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

Emily Leslie*  Riley Wilson*

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Abstract

The COVID-19 pandemic has led to a worldwide economic slowdown as more people practice social distancing and shelter at home. The increase in time families spend in isolation, unemployment, and economic stress have the potential to increase domestic violence. In this paper, we document the impact of the COVID-19 crisis on police calls for service for domestic violence. The pandemic and accompanying public health response led to a 10.2 percent increase in domestic violence calls. The increase in reported domestic violence incidents begins before official stay-at-home orders were put into place, is not driven by any particular demographic group, but does appear to be driven by households without a prior history of domestic violence.

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

JEL Codes: J12, I18

*Brigham Young University, Department of Economics.
Email: emily.leslie@byu.edu, riley_wilson@byu.edu.

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1 Introduction

The worldwide COVID-19 pandemic and associated social distancing has pushed households to spend more time at home amidst rising unemployment rates and economic stress. The increase in at-home time, during stressful times, has the potential to increase domestic violence. In fact, several high-profile news outlets have reported increased traffic at abuse hotlines and abuse help websites in both Europe and the US.\footnote{See for example, https://www.cnn.com/2020/04/07/us/nyc-domestic-violence-website-surge/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.} However, as seen in Figure 1, there is typically an upswing in reported domestic violence incidents in the spring, suggesting some of the current reported rise might be due to seasonal trends.

In this paper, we use difference-in-differences and event study methods to compare domestic violence police calls for service in fifteen large, US cities before and after social distancing began, relative to trends during the same period in 2019. The social distancing\footnote{When we talk about the effects of social distancing, we refer to the combined effect of increased physical isolation, economic stress, and other general anxiety induced by the pandemic and the public health countermeasures against it.} associated with the COVID-19 pandemic led to a 10.2 percent increase in calls for service about domestic violence. Failing to account for seasonal trends would overestimate the impacts on domestic violence by approximately 46 percent. The increase in reported domestic violence begins around March 9th, when data on seated restaurant customers and cellphone GPS tracking suggest people started
spending more time at home. Importantly, the increase in domestic violence begins before any state-mandated stay-at-home orders or school closures occur, suggesting this was not a response to mandated quarantine and thus might not automatically reverse when the mandates are lifted.

The CDC estimates that over 25 percent of women and 10 percent of men will experience intimate partner violence during their lifetime (D’Inverno et al., 2019), with the economic cost of domestic violence among women around 5.8 billion dollars a year (Aizer, 2010; Centers for Disease Control and Prevention, 2003). Intimate partner domestic violence leads to injury, lost productivity, and in rare circumstances death (Centers for Disease Control and Prevention, 2003). In the Netherlands, domestic violence victimization has been shown to reduce earnings by 14-18 percent and increase dependence on transfer payments for up to four years (Bindler and Ketel, 2019). Domestic violence has also been shown to have negative impacts on infant health outcomes (Aizer, 2011; Currie et al., 2018).

Previous work examines the prevalence of domestic violence. Using 911 calls and arrest reports, Aizer and Bo (2009) show that “no-drop” domestic violence policies increase reporting of domestic violence. Aizer (2010) shows that when women’s wages increase relative to men’s, the incidence of domestic violence falls. Similarly, in the UK, increases in the male unemployment rate are associated with decreases in domestic abuse, while increases in the female unemployment rate are associated with increases in domestic abuse (Anderberg et al., 2016). Lindo et al. (2018) find that a reduction in employment opportunities for men leads to an increase in child abuse while reductions in female employment opportunities have the opposite effect. The
authors suggest that this pattern is consistent with changes in time spent with the child leading to changes in the prevalence of abuse or with the mental health impacts of unemployment playing a role. Card and Dahl (2011) exploit upsetting losses in professional football to show that emotional cues lead to increased family violence in the home team’s city. The COVID-19 pandemic has the potential to impact the amount of together time, employment prospects, as well as trigger emotional cues. We add to this literature by estimating how the COVID-19 pandemic and its accompanying public health social distancing impacts the prevalence of domestic violence incidents to better understand one dimension of the costs of the COVID-19 pandemic.

