

# Uniform Crime Reporting (UCR) Program Data: A Practitioner's Guide

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# Chapter 1

## Preface

If you've read an article about crime or arrests in the United States in the last half century, in most cases it was referring to the FBI's Uniform Crime Reporting Program Data, otherwise known as UCR data. UCR data is, with the exception of the more detailed data that only covers murders, a *monthly number of crimes or arrests reported to a single police agency* which is then gathered by the FBI into one file that includes all reporting agencies. Think of your home town. This data will tell you how many crimes were reported for a small number of crimes or how many people (broken down by age, sex, and race) were arrested for a (larger) set of crimes in that city (if the city has multiple police agencies, it will use the agency which is the primary agency on the case, usually the local police department) in a given month. This is a very broad measure of crime, and its uses in research - or understanding crime at all - is fairly limited. Yet it has become - and will likely remain among researchers for at least the next decade - the most important crime data in the United States.

UCR data is important for three reasons:

1. The definitions are standard and all agencies follow them so you can compare across agencies and over time

2. The data is available since 1960 so there is a long period of available data
3. The data is available for most of the 18,000 police agencies in the United States so you can compare across agencies

More than most datasets, there are a lot of times when using UCR data that you'll think "that's weird". This book will cover this weirdness and when we think the weirdness is just an odd - but acceptable - quirk of the data, and when it is a sign of a big problem in the data or that particular variable and that we should avoid using it. For most of this book we'll be discussing the caveats of the above reasons - or, more directly, why these assumptions are wrong - but these are the reasons why the data is so influential.

## 1.1 Goal of the book

By the end of each chapter you should have a firm grasp on the dataset the covered and how to use it properly. However, this book can't possibly cover every potential use case for the data so make sure to carefully examine the data for your own particular use.

I get a lot of emails from people asking questions about this data so my own goal is to create a single place that answers as many questions as I can about the data. Again, this is among the most commonly used crime datasets and there are still many current papers published with incorrect information about the data (including such simple aspects like what geographic unit data is in and what time unit it is in). So hopefully this book will decrease the amount of misconceptions about this data, increasing overall research quality.

Since manuals are boring, I'll try to include graphs and images to try to alleviate the boredom. That said, I don't think it's possible to make it too fun so sorry in advanced. This book is a mix of facts about the data, such as how many years are available, and my opinions about it, such as whether it is reliable. In cases of facts I'll just say a statement - e.g. "the offenses

data is available since 1960”. In cases of opinion I’ll temper the statement by saying something like “in my opinion...”

## 1.2 Structure of the book

This book will be divided into eight chapters: an intro chapter briefly summarizing each dataset and going over overall issues with UCR data, and seven chapters each covering one of the seven UCR datasets. Each chapter will follow the same format: we’ll start with a brief summary of the data such as when it first became available and how it can be used. Next we’ll look at how many agencies report their data to this dataset, often looking at how to measure this reporting rate a couple of different ways. Finally, we’ll cover the variables included in the data and how to use them properly (including not using them at all) - this will be the bulk of each chapter.

## 1.3 Citing this book

If this data was useful in your research, please cite it. To cite this book, please use the below citation:

Kaplan J (2021). *Uniform Crime Reporting (UCR) Program Data: A Practitioner’s Guide*. <https://ucrbook.com/>.

BibTeX format:

```
@Manual{ucrbook,  
  title = {Uniform Crime Reporting (UCR) Program Data: A Practitioner's Guide},  
  author = {{Jacob Kaplan}},  
  year = {2021},  
  url = {https://ucrbook.com/},  
}
```

## 1.4 Sources of UCR data

There are a few different sources of UCR data available today. First, and probably most commonly used, is the data put together by the [National Archive of Criminal Justice Data \(NACJD\)](#). This a team of out of the University of Michigan who manages a huge number of criminal justice datasets and makes them available to the public. If you have any questions about crime data - UCR or other data - I highly recommend you reach out to them for answers. They have a collection of data and excellent documentation available for UCR data available on their site [here](#). One limitation to their data, however, is that each year of data is available as an individual file meaning that you'll need to concatenate each year together into a single file. Some years also have different column names (generally minor changes like spelling robbery "rob" one year and "robb" the next) which requires more work to standardize before you could concatenate. They also only have data through 2016 which means that the most recent years (UCR data is available through 2019) of data are (as of this writing) unavailable.

Next, and most usable for the general public but limited to researchers, is the FBI's official website [Crime Data Explorer](#). On this site you can chose an agency and see annual crime data (remember, UCR data is monthly so this isn't as detailed as it can be) for certain crimes. This is okay for the general public but only provides a fraction of the data available in the actual data so is really not good for researchers.

Finally, I have my own collection of UCR data [<https://www.openicpsr.org/openicpsr/search/studies?start=0&ARCHIVE=openicpsr&sort=score%20desc%20CDATEUPDATED%20desc&rows=25&q=jacob%20kaplan%27s%20concatenated%20files>] (available publicly on openICPSR), a site which allows people to submit their data for public access. For each of these datasets I've taken the raw data from the FBI (for early years of homicide data this is actually from NACJD since the FBI's raw data is wrong and can't be parsed. For later years of homicide data this is from the FBI's raw data.) and read it into R. Since the data is only available from the FBI

as fixed-width ASCII files, I created a setup file (we'll explain exactly how reading in this kind of data works in the next chapter) and read the data and then very lightly cleaned the data (i.e. only removing extreme outliers like an agency having millions of arsons in a month). For each of these datasets I detail what I've done to the data and briefly summarize the data (i.e. a very short version of this book) on the data's page on openICPSR. The main advantage is that all my data has standard variable names and column names and, for data that is small enough, provide the data as a single file that has all years. For large datasets like the arrest data I break it down into parts of the data and not all years in a single file. The downside is that I don't provide documentation other than what's on the openICPSR page and only provide data in R and Stata format. I also have a similar site to the FBI's Crime Data Explorer but with more variables available, that site is available [here](#).

It's worth mentioning a final source of UCR information. This is the annual Crimes in the United States report released by the FBI each year around the start of October.<sup>1</sup> As an example, here is the [website for the 2019 report](#). In this report is summarized data which in most cases estimates missing data and provides information about national and subnational (though rarely city-level) crime data. As with the FBI's site it is only a fraction of the true data available so is not a very useful source of crime data. Still, this is a very common source of information used by researchers.

### 1.4.1 Where to find the data used in this book

The data I am using in this book is the cleaned (we'll discuss in more detail exactly what I did to clean each dataset in the dataset's chapter but the short answer is that I did very little.) and concatenated data that I put together from the raw data that the FBI releases. That data is available

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<sup>1</sup>They also release a report about the first 6-months of the most recent year of data before the October release but this is generally an estimate from a sample of agencies so is far less useful.

on my website <https://jacobdkaplan.com/data.html>. I am hosting this book through GitHub which has a maximum file size allowed that is far smaller than these data so you'll need to go to my site to download the data, it's not available through this book's GitHub repo. For some examples I'm using the data before I cleaned it of outliers (as an example of the outliers present before I removed them) so that data is not publicly available.



# About the Author

**Jacob Kaplan** holds a PhD and a master's degree in criminology from the University of Pennsylvania and a bachelor's degree in criminal justice from California State University, Sacramento. His research focuses on Crime Prevention Through Environmental Design (CPTED), specifically on the effect of outdoor lighting on crime. He is the author of several R packages that make it easier to work with data, including [fastDummies](#) and [asciiSetupReader](#). His [website](#) allows easy analysis of crime-related data and he has released over a [dozen crime data sets](#) (primarily FBI UCR data) on openICPSR that he has compiled, cleaned, and made available to the public.

For a list of papers he has written (including working papers), please see [here](#).

For a list of data sets he has cleaned, aggregated, and made public, please see [here](#).

For a list of R packages he has created, please see [here](#).



# Chapter 2

## Overview of the Data

One of the first, and most important, questions I think people have about crime is a simple one: is crime going up? Answering it seems simple - you just count up all the crimes that happen in an area and see if that number of bigger than it was in previous times.

However, putting this into practice invites a number of questions, all of which affect how we measure crime. First, we need to define what a crime is? Not philosophically what actions are crimes - or what should be crimes - but literally which of the many thousands of different criminal acts (crimes as defined by state law) should be considered in this measure. Should murder count? Most people would say yes. How about jaywalking or speeding? Many would say probably not. Should marital rape be considered a crime? Now, certainly most people (all, I would hope) would say yes. But in much of the United States it wasn't a crime until the 1970s ([Bennice and Resick, 2003](#); [McMahon-Howard et al., 2009](#)).

Next, we have to know what geographic and time unit to measure crimes at since these decisions determine how precise we can measure crime and when it changed. That is, if you are mugged on Jan 1st at exactly 12:15pm right outside your house, how do we record it? Should we be as precise as including the exact time and location (your home address or coordinates for

the address)? Out of privacy concerns to the victim, should we only include a larger time unit (such as hour of the day or just the day without any time of day) or a larger geographic unit (such as a Census Tract or the city)?

The final question is that when a crime occurs, how do we know? That is, when we want to count how many crimes occurred do we ask people how often they've been victimized, do we ask people how often they commit a crime, do we look at crimes reported to police, crimes charged in a criminal court? Each of these measures will likely give different answers as to how many crimes occurred.<sup>1</sup>

The FBI answered all of these questions in 1929 when they began the Uniform Crime Reporting (UCR) Program Data, or UCR data for short. **Crime consists of eight crime categories - murder, rape, robbery, aggravated assault, burglary, motor vehicle theft, theft, and simple assault - that are reported to the police and is collected each month from each agency in the country.** These decisions, born primarily out of the resource limitations of 1929 (e.g. no computers), have had a major impact on criminology research. The first seven crime categories - known as "Index Crimes" or "Part 1 crimes" (or "Part I" sometimes) - are the ones used to measure crime in many criminology papers, even when the researchers have access to data that covers a broader selection of crimes than these.<sup>2</sup> The crime data actually also includes the final crime, simple assault, though it is not included as an index crime and is, therefore, generally ignored by researchers - a relatively large flaw in most studies that we'll discuss in more detail in Section @ref(index\_crimes).

If you think that decisions made nearly a century ago are probably not the most useful for current research - and they're almost certainly not the decisions that you would have made - then you've struck at the core of this book.

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<sup>1</sup>The Bureau of Justice Statistics does measure crime by asking a random sample of people whether they were the victim of a crime. For more on this, please see their National Crime Victimization Survey reports

<sup>2</sup>Arson is also an index crime but was added after these initial seven were chosen and is not included in the crimes dataset (though is available separately) so is generally not included in studies that use index crimes.

As researchers, we are relying on datasets whose creation was made so long ago that

## 2.1 Crimes included in the UCR datasets

UCR data covers only a subset - and for the crime data, a very small subset - of all crimes that can occur. It also only includes crimes reported to the police. So there are two levels of abstraction from a crime occurring to it being included in the data: a crime must occur that is one of the crimes included in the UCR collection (we detail all of these crimes below) *and* the victim must report the incident to the police. While the crimes included are only a small selection of crimes - which were originally chosen since at the time the UCR was designed these were considered important offenses and among the best reported - this is an important first step to understanding the data. In this section we'll go over the crimes included in the two main UCR datasets: Offenses Known and Clearances by Arrest and (which I like to call the "crime" dataset) and the Arrests by Age, Sex, and Race (the "arrests" dataset). These are the most commonly used UCR datasets and the stolen property and homicide datasets are simply more detailed subsets of these datasets. The hate crime dataset can cover a broader selection of offenses than in the crimes or arrests data, so we'll discuss those in the hate crimes chapter.

### 2.1.1 Crimes in the Offenses Known and Clearances by Arrest dataset

As mentioned above - and as most criminology papers will tell you - the crimes included in the UCR's Offenses Known and Clearances by Arrest data are the seven index crimes (eight when including arson, though arson is in its own dataset) - homicide, rape, robbery, aggravated assault, burglary, theft, and motor vehicle theft - as well as simple assault. This is true but

incomplete. The data also includes subcategories for all crimes other than theft - though theft has its own UCR dataset which goes into detail about the thefts. Both robbery and aggravated assault, for example, have subcategories showing which weapon the offender used (if any) during the crime. This allows for a more detailed understanding of the crime than looking only at the broad category. I'm not sure why most research includes only the broader categories and doesn't tend to look at subcategories, but that seems to be the case in most studies that I have read. Some police agencies only report the broader categories and don't report subcategories, but most report subcategories so this is an under-exploited source of data.

1. Homicide

- Murder and non-negligent manslaughter
- Manslaughter by negligence

2. Rape

- Rape
- Attempted rape

3. Robbery

- With a firearm

- With a knife of cutting instrument
- With a dangerous weapon not otherwise specified
- Unarmed - using hands, fists, feet, etc.

4. Aggravated assault (assault with a weapon or causing serious bodily injury)

- With a firearm
- With a knife of cutting instrument
- With a dangerous weapon not otherwise specified
- Unarmed - using hands, fists, feet, etc.

5. Burglary

- With forcible entry
- Without forcible entry
- Attempted burglary with forcible entry

6. Theft (other than of a motor vehicle)

## 7. Motor vehicle theft

- Cars
- Trucks and buses
- Other vehicles

## 8. Simple Assault

### **2.1.2 Crimes in the Arrests by Age, Sex, and Race dataset**

The crimes included in the Arrests by Age, Sex, and Race - the “arrest” data tells you how many people were arrested for a particular crime category - are different than those in the crime data. The arrest data covers a wider variety of crimes, including drug and alcohol crimes, gambling, and fraud. However, it is also less detailed than the crime dataset when it comes to violent crime. While it covers the same broad categories of violent crimes as the crimes data - murder, rape, robbery, aggravated assault, and simple assault - it doesn’t include the more detailed breakdown that is available in the crime data. For example, in the crime data robbery is included as well as the subcategories of robbery with a gun, robbery with a knife, robbery with another dangerous weapon, and robbery without a weapon. In comparison, the arrest data only includes robbery without any subcategories.

## 1. Homicide

- Murder and non-negligent manslaughter
- Manslaughter by negligence



2. Rape
3. Robbery
4. Aggravated assault
5. Burglary
6. Theft (other than of a motor vehicle)
7. Motor vehicle theft
8. Simple assault
9. Arson
10. Forgery and counterfeiting
11. Fraud
12. Embezzlement
13. Stolen property - buying, receiving, and possessing
14. Vandalism
15. Weapons offenses - carrying, possessing, etc.
16. Prostitution and commercialized vice
17. Sex offenses - other than rape or prostitution
18. Drug abuse violations - total
  - Drug sale or manufacturing
    - Opium and cocaine, and their derivatives (including morphine and heroin)
    - Marijuana
    - Synthetic narcotics
    - Other dangerous non-narcotic drugs
  - Drug possession
    - Opium and cocaine, and their derivatives (including morphine and heroin)
    - Marijuana
    - Synthetic narcotics
    - Other dangerous non-narcotic drugs
19. Gambling - total

- Bookmaking - horse and sports
  - Number and lottery
  - All other gambling
20. Offenses against family and children - nonviolent acts against family members. Includes neglect or abuse, nonpayment of child support or alimony.
  21. Driving under the influence (DUI)
  22. Liquor law violations - Includes illegal production, possession (e.g. underage) or sale of alcohol, open container, or public use laws. Does not include DUIs and drunkenness.
  23. Drunkenness - i.e. public intoxication
  24. Disorderly conduct
  25. Vagrancy - includes begging, loitering (for adults only), homelessness, and being a “suspicious person.”
  26. All other offenses (other than traffic) - a catch-all category for any arrest that is not otherwise specified in this list. Does not include traffic offenses. Very wide variety of crimes are included - use caution when using!
  27. Suspicion - “Arrested for no specific offense and released without formal charges being placed.”
  28. Curfew and loitering law violations - for minors only.
  29. Runaways - for minors only.

### 2.1.3 What is an index (or part 1) crime?

One of the first (and seemingly last) thing that people tend to learn about UCR crime data is that it covers something called an “index crime.”<sup>3</sup> Index crimes, sometimes written as Part 1 or Part I crimes, are the seven crimes originally chosen by the FBI to be included in their measure of crimes as

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<sup>3</sup>Index crimes are sometimes capitalized as “Index Crimes” though I’ve seen it written both ways. In this book I keep it lowercase as “index crimes.”

these offenses were both considered serious and generally well-reported so would be a useful measure of crime. Index crimes are often broken down into property index crimes - burglary, theft, and motor vehicle theft (and arson now, though that's often not included and is poorly reported) - and violent index crimes (murder, rape, robbery, and aggravated assault). The "index" is simply that all of the crimes are summed up into a total count of crimes (violent, property, or total) for that police agency.

The biggest problem with index crimes is that it is simply the sum of 8 (or 7 since arson data usually isn't available) crimes. Index crimes have a huge range in their seriousness - it includes, for example, both murder and theft - so summing up the crimes gives each crime equal weight. This is clearly wrong as 100 murders is more serious than 100 thefts. This is especially a problem as less serious crimes (theft mostly) are far more common than more serious crimes. In 2017, for example, there were 1.25 million violent index crimes in the United States. That same year had 5.5 million thefts. So using index crimes as your measure of crimes undercounts the seriousness of crimes. Looking at total index crimes is, in effect, mostly just looking at theft. Looking at violent index crimes mostly measures aggravated assault. This is especially a problem because it hides trends in violent crimes. San Francisco, as shown in Figure 2.1, has had a huge increase in index crimes in the last several years. When looking closer, that increase is driven almost entirely by the near doubling of theft since 2011. During the same years, index violent crimes have stayed fairly steady. So the city isn't getting more dangerous - at least not in terms of violent index crimes increasing - but it appears like it is due to just looking at total index crimes.

While many researchers divide index crimes into violent and nonviolent categories, which helps but even this isn't entirely sufficient. Take Chicago as an example. It is a city infamous for its large number of murders. But as a fraction of index crimes, Chicago has a rounding error worth of murders. Their 653 murders in 2017 is only 0.5% of total index crimes. For violent index crimes, murder makes up 2.2%. As seen in Figure 2.2, in no year where data is available did murders account for more than 3.5% of violent index

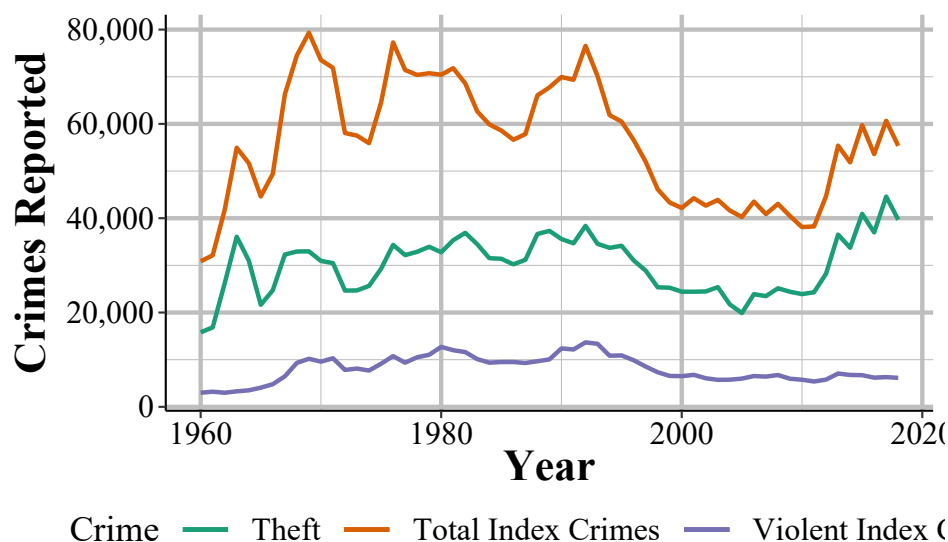


Figure 2.1: Thefts and total index crimes in San Francisco, 1960-2018.

crimes; and, while murders are increasing as a percent of violent index crimes they still account for no more than 2.5% in most years. What this means is that changes in murder are very difficult to detect. If Chicago had no murders this year, but a less serious crime (such as theft) increased slightly, we couldn't tell from looking at the number of index crimes, even from violent index crimes. As discussed in the below section, using this sample of crimes as the primary measure of crimes - and particularly of violent crimes - is also misleading as it excludes important - and highly common relative to index crimes - offenses, such as simple assault.

### 2.1.3.1 What is a violent crime?

An important consideration in using this data is defining what a “violent crime” is. One definition, and the one that I think makes the most sense, is that a violent crime is one that uses force or the threat of force. For example, if I punch you in the face, that is a violent crime. If I stab you, that is a violent crime. While clearly different in terms of severity, both incidents used

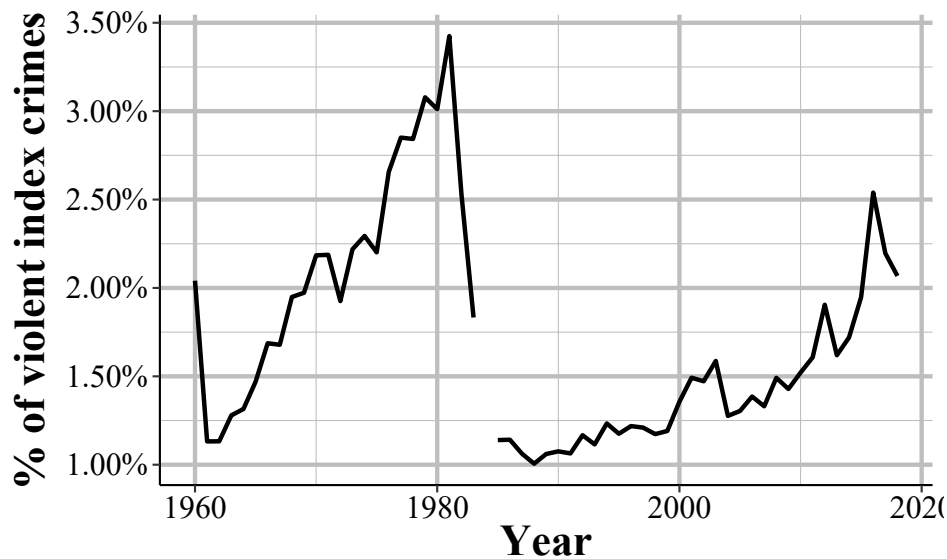


Figure 2.2: Murders in Chicago as a percent of violent index crimes, 1960-2018.

force so I believe would be classified as a violent crime. The FBI, and most researchers, reporters, and advocates would disagree. Organizations ranging from the [FBI itself](#) to [Pew Research Center](#) and advocacy groups like the [Vera Institute of Justice](#) and the [ACLU](#) all define the first examine as a non-violent crime and the second as a violent crime. They do this for three main reasons.

