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Final Report

New Estimates of the Costs of Criminal Victimization

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METHODS TO COST CRIME VICTIMIZATION: STATISTICAL MODELLING WITH INTEGRATED AND SURVEY DATA TO COMPREHENSIVELY MEASURE HARM INTRODUCTION

SUMMARY OF THE PROJECT

The HAVEN Project (Harms After Victimization: Experience and Needs) was launched in 2020 by researchers at NORC at the University of Chicago and Temple University with support from the National Institute of Justice[1] to address three gaps in the violence literature. First, the project was designed to update the pioneering 1996 NIJ study, *Victim Costs and Consequences: A New Look* using data, measurement and analytic tools that were not available thirty years ago, and that is the subject of this report[2]. In the same spirit, the project developed an expanded taxonomy of harms from victimization and develops a survey instrument and methodology to facilitate the collection of self-reported data on the harms from violent victimization across multiple dimensions that are commonly excluded from violent crime harms measurement. Finally, advances in criminology have included a growing reliance on causal models to estimate the effectiveness of crime and justice interventions and reforms: the HAVEN project introduced a regression-based cost-benefit model that can be integrated into causal models[3].

[1] Award #: 2020-V3-GX-0078.

[2] Miller, Ted R., Mark Cohen, and Brian Wiersema. 1996. Victim Costs and Consequences: A New Look. United States, U.S. Department of Justice, Office of Justice Programs, National Institute of Justice. See Lugo, et al., 2019 for a summary of the financial cost of crime literature.

[3] Roman, John, Anthony Washburn, Sofia Rodriquez, Caterina Roman, Elena Navarro, Jesse Brey and Ben Reist. 2023. *Cost-Benefit Analysis: Methods for Incorporating CBA into RCT and Quasi-Experimental Designs*. Chicago, IL: NORC at the University of Chicago.

KEY RESEARCH QUESTIONS

1. Are regression models of victimization harms, including estimates of the variance in harms experienced by victims, feasible?
2. How can integrated data systems (IDS) be employed to estimate trajectories of harms using the harm taxonomy developed? What are the strengths and limitations of these data systems? Does the IDS offer ways to more directly estimate harms for non-injury producing crime, in addition to the injury-producing crimes?
3. Do these new definitions of direct and indirect harms to victims change estimated costs of victimization? Are these new definitions applicable to all crimes?
4. Can household survey data generate estimates of the incidence of each victimization trajectory? What can we learn from the analyses about those harms that may not require hospitalization due to palpable injuries?
5. Can new cost benefit analysis (CBA) methodologies improve the quality of evaluations of programs that include harms to victims?
6. Which types of victimization are most harmful, and how do they compare to each other?

RESEARCH DESIGN, METHODS, ANALYTICAL AND DATA ANALYSIS TECHNIQUES

HAVEN Integrated Data Cost Modeling Methodology

The project team combined several sources of administrative and survey data to create violent victimization cost estimates for four types of crime: aggravated assault, robbery, sexual assault, and simple assault. The majority of the administrative data came from two integrated data systems—the Allegheny County Department of Human Services Data Warehouse and the Camden Coalition Health Information Exchange (HIE). These integrated data systems, among other sources, link criminal justice and medical claims data to provide a comprehensive record of criminal justice and health care utilization at the person level rather than at the aggregate level. The use of integrated data overcomes a key limitation of previous research on victimization medical costs that relies on diagnostic criteria to identify victims in medical claims data. Because many health care providers are either unwilling or unable to assess criminal intent behind injuries, many medical episodes that are the result of victimization go uncounted in purely medical claims diagnostic studies. Key for our purposes, the integrated data allows one to more accurately match medical experiences to proximate victimization experiences instead of strictly relying on medical diagnostic criteria to infer victimization.

In addition to integrated administrative data, the project team used the National Crime Victimization Survey (NCVS) and the Uniform Crime Report (UCR) to estimate prevalence of violent victimization as well as costs related to productivity losses and property losses/damages. Each of these data sources will be described in turn before turning to the cost estimate methodology that combines these disparate estimates into a single cost estimate.

Allegheny County (Pennsylvania) Integrated Data

Integrated data from Allegheny County consists of court data from the Allegheny County Common Pleas Court and Medicaid physical and behavioral health claims. Allegheny County is part of the Pittsburgh Metropolitan Statistical Area and is home to 130 municipalities including Pittsburgh, its largest municipality. The county is roughly 730 square miles and is home to 1.2 million people. The court data were obtained from Allegheny County Department of Human Services (DHS). DHS launched their data warehouse in 1999, and since that time, have been a leader in sharing integrated data that can support the quality and coordination of services provided to Allegheny County residents.

The data provided to the HAVEN team contain information on cases processed by the Criminal Division of Allegheny County Courts where victims of crimes are specifically identified along with the crime of which they are a victim and regular case processing information like offense date, offense type, charges, etc. along with basic demographic information. Victims identified in the court data had offense dates that ranged from 1/1/2007 to 12/14/2021. These victims were matched to Medicaid physical and behavioral health claims by the Allegheny County Data Warehouse team. The medical data will be referred to as “claims” data. Claims data from Allegheny County only include individuals who are on Medicaid and hence, do not include data on individuals who have private health insurance or are uninsured. The physical health claims data covered dates from 1/4/2015 to 1/12/2022 and the behavioral health claims data covered dates from 1/1/2007 to 8/15/2023. All claims have a three-month lag in the availability.

