CrimRxiv

Using Victimization Reporting Rates to Estimate the Dark Figure of Domestic Violence

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Published on: Oct 20, 2024

DOI: https://doi.org/10.21428/cb6ab371.e76ca40a

ABSTRACT

Objectives: To illustrate how factoring in variables associated with reporting and underreporting can be used to adjust official statistics and generate an estimate of the true prevalence of domestic violence in a community. Methods: Combine data from the Federal Bureau of Investigation National Incident Based Reporting System as well as the Bureau of Justice Statistics National Crime Victimization Survey. Results: We show several jurisdictions that have increased aggravated domestic rates in recent NIBRS data. Our up-adjusted total crime counts suggest using only NIBRS data is on average 40% smaller, with the underreporting varying from 23% to 76% across larger NIBRS reporting agencies. Conclusions: Combining law enforcement reports and victimization survey data, we provide more accurate estimates of the number of aggravated domestic violence incidents that occur in individual jurisdictions. Work supported by the Council on Criminal Justice. Replication materials at https://github.com/apwheele/dvtrends.

Introduction

There has been a considerable volume of research and attention given to domestic violence over the past 50 years and can be traced, in large part, to the start of the battered women's movement of the 1970s by national organizations (Schechter, 1982). While interest has ebbed and flowed since, an increased amount of attention was placed on incidents of domestic violence that occurred amid stay-at-home orders issued during the COVID-19 pandemic (see e.g., Kourti et al., 2023; Piquero et al., 2021). Still, this crime type remains one of the most difficult and perplexing to examine, due to varying definitions of what constitutes domestic violence, underreporting of domestic violence to law enforcement, and challenges stemming from the existence of multiple avenues of reporting and multiple agencies that receive reports. Because of such factors, the United States has no solid grasp on how much domestic violence actually occurs in communities.

The absence of a true prevalence rate for domestic violence hinders the development of effective prevention programs, policy options, and responses to the crime. Documenting the extent of domestic violence is important to help service providers, policymakers, and law enforcement better understand current trends and identify what works and what does not work when implementing interventions in response to those trends. An accurate measure of domestic violence at the local level would allow agencies to effectively allocate resources and identify specific populations who may underreport victimization.

Domestic violence can be counted in the following data collection systems: (1) Official reporting to law enforcement through the Federal Bureau of Investigation's (FBI's) National Incident-Based Reporting System (NIBRS); (2) Self-report survey data collected through the Bureau of Justice Statistics' National Crime Victimization Survey (NCVS); and (3) Informal reports that are received by local and national domestic violence hotlines, domestic violence shelters, social service agencies, pastors, doctor's offices, and emergency rooms that are not captured or not coded. The range of reporting avenues for domestic violence underscores how difficult it is to arrive at a true prevalence, both in general and across demographic and other categories. It is possible that the same victimization experience may be documented in one or more of the data sources – or perhaps not even at all.

Given these challenges, this paper estimates *sub-national* domestic violence trends, using a combination of the National Crime Victimization Survey (NCVS) and the FBI's National Incident Based Reporting System (NIBRS).[1] The novel contribution of this approach is that it not only recognizes the underreporting that exists with respect to domestic violence, but also offers a methodology that fully takes this underreporting into account. Additionally, the proposed methodology can easily be applied to other crime types where similar underreporting is problematic, such as hate crimes.

Background

When analyzing crimes reported to police, an ever-present problem is whether characteristics of those reported crimes reflect the true underlying distribution of those crimes. Or if any of the observed patterns are merely reflective of changing patterns of reporting rates over time.

Traditionally criminologists have addressed this via victimization surveys – asking individuals if they have been victimized. The National Crime Victimization Survey (NCVS) is one such survey in the United States (Lauritsen and Rezey 2013). In a year, the NCVS may interview over 40,000 households and 70,000 individuals. Despite being an incredibly large sized survey, generating sub national level estimates is still a challenge. Most of the work is on state level estimates (Fay, Planty, and Diallo 2013), although some are for metro areas or specific cities (Rezey and Lauritsen 2023). Herein, we propose a methodology that can more easily generate city (or even sub-city) level results and show how one can leverage reported crimes, along with estimated reporting rates of victimization to the police, to produce *local* estimates of the dark figure of crime. This case study we focus on aggravated domestic violence, although the methodology could be extended to other crime types in future work.

Data & Methods

The goal of this methodology is to take the aggravated domestic violence incidents reported to individual law enforcement agencies and *adjust* them for underreporting. For example, if a law enforcement agency had 100 domestic violence incidents reported in 2022, then the number of domestic violence incidents that actually occurred in that jurisdiction is unclear, given that we know that 100 reported incidents *is an undercount*.

If one knows that the reporting rate for domestic violence events was only 50%, one would then up-adjust the observed rate of 100 events by 100/0.5, which would suggest there are a total of 200 events. Yet not all crime events have the same reporting rate. Imagine that out of the 100 events, 80 were for older victims, who had a reporting rate of 50%, and 20 were for younger victims, who had a reporting rate of 40%. In this scenario, the total up-adjusted weight for the jurisdiction will be 80/0.5 + 20/0.4, which would suggest that 210 incidents actually occurred. The older individuals in the sample could be weighted to adjust for their lower reporting rates.

This paper shows how to take this methodology further by allowing every observed criminal incident to have its own weight to up-adjust. Using a set of normalized data across the NCVS and NIBRS, this paper shows how to create tailored estimates to up-adjust incidents of domestic violence reported to law enforcement. This uses not only the age of the victim, as discussed in the above hypothetical, but also other demographic characteristics (gender, race and ethnicity), regional characteristics (region of nation and population size of jurisdiction), as well as the year in which the report was filed.