The first reason is that simple assault is not an index crime, so they don't include it when measuring violent crime. It is almost a tautology in criminology that you use index crimes as the measure of crime since that's just what people do. As far as I'm aware, this is really the main reason why researchers justify using index crimes: because people in the past used it so that's just what is done now.<sup>4</sup> This strikes me as a particularly awful way of doing anything, more so since simple assault data has been available almost

<sup>4</sup>I've also seen the justification that aggravated assault is more serious since it uses a weapon, though as the UCR subcategory of aggravated assault without a weapon clearly shows, aggravated assault does not require use of a weapon.

as long as index crime data.<sup>5</sup>

The second reason - and one that I think makes sense for reporters and advocates who are less familiar with the data, but should be unacceptable to researchers - is that people don't know that simple assault is included, or at least don't have easy access to it. Neither the FBI's annual report [page](#) nor their official [crime data tool website](#) include simple assault since they only include index crimes. For people who rely only on these sources - and given that using the data itself requires at least some programming skills, I think this accounts for most users and certainly nearly all non-researchers - it is not possible to access simple assault crime data (arrest data does include simple assault on these sites).

The final reason is that it benefits some people's goals to classify violent crime as only including index crimes. This is because simple assault is extremely common compared to violent index crimes - in many cities simple assault is more common than all violent index crimes put together - so excluding simple assault makes it seem like fewer arrests are violent than they are when including simple assault. For example, a number of articles have noted that marijuana arrests are more common than violent crime arrests ([Ingraham, 2016](#); [Kertscher, 2019](#); [Devito, 2020](#); [Earlenbaugh, 2020](#); [Edwards et al., 2020](#)) or that violent crime arrests are only 5% of all arrests ([Neusteter and O'Toole, 2019](#); [Speri, 2019](#)).<sup>6</sup> While true when considering only violent index crimes, including simple assault as a violent crime makes these statements false. Some organizations call the violent index crimes "serious violent crimes" which is an improvement but even this is a misnomer since simple assault can lead to more serious harm than aggravated assault. An assault becomes aggravated if using a weapon or there is the *potential* for serious harm, even if no harm actually occurs.<sup>7</sup>

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<sup>5</sup>Simple assault is first available in 1964. Index crime data is available since 1960.

<sup>6</sup>The FBI's report for arrests does include simple assault so the second reason people may not include it does not apply here.

<sup>7</sup>UCR data provides no information about the harm caused to victims. The new FBI dataset NIBRS actually does have a variable that includes harm to the victim so if you're interested in measuring harm (an understudied topic in criminology), that is the dataset

As an example of this last point, 2.3 shows the number of violent index crimes and simple assaults each year from 1960 to 2018 in Houston, Texas (simple assault is not reported in UCR until 1964, which is why 1960-1963 show zero simple assaults). In every year where simple assault is reported, there are more simple assaults than aggravated assaults. Beginning in the late 1980s, there are also more simple assaults than total violent index crimes. Excluding simple assault from the being a violent crime greatly underestimates violence in the country.

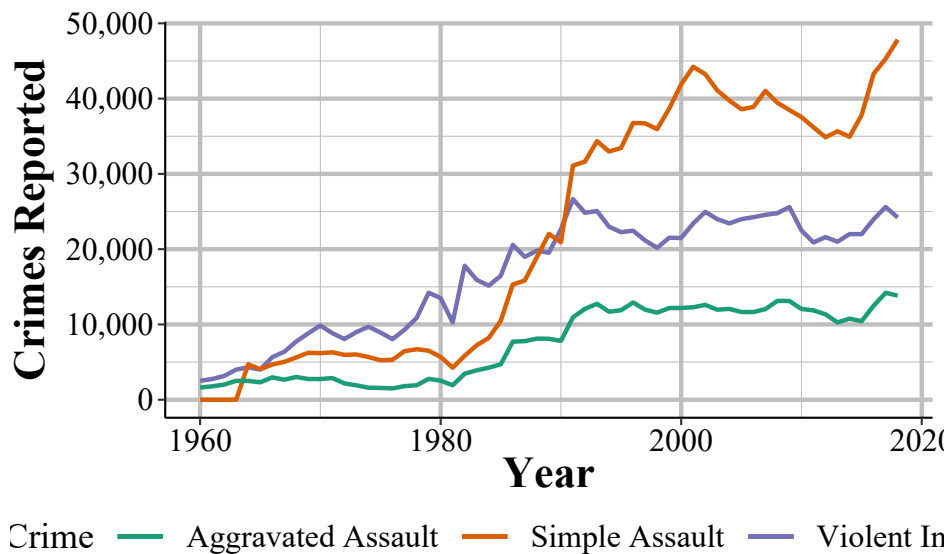


Figure 2.3: Reported crimes in Philadelphia from 1960 to 2018. Violent index crimes are aggravated assault, rape, robbery, and murder.

## 2.2 Issues common across UCR datasets

In this section we'll discuss issues common to most or all of the UCR datasets. For some of these, we'll come back to the issues in more detail in the chapter for the datasets most affected by the problem.

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to use.

### 2.2.1 Negative numbers

One of the most common questions people have about this data is why there are negative numbers, and if they are a mistake. Negative numbers are not a mistake. The UCR data is monthly so police agencies report the number of monthly crimes that are known to them, either reported to them or discovered by the police. In some cases the police will determine that a crime reported to them didn't actually occur - which they called an "unfounded crime." An example that the FBI gives for this is a person reports their wallet stolen (a theft) and then later finds it, so a crime was initially reported but no crime actually occurred.

How this works when the police input the data is that an unfounded crime is reported both as an unfounded crime and as a negative actual crime - the negative is used to zero out the erroneous report of the actual crime. So the report would look like 1 actual theft (the crime being reported), -1 theft (the crime being discovered as not have happened), and 1 unfounded theft. If both incidents occurred in the same month then this would simply be a single unfounded theft occurring, with no actual theft - literally a value of  $1 + -1 = 0$  thefts.

Negative values occur when the unfounding happens in a later month than the crime report. In the theft case, let's say the theft occurred in January and the discovery of the wallet happens in August. Assuming no other crimes occurred, January would have 1 theft, and August would have -1 thefts and 1 unfounded theft. There is no way of determining in which month (or even which year) an unfounded crime was initially reported in. When averaging over the long term, there shouldn't be any negative numbers as the actual and unfounded reports will cancel themselves out. However, when looking at monthly crimes - particularly for rare crimes - you'll still see negative numbers for this reason. Since crimes can be unfounded for reports in previous years, you can actually see entire year's crime counts be negative, though this is much rarer than monthly values.<sup>8</sup>

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<sup>8</sup>From 1960-2018, there were 39 agency-years with a negative count of murders.



### 2.2.2 Agency population value

Each of the UCR datasets include a population variable that has the estimated population under the jurisdiction of that agency.<sup>9</sup> This variable is often used to create crime rates that control for population. In cases where jurisdiction overlaps, such as when a city has university police agencies or county sheriff's in counties where the cities in that county have their own police, UCR data assigns the population covered to the most local agency and zero population to the overlapping agency. So an agency's population is the number of people in that jurisdiction that isn't already covered by a different agency.

For example, in the city of Los Angeles in California has nearly four million residents according to the US Census. There are multiple police agencies in the city, including the Los Angeles Police Department, the Los Angeles County Sheriff's Office, the California Highway Patrol that operates in the area, airport and port police, and university police departments. If each agency reported the number of people in their jurisdiction - which all overlap with each other - we would end up with a population far higher than LA's four million people. To prevent double-counting population when agency's jurisdictions overlap, the non-primary agency will report a population of 0, even though they still report crime data like normal. As an example, in 2018 California State University - Los Angeles reported 92 thefts and a population of 0. Those 92 thefts are not counted in the Los Angeles Police Department data, even though the department counts the population. To get complete crime counts in Los Angeles, you'd need to add up all police agencies within in the city; since the population value is 0 for non-LAPD agencies, both the population and the crime sum will be correct.

The UCR uses this method even when only parts of a jurisdiction overlaps. Los Angeles County Sheriff has a population of about one million people, far

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<sup>9</sup>Jurisdiction here refers to the boundaries of the local government, not any legal authority for where the officer can make arrests. For example, the Los Angeles Police Department's jurisdiction in this case refers to crimes that happen inside the city or are otherwise investigated by the LAPD - and are not primarily investigated by another agency.

less than the actual county population (the number of residents, according to the Census) of about 10 million people. This is because the other nine million people are accounted for by other agencies, mainly the local police agencies in the cities that make up Los Angeles County.

The population value is the population who reside in that jurisdiction, and does not count people who are in the area but don't live there, such as tourists or people who commute there for work. This means that using the population value to determine a rate can be misleading as some places have much higher numbers of non-residents in the area (e.g. Las Vegas, Washington D.C.) than others.

### **2.2.3 Reporting is voluntary ... so some agencies don't (or report partially)**

When an agency reports their data to the FBI, they do so voluntarily - there is no nationally requirement to report.<sup>10</sup> This means that there is inconsistency in which agencies report, how many months of the year they report for, and which variables they include in their data submissions. This can lead

In general, more agencies report their data every year and once an agency begins reporting data they tend to keep reporting. The UCR datasets are a collection of separate, though related, datasets and an agency can report to as many of these datasets as they want - an agency that reports to one dataset does not mean that they report to other datasets. Figure 2.4 shows the number of agencies that submitted at least one month of data to the Offenses Known and Clearances by Arrest data in the given year. For the first decade of available data under 8,000 agencies reported data and this grew to over 13,500 by the late 1970s before plateauing for about a decade. The number of agencies that reported their data actually declined in the 1990s, driven primarily by many Florida agencies temporarily dropping out, before growing steadily to nearly 17,000 agencies in 2010; from here it kept

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<sup>10</sup>Some states do mandate that their agencies report, but this is not always followed.

increasing but slower than before.

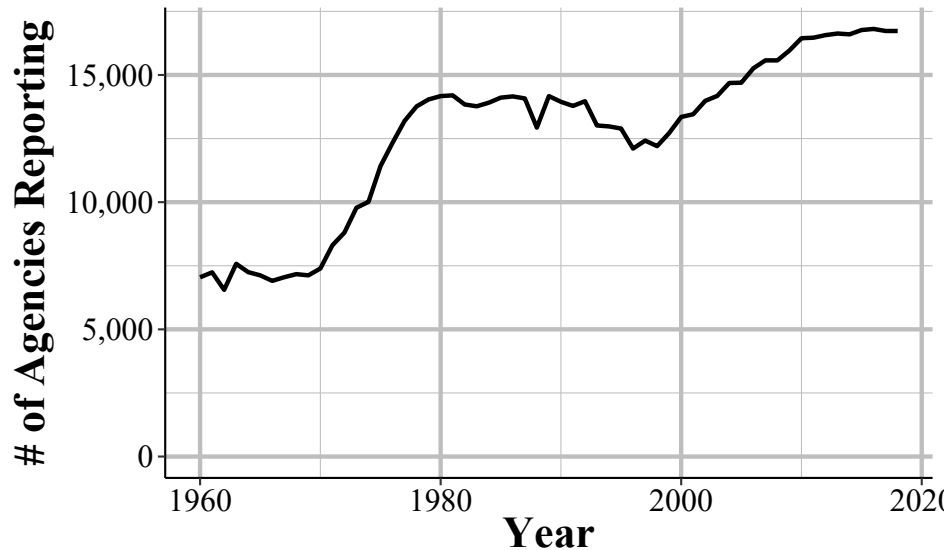


Figure 2.4: The annual number of agencies reporting to the Offenses Known and Clearances by Arrest dataset. Reporting is based on the agency reporting at least one month of data in that year.

There are approximately 18,000 police agencies in the United States so recent data has reports from nearly all agencies, while older data has far fewer agencies reporting. When trying to estimate to larger geographies, such as state or national-level, later years will be more accurate as you're missing less data. For earlier data, however, you're dealing with a smaller share of agencies meaning that you have a large amount of missing data and a less representative sample.

Figure 2.5 repeats this figure but now including only agencies with 100,000 people or more in their jurisdiction. While these agencies have a far more linear trend than all agencies, the basic lesson is the same: recent data has most agencies reporting; old data excludes many agencies.

This voluntariness extends beyond whether they report or not, but into which variables they report. While in practice most agencies report every crime

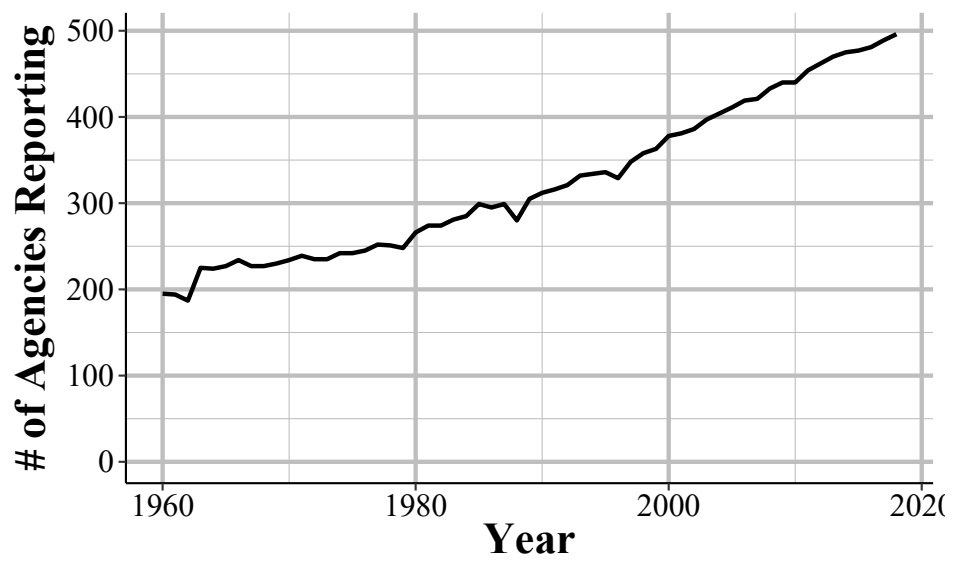


Figure 2.5: The annual number of agencies with a population of 100,000 or higher reporting to the Offenses Known and Clearances by Arrest dataset. Reporting is based on the agency reporting at least one month of data in that year.

when they report any, they do have the choice to report only a subset of offenses. This is especially true for subsets of larger categories - such as gun assaults, a subset of aggravated assaults, or marijuana possession which is a subset of drug possession. As an example, Figure 2.6 shows the annual number of aggravated assaults with a gun in New York City. In 2003 the New York Police Department stopped reporting this category of offense, resuming only in 2013. They continued to report the broader aggravated assault category, but not any of the subsections of aggravated assaults which differentiate the weapon used.

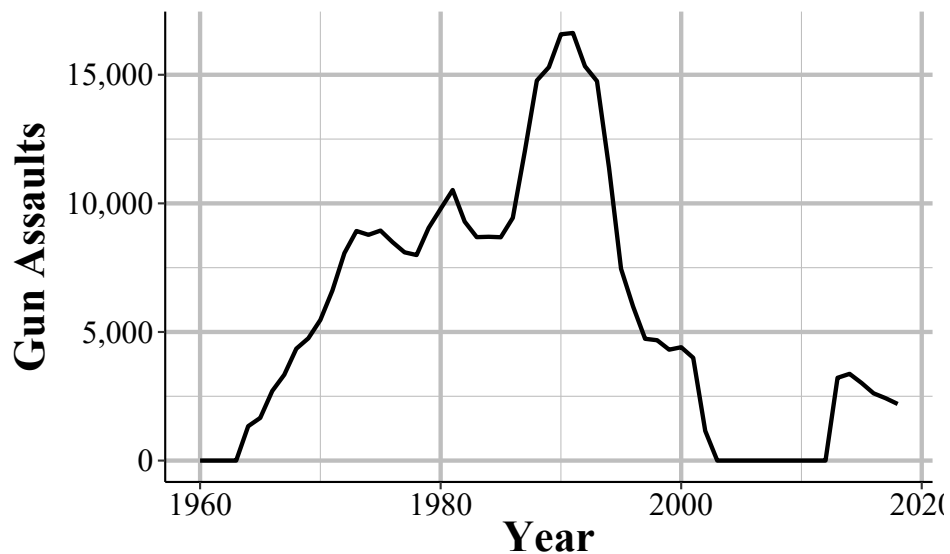


Figure 2.6: Monthly reports of gun assaults in New York City, 1960-2018.

Given that agencies can join or drop out of the UCR program at will, and report only partial data, it is highly important to carefully examine your data to make sure that there are no issues caused by this.

Even when an agency reports UCR data, and even when they report every crime category, they can report fewer than 12 months of data. In some cases they simply report all of their data in December, or report quarterly or semi-annually so some months have zero crimes reported while others count

multiple months in that month's data. One example of this is New York City, shown in Figure 2.7, in the early-2000s to the mid-2010s where they began reporting data quarterly instead of monthly.

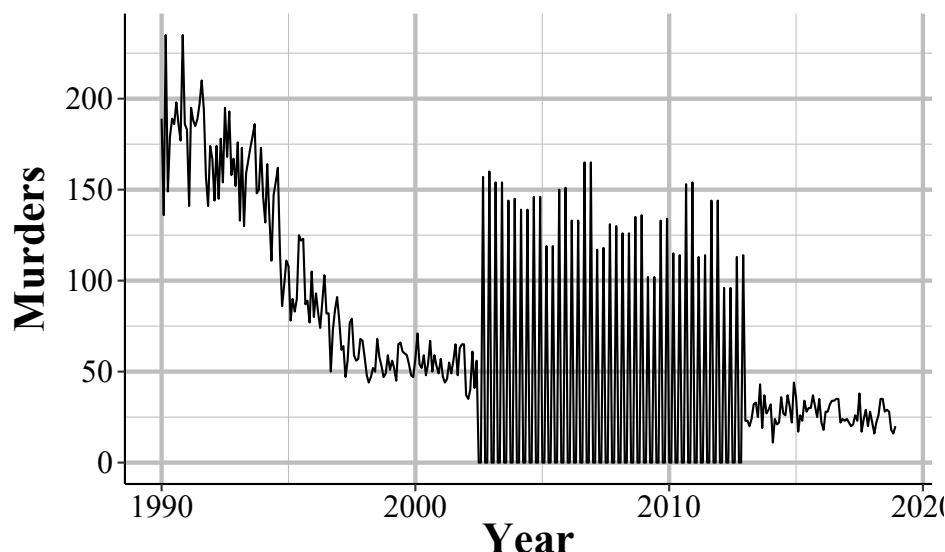


Figure 2.7: Monthly murders in New York City, 1990-2018. During the 2000s, the police department began reporting quarterly instead of monthly and then resumed monthly reporting.

When you sum up each month into an annual count, as shown in Figure 2.8, the problem disappears since the zero months are accounted for in the months that have the quarterly data. If you're using monthly data and only examine the data at the annual level, you'll fall into the trap of having incorrect data that is hidden due to the level of aggregation examined. While cases like NYC are obvious when viewed monthly, for people that are including thousands of agencies in their data, it is unfeasible to look at each agency for each crime included. This can introduce errors as the best way to examine the data is manually viewing graphs and the automated method, looking for outliers through some kind of comparison to expected values, can be incorrect.

In other cases when agencies report fewer than 12 months of the year, they simply report partial data and as a result undercount crimes. Figure 2.9

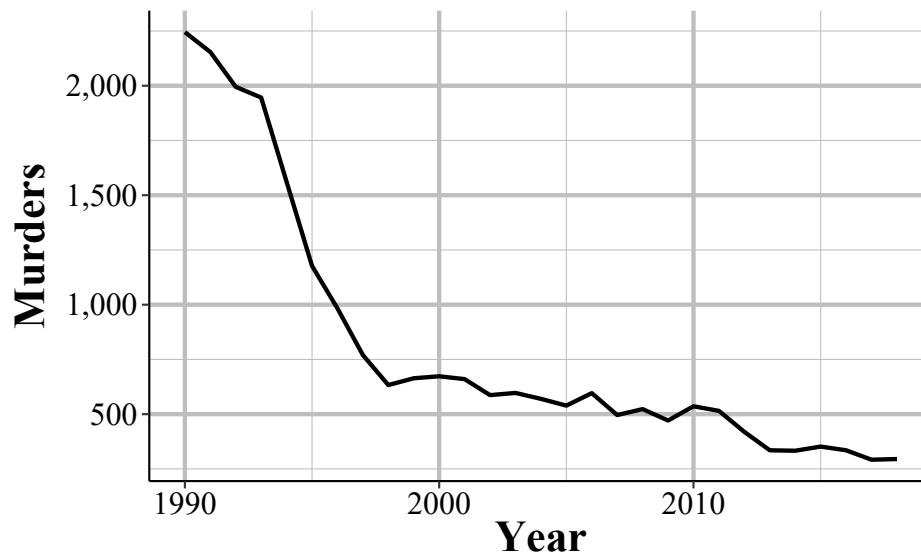


Figure 2.8: Annual murders in New York City, 1990-2018.

shows annual murders in Miami-Dade, Florida and has three years of this issue occurring. The first two years with this issue are the two where zero murders are reported - this is because the agency didn't report any months of data. The final year is in 2018, the last year of data in this graph, where it looks like murder suddenly dropped significantly. That's just because Miami-Dade only reported through June, so they're missing half of 2018.