Specifically, victims identified in the court data were matched to claims data on any available demographic information including birthdate, name, sex, and social security number. For Cohort 1, all medical services including all relevant diagnoses and procedure codes were linked by a unique identifier. Because of the nature of reporting on the criminal justice end, we allowed a buffer of 10 days between reported offense date in the court system and service date of the medical episode such that any medical services that occurred from 10 days before the offense date onward were included. As with any matching procedure there are a few potential caveats to consider. Names were often missing in the court criminal data and any missing or inaccurate information could potentially affect the ability to match records between court data and claims.

The Allegheny matching process yielded two cohorts of cases. Cohort 1 consists of court-identified victim cases that have at least one matched record in the claims data. Cohort 2 consists of court-identified victim cases that have no matched records in the claims data. Most victim cases had more than one crime type associated with the case. Because most crime victimizations do not result in extensive medical treatment costs, we used the universe of victims from both cohorts to create our sample of victims.

There are two main reasons why victims in Cohort 2 might not have medical claims data in the Medicaid system: 1) they have private insurance, and/or 2) they did not experience any injuries that would necessitate a hospital or outpatient visit. Based on previous research, we know that the majority of violent crime victims use Medicaid insurance (approximately 70%). Therefore, we believe that most likely explanation of why victims in Cohort 2 (court identified, but no matching claims) do not have Medicaid claims is that they did not experience injuries that necessitated medical treatment (or they experienced serious injury but chose to not seek formal medical treatment). However, to account for the potential alternative explanation of private insurance, we weighted the Cohort 2 sample by the percentage of violent victims expected to be on Medicaid (e.g., 70%), effectively down weighting the sample of non-injured victims. Cohort 2 then served as our sample of crime victims who experienced no medical costs.

The project team ranked the crimes in order of severity as used by FBI standards from Uniform Crime Reporting, categorizing each case crime type by the most severe crime. For example, if robbery and simple assault charges were filed, the case was categorized as a robbery only. We decided to restrict our sample to only victims of aggravated assault, robbery, sexual assault, and simple assault, which meant excluding burglary and personal theft. The observed medical costs associated with burglary and theft indicated that these cases were likely pled down from more serious offenses like robbery where bodily injury occurred. We could not be certain, however, that this was the case, so to err on the side of caution, we decided to limit our analysis to violent crimes where we know there was at least potential for bodily injury.

For our analyses—to calculate costs—we limited the follow-up period to one year post victimization. Therefore, all medical episodes occurred anywhere from 10 days before the offense date to 365 days after the offense date.

To calculate costs from medical claims data, one needs to monetize the medical procedures that were conducted during each visit. The Allegheny County claims data contain information on the procedure codes that were billed on the claim for each visit. Depending on the severity of the injury, some medical visits may have as many as 50 procedures billed and some may only have one billed. The Allegheny County data warehouse team did not provide costs associated with each procedure code, so the project team had to link procedure costs from a third-party source—the Allegheny Health Network. Procedure costs were obtained from the Allegheny General Hospital (the largest hospital in Allegheny County) charges list. These costs were then linked to the Allegheny County data to get a cost estimate for each procedure in the data.

We categorized each procedure into one of four cost types: inpatient, outpatient, long-term, or mental health. Inpatient and outpatient costs were identified by the type of procedure code used as some codes were only used in inpatient settings. Long-term procedure codes and mental health procedure codes were identified by matching a priori categories as described by the Healthcare Common Procedure Coding System (HCPCS) from the Centers for Medicare and Medicaid Services (CMS). The total cost and cost per treatment type category per medical episode was computed as the sum off costs for all procedures during that visit (i.e., with the same service dates) grouped by treatment type category and overall.

We ended up with a final victimization sample from Cohort 1 of 653 people and a victimization sample from Cohort 2 of 918 people. The Cohort 2 victims were given $0 for all cost categories and combined into one sample with the Cohort 1 victims, creating a combined sample of 1,571 victims from the Allegheny County data.

Camden County (New Jersey) Integrated Data

Integrated data from Camden County was provided to the research team by The Camden Coalition of Health Care Providers. Camden County is part of the Philadelphia Metropolitan Statistical Area and is home to 36 municipalities including the city of Camden, its second largest municipality after Cherry Hill. The integrated data system (Health Information Exchange) was launched in 2010 with the intent to provide real-time data to providers to better serve their patients. The Camden Coalition Health Information Exchange integrates medical information from regional hospitals, primary care providers, laboratories, correctional facilities, and other licensed healthcare facilities.

Integrated data received from the Camden Coalition consists of data from the Camden County Police Department and the Health Information Exchange (HIE). The police data contains incident-level data from the department record management systems where a victim was identified by the police and the crime was recorded via UCR code. Victims identified in the police data had offense dates that ranged from 1/6/2018 to 12/22/2022. The Camden Coalition data warehouse team used personal identifiers from the police records to match police incident data to medical claims data from the HIE. These data included diagnoses codes recorded on each claim but did not include procedure codes. The Camden Coalition team matched records across the HIE and police department data using FastLink, an R package that utilizes a Felligi-Sunter probabilistic record linkage model and expectation-maximization algorithm. Given that the police department data contained only a subset of the personal identifiers of the HIE data, they relied on name components and birthdate to do the match using the default parameters for FastLink. The area of coverage included all of Camden County.

