Quantifying Domestic Violence in Times of Crisis: An Internet Search Activity-Based Measure for the COVID-19 Pandemic*

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Abstract

In contrast to widespread concerns that COVID-19 lockdowns have substantially increased the incidence of domestic violence, research based on police-recorded crimes or calls-for-service has typically found small and often even negligible effects. One explanation for this discrepancy is that lockdowns have left victims of domestic violence trapped in-home with their perpetrators, limiting their ability to safely report incidents to the police. To overcome this measurement problem, we propose a model-based algorithm for measuring temporal variation in domestic violence incidence using internet search activity and make precise the conditions under which this measure yields less biased estimates of domestic violence problem during periods of crisis than commonly-used police-recorded crime measures. Analyzing the COVID-19 lockdown in Greater London, we find a 40 percent increase in our internet search-based domestic violence index at the peak occurring 3-6 weeks into the lockdown, 7-8 times larger than the increase in police-recorded crimes and much closer to the increase in helpline calls reported by victim support charities. Applying the same methodology to Los Angeles, we find strikingly similar results. We conclude that evidence based solely on police-recorded domestic violence incidents cannot reliably inform us about the scale of the domestic violence problem during crises like COVID-19.

Keywords: Domestic violence, COVID-19, lockdown

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1 Introduction

During the 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, France, the United Kingdom, the United States and China raised significant concerns from an early stage of the crisis, 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, Aziani, & Favarin 2020; Ivandic et al. 2021; Leslie & Wilson 2020; McCrary & Sanga 2020; Mohler et al. 2020; Payne & Morgan 2020; Piquero et al. 2020). Indeed, a recent systematic review and meta-analysis (Piquero et al. 2021) combined 37 estimates from a total of 18 studies of the change in domestic violence (henceforth, DV) incidence during the early stages of the pandemic. The majority of the studies included in the review were based on police records, while a few of the included studies used data from health records and hotline registers. Eight of the included estimates showed a decrease in DV incidence while 29 showed an increase (with an overall average of about 8 percent), thus highlighting the contradictory nature of evidence in the literature.

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 crisis, and (2) to propose an algorithmic methodology for measuring short- to medium-term 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 crises like COVID-19 pandemic on DV: at times 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 in the spring of 2020 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 believe that reporting behavior itself would have 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 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 crisis and lockdown. 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.

To complement available data sources, we propose a simple model that (i) delivers 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 the 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 DV-related terms 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. 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, and has hampered help-seeking through police relatively more than via the internet.

We present four results. First, after using the pre-2020 data to train our algorithm, we use the first 75 days of 2020 to test the validity of DV index. We find that our search-based index exhibits positive correlation and simple co-movement with the recorded DV-crimes. Further verification of validity of our approach is offered by the fact that our search-based DV index and the police-recorded DV-crimes exhibit similar relationships to a key time-varying exogenous factor: weather (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 of spring 2020, 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 for helpline 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.

Research use of Google data has expanded rapidly in the last decade. There are three broad circumstances – all relevant here – where such data has proven particularly useful. First, where there are issues in relation to obtaining accurate/truthful reporting. For instance, Stephens-Davidowitz (2014) used Google search data on terms involving racially charged language and showed that the local racially charged search rate is a robust negative predictor of Obama's vote share. Second, where it is possible to identify search terms that are specific to the topic of interest, and when the act of searching itself may be closely related to it. For instance, noting that job search activity is notoriously difficult to measure, Baker & Fradkin (2017) develop a job search index based on Google searches for both broader terms such as "jobs" and specific terms such as "Dallas jobs" or "tech jobs". Third, when there is a need to track developments in real time. An early contribution showing the potential for "nowcasting" across multiple settings using Google search data was Choi & Varian (2012). More recently, Ferrara & Simoni (2020) show that Google data can be provide information for nowcasting GPD until official macroeconomic information becomes available.

2 Setting and Statistical Framework

Starting mid-March 2020 the UK government 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 and all non-essential shops and services were ordered to close. 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 (Batty et al. 2021).[1] 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. Our focus will be on this initial lockdown with our sample period running through to June 22, 2020. Hence we will focus on this initial crisis response as an event study and our framework presented below will correspondingly be cast in terms of a pre-lockdown and a lockdown regime.

After the initial lockdown, there have been two further national lockdowns in October of 2020 and in January of 2021 (mixed in with regionally implemented policy measures for most of 2020). However, the impact on mobility of each of these subsequent lockdown was substantially lower than the initial spring 2020 lockdown (see previous footnote for reference).

We now set out a simple framework that gives rise to an algorithmic methodology for measuring temporal variation in DV incidence based police-reported DV-crimes and DV-relatred internet search data.

[1] See `https://data.london.gov.uk/dataset/coronavirus-covid-19-mobility-report` for several mobility measures.

2.1 Setup

Let $t \in \{1, ..., T\}$ denote time, where the 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 help-seeking actions may occur. We will, however, in the following assume that p_{it} and y_{it} are statistically independent. A reason why this may not be realistic is that victims may use Google searches to find information about how to contact the police. This motivates one of our robustness checks (see Section 4.4) in which we remove all search terms directly related to police. For DV, repeat victimization is also common whereby the same individual i may seek help on multiple occasions through alternative channels. This could potentially cause correlation between p_{it} and $y_{it'}$ within an individual across different points in time, and hence between P_t and $Y_{t'}$. As our algorithm will focus on same (or contiguous) day correlations, any potential autocorrelation stemming from repeat victimization will not influence our analysis.

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 $Y_t \equiv \sum_{i=1}^{n_t} y_{it}$. 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 net systematic (or "common") benefit to a victim from taking action $k \in \{p, y\}$ in regime $R \in \{0, 1\}$.

