Journal of Criminal Justice 68 (2020) 101692

Contents lists available at ScienceDirect

Journal of Criminal Justice

journal homepage: www.elsevier.com/locate/jcrimjus

Impact of social distancing during COVID-19 pandemic on crime in Los Angeles and Indianapolis

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ARTICLE INFO

Keywords:
Crime
Policing
Routine activities
Natural experiment
Interrupted time series

ABSTRACT

Governments have implemented social distancing measures to address the ongoing COVID-19 pandemic. The measures include instructions that individuals maintain social distance when in public, school closures, limitations on gatherings and business operations, and instructions to remain at home. Social distancing may have an impact on the volume and distribution of crime. Crimes such as residential burglary may decrease as a byproduct of increased guardianship over personal space and property. Crimes such as domestic violence may increase because of extended periods of contact between potential offenders and victims. Understanding the impact of social distancing on crime is critical for ensuring the safety of police and government capacity to deal with the evolving crisis. Understanding how social distancing policies impact crime may also provide insights into whether people are complying with public health measures. Examination of the most recently available data from both Los Angeles, CA, and Indianapolis, IN, shows that social distancing has had a statistically significant impact on a few specific crime types. However, the overall effect is notably less than might be expected given the scale of the disruption to social and economic life.

1. Introduction

In response to the ongoing COVID-19 pandemic, governments across the United States have implemented social distancing regulations with varying degrees of stringency. Social distancing is a long-established public health tool, which seeks to reduce opportunities for an infectious agent to spread among individuals and to reduce the overall speed of transmission (Caley, Philp, & McCracken, 2008; Hatchett, Mecher, & Lipsitch, 2007). Social distancing measures include instructions that individuals maintain a distance from one another when in public, limitations on gatherings, limitations on the operation of businesses, and instructions to remain at home. Rapid implementation of comprehensive social distancing is particularly important the more infectious the disease (Bootsma & Ferguson, 2007; Kelso, Milne, & Kelly, 2009).

Individuals, however, may prove resistant to social distancing orders. Because the benefits of social distancing accrue to the community at large, individuals have weak incentives to pay the costs (including economic strain, inconveniences to everyday life, and emotional effects among others) themselves (Reluga, 2010). In addition, individuals are typically bad at estimating the risks of disease transmission (Cho, Lee, & Lee, 2013), and may be influenced by mixed messaging emanating from different levels of government and misleading information from various media sources (Sha, Al Hasan, Mohler, & Brantingham, 2020). In a notable public display of these tendencies, California residents congregated on beaches over the weekend of March 21–22, 2020, despite the state's comprehensive "shelter in place" order (Reyes-Velarde, Vives, & Newberry, 2020).

Where fully implemented, social distancing measures create a variety of secondary impacts beyond the disruption of disease transmission. Importantly, there are strong reasons to expect that social distancing will alter both the volume and distribution of crime and disorder. This expectation flows from two fundamental principles of crime pattern formation (Cohen & Felson, 1979). First, crimes can only

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https://doi.org/10.1016/j.jcrimjus.2020.101692
Received 30 March 2020; Received in revised form 25 April 2020
Available online 01 May 2020

occur where motivated offenders encounter suitable targets in the absence of capable guardians that would otherwise disrupt the crime. Second, people going about their normal daily routines are sufficient to generate the physical conditions for most crime incidents. Social distancing measures on the scale presently being imposed throughout much of the United States should drive a massive disruption of daily routines, significantly altering and disrupting the material conditions under which crime may occur.

Under an effective social distancing regime, we expect that 1) the impact on crime will be significant and 2) that the nature of the impact will vary by the type of crime. Residential burglars, for instance, rely on homes being empty during the day while individuals are at work or school (Nee & Taylor, 2000). As a result, a large-scale shelter in place order should remove most residential targets from consideration. Residential burglary should fall precipitously under these conditions. The same order, however, could increase the volume of domestic or intimate partner violence, which thrives behind closed doors. Potential victims and offenders are limited in their ability to separate, while coping with burdens of social distancing on daily lives may generate additional stress among family and partners (DeLuca, Coleman, Papageorge, Mitchell, & Kalish, 2020).

Crime patterns may also provide valuable insights into whether individuals and communities are meaningfully complying with critical public health measures. Wide-spread non-compliance, for instance, may result in crime patterns that remain stable despite changes in government policy.

