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Quantifying Domestic Violence in Times of Crisis

Abstract

We propose a model that (i) provides an algorithm for measuring temporal variation in domestic violence incidence based on internet search activity and (ii) makes precise the conditions under which this measure yields less biased estimates of the domestic violence problem during periods of crisis than traditional, police-recorded crime measures. Analyzing the COVID-19 lockdown in Greater London, we find a 40 percent peak increase in our internet search-based domestic violence index, 7-8 times larger than the increase in police recorded crimes and much closer to the increase reported by victim support charities in relation to helpline calls.

JEL-Codes: J120, I180.

Keywords: COVID-19, domestic violence, police-recorded crime, internet search data, signal-to-noise.

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1 Introduction

During the ongoing COVID-19 pandemic, there has been a major discrepancy between crisis-induced surges in domestic violence as perceived by practitioners in the field and the effects reported in empirical studies based on police records of domestic violence incidents. Reports from women's support charities, domestic abuse helplines, and frontline workers in countries such as Australia, China, France, the United Kingdom, or the United States have raised significant concerns, suggesting increases in domestic violence help-seeking following the implementation of self-isolation and quarantine measures of anywhere between 25 percent and 80 percent (see, e.g., Allen-Ebrahimian 2020; Human Rights Watch 2020; UN Women 2020; Wagers 2020). Yet, in stark contrast to these alarming numbers, recent empirical studies exploiting police records of domestic violence incidents have found either relatively modest or no increases in family violence following lockdowns and self-isolation (Campedelli et al. 2020; Ivandic et al. 2020; Leslie & Wilson 2020; McCrary & Sanga 2020; Mohler et al. 2020; Payne & Morgan 2020; Piquero et al. 2020). Against this background, this paper has two objectives: (1) to highlight the potential limitations and biases in using police data to quantify the scale of the domestic violence problem during this period of crisis, and (2) to propose an algorithmic methodology for measuring temporal variation in domestic violence incidence based on internet search data.

From a policy perspective, there is an urgent need to quantify the impact of the unfolding COVID-19 pandemic on domestic violence (henceforth, DV): at a time where governments face unprecedented demands on limited resources, optimal policy responses to support victims of DV can only be implemented if the scale of the problem is known. However, the quantification of the prevalence of DV is difficult at the best of times due to data limitations, and the pandemic has exacerbated this difficulty in various ways. Victimization surveys have, under normal circumstances, become an accepted way of estimating prevalence rates for DV. However, these surveys are neither available in real-time nor do they provide temporally granular enough information to adequately analyze the consequences of the COVID-19 crisis. By contrast, police records of DV incidents are often available at daily frequencies and even in real-time, and in many cases contain fine-level information on location. We present evidence, based on daily counts of DV-related crimes recorded by the London Metropolitan Police Service (MPS) and a simple regression accounting for an overall trend, seasonality, day-of-week, and weather effects, that the London lockdown brought about an increase in recorded DV crimes of around 5-7 percent (at peak) compared to levels before the pandemic.

However, the vast majority of victims of DV do not report these crimes to the police (see, e.g., Podaná et al. 2010; UN Women 2020) and, importantly, there is every reason to conjecture that reporting behavior itself has been significantly affected by quarantines and self-isolation. For example, recent evidence presented by Campbell et al. (2020) shows that among DV victims who decide to contact the police for help, a large portion report waiting for the perpetrator to leave the scene before calling 911. The pandemic and associated lockdown measures implemented by many governments conceivably have left victims of DV trapped in-home with their perpetrators, limiting their opportunity to safely report incidents to the police (Campbell 2020; Kofman & Garfin 2020). Thus, any analysis of police-recorded DV incidents runs the risk of underestimating the DV problem during this pandemic. Help-seeking behaviors other than police contact, although also having become more difficult, are likely to have been less affected by self-isolation and quarantine measures, as they generally allow for more anonymity and carry less consequences for both victim and perpetrator. We contrast our findings based on MPS data with information on average daily calls and contacts (per week) received by the UK's National Domestic Abuse Helpline, showing that helpline contacts increased in the order of 60 percent in the first few weeks after the London lockdown compared to levels before the pandemic. However, this data, too, is imperfect as it is not gathered systematically over time. Thus, it does not allow us to account for an overall trend or seasonal effects, which likely results in an upwardly biased estimate. Indeed, Leslie & Wilson (2020) show that failing to account for seasonal trends results in over-estimating the effect of the COVID-19 crisis on DV by almost 50 percent.

In an attempt to complement available data sources, we propose a simple model that (i) gives rise to an algorithmic methodology for measuring temporal variation in DV incidence based on DV-related internet search activity and (ii) makes precise the conditions under which this measure provides us with a less biased estimation of the DV problem during this period of crisis than traditional, police-recorded crime measures. Our approach uses pre-crisis data—in our case over five years—to relate daily internet search activity for terms related to DV to daily police-recorded DV incidents (both observed). The intuition for the approach is that both reflect the same underlying (unobserved) temporal variation in DV incidence, leading to a positive correlation that is stronger for the most relevant/least noisy internet search terms. Our algorithmic design further accounts for differential trends, seasonality and searches occurring on days contiguous to the underlying incident. More critically, it allows us to use estimated signal-to-noise ratios to create a composite measure of DV-related search activity, which we interpret as a search-based DV-index. Our model shows that there are two conditions under which this measure yields estimates of the DV problem during this pandemic that are less downwardly biased than those based on police-recorded crime data: quarantine and self-isolation measures have made help-seeking generally more difficult for DV victims,[1] and has hampered help-seeking through police relatively more than through internet services.

We present four results. First, empirical research investigating the relationship between weather and crime shows that temperature is positively correlated with aggressive behavior, especially domestic violence (see, e.g., Butke & Sheridan 2010). Reassuringly, we find that higher temperatures are not only significant predictors of DV-incidents recorded by the London MPS but are also highly correlated with our search-based DV-index. Second, analyzing the London lockdown, we observe a closely aligned timing of increases in DV-incidents recorded by the London MPS and increases in our composite DV index: while the lockdown had no immediate impact, a significant effect emerged somewhere between 3-6 weeks into the lockdown. Third, in level terms however, we find a 40 percent increase (at peak) in our search-based DV index, 7-8 times larger than the increase in police recorded crimes but only about half the size of the increase noted

[1] There is one well-established characteristic of DV that suggests that lockdown measures have made any type of help-seeking behavior more difficult for victims. In particular, DV is often accompanied by controlling and coercive behavior on the part of the perpetrator. Indeed, 60 to 80% of abused women report experiencing coercive control beyond physical and emotional abuse (see, e.g., NYS Office for the Prevention of Domestic Violence 2013).

for helpline calls and contacts. Fourth, replicating our results for London using daily police and internet search data for the city of Los Angeles, California, we obtain qualitatively remarkably similar results.

