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Comparing 911 and Emergency Hotline Calls for Domestic Violence in Seven Cities: What Happened When People Started Staying Home Due to COVID-19? *

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We examine changes in help-seeking for domestic violence (DV) in seven U.S. cities during the COVID-19 pandemic. Using Bayesian structural time-series modeling with daily data to construct a synthetic counterfactual, we test whether calls to police and/or emergency hotlines varied in 2020 as people stayed home due to COVID-19. Across this sample, we estimate there were approximately 1,030 more calls to police and 1,671 more calls to emergency hotlines than would have occurred absent the pandemic.Inter-agency data analysis holds great promise for better understanding localized trends in DV in real time. Research-practitioner partnerships can help DV coordinated community response teams (CCRTs) develop accessible and sustainable dashboards to visualize data and advance community transparency. As calls for drastic changes in policing are realized, prioritization of finite resources will become critical. Data-driven decision-making using CCRTs provides an opportunity to work within resource constraints without compromising the safety of DV victims.

Keywords: policing, COVID-19, domestic violence, victims

Introduction

Since the earliest days of the COVID-19 pandemic, there has been significant discussion regarding the impact of stay-at-home orders on the prevalence of domestic violence (DV). The pandemic fostered increases in a range of stressors such as unemployment, financial instability, and parental stress, all of which are associated with DV (Anderberg et al., 2016; Aizer, 2010; C. Moore et al., 2007). Concurrently, alcohol consumption in the home increased (Chalfin et al., 2021), which can catalyze violence between family members (Bushman, 2002; Foran & O'Leary, 2008; Livingston, 2010). With non-essential businesses shut down, schools and churches closed, and citizens' movement limited, victims and their children were separated from support systems and confined with their abusers. Further, many victim advocacy agencies reduced their capacity or moved their services online. Given fears about COVID transmission, victims' ability to seek safety with family and friends was also likely limited. Taken together, scholars and practitioners suggested that DV

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incidents would increase significantly in both frequency and severity, while the United Nations recognized DV as a "shadow pandemic" across the globe (U.N. Women, 2020).

Months into the pandemic, a limited but rapidly growing body of research provided empirical evidence that DV-related calls for service to police in the U.S. did increase directly after stay-at-home orders (e.g., Piquero et al., 2020), but longer-term studies also showed that trends in calls often normalized quickly after these rapid escalations (Leslie & Wilson, 2020; McCrary & Sanga, 2020). Taken together, a meta-analysis of 12 U.S. studies estimated an 8% increase in DV during the pandemic (Piquero et al., 2021). In addition, at least one study demonstrated localized differences in trends for DV calls for service across different jurisdictions (Nix & Richards, 2021). Further, evidence showed that increases in calls for DV service were concentrated among households who had not previously called police for DV service (Leslie & Wilson, 2020; McCrary & Sanga, 2020), suggesting potential pandemic-related changes in DV victimization, DV reporting, or both, which requires further examination.

Prior research has consistently demonstrated that most DV victims do not call police after incidents of partner violence (Morgan & Truman, 2020). Victims of DV describe a range of barriers to reporting to police, including concerns that they will not be believed or that nothing will be done, fears of retaliation by the perpetrator, and a reliance on the perpetrator for material resources (e.g., housing, financial support), among others (Robinson et al., 2020). The pandemic-related economic downturn has likely increased concerns regarding negative consequences of reporting to police, and victims may be inclined to access support and resources from other sources like emergency hotlines (Sorenson et al., 2021). As such, victim reports to emergency DV hotlines provides an important source of data regarding incidents of DV during COVID-19.

This study adds to the limited research on the impact of COVID-19 on DV by examining DV calls for service to both police and victim service organizations' emergency DV hotlines in seven U.S. cities from January 1, 2018 to October 31, 2020. Using Bayesian Structural Time Series (BSTS) modeling we first examine the observed trend in DV calls for service to police and emergency hotlines during the entire study period. Using the resulting BSTS models, we estimate the expected trend (i.e., counterfactual) in DV calls for service to police and emergency hotlines during the corresponding COVID-19 period (March 9 to October 31, 2020). Finally, we compare mean differences between the observed and expected trends for the COVID-19 period, providing estimates of the impact of COVID-related social isolation on calls to police and emergency hotlines in each city.

DV-Related Calls for Police Service During COVID-19

One of the first studies on the impact of stay-at-home orders on DV calls for service compared the number of calls for service for "family violence" (including domestic violence, elder abuse, child abuse, and sexual assault) in the 35 days after the implementation of a stay-at-home order in Dallas (TX) to the 83 days prior to the order (Piquero et al., 2020). Results showed an increase in calls in the two weeks after the stay-at-home order (i.e., March 2020), but these increases quickly dissipated. Other studies published around the same time reported similar findings in Chicago (Bullinger et al., 2020), Indianapolis, and Los Angeles (Mohler et al., 2020). Indeed, using mobile device location data to assess "sheltering in place," Hsu and Henke (2021) found that DV calls for service increased by more than 5 percent in March and April 2020 across 36 U.S. cities.