Law enforcement may be pulled in different directions based on how crime patterns are impacted by social distancing measures. While a reduction in residential burglaries may free up time, an increase in other crimes may rapidly fill that void. If the crimes that increase under social distancing are more challenging to deal with and more harmful, then the response capacity of police departments and local governments may be compromised. Stable patterns of crime despite the imposition of new measures, meanwhile, may suggest the need to devote resources towards the enforcement of social distancing. Understanding how crime patterns are being impacted by new measures, as a result, is critical to managing the current crisis and planning for the future.

Here we examine patterns in police calls-for-service and reported crime over the course of the unfolding pandemic. We contrast Los Angeles, CA, where state-wide and local shelter in place orders were implemented starting March 20, 2020, and Indianapolis, IN, where such an order was put in place effective March 24, 2020. School, restaurant and bar closures were ordered in both Los Angeles and Indianapolis as of March 16, 2020.

2. Methods

We analyze daily counts of calls for service in Los Angeles from January 2, 2020 to April 18, 2020 and in Indianapolis, Indiana from January 2, 2020 through April 21, 2020. We test for differences in means from a baseline period, defined to be the time period prior to school, restaurant and bar closings (January 2 to March 16, 2020). The treatment time period is defined to be after shelter in place orders were given: March 20, 2020 to April 18, 2020 in Los Angeles, and March 24, 2020 to April 21, 2020 in Indianapolis. In our first analysis we exclude the time period between school closings and shelter in place (March 16 to March 20 in Los Angeles, March 16 to March 24 in Indianapolis) in order to compare full social distancing effects (post stay-at-home orders) to a baseline with no social distancing measures yet implemented.

To test for a difference in means we run regressions for each incident type i of the form,

$$y_t^i = c_0^i + c_1^i 1\{t > t_{sh}\} + \sum_j w_j^i 1\{dw(t) = j\} + \sum_k m_k^i 1\{wm(t) = k\} + \epsilon$$

Here y_t^i is the number of calls for service of type i on day t and $1\{t > t_{sh}\}$ is an indicator for the treatment period after the shleter in place order. We control for seasonal effects in the regression, letting $1\{dw(1) = j\}$ be an indicator variable for the day of the week $dw(t) = j$ and $1\{wm(t) = k\}$ be an indicator variable for week of the month, $wm(t) = k$.

Because adherence to shelter in place orders may be delayed and/or vary by location and date, we also run a second regression using daily Google residential mobility indices (Google, 2020) of the form,

$$y_t^i = c_0^i + g^i x_t + \sum_j w_j^i 1\{dw(t) = j\} + \epsilon$$

Here x_t is the Google residential mobility index on day t and g^i is the coefficient of the mobility index for crime category i. The Google mobility indices are defined at the county level and are based on anonymized cell phone location history, normalized by a baseline level of activity. While other mobility index types are available (see Fig. 4), they are highly correlated with residential mobility. Reports are published in PDF-form by Google, which are then parsed using an open source python tool (PDF Reader, 2020). We present these results in the Discussion as a cross-check for our main analyses.

We apply the same regression methodologies to verified crime reports from Los Angeles and Indianapolis. We shorten the observation period to January 2, 2020 - April 10, 2020 in Los Angeles and January 2, 2020 - April 18, 2020 in Indianapolis to account for reporting lag in the last three days of each dataset.

3. Results

In Fig. 1 we display trends in the volume of calls-for-service from January 2, 2020 to April 21, 2020 and in Table 1 we include p-values for a change in means across the two time periods (pre- school closings and post- stay at home orders). Social distancing should increase guardianship of residential properties, and remove people from public settings where they are more vulnerable to certain violent crimes. Burglary calls were statistically lower in Los Angeles after shelter in place, even with a conservative adjustment for comparisons of $m = 12$ different calls-for-service models (i.e., $\overline{\alpha} = \alpha_{0.05}/m = 0.0042$) (Bland & Altman, 1995). Burglary calls were lower in Indianapolis after the stay at home order, but the change is not statistically significant. Robbery calls were significantly down in Los Angeles, but only marginally so in Indianapolis when accounting for multiple comparisons. Assault/battery calls were statistically unchanged in both locations.

Domestic violence, on the other hand, is expected to increase following social distancing due to increased opportunity for conflict in the home. Both Los Angeles and Indianapolis saw significant increases in domestic violence calls (Fig. 1, Table 1).