Our paper relates to two strands of literature. First, researchers before us have highlighted the limitations of police-recorded crime data, such as calls-for-service or reported crimes, to act as a proxy for the actual incidence of crime (see, e.g., Carr & Doleac 2018; Pepper et al. 2010). For example, in a study on juvenile curfews and gun violence, Carr & Doleac (2018) argue that policy interventions aimed at reducing gun-involved crime also affect reporting rates, and exploit ShotSpotter data as a proxy in place of unobserved gun crime incidence. Second, and as mentioned at the outset, a set of recent contributions have used police recorded calls-for-service and/or crime data to estimate impacts of COVID-19 lockdowns on police-recorded DV incidents. Ivandic et al. (2020) provide a thorough overview of this literature and, in analyzing the COVID-19 lockdown in Greater London, provide insights on how changing patterns of DV might explain differences in magnitudes reported across these studies.

2 Framework

Evidence based on police DV incident reports is unlikely to provide us with a reliable picture of the scale of the DV problem during this pandemic, since shelter in-place measures have limited victims' ability to safely report to the police. Moreover, the way in which data on helpline calls and contacts is currently collected and made available is highly unsystematic, rendering it unsuitable for thorough (regression) analysis. Thus, there is a need for exploring alternative sources of data that can capture help-seeking behavior by victims and measure changes in DV-incidence. We now set out a simple framework that gives rise to an algorithmic methodology for measuring temporal variation in DV incidence based on internet search data.

2.1 Setup

Let $t \in \{1, ..., T\}$ denote time, where a unit of time is a day. Lockdown occurs at some time t_0 and continues to the end of the sample period. Hence the overall sample period is split into two regimes, $R \in \{0, 1\}$, with $R_t = 0$ (pre-lockdown) if $t < t_0$ and $R_t = 1$ (lockdown) if $t \geq t_0$. Let n_t denote the number of DV-incidents/victims at time t. Although not directly observed, n_t will have some distribution, and the concern is that this will have changed with the lockdown. Hence let $f_R(n)$ be the probability mass function for n in regime R.

A given victim of abuse i at time t, may seek help through alternative routes. Let $p_{it} \in \{0, 1\}$ indicate whether she contacts the police, leading to a recorded DV-crime. Similarly, let $y_{it} \in \{0, 1\}$ denote whether she seeks support via an internet search. Note that the two help-seeking responses are not mutually exclusive: for any given victim, either none, either, or both may occur. For expositional convenience we will assume that p_{it} and y_{it} are statistically independent, but nothing in the below hinges on this assumption. In the data we observe the daily count of incidents recorded by the police. This is, we observe $P_t \equiv \sum_{i=1}^{n_t} p_{it}$. Similarly, assume for now that we also observe the daily search intensity $Y_t \equiv \sum_{i=1}^{n_t} y_{it}$.[2] One of the issues below will be the construction of the measure Y_t.

2.2 Help-Seeking Behavior Across Regimes

Each help-seeking behavior is guided by the net benefit to victim i from taking that action, which may be regime-specific. Hence let V_k^R denote the systematic (or "common") net systematic benefit to a victim from taking action $k \in \{p, y\}$ in regime $R \in \{0, 1\}$. In addition, a given victim i perceives an individual-specific utility component to either taking or not taking each action, and if these are i.i.d. extreme value distributed, the probability of any given victim i in regime R taking action k will take the standard logit form,[3]

$$\pi_k^R = \Pr\left(k_{it} = 1 | R\right) = \frac{\exp\left(V_k^R\right)}{1 + \exp\left(V_k^R\right)}, \text{ for } k \in \{p, y\} \text{ and } R \in \{0, 1\}. \tag{1}$$

This highlights the key issue of potential changes to help-seeking behavior. For instance, only if $V_p^1 = V_p^0$, and hence $\pi_p^1 = \pi_p^0$, will the observed proportional change in P_t, accurately reflect the proportional change in the DV incidence level. A similar argument of course applies to help-seeking via the internet. Hence we cannot a priori assume that $V_k^1 = V_k^0$ for either action. Under the weaker assumption that the lockdown measures made help-seeking generally more difficult for victims, whereby $\Delta V_k \equiv V_k^1 - V_k^0 \leq 0$ for both actions $k = \{p, y\}$, the observed proportional change in either action serves as a lower bound for the underlying proportional change in abuse incidence. Moreover, if help-seeking via the police was discouraged relative more, $\Delta V_p < \Delta V_y$, then the proportional change in help-seeking via the internet provides a less downwardly biased estimator of the change in DV incidence. A potential threat to the assumption $\Delta V_k \leq 0$ for both actions would be "substitutability": if the lockdown decreased the perceived benefit to contacting the police, this could potentially have shifted help-seeking onto alternative routes.[4]

2.3 Relating Internet Searches to Police Reports

Daily police recorded DV-crimes and daily search activity will be correlated as both reflect the same underlying temporal variation in DV-incidence. To see this, consider the covariance between P_t and Y_t within either given regime $R_t \in \{0, 1\}$. Using the law of iterated expectations,

[2] In the empirical application, both P_t and Y_t will be in index form. As this merely re-scales each by a multiplicative constant, the statistical properties are preserved.

[3] Specifically, a given victim i obtains an additive random utility ε_{i1}^k from *taking action* k and an additive random utility ε_{i0}^k of *not taking action* k which are assumed to be i.i.d. extreme value distributed across individuals and actions.

[4] The latest statistics for England and Wales indicate that the number of adults (aged 15-59) in England and Wales experiencing domestic abuse annually is around 2 million (Office for National Statistics 2019). The best available estimates of repeat victimization suggests that the average number of incidents per victim per year is around 20 (Walby & Allen 2004). As the number of DV-crimes recorded by the police is currently around 600,000, this suggest that the proportion of incidents that gets recorded as crimes in the police records is less than 2 percent. This in turn suggests that bias caused by substitution away from contacting to the police towards seeking help via the internet is likely to be limited.

it is easily shown that,

$$Cov\left(P_t, Y_t | R_t\right) = \pi_p^{R_t} \pi_y^{R_t} Var\left(n_t | R_t\right) > 0. \tag{2}$$

Intuitively, P_t and Y_t are positively correlated as both tend to be large on days when n_t is large.

In practice, we observe daily search intensities Y_{jt} (in index form) for a set J of DV-related search terms. Hence, in order to create a single composite measure Y_t we need to apportion relative weight across the various terms. To do so, we will use pre-lockdown data and draw on (2). This equation can be taken to apply for each term $j \in J$, whereby the *relative* covariances of the various Y_{jt}'s with P_t will indicate the *relative* frequency with which victims use the J terms: using π_{jy}^0 to denote the pre-lockdown propensity for a victim to search on term $j \in J$ it follows from (2) that for two alternative terms, j and j', $Cov\left(P_t, Y_{j't} | R_t = 0\right) / Cov\left(P_t, Y_{jt} | R_t = 0\right) = \pi_{j'y}^0 / \pi_{jy}^0$. Note that if data were pooled across regimes and $\pi_{jy}^R / \pi_{j'y}^R$ remained constant, the relative covariance $Cov\left(P_t, Y_{jt}\right) / Cov\left(P_t, Y_{j't}\right)$ would only correspond to the relative search frequency if the component frequencies π_{jy}^R and $\pi_{j'y}^R$ remained constant also in level terms.

