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Household occupancy and burglary: A case study using COVID-19 restrictions

Michael J. Frith [a,b], Kate J. Bowers [b], Shane D. Johnson [c,*]

[a] Department of Sociology and Human Geography, University of Oslo, 0851 Oslo, Norway
[b] Department of Security and Crime Science, University College London, London WC1H 9EZ, UK
[c] Dawes Centre for Future Crime at UCL, Department of Security and Crime Science, University College London, London WC1H 9EZ, UK

A R T I C L E I N F O

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A B S T R A C T

Introduction: In response to COVID-19, governments imposed various restrictions on movement and activities. According to the routine activity perspective, these should alter where crime occurs. For burglary, greater household occupancy should increase guardianship against residential burglaries, particularly during the day considering factors such as working from home. Conversely, there should be less eyes on the street to protect against non-residential burglaries.

Methods: In this paper, we test these expectations using a spatio-temporal model with crime and Google Community Mobility data.

Results: As expected, burglary declined during the pandemic and restrictions. Different types of burglary were, however, affected differently but largely consistent with theoretical expectation. Residential and attempted residential burglaries both decreased significantly. This was particularly the case during the day for completed residential burglaries. Moreover, while changes were coincident with the timing and relaxation of restrictions, they were better explained by fluctuations in household occupancy. However, while there were significant decreases in non-residential and attempted non-residential burglary, these did not appear to be related to changes to activity patterns, but rather the lockdown phase.

Conclusions: From a theoretical perspective, the results generally provide further support for routine activity perspective. From a practical perspective, they suggest considerations for anticipating future burglary trends.

1. Introduction

In response to the growing danger from the COVID-19 pandemic, in 2020 the UK government imposed various restrictions on movement and activities that could legally take place. At one end of the spectrum, full lockdowns banned all but essential activities and discouraged others – such as travelling to work. At the other end there were more limited curfews which targeted specific types of premises (e.g., pubs) and activities. There were also periods with few overall restrictions. Although designed to limit the spread of COVID-19, these policies had the potential to – and did – shape or potentially more accurately re-shape crime patterns. For example, in the context of the UK, in their UK-wide study, Halford, Dixon, Farrell, Malleson, and Tilley (2020) found that by the end of the first week of the national lockdown, overall police-recorded crime had fallen by 41%. This included reductions of around 25% for different types of burglary, and around 62% for shoplifting offences.

These changes to crime patterns are however expected. They would be predicted by the central theories of environmental criminology. In particular, the routine activities perspective (Cohen & Felson, 1979) that states that offences only occur if motivated offenders meet suitable targets in the absence of capable guardianship. As such, structural changes to mobility patterns, such as those generated by COVID-19 policies, would be expected to alter where and when these interactions (can) take place. These changes will though differ for different types of crimes (Farrell & Tilley, 2020). For the case of burglary – the focus of this paper – the locations of targets are fixed, and hence this type of crime would be expected to be largely influenced by changes in the supply and the quality of guardianship and surveillance.

By banning or discouraging activities outside the home (or as a consequence of residents restraining from engaging in them to limit their potential exposure to COVID-19), on average, the proportion of

* Corresponding author at: Dawes Centre for Future Crime at UCL, Department of Security and Crime Science, University College London, London WC1H 9EZ, UK.
E-mail addresses: michael.frith@sosgeo.uio.no (M.J. Frith), shane.johnson@ucl.ac.uk (S.D. Johnson).

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time spent at home by residents (i.e. household occupancy) is likely to have increased significantly. In turn, this should have increased active guardianship within the home, and to some extent, for other nearby properties (Felson, 1995). Unpacking aggregate changes to guardianship a little, it is likely that changes to occupancy would likely be most pronounced during the day as many or most households would previously have been left unoccupied due to inhabitants going to work or school. However, there should also have been some increases in guardianship during the evening and night-time due to the closure of (or restrictions associated with) the night-time economy and other businesses that usually operate overnight. On the other hand, these changes may have reduced the ambient guardianship – or 'eyes on the street' – provided by passers-by which can have its own protective effect (e.g., Jacobs, 1961). Considering other types of locations, many (non-essential) businesses and community buildings were closed during periods of lockdown. At these locations, there may have been little or no active guardianship and the place management (Madensen & Eck, 2013) provided by employees would have been significantly reduced. Instead, guardianship would only have been provided by that associated with other nearby open properties, nearby occupied households, passers-by, or security devices such as CCTV located on or nearby the premises.

In general, we therefore expect that COVID-19 related restrictions – especially those associated with changes to household occupancy – lead to a reduction in residential burglaries. This is in line with the general findings of existing studies in the UK (Halford et al., 2020; Langton, Dixon and Farrell, 2021a) and elsewhere (de la Miyar, Hoehn-Velasco, & Silverio-Murillo, 2021; Felson, Jiang, & Xu, 2020; Gerell, Kardell, & Kindgren, 2020; Mohler et al., 2020; Nivette, 2021; for exceptions, see Ashby, 2020; Campedelli, Aziani, & Favarin, 2021; Hodgkinson & Andresen, 2020; Payne & Morgan, 2020). However, we also expect this effect to be most pronounced during the daytime when levels of guardianship would most likely have been affected by policies associated with COVID-19 (e.g., work from home orders). Moreover, residential burglaries can be conducted in a variety of ways, and these vary in terms of the extent to which occupancy helps or hinders offending. For example, some types of burglary, such as 'distraction burglary', require a resident to be present for them to be distracted or tricked. As far as we are aware, an analysis of how patterns of burglary changed during the pandemic by time of day and type of burglary has not so far been conducted.

