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Research paper

Drug markets and COVID-19: A spatiotemporal study of drug offence detection rates in Brisbane, Australia

Jason L. Payne*, Cameron T. Langfield

University of Wollongong, School of Health and Society, Australia

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ABSTRACT

In many parts of the world, the social mobility restrictions and stay-at-home orders introduced during the early months of the COVID-19 pandemic have been associated with significant reductions in crime. However, contrary to this general finding, illicit drug offence detections increased significantly. In this study, we explore the geographical distribution of the increase in Queensland, Australia, using spatiotemporal generalised additive model (GAM) to identify locations in the Local Government Area (LGA) of Brisbane where drug offence detection rates were unusually high during the three months of the COVID-19 lockdown (April-June 2020). Contrary to expectation, we find that the increase in drug offence detection rates appears to have been modest in most places, but widespread and diffuse throughout the city. We conclude that drug offence detections are most likely to have increased incidentally, probably as a consequence of general street policing initiatives which saw an increase in the visibility and vulnerability of drug user communities. We do, however, identify several locations in Brisbane where the drug offence detection rate exceeded the prediction by a considerable margin (in one case, more than double the upper limit of the prediction). We argue that in these locations the increase was likely the result of some spatial displacement of inner-city drug markets coupled with a series of targeted policing activities. Further research is needed to clarify the true mechanism of change in these locations.

Introduction

The global health and social policy response to COVID-19 has been highly variable. In Australia, efforts to curb transmission centred on an almost immediate halt to international passenger arrivals along with strict stay-at-home and social distancing regulations. Although each state and territory managed their local risks through a unique set of public health orders (O'Sullivan et al., 2020), Australia as a whole has been heralded as a significant public health success story (Glover, 2021 see also O'Sullivan et al., 2020). However, extreme interventions of the kind seen in Australia are not without their consequences. Strict orders to 'stay-at-home' and a heavy investment in the policing of public health orders is likely to have a disproportionate effect on vulnerable individuals and communities (Bonn, 2020). One potential indicator of this disparity, as demonstrated by Langfield et al. (2021), is the statistically significant increase in the police detection of drug offences (possession, in particular) (see Fig. 1) while all other recorded crime rates were significantly below trend through the earliest months of the pandemic (see, for example, Ashby, 2020a, 2020b; Campedelli et al., 2020a; 2020b; Payne et al., 2020, 2021).

There is not likely to be a single reason for the increase in drug offence detections. Some have argued that the emotional and social pressure of lockdown may have led to an increase in rates of community-level drug use (Australian Bureau of Statistics, 2020; Dietze & Peacock, 2020; Lee & Bartle, 2020; McGowan, 2020). There is some merit in the argument that higher levels of drug use among existing users could result in higher levels of drug market activity, especially if that meant more frequent episodes of drug purchasing. Indeed, results from Australia's Drug Use Monitoring in Australia (DUMA) study indicate that average consumption rates for cannabis increased (Doherty et al., 2021) during the lockdown, although this was offset by a decline in methamphetamine consumption (Voce et al., 2021) and could well signal a change in the composition of the detainee population, rather than a change in drug use behaviour, per se. A second explanation is that, as other crime types fell, residual policing resources were redirected to general street-based policing activity or possibly even targeted activities in known hotspots. Some anecdotal evidence supports this view (Levin & Kashyap, 2020), however, there are very few local geographical studies (see Campedelli et al., 2020b) which have looked more discretely at the possible spatial clustering of drug offence detection rates. It is unclear, therefore, whether the rapid increase in police drug detection is more a result of incidental detection rather than the targeted and purposive actions of the police at a small number of specific sites. A third explanation argues that there was no change in drug use or drug market activity, but that those who participate in drug markets suddenly became more vulnerable to police detection as urban centres and city streets were deserted during lockdown (Dietze & Peacock, 2020). The

* Corresponding author.
E-mail address: jason.payne@uow.edu.au (J.L. Payne).

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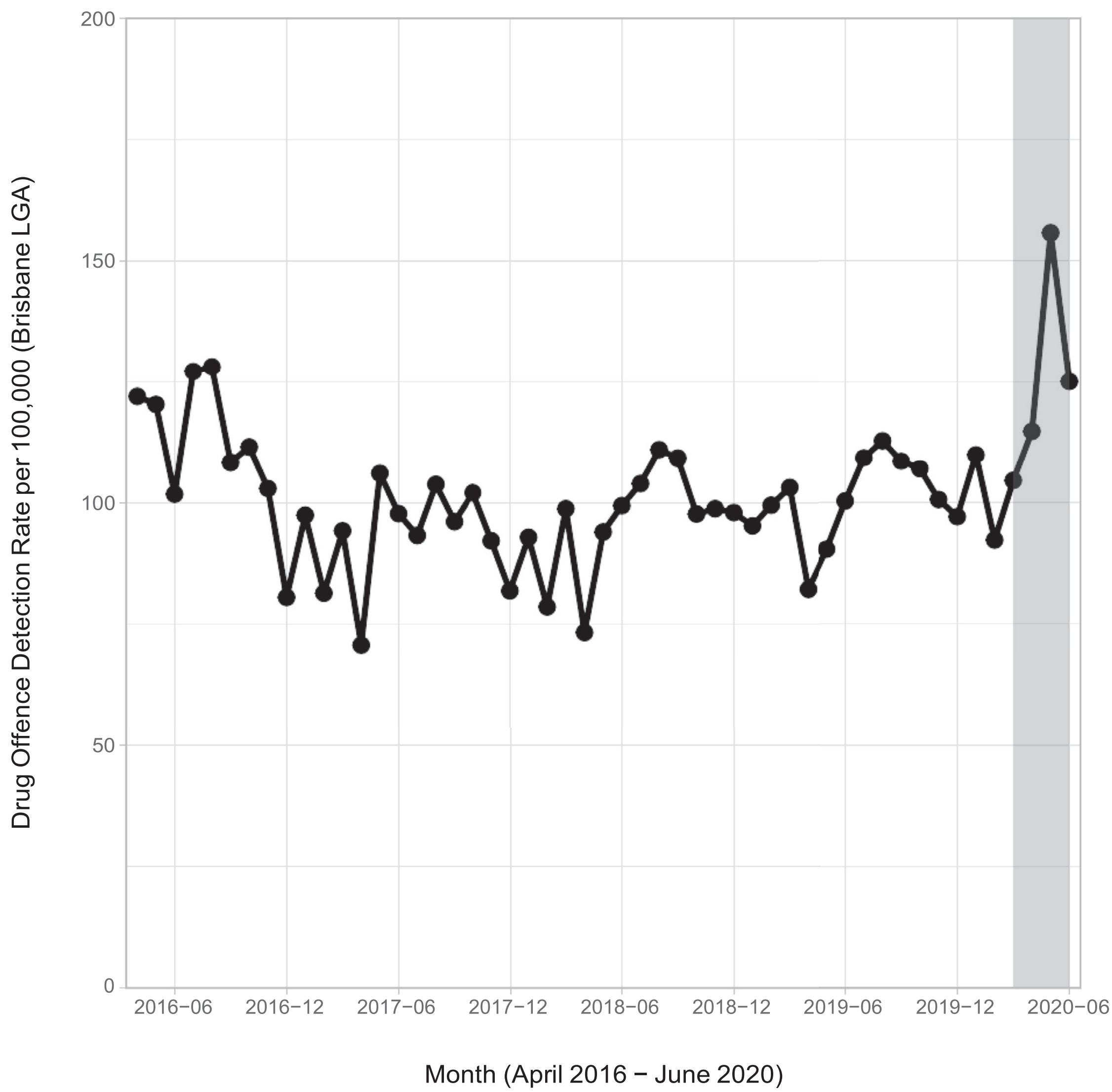

