A Case Study of Family Violence During COVID-19 in San Antonio

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Abstract
The current study investigates the effects of coronavirus restrictions on family violence in the seventh largest city in the country, San Antonio, Texas. Two streams of data were used to evaluate the potential change between what occurred during the lockdown period versus what would have been expected, including the COVID-19 Government Response Stringency Index and police calls for service from the San Antonio Police Department. The methodological approach used takes advantage of feature engineering, various machine learning time series forecasting techniques commonly leveraged in financial technical analysis, as well as cross-validation for optimized model selection. These techniques have not been considered in previous domestic or family violence-related research. During the lockdown period in San Antonio, we observed a larger than expected increase in calls to police for family violence incidents. Specifically, an increase of over fourteen percent of police calls for family incidents was observed. The findings of the current

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study suggest that social service and social welfare agencies consider and plan for how future pandemics or other major disasters will affect the incidence of family violence and take appropriate steps now to bolster resources and scale up for the future.

**Keywords**
family violence, domestic violence, COVID-19, counterfactuals, stringency index, police calls

**Introduction**

When the novel coronavirus began spreading across the United States in early 2020, it resulted in widespread hospitalizations and mass deaths. As of August 2021, the Centers for Disease Control and Prevention (CDC, 2021a) reported more than 620,000 deaths due to COVID-19. Extensive sickness and death has not been the only consequence of this global pandemic. Unfortunately, there has also been evidence of other deleterious social consequences such as increases in joblessness, depression, and anxiety (Morath, 2020; Salari et al., 2020). Studies have also discovered increases in certain crime types (Boman & Gallupe, 2020; Campedelli et al., 2020; Felson et al., 2020; Mohler et al., 2020; Rmandic et al., 2020), such as homicide/shootings (Rosenfeld et al., 2021), as well as domestic and family violence (Boman & Gallupe, 2020; Mohler et al., 2020; Piquero et al., 2020; Piquero et al., 2021a; Rmandic et al., 2020).

In an attempt to slow the spread of COVID-19 many restrictions were implemented including, stay at home orders, mask mandates, limits on public and private gatherings, and constraining business operations. While each of these restrictions had the potential to impact crime rates for varying reasons, experts were particularly concerned that implementing strict stay at home orders could lead to increases in domestic and family violence (World Health Organization, 2020). Specifically, it was feared that rates of domestic and family violence would increase because the victims of these crimes would be forced into lockdown with their abusers and be isolated from anyone who might be able to help (Piquero et al., 2021a). Research has in fact confirmed this initial concern, as multiple studies reported increases in domestic and family violence after stay at home orders were implemented (Boman & Gallupe, 2020; Evans et al., 2020; Mohler et al., 2020; Piquero et al., 2020; Piquero et al., 2021b; Rmandic et al., 2020). This is an important finding as information on the consequences of COVID-19 related restrictions are of crucial importance to the criminological community, the practitioner community, and beyond.
The majority of the studies that investigate the effects of COVID-19 stay at home orders on domestic and family violence use methodological techniques such as ARIMA models, differences-in-differences, time series analyses, event-studies, and regression. While these are worthwhile statistical approaches, more advanced forecasting techniques have yet to be used in the field of criminology to study the impacts of COVID-19 restrictions on domestic and family violence. As such, the methodological approach used in the current study takes advantage of feature engineering, various machine learning time series forecasting techniques commonly leveraged in financial technical analysis, as well as cross-validation for optimized model selection which provide additional and unique insight into any changes in family violence during this period. The value of determining the effect of COVID-19 policies on the serious crime of domestic and family violence cannot be understated, as approximately 1 in 4 women and 1 in 10 men experience some form of intimate partner violence in their lifetime (CDC, 2021b). Thus, no “statistical stone” should be left unturned in estimating this relationship and we believe, as will be described below, that the approaches we take offer some useful advantages and unique insights.