This methodology fills a critical gap in our current data ecosystem: While the NCVS provides domestic violence rates for the entire nation, it does not allow users to drill down into more specific geographics. The approach presented here allows individuals to account for underreporting and generate estimates for counties, cities, and jurisdictions. Given that law enforcement agencies can report NIBRS data in a timely manner, this methodology also provides an opportunity for jurisdictions to document trends in near real-time, rather than relying on the NCVS, which is published every fall.

Mathematical Model

We start with two identities, first:

$$T = R + N$$

Where T is the total number of crimes, R is the count of *reported* crimes, and N is the count of *non-reported* crimes. Second, we have:

$$p = \frac{R}{T} = \frac{R}{R + N}$$

Where p is the probability of reporting the crime to the police, i.e., the reporting rate. Here crimes are specifically aggravated domestic violent victimizations, but the mathematical presentation is generic and not specific to only domestic violence.

The main contribution of this work is that you can estimate T, the total number of crimes, via the observed number of crime reports , and an estimate of the probability of reporting, what we denote as $\hat{p}$. So, we may wish to estimate two different quantities. First one can estimate N via:

$$\hat{N} = \frac{R \cdot (1 - \hat{p})}{\hat{p}}$$

But here we mostly focus on estimating $\hat{T}$ via:

$$\hat{T} = R + \frac{R \cdot (1 - \hat{p})}{\hat{p}}$$
$$\hat{T} = R / \hat{p}$$

Thus, if you had a city with 500 reported crimes, and the reporting rate estimate for that crime is 40%, the estimate for the total number of crimes in that city is $500/0.4 = 1,250$.

Here, we suggest using the NCVS to estimate $\hat{p}$. One can observe R via a specific police jurisdictions reporting, such as via the National Incident Based Reporting System (NIBRS). This somewhat begs the question of why not use NCVS to estimate $\hat{T}$ directly. In practice if one wants an estimate for a specific city, e.g. I want to know how many total crimes are in Dallas, even given the size of NCVS there are unlikely enough surveys of a particular city to generate reasonably accurate estimate. One, however, can take the reporting rate from the NCVS, and it is likely a reasonable estimate for the reporting rate for a specific jurisdiction (Rezey and Lauritsen 2023).

If one is willing to run a survey for a specific jurisdiction, it hinges on whether the standard error around $\hat{p}$ versus $\hat{T}$ to determine which estimate you would prefer. There are scenarios where either could be true. For rare crimes, both will require very large sample sizes to get reasonably accurate estimates. Figure 1 shows a simulated example where the *reporting* rate estimator has a smaller confidence interval once you eclipse a total of 2,000 surveys.[2]

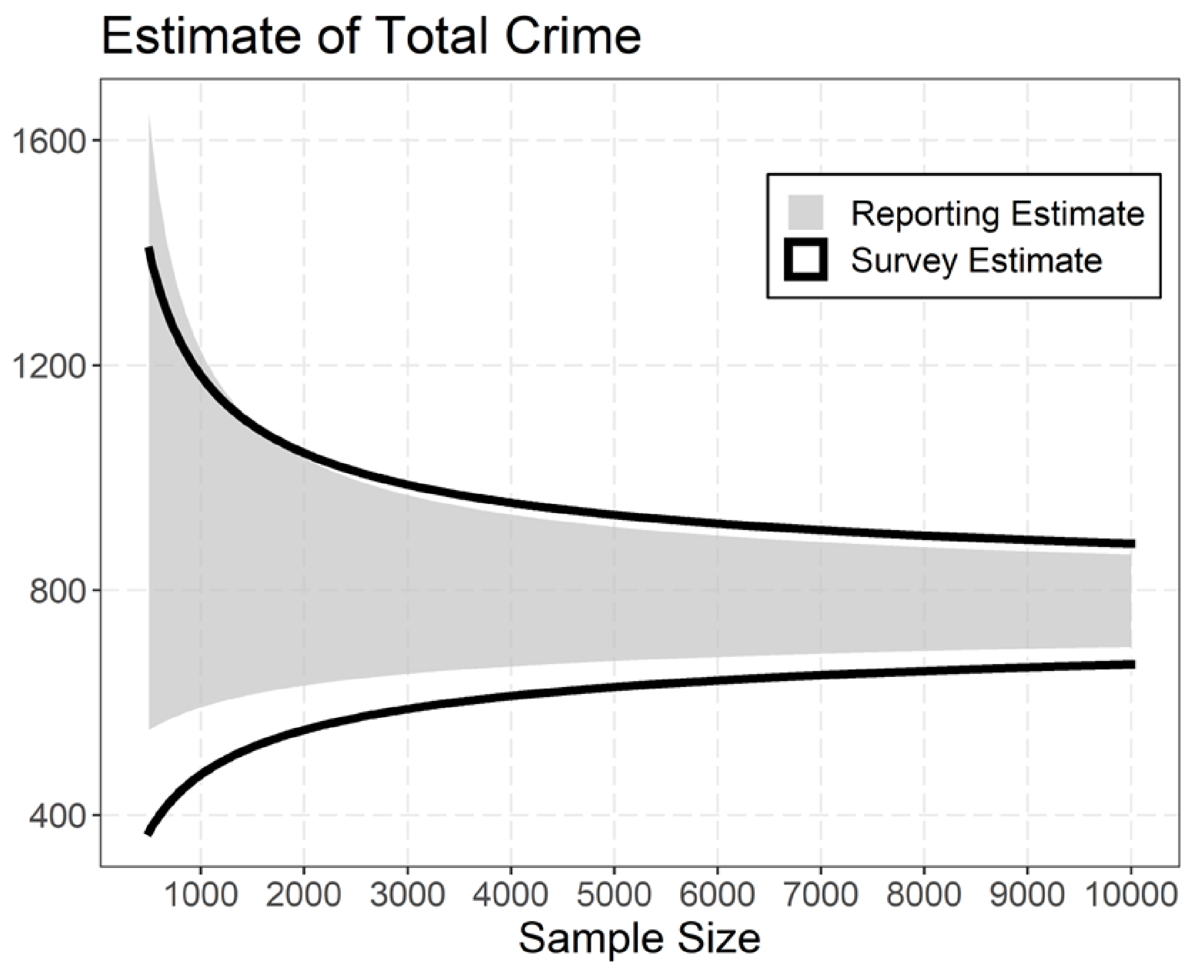

Figure 1. Example estimates for total crimes using survey samples versus the reporting rate. The error ranges represent 95% binomial Clopper-Pearson exact intervals. Based on observed 500 crimes, a victimization rate of 2%, and a reporting rate of 65%.