We find that social distancing leads to 10.2 percent more domestic violence calls. The increase is concentrated on weekdays. Using the reported city block, 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 domestic violence calls. Meanwhile, the effect for city 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. The point estimates are larger in neighborhoods where the predicted unemployment effects (based on 2018 industry composition) were smaller, but not significantly different. As nearly all census tracts saw large increases in predicted unemployment, we cannot rule out the role of increased economic, or financial stress.
Domestic violence calls exhibit similar increases in census tracts that experienced both large and small increases in home isolation, suggesting this is not simply the result of more time together. The 10 percent increase in domestic violence calls for service indicate another cost created by the COVID-19 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 15 large metropolitan cities or areas: Baltimore, Maryland; Bloomington, Indiana; 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. Throughout we will refer to these as “cities,” even though the Montgomery County Police Department covers multiple cities. Although data for several cities is available virtually in “real-time”, it has several limitations. First, 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. In general, we code calls as domestic violence related if the incident description contains the term “domestic violence”,

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. 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.
“domestic disturbance”, “family fight”, or “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 for each city are provided in Appendix Table A1.

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). As such, police calls for service for abuse incidents are likely to be a better measure of reports of child abuse occurring outside the home, rather than domestic abuse.4 Recent work suggests that COVID-19 induced school closures in Florida are associated with a 27 percent 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).

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. Changes in domestic violence calls for service could be due to changes in the prevalence of abuse (and suspected abuse) or changes in reporting. On one hand, social distancing increases the likelihood of neighbors being home, potentially increasing third-party reporting. On the other hand, when abusers and victims spend more time together at home, there might be a drop in self-reporting by victims.5 We will document the impact of social distancing on calls for service to likely domestic violence incidents with these caveats in mind, and provide

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4In the appendix, we show that our results are robust to including “abuse”-coded incidents in our measure of likely domestic violence incidents.

5Estimates 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).
suggestive evidence that our results are not generated by an increase in third party reporting.\textsuperscript{6}

\subsection*{2.2 Social Distancing Data}

To estimate the impact of the pandemic on domestic violence service calls we must determine when social distancing began. A natural starting point would be when states implemented mandatory stay-at-home orders. However, households might start self-isolating before these mandates occur. Using several data sources, we show in Figure 2 a substantial decline in away-from-home time nearly two weeks before the first state-mandated stay-at-home order on March 19th (see Appendix B for a detailed data description).

In the top left panel, cellphone location data from \textit{SafeGraph (2020)} indicates that across all states the share of people staying home all day starts to increase around March 9th and has nearly doubled by the end of March. Similar cellphone based measures from \textit{Unacast (2020)}, show a similarly timed drop in non-essential travel (top right panel). \textit{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).\textsuperscript{7} 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). Self-isolation practices, and

\textsuperscript{6}Calls for service summary statistics are available in Appendix Table A2.

\textsuperscript{7}The Unacast and OpenTable data is measured to account for day of week effects. The SafeGraph data is not, leading to a more volatile series.
potentially effects on domestic violence, began much earlier than shelter-in-place policies.

3 Empirical Strategy

We estimate the impact of COVID-19, and the related social distancing and economic and other stress, 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 begins 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 will 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 the previous year, 2019. The difference-in-differences estimation requires that we assign a date that treatment began. Given the decline in eating out and cellphone travel that precedes state stay-at-home orders by 1 to 2 weeks, using stay-at-home orders to define treatment timing would bias estimates towards zero. Based on the cellphone tracking and dining data, we assign treatment to start March 9th. This was the first day with a double-digit drop in OpenTable diners as well as the first day of the sustained drop. We will define weeks as 7-day periods, such that March 9th is the beginning of the 10th week of each year. To maximize the number of

\[\text{For our main results, we construct the sample window to maximize the number of cities in a balanced panel. Data for some cities is not available prior to 2019. In Table A3, we show that the results are robust to estimation on a balanced panel extending back through 2017.}\]

\[\text{In column (2) of Appendix Table A3 we show that the estimate is similar if we identify city-specific treatment timing using SafeGraph, OpenTable, and Unacast data.}\]
cities in the sample, we end our balanced panel on March 31, 2020. We estimate the following difference-in-differences equation:

\[
DV_{calls_{cdy}} = \beta Post_d \times Year2020_y + \alpha_c + \phi_y + \delta_{week} + \theta_{dow} + \epsilon_{cdy}
\]  