In addition to using a different analytic technique to analyze the effects of stay at home orders on family violence than previous studies, the current study also investigates this relationship using a previously unstudied city, San Antonio, Texas—the seventh largest city in the country (U.S. Census Bureau, 2019). While San Antonio is one of the most populous cities in the United States, there are at least two additional compelling reasons as to why it is important to study the impacts of COVID-19 restrictions that were implemented there. First, nearly two thirds (64.2%) of the city’s population report being Hispanic (U.S. Census Bureau, 2019). Second, San Antonio had high rates of domestic violence prior to the start of the pandemic with researchers reporting the city had significantly higher rates of domestic murders in 2017 than other large Texas cities including Dallas, Austin, and Houston (Sáenz & Casura, 2019). As there is evidence which suggests that Hispanics are disproportionately affected by domestic violence (Caetano et al., 2005; Tjaden & Thoennes, 2000), this makes for an important addition to the literature.

**Literature Review**

**Prior Research on COVID-19 and Domestic Violence**

Many studies examining the impact of COVID-19 restrictions, such as stay at home orders, on domestic and family violence have found increases for this crime type (Gosangi et al., 2021; Hsu & Henke, 2021; Iesue et al., 2021;
Leslie & Wilson, 2020; McLay, 2021; Mohler et al., 2020; Nix & Richards, 2021; Piquero et al., 2020; Piquero et al., 2021a; Ravindran & Shah, 2020). For example, Piquero et al. (2020) examined the impact of stay at home orders in Dallas, Texas and found evidence of a short term spike in the incidence of domestic violence in the 2 weeks following the lockdown order. Similar results of short term increases during peak shelter in place orders have been detected in other major cities including: New Orleans, Seattle, Salt Lake City, Phoenix, Chicago, Baltimore, Cincinnati, Detroit, Los Angeles, Sacramento, and Virginia Beach (Leslie & Wilson, 2020; McLay, 2021; Nix & Richards, 2021). Importantly, the results of a recent meta-analysis of 18 empirical articles examining the impact of COVID-19 on domestic violence found that most studies observed an increase in rates of domestic violence after the implementation of COVID-19 restrictions (Piquero et al., 2021a).

However, not all studies find increases in domestic and family violence, as some report no change or slight decreases in domestic violence during the coronavirus pandemic (Ashby, 2020; Campedelli et al., 2021; De la Miyar et al., 2021; Hoehn-Velasco et al., 2021; Payne et al., 2020; Takaku & Yokoyama, 2021)—especially as the length of follow-up is extended (Piquero et al., 2021b). For example, two studies assessed the effects of COVID-19 restrictions on domestic violence in Mexico, and both found decreases in domestic violence during the months corresponding to stay at home orders (De la Miyar et al., 2021; Hoehn-Velasco et al., 2021). Additionally, Campedelli et al. (2021) found an increase in intimate assaults during periods of COVID-19 restrictions, but the increases were not statistically significant. It should be noted that one study discovered an increase in domestic violence related calls for police service in Chicago after stay at home orders were issued, but also found a decrease in reported domestic crimes and arrests during the same period (Bullinger et al., 2021). This suggests that there may be a potential gap between the effects of calls for police service and reports/arrests.

**Methodological Approaches Used in Prior Research**

The impact of COVID-19 restrictions on domestic and family violence has been examined using a wide range of methodological techniques over a multitude of cities and countries. The most common approaches used in the literature are ARIMA models, differences-in-differences, time series analyses, event-studies, and regression. Given the different analytical approaches used and varying locations studied, it is not entirely surprising that findings have been somewhat mixed. For instance, two studies that used ARIMA models came to differing conclusions. Ashby (2020)
suggested that “concerns of a surge in domestic violence may have been unfounded” as their study covering 16 major cities found serious assaults in residences to be above forecast in five cities and below forecast in three cities, but all were within the confidence interval of the model estimates (Ashby, 2020, p. 14). On the other hand, Piquero et al. (2020) also used ARIMA models in their Dallas study and found evidence of a short-term spike in the 2 weeks after lockdown orders were issued followed by a decrease afterward.

