On the Impact of COVID-19 on Crime in the US: Evidence from Maricopa County, Arizona and Los Angeles County, California

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ABSTRACT

This paper investigates the short-term impact of COVID-19 and stay-at-home orders on crime in one Police Department in Maricopa, Arizona and three Police Departments in Los Angeles, California. Using daily data from Community Crime Map between January 2019 to June 2019 and January 2020 to June 2020, this paper finds that overall crime decreased by 0.4 percentage points during the pandemic. Using variation in the implementation of stay-at-home orders across the two states, this paper also finds that these policies led to a 1 percentage point decrease in overall crime. Conforming with anecdotal and empirical evidence, this paper finds heterogeneity across criminal offences. Analyzing the top 5 criminal offences in these two counties, it was seen that stay-at-home orders led to a statistically significant decrease in residential burglary and aggravated assault. However, these policies led to an increase in general theft, motor vehicle theft and commercial burglaries. The plausible channels through which COVID-19 impacts crime and explanations behind heterogeneity are discussed.

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1 Introduction

Coronavirus Disease 2019 or COVID-19, which is caused by severe acute respiratory syndrome coronavirus (SARS-CoV-2), has led to a global health crisis. It was declared as a pandemic on 11 March 2020 (World Health Organization, 2020a). By the end of November 2020, there were more than 63 million cases of COVID-19 and over 1.4 million deaths (John Hopkins University, 2020). According to the World Health Organization (2020b), COVID-19 spreads through aerosolized respiratory droplets, surface contact, or both. Therefore, to curb the spread of the virus, different countries in the world have implemented various levels of social distancing measures.[1] These measures generally involve staying indoors unless undertaking essential activities, maintaining physical distance from one another in public, limiting large gatherings, closing businesses, and working from home whenever possible (Fong et al., 2020).

Perhaps more than any other country in the world, COVID-19 has negatively affected the United States of America (US). Since 26 March 2020, the US has had the highest number of COVID-19 cases and deaths in the world (John Hopkins University, 2020). US state and county officials implemented stay-at-home orders during the second half of March 2020.[2] However, the timing of implementation has varied considerably. For example, the first state to issue stay-at-home orders was California on 19 March 2020. In the following weeks, 18 more states gave similar orders. By the end of April 2020, 43 states (including the District of Columbia) had implemented some form of state lockdown (Mervosh et al., 2020). Nonetheless, not all US states and counties implemented stay-at-home orders in response to COVID-19.[3]

Research has shown that social distancing measures and lockdowns have reduced the spread of the virus and saved numerous lives (e.g., Anderson et al. (2020), Fang et al. (2020), Friedson et al. (2020), Hsiang et al. (2020)). However, the trade-off is greatly reduced economic activity and continued economic uncertainty. In

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[1] This paper uses the terms “social distancing”, “lockdowns”, “stay-at-home orders” interchangeably as they indicate the same.

[2] According to Wetter & Gostin (2020), the US cannot order a national lockdown policy as the US President and the federal government have limited powers within states. Only state governors and county officials have the authority to impose state-wide and county-wide lockdowns respectively.

[3] Allcott et al. (2020) and Baccini and Brodeur (2020) explore some of the determinants behind implementation of stay-at-home orders, which include partisan beliefs, governor term limits and others.

addition, the lockdown measures have led to a broad range (mostly negative) of socioeconomic outcomes. These include, but are not limited to, unemployment/job losses (e.g., Adams-Prassl et al. (2020a), Béland et al. (2020a), Coibion et al. (2020), Gupta et al. (2020)), mental health issues (e.g., Adams-Prassl et al. (2020b), Béland et al. (2020b), Hamermesh (2020), Tubadji et al. (2020)) and gender & racial inequality (e.g., Alon et al. (2020), Bartos et al.(2020), Fairlie et al. (2020), Schild et al. (2020)).

Another plausible socio-economic impact of COVID-19 and stay-at-home orders is a reduction in crime. After the increase in COVID-19 cases and implementation of stay-at-home orders, it was documented that the number of crimes had decreased in many US cities.[4] For instance, according to a report from the Wall Street Journal, the number of serious felonies reported in New York City (once the largest epicenter of COVID-19 in the US) between 16 March and 22 March dropped by 16.6 percent compared to the same period last year (Chapman, 2020). US News reports that crime numbers had also dropped in several cities such as Salt Lake City, Chicago, Los Angeles and others (Haynie, 2020). However, it remains unclear whether all types of crimes have been affected similarly. For example, certain crimes such as robberies and sexual assaults might have declined dramatically, while others, such as online fraud might have been on the rise (Goldsworthy, 2020). There have been no declines in homicides and shootings, whereas there has been an increase (though not statistically significant) in commercial burglary and car thefts (Abrams, 2020). Nonetheless, there has been a steady rise in cases of domestic violence (Boserup et al., 2020).[5]

It is difficult to analyze the causal effect of stay-at-home orders on criminal activity. Most research highlights a year over year comparison (e.g., burglary in a county in June 2020 compared to June 2019). This type of analysis relies on strong assumptions to identify the causal effect of the policy. Different counties have different pre-existing crime patterns. There is a possibility of omitted variable bias. For instance, mobility patterns might affect crime, and mobility might have dropped before stay-at-

[4] The first case of COVID-19 in US was detected during January 2020 (Holshue et al., 2020).
[5] The variability in crime can be explained by change in group dynamics due to social distancing measures and change in routine activities induced by stay-at-home orders (Ashby, 2020; Boman & Gallupe, 2020). For violent crimes such as homicides and shooting, potential offenders might be acting alone and are not deterred by stay-at-home orders (Abrams, 2020). Section 2 of this paper discusses the potential channels through which COVID-19 and stay-at-home orders affect crime in detail.

home orders were issued (Halford et al., 2020). There might be other unobservable variables that might affect the issuance of lockdowns and crime. These factors need to be accounted for to identify the causal effect of the policy.

This paper investigates the effect of COVID-19 and stay-at-home orders on criminal activities. The focus, to the extent that is possible, is on crimes committed in two US counties – Maricopa and Los Angeles – in two different US states – Arizona and California respectively. The crime data are taken from the Community Crime Map compiled by LexisNexis® Risk Solutions. Community Crime Map compiles crime data and other information directly from law enforcement agencies. The paper relies on crime data for one Police Department (PD) for Maricopa and three PDs for Los Angeles.

The paper uses a pre/post regression design to assess the impact of COVID-19 on crime in both these counties. Accounting for the variation in time between the implementation of stay-at-home orders in California and Arizona, this paper employs a difference-in-differences (DID) framework to analyze the causal effect of stay-at-home orders on crime. This empirical strategy includes indicators of overall crime and the top five criminal offences committed in both counties during the sample period. The latter helps to take cognizance of the effect of stay-at-home orders on different criminal offences.

