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COVID-19, staying at home, and domestic violence

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Abstract

We analyze how staying at home during the COVID-19 pandemic affects the rates of domestic violence in the U.S. Using police dispatch and crime data from 36 police and sheriff's departments and mobile device tracking data, we find that reported incidents of domestic violence increase as more people stay at home. Specifically, we estimate that staying at home due to COVID-19 increased domestic violence by over 5% on average from March 13 to May 24, 2020. This is consistent with a theory of exposure reduction, where victims and abusers stuck at home are more likely to fight.

Keywords Domestic violence · COVID-19 · Social distancing · Exposure reduction · Pandemics

JEL codes J12 · D19 · I18

1 Introduction

The COVID-19 pandemic changes both individual behavior and government policy with respect to social distancing, broadly defined as being physically distant from other people. One example of social distancing is staying at home except for essential activities. While there are obvious health benefits to staying at home, it may force victims of domestic violence to spend more time with their abusers, heightening tensions and creating more opportunities for violence.

We use the natural experiment of the pandemic to analyze the effect of staying at home on domestic violence incidents in the U.S. Using daily mobile device tracking data and dispatch and crime data from 36 police departments in 22 states, we first examine the strong co-movement between police reports of domestic violence and staying at home from March to May. We then estimate that the increase in staying at home due to COVID-19 increased domestic violence by over 5% from March 13 to

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May 24, 2020. If victims are less inclined to report while staying at home, this is an under-estimate of the true effect of staying at home on domestic violence.

Our work builds upon a new strand of research on COVID-19, social distancing, and police incidents. Leslie and Wilson (2020) use open police report data from 15 police and sheriff's departments in the U.S. They employ a difference-in-difference method, identifying the estimated start of social distancing as the start of the treatment. They find that the "social distancing" event increased domestic violence calls for service by 10% from March 9 to March 31. Henke and Hsu (2020a) find similar results using shelter-in-place orders, social distancing data, and open police data, finding that sheltering in place increased domestic violence by 6% in March and April. Silverio-Murillo and de la Miyar (2020) use data on a women's call center service in Mexico and find increased requests for psychological services and decreased requests for legal aid after lockdowns.

This article complements and supports the literature on staying at home and domestic violence by improving the robustness and scope of the initial findings. We improve the data by expanding the number of cities and by including the month of May, a key month when staying at home began to decline. In addition, we control for temperature, which has a potentially strong confounding effect as it both causes domestic violence (Henke and Hsu 2020b) and is related to COVID-19 and social distancing efforts (Zhu and Xie 2020).

Furthermore, we estimate staying at home directly using mobile device tracking data instead of a binary treatment variable. This way, we utilize the fact that different cities had different behaviors at different times. We also control for confounding variables, such as the concurrent increase in unemployment in the sample period. Controlling for unemployment helps us to isolate the effect of staying at home from the effect of economic stress on domestic violence.

This result is consistent with an exposure reduction theory of domestic violence, where domestic violence is modeled as a crime of opportunity and being near an abuser for longer periods creates more opportunities for violence. For instance, an employed woman experiences less domestic violence because she spends less time at home in a vulnerable position (Chin 2012). This effect is unrelated to both the feelings of an abuser and the economic bargaining power of the potential victim. Staying at home due to the pandemic increases the amount of time abuser and victim are in the same dwelling. Therefore, exposure reduction theory predicts that staying at home increases cases of domestic violence.

Our results are also consistent with a classic household bargaining theory of domestic violence, which predicts that increases in women's bargaining power over men reduces violence against women.[1] In the context of cooperative bargaining with male-on-female violence, violence benefits the abusive man while being costly to the woman, and the couple negotiates over the "optimal" degree of violence in the relationship. The man effectively pays for violence with transfers, and the cost of violence depends on options outside of the relationship. A key implication of this theory is that a woman's bargaining power, determined by economic opportunities outside the relationship and the cost of separation, reduces violence against women. Brassiolo (2016) finds that a reduction of the cost of divorce reduces domestic violence in Spain.

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[1] See McElroy and Horney (1981) for the classic household bargaining model without domestic violence.