However, measured search intensities can be expected to contain a fair amount of noise, e.g. due to random searches by non-victims. Hence consider the regression specification,

$$Y_{jt} = \alpha_j + \lambda_j P_t + v_{jt}, \text{ for } j \in J, \tag{3}$$

where v_{jt} represents noise. The ordinary least squares estimator of λ_j is of course $\widehat{\lambda}_j = \widehat{Cov}\left(P_t, Y_{jt}\right) / \widehat{Var}\left(P_t\right)$. Applying this on pre-lockdown data will allow us to identify search terms that are more commonly used by victims—as indicated by their relative values of $\widehat{\lambda}_j$—and that contain relatively less noise. We will use this approach to construct our measure Y_t. In particular, we will estimate (a version of) equation (3) for each $j \in J$, and terms with an estimated positive correlation, $\widehat{\lambda}_j > 0$, will be given a weight in the composite index that corresponds to its signal-to-noise ratio.

2.4 Data and Algorithm

The exact algorithm used in constructing the composite index Y_t accounts for two further complications. First, to account for the possibility that police reports and internet searches have different growth over time, seasonality etc., rather than directly relating Y_{jt} to P_t, we relate the *unexpected component* of Y_{jt} to the corresponding *unexpected component* of P_t after removing year-, month-, and day-of-the-week effects. Second, while victims can be expected to contact the police at the time of a DV-incident, on-line help-seeking may be distributed around the time of the event, either in the days following the event or, if tensions are building in advance, in the days before. To account for this, we relate the unexpected component of P_t to the unexpected components of $Y_{j\tau}$ for a set of days τ *around* t.

To implement our algorithm, we use data on daily counts of DV-related crimes, P_t, recorded by the London MPS, from 1st April 2015 through to 22nd June, 2020. With the London lockdown occurring on March 23 (more on this below), this effectively gives us five pre-crisis years and three lockdown months.[5] As for internet search data, we select a set J of 35 potentially DV-relevant search terms. For each search term $j \in J$, we used Google Trends to generate a daily search index Y_{jt}, spanning our full sample period. We eliminate all terms that show low daily variation, having zero entries for a majority of days. This left us with a reduced set $J_0 \subset J$ containing 23 search terms from which we generate our composite measure Y_t.[6] Using these remaining terms, we apply the following algorithm.

1. We regress P_t, on year-, month-, and day-of-the-week dummies using pre-lockdown data, $t \leq t_0$ and obtain the residual, denoted $\widehat{\varepsilon}_t$. These represent the *unexpected daily variation* in DV-crimes.

2. We correspondingly regress each search term intensity Y_{jt}, $j \in J_0$, on year-, month-, and day-of-the-week dummies again using $t \leq t_0$ and obtain the residuals, denoted $\widehat{\epsilon}_{jt}$. These represent the *unexpected daily variation* in the search intensity for term j.

3. Still using $t \leq t_0$, we relate $\widehat{\varepsilon}_t$ to $\widehat{\epsilon}_{j,\tau}$ for a set of $\pm K$ days around t by estimating $\widehat{\epsilon}_{j,t+s} = \alpha_j^s + \lambda_j^s \widehat{\varepsilon}_t + \omega_{j,t+s}$ for each $j \in J$ and $s \in \{-K, ..., +K\}$, and we compute (j,s)-specific signal-to-noise ratios, denoted $\sigma_{js} = (\widehat{\lambda}_j^s)^2 \widehat{Var}\left(\widehat{\varepsilon}_t\right) / [(\widehat{\lambda}_j^s)^2 \widehat{Var}\left(\widehat{\varepsilon}_t\right) + \widehat{Var}\left(\omega_{j,t+s}\right)]$.

4. Using the estimated signal-to-noise ratios as weights we construct a composite index , $Y_t = \sum_{j \in J_0} \sum_s \sigma_{js} Y_{j,t+s}$, from the individual search terms for the full sample period.

The final daily composite index Y_t is therefor a weighted average of the original J_0 search indices, along with their leads and lags. The search terms that get the highest weight in our internet search-based DV index are “abuse helpline”, “domestic violence”, “domestic abuse”, “abusive relationship”, “emotional abuse”, “psychological abuse”, and “domestic violence law”.[7] In our leading case, we use a window of ± 3 days.[8] We re-scale Y_t to have a mean of 100 over the period 1 April 2015 to 8 March 2020. To to ease comparison of results, we also re-scale P_t to have a mean of 100 over the same period.

It should be noted that while we use DV-crime data from the London MPS, the Google Trends data is for England. There are two reasons why our methods can be expected to be robust to this geographical discrepancy. First, the MPS is by far the largest territorial police force in England, covering over 8 million people, or about 15 percent of the entire population of England.[9] Second, whilst we refer to some dates as having “unexpectedly” high levels of DV-crimes, this is only in relation to the year, month and day-of-the-week that are controlled for. In fact, many of the days involved are highly predictable and include, for instance, all New Year’s Days, many bank holiday weekends etc. which are, of course, common across the whole of England. Hence, one way to view the algorithm is that it uses the crime data to statistically identify high-risk days and then identifies search terms that spike on nearby days.

[5] Online Appendix A provides a more detailed description of the London MPS data.
[6] Online Appendix B details the search terms contained in both J and J_0
[7] See Online Table B1 for the full weighting structure underlying our composite DV-index.
[8] In our leading case, we thus estimate $23 \times 7 = 161$ signal-to-noise ratios and just over two-thirds (110) of these was positive and hence used in construction of the composite index.
[9] Non-London-based DV-related searches will in this respect be absorbed into the noise term, v_{jt}.

3 Results

Starting mid-March the UK government's implemented a string of measures to limit the spread of the coronavirus. On March 16, the Prime Minister announced that everyone should begin social distancing. Later the same week, schools, theatres, nightclubs, cinemas, gyms and leisure centres were ordered to close. Finally, on the evening of March 23, a stay-at-home order effective immediately was announced. All non-essential shops and services were ordered to close. People were instructed to stay home, except for exercise once a day, shopping for essential items, any medical need, providing care to a vulnerable person, or travelling to work that could not be done from home. The police were granted powers to issue fines and send people home.

The impact of the policy-measures on people's movement was strong. A sharp drop in mobility followed after social distancing was announced, and after the announcement of the full stay-at-home order, mobility was down to 10-20 percent of the pre-lockdown level.[10] The easing of the lockdown was gradual from mid-May. Nevertheless, mobility remained below 50 percent of pre-lockdown levels through to the end of June.

3.1 Descriptive Evidence

In Panel (A) of Figure 1, we collapse daily counts of DV-related crimes recorded by the London MPS to the weekly level, and plot average daily DV crimes between February 1 and June 22, 2020. The figure suggests that the London lockdown was associated with steady increase in DV crimes starting after April 1 and right through the end of May, with a peak increase of slightly below 20 percent compared to pre-lockdown levels.