Leslie and Wilson (2020) used data on citizen movement (e.g., OpenTable reservations, mobile device location data) to assess the impact of pandemic-related social distancing on the aggregate number of DV calls for service in 14 cities. The authors were able to account for whether these calls stemmed from city blocks with prior DV calls or blocks with no DV call history. Weekly DV calls from March to May 2020 were compared to calls in the same weeks in 2019, which allowed for the consideration of seasonal trends in calls for service. Findings showed that social distancing was associated with a 7.5 percent increase in DV calls during the study period, with the largest increases (10%) in the first five weeks after social distancing practices took effect. Further, effects were largest on weekdays, when families were likely to experience the greatest increase in time together relative to their pre-pandemic schedules. Finally, results demonstrated significant increases from city blocks without previous DV calls for service. McCrary and Sanga (2020) also analyzed cell phone location data and DV-related calls for police service for thirteen U.S. cities and one county, finding that during the pandemic, DV calls increased by about 12% on average. Here again, the authors observed that increases were most pronounced during traditional work and school hours and concentrated in neighborhoods with no recent history of DV calls for service. Taken together, these studies suggest that DV calls for police service increased from 5 to 12% on average in the days after people began sheltering in place. Further, the fact that calls from victims/families who had not previously called police increased provides preliminary evidence of changes in either DV victimization, reporting behavior, or both.

A common theme among all these studies is that they were conducted during the earliest days of the pandemic – before it became clear just how long everyone's lives would be disrupted. One exception is Nix and Richards (2021)'s study examining DV and non-DV calls for police service in six U.S. cities from January 1, 2018 to December 31, 2020. Consistent with prior work, findings showed an immediate effect of stay-at-home orders: a significant increase in DV calls for service in every jurisdiction except one (Cincinnati, OH). Throughout the remainder of 2020, DV calls for service declined in five of the six jurisdictions (Salt Lake City, UT was the lone exception). However, among those five jurisdictions, the difference in the linear slope of weekly DV calls for service relative to that of the period before stay-at-home orders went into effect was only significant in Montgomery County, MD (where the declining slop became more pronounced) and Phoenix, AZ (where the slope changed direction). One clear takeaway of this study is that pandemic-related changes in DV calls for service varied by jurisdiction; thus, more examination of trends across different jurisdictions is warranted.

Reporting DV to Law Enforcement

The evidence compiled to date strongly suggests that DV increased during the pandemic. However, most studies have relied on official data such as reported crimes or calls for police service, and it is well established that domestic violence is underreported to law enforcement. In fact, recent victimization surveys suggest that less than half of all DV incidents are reported (Langton et al., 2012; Morgan & Truman, 2020). Victims choose not to report for myriad reasons, including feelings of shame regarding the abuse, emotional connections to the perpetrator, desires to keep their family together, and dependence on their abuser for financial support, among others (Erez & Belknap, 1998; Fischer & Rose, 1995; Logan & Valente, 2015). Victims also refrain from reporting due to fear: abusers often threaten to kill their victims and/or their children if they leave (Erez & Belknap, 1998). Research evinces that such threats should be taken seriously as victims are most at risk of lethal violence in the days and months after separating from an abuser (i.e., "separation assault"; Campbell et al., 2003; Mahoney, 1991).

Real and anticipated behavior by police also serves as a barrier to reporting. Victims cite fear that they will not be believed, that law enforcement will not or cannot help, and/or that they will be blamed for the abuse as reasons for non-reporting (Erez & Belknap, 1998; Langton et al., 2012; Logan & Valente, 2015). Victims also report anxiety that calling the police will "make matters worse" by further provoking the perpetrator, exposing their children to police intervention, or even resulting in their own arrest (i.e., arrest of the victim; Logan & Valente, 2015). Scholars who study violence against women suggest that victims tend to report DV to police only after a pattern of violence over time, once the victim reaches a point where "enough is enough" (Fischer & Rose, 1995). This tipping point may be reached when violence has escalated in frequency and/or severity, has become increasingly unpredictable, or when the victim fears that the violence may become lethal (Buzawa et al., 1999; Erez & Belknap, 1998; Fischer & Rose, 1995). It is also recognized that some victims of DV may never call law enforcement, even after long periods of violence; however, some of these same victims do seek out help from victim service organizations (Logan & Valente, 2015), and a common pathway to victim service organizations is through an emergency DV hotline.

Reporting DV to Emergency Hotlines

Emergency DV hotlines are an essential service provided annually to millions of victims by local domestic violence service agencies, state coalitions, and national organizations (*The National Domestic Violence Hotline*, 2020). In the U.S. in 2019, the National Domestic Violence Hotline answered more than 620,000 calls, online chat requests, and text messages (*The National Domestic Violence Hotline*, 2020). Emergency hotlines are staffed 24-hours a day with service providers and/or trained volunteers who offer callers emotional support, crisis management, and referrals to supportive services (e.g., counseling; Macy et al., 2009). There is a paucity of research on the context or impact of emergency hotline use by DV victims (Nix & Richards, 2021); however, it remains unclear whether changes in hotline usage or call volume occurred during the COVID-19 pandemic.