Fig. 1. Monthly drug detection rate (per 100,000), Brisbane LGA (April 2016 - June 2020). Source: Queensland Government Open Data Portal - Computer file.

compulsive nature of drug dependency, coupled with the socioeconomic vulnerability of drug user communities, likely means that drug markets remained active despite the government's order to stay-at-home (see Eligh, 2020; Hamilton & Stevens, 2020; Namli, 2021; Winstock et al., 2020) and this activity was likely more visible to law enforcement.

These competing hypotheses have been developed mostly in response to the evidence of aggregate data showing state-wide or city-wide changes in drug offence arrest rates (see Andresen & Hodgkinson, 2020; Langfield et al., 2021; Langton et al., 2021). Few studies have drilled down into the geospatial data to examine the spatiotemporal patterns and their implications for understanding both drug markets and policing during the pandemic. We argue here that different patterns signal different mechanisms and this can be valuable for understanding how drug users, drug sellers and police responded to the pandemic. For example, we might expect intensive police targeting of known drug markets to have resulted in a small number of drug offence detection clusters where the detection rates far exceeded normal expectations. In addition we might also expect these clusters to be temporary if the market interdiction efforts were of the kind normally described as 'hotspot interventions' or 'crack downs' (see Mazerolle et al., 2007 and Mazerolle et al., 2020). Conversely, if drug offence detections were incidental to other policing activities and mostly the result of an increase in the visibility and vulnerability of drug market participants, then we might expect the increase to manifest across a larger and more widely spread number of locations, each with a relatively modest increase overall. In any case, the spatiotemporal pattern of drug offence detections will likely contain valuable insights about the mechanisms of change during COVID-19.

This current study uses a spatiotemporal generalised additive model to identify geographical locations in the Local Government Area of Brisbane, Australia, where drug offence detection[1] rates were unusually high during the three months of the COVID-19 lockdown (April-June 2020, see Fig. 1). We operationalise three separate indicators of change. The first is a binary indicator identifying locations where the detection rate surpassed the model-derived upper 95% prediction interval in at least one of the three months of the lockdown. The second measure examines whether the increase was temporary or sustained, counting for each location the number of months that drug offence detections were statistically higher than predicted. The final measure considers the relative extent to which the actual detection rate exceeded the Bonferroni-corrected prediction at each location. In this case, we calculate the number of detections above the upper 95% prediction interval (we call these

[1] We remind readers that drug offence detection data are those recorded by the police upon the apprehension of an individual for possession (mostly), trafficking or other illicit drug offences. Detected drug offences are largely influenced by policing priorities and practices and do not necessarily reflect the behaviour of most drug users

'excess' detections) and we then divide that number by the same upper interval. The result is a relative measure of 'excess' where, for example, a location with 15 drug detections and an upper 95% interval of 10 would have 5 excess offences for a relative 'excess' of 50%. We then map the outcomes of each measure and describe their spatial distribution.

Prior literature

Our analysis of COVID-19-related changes in drug market activity builds on a comprehensive history of drug market research which has shown drug markets to be complex structures that are resilient to change and intervention. Specifically, drug markets exist to facilitate the trade of illicit products, while at the same time minimising the risk of detection and apprehension. Each market is unique and their locations, among all other possible locations, have likely been carefully selected to maximise profits and minimise transaction costs. The illicit transaction calculus is multifaceted and accounts for both the location and size of nearby drug user populations, as well as the presence (or absence) of capable guardians. Rengert (1996), for example, argued that the "quality of [a drug selling] location is directly related to the quantity of profit" (Rengert, 1996) while Eck (1994) argued that location selection was ultimately a trade-off between accessibility and security because for illicit goods that are unregulated by legimtiate market protections the exchange process is inherently "very risky" (Eck, 1994, p. 71). To this, Reuter and MacCoun (1992) add that successful drug markets typically establish in locations where drug buyers and sellers can stay safe, remain unnoticed and, ultimately, avoid violence from other drug market participants as well as detection by the police.

In 1994, Eck (1994) proposed two alternative drug market models. The first is a social network market where drug transactions are limited to a network of familiar and trusted associates. These trusted networks provide opportunities to pre-arrange the illicit transaction, oftentimes in places or contexts which significantly limit the risk of detection. The second is a routine activities market where drug transactions are unplanned, often between strangers or unfamiliar acquaintances. As the name suggests, this second market type operates at the intersection of the drug buyers' and drug sellers' routine activities, commonly at points of commuter convenience such as train stations, shopping centers and night time economy establishments (see, for instance, Barnum et al., 2017; Bernasco & Jacques, 2015; Bouchard, 2007; Eck, 1995; Haracopos & Hough, 2005; May & Hough, 2004; Reuter & Pollack, 2012; Robinson & Rengert, 2006; St. Jean, 2007).

Two years earlier, in an analysis in Washington DC, Reuter and MacCoun (1992) devised a different typology, making a clear distinction between four different market categories. They called them Local Markets, Import Markets, Export Markets and Public Markets, and they distinguished between them using different models of participant mobility in an effort to define who travels where, and why (Reuter & MacCoun, 1992). Although somewhat limited in its capacity to describe contemporary, technologically connected market networks, the framework is useful for understanding how different street-markets evolve and it reminds us that accessibility is key to the emergence and long term success of established street-level drug markets (see Adler, 1993; Agar, 1973; Eck, 1995; see also the work of Johnson, 2009, 2016 for empirical tests of the typology).

In addition, research has shown street-level drug markets are more likely to proliferate in "business- friendly" (Eck, 1995; McCord & Ratcliffe, 2007; Rengert, 1996)) neighbourhoods with comparatively low levels of informal social control (Forsyth et al., 1992; McCord & Ratcliffe, 2007). Conversely, they seem not to proliferate in areas where legitimate place managers (i.e., local residents and business operators) are actively engaged in efforts of collective control and self-regulation (see Willits et al., 2015). In fact, even in areas that might normally attract drug sellers–for example, areas which service multiple complementary routine activities, especially for unemployed, poor, and under-educated populations (Willits et al., 2015)–markets might not emerge when local guardians have both the resources and the collective will to deter illicit conduct (Willits et al., 2015).