Table 1 Cities in the sample

City	Data type	City	Data type	City	Data type
Austin, TX	Crime	Kansas City, MO	Crime	Phoenix, AZ	Calls
Baltimore, MD	Calls	Los Angeles, CA	Calls	Sacramento, CA	Calls
Baton Rouge, LA	Crime	Louisville, KY	Crime	Salt Lake, UT	Calls
Burlington, VT	Incident	Memphis, TN	Incident	San Francisco, CA	Incident
Chandler, AZ	Calls	Mesa, AZ	Calls	San Jose, CA	Calls
Chicago, IL	Crime	Minneapolis, MN	Incident	Santa Monica, CA	Calls
Cincinnati, OH	Calls	Montgomery County, MD	Calls	Santa Rosa, CA	Calls
Denver, CO	Crime	Montgomery, AL	Crime	Seattle, WA	Calls
Durham, NC	Crime	Nashville, TN	Incident	St John, IN	Calls
Fayetteville, NC	Incident	New Orleans, LA	Calls	St Paul, MN	Incident
Gilbert, AZ	Calls	Norfolk, VA	Incident	St Petersburg, FL	Calls
Hartford, CT	Incident	Omaha, NE	Incident	Tucson, AZ	Calls

Crime means the data report crimes; Calls means the data report police calls for service; Incident means the data report "police incidents", which are similar to calls for service

Fajardo-Gonzalez (2020) finds that women hold jobs to maintain a better exit option in abusive relationships. Aizer (2010) finds that increasing women's relative wage in a local labor market decreases violence against women. Thus, if a pandemic increases the cost of leaving a relationship by making it harder and more dangerous to relocate to a new neighborhood or find a new job, domestic violence should increase.

2 Data and methods

2.1 Data

We collect publicly available data sets on police incidents, calls for service, and crimes that clearly and reliably identify domestic violence from 35 cities and one county in 22 states.[2] See Table 1. All data sets cover from January 1, 2020 to May 24, 2020.[3] We select cities by searching for open data sets abiding by these criteria among the 200 most populous cities in the U.S., along with some smaller cities we found using the Police Data Initiative.

Domestic violence is a broad term covering many types of violence in the family, such as child abuse. The theories listed in the introduction apply to intimate partner violence (IPV). Therefore, to construct the daily domestic violence count, we consider incidents as close to IPV as possible. We include reports of domestic assault,

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[2] Hereafter, we refer to all jurisdictions as cities, even though Montgomery County, MD includes multiple cities.

[3] May 24 is chosen as the last day of the sample instead of May 31 to avoid any confounding effects of the killing of George Floyd on May 25 and the following protests for racial justice and police reform. In an alternative specification, we include May 25-31 while attempting to control for protest incidents. Additionally, we ensure all crime data goes back to at least January 1, 2019 so we may control for crime in the previous year.

domestic battery, or a family fight and exclude threats, child abuse, child neglect, domestic sexual assaults, protective order violations, and nonviolent family disturbances. We keep data that only report "domestic violence", "domestic disturbance", "family fight", or "family disturbance" with no other details.[4] When there are multiple victims or offenses in the same incident, we only count one incident. When possible, we collect data on police calls for service to capture incidents of domestic violence which may not be reported as a crime.[5]

Our main measure for staying at home is the estimated fraction of mobile devices that stay at home all day using data provided by the SafeGraph Data Consortium.[6] 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.[7] We count the number of devices that remained home all day and divide by the total number of sampled devices by county.

Our primary identification strategy is the assumption that the COVID-19 pandemic and ensuing individual decisions to stay at home represent a natural experiment. Figure 1 plots the weekly domestic violence rate, the fraction of people staying home all day, and the dates when local governments first imposed stay-at-home orders in our sample. The weekly variables in the plot are standardized by scaling them down to a mean of zero and a standard deviation of 1. Figure 1 shows an increase in staying at home in early March following well-publicized national reports of community spread (Golliver 2020). This coincides with newspaper reports of increased calls to domestic violence hotlines (Mithani 2020). At roughly the same time, police incidents of domestic violence sharply increase. By itself, this sharp co-movement offers suggestive evidence of a strong association between staying at home and domestic violence, which we can then confirm using more careful regression analysis.

Daily county-level maximum temperature data are compiled from the Global Historical Climatological Network (GHCN). The GHCN daily weather records are retrieved from the National Oceanic and Atmospheric Administration. If there are multiple weather stations in one county, we select the station with more coverage of historical weather information.

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[4] More than 99% of domestic violence incidents in Baltimore and San Jose are reported as "family disturbance"; 59% in Cincinnati are reported as "family trouble"; 55% in Montgomery, AL are reported as "disturb domestic violence"; 84% in Montgomery county, MD are reported as "domestic disturbance/violence"; 99% in Phoenix are reported as "domestic violence"; 100% in Sacramento are reported as "domestic violence"; 36% in Salt Lake are reported as "domestic disturbance/physical"; 77% in Santa Monica are reported as "family disturbance"; 73% in Santa Rosa are reported as "disturbance domestic"; 100% of domestic violence incidents in Mesa are reported as "family fight". 59% of domestic violence incidents in Tucson are reported as "DV". To ensure that these cities do not drive the results, we exclude them in an alternative specification.