Research from Peru indicates that calls to the national DV emergency hotline increased after the implementation of stay-at-home orders and that these increases were sustained throughout the summer months of 2020 (Aguero, 2021). Meanwhile, research comparing DV calls to police and the emergency hotline in Mexico City, Mexico found that DV-related official police reports declined by 27% while hotline calls increased by 30% in the weeks after the stay-at-home orders in 2020 (relative to the same weeks in 2018 and 2019; see Silverio-Murillo et al., 2020). In Buenos Aires, Argentina, calls to a hotline for victims and witnesses of DV as well as for law enforcement officers responding to DV increased by 32% from the implementation of a stay-at-home order on March 20, 2020 to April 30, 2020 (relative to the same period in 2017, 2018, and 2019; see Perez-Vincent et al., 2020). Upon further assessment of hotline caller type, Perez-Vincent et al. (2020) found a substantial "substitution effect," in that calls to the emergency hotline from DV victims increased by 127%, while calls from law enforcement officers responding to DV dropped by 62%.

In the U.S., the National Domestic Violence Hotline noted year-over-year fluctuations in calls for services from 2019 to 2020 that it associates with the implementation and cessation of stay-at-home orders (*The National Domestic Violence Hotline*, 2020). However, we are aware of only one U.S. study that has rigorously analyzed emergency hotline call data during the pandemic. In Philadelphia, Sorenson et al. (2021) examined calls to 911, the domestic violence hotline, and the sexual assault hotline from January to May 2020. The authors uncovered a gradual increase in DV hotline calls after the implementation of stay-at-home orders; meanwhile, calls to police for domestic violence remained relatively unchanged. In their words:

> The analysis underscores the importance of distinguishing between the violence itself, calls to police, and calls to helplines when claims are made about changes over time in violence against women. The opportunities and constraints for each can differ widely under usual circumstances, circumstances that were altered by public health interventions related to the pandemic (Sorenson et al., 2021, p. 1).

Limitations of their study include that it was restricted to one city and the study period covered only 5 months, inhibiting the authors' ability to conclude with confidence how much of the variation they observed was a function of COVID19 (as opposed to normal seasonal variation or changes in the weather). As Leslie and Wilson (2020) point out, in the 14 cities they studied, "failing to account for seasonal trends in domestic violence calls would result in overestimating the treatment effect by a factor of two" (p. 4). Nevertheless, Sorenson et al. (2021) show that official data (i.e., calls for police service, reported crimes) provides an incomplete portrayal of the effects of COVID-19 on help-seeking for DV. More research drawing on official and unofficial data is sorely needed.

The Current Study

The purpose of this study was to assess trends in help-seeking for domestic violence during the COVID-19 pandemic. For each of seven U.S. jurisdictions, we secured calls for service data from the municipal police department as well as emergency hotline call data from the local victim service agency. We employ rigorous statistical analyses (described below) to determine how daily call patterns to each entity in 2020 deviated from the patterns observed from 2018 to 2019. Our approach enables a fuller understanding of changes in DV help-seeking during the pandemic, since it is well-established that many victims do not seek help from law enforcement following incidents of partner violence (Logan & Valente, 2015; Morgan & Truman, 2020). It also addresses key limitations of the one study to date that has analyzed both police and DV emergency hotline data by (1) focusing on several jurisdictions across the U.S. and (2) analyzing nearly three years' worth of call data (enabling us to observe variation in 2020 compared to variation in previous years when COVID19 was not a factor).

Data

We analyze daily counts of DV calls for service (CFS) to police agencies and victim service agencies' emergency hotlines (VSA) for seven cities from January 2018 through October 2020. Calls for service data were downloaded from The Police Data Initiative – a website operated by The National Police Foundation and the International Association of Chiefs of Police that contains 200+ datasets from 130+ police departments. Emergency hotline data were provided by staff at each victim sevice agency. The seven cities are Baltimore (MD), Cincinnati (OH), Hartford (CT), Orlando (FL), Sacramento (CA), Salt Lake City (UT), and St. Petersburg (FL).[1] Accordingly, there are a total of

[1] DV-calls were extracted by mining for the following text: in Baltimore, description included "FAMILY DISTURB"; in Cincinnati, incident_type_id included "DOMVIO," "U-DOMESTIC VIOL IN PROGRESS," "FAMTB", or "DOMINP-COMBINED"; in Hartford, call_initiated_by = "CITIZEN" and description_1 or description_2 included "DOMESTIC"; in Orlando, IncidentType included "DOMESTIC"; in Sacramento, description included "DO-

1,035 CFS and VSA observations for each jurisdiction, except for Orlando, where CFS data were only available through June 2020 (a total of 912 data points).

The only two variables for which missing data were noted were the VSA data in Baltimore and Salt Lake City. Missingness for the Baltimore VSA variable was 7.1%. Missingness for the Salt Lake City VSA variable was 8.5%.[2] Social scientists have increasingly recognized multiple imputation as a superior strategy for analyzing missing data to the often-used method of listwise deletion, which assumes the absent data is missing completely at random (Lall, 2016). The imputation method used for the missing data in this analysis (described below) can account for the absent data, whether it is missing at random or not.