In practice using reasonable values for victimization rates and reporting rates, they both tend to be very similar in terms of overall crime estimates. And one may even be able to construct a more accurate estimate by combining both (the reporting rate estimate has a better lower bound).[3]

One could use the overall reporting rate for the entire NCVS to up-adjust observed NIBRS counts in a specific jurisdiction. But there is a more bespoke way to take into account differential composition of the crime reporting demographics for a particular jurisdiction. Consider a breakdown of our total crime estimate into sub-estimates a and b.

$$\hat{T}_a = R_a / \hat{p}_a$$
$$\hat{T}_b = R_b / \hat{p}_b$$

Where our estimate of total crime is $\hat{T} = \sum_{i=1}^{k} \hat{T}_k$ for each subset k.

Consider, for instance, that the subgroups are older and younger victims, and that younger victims have a higher victimization reporting rate. If one city has a larger number of older victims, they should have a higher adjustment. In practice, one can extend this so that *every individual reported crime* has its own probability estimate of reporting to the police. That is, we have:

$$\hat{T}_i = R_i / \hat{p}_i$$

Where i can index all the different characteristics for an individual reported crime. We took as motivation for this the literature on post-stratification (Circo and Wheeler 2023). In that literature, the post-stratification weights are typically taken from census demographics, here the post-stratification weights though are taken from the NIRBS reporting data.

Here we estimate $\hat{p}_i$, the reporting rate for *aggravated domestic violent assaults* using a logistic regression for NCVS using:

$$\begin{aligned} g(\hat{p}_i) =& \beta_0 + \beta_1 \text{Female} + \beta_2 \text{Hispanic} + \Sigma \beta_k \, s(\text{Year}_k) + \Sigma \beta_l \, s(\text{Age}_l) + \\ & \Sigma \beta_g \text{Race}_g + \Sigma \beta_h \text{Region}_h + \Sigma \beta_i \text{PopGroup}_i \end{aligned}$$

Where g is the logit function. The model does not include sampling weights in its estimates. Those are typically not included in regression modeling, only for estimating national level rates (Powers and Bleeker 2023). The sample is restricted to all those victims who reported having an aggravated domestic violent incident.

The variables included in the logistic regression on the right-hand side are whether the victim is female, Hispanic, their racial group (Asian/Pacific Islander, Black, Native American, Two or more races, with white as the reference group), and geographic region (Northeast, Midwest, South, West). For the NCVS, region was only included post 1994, and so for earlier years we use the missing region as the reference category in the regression. For population groups, we include variables for cities of 50,000 to 250,000, another category for over 250,000, and the reference group of cities under 50,000 population.

The model also includes non-linear restricted cubic spline terms for the victim's age (with knots at 25, 40, and 65), and year spline variables (with knots at 1999, 2007, 2015). Restricted cubic splines typically have better tail behavior than polynomial terms (Harrell et al. 2001).

It is necessary to use variables that are available in both NCVS and NIBRS to conduct such an analysis, but one can use different methods of estimating , such as machine learning. Here we use logistic regression, as in the authors experience the sample size is too small to reliably use non-linear machine learning models, such as random forest or boosted regression models (Circo and Wheeler 2022). It is also the case that when using generalized linear models, one has an estimate of the standard error of , which we use in further data visualizations.

We use the open-source library R to conduct statistical analysis and the library ggplot2 to create graphs (R Core Team 2022; Wickham 2016). Replication results can be seen at https://github.com/apwheele/dvtrends. Data used for the analysis is the concatenated NCVS file, and the NIBRS concatenated files provided by Jacob Kaplan (Kaplan 2024; Justice Statistics 2023).[4]

Results

Regression Results

First, we describe the regression equation predicting the probability of reporting an aggravated domestic violence assault to the police, the results of which may be found in Table 1. The large intercept term is only so large because of the idiosyncratic reference categories we used for the omitted dummy variable (missing region in 1992-1994, non-Hispanic, white, in population under 50,000). Those who multi-race have lower reporting rates, and Hispanics (which is a separate category from race in the NCVS) have higher reporting rates.

Table 1. Logistic regression results, predicting the probability of reporting to the police for 1,527 observations in the NCVS sample from 1992 through 2022.

	Estimate	Std. Error	z value	Pr(>|z|)
Int.	-78.61	42.92	-1.83	0.07
s1(year)	0.04	0.02	1.82	0.07
s2(year)	-0.04	0.02	-1.52	0.13
s1(age)	0.03	0.01	3.60	0.00
s2(age)	-0.05	0.02	-2.51	0.01
Female	0.15	0.12	1.23	0.22
Black	0.14	0.16	0.90	0.37
Native American	0.09	0.36	0.24	0.81
Asian/Islander	-0.23	0.42	-0.53	0.59
Multi-Race	-1.19	0.29	-4.10	0.00
Hispanic	0.57	0.19	3.04	0.00

Northeast	-0.10	0.26	-0.39	0.70
Midwest	-0.20	0.24	-0.83	0.41
South	-0.10	0.23	-0.44	0.66
West	-0.24	0.24	-1.00	0.32
Pop. 50k to 250k	0.18	0.15	1.21	0.23
Pop. over 250k	0.21	0.16	1.31	0.19

It is easier to visualize the changes in the reporting rates over time and by years via marginal effect plots (see Figure 2). For changes over years, the reporting rate peaked in 2008 at slightly over 70% and has since been decreasing. For the marginal effects for age, the reporting rate peaks around 40 years old at over 70% and is lower than 60% for both very young teenagers and individuals over 75 years of age.

