Sheltering in Place and Domestic Violence: Evidence from Calls for Service During COVID-19

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Abstract

The COVID-19 pandemic has led to an economic slowdown as more people practice social distancing and shelter at home. The increase in family isolation, unemployment, and economic stress has the potential to increase domestic violence. We document the pandemic's impact on police calls for service for domestic violence. The pandemic increased domestic violence calls by 7.5% during March through May of 2020, with effects concentrated during the first five weeks after social distancing began. The increase in reported domestic violence incidents began before official stay-at-home orders were mandated. It is not driven by any particular demographic group but does appear to be driven by households without a previous history of domestic violence.

Keywords: coronavirus, COVID-19, domestic violence, calls for service
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1 Introduction

The COVID-19 pandemic led to strict public health policies of social distancing and a dramatic reduction in activity and mobility in the US. Tens of millions of workers lost jobs or worked fewer hours (Cajner et al., 2020; Coibion et al., 2020; Cowan, 2020), and demand for new workers fell nearly 30% (Kahn et al., 2020; Campello et al., 2020). Approximately 35% of workers shifted to working remotely (Dingel and Neiman, 2020; Papanikolaou and Schmidt, 2020; Brynjolfsson et al., 2020) as public school children shifted to learning remotely. The labor market impacts were closely followed by sweeping economic policies directed towards both firms and households (Granja et al., 2020; Ganong et al., 2020).

Changes in economic opportunities and uncertainty, increased parental time at home during unemployment, and emotional cues have all been found to impact the prevalence of domestic violence (Aizer and Bo, 2009; Aizer, 2010; Anderberg et al., 2016; Lindo et al., 2018; Card and Dahl, 2011). Since the start of the pandemic, several high-profile news outlets have reported increased traffic at abuse hotlines and abuse help websites in both Europe and the US.[1] However, as seen in Figure 1, reported domestic violence incidents typically increase in the spring, suggesting some of the current reported rise might be due to seasonal trends.[2]

[1] See, e.g.,
https://www.cnn.com/2020/04/07/us/nyc-domestic-violence-website-surging/index.html.
https://www.cnn.com/2020/04/02/europe/domestic-violence-coronavirus-lockdown-intl/index.html.
https://www.nytimes.com/2020/04/06/world/coronavirus-domestic-violence.html.
https://www.nytimes.com/reuters/2020/04/24/world/europe/24reuters-health-coronavirus-britain-violence.html.
https://www.economist.com/graphic-detail/2020/04/22/domestic-violence-has-increased-during-coronavirus-lockdowns?utm_campaign=the-economist-today&utm_medium=newsletter&utm_source=salesforce-marketing-cloud&utm_term=2020-04-22&utm_content=article-link-4.

[2] Figure 1 shows trends for the inverse hyperbolic sine of domestic violence calls. Appendix Figure A.1 presents the data in levels.

We use difference-in-differences and event study methods to compare domestic violence calls for service in 14 large US cities before and after social distancing began, relative to trends during the same period in 2019. The pandemic led to a 7.5% increase in calls for service during March, April, and May. The biggest increase came during the first five weeks after widespread social distancing began, when domestic violence calls were up 9.7%. Failing to account for seasonal trends would overestimate the effects by 100%. The increase in reported domestic violence began around March 9, when data on cellphone GPS tracking and seated restaurant customers show people started spending more time at home. State-mandated stay-at-home orders or school closures came later, suggesting it was not a response to mandated quarantine and so might not reverse when the mandates are lifted.

We add to recent work exploring the impact of COVID-19 on domestic violence in Dallas (Piquero et al., forthcoming), child abuse reports in Florida (Baron et al., 2020), and crime in Los Angeles (Campedelli et al., 2020) by identifying impacts in cities across the US. We also use fine geographic detail for calls in some cities to study the uniformity of effects across groups. We find that social distancing leads to a large and statistically significant increase in domestic violence calls from city blocks without a recent history of domestic violence calls, suggesting COVID-19 has led to an extensive margin increase with new households placing calls. Meanwhile, the effect for blocks with a history of domestic violence calls is negative but very imprecise. We link the calls for service to census tract characteristics and find the rise in domestic violence calls is not driven by any particular demographic, income, or industry group. Effects are largest on weekdays, when families were likely to experience the greatest increase in time together and the most dramatic disruption to their routines. Sanga and McCrary (2020) perform a similar analysis and come to similar conclusions.

We measure the reduced-form impact of the pandemic on domestic violence calls in the US, with the understanding that any estimated impact could be driven by the public health response or economic consequences of the virus itself. Working with calls to police means we cannot disentangle changes in domestic violence incidence with changes in reporting patterns. We present suggestive evidence that the increase in calls is not driven by an increase in third-party reporting. If the pandemic depressed first-party reporting rates, our results would understate the effect on incidents. The significant increase in domestic violence calls for service indicate another cost created by the pandemic and the associated public health mitigation strategy.

2 Data

2.1 Police Calls for Service Data

We collect data on police calls for service from 14 large metropolitan cities or areas: Baltimore, Maryland; Chandler, Arizona; Cincinnati, Ohio; Detroit, Michigan; Los Angeles, California; Mesa, Arizona; Montgomery County, Maryland; New Orleans, Louisiana; Phoenix, Arizona; Sacramento, California; Salt Lake City, Utah; Seattle, Washington; Tucson, Arizona; and Virginia Beach, Virginia.[3] Throughout the paper,

[3]All of these cities except Phoenix participate in the Police Data Initiative. Of the 32 police agencies participating, these cities had up-to-date incidence data and provided adequate documen-

we refer to these as "cities," even though the Montgomery County Police Department covers multiple cities. Our sample includes cities in the West, Midwest, South, and Mid-Atlantic (see Appendix Figure A.2). All of the cities are in counties that initially had above-median cases per person; six were in the top quartile, and Orleans County (New Orleans) had the eighth highest per capita cases on March 31 (496 cases per 100,000).[4] We observe each individual call for service, including the date, time, and a brief description. Most cities in our sample provide enough information to match calls with census tracts. We aggregate calls to the city-by-day level because this is the smallest unit of geography available for all of the cities (see Data Appendix for details).

Although data for several cities are available virtually in real time, they have several limitations. First, call descriptions are not uniformly coded across cities in the data, and we must infer which calls are likely related to domestic violence. We code calls as domestic violence if the incident description contains the term "domestic violence," "domestic disturbance," "family fight," "family disturbance," or some variation. None of the cities in our sample employ all of these terms in their incident coding. The specific terms used by each city are provided in Appendix Table A.1.

We do not include incidents referring to child abuse for our main results. Most child maltreatment by parents or caretakers is managed by welfare agencies, while law enforcement handles abuse by out-of-home perpetrators (Gateway, 2019). Consequently, police calls for service for abuse incidents are likely to be a better measure of

tation to identify calls about domestic-violence-related incidents.

[4]For reference, New York City had 518 cases per 100,000 at this same time.

reports of child abuse occurring outside the home rather than domestic abuse. Recent work shows that COVID-19-induced school closures in Florida are associated with a 27% drop in reports of child maltreatment (Baron et al., 2020), consistent with educators playing an important role in child maltreatment reporting (Fitzpatrick et al., 2020).[5]

Second, police calls for service are an imperfect measure of domestic violence incidents. Not all domestic violence incidents are reported, and not all domestic violence claims are substantiated. Of intimate partner violence incidents recorded in the National Crime Victimization Survey (which may itself suffer from under-reporting) from 2014 to 2018, about 50% were reported to the police. Changes in domestic violence calls for service could be due to changes in the prevalence of abuse (and suspected abuse) or changes in reporting. Social distancing increases the likelihood of neighbors being home, potentially increasing third-party reporting. On the other hand, victims may self-report less when they spend more time together at home with their abusers.[6] We document the impact of social distancing on calls for service to likely domestic violence incidents with these caveats in mind and provide suggestive evidence that our results are not generated by an increase in third-party reporting.[7]

[5]In Appendix Table A.3 we document a decline in "abuse"-coded calls to the police and show our results are largely robust to including abuse-coded incidents in our measure of likely domestic violence incidents. The drop in "abuse" calls means that our estimated effects attenuate when we include them in our measure of domestic violence.

[6]Estimates suggest that approximately one-third of reported domestic violence is reported by a third party, while two-thirds are reported by the victim (Felson and Pare, 2005).

[7]Calls for service summary statistics are available in Appendix Table A.2.

2.2 Social Distancing Data

To estimate the pandemic's impact on domestic violence service calls, we must determine when it began to affect behavior. A natural starting point would be when states implemented mandatory stay-at-home orders. However, there is evidence that government-mandated stay-at-home orders can only explain a portion of the pandemic's economic impact (Rojas et al., 2020; Gupta et al., 2020; Aum et al., 2020). Using several data sources, Figure 2 shows a substantial decline in away-from-home time over a week before the first state-mandated stay-at-home order on March 19 (see Appendix B for a detailed data description).