Similar to Allegheny, the matching process for Camden resulted in two cohorts of victims. Cohort 1 consists of police-identified victim cases that have at least one matched record in the medical claims data. Cohort 2 consists of police-identified victim cases that have no matched records in the claims data. Because the Camden sample includes all payers and is not limited to Medicaid claims, we can more assuredly assume that any victims in Cohort 2 did not experience any acute injuries because of their victimization. Therefore, no adjustment needed to be made to the Cohort 2 victim sample.

The project team followed the same general procedure for Camden as was used for Allegheny in terms of categorizing crimes into the main FBI categories. Because the police data were derived from UCR reported data, the records typically only provided one UCR description for each criminal incident, so there was no need to rank crime types before categorization. Instead, the UCR descriptions were aggregated into the larger categories of aggravated assault, robbery, sexual assault, and simple assault. Similar to the time buffers used for the Allegheny County matching, we limited the medical episodes to occurring anywhere from 10 days before the victimization event to 365 days after the event.

Because the claims data did not include procedure data, we could not make direct cost estimates from the Camden data. Instead, we had to impute the costs observed in the Allegheny data onto the combination of diagnoses used in the Camden data per each unique medical episode. We used the StatMatch package in R to match costs observed in Allegheny to diagnoses observed in Camden. Specifically, we used nearest neighbor hot deck imputation where each combination of the top nine diagnoses for each Camden procedure was matched to the nearest donor case in the Allegheny data. The imputation method used Gower's distance to compute the similarity between groups of diagnoses. Each combination of diagnoses is compared to all other combinations to find the cases that have the most diagnoses in common. The imputation method does this for each case in the Camden data set and imputes the cost associated with the nearest neighbor, in terms of Gower's distance, from the Allegheny data. All the cost measures were imputed onto the Camden data set, including total, inpatient, outpatient, long-term, and mental health costs. See Table 1 for a list of data available from each administration data source.

Table 1. Sources of Administrative Data from Camden and Allegheny

Dataset	Identifier	Timeframe	Allegheny	Camden
Emergency Department Data	Y	2015-2022	Yes	Yes
Inpatient Data	Y	2015-2022	Yes	Yes
Outpatient Data	Y	2015-2022	Yes	Yes
Behavioral Health Outpatient Data	Y	2007-2022	Yes	Yes
Includes Usable Information on Procedures			Yes	No
Includes Usable Information on Financial Costs of Procedures			No	No
Court Data	Y	2007-2022	Yes	NOT AVAIL
Police Incident Data	Y	2018-2022	NOT AVAIL	Yes
Calls for Service Data	Y	2018-2022	NOT AVAIL	Yes
Arrest Data	Y	2018-2022	NOT AVAIL	Yes

Once the costs were imputed and the categories of crime victimization were restricted to the main four crimes of interest, the Camden data had 988 police-identified victim cases with medical costs and 4,625 police-identified victim cases without medical costs, creating a combined sample of 5,613 victims. The Camden and Allegheny data was combined into a single dataset consisting of 7,184 total victims.

National Crime Victimization Survey and Uniform Crime Report Data

In addition to medical costs associated with violent victimization, the project team also wanted to incorporate costs related to productivity loss and property damage/loss. To measure productivity and property loss, we used the 2022 National Crime Victimization Survey (NCVS) estimates for each type of crime and imputed them onto the combined medical cost dataset. We used weighted random hot deck imputation from the StatMatch package in R to impute productivity and property costs stratified by class and weighted by the NCVS sample weights. By imputing within class, we made sure that estimates within class were more homogeneous and by using the survey weights, we were able to make sure that the productivity and property estimates with the highest weights were more likely to be selected.

Because our sample, by default, does not include any homicides, we needed to create a way to incorporate the cost of homicide into our existing estimates. Rather than trying to count the number of homicides over the same time frame as our current victimization data, we incorporated a risk of death estimate for each type of crime. Essentially, the risk of death is the probability that any one crime victimization will result in death. As one can imagine, the risk of death for an aggravated assault is higher than the risk of death for a simple assault. To estimate the risk of death we used data from the 2020 Uniform Crime Report Supplemental Homicide Report (SHR) which details the circumstances surrounding recorded homicides each year.

Importantly, the SHR tracks the underlying circumstance, or the crime that occurred that precipitated the homicide (e.g., assault versus robbery). We, therefore, counted the number of homicides with precipitating crimes that fell into one of our four main crime categories and divided that number by the total number of each of those crimes that was reported in the same year. Essentially, this provides a case fatality rate for each type of crime. We then multiplied this risk estimate by the value of a statistical life, which was estimated to be around 12 million dollars in 2022. The risk of death cost estimate, therefore, folds in the cost of homicide split among the crime cases that do not result in death. For most crimes, the risk of death cost was smaller than the observed medical costs.

Analytic Dataset and Strategy

The final analytic dataset for estimating costs consisted of 7,184 victims of either aggravated assault, robbery, sexual assault, or simple assault with observed or imputed one-year costs for inpatient visits, outpatient visits, long-term visits, and mental health visits. Additionally, the dataset contains estimates of productivity loss, property damage, and costs related to risk of death. Finally, the dataset contains a total cost estimate which sums across costs.