Additionally, a given victim i obtains an individual-specific 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. Under these assumptions the probability of any given victim i in regime R taking action k will take the standard logit form,

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

As specified, the action $k_{it} \in \{0, 1\}$ is independent across i for any given t. Moreover, as the probability π_k^R of taking this action is common across i it follows that both count variables P_t and Y_t are, given n_t, both binomially distributed and independent of each other.

A key issue is that the perceived individual benefit from seeking help, and hence help-seeking behaviour as represented by π_k^R, may differ across the regimes, making it challenging to infer the change in DV incidence from help-seeking data. 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. In general, 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 relatively 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.

Further related concerns include the possibilities that the lockdown meant that individuals had more time available for doing internet searches and that, as a result of people spending more time at home, DV-incidence became more visible to neighbours and leading to more third-party reporting and searches. We will return to discuss these potential caveats below.

2.3 Relating Internet Searches to Police Reports

Daily counts of police-recorded DV-crimes and daily search activity will be correlated as both reflect the same underlying (unobserved) 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 that P_t and Y_t are, conditional on n_t, both binomially distributed and independent, and using the law of iterated expectations, 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 DV-incidence n_t is large. In our empirical application, P_t and Y_t will both be used in index form. As this merely re-scales each by a multiplicative constant, the statistical properties are preserved.

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 conditioning on pre-lockdown in central here: if data were pooled across regimes, 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 π^R_{jy} and $\pi^R_{j'y}$ remained constant not only in relative- but also in absolute terms. For this reason, we will use pre-lockdown data to construct our composite DV index.

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 use pre-lockdown data to 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 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 $Y_{j,t+s}$ for a set of days *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, and presented in detail in the following section. With the lockdown occurring on March 23 (after an initial announcement a week earlier, see above), this effectively gives us five pre-crisis years and three lockdown months. In order to test the validity of our search-based DV index, we "train" our algorithm on data up to the end of 2019, and use the first 75 days of 2020 as "testing" period. As for internet search data, we select a set J potentially DV-relevant search terms, also presented below. For each search term $j \in J$, we used Google Trends to generate a daily search index Y_{jt}, spanning our full sample period. 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-2020 data, 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}, $j \in J$, on year-, month-, and

day-of-the-week dummies and obtain the residuals, denoted $\widehat{\epsilon}_{jt}$. These represent the *unexpected daily variation* in the search intensity for term j.

3. Still using pre-2020 data, we relate $\widehat{\varepsilon}_t$ to $\widehat{\epsilon}_{j,t+s}$ 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 , $Y_t = \sum_{j \in J} \sum_s \sigma_{js} Y_{j,t+s}$, from the individual search terms for the full sample period.

The final daily composite index Y_t is therefore a weighted average of the original J search indices, along with their leads and lags. In our leading case, we use a window of ± 3 days which has the advantage that the index value on any given day t will reflect searches done on all days of the week. 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.

We re-scale Y_t to have a mean of 100 over the "training period" (1 April 2015 to 31 December 2019). For ease of comparison, we also re-scale P_t to have a mean of 100 over the same period.

3 Data

The main data sources used for the current analysis are thus daily data on DV crimes recorded by the London MPS and a data on DV-related Google searches.

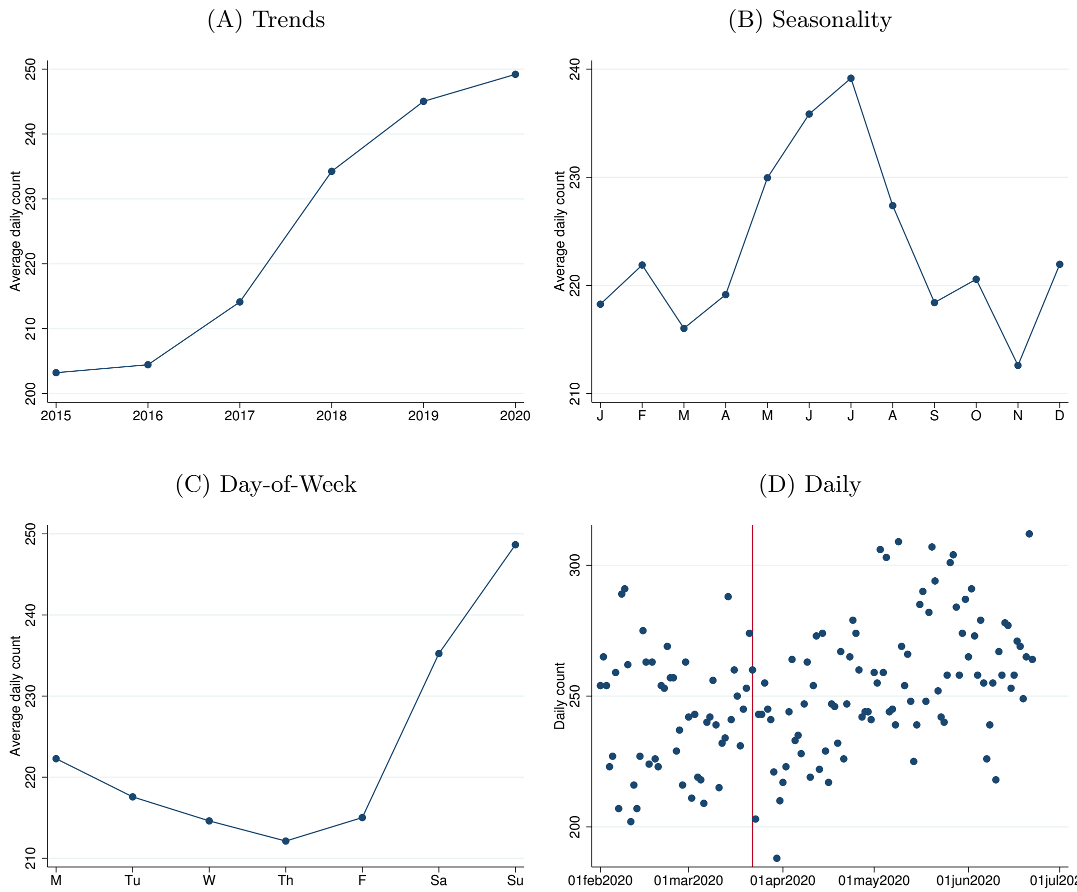
MPS Domestic Violence Crime Data

Data on the daily count of DV-related crimes recorded by the MPS was obtained by a Freedom of Information request. As noted above, our data covers the period April 1, 2015, to June 22, 2020. The data exhibit some general time patterns. Figure 1 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 first 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.