In the top left panel, cellphone location data from SafeGraph (2020) indicates that across all states, the share of people staying home all day starts to increase around March 9 and has nearly doubled by the end of March. Similar cellphone-based measures from Unacast (2020) show a similarly timed drop in non-essential travel (top right panel). OpenTable restaurant reservation data also show that the number of seated diners fell dramatically starting around March 9, 2020 relative to 2019 (bottom left panel). All three of these data sources suggest social distancing began as many as ten days before the first stay-at-home order on March 19, 2020. Consistent with these trends, Google Search interest in "social distancing" starts to increase around the same period (bottom right panel).

3 Event Study Model

We estimate the impact of COVID-19 on domestic violence calls for service using both difference-in-differences and event study methods. Simply comparing the number of domestic violence calls in 2020 before and after social distancing began will not account for seasonal changes in domestic violence (see Figure 1). To account for seasonal trends and city-level differences in the incidence of domestic violence we compare daily domestic violence call counts within a given city before and after the social distancing "treatment" has occurred relative to daily domestic violence call counts in the city in 2019.[8]

We begin by estimating a weekly event study model to check for parallel trends during the pre-period and to examine the timing of effects. Doing this allows us to remain agnostic about the exact point when the pandemic started to impact people. The regression equation is

$$DVCalls_{cdy} = \sum_{\tau=0}^{13} \beta_\tau \mathbf{1}(Week\ \tau)_d * Year2020_y + \phi_{cy} + \delta_{c,week} + \theta_{c,dow} + \epsilon_{cdy}. \quad (1)$$

The outcome is the number of domestic violence calls in city c on day-of-the-year d in year y, or the inverse hyperbolic sine of the daily number of domestic violence calls, to account for level differences and to estimate percent effects. The indicator function $\mathbf{1}(Week\ \tau)_d$ takes a value of one if the day is in week τ. Our weeks begin on Mondays, with week 1 starting on the first Monday of each year. The sample is

[8]Data for some cities are not available before 2019. Table A.3 shows that the results are robust to estimation on a balanced panel extending back through 2017.

restricted to weeks 1 through 21 in 2019 and 2020, taking us through the end of May in 2020. $Year2020_y$ is an indicator for days in 2020. The β_τ coefficients trace out weekly changes in the number of domestic violence calls during the first 21 weeks of 2020 relative to 2019. The ninth week of the year is the reference week. During week 10 in 2020, which began on March 9, the NBA suspended its season, the WHO declared COVID-19 a pandemic, Donald Trump declared a national emergency, and the OpenTable, Unacast, SafeGraph, and Google Trends data suggest social distancing began in earnest. The state-ordered closure of non-essential businesses also fell between the onset of observed social distancing and the implementation of official stay-at-home orders for most states.

The incidence of domestic violence might vary substantially across cities, potentially resulting in different levels, seasonal trends, and day-of-week effects. For this reason, we include city-by-year (ϕ_{cy}), city-by-week ($\delta_{c,week}$), and city-by-day-of-week ($\theta_{c,dow}$) fixed effects to allow for city-specific trends in domestic violence calls across years, by season, or by day of week. As a result, we make within-city comparisons of daily call counts in 2020 relative to 2019. Because we only have 14 cities, we report wild bootstrapped confidence intervals and p-values to account for clustering at the city-level.[9]

Figure 3 presents event study coefficients for the inverse hyperbolic sine of daily domestic violence calls. Coefficients analyzing level effects are available in Appendix Figure A.3. Estimated effects for weeks 1 to 9 in January and February are relatively

[9]Bootstrapped confidence intervals need not be symmetrical around the point estimate. Because the treatment group is composed of 2020 city-year observations and the control group is composed of 2019 city-year observations, one might consider clustering standard errors at the city-year level. This does not have a substantive impact on our estimates' precision.

small, indicating flat pre-trends. Week 10 marks a clear break from the pattern of earlier weeks, kicking off five weeks of systematically high coefficients. The point estimates during weeks 10 through 14 indicate increases in domestic violence calls ranging from 6.4% to 9.4% relative to week 9. The point estimates drop off again starting in week 15, though they return to their previous levels in weeks 20 and 21. There are several factors that could drive the pattern of point estimates. Stress associated with the initial shock of school closures, food shortages, and workplace adjustments may have diminished over time. Compliance with social distancing measures also appears to have dropped off around this time, as evidenced by a reduction in the percentage of mobile devices staying completely at home (see Appendix Figure A.4). The majority of CARES Act stimulus checks went out in the middle of week 15, on April 15, 2020 and may have provided some relief from financial strain (Chetty et al., 2020).

Taken together, the event study results provide evidence that trends in 2019 and 2020 were similar in the pre-pandemic weeks. There was a marked divergence of trends between the two years coinciding with drastic shifts in behavior and signals about the severity of the pandemic. The increase in domestic violence persisted for several weeks before attenuating around the middle of April.

4 Difference-in-Differences Model

To quantify average effects, we estimate a difference-in-differences model comparing domestic violence calls in 2020 and 2019, before and after the ninth week of the year.[10] We estimate the following difference-in-differences equation:

$$DVCalls_{cdy} = \beta Post_d * Year2020_y + \phi_{cy} + \delta_{c,week} + \theta_{c,dow} + \epsilon_{cdy}. \qquad (2)$$

$Post_d$ is an indicator that equals one if the day is in the tenth week of the year or later (after March 9). The coefficient of interest is β, which represents the change in domestic violence calls after social distancing treatment begins for days in 2020 relative to the same period of time in 2019. We include the same set of rich fixed effects as in equation (1). The *Post* indicator is omitted because it is collinear with the city-by-week fixed effects. The identifying assumption is a parallel trends assumption. We must assume that daily domestic violence call counts would have continued on the same trend after the ninth week of 2020 as it did after the ninth week in 2019 if the pandemic and associated social distancing had not occurred.

Table 1 presents difference-in-differences results for both percent and level effects. For reference, in column (1) we also provide the simple difference estimated impact of social distancing on the number of domestic violence calls using only 2020 data (i.e., not accounting for seasonal trends).[11] The simple difference estimate would suggest there were, on average, 6.2 (or 14.8%) more domestic violence calls in each city every day after March 9, 2020 relative to earlier in the year. Column (2) presents difference-in-difference estimates with fixed effects for city, year, week of year, and day of week, and column (3) shows estimates with the city-interacted fixed effects in equation

[10]In column (2) of Appendix Table A.3 we show that the estimate is similar if we identify city-specific treatment timing using SafeGraph, OpenTable, and Unacast data.

[11]To do this, we estimate $DVCalls_{cd2020} = \beta Post_d + \phi_{c2020} + \theta_{c,dow} + \epsilon_{cd2020}$. Using only 2020 data, the $Post_d$ indicator would be subsumed by the city-by-week fixed effects which control for city-specific seasonal trends, so these fixed effects cannot be included.

(2). Both difference-in-differences specifications suggest there were, on average, 7.5% more domestic violence calls after social distancing began. Failing to accounting for seasonal trends in domestic violence calls would result in overestimating the treatment effect by a factor of two. Column (4) reports coefficients if we restrict the post-period to weeks 10 through 14, where the event study showed effects were concentrated. In the five weeks after social distancing began, domestic violence calls increased by 9.7%, or about 3.4 calls per day per city.

5 Robustness

The difference-in-differences point estimate is stable if we exclude each city one-by-one (see Appendix Figure A.5) or include city-by-day-of-year fixed effects, which would allow for very flexible city time trends (Appendix Table A.3).[12] In Appendix Figure A.6 we plot the difference-in-differences coefficients when we assign the beginning of treatment forward or backward up to seven days. The point estimates are stable. Our estimates are also insensitive to using SafeGraph, OpenTable, and Unacast data to define city-specific treatment start dates (Appendix Table A.3). They are insensitive to using the full year of data in 2019, adding 2017 and 2018 as additional pre-period years (which excludes Detroit and Montgomery County), or using a Poisson or negative binomial count estimator (Appendix Table A.3).

As a placebo check, we see if the estimated effects are different than the effects that would be estimated in an earlier period when no social distancing occurred. To do this, we randomly choose 100 days between March 9, 2019 and October 7,

[12]Event study estimates are also similar if we exclude each city one-by-one.

2019 and assign this date as the beginning of the "treatment" period.[13] We then compare the 2019 placebo treatment period to the same period in 2018.[14] In Figure 4 we plot the distribution of these 100 coefficients as well as our baseline estimate from column (3) and the estimate from a regression like equation (2), with 2018 used as the control year rather than 2019. Both estimates are larger than all of the placebo estimates, suggesting these effects would not likely be observed if there was no treatment. The concentration of the placebo estimates around zero illustrates that the trends in 2019 were similar to trends in 2018, reassuring us that 2019 is a reasonable control to capture typical seasonal patterns.

6 Heterogeneity

There are several channels through which social distancing and other effects of the COVID-19 pandemic might affect domestic violence calls. Social distancing could have a direct effect on reporting rates. If victims find it more difficult to report domestic violence because their abusers spend more time at home, then our estimates would understate the impact on incidents. On the other hand, third-party reporting could increase due to more neighbors being at home. In this case, we might expect to see larger effects in areas with higher population density. Figure A.7 plots estimates of the pandemic's impact during the first five weeks after social distancing began (coefficients on $Post_d * Year2020_y$ from equation (2)) for various subgroups.[15] When

[13] We only choose dates through October 7 to allow for a full 12 weeks after treatment starts.

