Offline crime returns to pre-COVID levels, cyber doesn’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

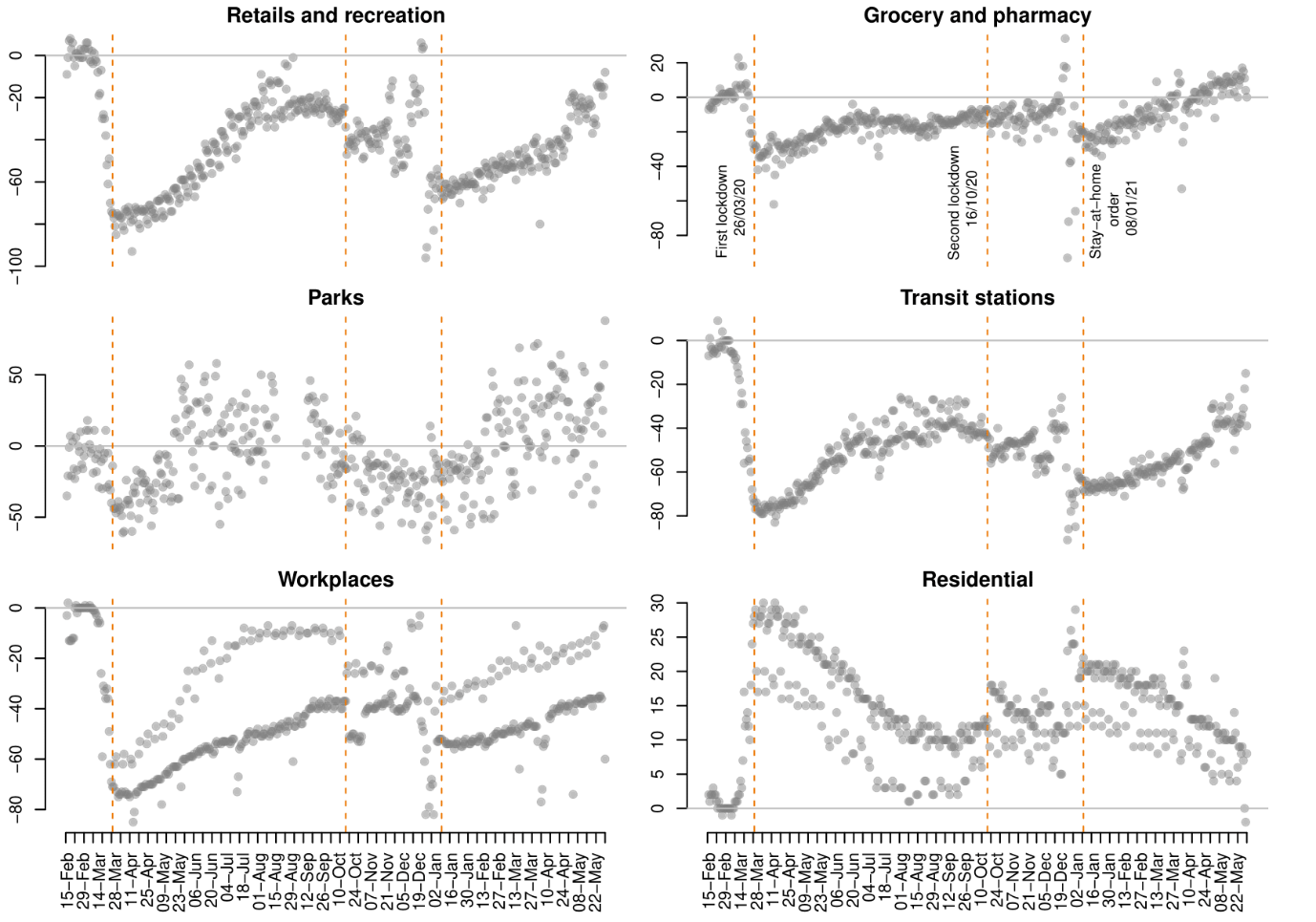
The COVID-19 pandemic and the associated stay-at-home orders imposed by national and regional governments to control the spread of the virus caused unprecedented changes in the everyday lives of millions worldwide. Due to the quick spread and mortality of the virus (on 29th June 2021, the World Health 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), Mexico (Estévez-Soto, 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 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 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 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. Section 3 describes how changes in routine activities during COVID-19 affected crime rates in different parts of the world. Section 4 introduces the data and analytical strategy. Section 5 presents the results of the analysis, and Section 6 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.*** *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 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) observed that property and violent crime was increasing 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 lockdowns were announces 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 COVID-19 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 see 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 lockdown measures 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 in the UK. Lallie et al. (2021) searched for cyber-attacks reported globally through online search engines and observed an increase in frequency of 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 imposed by governments to control the virus 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, which created new opportunities for cybercrime. 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 large 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 an important 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 while domestic violence calls for services increased during the first stay-at-home order in six police jurisdictions in the US, calls for police services 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 a long term effect 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 data recorded by the Police Service of 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 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 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 injury, violence 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 or 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, driving licence 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. 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, in the case of investment and advance free fraud, Pyramid schemes or ‘419’ frauds can be enabled by the internet in some cases, but they can also be committed offline). Cyber-dependent crimes can only take place online. Moreover, while some of these crime types are typically 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, cyber-dependent crime), which will also enable us to foreground potential disruptions in seasonal crime 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 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., 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 the model results using tables and 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 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 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 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 approach is used for 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 test and the Ljung-Box test 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 had to be adjusted manually to ensure that model assumptions were met. We will use the results of the multivariate ARIMA error models 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 assistance of the ‘forecast’ package (Hyndman et al., 2020), and all data and codes are available from a Github repository (anonymised repository: ADD URL).