3.1 Google Search Data

Daily data for a set J of 35 DV-related search terms were obtained. The initial selection of terms was made to be deliberately broad in order to subsequently narrow the set down by studying

Figure 1: 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.

their variation and covariation with the DV-crimes data. Based on listing of terms commonly used in relation to DV (NCDSV, 2017), terms were selected 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.

A complication when using daily Google search data is that daily data is only available for search windows up to 9 months. In the online Appendix, we describe how daily data series are generated for our full sample period. 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

Table 1: 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	0.023	abusive partner	High	0.200
abuse helpline	High	1.268	abusive relationship	High	2.884
abuse support	High	0.307	threat of violence	Low	-
refuge	High	1.294	partner violence	Low	-
women's refuge	High	0.280	domestic violence	High	4.207
refuge helpline	Low	-	domestic abuse	High	3.317
refuge centre	Low	-	emotional abuse	High	1.184
London refuge	Low	-	psychological abuse	High	1.625
violence refuge	Low	-	controlling relationship	High	0.735
shelter	How	0.715	coercive control	High	0.250
London abuse	High	0.057	**Group 3: Police/Legal Protection**		
women's aid	High	0.635	domestic violence protection	Low	-
victim support	High	0.042	report domestic abuse	Low	-
national domestic violence helpline	Low	-	abuse police	High	0.718
domestic abuse charity	Low	-	abuse protection	High	0.302
domestic violence support	High	0.269	reporting abuse	High	0.303
domestic violence help	Low	-	domestic violence police	High	0.809
			domestic violence law	High	1.575
			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.

terms eliminated, reducing our set to 23 terms. Table 1 lists all terms used and which terms had "high/low" variation.

Turning to the covariation with the DV-crimes data and the implementation of our algorithm, 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 of the 23 terms with high daily variation, the table shows its relative weight, averaged over days s. The search terms that, based on their covariation with recorded DV-crimes, got the highest weight in our internet search-based DV index include "abuse helpline", "domestic violence", "domestic abuse", "abusive relationship", "emotional abuse", "psychological abuse", and "domestic violence law".

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. Second, whilst our algorithm relates the unexpected daily variation in Google searches to the unexpected daily variation in DV-crimes, these "unexpected" components are in relation to the year, month and day-of-the-week that are controlled for. In fact, many of the days with high levels of DV-crimes are highly predictable and include, for instance, all New Year's Days, many bank holiday weekends etc. and these are, of course, common across the whole of England.

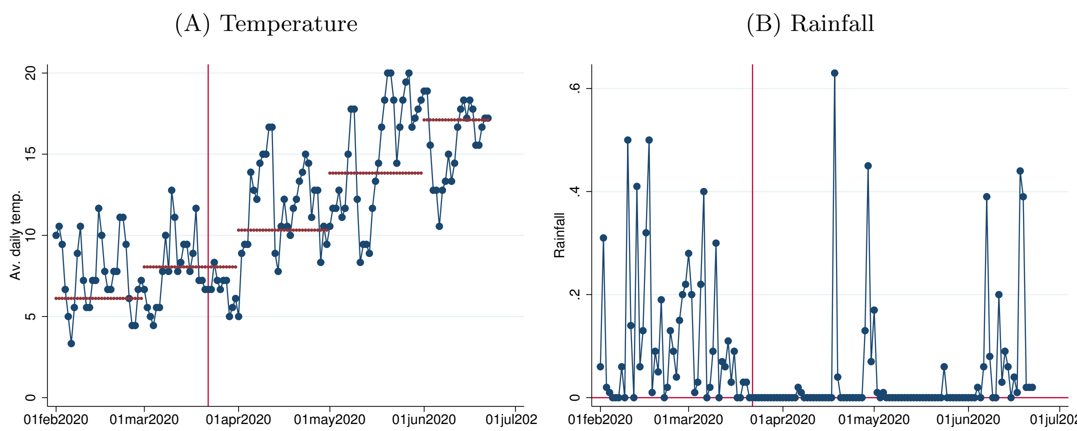
Hence, one way to view the algorithm is that it uses the crime data to statistically identify high-risk days and then identifies search terms that spike on nearby days.

The lockdown that is the subject of the current study was of course national. Nevertheless, when comparing the DV-crimes recorded by the MPS and DV-related Google search intensities for England, the caveat remains that the impact of the lockdown may have been different in London compared to the rest of the country. For instance, London being an urban area naturally has a high population density which may affect both DV-incidence and its reporting (Peek-Asa et al. 2011). Related to the lockdown (but not DV), it has been shown by Sun et al. (2021) that even within London, local crime rates – for instance for robbery, burglary and theft – in March through May 2020, had some association with the local COVID-19 infection rate. Similarly, Campedelli, Favarin, et al. (2020) found that COVID-19 containment policies in Chicago impacted crime in different ways across local areas.

Weather Data

In our analysis below we will further account for weather as a factor affecting DV incidence. We use data on daily average temperature (in $°C$) 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 2 shows the daily average temperature (in $°C$) 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.

Figure 2: Daily Average Temperature and Rainfall since February 2020



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.