[14] Information on domestic violence calls is not available in Detroit until November 2018. As such, we exclude Detroit from this exercise. We also plot the difference-in-difference coefficient from the 2018 to 2020 comparison, which does not include Detroit.

[15] Figure A.7 compares census tracts above and below the median for a variety of characteristics.

we estimate effects for high- and low-multi-unit housing census tracts separately, the point estimates are nearly identical: 8.6% versus 8.8%. Reports from the National Domestic Violence Hotline also suggest the fraction of third-party calls did not change from 2019 to 2020 (National Domestic Violence Hotline, 2019, 2020). We conclude that an increase in third-party reporting is unlikely to be driving the increase in domestic violence calls.[16]

Financial vulnerability during a time of economic downturn, restructured living patterns including more time at home, unemployment, and general stress surrounding the pandemic and uncertainty about the future could all increase the incidence of domestic violence. The variation across cities in the timing and intensity of outbreaks is limited and correlated with the timing of other policy interventions, like the closure of non-essential businesses. Unfortunately, with the tight timing and limited number of cities, we cannot clearly decompose how much of the increase is attributable to each channel.

Economic effects and increases in time spent at home were pervasive, so we are unable to compare harder hit areas to relatively unscathed ones. When we predict employment losses for each tract based on baseline industry composition in 2018 and national unemployment rates by industry in the April 2020 jobs report, we find that losses are large across all census tracts, with little variation above (mean of 16.8%) or below the median (mean of 13.8%). Perhaps it is not surprising, then, that when we look at effects within groups that may be most financially vulnerable and/or

[16] Death/homicide data could be useful for separating trends in reporting versus incidence. Unfortunately, data with sufficient detail to test for evidence of changes in female or intimate partner homicide are not yet available.

disadvantaged in the labor market, we do not find systematically higher effects. Overall, the estimates in Figure A.7 show economically significant effects for almost all subgroups, suggesting this is not driven by any one particular group. Effects are largest on weekdays, when families were likely to experience the greatest increase in time together and the greatest disruption to their routines.

Using the reported city block, we also consider whether social distancing has increased domestic violence among households with a history of domestic violence (intensive margin) or has led to domestic violence in households without a history of abuse (extensive margin). House-level addresses are not reported, so we can only document whether the increase is concentrated among "repeat" offending city blocks or new blocks in the 12 cities that provide city block addresses (see Appendix Table A.4). The estimated effect for repeat-offending blocks is large and negative but imprecisely estimated. During the first five weeks of the pandemic, we estimate a significant increase in domestic violence service calls from blocks without a history of domestic violence. Because the effect for repeat-offending blocks is imprecisely estimate, we cannot reject that these effects are the same, but we can conclude that social distancing has led to an extensive margin increase in domestic violence calls.[17]

7 Conclusion

We find that the COVID-19 pandemic is associated with a 7.5% increase in domestic violence service calls during the 12 weeks after social distancing began. Effects were

[17]During this same period, calls for service in other categories, such as traffic and theft, as well as the total number of calls for service, fell (Appendix Figure A.8).

largest in the first five weeks, when domestic violence calls increased by nearly 10%, comparable to the effect of a home team upset loss or a hot day (Card and Dahl, 2011). If the pandemic impacted domestic violence calls similarly across the US, the result would be about 1,330 more calls per day during the first five weeks.[18] Based on the CDC's 2003 estimates, 1,330 domestic violence incidents would generate $5.7 million (2019$) a day in short run medical and productivity costs. This amount does not include any long-run costs due to impacts on physical health, mental health, or earnings (Bindler and Ketel, 2019; Aizer, 2011; Currie et al., 2018). Given the likely under-reporting of domestic violence incidents, the increase in actual incidents could be much greater. In the event of longer lasting periods of isolation alongside economic distress, the accumulated impact could have large, significant impacts in the short and long run.

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Tables and Figures

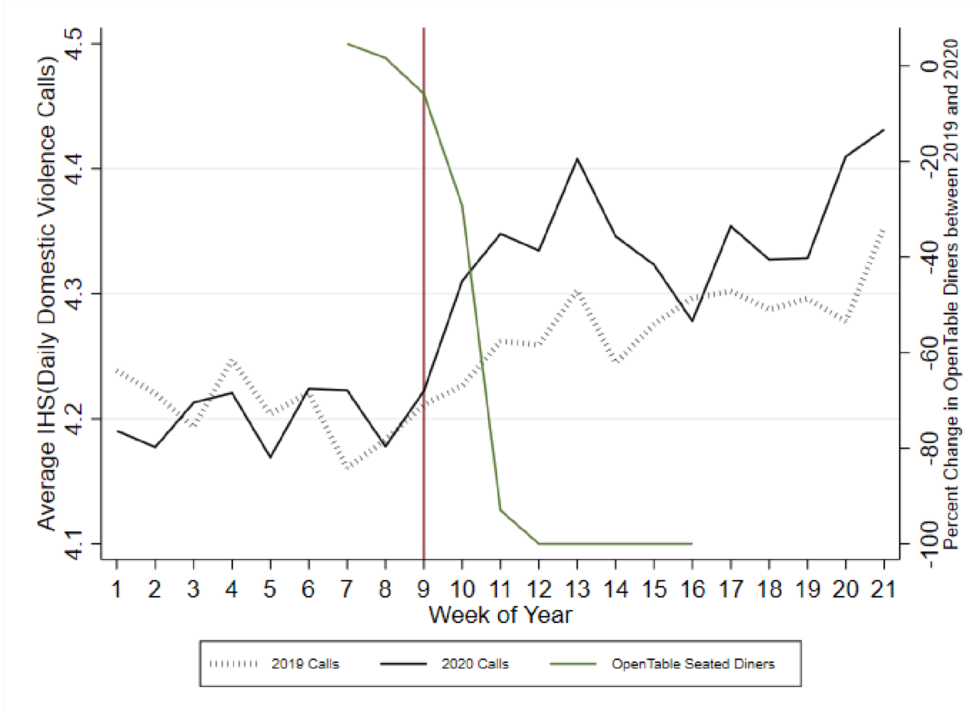

Figure 1: Trends in Domestic Violence Service Calls in 2019 and 2020

Note: The figure plots inverse hyperbolic sine of the average number of daily domestic violence service calls across 14 cities by week of year for 2019 and 2020. The downward sloping green curve uses OpenTable data to show the percent change in the number of seated restaurant diners in 2020 compared with 2019. The vertical red line falls on the week of March 2, 2020, one week before social distancing measures became widespread.

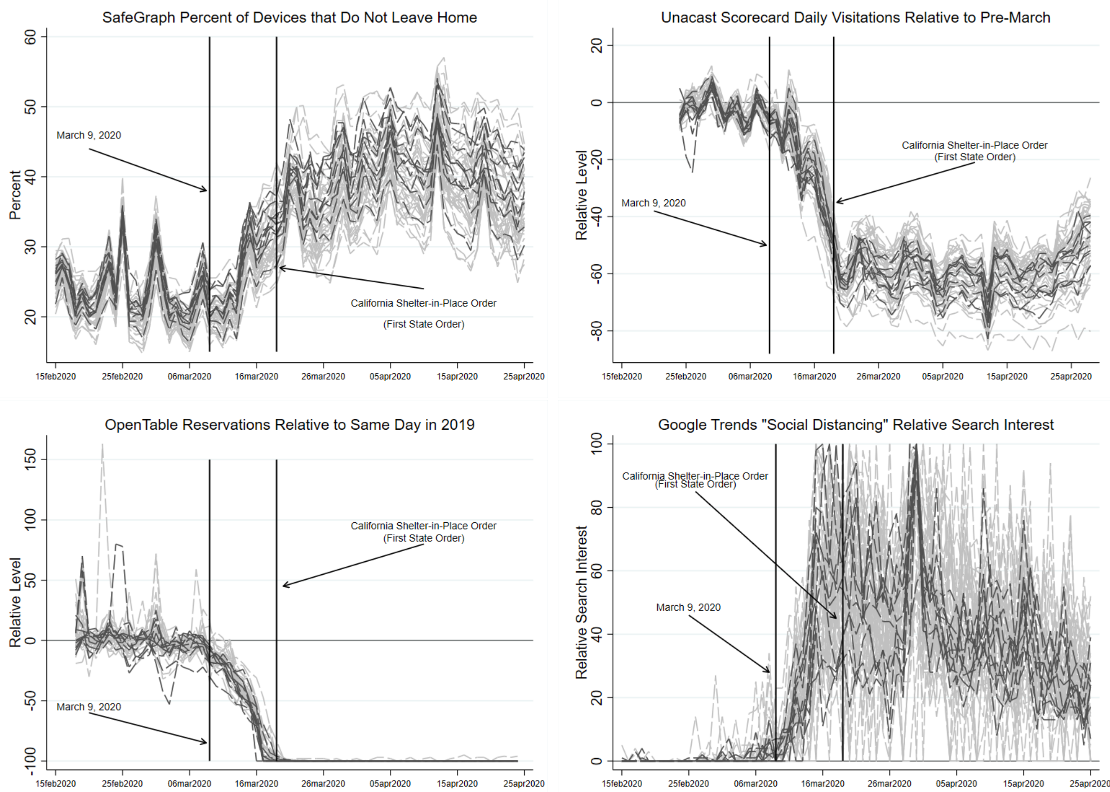

Figure 2: Evidence of Social Distancing

Note: Each graph uses data from a different source as a measure of social distancing intensity. There is a line in each graph for every state in the US. States with cities in our sample are plotted in dark gray. The top left panel plots the SafeGraph percent of tracked cellphone devices that do not leave home during the day. The top right panel plots Unacast non-essential travel relative to the same day of the week the previous year. The bottom left panel plots the number of seated diners at OpenTable restaurants in 2020 relative to 2019. The Unacast and OpenTable data are measured to account for day-of-week effects; the SafeGraph data are not, leading to a more volatile series. The bottom right panel plots Google Trends search intensity for "social distancing" by state in 2020. A value of 100 is the maximum search interest during the time period. March 9 is the day we assign the beginning of treatment for our difference-in-differences model.