(1)

The outcome is the number of domestic violence calls for service 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 estimate percent effect impacts. \(Post_d\) is an indicator that equals one if the day is in the 10th week of the year or later (after March 9th). The sample is restricted to the same period, January-March, in 2019 and 2020. The coefficient of interest is \(\beta\), 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. City fixed effects (\(\alpha_c\)) control for time-invariant differences across cities, year fixed effects (\(\phi_y\)) control for secular trends in the prevalence of domestic violence, week-of-year fixed effects (\(\delta_{week}\)) control for potential seasonal trends, and day-of-week fixed effects (\(\theta_{dow}\)) day-of-week differences in domestic violence. The \(Post\) indicator is omitted because it is collinear with the week fixed effects. Because we only have 15 cities, we will report wild bootstrapped confidence intervals and p-values, to account for clustering at the city-level.\(^{10}\)

The incidence of domestic violence might vary substantially across cities, potentially resulting in different levels, seasonal trends, and day of week effects. For this

\(^{10}\)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 the precision of our estimates.
reason, our preferred estimation includes a richer set of fixed effect controls as follows:

\[ DVCalls_{cdy} = \beta Post_d \times Year2020_y + \phi_{cy} + \delta_{c,week} + \theta_{c,dow} + \epsilon_{cdy} \]  

(2)

We now include city-specific year, week-of-year, and day-of-week fixed effects. City-by-year fixed effects \((\phi_{cy})\) will control for within-city differences in domestic violence calls from one year to the next; city-by-week fixed effects \((\delta_{c,week})\) will control for city-specific seasonal trends; and city by day-of-week fixed effects \((\theta_{c,dow})\) will control for city-specific day-of-week differences in domestic violence. 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 week of March 9th, 2020 as it did after the week of March 9th in 2019 if the pandemic and associated social distancing had not occurred.  

When estimating the difference-in-differences specification we must take a stance on when social distancing began. We also estimate weekly event study models so that we can remain more agnostic about the precise start of treatment and to examine the plausibility of the parallel trends assumption. We will estimate the following

\[ DVCalls_{cdy} = \beta Post_d \times Year2020_y + \phi_{cy} + \delta_{c,week} + \theta_{c,dow} + \epsilon_{cdy} \]  

(2)

Card and Dahl (2011) shows that sporting event outcomes affect domestic violence rates. In response to COVID-19, the NBA postponed the season on March 11, 2020 followed by most other professional and collegiate sports. The state-ordered closure of bars and liquor stores, along with other non-essential businesses, also fell between the onset of observed social distancing and the implementation of official stay-at-home orders for most states. Stopping sporting events and limiting access to alcohol could reduce some types of domestic violence. Our estimates will capture the total effect of the COVID-19 pandemic and shutdown on domestic violence calls for service.
equation:

\[
DVCalls_{cdy} = \sum_{\tau=0}^{13} \beta_\tau (Week \, \tau)_d \times Year2020_y + \phi_c + \delta_{c,\text{week}} + \theta_{c,dow} + \epsilon_{cdy} \tag{3}
\]

Now the \( \beta_\tau \) coefficients trace out weekly changes in the daily number of domestic violence calls through January, February, and March in 2020 relative to 2019. The ninth week of the year (one week before March 9th) is omitted making this the reference week. The OpenTable, Unacast, SafeGraph, and Google Trends data suggest social distancing began in earnest in early to mid March. We test for parallel pre-trends in January and February. The same rich set of fixed effects from equation (2) are included, making this a within-city comparison of daily call counts in 2020 relative to 2019.