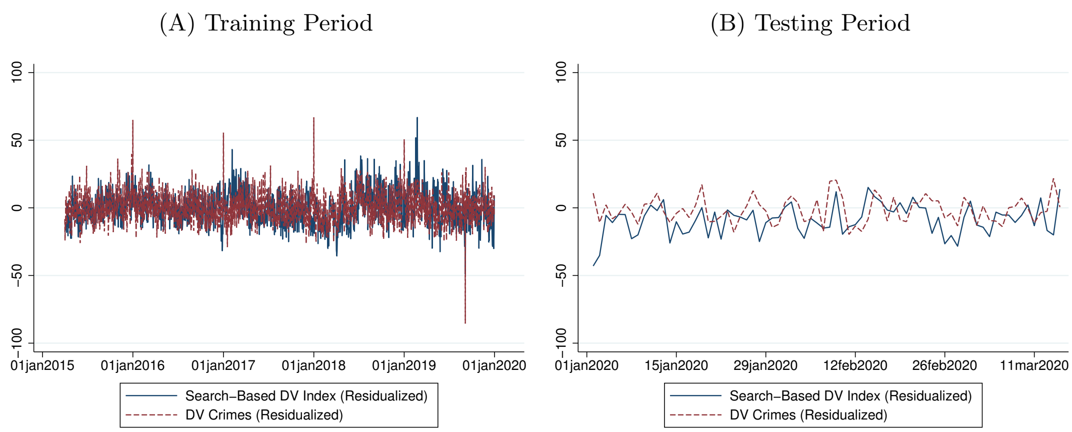
4 Results

The main aim of this section is to compare how the effect of lockdown on the two different measures of DV-incidence, the police-reported crimes and our search-based DV index. But we will start by first present the results from a validation exercise and some descriptive analysis of how the measures compare. Later on we will also present a set of robustness checks and the results from a corresponding analysis using data from Los Angeles.

4.1 Validation

Since we used pre-2020 data to train our algorithm we can use pre-lockdown 2020-data for checking the validity of our index as a measurement of temporal variation in DV-incidence. In particular, we will use the first 75 days of 2020, from 1 January through to March 15, as our testing period over which we can check that our search-based DV index has predictive power for recorded DV-crimes.

Figure 3: Daily DV Crime Counts and DV Index Residuals



Notes: The figure shows the residuals of the normalized daily counts of DV-crimes recorded by the London MPS and of the search-based DV index after removing year-, month- and day-of-the-week fixed effects from each series. The initial normalization rescaled both variables to have a mean of 100 over the algorithm training period of 1st April 2015 to 31st of December 2019. The residualized series are shown in Panel (A) for the training period, and in Panel (B) for the testing period 1st January to 15th March 2020.

In Figure 3 we plot the residualized daily series for the DV index and the DV-crimes, in each case having removed year-, month- and day-of-the-week fixed effects to account for potentially different trends and seasonality (see above). Panel (A) plots the two series for the training period from 1st April 2015 to 31st December 2019. The figure visually highlights co-movement between the two series, with a simple Pearson correlation coefficient of 0.27. The figure highlights key spikes in the DV-crime series around each New Year. Panel (B) plots the continuation of the same residualized series for the testing period of 1st January to 15th March 2020. Simple visual inspection suggests that the two series remain highly correlated. Indeed, the correlation is 0.23 (when leaving out New Year's Day), which is only marginally lower than for the training period.

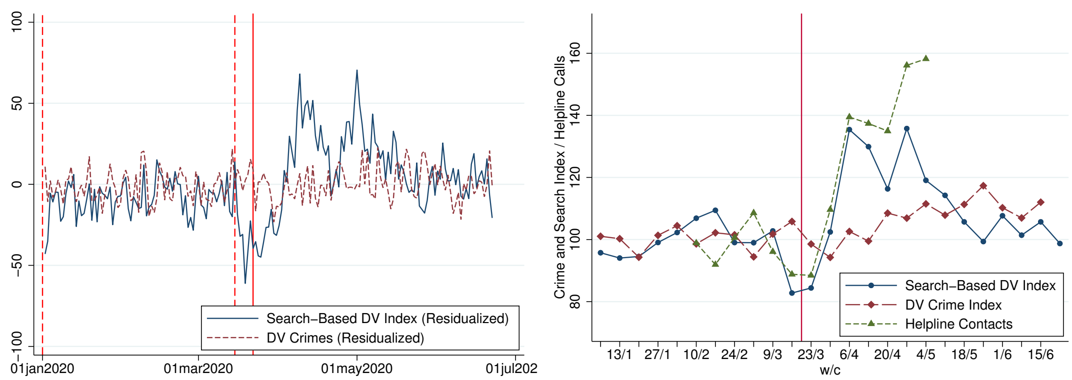
In the Online Appendix (see Table A.1), we provide further evidence on the synchrony of the two series within the testing period by regressing the daily DV-crimes on the DV index. We present regressions both in levels and first-difference form and specifications that include a lead and a lag of the DV index. The results are particularly strong in the first-difference form, highlighting that day-to-day changes in the DV index is associated with same day changes in DV-crimes.

4.2 Descriptive Evidence

In Figure 4 we provide some first descriptive evidence of how the search-based DV index and the recorded DV-crimes compare over the lockdown. In Panel A we first show the continuation, into the lockdown, of the series plotted in Figure 3 above, that is, the residualized DV index and DV-crimes. This shows that, while the two series followed each other closely over the testing period, this feature breaks down after mid-March of 2020.