The cost data are not normally distributed. Except for risk of death, the cost measures have either a gamma or Poisson distribution with zero inflation. In other words, most of the cost estimates are zero or very low with a few high-cost outliers. To analyze such data, the distribution must be explicitly considered, otherwise estimates will be biased. Hurdle, or two-part, models are particularly suited for analyzing zero-inflated cost data. In essence, a hurdle model jointly models the likelihood of incurring a cost (e.g., cost vs. no cost) as well as the amount of the cost once a cost is incurred, or once the “hurdle” of incurring a cost is passed. In other words, the fit of the cost estimate is conditioned on the likelihood of obtaining a cost, and marginal mean estimates consider both models to create standard errors that reflect the joint distributions.

For each cost outcome a two-part model is fitted that predicts the cost estimate from each type of crime where the first model uses a logistic regression model to predict incurring any cost or not, and the second model uses a generalized linear model with a log link and gamma distribution to model the non-zero costs. The marginal means are calculated from the model and pair with 95% confidence intervals that appropriately take into account the zero-inflation and non-normality of the cost distribution. These marginal means represent the average cost (total or inpatient or outpatient, etc.) for each type of crime victimization for one-year post-victimization. To estimate annualized sums of costs, these means are multiplied by the yearly counts of each type of crime.

THE HAVEN SURVEY

Given the numerous benefits with in-person surveys including the goal of more fully capturing victimization harms to underserved populations that could be used to validate or expand cost estimates, the HAVEN research team designed a survey to be administered in person in one high-crime city, with a sampling plan to oversample high crime neighborhoods. Because the intent was to delve deeply into costs accrued to victims of assaultive violence, as well as the victim's family and close social network, we defined victim costs across nine domains outlined below. Organizing the survey into these domains helped enable a seamless understanding of how a range of costs might accrue over time in the full theorized set of domains.

(1) <u>Emergency and immediate health care/costs (up to two weeks after the victimization)</u>. These are the direct physical harms and associated medical procedures and services, and victim services that can be sought or provided post-victimization. Typically, surveys and administrative

data include these harms and costs. To facilitate the flow of survey questions, the survey separated out the medical and other health and social services received in the first two weeks after the victimization from longer-term medical care follow-up and potential downstream physical and behavioral health consequences and associated costs. The HAVEN survey includes a detailed series of questions starting with whether the injury sent the respondent to the ER, if they stayed overnight and for how many days, the type of treatment they received there, if any surgeries were needed, the type of surgery, whether general anesthesia was needed, and any other treatment needed. HAVEN also breaks down costs into detail by asking for the amount of insurance paid, out of pocket expenses paid and whether all the procedures were covered by insurance. Additionally, HAVEN asks if after the initial hospitalization (but within two weeks) the respondent had to seek additional medical care or be admitted to the hospital and specifics about drug prescriptions.

(2) Victim services. The HAVEN survey was designed to obtain a deep understanding of the array of victim services sought, obtained, and the factors influencing decisions and actions around receipt of victim services. Importantly, measuring access to and use of victim services and other social services that are not captured in medical record data. Many victim service entities are provided through community-based organizations that not considered health-related services reimbursable by insurance. Hundreds of millions of dollars flow from the federal government through the federal Victims of Crime Act (VOCA) program to states and localities to provide free victim services. In general, there is little research on access and use of victim of services. Historically, with regard to *survey*-based research, outside of domestic violence and sexual assault, there has been little scholarship on the role victim services play in the short- and long-term well-being of victims of violence (Roman, 2021). Having details about the path to

victim services is not only can be used for examining rates of victim services use, but also for assessing how victim services may be associated with post-victimization trajectories related to criminal justice outcomes and aspects of health.

(3) Economic and educational loss and related hardship. The HAVEN survey captures detailed information about hourly wages before and after the victimization, whether hours were continuously missed or reduced after the victimization, and asks similar questions related to school (e.g., including grades, changing schools, missed school days). The HAVEN survey also asks participants to put a dollar amount on the time lost from work, which helps provide a deep perspective on the economic impact this has for individuals, families and communities. Essentially, these questions can help provide information beyond the simple "dollars lost" in wages and more precisely measure productivity losses and associated harms.

(4) Long-term physical consequences and any exacerbation of existing health issues. The HAVEN survey separates out immediate medical care from care that is received after the first two weeks. These include harms and costs which may arise due to complications from the victimization, or simply include the long-term medical services received (or sought) for injuries and medical problems resulting from the injury. In addition, there is some evidence that exposure to violence through victimization can lead to biological alterations known to be associated with elevated risk for heart disease, metabolic and immune system-related diseases, stroke, and even dementia (Danese & McEwen, 2012; Miller, Chen & Parker, 2011; Taylor, Way & Seeman, 2011). Yet, to date, there are no victimization surveys that have been designed to examine these longer-term physical harms.

The survey asks detailed questions about whether any additional medical care was needed (including therapeutic services) or new medications required after the initial two weeks. HAVEN also asks detailed questions about physical therapy and long-term physical rehabilitation (how long the sessions were, how many sessions overall, out of pocket costs for physical therapy etc.), as past studies show rehabilitative services are often typical among those seriously injured and not easily captured in extant victimization cost estimates (Kamenov et al., 2019).

(5) Behavioral health. For HAVEN, behavioral health issues and associated costs include all aspects of mental health issues and related behavior, substance abuse and other behavioral outcomes, such as smoking, drinking, risky sex, phobias, reduction in walking/exercising, and changes in routines due to fear of crime. Mental health disorders are widely prevalent in the U.S. population—one in three people develop a mental health disorder in their lifetime (Chesney, et al., 2014) and were the second largest source of disability globally (IHME, 2020). Other costs from behavioral changes due to victimization—for instance, fear of walking outside and take-up of harmful behaviors (e.g., smoking, risky sex, and over-eating ((Brown et al., 2014; Crane, et al., 2014; Pengpid & Peltzer, 2020))—are commonly omitted from COI studies (and even studies simply assessing harms) because these outcomes are difficult to measure with validity (Turanovic, 2019). This domain is one of the key highlights of the information collected on the HAVEN survey, as the NCVS does not ask questions in this area with the exception of a few questions on emotional distress and anxiety.