# 5. Results

This section presents the results of the ITS analysis based on segmented linear regressions. Results are presented for different types of crimes. The results of the multivariate models with ARIMA errors are presented in the Appendix as a sensitivity check.

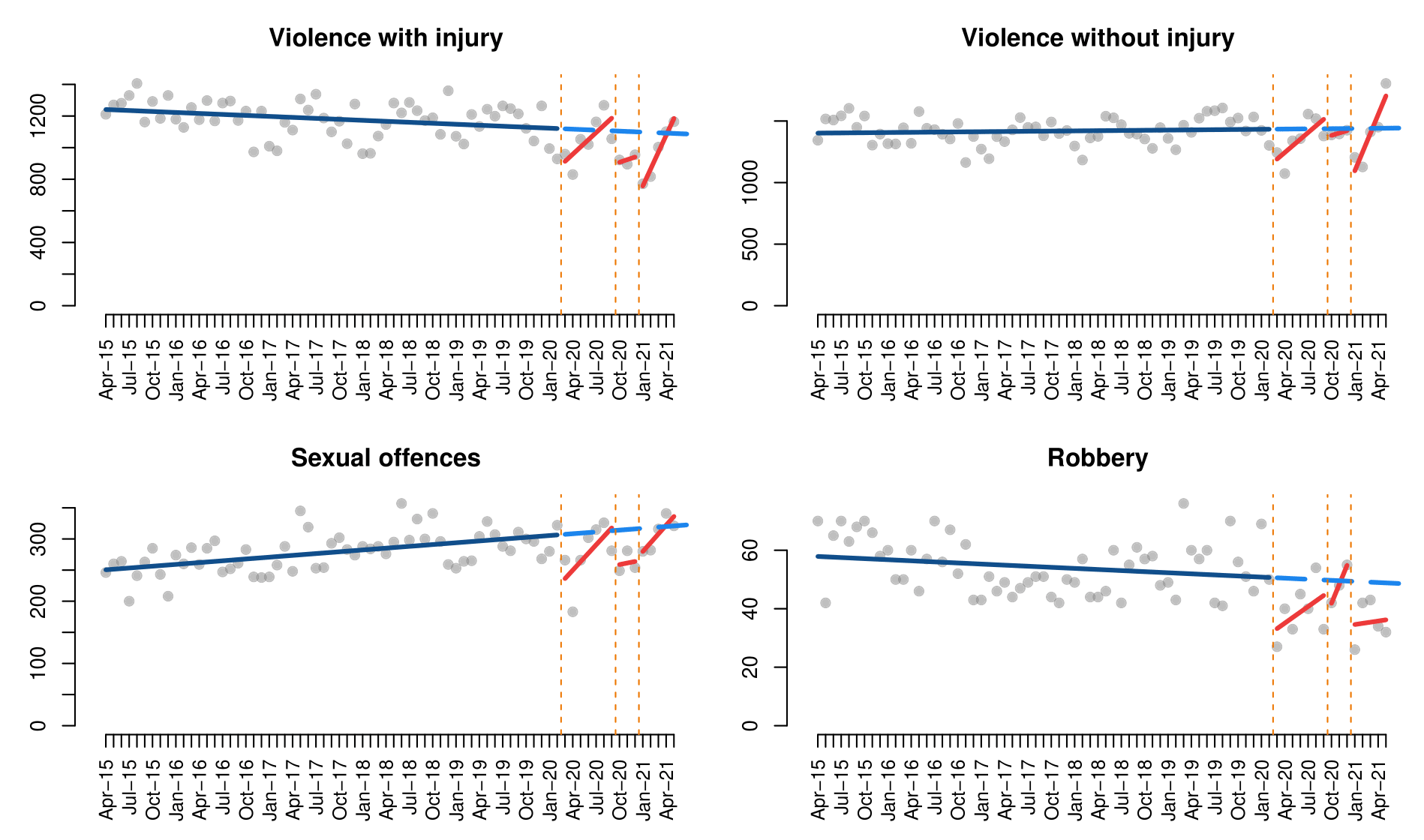
Overall, as shown in Figure 2, crime suffered an important decrease after the first and third lockdowns in Northern Ireland, while the effect of the second lockdown was less evident. Crime records progressively returned to pre-COVID levels after each lockdown. However, as described above in the literature review, this is likely to mask huge differences between crime types, and may be affected by seasonal patterns in crime 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 crimes, including violence with injury, violence without injury, sexual offences and robbery, show that crime levels decreased immediately after each COVID-19 lockdown, and rapidly returned to pre-COVID levels after each lockdown (see 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 COVID-19 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; (c) violent crime with and without injury significantly decreased immediately after the third lockdown, and returned to pre-COVID levels during the next months as lockdown restrictions were lifted. The results of the multivariate models with ARIMA errors, shown in the Appendix, show remarkably similar results, but they also indicate that, in the case of robbery, the effect of the second lockdown (negative), time since second lockdown (positive), and third lockdown (negative) on crime was likely to be statistically significant.