The pre/post regression results show that there is a decrease in the overall crime rate by about 0.4 percentage points after the incidence of COVID-19 in the four PDs in these two counties. The estimate is statistically significant at conventional levels. The DID results show that the implementation of stay-at-home orders led to a reduction in overall crime rate by about 1 percentage point. Accounting for the top 5 criminal offences in these four PDs in these two counties, the results show that motor vehicle theft rate and commercial burglary rate increased after the issuance of stay-at-home orders, although the estimates were not statistically significant at conventional levels. On the other hand, there was a statistically significant decrease in residential burglary and aggravated assault rates after the issuance of stay-at-home orders. Surprisingly, there was an increase in theft rate, which is contrary to predictions based on theory and previous empirical research.

There has been a significant increase in the economics literature on COVID-19 and stay-at-home orders.[6] This paper contributes to the emerging literature on the effect of COVID-19 and stay-at-home orders on crime (e.g., Abrams (2020), Ashby (2020), Béland et al. (2020c), Campedelli et al. (2020), Hawdon et al. (2020), Hodgkinson and Andresen (2020), McDonald and Balkin (2020), Mohler et al. (2020), Stickle and Felson (2020)). This paper mainly contributes to the literature by trying to disentangle the effects of COVID-19 and stay-at-home orders on crime using a regression framework. To the best of my knowledge, other studies do not include this feature in their analysis.

The rest of the paper is structured as follows. Section 2 discusses the conceptual framework behind how COVID-19 and stay-at-home orders affect crime. Section 3 elaborates on the data on crime, COVID-19 cases and deaths and stay-at-home orders. Section 4 discusses the identification strategy. Section 5 describes the results and findings. Section 6 concludes.

2 Conceptual Framework

The literature on the economics of crime establishes that offenders measure the expected benefit of committing a crime against the expected costs (Becker (2000), Ehrlich (1973)). Balkin and McDonald (1981), using a neo-classical approach, determine that crimes occur through offenders 'supplying' time to search for victims and victims 'demanding' to expose themselves to offenders and hence the crime. Fu and Wolpin (2018) find that crime rates are joint outcomes of the number of police, the arrest rates, income and employment levels in a given area. Crimes are also a function of opportunities. The routine activity theory by Cohen and Felson (1979) explains that a crime occurs in a given space and time if three conditions are met: i) presence of a motivated offender, ii) accessible target, and iii) absence of capable guardians who can intervene.

COVID-19 and stay-at-home orders have disrupted the daily routine of individuals and changed the policing framework. Additionally, it can reasonably affect

[6] See Brodeur et al. (2020a) for a detailed literature review on the consequences of COVID-19 and stay-at-home orders.

the expected cost-benefit stakes of committing a crime, the time dimension for offenders and victims and other factors as suggested by these theories. However, as the theoretical framework and implications vary across the literature, it is important to formally highlight the channels through which COVID-19 and stay-at-home orders affect crime. This paper identifies three such possible channels, which are described below.

The first channel through which COVID-19 has affected crime levels is through people staying at home. In the wake of the pandemic, there has been a proliferation in GPS-based mobility data.[7] Using mobility data, recent studies (e.g., Abouk and Heydari (2020), Brodeur et al. (2020b), Brodeur et al. (2020c), Coven and Gupta (2020), Jacobsen and Jacobsen (2020)) have shown that people are more likely to stay at home during the pandemic. In particular, Engle et al. (2020) show that stay-at-home orders in the US led to a greater reduction in mobility compared to the local infection rates.This change in mobility behavior has led to a reduction in opportunities to commit a crime, as suggested by the routine activity theory by Cohen and Felson (1979). For example, there might have been a decrease in residential burglaries because potential offenders could not find unoccupied houses (lack of accessible target) as families were staying indoors (presence of guardians). However, it might have created opportunities to engage in other crimes, particularly domestic violence (e.g., Boserup et al. (2020), Hodgkinson and Andresen (2020), Piquero et al. (2020)), and cybercrimes (e.g., Hawdon et al. (2020)).

The second channel through which COVID-19 might affect crime is the economic consequences of lockdowns. As mentioned before, several studies have focused on these economic consequences, particularly in terms of labor market implications (e.g., Adams-Prassl et al. (2020a), Béland et al. (2020a), Coibion et al. (2020)). For example, Gupta et al. (2020) find that, after accounting for cross-state variation in the timing of business closures and stay-at-home mandates, the employment rate in the US fell by 1.7 percentage points for every extra 10 days that a state experienced lockdowns during the period March to April 2020. The job losses and the rise in income inequality are likely to lead to an increase in crime levels. This

[7] See Brodeur et al. (2020a) for a review on mobility data, in particular, their sources, uses and caveats.

is supported by the economics of crime literature (e.g., Choe (2008), Machin and Meghir (2004)). The increase in financial worries resulting from lockdowns might also affect crime levels, particularly domestic violence (Béland et al., 2020c).

The third channel through which the pandemic might affect crime levels consists of changes in crime detection and policing. Crime numbers vary by their source of detection, where reports by the public or victim are the main sources (Abrams, 2020). The substantial decline in mobility is expected to reduce the probability of crime observation by the public. However, the chance of committing some crimes (e.g., breaking into a commercial business) might decrease given that an offender will tend to stand out with fewer people around (Cheung & Gunby, 2020). On the other hand, according to Elinson and Chapman (2020), police have reduced arrests for small-time crimes, as many police officers are getting affected by COVID-19. Prosecution of crime has decreased, while convicted criminals are being released due to COVID-19 outbreaks in jails (Sisak et al., 2020). Police resources are being diverted to enforce stay-at-home orders. These changes in policing and law enforcement practices might lead to increases (decreases) in crime levels, as the expected costs (benefits) decrease for offenders. Therefore, this confluence of factors might lead to changes in crime levels during COVID-19 and enforcement of stay-at-home orders.

3 Data

3.1 Crime Data

This paper draws on crime data from Community Crime Map by LexisNexis® Risk Solutions.[8] The main objective of the database and the website is to connect law enforcement with the general community by helping people monitor crime activity in different areas so that they can make informed decisions.

According to Community Crime Map (2020), when an incident takes place, the police officers who respond to the incident write a detailed report. This includes information about the event such as location, people involved, and others. This is

[8] The Community Crime Map is available at: www.communitycrimemap.com

stored by individual law enforcement agencies in secured databases. However, between different police departments across states, these databases tend to vary in terms of structure and complexity. The reporting standards to describe an event might also vary between police departments, i.e., the data on the same crime might be reported differently by two different police stations. These discrepancies make it difficult for two neighboring cities to share crime data or analyze different events and/or offenders. LexisNexis® Risk Solutions help centralize and standardize the data in these police reports into a national crime database. To uphold standards of quality, LexisNexis® Risk Solutions works with each law enforcement agency to set up an automated feed from their crime database into the company's national database. This ensures that the data are always up to date, accurate, and complete. Moreover, Community Crime Map takes this data, cleans it to remove personal information to protect victim privacy, and makes it available to the general public. I collected crime data for two counties from two different states – Maricopa County, Arizona and Los Angeles County, California. For Maricopa, the data were taken for Phoenix PD. For Los Angeles, the data were taken for: i) Culver City PD; ii) Hawthorne PD; and iii) San Marino PD.