For the current study, it is important to recognise that in so-called normal times street-level drug markets typically establish in locations that offer "a balance between the spatial distribution of those who demand the product and the distance they would be required to travel to the market" (Tarkhanyan, 2014, p. 5000). The preferred locations are usually at or nearby clearly identifiable landmarks, making it easier to organise multiple 'deals' with different buyers. Importantly, they are also typically busy places with a mix of different legitimate uses–places where it would not be uncommon for drug market participants to 'blend in' (Tarkhanyan, 2014) with the general public as they loiter while waiting for a family member to finish in a nearby shop or a friend to arrive on the next train. Critically, it is the frenetic and multi-purpose nature of these locations that affords drug market participants the cover of anonymity and, if questioned by the police, a plausible deniability (see St. Jean, 2007 for a discussion).

However, the first few months of the COVID-19 period in Brisbane were anything but normal. Never before had the entire city been locked down to restrict community interaction and pedestrian movement so never before has there been an opportunity to witness the drug market response. Like other cities in Australia, Brisbane has a main open-air street market in an inner-city entertainment and red-light district known as Fortitude Valley, or 'The Valley'. Not unlike Kings Cross in Sydney and Footscray in Melbourne, the vast majority of Brisbane's drug offence detections are recorded in Fortitude Valley and there has been some research conducted in and around the area (see (Arnold, 2002; Davies, 2011; Manning, Mazerolle, Mazerolle, & Collingwood, 2016; Wickes, Mazerolle, & Riseley, 2005). Further afield, smaller 'hotspots' appear in the city's CBD, particularly nearby to the Roma Street train station (the train station servicing major regional and interstate connections), as well as the Brisbane Casino. Drug supply is most likely coordinated through social supply networks using mobile and other messaging devices (for international examples see, for instance, Barendregt et al., 2006; Curtis et al., 2002; May & Hough, 2004), although there has been much less research on Brisbane's urban markets than there has been in Sydney or Melbourne. In terms of drug profile, cannabis and amphetamine type substances (principally methamphetamine) are the most commonly used in Brisbane, with more police detainees in Brisbane reporting methamphetamine than any other drug type (51% testing positive, Voce & Sullivan, 2020). By comparison, the use of opiates is less common (i.e. one in four police detainees test positive), however the rate has remained relatively stable for the past 20 years (Voce & Sullivan, 2020). In terms of illicit drug policing, most large international and interstate importation and trafficking detections are managed by the Australian Federal Police and Customs whereas local drug enforcement is managed by State police agencies, usually through drug law enforcement squads (for large raids and major detections) or local police commands (for street-level market activity)[2].

Method

At its heart, this study is an analysis of prediction error. Specifically, it explores the difference between the actual rate of drug offence detection with a model predicted geospatial estimate for the three month period of the COVID-19 lockdown. The site of our analysis is the Local Government Area of Brisbane, which is the capital city of Queensland, Australia, and where the government mandated stay-at-home and social distancing regulations were in-place for the three months of April, May and June, 2020[3] (Queensland Department of the Premier and Cabi-

[2] Readers should note that because we use Queensland Police data on drug offence detections, our analysis principally reflects street-level policing activity, not major investigative activities or raids by federal authorities.

[3] The Queensland Government introduced its first restrictions on gatherings on 19 March, with no non-essential indoor gatherings of over 100 people and

net, 2020; Queensland Government, 2020a, 2020c). In the international context, Australia is a particularly unique and important study site for a number of reasons. First, Australia has had comparatively few COVID-19 cases (just 30,000 cases in total, as at May 1, 2021 Australian Government Department of Health, 2020) and, relative to other countries, very little community transmission (Australian Government Department of Health, 2020). Second, Australia was an early adopter of some of the most stringent social-distancing and stay-at-home regulations seen across the world (Chang et al., 2020; O'Sullivan et al., 2020). Third, the so-called lockdowns in Australia were relatively short in comparison to other countries and most state and territory jurisdictions were 'opening up' in a context of low or no community transmission as early as July 2020 (O'Sullivan et al., 2020). Finally, being in the global south, Australia was heading into the cooler months of autumn as the pandemic hit – a time when, in the normal annual cycle, crime rates are usually trending down (McDowall et al., 2012).

Our data are drawn from the Queensland Government's Open Data Portal (Queensland Government, 2020b) where unit records for all drug offence detections are available for the past 5 years. We have used the full complement of all data that was available at the time of download (from April 2016 to June 2020). For this study we model the data at Level 2 of the Australian Geographical Standard (herein described as SA2), which define statistical boundaries of communities where there is an average of 10,000 residents who 'interact socially and economically' (Australian Bureau of Statistics, 2011). There are 135 SA2s within the Brisbane Local Government Area, however for the purposes of this study we have excluded seven commercial or recreational locations which have zero or very few residents.[4]

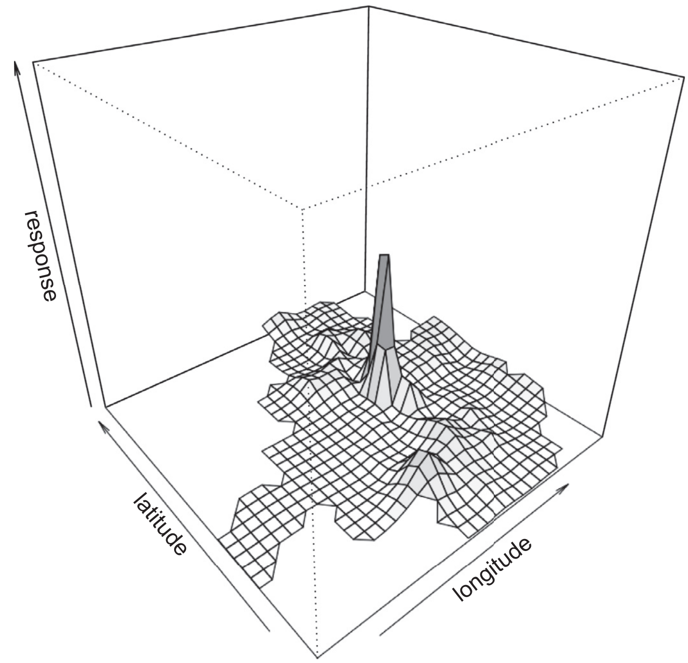

Fig. 2. Visual representation of a GAM estimated geospatial thin-plate spline / tensor product (Drug Detections, Brisbane LGA). Source: Queensland Government Open Data Portal [computer file].

