the use of police-recorded crime statistics as a primary source of data. Police-recorded crime data are known to be severely affected by measurement error arising from underreporting and underrecording, and it is yet unknown the extent to which the COVID-19 pandemic has not only affected crime but also the measurement properties of crime statistics (Wallace et al., 2021). This may be particularly problematic in the case of cybercrime given the low reporting rates that define these offences (van de Weijer et al., 2019). Future research is needed to explore if reporting and recording practices that affect crime data were affected by COVID-19, thus illuminating the extent to which research using police-recorded crime data to study changes in crime may be affected by measurement error.

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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 | Robbery | Possession of drugs | Drug trafficking |
| First lockdown | **-113.8** [-225.1, -2.5] | **-157.2** [-255.0, -59.4] | **-77.0** [-113.4, -40.7] | **-28.2** [-38.4, -18.0] | **-53.3** [-103.0, -3.5] | **-30.2** [-44.4, -16.1] |
| Time since first lockdown | **41.9** [9.8, 73.9] | **24.9** [3.2, 46.6] | 7.4 [-3.8, 18.6] | 1.9 [-1.0, 4.9] | 9.1 [-1.8, 20.1] | **5.2** [0.9, 9.5] |
| Second lockdown | -134.5 [-368.3, 99.2] | -53.1 [-183.7, 77.5] | -68.8 [-149.5, 12.0] | **-22.5** [-44.2, -0.8] | -17.6 [-105.5, 70.2] | 8.6 [-22.5, 39.7] |
| Time since second lockdown | 40.4 [-23.6, 104.5] | 27.4 [-25.8, 80.6] | 4.6 [-14.6, 25.8] | **7.0** [1.1, 12.9] | **40.5** [5.4, 75.5] | 4.1 [-4.2, 12.4] |
| Third lockdown | **-321.2** [-578.9, -63.4] | **-453.0** [-578.6, -327.4] | -54.4 [-145.0, 36.3] | **-24.6** [-48.6, -0.6] | -12.0 [-86.7, 62.7] | -14.2 [-49.1, 20.6] |
| Time since third lockdown | **106.5** [65.8, 147.1] | **152.8** [117.2, 188.3] | 13.3 [-0.8, 27.3] | 0.5 [-3.3, 4.2] | **21.9** [4.9, 38.8] | **8.0** [2.6, 13.4] |
| Model components | (1, 1, 0) | (0, 0, 2) | (1, 1, 0) | (1, 1, 0) | (1, 1, 2) | (1, 1, 0) |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Public order and possession of weapons | Criminal damage | Residential burglary | Non-residential burglary | Theft from person | Bicycle theft |
| First lockdown | **-40.6** [-67.4, -13.9] | **-241.2** [-397.3, -85.1] | **-67.3** [-123.6, -11.0] | 12.1 [-11.0, 35.2] | -14.5 [-28.9, 0.0] | -4.8 [-24.0, 14.4] |
| Time since first lockdown | 17.2 [-4.2, 38.6] | **52.8** [16.2, 89.4] | 0.2 [-16.6, 17.0] | 8.0 [-10.7, 26.8] | 0.4 [-13.2, 14.1] | 2.0 [-2.5, 6.5] |
| Second lockdown | 60.0 [-83.9, 203.9] | **369.4** [93.2, 645.7] | 2.4 [-119.4, 124.2] | 84.1 [-41.8, 210.1] | -27.4 [-117.7, 63.0] | **41.9** [11.1, 72.7] |
| Time since second lockdown | 7.2 [-23.4, 37.7] | **-186.0** [-277.8, -94.3] | -15.0 [-47.1, 17.0] | 2.6 [-24.1, 29.3] | 13.1 [-8.0, 34.2] | **-27.5** [-40.5, -14.5] |
| Third lockdown | 50.8 [-163.7, 265.2] | **-295.4** [-570.2, -20.6] | -109.4 [-246.0, 27.1] | 65.5 [-122.4, 253.3] | -7.7 [-143.2, 127.9] | **-40.9** [-68.6, -13.3] |
| Time since third lockdown | 17.0 [-19.4, 53.4] | **73.5** [23.9, 123.2] | 0.4 [-20.7, 21.4] | 14.2 [-17.8, 46.1] | 9.8 [-21.7, 41.4] | 3.3 [-4.4, 11.0] |
| Model components | (2, 2, 0) | (0, 1, 1) | (1, 1, 0) | (2, 2, 0) | (4, 3, 0) | (1, 0, 1) |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | Theft of/ from vehicle | Shoplifting | Investment and advance fee fraud | Consumer fraud offline | Consumer fraud online | Other fraud | Cyber-dependent crime |
| First lockdown | -34.0 [-74.8, 6.8] | **-265.5** [-308.7, -222.3] | **-22.5** [-40.3, -6.7] | **-24.2** [-31.7, -16.7] | **-127.2** [-151.8, -102.6] | -6.4 [-39.5, 26.7] | **11.4** [3.6, 19.3] |
| Time since first lockdown | -4.3 [-13.8, 51.] | **12.6** [2.6, 22.7] | **7.8** [4.2, 11.4] | -6.1 [-14.6, 2.3] | **60.0** [30.5, 89.4] | 21.6 [-15.8, 58.9] | -0.1 [-1.9, 1.7] |
| Second lockdown | -19.1 [87.9, 49.8] | 90.6 [-17.0, 198.2] | **33.5** [7.7, 59.5] | -53.3 [-108.4, 1.8] | **313.6** [120.7, 506.5] | 85.9 [-161.3, 333.2] | -0.6 [-14.4, 13.2] |
| Time since second lockdown | -13.1 [-37.5, 11.4] | **-103.6** [-142.4, -64.7] | -4.9 [-15.1, 5.3] | **-28.2** [-45.2, -11.2] | -3.8 [-59.4, 51.8] | 10.2 [-41.4, 61.8] | **13.5** [8.5, 18.6] |
| Third lockdown | **-80.5** [-145.2, -15.8] | **-407.3** [-501.0, -313.7] | 19.8 [-2.8, 42.5] | **-158.4** [-248.0, -68.8] | 204.7 [-112.1, 521.5] | 5.3 [-338.9, 349.6] | 6.5 [-6.4, 19.5] |
| Time since third lockdown | 0.7 [-13.2, 14.6] | **36.2** [16.5, 55.9] | 0.6 [-5.0, 6.1 | -19.1 [-49.5, 11.2] | 7.3 [-79.8, 94.4] | **100.5** [14.9, 189.0] | 1.8 [-0.7, 4.4] |
| Model components | (1, 1, 1) | (1, 2, 8) | (1, 1, 1) | (4, 5, 0) | (4, 5, 0) | (5, 4, 0) | (0, 1, 1) |