The data are at the daily frequency and comprise of the following 13 different crime categories: i) homicide; ii) attempted homicide; iii) sexual assault, iv) robbery (commercial); v) robbery (individual); vi) aggravated assault; vii) burglary (commercial); viii) burglary (residential); ix) theft; x) fraud; xi) motor vehicle theft; xii) arson; and xiii) driving under the influence (DUI). The summation of these 13 categories forms the total crime numbers for the two counties for the purposes of this analysis. Following the literature, this paper also calculates the crime rate i.e., total number of crimes per 10,000 inhabitants in the county. The population data are collected from the US Census data. The time period is between 1 January 2019 to 30 June 2019 and 1 January 2020 to 30 June 2020. The availability of data for the same days one year prior to COVID-19 enables day by day matching and makes for a better comparison of crime levels.

Figure 1 shows the total crime numbers at the daily level for the 4 police departments in the two counties - Maricopa and Los Angeles. The top panel shows the data for the first half of 2019 and the bottom panel shows the data for the first half of 2020. Figure 2 shows the crime rate for both counties. As it can be seen from the figure, the Phoenix PD in Maricopa has higher crime numbers compared to the three PDs in Los Angeles. Notably, there is no discernable change in pattern for the crime numbers or crime rates between March to May 2020, when COVID-19 cases began to rise, and lockdowns were implemented. However, there is a dip in numbers during June 2020, particularly for Maricopa County.

Table 1 provides the summary statistics for crime numbers, COVID-19 cases and deaths. From the table, it can be seen that the top five criminal offences in the four PDs in these two counties during the sample period are: i) motor vehicle theft; ii) burglary – residential; iii) aggravated assault; iv) burglary – commercial; and v) theft. On the other hand, the bottom five criminal offences are: i) attempted homicide; ii) fraud; iii) DUI; iv) robbery – commercial; and v) homicide.

3.2 COVID-19 and Lockdowns

The COVID-19 known cases and death numbers are derived from the Coronavirus Resource Center at John Hopkins University. The Coronavirus Resource Center collects data from different sources (including the WHO, government agencies etc.). For the US in particular, the daily COVID-19 data are available at the county level. The Center maintains a GitHub repository where all the data are stored.[9] Figures 3 and 4 show the COVID-19 cases and deaths respectively in Maricopa and Los Angeles. As it can be seen, the case numbers picked up in Los Angeles County, California from the beginning of March 2020. On the other hand, cases started increasing in Maricopa County, Arizona in the middle of March 2020. The death toll started to pick up approximately one week after the case numbers started to rise. By the end of June 2020, Los Angeles had over 100,000 cases and 3,000 deaths. During the same period, Maricopa County had about 50,000 cases and 800 deaths.

The data on stay-at-home orders at the county and state-level are drawn from the National Association of Counties.[10] As mentioned before, there is variation between county and state stay-at-home orders. However, state lockdown orders supersede county lockdown orders. Los Angeles County, California issued stay-at-home orders on March 19, 2020. Maricopa County declared a 'state of emergency' on

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[9] The COVID-19 case and death numbers are here: www.github.com/CSSEGISandData/COVID-19
[10] The US state and county lockdown data are here: https://www.naco.org/resources/featured/counties-and-covid-19-safer-home-orders

March 18, 2020. However, this is different from stay-at-home orders, which were not implemented by the county officials. The state of Arizona issued stay-at-home orders on March 31, 2020, which is used for the analysis in this paper.

4 Identification Strategy

4.1 Pre/Post: COVID-19

To assess the impact of COVID-19 on crime, this paper first conducts a simple pre/post analysis. The model is:

$$y_{ct} = \alpha + \beta POSTCOVID_t + \varphi_c + \rho_t + \varepsilon_{ct} \qquad [1]$$

where y_{ct} is the outcome variable – crime rate – for PDs in county *c* at day *t*. The data are at the daily frequency, and the time period is between January 2019 to June 2019 and January 2020 to June 2020. $POSTCOVID_t$ is a dummy variable equal to 1 after COVID-19 cases started increasing in the US (i.e., from 1st March 2020 and onwards) and 0 in the preceding days. β is the coefficient for $POSTCOVID_t$ and is the coefficient of interest. φ_c represents county fixed effect to account for time-invariant county characteristics. ρ_t represents week fixed effects. These week fixed effects help account for the seasonal pattern in crime.

4.2 Difference-in-Differences: Stay-at-Home Orders

To estimate the impact of stay-at-home orders on crime, this paper uses a DID strategy by exploiting variation between implementation of policies between the two states. The DID model is:

$$y_{ct} = \alpha + \pi LOCKDOWN_{st} + \gamma CASES_{ct} + \delta DEATH_{ct} + \varphi_c + \rho_t + \varepsilon_{ct} \qquad [2]$$

where y_{ct} is the outcome variable – total crime rate and top five criminal offences rates – for PDs in county *c* at day *t*. The top five criminal offences include: i) motor vehicle theft, ii) burglary – residential, iii) aggravated assault, iv) burglary – commercial, and v) theft. The time period is between January 2019 to June 2019 and January 2020 to June 2020. $LOCKDOWN_{st}$ is a dummy variable equal to 1 after the stay-at-home orders were issued by state *s* (i.e. March 19, 2020 onwards for California and March 31, 2020 onwards for Arizona) and 0 otherwise. Therefore, π is the coefficient of interest in Equation [2].

In this specification, crime rates may be endogenously related to the severity of the virus. Therefore, county-day COVID-19 known cases and deaths (i.e., $CASES_{ct}$ and $DEATH_{ct}$) are added as controls. The coefficients for $CASES_{ct}$ and $DEATH_{ct}$ are γ and δ respectively. The main identification assumption is that, if no stay-at-home orders were issued, crime rates in Los Angeles and Maricopa counties follow a similar time trend i.e., the parallel trends assumption.

4.3 Graphical Analysis – Leads & Lags

In addition to the regression framework, this paper provides a visual summary of the impact of stay-at-home orders on crime. The figure plots the estimated coefficient of the number of crimes at the daily level pre-and-post issuance of stay-at-home orders. The equation is as follows:

$$y_{ct} = \alpha + \sum_{n=-30}^{30} \tau(DaysSinceLockdown = n) + \varphi_c + \rho_t + \varepsilon_{ct} \qquad [3]$$

The specification in Equation [3] breaks down the crime series by days before and since stay-at-home orders are issued (n=0). The regression includes county and week fixed effects. This controls for crime patterns in both counties and seasonal changes in crime during the sample period. The difference in crime is compared to the date that the stay-at-home order was implemented (which is set to zero in the figure). The time horizon is 2 months i.e., 30 days before to 30 days after the policy is implemented. The figure includes robust 95% confidence intervals.