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

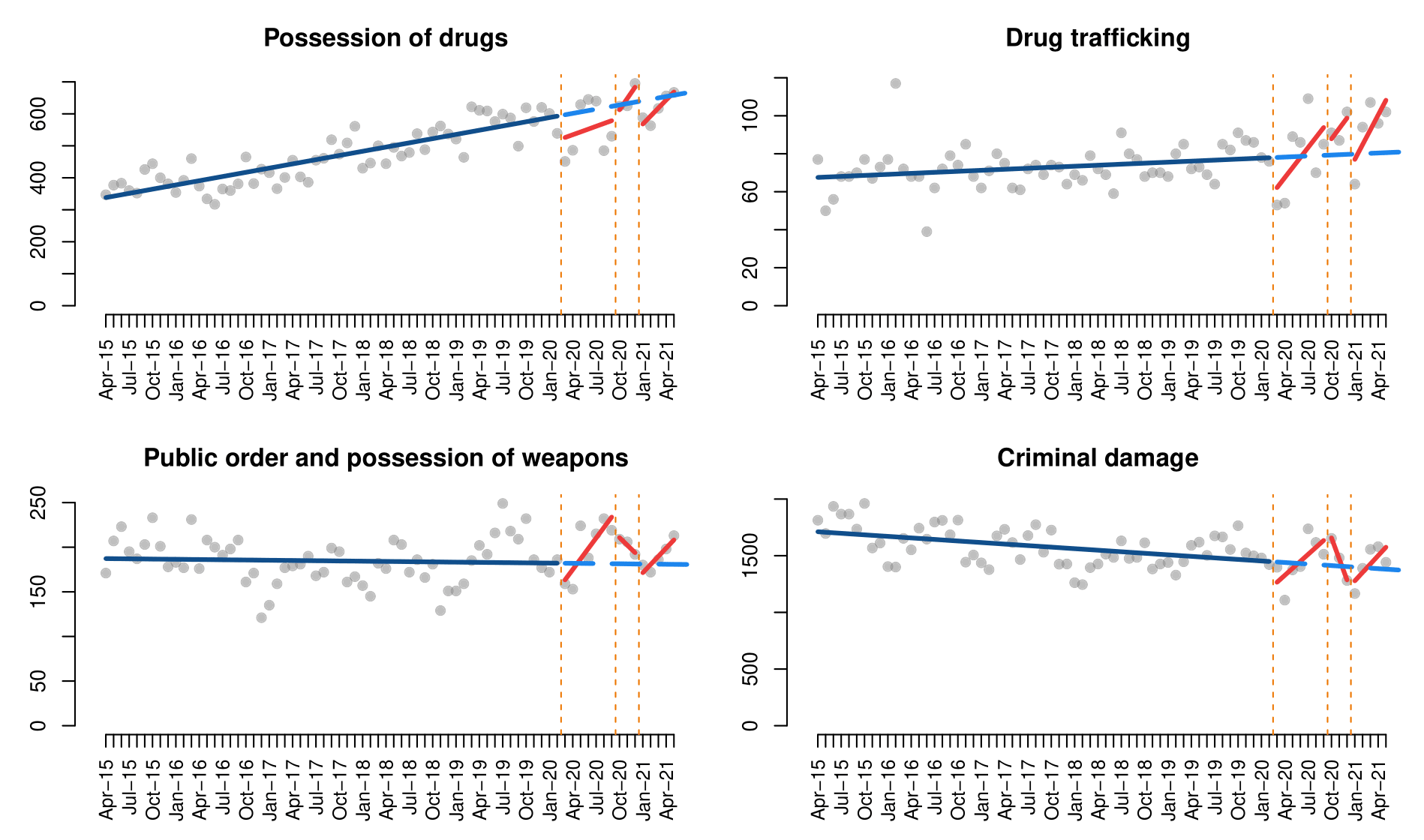
***Table 1.*** *Interrupted time series models of violent and sexual crimes*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | 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 seen in Figure 4, the trends of public order and criminal damage during the pandemic follow remarkably similar patterns to those seen before COVID-19, with increases in crime during summer and lower 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 regression models with ARIMA errors (Appendix), but there are not notable differences regarding the statistical significance of some variables. For instance, the multivariate 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 immediate 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. We also see that the directionality of the effect of time since the second lockdown and third lockdown on public order and possession of drugs is the opposite in the multivariate ARIMA error model, but it is non-significant in both the segmented linear and the multivariate ARIMA error models.