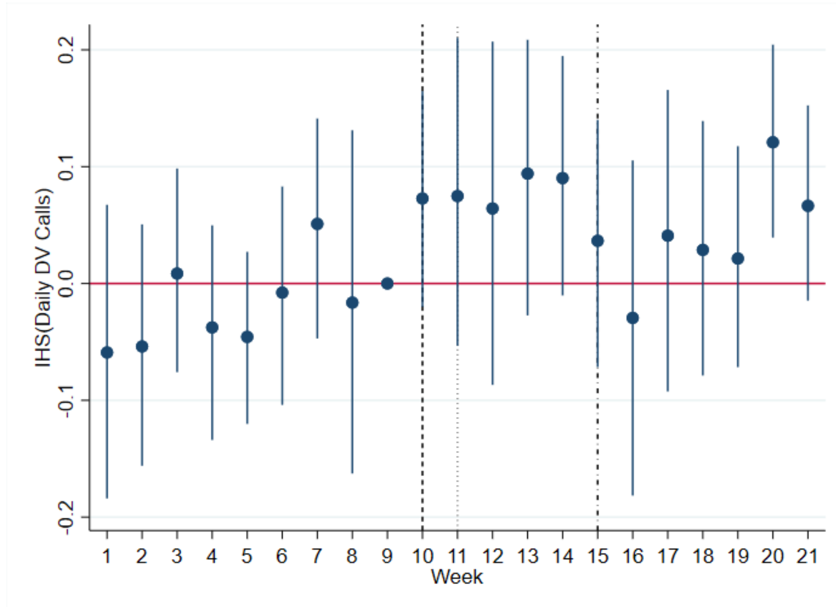

Figure 3: Event Study: Daily Domestic Violence Service Calls in 2020 Relative to January through March 2019

Note: The figures shows the plots of regression coefficients from the equation(1) where the outcome is the inverse hyperbolic sine of the number of domestic violence service calls at the city-by-day level. Only data from the first 21 weeks of 2019 and 2020 are included, bringing the sample period through the end of May in 2020. City-by-year, city-by-week-of-year, and city-by-day-of-week fixed effects are included. The vertical lines for each coefficient show 95% confidence intervals, cluster corrected at the city level using the wild bootstrap. The omitted week is the week 9 (beginning on March 2 in 2020). Our social distancing measures indicate that behavior began to change at the beginning of week 10 in 2020 (marked with a vertical dashed line). The first stay-at-home order went into effect during the second half of week 11 (marked with a vertical dotted line). The majority of stimulus checks went out during week 15 (marked with a vertical dash-dot line).

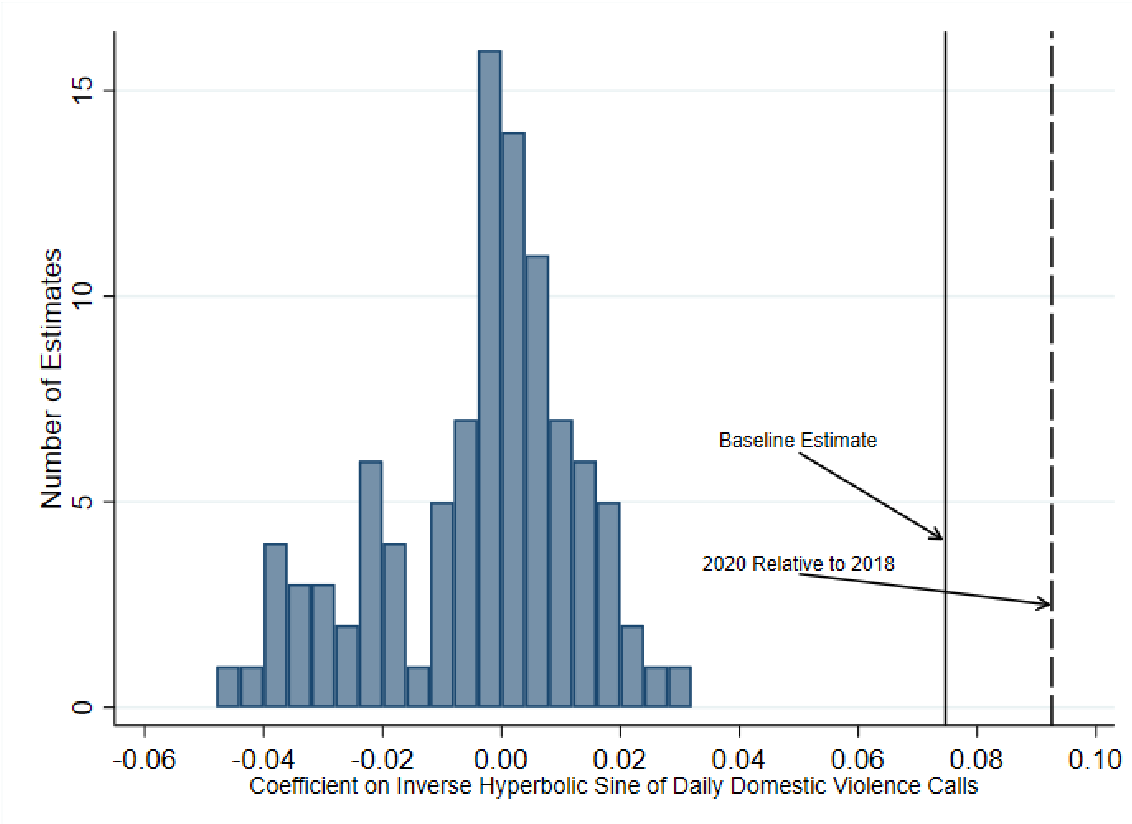

Figure 4: Placebo Tests: "Treatment Effects" for 100 Random Treatment Dates between March 9 and October 7, 2019

Note: The figure plots the regression coefficients from a regression similar to equation (2) where the outcome is the inverse hyperbolic sine of the number of domestic violence service calls at the city-by-day level, but compares 2018 to 2019. We also indicate our baseline estimate as well as the treatment effect estimate comparing 2018 to 2020. City-by-year, city-by-week-of year, and city-by-day-of-week fixed effects are included. Only dates through October 7 are used to allow for a full 12-week treatment period. Domestic violence call data for Detroit are not available until November 2018, so they are excluded from all 2018 comparisons. Wild bootstrapped standard errors are corrected for clustering at the city level.

Table 1: Impact of COVID-19 Social Distancing on Domestic Violence Service Calls

	(1) Weeks 1-21 2020	(2) Weeks 1-21 2020 and 2019	(3) Weeks 1-21 2020 and 2019	(4) Weeks 1-14 2020 and 2019
Outcome: IHS(Daily DV Calls)				
Post-Mar 9	0.148			
	[0.121, 0.176]			
	(0.000)			
Post-Mar 9*Year 2020		0.075	0.075	0.097
		[0.027, 0.119]	[0.030, 0.120]	[0.042, 0.153]
		(0.003)	(0.004)	(0.002)
Mean of dep. var.	4.286	4.269	4.269	4.269
Outcome: Daily DV Calls				
Post-Mar 9	6.164			
	[3.972, 8.485]			
	(0.000)			
Post-Mar 9*Year 2020		2.572	2.572	3.449
		[0.747, 4.453]	[0.710, 4.605]	[1.230, 5.706]
		(0.009)	(0.009)	(0.002)
Mean of dep. var.	43.495	43.110	43.110	43.110
N	2058	4116	4116	2744
FE	yes	yes	yes	yes
FE x City	yes	no	yes	yes

Note: Observation at the city-by-day level for 14 US cities. Data from the first 21 weeks of 2020 (January 6–May 31) are included in column (1). Data from the first 21 weeks in both 2019 and 2020 are included in columns (2), (3), and (4). The outcome in the top panel is the inverse hyperbolic sine of the daily number of domestic violence service calls. The inverse hyperbolic sine transformation is used to estimate percent effects, but unlike the natural log, it is defined at zero. The outcome in the bottom panel is the measure in levels. Column (1) includes city and city-by-day-of-week fixed effects. Column (2) includes city, week-of-year, year, and day-of-week fixed effects. Columns (3) and (4) include city-by-year, city-by-week-of-year, and city-by-day-of-week fixed effects to control for city-specific secular trends, seasonality, and day-of-week differences. 95% confidence intervals from wild bootstrapped standard errors corrected for clustering at the city-level are reported in brackets, with the associated p-value in parentheses.