Figure 4: Descriptive Evidence on DV During the Lockdown

(A) Crime Counts and DV Index Residuals (B) Search, Crimes and Helpline Contact Indices



Notes: Panel (A) extends the series plotted in Figure 3 to include the lockdown period. See notes to Figure 3. Panel (B) shows daily counts of DV-crimes recorded by the London MPS between January 1 and June 22, 2020, collapsed a daily average by week. It also shows the corresponding daily average, by week, for our search-based DV index. Finally, it shows average daily helpline contacts per week for the period February 10 through May 4, provided to us by the charity Refuge, wyhich operates the UK's National Domestic Abuse Helpline. For the purpose of this diagram, we re-scale each of the three weekly variables to have mean of 100 between January 1 and March 23, 2020.

In order to show this divergence more clearly we collapse the 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 (Panel B). The figure suggests that the London lockdown was associated with a steady increase in DV-crimes starting after April 1 and continuing through to the end of May, with a peak increase of slightly below 20 percent compared to pre-lockdown levels.

In the same panel we contrast the 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 starting March 16 (the day of the first announcement about social distancing) and March 23 (the start of the official stay-at-home order), 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 presented here is however 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). Relatedly, 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; 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.

4.3 Regression Analysis

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:

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

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 in 2020. To account for this, we use data on daily average temperature (in $°C$) and rainfall (in mm) in London over the sample period, and x_t thus includes controls for temperature and rainfall. Turning to the lockdown, $I_{t \geq t_0}$ is a dummy for t being within the lockdown period, and $f(t - t_0)$ is a flexible, but continuous, function of lockdown duration. Note that $f(0)$ is not restricted to be zero. Hence it allows for an immediate lockdown effect. Our baseline specification for $f(\cdot)$ is a quadratic function, possibly with a distinct effect at weekends,

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

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

Table 2: 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)	-7.778**	-6.411*	-4.710	-7.417	-6.724	-6.745
	(3.804)	(3.695)	(3.622)	(7.667)	(7.590)	(7.721)
Days of Lockdown (ϕ_1)	0.435**	0.371**	0.380**	2.182***	2.159***	2.159***
	(0.170)	(0.162)	(0.158)	(0.323)	(0.322)	(0.322)
Days Sq. (ϕ_2)	-0.00405**	-0.00329**	-0.00333**	-0.0238***	-0.0235***	-0.0235***
	(0.00165)	(0.00158)	(0.00158)	(0.00318)	(0.00318)	(0.00318)
Temperature ($^{\circ}C$)		0.843***	0.845***		0.293***	0.292***
		(0.0685)	(0.0680)		(0.103)	(0.103)
Precipitation (mm)		-3.063**	-2.989**		2.076	2.075
		(1.525)	(1.522)		(1.660)	(1.662)
Weekend × Lockdown (ϕ_3)			-7.138***			0.0878
			(2.293)			(4.263)
Observations	1,910	1,910	1,910	1,905	1,905	1,905

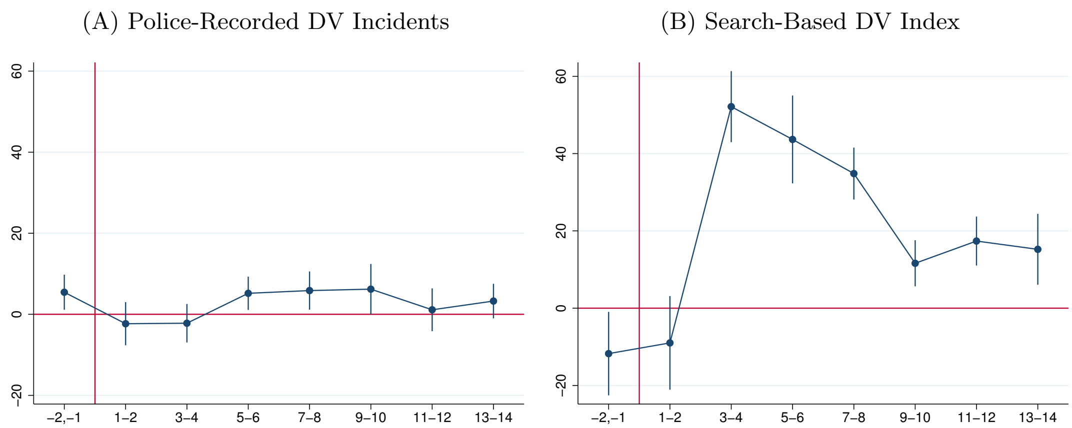
Standard errors in parentheses

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

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 31 December 2019). 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 31 December 2019). All regressions include year, month, and day-of-week fixed effects.

The first three columns of Table 2 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 ($= -\phi_1/(2\phi_2)$), aligning well with the visual impression from Panel A of Figure 4. The finding that the impact of the lockdown grew with duration naturally accords with General Strain Theory (Agnew 1992) which would suggest that reduced freedom of mobility, increased uncertainty, financial and emotional pressure could lead to the build-up of negative emotions, leading to a gradually increasing impact on DV incidence. 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 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 negative effect here indicates that recorded DV-crimes during the lockdown had a much smaller weekend-weekday difference than pre-crisis. The estimated coefficient translates

Figure 5: Bi-Weekly Effects of the London Lockdown



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.

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 1). However, our coefficients of interest are barely affected by the inclusion of weekend effects.

In the last three columns of Table 2, 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. 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. In column (vi), we find no indication of any differential impact of the lockdown on DV-related searches on weekends versus weekdays.

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.

The results are presented Figure 5. 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 fell back down towards pre-lockdown levels, but remained significantly above the pre-lockdown level.

Relating back to the conceptual framework from Section 2.1, if we were to assume that the increase in the search-based DV index accurately reflects the impact of the lockdown on DV incidence, whereas the lower increase in DV-related crimes reflects a reduced reporting rate by victims, then we can make a back-of-the-envelope estimation of the "missing" number of recorded DV-crimes over the sample period. Specifically, under this assumption and using that the average difference between the estimated effects in Figure 5 is 22 percent and the average number of recorded DV-crimes per day over the baseline period is 221, this suggests that there were on average 48 missing recorded DV-crimes per day. Hence the model predicts that the MPS would have recorded a further 4,700 DV crimes over the sample period had the rate of reporting to the police itself not been lowered by the lockdown.