Panel (B) of Figure 1 contrasts the evidence based on MPS data with our search-based DV index and with data on helpline calls and contacts obtained by the UK's National Domestic Abuse Helpline. Compared to police-recorded DV crimes, the increase in the search-based DV index after lockdown measures were implemented was substantially larger and sharper. Indeed, after an initial drop for the two weeks pre- and succeeding the London lockdown, the search-based DV index strongly increased early in April, peaking at around 35 percent above pre-lockdown levels throughout the entire month. Strikingly, the post-lockdown increase in our search-based DV index closely follows the increase reported by the UK's National Domestic Abuse Helpline in relation to helpline contacts and calls. However, whereas the search-based DV index increased by roughly 35 percent at peak, helpline contacts increased in the order of roughly 60 percent compared to levels before the London lockdown.

The evidence provided so far is purely descriptive. It is well understood that intimate partner violence exhibits seasonal variation, with DV incidents more likely to occur during the summer months, starting in May (see, e.g., Campbell et al. 2020).[11] Relatedly, empirical research investigating the relationship between weather and crime shows that temparature is positively

[10] See `https://data.london.gov.uk/dataset/coronavirus-covid-19-mobility-report` for mobility measures from Citimapper, Google, Apple, and Transport for London.

[11] As Online Figure A1 shows, this seasonal variation is also apparent in the London MPS crime data.

correlated with aggressive behavior, especially domestic violence (see, e.g., Butke & Sheridan 2010; Sanz-Barbero et al. 2018). Thus, in assessing the impact of the pandemic and associated lockdown measures, it is important to account for time and meteorological effects. This eliminates one of our data sources—information on helpline contacts—from any further analysis, since it was made available to us for a very limited time span only (February 10 to May 4, 2020) and at lower temporal granularity.

3.2 Accounting for Time and Meteorological Effects

To assess the impact of the London lockdown, we estimate a regression that accounts for an overall trend, seasonality, and day-of-week effects. Hence our model for outcome $D_t \in \{P_t, Y_t\}$ is given by:

$$D_t = \alpha + \beta_y + \gamma_m + \delta_d + \zeta x_t + f\left(t - t_0\right) I_{t \geq t_0} + \varepsilon_t, \quad t = 1, ...T, \tag{4}$$

where β_y, γ_m and δ_d are year-, month-, and day-of-the-week fixed-effects, controlling for a trend, seasonality, and weekly cycles respectively. Moreover, and as mentioned above, one factor that may have played a role was the weather. Hot weather is a well-documented factor that increases the DV-incidence, and London saw a particularly warm and dry April this year. To account for this, we use data on daily average temperature (in $^{\circ}C$) and rainfall (in mm) in London over the sample period, and x_t thus includes controls for temperature and rainfall.[12] Turning to the lockdown, $I_{t \geq t_0}$ is a dummy for t being within the lockdown period, and $f\left(t - t_0\right)$ is a flexible, but continuous, function of lockdown duration. Note that $f\left(0\right)$ is not restricted to be zero. Hence it allows for an immediate lockdown effect. Our baseline specification for $f\left(\cdot\right)$ is a quadratic function, possibly with a distinct effect at weekends,

$$f\left(\tau\right) = \phi_0 + \phi_1 \tau + \phi_2 \tau^2 + \phi_3 I_{wkend}, \tag{5}$$

where I_{wkend} is a weekend (Saturday/Sunday) indicator.

The first three columns of Table 1 present estimates of (4) using daily MPS counts of DV crimes as dependent variable. In column (i), we estimate a basic version of (4), ignoring weather and separate weekend effects. The estimates suggest, if anything, a negative immediate effect. However, a positive effect emerged over the following weeks and peaked after about 50 days of lockdown ($= -\phi_1 / \left(2\phi_2\right)$), aligning well with the visual impression from Panel A of Figure 1. The finding that the impact of the lockdown grew with duration naturally accords with the notion that tensions between intimate partners built up gradually in a crisis like the current one. The estimated coefficients imply an increase in DV crimes of around 5 percent at the peak compared to pre-lockdown levels. In column (ii), we add controls for weather, confirming a strong effect of temperature: a one degree Celsius increase in the daily (average) temperature is associated with a 0.8 percent increase in DV-crimes per day. Rainfall is estimated to have a negative, but less precisely estimated, impact. However, the prolonged period of above-average

[12]Online Appendix C describes the weather data.

temperature and dry weather observed for April and May only accounts for a small part of the rise in reported DV-crimes during the lockdown period. Finally, in column (iii), we allow for the lockdown to have a differential effect on weekends. The strong negative effect here indicates that recorded DV-crimes during the lockdown had a much smaller weekend-weekday difference than pre-crisis.[13] However, our coefficients of interest are hardly affected by the inclusion of weekend effects.

In the last three columns of Table 1, we re-estimate (4) with our internet search-based DV index as dependent variable. The estimates in column (iv) suggest that, while the timing of the increase in DV search intensity is more or less identical to that of DV-crimes (both peaking roughly after 50 days of lockdown), the magnitude of the increase is about 7-8 times larger with an estimated increase of about 35-40 percent at the peak. In column (v), we further control for weather. Here we find, reassuringly, that higher temperatures generate more DV-related searches according to our composite index: a one degree Celsius increase in the daily temperature is associated with close to a 0.3 percent increase in DV-related searches. The estimated effect of rainfall is, in contrast, highly imprecise.[14] In column (vi), we find no indication of any differential impact of the lockdown on DV-related searches on weekends versus weekdays. This is expected given that our index Y_t is a composite of $\pm K$ days around t.

In order to avoid influence of the parametric form, we next replace the function $f(t - t_0)$ with a set of dummies for two-week periods relative to the time of lockdown, starting with the two weeks leading up to the formal lockdown.[15]

The results are presented Figure 2. Panel (A) shows that there was no significant effect on the number of DV-related crimes recorded by the MPS early on in the lockdown. There was however a significant increase in recorded DV-crimes from the end of April through into early June (weeks 5-10). Nevertheless, the estimated effects are generally quite small – an increase of $5 - 7$ percent, at peak, compared to the pre-lockdown average. Panel (B) shows the corresponding estimates for the search-based DV index. The two figures again exhibit similar timing, suggesting that the first few weeks of the lockdown remained relatively quiet. However, after that, our index shows a sharp increase approaching mid-April. At this stage, DV-related searches were about 40 percent higher than their pre-lockdown average. Over the following two months, searches gradually fall back down towards pre-lockdown levels, but remains significantly above the pre-lockdown level.

We have carried out a number of sensitivity checks in relation to our estimates for the search-based DV index.[16] In particular, we have verified the results are robust to the choice of the window used in the construction of Y_t. As the potential impact of the lockdown on domestic violence received a substantial amount of media attention during the spring, we also checked that our results are robust to excluding the term “domestic violence” from the composite measure.

[13] The estimated coefficient translates into about 15 DV-crimes per day, implying that the weekend-weekday difference during the lockdown was only about half of pre-crisis difference. See Figure A1.

[14] The lower estimates and precision is natural given that the weather measurements are local to London whereas the search data is for the whole of England.

[15] Note that this means that the left-out “reference period” (1st April 2015 - 8th March 2020) corresponds to the period used as base for the indexing of the DV-crime variable (index = 100).

[16] Online Appendix D describes these sensitivity checks in detail.