Finally, we analyze event call categories for which the impact of social distancing is ambiguous from the perspective of routine activities theory. Social distancing and shelter in place may increase local guardianship near the home, but also change the distribution of targets in ways that encourage offending. Here we found that calls related to vehicle theft were marginally higher in Los Angeles, but were unchanged in Indianapolis (Fig. 1, Table 1). Vandalism calls moved in opposite directions in Los Angeles (lower) and Indianapolis (higher), but neither outcome was significant after correcting for multiple model comparisons.

Traffic stops are a type of officer-initiated call. In Indianapolis traffic stops were significantly down after school closings and remained lower after shelter in place (Fig. 2). Traffic stops were also significantly lower in Los Angeles following the stay at home order. Reduced traffic stops could be partially explained by the overall reduction in traffic flow due to people complying with shelter in place orders. In Indianapolis, patrol officers were also instructed to exercise discretion in conducting traffic stops to mitigate less than necessary social contact. In Los Angeles, no such directive was issued, but individual discretionary choice by officers may be at play.

Comparable patterns were also observed for reported crime (Fig. 3,

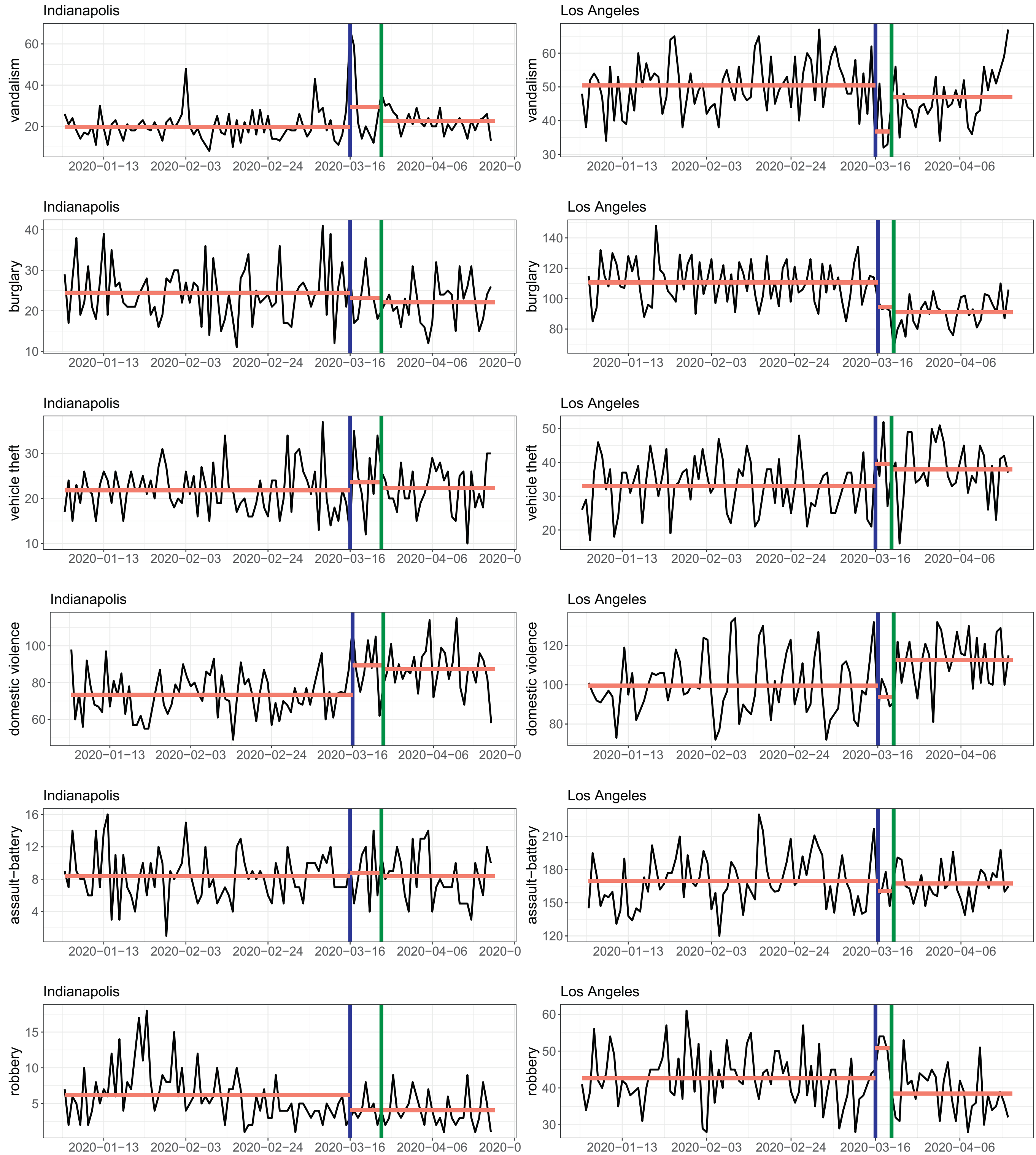

Fig. 1. Time series of calls for service per day (black) along with mean calls per day (red line) over each of the three time periods. Blue vertical line indicates the date schools, restaurants and bars closed and green vertical line indicates the date of the shelter in place order. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2). Reported crime derives predominantly from calls to the police by the public (Klinger & Bridges, 1997), but includes some amount of investigative validation by officers in the field. Reported burglary was statistically unchanged in Los Angeles and Indianapolis after shelter in place, when adjusting for comparison among multiple models (i.e., $\bar{\alpha} = \alpha_{0.05}/8 = 0.00625$) (Table 2). Reported robbery was significantly down in Los Angeles, but not in Indianapolis. Reported aggravated assault was statistically unchanged in both Los Angeles and Indianapolis after shelter in place. Domestic violence makes up a portion of the reported aggravated assaults, but we are unable to distinguish

Table 1
Regression of daily calls for service rate against stay-at-home order indicator controlling for day of the week and week of the month effects.

Type	City	Intercept	$c_1^i 1\{t > t_{sh}\}$	st. err.	*p*-val
Burglary	Los Angeles	101.9604	**−19.2569↓**	2.6645	**< 0.0001***