4.4 Robustness Checks

We have carried out a number of sensitivity checks in relation to our estimates for the search-based DV index which we describe in Table A.2 in the online Appendix.

As a first set of checks, we have verified that the results are robust to the choice of window used in the construction of Y_t: while our main specification (reiterated in column 1 of Table A.2) uses ± 3 days, columns 2-4 shows that the results are robust to using ± 2 and ± 1, and also to using only 3 lags and no leads. In each of these alternative specifications, the key pattern on the estimated coefficients remains: the point estimates of the immediate effect of the lockdown ϕ_0 are all negative but not significant, whilst the estimated effects of the lockdown duration, ϕ_1 and ϕ_2, remain positive and negative respectively and within $\pm 20\%$ relative to our main estimates and always highly statistically significant.

Our second set of checks concerned the choice of terms and we present three alternative specifications (columns 5-7). First, as the potential impact of the lockdown on domestic violence received a substantial amount of media attention during the spring lockdown, we checked that our results are robust to excluding the generic term "domestic violence" from the composite measure as it was commonly used in media and hence a natural "focal term" for anyone doing internet searches to follow up on these news stories.[2]

Second, as noted above, the key relationship (2) between help-seeking via the police P_t and internet searches Y_t that formed the basis for our algorithm was derived under the assumption of independence between p_{it} and y_{it}. This assumption could easily be violated if victims of abuse use internet searches for information on potential police protection. Hence we present a specification where we exclude all terms involving the word "police" from our composite measure.

[2]See for instance `https://www.theguardian.com/society/2020/apr/12/domestic-violence-surges-seven-hundred-per-cent-uk-coronavirus`.

Third, one concern could be that searches on some of the included terms (see Table 1) could be related other forms of non-domestic abuse. Hence we present a specification where we exclude all terms that are not specifically DV-related. All three reductions of the set of search terms have only a minor impact on the estimated coefficients.

The third and final set of specification checks presented in Table A.2 (columns 8-9) test for robustness with respect to key dates. As noted above, bank holidays are days with comparably high levels of DV incidence. Hence we present the results from a specification that includes dummy variables to control for day t being one of the eight annual bank holidays (of which there were four within the lockdown days included in the estimation). Also, internet search activity on DV-related terms may be affected by efforts to raise awareness etc., most notably through DV campaigns. The launch of DV campaigns are commonly timed to coincide with two key days of the year: the International Women's Day on March 8 and the International Day for the Elimination of Violence Against Women on November 25 (Agüero, 2019).[3] Hence in the final robustness check we include controls to day t being within a week of either of these two key dates. The results from these final two specifications are largely indistinguishable from our main specification.

4.5 Results for Los Angeles, California

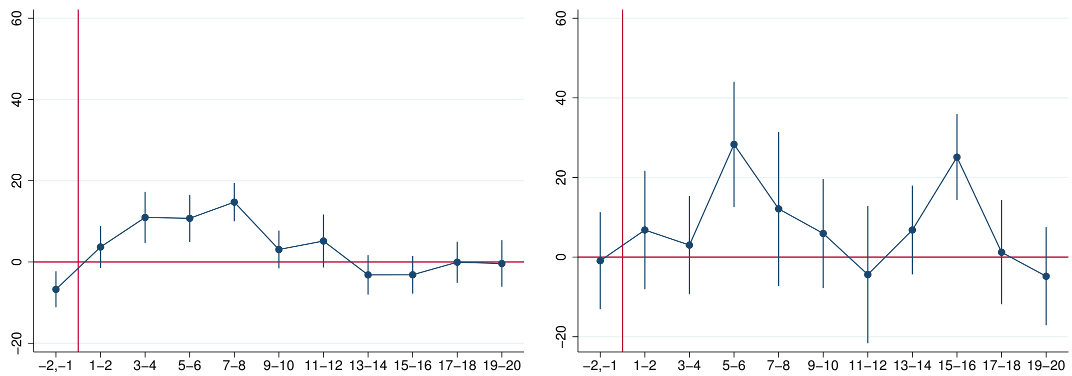
We next repeat the analysis for the city of Los Angeles, California. To that end, we combine three data sources for the period April 1, 2015 through July 31, 2020: (i) daily counts of DV-related calls for police service recorded by the Los Angeles Police Department (LAPD); (ii) daily search intensities 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). Further details about the Los Angeles data, including sources, trends and search-term selection, are provided in the online Appendix. 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 6 shows the LA counterpart of Figure 5. 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 a 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. Our results here are similar to Miller et al. (2020) et al. Focusing specifically on Los Angeles, they find an increase in DV-related 911 calls (and in calls to a DV hotline) at the initial lockdown , but a decrease in recorded DV-crimes. 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 DV index was around 30 percent. There is also a second significant spike in our search-based DV index after

[3] Examples of UK campaigns launched on these days include "16 Days:16 Women" and "Define the line" – see `https://www.refuge.org.uk/our-work/campaigns/hide-and-seek/`.

Figure 6: Bi-Weekly Effects of the LA Lockdown

(A) Police-Recorded DV Calls (B) Search-Based DV Index



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.

15-16 weeks of lockdown.

5 Discussion

Many types of crises—be it disease outbreaks like the current pandemic, severe economic downturns, or natural disasters—carry the risk of increasing DV (Anastario et al. 2009; Anderberg et al. 2016; Bermudez et al. 2019; Onyango et al. 2019). Effective policy responses require up-to-date reliable data on the scale of the problem. However, conventional data sources have severe limitations in this respect. Police-recorded DV is a particular case in point: victims of DV frequently do not report their abuser to the police, and COVID-19 and its associated restrictions has made reporting an abusive partner even more difficult.