Using a differences-in-differences approach, Leslie and Wilson (2020) found that domestic violence calls increased in the 5 weeks following the beginning of social distancing by about 9.7% or approximately 3.4 calls per day per city across 14 different large cities. Similarly, another study using differences-in-differences, but examining the effects of COVID-19 restrictions in India, discovered a 131% increase in the number of domestic violence complaints (Ravindran & Shah, 2020). Conversely, the same analytical approach led researchers studying this relationship in Mexico to find a decrease in domestic violence reports during week 10 of the pandemic (De la Miyar et al., 2021). Time series designs have also shown mixed results with two studies that used interrupted time series designs and covered eight large cities found increases in domestic violence calls for service in most cities (Mohler et al., 2020; Nix & Richards, 2021), while a study that used Bayesian structural time-series models in Los Angeles found non-statistically significant increases in intimate assaults after the implementation of COVID-19 restrictions (Campedelli et al., 2021).

Event studies and regression techniques have also been used to study the impact of COVID-19 policies on domestic and family violence. Two of the analyses that used event studies in Mexico found sharp decreases in domestic violence reports during the months of the stay at home orders (De la Miyar et al., 2021; Hoehn-Velasco et al., 2021). Specifically, Hoehn-Velasco et al. (2021) discovered a 35% reduction and De la Miyar et al. (2021) found a decrease of 4.9 domestic violence reports per 100,000 inhabitants. On the other hand, using the same methodological approach, Leslie and Wilson (2020) found an increase in domestic violence calls ranging from 6.4% to 9.4% in the weeks of after COVID-19 restrictions were implemented across 14 different cities. Additionally, three studies that used regression techniques found increases in domestic violence during the pandemic (Gosangi et al., 2021; Hsu & Henke, 2021; McLay, 2021). For example, Hsu and Henke (2021) examined 35 cities in 22 states and estimated that domestic violence increased by about 5.31% during stay at home orders. Importantly this study controlled for factors such as insured unemployment rate, seasonality, day of the week, holidays, temperature, and time-invariant city fixed effects.
However, one study using a regression discontinuity design in Japan found no significant effects on domestic violence (Takaku & Yokoyama, 2021).

**Domestic and Family Violence in San Antonio**

The research investigating the effects of COVID-19 policies on domestic and family violence has covered a large array of cities across many states and several countries. Unfortunately, the City of San Antonio has yet to be examined but is a noteworthy city for this type of research for two reasons. First, it is the seventh largest city in the country and home to a largely Hispanic population. Specifically, 64.2% of the city’s population reports being Hispanic (U.S. Census Bureau, 2019), making it one of the cities with the highest number of Hispanic residents. The demographics of San Antonio provide a compelling reason to study this city in the context of how COVID-19 policies impacted domestic and family violence because some research has suggested that Hispanics are disproportionately affected by domestic violence (Caetano et al., 2005; Tjaden & Thoennes, 2000). Studies have found that in Hispanic groups, male unemployment and alcohol use increase a female partner’s risk of violent victimization (Caetano et al., 2000; Cunradi et al., 2000). Unfortunately, there is evidence that both of these risk factors increased during the pandemic (Morath, 2020; Pollard et al., 2020). In addition, Hispanic women often encounter unique problems associated with managing domestic violence victimization such as language barriers, stressors related to immigration, economic issues, and culture differences (Mattson & Rodriguez, 1999; Murdaugh et al., 2004; National Women’s Law Center, 2000).

Second, before the COVID-19 pandemic began, San Antonio identified an increase in domestic violence related murders in the city and proposed a comprehensive 5-year plan to try to reduce rates of domestic violence (City of San Antonio, 2019). Specifically, San Antonio commissioned a report called “The Status of Women” to determine the standing of women in San Antonio across several indicators, including violent victimization, in comparison to women in other large Texas cities (Austin, Dallas, and Houston). This report found that women in San Antonio had higher rates of rape and murder by male partners than women in Austin, Dallas, and Houston. Additionally, the number of women murdered by male intimate partners had been steadily increasing in San Antonio, tripling between 2012 and 2017, while this rate remained steady or decreased in Austin, Dallas, and Houston (Sáenz & Casura, 2019). The City of San Antonio’s comprehensive 5-year plan adds that women in San Antonio have lower rates of wages earned, bachelor’s degree completion, and a wider earnings gender gap than women in Austin, Dallas, and Houston. As such, the plan suggests that “taken in combination, women in San Antonio lack access to
economic resources, increasing their vulnerability to financial abuse, and potentially limiting their options for leaving an abusive relationship” (City of San Antonio, 2019, p. 8). Additionally, during the pandemic the City of San Antonio added information and resources for abuse and domestic violence to the city’s official COVID-19 website (https://covid19.sanantonio.gov/Resources/Abuse-Domestic-Violence).