[5] When a city has both crime and calls for service data, we use the calls for service data. The following cities only have crime data: Austin, Baton Rouge, Chicago, Denver, Durham, Fayetteville, Kansas City (MO), Louisville, and Montgomery (AL).

[6] 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.
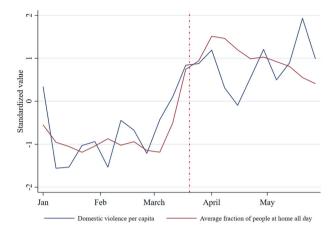
[7] Specifically, SafeGraph regularly sends online queries to mobile devices and obtains location and time data if available.

Fig. 1 Standardized measures of DV, staying at home, and COVID-19. The vertical dotted line represents March 20, when the first stay-at-home orders come into effect in our sample. 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. The date range is from 1/1/2020 to 5/31/2020

Table 2 Summary statistics

	N	Mean	SD
Domestic violence per 100,000 people	5220	3.08	2.43
Fraction of people staying at home	5220	0.33	0.10
Maximum Temperature (°C)	5220	17.54	8.72

City and county population estimates are from the U.S. Census Bureau. Weekly state-level unemployment insurance (UI) claims data are from the U.S. Department of Labor.

On average, cities in the sample report 3.08 domestic violence incidents per 100,000 people per day with a standard deviation of 2.43. See Table 2. The average fraction of people staying at home all day in the sample is 0.33, with a standard deviation of 0.10.

2.2 Methods

Our primary specification tests the hypothesis that the fraction of people staying at home increases police incidents of domestic violence. We employ the following fixed effects model, weighted by city population:

$$DV_{c,t} = \alpha + \beta X_{c,t} + \gamma Stay_{c,t} + \delta_c + \zeta_{month} + \eta_{dayofweek}$$
$$+ \lambda PriorDV_{c,t} + \in_{c,t}$$

The dependent variable DV is the count of domestic violence cases for city c on date t per 100,000 people.[8] The independent variable is $Stay$, the daily average fraction of people who stay at home all day by county. $PriorDV$ is the domestic

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

Table 3 Main results

	(1)	(2)	(3)
Fraction of people staying at home	0.7448[***] (0.2375)	0.7789[***] (0.2431)	0.9922[***] (0.2482)
Prior year domestic violence rate	N	Y	Y
Maximum temperature	N	N	Y
Observations	5220	5220	5220
R^2	0.8972	0.8972	0.8977

All regressions are weighted by population and include month, day of week, city, holiday dummies and the lagged domestic violence rate. Robust standard errors are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

violence rate on the same day-of-year in 2019.[9] X is a vector of controls including the daily maximum temperature in degrees Celsius by county, a dummy for each U.S. federal holiday, and the weekly insured unemployment rate by state. City fixed effects control for the time-invariant characteristics of each city; 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.

3 Results

3.1 Main results

In Table 3, column 3 displays the results for the preferred specification. The dependent variable is the daily count of domestic violence per 100,000 people. After controlling for the insured unemployment rate, seasonality, day of the week, holidays, temperature, and time-invariant city fixed effects, for every increase of 0.1 in the average fraction of people who stay home all day, we observe 0.10 additional daily reports of domestic violence per 100,000 people, a 3.22% increase relative to the sample mean.

From Fig. 1, we can see that the rates of staying at home appeared to increase in earnest around March 13 in our sample, where we estimate the fraction of people staying at home all day at 0.230. Setting this as a baseline, the average change in the fraction of people staying at home from March 13 to May 24 is 0.165.[10] Applying this to the estimated effect of staying at home on domestic violence, we estimate that domestic violence increased by 5.31% during this period. If victims who are trapped at home or economically disadvantaged during shutdowns report to the police less

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[9] We set *PriorDV* for February 29, 2020 to the local domestic violence rate for February 28, 2019. Also, Kansas City, MO lacked complete data in 2019 from January to March, so for that city in that date range we used 2018 data.

[10] Setting the baseline date further back slightly increases the estimated change in staying at home, and setting the baseline date forward slightly decreases the estimated change in staying at home.

often, this is an underestimate of the true effect of staying at home on domestic violence (Li and Schwartzapfel 2020).

3.2 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 include leads of the insured unemployment rate. Third, we restrict the analysis to more uniform sets of calls for service and police incident data. Fourth, we cluster errors at the state level. Fifth, we combine cities in the same county into one data unit. Sixth, we include May 25-31 in the sample and add a dummy for this period. Finally, we re-run the main specification excluding one city at a time.