5 Effect of COVID-19 and Stay-at-Home Orders on Crime

This section analyzes the impact of COVID-19 and stay-at-home orders on crime. This is carried out through: i) a pre/post regression analyzing the effect on crime before and after COVID-19; ii) DID strategy exploiting variation between state orders; and iii) graphical analysis of leads and lags before and after issuance of stay-at-home orders.

5.1 Pre/Post Analysis

Table 2 presents the results of Equation 1. In Columns 1, 2 and 3, the dependent variable is crime rate i.e. total number of crimes per 10,000 inhabitants for the four

PDs in the two counties. Column 1 does not include the time and county fixed effects. Column 2 includes week fixed effects to control for seasonality in crime rate. Column 3 includes only county fixed effects to control for time-invariant characteristics. Column 4 includes both county and week fixed effects.

As it can be seen, the estimate of *POSTCOVID* is negative in all columns. However, in Columns 1, 2 and 3, it is not statistically significant at conventional levels. In Column 4, the estimate of POSTCOVID is negative and statistically significant at 5% significance level. In all specifications, the regression constant is the average number of crimes in the pre-COVID-19 period. Using the preferred specification in Column 4, after the outbreak of COVID-19 in the US, there is a statistically significant decrease in crime rate of about 0.4 percentage points.

5.2 DID Analysis

Table 3 presents the results of Equation 2. In Columns 1, 2 and 3, the dependent variable is crime rate. All the columns include the variable of interest and county and week fixed effects as controls. Columns 1 shows the estimates without COVID-19 cases and death rates, i.e. numbers per 10,000 inhabitants. Column 2 shows the results with COVID-19 case rates. Column 3 includes COVID-19 death rates. The focus is on the estimates for *LOCKDOWN.*

For the DID equation, the estimate of *LOCKDOWN* in Column 1 is negative, which suggests that the implementation of stay-at-home order caused a reduction in crime in the four PDs in Maricopa County and Los Angeles County. More precisely, the estimate is significant at the 1% level and suggests that crime rates decreased by 1 percentage point after the lockdown.

Columns 2 and 3 control for COVID-19 cases and deaths. In Column 2, with COVID-19 case rates included as a control, the estimate for *LOCKDOWN* is not statistically significant at conventional levels. However, with COVID-19 death rates included as a control in Column 3, the estimates are significant at 1% significance level. Note that these control variables are possibly poor-quality controls as the lockdowns aim at preventing cases and deaths. Therefore, these estimates should be viewed with caution, and the preferred specification is the one in Column 1.

Table 4 presents the results for Equation 2 for the top 5 criminal offences. In the table, Panels A, B, C, D and E show the results for motor vehicle theft, residential burglary, aggravated assault, commercial burglary and theft, respectively. As before, Column 1 shows the estimates without including COVID-19 cases and death rates. Columns 2 and 3 show the results including the variables of COVID-19 case rates and death rates respectively. All the columns include county and week fixed effects as controls. As mentioned before, the preferred specification is the one in Column 1.

As can be seen for Panel A, with motor vehicle theft rate as the dependent variable, the estimates for *LOCKDOWN* are positive. This shows that motor vehicle theft rate increased after the implementation of stay-at-home orders. However, the results are not statistically significant at conventional levels. In Panel B, the estimates for residential burglary rate decreased by 0.66 percentage points after the implementation of stay-at-home orders and the result is significant at 1% significance level. Similarly, for Panel C, the estimates show that stay-at-home orders caused 0.25 percentage point decrease in aggravated assault rate, which is statistically significant at the 10% level. For the commercial burglary rate, the estimates in Panel D are positive, however, not statistically significant at conventional levels. For the theft rate variable, the estimates in Panel E are positive and statistically significant at conventional levels. This shows that stay-at-home orders caused 0.11 percentage point increase in theft rates in the four PDs in these two counties.

From a theoretical perspective, the positive estimates for motor vehicle theft as well as commercial burglary (though not statistically significant), and negative estimates for residential burglary and aggravated assault, make sense. For example, as per the routine activity theory, motor vehicles and vacant commercial premises are more accessible after the issuance of stay-at-home orders, and there might be a lack of adequate security during this time. On the other hand, residential areas are occupied, and opportunities for aggravated assault are relatively low after stay-at-home orders are in place. Researchers (e.g., Abrams (2020), Mohler et al. (2020)) have also found similar results in other cities across the US such as Chicago, Indianapolis, New York City, Philadelphia, Pittsburgh, San Francisco and Washington DC.

However, the positive estimates for theft (i.e., any theft apart from the ones of motor vehicles) after issuance of stay-at-home orders are contrary to expectations and other empirical findings. There might be several plausible explanations for this trend. According to Stickle and Felson (2020), the definition of ‘theft’ itself is a broad category, and specific types of theft might not be decreasing.[11] For example, retail theft may persist (and may even see an increase) within stores that remain open during lockdowns, such as grocers, construction supplies, convenience stores, pharmacies, and other ‘essential’ retailers. Offenders might change their behavior (i.e., shift from targeting specific stores, which are open) due to panic buying (purchase limits on essential products may result in theft), or due to reduced security within stores (lower number of employees operating during the pandemic are more focused on providing service than preventing crime). An increase in package theft might also explain the increase in the broad category of ‘theft’. Online ordering has gained significant traction during the pandemic and unattended delivery creates an opportunity for offenders to steal packages after delivery and before the resident collects them (Stickle et al., 2020). Moreover, a reduction in arrests over small or petty crimes might explain an increase in thefts (Elinson & Chapman, 2020).

5.3 Leads & Lags Analysis

Figure 5 shows that the number of crimes in these two counties were stable 30 days prior to and after the issuance of stay-at-home orders. The dashed lines represent robust 95% confidence intervals. Around two weeks before state orders came into effect, there is an upward trend in crime. After the implementation of lockdown orders (at n=0), there is an immediate drop in crime numbers, with a larger decrease in the following days. After 25 days of implementation, there is an increase in the number of crimes, which reach pre-stay-at-home order levels.

Even though these estimates mask the heterogeneity across different types of crimes, there is evidence that overall crime numbers started to rise back in the midst of the pandemic and stay-at-home orders in the four PDs in these two counties. Notably, the increase in number of crimes prior to the lockdown orders may reflect the

[11] For the Community Crime Map dataset, ‘theft’ indicates a range of offences such as petty larceny, grand larceny, mail theft, theft from building, pickpocket/purse snatching (especially elder people) etc.

behavior to commit more crimes in anticipation of the impending policy date, based on the observation of the pandemic and the overall situation.