For burglaries that occur at business and community properties (hereafter, non-residential burglaries), a clear and justifiable prediction as to how levels of offending might have changed is less forthcoming. On the one hand, direct guardianship at many of these properties would have been reduced, making them more vulnerable. However, the same mobility restrictions would also limit if and how offenders could search for suitable targets, and potentially make their presence more suspicious. On the other hand, deprived of residential targets, it might be expected that some offenders would displace their activity and target non-residential properties instead. On this issue, the findings from previous studies vary. Halford et al. (2020) found a large decrease in non-residential burglary, Gerell et al. (2020) found a modest decrease, whereas Hodgkinson and Andresen (2020) and Ashby (2020) found no notable change and a modest increase, respectively. That said, as with residential burglary, we would expect any variation due to changes in activity to be during their hours of operation, which for most, but arguably not all, non-residential properties would be during the daytime.

To date, much of the research on the effects of COVID-19 on crime has examined temporal patterns at the aggregate level, with few studies considering spatial variation at the small or *meso* area level (for exceptions, see Felson et al., 2020; Langton, Dixon, & Farrell, 2021b) and none have examined changes in risk over the course of the day. Accounting for spatial variation in changes in occupancy and crime would provide an opportunity to conduct a more robust test of the link between occupancy rates and levels of burglary. To date, research has assumed – rather than modelled – changes in occupancy at the smaller area level, with analyses limited to using blanket city-level mobility data to examine shifts in activity patterns. To address this shortcoming, in the present analysis we use police-recorded crime data from London (UK) to build upon previous research on COVID-19 and crime in three ways. First, we look in more detail at how specific types of burglary were affected. As discussed, burglary can occur at residential and non-residential properties (e.g., businesses), but burglaries also differ in terms of whether they were successful or not, whether they involve violence (aggravated burglaries), and whether they involve direct contact with the victim with the aim of distracting or tricking them while the burglary takes place (distraction burglaries). We examine variation in these different types of offences here. Second, to test our key hypotheses, we examine changes in burglaries that occurred during the daytime and those that occurred at night. Thirdly, we do this using a statistical approach that allows us to test and differentiate between the general impact of different stages of the 2020 COVID-19 lockdown and household occupancy whilst accounting for spatial variation using a spatial-temporal modelling approach at the London Borough level.

The remainder of the article is organised as follows. Next, we briefly explain the mobility restrictions that occurred in 2020 in the UK and London more specifically. We then hypothesise how these would have affected different types of burglary. In the following two sections we describe the data and methodology employed to test hypotheses and present the results. Lastly, we discuss our findings and their implications.

2. COVID-19 mobility restrictions in England

Up to the end of September 2020, the majority of the UK, including London, experienced four general phases of mobility restrictions (see Fig. 1). The first, which can be described as pre-lockdown, ran from the start of 2020 until 23 March when England officially entered its first national lockdown. For most of this period there were no official restrictions on movement or activity. That said, as COVID cases increased, non-essential activity, including travelling to work, was discouraged and some premises, notably pubs, restaurants, gyms, and cinemas, were required to close their doors slightly earlier than 23 March 2020.

During the second phase, which covered the period from 23 March to 13 June 2020, England was placed under a national lockdown. All non-essential shops were closed, and the government ordered everyone to stay at home except for essential activities. This included a requirement to work from home, if possible, and the creation of a furlough scheme to support employers affected by the lockdown, placing employees on temporary leave from work. In short, for all but a minority of employees, everyone worked from home or was on leave.

On 14 June 2020, the national lockdown officially ended, and mobility and activity restrictions were gradually lifted. This included allowing non-essential activity outside of the home, such as social gatherings and for non-essential shops and premises to re-open. From August to mid-September 2020, the UK government also encouraged a physical return to workplaces through their 'back to work' campaign and a 'eat out to help out' food discount scheme intended to persuade customers to dine outside the home.

Finally, with respect to the time-period covered by this analysis, due to increasing COVID-19 cases, from 24 September 2020 to 14 October 2020 a new tiered system was introduced, and the government placed a 10 pm curfew on hospitality venues such as pubs and restaurants. While this only directly affected reasons for people to travel outside of the home at night, it occurred against a backdrop of the population being encouraged to return to working from home.

3. Mobility restrictions and burglary

With these phases in mind, we now discuss our expectations for how the restrictions associated with policy responses to COVID-19 would