(6) General quality of life. The HAVEN survey was designed to obtain nuanced measures of quality of life by asking respondents a long series of items using extant validated scale measures. The HAVEN survey also includes questions specifically asking if respondents had prior health problems made worse by the victimization. (Respondents are asked about 11 medical conditions.) HAVEN also uses the EuroQol EQ-5D-5L self-rated health status to have respondents rate their own health across five dimension (mobility, self-care, usual activities,

pain/discomfort, and anxiety/depression. Each dimension has five response categories: no problems, slight problems, moderate problems, severe problems or fully unable to do. The EQ-5D-5L is a standardized measure of health status developed by the EuroQol Group in order to provide a simple, generic measure of health for clinical and economic uses (Herdman et al., 2011). This allows the HAVEN survey to generate a "health status" for each participant in five areas, which can also be aggregated to create a single score. This measure allows the calculation of quality-adjusted life years (QALYs) that can be applied in cost analysis. In addition, the HAVEN survey asks respondents to rate their own health on a scale of 1-100. Last, HAVEN ends this section by asking if any health needs are going unmet, why they these needs are unmet, and the impact unmet needs may have on them (e.g., physical, mentally, financially).

(7) <u>Loss that accrues to family members and close friends associated with victim</u>. Given that most victimization surveys are focused on carefully estimated prevalence of crimes, most surveys do not ask questions about losses that accrue to others due the victim's injury and health consequences or about the effects of witness or co-victim exposure to the incident. The HAVEN survey asks detailed questions about who was present, specifically how they were victimized, people that witnessed the incident but were not victimized, whether any of them whom the respondent knew also missed work or school, if they were friends or family, whether the respondent was providing any financial assistance to family or friends that stopped due to the victimization, and specifically how much support was being provided. In addition, the survey asks respondents to estimate whether there were family and friends who had incurred expenses or lost productivity in order to provide financial, social or emotional support to the victim.

(8) <u>Re-victimization</u>. The nature and extent of re-victimization, also referred to as "repeat" victimization, has been explored in prior studies using various longitudinal data sources and

hospital-based samples of victims of intentional violent trauma. Taken together, studies suggest that re-victimization is not an uncommon experience (Menard, 2000). However, neither administrative data nor existing survey data can easily capture the likelihood that a subsequent victimization was related to a previous one, particularly with regard to community or street violence (Oudekerk and Truman, 2017). Offender behavior—norms supporting gang membership, gun carrying, and other behaviors related to street lifestyle greatly increase the likelihood of revictimization (Menard & Huizinga, 2001; Tillyer, 2014). To understand re-victimization, the NCVS has mostly been used to estimate "series victimization"—defined as six or more related victimizations occurring within a six-month period (Lynch, Berbaum, & Planty, 2002; Planty & Strom, 2007); those data are not designed to easily elucidate costs of associated with re-victimization.

(9) New criminal justice contact. Some studies show that odds of being arrested or stopped are associated with previous victimization (Berg & Mulford, 2020; Berg et al., 2012; Stogner, Gibson, and Miller, 2014). The HAVEN survey asks a series of questions related to any crimes committed by the respondent (as well as arrest and conviction information) that are directly related to the victimization. This includes asking the respondent if they wanted to take matters into their own hands, if they've been fighting since the time of the victimization, or if they've done anything illegal. While these questions are related in some ways to the respondent's behavioral health, they are unique in specifically asking the respondent about actions or behaviors that could result in criminal justice system contact.

In addition to including items representing the above harm and cost domains, the survey also asked about historical (i.e., life course) use of services and key demographic and residential information. The end of the survey also had a set of questions asking whether respondents would be willing to provide information about themselves that would allow for longer-term contact and follow-up, as well as identifying information, such as social security number and birthdate. This was done to collect general information about the feasibility of turning HAVEN into a longitudinal study and directly integrating administrative medical record data by person into the survey data captured. The survey was programmed into SurveyToGo to be used by field interviewers on a tablet.

The survey component was designed to focus eligibility on residents who generally have higher risk of violent victimization—individuals between the ages of 12 and 55 living in high-poverty and high-crime areas. Hence the final questionnaire and initial in-person screening procedures were developed to screen for and only survey those who had experienced a violent victimization (rape/sexual assault, robbery, carjacking, threats of force or any type of physical attack), or a burglary in the past 24 months. Burglary was included because high costs accrue to victims with the loss of property and time taken to recovery property. The research team planned the survey to go into the field in June of 2022 with the initial goal of reaching the targeted response rate by October 2022.

EXPECTED APPLICABILITY OF THE RESEARCH

We believe the proposed study will have wide-ranging implications for a variety of stakeholders and ultimately help policy-makers better target government spending on effective crime prevention and violence reduction strategies. This will greatly reduce costs to the criminal justice system and reduce costs from healthcare, homelessness and unemployment, to name a few. Table 1, from Lugo and Przybylski’s 2019 report (79), lists the critical policy questions informed by comprehensive victim harm estimates. Our proposed study has been carefully crafted to allow future researchers to use our new methods to design evaluation studies and complementary CBA studies that answer the critical question: How much would government investment in crime prevention offset the need for later spending to respond to victimization?