It should be noted that although a definitional difference exists between domestic violence and family violence, in the state of Texas courts use the term family violence to address crimes associated with domestic violence. As per the Texas Family Code, Texas defines family violence as “an act by a member of a family or household against another member of the family or household that is intended to result in physical harm, bodily injury, assault, or sexual assault or that is a threat that reasonably places the member in fear of imminent physical harm, bodily injury, assault, or sexual assault, but does not include defensive measures to protect oneself.” The definition of family violence in Texas may also include child abuse or dating violence (https://statutes.capitol.texas.gov/docs/fa/htm/fa.71.htm). As the current study will be investigating the effects of COVID-19 policies in San Antonio, Texas, the term family violence will be used when describing the data used in this study.

The Current Study

Given the possibility that COVID-19 restrictions impacted cities differently, that various methodological techniques may yield differing insight, and the use of different ways of measuring family violence may influence study results, this study contributes to this literature by examining the impact of COVID-19 restrictions on family violence in San Antonio, Texas, an unstudied large city, with an overwhelmingly Hispanic population and high rates of domestic violence. Additionally, we use a more advanced forecasting technique that is rarely used in criminology, but greatly aids in this investigation. Most quantitative criminological research focuses on explanatory models where the objective is to test an aspect of a theory or hypothesis. To build explanatory models, deliberate choices need to be made about what statistical approach is the most logical for the specified data. However, with predictive approaches a researcher can choose many different statistical approaches simultaneously to see which provides the most accurate prediction. This is done through cross-validation. Specifically, the training data (i.e., the data before your test period or intervention) is used to train many different models, then a forecast is generated for the test period with all the different approaches. Forecasting error can be measured in many ways, but they all try to measure how close the predication from the models are to the actual data.
The model that has the least forecasting error is selected and then evaluated against the data from your test period.

**Data**

Two streams of data were utilized for evaluating the potential change between what occurred during the lockdown period versus what would have been expected in the absence of the COVID-19 pandemic and the associated stringencies put into place to help curb the spread of the virus.

The first dataset used was the COVID-19 Government Response Stringency Index developed by Oxford University’s Blavatnik School of Government and available through an associated GitHub repository (https://github.com/OxCGRT/USA-covid-policy) for the period between March 11, 2020 and February 28, 2021 (Hale et al., 2020). The stringency index is a tool developed to track and compare policy responses by governments around the world (and individual U.S. States), rigorously and consistently and has been linked to the incidence of cases and deaths associated with COVID-19 (Piquero & Kurland, 2021). It is a simple composite score of nine indicators (eight of which are stringencies) that include: school closings, workplace closings, canceled public events, restrictions on gathering size, closed public transport, “shelter-in-place” and home confinement orders, restrictions on internal movement, restrictions on international travel, and a standardized measure of policy that applies in general way measured on an ordinal scale and rescaled to vary from 0 to 100 to gauge the appropriateness or effectiveness of a response. Figure 1 are time series of the eight stringencies for the State of Texas between January 1, 2020 and February 28, 2021 that were aggregated to generate the overall index.

To better understand the nature and periodicity of the collective impact of stringencies across Texas, a time series of the stringency index was also generated. Figure 2 provides a clearer picture of the impact of these measures on the overall level of socio-structural change that citizens of the state were mandated to endure during the pandemic. The peak period with the greatest level of restrictions for the measures that were put in place occurred between March 27, 2020 and May 20, 2020. While there is no San Antonio specific Stringency Index, the city followed the policies and restrictions set forth by the Texas Governor. The Mayor of San Antonio issued emergency public health declarations in line with state orders throughout 2020 to implement and enforce COVID-19 public health restrictions (https://covid19.sanantonio.gov/About-COVID-19/Declarations-Orders#mayors-declaration).

