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An Ecological Model for Examining the Impact of COVID-19 on Child Abuse and Neglect Across Time and Space in the City of Los Angeles, California

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A Spatiotemporal Analysis of the Impact of COVID-19 on Child Abuse and Neglect in the City of Los Angeles, California

Background: Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2; COVID-19) has created an urgent need to identify child abuse and neglect (CAN) and efficiently allocate resources to improve the coordination of responses during a public health crisis.

Objective: To provide unique insights into the spatial and temporal distribution of CAN in relation to COVID-19 outcomes and identify areas where CAN has increased or decreased during the pandemic.

Participants: Children under 18 years old reported to the Los Angeles Police Department for CAN.

Setting: CAN incidents in the city of Los Angeles.

Methods: Negative binomial regression was used to explore associations between the implementation of social distancing protocols and reported CAN during COVID-19. Spatiotemporal analysis identified locations of emerging hot and cold spots during the pandemic. Associations between neighborhood structural factors (e.g., school absenteeism, poverty, unemployment, housing insecurity and birth assets) and hot and cold spot patterns were explored.

Results: There was a statistically significant decline in reports of CAN during the COVID-19 pandemic but no significant trends following the implementation of social distancing measures (e.g. safer at home orders, school closures). Compared to consecutive cold spots, severe housing burden, the number of assets children have at birth, poverty, school absenteeism and labor force participation were significantly associated with new and intensifying hotspots of CAN during the COVID-19 pandemic.

Conclusions: Our findings reinforce the utility of developing intervention strategies that minimize harm to children by targeting resources to specific challenges facing families enduring the COVID-19 experience.

The Impact of Covid-19 on Child Maltreatment Across Time and Space

Introduction

COVID-19 (also known as Severe Acute Respiratory Syndrome 2 or SARS-CoV-2) has caused serious disruption to the health and well-being of millions of people around the world and has resulted in substantial human, economic and material losses. The World Health Organization declared COVID-19 a public health emergency of international concern on January 30th, 2020 whereas the CDC deemed COVID-19 as being the most significant medical and public health disaster in decades (Jack, 2020). In the United States, some areas, such as Los Angeles County, have been more affected by COVID-19 compared to others. As of September 4, 2020, according to official statistics from the Los Angeles County Department of Public Health, the number of novel coronavirus cases in Los Angeles County totaled 234,266 and among those who contracted the coronavirus 5,656 have died—a death rate of about 54 people per 100,000 population (Los Angeles County Department of Public Health, 2020a). In Los Angeles County, these statistics further reveal that Native Hawaiians and Pacific Islanders currently have the highest population rate of COVID-19 deaths (71 per 100,000), followed by African Americans (13 per 100,000), Latinos (10 per 100,000), Asians (8 per 100,000), whites (6 per 100,000) and American Indian or Alaska Natives (3 per 100,000) (Los Angeles County Department of Public Health, 2020b). Moreover, age-adjusted rates indicate a social gradient in confirmed cases whereby those living in the highest poverty areas have the highest population rate of confirmed cases (263 per 100,000) and those living in the lowest poverty areas have the lowest (137 per 100,000) (Los Angeles County Department of Public Health, 2020b). Whereas the number of daily cases in LA County peaked on July 13, 2020, the daily case fatality rate as of the time of this writing (September 4, 2020) remains the highest since the pandemic began (Los Angeles County Department of Public Health, 2020c). On this basis, public health experts have opined that the virus could easily become the leading cause of death in Los Angeles County and may have a devastating long-term impact on distressed low-income communities (Mossburg, 2020).

Identifying neighborhoods that lack the resources necessary to respond holistically to a public health crisis is a critical component of addressing both the direct effects on individual health attributed to the virus itself (e.g. illness and deaths), as well as indirect and serious effects via stress on parent child

relationships (e.g. family violence). A holistic response to the COVID-19 pandemic is determined by community access to a broad range of resources such as necessary adult/child health care or individual/family support networks in order to effectively respond to the potential challenges brought on by this public health crisis. The present study addresses the critical issue of the impact of COVID-19 on families, focusing on the contextualization of the sources of stress that strain parent-child relationships conducive to possible CAN. More specifically, in this paper, we aim to: 1) examine spatiotemporal trends in CAN both before and during the first 181 days of the COVID-19 pandemic; 2) explore differences between communities that are high and low risk for child victimization as filtered through neighborhood vulnerabilities that have been exacerbated by the pandemic; and 3) map the distribution of risk factors that are most highly associated with CAN for the purpose of resource allocation during a public health crisis.

Background

On March 4, 2020, California was the first state in the United States of America to declare a national emergency as a result of the spread of the coronavirus. Fifteen days later, on March 19, 2020, both the city and county of Los Angeles responded to the pandemic by issuing emergency order 'safer at home,' limiting activities outside of the home and mandating school closures. The declaration of a national emergency coupled with the 'safer at home' mandate led to massive unemployment and social distancing protocols (U.S. Bureau of Labor Statistics, August 2020; City of Los Angeles Public Order, 2020). The stressors resulting from the pandemic such as unemployment, unpaid sick leave, and lack of childcare magnified the stress of social isolation resulting from the pandemic and also created more awareness of the social disparities that preceded them. In other words, based on already existing social disparities, individuals and communities have been differentially impacted by the COVID-19 pandemic, public health measures designed to flatten the curve, and the economic and social outcomes that followed. For example, as of July 22, 2020, an estimated 2,395,000 households in California (42.7% of all households) were unable to pay rent and were at risk of eviction. According to Household Pulse Survey data collected by the U.S. Census Bureau between July 9 – July 14, almost 2,400,000 individuals living in the greater metro area of Los Angeles County– about one-third of the population aged 18 and over --

either missed the previous month's rent or reported little to no confidence in their ability to pay it. According to the same survey, slightly over two-thirds of adults in households lost some income since the state of California declared a national emergency. Further, about one in ten adults in households reported that they either 'sometimes' or 'often' did not have enough to eat in the previous week.

Families lacking resources face relatively greater social, psychological and economic pressures in the face of natural disasters (Seddighi, Salmani, Javadi, Seddighi, 2019). Housing and food insecurity combined with layoffs and loss of income disproportionately affect children living in low income neighborhoods who depend on school to provide breakfast and lunch. Additionally, students who are already struggling may fall further behind because they lack the technology necessary for an online education such as insufficient electronic devices, limited home internet connection, and the need for attention by caregivers who may themselves lack social support (Teo and Griffiths, 2020). Not surprisingly, a recent report based on data from the Kaiser Family Foundation Health Tracking Poll suggests that the pandemic has adversely impacted the mental health of nearly half of all Americans (Panchal, Kamal, Orgera, Cox, Garfield et al., 2020). The report further indicated that individuals with mental health issues prior to the pandemic have been cut off from the mental health resources they need. A report issued by the Journal of Pediatrics and Childcare (Teo and Griffiths, 2020) anticipates that children's mental health and psychosocial functioning will be negatively impacted as a result of COVID-19, particularly in response to the social distancing measures taken to impede the spread. A recent study from China suggests that young adults may be even more likely to develop mental health symptoms, including anxiety, compared to older adults (Huang and Zhao, 2020).