## 5.3 Burglary

The effect of the COVID-19 pandemic on burglary trends in Northern Ireland 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 any of the COVID-19 lockdowns (see Figure 5). None of the lockdowns, nor the time since each lockdown, had significant effects on non-residential burglary. In the case of residential crime, 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 multivariate ARIMA error model indicates that only the effect of the first lockdown was statistically significant.



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

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

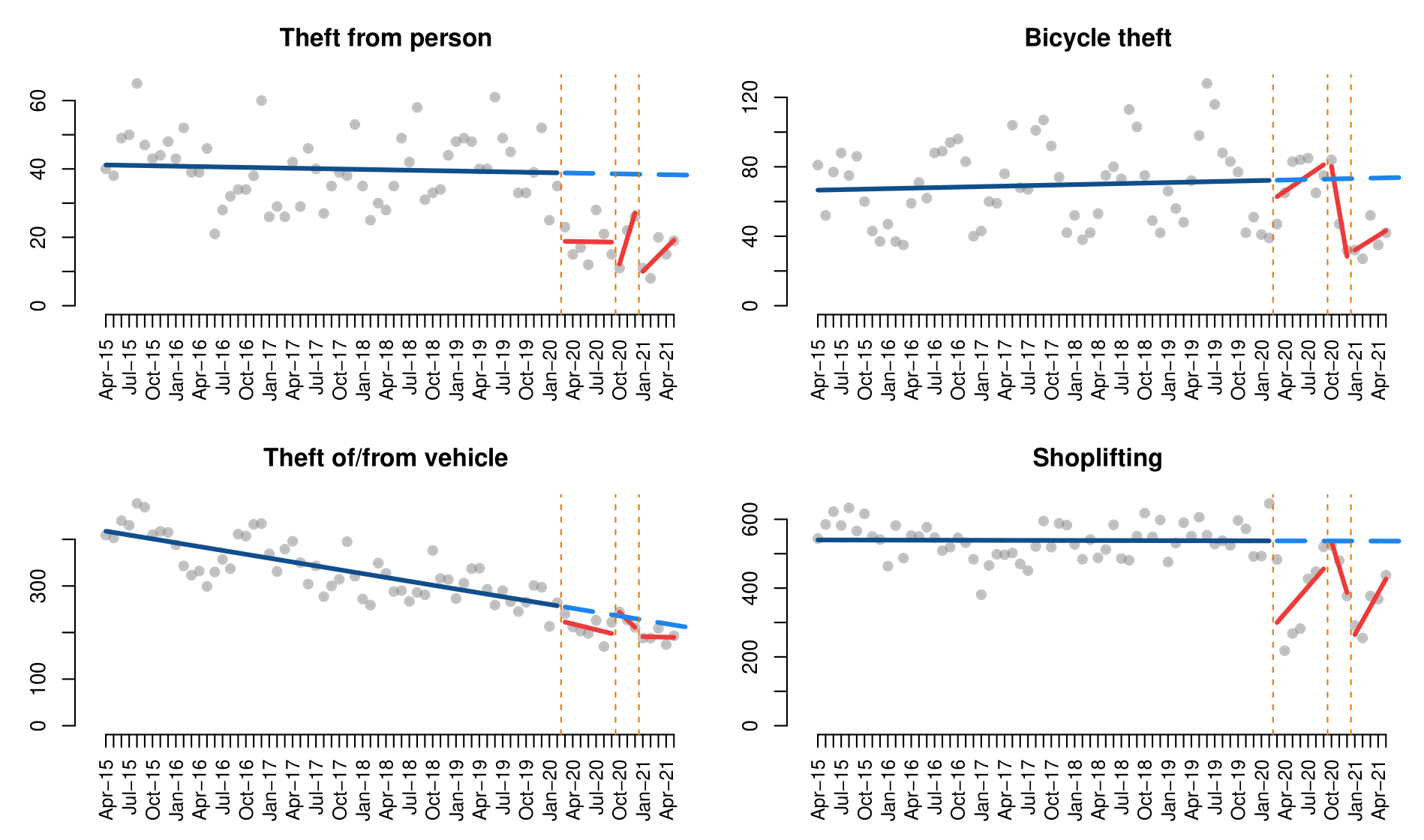
|  |  |  |
| --- | --- | --- |
|  | Residential burglary | Non-residential burglary |
| (Intercept) | 465.2\*\*\* | 248.9\*\*\* |
| Time | -1.7\*\*\* | -2.6\*\*\* |
| First lockdown | -98.3\* | 4.4 |
| Time since first lockdown | 2.9 | -1.8 |
| Second lockdown | -11.5 | 18.1 |
| Time since second lockdown | -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 different types of theft: theft from the person, bicycle theft, theft of/from motor vehicle, and shoplifting. As can be observed in Figure 6 and Table 4, there are important differences in trends across these types of theft. First, reports of theft from person decreased significantly 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 none of those changes are statistically significant (see 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 during winter. We note, however, that 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 multivariate 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.