#### 2.2.4 Zero crimes vs no reports

When an agency does not report, we see it in the data as reporting zero crimes, not reporting NA or any indicator that they did not report. In cases where the agency says they didn't report that month we can be fairly sure (not entirely since that variable isn't always accurate) that the zero crimes reported are simply that the agency didn't report. In cases where the agency says they report that month but report zero crimes, we can't be sure if that's a true no crimes reported to the agency or the agency not reporting to the UCR. As agencies can report some crimes but not others in a given month and

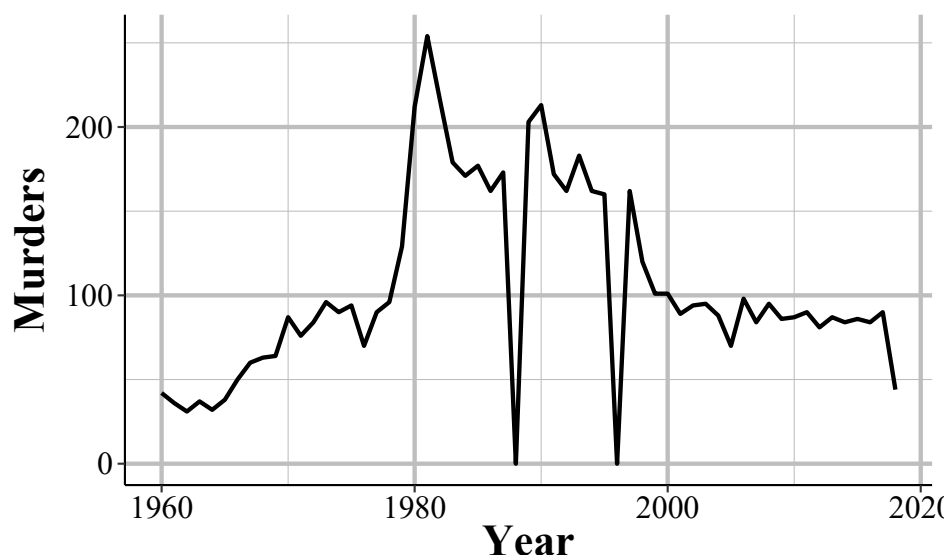


Figure 2.9: Annual murders in Miami-Dade, Florida, 1960-2018.

still be considered reporting that month, just saying they reported doesn't mean that the zero is a true zero.

In some cases it is easy to see when a zero crimes reported is actually the agency not reporting. As Figure 2.6 shows with New York City gun assaults, there is a massive and sustained dropoff to zero crimes and then a sudden return years later. Obviously, going from hundreds of crimes to zero crimes is not a matter of crimes not occurring anymore, it is a matter of the agency not reporting - and New York City did report other crimes these years so in the data it says that they reported every month. So in agencies which tend to report many crimes - and many here can be a few as 10 a year since going from 10 to 0 is a big drop - a sudden report of zero crimes is probably just non-reporting.

Differentiating zero crimes and no reports becomes tricky in agencies that tend to report few crimes, which most small towns do. As an example, Figure 2.10 shows the annual reports of rape in Danville, California, a city of approximately 45,000 people. The city reports on average 2.8 rapes per year



and in five years reported zero rapes. In cases like this it's not clear whether we should consider those zero years as true zeros (that no one reported their rape to the police) or whether the agency simply didn't report rape data that year.

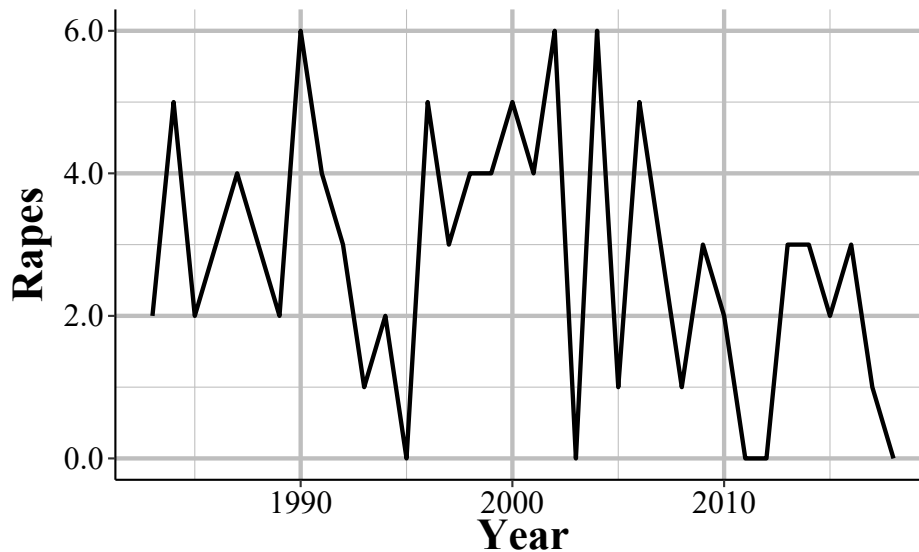


Figure 2.10: Annual rapes reported in Danville, CA, 1960-2018.

## 2.3 A summary of each UCR dataset

UCR data can be roughly summarized into two groups: crime data and arrest data. While there are several datasets included in the UCR data collection, they are all extensions of one of the above groups. For arrest data, you have information about who (by race and by age-gender, but not by race-gender or race-age other than within race you know if the arrestee is an adult or a juvenile). For crime data, you have monthly counts of a small number of crimes (many fewer than crimes covered in the arrest data) and then more specialized data on a subset of these crimes - information on homicides, hate crimes, assaults or deaths of police officers, and stolen property.

Each of these datasets will have its own chapter in this book where we discuss the data thoroughly. Here is a very brief summary of each dataset which will help you know which one to use for your research. I still recommend reading that data's chapter since it covers important caveats and uses (or misuses) of the data that won't be covered below.

### **2.3.1 Offenses Known and Clearances by Arrest**

The Offenses Known and Clearances by Arrest dataset - often called Return A, "Offenses Known" or, less commonly, OKCA - is the oldest and most commonly used dataset and measures crimes reported to the police. For this reason it is used as the main measure of crime in the United States and I tend to call it the "crimes dataset." This data includes the monthly number of crimes reported to the police or otherwise known to the police (e.g. discovered while on patrol) for a small selection of crimes, as well as the number of crimes cleared by arrest or by "exceptional means" (a relatively flawed and manipulable measure of whether the case is "solved"). It also covers the number reported but found by police to have not occurred. Since this data has monthly agency-level crime information it is often used to measure crime trends between police agencies and over time. The data uses something called a Hierarchy Rule which means that in incidents with multiple crimes, only the most serious is recorded - though in practice this affects only a small percent of cases, and primarily affects property crimes.

### **2.3.2 Arrests by Age, Sex, and Race**

The Arrests by Age, Sex, and Race dataset - often called ASR or the "arrests data" - includes the monthly number of arrests for a variety of crimes and, unlike the crime data, breaks down this data by age and gender. This data includes a broader number of crime categories than the crime dataset (the Offenses Known and Clearances by Arrest data) though is less detailed on violent crimes since it does not breakdown aggravated assault or robberies

by weapon type as the Offenses Known data does. For each crime it says the number of arrests for each gender-age group with younger ages (15-24) showing the arrestee's age to the year (e.g. age 16) and other ages grouping years together (e.g. age 25-29, 30-34, "under 10"). It also breaks down arrests by race-age by including the number of arrestees of each race (American Indian, Asian, Black, and White) are the only included races) and if the arrestee is a juvenile (<18 years old) or an adult. The data does technically include a breakdown by ethnicity-age (e.g. juvenile-Hispanic, juvenile-non-Hispanic) but almost no agencies report this data (for many years zero agencies report ethnicity) so in practice the data does not include ethnicity. As the data includes counts of arrestees, people who are arrested multiple times are included in the data multiple times - it is not a measure of unique arrestees.

### 2.3.3 Law Enforcement Officers Killed and Assaulted (LEOKA)

The Law Enforcement Officers Killed and Assaulted data, often called just by its acronym LEOKA, has two main purposes.<sup>11</sup> First, it provides counts of employees employed by each agency - broken down by if they are civilian employees or sworn officers, and also broken down by gender. And second, it measures how many officers were assaulted or killed (including officers who die accidentally such as in a car crash) in a given month. The assault data is also broken down into shift type and type (e.g. alone, with a partner, on foot, in a car, etc.), the offender's weapon, and type of call they are responding to (e.g. robbery, disturbance, traffic stop). The killed data simply says how many officers are killed feloniously (i.e. murdered) or died accidentally (e.g. car crash) in a given month. The employee information is at the year-level so you know, for example, how many male police officers were employed in a given year at an agency, but don't know any more than that such as how many officers were on patrol, were detectives, were in special units, etc. This dataset is commonly used as a measure of police employees and is a gener-

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<sup>11</sup>This data is also sometimes called the "Police Employees" dataset.

ally reliable - though imperfect as we'll see - measure of how many police are employed by a police agency. The second part of this data, measuring assaults and deaths, is more flawed with missing data issues and data error issues (e.g. more officers killed than employed in an agency).

### 2.3.4 Supplementary Homicide Reports (SHR)

The Supplementary Homicide Reports dataset - often abbreviated to SHR - is the most detailed of the UCR datasets and provides information about the circumstances and participants (victim and offender demographics and relationship status) for homicides.<sup>12</sup> For each homicide incident it tells you the age, gender, race, and ethnicity of each victim and offender as well as the relationship between the first victim and each of the offenders (but not the other victims in cases where there are multiple victims). It also tells you the weapon used by each offender and the circumstance of the killing, such as a "lovers triangle" or a gang-related murder. As with other UCR data, it also tells you the agency it occurred in and the month and year when the crime happened.

### 2.3.5 Hate Crime Data

This dataset covers crimes that are reported to the police and judged by the police to be motivated by hate. More specifically, they are, first, crimes which were, second, motivated - at least in part - by bias towards a certain person or group of people because of characteristics about them such as race, sexual orientation, or religion. The first part is key, they must be crimes - and really must be the selection of crimes that the FBI collects for this dataset. Biased actions that don't meet the standard of a crime, or are of a crime not included in this data, are not considered hate crimes. For example, if someone yells at

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<sup>12</sup>If you're familiar with the National Incident-Based Reporting System (NIBRS) data that is replacing UCR, this dataset is the closest UCR data to it, though it is still less detailed than NIBRS data.

a Black person and uses racial slurs against them, it is clearly a racist action. For it to be included in this data, however, it would have to extend to a threat since “intimidation” is a crime included in this data but lesser actions such as simply insulting someone is not included. For the second part, the bias motivation, it must be against a group that the FBI includes in this data. When this data collection began crimes against transgender people were not counted so if a transgender person was assaulted or killed because they were transgender, this is not a hate crime recorded in the data.<sup>13</sup>

So this data is really a narrower measure of hate crimes than it might seem. In practice it is (some) crimes motivated by (some) kinds of hate that are reported to the police. It is also the most under-reported UCR dataset with most agencies not reporting any hate crimes to the FBI. This leads to huge gaps in the data with some states having extremely few agencies reporting crime - see, for example Figure 2.11 for state-level hate crimes in 2018 - agencies reporting some bias motivations but not others, agencies reporting some years but not others. While these problems exist for all of the UCR datasets, it is most severe in this data. This problem is exacerbated by hate crimes being rare even in agencies that report them - with such rare events, even minor changes in which agencies report or which types of offenses they include can have large effects.

### 2.3.6 Property Stolen and Recovered (Supplement to Return A)

The Property Stolen and Recovered data - sometimes called the Supplement to Return A (Return A being another name for the Offenses Known and Clearances by Arrest dataset, the “crime” dataset) - provides monthly information about property-related offenses (theft, motor vehicle theft, robbery, and burglary), including the location of the offense (in broad categories like “gas station” or “residence), what was stolen (e.g. clothing, livestock,

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<sup>13</sup>The first year where transgender as a group was a considered a bias motivation was in 2013.

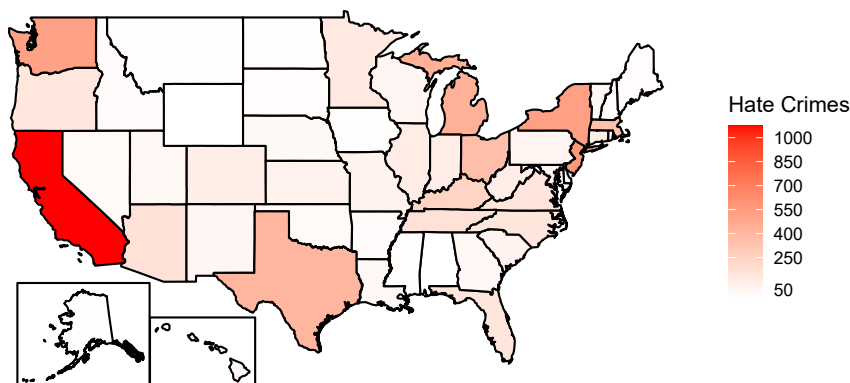


Figure 2.11: Total reported hate crimes by state, 2018.

firearms), and how much the stolen items were worth.<sup>14</sup> The “recovered” part of this dataset covers the type and value of property recovered so you can use this, along with the type and value of property stolen, to determine what percent and type of items the police managed to recover. Like other UCR datasets this is at the agency-month level so you can, for example, learn how often burglaries occur at the victim’s home during the day, and if that rate changes over the year or differs across agencies. The data, however, provides no information about the offender or the victim (other than if the victim was an individual or a commercial business [based on the location of the incident - “bank”, “gas station”, etc]). The value of the property stolen is primarily based on the victim’s estimate of how much the item is worth (items that are decreased in value once used - such as cars - are supposed to be valued at the current market rate, but the data provides no indication of when it uses the current market rate or the victim’s estimate) so it should be used as a very rough estimate of value.

<sup>14</sup>It also includes the value of items stolen during rapes and murders, if anything was stolen.

### 2.3.7 Arson

The arson dataset provides monthly counts at the police agency-level for arsons that occur, and includes a breakdown of arsons by the type of arson (e.g. arson of a person's home, arson of a vehicle, arson of a community/public building) and the estimated value of the damage caused by the arson. This data includes all arsons reported to the police or otherwise known to the police (e.g. discovered while on patrol) and also has a count of arsons that lead to an arrest (of at least one person who committed the arson) and reports that turned out to not be arsons (such as if an investigation found that the fire was started accidentally). For each type of arson it includes the number of arsons where the structure was uninhabited or otherwise not in use, so you can estimate the percent of arsons of buildings which had the potential to harm people. This measure is for structures where people normally did not inhabit the structure - such as a vacant building where no one lives. A home where no one is home *at the time of the arson* does not count as an uninhabited building. In cases where the arson led to a death, that death would be recorded as a murder on the Offenses Known and Clearances by Arrest dataset - but not indicated anywhere on this dataset. If an individual who responds to the arson dies because of it, such as a police officer or a firefighter, this is not considered a homicide (though the officer death is still included in the Law Enforcement Officers Killed and Assaulted data) unless the arsonists intended to cause their deaths. Even though the UCR uses the Hierarchy Rule, where only the most serious offense that occurs is recorded, all arsons are reported - arson is exempt from the Hierarchy Rule.

## 2.4 How to identify a particular agency (ORI codes)

In the UCR and other FBI data sets, agencies are identified using **OR**iginating Agency **I**dentifiers or an ORI. An ORI is a unique ID code

used to identify an agency.<sup>15</sup> If we used the agency's name we'd end up with some duplicates since there can be multiple agencies in the country (and in a state, those this is very rare) with the same name. For example, if you looked for the Philadelphia Police Department using the agency name, you'd find both the "Philadelphia Police Department" in Pennsylvania and the one in Mississippi. Each ORI is a 7-digit value starting with the state abbreviation (for some reason the FBI incorrectly puts the abbreviation for Nebraska as NB instead of NE) followed by 5 numbers.<sup>16</sup> When dealing with specific agencies, make sure to use the ORI rather than the agency name to avoid any mistakes. In this book when discussing a particular agency I'll generally refer to it both by name and by ORI, but in the code used to generate figures and tables I identify that agency through their ORI code.<sup>17</sup>

For an easy way to find the ORI number of an agency, use [this page](#) on my site. Type an agency name or an ORI code into the search section and it will return everything that is a match.

## 2.5 The data as you get it from the FBI

We'll finish this overview of the UCR data by briefly talking about format of the data that is released by the FBI, before the processing done by myself or [NACJD](#) that converts the data to a type that software like R or Stata or Excel can understand. The FBI releases their data as fixed-width ASCII files which are basically just an Excel file but with all of the columns squished together. As an example, below is the data as you receive it from the FBI for the Offenses Known and Clearances by Arrest dataset for 1960, the first year with data available. In the figure, it seems like there are multiple rows but that's just because the software that I opened the file in isn't wide enough -

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<sup>15</sup>I will refer to this as an "ORI", "ORI code", and "ORI number", all of which mean the same thing.

<sup>16</sup>In the NIBRS data (another FBI data set) the ORI uses a 9-digit code - expanding the 5 numbers to 7 numbers.

<sup>17</sup>Since this isn't a programming book I won't include the code.



[illegible]

The “fixed-width” part of the file type is how this works (the ASCII part basically means it’s a text file). Each row is the same width - literally the same number of characters, including blank spaces. So you must tell the software you are using to process this file - by literally write code in something

called a “setup file” but is basically just instructions for whatever software you use (R, SPSS, Stata, SAS can all do this) - which characters are certain columns. For example, in this data the first character says which type of UCR data it is (1 means the Offenses Known and Clearances by Arrest data) and the next two characters (in the setup file written as 2-3 since it is characters 2 through 3 [inclusive]) are the state number (01 is the state code for Alabama). So we can read this row as the first column indicating it is an Offenses Known data, the second column indicating that it is for the state of Alabama, and so on for each of the remaining columns. To read in this data you’ll need a setup file that covers every column in the data (some software, like R, can handle just reading in the specific columns you want and don’t need to include every column in the setup file).

The second important thing to know about reading in a fixed-width ASCII file is something called a “value label.”<sup>18</sup> For example, in the above image we saw the characters 2-3 is the state and in the row we have the value “01” which means that the state is “Alabama.” Since this type of data is trying to be as small as efficient as possible, it often replaces longer values with shorter one and provides a translation for the software to use to convert it to the proper value when reading it. “Alabama” is more characters than “01” so it saves space to say “01” and just replace that with “Alabama” later on. So “01” would be the ‘value’ and “Alabama” would be the ‘label’ that it changes to once read.

Fixed-width ASCII files may seem awful to you reading it today, and it is awful to use. But it appears to be an efficient way to store data back many decades ago when data releases began but now is extremely inefficient - in terms of speed, file size, ease of use - compared to modern software so I’m not sure why they *still* release data in this format. But they do, and even the more *modern* (if starting in 1991, before I was born, is modern!) NIBRS data comes in this format. For you, however, the important part to understand is

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<sup>18</sup>For most fixed-width ASCII files there are also missing values where it’ll have placeholder value such as -8 and the setup file will instruct the software to convert that to NA. UCR data, however, does not have this and does not indicate when values are missing in this manner.

not how exactly to read this type of data, but to understand that people who made this data publicly available (such as myself and the team at NACJD) must make this conversion process.<sup>19</sup> **This conversion process, from fixed-width ASCII to a useful format is the most dangerous step taken in using this data - and one that is nearly entirely unseen by researchers.**

Every line of code you write (or, for SPSS users, click you make) invites the possibility of making a mistake.<sup>20</sup> The FBI does not provide a setup file with the fixed-width ASCII data so to read in this data you need to make it yourself. Since some UCR data are massive, this involves assigning the column width for thousands of columns and the value labels for hundreds of different value labels.<sup>21</sup> A typo anywhere could have potentially far-reaching consequences, so this is a crucial weakpoint in the data cleaning process - and one in which I have not seen anything written about before. While I have been diligent in checking the setup files and my code to seek out any issues - and I know that NACJD has a robust checking process for their own work - that doesn't mean our work is perfect.<sup>22</sup> Even with perfection in processing the raw data to useful files, decisions we make (e.g. what level to aggregate to, what is an outlier) can affect both what type of questions you can ask when using this data, and how well you can answer them.

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<sup>19</sup>For those interested in reading in this type of data, please see my R package `asciiSetupReader`.

<sup>20</sup>Even highly experienced programmers who are doing something like can make mistakes. For example, if you type out "2+2" 100 times - something extremely simple that anyone can do - how often will you mistype a character and get a wrong result? I'd guess that at least once you'd make a mistake.

<sup>21</sup>With the exception of the arrest data and some value label changes in hate crimes and homicide data, the setup files remain consistent you a single file will work for all years for a given dataset. You do not need to make a setup file for each year.

<sup>22</sup>For evidence of this, please see any of the openICPSR pages for my detail as they detail changes I've made in the data such as decisions on what level to aggregate to and mistakes that I made and later found and fixed.