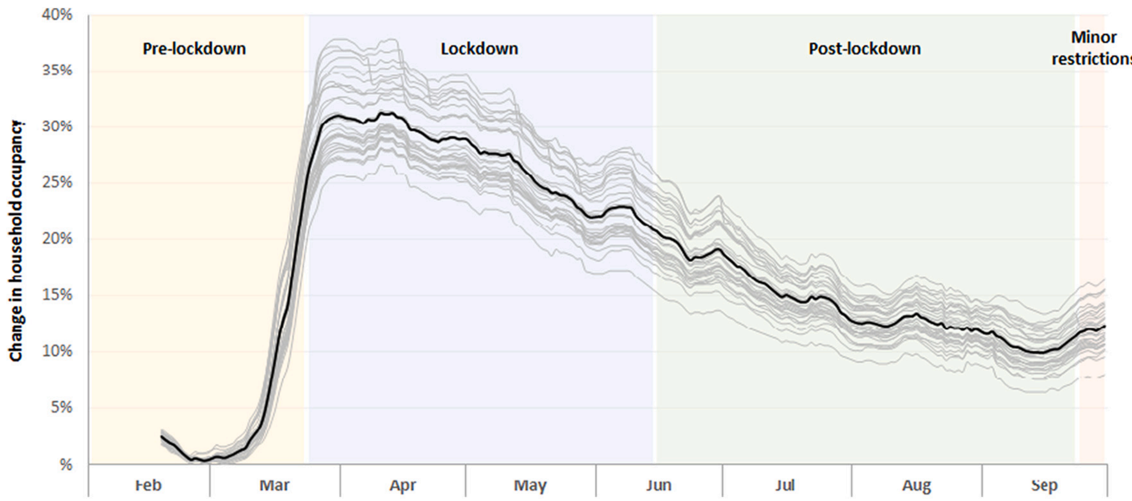

Fig. 1. Seven-day rolling average change in household occupancy (time spent at home) in 2020 (relative to the median level between January 3rd and February 6 that year) for each of the 33 London boroughs (grey) and the London average (black).

shape patterns of burglary. Relative to the pre-lockdown phase, during which patterns of mobility and household occupancy (i.e. relative time spent at home, which is discussed in more detail below) levels would have been relatively "normal" (see Fig. 1), we hypothesised that because mobility outside the home was discouraged or otherwise banned in various ways throughout the other phases, the resulting increase in household occupancy and therefore guardianship would mean that in a simple model of residential burglaries:

(1) There would be fewer residential burglaries during the (so-called) lockdown, post-lockdown, and time-periods when minor restrictions were in place.

As we expect these effects to be largely driven by increases in guardianship due to greater household occupancy, in a model using a direct measure of household occupancy at the area level, we expect:

(2) Spatial variation in levels of residential burglary to be associated with spatial variation in levels of household occupancy (see Fig. 1).

Also, when using variables that capture the mobility restrictions phases *and* household occupancy:

(3) Residential burglary levels will be unrelated to the timing of restrictions after levels of household occupancy have been accounted for as it is the effect on routine activities that we anticipate will affect levels of crime (not the policies themselves).

Although the mobility restrictions imposed were intended to affect activities that could take place at any time of the day, for most people the main reason for spending time outside the home is to go to work or school and this is typically done during the daytime. Therefore, and although the available (Google) mobility data used here does not distinguish between time spent outside the home by time of the day, we hypothesised:

(4) The effect of household occupancy on residential burglary would be greater during the day- than night-time.

While we expected to find evidence to support these hypotheses for attempted and successful burglaries, different patterns may be expected for aggravated and distraction burglaries. To elaborate, to be classified as an aggravated burglary, there must be evidence that a weapon was brought to the crime scene. This is more likely to be recorded when there are witnesses (e.g., when occupants are home) or offenders are caught in the act. In the case of distraction burglaries, by definition, these offences require an occupant to be present. Such offences often involve two offenders, one of whom distracts the homeowner, sometimes posing as an official of some kind (e.g., a utility company representative), while the other enters and burgles the home. Hence, for both of these forms of offending, it would be plausible to observe increases in their frequency.

Finally, for burglaries of business and community properties where (household) occupation is less relevant, we expect there to be no relationship between household occupancy (time spent at home) and non-residential burglaries. This type of crime thus serves as a form of non-equivalent dependent variable (see Cook, Campbell, & Shadish, 2002) that allows us to check that patterns were selective and in line with theoretical expectation.

4. Data and methodology

4.1. Crime data

To test hypotheses, we use official police-recorded crime (burglary) data provided by the London Metropolitan Police Service (MPS). The data cover the period January 2019 to September 2020 (though only the data from 2020 is used as our dependent variable). The MPS polices 32 of the 33 London boroughs,[1] which cover an area of approximately 1500km^2 in Greater London (see also Fig. 2). Included in this dataset are a total of 44,682 burglaries. In contrast to other sources of data, such as that which is publicly available data from police.uk (which are available for a longer time-period), these burglaries can be broken down into detailed subcategories and the time of day that they occurred. Here, we consider the function of the targeted building (residential or business and community), whether offences were successful or not, whether a weapon was involved (aggravated burglary), and whether deception or distraction was used (distraction burglary).

For the purposes of this analysis, we also categorise burglaries according to the time they occurred and whether this was during the day, here defined as 8 am to 7:59 pm, or during the night (8 pm – 7:59 am).

[1] The exception is the City of London which is policed by its own force and covers nearly 3km^2 in the centre of London. This borough however contains very few dwellings (5500) compared to the other boroughs - which average 104,770 dwellings - and so its omission from analysis is unlikely to have a major impact.