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.

Other sources of data specifically related to DV incidence include helpline data. Indeed, the data on calls and contacts from the UK's National Domestic Abuse Helpline presented above showed an increase in the order of 60 percent in the first few weeks after the London lockdown compared to pre-pandemic levels. However, this data, too, is imperfect as it is not gathered sufficiently systematically over time to allow for a finer analyisis. 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. Similarly, data on homicides suggest a compositional shift towards domestic cases during the crisis. In 2020, the MPS launched 126 murder investigations while the corresponding number in 2019 was 150.[4] However, out of those 22 (17.5 percent) were domestic killings in 2020 compared to only 16 (10.7 percent) in 2019. The numbers are however (fortunately) too low for any conclusive statistical analysis.

In this paper we have adopted and implemented a framework for generating a DV index based on DV-related internet search activity. This has clear advantages compared to police and helpline calls data. However, it also shares some caveats. First, it is difficult to disentangle help-seeking by victims from that of third-party individuals. Indeed, non-victims may have increased their DV-related search intensity either due following up on the increased media attention devoted to DV-incidence during the lockdown or due to being more likely to overhear DV-incidents among neighbours. The literature on DV-incidence during the lockdown has made some attempts to disentangle the issue (Ivandic et al. 2021; Leslie & Wilson 2020) but one recent major review (Piquero et al. 2021) remained silent on it. The same caveat applies to the current paper. We do show in our robustness analysis that our findings are robust to eliminating the most frequent and generic search term "domestic violence". If this term would be relatively more used by non-victims, this would suggest that our results are not driven by third-party individuals.

A second caveat is that a lockdown means that individuals have more time available to spend on the internet. Indeed, there is evidence, for instance from the American Time Use Survey, that suggests that individuals spent more time playing games and using computers for leisure purposes.[5] What speaks against the possibility that our results might simply reflect larger time availability is the finding that searches did not increase proportionately more during weekdays when time availability would likely have changed the most.

Our findings show 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.

The broader lesson from our analysis is that it cautions against relying solely on police-recorded crimes or calls-for-service to assess the scale of the DV problem during crises like COVID-19. In such assessments, the use of complementary data sources is important, as it would allow researchers to move towards demarcating the lower and upper bounds of likely impacts on DV. One promising avenue in this respect is to engage with organizations supporting DV victims, encouraging the collection and provision of systematic data from DV helplines. Our algorithm for measuring temporal variation in DV incidence using internet search activity provides another viable strategy to complement assessments based on police records. Although our analysis by no means provides a definite answer to how to best construct a real-time indicator of DV, it can

[4] See `https://www.bbc.co.uk/news/uk-england-london-55812483`.
[5] See `https://www.bls.gov/news.release/atus.t09.htm`.

hopefully serve as a starting point that can be extended and further validated.

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Online Appendix

Construction of Search Term Time-Series

A set of features of Google Trends data complicate their usability as longer-term high-frequency time-series. i) Google Trends data at daily frequency is only available for search windows up to 9 months; after that the returned frequencies become weekly and then monthly. ii) Search volumes are always normalized to 100 for the highest search volume over the investigated time period. iii) When drawing data on more than one search term at the same time, Google Trends will normalize with respect to the highest search volume across the terms used.

To overcome these issues, we proceed as follows. We draw data for each search term individually for a sequence of overlapping search windows and merge the time series for each search term. In particular, we draw time series blocks of 7 months, where the first month is overlapping with the last month of the previously drawn time series block. When merging the individual blocks, we use the overlapping month to rescale the new block to create a consistent time series over the full period. After merging all blocks to the full time series, we rescale the full time series to 100 for the highest occurrence of the search term over the full sample period.

Further Validation Results

In Table A.1 we show the results of regressing the daily counts of DV-crimes on the search-based DV index, both in the residualized form, within the testing period (excluding New Year's Day). The positive coefficient in specification (i) shows that an above average value of the search-based index is associated with an above average level of DV-crimes. This reflects the correlation between the two series. In specification (ii) we extend this regression to include a lag and a lead on the search-based DV index. This shows that the daily variation in the DV-crime counts is most strongly associated with the variation in the same-day value of the DV index and not with its first lag and lead. In specification (iii) we regress the first difference in the (residualized) DV-crimes on the corresponding first difference in the search-based DV index. Hence this checks whether day-on-day changes in the index is associated with corresponding changes in the DV-crime counts. Finally, in specification (iv) we add a lag and a lead on the first difference in the search-based DV index. Overall, all four specification indicate that daily variation in the DV index is associated with daily variation in the DV-crime counts.

Robustness

Section 4.4 discussed the results from a set of specifications aimed at establishing the robustness of our findings. The results from these alternative specifications are shown in Table A.2.

Table A.1: Relating Daily Variation in DV-Crimes to Daily Variation in the DV index

	Level Specs.		First Diff. Specs.	
	(i)	**(ii)**	**(iii)**	**(iv)**
$DVIndex_t$	0.195*	0.194*	0.318***	0.481***
	(0.110)	(0.109)	(0.117)	(0.152)
$DVIndex_{t-1}$		0.0684		0.215
		(0.0866)		(0.154)
$DVIndex_{t+1}$		-0.090		0.174
		(0.151)		(0.157)
Observations	74	74	74	74

Robust standard errors in parentheses.

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

Notes: The dependent variable is the residualized daily count of DV-related crimes. This variable was constructed from the daily count of DV-crimes recorded by the MPS, by normalizing to a mean of 100 over the period between 1 April 2015 and 31 December 2019, and then obtaining the residuals after removing year- and month fixed effects. The search-based DV-index was normalized and residualized in the same way. The sample includes the "testing period" of 2020 up to and including March 15, but excluding New Year's Day.

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 A.3.