3.2.1 Average time spent at home

To test whether our result holds for a different measure of staying at home, we estimate the average time spent at home using SafeGraph data. SafeGraph calculates the median time spent at home for all pinged devices in a census block group. 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 estimated fraction of time spent at home by county and day. The average fraction of time spent at home in the sample is 0.47, with a standard deviation of 0.10. Column 1 of Table 4 estimates the effect of average time at home instead of the percentage of people at home all day; the results are qualitatively similar to the main specification. Increasing time spent at home statistically significantly increases reports of domestic violence.

Table 4 Robustness checks

	Different distancing measures		UI leads
	(1)	(2)	(3)
Fraction of time staying at home	0.8064*** (0.2309)		
Device exposure index (DEX)		-0.0190 (0.0216)	
Fraction of people staying at home			0.9589*** (0.2570)
Observations	5220	4536	5148
R^2	0.8976	0.8991	0.8975

DEX is available since January 20, 2020. All regressions are weighted by population and include month, day of week, city, holiday dummies, local maximum temperature, and the lagged domestic violence rate. Robust standard errors in parentheses are clustered by state. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

3.2.2 Device exposure index

While SafeGraph data measures the degree to which people stay at home, other cell phone tracking data measure different types of social distancing efforts, including the degree to which people congregate in commercial venues. Here we use an alternative measure developed by Couture et al. (2020) called the Device Exposure Index (DEX). DEX comes from PlaceIQ movement data and measures how often people visit the same commercial venues, i.e., how little they are social distancing. Starting on 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 111.97, and the standard deviation is 93.31. To increase the ease of interpretation we divide the measure by 100, so the coefficient measures the marginal effect of DEX increasing by 100. We do not find a statistically significant effect of DEX on domestic violence; see column 2 of Table 4.

3.2.3 Unemployment leads

Delays in unemployment insurance claims mean that we may measure lagged unemployment in a rapidly changing labor market. 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 domestic violence can itself influence future unemployment. Column 3 of Table 4 indicates that the main results still hold.

3.2.4 Restricted sample

Some data included in the sample are crime data, and other data lack a description of the incident that allows us to identify domestic assaults as opposed to other forms of domestic violence such as child abuse. To ensure that these differences in data sources do not drive the results, we restrict the analysis to data where we can identify domestic assaults. Specifically, we omit Baltimore, Cincinnati, Mesa, Montgomery (AL), Montgomery County (MD), Phoenix, Sacramento, Salt Lake City, San Jose, Santa Monica, Santa Rosa, St. John, and Tucson. In column 1 of Table 5 in the Appendix, we find that the results hold in the more restrictive sample. We then further restrict the sample by excluding crime data, which eliminates Austin, Baton Rouge, Chicago, Denver, Durham, Fayetteville, Kansas City (MO), and Louisville. Column 2 of Table 5 shows that the results still hold.

3.2.5 Errors clustered at the state level

Cities and counties within the same state enacted shelter-in-place orders at different times, and efforts to stay at home varied significantly for different cities in the same state.[11] That

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[11] The exception are the cities which are all in one county, a concern covered by the next alternative specification.

said, there could still be some within-state correlation for staying at home. For that reason, in Column 3 of Table 5 estimate we cluster standard errors at the state level and find that the results remain significant.

3.2.6 Combining cities in the same county

Some cities included in the sample are in one county. Chandler, Gilbert, Mesa and Phoenix are all in Maricopa County, and Santa Monica and Los Angeles are both in Los Angeles County. Here, we combine all cities in the same county into one data unit with a combined population and daily count of crime. The results in column 4 of Table 5 indicate that this does not change the result.

3.2.7 Including the end of May

We exclude May 25–31, 2020 from the sample to avoid confounding issues surrounding contemporary protests over police violence. Here, we include this data in the sample and add a dummy indicating this range of dates. From column 5 of Table 5, we see that the results do not substantially change.

3.2.8 Omitting cities

We omit one city at a time from the analysis to ensure the results are not driven by any single city. See Fig. 2 in the Appendix. The coefficient of staying at home remains significant at a 5% level.