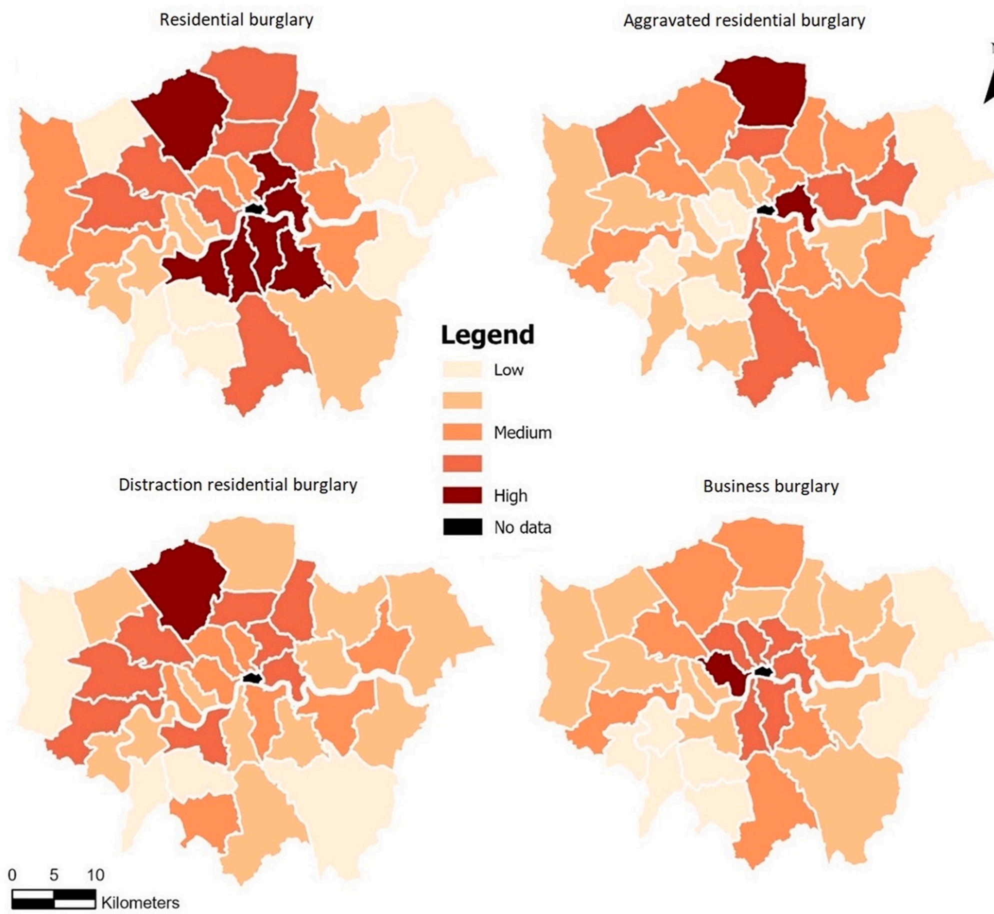

Fig. 2. Maps of the spatial distribution of various types of burglary.

For some offences, especially burglaries, the precise time of the offence can be uncertain (e.g., Ashby & Bowers, 2013; Ratcliffe, 2000) as the residents may be away from home at the time of the offence and there may be no witnesses. For such offences, there is a well-known issue where only the approximate earliest and latest time and date an offence could have occurred are recorded. In such cases, because our time-windows are 12 h long (e.g., daytime), we only include burglaries for which the time window in which the offence could have occurred was 18 h or less. Assuming that the offence was equally likely to have occurred at any point within that interval, the times of the offences were coded according to the *time window* within which they were most likely to have occurred (i.e., day or night). Under these assumptions, we can be confident that each burglary would have occurred within the time window to which it was assigned with at least a (12/18=) 67% chance. Using this strategy, we were able to code 88% of the data, which appeared to be a pragmatic trade-off.[2] All other burglaries were coded as occurring at an unknown time. The total number of each type of burglary and the proportion in each period of the day is shown in Table 1. As would be expected, most distraction burglaries took place during the day, while the "typical" or less complicated type of residential burglaries, took place at various times of the day. This latter finding is consistent with findings from the Crime Survey of England and Wales (e.g., Office for National Statistics, 2017). Maps showing the spatial distribution of four of the main types of burglary in London are shown in Fig. 2.

Table 1
The total number of each type of burglary and the proportion that occurred during each time period of the day

	All	Daytime	Night-time	Unknown
Residential-related burglaries				
Residential burglary	25,961	37%	38%	25%
Attempted residential burglary	6605	34%	50%	16%
Aggravated residential burglary	432	33%	66%	1%
Distraction residential burglary	493	87%	11%	2%
Attempted distraction residential burglary	46	89%	7%	4%
Business-related burglaries				
Business burglary	9753	28%	54%	18%
Attempted business burglary	1358	17%	67%	16%
Aggravated business burglary	34	29%	68%	3%

As the analysis that follows compares variations in burglary at different times of the year, we also account for expected seasonal variation. To do this, we produced a variable with a count of the number of each type of burglary in each borough on the equivalent day in the

[2] Alternatives to this were considered. At one extreme, for example, using a 90-min maximum interval results in a significant 61% of all burglaries in the dataset having an unknown time (compared to 12% with the current strategy). At the other end of the spectrum, we could allow all burglaries but the time window (and date) to which they would be coded would be ambiguous. More advanced aoristic techniques (e.g. Ashby & Bowers, 2013; Sorensen, 2004) are also possible but these would require further assumptions.

previous year (2019).[3]

4.2. Mobility and occupancy

To look at the effects of mobility restrictions and household occupancy we use two measures. The first, and simplest, is an indicator that represents the phase of the lockdown and the overall type of mobility restrictions in place (in London). These were:

- 'Pre-lockdown' which covers the period of 2020 up to 23 March (and the start of the first national lockdown).
- 'Lockdown' which covers the subsequent period of national lockdown up to 14 June 2020.
- 'Post-lockdown' which covers the following period to 23 September 2020.
- 'Minor restrictions' which covers the final period of our dataset, which is up to 30 September 2020.