Child Abuse & Neglect During A Public Health Crisis

The emergency order 'safer at home' has caused mass disruption to the routines in which domestic crimes may occur due to the limited ability of partners to separate while coping with the stress and burdens of the pandemic (Mohler et al. 2020). The "safer at home" order issued on March 19, 2020 in Los Angeles County called for nonessential businesses that require workers to be present in person to cease operations and for residents to stay at home while not participating in essential activities such as

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"visiting a health or veterinary care professional, obtaining medical supplies or medication, obtaining grocery items … for their household or to deliver to others, or for legally mandated government purposes" (Public Order Under City of Los Angeles Emergency Authority, March 19, 2020, p. 3). The order further prohibited all public and private group events and gatherings of more than 10 people and mandated the closure of all indoor malls, shopping centers, nonessential retail establishments and both indoor and outdoor playgrounds. However, outdoor activities, such as walking, running, and bicycling were allowed as long as social distancing measures were observed.

As a result, the COVID-19 pandemic has substantially increased the risk of potentially life-threatening situations for vulnerable populations, including women and children, who have been forced into quarantine with their abusers as a result of the emergency order 'safer at home' (Abramson, 2020). Although unintentional, such orders may have created barriers for the identification of family violence and limited treatment options (Panchal et al., 2020). While current research regarding the COVID-19 pandemic and child abuse is in its infancy, previous research has investigated changes in domestic violence prevalence during natural disasters more generally. These studies have yielded mixed results, however. A recent study by Baron, Goldstein, and Wallace (2020), estimated a counterfactual distribution of child maltreatment allegations for March to April 2020 in Florida in response to school closures, and found about 15,000 fewer allegations of child abuse. The decline in CAN during the COVID-19 outbreak has been attributed to the lack of mandated reporters (Baron et al., 2020), who are a predominant source of recognition for maltreatment in schools (Sedlack et al., 2010), and/or the inability of families to access preventive services at the same rate as before the emergency order 'safe at home' (Whaling, et al., 2020).

Other studies, in contrast, have demonstrated that the impact of public health crises on rates of domestic violence depend on the nature and location of where the disaster occurred (Curtis, Miller, & Berry 2000). Mohler et al. (2020) analyzed daily counts of calls for service in Los Angeles from January 2, 2020 to April 18, 2020 and tested for differences in means from a baseline period corresponding to the "time period prior to school, restaurant and bar closings (January 2 to March 16, 2020)" (Mohler et al., 2020, p. 2). The treatment time period was defined as the period after "shelter in place" orders were given

on March 20, 2020 to April 18, 2020. They found that domestic violence calls substantially increased following the implementation of "shelter in place." Comparably, a study analyzing child abuse reports and substantiations, by county, for 1 year before and after Hurricane Hugo in South Carolina, the Loma Prieta Earthquake in California, and Hurricane Andrew in Louisiana, found increases in reported domestic violence and child abuse cases in the 6 months following Hurricane Hugo and the Loma Prieta Earthquake but did not find similar increases following Hurricane Andrew (Curtis, Miller, Berry, 2000). Similarly, Seddighi et al., (2019) found that child abuse increased significantly during a natural disaster which they attributed to lack of food security and shelter in families. This is consistent with research attributing child maltreatment to parent's experiences of chronic stress over rental payments, eviction notices, and/or the threat of being homeless more generally (Barboza, 2020). Another study compared regions both affected and unaffected by Hurricane Floyd in North Carolina and found increases in purposeful and non-purposeful Traumatic Brain Injuries (TBI) in children 24-months and younger in the 6 months following the disaster compared to a comparable period preceding it (Keenan, Marshall, Nocera, & Runyan, 2004).

Spatiotemporal Characteristics of Child Maltreatment & COVID-19

The COVID-19 pandemic has differentially impacted certain communities characterized by structural vulnerabilities, particularly low-income communities. Like COVID-19, there is strong evidence that child maltreatment is spatially and temporally clustered in socially and physically disorganized, densely populated, urban areas (Klein & Merritt, 2014; Korbin, Coulton, Chard, Platt-Houston, & Su, 1998; Sampson et al., 1995). The risk factors previously identified to increase child welfare involvement and substantiated child maltreatment have been magnified as a result of COVID-19. For example, a large body of research has linked child maltreatment with heightened parental stress levels resulting from unemployment, minimal social support, housing and food insecurity. Data from the Fourth National Incidence Study of CAN (NIS-4) revealed that child maltreatment is two to three times more likely when both parents are unemployed and five times more likely among individuals whose household income is $15,000 a year or less (Sedlack et al., 2010). As well, childhood victimization rates have been shown to

increase with increasing levels of neighborhood poverty (Garbarina, 1997), percentage of individuals lacking health insurance (Berger, 2004; Zielinski, 2009) and school absenteeism (Leiter & Johnson, 1994; Hagborg, Berglund, & Fahlke, 2017). The use of social disorganization theory emphasizing the role of social conditions and neighborhood economic status to explain why areas with these structural risk factors have higher rates of child abuse (Coulton, Korbin, & Su, 1999; Coulton, Korbin, Su, & Chow, 1995; Freisthler, 2004; Klein & Merritt, 2014; Schuck & Widom, 2005) can also explain why some communities are disproportionately impacted by COVID-19. As well, research has uncovered that these structural inequalities result from spatial heterogeneity in the risk factors that underlie child maltreatment in different geographical contexts (Barboza, 2019). One study examining spatial 'regimes' of child maltreatment allegations in San Diego, for example, found different clusters of neighborhoods with different risk factors meaning that the same risk factors were differentially associated with child welfare in different areas. Similarly, during a pandemic, the level at which communities adopt social distancing protocols and other preventive measures can interact with pre-existing vulnerabilities. From a policy perspective, previous studies reinforce the importance of developing targeted, public health intervention efforts in areas characterized by multiplicative risks that are highly associated with rates of child victimization (Barboza, 2020).

Current Study

COVID-19 has created an urgent need for alternative methods of CAN surveillance. Los Angeles county has met this need by providing spatiotemporal incident data in real time[1]. Evidence-based databases that provide up to the minute information on child welfare are critical to enhance security and prevent injury or death (Boyd et al., 2017). In the wake of COVID-19, large, publicly available data sets can 1) provide unique insights about the spatial and temporal distribution of CAN and its relation to disease progression; and 2) identify where the most vulnerable populations may be impacted even after

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[1] It is worth noting that Los Angeles County and the city of Los Angeles both have emphasized the importance of transparency through data thereby facilitating the present analysis. Other states, counties and cities have similarly provided massive amounts of data that are made available to the public, albeit the indicators may differ. In order to facilitate other researchers to perform similar analyses of "big data" we provide the code and analysis we performed here at github.com/elisegia.

the outbreak has subsided (Boyd et al., 2017). These data additionally allow for the implementation of Geographic Information Systems (GIS) techniques to create maps of selected areas of vulnerability that address additional focal areas of need (Hames et al., 2016). In this paper, we combine the CAN incident data with additional datasets to provide an innovative analysis that explores the dual trajectories of COVID-19 and child maltreatment in the city of Los Angeles, drawing heavily on spatial analysis for exploring social and disease vulnerability.