Burglary	Indianapolis	20.3382	−2.4129	1.3392	0.0749
Robbery	Los Angeles	37.8371	**−4.9570↓**	1.4449	**0.0009***
Robbery	Indianapolis	5.9317	**−2.0013↓**	0.7333	**0.0076**
Assault-battery	Los Angeles	189.2834	−2.5879	3.7693	0.4941
Assault-battery	Indianapolis	10.1304	−0.0026	0.6651	0.9969
Vehicle theft	Los Angeles	29.4776	**4.4446↑**	1.5796	**0.0060**
Vehicle theft	Indianapolis	18.6877	0.3703	1.0921	0.7354
Domestic violence	Los Angeles	114.5681	**13.1684↑**	2.7466	**< 0.0001***
Domestic violence	Indianapolis	87.4505	**13.7113↑**	2.3046	**< 0.0001***
Vandalism	Los Angeles	51.3657	−2.9531	1.6179	0.0712
Vandalism	Indianapolis	23.0774	2.7723	1.4629	0.0613
Traffic stops	Los Angeles	326.356	**190.8056↓**	18.1511	**< 0.0001***
Traffic stops	Indianapolis	252.7118	**231.1052↓**	12.6032	**< 0.0001***

Significant results prior to Bonferroni correction are indicated with boldface.
* Significant after conservative Bonferroni correction with critical value $\bar{\alpha} = 0.0042$.

these events in the reported crime data. However, we note that the significant increases in domestic violence calls-for-service were not enough to drive changes in reported aggravated assaults overall. Reported vehicle thefts were significantly higher in Los Angeles, but unchanged in Indianapolis.

4. Discussion

Our results suggest that social distancing and shelter in place has had some impact on crime and disorder, but only for a restricted collection of crime types and not consistently across places. A recent study (Campedelli, Aziani, & Favarin, 2020) found crime rates to be marginally lower in Los Angeles. Burglary does show some signs of being down, but primarily based on lower calls-for-service in Los Angeles. Robbery calls and reported crimes were also down in Los Angeles. Vehicle crimes show some signs of being up, but again primarily based on calls-for-service in Los Angeles. The most robust patterns to emerge, in both Los Angeles and Indianapolis, were a substantial decrease in traffic stops and a substantial increase in domestic violence calls-for-service. However, the increase in domestic violence calls did not appear to seriously impact reported aggravated assaults. We note that not all domestic violence calls are assaults involving aggravating circumstances. Many such calls prove to be domestic disturbances without violence (MacDonald, Manz, Alpert, & Dunham, 2003). This finding also has implications for officer safety. Incidents of domestic violence present one of the riskiest incidents for officer injury (Johnson, 2008, 2011) and also use of force (MacDonald et al., 2003). Thus, agencies should consider mechanisms to reinforce training of how to effectively and safely respond to domestic violence calls for service in light of social distancing.

