The effect of social distancing on police reports of domestic violence[*]

LIN-CHI HSU[†] and ALEXANDER HENKE

Department of Economics

Howard University

May 31, 2020

Abstract We analyze the effect of social distancing related to COVID-19 on domestic violence incidents in the U.S. using novel daily mobile device tracking data, the timing of stay-at-home orders, and dispatch and crime data from twenty-eight police departments. We find that reported incidents of domestic violence increase after local stay-at-home orders are enacted and that domestic violence increases with mobile device tracking measures of social distancing. Our result is consistent with an exposure reduction theory of domestic violence. When applied to the entire U.S., we estimate that social distancing increased domestic violence by approximately 6 percent, or more than 24,000 cases, from March 16 to April 30, 2020.

Keywords: Domestic violence, COVID-19, Stay-at-home orders, Social distancing, Exposure reduction, Pandemics

JEL Codes: J12 · D19 · I18

[*] We would like to thank Shamma Alam, Shoshana Grossbard, and Rachel Heath for helpful comments and the police departments in the U.S. with open data and the SafeGraph Data Consortium that made this research possible. Any errors are our own.

[†] Department of Economics, Howard University, 2400 6th St NW, Washington, DC 20059. Email: linchi.hsu@howard.edu

1. Introduction

In response to the COVID-19 pandemic, individuals have practiced social distancing, broadly defined as efforts to avoid getting physically close to other people. Governments in many countries have issued orders for their residents to stay at home. Since March 2020, state and local governments in the U.S. have issued such orders, generally called either "shelter-in-place" orders or "stay-at-home" orders.[1] While stay-at-home orders in the U.S. are less restrictive than lockdown orders in other hard-hit countries such as Italy or China, victims of domestic violence may still feel trapped at home with their abusers. National news outlets have reported surges in calls to U.S. domestic violence call centers after implementing stay-at-home orders (Taub 2020; Mithani 2020).

The pandemic and the government response create a natural experiment we use to analyze the effect of social distancing on domestic violence incidents in the U.S. Using novel daily mobile device tracking data, the timing of stay-at-home orders, and dispatch and crime data from twenty-eight police departments, we find that reported incidents of domestic violence increase after local stay-at-home orders are effective and that domestic violence increases with social distancing. Applying our result to the entire U.S., we estimate that social distancing increased domestic violence by over 6 percent, or more than 24,000 cases, from March 16 to April 30, 2020. This work serves as the first step in a new branch of literature on how COVID-19 affects domestic violence. We invite more work using different countries, data, and methodologies to examine this important research question.

[1] Hereafter, we refer to these types of orders broadly as "stay-at-home" orders.

Because the COVID-19 pandemic is recent and ongoing, data availability poses a challenge to researchers who seek to systematically identify the effects of the crisis. Many national crime and victimization data sets, such as the National Incident-Based Reporting System in the U.S., take at least one year to be released to the public. We overcome this challenge by searching more than 200 U.S. cities for timely, open, detailed police data, and ultimately locate twenty-eight police and sheriff's departments in eighteen states that meet the requirements for this type of analysis.

There has been concern that fewer victims are reporting domestic violence to the police during the pandemic, in part because it is difficult to leave the relationship during a pandemic and in part because victims may not want their partners to contract the virus in jail (Li and Schwartzapfel 2020). If victims choose to report less often during the pandemic, our estimates represent a lower bound of the true effect of social distancing on domestic violence.

COVID-19, social distancing, and domestic violence

One impact of COVID-19 on domestic violence is that social distancing increases the time abusers spend with victims. Peterman et al. (2020) review several ways a pandemic affects domestic violence, including the increased exposure to abusers. Bandiera et al. (2019) study the impact of the Ebola crisis on women in Sierra Leone and its interaction with the creation of protective spaces (clubs) for women. While the Ebola crisis generally led to women spending more time with men, areas with protective spaces mostly reversed this effect. Exposure reduction theory states that domestic violence increases in the amount of time victim and abuser are in the same location (Chin 2012). Hence, the theory predicts that social distancing increases domestic violence.