Online Appendix

A Additional Tables and Figures

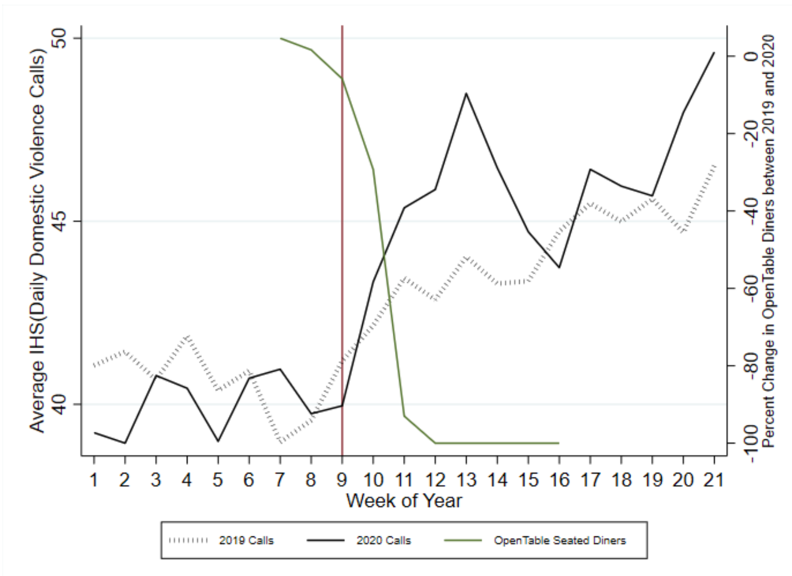

Figure A.1: Trends in Domestic Violence Police Service Calls in 2019 and 2020, Levels

Note: The figure plots the average number of daily domestic violence service calls across 14 cities by week of year for 2019 and 2020. The downward sloping green curve uses OpenTable data to show the percent change in the number of seated restaurant diners in 2020 compared with 2019. The vertical, red line falls on the week of March 2, 2020, one week before social distancing measures became widespread during the week of March 9, 2020.

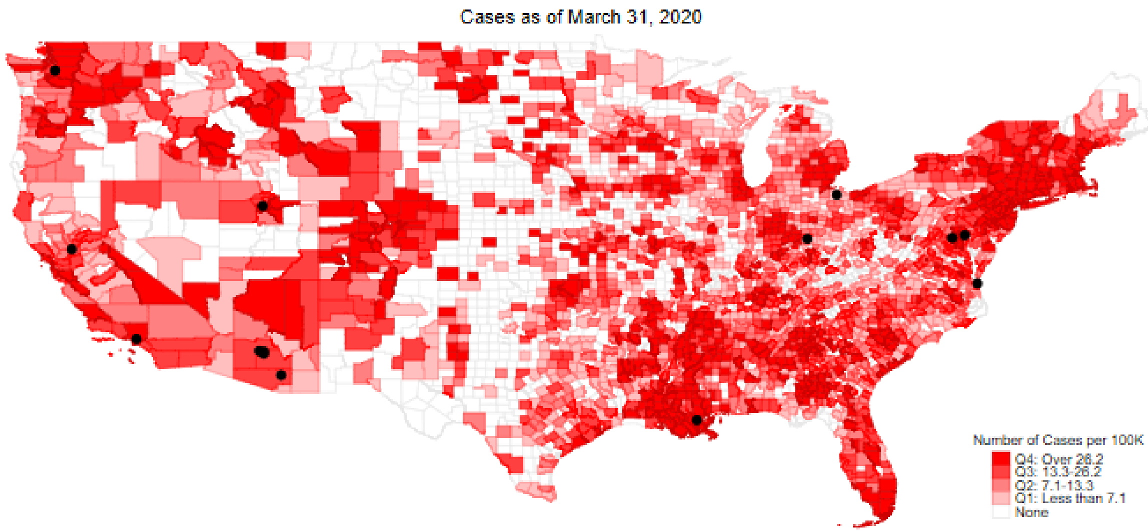

Figure A.2: County-level COVID-19 Infection Rates by March 31, 2020

Note: The figure plots the total number of COVID-19 positive cases per 100,000 people at the county level. Cities in our Call for Service sample are marked with a black dot.

Source: COVID-19 case counts provided by the New York Times.

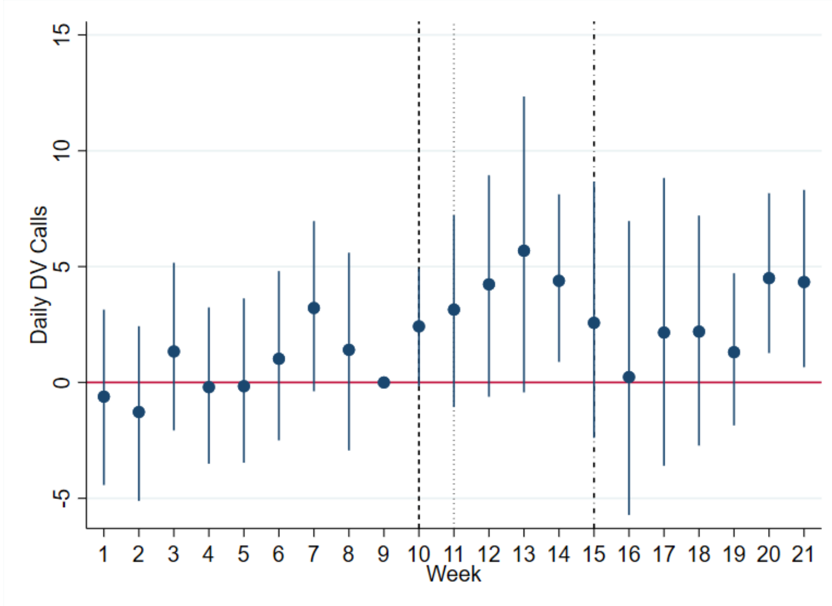

Figure A.3: Event Study: Daily Domestic Violence Service Calls in 2020 Relative to January through March 2019.

Note: The regression coefficients from the equation(1) where the outcome is the number of domestic violence service calls at the city-by-day level are plotted. Only data from the first 21 weeks of 2019 and 2020 is included, bringing the sample period through the end of May in 2020. City-by-year, city-by-week of year, and city-by-day of week fixed effects are included. The vertical lines for each coefficient show 95% confidence intervals, cluster corrected at the city level using the wild bootstrap. The omitted week is the week 9 (beginning on March 2 in 2020), Our social distancing measures indicate that behavior began to change at the beginning of week 10 in 2020 (marked with a vertical dashed line). The first stay-at-home order went into effect during the second half of week 11 (marked with a vertical dotted line). The majority of stimulus checks went out during week 15 (marked with a vertical dash-dot line).

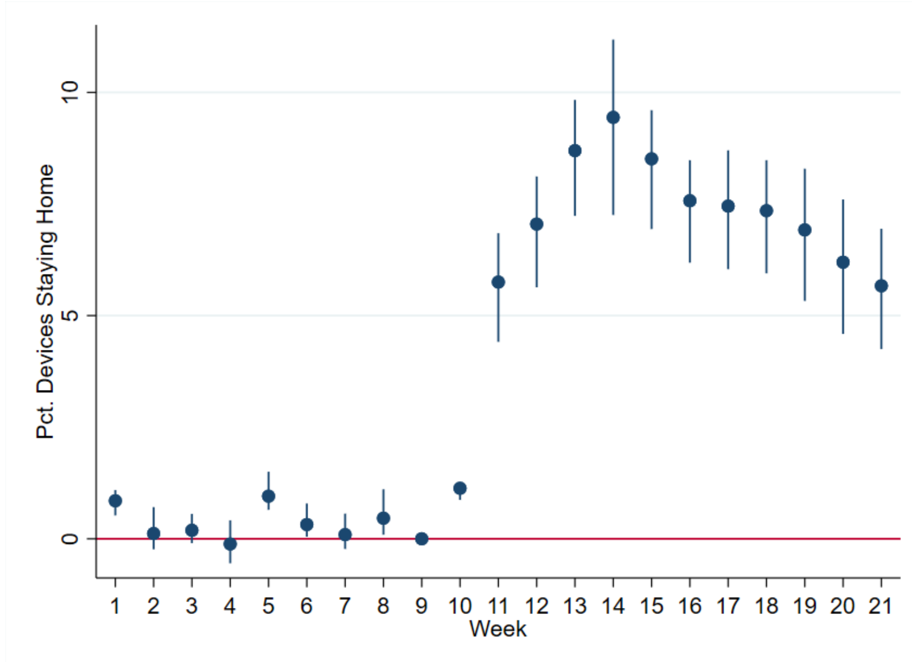

Figure A.4: Trends in the SafeGraph Percent of Devices Completely Staying Home

Note: Regression coefficients for weekly indicators from the regression of the percent of devices that stay home completely on week indicators, county-by-day-of-week fixed effects, and census tract fixed effects are plotted. The level of observation is the tract by day level from January 6, 2020 through May 31, 2020 (the first 21 weeks of 2020). Wild bootstrapped standard errors are corrected for clustering at the county level. The omitted week is the week of March 2, one week before OpenTable and Unacast data suggest social distancing began.