Modelling strategy and outcomes

Our model is built using R (R Core Team, 2021) as a generalized additive model (GAM, see Hastie, 2020 for the GAM routine in R) which assumes a negative binomial distribution (for over-dispersed count data). GAM models are a flexible method for capturing non-linear relationships and have recently been used to model SARS-CoV-2 infection rates in the UK (see Wood, 2021) as well as the spatiotemporal patterns of such things as mean global temperatures (see, for example, Peristeraki et al., 2019). Specifically, geospatial correlation (i.e. the predictable statistical relationship between neighbouring locations) is captured through a spatial thin-plate spline (see Fig. 2) while the long term trends and seasonality of the series are captured through a cubic regression spline. In this case, it is easiest to think of GAM tensor products and splines as 'smoothed' parameters representing non-linear effects (see also Wood, 2017). For spatial correlation the smoothed effect is captured through the cross-product of longitude and latitude (measured at the centre-most point of each SA2) and each point in the spatial field is permitted to vary in overall trend and seasonality (for more information on GAM models see Wood, 2017).

Five location-specific covariates were included to explain any residual variance not captured in the geospatial and temporal correlation. These covariates were: (1) the relative preponderance of businesses providing food, accommodation and retail services; (2) the relative economic prosperity of local residents; (3) the relative education and occupation status of local residents; (4) the proportion of local residents that are aged between 15 and 24 (i.e. young adults); and (5) the proportion of local residents that were born overseas. Our choices here were informed by our reading of the prior literature which has demonstrated that drug markets tend to establish in or nearby to areas of low collective efficacy (Forsyth et al., 1992; McCord & Ratcliffe, 2007), high pedestrian and business activity (see, for instance, Barnum et al., 2017; Bernasco & Jacques, 2015; Eck, 1995; Haracopos & Hough, 2005; St. Jean, 2007; Willits et al., 2015) and where local residents are disproportionately young people or of low socioeconomic status (Rengert, 1996).

As for the local business data, we have used SA2 level estimates reported by the Australian Bureau of Statistics (ABS) and scaled these estimates into a relative measure for the Brisbane LGA. Where the relevant measure for an SA2 is coded as zero, this means that the number of businesses in that SA2 is equal to the average of all SA2s in the Brisbane LGA. A value of one (1) indicates an SA2 where the number of businesses is one standard deviation above the average for the region. For economic, education and occupation indicators we use the Index of Economic Resources (IER) and the Index of Education and Occupation (IER) derived by the ABS from the most recent Census of the Population (Australian Bureau of Statistics, 2016a). As with the local business data, we have standardised this to the average of all SA2s in the Brisbane LGA such that zero indicates an area where the IER or IEO score was equal to the average score across the region. Finally, we use Census data to measure the number of young adults (aged 15-24) and the number of residents born overseas as percentages of the local population.

For modelling purposes, we execute the analysis on data from April 2016 to March 2020 (48 months), holding out data for the three months

no non-essential outdoor gatherings of over 500 people allowed. On 24 March, all non-essential businesses (e.g., bars, gyms, cafes) were directed to close. State border restrictions were introduced on 25 March, whereby all arrivals to Queensland had to complete mandatory quarantine for 14 days. Indoor gatherings were restricted to no more than 10 people on 27 March, and people were directed to stay-at-home unless for essential reasons from 29 March. 31 March saw the closure of the Queensland border to all non-essential travel. On 2 April, indoor gatherings were further restricted to no more than 2 people, and Queensland schools closed on 4 April, except for students of essential workers and those deemed as vulnerable. Students began distance learning on 20 April. May saw the easing of restrictions, first with the return of younger grades and senior high school students to the classroom on 4 May. By the 25th May, all school students had returned to the classroom. June and July saw the easing of indoor gathering restrictions, first to no more than 20 people (1 June) and then to no more than 100 people (3 July).

[4] We note that drug detections can occur in locations with no or very few residents; however, we have erred on the side of per-capita standardisation using the usual resident population estimate as the denominator. Comparable 'rates' could not be estimated for locations and time periods when drug detections did occur, but where there is no resident population against which to calculate a standardised rate.

Table 1
Spatiotemporal GAM model of pre-COVID drug offence detection rates (April 2016-March 2020).

Main effects	Specification	Mean (sd)	b	s.e	p
Inner-city region	(Dichotomous)	0.25 (0.44)	-1.88	0.50	0.00
City centre	(Dichotomous)	0.02 (0.12)	-2.25	0.62	0.00
Fortitude Valley	(Dichotomous)	0.01 (0.09)	2.53	0.52	0.00
Accommodation and Entertainment Density	(Scaled - Number of outlets)	0 (1)	0.37	0.07	0.00
Relative Economic Disadvantage	(Scaled - IER Index)	0 (1)	-0.68	0.11	0.00
Relative Education/Occupation Disadvantage	(Scaled - IEO Index)	0 (1)	0.003	0.13	0.99
Young adults	(% of residents aged 15-24)	14.7 (4.6)	-0.04	0.01	0.00
Overseas born residents	(% of residents born overseas)	29.4 (10.8)	-0.02	0.01	0.02
Inner-city*IER	interaction	–	0.19	0.18	0.31
Inner-city*IEO	interaction	–	-0.03	0.23	0.91
Inner-city*young adults	interaction	–	0.04	0.28	0.13
Inner-city*overseas born	interaction	–	0.05	0.02	0.01
Constant/intercept	–	–	3.07	0.32	0.00
GAM estimated smoothed effects			EDF		p
Spatiotemporal Trend (longitude, latitude, year)			221		0.00
Spatiotemporal Seasonality (longitude, latitude, year)			25		0.00
Model fit diagnostics					
N					6096
Negative Binomial Scale					3.47
REML					17189
Adjusted R^2					0.85
AIC					33773.77

Notes: EDF = estimated degrees of freedom, REML = Restricted Maximum Likelihood, AIC = Aikaike Informaiton Criteria
Source: Queensland Government Open Data Portal.

when COVID-19 restrictions were in place (April-June 2020). We then use the model parameters to predict the crime rate for each location and each month of the COVID-19 lockdown. Recognising the inevitable presence of prediction uncertainty and the likelihood that the degree of this error will vary from location to location, we use a Bayesian simulation procedure to compute 10,000 simulations of the model predictions at each location. From this we generate 95% prediction intervals to reflect the range of values within which we should confidently expect the true value to fall had the COVID-19 lockdown not occured.

The statistical model parameters and model diagnostics are provided in Table 1. Overall, the model explains approximately 85% of the variance and, when tested, the residuals were found to be randomly distributed, meaning that there was no spatial (p = 0.96) or temporal autocorrelation (p = 0.98) in the error term. In the final model, both spatiotemporal smooth terms are statistically significant (EDF(Spatial/Trend) = 221, p = 0.00 and EDF(Spatial/Seasonality) = 25, p = 0.00). This tells us that there is strong spatial correlation which changes both in the long term (trend) and in a predictable seasonal pattern. Of the location-specific covariates, the model shows that pre-COVID drug offence detections were higher in locations where there are more food and accommodation businesses (b=0.37, p = 0.00). This means that in areas where the number of food and accommodation businesses was above average (one standard deviation above the mean), the drug offence detection rate was approximately 40 percent higher. Similarly, detections were higher in locations with higher levels of economic disadvantage (b=-0.68, p = 0.00, i.e. 97% higher in areas where disadvantage was one standard deviation below the mean), but lower in areas where there was a higher proportion of young adults (b=-0.04, p = 0.00, i.e. 4% fewer detections for each percentage increase in the young adults population) and/or residents born overseas (b=-0.02, p = 0.02, i.e. 2% lower for each percentage increase in the proportion of overseas born residents).