To summarize, the London lockdown led to a gradual increase in the DV-related crimes recorded by the MPS and the effect of the lockdown remained positive until mid-June. The impact was nevertheless modest, with about 10-15 extra DV-crimes per day relative to a normal average of over 200 crimes per day. In sharp contrast, although exhibiting a similar lockdown timing structure, we find a 40 percent increase (at peak) in our search-based DV index, 7-8 times larger than the increase in police recorded crimes and much closer to the increase reported by the UK's National Domestic Abuse Helpline in relation to helpline calls and contacts.

3.3 Results for Los Angeles, California

To understand whether our conclusions for London carry over to other settings, we next repeat the analysis for the city of Los Angeles, California. To that end, we combine three data sources for the period April 1, 2015 through July 31, 2020: (i) daily counts of DV-related calls for police service recorded by the Los Angeles Police Department (LAPD); (ii) daily search intensities in the State of California for a set 37 DV-related search terms from Google Trends; and (iii) information on average daily temperature and rainfall in LA from the National Centers for Environmental Information (NCEI). In implementing our algorithm, we find that the search terms that get the highest weight in the search-based DV index for LA are "domestic violence hotline", "abusive husband", "reporting abuse", "abuse support", and "domestic violence charges".

Figure 3 shows the LA counterpart of Figure 2. The evidence is qualitatively remarkably similar to the London case, despite institutional heterogeneities, different approaches in dealing with the pandemic, and differences in the relationship between the police force and the general public. Panel (A) shows that the LA lockdown led to gradual increase in DV-related calls for police service, peaking after 7-8 weeks at roughly 15 percent above pre-lockdown levels, followed by a gradual decline. Turning to Panel (B), we observe that the increase in our search-based DV index had a similar timing structure, but, whereas the increase in recorded DV calls was about 15 percent at peak, the increase in the our DV index was around 30 percent. There is also a second significant spike in our search-based DV index after 15-16 weeks of lockdown.

4 Discussion

Many types of crises—be it disease outbreaks like the current one, severe economic downturns, or natural disasters—carry the risk of increasing domestic violence (Anastario et al. 2009; Anderberg et al. 2016; Bermudez et al. 2019; Onyango et al. 2019). To be effective during such crises, policy responses require the most current and reliable evidence on the scale of the problem. However, conventional data sources, including police-recorded DV-incidents, have severe limitations in this respect. Although available in real-time in some countries, regions and cities, incidents recorded by the police only represent the "tip of the iceberg". In times of crisis, under-reporting is further likely exacerbated as DV victims may be trapped with and/or economically dependent on their perpetrator. The reports from charities and practitioner and the empirical evidence from our internet search-based DV index jointly suggest that police-based evidence may be seriously underestimating the consequences of the current pandemic.

The current paper by no means provides a definite answer to how to best construct a real-time indicator of DV, but can hopefully serve as a very basic starting point for further thought and analysis. Although we believe that the type of methods that we have proposed hold the promise of generating DV indicators that are contemporaneously available, have a fine temporal resolution, allow for international or regional comparisons, and exhibit a demonstrated validity, it would seem equally important to engage with governmental and non-governmental organizations supporting DV victims. If gathered systematically, information on helpline calls and online contacts could also become an important jigsaw piece in the complex task of quantifying DV in times of crisis and beyond.

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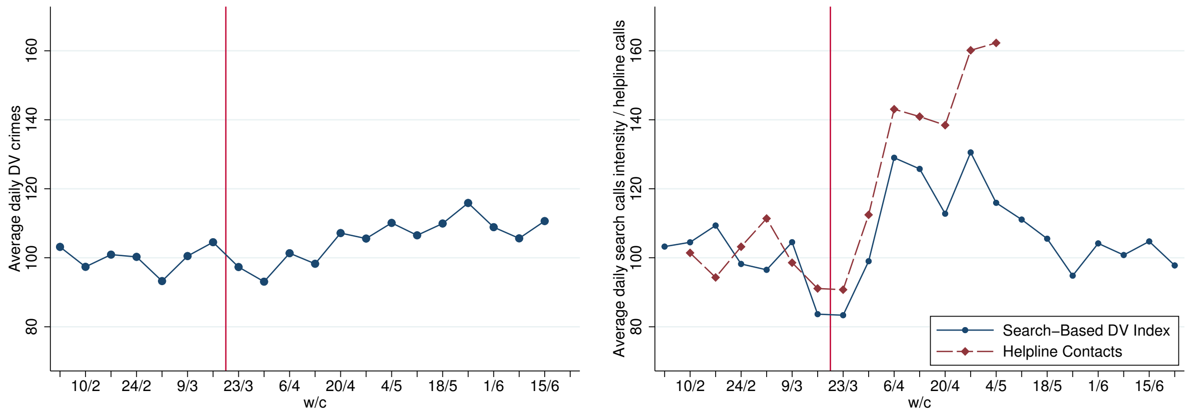
Exhibits

Figure 1: Descriptive Evidence

(A) Police-Recorded DV Incidents (B) Search-Based DV Index and Helpline Contacts



Notes: Panel (A): The sample consists of daily counts of DV crimes recorded by the London MPS between February 1 and June 22, 2020, which we collapse to obtain average daily DV crimes per week. Panel (B), Search-Based DV Index: The sample consists of our daily search-based DV index for the period February 1 through June 22, 2020, which we collapse to obtain average daily index values per week. Panel (B), Helpline Contacts: The sample consists of average daily helpline contacts per week made available to us by the charity Refuge, which operates the UK's National Domestic Abuse Helpline, for the period February 10 through May 4, 2020. For the purpose of this diagram, we re-scale each of the three weekly variables to have mean of 100 for the pre-lockdown period until March 23, 2020.

Table 1: The Effect of the London Lockdown on Domestic Violence

	Police-Recorded DV Incidents			Search-Based DV Index		
	(i)	**(ii)**	**(iii)**	**(iv)**	**(v)**	**(vi)**
Lockdown (ϕ_0)	-7.752**	-6.389*	-4.694	-10.56	-9.945	-10.09
	(3.791)	(3.683)	(3.610)	(6.990)	(6.927)	(7.086)
Days of Lockdown (ϕ_1)	0.433**	0.370**	0.379**	1.928***	1.907***	1.906***
	(0.169)	(0.162)	(0.158)	(0.298)	(0.297)	(0.297)
Days Sq. (ϕ_2)	-0.00403**	-0.00328**	-0.00332**	-0.0205***	-0.0203***	-0.0202***
	(0.00164)	(0.00157)	(0.00157)	(0.00294)	(0.00294)	(0.00294)
Temperature ($^{\circ}C$)		0.840***	0.842***		0.275***	0.274***
		(0.0683)	(0.0678)		(0.104)	(0.104)
Precipitation (mm)		-3.053**	-2.979**		1.361	1.355
		(1.519)	(1.517)		(1.630)	(1.633)
Weekend × Lockdown (ϕ_3)			-7.114***			0.617
			(2.285)			(3.712)
Observations	1,910	1,910	1,910	1,905	1,905	1,905

