COVID-19 and Domestic Violence: Economics or Isolation?

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Abstract
Recent studies estimate that the COVID-19 pandemic significantly increases reports of domestic violence in several countries. Using mobile device tracking data, city-level unemployment data, and new data on labor market conditions caused by the coronavirus pandemic, we isolate the effects of unemployment and staying at home on incidents of domestic violence. We find that unemployment decreases domestic violence after controlling for the degree to which people stay at home. We also provide evidence that staying at home increases domestic violence. However, we find that the effects of unemployment and staying at home are concentrated right after an initial shock from mid-March to mid-June 2020. Finally, we find that some labor market conditions linked to COVID-19, such as being prevented from looking for work due to the pandemic, decrease domestic violence, and these labor market effects are often gendered.

Keywords Domestic violence · Intimate partner violence · Pandemic · COVID-19 · Staying at home · Unemployment

Introduction

Various measures of domestic violence, including police reports, online search trends, and calls to domestic violence hotlines, increased dramatically after the COVID-19 pandemic began to spread extensively near the beginning of 2020 (Arenas-Arroyo et al., 2021; Ivandic et al., 2020; Köksal et al., 2021; McCrary & Sanga, 2021; Ravindran & Shah, 2020; Silverio-Murillo et al., 2020). A new strand of research has emerged that estimates the pandemic's impact on domestic violence; these studies often use an event-study approach with either the implementation of stay-at-home orders issued by local governments or an estimate of people staying at home to mark the beginning of the "event" (Agüero, 2021; Bullinger et al., 2021; Leslie & Wilson, 2020). These studies do the important work of estimating the overall effect of the pandemic on domestic violence; however, this approach does not identify potential mechanisms that explain how the pandemic has increased reports of domestic violence. Also, early studies only cover the beginning of the pandemic and may not provide a complete picture of the pandemic's effects in the long run.

When allocating resources to respond to an increase in domestic violence, it is important that policymakers know how much of the increase is caused by concurrent changes in economic and other factors. Our contribution is to investigate two possible channels of the impact of the pandemic on domestic violence: people staying at home and labor market conditions related to COVID-19. If the main culprit for an increase in violence is a shift in labor demand, then interventions should focus on the labor market and direct financial assistance. If the bigger issue is simply that unhappy couples are cooped up together all day, isolated from everyone else, then economic interventions are insufficient. In addition, it is important to know whether the pandemic has a long-lasting effect or whether it acts as a one-time shock so that policymakers will understand how to respond: Should they devote resources to mitigate the current shock or invest in resources to prevent the next shock?

We use a unique data set that allows us to conduct timely tests. To estimate the prevalence of domestic violence, we collect data on daily police calls for service, police incidents, and crimes from 32 cities in the US. To estimate the daily

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proportion of people staying at home, we use a country-wide smartphone tracking data set from the SafeGraph Data Consortium. To estimate economic conditions, we use city-level unemployment data from the Bureau of Labor Statistics and data on COVID-19-related labor market outcomes provided by the Current Population Survey (CPS).

Using these data, we find that an increase in the fraction of people staying at home all day increases police reports of domestic violence. We also find that local unemployment decreases domestic violence, suggesting that a broad decrease in overall unemployment is not a sufficient policy tool to mitigate incidents of violence. To examine the overall effect of the pandemic over time, we employ a flexible event study method and find that the pandemic's monthly effect on domestic violence fades, which suggests that the effects we observe are caused by an early shock from mid-March to mid-June 2020. We test for these potential heterogeneous effects and find that the effects of both unemployment and staying at home are indeed significantly stronger in this early period.

To disentangle the economic effects of the pandemic, we use recently released economic variables linked directly to the COVID-19 pandemic from the CPS. Similar to our results on unemployment, we find that the pandemic preventing men and women from looking for work decreases domestic violence. We also find that there is a heterogeneous effect on receiving payment for hours not worked by gender: Women receiving pay for hours not worked decreases domestic violence, but men receiving pay for hours not worked increases domestic violence.

This article advances the literature on the effects of COVID-19 and domestic violence by extending the analysis to later months of the pandemic to validate early research. While the initial shock has strong effects, the marginal effect of the pandemic may have faded after mid-June 2020. This has important policy implications, since policymakers may devote resources to mitigate the next shock from having such a significant impact on domestic violence. We also disentangle the economic effects of the pandemic from other causes using new data directly related to COVID-19 and identify gendered labor market effects of the pandemic on domestic violence.

Economic Theories of Domestic Violence

When we discuss theories of domestic violence and interpret some empirical results, we assume the perpetrator is male and the victim is female, because men are more likely to be perpetrators (World Health Organization, 2012) and also some theories, such as male backlash, explicitly model violence against women. However, our reduced-form empirical results are not sensitive to this framing; rather, our interpretation may be sensitive to it.

Exposure reduction theory examines the opportunity for and temptation of crime; the more often a prospective criminal is exposed to opportunities for crime, the more often crime will occur. In the case of domestic violence, a potential victim who is away when the abuser is home is less likely to be abused than one who is at home with the abuser (Chin, 2012; Hsu & Henke, 2021a, 2021b). The pandemic shutdowns and efforts to stay at home to reduce infection create an extreme test of this, whereby abusers and victims are at home with each other all day.

While exposure reduction theory focuses on the opportunity to commit violence, household bargaining theory focuses on the cost of committing violence. Within this framework, an abuser enjoys the use of "expressive" violence against his partner as a way to relieve frustration (Card & Dahl, 2011). The abuser is willing to "pay" the victim for violence in the form of intrahousehold transfers; the level of abuse depends on the abuser's taste for violence and the victim's bargaining power, which allows her to charge a high "price" for abuse by threatening to leave the relationship. The abuser's taste for violence varies over time—for instance, emotional cues such as professional football losses can increase an abuser's frustration, and thus increase his utility of committing acts of domestic violence (Card & Dahl, 2011). This could also apply to the emotional rigors of isolation, in which exposure reduction theory and household bargaining theory interact. In other words, exposure itself may temporarily increase preferences for violence. Furthermore, household bargaining theory predicts that domestic violence will shift based on who has more economic bargaining power. For example, if an abusive partner is unemployed while the potential victim is employed, the potential victim can credibly threaten to leave. In another example, if daycare closures increase the demand for household labor, then the primary caretaker or household labor provider requires more transfers to stay in the relationship.