4 Results

Difference-in-differences results for both percent and level effects are presented in Table 1. 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).\(^\text{12}\) The simple difference estimate would suggest that there were on average 5.2 (or 14.9 percent) more domestic violence calls in each city every day after March 9th, 2020 relative to earlier in the year. Column (2) presents the difference-in-difference estimates from equation (1). When we allow

\(^\text{12}\)To do this we estimate \( DVCalls_{c,d2020} = \beta Post_d + \phi_{c,2020} + \delta_{c,dow} + \epsilon_{c,d2020} \). 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.
seasonal trends, day-of-week effects, and year trends to vary across cities (in column (3)) the effects are similar. The difference-in-differences specification suggests that there were on average 10.2 percent more domestic violence calls after social distancing began. Failing to accounting for seasonal trends in domestic violence calls would result in over-estimating the treatment effect by 4.7 percentage points, or 46 percent.

In the bottom panel of Table 1 we present estimates in levels. Social distancing led to on average 3.3 more domestic violence calls in each city every day after March 9, 2020, or 8.5 percent at the mean. Survey evidence suggests that domestic violence is underreported; of intimate partner violence incidents recorded in the National Crime Victimization Survey (which may itself suffer from underreporting) from 2014 to 2018, about 50% were reported to the police. To the extent that our measure is an accurate reflection of domestic violence reporting, we might expect the true impact on the number of domestic violence incidents to be on the order of twice the size of our calls-for-service effects.

Event study coefficients from equation (3) are presented in Figure 3. Estimated effects for weeks one to nine in January and February are not significantly different from zero and indicate flat pre-trends. This would suggest that daily domestic violence calls in 2020 prior to social distancing were not significantly different than in 2019. The week of March 9th, the estimate rises to a significant 10.7 percent. The estimates for the next two weeks are 3.1 percent and 7.0 percent respectively, with a significant increase of 21.5 percent in the last week of March. This is indicative of a rise in domestic violence calls once social distancing began.

The estimate in the last week of our sample is much larger, suggesting the effect
is potentially growing over time. To check this, we limit our sample to the 12 cities that have data available through April. As seen in Appendix Figure A1, the increase in domestic violence cases peaks in the last week of March, before declining back to 2019 levels by the end of April. 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. Congress passed its first stimulus bill on March 27, bringing with it the expectation of some relief from financial strain. 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 A2).

4.1 Robustness

The difference-in-differences point estimate is stable if we exclude each city one by one (see Appendix Figure A3) or include city-by-day-of-year fixed effects, which would allow for very flexible city time trends (Appendix Table A3). In Appendix Figure A4 we plot the coefficient on the difference-in-difference interaction for the inverse hyperbolic sine of daily domestic violence calls when we assign the beginning of treatment forward or backward up to seven days. The point estimates are stable, and only start to decline about a week after March 9th. Our estimates are also insensitive to using SafeGraph, OpenTable, and Unacast data to define city specific treatment start dates (Appendix Table A3). 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 A3).

As a placebo check, we test to see if the estimated effects are different than the effects that would be estimated in an earlier period when no social distancing was occurring. To do this, we randomly choose one hundred days between March 9, 2019 and October 31, 2019 and assign this date as the beginning of the “treatment” period.\(^{13}\) We then compare the 2019 “treatment” period to the same period in 2018.\(^{14}\) In Appendix Figure A5 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 of these estimates are larger than all of the placebo estimates, suggesting these effects would not likely be observed if there was no treatment.

### 4.2 Heterogeneity

Reporting rates may be directly affected by social distancing. 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 domestic violence 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. Estimates of the coefficients on $Post_d \times Year_{2020}$ from equation (2) for various subgroups are in Figure 4.\(^{15}\) When we estimate effects for high-

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\(^{13}\)We only choose dates through October 31 to avoid holidays at the end of the year.  
\(^{14}\)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 4 compares census tracts above and below the median for a variety of characteristics. The same comparisons for the top and bottom quartiles can be found in Figure A6.
and low-multi-unit housing Census tracts separately, the point estimates are nearly identical. We conclude that an increase in third party reporting is unlikely to be driving the increase in domestic violence calls.\textsuperscript{16}

There are several channels through which social distancing and other effects of the COVID-19 pandemic might affect domestic violence. 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 play a part.