## Chapter 3

# Offenses Known and Clearances by Arrest

The Offenses Known and Clearances by Arrest dataset - often called Return A, “Offenses Known” or, less commonly, OKCA - is the oldest and most commonly used dataset and measures crimes reported to the police. For this reason it is used as the main measure of crime in the United States and I tend to call it the “crimes dataset.” This data includes the monthly number of crimes reported to the police or otherwise known to the police (e.g. discovered while on patrol) for a small selection of crimes, as well as the number of crimes cleared by arrest or by “exceptional means” (a relatively flawed and manipulable measure of whether the case is “solved”). It also covers the number reported but found by police to have not occurred. Since this data has monthly agency-level crime information it is often used to measure crime trends between police agencies and over time. The data uses something called a Hierarchy Rule which means that in incidents with multiple crimes, only the most serious is recorded - though in practice this affects only a small percent of cases, and primarily affects property crimes.

### 3.1 Which crimes are included?

This data set contains information on the number of “Index Crimes” (sometimes called Part I crimes) reported to each agency. These index crimes are a collection of eight crimes that, for historical reasons based largely by perceived importance and reliability of their reporting in the 1920’s when the UCR program was first developed, are used as the primary measure of crime today. Other data sets in the UCR, such as the Arrests by Age, Sex, and Race data and the Hate Crime data have more crimes reported.

The crimes are, in order by the Hierarchy Rule (which we’ll discuss next):

1. Homicide

- Murder and non-negligent manslaughter
- Manslaughter by negligence

2. Rape

- Rape
- Attempted rape

3. Robbery

- With a firearm
- With a knife or cutting instrument
- With a dangerous weapon not otherwise specified
- Unarmed - using hands, fists, feet, etc.

4. Aggravated Assault (assault with a weapon or causing serious bodily injury)
  - With a firearm
  - With a knife of cutting instrument
  - With a dangerous weapon not otherwise specified
  - Unarmed - using hands, fists, feet, etc.
5. Burglary
  - With forcible entry
  - Without forcible entry
  - Attempted burglary with forcible entry
6. Theft (other than of a motor vehicle)
7. Motor Vehicle Theft
  - Cars
  - Trucks and buses
  - Other vehicles
8. Arson
9. Simple Assault

Arson is considered an index crime but is not reported in this data - you need to use the separate Arson data set of the UCR to get access to arson counts. See Chapter 2.3.7 for an overview of the Arson data. The ninth crime on that list, simple assault, is not considered an index crime but is nevertheless included in this data.

Each of the crimes in the list above, and their subcategories, are included in the UCR data. In most news and academic articles, however, you'll see them reported as the total number of index crimes, summing up categories 1-7 and reporting that as "crime." These index crimes are often divided into violent index crimes - murder, rape, robbery, and aggravated assault - and property index crimes - burglary, theft, motor vehicle theft.

### 3.1.1 Hierarchy Rule

This dataset uses what is called the Hierarchy Rule where only the most serious crime in an incident is reported (except for motor vehicle theft and arson, which are always included). For example if there is an incident where the victim is robbed and then murdered, only the murder is counted as it is considered more serious than the robbery. That the data uses the Hierarchy Rule is an oft-cited (by academics, reporters, random people on Twitter) criticism of the data that are, in my opinion, overblown.

In practice, the Hierarchy Rule has only modest effects on the data, under-counting few crimes. Though the Hierarchy Rule does mean this data is an under-count, data from other sources indicate that it isn't much of an under count. The FBI's other data set, the National Incident-Based Reporting System (NIBRS) contains every crime that occurs in an incident (i.e. it doesn't use the Hierarchy Rule). Using this we can measure how many crimes the Hierarchy Rule excludes (Most major cities do not report to NIBRS so what we find in NIBRS may not apply to them). In over 90% of incidents, only one crime is committed. Additionally, when people talk about "crime" they usually mean murder which, while incomplete to discuss crime, means the UCR data here is accurate on that measure.



The FBI also released a report [available here](#) in 2015 that directly examined this issue by taking NIBRS data from 2014 and examined how NIBRS data (which includes all crimes) compares to using the Hierarchy Rule and keeping only the most serious crime. Figure @ref{fig:fbiHierarchy} is a screenshot from their report showing the percent increases in crimes when including all crimes in an incident relative to following the Hierarchy Rule. They find that 10.6% of incidents have multiple crimes occurring, which is similar to other years that I have examined myself. For violent crime, murder and rape have no change; for the remaining violent crimes - robbery and aggravated assault - crimes increased by 0.6%.<sup>1</sup> Burglary increased by 1% and the largest increases came from theft and motor vehicle theft, increasing by 2.6% and 2.7%, respectively. Curiously motor vehicle theft increased even though the FBI's documentation for this data says that it is exempt from the Hierarchy Rule and should always be reported. This suggests either non-compliance or that the manual is incorrect.

- Rape: No effect.
- Robbery: Increased 0.6 percent.
- Aggravated Assault: Increased 0.6 percent.
- Burglary: Increased 1.0 percent.
- Larceny: Increased 2.6 percent.
- Motor Vehicle Theft: Increased 2.7 percent.
- Total SRS Offenses: Increased 2.1 percent.
- Incidents that involved multiple offenses: 10.6 percent of all reported incidents.

Figure 3.1: The FBI's findings of how crime reporting changes when using the Hierarchy Rule using NIBRS 2014 data.

So using the Hierarchy Rule does undercount crime, but this is a small undercounting and is primarily led by property crime. Violent crime is only slightly undercounted. Please keep in mind that this is for crimes that the police record and is unaffected by outside decisions like what the district attorney charges or what the defendant is ultimately convicted of.

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<sup>1</sup>Murder is not shown in this figure since murder is always reported so cannot change.

### 3.1.2 The problem with using index crimes

The biggest problem with index crimes is that it is simply the sum of 8 (or 7 since arson data usually isn't available) crimes. Index crimes have a huge range in their seriousness - it includes both murder and theft. This is clearly wrong as 100 murders is more serious than 100 thefts. This is especially a problem as less serious crimes (theft mostly) are far more common than more serious crimes (in 2017 there were 1.25 million violent index crimes in the United States. That same year had 5.5 million thefts.). So index crimes under-count the seriousness of crimes. Looking at total index crimes is, in effect, mostly just looking at theft.

This is especially a problem because it hides trends in violent crimes. San Francisco, as an example, has had a huge increase in index crimes in the last several years. When looking closer, that increase is driven almost entirely by the near doubling of theft since 2011. During the same years, violent crime has stayed fairly steady. So the city isn't getting more dangerous but it appears like it is due to just looking at total index crimes.

Many researchers divide index crimes into violent and nonviolent categories, which helps but is still not entirely sufficient. Take Chicago as an example. It is a city infamous for its large number of murders. But as a fraction of index crimes, Chicago has a rounding error worth of murders. Their 653 murders in 2017 is only 0.5% of total index crimes. For violent index crimes, murder makes up 2.2%. What this means is that changes in murder are very difficult to detect. If Chicago had no murders this year, but a less serious crime (such as theft) increased slightly, we couldn't tell from looking at the number of index crimes.

## 3.2 Agencies reporting

Figure 3.2 shows the annual number of police agencies that reported at least one month that year. With data starting in 1960, there were a little under

7,500 agencies reporting a year until 1970 when the number of agencies began increasing. This continued until the late 1970s when about 14,000 agencies reported, and this remained steady for over a decade before declining in the 1990s until about 12,500 in the latter half of the decade. Then the number of agencies reporting increased steadily until about 16,500 agencies reported in 2010. The number of agencies have slowly increased since then, adding a few hundred agencies from 2010 to 2018. While this data is available through 2019, this graph only shows data through 2018. As this graph shows agencies that report at least one month, it overcounts reporting agencies as some report fewer than every month in the year. Agencies that do report, however, tend to report all 12 months of the year so this problem is not serious.

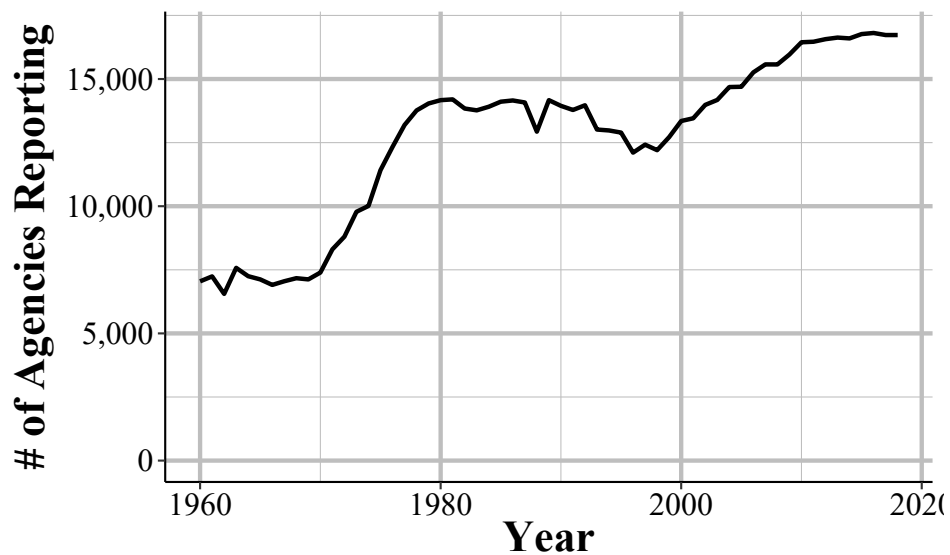


Figure 3.2: The annual number of agencies reporting to the Offenses Known and Clearances by Arrest dataset. Reporting is based on the agency reporting at least one month of data in that year.

### 3.3 Important variables

For each crime we have four different categories indicating the number of crimes actually committed, the number cleared, and the number determined to not have occurred.

#### 3.3.1 Actual crimes

This is the number of offenses that *actually* occurred - where *actually* means that a police investigation found that the crime report was accurate. For crimes that are reported that the police find did not occur (e.g. report of an arson but turns that the fire began accidentally) are called “unfounded” crimes. So this variable is the one people use to measure *crime*. For example if 10 people are murdered in a city the number of “actual murders” would be 10.

#### 3.3.2 Total cleared crimes

A crime is cleared when an offender is arrested or when the case is considered cleared by exceptional means. To be more specific, this data counts crime as a crime incident, regardless of the number of offenders. For example, if 3 people robbed a person, that is one crime of robbery, not 3 separate crimes. This crime is cleared when one of the three robbers is arrested - no matter the outcome for the other two robbers. Arresting all 3 still counts as a single robbery cleared.

Even though this dataset is formally named “Offenses Known and Clearances by Arrest” it does include clearances where no one is arrested, which are called “exceptional clearances” or “clearances by exceptional means.” For exceptional clearances, police must have identified the offender, have sufficient evidence to arrest that offender, know where they are (so they can actually be apprehended) and only then be unable to make the arrest. Exceptional clearances include cases where the offender dies before an arrest

(by any means, including suicide, accidental, illness, killed by someone including a police officer) or when the police are unable to arrest the person since they are already in custody by another jurisdiction (including out of the country or in custody of another agency) and extradition is denied. Two other potential causes of exceptional clearance is when prosecution of the case cannot go forward because the district attorney refuses to prosecute the case, for reasons other than lack of evidence, or when a victim refuses to assist the prosecution in the case.

Unfortunately, this data does not differentiate between clearances by arrest or by exceptional means so there's no way to determine how many clearances mean the offender is actually arrested - and even more problematic, how many clearances have all of the offenders arrested.<sup>2</sup> There is also evidence that police agencies report classify large numbers of clearances as clearances through exception means (again, we have no way to tell which is which using this data) even though exceptional clearances should be rare given that times where the offender is known but cannot be arrested are likely far less common than when they are arrested. This is particularly a problem in the case of rapes where in some cases there are far more exceptional clearances than clearances by arrest (Yeung et al., 2018). For an excellent investigation into this issue, please read the Yeung et al. (2018) article available on ProPublica's website [here](#)

Clearances are reported in the month that they occur, regardless of when the crime they are clearing occurred. In practice, however, most crimes are cleared in the month that they occur. According to the 2019 NIBRS, it takes on average 7 days between the incident and the arrest (median = 0 days) date when averaging across all crimes - for individual crimes these values will be different. This means that most of the clearances will be for the same month as the initial crime - though less so as the month comes to a close. Of course, police agencies can solve older cases - and even target cold cases to be solved - so this is still a degree of uncertainty for which month these clearances are for.

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<sup>2</sup>NIBRS data does differentiate these types of clearances

Still, there are occasionally months - and even years - where there are more reported crimes cleared than crimes that occur. Figure 3.3 shows the number of actual and cleared murders from the Montgomery County Police Department in Maryland. Several years have more murders cleared than were committed - a sign that the month of clearance does not correspond to the month of occurrence, rather than the police solving crime before it happened.<sup>3</sup>

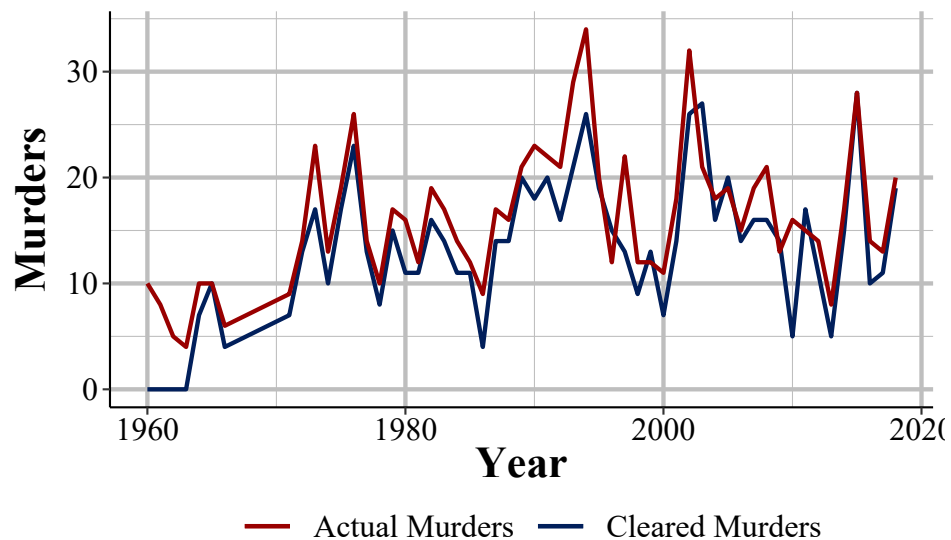


Figure 3.3: The annual number of actual and cleared murders from the Montgomery County Police Department, MD, 1960-2018.

### 3.3.3 Crimes cleared where all offenders are under 18 years old

This variable is a subset of the Total Cleared variable and only includes clearances for offenses in which **every** offender is younger than age 18. This requires that the police know, or at least believe, the age of every offender, it is probably highly inaccurate. This category includes cases where the

<sup>3</sup>The Minority Report is not yet a documentary.

juvenile is given a citation to show up in court for their trial and is not formally arrested and taken into custody.

### 3.3.4 Unfounded crimes

An unfounded crime is one in which a police investigation has determined that the reported crime did not actually happen. For example I observed during a ride-along a report of a burglary where the homeowners said that they came home and the front door was open and they thought it might have been their son who forgot to close it but could also be a burglar so they called the police just in case. This would be recorded as a burglary and if it turned out to be the son, the police would then record this as an unfounded burglary.

Other unfounded crimes would include when someone reports a crime but later says that the report wasn't true. For example, a person could report a burglary to the police to collect insurance money on the items they claim was stolen. If the police discover this they would unfound the case - and the lying to the police and fraud would not be counted as neither of those are crimes included in this dataset. Unfounding crimes are especially common for rapes. If a person reports that they were raped and then later say that this report isn't true - and doing so is relatively common, especially for child sexual abuse victims, even when the rape did actually happen - then the police will unfound the case [4].

Figure 3.4 provides one example of this by showing the number of actual - that is, rapes that the police say actually occurred - and unfounded rapes annually from 1960-2018 in Philadelphia, PA. Interestingly, the spike in actual rapes in 2013 due to the new rape definition that year does not correspond to a spike in unfounded rapes - which suggests that this variable is not being reported properly. It is unlikely that the number of rapes would spike so much without any corresponding increase - and an actual decrease - in unfounded rapes. Since unfounded rapes are so common, especially compared to other crimes - and evidence that police also misreport clearances for rape

- this variable is likely to be manipulated by the police to make it appear that there are fewer rapes than there actually is. As such, this variable is not reliable, especially for rapes.

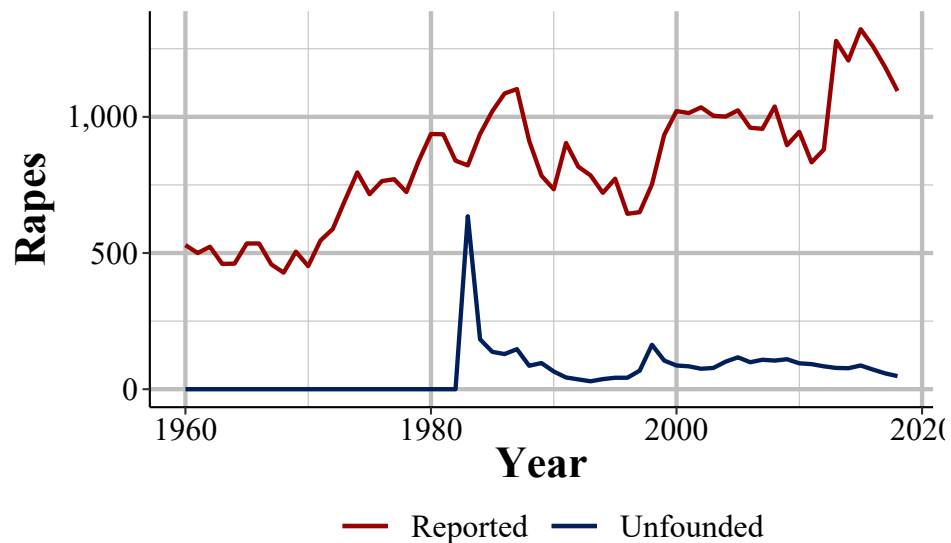


Figure 3.4: The annual number of actual and unfounded rapes in Philadelphia, PA, 1960-2018.

Another way to look at this data is the percent of rapes that were unfounded. Since unfounded and actual rapes are distinct categories, we'll need to divide unfounded rapes by the sum of actual and unfounded rapes and then multiple the result by 100. Please note that unfounding occurs in the month the police discover the case to be unfounded, it is not tied to the month of the original report. So this graph isn't really showing the percent that year that were unfounded - but for our purposes of getting a general sense it is acceptable. Usually about 10% of reported rapes are unfounded in Philadelphia. The 44% in 1983, the first year with data, is probably high due to it accounting for unfounded cases in previous years that weren't reported in the data until 1983.

As a comparison, Figure 3.6 shows the percent of robberies that are recorded as unfounded in Philadelphia over the same time period. While the percent



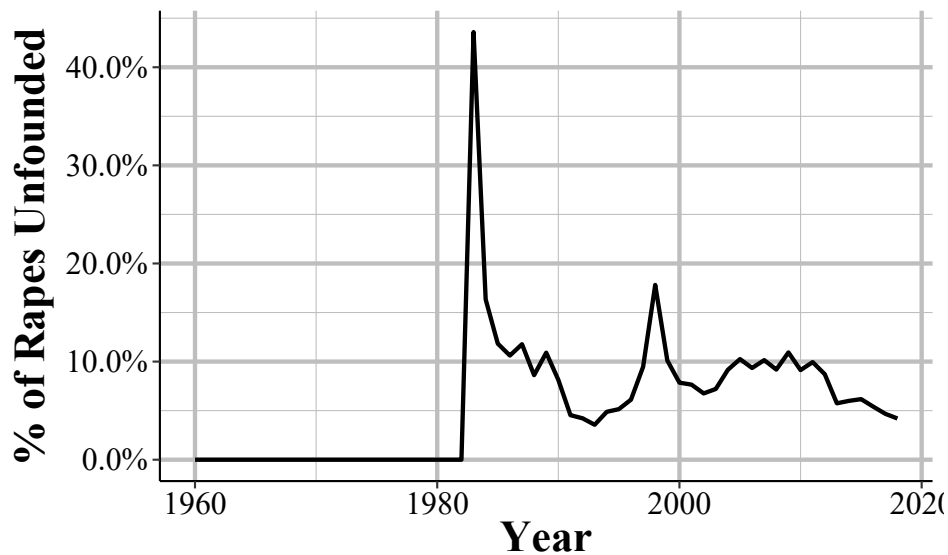


Figure 3.5: The percent of reported rapes that the police recorded as unfounded in Philadelphia, PA, 1960-2018.

has been increasing, for most of the data it is under 1% and never exceeds 3%. To me this suggests that the Philly Police, and they aren't unique, are overcounting rapes as unfounded to improve their rape statistic data.