Identifying hotspots

A comparison of the actual and predicted drug offence detection rate is used to compute three measures of 'change'. Our first measure is a binary indicator of any location where the drug offence detection rate was higher than the 95% prediction interval for at least one of three months during the COVID-19 lockdown. The prediction interval is calculated through a simulation procedure where the distribution of pre-COVID drug offence detection rates at each location is used to create a parameter vector from which predicted observations are drawn. The process is then repeated 10,000 times at each location such that a 95% prediction interval can be calculated from the distribution of simulated observations. Since we are computing prediction intervals for 128 locations, we erred on the side of caution and adjusted the 95% prediction interval alpha value using a Bonferroni correction.

Our second indicator highlights locations where the drug offence detection rate was statistically higher than predicted for two or three of the lockdown months. We think these locations are particularly important since statistically significant results across multiple or consecutive months is probabilistically unlikely to occur by chance alone and suggest something more systematic underlies the changes in local drug market activity. Finally, the third measure examines what we describe as 'excess' drug offence detections. These are locations where, over the three month lockdown, there was an 'excess' of detections above the upper 95% prediction interval (Bonferroni corrected). We aggregate these excess detections across the three month period, and then divide the result by the aggregate of the three upper 95% prediction intervals. Our measure, therefore, represents the relative excess of drug detections at each location.

Results

The aggregate drug offence detection rates for Brisbane show a considerable spike in May 2020 (Fig. 1). Although not as high, drug offence detections in June were among the highest since 2016 and certainly higher than the average detection rate of the past two years. Suffice it to say that, coinciding with the introduction of the COVID-19 stay-at-home and social distancing regulations, Brisbane experienced a unprecedented increase in drug offence detections, recording the single greatest month-to-month increase (April to May) and resulting in the highest per-capita rate on record (May).

To answer our first question, Fig. 3 maps SA2 locations in the Brisbane LGA where the total number of drug offence detections during the lockdown exceeded the three-month model-derived prediction (shaded grey). Areas where the increase was statistically significant are flagged,

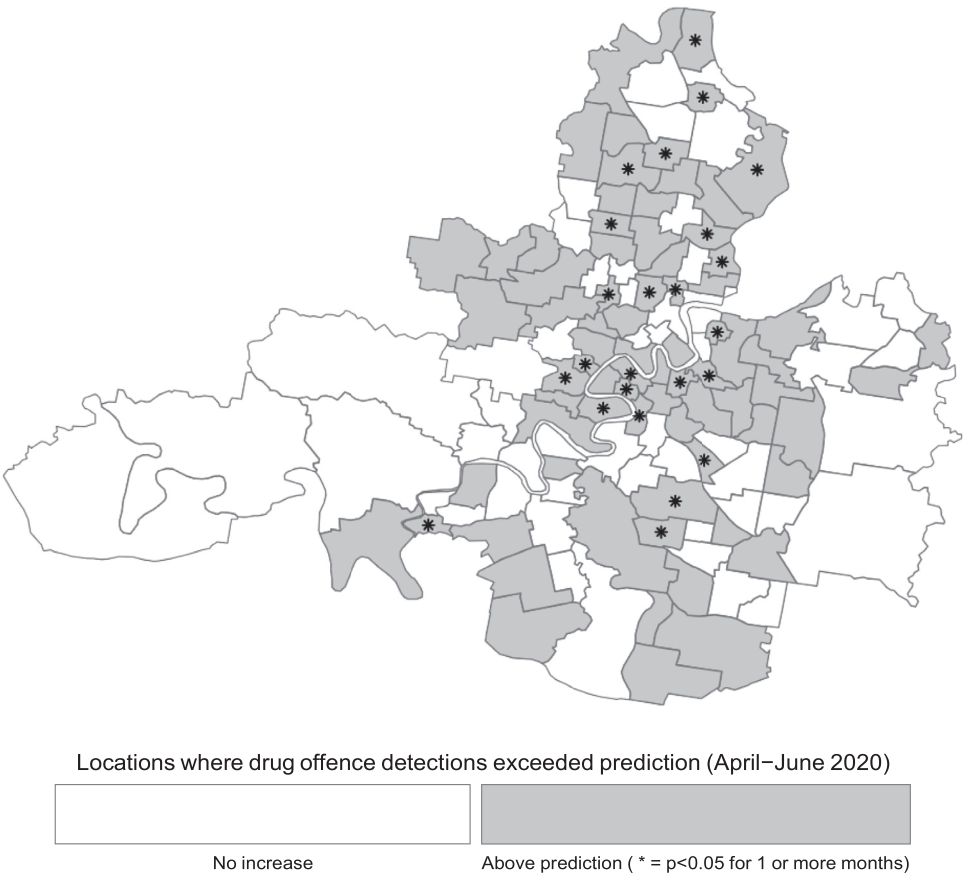

Fig. 3. Locations where drug detections were significantly higher (at p<0.05) than predicted for at least one month (April-June 2020).Source: Queensland Government Open Data Portal [computer file].Note: Areas in grey are those where over three months there was an overall 'excess' of drug offence detections. Prediction intervals for significance testing were adjusted using Bonferroni Correction.

meaning that the number of detected drug offences was higher than the 95% prediction interval (Bonferroni corrected) for at least one of the three lockdown months. Overall, 23 of 128 SA2s experienced a statistically significant increase. Generally, the spatial pattern appears widespread and diffuse, with a slight tendency to the inner-city and to the suburbs north of the Brisbane River. Importantly, the overall increase in drug offence detections in Brisbane was not heavily concentrated in a small number of areas.

Of the 23 locations where drug offence detections were significantly higher than predicted, the majority were above the prediction for just one of the three months of the lockdown period (predominately the month of May) (Fig. 3). This confirms that for most places in the city the increase did not occur until after the first month of lockdown, likely after restrictions were eased somewhat, and was a relatively temporary phenomenon.

In three locations, however, drug offence detections were statistically above the prediction for two (n = 2) or three months (n = 1, Fig. 4). Two of these locations were on the north-western side of the Brisbane River, one to the west in a township known as Toowong and the other to the north in a locale known as Stafford Heights. The third site was to the south-east in a place known locally as East Brisbane.