When we look at effects within groups that may be most financially vulnerable and/or disadvantaged in the labor market, we do not find systematically higher effects. The estimated effects are higher in census tracts with fewer low-income households, fewer Hispanic households, and higher levels of education relative to areas with more low-income and Hispanic adults and lower levels of education (see Figure 4). Based on what we can observe, the economic stress induced by COVID-19 does not translate into relatively more domestic violence calls for groups that we might expect to be especially vulnerable.

We find suggestive evidence that increased time at home, particularly by men, drives the domestic violence calls effects. We see larger coefficients on weekdays relative to weekends. In census tracts where fewer people appear to be leaving home for work (based on mobile device tracking) compared with tracts where more people appear to continue working away from home (Figure 4). These patterns are

\textsuperscript{16}Death/homicide data could be useful for separating trends in reporting vs. incidence. Unfortunately, data with sufficient detail to test for evidence of changes in female or intimate partner homicide are not yet available.
consistent with larger effects at times when fewer people would typically be at home. Estimated effects are also slightly larger in tracts where a greater share of people spend entire days at home. Areas where more men were working pre-COVID-19 likely experienced greater increases in time spent at home by men. Consistent with the theory that time men spend at home is especially relevant to domestic violence, we see larger point estimates in areas that had higher employment-to-population ratios among men in 2018. However, none of the differences described above are statistically distinguishable.

Unemployment and higher levels of stress and anxiety generally may also be at play. Counterintuitively, the pattern of results for low vs. high predicted layoff areas (based on baseline industry composition and national unemployment rates by industry in the April 2020 jobs report) shows higher effects for low predicted layoff areas. However, predicted employment losses are large across all census tracts, with little variation above (mean of 16.8 percent) or below the median (mean of 13.8 percent), so we cannot rule out that the rise in domestic violence is driven by jobless or increased employment uncertainty.\textsuperscript{17} Similarly, without spatial variation in pandemic-induced anxiety separate from the dimensions we have already explored, we cannot investigate its relative importance to the domestic violence calls effects. Though we lose precision as we analyze subsets of the data, the estimates in Figure 4 indicate economically significant effects for almost all subgroups.

Using the reported city block, we also consider whether social distancing has increased domestic violence among households with a history of domestic violence

\textsuperscript{17}This is also true if looking at predicted employment loss for men or women separately.
(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 are only able to document whether the increase is concentrated among “repeat” offending city blocks or new blocks (see Appendix Table A4). The estimated effect for repeat-offending city blocks is large and negative, but imprecisely estimated. We estimate a significant increase in domestic violence service calls from city 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.\footnote{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 A7).}

## 5 Conclusion

We find that the COVID-19 pandemic is associated with a 10 percent rise in domestic violence service calls, comparable to the effect of a home team upset loss or a hot day (Card and Dahl, 2011). If the COVID-19 pandemic impacted domestic violence calls similarly across the United States, the result would be about 1350 more calls per day.\footnote{Census Bureau population estimates for 2018 suggest that 3.66\% of the U.S. population, live in the 15 cities for which we have data. Based on the CDC’s 2003 estimates, the short-run medical and productivity costs from missed work alone would imply a $211,000 daily cost in our 15 cities, or $5.8 million (2019$) a day for the entire country. This does not include any long-run costs due to impacts on physical health, mental health, or earnings.} 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 both the short and long run.

References


Jason Lindo, Jessamyn Schaller, and Ben Hansen. Caution! men not at work:


Tables and Figures

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

Note: The left panel plots the inverse hyperbolic sine of the average number of daily domestic violence service calls across 15 cities by week. The right panel plots this in levels. The vertical, red line indicates March 2, 2020, one week before social distancing measures became widespread.