In contrast, the theories of instrumental violence and male backlash predict that a woman's economic power can increase violence. Increasing a woman's economic bargaining power may cause the man to feel powerless and lash out violently (Chin, 2012). Angelucci and Heath (2020) find that the women's empowerment program in the Democratic Republic of the Congo may increase intimate partner violence if the woman is the main breadwinner. Moreover, an increase in a woman's bargaining power may cause the abuser to use violence as a tool to re-establish control, provided that the woman would not leave the relationship in response to any violence. In the daycare closure example above, the abuser may use violence to force his partner to provide household labor/childcare at a lower price.

Possible Effects of COVID-19 on Domestic Violence

Identifying different channels of the pandemic is difficult. To isolate one effect, we must adequately control for all potential channels, since they are all related. Hsu and Henke (2021a) use mobile device tracking data and include a variety of important confounders, such as weekly unemployment insurance claims, to distinguish the effect of staying at home on domestic violence in March and April 2020. We improve on this study by creating tests using new data and a longer sampling period. Prior studies have identified the effect of unemployment on domestic violence, albeit not in the context of a pandemic. Anderberg et al. (2016) estimate the impact of unemployment on domestic violence during the great recession of the mid-2000s in the UK. They find that male unemployment decreases domestic violence and female unemployment increases domestic violence. Alonso-Borrego and Carrasco (2017) find that an abuser's employment increases violence, but female employment only decreases violence if the partner works as well. Unemployment in the context of the pandemic may impact domestic violence differently. While our main measure of unemployment is not gendered, we complement that data with gendered labor market conditions from the CPS.

Our work also creates an empirical test for competing theoretical channels of domestic violence.[1] The most direct channel for violence is that victims and abusers spend more time with each other during a pandemic. We measure exposure in two ways: by measuring the fraction of people who stay at home all day and then, as a robustness check, measuring the fraction of time spent at home. The use of mobile device tracking data to measure isolation complements recent studies that use survey data such as that of Béland et al. (2020). Finally, we explore how labor market conditions, specifically impacted by COVID-19, affect domestic violence, using theories of household bargaining, male backlash, and instrumental violence as a guide.

Data

Crime and Police Calls for Service

We obtained open data sets on police incidents, police calls for service, and crimes from 32 cities during the sample period of January 1, 2019, through November 30, 2020.[2] See Appendix Table 5 for a list of cities in the sample and the type of data collected.

Each call was accompanied by a text description, and we constructed a daily domestic violence count focused on intimate partner violence by including reports of domestic assault, domestic battery, or a family fight. Threats, child abuse, child neglect, domestic sexual assaults, protective order violations, and nonviolent family disturbances were excluded. We counted each incident only once, even if there were two victims. Our preferred record of domestic violence is police calls for service since some domestic violence is never reported as a crime.

To construct a crime rate, we used city and county population estimates from the U.S. Census Bureau in 2019. The domestic violence rate was the number of qualified calls or incidents per 100,000 people by city and day.

Staying at Home

We measured staying at home by estimating the fraction of mobile devices at home all day using data provided by the SafeGraph Data Consortium.[3] SafeGraph pings 45 million mobile devices in the US and its territories to see where and for how long each device has traveled from its home location. We counted the number of devices that remained home all day and divided by the total number of sampled devices by county and day, obtaining a fraction of people at home all day each for city-day in the sample.

Unemployment and Economic Conditions Related to COVID-19

Our monthly unemployment data came from the Local Area Unemployment Statistics (LAUS) program of the U.S. Bureau of Labor Statistics (BLS). LAUS allowed us to collect city-level data on the unemployed population and

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[1] In particular, we considered theories of intimate partner violence and tailored our data to focus as closely as possible on incidents between intimate partners.

[2] The use of police incidents and police calls for service are popular for studies of the pandemic's effect on crime (Bullinger et al., 2021; Ivandic et al., 2020; Leslie & Wilson, 2020; McCrary & Sanga, 2021; Miller et al., 2020). These studies also use keywords in the police incident data to identify cases of domestic violence. We selected cities by searching for open police data sets that met these criteria in populous cities in the U.S. We found some smaller cities using the Police Data Initiative. The last day for Santa Rosa, CA was 8/24/20. Kansas City, MO does not have complete data from January to March 2019.

[3] SafeGraph is a data company that aggregates anonymized location data from numerous applications 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.

Table 1 Summary statistics

	N	Mean	SD
Domestic violence rate (counts per 100,000 people)	22,219	3.01	2.70
Unemployment rate (unemployed ÷ labor force × 100)	22,219	6.13	3.94
Fraction of people staying at home all day	22,219	0.32	0.06
Fraction of people received pay for hours not worked	6750	0.14	0.12
Female	6750	0.14	0.16
Male	6750	0.14	0.15
Fraction of people who worked remotely for pay	6750	0.33	0.14
Female	6750	0.37	0.15
Male	6750	0.30	0.15
Fraction of people who prevented from looking for work	6750	0.07	0.05
Female	6750	0.06	0.05
Male	6750	0.07	0.06
Fraction of people who are unable to work	6750	0.12	0.06
Female	6750	0.11	0.07
Male	6750	0.12	0.06

labor force.[4] We used this to calculate the city-month-level unemployment rate in percentage form.