The second dataset, police calls for service, was sourced from the San Antonio Police Department (SAPD) website portal (https://www.sanantonio.
Figure 1. Time series for the cancelation of public events, closure of public transport, international travel restrictions, controls on the volume of people at gatherings, internal movement restrictions, school closings, stay-at-home requirements, collected for the State of Texas during the COVID-19 pandemic. Note, the time series on the bottom left should read “Restrictions on internal movements.”
SAPD categorize their calls for service under four dispatch problem categories, property crime calls, crimes against persons calls, traffic calls, and other calls. Each of these problem categories has many specific problem types associated with them. The problem types that relate directly to family violence are “Disturbance Family Gun Involved” (crimes against persons calls category), “Disturbance Family Knife Involved” (crimes against persons calls category), and “Disturbance Family” (other calls category). As these are the only specific problem types that relate directly to family violence, these were the only SAPD calls for service used in the current study. Thus, all calls for service categorized as “Disturbance Family Gun Involved,” “Disturbance Family Knife Involved,” and “Disturbance Family” were aggregated into a singular daily time-series for the period between January 1, 2019 to May 20, 2020. This was done by summing each respective daily count for the time series for every day in the series to create a singular family violence series. The latter date was identified as the end of the period of interest as it demarcates the final day prior to the loosening of restrictions according to the stringency index.

Figure 2. Time series of the stringency index for the period between January 1, 2020 and February 28, 2021 for the State of Texas.
Methods

The extant empirical COVID-19 studies on crime have taken advantage of forecasting techniques generating models from crime data before the start of the COVID-19 period, \( \{ y_1, \ldots, y_N \} \). They have used different forecasting techniques, \( \theta \), to produce counterfactuals for the COVID-19 pandemic period, \( \{ \tilde{y}_{N+1}, \ldots, \tilde{y}_O \}^\theta \) (Ashby, 2020; Borrion et al., 2020; Campedelli et al., 2020; Payne et al., 2020, 2021; Piquero et al., 2020). Differences can be expected between the outputs of these techniques. Even with the same forecasting technique, the counterfactuals may vary with the amount of data used to create the forecast model, for example. Evaluating the accuracy of the counterfactual is therefore essential. By the nature of the exercise, however, there is no ground truth that can be used to estimate it. Put differently, what the patterns would have been in the absence of COVID-19 and the associated stringencies is simply not possible, but we can have greater confidence in the forecasts that are generated by using a test window (a period in which we have a ground truth) prior to the lockdown to evaluate the performance of candidate models. To address this issue, we utilized a hold-out cross-validation technique commonly adopted in data science that involves making a prediction on another temporal window for which data are available (Bergmeir & Benítez, 2012). Cross-validation is necessary to estimate model performance in the time series forecasting domain.

The approach utilized herein for the development of counterfactuals comprised three steps represented in Figure 3:

- **Feature Engineering and Partitioning:** The first step involved using the dates to create 150 date related features such as the day of the week, month of the year, week of the year, and holidays to use as external regressors to account for seasonality along with harmonics to improve the overall potential forecasting accuracy of the models. The second step involved extracting two contiguous timeseries from the pre-COVID-19 dataset, \( \{ y_1, \ldots, y_N \} \). These are referred to as the training dataset, given by \( \{ y_1, \ldots, y_M \} \) and the test dataset, given by \( \{ y_{M+1}, \ldots, y_N \} \). It is common for researchers to allocate 80% of the original time series to the training dataset and the remainder to the test dataset (Hyndman & Athanasopoulos, 2018). Here we use the period between January 1, 2019 and February 2, 2020 as our training set. The training dataset is used to fit the model while the test dataset, the period between February 3, 2020 and March 26, 2020, provides an unbiased evaluation of a model fit (Russell & Norvig, 2016). A generalized linear model (GLM), a random forest model (RF), a gradient boosting
machine (GBM), and an ensemble model were generated using the training data.