Because we believe that few cost methodologies can accurately capture the full-harms (and hence costs) of aggravated assaults (shootings, stabbings, and beatings), new methods with a focus on these costly assault-related crimes will have wide-ranging implications. The methods developed here are of interest both to researchers who will apply them to studies of policy and programs, but also to policymakers grappling with how to make productive use of scarce resources. Widespread use of the new methods, ultimately, should make government more efficient and effective overall, not just for criminal justice system stakeholders. Health and victim services practitioners will benefit because their services and programs are likely to be prioritized for funding. As well, victim service providers are eager for more nuanced estimates for costs of crime and cost-effectiveness information. Finally, because the solicitation prioritizes applied research in “Qualified Opportunity Zones” (QOZ) (NIJ-2020-17326, 2020: 10), we have chosen cities that have a large number of tracts designated as QOZs and will be conducting the in-person survey with oversampling in high-crime areas, which in most cases, are the QOZ.

PARTICIPANTS AND COLLABORATING ORGANIZATIONS

Grant Partners for Integrated Data (Allegheny County, Pennsylvania; Camden County/Camden, New Jersey)

Ms. Golnar Teimouri, Policy Advisor for Research and Data Public Safety, **Office of the Mayor at the City of Chicago**.

Ms. Erin Dalton, Director, Department of Human Services for **Allegheny County, PA, Ms. Katy Collins**, Chief Analytics Officer, and **Mr. Wilson Mui,** Data Lead of Criminal Justice

Data Analytics Team. They run one of the most well-known, and longest running integrated data systems that serves as a model for the country.

Mr. Aaron Truchil, Director of Strategy & Analytics at the **Camden Coalition of Healthcare Providers** (Camden NJ) oversees the organization's data and research activities, including the Coalition's ARISE (Administrative Records Integrated for Service Excellence) integrated data system.

CHANGES IN APPROACH FROM ORIGINAL DESIGN AND REASON FOR CHANGE, IF APPLICABLE

With respect to the administrative data collection from the three integrated data sites, the main change from the original proposal was to focus on two (Camden, NJ and Allegheny, PA) and not include Chicago data. In the proposal, NORC requested a small amount of money to explore the possibility of creating an integrated data system from available Chicago data (by contrast, the Allegheny and Camden sites already had fully integrated data). After extensive discussions with our partner at Chapin Hall at the University of Chicago, we entered into negotiations with the city of Chicago to access data. Project staff met with senior staff in the Chicago Mayor's office multiple times to secure a master data agreement to allow NORC access to Chicago data. After extensive negotiation, and a subsequent change in mayoral administration, the city was not able to execute the agreement.

With respect to the survey, a number of changes were made. The period during which the survey was in the field entirely overlapped with the COVID-19 pandemic, which severely restricted our ability to: 1) hire and retain field interviewers and 2) complete interviews as many people were unwilling to conduct face-to-face interviews. In addition, the original plan to conduct interviews within the highest violence neighborhoods in Camden proved infeasible.

Given constrained resources, the research team estimated that the only feasible approach to completing interviews was to focus on neighborhoods with high rates of violence which would increase the chance that a randomly identified household would include someone with a recent victimization experience, thus reducing the number of doors to be knocked on and limiting costs to an acceptable level. As described below, for the safety of our interviewers, many households could not be approached.

During the grant proposal stages and initial stages of the awarded project the research team narrowed the survey site to one locale—Camden. Camden is a small city and has a crime rate higher than the average city—providing the opportunity for a field team to cover more ground when they are in the field, as well an increasing the likelihood that a randomly-sampled household would have an individual meeting the eligibility criteria of age and have experienced a victimization. In addition, the research team decided to concentrate all their survey resources in one site because they knew there would be lingering issues related to the COVID-19 pandemic that would reduce the efficiency of typical survey administration procedures, and increase costs, such as the likelihood of increased refusals due to residents wanting to limit contact with strangers (Uleanya & Yu, 2023). Focusing all resources in one site would increase the resources available to troubleshoot if challenges were to arise. The sample size goal was to interview 200 respondents in Camden.

Due to the heightened health risks associated with the COVID-19 pandemic, in-person data collection was paused and a 9-month no cost-extension was requested and processed in order for us to safely visit addresses selected for the in-person data collection. We need to conduct these interviews in-person due to the sensitive nature of our survey battery. As city, state, and federal guidelines continue to change regarding COVID-19, we want to do our due diligence and minimize health risks to our interviewers and respondents.

The sampling design for this survey was based on the goal of reaching 200 completed surveys. The sampling statistician drew an address-based sample (ABS) from NORC's licensed copy of the USPS Computerized Delivery Sequence File (CDS) in high crime 2010 Census block groups in Camden. High crime block groups were identified based on violent crime rates in 2020 and 2021 provided by the City of Camden. Since the recall window for this study was the past two years, we used the two-year Camden violent crime rate 2020/21 with some adjustments. The violent crime rate was doubled to account for burglaries (because burglaries were included in the eligibility criteria). The assumption that the burglary plus violent crime rate was about twice the violent crime rate was based on what is typically seen in the NCVS for the nation. To account for under reporting of crime the violent crime plus burglary, the rate was divided by 0.4 (NCVS data show only 40% of crime is reported). Initially based on this adjusted burglary plus violent crime rate, block groups with crime rates above 39% were deemed to be "high crime block groups."