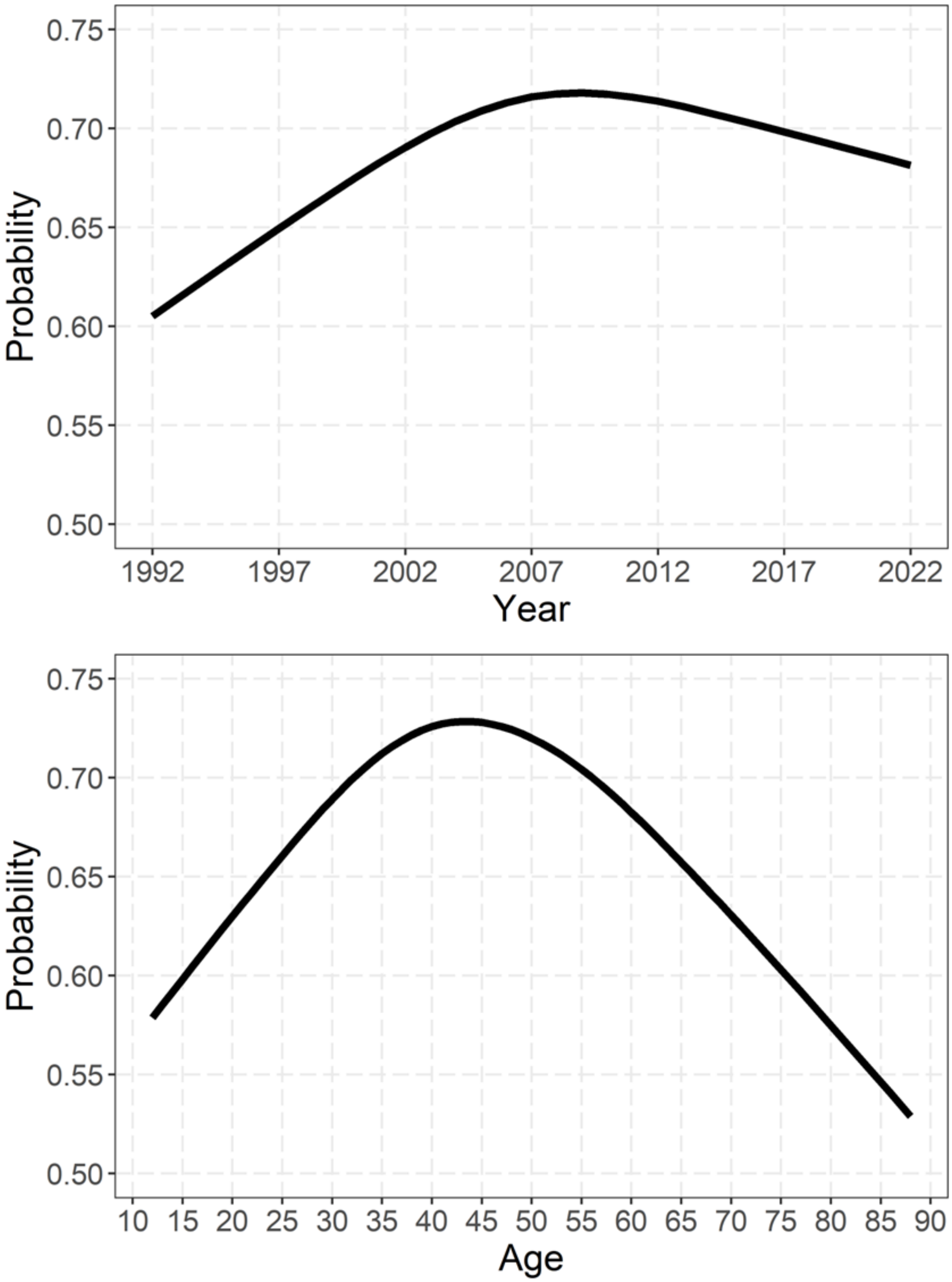

Figure 2. Marginal Effect of Reporting Rate by Year and by Age

The regression equation is only important insomuch as it generates accurate probabilities for reporting for said demographics. It does not matter if the demographics have a particular causal interpretation, nor does it matter if the coefficients are statistically significant. To assess the fit of the model, we use a Hosmer-Lemeshow test to illustrate the predicted probabilities are well calibrated (Agresti 2012). Table 2 presents these results.

Table 2. Hosmer-Lemeshow calibration table, p-value= 0.43

Prob. Bin	Obs.	Exp.	Samp. Size
[0.308,0.561)	74	75.4	153
[0.561,0.611)	95	89.8	153
[0.611,0.643)	91	96.1	153
[0.643,0.668)	104	101.7	155
[0.668,0.686)	95	101.6	150
[0.686,0.702)	109	106.1	153
[0.702,0.719)	116	108.0	152
[0.719,0.741)	105	111.7	153
[0.741,0.776)	122	117.2	155
[0.776,0.886]	118	121.4	150

Estimating City Level Trends

First, we show a sample of the twenty police jurisdictions with the highest reported totals of aggravated assault domestic violence incidents in NIBRS. Note this sample is both idiosyncratic to what police departments reported to NIBRS in 2022 (New York City for example did not). Some police jurisdictions also cover more than just a city – Las Vegas metro police department covers all of Clark County, not just Las Vegas proper.[5]

Figure 3 shows the original NIBRS counts in the lighter color, and our up-adjusted total estimates as an additional darker color added on the top bars. Thus, the darker green color is the estimate of the non-reported aggravated domestic violence assaults. The up-adjusted proportion is typically by around 40%, but in the 2022 data, for jurisdictions with over 50 reported incidents, that up-adjustment factor can range from 23% to 76%.