Methods

Data

Dependent Variables

      Child abuse and neglect. In order to measure CAN, geographic locations (to the nearest 100th block) for every crime reported to the Los Angeles Police Department (LAPD) from July 24, 2019 to July 19, 2020 were obtained from the City of Los Angeles Open Data portal (https://data.lacity.org/) through the Application Programming Interface (API) and downloaded into the R statistical programming package. The R package `dplyr` was used to filter the data for distinct codes indicative of physical child abuse (both aggravated and simple assault) and neglect of child. In California, *child abuse* is defined by Penal Code (PC) 273d as the imposition of physical injury or cruel punishment on a child (e.g., slapping a child hard enough to leave a mark or hitting a child with a belt harder than is deemed 'reasonable'); *neglect* is defined by PC 270 as the willful refusal of a parent to provide for a child's basic needs including clothing, food, medicine and shelter. In addition to the type of harm, the data includes individual-level information on the race, gender and age of the victim as well as the locus of harm (e.g. single-family residence, apartment complex) and the geographic location (latitude/longitude).

Independent Variables

Several independent variables were included in our analysis and merged to the aggregated counts of CAN by census tract.[2] All data utilized in this study are freely accessible to the public and do not involve human subjects making them exempt from the Institutional Review Board (IRB). Missing values on independent variables were removed from the analysis.

Spatial Analysis

California Strong Start Index (CASSI) Score. The California Strong Start Index (CASSI) (USC School of Social Work Children's Data Network, 2017) comprises a total of 12 variables that fall into four domains summarizing the conditions into which children are born: 1) *Family* (legal status of parentage at birth, whether the child was born to non-teen parents, and whether the child was born to parents with at least a high school degree; 2) *Health* (healthy birthweight/absence of congenital anomalies, abnormalities, or complications at birth); 3) *Service utilization* (access to and receipt of timely prenatal care, receipt of nutritional services, WIC, if eligible, and whether the child was born at a hospital with a high percentage of births and quality prenatal care); and 4) *Financial resources* (parental ability to afford and access healthcare, whether at least one parent had a college degree, and whether the child was born to parents with an employment history). Each question was scored as 0 = no; 1 = yes to yield an overall "birth asset scores," ranging from zero to 12 with higher scores indicative of more birth assets. The average cumulative scores, which are comparable across communities (USC NDSC, 2020), for each census tract utilized. Low scores are associated with involvement with child protective services or death by age 5 and can help identify which communities may benefit from additional support (USC NDSC, 2020). For more on the methodology, see https://www.datanetwork.org/wp-content/uploads/cassi.pdf.

School Absenteeism. School absenteeism measures the percentage of students who are absent on 10% or more of the school days they are enrolled in for a school year. The data for each census tract were provided by California Department of Education (CDE) Ed-Data/Data Quest for the 2017 – 2018 school

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[2] The CASSI index, school absenteeism, poverty, labor force participation rate and severe rental burden can be downloaded from the Neighborhood for Social Change (NDSC) Platform, a publicly available open data platform provided by the University of Southern California Center for Social Innovation (https://socialinnovation.usc.edu/).

year and made available through USC's NDSC. Unlike truancy which focuses on legal and regulatory compliance with school rules, school absenteeism incorporates both unexcused and excused absences and suspensions. As such, this measure implicitly acknowledges the plethora of different reasons why students miss school, including health reasons, homelessness and/or transportation issues (Attendance Works, 2018).

Poverty. The percentage of persons living below 100% of the federal poverty threshold for each census tract, which is based on the number of adults and children in a household, was provided by the American Community Survey (ACS), 5-year estimates (Table C17002) for 2014 – 2018 made available through USC's NDSC interactive platform. The ACS determines poverty status by comparing annual income to a set of dollar values (called poverty thresholds) that vary by family size, number of children, and the age of the householder. If a family's before-tax money income is less than the dollar value of their threshold, then that family and every individual in it are considered to be in poverty. For more information about how the Census Bureau measures poverty see https://www.census.gov/topics/income-poverty/poverty/guidance/poverty-measures.html.

Labor Force Participation. The labor force participation rate is defined as the percentage of the population over the age of 16 who are either employed or unemployed and actively seeking work, excluding people who are unemployed but have given up looking for work, or active military members. The labor force participation rate is calculated by dividing the total number of people in the labor force by the total population in each census tract. The estimate used in this study were based on the American Community Survey, 5 Year Estimates, for 2014 – 2018 (Table B23001), made available through the USC's NDSC.

Housing Affordability. Housing affordability was operationalized as severe rental burden, defined as the percentage of renters paying more than 50 percent of their monthly income on rent and utilities. The numerator was defined as the total number of households in a census tract that spend 50 percent or more of their household income on housing. The denominator was the total occupied housing units for which housing cost burden is computed in each census tract. The 50 percent threshold has been

used in previous studies to capture a severe housing-cost burden that is likely to interfere with a family's ability to pay for other basic household expenditures thereby causing significant family stress (Warren & Font, 2015). The measure was based on American Community Survey, 5-year estimates, Table B25070 for 2014 – 2018, made available through USC's NDSC platform.

Temporal Analysis

Apple Mobility Trends Report (Apple, Inc. https://www.apple.com/covid19/mobility) provided data on the number of requests made to Apple Maps service for walking, driving and transit directions in the city of Los Angeles each day. Apple mobility trends data are made available starting from January 13, 2020 and were included to control for variation in adherence to safer at home orders over the time period. For consistency, we included data from baseline (January 21, 2020) through July 19, 2020. The baseline date of January 21, 2020 was selected for this study because it corresponds to the first US case of coronavirus confirmed by the Centers for Disease Control (Schuchat, 2020). Percent increases or decreases in Maps data is gauged from the baseline date which is indexed at 100. The data were merged with aggregate daily counts of reported CAN cases by date (day and month).

Statistical Analysis

Risk surface measurement. To perform the spatial analyses, the incident data was converted to a spatial point data set and projected into the NAD 1983 UTM Zone 11N coordinate system. The spatial boundary for our study was a shapefile of the 1,012 census tracts in the city of Los Angeles which was downloaded from the city's Geospatial Hub (http://geohub.lacity.org/). We used the similarity search tool in ArcGIS to rank all census tracts in the city according to their degree of similarity with a set of input features comprised of the highest levels of risk – i.e. the highest values of severe rental burden, school absenteeism, poverty and the lowest values of labor force participation and the strong start index. A *Z*-transform was applied to standardize the variables, candidate values were subtracted from the target values associated with high risk and the differences were squared. Then, the sum of the squares for each of the attributes was calculated and the shortest distance was considered the tract that was most like the highest risk tract for that variable. This process resulted in a ranking of each census tract from least to

most similar in relation to the set of input features, with higher ranks corresponding to the most

vulnerable areas.