Multivariate imputation by chained equations (MICE) was used to impute the missing values with 100 iterations of 50 imputations. MICE is advantageous because by using chained equations, the imputation model accounts for the process that created the missing data, preserves the relations in the data, and preserves the uncertainty about these relations (Groothuis-Oudshoorn & Van Buuren, 2011). Multiple imputation is a Monte Carlo method that simulates values to impute each missing value. These simulated values are pooled together for the final output. The missing data were imputed multiple times with a random sample from the observed data to account for the uncertainty about the missing data's actual values. Upon completion of the imputation, density plots and distributions were examined. None of these evaluations raised concerns with the imputation process or outcomes for the VSA variable in Baltimore or Salt Lake City.

As the study seeks to understand the impact of COVID-19 related social distancing, where to place the beginning of that distancing is a critical analytic decision. While some researchers use official emergency orders from various government levels, others attempt to distinguish a specific date (or range) tied to large-scale behavioral change in the populace. This study uses the latter method and relies on the work of Leslie and Wilson (2020), who use four different metrics to identify March 9, 2020, as the date of large-scale behavior change in the U.S., including four of the seven cities studied here. To identify the date of behavioral change consistent with the onset of social distancing, Leslie and Wilson (2020) (see Data Appendix B) combine four data

MESTIC" or "DISTURBANCE-FAMILY"; in Salt Lake City, case_type_translation included "DOMESTIC"; and in St. Petersburg, typeofevent included "DOM VIOL" or "DOMESTIC."

[2]Upon following up with staff at these VSAs, we were reassured that missing cells should be treated as missing values (rather than zeros), as they likely reflected staff members forgetting to log the number of calls received on those days.

measures: SafeGraph (2020) cellphone stay-at-home measures, Unacast (2020) cellphone social distancing scorecard, OpenTable restaurant reservations, and Google Trends search data for "social distancing." Using the four measures, Leslie and Wilson find that social distancing began on March 9, 2020, at least a week before state-mandated orders were issued in the studied cities. Using this date in our analysis allows the models to capture the full range of changes in calls-for-service (CFS) and victim service agencies (VSA).

Method

Bayesian Structural Time Series (BSTS) modeling was used for the analysis. BSTS models are flexible and modular, allowing researchers to determine the model's structure by considering whether and how to include regressors, whether short- or long-term predictions are more important, and whether seasonal model components are necessary (Brodersen et al., 2015; Scott, 2017). Further, by working in a Bayesian framework, investigators can better acknowledge and incorporate uncertainty into statistical models and discuss outcomes in probabilities, which tend to be more intuitive (Mourtgos & Adams, 2021).

BSTS models are best described as observation equations, linking observed data with an observed latent state and transition equation. The transition equation describes the latent state's development over time (Brodersen et al., 2015; Mourtgos et al., 2021). Accordingly, based on 2018 and 2019 data, we use BSTS models to make probabilistic estimations of what a jurisdiction's CFS or VSA 'should' have been in 2020 without the intervention of COVID-related social isolation (i.e., a synthetic counterfactual). This method allows us to compare the volume of a jurisdiction's CFS and VSA following COVID-related social isolation with what we would have expected without that exogenous socio-behavioral pattern shock.

Results

The analysis proceeds in three steps. First, BSTS models are estimated for each measure (i.e., CFS and VSA) in each jurisdiction. The models are constructed using 2018 and 2019 data, thus building a probabilistic model based on 'normal' (i.e., non-COVID period) crime data within each city. Second, the resulting BSTS models are used to estimate a synthetic counterfactual for the

CFS and VSA in each city between March 9, 2020, and October 31, 2020. Third, mean differences between the observed measures and counterfactual measures are calculated for the COVID-related period, providing estimates of the impact COVID-related social isolation had on DV crimes. We examine these effects for and across the entire post-social isolation period.

BSTS Models

A BSTS model was estimated for each city's measures with a semi-local linear trend state component, an annual seasonal state component using a harmonic trigonometric function, and a weekly seasonal component. A semi-local linear trend is similar to a local linear trend in that it assumes the level component moves according to a random walk. However, the semi-local linear trend is more appropriate for long-term forecasting because it assumes the slope component moves in an AR(1) process rather than a random walk. This allows the model's trend component to provide more reasonable uncertainty estimates in extended forecasts (Scott, 2020).

The harmonic trigonometric function accounts for the well-documented annual seasonal fluctuation in crime (Baumer & Wright, 1996; Cohn, 1990; McDowall et al., 2012) by joining time points one cycle apart together in a smoothing function. Smoothing allows the model to impose continuity between neighboring periods (Harvey, 2006; Hindrayanto et al., 2013; Stolwijk et al., 1999). Finally, with daily data available, a weekly seasonal component is appropriate and prudent to account for weekly patterns in CFS and VSA.

The pre-COVID time series began in January 2018 and ended in December 2019. Accordingly, the pre-COVID series is 730 data points in length. Ten thousand Markov Chain Monte Carlo (MCMC) iterations were simulated to fit each model. For each model, autocorrelation plots were generated. We expected to find some autocorrelation in the model due to the nature of time series analysis. Plots did indeed indicate some autocorrelation; however, the autocorrelation was not impairing and was cyclical as is expected when using a trigonometric function.

Further, Q-Q plots were generated by sorting the MCMC draws by their means and placing the set of curves against the quantiles of the standard normal distribution. No significant variations were observed, except Cincinnati's VSA data indicating moderately more extreme values than expected. However, based on robustness checks (described below), this was not deemed problematic.