In this regard, the changes in trends of theft from person resemble the trends in violence offences seen above, while bicycle theft trends resemble public order and criminal damage trends, and changes in theft of/from vehicle trends are quite similar to that of non-residential burglary. Changes in shoplifting, however, do not equate any of the other crime types analysed before.



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

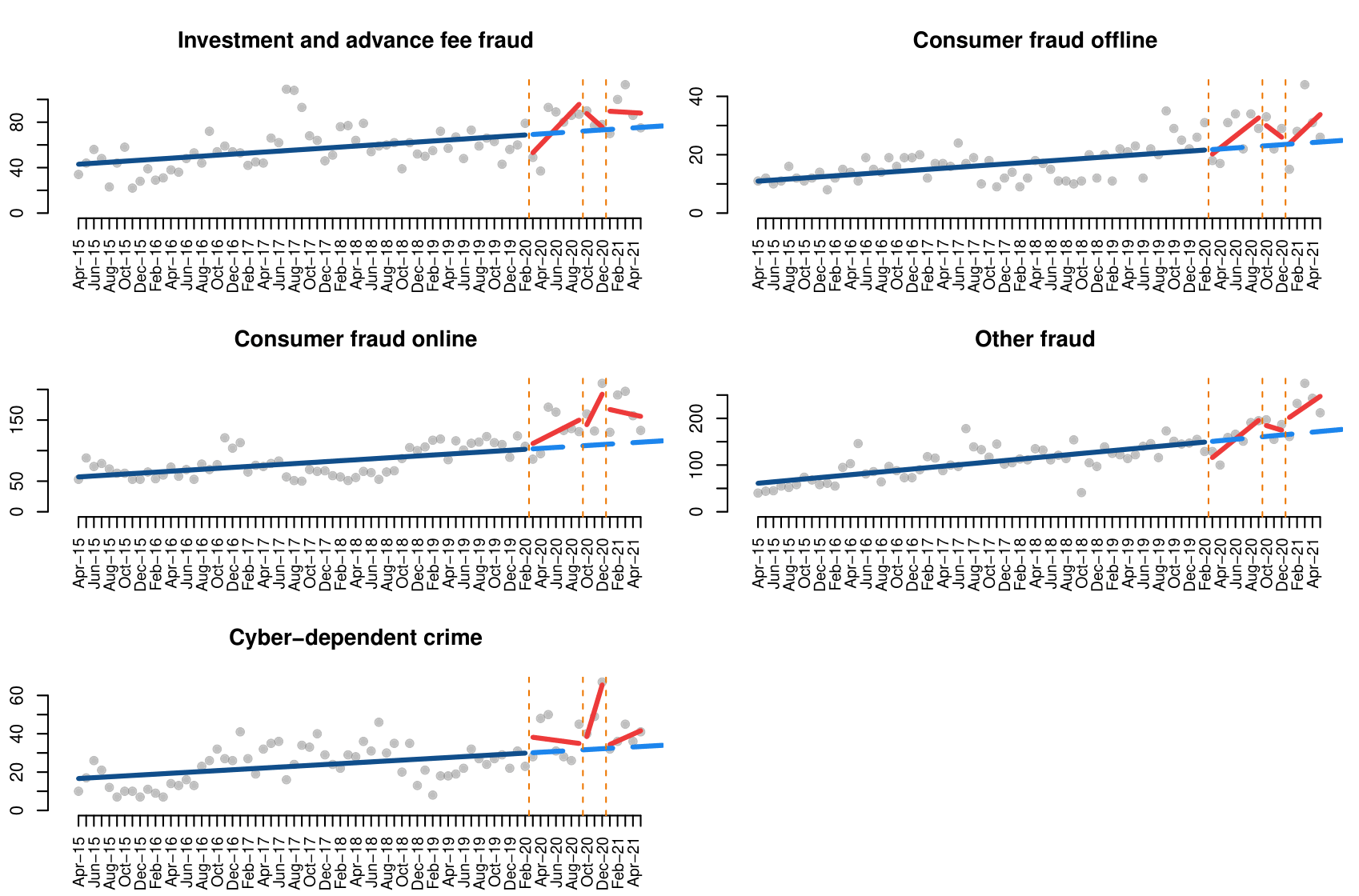
***Table 4.*** *Interrupted time series models of theft and robbery*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | 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