Temporal Trends measurement. To gauge time trends, daily counts of CAN incidents were

aggregated to facilitate comparisons in CAN trends before and after the pandemic. Temporal trends were

assessed using an approach similar to that provided by Mohler et al 2020. With daily counts of reported

CAN cases in the city of Los Angeles from January 21, 2020 to July 19, 2020 as our dependent variable,

we merged Apple's daily mobility changes in routing requests data by month and day to gauge the impact

of temporal trends in daily mobility on CAN. Similar to Mohler, a series of dummy variables coded

treatment effects associated with (1) the declaration of a national emergency in California on March 4,

2020; (2) the safer at home order (which included school closures) that began on March 19, 2020; (3) the

implementation of the federal stimulus package on April 15, 2020; and (4) the date that businesses began

re-opening on May 8, 2020. Mohler et al (2020) was extended by incorporating treatment effects for the

emergency order, release of stimulus funds and the date that the city allowed businesses to re-open as

well, to examine how social and economic measures may impact temporal trends in abuse and neglect

reports over time. Whereas we tested for difference in means using a negative binomial regression model

consistent with the nature of our dependent variable, we used a similar functional form, i.e.,

$$y_t = c_0 + ax_t + \sum_i c_i 1\{t > t_d\} + \sum_j w_j 1\{dw(t) = j\} + \sum_k m_k 1\{dw(t) = k\} + \epsilon$$

In our model, y_t is the number of reported CAN calls on day t, c_0 is the intercept, x_t is the Apple

residential mobility index on day t and a is the coefficient of the mobility index, $c_i 1\{t > t_d\}$ is an

indicator corresponding to four different treatment periods (1) stay at home and school closures; (2)

school hours, defined as 7am – 4pm, Mon – Fri; (3) release of the stimulus check by the federal

government; and (4) the order allowing businesses to re-open. We controlled for seasonal effects by

letting $1\{dw(t) = j\}$ be an indicator variable for the day of the week and $1\{dw(t) = k\}$ be an indicator

for week of the month (see for example, Mohler et al., 2020). We used the R statistical programming

package for the temporal trend analysis due to its sophisticated date/time procedures and graphic

capabilities.

       Spatiotemporal Patterns. To explore spatiotemporal trends in CAN during COVID-19, we used

the spacetime pattern mining tool available in ArcGIS version 2.3. The CAN incidences were first

transformed into a netCDF (Network Common Data Form) data cube structure by spatially and

temporally aggregating each location into 788 meter-high hexagon bins (representing approximately 5

city blocks) and 1-month time slices representing a total of 362 days (181 days during the pandemic from

January 21 – July 19 and a similar time frame preceding the pandemic, spanning the 181 days from July

24, 2019 – January 20, 2020). To minimize bias, we selected the same number of days to explore before

the pandemic began (January 21, 2020) as our analysis time frame corresponding to the pandemic

(January 21 – July 19, 2020). We extended the time frame to include the period immediately preceding

the COVID-19 pandemic in order to assess continuous time trends and to have enough data points for the

Emerging hot spot analysis. The neighborhood time step interval was parameterized for consistency with

the time trend analysis above such that the most recent time step corresponded to the period spanning

January 21, 2020 – July 19, 2020. The Mann-Kendall trend test (Mann 1945, Kendall and Gibbons 1990)

was used at each location to assess the presence of statistically significant increasing or decreasing

temporal trends over the region. Using the space time cube as input, the Emerging Hot Spot Analysis tool

was next used to identify spatiotemporal hot and cold spots by calculating the Getis-Ord Gi statistic (Ord

and Getis 1995). The Emerging Hot Spot Analysis tool categorizes the hot and cold spots into 17 possible

patterns (see Table 1 for categories and definitions).

<div align="center">[Table 1 here]</div>

       To explore the relationship between hot and cold spot areas during the COVID-19 outbreak (i.e.

emergent hot spot locations) and predictor variables, we first used the intersect tool in ArcGIS to spatially

join the hot spot locations to the aggregate count of CAN in each census tract and the spatially referenced

independent variables. The merged dataset therefore provided an indicator corresponding to the type of

trend (see Table 1) that characterized each census tract. Given that our dependent variable was the

number of CAN cases, we first estimated a Poisson regression model. However, the variance of our dependent variable was significantly greater than the mean ($Z = 7.542$, p < .001) indicating overdispersion. To account for overdispersion, we estimated a negative binomial regression model using the `glm.nb` function in R. We included the number of children under 18 years old as an offset variable to account for differential risk exposure in each tract. Our final model was as follows:

$$\log(y) = c_0 + \sum_i X_i \beta_i + \log(n),$$

where y = the count of CAN incidents in each hot spot census tract characterized by increasing trends during the COVID-19 pandemic, c_0= the intercept, the $X_i, i = 1 \ldots 6$, represented the five independent variables used to create our risk surface and a dummy variable corresponding to the type of hot/cold spot pattern (including no pattern) identified by the previous analysis, and n represented the total number of children under 18 in each census tract. In order to interpret the model coefficients, we computed the percentage change in expected counts, i.e. $100 \, x \, [\exp(\beta x \Delta) - 1]$ where β is the regression coefficient from the negative binomial regression and is the amount of change in the predictor, which was set to reflect a one-unit change in the independent variables.

Results

[Table 2 here]

Table 2 shows the descriptive characteristics of CAN incidents for the 181 days before (baseline; July 24, 2019 – January 20, 2020) and during the COVID-19 pandemic (January 21, 2020 – July 19, 2020). There was a 7.95% decrease in the number of CAN reports during the COVID-19 pandemic compared to the same time period immediately preceding it. As well, there was a statistically significant difference in the location of the abuse/neglect ($\chi^2 = 68.35$, $p < .001$), with fewer cases reported in single family dwellings (288 v. 255) and about four times as many cases reported on sidewalks during the pandemic compared to the comparable time period before (21 v 76) (see Table 2). Statistically significant differences were also noted for the manner of injury, with 'strong arm' and 'other' methods of injury (including rope, hammer, club/bat, knife and firearm) being less likely during the pandemic ($\chi^2 = 13.01$,

p = .023). No differences were observed on the other indicators; however, it is worth noting that five of

the twenty-five police bureaus had the most reports of CAN both before and after the pandemic,

accounting for 44% and 49% of all reported cases, respectively.

Figure 1 shows the time series of CAN case counts in the City of Los Angeles during the study

period. The red line shows the time trend of CAN cases during the same time period immediately

preceding the COVID-19 pandemic whereas the blue line shows the time trend during the COVID-19

pandemic. As shown by the figure, the incidence of CAN fluctuated during both periods, but a steeper

downward trend is observable for the period corresponding to the pandemic. The most incidents in a

single day before and after the COVID-19 outbreak were 10 (daily average = 3.71) and 14 (daily average

3.28), respectively.

[Figure 1 here]

[Table 3 here]

Social and Economic Trends in CAN During COVID-19. Table 3 shows the results from the

negative binomial regression of reported CAN counts using treatment effects to codify time periods

associated with key social and economic measures taken to prevent the spread of COVID-19. Results

show no statistically significant differences in counts of CAN as a result of either social distancing

measures, economic stimulus or changes to mobility patterns (see Table 3). Nor were there any

statistically significant differences in counts of abuse and neglect during school hours or following the

release of stimulus checks. It is interesting to note the pattern of coefficients which suggest counts were

higher after businesses began re-opening but lower at the height of the quarantine period and following

the release of stimulus funds.

Spatiotemporal Trends in CAN. The space time cube aggregated 1,209 points into 5,808 hexagon

grid locations over 12-time step intervals. Of the 5,808 locations, 598 (10.30%) contain at least one point

for at least one-time step interval. The nonparametric Mann-Kendall statistic tested for increasing or

decreasing trends by evaluating count values for the locations in each 1-month time-step interval for the

study. Consistent with Figure 1, the trend statistic showed a decreasing trend in the city during the time frame (Mann-Kendall statistic= -3.04, p <.001). Among all locations, 1,114 demonstrated different patterns compared to the overall downward trend. The analysis showed 339 hot spots categorized into three patterns (15 new hot spots; 123 intensifying and 201 consecutive) and 669 cold spots categorized into two patterns (17 new cold spots and 652 consecutive cold spots). No patterns spatiotemporal trends were identified in other locations. The map in Figure 2, Panel A shows the results of our census tract ranking of co-occurring risks and Panel B shows the emerging hot and cold spots of CAN. The visual representation demonstrates that areas associated with the highest levels of structural risk (i.e. census tracts ranked from 1 - 201) are also areas identified as consecutive hot spots or intensifying and new hot spots during COVID-19 whereas areas associated with consecutive or new cold spots were areas associated with the lowest risk.