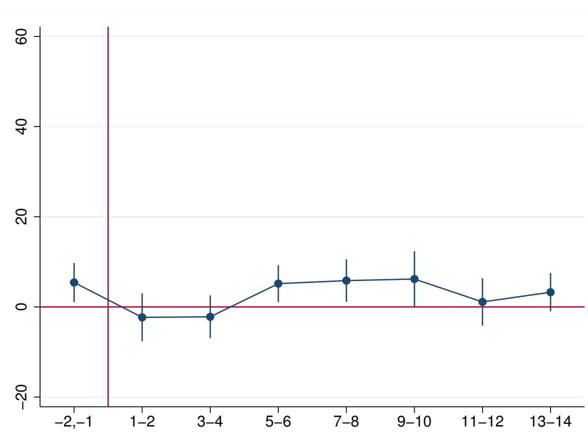
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

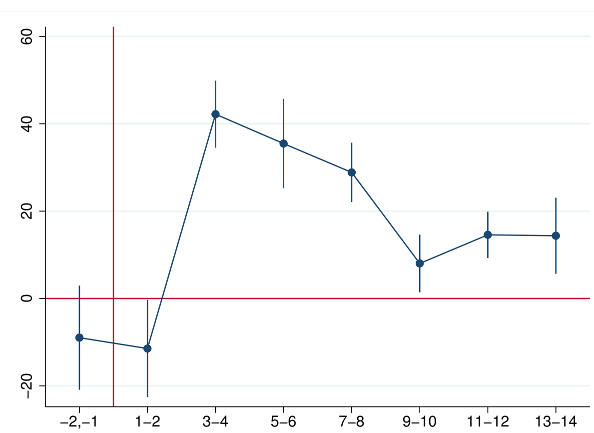
Notes: The dependent variable in specifications (i) to (iii) is the daily count of DV-related crimes recorded by the London MPS between 1 April 2015 and 22 June 2020 in index form (100 = average daily count over the period 1 April 2015 to 8 March 2020). The dependent variable in specifications (iv) to (vi) is a composite index of DV-related search intensity at daily frequency (100 = average daily intensity over the period 1 April 2015 to 8 March 2020). All regressions include year, month, and day-of-week fixed effects.

Figure 2: Bi-Weekly Effects of the London Lockdown

(A) Police-Recorded DV Incidents

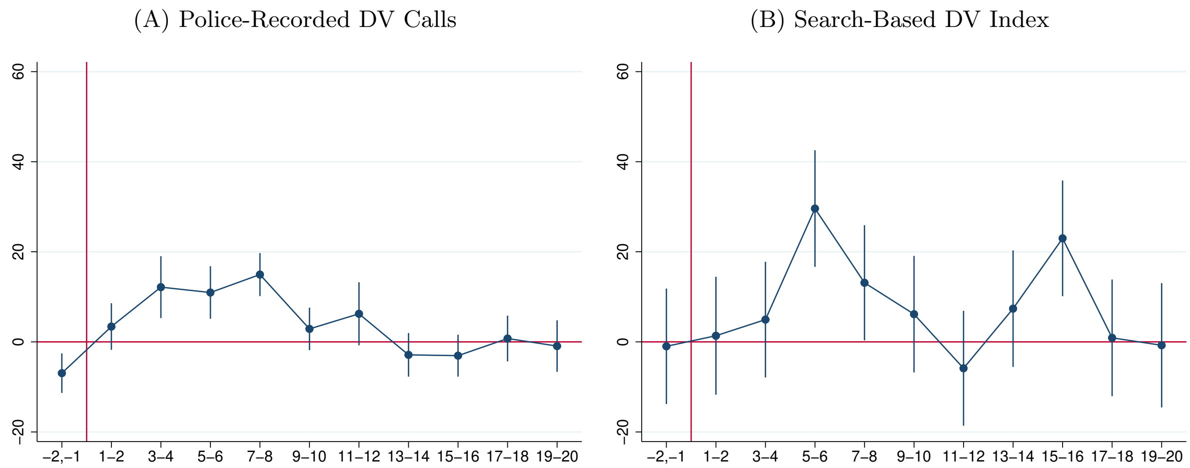


(B) Search-Based DV Index



Notes: The figure plots the coefficients from two regressions estimating the effect of the London lockdown on $D_t \in \{P_t, Y_t\}$ respectively by two-week intervals . The regressions control for year-, month-, and day-of-the-week effects, as well as for temperature and rainfall.

Figure 3: Bi-Weekly Effects of the LA Lockdown



Notes: The figure plots the coefficients from two regressions estimating the effect of the Los Angeles lockdown on $D_t \in \{P_t, Y_t\}$ respectively by two-week intervals . The regressions control for year-, month-, and day-of-the-week effects, as well as for temperature and rainfall.

Online Appendix

In this appendix we present (i) further descriptive details of the data used, and (ii) results from the robustness analysis.

A MPS Domestic Violence Crime Data

Data on the daily count of DV-related crimes recorded by the MPS was obtained by a Freedom of Information request. Our data covers the period April 1, 2015, to June 22, 2020. The data exhibit some general time patterns. Figure A1 shows the average daily count of DV-related crimes by year, month and day of the week. Panel A shows that the daily average has increased from about 205 in 2015 to 245 in 2019, which corresponds to an average annual increase of 4.5 percent. The data for 2020 covers only the time up to June 22 and, of course, incorporates the lockdown period. The steady growth over time makes simple comparisons – for instance comparing a given week to the corresponding week a year before – somewhat problematic. Panel B shows a strong seasonal pattern, with reported DV-incidence being lower in the first and fourth quarter and higher between late spring and end of summer. Panel C shows a strong day-of-the-week pattern, with incidence being about 10 percent higher on weekends than during weekdays. Finally, panel D shows the daily counts from 1st February 2020 to the end of the sample period.

B Selection of Search Terms

Search terms were selected in order to cover three broad categories.