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



***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

Discuss seasonality for some crime types

Shoplifting – open shops

# References

Abedi, V., Olulana, O., Avula, V., Chaudhary, D., Khan, A., Shahjouei, S., Li, J., and Zand, R. (2021). Racial, economic, and health inequality and COVID-19 infection in the United States. *Journal of Racial and Ethnic Health Disparities*, 8, 732-742. <https://doi.org/10.1007/s40615-020-00833-4>

Abrams, D. S. (2021). COVID and crime: An early empirical look. *Journal of Public Economics*, 194, 104344. <https://doi.org/10.1016/j.jpubeco.2020.104344>

Ashby, M. P. J. (2020). Initial evidence on the relationship between the coronavirus pandemic and crime in the United States. *Crime Science*, 9, 6. <https://doi.org/10.1186/s40163-020-00117-6>

Balmori de la Miyar, J. R., Hoehn-Velasco, L., and Silverio-Murillo, A. (2021). The U-shaped crime recovery during COVID-19: Evidence from national crime rates in Mexico. *Crime Science*, 10, 14. <https://doi.org/10.1186/s40163-021-00147-8>

Bartik, A. W., Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M., and Stanton, C. (2020). The impact of COVID-19 on small business outcomes and expectations. *Proceedings of the National Academy of Sciences of the United States of America*, 117(30) 17656-17666. <https://doi.org/10.1073/pnas.2006991117>

Bergeron, A., Décary-Hétu, D., and Giommoni, L. (2020). Preliminary findings of the impact of COVID-19 on drugs crypto markets. *International Journal of Drug Policy*, 83, 102870. <https://doi.org/10.1016/j.drugpo.2020.102870>

Buil-Gil, D., Miró-Llinares, F., Moneva, A., Kemp, S., and Díaz-Castaño, N. (2021). Cybercrime and shifts in opportunities during COVID-19: A preliminary analysis in the UK. *European Societies*, 23(sup1), S47-S59. <https://doi.org/10.1080/14616696.2020.1804973>

Buil-Gil, D., and Zeng, Y. (2021). Meeting you was a fake: Investigating the increase in romance fraud during COVID-19. *Journal of Financial Crime*. <https://doi.org/10.1108/JFC-02-2021-0042>

Campedelli, G. M., Aziani, A., and Favarin, S. (2020a). Exploring the immediate effects of COVID-19 containment policies on crime: An empirical analysis of the short-term aftermath in Los Angeles. *American Journal of Criminal Justice*. <https://doi.org/10.1007/s12103-020-09578-6>

Campedelli, G. M., Favarin, S., Aziani, A., and Piquero, A. R. (2020b). Disentangling community-level changes in crime trends during the COVID-19 pandemic in Chicago. *Crime Science*, 9, 21. <https://doi.org/10.1186/s40163-020-00131-8>

Cohen, L. E., and Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review*, 44, 588-608. <https://doi.org/10.2307/2094589>