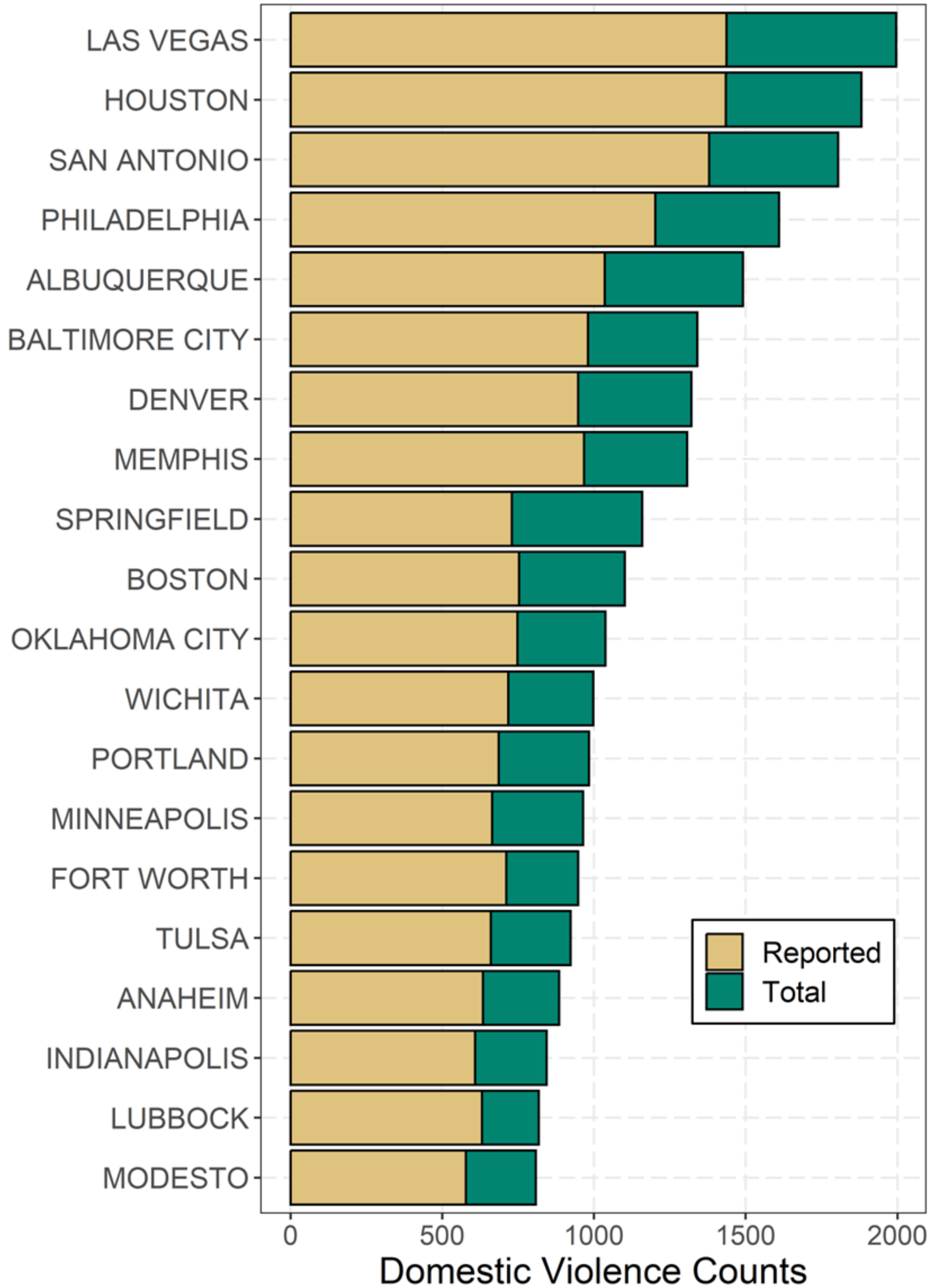

Figure 3. Up-adjusted Total Aggravated Domestic Violence, Top 20 Cities in NIBRS 2022 data

One can then examine specific cities over time. Figure 4 presents a graph for Denver, who started reporting to NIBRS in 2005. One can see the overall trends are the same whether examining just the reported crimes or our overall total estimate. But the overall total estimate shows a greater increase in years post 2015.