6 Conclusion

Along with the negative health and economic impacts, COVID-19 has led to a dramatic change in human behavior. One of those behavioral changes is reflective in the alteration in crime patterns after the emergence of the pandemic. Anecdotal evidence suggests that, after the incidence of COVID-19 and the resulting social distancing measures, the overall number of crimes has decreased. However, there is variation across criminal offences, with increases in some type of offences and decreases in others. This paper investigates the effect of COVID-19 and stay-at-home orders on criminal activities in four PDs in two US counties – Maricopa and Los Angeles. The data from Community Crime Map, which contains the number of different crimes reported to the police, is available at the daily level for the first 6 months of 2019 and 2020. To understand the impact of the incidence of COVID-19 on overall crime, a simple pre/post regression is utilized. Additionally, to gauge the impact of stay-at-home orders, this paper undertakes a DID estimation by exploiting the variation between issuance of stay-at-home orders. A leads and lags analysis show the evolution of crime rates 30 days prior and after stay-at-home orders were imposed in the two counties.

The pre/post regression results show that after the event of COVID-19, there is a statistically significant decrease in overall crime rate by about 0.4 percentage points in the four PDs in these two counties. It should be noted that the observed decrease in crime rates could be biased downwards if individuals are less likely to report crimes during the pandemic. This might be an issue for crimes such as domestic violence. The DID results show that the implementation of stay-at-home orders led to a statistically significant reduction in overall crime rate by 1 percentage point. The leads and lags analysis show that the overall crime rate 'bounced back' around 25 days after lockdowns were issued.

Looking at the top five criminal offences in the two counties, stay-at-home orders caused an increase in motor vehicle theft and commercial burglaries rates, although the estimates were not statistically significant. On the other hand, there was a statistically significant decrease in residential burglaries and aggravated assault rates. The increase in theft rate for these two counties, which is contrary to what theory would lead us to expect, may be explained by a change in crime opportunities, policing patterns, and overall change in people’s behavior resulting from the pandemic (e.g., the rise in online shopping and home delivery).

Understanding the impact of social distancing on crime is critical not only for the general public but also for law enforcement agencies and government officials, especially in terms of police resource deployment and crime prevention methods. Moreover, how social distancing policies impact crime may provide insights into whether people are complying with public health measures. The main limitation of this study is that findings from the four PDs in Maricopa and Los Angeles counties cannot be generalized to other parts of the US. However, with the continued proliferation of COVID-19 cases and deaths in the US, these findings (e.g., increase in thefts) and future research will help develop robust theories in the criminology-economics nexus and better inform policy decisions.

7 References

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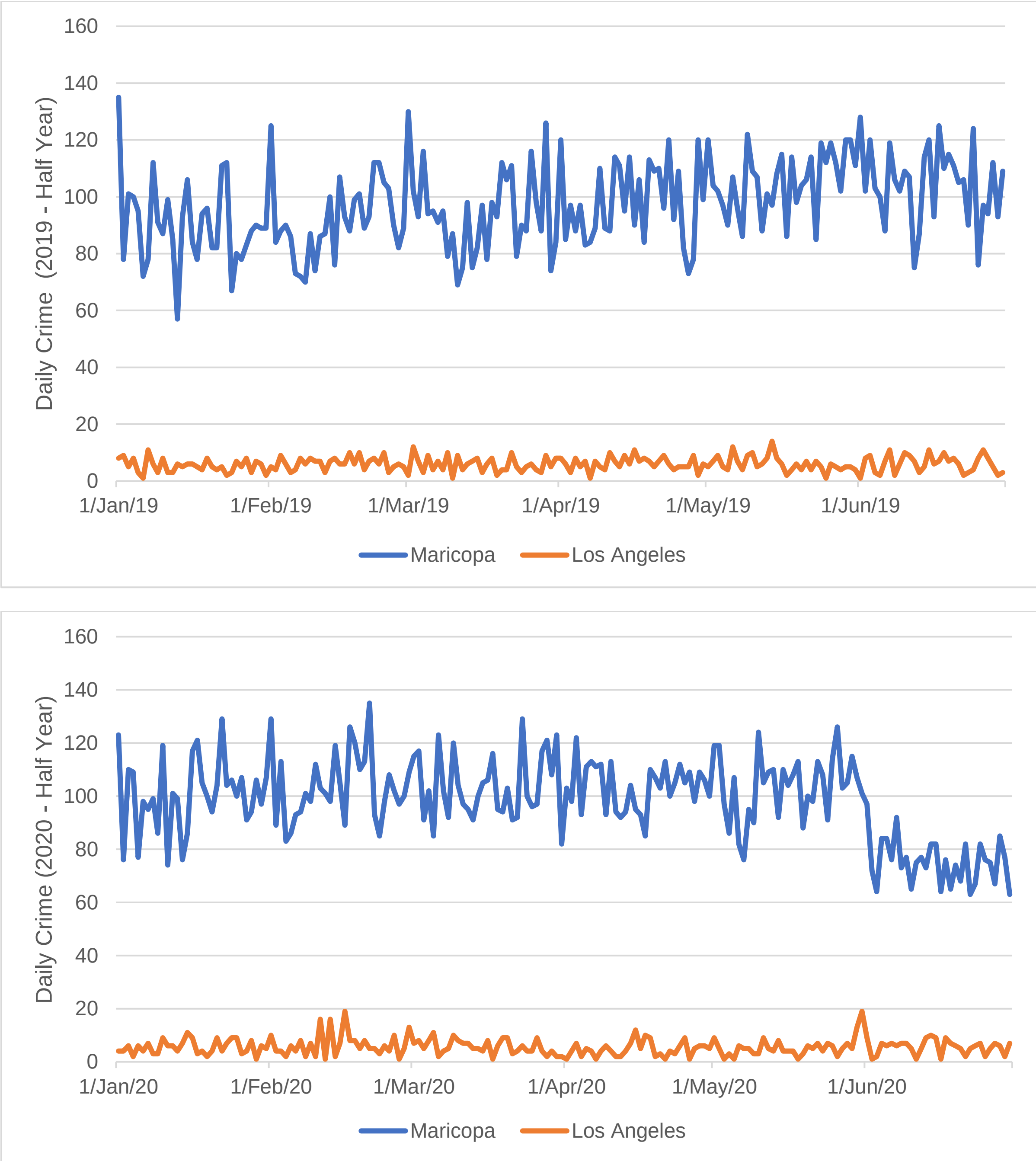
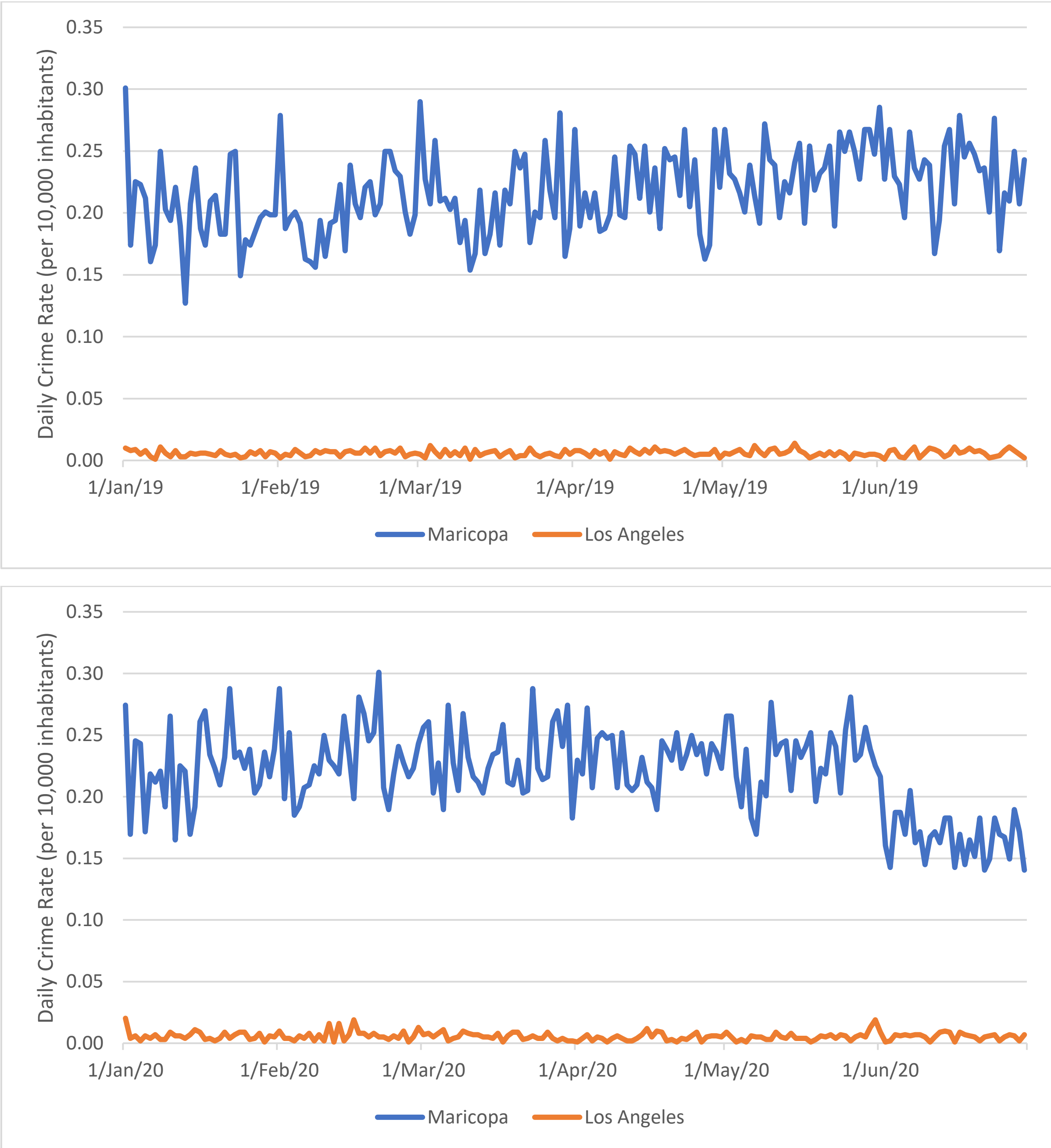
8 Figures