At least three other theories of domestic violence are relevant to our analysis: Classic household bargaining, instrumental violence, and backlash theory. Together, the predicted theoretical effect of social distancing is ambiguous. First, a classic household bargaining theory of domestic violence predicts that increases in women's bargaining power over men reduces violence against women. See Marjorie B. McElroy and Mary Jean Horney (1981) for the classic household bargaining model and Alexander Henke and Lin-chi Hsu (2020) for how the bargaining model applies to domestic violence. Pablo Brassiolo (2016) finds that domestic violence decreases after the cost of divorce decreases in Spain. Thus, if a pandemic increases the cost of leaving a relationship, domestic violence should increase. In addition, social distancing increases unemployment. Increases in female unemployment increase violence, and increases in male unemployment decrease violence (Anderberg et al. 2016). Alon et al. (2020) find that female-dominated industries have been hit the hardest by the COVID-19 shutdowns, which implies that violence against women will increase.

Instrumental violence theory states that abusers use violence to control contested household resources. Lin-chi Hsu (2017) finds that women in the U.S. receive more violent threats from their intimate partners immediately after receiving welfare payments. Similarly, abusers may use violence to extort income from employed intimate partners or to control their behavior. Using data on Bangladeshi garment workers, Rachel Heath (2014) finds that women with low education in the labor force experience more domestic violence as men use violence to reassert control over their spouses. Applying the theory to a pandemic, an environment with less employment and more restrictions on time use may reduce violent arguments over household resources.

While instrumental violence is strategic, a theory of backlash offers similar predictions with an emotional motivation. An abusive man may feel that a woman's decision to enter the labor force challenges his status in the relationship, triggering a backlash (Chin 2012; Angelucci and Heath 2020). During the Ebola outbreak, women in more highly impacted areas of Sierra Leone experienced less domestic violence (Bandiera et al. 2019). However, Jana Lenze and Stephan Klasen (2017) find that the backlash effects of female labor force participation disappear after using the local average of women's working status as an instrument to correct for reverse causality. To summarize, increased exposure and stress combined with a lack of female labor market opportunities might increase domestic violence; in contrast, a lack of male labor market opportunities and diminished incentives to fight over the control of household resources and the dominant position in the relationship might reduce domestic violence.

2. Data

Calls for service, incidents, and crime reports

We collect publicly available data sets on police incidents, calls for service, and crimes that clearly and reliably identify domestic violence from twenty-seven cities and one county in eighteen states. The eighteen states are Alabama, Arizona, California, Florida, Illinois, Indiana, Kansas, Louisiana, Maryland, Minnesota, Missouri, Nebraska, North Carolina, Ohio, Texas, Vermont, Virginia, and Washington. Table 1 lists the cities in the sample. We select data sets that start before the enactment of local stay-at-home orders and are available until April 30, 2020. We construct this list by searching the 200 most populous cities in the U.S. for data sets that abide by these criteria. We also include some smaller cities we found using the Police Data Initiative.

To construct the daily domestic violence count, we consider incidents with a description of domestic assault, domestic battery, or a family fight, and we exclude documented incidents of threats, child abuse, child neglect, protective order violations, and nonviolent family disturbances. We keep data that only report "domestic violence," "domestic disturbance," or "family fight" with no other details.[2] When there are multiple victims or offenses in the same identified incident, we only count one incident.

When possible, we collect data on police calls for service or police incidents to capture incidents of domestic violence which may not be reported as a crime. The following cities do not have incident or call data that clearly identifies domestic violence, but they do have qualifying crime data: Austin, Baton Rouge, Chicago, Durham, Fayetteville, Kansas City, Montgomery (AL), Omaha, St. Paul, and Wichita. Additionally, we remove periods of the sample with no information.

Stay-at-home orders

In the U.S., the decision to impose stay-at-home orders is left up to local instead of federal authorities; this provides some variation in policy responses. We collect the dates of executive orders from news reports of U.S. city mayors, county commissioners, and state governors. We focus on orders that direct individuals to remain at home except for essential activities such as grocery shopping. Using the dates from the executive orders, we construct a dummy indicating whether a local stay-at-home order is in place for the entire day starting at 12:01 am. This means

[2] More than 99 percent of domestic violence incidents in Baltimore and San Jose are reported as "family disturbance." 100 percent of domestic violence incidents in Mesa are reported as "family fight." 59 percent of domestic violence incidents in Tucson are reported as "DV." As expected, these cities have a higher rate of incidents. To ensure that these cities do not drive the results, we exclude them in an alternative specification.

we often code an order as beginning the day after its official start date. No jurisdiction in our analysis fully lifted stay-at-home orders on or before April 30, 2020.