Forecast

A 305-day forecast was estimated for each model from January 1, 2021 through October 31, 2021 (except for the Orlando CFS model having a 182-day forecast through June 30, 2021). **Figures 1 and 2** plot the observed and counterfactual data for the CFS and VSA models, respectively.

[Figure 1 here]

As seen in **Figure 1**, there are three patterns among the seven cities with respect to calls for service. Compared to the synthetic counterfactual, cities experienced either a sustained increase (Baltimore, Sacramento, and Salt Lake City), an initial increase with a subsequent return to average call volume (Orlando and St. Petersburg), or a decrease in calls (Cincinnati and Hartford) following the onset of social distancing on March 9, 2020.

Figure 2 demonstrates a substantial increase in calls to victim services agencies in all cities but one, Sacramento, which saw a sustained decrease in calls compared to the synthetic counterfactual. Of the six cities that experienced increased calls to VSAs, four saw sustained increases throughout the study period (Baltimore, Hartford, SLC, and St. Petersburg). Two cities saw an initial substantial increase in these calls before the observed average call demand closed with the counterfactual trend (Orlando) or reversed position after an initial surge in observed calls (Cincinnati).

[Figure 2 here]

As a robustness check, the model estimates were overlaid with the observed data from January 1, 2021, through March 8, 2021—the intervening time between the periods for which the models were estimated and when differences between observed and counterfactuals were calculated. Model estimates remained within the 95% credible intervals and the observed values clustered around the counterfactual model trend line in all models. This provides confidence in the models' credibility, as the estimated counterfactuals coincide with the observed data during the pre-social isolation period.

Counterfactual and Effect

Next, the mean difference between observed and counterfactual values during the post-social isolation period (i.e., March 9, 2020, and beyond) was calculated for each jurisdiction. The difference in means was then evaluated with Bayesian estimation using weakly informative priors and 100,000 MCMC samples. Observed and counterfactual mean values, difference in mean values, 95% Highest Density Intervals (HDIs), and probability values for the effect size are provided in **Table 1.**

[Table 1 here]

Table 1 shows how each jurisdiction experienced an overall change in DV-related calls during the social-distancing period, as related to both CFS and VSA calls. Two cities saw the overall average call volume increase for both CFS and VSA (Baltimore and Salt Lake City). Only one city saw overall decreases in both CFS and VSA (Orlando). Three cities saw a mean average decrease to CFS and a corresponding increase to VSA (Cincinnati, Hartford, and St. Petersburg). Finally, just one city saw an overall average increase for CFS and decreased VSA (Sacramento).

The varied patterns between CFS and VSA calls in the studied cities are not the only source of variability in these findings. It is worth noting that the size of the effect across jurisdictions was highly heterogeneous as well. The average mean difference in volume for both CFS and VSA calls across the study period is one way of estimating the systemic demand each city experienced over the 237 days in the post-period. In descending order of impact, Baltimore experienced an increase of 1533 CFS calls and 815 VSA calls, for a total increased systemic demand of 2348 calls. SLC experienced an increase of 388 CFS calls and 843 VSA calls, for a total increased systemic demand of 1232 calls. St. Petersburg experienced a decrease of 372 CFS calls and an increase of 1317 VSA calls, for a total increased systemic demand of 945 calls. Hartford experienced a decrease of 841 CFS calls and an increase of 1099 VSA calls, for a total increased systemic demand of 258 calls. Orlando experienced a decrease of 164 CFS calls[3] and a decrease of 120 VSA calls, for a total decrease in systemic demand of 285 calls. Cincinnati experienced a decrease of 1211 CFS calls and an increase of 547 VSA calls, for a total decrease in systemic demand of 663 calls. Finally, Sacramento experienced an increase of 1696 CFS calls and a decrease of 2832 VSA calls, for a total decrease in systemic demand of 1135 calls.

However, we are not only interested in the effect size across the COVID-related social isolation period in its entirety. **Figures 1 and 2** indicate that while some sustained increases were experienced, other jurisdictions experienced an immediate increase in CFS or VSA, with a subsequent

[3] Data for Orlando CFS restricted to 119 days, as the data is only available for that period.

decrease. To better analyze these patterns, rather than solely examining mean values for the entire social isolation period, **Figure 3** plots mean differences between observed and counterfactual variables across time for both CFS and VSA, revealing interesting patterns over the study period. Some cities experienced relatively stable patterns. For example, Hartford saw immediate and sustained increased VSA demand, while CFS demand was suppressed below counterfactual levels across the study period. Sacramento saw similar stability as Hartford but sustained increased demand to CFS, while VSA demand was suppressed throughout.

[Figure 3 here]

Two other interesting patterns over time to note in **Figure 3** occur in Baltimore and SLC. In Baltimore, we see a sharp initial increase in CFS demand and a relatively minor increase in VSA. However, by mid-May, CFS demand was almost to what would be expected in the counterfactual, while VSA demand had steadily increased. By July, the demand on CFS had once again spiked, while VSA demand had plateaued. These trends continued, and by the end of the study period, demand on CFS was continuing a notable increase over what was expected. In contrast, VSA demand had returned to nearly no difference in the observed data versus the counterfactual model. Salt Lake City may demonstrate a transference effect between CFS and VSA, even while overall demand on both was increasing. This can be observed in the mirroring between the trends shown. Overall, VSA calls were increased throughout the period and at a higher rate than CFS, which were also increasing. However, by the end of the study, the increase in CFS had surpassed the increase to VSA.