The final dimension of our analysis explored the relative size of the increase in drug offence detections, dividing the number of excess offences by the upper 95% confidence interval to yield an estimate of the percentage increase over the three months of the COVID-19 lockdown. By this measure, an increase of 100% would indicate that the number of excess offences was at least double what was predicted. In other words, for an SA2 where the upper confidence interval of predicted drug offence detection rate was 30, the relative increase would be 20% if the actual number of offences was 36 (6 excess offences). Similarly, the relative increase would be 50% if the actual number of offences was 45 (15 excess offences), and 100% if the actual number of offences was 60 (30 excess offences). Fig. 5 maps the spatial distribution of these data, showing that in all but six SA2s, the relative increase in drug offence detections was between 1% and 25%. Three locations recorded a relative increase of greater than 25% (but less than 50%), while in another three locations the number of excess offences exceeded the prediction by more than 50%.

To this point we have classified locations based on two different criteria: how long the increase in drug offence detections was sustained, and how large the increase was, relative to the local-area prediction. We end this analysis with a geospatial depiction (Fig. 6) of their cross-classification. Here, we identify four categories of change. The largest in number are those SA2s that increased for one month only and where the increase was relatively modest (<25%, 'likely incidental'). The second largest in number are those SA2s which experienced an increase in drug offence detections for just one month, but where the overall increase during COVID-19 was moderate. In these locations, an unusually large detection rate for just one month pushed the total number of excess offences to somewhere between 25% and 50% above what was predicted.

Two locations were identified as having accumulated an unusually high rate of drug offence detection over multiple months. We think that these five locations are places in the Brisbane LGA where there may have been a concerted and focused effort to police drug-related activities.

Discussion

Several studies have now documented a significant increase in drug offence detections during the lockdown associated with COVID-19 (see, for example, Langfield et al., 2021; Langton et al., 2021), although few have documented their geospatial distribution (however see Campedelli et al., 2020b). Knowing where drug offence detections increased in a city, for how long, and by how much, will likely be important lines of inquiry because different geospatial patterns may shed light on different mechanisms of change. In this study, we rise to the challenge with a comparison of actual and predicted drug offence de-

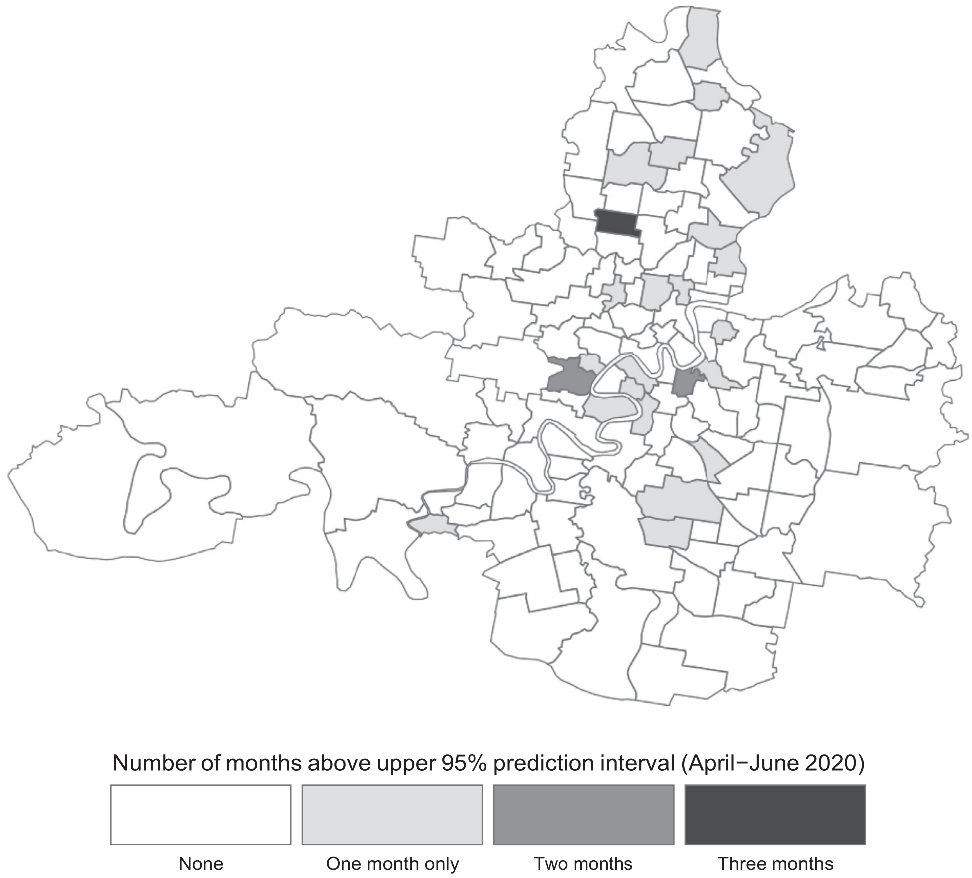

Fig. 4. Number of months (of three) where drug detections were significantly higher (at $p<0.05$) than predicted (April-June 2020). Source: Queensland Government Open Data Portal [computer file] Note: Prediction intervals for significance testing were adjusted using Bonferroni Correction.