Panel A of Figure A.1 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 A.4.

Table A.2: The Effect of Lockdown on DV-Related Search Intensity: Robustness to index Construction

	(1) Window ±3 days	(2) Window ±2 days	(3) Window ±1 day	(4) Window 3 Lags	(5) No "Dom. Viol."	(6) No "Police"	(7) Only DV-Related	(8) Bank Holiday	(9) Awareness Weeks
Lockdown (ϕ_0)	-6.745	-6.305	-13.84	-12.94	-10.68	-8.628	-7.451	-6.702	-5.933
	(7.721)	(7.793)	(8.691)	(8.135)	(7.732)	(8.237)	(8.746)	(7.759)	(7.657)
Days of Lockdown (ϕ_1)	2.159***	1.948***	2.172***	2.594***	2.225***	2.212***	2.311***	2.155***	2.132***
	(0.322)	(0.330)	(0.376)	(0.376)	(0.327)	(0.342)	(0.365)	(0.323)	(0.320)
Days Sq. (ϕ_2)	-0.0235***	-0.0218***	-0.0242***	-0.0280***	-0.0238***	-0.0244***	-0.0252***	-0.0235***	-0.0233***
	(0.00318)	(0.00328)	(0.00393)	(0.00399)	(0.00325)	(0.00334)	(0.00358)	(0.00318)	(0.00316)
Weekend × Lockdown (ϕ_3)	0.0878	0.220	-0.121	0.678	-0.159	-0.212	0.726	0.0551	0.0771
	(4.263)	(4.388)	(5.371)	(5.458)	(4.558)	(4.525)	(4.695)	(4.261)	(4.240)
Temperature ($^{\circ}C$)	0.292***	0.221**	0.152	0.433***	0.285**	0.317***	0.334***	0.302***	0.299***
	(0.103)	(0.104)	(0.137)	(0.136)	(0.112)	(0.105)	(0.113)	(0.103)	(0.103)
Precipitation (mm)	2.075	1.489	0.565	-1.109	3.790**	2.041	1.563	2.287	2.135
	(1.662)	(1.806)	(2.662)	(2.159)	(1.899)	(1.712)	(1.857)	(1.653)	(1.662)
Observations	1905	1905	1905	1905	1905	1905	1905	1905	1905

Standard errors in parentheses

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

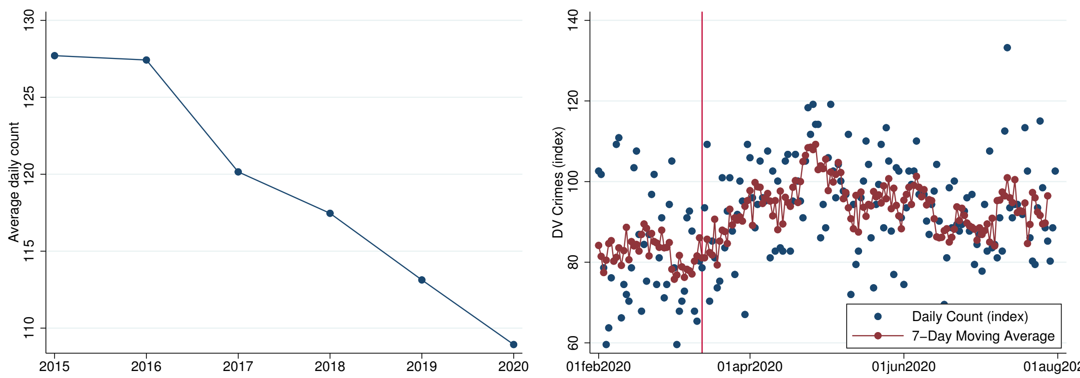
Notes: The outcome variable is a composite index of DV-related search intensity at daily frequency (100 = average daily intensity over the period 1 April 2015 to 31 December 2019). The sample period is 1 April 2015 to 22 June 2020. All regressions include year, month, and day-of-week fixed effects. Specification 1 reiterates the final and main specification from Table 2. Specifications 2 to 4 reduce the window of days used in the construction of the DV-search index. Specification 5 specifically leaves out the term "domestic violence" from the construction of the DV-search index, whereas specification 6 leaves out the terms "abuse police", and "domestic violence police". Specification 7 leaves out the terms "London abuse", "abuse police", "refuge", and "shelter". Specification 8 includes dummies for each of the eight annual bank holidays. Specification 9 includes a dummy for day t falling on or within a week of either the International Women's Day (March 8) or the International Day for the Elimination of Violence Against Women (November 25).

Table A.3: 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 A.1: Trend and Daily Counts for DV-related Calls-for-Service to the LAPD

(A) Trends (B) Daily



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

Table A.4: 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	0.124	abusive partner	Low	-
abuse hotline	High	0.922	abusive relationship	High	0.004
abuse support	High	1.106	threat of violence	Low	-
refuge	High	0.723	partner violence	Low	-
women's shelter	High	0.801	domestic violence	High	0.110
domestic violence help	High	0.069	domestic abuse	High	0.690
shelter	Low	-	emotional abuse	High	1.274
LA shelter	Low	-	psychological abuse	High	0.203
shelter LA	Low	-	controlling relationship	Low	-
domestic shelter	Low	-	LA domestic violence	Low	-
victim support	Low	-	intimate partner violence	High	0.013
National domestic violence hotline	Low	-	abusive husband	High	2.432
domestic violence support	High	0.209	**Group 3: Police/Legal Protection**		
domestic violence help	Low	-	report domestic violence	High	1.357
domestic violence victim	High	0.036	abuse police	High	0.534
domestic violence hotline	High	5.003	abuse protection	Low	-
LA abuse	High	1.689	reporting abuse	High	2.544
			domestic violence police	High	0.146
			domestic violence law	High	1.304
			domestic violence charges	High	1.709
			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.