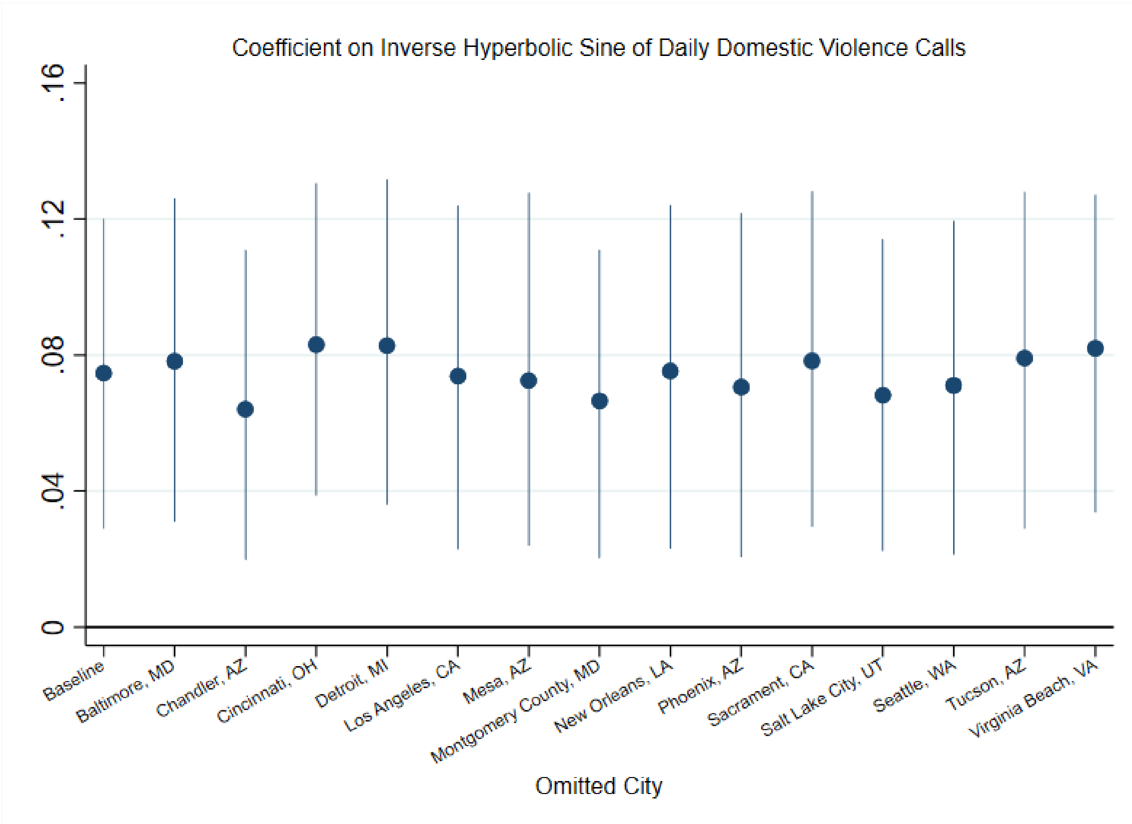

Figure A.5: Sensitivity of Point Estimate to Each City

Note: The regression coefficients from the equation (2) are plotted where the outcome is the inverse hyperbolic sine of the number of domestic violence service calls at the city by day-level. For each point, one city is excluded. City-by-year, city-by-week of year, and city-by-day of week fixed effects are included. Wild bootstrapped standard errors are corrected for clustering at the city-level.

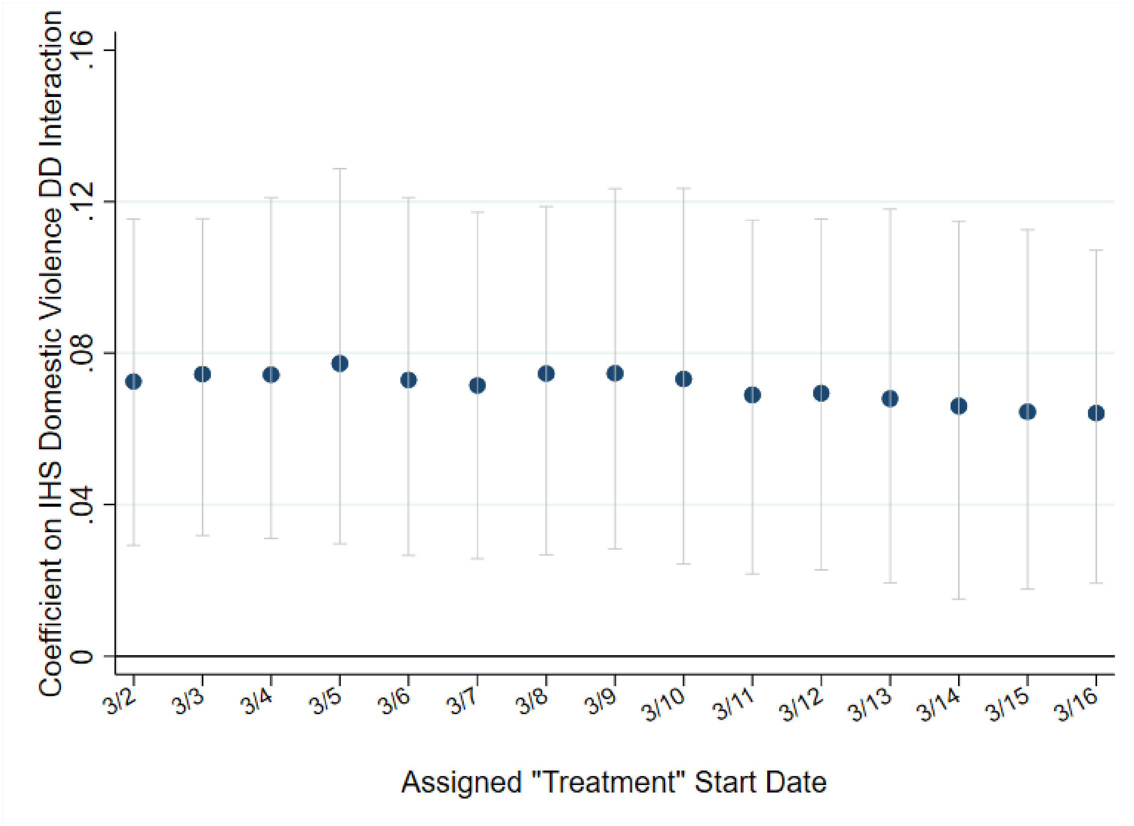

Figure A.6: Sensitivity of Point Estimate to Exact Date of Treatment

Note: The regression coefficients from the equation (2) are plotted where the outcome is the inverse hyperbolic sine of the number of domestic violence service calls at the city by day-level. For each point, the treatment date is moved forward or backward to that day. City-by-year, city-by-week, and city-by-day of week fixed effects are included. Wild bootstrapped confidence intervals are corrected for clustering at the city-level.

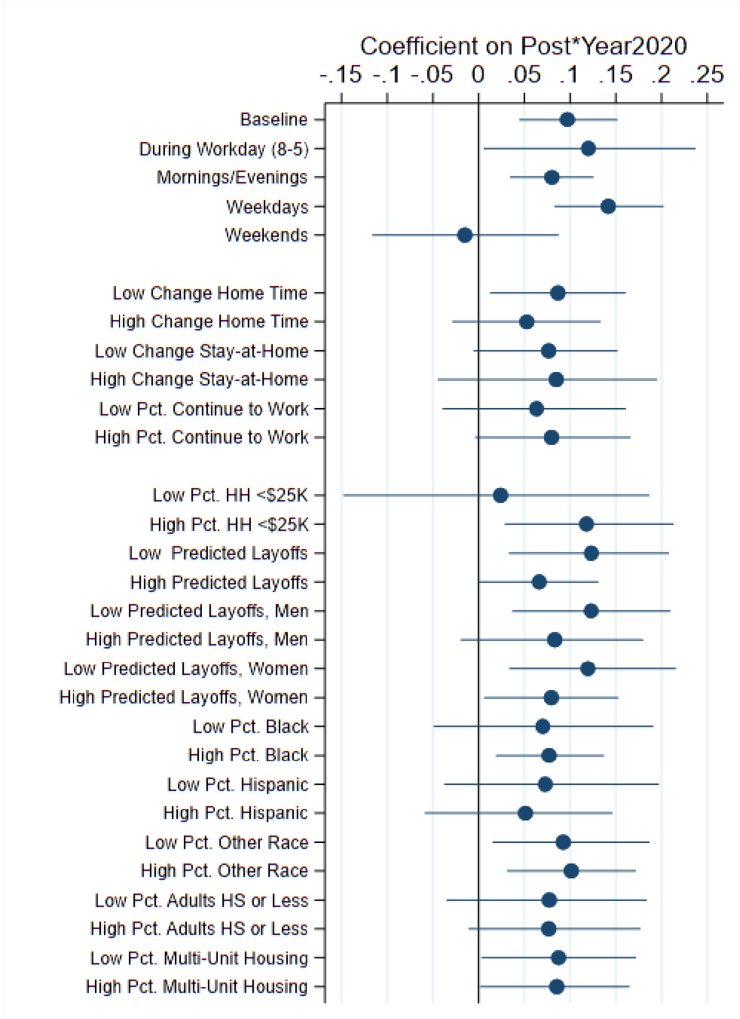

Figure A.7: Heterogeneous Impacts of the COVID-19 Pandemic on Domestic Violence Service Calls

Note: Coefficients from the city-by-day-level regression in equation (2), where either the outcome is a subset of total domestic violence calls (e.g., calls between 8 am and 5 pm) or the sample is restricted to a subset of the data (e.g., only weekdays). The sample period is the first 14 weeks of 2019 and 2020, so that coefficients reflect estimated effects during the first five weeks after social distancing began, when the event study results in Figure 3 suggest average effects were largest. "Low" census tract measures refers to below the median, "high" refers to above the median. Outcomes by census tract demographics only include 11 cities that have sufficient address information to link the incidents to census tracts. Salt Lake City also has some address information, but a smaller fraction of service calls can be linked to the census tract so it is excluded. 95% confidence intervals are obtained by wild bootstrap clustering.