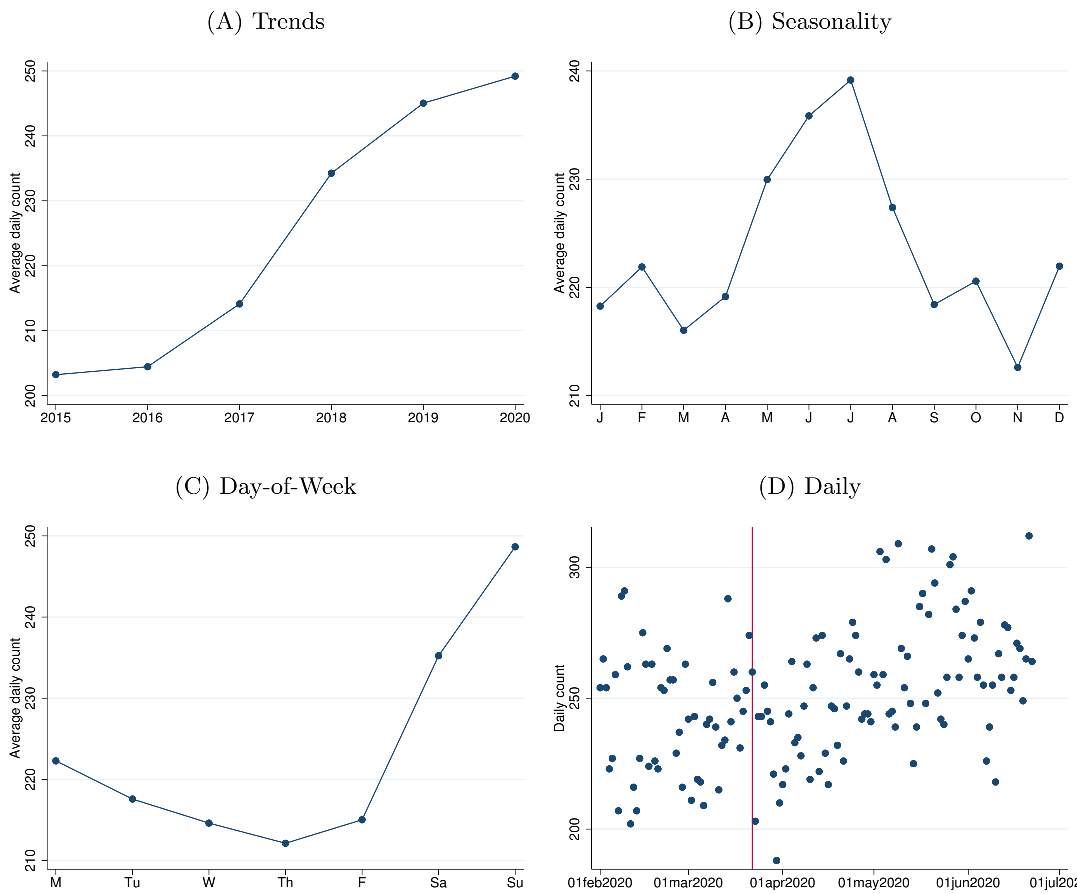
1. Terms that relate to general help seeking from helplines and charities.
2. Terms that describe abusive relationships and forms of abuse
3. Terms that relate to police- and legal-protection.

Overall, daily data for a set J of 35 search terms were obtained. Google Trends provides search intensities in index form with values between 0 and 100 where a value of 0 is given for terms/days with low search volume. 12 out of the 35 terms had zeros on majority of days and thus low variation; these terms eliminated, leaving a subset J_0 containing 23 terms.

Table B1 lists all terms used and which terms had "high/low" variation.

Our main specification includes three leads/lags, that is s in the range ± 3. The (relative) weight placed on term j and day s in the construction of the composite index was $\widetilde{\sigma}_{j_s} = \sigma_{j_s} / \left[\sum_{j' \in J_0} \sum_s \sigma_{j'_s}\right]$. For each term with high variation, the table shows its relative weight, averaged over days s.

Figure A1: Trends, seasonality and weekly patterns of DV-reported crimes and daily counts



Notes: The sample consists of daily counts of domestic violence-related crimes recorded by the London MPS between 1 April 2015 and 22 June 2020.

C Weather Data

We use data on daily average temperature (in $^{\circ}C$) and rainfall (in mm) from the London Heathrow weather station covering the full sample period, obtained from the National Climatic Data Centre. As noted, April and May of this year were unusually warm and dry. Panel A of Figure C2 shows the daily average temperature (in $^{\circ}C$) with the horizonal red lines indicating the average temperature by month over the past five years. The second half of May was also unusually warm. Panel B shows rainfall per day, indicating that the key period from the beginning of the lockdown through to early June saw barely any rainfall at all.

Table B1: Selection of search terms

Search Term	Daily Variation	Relative Weight	Search Term	Daily Variation	Relative Weight
Group 1: Seeking Support			**Group 2: Searching on Abuse**		
abuse help	High	0.099	abusive partner	High	0.065
abuse helpline	High	0.933	abusive relationship	High	3.037
abuse support	High	0.377	threat of violence	Low	-
refuge	High	1.550	partner violence	Low	-
women's refuge	High	0.261	domestic violence	High	4.484
refuge helpline	Low	-	domestic abuse	High	2.367
refuge centre	Low	-	emotional abuse	High	1.367
London refuge	Low	-	psychological abuse	High	1.883
violence refuge	Low	-	controlling relationship	High	0.882
shelter	How	0.876	coercive control	High	0.188
London abuse	High	0.063	**Group 3: Police/Legal Protection**		
women's aid	High	0.457	domestic violence protection	Low	-
victim support	High	0.015	report domestic abuse	Low	-
national domestic violence helpline	Low	-	abuse police	High	0.611
domestic abuse charity	Low	-	abuse protection	High	0.407
domestic violence support	High	0.296	reporting abuse	High	0.199
domestic violence help	Low	-	domestic violence police	High	0.835
			domestic violence law	High	1.749
			domestic violence charges	Low	-

Notes: The tables lists the Google search terms used in the construction of the composite DV-search intensity index. The daily variation for a given search term is classified as "Low" ("High") if it contains zeros on more (less) than half of all days. For terms with high variation, the table reports the relative weight place on that term, averaged over the $\pm K$ days used in the construction of the composite index.

D Robustness

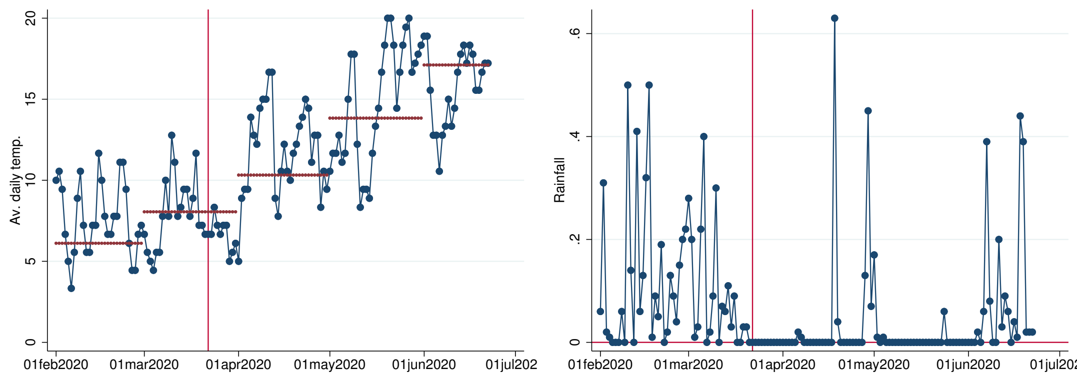
In our main specification we used a 7-day (± 3) window when constructing our DV-related search intensity measure. In Table D2 we show that our results are not sensitive to the window used. Specification (i) reiterates the main specification (vi) from Table 1. Specifications (ii) and (iii) successively narrow down the window to ± 2 and ± 1, respectively, whilst specification (iv) uses on lagged searches (up to 3). In all cases, the overall estimated of the lockdown remain stable.

After the lockdown, the potential impact on domestic violence was much debated in the media etc. A concern is hence that this might have fueled a general interest in the issue, and hence more Google searches. As the most likely search term in that case would have been "domestic violence", we might be worried that our composite index places a large weight on this particular term.[17] Hence, in specification (v) we set the weight on "domestic violence" to zero when constructing our composite index, verifying that this was not driving our results.

[17] Note however that the signal-to-noise ratios used as weights were determined entirely from the pre-lockdown data.

Figure C2: Daily average temperature and rainfall since February 2020

(A) Temperature (B) Rainfall



Notes: The figure shows the daily average temperature in degrees Celsius and the daily rainfall in *mm*. The data is from National Climatic Data Centre and is for the London Heathrow weather station.