The marginal decline in residential burglaries, marginal increase in auto thefts, and increase in domestic violence calls, points to shifts in crime patterns to which police departments will necessarily have to respond. These shifts, however, are perhaps less substantial than might be expected from the wholesale disruption of social and economic life brought on by COVID-19. Despite the imposition of broad social distancing regulations, our findings suggest that the routines of daily life that help to generate crime remain unchanged in most ways. Social distancing policies have had an important, but less than complete, impact on day-to-day life.

This conclusion is reinforced when we examine calls-for-service and reported crime volume against Google mobility data. Fig. 4 shows activity distributions derived from device location information and known or inferred location types. In Los Angeles and Indianapolis, routine activities begin to change approximately 8–10 days before shelter in place orders. The data show a definite shift towards activity concentrated in and around people's homes. Burglary and vandalism calls were significantly lower in Los Angeles as a function of the shift in activity to the home, taking into account multiple model comparisons (Table 3). Vehicle theft calls increased significantly in Los Angeles. Domestic violence calls increased significantly as a function of the activity shift in both Los Angeles and Indianapolis. The results for reported crime are very similar. Burglary and robbery events were down and vehicle thefts up in Los Angeles, while the effects on aggravated

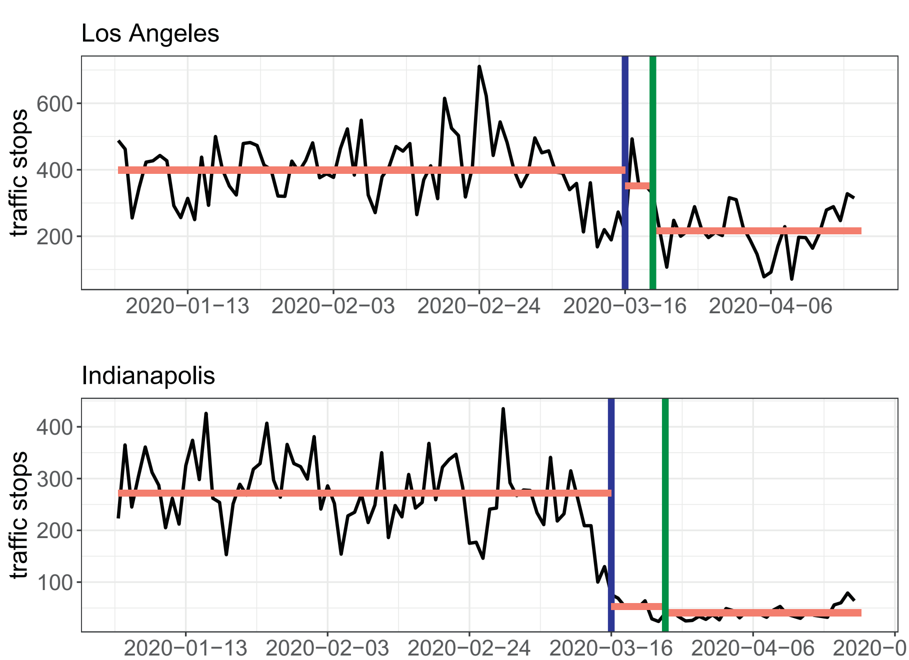

Fig. 2. Time series of traffic stops per day (black) along with mean calls per day (red line) over each of the three time periods. Blue vertical line indicates the date schools, restaurants and bars closed and green vertical line indicates the date of the shelter in place order. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