For these periods, we expect levels of occupancy to be highest during the lockdown, followed by the periods when there were minor restrictions. To capture household occupancy more directly, we use Google Community Mobility data (Google, 2021). As used in various other studies (e.g. Sulyok & Walker, 2020), this data is collated from users of Google applications on mobile devices who have opted into the passive recording of their 'location history'. This data is then categorised (e.g. based on the type of location the activity) as belonging to one of six categories before it is anonymised and spatially aggregated (see also Aktay et al., 2020). For the purposes of this analysis, we use the 'residential' category which measures the percentage change in the time spent at places of residence compared to the baseline (median) level in each borough for the equivalent day of the week for the period 3 January to 6 February 2020 (this period being selected by Google). The data are available between 15 February and 30 September 2020 for each London borough. Greater values for a given day of the week indicate that – relative to the baseline – more time is, on average, spent in residences, and consequently that there is greater occupancy on that day. Fig. 2 shows that while the overall pattern was similar across boroughs, the precise levels and exact signatures varied.

Although it is expected that there will be some collinearity between the stage of the lockdown and the level of occupancy, checks for multicollinearity revealed that with one exception, variation inflation factor (VIF) scores were below 3. Values below 4 are generally considered to be acceptable, with only those above 10 indicating a cause for concern (Pardoe, 2021). The exception was for the variable that captured the actual lockdown stage (24/03–14/06) and models that also included residential occupancy (see below). For these models, the VIF scores ranged from 4.52 to 4.93, depending on the particular analysis (see later). These VIFs indicate that the variances of the associated estimated IRRs will be inflated nearly five-fold, meaning that these findings should be interpreted carefully.

4.3. Analytical approach

In what follows, we model the count of burglary in each borough each day. Consequently, our unit of analysis is the borough-day. Two aspects of the data are important to address in the modelling enterprise. First is the fact that the data are (low frequency) counts and hence we employ a count model as opposed to Ordinary Least Squares regression. Second is the structure of the data. Each borough differs on important variables that can affect the count of crime and hence it is important to explicitly model these. As most of these variables are time stable, or at least they can be expected to be for the period of analysis covered here, it is possible to account for them using a panel-based regression model with borough level fixed effects (FE).

In addition to unmeasured spatial variance, there may also be unmeasured variation for different days of the week. For example, people's routine activities tend to differ on weekends and weekdays, which can affect crime risk. The latter may be consistent for all boroughs, but it might also differ across them. For this reason, we include borough-day fixed effects in the model. The general form of our statistical model is thus:

$$log\left(C_{i,d,t}\right) = \beta_1 Z_{i,d} + \beta_2 LD_t + \beta_3 PL_t + \beta_4 MR_t + \beta_5 Occ_{i,t} + \beta_6 2019_{i,t}$$

Where, $C_{i,\,d,\,t}$ is the count of burglary in borough i, on day of the week d on day t of the time series. The $Z_{i,\,d}$ terms are fixed effects for each borough (i) for each day of the week (d). The LD (full lockdown), PL (post-lockdown) and MR (minor restrictions) terms are binary indicators to indicate the lockdown status on day t (with the reference category being the pre-lockdown period in 2020). $Occ_{i,\,t}$ specifies the level of occupancy in borough i on day t and $2019_{i,\,t}$ specifies the level of burglary in borough i on day t in 2019.

As the dependent variable is made up of (low frequency) count data, a negative binomial (NB) model would typically be preferred (compared to a Poisson equivalent), since such models are robust to overdispersion. However, it is well known that NB models can yield inconsistent estimates for fixed effects models by failing to eliminate unit-level differences (e.g., Greene, 2005; Guimarães, 2008). We therefore estimate FE Poisson models using quasi-maximum likelihood.[4] These are known to be consistent even under overdispersion (Wooldridge, 1999). In particular, we use the glm command in Stata 17 (StataCorp, 2021).

One final set of issues is worth noting. The mobility data for some boroughs (for 1.4% of eligible days) was not available for days on which there was insufficient data to preserve user privacy. Therefore, to ensure comparability across the models where we do not use this mobility data (e.g., the models labelled (1) and (3) in the results), these borough-days are omitted from all analyses. Across the (7 days of the week x 32 boroughs=) 224 panels, there is an average of 32.2 observations for each day of the week within the time-period, which results in a total of 7222 possible observations. For each regression, as with all other FE models, panels (sets of observations) are dropped if there is no within-unit variation in the count of burglaries. For most regressions this resulted in a small number of observations being dropped - <10% of observations dropped for 11 of the 14 regression models. For the three remaining models, there are far fewer burglaries and so there are some (borough-day) panels where the count does not vary from 0 resulting in their exclusion. Specifically, 2111 (or 29%) of observations were dropped for aggravated residential burglaries, 1685 (23%) for distraction residential burglaries, and 3825 (53%) for day-time non-residential burglaries.

5. Results

Tables 2, 3 and 4 present the results for residential and attempted residential burglary (Table 2), aggravated and distraction burglary (Table 3) and non-residential burglary (Table 4). Analyses are shown for all burglaries, regardless of when they took place, and for those that (most likely) occurred during the day and for those that occurred at night. For each type of burglary, we compute incident rate ratios (IRRs) – which express the multiplicative effect of a unit change in a continuous predictor or versus the reference category for a categorical independent variable - for three models. The first simply includes variables to indicate the type of movement restriction in place for each borough-day. The second includes only the household occupancy variable, while the third

[3] This is calculated considering the day of the week such that Saturday 15th February 2020 (the first day Google Mobility data is available) is paired with Saturday 16th February 2019, and so on.

[4] We also compute equivalent OLS regressions with a logged dependent variable but as they produced consistent results and so are not shown.