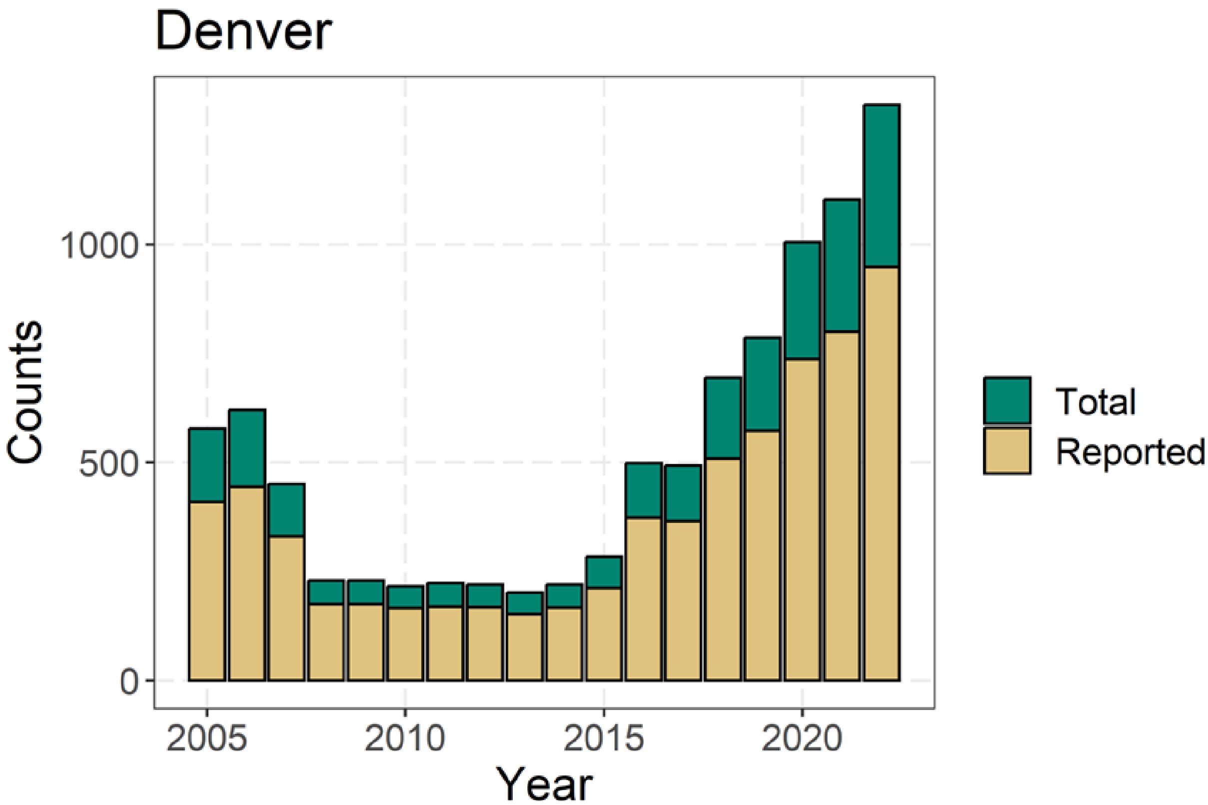

Figure 4. Estimates of Total Domestic Aggravated Assaults in Denver

One can plot the rates of victimization, here we estimate the variance in our statistical estimator via simulation. Each has a standard error, as so we generate 1,000 simulations, randomly generating a simulated estimate of , and then aggregate up to our estimate of . The band shown is the 98% confidence interval surrounding the estimate based on those totals. The population denominator is taken from the NIBRS reporting.

Next, Figure 5 showcases Honolulu, which has reported to NIBRS since 2018. The rate per 100,000 has increased slightly, from around 15 per 100,000 to now over 30 in 2022. The standard error of the estimate is quite small relative to the year-to-year variance in the domestic violence rate.