Czymara, C. S., Langenkamp, A., and Cano, T. (2021). Cause for concerns: gender inequality in experiencing the COVID-19 lockdown in Germany. *European Societies*, 23(sup1), S68-S81. <https://doi.org/10.1080/14616696.2020.1808692>

Estévez-Soto, P. R. (2021). Crime and COVID-19: Effect of changes in routine activities in Mexico City. *Crime Science*, 10, 15. <https://doi.org/10.1186/s40163-021-00151-y>

Fei, G., Li, X., Sun, Q., Qian, Y., Stallones, L., Xiang, H., and Zhang, X. (2020). Effectiveness of implementing the criminal administrative punishment law of drunk driving in China: An interrupted time series analysis, 2004-2017. *Accident Analysis & Prevention*, 144, 105670. <https://doi.org/10.1016/j.aap.2020.105670>

Felson, M., Jiang, S., and Xu, Y. (2020). Routine activity effects of the Covid-19 pandemic on burglary in Detroit, March, 2020. *Crime Science*, 9, 10. <https://doi.org/10.1186/s40163-020-00120-x>

Gerell, M., Kardell, J., and Kindgren, J. (2020). Minor covid-19 association with crime in Sweden. *Crime Science*, 9, 19. <https://doi.org/10.1186/s40163-020-00128-3>

Halford, E., Dixon, A., Farrell, G., Malleson, N., and Tilley, N. (2020). Crime and coronavirus: Social distancing, lockdown, and the mobility elasticity of crime. *Crime Science*, 9, 11. <https://doi.org/10.1186/s40163-020-00121-w>

Humphreys, D. K., Eisner, M. P., and Wiebe, D. J. (2013). Evaluating the impact of flexible alcohol trading hours on violence: An interrupted time series analysis. *PLoS ONE*, 8(2), e55581. <https://doi.org/10.1371/journal.pone.0055581>

Hyndman, R., Athanasopoulos, G., Bergmeir, C., Caceres, G., Chhay, L., O'Hara-Wild, M., Petropoulos, F., Razbash, S., Wang, E., and Yasmeen, F. (2020). *forecast: Forecasting functions for time series and linear models*. R package version 8.12.

Hyndman, R. J., and Khandakar, Y. (2008). Automatic time series forecasting: The forecast package for R. *Journal of Statistical Software*, 26(3), 1-22. <https://doi.org/10.18637/jss.v027.i03>

Kalist, D. E., and Lee, D. Y. (2016). The National Football League: Does crime increase on game day? *Journal of Sports Economics*, 17(8), 863-882. <https://doi.org/10.1177/1527002514554953>

Kemp, S., Buil-Gil, D., Moneva, A., Miró-Llinares, F., and Díaz-Castaño, N. (2021). Empty streets, busy internet: A time-series analysis of cybercrime and fraud trends during COVID-19. *Journal of Contemporary Criminal Justice*. <https://doi.org/10.1177/10439862211027986>

Kim, D., and Phillips, S. W. (2021). When COVID-19 and guns meet: A rise in shootings. *Journal of Criminal Justice*, 73, 101783. <https://doi.org/10.1016/j.jcrimjus.2021.101783>

Krendl, A. C., and Perry, B. L. (2021). The impact of sheltering in place during the COVID-19 pandemic on older adults’ social and mental well-being. *The Journals of Gerontology: Series B*, 76(2), e53-e58. <https://doi.org/10.1093/geronb/gbaa110>

Lallie, H. S., Shepherd, L. A., Nurse, J. R. C., Erola, A., Epiphaniou, G., Maple, C., and Ballekens, X. (2021). Cyber security in the age of COVID-19: A timeline and analysis of cyber-crime and cyber-attacks during the pandemic. *Computers & Security*, 105, 102248. <https://doi.org/10.1016/j.cose.2021.102248>

Langton, S., Dixon, A., and Farrell, G. (2021a). Six months in: pandemic crime trends in England and Wales. *Crime Science*, 10, 6. <https://doi.org/10.1186/s40163-021-00142-z>

Langton, S., Dixon, A., and Farrell, G. (2021b). Small area variation in crime effects of COVID-19 policies in England and Wales. *Journal of Criminal Justice*, 75, 101830. <https://doi.org/10.1016/j.jcrimjus.2021.101830>

Leitner, M., Barnett, M., Kent, J., and Barnett, T. (2011). The impact of hurricane Katrina on reported crimes in Louisiana: A spatial and temporal analysis. *The Professional Geographer*, 63(2), 224-261. <https://doi.org/10.1080/00330124.2010.547156>