Social distancing metrics

Social distancing represents a broader, more personal effort to limit close contact with other individuals. Stay at home orders represent an "intention to treat" effect, and social distancing represents the actual treatment. Our main social distancing metric is the estimated percentage of people who stay at home all day using data from the SafeGraph Data Consortium.[3] SafeGraph pings a large sample of mobile devices in the U.S. and its territories to see where and for how long each device has traveled from its home location. In March 2020, we estimate that SafeGraph pinged an average of 19.6 million mobile devices per day. We count the number of pinged devices that never left their home in a day and divide by the total number of sampled devices by county. SafeGraph data are available starting January 1, 2020.

Other data sources

City and county population estimates are from the U.S. Census Bureau. Weekly state-level unemployment insurance claims data are from the U.S. Department of Labor. Unemployment insurance data enjoy three key advantages. First, the data set is an official count of unemployment as opposed to a survey. Second, in a rapidly changing labor market, it updates weekly instead of monthly or yearly. Third, the data are more likely to capture labor market shifts that may be coded as "employed but not at work," or similarly, in other surveys. Using data from the Current Population Survey (CPS) provided by the Integrated Public Use Microdata

[3] SafeGraph is a data company that aggregates anonymized location data from numerous applications in order to provide insights about physical places. To enhance privacy, SafeGraph excludes census block group information if fewer than five devices visited an establishment in a month from a given census block group.

Series (Flood et al. 2020), we derive the following demographic variables: Average household income, sex ratio, and the fraction of the population that is white, black, foreign-born, married, and Hispanic. The key advantage of using the CPS is that it is monthly and is available in April 2020.

Summary statistics

See Table 1 for city-level summary statistics, dates in the sample, and stay-at-home order enactment dates. On average, cities in the sample report 2.69 domestic violence incidents per 100,000 people per day with a standard deviation of 2.53. The average fraction of mobile devices staying at home all day in the sample is 0.31, with a standard deviation of 0.09. In our sample, stay-at-home orders begin on March 20, 2020, and the last one comes into effect on April 5, 2020.

[Table 1 goes here]

Our identification strategy relies on the idea that the COVID-19 pandemic provides plausibly exogenous variation in social distancing efforts, both with respect to stay-at-home orders and individual social distancing. Figure 1 plots the weekly standardized domestic violence rate and the standardized fraction of people staying home all day and illustrates the range of dates when local governments imposed stay-at-home orders. The variables in the plot are standardized by scaling them down to a mean of zero and a standard deviation of 1. Figure 1 shows that social distancing increases in early March; this rise follows well-publicized national reports of community spread and ensuing shutdowns, such as the National Basketball Association suspending its season after Utah Jazz star Rudy Gobert tested positive for COVID-19 (Golliver 2020). In addition, Figure 1 shows that reports of domestic violence rise with social distancing; then, as social distancing efforts slowly relax, reports of domestic violence also decline.

[Figure 1 goes here]

3. Methods

Stay-at-home order specification

Our first specification is the event study of stay-at-home orders using the following linear fixed-effects model:

$$(1)\ DV_{c,t} = \alpha + \beta Order_{c,t} + \gamma X_{c,t} + \delta_c + \zeta_{year} + \eta_{month} + \theta_{dayofweek} + \epsilon_{c,t}.$$

The dependent variable DV is the count of domestic violence cases for city c on date t per 100,000 people.[4] The independent variable, $Order$, is a dummy variable indicating whether a stay-at-home order is in effect within that jurisdiction on that day. X is a vector of controls including a dummy for each U.S. federal holiday, the weekly insured unemployment rate by state, and the monthly sex ratio, average household income, and the percentage of the population that is white, black, Hispanic, married, and foreign-born by county. Controlling for the sex ratio is important because it influences a woman's labor force participation and power in the relationship (Amuedo-Dorantes and Grossbard 2007). City/county fixed effects control for the time-invariant characteristics of each city/county; month fixed effects control for crime seasonality; day-of-week fixed effects control for the variance in domestic violence across the day of the week.