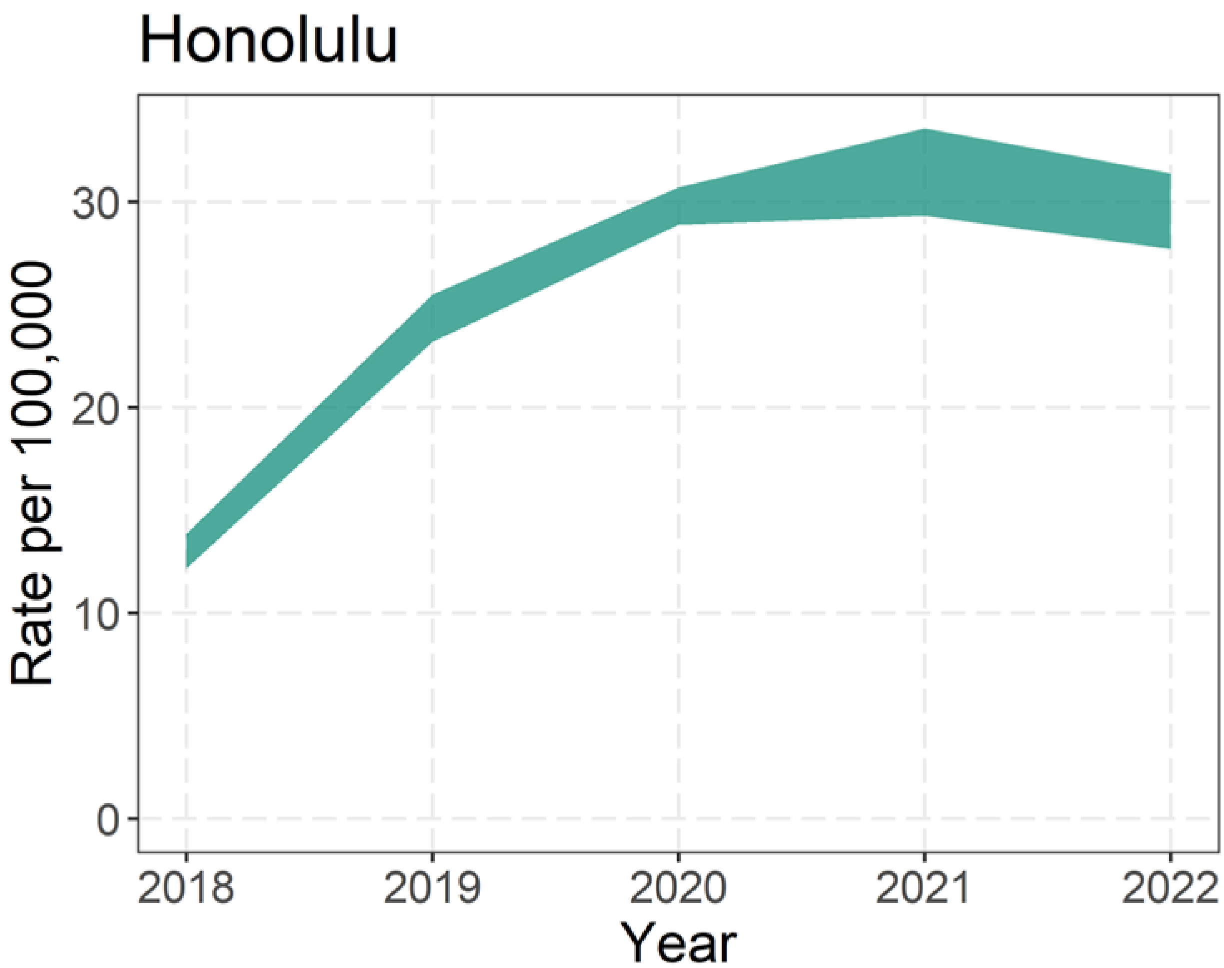

Figure 5. Estimates of Total Domestic Aggravated Assault Rate with Simulated Confidence Intervals in Honolulu

There are well over 10,000 departments reporting to NIBRS in 2022, and since we cannot provide an overview of all of their trends, below is a select sample of cities. Here we just plot , as the standard errors tend to be very small. But one needs to keep into account when using this estimator that police data itself can have reporting errors (Maltz 2010). As shown in Figure 6, we can see it is likely the large up-trend in Wichita is due to a reporting error over time. Differences in the levels across each of these jurisdictions could also be due to how police departments determine what counts as an aggravated domestic violent incident. NIBRS is intended to help standardize definitions, but no doubt there will be differences in the nature of reporting (either due to differences in state laws or idiosyncratic local practices).

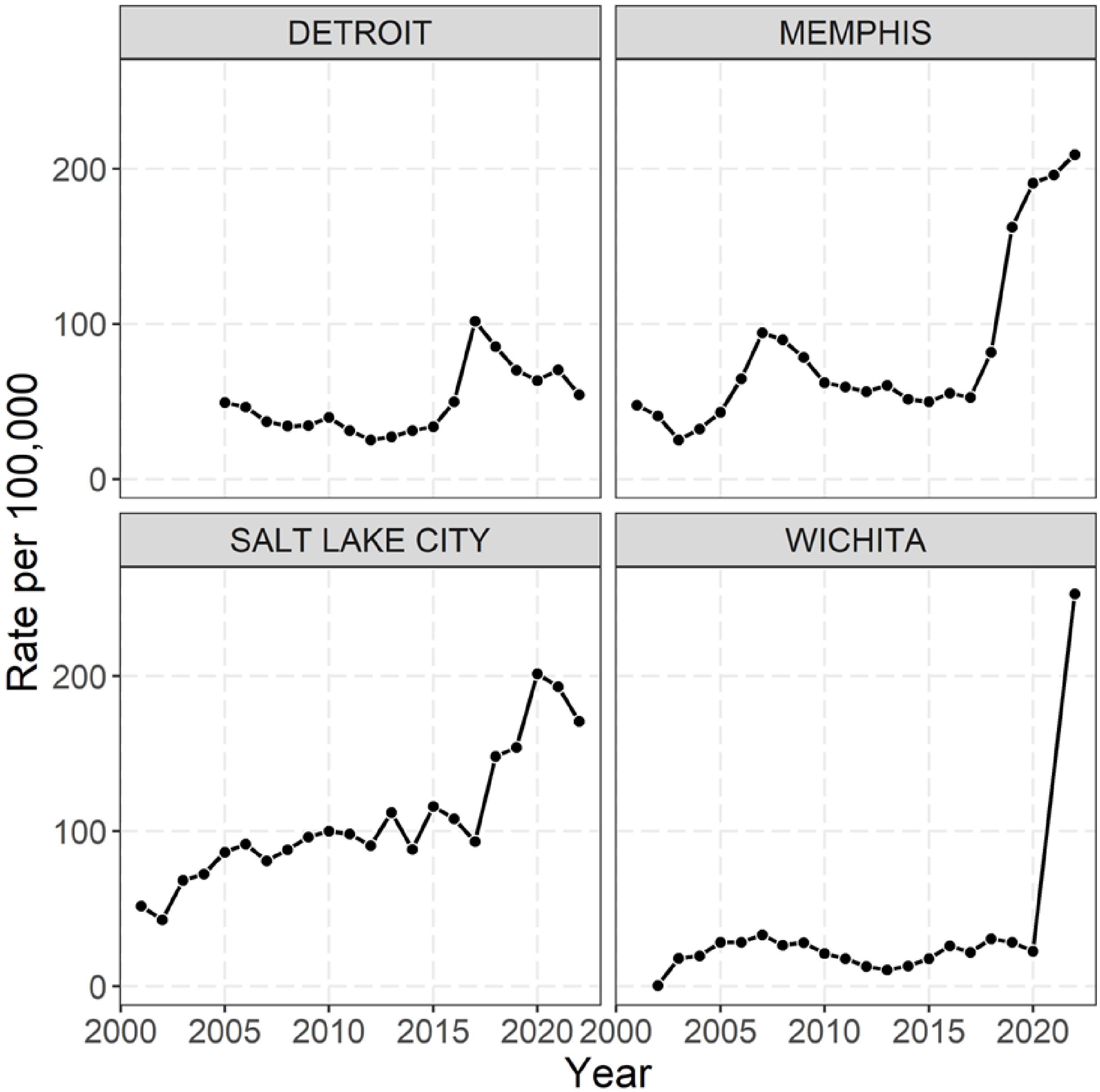

Figure 6. Estimates of Total Domestic Aggravated Assault Rates for Selected Jurisdictions

Discussion

The main contribution of this work is a methodology to reliably estimate the dark figure of domestic violence. Using observed police reported statistics, and the estimated non-reporting rate, we have shown that we can generate a better estimate of the total number of crimes. Under-reporting of aggravated domestic violence incidents ranges from 20% to 80% across many of the larger jurisdictions in the US. Accurately estimating the levels of such problems should be an important component in calculating the cost and benefits of reducing such violence, as well as determining trends and changes to any policy interventions.