The block groups were then stratified into two strata with rates above 50% and block groups with rates between 39% and 50%. To ensure high "screen-in" rates (i.e., the household would likely have an eligible respondent who was a crime victim), 75% of the sample was allocated to the strata with rates above 50%. Within strata a simple random sample of addresses was drawn. Then an initial sample size of 1,700 housing units was drawn. Accounting for expected vacancy rates, screener response rates, screen in rates, response rates to the main questionnaire, we expected 1,700 sample addresses to yield approximately 440 completed interviews. The sample was divided in to subsamples of 100 addresses to facilitate roll out of the sample to field interviewers.

Early in data collection, the research team determined that many of the addresses in the Camden sample, especially in the higher crime strata, were too unsafe for interviewers to visit. Because of this in-person data collection was discontinued in the original two strata. An additional sample was then drawn in two new strata. These two strata were block groups with adjusted burglary plus violent crime rates of 27% to 39% and 22% to 27%. Simple random samples of 550 addresses in each stratum were selected for an additional 1,100 addresses. This sample was once again divided into subsamples of 100 addresses.

Job postings for four interviewer positions were placed on NORC Careers in March 2022. By the start of data collection (June 2022), two field interviewers were hired and trained. The location of Camden created challenges for recruiting interviewers, so the recruitment period was extended through October 2022. Continued recruitment efforts focused on finding interviewers who lived in or near the Camden community with hopes of increasing trust and buy-in from community members and comfortability among interviewers. NORC used web-based and word-of-mouth outreach to existing NORC interviewers living near the Camden area. Strategies included contacting local community-based organizations such as Youth for Change, Neighborhood Housing Services, Woodland Community Development, Camden Lutheran Housing, Boys and Girls Club Camden, Center for Family Services, and the NJ Unemployment manager in Camden. Many organizations did not respond due to COVID closings. Over the seven-month period, 70 applicants applied; 57 were not selected due to location or not meeting basic qualifications; eight applicants withdrew after interviewing. However, only one field interviewers joined the two interviewers hired earlier. Due to turnover and challenges with in-person data collection, the NORC and Temple teams added four additional interviewers to do outreach and data collection by phone.

OUTCOMES

Activities/accomplishments

- NORC/Temple researchers developed a new taxonomy for measuring harms to victims of crime and created new estimates of the harms from violent victimization (see Roman, et al., 2023).

Working with the Allegheny IDS data, NORC:

- Created a subset of the Cohort 1 data to be used in matching procedure costs to victimization and diagnosis data from Camden.
- Applied statistical method to victimization cost estimates to account for low prevalence of victimization in the population.
- Applied statistical method to extrapolate Medicaid-only claims information to other insurance payers.

Working with the Camden IDS data, NORC:

- Coded all victimization events in the Victim cohort (records matching both police-identified victim data and health data) and the Health cohort (records included based on ICD10 diagnoses indicative of a victimization) into broader crime categories (e.g., Agg Assault, Robbery, etc.) based on either the reported crime from the police data cohort or on diagnosis code for the health data cohort.
- Collated the relevant diagnosis codes pertaining to each victimization event to be used for matching with procedures and costs from the Allegheny dataset.

- Computed descriptive statistics of counts of medical episodes and diagnoses per crime type as well as by Police vs. Health cohort.
- Matched crime type and diagnosis combinations to health care procedure costs from Allegheny, which required the use of predictive mean matching based on the type of crime and top diagnosis codes. Estimates of costs per victimization event were imputed and summarized at the crime level.

RESULTS AND FINDINGS

We estimate the mean harm per victim, including emergency department (ED), inpatient, outpatient, rehabilitation/long-term care, mental health, productivity, property loss and risk of death, for victims of violent, interpersonal crime:

- Aggravated assault: $49,491 [$37,188, $61,793]
- Sexual assault: $13,892 [$5,233, $22,550]
- Simple assault: $10,114 [$8,543, $11,685]
- Robbery: $58,606 [$36,146, $81,066]

We note that catastrophic harms drive average victim costs: a few victims of crime experience harms an order of magnitude (or more) larger than average. This includes victims of violence who experience severe emotional trauma, traumatic brain injuries (TBI), spinal cord injuries (SCI), loss of kidney function and other chronic conditions.

We estimate the total cost of violent crime, including emergency department (ED), inpatient, outpatient, rehabilitation/long-term care, mental health, productivity, property loss and risk of death, for victims of violent, interpersonal crime:

- Aggravated assault: $76,221,682,992 [$57,273,685,056, $95,168,140,816]
- Sexual assault: $7,387,848,952 [$2,782,940,798, $11,992,225,300]

- Simple assault: $39,021,612,292 [$32,960,414,654, $45,082,809,930]
- Robbery: $40,722,672,130 [$25,116,228,830, $56,329,115,430]

Two main finding are emerging from the study. First, conventional studies of harms focus on acute care costs of emergency department and inpatient stays immediately following victimization, along with lost wages. HAVEN finds that post-release costs, including outpatient and long-term care, trauma, morbidity, disability and lost quality of life cause harms to victims that are larger than the acute harms. Second, harms from victimizations are not normally distributed in the population. A relatively small proportion of cases (about 10%) have costs that are 10 times (or more) the median costs. This 'Power Law' distribution suggests that catastrophic costs in this subpopulation explain a disproportionate part of total victimization harms.