E Los Angeles Data

For Los Angeles, we obtained data on DV-related calls for service received by the LAPD from the Los Angeles Open Data Portal. In identifying DV-relevant calls, we followed McCrary & Sanga (2020) and used the call descriptors listed in Table E3.

Panel A of Figure E3 shows the long-run trend in DV-related calls for service. Panel B shows the daily counts from 1st February 2020 up to the end of our sample period.

Daily data on temperature and rainfall in Los Angeles was obtained from the National Centers for Environmental Information (NCEI).

For Google search data, we used a slightly modified list of search terms used for London, reflecting variation in terminology. Nevertheless, the list of terms used followed the same structure of including terms relating to seeking support, searching on abuse, and seeking police/legal protection. Data was gathered for the state of California. Our starting list J contained 37 terms. This was reduced to a set J_0 containing 23 terms after eliminating terms with low variation, defined in this case has having 75 percent or more zero entries. The list of terms and the relative weights given to each are provided in Table E4.

Table D2: The effect of lockdown on DV-related search intensity: Robustness to index construction

	(1) 7 Day Window	(2) 5 Day Window	(3) 3 Day Window	(4) 3 Lags	(5) No "Dom. Viol."
Lockdown (ϕ_0)	-10.09	-9.099	-18.98**	-16.08**	-14.55**
	(7.086)	(7.542)	(8.530)	(7.640)	(6.894)
Days of Lockdown (ϕ_1)	1.906***	1.620***	1.734***	2.178***	1.896***
	(0.297)	(0.320)	(0.378)	(0.354)	(0.292)
Days Sq. (ϕ_2)	-0.0202***	-0.0178***	-0.0188***	-0.0229***	-0.0196***
	(0.00294)	(0.00321)	(0.00404)	(0.00376)	(0.00292)
Weekend × Lockdown (ϕ_3)	0.617	2.970	3.366	2.871	0.576
	(3.712)	(4.032)	(5.272)	(4.859)	(3.864)
Temperature ($^\circ C$)	0.274***	0.178*	0.0383	0.422***	0.261**
	(0.104)	(0.108)	(0.148)	(0.139)	(0.114)
Precipitation (mm)	1.355	0.334	-1.232	-2.399	3.248*
	(1.633)	(1.901)	(2.909)	(2.226)	(1.887)
Observations	1,905	1,905	1,905	1,905	1,905

Standard errors in parentheses

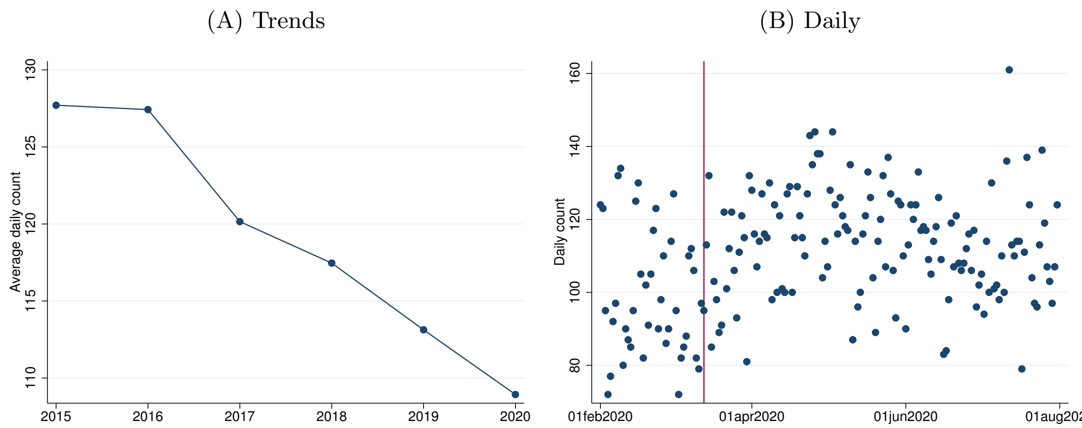
* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: The outcome variable is a composite index of DV-related search intensity at daily frequency (100 = average daily intensity over the period 1 April 2015 to 8 March 2020). The sample period is 1 April 2015 to 22 June 2020. All regressions include year, month, and day-of-week fixed effects.

Table E3: Call descriptors used to identify DV-related calls in the Los Angeles calls-for-service data

ADW POSS DOM VIOL	CZN HLDG DOM VIOL	DOM VIOL SUSP J/L
AMB DOM VIOL	DOM VIOL	DOM VIOL SUSP NOW
AMB DOM VIOL J/O	DOM VIOL IN PROGRESS	OFCR HLDG AMB DOM VI
AMB DOM VIOL SUSP	DOM VIOL INVEST	OFCR HLDG DOM VIOL
AMB DOM VIOL INVEST	DOM VIOL INVESTIGATI	POSS AMB DOM VIOL
ATT DOM VIOL	DOM VIOL J/O	POSS DOM VIOL
ATT DOM VIOL SUSP	DOM VIOL R/O	POSS DOM VIOL I/P
BATTERY DOMESTIC VIO	DOM VIOL R/O VIOLATI	POSS DOM VIOL SUSP
CITZ HLDG DOM VIOL	DOM VIOL SUSP	

Figure E3: Trend and daily counts for DV-related calls for service to the LAPD



Notes: The sample consists of daily counts of DV-related calls for service to the LAPD.

Table E4: Selection of search terms for Los Angeles / California

Search Term	Daily Variation	Relative Weight	Search Term	Daily Variation	Relative Weight
Group 1: Seeking Support			**Group 2: Searching on Abuse**		
abuse help	High	0.088	abusive partner	Low	-
abuse hotline	High	0.871	abusive relationship	High	0.070
abuse support	High	1.564	threat of violence	Low	-
refuge	High	1.135	partner violence	Low	-
women's shelter	High	0.690	domestic violence	High	0.299
domestic violence help	High	0.053	domestic abuse	High	0.787
shelter	Low	-	emotional abuse	High	1.476
LA shelter	Low	-	psychological abuse	High	0.503
shelter LA	Low	-	controlling relationship	Low	-
domestic shelter	Low	-	LA domestic violence	Low	-
victim support	Low	-	intimate partner violence	High	0.005
National domestic violence hotline	Low	-	abusive husband	High	2.574
domestic violence support	High	0.196	**Group 3: Police/Legal Protection**		
domestic violence help	Low	-	report domestic violence	High	1.161
domestic violence victim	High	0.001	abuse police	High	0.456
domestic violence hotline	High	5.120	abuse protection	Low	-
LA abuse	High	0.642	reporting abuse	High	2.217
			domestic violence police	High	0.141
			domestic violence law	High	1.434
			domestic violence charges	High	1.518
			domestic violence protection	Low	-

Notes: The tables lists the Google search terms used in the construction of the composite DV-search intensity index. The daily variation for a given search term is classified as "Low" ("High") if it contains zeros on more (less) than three quarters of all days. For terms with high variation, the table reports the relative weight place on that term, averaged over the $\pm K$ days used in the construction of the composite index.