## 3.4 Important issues

### 3.4.1 Rape definition change

The FBI changed the definition of rape for UCR data starting in 2013 to a broader definition than the older definition, which is commonly called the “legacy definition” or “legacy” or “historical” rape. The legacy definition is “the carnal knowledge of a female **forcibly** and against her will” (emphasis added). This means that only rape is only included in UCR data when it is a female (or any age, there is no differentiation for child victims) forcibly vaginally penetrated by a penis. This is a narrow definition and excludes a

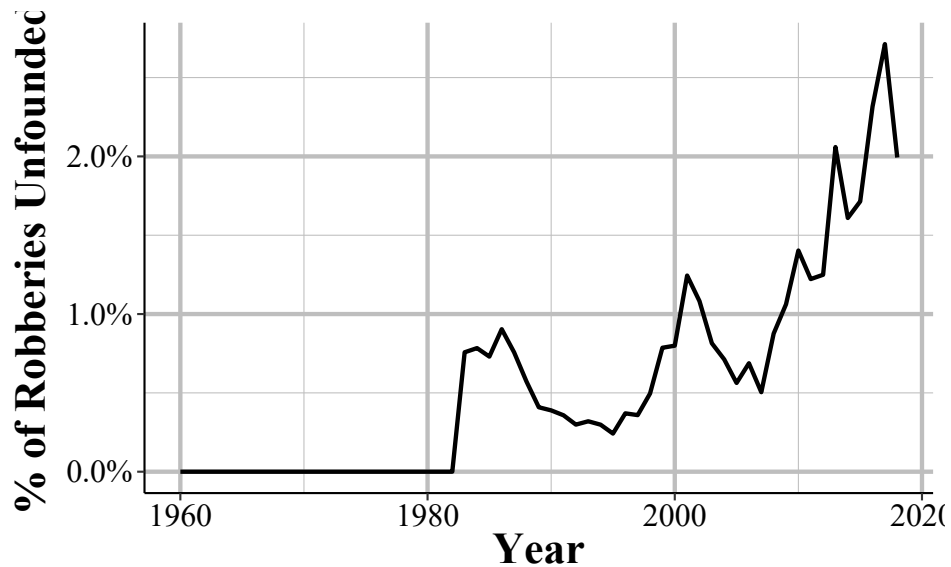


Figure 3.6: The percent of reported robberies that the police recorded as unfounded in Philadelphia, PA, 1960-2018.

number of sexual acts that people may consider rape such as forced oral or sex, and cases with a male victim.

The new (and current) definition “penetration, no matter how slight, of the vagina or anus with any body part or object, or oral penetration by a sex organ of another person, without the consent of the victim.” Starting in 2013, rape has a new, broader definition in the UCR to include oral and anal penetration (by a body part or object) and to allow men to be victims. The new definition is: “Penetration, no matter how slight, of the vagina or anus with any body part or object, or oral penetration by a sex organ of another person, without the consent of the victim.” The previous definition included only forcible intercourse against a woman. This definition is far broader and is effectively any non-consensual sexual act. It also includes male victims though the data does not differentiate between male or female (or any other gender) victims.

Both the current and legacy definitions exclude statutory rape and incest

other than forcible incest. They both also include lack of consent as cases where the victim cannot give consent, such as if they are too young or are mentally or physically incapacitated - they specifically give the example of being temporarily incapacitated through drugs or alcohol.

As this revised definition is broader than the original one post-2013, rape data is not comparable to pre-2013 data. 2013, however, is simply the year that the FBI changed the definition which means that agencies should have changed their reporting to the new definition. As might not be too surprising, not all agencies followed this requirement. We'll look at four examples to show when there is clear evidence that the agency did change their definition in 2013, when it's clear they did so a year later, when it's unclear exactly when they made the change, and when the agency seems to not follow the change at all.

We'll start with the Philadelphia Police Department in Philadelphia, PA, shown in Figure 3.7 which shows the annual number of rapes from 2000-2018. It's declining slowly but steadily over the 2000-2012 time period until spiking sharply in 2013. Since the rape definition change in 2013 is far broader than previous year's definition, this makes sense. A broader definition should lead to a sudden increase in reported rapes if the agency is reporting correctly.

In comparison, New York City has the sudden spike a year later, which indicates that they didn't start using the new definition until 2014. Figure 3.8 shows that rape is fairly steady, though increasing, in the years leading up to 2013 and has almost no change from 2012 to 2013, but a huge increase in 2014 and then steadily increases from there, spiking again in 2018. This seems like a fairly clear indicator that NYC simply didn't follow the new definition until 2014.

Less clear is what's happening in San Francisco, California, shown in Figure 3.9. Here we do see an increase in 2013 which while it appears small on the graph is actually a 49% increase from 2012. Then there is a much larger spike in 2014 - a 120% increase - which may suggest that part of the agency started following the new definition in 2013 and the remainder followed in 2014.

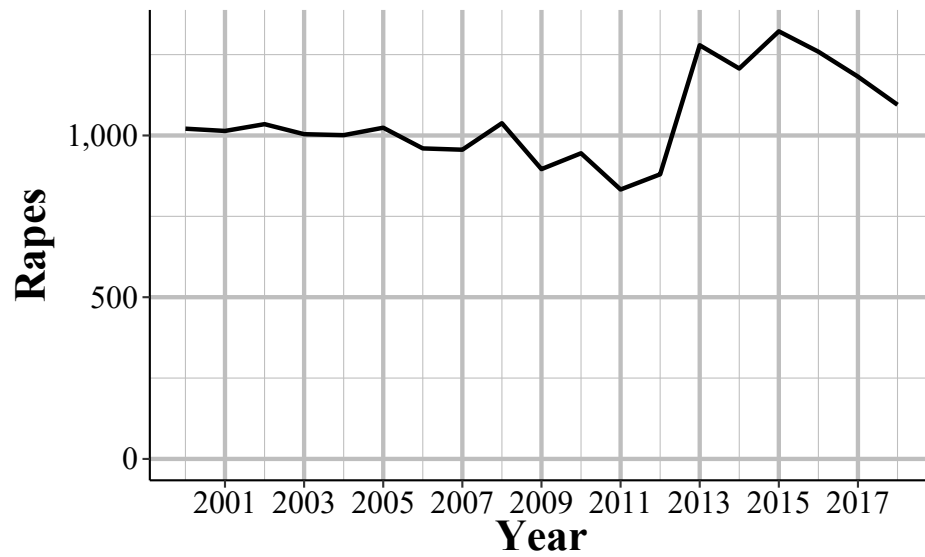


Figure 3.7: The annual number of rapes reported in Philadelphia, Pennsylvania, 2000-2018.

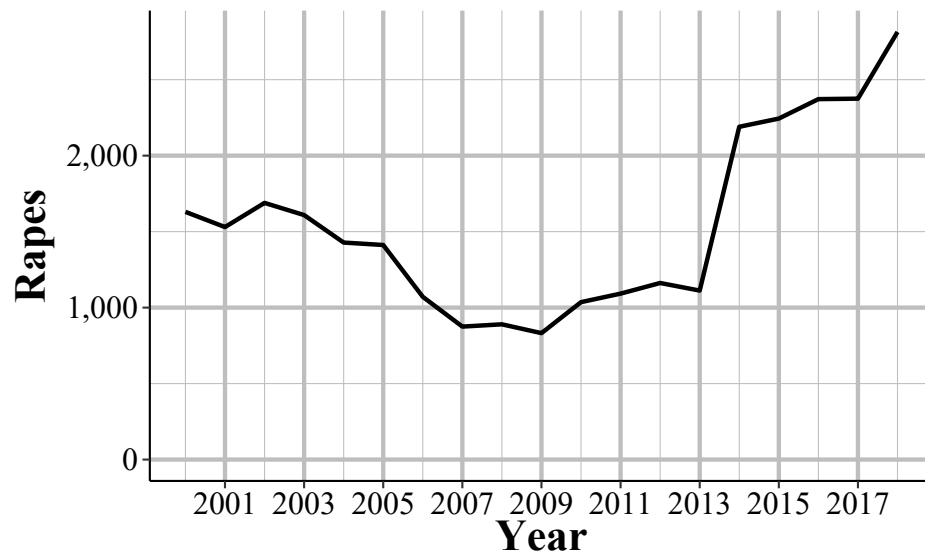


Figure 3.8: The annual number of rapes reported in New York City, 2000-2018.

However, large increases or decreases are relatively common in San Francisco so it could also be that the agency only switched to the new definition in 2014 and the spike in 2013 is just a coincidence

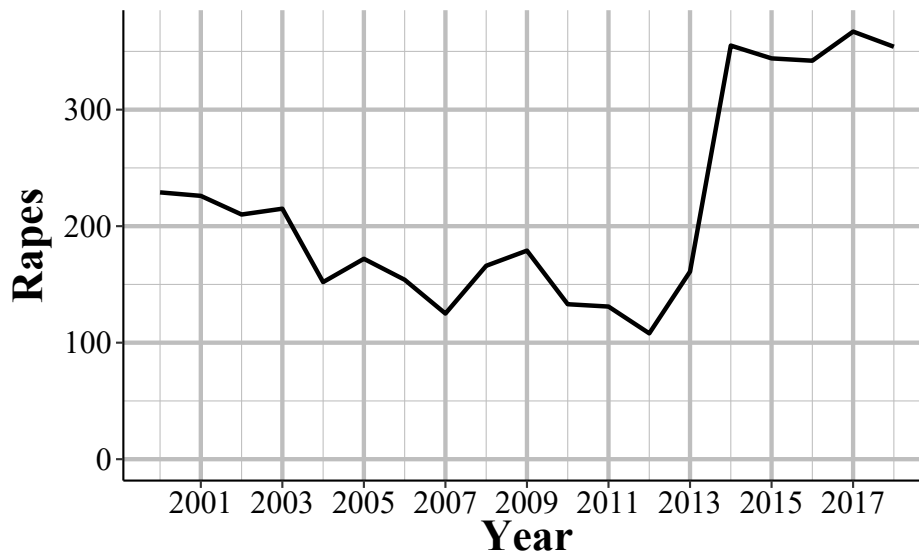


Figure 3.9: The annual number of rapes reported in San Francisco, California, 2000-2018.

Finally, we'll look at Jackson Police Department in Mississippi where the definition change seems to have had no effect. As seen in Figure 3.10, reported rapes start to undulate in 2010 with 2013 data perfectly in line with the before and after trends - no sign that there is a change in reporting. This suggests that Jackson simply did not follow the definition change and continues to report using the old definition.

My takeaway from this is that rape should not be used at all for years after 2012. While the definition change makes pre-2013 and 2013+ years non-comparable, the differences in agency responses to this change - i.e. if they follow the rules or not - is such a mess that the data is too flawed to use.

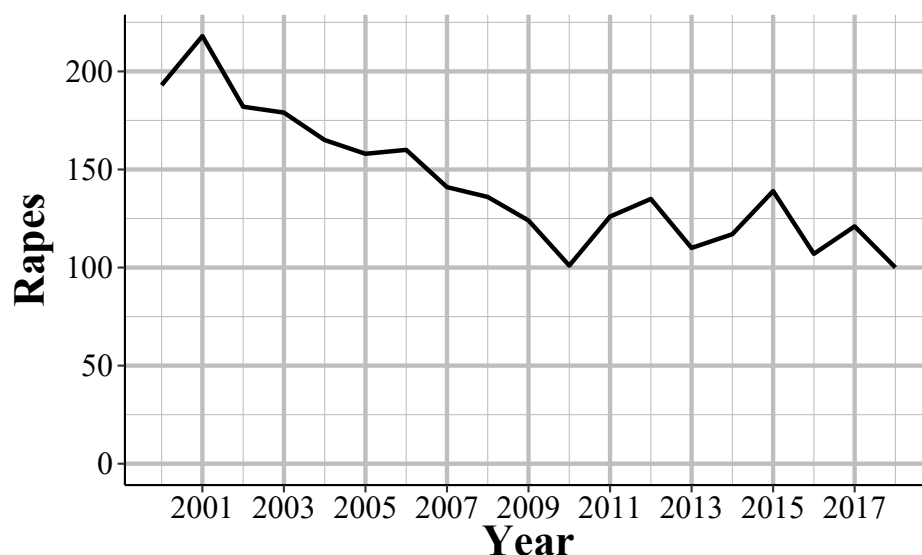


Figure 3.10: The annual number of rapes reported in Jackson, Mississippi, 2000-2018.

### 3.4.2 The decline of manslaughter

This data contains two different crime subcategories for homicide: murder and non-negligent manslaughter, and manslaughter by negligence. The first is our measure of murder, and it includes everything we traditionally think of when it comes to murder - shootings, stabbings, strangulation, basically any intentional killing of another person.<sup>4</sup> Suicides, killing a fetus, and accidental killings (e.g. car crashes) are not considered murders.<sup>5</sup> The second, manslaughter by negligence - usually called just “manslaughter” - is when someone kills another person through “gross negligence” but does not kill them intentionally. This can include accidental killings when the death was caused by gross negligence. The FBI provide examples of this as kids playing with guns and shooting each other (and not knowing the gun was loaded) or a hunter accidentally shooting someone while hunting.

<sup>4</sup>Attempted murder is usually classified as an aggravated assault.

<sup>5</sup>Even the intentional killing of a fetus is classified as an aggravated assault against the mother, not a murder of the fetus.

I would assume that manslaughter by negligence would remain at a relatively steady rate - though increasing in raw numbers as population increases - as it is due to largely unintentional behavior that would be unaffected by crime-reduction policies.<sup>6</sup> I was wrong though. One of the most curious findings from my exploration of this data is the sudden and national decline in manslaughter by negligence in the 1970s - and the extremely high number of manslaughter before that. Figure 3.11 shows the annual number of murders, manslaughter, and the sum of the two nationwide from 1960-2018. This just sums up the total reported counts from every agency each year so part of the increase is simply due to more agencies reporting as the year gets closer to the present day - so please pay attention to the diverging paths of each crime, not the trend for the individual crime over time.

Murder is always more common than manslaughter but these values are not that far apart in the early decade of data and manslaughter doesn't become rare until the end of the 1970s. This makes me suspicious that what was recorded as manslaughter were actually murders but simply misclassified. If this is true then, as seen in Figure 3.11 in the purple line, murders actually peaked in the United States in the middle of the 1970s, not the early 1990s as has been oft-been claimed - and generally using this data as evidence. Certainly not all reported manslaughter by negligence in the 1960s and 1970s were actually murders, but it seems extremely unlikely that the entire decline is truly due to a decline in people killing others through negligence; such a sudden and persistent decline cannot occur in nature.

Figure 3.12 shows another way to look at this data: manslaughter as a percent of reported murder. In the early years of our data manslaughter was fairly common, with about 70-80% as many manslaughters reported as murders. This declined sharply in the mid-1960s until there were around 45% as many manslaughters as murders in the mid-1970s. Again this declined until it was about 4% in 1980, and it has remained around there ever since.

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<sup>6</sup>Though policies that encourage people to lock up their guns would likely reduce manslaughter by negligence.

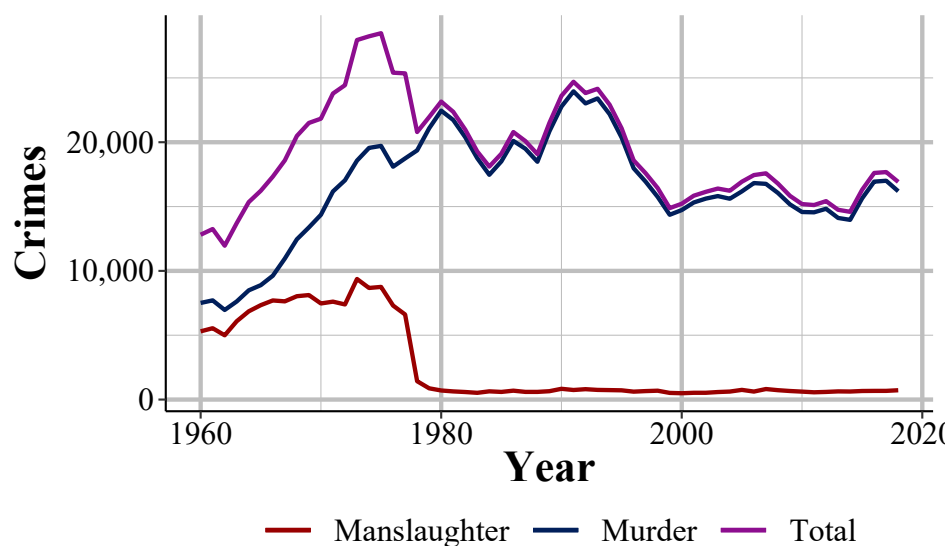


Figure 3.11: The annual number of murder and non-negligent manslaughter, manslaughter by negligence, and the sum of the two, nationwide from 1960-2018.

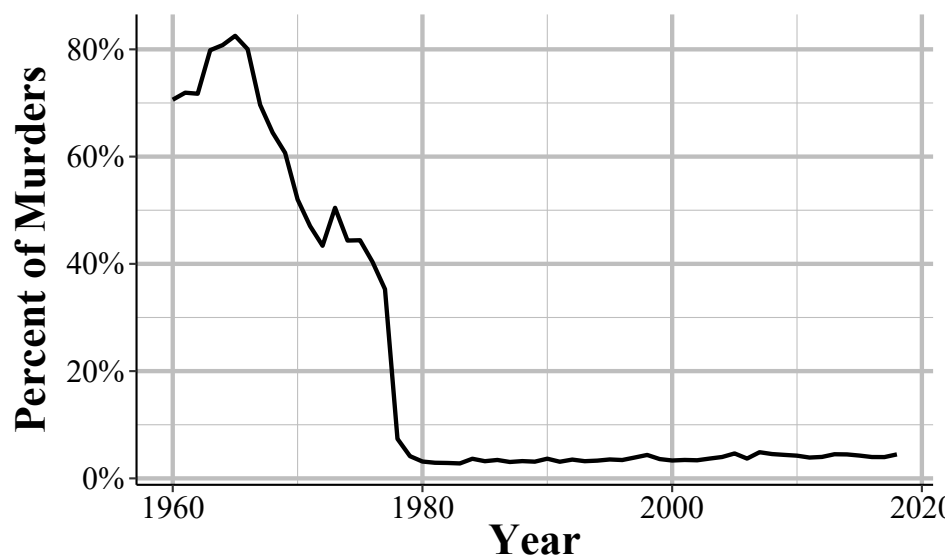


Figure 3.12: Reported manslaughter by negligence as a percent of reported murder and non-negligent manslaughter, nationwide 1960-2018.



## Chapter 4

# Arrests by Age, Sex, and Race

The Arrests by Age, Sex, and Race dataset - often called ASR or the “arrests data” - includes the monthly number of arrests for a variety of crimes and, unlike the crime data, breaks down this data by age and gender. This data includes a broader number of crime categories than the crime dataset (the Offenses Known and Clearances by Arrest data) though is less detailed on violent crimes since it does not breakdown aggravated assault or robberies by weapon type as the Offenses Known data does. For each crime it says the number of arrests for each gender-age group with younger ages (15-24) showing the arrestee’s age to the year (e.g. age 16) and other ages grouping years together (e.g. age 25-29, 30-34, “under 10”). It also breaks down arrests by race-age by including the number of arrestees of each race (American Indian, Asian, Black, and White) are the only included races) and if the arrestee is a juvenile (<18 years old) or an adult. The data does technically include a breakdown by ethnicity-age (e.g. juvenile-Hispanic, juvenile-non-Hispanic) but almost no agencies report this data (for many years zero agencies report ethnicity) so in practice the data does not include ethnicity. As the data includes counts of arrestees, people who are arrested multiple times are included in the data multiple times - it is not a measure of unique arrestees.

## 4.1 Crimes included

1. Homicide

- Murder and non-negligent manslaughter
- Manslaughter by negligence

2. Rape

3. Robbery

4. Aggravated assault

5. Burglary

6. Theft (other than of a motor vehicle)

7. Motor vehicle theft

8. Simple assault

9. Arson

10. Forgery and counterfeiting

11. Fraud

12. Embezzlement

13. Stolen property - buying, receiving, and possessing

14. Vandalism

15. Weapons offenses - carrying, possessing, etc.

16. Prostitution and commercialized vice

17. Sex offenses - other than rape or prostitution

18. Drug abuse violations - total

- Drug sale or manufacturing
  - Opium and cocaine, and their derivatives (including morphine and heroin)
  - Marijuana
  - Synthetic narcotics
  - Other dangerous non-narcotic drugs
- Drug possession

- Opium and cocaine, and their derivatives (including morphine and heroin)
- Marijuana
- Synthetic narcotics
- Other dangerous non-narcotic drugs

## 19. Gambling - total

- Bookmaking - horse and sports
  - Number and lottery
  - All other gambling
20. Offenses against family and children - nonviolent acts against family members. Includes neglect or abuse, nonpayment of child support or alimony.
21. Driving under the influence (DUI)
22. Liquor law violations - Includes illegal production, possession (e.g. underage) or sale of alcohol, open container, or public use laws. Does not include DUIs and drunkenness.
23. Drunkenness - i.e. public intoxication
24. Disorderly conduct
25. Vagrancy - includes begging, loitering (for adults only), homelessness, and being a “suspicious person.”
26. All other offenses (other than traffic) - a catch-all category for any arrest that is not otherwise specified in this list. Does not include traffic offenses. Very wide variety of crimes are included - use caution when using!
27. Suspicion - “Arrested for no specific offense and released without formal charges being placed.”
28. Curfew and loitering law violations - for minors only.
29. Runaways - for minors only.