Source: Authors’ own calculations using 911 Calls for Service data from 15 cities and OpenTable Seated Diner data.
Note: March 9th is the day we assign the beginning of social distancing treatment. 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 in the four weeks preceding March 8th. The bottom left panel plots the number of seated diners at OpenTable restaurants in 2020 relative to 2019. 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.

Source: Author’s own calculations using SafeGraph, Unacast, OpenTable, and Google Trends data.
Figure 3: Event Study: Daily Domestic Violence Service Calls in 2020 Relative to January through March 2019.

Note: The left panel plots the regression coefficients from the equation (3) where the outcome is the inverse hyperbolic sine of the number of domestic violence service calls at the city by day level. The right panel plots the regression coefficients from the equation (3) where the outcome is in levels. Only data from January to March is included. 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. The omitted week is the week of March 2, one week before OpenTable and Unacast data suggest social distancing began.

Source: Authors’ own calculations using 911 Calls for Service data from 15 cities.
Figure 4: 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). "Low" census tract measures refers to below the median, "high" refers to above the median. Outcomes by census tract demographics only include 10 cities that have sufficient address information to link the incidents to census tracts. Salt Lake City and Phoenix also have address information, but only a small fraction of service calls can be linked to the census tract. 95 percent confidence intervals are obtained by wild bootstrap clustering.

Source: Author’s own calculations using Calls for Service data.
Table 1: Impact of COVID-19 Social Distancing on Domestic Violence Police Service Calls

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<tr>
<td><strong>Outcome: IHS(Daily DV Calls)</strong></td>
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<tr>
<td>Post-Mar 9</td>
<td>0.149</td>
<td>[0.097, 0.203]</td>
<td>(0.000)</td>
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<tr>
<td>Post-Mar 9*Year 2020</td>
<td>0.102</td>
<td>[0.054, 0.152]</td>
<td>(0.003)</td>
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<td></td>
<td>0.102</td>
<td>[0.050, 0.152]</td>
<td>(0.002)</td>
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<tr>
<td>Mean of dep. var.</td>
<td>4.087</td>
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| **Outcome: Daily DV Calls** |           |           |           |
| Post-Mar 9               | 5.165     | [3.284, 7.069] | (0.000)   |
| Post-Mar 9*Year 2020     | 3.326     | [1.085, 5.406] | (0.009)   |
|                      | 3.314     | [1.290, 5.409] | (0.001)   |
| Mean of dep. var.       | 38.934    | 38.900    | 38.900    |
| N                      | 1289      | 2579      | 2579      |
| FE                     | yes       | yes       | yes       |
| FE x City              | yes       | no        | yes       |

*Note:* Observation at the city by day-level for 15 US cities. Data from January 5, 2020- March 31, 2020 is included in column (1). Data from January 5-March 31 in both 2019 and 2020 are included in columns (2) and (3). 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 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) included city, week of year, year, and day of week fixed effects. Column (3) includes 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 percent 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

Table A1: Dates of Data Availability and Service Description Domestic Violence Terms for Sample Cities