Negative Binomial Regression

Using the spatial overlay feature of ArcGIS we were able to create a dataset that characterized each census tract as a hot or cold spot (or no pattern). Table 4 shows beta coefficient, incident rate ratio (exp(β)), and *p* value for the NBR of aggregated counts of CAN in census tracts identified as new or intensifying hot spots or new or consecutive cold spots along with the mean and standard deviation for each independent variable. As shown in the table, for each one-unit increase in the Strong Start Index the expected log count of the number of CAN cases decreased by 0.109, or 10.4%. As well, for each one-unit increase in labor force participation, the expected log count of the number of CAN cases decreased by .882 (58.7%). Severe rental burden and school absenteeism were also strongly related to the number of CAN reports in each census tract with each 1-unit increase expected to increase the number of CAN reports by a factor of 1.29 and 2.66, respectively. The incident rate for areas classified as intensifying or new hot spots is 2.88 and 1.66 times the incident rate for consecutive cold spots (the reference group). Likewise, every-one unit increase in the percent of severely burdened households increased the incident rate by 83.1%.

[Table 4 here]

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Figure 3 shows predicted counts of CAN resulting from the NBR in hot and cold spots for school absenteeism, severe rental burden, poverty, the strong start index and labor force participation. As shown by the figure, the variables measuring the impact of severe rental burden and the strong start index have the largest effect on predicted CAN counts in intensifying hot spots and little to no effect on areas identified as consecutive cold spots.

[Figure 3 here]

Discussion

The purpose of this study was to reveal patterns and associations between CAN incidence in vulnerable neighborhoods before and during the COVID-19 pandemic using spatial statistics and geographic data mining analytics that allow for spatial-temporal variation across neighborhoods. The analysis highlights the utility of using GIS to analyze trajectory patterns and to identify priority areas for prevention and intervention, as has been established in previous studies. In general the findings demonstrated the utility of spatiotemporal analyses, based on the contextual contributions of structural risk factors for both understanding CAN outcomes before and during a major public health crisis and for the development of sensitive and effective policies and interventions that minimize the cumulative impact of co-occurring harms on children during a public health catastrophe.

Temporal Context and Outcomes

Our results point to a statistically significant 8% decline in the number of CAN reports as well as a steep overall decline during the COVID-19 pandemic as compared to the same time period immediately preceding it. These results are consistent with reports of declines in the number of calls to the child abuse hotline from the Los Angeles County Department of Children and Families. For example, the CAN Hotline for Los Angeles county reported a decrease by 50% in child maltreatment allegations in the month of April following the COVID-19 outbreak (Thomas, Anurundran, Robb & Burke, 2020; Department of Children and Family Services, 2020).

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However, the decreasing case counts and overall time trend in CAN reports across the city must be viewed in light of two additional findings. First, the decreasing trend was not characteristic of all areas of the city and most areas showed no trend. Whereas our spatiotemporal analysis uncovered that most areas were characterized by no pattern, importantly we identified areas characterized by different space-time trends during the COVID-19 period which were characterized as new, intensifying and consecutive hot and cold spots. Second, compared to consecutive hot spot areas, new and intensifying hot spot areas demonstrated increasing rates of CAN during the COVID-19 pandemic that were highly associated with lower labor force participation, school absenteeism, severe housing burden, poverty and the birth asset score (CASSI) index. Moreover, our risk surface map showed that the areas associated with high case counts and increasing trends in CAN during COVID-19 were in the most vulnerable parts of the city before the onset of the pandemic. In addition, we selected the risk factors that have been most exacerbated by COVID-19 – threat of eviction, school absence, lack of health insurance and compromised socio-emotional development in children. Therefore, despite the overall decline in the number of CAN incidents, the contextual factors we used in this study provide an ideal mechanism for preventative interventions for children living in areas where child abuse has increased during the COVID-19 pandemic. Such explanations do not target individuals or families but rather potentially harmful situational characteristics that determine how well communities will respond, or not, to public health crises that by itself increases the likelihood of abuse and neglect among children living in vulnerable areas.

Spatial Contexts and Outcomes

Despite the overall decline in cases during the pandemic, our spatial model was parameterized so that the most recent time step interval corresponded to the COVID-19 outbreak. Therefore, we were able to identify new and intensifying hot and cold spots that showed increasing and decreasing space-time trends during the COVID-19 pandemic. Our regression model demonstrated that compared to consecutive cold spots, both new and intensifying hot spots were located in areas where abuse and neglect may have increased in response to new vulnerabilities created by the pandemic. Conversely, whereas new cold spots

may be located in areas where reported cases of abuse or neglect are difficult to detect because of stay at home mandates and/or other social distancing protocols, our analysis showed these areas were associated with very low counts of CAN before the pandemic, as well as areas of lower risk. As well, we found no evidence of historical hot or cold spots which would characterize the most recent time period (i.e. the time period characterizing the COVID-19 pandemic) as cold even though 90% of previous time periods were hot (see Table 1).

Our results regarding the impact of school absenteeism on increases in CAN rates during COVID-19 is consistent with previous research that highlights the structural and systemic problems that interfere with the ability of child welfare systems to identify and respond to child maltreatment in the face of a public health disaster. Under California law, professionals who reasonably suspect child maltreatment are required to report it to authorities (Ho, Gross, Bettencourt, 2017). Research has revealed that most child maltreatment reports are from mandated professionals such as, law enforcement, teachers, health care providers, social service personnel, childcare providers, and mental health clinicians (Child Maltreatment- HHS, 2018). Just as mandated reporters have less contact with children during a stay at home order, they also have less contact with children who are absent from school. Our results showed that rates of CAN are higher in areas with high percentages of chronically absent students above and beyond other neighborhood vulnerabilities. Large numbers of chronically absent students could indicate systemic problems that affect the quality of the educational experience and/or the healthy functioning of the entire community (Chang & Romero, 2008). As such, our results reinforce the critical role of schools in monitoring student absenteeism during the COVID-19 pandemic to determine the reason for the absence, specifically whether it is due to COVID-19, or related issues, or due to other factors entirely. School absenteeism data captures the plethora of reasons why a child may be chronically absent from school including safety concerns, housing insecurity, unreliable transportation, and lack of access to health care, all of which protects children from victimization. Therefore, during a pandemic, policies that exempt administrative entities from collecting school absentee data may impede the ability of schools to identify at children at risk for abuse or neglect. For example, in the United States, the Department of Education is

offering schools a one-year waiver that would exclude them from having to collect student absenteeism data from their accountability rubric and some states have taken measures to disregard absenteeism by not counting days missed due to public health emergencies.