4 Conclusion

Using up-to-date police data from 36 cities in 22 states in the U.S. and mobile device tracking data, we find that the increase in efforts to stay at home in the U.S. increased domestic violence by over 5% from March 13 to May 24, 2020. This is consistent with exposure reduction theory. This study builds upon a growing new literature. We control for temperature and use mobile device tracking data to overcome empirical challenges in identifying the effect of staying at home. This paper emphasizes the need for resources devoted to victims of domestic violence who are stuck with their abusers. It further supports the theory of exposure reduction, which emphasizes the need to give victims a place away from their abusers such as a shelter, even if it may be more difficult to provide these resources.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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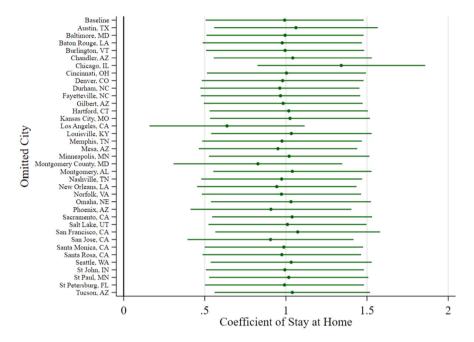
5 Appendix

Figure 2 and Table 5

Fig. 2 Removing one city, stay at home

Table 5 Alternative specifications

	Must ID assault	Must ID assault, no crime	cluster	Combined cities	Include late May
	(1)	(2)	(3)	(4)	(5)
Fraction of people staying at home	0.8591***	1.3480***	0.9922**	0.9957***	1.0178***
	(0.2749)	(0.3569)	(0.4639)	(0.2522)	(0.2453)
Observations	3770	2610	5220	4640	5400
R^2	0.9058	0.9157	0.8977	0.9052	0.8990

All regressions are weighted by population and include local maximum temperature, the lagged domestic violence rate, insured unemployment rate, and month, day of week, city, and holiday dummies. Robust standard errors are in parentheses. Robust standard errors clustered at state level are in parentheses in column 3. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

References

Aizer, A. (2010). The gender wage gap and domestic violence. *American Economic Review*, *100*(4), 1847–59.

Brassiolo, P. (2016). Domestic violence and divorce law: when divorce threats become credible. *Journal of Labor Economics*, *34*(2), 443–77.

Chin, Y.-M. (2012). Male backlash, bargaining, or exposure reduction?: Women's working status and physical spousal violence in India. *Journal of Population Economics*, *25*(1), 175–200.

Couture, V., Dingel J., Green, A., Handbury, J., Williams, K. (2020). Covid Exposure Indices. https://github.com/COVIDExposureIndices/.

Fajardo-Gonzalez, J. (2020). Domestic violence, decision-making power, and female employment in Colombia. *Review of Economics of the Household*, 1–22. https://doi.org/10.1007/s11150-020-09491-1.

Golliver, B. (2020). NBA suspends season after Jazz's rudy gobert tests positive for coronavirus. *Washington Post*. https://www.washingtonpost.com/sports/2020/03/11/nba-suspends-play-player-test-coronavirus/.

Henke, A., & Hsu, L-C. (2020a). The effect of sheltering in place on police reports of domestic violence in the US. *Feminist Economics*. Forthcoming.

Henke, A, & Hsu, L-C. (2020b). The gender wage gap, weather, and intimate partner violence. *Review of Economics of the Household*, *18*, 413–429.

Leslie, E, & Wilson, R. (2020). Sheltering in place and domestic violence: evidence from calls for service during COVID-19. *Journal of Public Economics*, Forthcoming, Available at SSRN: https://ssrn.com/abstract=3600646 or https://doi.org/10.2139/ssrn.3600646.

Li, W, & Schwartzapfel, B. (2020). Is domestic violence rising during the coronavirus shutdown? Here's what the data shows. *The Marshall Project*. April 22, 2020. https://www.themarshallproject.org/2020/04/22/is-domestic-violence-rising-during-the-coronavirus-shutdown-here-s-what-the-data-shows.

McElroy, M.B., & Horney, M.J. (1981). Nash-bargained household decisions: Toward a generalization of the theory of demand. *International Economic Review*, *22*, 333–349.

Mithani, J. (2020). What we know about crises and domestic violence—and what that could mean for COVID-19. *FiveThirtyEight*. May 4, 2020. https://fivethirtyeight.com/features/what-we-know-about-crises-and-domestic-violence-and-what-that-could-mean-for-covid-19/.

Silverio-Murillo, A., Balmori de la Miyar, J.R., & Hoehn-Velasco, L. (2020). Families under Confinement: COVID-19, Domestic Violence, and Alcohol Consumption. Andrew Young School of Policy Studies Research Paper Series Forthcoming, Available at SSRN: https://ssrn.com/abstract=3688384 or https://doi.org/10.2139/ssrn.3688384.

Zhu, Y. & Xie, J. (2020). Association between ambient temperature and COVID-19 infection in 122 cities from China. *Science of the Total Environment*, *724*, 138201.