### 4.1.1 Age

- Female
  - Under 10
  - 10-12
  - 13-14
  - 15
  - 16
  - 17
  - 18
  - 19
  - 20
  - 21
  - 22
  - 23
  - 24
  - 25-29
  - 30-34
  - 35-39
  - 40-44
  - 45-49
  - 50-54
  - 55-59
  - 60-64
  - 65 and older
- Male
  - Under 10
  - 10-12
  - 13-14
  - 15
  - 16
  - 17

- 18
- 19
- 20
- 21
- 22
- 23
- 24
- 25-29
- 30-34
- 35-39
- 40-44
- 45-49
- 50-54
- 55-59
- 60-64
- 65 and older

#### 4.1.2 Race

- Adult
  - American Indian
  - Asian
  - Black
  - White
- Juvenile
  - American Indian
  - Asian
  - Black
  - White

### 4.1.3 Ethnicity

- Adult
  - Hispanic
  - Non-Hispanic
- Juvenile
  - Hispanic
  - Non-Hispanic

## Chapter 5

# Law Enforcement Officers Killed and Assaulted (LEOKA)

The Law Enforcement Officers Killed and Assaulted data, often called just by its acronym LEOKA, has two main purposes.<sup>1</sup> First, it provides counts of employees employed by each agency - broken down by if they are civilian employees or sworn officers, and also broken down by gender. And second, it measures how many officers were assaulted or killed (including officers who die accidentally such as in a car crash) in a given month. The assault data is also broken down into shift type and type (e.g. alone, with a partner, on foot, in a car, etc.), the offender's weapon, and type of call they are responding to (e.g. robbery, disturbance, traffic stop). The killed data simply says how many officers are killed feloniously (i.e. murdered) or died accidentally (e.g. car crash) in a given month. The employee information is at the year-level so you know, for example, how many male police officers were employed in a given year at an agency, but don't know any more than that such as how many officers were on patrol, were detectives, were in special units, etc. This dataset is commonly used as a measure of police employees and is a generally reliable - though imperfect as we'll see - measure of how many police are employed by a police agency. The second part of this data, measuring

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<sup>1</sup>This data is also sometimes called the "Police Employees" dataset.

assaults and deaths, is more flawed with missing data issues and data error issues (e.g. more officers killed than employed in an agency).

## 5.1 Common uses of this data

This data, as well as the privately-run site [Officer Down Memorial Page](#) which covers law enforcement officers who have died, has also been used lately in the context of police using force against people out of fear of being harmed by that person. The discussion revolves around whether police are actually in high danger of being harmed by comparing the rate at which officers die to that of other professions. In general they find that police officers are among the most likely profession to die but are not at the top of this measure.

## 5.2 Important variables

### 5.2.1 Number of employees

### 5.2.2 Officers killed

### 5.2.3 Assaults by injury and weapon

- Assaults with injury
  - Offender has firearm
  - Offender had knife
  - Offender had other weapon
  - Offender was unarmed
- Assaults without injury
  - Offender has firearm
  - Offender had knife



- Offender had other weapon
- Offender was unarmed

#### **5.2.4 Assaults by call type**

- Disturbance call (e.g. domestic violence, person carrying a gun in public)
- Burglary
- Robbery
- Officers arresting someone for another crime
- Civil disorder
- Officer has custody of prisoners
- Suspicious persons
- Officers are ambushed
- Mentally deranged person
- Traffic pursuit and traffic stops
- All other call types
- Offender weapons
  - Offender has firearm
  - Offender had knife
  - Offender had other weapon
  - Offender was unarmed
- Type of officer assignment
  - In a vehicle with two officers

- In a vehicle alone
- In a vehicle alone but assisted by other officers
- Detective or special unit alone
- Detective or special unit assisted by other officers
- Other assignment alone
- Other assignment assisted by other officers

### 5.2.5 Assaults by time

- 12:01am - 2:00am
- 2:01am - 4:00am
- 4:01am - 6:00am
- 6:01am - 8:00am
- 8:01am - 10:00am
- 10:01am - 12:00pm
- 12:01pm - 2:00pm
- 2:01pm - 4:00pm
- 4:01pm - 6:00pm
- 6:01pm - 8:00pm
- 8:01pm - 10:00pm
- 10:01pm - 12:00pm

## Chapter 6

# Supplementary Homicide Reports (SHR)

The Supplementary Homicide Reports dataset - often abbreviated to SHR - is the most detailed of the UCR datasets and provides information about the circumstances and participants (victim and offender demographics and relationship status) for homicides.<sup>1</sup> For each homicide incident it tells you the age, gender, race, and ethnicity of each victim and offender as well as the relationship between the first victim and each of the offenders (but not the other victims in cases where there are multiple victims). It also tells you the weapon used by each offender and the circumstance of the killing, such as a “lovers triangle” or a gang-related murder. As with other UCR data, it also tells you the agency it occurred in and the month and year when the crime happened.

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<sup>1</sup>If you’re familiar with the National Incident-Based Reporting System (NIBRS) data that is replacing UCR, this dataset is the closest UCR data to it, though it is still less detailed than NIBRS data.

## 6.1 Agencies reporting

This data only has a report when the agency has a murder that year and since murder is rare it is difficult to measure underreporting. One way we can look at reporting is to compare murders in the SHR data with that of other datasets. We'll look at two of them: the Offenses Known and Clearances by Arrest which is covered in detail in Chapter @ref(<https://wonder.cdc.gov/>), and the Center for Disease Control and Prevention (CDC) detail on national deaths from homicide.<sup>2</sup> Both this dataset and the Offenses Known and Clearances by Arrest data are UCR datasets so you may think that the numbers of murders from each dataset should be the same. That is a perfectly reasonable assumption, but since this is UCR data we're talking about, you'd be wrong. Police agencies are free to report to either, both, or neither dataset so while the number of murders are close for each dataset, they are never equal. CDC WONDER data aggregates mortality data (among other data) from state death certificates which reduces the issue of voluntary reporting that we have in UCR data.

Figure 6.1 shows the annual number of murder victims from each of these datasets starting in 1976 for the UCR data and in 1999 for the CDC data.<sup>3</sup> For the UCR data, in every year the numbers are fairly similar and the trends are the same over time, but the number of murders is never equal. The numbers have actually gotten worse over time with the difference between the datasets increasing and the Offenses Known data having consistently more murders reported than the SHR data since the late 1990s. Compared to the CDC data, however, both UCR datasets - and in particular the SHR data - undercount the number of murders. While trends are the same, UCR data reports thousands fewer murders per year than the CDC data, indicating how much of an issue underreporting is in this data.

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<sup>2</sup>CDC WONDER data is available here: <https://wonder.cdc.gov/>

<sup>3</sup>1975 is actually the first year that the Supplementary Homicide Reports data is available but that dataset only has info for a single victim and offender - all later years has info for up to 11 victims and offenders - so 1976 is often used as the first year of data

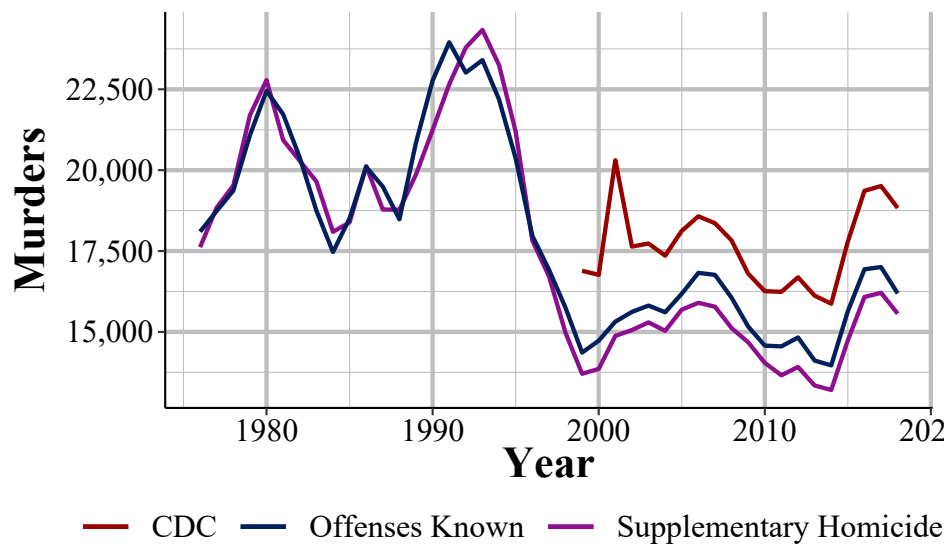


Figure 6.1: The annual number of murders from the Supplementary Homicide Report and the Offenses Known and Clearances by Arrest dataset. Numbers differ because agencies voluntarily report and may not report to both datasets.

## 6.2 Important variables

There data has demographic information for up to 11 victims and 11 offenders, as well as the information on the weapon used by each offender, the relationship between the first victim and each offender, and the circumstance of the murder. The data also has the traditional UCR set of variables about the agency: their ORI code, population, state, region and the month and year of this data. One key variable that is missing is the outcome of the homicide: there is no information on whether any of the offenders were arrested.

While there is information on up to 11 victims and offenders, in most cases, there is only a single victim and a single offender in each incident. To see how the breakdown for the number of victims in each incident looks, Figure 6.2 shows the percent of incidents with each possible number of victims.<sup>4</sup> In nearly all incidents - 96.1% - there was only a single victim. This drops to 3.2% of incidents for two victims, 0.5% for three victims, and only about 0.2% of incidents have four or more victims.

Figure 6.3 shows the breakdown of the number of offenders per homicide incident.<sup>5</sup> It's a little less concentrated than with victims but the vast majority of homicides are committed by one offender - or at least the police only report one offender. About 88% of homicides have only one offender, 8.2% have two, 2.4% have three, and fewer than 1% have four. Fewer than 0.5% of homicides have more than four offenders. However, this is all a bit misleading. In cases where there is no information about the offender, including how many offenders there is, the data simply says that there is a single offender. So the number of homicides with a single offender is an overcount while the number with more offenders is an overcount.

The variable “situation” says what type of victim-offender number combi-

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<sup>4</sup>There is one incident where there are a reported 12 victims. For simplicity of the graph, this incident is not included.

<sup>5</sup>There is one incident where there are a reported 22 offenders and one with 12 offenders. For simplicity of the graph, these incidents are not included.



Figure 6.2: The percent of incidents from 1976-2018 that have 1-11 victims.

nation the incident is - e.g. “multiple victims/single offender”, “single victim/multiple offenders”, etc. - and does indicate if the number of offenders is unknown (though curiously there are over 4,000 instances where the number of offenders is unknown but they still say there are two offenders) so you can use this variable to determine if the police don’t know how many offenders there is. You’re still limited, of course, in that the number of offenders is always what the police think there are, and they may be wrong. So use this variable - and anything that comes from it like the percent of offenders of a certain race - with caution.

We’ll now look at a number of important variables individually. Since the data can potentially have 11 victims and 11 offenders - but in practice has only one each in the vast majority of cases - we’ll only look at the first victim/offender for each of these variables. Therefore, the results will not be entirely accurate, but will still give you a good overview of the data. The figures below will use data for all homicides from 1976 to 2018 so will cover all but the most recent year of data.

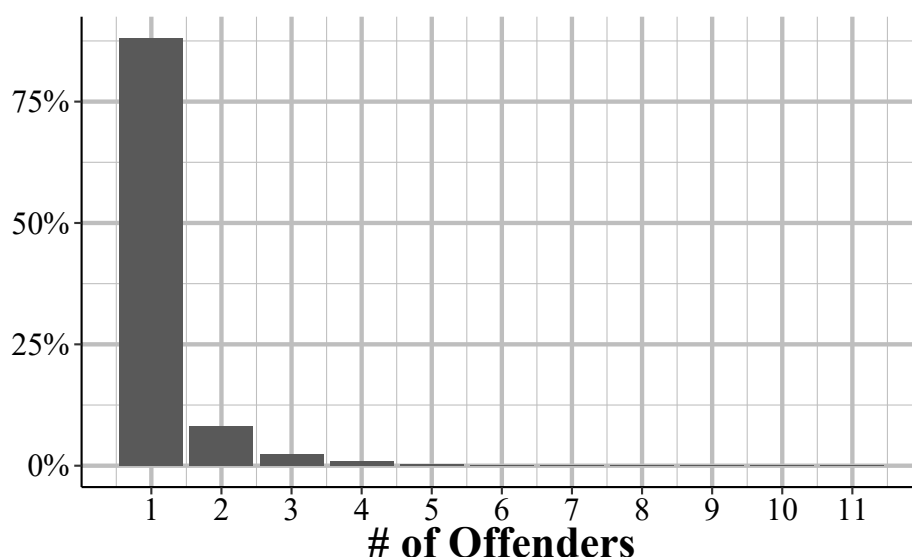


Figure 6.3: The percent of incidents from 1976-2018 that have 1-11 offenders.

## 6.2.1 Demographics

There are two broad categories of variables that we’ll cover: demographics of the victim and offenders, and characteristics of the case. We start with demographics.

### 6.2.1.1 Age

This data includes the age (in years) for each victim and each offender. For those under one years old, it also breaks this down into those from birth to six days old “including abandoned infant” and those seven days old to 364 days old. So there’s a bit more info on baby murders. It also maxes out the age at 99 so for victims or offenders older than that we don’t get their exact age, just text that says “99 years or older” (which I turn to the number 99 in the figures below).

Figure 6.4 shows the percent of murders from 1976-2018 where the first offender in the case is of each age from 0-99. Offenders with unknown ages



are excluded from this graph and make up about 27% of cases. The average (mean) age is 30.9 years old (shown in orange) which is due to a long right tail; the median age is 28 years old. If you look closely at the left side of the graph you can see that there are some very young offenders, with at least one offender aged 0-10 included in the data. It's not clear from this alone that these ages are a data entry. While a two-year-old certainly couldn't murder someone, the data does include deaths caused by "children playing with gun" (homicide circumstances will be discussed in Section 6.2.2.3) so these ages could potentially be correct.

If you're familiar with the age-crime curve in criminology - which basically says crime peaks in late teen years then falls dramatically - this shows that exact curve, though doesn't decline as the individual ages as quickly as we see with less serious crimes.

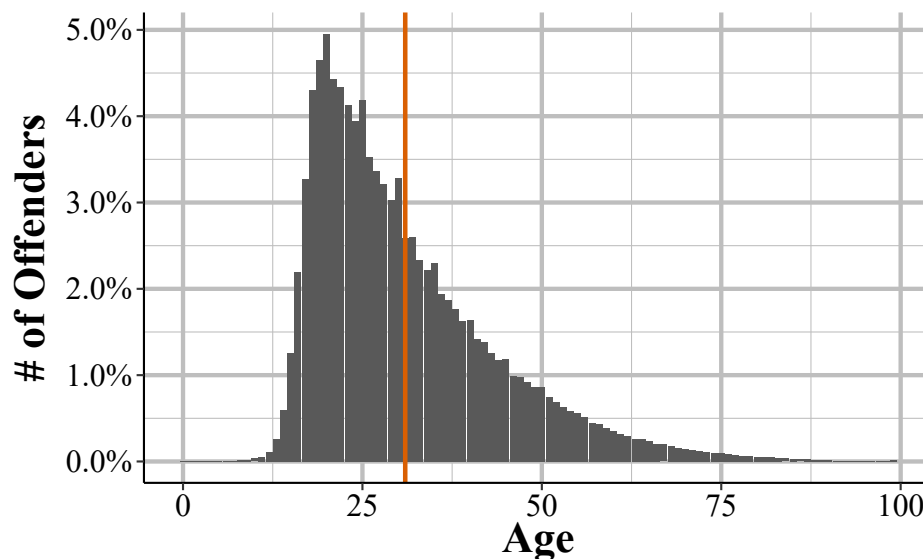


Figure 6.4: The age of homicide offenders, based on the first offender in any homicide incident. Victims under age 1 (classified as 'birth to 7 days old, including abandoned infant' and '7 days to 364 days old') and considered 0 years old. Victims reported as '99 years or older' are considered 99 years old.

Figure 6.5 repeats Figure 6.4 but with victim age rather than offender age.

The mean victim age (shown in orange) is 32.9 and the median age is 30. Though the age victim age is a bit younger than the average offender age, trends are relatively similar for teenagers and older where deaths spikes in the late teen years and then declines steadily. The major difference is the U-shape for younger victims - for victims under age 15, homicides peak at age 0 (i.e. younger than their first birthday) with ~1.5% of all homicides being this this age. They then decline until plateauing at around age 6 before increasing again in the early teen years.

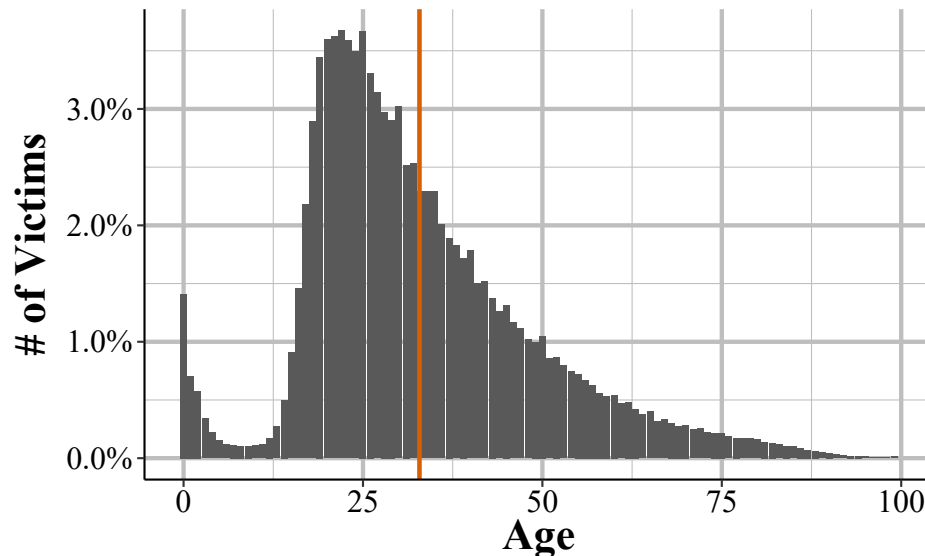


Figure 6.5: The age of homicide offenders, based on the first offender in any homicide incident. Victims under age 1 (classified as 'birth to 7 days old, including abandoned infant' and '7 days to 364 days old') and considered 0 years old. Victims reported as '99 years or older' are considered 99 years old.

### 6.2.1.2 Sex

We'll next look at victim and offender sex, a simple variable since only male and female are included.

About 62% of offenders, as seen in Figure 6.6 are male and about 8% are

female, indicating a large disparity in the sex of homicide offenders. The remaining 30% of offenders do not have sex data available because the police do not know the sex of this individual. For offenders who aren't arrested, this variable may be inaccurate since it is perceived sex of the offender.

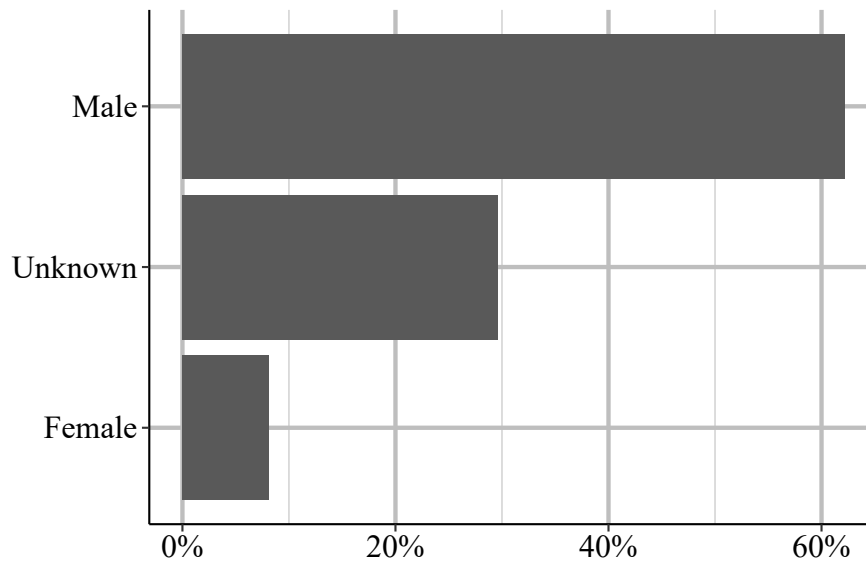


Figure 6.6: The sex of offenders, 1976-2018.

There is far less uncertainty for victim sex, with under 0.15% of victims having an unknown sex. Here again there is a large disparity between male and female with about 78% of victims being male and 22% being female. While there are more male victims than male offenders, this is probably just due to there being so many unknown offenders.

### 6.2.1.3 Race

This data also includes the race of the victims and offenders. This includes the following races: American Indian or Alaskan Native, Asian, Black, Native Hawaiian or Other Pacific Islander, and White. These are the only races included in the data; Hispanic is considered an ethnicity and is available as

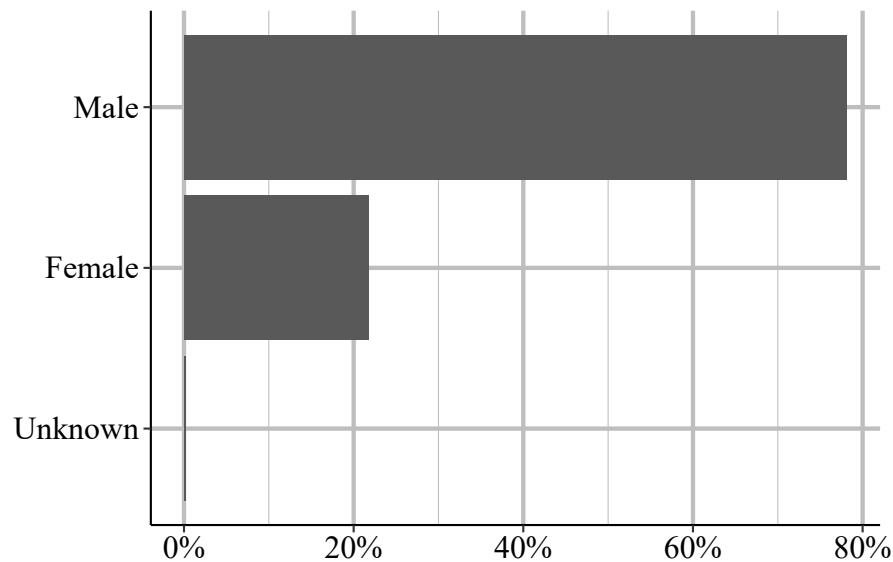


Figure 6.7: The sex of victims, 1976-2018.

a separate, though flawed, variable. There is no category for bi- or multi-racial. As with other demographics info for offenders, in cases where no arrest is made (and we don't know in this data if one is made), there's no way to confirm the person's race (and race itself is hard to put into discrete boxes like done here) so these results may not be entirely accurate.