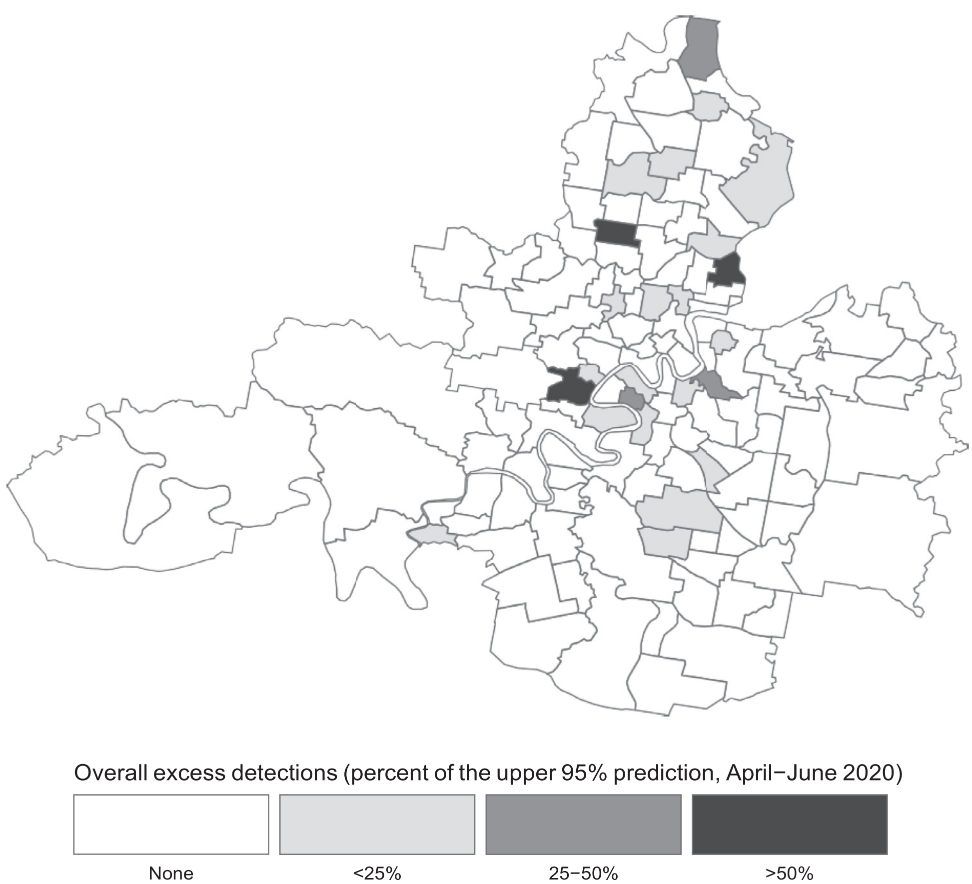

Fig. 5. Relative increase in drug offence detections (excess offences as a percentage of the upper 95% prediction interval, April-June 2020). Source: Queensland Government Open Data Portal [computer file] Note: Prediction intervals for significance testing were adjusted using Bonferroni Correction.

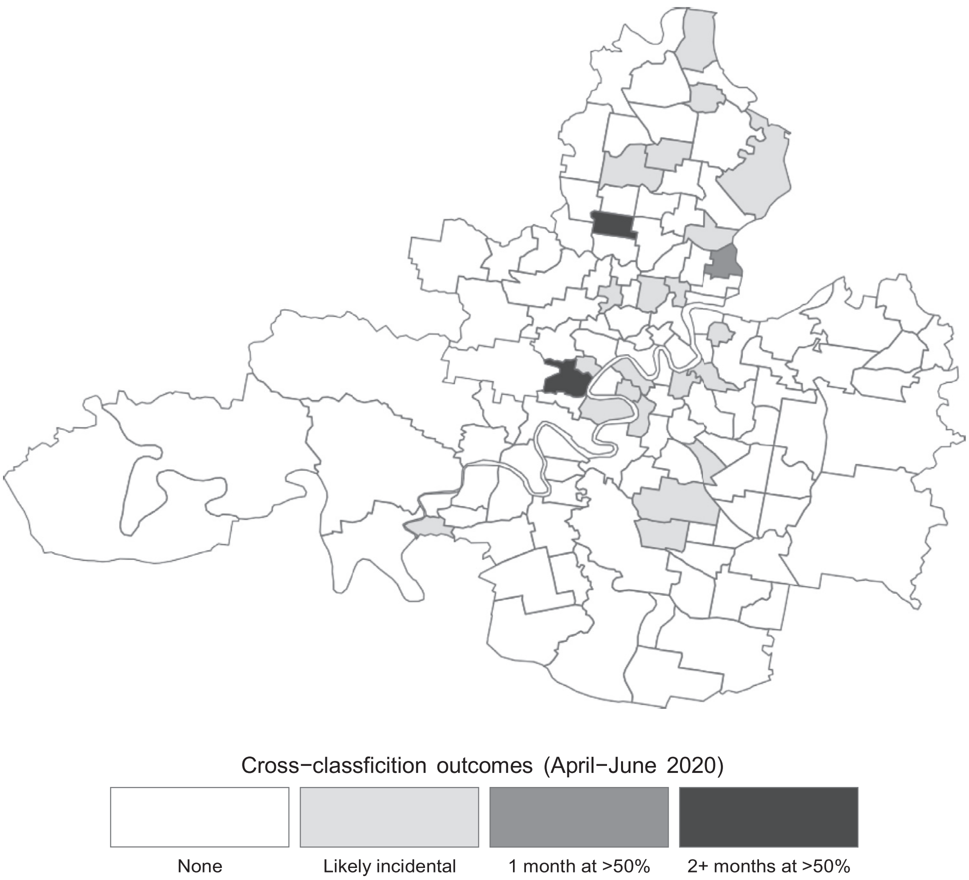

Fig. 6. Cross-classification of drug offence detections (number of months by relative increase, April-June 2020). Source: Queensland Government Open Data Portal [computer file] Note: Prediction intervals for significance testing were adjusted using Bonferroni Correction.

tection rates across 128 statistical local areas of the Brisbane LGA in Queensland, Australia.

We found strong evidence that the increase in drug offence detections illustrated by Langfield et al. (2021) was geospatially diffuse with a higher-than-predicted number of drug detections in two thirds of all 128 SA2s. Of these, 23 recorded a statistically significant increase, meaning that the actual recorded drug offence detection rate exceeded the 95% prediction interval for at least one of the three months of the lockdown. Given that our threshold of statistical confidence was set high using a Bonferroni corrected 95% prediction interval, this signals a fairly generalised and widespread phenomenon.

To explain this, we think that in most places across Brisbane drug users and drug sellers will have become increasingly visible and vulnerable to detection, although we credit this to a number of competing and intersecting mechanisms. First, we know that police are likely to have had more time to dedicate to street-based operational activities since all other crime types were in considerable decline (Langfield et al., 2021; Payne et al., 2020) and since policing priorities during COVID-19 were focused on public health and regulatory compliance (Maskály et al., 2021). This will have likely increased police attention on unusual or suspicious conduct, thus increasing the frequency of direct contact between the police and those members of the community who were not staying at home as directed.

Second, we expect that stay-at-home orders will have reduced pedestrian activity across the city, in particular the inner-city where daily foot traffic is usually high. Whereas busy streets likely provide some coverage and protection for drug market transactions (see, for example, Haracopos & Hough, 2005 and May & Hough, 2004), this protection is likely to have diminished during COVID-19 as large segments of the population avoided public spaces and went out for essential activities only (see Stickle & Felson, 2020 and also Murphy et al., 2020 for an analysis of the COVID-19 public health order compliance rates). No longer were drug transactions able to be covertly hidden within the hustle and bustle of everyday urban life. Instead they were increasingly overt enterprises that came with an increased risk of being watched or seen. To be sure, others have indicated a COVID-19-related shift to the more frequent use of 'home delivery' and 'take away' style transactions (see Namli, 2021 and Eligh, 2020), but still this will have required at least one party to travel away from home for non-essential reasons.