Figure 1: Daily Crime Numbers for Maricopa County (Arizona) and Los Angeles County (California)



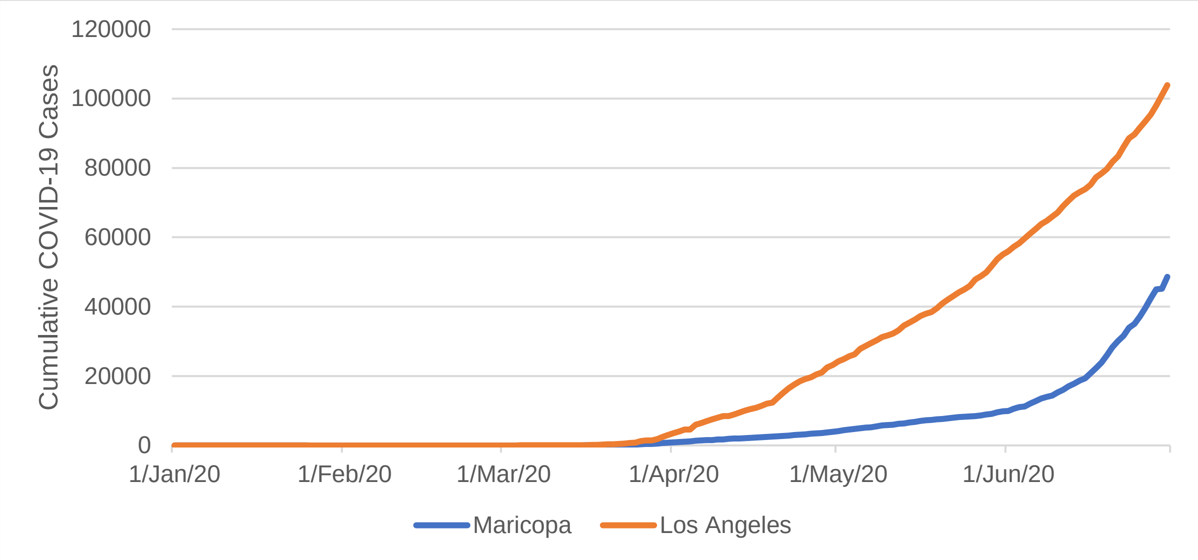
Note: The daily crime numbers in 1 PD in Maricopa County (Arizona) and 3 PDs in Los Angeles County (California), respectively. The data is collected from the Community Crime Map by LexisNexis® Risk Solutions. The top panel shows crimes between 1 January 2019 and 30 June 2019. The bottom panel shows crime between 1 January 2020 and 30 June 2020. The blue line represents crime numbers for Maricopa County, while the orange line shows the same for Los Angeles.

Figure 2: Daily Crime Rates for Maricopa County (Arizona) and Los Angeles County (California)