Figure 6.8 shows the percent of homicides in the data by race. Black and White victims are included are similar percents, at 34.2% and 33.8% of victims, respectively. Given that Black people are only about 13% of the population while White people are 76% of the population, according to 2019 Census data, this shows a large disparity in offender race rates. There are far more Black and far fewer White offenders than would be expected from their percent of the total United States population. The next most common group is Unknown at about 30.5% of offenders. Given that so many offenders have an unknown race, the reliability of the other race measures is limited. The remaining races are Asian at 0.9% of offenders, American Indian or Alaskan Native at 0.6%, and Native Hawaiian or Other Pacific Islander at 0.004%.

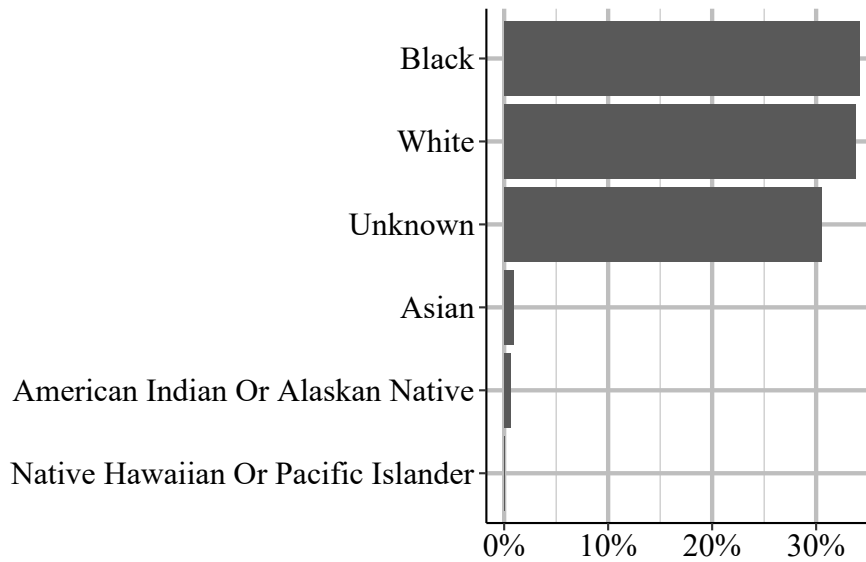


Figure 6.8: The race of offenders, 1976-2018.

For victim race, seen in Figure 6.9, only about 1% of victim race's are unknown. This means we can be a lot more confidence in the race of the victims than in the race of the offender. Or, at least the challenge of categorizing people by race is not the major problem, not missing people. As with offenders, White and Black victims are the two most common races, with 49% and 47.7% of victims, respectively. There are almost double the percent of Asian victims than Asian offenders at 1.51% of victims (and 0.9% of offenders). American Indian or Alaskan Natives make up 0.8% of victims while Native Hawaiian or Pacific Islanders make up 0.005% of victims.

#### 6.2.1.4 Ethnicity

The final demographic variable is ethnicity which is whether the victim or offender is Hispanic or not Hispanic. The UCR data has a weird relationship with this variable (which is also in the Arrests by Age, Sex, and Race dataset, discussing in Chapter 4) where ethnicity is technically a variable in the data but very rarely collected. As such, this is an unreliable variable that if you

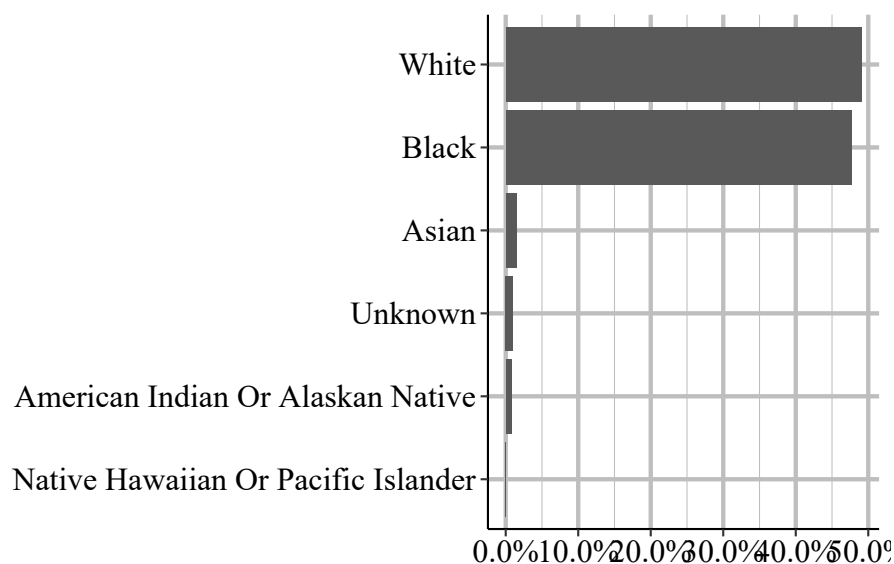


Figure 6.9: The race of victims, 1976-2018

really want to use, needs careful attention to make sure it is being reported consistently by the agencies that you are looking at.

The vast majority - 71.6% - of offenders have an unknown ethnicity while 21.5% are not Hispanic and 6.9% are Hispanic.

Unlike the other demographic variables, there is still a huge amount of underreporting when it comes to victim ethnicity, though still less than for offender ethnicity. 59% of victims have an unknown ethnicity. Nearly 30% of victims are reported as not Hispanic while 10.8% are reported as Hispanic.

## 6.2.2 Case characteristics

### 6.2.2.1 Weapon used

The first variable we'll look at is the weapon used by each offender. Table ?? shows the weapon used by the first offender in every incident from 1976 to 2018. Each offender can only be reported as having a single weapon, so

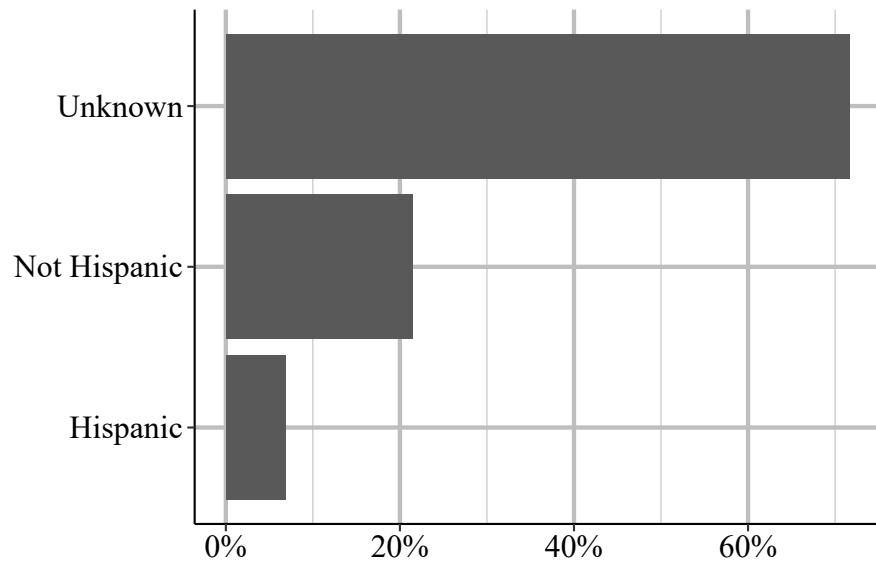


Figure 6.10: The ethnicity of offenders, 1976-2018.

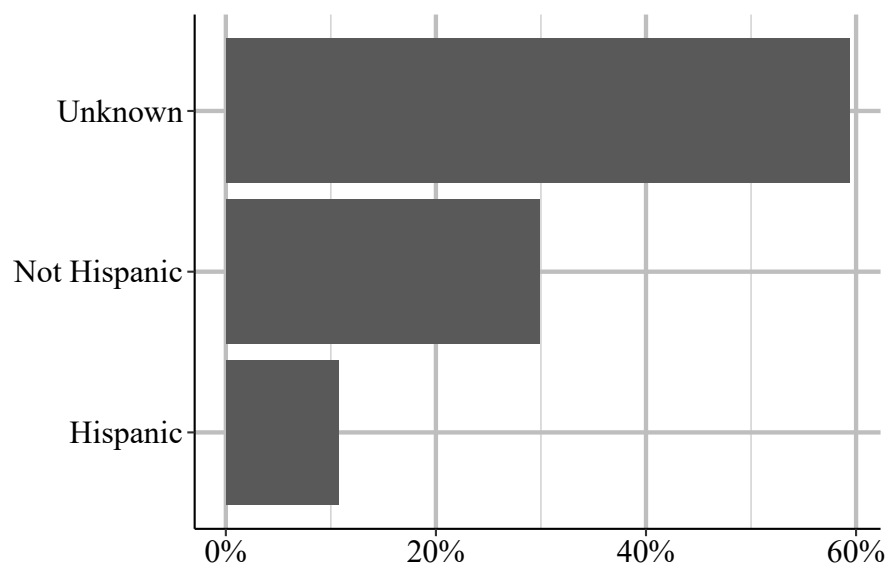


Figure 6.11: The ethnicity of victims, 1976-2018.

this table essentially shows the number (and percent) of murders caused by this weapon. This isn't entirely true since in reality an offender could use multiple weapons and there can be multiple offenders.

The most commonly used weapon is a handgun, which is used in nearly half of murders. This is followed by a knife or other sharp weapon used to cut at 15% of murders, and then by "firearm, type not stated" which is just a firearm where we don't know the exact type (it can include handguns) at 7.3% of murders. The fourth most common weapon is "personal weapons" at nearly 6% of murders. "Personal weapons" is a weird term to mean that there was no weapon - the "weapon" was the offender who beat the victim to death. Shotguns are involved in 5% of murders and all other weapons are involved in fewer than 5% of cases. In total there are 19 different weapons included though most are relatively uncommon.

\begin{figure}



Show  entries

Search:

	Weapon	# of Incidents	% of Incidents
1	Handgun	359,188	49.75%
2	Knife Or Cutting Instrument	109,670	15.19%
3	Firearm, Type Not Stated	52,638	7.29%
4	Personal Weapons - Includes Beating	42,763	5.92%
5	Shotgun	36,072	5.00%
6	Other Or Unknown Weapon	35,073	4.86%
7	Blunt Object	33,291	4.61%
8	Rifle	26,314	3.64%
9	Strangulation - Includes Hanging	9,619	1.33%
10	Fire	5,089	0.70%
11	Asphyxiation - Includes Death By Gas	4,420	0.61%
12	Other Gun	2,668	0.37%
13	Narcotics/Drugs - Includes Sleeping Pills	2,058	0.29%
14	Drowning	1,367	0.19%
15	Other Or Type Unknown	586	0.08%
16	Poison - Does Not Include Gas	467	0.06%
17	Explosives	374	0.05%
18	Pushed Or Thrown Out of Window	251	0.03%
19	Narcotics Or Drugs	48	0.01%

Showing 1 to 19 of 19 entries

Previous  Next

{

### 6.2.2.2 Relationship between first victim and offenders

An interesting and highly useful variable is the relationship between the first victim and each offender. To be clear, this is only for the first victim; we don't have the relationship between other victims and offenders.

However, as seen earlier, this isn't *too much* of an issue since nearly all incidents only have a single victim. There are 29 possible relationship types (including "unknown" relationship) which are broken into three categories: legal family members, people known to the victim but who aren't family, and people not known to the victim.

\begin{figure}

Show  entries Search:

	Relationship	Category	# of Incidents	% of Incidents
1	Unknown		263,237	36.46%
2	Acquaintance	Not family (but known)	147,741	20.46%
3	Stranger	Not known	111,955	15.51%
4	Other - Known To Victim	Not family (but known)	33,426	4.63%
5	Wife	Family	26,353	3.65%
6	Friend	Not family (but known)	26,143	3.62%
7	Girlfriend	Not family (but known)	19,194	2.66%
8	Husband	Family	11,700	1.62%
9	Other Family	Family	10,400	1.44%
10	Son	Family	10,342	1.43%
11	Boyfriend	Not family (but known)	9,041	1.25%
12	Neighbor	Not family (but known)	7,569	1.05%
13	Daughter	Family	7,436	1.03%
14	Brother	Family	6,403	0.89%
15	Father	Family	5,059	0.70%
16	Mother	Family	4,578	0.63%
17	In-Law	Family	4,392	0.61%
18	Common-Law Wife	Family	3,209	0.44%
19	Common-Law Husband	Family	2,690	0.37%
20	Ex-Wife	Not family (but known)	2,205	0.31%
21	Stepfather	Family	1,693	0.23%
22	Homosexual Relationship	Not family (but known)	1,663	0.23%
23	Stepson	Family	1,381	0.19%
24	Sister	Family	1,344	0.19%
25	Ex-Husband	Not family (but known)	876	0.12%
26	Stepdaughter	Family	747	0.10%
27	Employer	Not family (but known)	530	0.07%
28	Employee	Not family (but known)	422	0.06%
29	Stepmother	Family	227	0.03%

Showing 1 to 29 of 29 entries Previous  Next

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### 6.2.2.3 Homicide circumstance

We also have information on the type of the murder, which this data calls the “circumstance”. This comes is relatively broad categories that leave a

lot to be desired in our understanding of what led to the murder. Table ?? shows the number and percent of each circumstance for the first victim of each murder from 1976 to 2018. This data has 33 possible circumstances which it groups into five main categories: murders that coincide with committing another crime (“felony type” murders), murders that don’t coincide with another crime (“non-felony type” murders), justifiable homicides, and negligent manslaughter.

The felony type murders are simply ones where another crime occurred during the murder. While this is called “felony type” it does included other crimes such as theft and gambling (which isn’t always a felony) so is a bit of a misnomer. The “non-felony type” are murders that happen without another crime. This includes gang killings (where, supposedly, only the murder occurred), children killed by babysitters, fights among intoxicated (both of alcohol and drugs), and “lover’s triangle” killings. Justifiable homicides are when a person (civilian and police officer who kill a person committing a crime.<sup>6</sup> Negligent manslaughter includes accidental shootings such as when children find and shoot a gun, but excludes deaths from traffic accidents.

The most common circumstances, accounting for 27.4%, 26.4%, and 12.5%, respectively, are “other arguments”, “unknown”, and “other non-felony type - not specified”. Since the data includes “argument over money or property” as one category, the “other arguments” mean that it’s an argument for a reason other than over money or property. The “other non-felony type” one does not mean that the murder did not occur alongside another crime, but also doesn’t fall into the non-felony categories included. Robbery is the only remaining circumstance with more than 5% of murders, at 8%.

\begin{figure}

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<sup>6</sup>This dataset is one source of information on how many people police kill each year. But it is a large undercount compared to other sources such as the Washington Post collection, so is not a very useful source of information on this topic.

Show  entries

Search:

	Circumstance	Category	# of Incidents	% of Incidents
1	Other Arguments	Non-Felony Type	197,905	27.41%
2	Unknown		190,837	26.43%
3	Other Non-Felony Type - Not Specified	Non-Felony Type	90,203	12.49%
4	Robbery	Felony Type	57,312	7.94%
5	Narcotic Drug Laws	Felony Type	26,489	3.67%
6	Juvenile Gang Killings	Non-Felony Type	23,292	3.23%
7	Felon Killed By Police	Justifiable Homicide	16,394	2.27%
8	Brawl Due To Influence of Alcohol	Non-Felony Type	15,174	2.10%
9	Argument Over Money Or Property	Non-Felony Type	14,667	2.03%
10	Other Felony Type - Not Specified	Felony Type	13,902	1.93%
11	All Suspected Felony Type	Felony Type	12,743	1.77%
12	Felon Killed By Private Citizen	Justifiable Homicide	12,376	1.71%
13	Lovers Triangle	Non-Felony Type	10,372	1.44%
14	Burglary	Felony Type	6,052	0.84%
15	Brawl Due To Influence of Narcotics	Non-Felony Type	4,704	0.65%
16	Gangland Killings	Non-Felony Type	4,693	0.65%
17	All Other Manslaughter By Negligence Except Traffic Deaths	Negligent Manslaughter	4,339	0.60%
18	Rape	Felony Type	4,086	0.57%
19	Other Negligent Handling of Gun Which Resulted In Death of Another	Negligent Manslaughter	3,266	0.45%
20	Arson	Felony Type	2,982	0.41%
21	Other Sex Offenses	Felony Type	1,408	0.20%
22	Child Killed By Babysitter	Non-Felony Type	1,297	0.18%
23	Children Playing With Gun	Negligent Manslaughter	1,272	0.18%
24	Motor Vehicle Theft	Felony Type	1,259	0.17%
25	Institutional Killings	Non-Felony Type	1,055	0.15%
26	Gambling	Felony Type	1,031	0.14%
27	Larceny	Felony Type	753	0.10%
28	Prostitution And Commercialized Vice	Felony Type	601	0.08%
29	Other - Not Specified	Felony Type	554	0.08%
30	Sniper Attack	Non-Felony Type	474	0.07%
31	Victim Shot In Hunting Accident	Negligent Manslaughter	329	0.05%
32	Gun Cleaning Death - Other Than Self-Inflicted	Negligent Manslaughter	125	0.02%
33	Abortion	Felony Type	10	0.00%

Showing 1 to 33 of 33 entries

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### 6.2.2.4 Homicide subcircumstance

The “subcircumstance” just tells you more information about justifiable homicides. This includes the circumstance leading up to the “felon” - which is how the person killed is described, though technically they don’t need to have committed a felony - was killed. It includes if this person attached an officer (the one who killed them), a different officer, a civilian, or was committing or fleeing a crime.

\begin{figure}

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	Subcircumstance	# of Incidents	% of Incidents	
1	Felon Killed In Commission of A Crime	10,320	35.87%	
2	Felon Attacked Police Officer	8,553	29.73%	
3	Felon Attacked A Civilian	4,498	15.63%	
4	Not Enough Information To Determine	2,423	8.42%	
5	Felon Resisted Arrest	1,226	4.26%	
6	Felon Attacked Fellow Police Officer	951	3.31%	
7	Felon Attempted Flight From A Crime	799	2.78%	
Showing 1 to 7 of 7 entries				Previous 1 Next

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# Chapter 7

## Hate Crime Data

This dataset covers crimes that are reported to the police and judged by the police to be motivated by hate. More specifically, they are, first, crimes which were, second, motivated - at least in part - by bias towards a certain person or group of people because of characteristics about them such as race, sexual orientation, or religion. The first part is key, they must be crimes - and really must be the selection of crimes that the FBI collects for this dataset. Biased actions that don't meet the standard of a crime, or are of a crime not included in this data, are not considered hate crimes. For example, if someone yells at a Black person and uses racial slurs against them, it is clearly a racist action. For it to be included in this data, however, it would have to extend to a threat since "intimidation" is a crime included in this data but lesser actions such as simply insulting someone is not included. For the second part, the bias motivation, it must be against a group that the FBI includes in this data. When this data collection began crimes against transgender people were not counted so if a transgender person was assaulted or killed because they were transgender, this is not a hate crime recorded in the data.<sup>1</sup>

So this data is really a narrower measure of hate crimes than it might seem.

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<sup>1</sup>The first year where transgender as a group was a considered a bias motivation was in 2013.

In practice it is (some) crimes motivated by (some) kinds of hate that are reported to the police. It is also the most under-reported UCR dataset with most agencies not reporting any hate crimes to the FBI. This leads to huge gaps in the data with some states having zero agencies report crime, agencies reporting some bias motivations but not others, agencies reporting some years but not others. While these problems exist for all of the UCR datasets, it is most severe in this data. This problem is exacerbated by hate crimes being rare even in agencies that report them - with such rare events, even minor changes in which agencies report or which types of offenses they include can have large effects.

My main takeaway for this data is that it is inappropriate to use for most hate crime research. At most it can be used to look at within-city within-bias-motivation trends, while keeping in mind that even this narrow subset of data is limited by under-reporting by victims and potential changes in police practices of reporting such as how many months of data they report per year.

## 7.1 Agencies reporting

We'll start by looking at how many agencies report hate crime each year. This is a bit tricky since

The 2,000 or so agencies that report each year are not the same every year. Figure 7.2 shows the cumulative number of agencies that have reported at least one hate crime between 1991 and 2018. There is a relatively steady growth in the cumulative number of agencies, with about 350 new agencies each year. This means that each year some new agencies report hate crimes while some agencies that reported a hate crime in the previous year don't report any hate crimes in the current year. Figure 7.3 puts this into hard numbers by showing the percent of agencies who reported a hate crime in a certain year who *also* reported a hate crime in the previous year. For most years between 50% and 60% of agencies which reported a hate crime in the



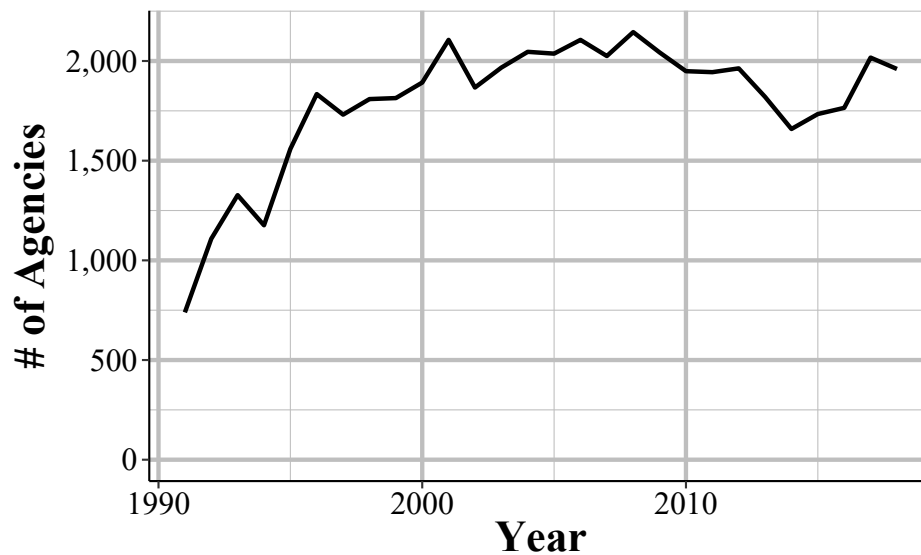


Figure 7.1: The annual number of police agencies that report at least one hate crime incident in that year.

year shown on the x-axis also reported a hate crime in the previous year, indicating somewhat high consistency in which agencies have hate crimes.