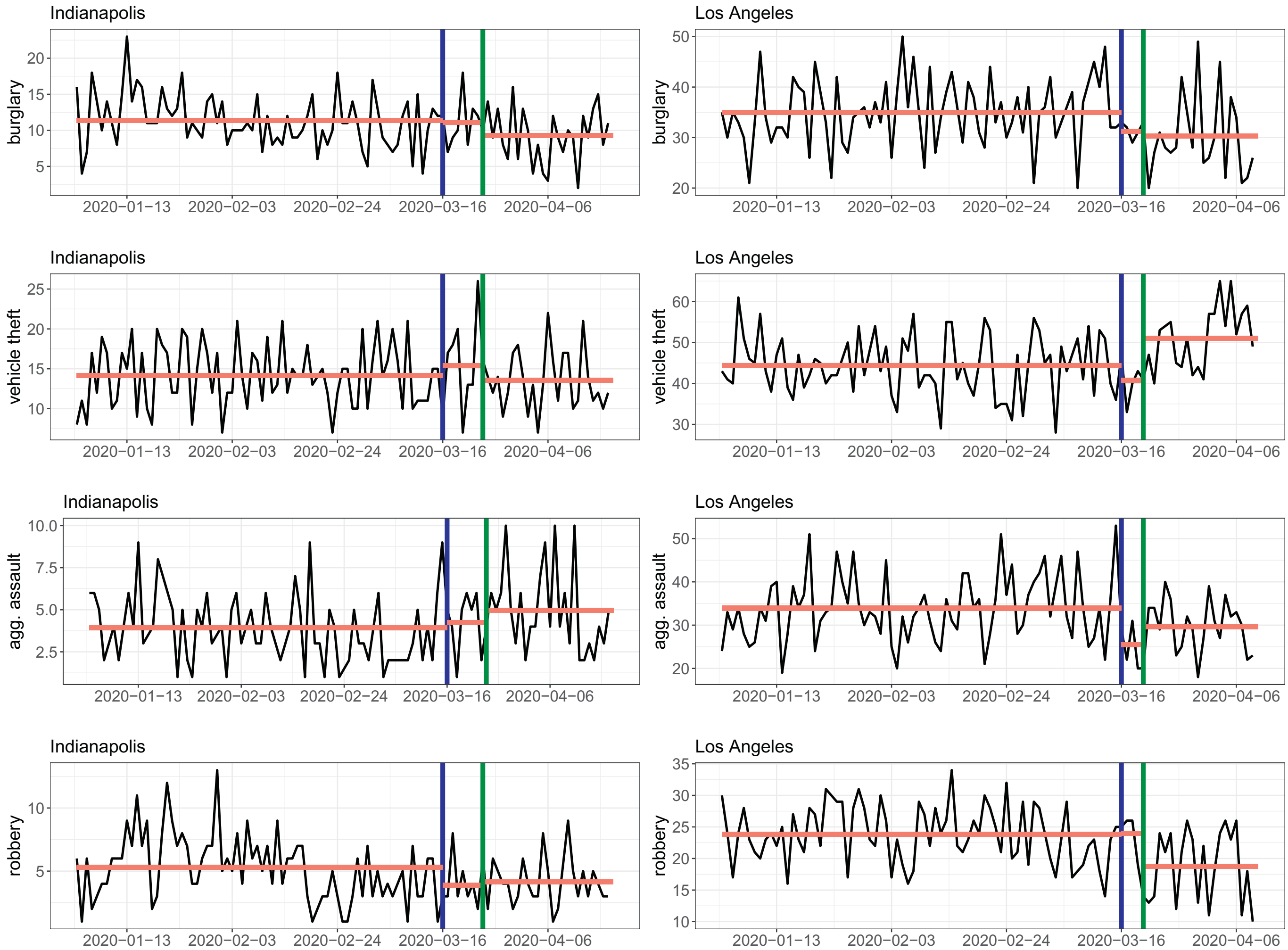

Fig. 3. Time series of verified crime reports per day (black) along with mean calls per day (red line) over each of the three time periods. Blue vertical line indicates the date schools, restaurants and bars closed and green vertical line indicates the date of the shelter in place order. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Regression of verified crime report rate against stay-at-home order indicator controlling for day of the week and week of the month effects

Type	City	Intercept	$c_1^i 1\{t > t_{sh}\}$	st. err.	*p*-val
Burglary	Los Angeles	31.3575	**−3.8629↓**	1.6233	**0.0196**
Burglary	Indianapolis	8.5156	**−2.0902↓**	0.8204	**0.0126**
Robbery	Los Angeles	24.2496	**−6.2263↓**	1.3106	**< 0.0001***
Robbery	Indianapolis	5.1276	−1.165	0.6174	0.0626
Agg. Assault	Los Angeles	40.5362	**−4.2857↓**	1.826	**0.0213**
Agg. Assault	Indianapolis	4.5379	0.9548	0.5051	0.0622
Vehicle theft	Los Angeles	46.798	**6.4768↑**	1.9476	**0.0013***
Vehicle theft	Indianapolis	11.039	−0.6564	0.8536	0.4440