We also used monthly data collected in response to the pandemic by the CPS and provided by the Integrated Public Use Microdata Series (Flood et al., 2020) and calculated percentages of respondents who answered "yes" to particular questions. Survey questions asked whether the respondent was prevented from looking for work, received any pay for the hours not worked, was unable to work, or teleworked for pay due to the pandemic in the last 4 weeks.[5] The unemployment rate only captured a portion of the negative labor market effects of the pandemic since some people who feared contracting COVID-19 due to unsafe working conditions were not looking for jobs. The key benefit of this data was that it asked specific questions related to the pandemic and provided a more accurate measure of negative labor market outcomes influenced by COVID-19. The main drawback was that the data were only available starting in May 2020, so we missed important early variation in the pandemic.

Summary Statistics

Table 1 presents sample averages and standard deviations of the primary variables used in our analysis, as we describe in each section above. On average, cities in the sample reported 3.01 domestic violence incidents per 100,000 people per day. The average fraction of people staying at home all day in the sample was 0.32 (32%), and the average unemployment rate was 6.13%. From May to November 2020, on average, 14% of workers who were unable to work due to pandemic-related closures or lost business received at least some pay for the hours not worked; 33% of employed people teleworked because of the pandemic; 7% of people who were not in the labor force were prevented from looking for work due to the pandemic; and 12% of the civilian noninstitutional population reported that they had been unable to work because their employer lost business or shut down.

Figures 1 and 2 plot the rates of staying at home and unemployment over time, respectively, and compare them with trends in the reported domestic violence rate in 2018, 2019, and 2020. Everything was standardized to mean 0 and standard deviation 1 and plotted as a 7-day moving average, except for unemployment.[6] The graphs show how the pandemic event led to changes in economic conditions (unemployment), isolation (staying at home), and domestic violence.

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[4] The LAUS program provided data on cities above 25,000 population. If the city population was less than 25,000, we used the metropolitan statistical area unemployment data from the LAUS.

[5] The survey only asked respondents whether they were prevented from looking for work if they were not in the labor force. Note that the measure of "unable to work" included those who were unable to work either because the entire business was shut down or because their work hours were reduced. People who were unable to work because they feared contracting the virus were not included in this measure. People whose telework was unrelated to the pandemic, such as people who worked entirely from home before the pandemic, were not included in the measure of telework.

[6] Unemployment was not plotted as a moving average because it was a monthly measure.

Fig. 1 Standardized 7-day moving average measures of domestic violence and staying at home. *Note* The vertical line indicates 3/17/2020, when the first shelter-in-place order went into effect in our sample. The 7-day moving averages of domestic violence and the fraction of people at home all day are weighted by population and standardized to mean zero and standard deviation 1 for the whole sample. The date range of domestic violence is from 1/1/2019 to 11/30/2020

Fig. 2 Standardized 7-day moving average measures of domestic violence and unemployment rate. *Note* The vertical line indicates 3/17/2020, when the first shelter-in-place order went into effect in our sample. The 7-day moving averages of domestic violence and the unemployment rate are weighted by population and standardized to mean zero and standard deviation 1 for the whole sample. The date range of domestic violence is from 1/1/2019 to 11/30/2020
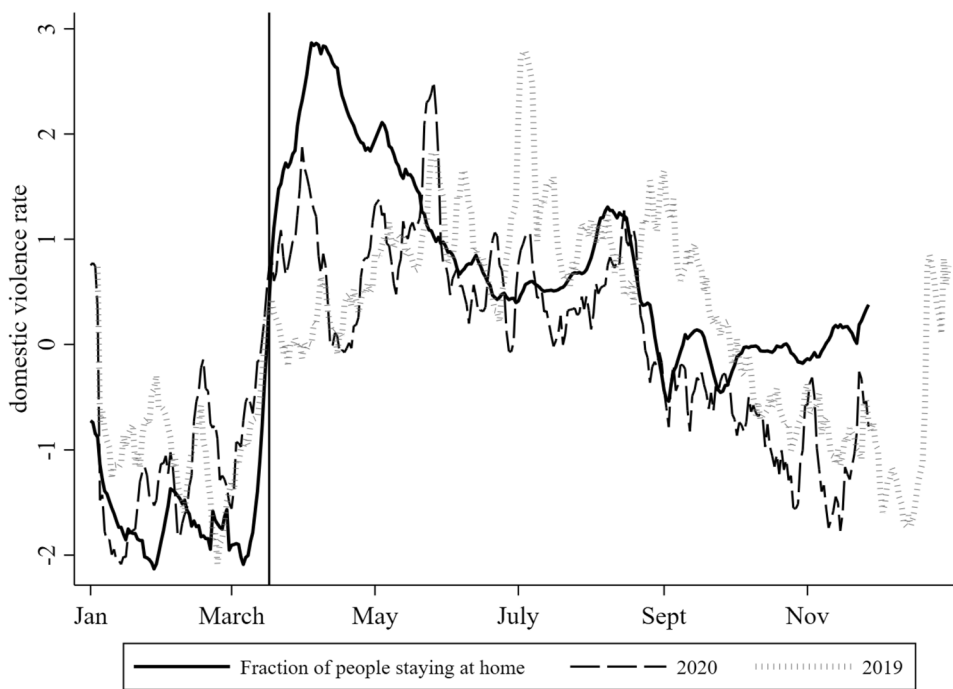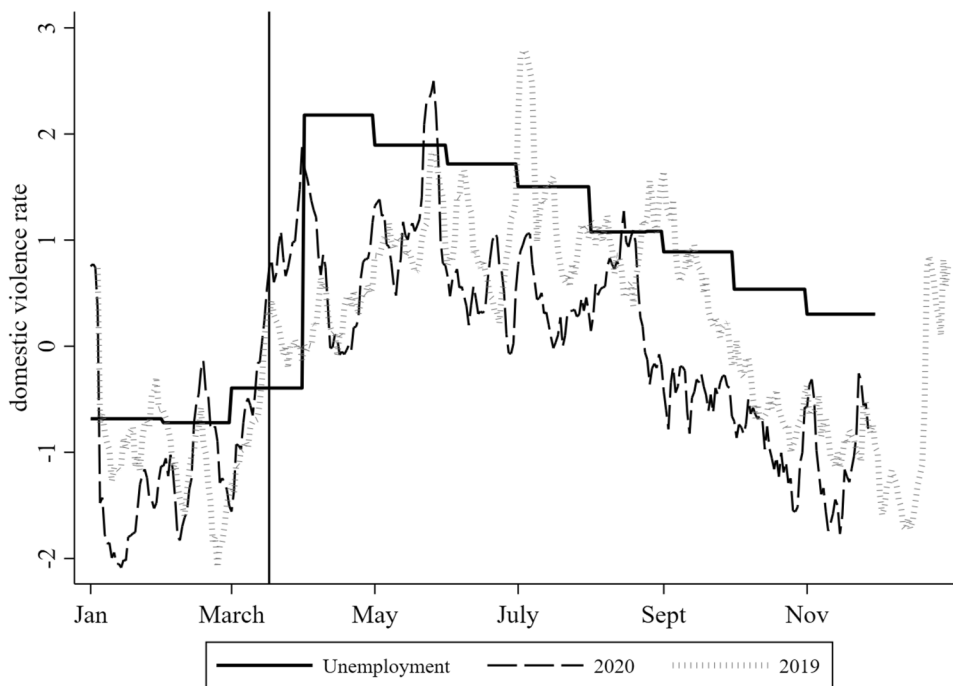