**Evaluation**: The point forecasts $\{\tilde{y}_{M+1}, \ldots, \tilde{y}_N\}^\theta$ generated from different forecasting techniques $\theta$ are then compared with the actual data for the same temporal window $\{y_{M+1}, \ldots, y_N\}$ and the result is used as a proxy measure of model accuracy. The smaller the error (root mean square error (RMSE)), mean absolute error (MAE), mean absolute percentage error (MAPE), mean percentage error (MPE)) of the forecast to the test data, the greater the confidence one can have in the forecast subsequently performed over the COVID-19 period. A multitude of error metrics were selected because no single metric captures all the distributional features of the errors when summarized across series. Indeed, Fildes et al. (2011) suggest selecting multiple metrics that capture the key characteristic of the results for this reason. Further, because all the series were on the same scale (daily), are positive and because they are much greater than 0, Hyndman and Koehler (2006) recommend these over other error measures like mean absolute scaled error that are better suited for evaluating forecasts across different scales, for example, daily to weekly, weekly to monthly, and so on.

**Figure 3.** The observed time-series of family violence-related police calls (black line) and a 14-day simple moving average (black dotted line) for the entire period of the study. The training data (January 1, 2019–February 2, 2020), the test data (February 3, 2020–March 26, 2020), and the lockdown period for which the counterfactual forecast was generated (March 27, 2020–May 20, 2020).
Selection: The technique with the least error, as estimated using the test data, is then selected to forecast the counterfactuals for the COVID-19 period that coincided with the highest average stringency-level. Now the entirety of the time-series \( \{ y_1, \ldots, y_N \} \) is used to build the final model and forecast.

Finally, the forecast for the period of interest generated from the most accurate model is compared to the actual counts for the lockdown period to quantify the difference between what was expected and what ultimately occurred.

Results

A Loess smoother was applied to the entire time-series of family related police calls for service for the entire period of interest to help visualize if there were any noticeable patterns that suggested an increase or change in the overall trajectory of domestic incidents across San Antonio. Figure 4 provides a compelling illustration of what appears to be an overall increase in the level of family related calls for service during the period in which the lockdown was in place at the far right of this series. More specifically, the start of the series, dating back to January 2019, shows the smoothed series around approximately 75 daily calls for family related incidents, but during the lockdown period the volume had increased to more than 100 per day. However, and importantly, there appears to be a longer trend in the overall series that suggests an increase in the volume of police calls for family related incidents in the period after New Year’s Day for 2019 that flattens toward July and then picks up again during the period shortly after New Year’s Day in 2020 suggesting that this is part of a seasonal trend that needed to be accounted for in the forecasting models.

All four training (validation) models performed reasonably well in generating the observed pattern for the period immediately before the lockdown (February 3, 2020–March 26, 2020). Figure 5 provides a visual of overall performance across the models.

To better assess performance model error was evaluated on the hold-out test data (February 3, 2020–March 26, 2020). As can be seen in Table 1, the overall top performing model with respect to all metrics was the ensemble model.

The hold-out test data was then combined with the training data to generate a model and forecast for the period of interest, the lockdown period (March 27, 2020–May 20, 2020). This forecast is a counterfactual against which the observed data was compared. Figure 6 provides a visualization that
helps identify the daily differences between the observed (black line) versus the expected (gray line), with the gray shaded areas highlighting all of the elevated counts in calls for service that were experienced.

Further analysis of the observed number of family related calls for service \((N=5,856)\) versus the counterfactual \((N=5,127.6)\) calls for service suggest that a total of 728.40 additional family related police calls for service occurred during this period than would have been expected in the absence of the COVID-19 pandemic and associated lockdown. Put differently, there was an increase of 14.21\% additional calls during the lockdown than would have been expected as compared to the counterfactual. Drilling down to the daily family related calls, there were approximately 13 additional family related calls for service per day.