* Significant after conservative Bonferroni correction with critical value $\bar{\alpha} = 0.00625$.

assaults were in opposite directions (Table 4). However, as many call and crime categories were not significantly altered as a function of the shift in routine activities. This is particularly true in Indianapolis, but also for certain crime types in Los Angles. It is worth noting that the practical differences in volume of calls per day are quite small. With the exception of burglary calls in Los Angeles (Δy = -19.27) and domestic violence calls in both Los Angeles and Indianapolis (Δy = 13.55 and Δy = 15.22, respectively), no other call or crime type experienced a change in volume of more than 8.8 events per day. In cities the size of Los Angeles (≈4 mil) and Indianapolis (≈0.8 mil), these are small differences in day-to-day crime and disorder. Overall, in spite of apparent changes to routine activities, people were still finding opportunities to commit crimes at approximately the same level as before the crisis.

Moving forward, calls-for-service and crime numbers can be compared with local data on new infections. Where individuals and communities avoid complying with existing social distancing measures, governments may consider alternative approaches. In some instances, police departments may find themselves engaged in more direct enforcement of limitations on social and economic activity. Meanwhile, as some jurisdictions consider relaxing social distancing measures, police departments may again face a changing crime environment.

Finally, we note several limitations of the present study. First, the results presented here are specific to Los Angeles and Indianapolis and may not generalize to other cities in the U.S. Second, though calls for service remain relatively stable during pre- and post-social distancing temporal periods examined here, we are not able to determine if social distancing influences whether individuals are more or less likely to report incidents of crime. However, despite domestic violence having been one of the crimes least reported to the police, with approximately half of all domestic victimization being unreported (Reaves, 2017), our results indicate that calls concerning domestic violence significantly increased in both Indianapolis and Los Angeles. Furthermore, police

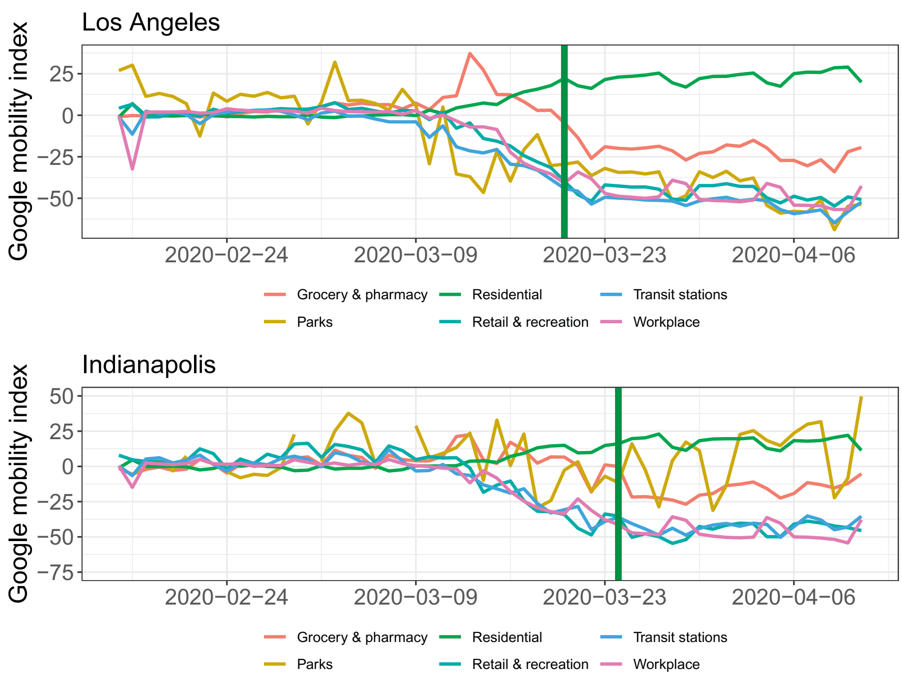

Fig. 4. Google mobility indices over time in Los Angeles County and Marion County (Indianapolis). Stay at home order date is indicated with green vertical line. Park mobility index in Indianapolis higher than 50 (prior to March 9) not shown. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Coefficients and *p*-values of daily calls for service rate regressed against Google daily residential mobility index controlling for day of the week