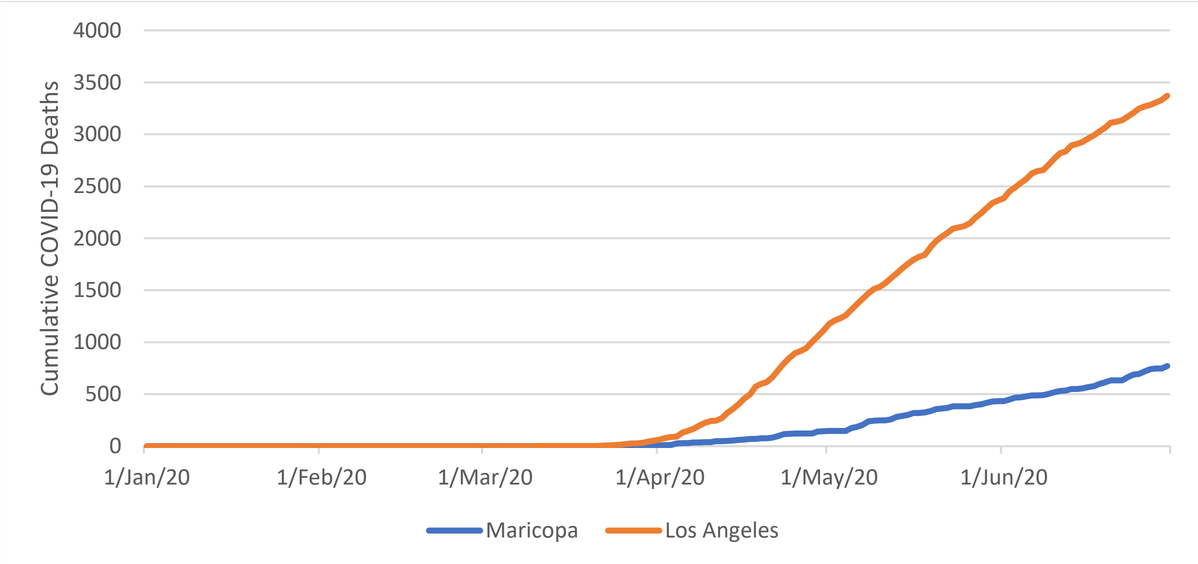
Note: The crime rate i.e. daily crime numbers per 10,000 inhabitants in 1 PD in Maricopa County (Arizona) and 3 PDs in Los Angeles County (California), respectively. The crime data is collected from Community Crime Map by LexisNexis® Risk Solutions. The population estimates are collected from the US Census estimates for the 2 counties. The top panel shows crime rate between 1 January 2019 and 30 June 2019. The bottom panel shows crime rate between 1 January 2020 and 30 June 2020. The blue line represents crime numbers for Maricopa County, while the orange line represents the same for Los Angeles.

Figure 3: Cumulative COVID-19 Cases for Maricopa County (Arizona) and Los Angeles County (California)



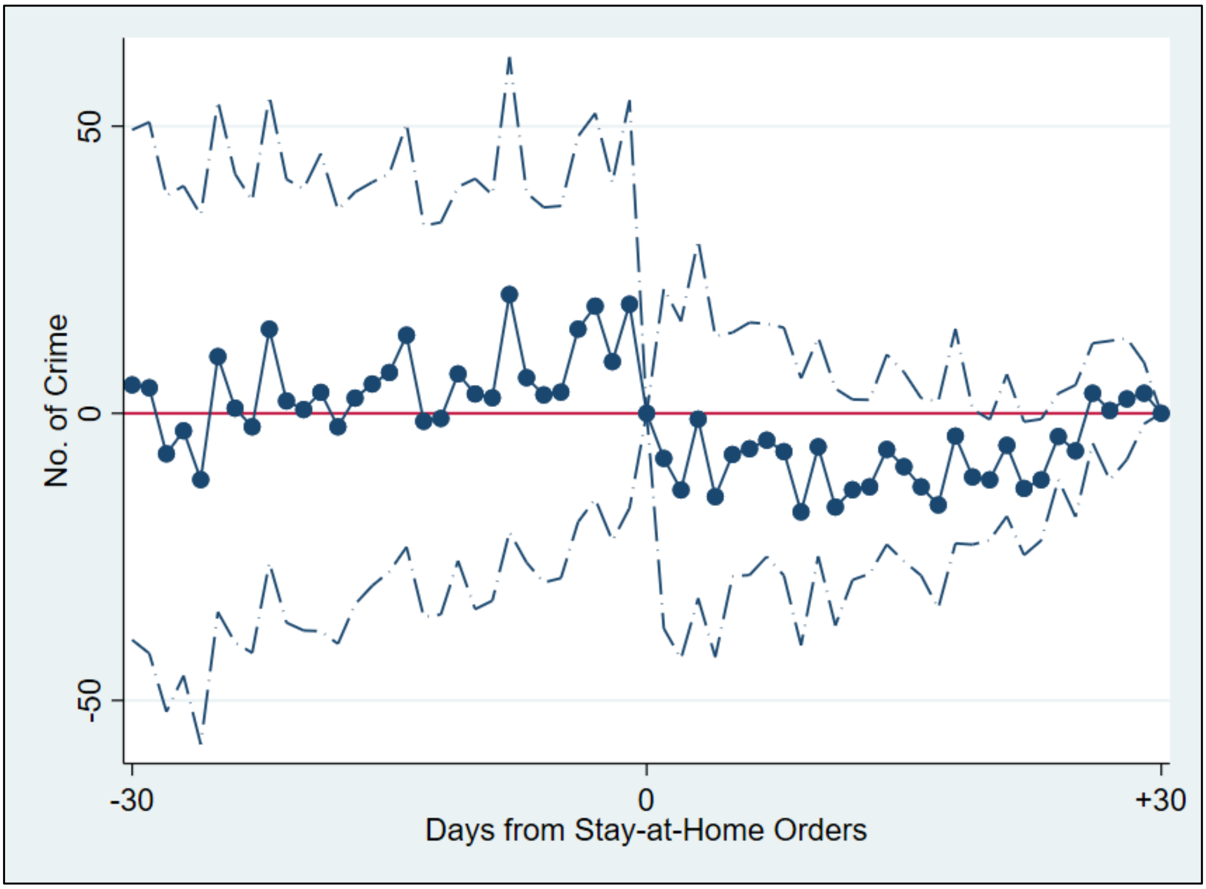
Note: The cumulative COVID-19 cases in Maricopa County (Arizona) and Los Angeles County (California). The data is collected from the Coronavirus Resource Center at John Hopkins University. The time period is between 1 January 2020 and 30 June 2020. The blue line represents the case count for Maricopa County, while the orange line represents the same for Los Angeles.

Figure 4: Cumulative COVID-19 Deaths for Maricopa County (Arizona) and Los Angeles County (California)



Note: The cumulative COVID-19 deaths in Maricopa County (Arizona), Los Angeles County (California) and Oklahoma City (Oklahoma). The data is collected from the Coronavirus Resource Center at John Hopkins University. The time period is between 1 January 2020 and 30 June 2020. The blue line represents the number of deaths for Maricopa County, the orange line represents the same for Los Angeles.

Figure 5: Effect of Stay-at-Home Orders on Crime (± 30 days from Implementation of Order)



Note: The figure presents regression coefficients for crimes committed in 1 PD in Maricopa County (Arizona) and 3 PDs in Los Angeles County (California) corresponding to the number of days before/after stay-at-home orders were issued in these states. The regressions include week and county fixed effects. The baseline is presented by the bold blue horizontal line at “No. of Crime = 0”. The dashed line represent the confidence intervals at 95% significance levels.