Table 2
IRR estimates from FE Poisson regressions of residential and attempted residential burglaries

	Residential burglary								
	Any time			Daytime			Night-time		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Pre-lockdown (baseline)	1.00		1.00	1.00		1.00	1.00		1.00
Lockdown	0.65** (0.05)		0.91 (0.08)	0.44** (0.03)		0.81* (0.08)	0.73** (0.06)		1.01 (0.12)
Post-lockdown	0.84* (0.06)		0.98 (0.07)	0.65** (0.05)		0.86 (0.07)	0.99 (0.09)		1.14 (0.10)
Minor restrictions	0.75** (0.05)		0.85* (0.07)	0.74** (0.06)		0.94 (0.09)	0.84 (0.09)		0.95 (0.11)
Occupancy (10%)		0.84** (0.03)	0.86** (0.03)		0.72** (0.02)	0.77** (0.03)		0.86** (0.03)	0.87** (0.03)
2019 level (10)	1.09* (0.04)	1.08* (0.04)	1.09* (0.04)	1.14 (0.11)	1.17* (0.11)	1.14 (0.11)	1.13 (0.11)	1.11 (0.11)	1.12 (0.11)
N	7222	7222	7222	7222	7222	7222	7222	7222	7222

	Attempted Residential burglary								
	Any time			Daytime			Night-time		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Pre-lockdown (baseline)	1.00		1.00	1.00		1.00	1.00		1.00
Lockdown	0.62** (0.04)		0.92 (0.09)	0.45** (0.04)		0.75 (0.13)	0.68** (0.05)		0.98 (0.16)
Post-lockdown	0.75** (0.04)		0.90 (0.06)	0.65** (0.05)		0.82* (0.08)	0.75** (0.05)		0.88 (0.09)
Minor restrictions	0.64** (0.07)		0.74** (0.08)	0.70* (0.13)		0.84 (0.14)	0.71* (0.11)		0.81 (0.11)
Occupancy (10%)		0.82** (0.02)	0.84** (0.03)		0.73** (0.03)	0.80** (0.06)		0.85** (0.03)	0.84** (0.05)
2019 level (10)	1.09 (0.14)	1.11 (0.14)	1.11 (0.14)	1.32 (0.57)	1.34 (0.56)	1.31 (0.55)	0.93 (0.34)	0.93 (0.33)	0.94 (0.33)
N	7222	7222	7222	7156	7156	7156	7185	7185	7185

$*p < 0.05$, $**p < 0.01$, standard errors in parentheses.

Table 3
IRR estimates from FE Poisson regressions of aggravated and distraction residential burglaries

	Aggravated residential burglary (any time)			Distraction residential burglary (any time)		
	(1)	(2)	(3)	(1)	(2)	(3)
Pre-lockdown (baseline)	1.00		1.00	1.00		1.00
Lockdown	0.61** (0.11)		1.34 (0.49)	0.63** (0.09)		0.55 (0.22)
Post-lockdown	0.82 (0.13)		1.17 (0.25)	1.25 (0.16)		1.17 (0.23)
Minor restrictions	0.51 (0.20)		0.68 (0.27)	0.64 (0.24)		0.61 (0.23)
Occupancy (10%)	–	0.79** (0.06)	0.71* (0.10)	–	−0.84** (0.03)	1.05 (0.16)
2019 level (10)	267.74** (489.96)	292.95** (533.17)	298.87** (543.94)	5.00 (7.10)	4.53 (6.43)	4.95 (6.93)
N	5111	5111	5111	5537	5537	5537

*p < 0.05, **p < 0.01, standard errors in parentheses.

includes both sets of explanatory variables. All models include data for the same period for the previous year (2019 level) to control for seasonal variation in burglary. The use of panel models also means that other (time-stable) factors that vary between boroughs are already controlled for.

As shown, for model (1) for residential and attempted residential burglary, most of the IRRs that represent the various types of movement restrictions are statistically significant, in the expected direction and with relatively large effects. That is, relative to the pre-lockdown period (the baseline), there were 0.65 and 0.62 times as many burglaries respectively than would be expected during the lockdown periods. The only exceptions to this in Table 2 are for residential burglaries that occurred during the night-time for which the only reliable effect was observed during the first (national) lockdown period.

When the direct measure of household occupancy is included – for the models labelled (2) – we find this to be a (statistically significant) negative predictor of burglary. In other words, relative greater levels of household occupancy were associated with fewer burglaries. This relationship remains statistically significant for all versions of model (3). However, for these models, most of the IRRs relating to the different types of mobility restrictions are small and no longer significant suggesting that, with a few exceptions, changes to household occupancy levels alone explain the changes in burglary levels and that there is no overall unexplained or residual effect associated with the lockdown phase.

As we predicted household occupancy to have a greater effect on residential burglaries during the daytime than those that occur at night, we compare IRRs across models. We find that the differences are significant for (successful) residential burglaries committed during the day compared to those at night ($chi2 = 10.36$, $p < 0.01$); but for attempted residential burglaries, the differences were non-significant ($chi2 = 0.37$, $p > 0.05$).