Discussion

A growing body of research shows that DV-related calls to police increased during the COVID-19 pandemic, and that increases were most pronounced directly after people started staying home (Piquero et al., 2021). However, studies also reveal significant variation in the impact of stay-at-home orders on police calls for DV service across cities (Nix & Richards, 2021). Meanwhile, it is well known that a substantial portion of DV victims do not seek help from police (Morgan & Truman, 2020), and researchers and practitioners alike have noted that an overreliance on police calls for service likely suppresses important information about DV help-seeking during the pandemic (Nix

& Richards, 2021; Piquero et al., 2021; Sorenson et al., 2021). This study aimed to advance our knowledge of DV help-seeking during the pandemic by examining data on DV-related calls to police and to emergency hotlines across seven cities over a 2+ year period.

So, did staying home during the pandemic increase DV-related calls for police service? What about calls to emergency hotlines? Our study shows a general increase in DV-related calls in this sample of seven cities from March to October 2020 compared to 2018 and 2019 – a net total of 2700 more calls than we estimate would have occurred absent the pandemic. But importantly, there were stark differences across jurisdictions in terms of whether they experienced increases in calls to police, emergency hotlines, or both. Indeed, some jurisdictions experienced decreases in calls for service across one or both measures.

Our findings highlight the importance of studying trends in local data for practitioners and policy makers. This is not to say that understanding national or statewide trends is unimportant. Rather, we must remember such analyses undoubtedly mask meaningful variation at smaller units of analysis. Take Florida for example. As seen here, the trends in calls to emergency hotlines in Orlando were not reflected in the trends observed in St. Petersburg. More generally, while there were several distinct patterns in the observed changes (e.g., initial increases, sustained increases, or decreases in calls), trends in any one city were not generalizable to any other city. Rather than relying on reported trends at the national or state level to inform responses to community problems, including DV, local stakeholders would be better served by timely analyses of the data they collect on a regular basis.

Several police departments have begun providing their calls for service data in an open access format (e.g., Police Data Initiative, individual agency "data dashboards" as in several major cities). In fact, some agencies post their data in close to real time, which allows for timely review and analysis by both researchers and practitioners. Unfortunately, there is not yet this same culture of data sharing amongst victim service agencies. In some cases, the only information available about victim help seeking and service provision from an agency comes from their annual report, which is primarily written for the agency's funders. At the time of dissemination of such reports, the data provided (e.g., the number of hotline calls received, the number of victim-survivors who were provided emergency shelter) are already at least a year old. While there are real and important concerns regarding victim privacy and safety, providing timely aggregate counts regarding services or referrals is easily accomplished and does not jeopardize victims or their families.

One important forum for local data sharing is coordinated community response teams (CCRTs), which bring stakeholders from police, victim advocacy, prosecution, health care, academia, and other sectors together for a holistic response to domestic violence (see Johnson & Stylianou, 2020; Shorey et al., 2014). CCRTs provide a natural forum for easy inter-agency data sharing and usage that could significantly advance DV prevention and intervention. CompStat transformed policing in the 1990s, in that it used data to identify crime hotspots, inform proactive policing, and hold leaders accountable (M. Moore & Braga, 2003). Marrying police calls for service with victim crisis and emergency shelter data could revolutionize the response to domestic violence. It could allow for identification of DV hotspots and the deployment of targeted resources such as pop-up advocacy at trusted neighborhood anchor institutions like libraries, food pantries, or churches. It could also better inform co-responder welfare checks for high-risk or repeat victims. That said, in their review of 18 published evaluations of community coordinated responses to DV, Johnson and Stylianou (2020) noted that heterogeneity in programs implemented and outcomes evaluated "make(s) it difficult for scholars to draw broader conclusions about the effectiveness of [community coordinated response] interventions" (p. 1). We hope that as CCRTs continue to proliferate, rigorous evaluation studies will shed light on their overall effectiveness as well as what works best, under what circumstances, and why.

Of course, our study is not without limitations. Chief among them is the challenge of working with police calls for service data, which required us to mine "incident description" fields for text referring to DV (Leslie & Wilson, 2020; Nix & Richards, 2021). Accordingly, we might have missed a small number of DV incidents as we constructed our time-series dataset. Some false positives may have also found their way into our data, as prior work demonstrates that many 911 calls are ultimately unfounded or determined upon officer arrival to be a problem other than what was originally reported (Ratcliffe, 2021; Sorenson, 2017). This just underscores the importance of seeking out alternative sources of data on DV help-seeking, like the emergency hotline data analyzed here (see also Sorenson et al., 2021). Finally, the data analyzed here merely reflected daily call counts, and were thus naïve to characteristics of the victims (e.g., age, race/ethnicity, gender) involved in, or the severity of, these reported incidents. Future research that can determine whether certain subgroups of the population were more vulnerable during stay-at-home orders or throughout the pandemic would be a valuable contribution to this growing literature.