[4] For Montgomery County, c indicates county. Cities are linked with the counties in which they reside; for instance, Seattle, WA is in King County.

Social distancing specification

Social distancing efforts sometimes precede official orders to stay at home. Our second specification better accounts for the timing of social distancing by estimating the daily fraction of people staying at home all day using SafeGraph data. The benefit of this method is that we capture the degree of individual social distancing efforts before and after official orders to stay at home. Although the SafeGraph data are only for 2020, that is also when the identifying variation in social distancing occurs. Given the structure of the data, we employ the following specification:

$$(2)\ DV_{c,t} = \alpha + \beta Stay_{c,t} + \gamma X_{c,t} + \delta_c + \eta_{month} + \theta_{dayofweek} + \lambda PriorDV_{c,t} + \epsilon_{c,t},$$

where $Stay$ is our key social distancing metric: The daily average fraction of people who stay at home all day by county and day. $PriorDV$ is the domestic violence rate on the same day-of-year in 2019. We set $PriorDV$ for February 29, 2020 to the local domestic violence rate for February 28, 2019. In specifications that include $PriorDV$ we lose two cities that lack a full year of domestic violence data: Wichita and Scottsdale. All other variables are the same as equation (1). The other key difference is that this regression goes from January 1 to April 30, 2020 and thus lacks a year dummy.

4. Results

Table 2 presents our estimates for the effects of stay-at-home orders and social distancing on domestic violence using the empirical strategy described in Section 3. The dependent variable is the daily count of domestic violence per 100,000 people. Columns (3) and (6) display the results for the specifications with full controls, as indicated in equations (1) and (2). After controlling for the insured unemployment rate, demographics, seasonality, year effects, day-of-week effects, holidays, and time-invariant city and county effects, we observe 0.205 additional daily reports of domestic violence per 100,000 people after implementing stay-at-home orders, a 7.37 percent increase relative to the sample mean. In addition, for every change of 0.1 in the average fraction of people who stay home all day, we observe 0.116 additional daily reports of domestic violence per 100,000 people, a 4.17 percent increase relative to the sample mean.

[Table 2 goes here]

One limitation is that we only observe incidents that involved the police. If victims who feel trapped under stay-at-home orders are less likely to report incidents to the police, our results represent a lower-bound estimate of the true effect of social distancing on domestic violence (Li and Schwartzapfel 2020).

Extrapolating the effect to the entire U.S.

Here, we extrapolate this result to the entire U.S. using country-level social distancing metrics and the U.S. population from the 2019 U.S. census. First, we calculate a country-wide baseline for social distancing by taking the average fraction of people who stay at home all day in the U.S. from February 7 to February 13 – roughly 0.257. This represents an early period of the metrics openly published by SafeGraph. Second, we calculate the average increase in social distancing in the U.S. by taking the average fraction of people who stay at home from March 16 to April 30 and subtracting the baseline level from this value, and obtain an estimate of 0.140.[5] Applying an increase in social distancing of 0.140 to our estimated regression coefficient of

[5] March 16 is chosen because it is the date on which social distancing begins to exceed the baseline. April 30 is the last day of our sample.

1.158, this implies that domestic violence increased by 5.83 percent on average over the selected period relative to the sample mean.

To obtain an absolute estimate, we multiply the estimated average change in social distancing by the estimated regression coefficient, the 46 days in the selected period, and the U.S. population (divided by 100,000). Using this method, we estimate that the increase in social distancing led to approximately 24,447 more cases of domestic violence from March 16 to April 30, 2020 in the U.S.

This extrapolation assumes that the effect estimated in our sample represents the true effect for the entire U.S. Our sample covers 18,950,912 people, or 5.77% of the U.S. population. For there to be a systematic difference between our estimate and the true effect in the U.S., data availability or our selection process would have to be connected to the effect of social distancing on domestic violence. For example, if rural and exurban areas – which are less likely to provide open police data – are more susceptible to the effect of social distancing on domestic violence, then this process underestimates the effect in the U.S. Another caveat is that we set a counterfactual level of social distancing based on a week in early February. Social distancing decreased until early March and may have continued to decrease if not for COVID-19. For both reasons we may underestimate the true increase in social distancing and therefore the effect of social distancing on domestic violence.