The results for the two other types of residential burglaries, aggravated and distraction burglaries, are shown in Table 3. Models were not estimated for the different times of the day due to there being relatively few incidents for each type. From the results we can see that for model (1), and for both types of burglary, there were large reductions in the number of burglaries during the initial lockdown period but not for the other periods. Estimated levels of occupancy is again a statistically significant predictor for model (2) for both types of crime. For model (3), we see that only estimated occupancy is a reliable predictor for aggravated burglary, suggesting that it was the effect of changes to routine activities that affected levels of offending for this type of burglary. For distraction burglary, no predictor variable was statistically significant when they were considered in combination in model (3). Note that the estimated effect of lockdown, and to a lesser degree the minor restrictions period, are relatively large and suggests a decrease of up to nearly half during these time-periods, they are not statistically significant as the associated standard errors are also relatively large.

The results from our models of non-residential burglaries are shown

Table 4
IRR estimates from FE Poisson regressions of non-residential and attempted non-residential burglaries.

	Non-residential burglary								
	Any time			Daytime			Night-time		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Pre-lockdown (baseline)	1.00		1.00	1.00		1.00	1.00		1.00
Lockdown	0.65** (0.05)		0.66** (0.05)	0.63** (0.06)		0.79 (0.10)	0.55** (0. 06)		0.56** (0.04)
Post-lockdown	0.67** (0.04)		0.67** (0.04)	0.71** (0.06)		0.79** (0.06)	0.63** (0.05)		0.63** (0.05)
Minor restrictions	0.70** (0.06)		0.70** (0.06)	0.76* (0.10)		0.83 (0.11)	0.69** (0.08)		0.69** (0.08)
Occupancy (10%)	–	0.89** (0.03)	1.00 (0.03)	–	0.84** (0.03)	0.90* (0.04)	–	0.84** (0.03)	1.00 (0.03)
2019 level (10)	1.00 (0.12)	0.98 (0.15)	1.00 (0.12)	0.83 (0.32)	0.82 (0.31)	0.80 (0.32)	0.95 (0.19)	0.92 (0.22)	0.95 (0.19)
N	7190	7190	7190	7102	7102	7102	7190	7190	7190

	Attempted non-residential burglary								
	Any time			Daytime			Night-time		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Pre-lockdown (baseline)	1.00		1.00	1.00		1.00	1.00		1.00
Lockdown	0.94 (0.08)		0.70* (0.11)	1.31 (0.34)		0.83 (0.28)	0.79* (0.09)		0.63* (0.14)
Post-lockdown	0.71** (0.06)		0.63** (0.07)	0.93 (0.24)		0.76 (0.21)	0.65** (0.07)		0.59** (0.09)
Minor restrictions	0.53** (0.11)		0.48** (0.10)	0.55 (0.34)		0.47 (0.29)	0.58* (0.16)		0.54* (0.15)
Occupancy (10%)	–	1.07* (0.04)	1.15* (0.07)	–	1.21 (0.13)	1.23 (0.21)	–	0.89 (0.04)	1.11 (0.09)
2019 level (10)	1.16 (0.70)	1.14 (0.66)	1.14 (0.69)	6.36 (28.81)	7.03 (31.84)	5.99 (27.19)	3.78 (3.29)	3.67 (3.05)	3.74 (3.26)
N	6931	6931	6931	3997	3997	3997	6546	6546	6546

*p < 0.05, **p < 0.01, standard errors in parentheses.

in Table 4. As with residential burglaries, the IRRs representing the effect of the various stages of lockdown for model (1) (which exclude the direct measure of occupancy) are large and in the direction expected. This indicates that there were relatively fewer of these types of burglaries than expected compared to the pre-lockdown period. The exceptions to this were for attempted non-residential burglaries (in the aggregate) during the first full lockdown, and for non-residential burglaries attempted through the day during all stages of the COVID-19 period.

In contrast to our models of residential burglary, while household occupancy seems to have some effect in model (2), when all variables are included in model (3), it is only found to have an overall effect on non-residential burglaries that were committed during the day and attempted non-residential burglaries (in the aggregate). In the case of the latter, this effect was positive (larger than 1), meaning that – and in contrast to the findings for residential burglary – attempted burglaries at non-residential properties increased as household occupancy rates rose. In short, as expected for non-residential burglaries, household occupancy was generally less important than was the phase of the lockdown. This selective pattern of results is thus in line with routine activity theory and provides confidence in our findings.

As we are modelling spatial data, it is, of course, possible that there is spatial autocorrelation in our modelled residuals. For instance, factors that affect crime in one borough, might also affect crime in those that are adjacent to it. In the event that this is true, we would observe a spatial pattern in the residuals. Spatial autocorrelation is generally more problematic for smaller areal units, but if present, this would violate the assumption that our observations are independent. For this reason, as a robustness check, we examined spatial autocorrelation in our models using the Moran's I test. As we have (daily) panel data for 8 months for each borough, the analysis is a little more complicated than for a standard spatial analysis for which data are usually only analysed for one interval of time. To do this, for each model, and each borough, we sample the data for one day per month (selected at random) and compute the Moran's I value based on borough contiguity. This leads to the computation of 8 Moran's I values for each of the 14 models (i.e. 112 Moran's I values). As our data are counts, we follow the advice in Zhang and Lin (2008) to compute the (deviance) residuals analysed. Moran's I values can range from -1 (perfect negative autocorrelation) to zero (no autocorrelation), to $+1$ (perfect positive autocorrelation). Of the 112 values computed, the median value of -0.03 (mean $= -0.01$) suggests that (overall) spatial autocorrelation was not an issue. Furthermore, only 6 of the tests (i.e. 0.053) were statistically significant, which is what we would expect on a chance basis for a Type I error threshold of 0.05.