<table>
<thead>
<tr>
<th>City</th>
<th>First Available Date</th>
<th>Last Available Date</th>
<th>Parsing Terms Used to Identify Domestic Violence Calls</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baltimore, MD</td>
<td>June 30, 2013</td>
<td>April 22, 2020</td>
<td>“family dis”, “dom”</td>
</tr>
<tr>
<td>Bloomington, IN</td>
<td>January 1, 2017</td>
<td>March 30, 2020</td>
<td>“domestic”</td>
</tr>
<tr>
<td>Chandler, AZ</td>
<td>January 1, 2017</td>
<td>March 30, 2020</td>
<td>“domestic disturbance”</td>
</tr>
<tr>
<td>Cincinnati, OH</td>
<td>September 30, 2014</td>
<td>April 22, 2020</td>
<td>“domestic”, “family trouble”</td>
</tr>
<tr>
<td>Detroit, MI</td>
<td>November 6, 2018</td>
<td>April 24, 2020</td>
<td>“dv”</td>
</tr>
<tr>
<td>Los Angeles, CA</td>
<td>January 1, 2017</td>
<td>April 24, 2020</td>
<td>“dom viol”</td>
</tr>
<tr>
<td>Mesa, AZ</td>
<td>January 1, 2017</td>
<td>April 26, 2020</td>
<td>“family fight”</td>
</tr>
<tr>
<td>Montgomery County, MD</td>
<td>April 2, 2017</td>
<td>April 26, 2020</td>
<td>“domestic”</td>
</tr>
<tr>
<td>New Orleans, LA</td>
<td>January 1, 2017</td>
<td>May 2, 2020</td>
<td>“domestic disturbance”</td>
</tr>
<tr>
<td>Phoenix, AZ</td>
<td>January 1, 2017</td>
<td>April 30, 2020</td>
<td>“domestic violence”</td>
</tr>
<tr>
<td>Sacramento, CA</td>
<td>January 1, 2017</td>
<td>April 13, 2020</td>
<td>“domestic”, “disturbance-family”, “child abuse”</td>
</tr>
<tr>
<td>Salt Lake City, UT</td>
<td>January 1, 2017</td>
<td>March 31, 2020</td>
<td>“domestic”</td>
</tr>
<tr>
<td>Seattle, WA</td>
<td>June 2, 2009</td>
<td>April 19, 2020</td>
<td>“dv” exclude “no welfare chk or dv”, “order” and “not dv”</td>
</tr>
<tr>
<td>Virginia Beach, VA</td>
<td>January 1, 2018</td>
<td>April 7, 2020</td>
<td>“domestic”</td>
</tr>
</tbody>
</table>

Note: Detroit has service call data available prior to November 6, 2018, but it does not include calls related to domestic violence.
Table A2: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>2019</th>
<th>2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total calls for service</td>
<td>1446.44</td>
<td>1497.20</td>
</tr>
<tr>
<td>Daily domestic violence calls</td>
<td>38.87</td>
<td>38.93</td>
</tr>
<tr>
<td>Calls between 8 AM and 5 PM</td>
<td>13.39</td>
<td>12.95</td>
</tr>
<tr>
<td>Calls at other times</td>
<td>25.48</td>
<td>25.99</td>
</tr>
<tr>
<td>Calls to street blocks with 3 month history</td>
<td>21.59</td>
<td>21.92</td>
</tr>
<tr>
<td>Calls to street blocks without 3 month history</td>
<td>15.52</td>
<td>16.07</td>
</tr>
<tr>
<td>Calls about theft</td>
<td>65.94</td>
<td>66.06</td>
</tr>
<tr>
<td>Calls about traffic incidents</td>
<td>193.24</td>
<td>179.54</td>
</tr>
<tr>
<td>Observations</td>
<td>1290</td>
<td>1289</td>
</tr>
</tbody>
</table>

*Note:* Each column shows average values for the cities in our sample from January 5 to March 31 of the indicated year.
Table A3: Robustness: Alternative Estimation

<table>
<thead>
<tr>
<th></th>
<th>HHS(Domestic Violence Calls)</th>
<th>Domestic Violence Calls</th>
<th>IHS(DV and Abuse)</th>
<th>IHS(Abuse)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>City by Day of Year F.E.</td>
<td>City-Specific Treatment Timing</td>
<td>Include April-Dec. 2019</td>
<td>Include 2017 and 2018</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Post-March 9 Year 2020</td>
<td>0.10</td>
<td>0.09</td>
<td>0.11</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td>[0.05, 0.15]</td>
<td>[0.04, 0.14]</td>
<td>[0.06, 0.16]</td>
<td>[0.05, 0.22]</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Dependent Mean</td>
<td>38.9</td>
<td>38.9</td>
<td>40.4</td>
<td>37.8</td>
</tr>
<tr>
<td>Observations</td>
<td>2,579</td>
<td>2,579</td>
<td>6,763</td>
<td>4,385</td>
</tr>
</tbody>
</table>