Drawing on both official and unofficial data, our study findings are consistent with the existing research in this area: COVID-19 increased DV help-seeking. At the same time, this general trend of increasing calls for service has not been universally observed across all studies (e.g., Nix & Richards, 2021; Sorenson et al., 2021), and indeed even in our sample of 7 cities, we saw significant variation in both the direction and severity of changes in calls for service. We must also acknowledge that DV was a significant public health problem prior to the COVID-19 pandemic, and it will continue to be a significant challenge after the pandemic is behind us. This focused attention on DV and DV help seeking should be used as a catalyst to make real change in prevention and intervention efforts. Although the financial support to DV services allocated in the recent American Rescue Plan (P.L. 117-2) is an important first step, the long-term economic stressors that are associated with DV and that have been exacerbated by COVID-19 will not be quickly or easily resolved. Our findings show that advancing a culture of data sharing among agencies responding to DV holds great promise for better understanding localized trends in DV help seeking, and in turn, better serving victims and their families.

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Table 1. Observed vs. Counterfactual Mean Daily Calls to Police and Victim Service Agency Hotlines.

	Calls for Police Service						*Calls to Victim Service Agency Hotlines*					
City	Observed Mean, Post-SD	Counterfactual Mean, Post-SD	Mean Diff.	95 % HDI		Diff. Probability	Observed Mean, Post-SD	Counterfactual Mean, Post-SD	Mean Diff.	95% HDI		Diff. Probability
Baltimore	60.39	53.92	6.47	4.93	7.98	p > .999	11.62	8.18	3.44	2.31	4.58	p > .999
Cincinnati	54.20	59.31	-5.11	-6.41	-3.85	p > .999	35.14	32.83	2.31	-0.39	4.94	p = .96
Hartford	17.11	20.66	-3.55	-4.21	-2.91	p > .999	18.67	14.03	4.64	3.70	5.58	p > .999
Orlando	14.98	16.41	-1.44	-2.33	-0.54	p = .99	2.00	2.51	-0.51	-0.75	-0.26	p > .999
Sacramento	29.20	22.05	7.16	6.17	8.13	p > .999	14.16	26.11	-11.95	-12.90	-11.00	p > .999
SLC	17.62	15.98	1.64	0.97	2.30	p > .999	6.27	2.71	3.56	3.00	4.13	p > .999
St. Pete	20.91	22.48	-1.57	-2.34	-0.82	p > .999	11.93	6.36	5.56	4.48	6.64	p > .999

ABBREVIATIONS: SD = Social Distancing; HDI = Highest Density Intervals. Note: Reported values are daily averages.