6. Discussion

In this paper we set out to advance prior research on the effects of COVID-19 and related policies on burglary and to investigate how different types of burglaries in London (UK) were affected. In contrast to most existing work, we took a spatio-temporal approach which explored the temporal relationship between burglary and occupancy at the London borough level, rather than using a city-wide design. As expected, and in line with other research, including that conducted in the UK (Halford et al., 2020; Langton et al., 2021a), we found significant reductions in levels of burglary during the pandemic restriction period. As expected, particular categories of burglary were affected differently demonstrating that it is highly advisable to consider specific types of burglary when predicting trends as a result of changes to mobility or when planning prevention initiatives. This is in line with the principles of situational crime prevention, which Clarke states should '…be characterized as comprising measures directed at highly specific forms of crime' (Clarke, 1983:225).

We found that, when not specifically accounting for household occupancy, overall residential and non-residential burglaries, and their attempted equivalents, decreased during the different stages of lockdown and mobility restrictions. The exceptions were for attempted non-residential burglaries which did not decrease significantly during the full lockdown. Aggravated and distraction burglaries, also only reduced substantively during the full lockdown phase.

More insight is provided by the analysis of patterns by time of the day. For both residential and attempted residential burglary, the impact of covid restrictions on crime was much more pronounced during the daytime. It is during the day that movement restrictions would impact most on household occupancy, and hence this finding supports the suggestion that an increase in the daytime occupancy of residential households – due to people working from home or being furloughed –increased surveillance and guardianship by residents, thus reducing opportunities for burglaries to occur at this time of day. This echoes the ideas raised by Cohen and Felson in their original routine activities paper which considered how changes to the workforce following the second world war affected home occupancy and subsequently victimisation risk (Cohen & Felson, 1979). Conversely, we do not see these clear effects for non-residential burglary. Indeed, in this case we often observed comparable or stronger decreases in non-residential burglaries at night during periods of COVID-19 restrictions- particularly for attempted non-residential burglaries.

With respect to the model results for residential burglary, our findings suggest that when we model changes to household occupancy at the borough level, the specific lockdown restrictions offered little to no additional explanatory value. Here, residential burglary rates were (largely or solely) negatively related to household occupancy rates. This suggests that the effect that COVID19 restrictions had on residential burglary worked indirectly through their influence on people's routine activities. From a theoretical perspective this provides further support for routine activity theory. From a practical perspective, it suggests that when attempting to anticipate future trends of residential burglary, it will be useful to model expected changes to mobility. For example, in areas where residents are expected to return to work, rates of burglary may be expected to return to pre-pandemic levels. In areas where residents might be expected to continue to work from home, however, the reductions observed here might be expected to persist. In areas where hybrid working is adopted, or where some residents return to work while others do not, the effect on burglary may well be mixed. Finally, at geographies small than those considered here, areas with dramatic changes to their mobility profiles might be expected to influence residential burglary risk in adjacent areas too. As well offering insight into longer-term changes, modelling patterns of mobility might offer utility for the short-term forecasting of residential burglary and the allocation of police resources.

Apropos non-residential burglaries and distraction burglaries, it appears that (for our data at least) variation in changes to household occupancy generally offered little to no additional explanatory utility (beyond that conveyed by the timing of restrictions). This is in line with expectations, since household occupancy should provide less guardianship to non-residential than residential properties, and in the case of distraction burglary, the positive effects of guardianship may have been offset by the increase in offending opportunities presented by people being more likely at home (i.e., distraction burglaries can only occur when someone is home). Importantly, this selective pattern of results predicted by theory also provides confidence in our findings.

It is also pertinent to consider the role of offenders in different types of burglary. The movement of offenders as well as other populations will have been restricted during the covid period. This is likely to particularly have been the case during the national lockdown period. At other times, there will have been more free movement, and those away from their homes would have been less obvious and more accepted as they would have plausible reasons to be elsewhere. By definition, aggravated and distraction burglary need a victim; they cannot take place in locations without those to aggravate or distract. It is interesting that there was only a meaningful decrease in these types of burglary during the official lockdown. In these cases, a lack of free movement of offenders might have been the limiting factor.

As with other similar research, these findings are based on official crime data and so are limited by reporting and recording practices. In our case, this means we rely on offences being correctly recorded. For example, a failed attempted burglary could be incorrectly recorded as criminal damage. This seems unlikely to change over the time interval of this study, but the point remains. Our analyses also depend on the accuracy of the reported start and end times that the burglaries (could have) occurred. For the day versus night analysis, it was necessary to omit data for some offences as the interval between these two points in time exceeded 18 h. Moreover, given the uncertainty associated with when (some of the) burglaries occurred, we were only able to estimate the interval of the day they occurred and there will be a margin of error associated with this.

Finally, we could only examine daily variation in mobility. Future studies may want to investigate the effects of occupancy at more finite resolutions if better data becomes available or can be reliably estimated. In terms of the Google data more generally, these are subject to known biases associated with the collection of digital data (for a discussion, see Solymosi & Bowers, 2018). For example, not all people use Google applications and not all those that do will agree to share their location (or other) data with Google, which can create a sample bias which the reader should bear in mind.

In conclusion, our findings suggest that burglary declined during the pandemic and that different types of burglary declined more or less at different times of the day and did so in a way that was consistent with the expectation that changes to mobility and household occupancy would affect guardianship dynamics and the protection that this affords. By modelling these effects across as well as within London boroughs, we avoid the types of statistical aggregation bias that might otherwise compromise interpretation of the findings. Our findings thus build on the existing literature and provide a more refined test of the impact of the pandemic on burglary.

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Declaration of interest

None.

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