Our results further demonstrated that housing insecurity, as defined by severe rental burden, was related to increasing trends of CAN in hot spots during COVID-19. These results suggest that measures designed to reduce housing burden will also protect children from victimization. This finding is consistent with research demonstrating the unique contribution of housing insecurity to maltreatment risk over and above measures of poverty and income (Barboza, 2019; Barboza, 2020). During a pandemic, households that were not previously rent burdened can quickly become so due to massive layoffs. Rent-burdened households generally have lower incomes than non-rent burdened households and less money to spend on other basic needs like food, clothing, transportation, and routine medical services thereby setting a context ripe for child neglect. The underlying mechanisms put forth to explain the relationship between housing insecurity and child maltreatment include parents' experiences of chronic stress over rental payments, eviction notices, and/or the threat of being homeless. On the neighborhood level, high rates of rent burden can lead to high resident turnover and a lack of community investment and cohesion (Coulton et al., 1995). In this regard, our results suggest that measures intended to shield families and communities from the devastating consequences of eviction will minimize child harm by alleviating situational stress and strengthening informal social networks which have been shown to decrease child abuse (Gaudin & Pollane, 1983). One such policy is the implementation of countywide ban on evictions for tenants who have been financially impacted by the COVID-19 pandemic. In light of the millions of individuals in Los Angeles and elsewhere that are housing insecure, coupled with the closing of schools and activities, our results strongly suggest that eviction bans should extend through the end of the pandemic in order to provide greater protections to children who are less visible.

In addition to finding that school absenteeism and housing insecurity are related to CAN reports, this investigation also pointed to the significant association between the California Strong Start Index (aka birth asset score) (CSSI) and the percent of individuals not in the labor force and CAN. The

dynamics of the connection of these two measures to CAN involve critical CSSI factors (e.g. family strength and stability, health of children, access to child health services) and family/child health coverage in addressing the challenges of behavioral health care utilization both pre- and post- COVID-19. These challenges are relevant to all families but, as our findings on COVID-19 in child abuse hotspots indicate, affect families living in severely at-risk census tracts more heavily. In this regard, our results are consistent with previous research showing that children born with fewer assets are at higher risk for adverse experiences such as child abuse (Foust, n.d.). From a policy perspective, our results suggest that early intervention programs that aim to minimize traumatic experiences in children by enhancing health and well-being, such as evidence-based home visitation programs, are critical services that should continue throughout a public health crisis. Nevertheless, a report issued by the California Budget & Policy Center found that in California, fewer children receive home visiting services compared to likely beneficiaries defined as children 0 – 2 born with 6 or fewer strong start assets (California Budget & Policy Center, 2019). Our findings suggest that efforts to continue delivering home based-services, either virtually or via other delivery methods that are in accordance with public safety guidelines, are critical to connect at risk families to needed services and to minimize the extra stress and social isolation due to COVID-19. Moreover, using a spatial analysis such as the current investigation can help communities target such resources more effectively to families with the greatest need.

Limitations & Future Directions

Despite the novelty of this study it is not without limitations. First, the COVID-19 pandemic is not over and hence its full impact cannot be determined at this time. One consequence is that few data sets are available for analysis, and therefore, at present, the best source of data to study the impact of COVID-19 on CAN is crime data collected by the police and made available to the public. Police incident data offers an additional benefit given the urgency of using real time data to assess current impact. The velocity with which these data are made available coupled with the fact that "… data from the child welfare system almost certainly cannot be considered a good representation of the magnitude of violent

crimes perpetrated against juveniles and reported to authorities (Finkelhor & Ormrod, 2001, p. 6)" makes it an important source of information to protect families during a major public health catastrophe. With that said, the data used in this study was drawn from police statistics and not from child protective services, and the later may maintain closer contact with families and may be more likely to receive reports of abuse and neglect from mandated reporters who report suspicions of maltreatment. Moreover, we only used data on physical abuse and neglect, however physical child abuse does not cover the full spectrum of child maltreatment cases, and maltreatment based on sexual and emotional abuse was not analyzed in this study. Limitations associated with the use of administrative data more generally include surveillance bias that might also be related to certain areas and also lead by social prejudice. From a methodological perspective, the emerging hot spot analysis results are highly dependent on the spatial and temporal scale chosen. As neighborhood size increases, and as time steps change, localized hot spot trends will change accordingly. While there is inevitably an element of subjectivity in choosing an appropriate value for neighborhood distance we believe that our choices of neighborhoods were not only appropriate they also resulted in intuitive patterns given the distribution of incidents across the city. As well, the time frame we chose made good analytical sense given our focus on explaining trends during COVID-19. Nevertheless, different spatiotemporal patterns will result in different model parameterizations. In that regard, our spatiotemporal analysis focused on the six months prior to the COVID-19 outbreak as the comparison period, which may have introduced bias due to seasonal effects that we did not account for and that may be present in different areas. Nevertheless, our temporal analysis did not uncover any seasonal differences in reporting behavior over the previous year. Finally, we included variables that are highly relevant considerations during the COVID-19 pandemic, but other factors may emerge as more or less salient for understanding CAN across densely populated urban areas. Future research should continue to explore spatiotemporal trends in CAN, preferably using different data sources and units of analysis.

Conclusion

We are just beginning to understand how the virus differentially impacts vulnerable communities. In this paper we have demonstrated a useful methodological approach for framing the critical dimensions

of such an improved understanding of the impact of COVID -19 on vulnerable communities is by contextualizing the sources of stress on such communities. The issues raised in this paper have been recurring problems for vulnerable communities In turn these recurring problems are likely more effectively addressed with policies and interventions that consider the spatiotemporal trends in CAN as well as the distribution of risk factors as important components of emergency planning. Understanding how COVID-19 has further impacted these communities will help direct important social and economic resources to communities in greatest need. While governments at local, state and national levels must implement measures designed to slow the spread of disease by framing messages around 'flattening the COVID-19 curve' we must not ignore the potential devastating long-term consequences that this pandemic will continue to have on individuals, families and communities. In the absence of proactive public policy, the ability of communities to respond to, and recover from, the coronavirus is clearly hampered by existing neighborhood structural factors. In this paper, we demonstrated these in relation to CAN to include, but not limited to, housing insecurity, lack of positive child assets at birth, school absences, and unemployment. As such, this paper represented an attempt to explore real time neighborhood level data on CAN using an innovative methodological design to holistically address child safety during a pandemic by identifying emergent hot and cold spots indicative of risk, and by further contextualizing the barriers that vulnerable communities face in identifying and responding to increases in CAN during the COVID-19 pandemic.

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Table 1. Definitions of Emerging 8 Hot and Cold Spot Patterns Used in the Study

New	A CAN location identified as a statistically significant hot (cold) spot since Jan 21, 2020 but was not previously identified as a statistically significant hot (cold) spot.
Consecutive	A CAN location with a single uninterrupted run of statistically significant hot (cold) spot bins in the final time steps including during the COVID-19 pandemic. The location has never been a statistically significant hot (cold) spot before the final hot (cold) spot run.
Intensifying	A CAN location that has been a statistically significant hot (cold) spot for ninety percent of the time including during COVID-19. In addition, the intensity of clustering of high counts for each time period increased (decreased) overall and that increase (decrease) was statistically significant.
Persistent	A CAN location that has been a statistically significant hot (cold) spot for ninety percent of the time-step intervals with no discernible trend indicating an increase or decrease in the intensity of clustering over time.
Diminishing	A CAN location that has been a statistically significant hot (cold) spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering in each time step is decreasing (increasing) overall and that decrease (increase) is statistically significant.
Sporadic	A CAN location that is an on-again then off-again hot (cold) spot. Less than ninety percent of the time-step intervals have been statistically significant hot (cold) spots and none of the time-step intervals have been statistically significant cold (hot) spots.
Oscillating	A statistically significant hot (cold) spot for the final time-step interval that has a history of also being a statistically significant cold (hot) spot during a prior time step. Less than ninety percent of the time-step intervals have been statistically significant hot (cold) spots.
Historical	The most recent time period is not hot (cold), but at least ninety percent of the time-step intervals have been statistically significant hot (cold) spots.
Table notes: Each of the 8 patterns can represent a hot or cold spot, yielding 16 possibilities, in addition to 'no pattern detected' resulting in 17 total patterns.	