Figure 1. Calls for Police Service Time Series

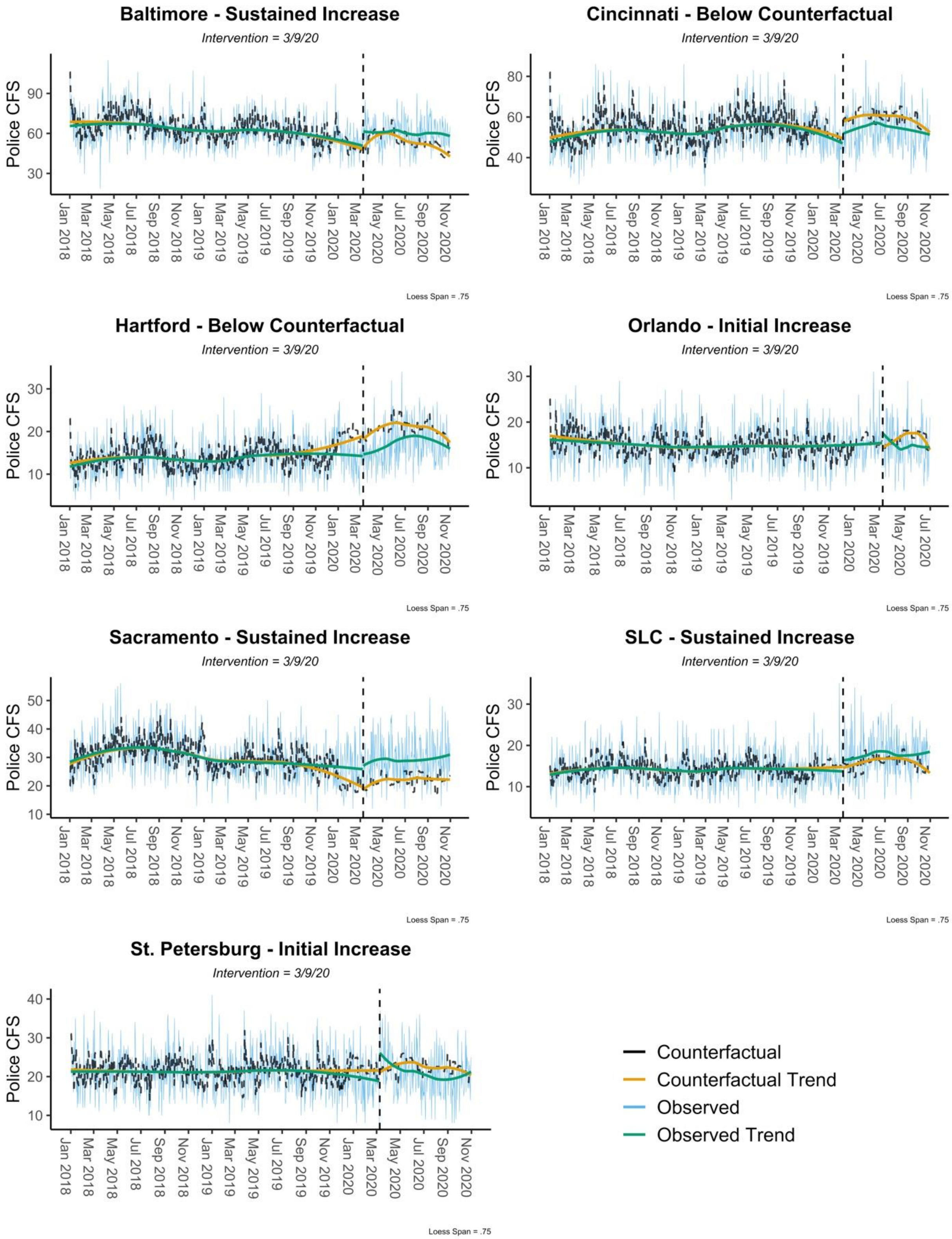

Figure 2. Calls to Victim Service Agencies' Emergency DV Hotlines Time Series

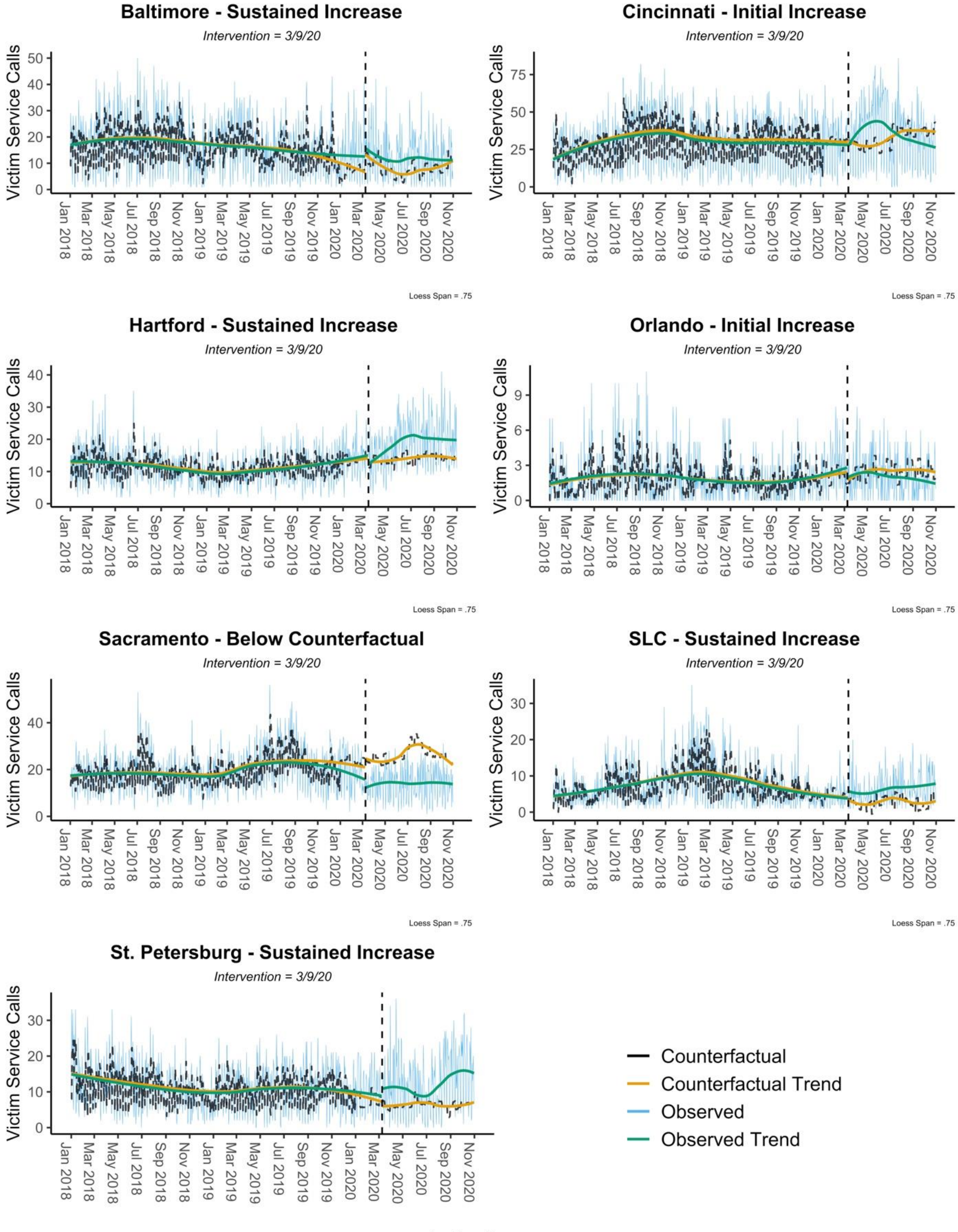

Figure 3. Differences Between Observed and Synthetic Counterfactual Trends.