Alternative specifications and robustness checks

In this section, we perform several alternative specifications and robustness checks. First, we use two alternative measures of social distancing, one based on time spent at home and one based on interactions between pinged smartphones in commercial venues. Second, we use the leads of the insured unemployment rate. Last, we restrict the analysis to a more uniform set of calls for service and police incident data.

Average time spent at home

To test whether our result holds for a different social distancing measure, we estimate the average time spent at home using SafeGraph data from January 1 to April 30, 2020. SafeGraph calculates the median time spent at home for all the devices in a census block group (a group of city blocks). We take a county-level average of this measure weighted by the sample size of devices in each census block group, and we divide by the minutes in a day to obtain the fraction of time spent at home. The average fraction of time spent at home is 0.47, with a standard deviation of 0.11. Column (1) of Table 3 shows the result, which is qualitatively similar to the main specification. Increasing time spent at home statistically significantly increases reports of domestic violence.

[Table 3 goes here]

Device exposure index

The second alternative measure, developed by Couture et al. (2020), is called the Device Exposure Index (DEX). DEX comes from PlaceIQ movement data and measures the opposite of social distancing: how much people congregate in commercial venues. Daily county-level PlaceIQ data are available starting January 20, 2020. DEX takes every smartphone in the sample, notes what commercial venues it visited, and measures how many other smartphones visited the same venue that day. It then averages this value across phones. We use adjusted DEX, which assumes the number of actual devices in the area has not declined over time, to account for smartphone sampling issues. The average of DEX is 117.59, and the standard deviation is 92.51. We find that an increase in DEX decreases the incidence of domestic violence, i.e., that less social distancing leads to less violence. This is consistent with our main result; see Column (2) of Table 3.

Unemployment leads

Delays in unemployment insurance claims may effectively cause our estimate of unemployment to be lagged (Haag 2020). One way to combat this is to include a one-week lead for unemployment to capture unemployed workers whose claims were delayed. The issue with this specification is that the lead for unemployment may well be influenced by domestic violence itself. Columns (3) and (4) of Table 3 indicate that the results are still positive and significant.

Restricted sample

Some data included in the main specification are crimes, and other data lack indicators which would allow us to identify domestic assaults. This is one reason why some cities have much higher average rates of incidents. To ensure that these differences in data sources do not drive the results, we restrict the analysis to only calls for service and police incident data with similar identifiers for qualifying cases of domestic violence. Specifically, we omit Austin, Baltimore, Baton Rouge, Chicago, Durham, Fayetteville, Kansas City, Mesa, Montgomery (AL), Omaha, San Jose, St. Paul, Tucson, and Wichita. In columns (5) and (6) of Table 3, we find that the results hold in the more restrictive sample.

5. Conclusion

Using up-to-date police data from twenty-seven cities and one county in eighteen states in the U.S., we find that reported incidents of domestic violence increase after local U.S. governments implement stay-at-home orders and more people stay at home all day. This result is consistent with exposure reduction theory. Applying our result to the entire U.S., we estimate that social distancing increased domestic violence by approximately 6 percent, or over 24,000 cases, from March 16 to April 30, 2020. This does not represent a full cost-benefit analysis of social distancing, as we only identify one cost. To our knowledge, this is the first study to find a systematic link between ongoing social distancing efforts and domestic violence.

Ample care must be taken before applying these results to other countries. Even if the true effect of social distancing on domestic violence is the same in other countries, measures of social distancing and specific policy responses may differ. More research is needed to complement and broaden these findings. As more information becomes available, we hope that this study will introduce a new strand of research on pandemic crises, social distancing, and domestic violence.