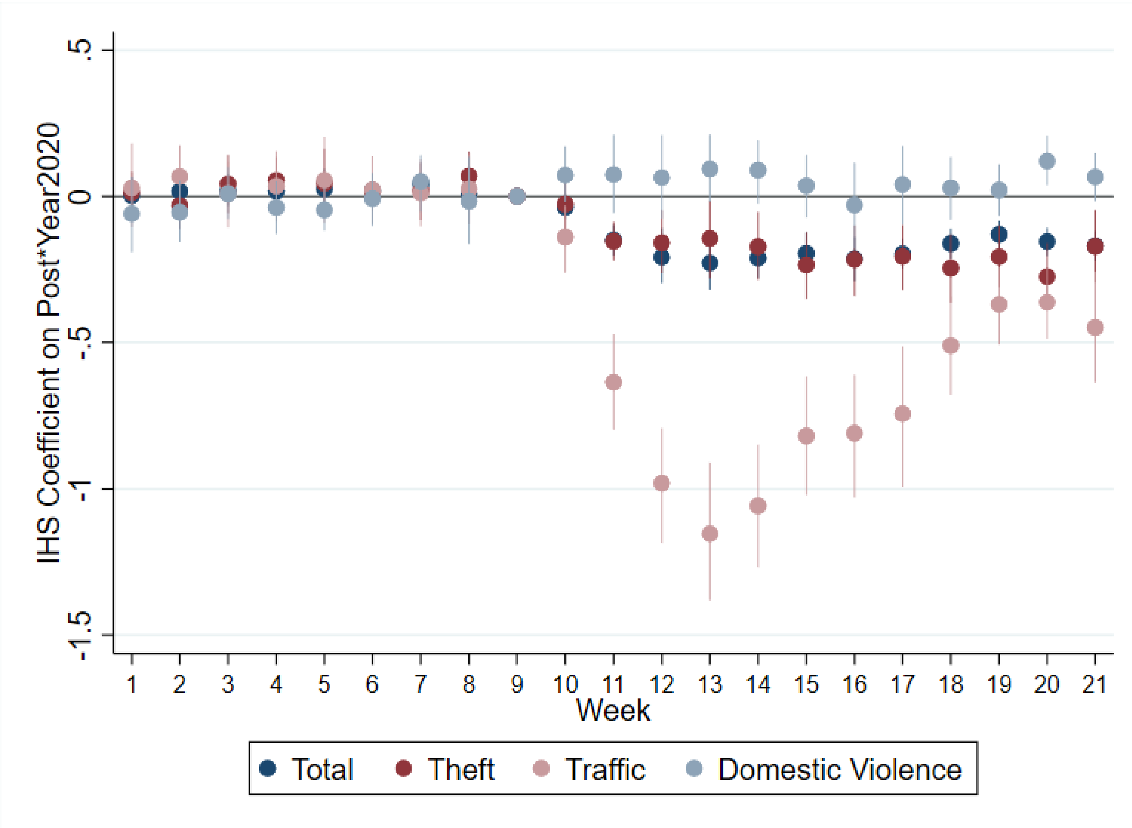

Figure A.8: Response of Total Service Calls, Theft Calls, and Traffic Calls to COVID-19 Social Distancing

Note: The regression coefficients from equation (1) are plotted where the outcome is the inverse hyperbolic sine of total calls, calls about theft, calls about traffic, and calls about domestic violence. City-by-year, city-by-week of year, and city-by-day-of-week fixed effects are included. Wild bootstrapped confidence intervals are corrected for clustering at the city-level.

Table A.1: Dates of Data Availability and Service Description Domestic Violence Terms for Sample Cities

(1) City	(2) Stay-at-Home Order in Place	(3) First Available Date	(4) Last Available Date as of June 22, 2020	(5) Geographic Data	(6) Parsing Terms Used to Identify Domestic Violence Calls
Baltimore, MD	March 30, 2020	June 30, 2013	June 22, 2020	Yes	“family dis”, “dom”
Chandler, AZ	March 31, 2020	January 1, 2017	June 22, 2020	Yes	“domestic disturbance”
Cincinnati, OH	March 24, 2020	September 30, 2014	June 22, 2020	Yes	“domestic”, “family trouble”
Detroit, MI	March 24, 2020	November 6, 2018	June 11, 2020	Yes	“dv”
Los Angeles, CA	March 19, 2020	January 1, 2017	June 13, 2020	No	“dom viol”
Mesa, AZ	March 31, 2020	January 1, 2017	June 22, 2020	Yes	“family fight”
Montgomery County, MD	March 30, 2020	April 2, 2017	June 22, 2020	Yes	“domestic”
New Orleans, LA	March 23, 2020	January 1, 2017	June 21, 2020	Yes	“domestic disturbance”
Phoenix, AZ	March 31, 2020	January 1, 2017	June 22, 2020	Yes	“domestic violence”
Sacramento, CA	March 19, 2020	January 1, 2017	June 10, 2020	Yes	“domestic”, “disturbance-family”
Salt Lake City, UT	March 27, 2020	January 1, 2017	May 31, 2020	Yes*	“domestic”
Seattle, WA	March 23, 2020	June 2, 2009	June 19, 2020	No	“dv” exclude “no welfare chk or dv”, “order” and “not dv”
Tucson, AZ	March 31, 2020	January 1, 2017	June 21, 2020	Yes	“dv”, “domestic viol” exclude “advisement”
Virginia Beach, VA	March 30, 2020	January 1, 2018	June 15, 2020	Yes	“domestic”

Note: Detroit has service call data available prior to November 6, 2018, but it does not include calls related to domestic violence. State mandated Stay-at-Home orders obtained from (Gupta et al., 2020). *Salt Lake City provides city block address, but without the zip code few incidents can reliably be geocoded so it is not included in the census tract analysis.

Table A.2: Summary Statistics

	(1) 2019	(2) 2020
Total calls for service	1616.72	1576.17
Daily domestic violence calls	42.72	43.50
Calls between 8 AM and 5 PM	14.57	14.50
Calls at other times	28.15	29.00
Calls to street blocks with 3 month history	22.21	22.87
Calls to street blocks without 3 month history	16.33	16.84
Calls about theft	72.29	66.27
Calls about traffic incidents	207.95	159.70
N	2058	2058

Note: Each column shows average values for the cities in our sample weeks one through 21 of the indicated year, where week one begins on the first Monday of the year.

Table A.3: Robustness: Alternative Estimation

	IHS(Domestic Violence Calls)				Domestic Violence Calls		IHS(DV and Abuse)	IHS(Abuse)
	(1) City by Day of Year F.E.	(2) City-Specific Treatment Timing	(3) Include Apr.-Dec. 2019	(4) Include 2017 and 2018	(5) Poisson	(6) Negative Binomial	(7)	(8)
Post-period: Weeks 10-21								
Post-Mar 9*Year 2020	0.077	0.075	0.072	0.128	0.059	0.060	0.039	-0.379
	[0.034, 0.126]	[0.031, 0.119]	[0.025, 0.116]	[0.066, 0.220]	[0.035, 0.083]	[0.035, 0.084]	[-0.004, 0.082]	[-0.540, -0.229]
	(0.002)	(0.003)	(0.011)	(0.000)	(0.006)	(0.016)	(0.076)	(0.000)
Mean of dep. var.	4.269	4.269	4.137	4.189	4.269	4.269	4.269	4.269
N	4116	4116	7632	6468	4116	4116	4116	4116
Post-period: Weeks 10-14								
Post-Mar 9*Year 2020	0.097	0.089	0.093	0.148	0.079	0.081	0.059	-0.399
	[0.046, 0.148]	[0.039, 0.139]	[0.041, 0.148]	[0.069, 0.252]	[0.046, 0.111]	[0.048, 0.114]	[-0.003, 0.115]	[-0.572, -0.218]
	(0.001)	(0.000)	(0.005)	(0.000)	(0.003)	(0.001)	(0.052)	(0.000)
Mean of dep. var.	4.241	4.241	4.101	4.171	4.241	4.241	4.241	4.241
N	2744	2744	3032	4312	2744	2744	2744	2744