Methods

Our primary specification tests two hypotheses: During the COVID-19 pandemic, did unemployment affect domestic violence, and did staying at home affect domestic violence? To test these hypotheses, we estimated the following fixed effects specification:

Table 2 The effect of staying at home and unemployment on domestic violence

	(1)	(2)	(3)	(4)	(5)
Fraction of people staying at home	0.212†		0.516***	0.138	-0.064
	(0.110)		(0.128)	(0.139)	(0.149)
Unemployment		− 0.005*	− 0.011***	− 0.012***	− 0.006†
		(0.002)	(0.003)	(0.003)	(0.003)
Fraction of people staying at home*(3/14–6/13)				0.412***	0.818***
				(0.072)	(0.145)
Unemployment*(3/14–6/13)					− 0.014**
					(0.005)
Observations	22,212	22,212	22,212	22,212	22,212
R^2	0.886	0.886	0.887	0.887	0.887

Note The dependent variable is the daily number of domestic violence calls or incidents per 100,000 people. All regressions are weighted by population and include year, month, day of week, city, holiday dummies, and the lagged 7-day moving average domestic violence rate in the previous year. Robust standard errors are in parentheses. Data are from 1/1/19 to 11/30/20

$^\dagger p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

$$DV_{c,t} = \alpha + \beta Unemp_{c,t} + \gamma Stay_{c,t} + \delta_c + \zeta_{month} \\ + \eta_{day\,of\,week} + \lambda X + \epsilon_{c,t} \qquad (1)$$

The dependent variable *DV* is the count of domestic violence cases for city c on date t per 100,000 people. *Unemp* is the unemployment rate. *Stay* is the daily average fraction of people who stay at home all day. δ is a city fixed effect, ζ is a month fixed effect, and η is a day-of-week fixed effect. X is a vector of controls that includes the 7-day moving average domestic violence rate of the previous year and holiday dummies.[7] Our empirical strategy relied on the assumption that the COVID-19 pandemic provided exogenous variation in both staying at home and unemployment, after accounting for the included controls.

We also tested for pre-trends and examined how the overall effect varied over time using a flexible event study approach akin to Leslie and Wilson (2020). Specifically, we employed their method using SafeGraph data to estimate the beginning of the pandemic "event" by observing when people began to increase their rates of staying at home; we found that this occurred on March 14, 2020, in our sample.[8] Then we constructed a reference month leading up to the event from February 14, 2020, to March 13, 2020. Finally, we modified the main specification by replacing *Unemp* and *Stay* with month dummies surrounding a reference month, as detailed in Eq. (2):

$$DV_{c,t} = \alpha + \sum_{i=1}^{16} \beta_i Month_i + \delta_c + \zeta_{month} + \eta_{day\,of\,week} + \lambda X + \epsilon_{c,t} \qquad (2)$$

where $Month_i$ is a dummy indicating it is month i, starting in June 2019, skipping the reference month, and ending in November 2020. The sample in this regression is from 6/14/19 to 11/13/20. All other controls are the same as in the main specification.

Results

Column 3 of Table 2 shows the results from the preferred specification described by Eq. (1).[9] After controlling for the 7-day moving average domestic violence rate of the previous year, seasonality, day of the week, holidays, and time-invariant city fixed effects, for every increase of 10% in the average percentage of people who stayed home all day (e.g., an increase from 30 to 40%), we observe 0.052 additional daily reports of domestic violence per 100,000 people, for a 1.7% increase relative to the sample mean. For every 1% increase in the unemployment rate, we observed 0.011 fewer daily reports of domestic violence per 100,000 people, a 0.4% decrease relative to the sample mean.

The estimate on staying at home is about half that of Hsu and Henke (2021b), whose data covered the period to May 2020. To test the hypothesis that the effect of staying at home diminishes over time, we used the flexible event-study specification from Eq. (2). Figure 3 showed a spike in

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[7] For missing 7-day moving average domestic violence rate in 2019 for Kansas City, MO, we replaced it with data in 2018.

[8] This estimate is similar to prior studies but not exactly the same, likely due to minor differences in our sample selection. For instance, we include 17 more cities in this sample; see Fig. 1.

[9] Unemployment and staying at home are potential confounders for each other, which is why our preferred specification includes both. As is typical, in Tables 2 and 3 we stagger the implementation of important controls to see whether there are major changes in the estimates.