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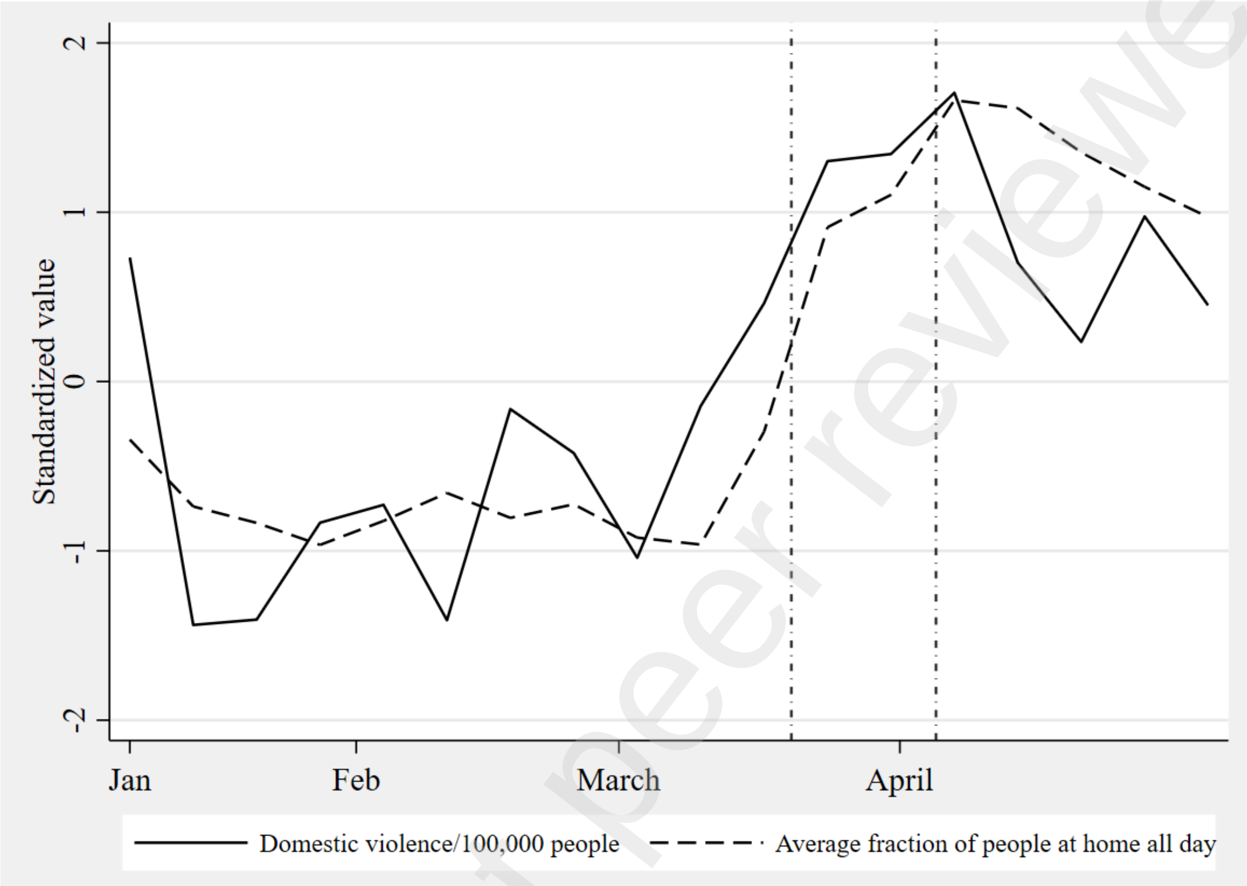
Table 1: Summary statistics and city information