Table 2. Individual and Contextual Similarities and Differences of Abused and Neglected Children pre and post COVID-19

	Pre-COVID-19 (N, %)	COVID-19 (N, %)	$\chi^2 p$-value
Total	661 (100)	614 (100)	--
Type			
Child Abuse (Simple)	463 (69.4)	416 (67.8)	
Child Neglect	131 (19.6)	126 (20.5)	ns
Child Abuse (Aggravated)	73 (10.9)	72 (11.7)	
Gender			
Male	329 (49.8)	309 (50.7)	
Female	332 (50.2)	301 (49.3)	ns
Race/Ethnicity			
Hispanic	430 (65.1)	365 (59.9)	
Black	152 (23.0)	162 (26.6)	ns
White	50 (7.6)	47 (7.7)	
Asian	8 (1.2)	7 (1.1)	
Other	21 (3.2)	28 (4.6)	
Manner of Abuse/Neglect			
Strong Arm	400 (60.5)	350 (57.0)	.023
Belt	56 (8.5)	53 (8.6)	
Unknown weapon	53 (8.0)	50 (8.1)	
Blunt Instrument/stick	6 (0.9)	18 (3.0)	
Vehicle	7 (1.1)	5 (0.8)	
Other manner	109 (16.5)	138 (22.6)	
Location			
Single Family Dwelling	288 (45.2)	255 (41.5)	<.001
Multi-unit dwelling	172 (26.0)	169 (27.5)	
Sidewalk	21 (3.2)	76 (12.4)	
Parking lot	12 (1.8)	15 (2.4)	
Elementary School	17 (2.6)	10 (1.6)	
Vehicle	2 (0.3)	9 (1.4)	
Motel/hotel	8 (1.2)	15 (2.4)	
Other location	141 (20.5)	65 (10.6)	
Neighborhoods (Top 5)_			
Southeast	88 (13.3)	80 (13.2)	ns
77th Street	56 (8.5)	47 (7.7)	
Mission	56 (8.5)	69 (11.2)	
Southwest	51 (7.7)	64 (10.4)	
Foothill	39 (5.9)	38 (6.2)	
Other neighborhoods	371 (56.1)	316 (51.5)	
Daily Trends			
Average Daily Counts[a]	3.71	3.28	

Notes: The pre-COVID-19 period covers the time period between July 24, 2019 – January 20, 2020. The COVID-19 covers the period between January 21, 2020 – July 19, 2020. Each time period spans 181 days. ns = not significant.
[a]Average counts per day computed as total number of CAN reports for each period divided by 181 days.
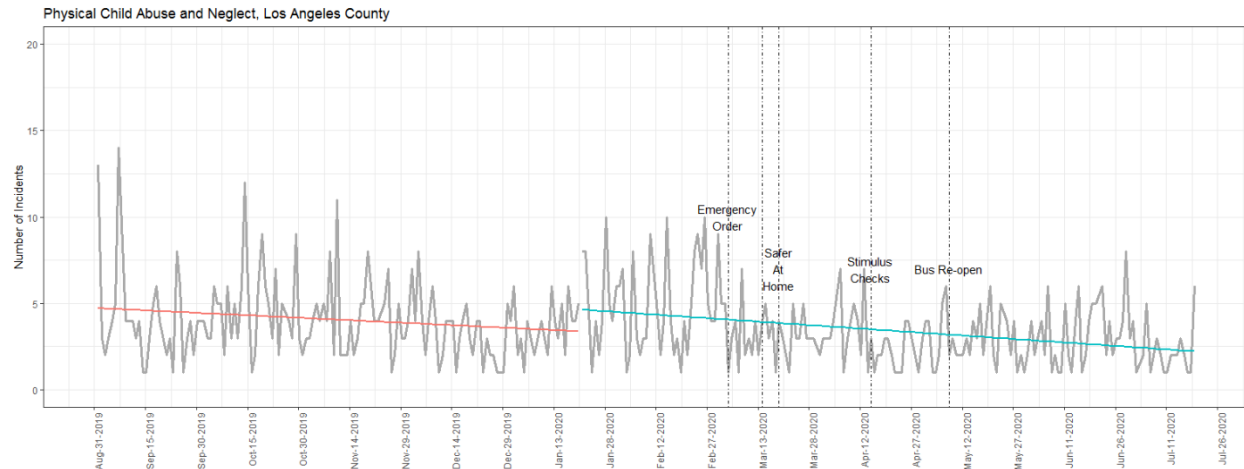
Figure 1. Time Trends of Child Abuse and Neglect Incidents Before and After COVID-19. For this study, the COVID-19 pandemic began on the date the first case was recorded in the United States (January 21, 2020). The last day of the study period was July 19, 2020. Vertical lines correspond to the Governor's declaration of a state emergency in California (March 4, 2020) social distancing orders (March 19, 2020), the distribution date for the stimulus checks (April 15, 2020) and the date that businesses began re-opening (May 8, 2020). The time trends based on a linear model reflect a slight downward trend for both periods.

Table 3. Negative Binomial Regression of Counts of Reported CAN and Social and Economic Consequences of the COVID-19 Pandemic Between 1/21/2020 – 7/19/2020