Martin, J., Cunliffe, J., Décary-Hétu, D., and Aldridge, J. (2018). Effect of restricting the legal supply of prescription opioids on buying through online illicit marketplaces: Interrupted time series analysis. *The BMJ*, 361, k2270. <http://doi.org/10.1136/bmj.k2270>

Mohler, G., Bertozzi, A. L., Carter, J., Short, M. B., Sledge, D., Tita, G. E., Uchida, C. D., and Brantingham, P. J. (2020). Impact of social distancing during COVID-19 pandemic on crime in Los Angeles and Indianapolis. *Journal of Criminal Justice*, 68, 101692. <https://doi.org/10.1016/j.jcrimjus.2020.101692>

Nivette, A. E., Zahnow, R., Aguilar, R., Ahven, A., Amram, S., Ariel, B., Arosemena Burbano, M. J., Astolfi, R., Baier, D., Bark, H., Beijers, J. E. H., Bergman, M., Breetzke, G., Concha-Eastman, I. A., Curtis-Ham, S., Davenport, R., Díaz, C., Fleitas, D., Gerell, M., Jang, K., Kääriäinen, J., Lappi-Seppälä, T., Lim, W., Loureiro Revilla, R., Mazerolle, L., Meško, G., Pereda, N., Peres, M. F. T., Poblete-Cazenave, R., Rose, S., Svensson, R., Trajtenberg, N., van der Lippe, T., Veldkamp, J., Vilalta Perdomo, C. J., and Eisner, M. P. (2021). A global analysis of the impact of COVID-19 stay-at-home restrictions on crime. *Nature Human Behaviour*. <https://doi.org/10.1038/s41562-021-01139-z>

Nix, J., and Richards, T. N. (2021). *The immediate and long-term effects of COVID-19 stay-at-home orders on domestic violence calls for service across six U.S. jurisdictions*. *Police Practice and Research*, 22(4), 1443-1451. <https://doi.org/10.1080/15614263.2021.1883018>

Nurse, J. R., Williams, N., Collins, E., Panteli, N., Blythe, J., and Koppelman, B. (2021). Remote working pre- and post-COVID-19: An analysis of new threats and risks to security and privacy. In C. Stephanidis, M. Antona and S. Ntoa (Eds.), *HCI International 2021 – Posters* (pp. 583-590). Cham: Springer. <https://doi.org/10.1007/978-3-030-78645-8_74>

Ofcom (2021). *Online nation. 2021 report*. Retrieved from: <https://www.ofcom.org.uk/__data/assets/pdf_file/0013/220414/online-nation-2021-report.pdf>

Office for National Statistics (2021). *Dataset: Retail Sales Index time series*. Retrieved from: <https://www.ons.gov.uk/businessindustryandtrade/retailindustry/datasets/retailsales>

Payne, J. L., Morgan, A., and Piquero, A. R. (2021). Exploring regional variability in the short-term impact of COVID-19 on property crime in Queensland, Australia. *Crime Science*, 10, 7. <https://doi.org/10.1186/s40163-020-00136-3>

Piatkowska, S. J., Messner, S. F., and Raffalovich, L. E. (2016). The impact of accession to the European Union on homicide rates in Eastern Europe. *European Sociological Review*, 32(1), 151-161. <https://doi.org/10.1093/esr/jcv086>

Piquero, A. R., Jennings, W. G., Jemison, E., Kaukinen, C., and Knaul, F. M. (2021). Domestic violence during the COVID-19 pandemic - Evidence from a systematic review and meta-analysis. *Journal of Criminal Justice*, 74, 101806. <https://doi.org/10.1016/j.jcrimjus.2021.101806>

R Core Team (2021). *R: A language and environment for statistical computing*. Vienna: R Foundation for Statistical Computing. <https://www.R-project.org/>.

Rajkumar, R. P. (2020). COVID-19 and mental health: A review of the existing literature. *Asian Journal of Psychiatry*, 52, 102066. <https://doi.org/10.1016/j.ajp.2020.102066>

Stechemesser, A., Wenz, L., and Levermann, A. (2020). Corona crisis fuels racially profiled hate in social media networks. *EClinicalMedicine*, 23, 100372. <https://doi.org/10.1016/j.eclinm.2020.100372>

Steinbach, R., Perkins, C., Tompson, L., Johnson, S., Armstrong, B., Green, J., Grundy, C., Wilkinson, P., and Edwards, P. (2015). The effect of reduced street lighting on road casualties and crime in England and Wales: Controlled interrupted time series analysis. *Journal of Epidemiology and Community Health*, 69(11), 1118-1124. <http://doi.org/10.1136/jech-2015-206012>

# 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) |