City	Fraction of people at home all day		Domestic violence rate		Stay-at-home order	Police data begins
	Mean	SD	Mean	SD	(M/D)	(M/D/Y)
Austin, TX [c]	0.25	0.07	1.40	0.38	3/25	1/1/2009
Baltimore, MD	0.33	0.07	9.41	1.66	3/31	3/3/2015
Baton Rouge, LA [c]	0.27	0.07	1.58	0.98	3/24	1/1/2011
Burlington, VT	0.30	0.09	0.37	0.90	3/25	1/1/2012
Chandler, AZ	0.30	0.08	4.49	1.66	4/1	1/1/2013
Chicago, IL [c]	0.33	0.10	2.28	0.56	3/22	1/1/2009
Cincinnati, OH	0.29	0.09	2.06	0.87	3/24	1/1/2015
Durham, NC [c]	0.33	0.08	1.22	0.67	3/31	1/1/2016
Fayetteville, NC [c]	0.31	0.06	1.83	1.01	3/31	1/16/2010
Gilbert, AZ	0.30	0.08	1.84	0.87	4/1	1/1/2009
Kansas City, MO [c]	0.30	0.08	2.63	0.90	3/24	1/1/2013
Los Angeles, CA	0.32	0.11	3.99	0.63	3/20	1/1/2010
Mesa, AZ	0.30	0.08	7.42	1.51	4/1	1/1/2017
Montgomery County, MD	0.35	0.14	3.34	0.90	3/31	4/6/2017
Montgomery, AL [c]	0.26	0.07	5.08	1.83	4/5	1/1/2018
New Orleans, LA	0.29	0.07	2.97	0.86	3/20	1/1/2011
Norfolk, VA	0.30	0.06	1.57	0.87	3/31	1/1/2015
Omaha, NE [c]	0.28	0.08	0.92	0.47	N/A	6/22/2015
Phoenix, AZ	0.30	0.08	3.77	0.78	4/1	11/1/2015
Sacramento, CA	0.33	0.09	2.50	0.98	3/20	1/1/2014
San Jose, CA	0.34	0.14	3.00	0.73	3/20	1/1/2010
Scottsdale, AZ	0.30	0.08	0.36	0.41	4/1	6/1/2019
Seattle, WA	0.33	0.10	1.11	0.42	3/24	6/3/2009
St John, IN	0.32	0.09	0.53	1.60	3/25	1/1/2009
St Paul, MN [c]	0.32	0.09	1.46	0.76	3/28	8/14/2014
St Petersburg, FL	0.30	0.08	2.45	0.96	3/27	1/2/2013
Tucson, AZ	0.32	0.07	11.27	1.67	4/1	1/1/2017
Wichita, KS [c]	0.31	0.08	3.99	1.81	3/25	2/13/2020
Total	0.31	0.09	3.02	2.78	--	--

Note: Fraction of people at home all day is the average fraction of sampled devices that do not leave home in that day in the county. All police data extends to April 30, 2020. The stay-at-home order date is the first full day of an official order, so if the order takes effect at for instance 5 pm we code the order as beginning the next day. Omaha did not implement any stay-at-home order in the sample period. Some cities have missing information and therefore we dropped these periods: 12/22/2013 to 12/31/2013 and 12/31/2018 to 3/24/2019 in Kansas City, 12/4/2019 to 12/31/2019 in San Jose, and 1/5/2017 to 2/22/2017 in St. Paul.

[c] indicates crime data.

Figure 1: Standardized measures of DV and social distancing in 2020



Note: The vertical dotted lines represent the range of dates when stay-at-home orders come into effect. Weekly averages of domestic violence and the fraction of people at home all day are standardized through a basic scaling procedure that sets the mean to zero and the standard deviation to 1.

Table 2: Main Results

	(1)	(2)	(3)	(4)	(5)	(6)
Stay-at-home order	0.038	0.192***	0.205***			
	(0.052)	(0.073)	(0.072)			
Fraction of people staying at home all day				1.294***	1.255***	1.158***
				(0.295)	(0.301)	(0.306)
Insured unemployment rate, household income	N	Y	Y	N	Y	Y
Sex ratio, race (%), foreign-born (%), married population (%), Hispanic (%)	N	N	Y	N	N	Y
Lag DV rate	N	N	N	N	Y	Y
Observations	75992	69556	69556	3345	3146	3146
R^2	0.7886	0.7942	0.7954	0.8910	0.8954	0.8963

Note: All regressions are weighted by population and include month, day of week, city, and holiday dummies. The first three columns include year dummies. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Alternative Specifications and Robustness Checks

	Other distancing data		Unemployment leads		Restricted sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Fraction of time staying at home	0.628^{**}					
	(0.288)					
Device exposure index (DEX)		-0.001^{**}				
		(0.000)				
Stay-at-home order			0.193^{**}		0.244^{***}	
			(0.076)		(0.090)	
Fraction of people staying at home				1.079^{***}		1.753^{***}
				(0.326)		(0.443)
Observations	3146	2652	69556	3146	35196	1452
R^2	0.8959	0.8958	0.7954	0.8963	0.7567	0.7368

Note: All regressions are weighted by population and include the insured unemployment rate, household income, sex ratio, race categories (%), foreign-born (%), married population (%), Hispanic (%), and month, day of week, city, and holiday dummies. All regressions except columns (3) and (5) also contain $LagDV$, and the regressions in columns (3) and (5) include year dummies. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$