Note: Observation at the city-by-day-level. The outcome in columns (1) through (4) is the inverse hyperbolic sine of the number of domestic violence calls. In column (2), state-specific OpenTable data, county-specific SafeGraph data, and county-specific Unacast data is used to identify when treatment begins in each area. To do this, we identify the first day that OpenTable diner data or Unacast cellphone travel data drops by at least 10% and continues to drop for at least two of the next four days, or SafeGraph cellphone stay-at-home percent increases by at least 10% and continues to rise for at least two of the next four days. We then use this day to indicate the start of "treatment". The beginning-of-treatment day is within one day of March 9 for 11 of the 15 cities with the earliest treatment beginning 12 days earlier. Column (3) includes all days from January 2019 to March 2020. Column (4) includes 2017 and 2018 with 2019 in the control period. This excludes Detroit and Montgomery County. Column (5) uses Poisson maximum likelihood estimation. Column (6) uses negative binomial maximum likelihood estimation. Column (7) expands the definition the outcome variable to include any references to "abuse" or "child abuse" (but does not include things like animal abuse). Column (8) only examines services calls for abuse. In columns (1) and (2) city-by-day of year rather than city-by-week of year fixed effects are included. Otherwise, all regressions include city-by-week of year, city-by-year, and city-by-day of week fixed effects. Constructing bootstrapped confidence intervals clustering at the city-level for the Maximum Likelihood-based estimators used in Poisson (5) and negative binomial (6) regressions is computationally burdensome, so we use conventional clustering by city/year for these specifications. (We can still reject that the coefficients equal zero when we bootstrap cluster-correct at the city-level.) 95% confidence intervals from wild bootstrapped standard errors corrected for clustering at the city-level are reported in brackets, with the associated p-value in parentheses.

Table A.4: Extensive vs. Intensive Margin: Impact on Domestic Violence Calls by Street Block History of Domestic Violence Calls

	(1) Baseline	(2) From Block with DV Call <3 Months	(3) From Block without DV Call <3 Months	(4) From Block with DV Call <6 Months	(5) From Block without DV Call <6 Months	(6) From Block with DV Call <1 Year	(7) From Block without DV Call <1 Year
Post-period: Weeks 10-21							
Post-Mar 9*Year 2020	0.070	-0.037	0.100	-0.074	0.137	-0.092	0.170
	[0.016, 0.126]	[-0.398, 0.179]	[-0.014, 0.284]	[-0.451, 0.157]	[-0.031, 0.394]	[-0.421, 0.141]	[-0.047, 0.471]
	(0.019)	(0.996)	(0.146)	(0.958)	(0.227)	(0.948)	(0.233)
Mean calls/day	39.123	22.537	16.586	26.559	12.565	29.957	9.167
N	3528	3528	3528	3528	3528	3528	3528
Post-period: Weeks 10-14							
Post-Mar 9*Year 2020	0.099	-0.117	0.186	-0.152	0.239	-0.161	0.281
	[0.034, 0.164]	[-0.601, 0.176]	[0.028, 0.411]	[-0.636, 0.145]	[0.053, 0.520]	[-0.684, 0.151]	[0.059, 0.634]
	(0.004)	(0.995)	(0.016)	(0.979)	(0.005)	(0.973)	(0.007)
Mean calls/day	37.979	21.955	16.024	25.846	12.133	29.145	8.834
N	2352	2352	2352	2352	2352	2352	2352

Note: Observation at the city-by-day-level. The outcome is the inverse hyperbolic sine of daily domestic violence calls. For each column only a subgroup of calls are included in the aggregation. For example, column (2) is the inverse hyperbolic sine of the sum of domestic violence calls from city block addresses where a domestic violence call was observed within the past three months while column (3) is the inverse hyperbolic sine of the sum of domestic violence calls from city blocks without a domestic violence call in the past three months. Only the city block level address is available (e.g., 6XX Main Street), so we can not identify repeat offending addresses, only repeat offending street blocks. All regressions include city-by-week of year, city-by-year, and city-by-day of week fixed effects. Wild bootstrapped confidence intervals and p-values corrected for clustering at the city-level are provided.

B Data Appendix

Call for Service Data

Call for Service data is provided individually by each city. We collect data on police calls for service from 14 large metropolitan cities or areas: Baltimore, Maryland; Chandler, Arizona; Cincinnati, Ohio; Detroit, Michigan; Los Angeles, California; Mesa, Arizona; Montgomery County, Maryland; New Orleans, Louisiana; Phoenix, Arizona; Sacramento, California; Salt Lake City, Utah; Seattle, Washington; Tucson, Arizona; and Virginia Beach, Virginia. All of these cities, but Phoenix, participate in the Police Data Initiative. Of the 32 police agencies that participate in the initiative, these are the cities that had up-to-date incidence data and provided adequate documentation to identify calls about domestic violence related incidents. Bloomington, Indiana has data available through March 31, 2020 and the results are unchanged if we include Bloomington and examine effects through the end of March. St. John, Indiana also has up-to-date incident data, but is much smaller than the other areas, with only a population of approximately eighteen thousand.

Call for service descriptions are not uniformly coded across cities in the data and we must infer which calls are likely to relate to domestic violence. We examine the descriptions in all sample cities to identify likely domestic violence calls. The specific terms used by each city are provided in Appendix Table A.1.

We observe each individual call for service, including the date, time, and a brief description. We have geographic information for each call in 11 of the 14 cities. Baltimore and Detroit provide the actual census tract of each call; Chandler, Mesa, Montgomery County, New Orleans, and Sacramento provide latitude and longitude coordinates; Phoenix, Salt Lake City, Tucson, and Virginia Beach provide city block addresses. For Chandler, Mesa, Montgomery County, New Orleans, and Sacramento we assign each call to the census tract with the closest population centroid. For Phoenix, Tucson, and Virginia Beach we use ArcGIS to geocode each address to a latitude and longitude, and then assign each call to the census tract with the closest population centroid. City block addresses in Salt Lake City were geocoded at a much lower rate than the other cities with more ties. For this reason, we do not include Salt Lake City in the tract-level analysis but it is included in the extensive/intensive margin analysis which only uses the city block address.

We do not know the exact mapping of census tracts into police jurisdictions. As such, we cannot perfectly distinguish between census tracts that do not report calls for service to the jurisdiction from census tracts that do not have calls for service. To avoid this problem, we assign calls for service to the closest census tract, divide census tracts in the counties of our sample cities above and below the median for each of the demographic characteristics we examine, and then sum up the number of calls from census tracts above (below) the median to the city by day-level. For example, this measure tells us the daily number of domestic violence calls from high (low) poverty census tracts in the city each day.

SafeGraph Cellphone Stay-at-Home Measures

SafeGraph is a marketing company that used cellphone data to create point-of-interest data and track foot traffic (SafeGraph, 2020). They provide census block-level daily number of mobile devices, number of devices that appear to engage in work-related commute travel, number of devices that do not leave a 150 yard square around their home, the average distance traveled, and the median minutes each device spends at home. For Figure 2 we aggregate the data to the state-level. We also use the SafeGraph data to estimate heterogeneous impacts by census tract level social distancing adherence. The SafeGraph data is only available from February 1, 2020 through April. In its raw form it does not adjust for differences by day of the week.

Unacast Cellphone Social Distancing Scorecard

Unacast is another marketing company that uses cellphone data to track people's mobility. They have generated the "Social Distancing Scorecard," which tracks how much geographic mobility and non-essential visits have changed since mid-February 2020 (Unacast, 2020). To do this, they compare day-of-week travel for the four weeks prior to March 8, 2020 to day-of-week travel in the subsequent weeks. We have access to the daily percent change in total distance traveled and non-essential visits at both the state and county level.

OpenTable Restaurant Reservations

OpenTable is a restaurant reservation booking platform that serves approximately 60,000 restaurants. OpenTable has provided year-over-year percent changes in the number of seated diners at OpenTable restaurants.[1] To do this they compare the number of diners during the same week of the year in 2019 and 2020 on the same day of the week. This data is available for all states with over 50 OpenTable restaurants (37 of 50 states plus DC) and starts on February 18th.

Google Trends Search Interest in "Social Distancing"

Google Trends provides measures of relative interest in a given search phrase. Within a specified region, a measure of the search interest, relative to the total number of searches is provided. The day or period with the highest relative search interest is assigned a value of 100, while every other day or period is assigned a number between 0 and 100, as a percent of the maximum value. As such, the levels are not directly comparable outside of the given geography-specific query. Google Trends measures can indicate when the search intensity of a given term increases relative to the total number of searches. As such, increases in the total number of searches could lead to a lower Google Trends measure of search intensity, even if the number of searches is constant or even increasing

[1] This includes online reservations, phone reservations, and walk-in customers.

slightly. Because the term “social distancing” was practically non-existent prior to March 2020, it is possible to observe increased search intensity even if the total number of searches has increased.

We have also examined the search intensity for terms related to domestic violence such as “abuse hotline”, bruise”, and “domestic violence”. Using a similar regression specification, we see search interest in these terms are unchanged and in some cases declining after March 9th. This is potentially due to an increase in total searches as more people remain at home. However, we do not observe the total number of searches. If there is not sufficient search interest in a particular term, the measure is suppressed. Specific phrases like “how to cover a black eye”, and “my husband hit me” are suppressed in most cities and states.

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