9 Tables

Table 1: Summary Statistics

	Observation	Mean	Std. Dev.	Min	Max
Crime Rate:					
Homicide	724	0.00050	0.00130	0	0.0089
Attempted Homicide	724	0.00002	0.00025	0	0.00229
Sexual Assault	724	0.00303	0.00413	0	0.02675
Robbery - Commercial	724	0.00041	0.00099	0	0.00668
Robbery – Individual	724	0.00957	0.10168	0	0.04013
Aggravated Assault	724	0.02105	0.02491	0	0.08917
Burglary – Commercial	724	0.01572	0.01655	0	0.06911
Burglary – Residential	724	0.02138	0.02285	0	0.09140
Theft	724	0.01072	0.00988	0	0.05350
Fraud	724	0.00010	0.00039	0	0.00298
Motor	724	0.02748	0.02874	0	0.89178
Arson	724	0.00208	0.00307	0	0.01561
DUI	724	0.00001	0.0003	0	0.00029
Total Crimes	724	0.11227	0.10900	0	0.30097
Case and Death Rates:					
Cases	724	8.4049	20.2631	0	108.334
Deaths	724	0.3063	0.7150	0	3.3578

Note: The daily crime rates (number of crimes per 10,000 inhabitants) for 13 different types of crimes reported in 4 PDs in the 2 counties – Maricopa and Los Angeles – Arizona and California. The data is collected from the Community Crime Map at LexisNexis® Risk Solutions. The daily COVID-19 cases and deaths for the 2 counties are taken from the database developed by the Coronavirus Resource Center at John Hopkins University. The daily crime, case and death rates are calculated based on the 2019 population estimates from the US Census data.

Table 2: Effect of COVID-19 on Crime in Maricopa County (Arizona) and Los Angeles County (California)

	(1)	(2)	(3)	(4)
VARIABLES	Crime Rate	Crime Rate	Crime Rate	Crime Rate
POSTCOVID	-0.003	-0.005	-0.003	-0.004**
	(0.009)	(0.010)	(0.002)	(0.002)
Constant	0.113***	0.099***	0.219***	0.205***
	(0.005)	(0.035)	(0.002)	(0.011)
County Fixed Effects	No	No	Yes	Yes
Week Fixed Effects	No	Yes	No	Yes
Observations	724	724	724	724
R-squared	0.0002	0.005	0.951	0.956

Note: Pre-post regression for the effect of COVID-19 on crime in 4 PDs in these 2 counties - Maricopa (Arizona) and Los Angeles (California). The time period is between 1 January 2019 to 30 June 2019 and 1 January 2020 to 30 June 2020. In all columns, the dependent variable is crime rates (crime number per 10,000 inhabitants). The rates are calculated based on the county population estimates from US Census data. Column 1 does not include county and week fixed effects. Column 2 includes only week fixed effects to control for seasonality in crime. Column 3 includes only county fixed effects to control for time-invariant county characteristics. Column 4 includes both county and week fixed effects. Robust standard errors are reported in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).

Table 3: Effect of Stay-at-Home Orders on Crime Maricopa County (Arizona) and Los Angeles County (California)

	(1)	(2)	(3)
VARIABLES	Crime Rate	Crime Rate	Crime Rate
LOCKDOWN	-0.010***	-0.002	-0.009***
	(0.002)	(0.003)	(0.003)
CASES		-0.0001***	
		(0.00003)	
DEATHS			-0.001
			(0.002)
Constant	0.208***	0.223***	0.209***
	(0.010)	(0.010)	(0.011)
County Fixed Effects	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes
Observations	724	724	724
R-squared	0.957	0.957	0.957

Note: DID regression for the effect of COVID-19 stay-at-home orders on crime in 4 PDs in the 2 counties - Maricopa (Arizona) and Los Angeles (California). The time period is between 1 January 2019 to 30 June 2019 and 1 January 2020 to 30 June 2020. In Columns 1, 2 and 3, the dependent variable is crime rate. The rates are calculated based on the county population estimates from US Census data. LOCKDOWN is a dummy variable equal to 1 after stay-at-home orders were given in the county and 0 otherwise i.e., the coefficient of interest. Column 1 does not include COVID-19 cases or deaths as controls. Column 2 includes only COVID-19 cases as controls. Column 3 includes only COVID-19 deaths as controls. All columns include county fixed effects and week fixed effects. Robust standard errors are reported in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).

Table 4: Effect of Stay-at-Home Orders on Top 5 Crimes in Maricopa County (Arizona) and Los Angeles County (California)

	(1)	(2)	(3)
VARIABLES	Crime Rate	Crime Rate	Crime Rate
Panel A: Motor Theft			
LOCKDOWN	0.0005	0.0012	0.0013
	(0.0008)	(0.0012)	(0.0011)
CASES		-0.0001	
		(0.0004)	
DEATHS			-0.0008
			(0.0005)
Constant	0.0535***	0.0549***	0.0543***
	(0.0013)	(0.0017)	(0.0014)
Panel B: Burglary - Residential			
LOCKDOWN	-0.0066***	-0.0073***	-0.0087***
	(0.0010)	(0.0015)	(0.0015)
CASES		0.0000	
		(0.0000)	
DEATHS			0.0020***
			(0.0007)
Constant	0.0418***	0.0405***	0.0399***
	(0.0028)	(0.0029)	(0.0025)
Panel C: Aggravated Assault			
LOCKDOWN	-0.0025*	-0.0043**	-0.0017
	(0.0014)	(0.0019)	(0.0020)
CASES		-0.0002***	
		(0.0001)	
DEATHS			-0.0008
			(0.0011)
Constant	0.0309***	0.0436***	0.0317***
	(0.0085)	(0.0075)	(0.0088)
Panel D: Burglary - Commercial			
LOCKDOWN	0.0008	0.0004	0.0001
	(0.0007)	(0.0010)	(0.0010)

CASES		-0.00001**	
		(0.00001)	
DEATHS			-0.0009*
			(0.0005)
Constant	0.0327***	0.0350***	0.0335***
	(0.0020)	(0.0021)	(0.0021)
Panel E: Theft			
LOCKDOWN	0.0011**	0.0008*	0.0015*
	(0.0005)	(0.0006)	(0.0008)
CASES		0.0000	
		(0.0000)	
DEATHS			-0.0005
			(0.0004)
Constant	0.0194***	0.0185***	0.0199***
	(0.0014)	(0.0015)	(0.0014)
County Fixed Effects	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes
Observations	724	724	724

Note: DID regression for the effect of COVID-19 stay-at-home orders on top 5 criminal offences reported to the police in 4 PDs in the 2 counties - Maricopa (Arizona) and Los Angeles (California). Panels A, B, C, D and E show the results for motor vehicle theft; burglary – residential; aggravated assault; burglary – commercial; and theft respectively. The time period is between 1 January 2019 to 30 June 2019 and 1 January 2020 to 30 June 2020. In all columns, the dependent variable is the crime rate. These rates are calculated based on the county population estimates from US Census data. As before, LOCKDOWN is a dummy variable equal to 1 after stay-at-home orders were given in the county and 0 otherwise. Column 1 does not include COVID-19 cases or deaths as controls. Column 2 includes only COVID-19 cases as control. Column 3 includes only COVID-19 deaths as control. All columns include county fixed effects and week fixed effects. Robust standard errors are reported in parentheses. (*** p<0.01, ** p<0.05, * p<0.1).