Notes: Observation at the city by day-level. The outcome in columns (1) and (2) 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.” This beginning of treatment day is within one day of March 9 for 11 of the 15 cities with the earliest treatment only 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 that definition 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 percent 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 A4: Extensive vs. Intensive Margin: Impact on Domestic Violence Calls by Street Block History of Domestic Violence Calls

<table>
<thead>
<tr>
<th></th>
<th>Inverse Hyperbolic Sine of Daily Domestic Violence Calls</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline Call &lt;3 Months Call &lt;3 Months Call &lt;6 Months Call &lt;6 Months Call &lt;1 Year Call &lt;1 Year Call 3-6 Months Ago</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
<td></td>
</tr>
<tr>
<td>Post-March 9*Year 2020</td>
<td>0.10 [-0.12, 0.20] -0.15 [0.20, 0.26] -0.15 [-0.15, 0.26] -0.15 [-0.31, 0.31] -0.33</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[ 0.05, 0.15] [ 0.06, 0.55] [ 0.06, 0.55] [ 0.06, 0.55] [ 0.06, 0.55] [ 0.06, 0.55]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dependent Mean</td>
<td>38.9 21.8 15.8 25.6 11.9 28.8 8.7 18.4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>2,579 2,064 2,064 2,064 2,064 2,064 2,064 2,064</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Observation at the city by day-level. The outcome is the inverse hyperbolic sine of daily domestic violence calls. For each column only a sub-group of calls are included. For example, column (1) 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 (2) 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 households, only repeat offending street blocks. Column (8) considers calls from city blocks where there was a call 3-6 months ago, to avoid any mechanical relationship created by considering calls between January and March. 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.
Figure A1: Extended Event Study: Daily Domestic Violence Service Calls on Limited Sample through April 24

Note: The regression coefficients from the equation (3) are plotted where the outcome is the levels (or inverse hyperbolic sine) of the number of domestic violence service calls at the city by day-level extended through April 24th for 12 cities. 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. The omitted week is the week of March 2, one week before OpenTable and Unacast data suggest social distancing began.

Source: Author’s own calculations using Calls for Service data from 12 cities.
Figure A2: 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 February 1, 2020 to April 24, 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.

Source: Author’s own calculations using SafeGraph cellphone data.
Figure A3: 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.

Source: Author’s own calculations using Calls for Service data from 15 cities.
Figure A4: 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-day of year, and city-by-day of week fixed effects are included. We include city-by-day of year effects rather than city by week of year effects to avoid weeks being structured around March 9th. Wild bootstrapped confidence intervals are corrected for clustering at the city-level.

Source: Author’s own calculations using Calls for Service data from 15 cities.
Figure A5: Placebo Tests: “Treatment Effects” for 100 Random Treatment Dates Between March 9- October 31, 2019

Note: The regression coefficients from a regression similar to equation (2), but comparing 2018 to 2019 are plotted where the outcome is the inverse hyperbolic sine of the number of domestic violence service calls at the city by day-level. 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. Domestic violence call data for Detroit is not available until November 2018, so it is excluded from all 2018 comparisons. Wild bootstrapped standard errors are corrected for clustering at the city-level.

Source: Author’s own calculations using Calls for Service data from 15 cities.
Figure A6: Heterogeneous Impacts of Social Distancing on Domestic Violence Service Calls, Top and Bottom Quartiles

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). "Low" census tract measures refers to the bottom quartile, "high" refers to the top quartile. Outcomes by census tract demographics only include 10 cities that have sufficient address information to link the incidents to census tracts. Salt Lake City and Phoenix also have address information, but only a small fraction of service calls can be linked to the census tract. 95 percent confidence intervals are obtained by wild bootstrap clustering.

Source: Author’s own calculations using Calls for Service data.
Figure A7: Response of Total Service Calls, Theft Calls, and Traffic Calls to COVID-19 Social Distancing

Note: The regression coefficients from the equation (3) 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.

Source: Author’s own calculations using Calls for Service data from 15 cities.
Online Appendix B. Social Distance Data Appendix

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. 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 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

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20 This includes online reservations, phone reservations, and walk-in customers.
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.