**Discussion**

The global coronavirus pandemic has affected the educational, employment, medical, sports, entertainment, and criminal justice systems in ways that
Figure 5. The upper-left panel is the observed family violence-related police calls for service against the forecast generated from the training data for the test (validation) window for the GLM. The upper-right panel is the same for the RF. Lower-left for the GBM and the lower-right is the Ensemble model forecast against the observed time-series.
seemed unimaginable to the scientific community a little over a year and a half ago. However, evidence around the short- and long-term impact of the virus and its associated policy responses is rapidly being assembled. Within criminology, researchers have documented increases in violent crimes, especially homicide (Rosenfeld et al., 2021) and domestic violence (Piquero et al., 2021a). This study provides further empirical evidence regarding the

### Table 1. Forecasting Error Measures for the Test Period (February 3, 2020 – March 26, 2020).

|       | MAE   | RMSE  | MAPE  | MPE  |
|-------|-------|-------|-------|------|
| RF    | 15.51 | 19.50 | 0.156 | 0.090|
| GBM   | 13.66 | 17.48 | 0.140 | 0.052|
| GLM   | 13.56 | 17.69 | 0.140 | 0.038|
| Ensemble | 12.10 | 15.97 | 0.125 | 0.033|

**Figure 6.** The observed daily (black line) for the peak lockdown period (March 27, 2020–May 20, 2020) versus the expected (gray line) generated from the ensemble model. Gray shaded areas highlight all of the elevated counts in family violence calls for service across the period of interest.
latter through the examination of family violence-related calls for service in San Antonio, Texas, a unique context due to its demographic composition and long-term high domestic violence/homicide problem, but does so using novel methodological techniques that have not been considered in previous domestic violence-related research or more broadly in the extant criminological literature.

Using police calls for service data, we evaluated the potential change between what occurred during the lockdown period (March 27, 2020 through May 20, 2020) versus what would have been expected in the absence of the COVID-19 pandemic and the associated stringencies put into place to help curb the spread of the virus. Before evaluating the impact on such calls during the lockdown period, we used a training data set for the period between January 1, 2019 and February 2, 2020 in order to fit our model and then used a test dataset for the period between February 3, 2020 and March 26, 2020, just prior to the lockdown, which provides an unbiased evaluation of a model fit. The main findings of our study were clear.

During the lockdown period in San Antonio, we observed a larger than expected increase in calls to police for family violence incidents. Specifically, an increase of over 14% of calls to police for family related incidents occurred during the lockdown than expected, or an approximate increase of about thirteen family violence calls per day. Our study adds to the literature using data from another city and with a more advanced methodological approach to indicate that the increase in domestic and family violence during pandemic lockdowns was a real occurrence.

To be sure, there is more that could be done that we were unable to do in the current study given data constraints. First, although the population of San Antonio is much more represented by persons with a Hispanic origin than many U.S. cities, we did not have information available about the demographic makeup of the family violence victims or perpetrators, thus we were unable to explore trends by race/ethnicity. As well, although the commonly-held view is that women (and children) comprise the large proportion of family violence victims, we were unable to provide a full documentation of these cases. Future studies that have demographic information available should examine the impact of COVID-19 on family violence calls for service by race/ethnicity, gender, and age. Second, San Antonio police calls for service data does not indicate whether any calls were unfounded or miscategorised. As such, we do not know the extent to which this occurred. Third, while this study includes 2 months of data following the implementation of stay at home orders (which is a longer follow-up period than many studies in this area), future research should seek to extend the window of follow-up more. Lastly, our data only capture those individuals who were able to call the police for
assistance. Given that family violence remains an under-reported crime, we anticipate that the level of family violence, including emotional violence, was likely even higher during the pandemic lockdown.

On the policy front, it is important that social service and social welfare agencies consider and plan for how future pandemics or other major disasters will affect the incidence of family violence and take appropriate steps now to bolster resources and scale up for the future. Local politicians and local influencers can also use their platforms to educate the public about the problem of family violence, where to get resources, and how exerting physical and emotional forms of violence are unacceptable. Lastly, police officers need to obtain specialized training on how to respond to domestic calls and, in turn, how to provide necessary services to domestic violence victims. Current efforts in policing today vis-à-vis mental health calls has some police officers responding to such calls in concert with mental health or social service professionals. To the extent feasible, some consideration should be given to the use of these types of approaches for domestic violence calls as well.

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