Third, we hypothesise that many areas will have benefited from an increase in capable guardian-ship because large segments of the community stayed home more often and for longer throughout the day. Although passive surveillance and neighbourhood guardianship is normally linked to lower levels of crime (Hollis-Peel et al., 2011), we think the reverse is true for drug offences during COVID-19. Specifically, we think it is likely that some 'excess' drug offence detections occurred in suburban SA2s because the residents, now working or staying at home during the day, more often identified suspicious behaviour and this may have resulted in more 'concerned citizens' reporting to the police (for a discussion on the public's willingness to report COVID-19 breaches see Sargeant et al., 2021).[5] Finally, while this might not explain the increase overall, we cannot discount the vulnerability and visibility that might have been caused by the displacement of drug transactions from the once busy city streets to the suburbs and urban backstreets. Although it

[5] Other research conducted by McCarthy et al. (2021) and Murphy et al. (2020) has shown that, at least in Australia, a large proportion of individuals did not fully abide by or follow the public health orders in the early months of the pandemic. These researchers found that defiant individuals, and those who had been subjected to, or witnessed police-initiated encounters they deemed to be 'procedurally unjust' were less likely to comply with the public health orders.

might be an act of detection evasion, it is possible that spatial displacement may have actually increased the visibility of drug transactions because buyers and sellers were forced to traverse unfamiliar terrain and take greater risks in an effort to transact. If nothing else, this displacement will have likely piqued the interest of concerned citizens as the extra and unusual traffic of unfamiliar vehicles and people in their street or neighbourhood became a cause to call the police.

That said, we did find a small number of locations which merit particular mention, either because they experienced statistically significant increases in multiple months, or because the increases were disproportionately large. The most notable of these was an area in the northern suburbs of Brisbane known as Stafford Heights, where the drug offence detection rate was significantly higher for all three months of the lockdown, and where the total number of excess offences exceeded the upper prediction limit by more than 50 percent. Stafford Heights is not a particularly unusual location. It is predominantly residential, having only a small retail shopping outlet at its northernmost border and two state schools to the east and southwest. Overall, the residents of Stafford Heights enjoy an above average income and are collectively above average on other major socio-economic indices (Australian Bureau of Statistics, 2016b). Within the area, however, there is some notable socioeconomic disparity. For example, the SA2 of Stafford Heights is made up of 15 smaller statistical boundaries (SA1s) and three of these rank in the two bottommost quintiles of the Index of Relative Social Disadvantage. By comparison, there are also two SA1s in Stafford Heights which rank among the state's most socio-economically advantaged areas. To be clear, Stafford Heights is not the only location which shares a diverse residential population, so why drug offence detections at this particular location were significantly high for every month of the lockdown remains unclear. That said, some media stories point to a concerted effort by the police to target drug related crime in the area and this may offer some insight (Queensland Police, 2021a, 2021b).

The second location of interest was a place called Toowong, situated to the southwest of the Brisbane CBD. It recorded a statistically significant increase in two of the three lockdown months and the excess offence rate exceeded 50% overall. Toowong is a major retail and transportation hub connecting residents from the south of the city to the CBD. It is a relatively wealthy inner-city residential location, where residents enjoy median incomes above the state average. Like Stafford Heights, there is nothing particularly unusual about Toowong that might explain the increase in drug detections, with the exception, perhaps, that Toowong is home to one of Brisbane's few federal services offices (known locally as Centrelink). In fact, the Centrelink office at Toowong services Brisbane's entire southwestern residential population and was one of few services which remained open during the three month lockdown. Importantly, Centrelink offices manage most of the Federal Government's social security and unemployment payments, including the new JobSeeker, JobKeeper and COVID-19 disaster payments (Worthington, 2020a, 2020b). There was considerable media coverage about the long queues of newly unemployed people seeking government assistance (Worthington, 2020c) and we speculate that Toowong was one of few SA2s in Brisbane which, despite the lockdown, attracted considerable pedestrian traffic and possibly even in increase in drug users and drug dealers looking to capitalise on the new routine activities of residents in the southwest.

There is one final observation that we think is important to make comment on here. Specifically, there was no COVID-related increase in drug offence detections in Brisbane's most well-known street-level drug market, Fortitude Valley (seen in Fig. 4 as the middle white area at the centre of the map, just north of the Brisbane river). In fact, taken together, Fortitude Valley recorded a lower-than-predicted number of drug offences throughout the three-month lockdown and further inspection of the data showed that the rate in all three months was within the lower bound of the 95% prediction interval. Given the usually open and visible nature of drug activity in Fortitude Valley, we might have expected drug offence detections to increase if the market was unaffected by the lockdown despite all other pedestrian and business activity having been considerably muted. Indeed, drug market participants would have likely been more vulnerable to police detection had their behaviour not changed so we believe that the street-level drug market in Brisbane's inner north was indeed muted during the lockdown. This was most likely in response to the increased risk of detection. To what extent the statistically significant increases elsewhere in the inner-city were the result of displacement is an important question that future research should address.

Of course, there are a number of important limitations which should be considered in light of our findings. In particular, we model police drug offence detection data which combined drug possession, drug trafficking and other drug offences, including the possession of drug utensils and paraphernalia.

It would have been preferable had we been able to disaggregate these offence types into separate models, but alas, to do that would have required a much more coarse geographical resolution that would have impeded the spatio-temporal analysis. Further, we also note that drug offence detection data are likely to be a relatively poor proxy for drug market activity as they speak only to a very small fraction of the overall activity across a city. With most detections being for possession (rather than trafficking) it is likely that our measure speaks mostly to the detection of drug users after purchase, but how long after and in what proximity to the site of purchase is unknown.

Conclusion

To conclude, this study finds that the aggregate increase in drug offence detections in Brisbane, Australia, was the consequence of several complementary mechanisms. First, a large number of areas across the Brisbane LGA experienced a modest and statistically significant increase, although this was temporary and likely incidental. Second, three areas experienced what we suggest was the consequence of an increase in the police targeting of drug users and in two of these areas the targeting appears to have been sustained over multiple months. Our results are different from those reported by Campadelli and colleagues (2020) who found that in Chicago narcotics-related offences declined during the pandemic. There are many possible reasons for this difference, not least of which is the different lockdown measures taken in each city and the implications this has had on policing activity. In Brisbane, considerable effort was taken by the police to enforce public health measures and this likely meant a significant increase in the interactions between police and those who continued to traverse the city streets. We argue that the increase seen in Brisbane is most likely a consequence of this incidental interaction in which drugs were then detected.

We are reminded that the COVID-19 effect on crime is best summarised as a fundamental transformation of social and routine activities caused by government mandated lockdowns. As others have noted (Stickle & Felson, 2020), the COVID-19 lockdown period represents an almost natural and unanticipated social experiment, and it is in view of these results that we ask a number of important questions that should inspire others to find answers in further research. Specifically, we wonder what the COVID-19 lockdown may have revealed about previously unknown drug markets. If it is true that drug users became more visible to the police and concerned residents, to what extent might this brief period of intensive focus have revealed things not previously known to the police? We also wonder to what extent the lockdown may have caused the displacement of market transactions into urban areas not previously affected? Will these new markets wither again as the pandemic subsides, or will they take hold and prosper? And, finally, what deterrent impact will the short-term increase in detection probabilities during the lockdown have on drug users–will the pandemic have heightened their perceived risk of apprehension and how long might such a change in perception last? Answering these questions will be important for not only understanding what happened, when, and where, but also the more important question of why.

Declarations of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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