Table 3 The effect of COVID-19-related economic/labor market outcomes on domestic violence

	(1)	(2)	(3)	(4)
Received pay for hours not worked due to COVID-19	− 0.045	− 0.041	− 0.052	− 0.048
	(0.160)	(0.160)	(0.160)	(0.160)
Worked remotely for pay due to COVID-19	− 0.297	− 0.301	− 0.220	− 0.223
	(0.296)	(0.296)	(0.292)	(0.292)
Prevented from looking for work due to COVID-19	− 2.110***	− 2.097***	− 1.891***	− 1.876***
	(0.427)	(0.427)	(0.418)	(0.418)
	(0.441)	(0.440)	(0.441)	(0.440)
Fraction of people staying at home		− 0.375		− 0.412
		(0.451)		(0.451)
Unemployment			− 0.023**	− 0.023**
			(0.007)	(0.007)
Observations	6750	6750	6750	6750
R^2	0.883	0.883	0.883	0.883

Note The dependent variable is the daily number of domestic violence calls or incidents per 100,000 people. All regressions are weighted by population and include month, day of week, city, holiday dummies, and the lagged 7-day moving average domestic violence rate in the previous year. Robust standard errors are in parentheses. Data are from 5/1/20 to 11/30/20

**$p < 0.01$, ***$p < 0.001$

Fig. 3 Event study. *Note* This figure plots the coefficients from Eq. (2) using data from 6/14/2019 to 11/13/2020. The regression is weighted by population and include month, day of week, city, holiday fixed effects, and the lagged 7-day moving average domestic violence rate in the previous year. The omitted month is from 2/14/2020 to 3/13/2020
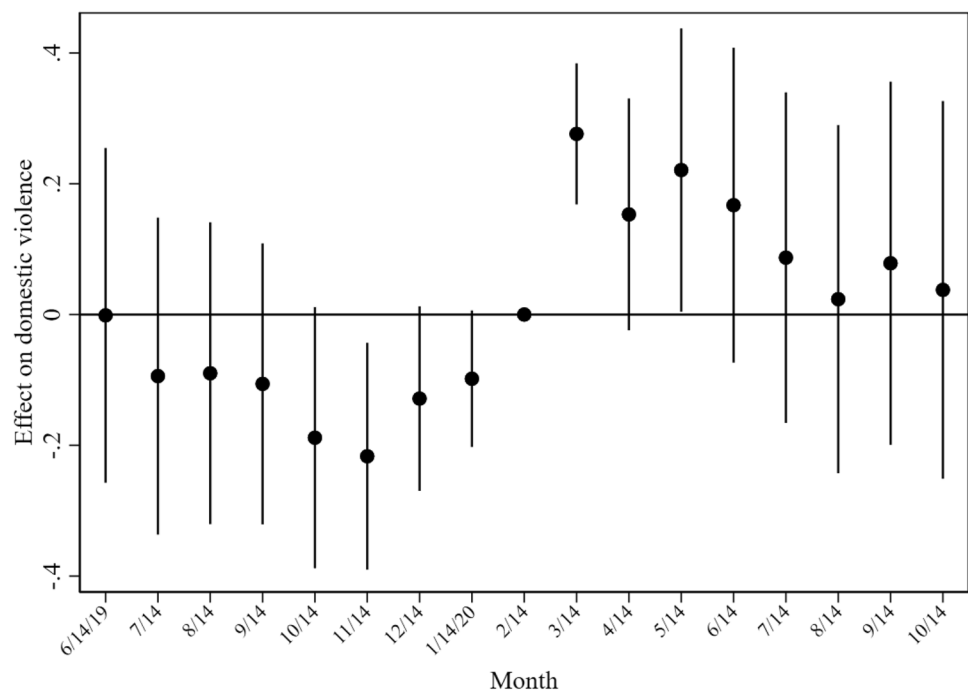
the effect of staying at home on domestic violence immediately following the "event" on March 14, consistent with studies with a shorter sample. As time went on, however, we found that the estimated overall effect of the pandemic tended toward zero and lost statistical significance.

A possible reason the effect of the pandemic diminished is that the marginal effects of unemployment and staying at home are strongest during an initial shock period. To test

this hypothesis, we modified Eq. (1) by adding an interaction term, $Stay_{c,t} * \theta_t$, where θ_t is a dummy indicating that the date is from March 14 to June 13, 2020.[10] We also constructed an interaction for unemployment, $Unemp_{c,t} * \theta_t$. In

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[10] We chose the first 3-month period after the pandemic "event" from Eq. (2) because the coefficient plot in Fig. 3 indicated that the effect of the pandemic declined after those 3 months.

Table 4 The effect of labor market outcomes linked to COVID-19 by gender on domestic violence

	(1)	(2)	(3)	(4)
Received pay for hours not worked—female	− 0.211*	− 0.215*	− 0.211*	− 0.216*
	(0.105)	(0.105)	(0.105)	(0.105)
Received pay for hours not worked—male	0.207*	0.231*	0.210*	0.234*
	(0.104)	(0.105)	(0.104)	(0.105)
Worked remotely for pay—female	− 0.696**	− 0.722**	− 0.696**	− 0.722**
	(0.219)	(0.220)	(0.219)	(0.220)
Worked remotely for pay—male	0.282	0.373†	0.276	0.367†
	(0.222)	(0.219)	(0.222)	(0.219)
Prevented from looking for work—female	− 1.341***	− 1.215***	− 1.332***	− 1.204***
	(0.350)	(0.347)	(0.350)	(0.347)
Prevented from looking for work—male	− 1.130***	− 1.027***	− 1.127***	− 1.023***
	(0.305)	(0.304)	(0.305)	(0.304)
Unable to work—female	− 0.087	− 0.093	− 0.062	− 0.066
	(0.363)	(0.363)	(0.362)	(0.362)
Unable to work—male	0.748*	0.881*	0.755*	0.890*
	(0.366)	(0.366)	(0.366)	(0.366)
Fraction of people staying at home			− 0.382	− 0.420
			(0.448)	(0.448)
Unemployment		− 0.026**		− 0.026**
		(0.008)		(0.008)
Observations	6750	6750	6750	6750
R^2	0.883	0.884	0.883	0.884