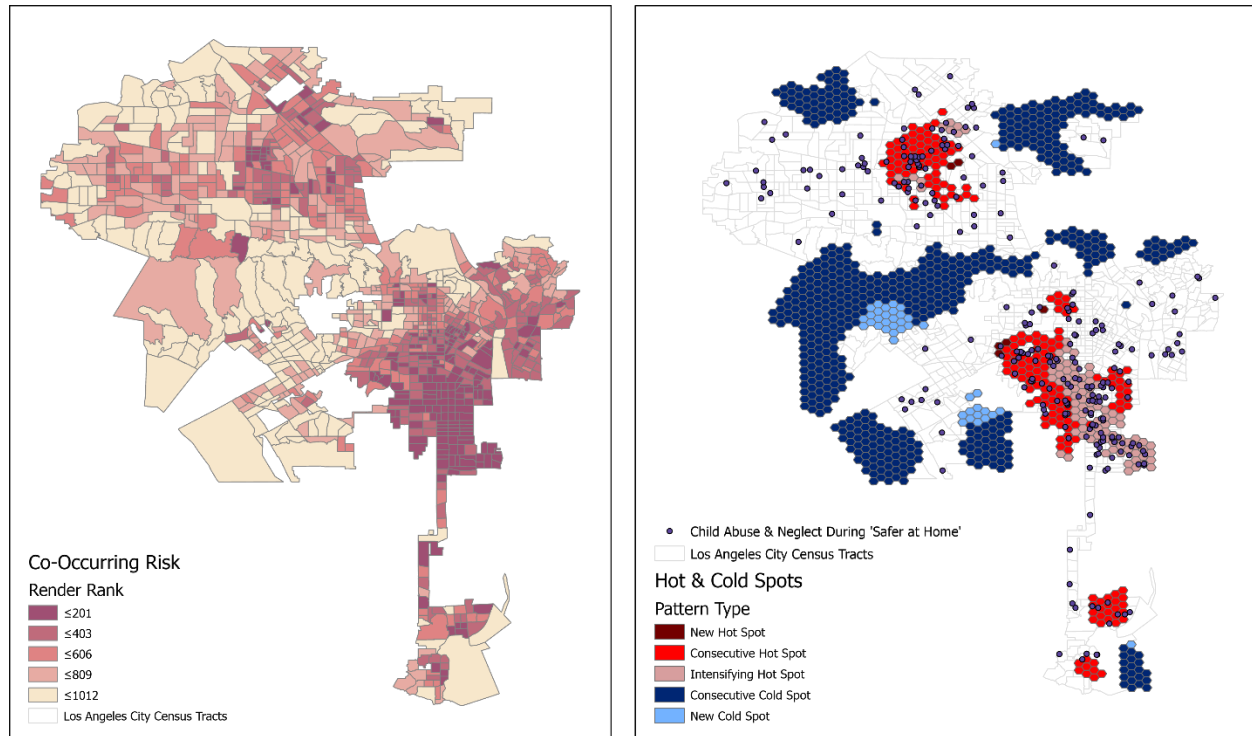|	Estimate	2.5 %	97.5 %	p
Intercept	1.11	.668	1.83	.685
Apple Mobility Index	.999	.990	1.01	.779
Emergency Order Issued	.913	.530	1.52	.735
Order 'Safer at Home'	.934	.433	2.13	.866
Businesses Re-open	1.01	.577	1.77	.973
Stimulus Checks Issued	.864	.535	1.38	.547
School Hours (M-F;7AM-4PM)	.992	.821	1.20	.936
Note: 2.5% and 97.5% provide the confidence intervals for the estimates				

Figure 2. (A) Census tract ranking of co-occurring risk factors indicating vulnerable areas of the city of Los Angeles (higher ranks = more vulnerable) and (B) Emerging Hot Spots of child abuse and neglect during the COVID-19 pandemic and locations of child abuse & neglect incidents following the city's 'Safer at Home' order on March 19, 2020.

Table 4. Negative Binomial Regression of Child Abuse and Neglect Counts in Hot and Cold Spots in the City of Los Angeles

	β	s.e.	*p*	exp(β)	Mean (sd)
Constant	2.36	.497	<0.001		--
Vulnerability					
Strong Start Index	-.109	.045	0.015	.896	7.940 (.549)
Severe Rental Burden	1.29	.191	<0.001	3.66	0.421 (.091)
Poverty	.748	.248	0.003	2.11	.278 (.111)
Chronic Absenteeism	2.66	.609	<0.001	14.41	0.142 (.038)
Labor Force	-.882	.467	0.059	.413	0.620 (.061)
Pattern					
Intensifying Hot Spot	1.03	.092	<0.001	2.80	--
New Cold Spot	-.111	.076	0.147	.894	--
New Hot Spot	.510	.126	<0.001	1.66	--
Consecutive Cold Spot	--	--	--	--	--

Note. β: Unstandardized coefficient; SE: Standard error; exp(β): Exponentiated regression coefficient (also referred to as IRR = incidence rate ratios). 2*(logL (m_*nb*) – logLik(m_*p*)) = 1.946185e-44 (*df*=8) where m_*nb* is the negative binomial model and m_*p* is the Poisson model suggesting the negative binomial model estimating the dispersion parameter is more appropriate. Null deviance = 421.64, *df* = 365 (*df* = degrees of freedom); Residual deviance: 380.08, 360 *df*; Akaike Information Criteria (AIC): 6199.462: R-squared McFadden=.179, Cragg-Uhler/Nagelkerke = .748.
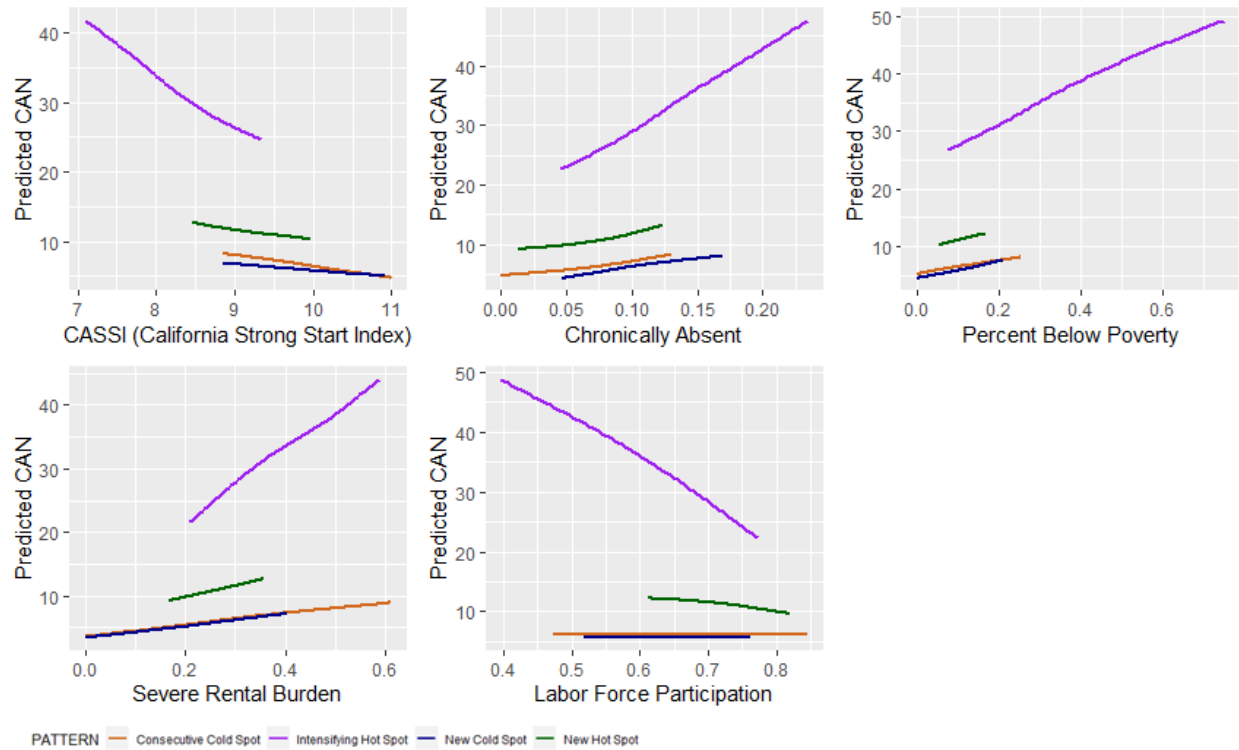
Figure 3. Predicted Counts of CAN from the NBR.
Notes: The figures show the relationship between each independent variable in the model and exponentiated predicted counts of CAN in new hot and cold spot areas during the COVID-19 pandemic, intensifying hot spots during the COVID-19 pandemic and areas identified as consecutive cold spots throughout the entire period. The minimum and maximum values for the independent variable are plotted along the x-axis and the predicted exponentiated counts of child abuse and neglect are plotted along the y-axis. In each plot the other variables in the model are held constant at their mean values (see Table 4, last column).