Type	City	Intercept	res. Mob. coef.	*p*-val	Δy†
Burglary	Los Angeles	100.5896	**−0.8875↓**	**< 0.0001***	**−19.2740**
Burglary	Indianapolis	18.8282	−0.131	0.1927	−2.3061
Robbery	Los Angeles	38.1009	−0.068	0.433	−1.4759
Robbery	Indianapolis	5.3363	0.0112	0.7278	0.1970
Assault-battery	Los Angeles	193.5346	**−0.3977↓**	**0.0471**	**−8.6362**
Assault-battery	Indianapolis	10.3443	0.0089	0.8383	0.1563
Vehicle theft	Los Angeles	25.3955	**0.3005↑**	**0.0009***	**6.5268**
Vehicle theft	Indianapolis	19.3494	0.0797	0.3906	1.4022
Domestic violence	Los Angeles	116.5062	**0.6239↑**	**0.0002***	**13.5495**
Domestic violence	Indianapolis	88.5106	**0.8643↑**	**< 0.0001***	**15.2112**
Vandalism	Los Angeles	53.4743	**−0.4069↓**	**0.0001***	**−8.8368**
Vandalism	Indianapolis	19.927	0.1657	0.3166	2.9156
Traffic stops	Los Angeles	335.0749	**−9.7213↓**	**< 0.0001**	**−211.1285**
Traffic stops	Indianapolis	203.3891	**−12.8343↓**	**< 0.0001**	**−225.8672**

† Expected call rate change computed by multiplying the estimated coefficient of residential mobility by the average residential mobility index post- shelter in place minus the average pre- school closing.
* Significant after conservative Bonferroni correction with critical value $\bar{\alpha} = 0.0042$.

Table 4
Coefficients and p-values of daily verified crime report rate regressed against Google daily residential mobility index controlling for day of the week.

Type	City	Intercept	res. Mob. coef.	*p*-val	Δy†
Burglary	Los Angeles	32.2002	**−0.2071↓**	**0.0106**	**−4.4614**
Burglary	Indianapolis	9.0286	**−0.0444↓**	**0.4237**	**−0.7818**
Robbery	Los Angeles	23.0183	**−0.1990↓**	**0.0040***	**−4.2866**
Robbery	Indianapolis	4.9948	0.0377	0.2481	0.6566
Agg. Assault	Los Angeles	43.2014	**−0.2787↓**	**0.0025***	**−6.0034**
Agg. Assault	Indianapolis	4.2007	**0.1227↑**	**0.0013***	**2.1518**
Vehicle theft	Los Angeles	43.6541	**0.3172↑**	**0.0045***	**6.8325**
Vehicle theft	Indianapolis	11.6931	0.0165	0.7923	0.2897
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† Expected call rate change computed by multiplying the estimated coefficient of residential mobility by the average residential mobility index post-shelter in place minus the average pre- school closing.
* Significant after conservative Bonferroni correction with critical value $\bar{\alpha} = 0.00625$.

departments across the country have undertaken both innovative and dramatic changes to reinforce available patrol resources in response to crime. Officers who contract COVID-19, had traveled leading up to the social distancing time period, or must accommodate children home from school, generate a reduced workforce for agencies. For example, the Police Executive Research Forum provides daily updates on its website that highlight contingency plans from agencies across the country. These strategies range from having officers work single-vehicle patrols and modified shift assignments, to reassigning detectives and investigative personnel to patrol duties. Specific to the locations of study, informal discussions between the authors, Los Angeles, and Indianapolis police departments suggests both agencies are responding to calls for service at levels consistent to pre-social distancing. In sum, we do not believe that possible under-reporting of crime or a reduced capacity to respond to calls for service have influenced the findings presented. Future scholarly inquiries in this area should focus on informing these limitations as additional data become available.

Acknowledgments

We would like to thank the Indianapolis Police Department and Los Angeles Police Department for their support in providing data and contextual understanding of events during this pandemic. Special thanks at IMPD to Chief Taylor and Deputy Chief Adams. Special thanks to LAPD Chief Michel Moore, the LAPD Senior Command Staff, Captain Vernon, Ms. Turner, Mr. Stolarov, and Mr. Dodge. This research was supported by NSF grants SCC-1737585, ATD-1737996, ATD-1737925, ATD-1737770 and DMS-2027438, Simons Foundation Math + X award 510776, and ARO MURI grant W911NF1810208. Authors PJB and GM serve on the board of PredPol.

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