Note The dependent variable is the daily number of domestic violence calls or incidents per 100,000 people. All regressions are weighted by population and include month, day of week, city, holiday dummies, and the lagged 7-day moving average domestic violence rate in the previous year. Robust standard errors are in parentheses. Data are from 5/1/20 to 11/30/20

$^†p < 0.10$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

columns 4 and 5 of Table 2, we found that the effects of both staying at home and unemployment were driven largely by this immediate 3-month period following the event. A smaller negative association between unemployment and domestic violence after the 3-month period remained significant at the 10% level.

Next, we used new CPS data to see whether various COVID-related labor market conditions affected domestic violence. Of four survey questions, in Table 3 we show that being prevented from looking for work due to COVID-19 reduced domestic violence.[11] We then explored the heterogeneous effects by gender. In Table 4, we find the following: When more female (male) workers received pay for hours not worked, domestic violence decreases (increases); more female (male) telework decreases (increases) domestic

violence; and more male workers prevented from looking for work decreases domestic violence.[12]

Discussion

Our evidence on staying at home and violence is consistent with exposure reduction theory. This exposure effect is strongest when people begin to stay at home starting in March of 2020, and the effect fades afterward. The "shock" of the lockdown may be more important than the prolonged effects of isolation in terms of its effect on domestic violence. This result also explains why the estimated effect of staying at home on domestic violence loses significance in specifications that use CPS data, since CPS data are only available starting in May 2020.

Overall, the effect of unemployment follows a similar pattern: Higher unemployment initially has a sharply negative effect on domestic violence, and then the effect diminishes.

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[11] Specifically, we found that a one-standard-deviation increase in the rate of being prevented from looking for work led to a roughly 0.1-standard-deviation decrease in domestic violence incidents, which was economically significant but not unreasonably large.

[12] Male telework was only marginally significant and only when we included unemployment as a control.

The effect of unemployment on domestic violence is theoretically ambiguous and has many potential channels. Unemployment can create family stress, which leads to more violence; additionally, household bargaining theory predicts that a sharp increase in female unemployment and a mild increase in male unemployment, as was the case in 2020 (Albanesi & Kim, 2021), would increase domestic violence due to a relative shift in economic bargaining power towards men. However, theories of male backlash and instrumental violence predict that female unemployment would lead to less domestic violence. When men are unemployed and their partners are employed, the theories predict that men seek to reassert dominance and the male role in the household through violence. Here, we find evidence that is consistent with male backlash and instrumental violence: If more women are unemployed, then fewer men use violence to establish their dominance.

In contrast to Béland et al. (2020), our regressions using CPS data on the labor market provide some evidence on gendered employment and work arrangement effects. These are consistent with a household bargaining theory of domestic violence: A woman who can telework or receive pay for hours not worked has a strong bargaining position and forces an abuser to pay a higher price for violence; a man who is prevented from searching for work lowers his bargaining position.

We also find evidence that is consistent with theories of male backlash and instrumental violence. For instance, increasing the proportion of female (male) workers who are prevented from looking for work reduces (increases) domestic violence. This suggests that the dominant mechanism for the pandemic's effect on domestic violence may depend on the type of jobs women have. Women who can telework are in a different position than ones whose work can only be performed on-site, and so bargaining power may be the primary effect in this case. Additionally, on average, the routines of female workers who work in person were disrupted more than those who telework, and this disruption could itself lead to conflict. Another way to reconcile these results is that women who received pay for hours not worked due to COVID-19 and women who telework may have more time for household labor. An additional caveat is that there may have specifically been a surge in female IPV victims during the pandemic (Morgan & Boxall, 2020). Thus, our analysis of gendered results may be influenced by this shift.

Disentangling the effect of economics and isolation on IPV, as well as considering gendered labor market effects, has important policy implications. Overall unemployment assistance, while generally useful, is not guaranteed to help combat IPV. Providing safe spaces is crucially important, especially when a pandemic presents unique difficulties. Finally, there is some suggestive evidence that job flexibility gives potential victims more bargaining power and makes their routine more robust to significant external shocks.

Any study that uses police data as a measure of domestic violence faces challenges. First, there is always a level of underreporting in police domestic violence data that attenuates any estimated effect. In other words, even if reported IPV is a constant fraction of IPV (e.g., half), then estimated effects will only reflect that fraction (e.g., half) of the true effect. Second, reporting behavior may have changed during the pandemic. For instance, victims may not wish to see their abusive significant others go to jail and risk infection; also, it may be harder to call the police, since the victim is stuck at home all day with the abuser. Therefore, our estimated effect of isolation on domestic violence is likely a lower bound. This is also why a granular measure of isolation is a key control when attempting to estimate the effect of economic pandemic channels on IPV. In addition, any study of domestic violence during the pandemic faces limitations. Because many important policies and events occurred at similar times, it is difficult to separate the effect of one event or policy from another. We have made our best effort to disentangle economic and exposure effects on domestic violence.

Alternative Specifications and Robustness Checks

First, we used unemployment insurance (UI) claim data instead of BLS unemployment data. Second, we used an alternative measure of staying at home: the average fraction of time spent at home. Third, we dropped the 2 weeks of data immediately following George Floyd's murder. Fourth, we aggregated cities in the same county to one unit. Fifth, we controlled for the daily number of participants in local political protests. Sixth, we clustered standard errors at the county level. Seventh, we controlled for the local maximum temperature. Last, we omitted one city at a time and check to see whether the main results held.