An overall AAPOR “Response Rate 4” of 4.47% was achieved for this survey (see Table X). During the beginning stages of data collection, field interviewers reported challenges approaching households due to homes no longer being occupied, feeling unsafe exiting vehicles, witnessing suspected criminal activity (i.e., open drug use/dealing or sex work), or households being inaccessible due to gated access. Interviewers worked with the field manager to identify themes regarding challenges and generated solutions such as providing community outreach letters to gated community buildings, pairing interviewers to visit households in teams to address safety concerns and having the study leads drive through sampled areas to review location specific issues mentioned by interviewers to determine how the sample strata should be prioritized given safety concerns.

Table 2. AAPOR Response Rate[a]	
Complete surveys (I)	32
Partial surveys (P)	1
Eligible refusals (R)	355
Ineligible (IE)	248

Unknown eligibility (UE)	540
Not attempted	525
Eligibility rate	0.609449
Response rate	4.61%

[a]AAPOR calculation: (I+P)/[I+P+R+e(UE)]

Table 3. Disposition of Sample	
Completed in-person	22
Completed phone	10
Disconnected number/wrong number	37
Final refusal	355
Fm review	2
Hung up during intro	3
Inaccessible - gated	13
Inaccessible - other	16
Ineligible - no eligible victimization	65
Ineligible - not in age range	40
Ineligible - unknown	37
Language barrier - Spanish	55
Not a housing unit	21
Not home	59
Not released/not attempted	525
Ring no answer/busy signal	17
Site visit needed	3
Text sent to r	1
Unsafe	271
Vacant	85
Voice mail	51
Wrong number - INF	11
Wrong number - R	1
Total	**1700**

LIMITATIONS

The advantages of the regression-based CBA described here should not imply that the approach solves all the problems endemic in CBA. It does not. As with any causal model, the validity and reliability of the CBA estimates are a function of the identification strategy in the model estimator. A second issue with CBA causal models is that costs are far easier to observe in most settings than benefits, and thus only a subset of outcomes are included in the CBA. For instance, preventing a violent assault saves the victim hospital costs and lost wages which are relatively easy to observe. But it also saves health costs from outpatient, rehabilitation, and long-term care, costs of disability and trauma, costs of poor quality of life, costs from an increased risk of revictimization, and costs from a now higher risk of committing a crime. And more. An analysis that monetizes only a limited set of outcomes will systematically underestimate the benefits of an intervention.

Second, the issue of standing must be addressed in CBA, though it is important to note that standing is an issue in any causal model. Standing is simply the determination of whose costs and benefits count in a CBA model. The classic example focuses on whether to count opportunity costs of people who are incarcerated—should their lost wages and welfare count as a cost of the policy or program that incarcerated them? Most cost-benefit analysts specify their unit of analysis: returns to investors, a government-only perspective, or a societal perspective. We recommend keeping in mind Sen's critique of omitting categories of benefits and keeping that perspective as wide as possible.

List of products

- Roman, J.K., A. Washburn, S. Rodriquez, C.G. Roman, E. Navarro, J. Brey and B. Reist. (2023). New Estimates of the Economic Costs of Victimization. Chicago, IL: NORC at the University of Chicago. (submitted to NIJ for review)

- Roman, J.K., A. Washburn, S. Rodriquez, C.G. Roman, E. Navarro, J. Brey and B. Reist. (2023). Cost-Benefit Analysis: Methods for Incorporating CBA into RCT and Quasi-Experimental Designs. Chicago, IL: NORC at the University of Chicago. (submitted to NIJ for review)

- The Financial Cost Calculator can be found here: https://rsconnect-stg.norc.org/havencost

The HAVEN team is currently finalizing the drafts of two academic-focused manuscripts:

1. The first paper was designed to highlight how integrated administrative data can be used to make large strides in both documenting the array of harms and the financial costs. Researchers studying harms from victimization use either survey data or administrative to gain an understanding of the negative health and social consequences after victimization—these data are rarely integrated to gain a more robust picture of harms. Furthermore, there is an acute shortage of studies that address the financial costs of victimization.

2. The second paper: Estimating the Financial Costs of Violent Victimization Using Survey Data: Thoughts for the Field highlights the intensive methods used by the HAVEN research team to develop and field a face-to-face survey in one city in the northeastern United States. The paper describes how nuanced and valid measures of costs associated with long- and short term medical and behavioral health are needed to shed light on the wide harms from violent victimization. The paper also discusses lessons learned from the field survey experience.

Data sets generated

- HAVEN survey data. These data involve the developed survey questionnaire and the results of the survey.

Dissemination activities

The HAVEN research team has presented at a number of conferences over the last two years, and will be presenting during the upcoming National Conference on Firearm Injury Research

(November 2023), and the Annual Meetings of the American Society of Criminology (November, 2023). The products outlined above will also be disseminated widely through other traditional channels such as social media and on company websites. The cost calculator/data visualization for practitioner and policymaker audiences will be advertised widely through email blasts, listservs and social media. We will also have conversations with NIJ to request that the brief **New Estimates of Harms from Violent Victimization** be published as a monograph by NIJ. This brief would in many ways be a follow-up to the NIJ report Victim Costs and Consequences: A New Look (Miller, Cohen and Wiersma, 1996). That paper has about 1,000 citations and it is difficult to conceive of an alternative publication strategy that could replicate that reach.

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