One of the main limitations of the technique, as we have shown, is that having inaccurate police reporting data will ultimately result in inaccurate total victimization estimates when using this technique. When examining individual cities, it is relatively simple to graph the data and detect any anomalies. If, however, one wishes to use the NIBRS data to generate larger area estimates, such as aggregating up to states, that will be more difficult. It may be at that point simply using the NCVS estimates is more practical. Still, if one wants specific city estimates, we believe our methodology offers a more promising approach. Another limitation of our work, more generally, is that the analysis was limited to large cities that submitted information on aggravated domestic violence to NIBRS in 2022. As noted earlier, NIBRS reporting is voluntary and not all jurisdictions report their crime data to NIBRS. Several large cities–notably Chicago, Los Angeles, Miami, New York City, Phoenix, and San Francisco–were not reporting to NIBRS in 2022.

We detail several potential extensions of this work. First is in terms of modelling . While our model here focuses on solely aggravated domestic violence, once subsetting the NCVS data there are only a handful of observations in any particular year. It is likely the case that one can *pool* victimization reporting to the police across different crime types. That is, one can estimate a model of reporting rates across all different victimization types, conditional on the person's demographics. This will likely result in more accurate estimates, not just for domestic violence but across all interpersonal crimes.

The second extension is potentially expanding such work to examine even sub-jurisdiction geographic areas. There is no fundamental reason why our methodology cannot be applied to smaller areas, and as such can be a way to improve specific spatial forecasts of either domestic violence (Johnson and Snowden 2024; Wright and Benson 2011) or in general all crime types (Brunton-Smith et al. 2024).

One aspect of this methodology we cannot stress enough is that to apply this methodology broadly across the US, it is contingent on continued funding of the NCVS. It is only possible to gain relatively accurate estimates of reporting rates for fairly rare crimes given the expansive reach of the NCVS. Simply asking police departments to voluntarily report their data timely and accurately is not enough. There will always be questions of reporting over time, and thus one *needs* to have estimates of those reporting metrics over time to get a true sense of crime data trends. Calls for better crime data in the United States are nothing new (National Academies of Sciences, 2016; Council on Criminal Justice, 2024; Criminal Justice Interagency Working Group, 2023), but the stakes are too high to not have as accurate, timely, and reliably as public health data more generally.

In the end, we have shown that the number of domestic violence incidents reported to law enforcement varies over time and across agencies. We have also shown that the level of underreporting varies over time, agencies, and respondent characteristics. The methodology presented in this paper illustrates how factoring in variables associated with reporting and underreporting can be used to adjust official statistics and generate a better estimate of the true prevalence of domestic violence in a community. Analyses indicate that solely using aggravated assaults for domestic violence reported to law enforcement and recorded in NIBRS undercount these incidents by about 40%. The estimates provided by our methodology offer a count of domestic violence that takes underreporting into account, and we believe offers an important path forward for better estimating the true nature of domestic violence in America. Only with more accurate, reliable, and timely data will researchers, practitioners, and policymakers be in a better position to prevent domestic violence and promote public health and public safety across the U.S.

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[1] After an extensive scoping review, it was determined that the NCVS, a survey of about 240,000 persons in 150,000 households, and NIBRS, which amasses incidents and arrests from the nation’s law enforcement

agencies were best suited to our purposes for generating sub-national estimates of domestic violence trends in a timely fashion.

[2] Using the Agresti-Coull method to estimate the reporting rate for smaller sample sizes reduces the variance of the reporting estimate to be smaller than the survey estimate at almost all sample sizes in this scenario. This would be reasonable if the reporting rates are expected to not be close to 0 or 1 (Agresti 2012).

[3] Still, given that we are not working with individual city surveys, we leave that to future researchers.

[4] To be clear, the following data were utilized. The first source is the concatenated file of the NCVS data from 1992 through 2022, available currently at ICSPR study number 38604. The analysis is limited to domestic violence assaults, using the same methodology and variable definitions as Powers and Bleeker (2023). Note that the NCVS only surveys individuals who are at least 12 years old. After filtering the data to domestic violence aggravated assaults, there remained a total of 1,527 reported incidents over the 21-year sample. Recall that the NCVS measures self-reported victimization from roughly 240,000 individuals in about 150,000 households. The second source is the concatenated files provided by Kaplan (2024). For these data, incidents were filtered to include those reported as aggravated assaults (via the victimization aggravated assault question, not the specific NIBRS crime category). Specifically, we focused on the aggravated assault circumstance variable that had a specified category of domestic violence. Since the NCVS only includes those who are at least 12 years old, NIBRS events for those under 12 were eliminated. Agency-years with only partial reporting were also removed; included agencies had reported crime incidents in all 12 months. For the NIBRS data, imputations were needed for the age, Hispanic status, and race of the victim for a small number of cases. A regression approach was performed, using the other variables available, to impute the age for each separate year of the NIBRS data. For Hispanic status, not-Hispanic was imputed, and for race multi-racial was imputed. The last data source are mappings of reported population-served estimates, downloaded from the FBI's Crime Data Explorer. These are derived from the Law Enforcement Officers Killed in Action data series. Agencies are represented in NIBRS using an originating agency identifier. When an agency-year does not have a reported population estimate, the missing data are imputed as having a population of the under 50,000 population category, as jurisdictions with a missing population estimate tend to be small or non-city law enforcement agencies.

[5] It is possible to conduct this same analysis on sub-jurisdiction geographic areas conditional on the geographic locations are available. In this regard, the methodology could be expanded to smaller neighborhoods.