Unemployment Insurance

To see whether our results were sensitive to the measurement of unemployment, we used unemployment insurance claims data instead of unemployment data from the BLS. The benefit of using UI is that it is available every week; however, it is only available at the state level. Another disadvantage of UI is that many people who are out of work due to the pandemic may not be measured by UI, and who applies (and thus is in the sample) may depend on location or circumstance. For example, UI does not provide benefits to those who are afraid of contracting COVID-19 due to unsafe work conditions, and therefore these people would

not be captured by UI data.[13] Weekly state-level unemployment insurance claims data are from the U.S. Department of Labor. In our sample, the mean of the insured unemployment rate is 3.82%, and the standard deviation is 4.65. In Appendix Table 5, column 1, we can see that the results are similar to the ones in Table 2, column 3.

An Alternative Measure of Staying at Home: The Fraction of Time Spent at Home

To see whether a different measure for staying at home changes our main results, we used an alternative measure: the average proportion of time at home, collected by SafeGraph. SafeGraph measures the average proportion of time spent at home at census block-group level. We calculated the county-level average proportion of time at home weighted by the number of pinged mobile devices in the block group. The average proportion of time at home is 0.44 in our sample and the standard deviation is 0.08. Column 2 of Table 5 shows the regression results replacing the proportion of people staying at home all day with the proportion of time spent at home, and our main results hold.

Dropping Black Lives Matter Protest Weeks

Here we dropped two Black Lives Matter (BLM) protest-intensive weeks following George Floyd's murder; specifically May 26, 2020, to June 8, 2020. During protest-intensive weeks, the police may have responded to domestic violence calls differently due to a shortage of manpower. In addition, political protests have a mixed relationship with domestic violence: They are positively associated with crimes but negatively associated with hotline calls (Miller et al., 2020). In column 3 of Table 5, we find that the results do not significantly change.

Combining Cities in the Same County

Most cities in our sample are the only city in that county. The exceptions are Santa Monica and Los Angeles, which are both in Los Angeles County, and Chandler, Mesa, and Phoenix, all of which are in Maricopa County. Since the estimate for staying at home is at the county level, here we combined cities in the same county into a single unit. In Table 5, column 4, we see that the results remain consistent.

Political Protests

To ensure that we did not miss any important connection between political protests and domestic violence, here we controlled for the number of participants in local political protests, similar to Miller et al. (2020). We collected daily-city-level data on the number of participants in political protests, marches, demonstrations, and rallies from the Crowd Counting Consortium.[14] In column 5 of Table 5, we see that the results are similar to the main results.

Clustering Standard Errors at the County Level

There may be some within-county correlation related to staying at home or unemployment. In column 6 of Table 5, we clustered standard errors at the county level. The coefficient of staying at home remained positively significant, while the coefficient of unemployment has lost statistical significance.

Weather

Here we controlled for local maximum temperature, which is known to increase domestic violence (Henke & Hsu, 2020). It is also positively associated with confirmed COVID-19 cases, and therefore the proportion of people staying at home (Xie & Zhu, 2020). Daily city-level maximum temperature data were compiled from the Global Historical Climatological Network (GHCN). GHCN daily weather records were retrieved from the National Oceanic and Atmospheric Administration. If there were multiple weather stations in one city, we selected the station with more coverage of historical weather information. Column 7 of Table 5 shows that the effect of staying at home is slightly larger and the effect of unemployment is slightly smaller.

Omitting One City at a Time

To see whether our results were driven by one city, we ran the main specification while omitting one city at a time. Appendix Fig. 4 shows that the coefficient of staying at home is robust. Appendix Fig. 5 shows that the coefficient of unemployment depends on Chicago, the second largest city in our sample, but otherwise remains consistent.

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[13] Accessed at < https://www.dol.gov/coronavirus/unemployment-insurance > on January 24, 2021.

[14] https://sites.google.com/view/crowdcountingconsortium/home.

Conclusion

Our study complements the literature on the effect of COVID-19 on domestic violence in several ways. First, we extend the timeframe of the analysis and show that the sharp increase in the rate of domestic violence incidents fades after 3 months. When preparing for the next pandemic, policy makers may anticipate a sharp shock in domestic violence that may not persist. Second, we identify mechanisms through which the pandemic affects domestic violence. We find that staying at home increases the reported rate of domestic violence, and that this effect is concentrated on the initial pandemic shock from mid-March to mid-June 2020. Lastly, we contribute to the literature by attempting to isolate several economic channels using unemployment data and new data from the CPS on labor market conditions specifically linked to the COVID-19 pandemic. We find that unemployment decreases domestic violence in aggregate, a result which is consistent with theories of male backlash and (male) instrumental violence rather than household bargaining.

We find a nuanced mix of results related to COVID-19-specific labor market conditions by gender. Combined, our results on economic channels of IPV during the pandemic suggest that macroeconomic labor market conditions are not a silver bullet to reducing IPV during a pandemic. Instead, we can consider a host of alternative mechanisms including disruption of household routines. We also identify a need for safe places for potential IPV victims to go, either to leave their partners or just to temporarily get away. Providing a safe place is both more difficult and more crucial during a pandemic.

An important caveat for these studies is that domestic violence is imperfectly measured and chronically underreported to the police (Durose et al., 2005). Our estimated effects may be attenuated not only due to typical issues caused by measurement error but also because reporting behavior may be negatively associated with the pandemic; being stuck at home with the abuser makes it harder for the victim to make the police phone call. Furthermore, the pandemic presents challenges to any researcher looking to disentangle specific policy-relevant effects. With time, more opportunities will arise for researchers to build on this emerging literature using new data and methods.

Appendix

See Tables 5 and 6; Figs. 4 and 5.

Table 5 Cities in the sample

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

Table 6 Alternative specification and robustness check

	(1) UI	(2) Fraction of time at home	(3) Dropping BLM	(4) Combine cities	(5) Political protests	(6) Cluster at county	(7) Maximum temperature
Fraction of people staying at home	0.585***		0.456***	0.584***	0.517***	0.516†	0.654***
	(0.145)		(0.130)	(0.129)	(0.128)	(0.253)	(0.129)
Insured unemployment rate	− 0.012***						
	(0.003)						
Unemployment		− 0.009***	− 0.008**	− 0.014***	− 0.011***	− 0.011	− 0.009**
		(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.003)
Fraction of time staying at home		0.496***					
		(0.123)					
Observations	22,212	22,212	21,764	20,119	22,212	22,212	22,212
R^2	0.887	0.887	0.886	0.904	0.887	0.887	0.887

Note The dependent variable is the daily number of domestic violence calls or incidents per 100,000 city population. All regressions are weighted by population and include month, day of week, city, holiday dummies, and the lagged 7-day moving average domestic violence rate in the previous year. Robust standard errors are in parentheses except in column 6, where standard errors are clustered at the county level. Data are from 1/1/19 to 11/30/20. In column 3, data from May 26, 2020 to June 8, 2020 is omitted. In column 4, the data unit is county-day, and county fixed effects are included instead of city fixed effects

†$p<0.10$, **$p<0.01$, ***$p<0.001$

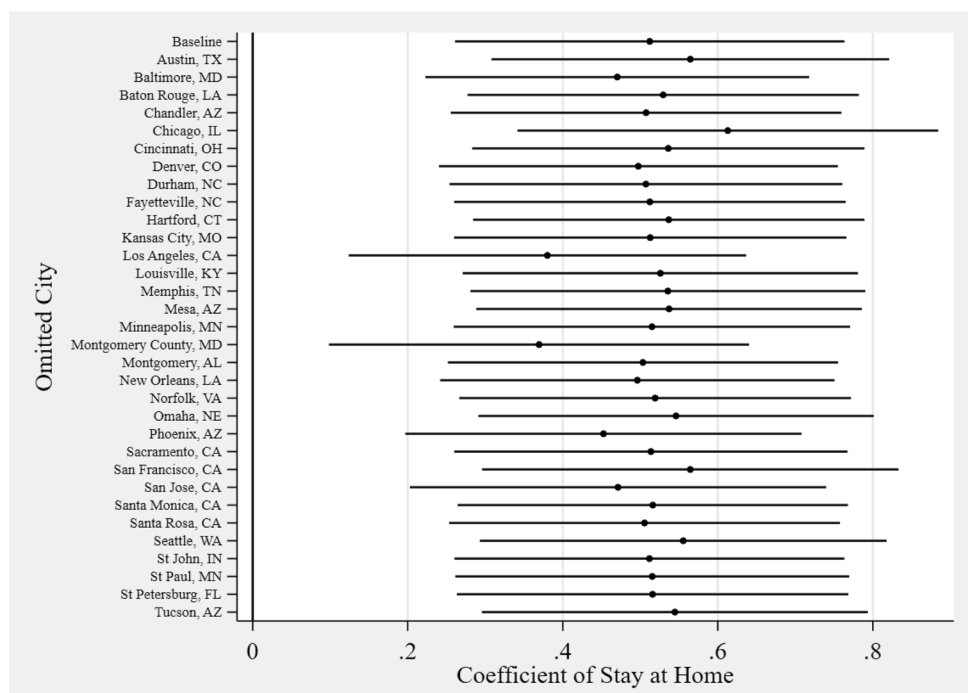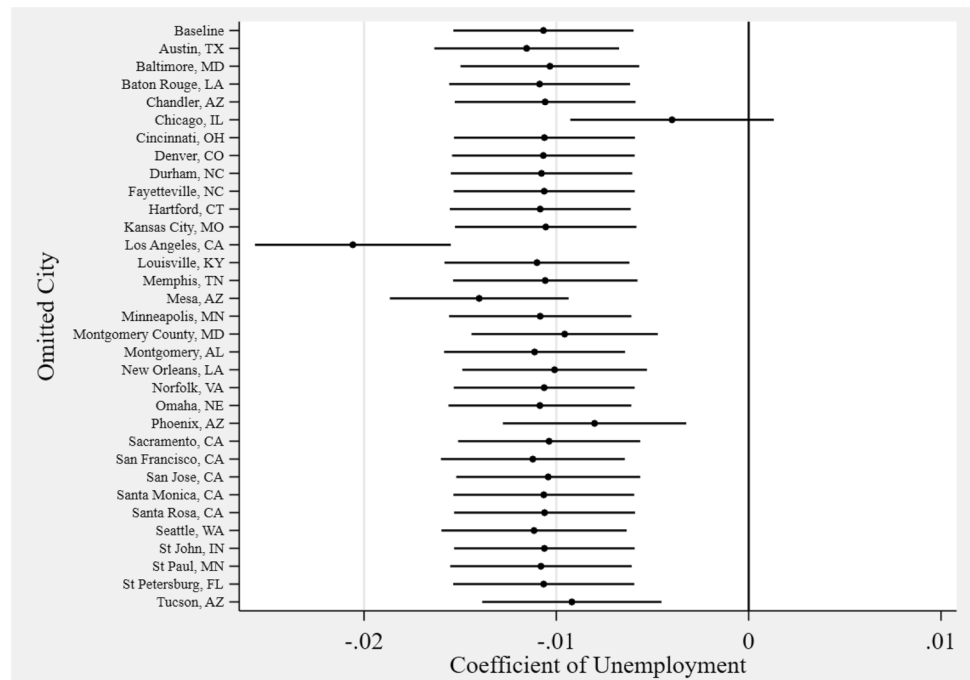
Fig. 4 Remove one city, coefficient of staying at home

Fig. 5 Remove one city, coefficient of unemployment rate

Declarations

Conflict of interest The authors have no conflict of interest and have received no funding.

Ethical Approval All data are publicly available, and the research involved no human subjects.

Informed Consent Not applicable.

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