Another way to understand reporting is to look at the number of reported hate crimes by state and see which states report and which don't. Figure 7.4 does this for 2018 data by showing the number of reported hate crime incidents by state. While every state other than Wyoming reporting at least one hate crime in 2018, there are large differences between states because even in states that have reporting agencies, not all agencies in that state report. For example, Alabama reported only two hate crimes in 2018, the least of any state other than Wyoming.

Since the number of state-wide hate crimes is partially influenced by population, we'll also look at it as the percent of agencies in the state that report at least one hate crime. Again this is limited by population as agencies in each state cover different populations - and most agencies are small so a few large agencies can account for a large share of crimes,

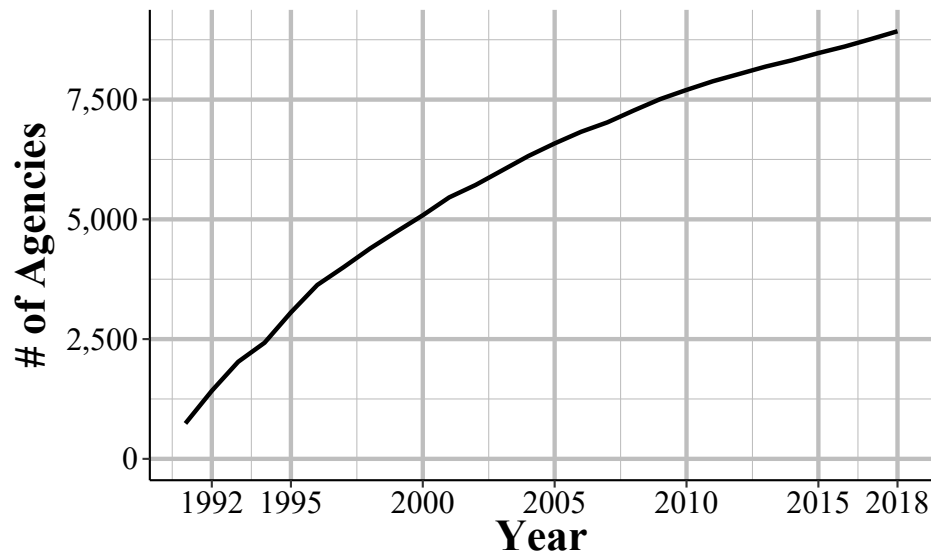


Figure 7.2: The cumulative number of agencies that have reported one or more hate crimes between 1991 to 2018.

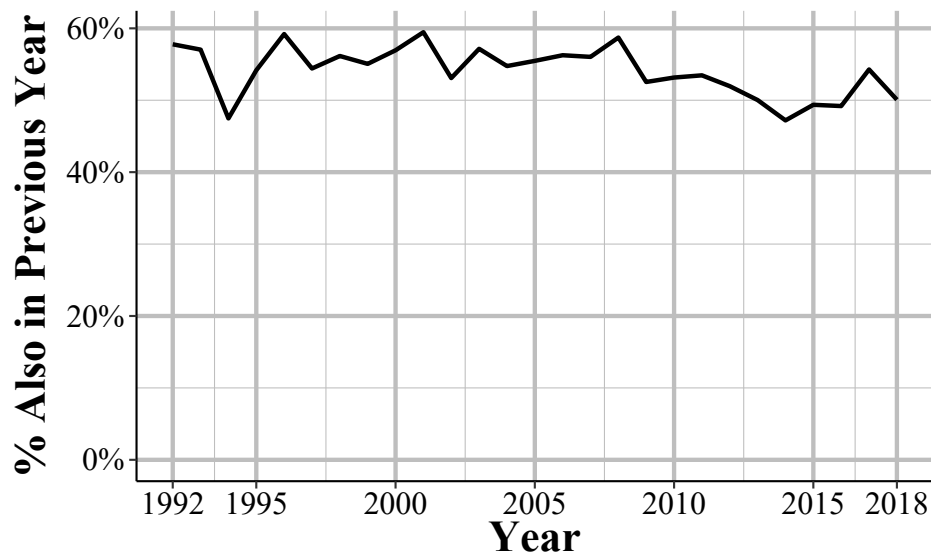


Figure 7.3: The percent of agencies that report a hate crime in a given year that also reported a hate crime in the previous year, 1992-2018.

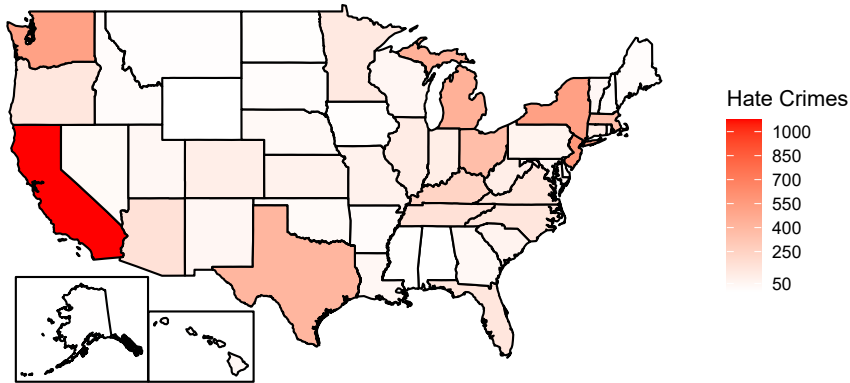


Figure 7.4: Total reported hate crimes by state, 2018.

including hate crimes. Still, this is a useful exercise as we can easily see where very few agencies report. Figure 7.5 shows the percent of agencies for each state that reported at least one hate crime in 2018. In Connecticut, the state with the highest percent of agencies reporting, 28% of agencies reported at least one hate crime. In 34 states, fewer than 10% of agencies reported a hate crime, and in 19 states fewer than 5% of agencies did so.

One interesting finding from this graph is the more liberal states - Connecticut, New Jersey, Vermont, California, Washington - have the highest share of agencies reporting a hate crime, indicating that the culture of the state may influence whether agencies report hate crimes.

## 7.2 Important variables

This data has the standard set of variables describing the agency that is reporting. This includes the agency ORI - which is the unique ID for that agency - the agency name, their state, and the population under their

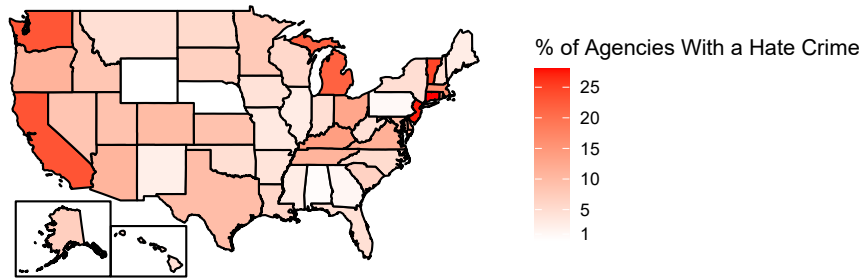


Figure 7.5: The percent of agencies in each state that reported at least one hate crime in 2018.

jurisdiction.

They also have a variable with the exact date that the hate crime occurred on - and not the date it was reported on. Figure 7.6 shows the percent of hates crimes between 1991 and 2018 that occurred on each day of the week.

Interestingly, the most common day for a hate crime to occur is on Wednesday, not on Friday or Saturday as non-hate crimes most frequently occur. This suggests that hate crimes don't follow the same trends as other crimes.

Each hate crime incident can cover up to 10 different crimes occurring - e.g. a person who burglarizes a synagogue and spray paints a swastika on the wall would be have both vandalism and burglary reported in this data.

With each crime, this data has the bias motivation for that crime, the location of the crime (in broad categories, not the actual location in the city like a street address would have), and the number of victims for that offense. In practice, in most hate crimes with multiple offenses recorded, the bias motivation, location, and victim count is the same for each offense.

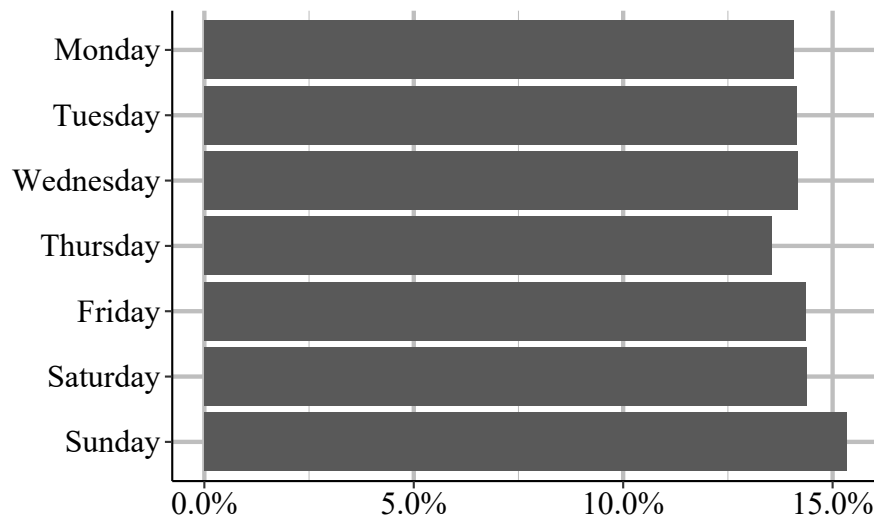


Figure 7.6: The day of the week that hate crimes occurred on, 1991-2018.

Figure 7.7 shows the number of crimes per incident for each hate crime reported between 1991 and 2018. In 96.6% of cases, there is only one offense in that incident.<sup>2</sup> This drops sharply to 3.2% of incidents having two offenses, 0.21% having three offenses, 0.016% having four offenses, and 0.002% having five offenses. Even though this data does allow up to 10 offenses per hate crime incident, there has never been a recorded case with more than five offenses.

### 7.2.1 The bias motivation (who the hate is against)

The most important variable in this data is the “bias motivation” which is the FBI’s term for the cause of the hate. A hate crime targeted against Black people would be an “anti-Black” bias motivation. For the police to classify an incident as a hate crime, and to assign a particular bias motivation, the police must have *some* evidence that the crime was

<sup>2</sup>In 0.0005% of hate crimes there is no recorded offense. This is not shown in the graph.

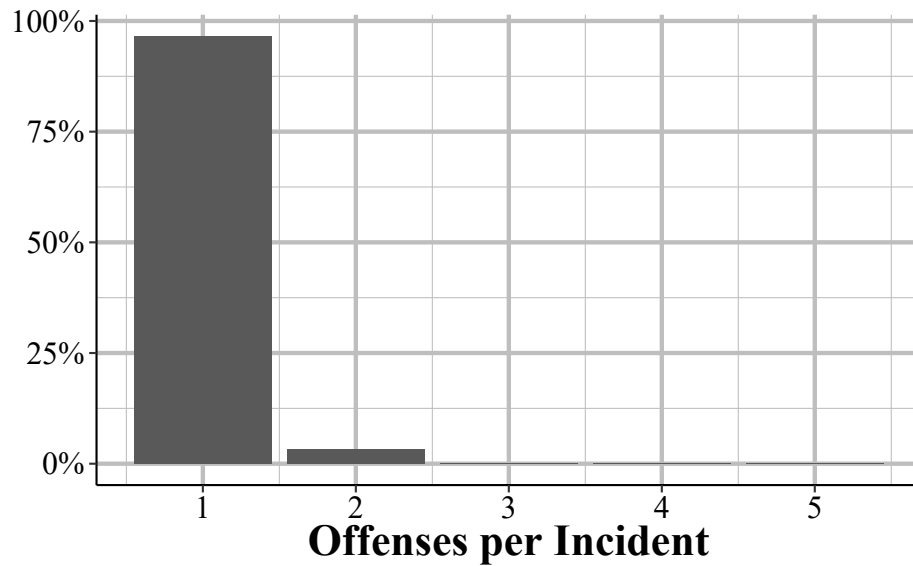


Figure 7.7: The number of offenses per hate crime incident.

motivated by hate. The victim saying that the crime is a hate crime alone is not sufficient - though if large portions of the victim's community believe that the crime is a hate crime, this is a factor in the police's assessment. The evidence required is not major, it includes things as explicit as racial slurs said during an incident and less obvious factors like the victim is celebrating their community (e.g. attending a holiday event) or the crime occurring on an important holiday for that community (e.g. Martin Luther King Day, religious holidays). The FBI also encourages police to consider the totality of the evidence even if none alone strongly suggests that the crime was a hate crime in making their determination about whether the incident was a hate crime or not.

This also means that many (likely most) hate crimes will not be recorded as hate crimes since there is no evidence that the crime is motivated by hate. For example, if a man committed a crime against Asian people for crimes because they are Asian, that would in reality be a hate crime. However, if the offender does not say anything anti-Asian to the victim, which is the mostly likely thing to indicate that this is a hate crime, the crime would not

likely be recorded as a hate crime. For example, at the time of this writing (Spring, 2021), there are numerous media reports discussing an increase in anti-Asian hate crimes as a result of racism relating to the pandemic.<sup>3</sup> This data would likely undercount both anti-Asian behavior and anti-Asian hate crimes. First, if someone walked to an Asian person and called them an anti-Asian slur, that is clearly a hateful act and would be classified as a hate crime under some organization's collections methods. However, as hateful as this incident is, *this alone* would not be classified as a hate crime in this dataset as a slur is not a crime. If accompanied by other criminal behavior, or if it continues to the point where it can be considered intimidation, it would then be classified as a hate crime. Second, crimes against Asian victims that are in fact hate crimes, but have no evidence that they are hate crimes would not be classified as hate crimes in this data.

Bias motivation is based on the offender's perceptions of the victim so even if they are incorrect in who their victim is, if they intended to target someone for their perceived group membership, that is still a hate crime. For example, if a person assaults a man because they think he is gay, that is a hate crime because the assault was motivated by hate towards gay people. Whether the victim is actually gay or not is not relevant - the offender perceived him to be gay so it is an anti-gay hate crime. To make this even more complicated, the offender must have committed the crime because they are motivated, at least to some degree, by their bias against the victim. Being biased against the victim but targeting them for some other reason means that the crime is not a hate crime.

The biases that the FBI includes in this data has grown over time, with new bias motivations being added in 1997, 2012, 2013, and 2015. Table ?? shows each bias motivation in this data, the year it was first reported, how many hate crimes there were for this bias motivation from 1991-2018 and what percent of hate crimes that bias motivation makes up. For ease of seeing how bias motivations changed over time, the table is sorted by year

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<sup>3</sup>This dataset for 2020 won't be released until Fall 2021 so this data is not useful for measuring urgent policies about current events.

and by frequency of incident within that year. If you're viewing this on a computer or phone, you can sort the table yourself. The year is the first year with that bias motivation - as hate crimes for certain groups are very rare, the bias motivation could have technically been available in previous years. The last column in this table shows the percent of hate crimes from 1991-2018, though this is a very rough measure since some groups are so small that even accounting for a small percent of total hate crimes can mean that are massively disproportionately targeted.

\begin{figure}



Show 100 entries Search:

	Bias Motivation	First Year Reported	# of Incidents	% of Incidents
1	Anti-Eastern Orthodox (Greek, Russian, Etc.)	2015	131	0.07%
2	Anti-Other Christian	2015	130	0.07%
3	Anti-Sikh	2015	80	0.04%
4	Anti-Hindu	2015	40	0.02%
5	Anti-Mormon	2015	38	0.02%
6	Anti-Jehovahs Witness	2015	20	0.01%
7	Anti-Buddhist	2015	19	0.01%
8	Anti-Transgender	2013	513	0.26%
9	Anti-Male	2013	77	0.04%
10	Anti-Native Hawaiian Or Other Pacific Islander	2013	49	0.02%
11	Anti-Gender Non-Conforming	2012	152	0.08%
12	Anti-Female	2012	142	0.07%
13	Anti-Mental Disability	1997	944	0.47%
14	Anti-Physical Disability	1997	503	0.25%
15	Anti-Black	1991	68,588	34.35%
16	Anti-Jewish	1991	25,943	12.99%
17	Anti-White	1991	23,366	11.70%
18	Anti-Male Homosexual (Gay)	1991	20,188	10.11%
19	Anti-Hispanic	1991	12,725	6.37%
20	Anti-Ethnicity Other Than Hispanic	1991	10,016	5.02%
21	Anti-Lesbian, Gay, Bisexual, Or Transgender, Mixed Group (LGBT)	1991	5,990	3.00%
22	Anti-Asian	1991	5,891	2.95%
23	Anti-Multi-Racial Group	1991	4,811	2.41%
24	Anti-Female Homosexual (Lesbian)	1991	4,221	2.11%
25	Anti-Muslim	1991	3,561	1.78%
26	Anti-Other Religion	1991	3,269	1.64%
27	Anti-American Indian Or Native Alaskan	1991	2,195	1.10%
28	Anti-Catholic	1991	1,458	0.73%
29	Anti-Protestant	1991	1,196	0.60%
30	Anti-Multi-Religious Group	1991	1,118	0.56%
31	Anti-Arab	1991	1,091	0.55%
32	Anti-Heterosexual	1991	542	0.27%
33	Anti-Bisexual	1991	527	0.26%
34	Anti-Atheism/Agnosticism	1991	149	0.07%

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2015 is the most year of new bias motivations, as of data through 2018.

This year added a number of religions such as Anti-Buddhist, Anti-Sikh, and Anti-Jehovah's Witness. In 2013, anti-Transgender was added and this is the most common of the bias motivations added since data began in 1991 with 513 hate crimes between 2013-2018 - 0.26% of all hate crimes from 1991-2018. That year also added anti-male and Anti-Native Hawaiian or Other Pacific Islander, which is the most recent racial group added. In 2012, anti-gender non-conforming and anti-female were included, while in 1997 both anti-mental and anti-physical disability were added. In part due to having fewer years of data available, these newer bias motivations make up a small percent of total hate crimes, accounting for ~1.4%.

The original hate crimes - that is, those in the data in 1991 when this dataset was released - are far more common. The most common bias motivation is anti-Black at 34% of hate crimes, anti-Jewish at 13%, anti-White at 12%, anti-male homosexual (gay) at 10%, anti-Hispanic at 6%, and anti-ethnicity other than Hispanic (this group means a crime against a ethnic group that isn't Hispanic, though it is occasionally reported as anti-non-Hispanic which is incorrect.) at 5%. All other bias motivations are less than 5% of hate crimes and consist of a variety of ethnic, racial, religious, or sexual orientation. Some hate crimes can potentially fall in multiple categories. For example, there is a bias motivation of "anti-male homosexual (gay)" and of "anti-lesbian, gay, bisexual, or transgender, mixed group (LGBT)" so there is some overlap between them.

### 7.2.2 The crime that occurred

The "crime" part of hate crimes is which criminal offense occurred during the incident. A hateful act where the action is not one of the crimes that the FBI records would not be considered a hate crime. This is likely most common when considering something like a person calling someone by a hateful slur (e.g. "You're a [slur]", "go back to your own country") but where the action is not technically a crime. Another layer of difficulty in using this data is that not all crimes that the FBI includes were initially

included when data become available in 1991. Every several years the FBI adds new crimes to be included in this data. Table ?? shows each crime in the data, the first year that this crime was reported, the total number of these crimes reported between 1991 and 2018, and the percent of all incidents this crime makes up.<sup>4</sup> This table is sorted with the most recent years first, and within year by how common the crime was.

Nearly all hate crimes are vandalism/destruction of property (31%), intimidation (30%), and simple assault (20%) or aggravated assault (11%) with no remaining crime making up more than 2% of total hate crimes.

\begin{figure}

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<sup>4</sup>This tables uses only the first offense in an incident so counts are slightly lower than if all crimes in every incident is used.

Show 100 entries Search:

	Offense	First Year Reported	# of Incidents	% of Incidents
1	Human Trafficking - Commercial Sex Acts	2017	1	0.00%
2	Fraud-Other	2016	17	0.01%
3	Bribery	2014	2	0.00%
4	Assisting Or Promoting Prostitution	2013	4	0.00%
5	Purchasing Prostitution	2013	2	0.00%
6	Wire Fraud	2006	18	0.01%
7	Impersonation	2001	108	0.05%
8	Prostitution	2001	12	0.01%
9	Statutory Rape	1999	12	0.01%
10	Theft From Coin-Operated Machine Or Device	1999	11	0.01%
11	Negligent Manslaughter	1999	3	0.00%
12	False Pretenses/Swindle/Confidence Game	1997	230	0.12%
13	Extortion/Blackmail	1997	41	0.02%
14	Incest	1997	7	0.00%
15	Stolen Property Offenses - Receiving, Selling, Etc.	1996	94	0.05%
16	Sexual Assault With An Object	1996	23	0.01%
17	Pocket-Picking	1996	19	0.01%
18	Welfare Fraud	1996	2	0.00%
19	Drug Equipment Violations	1995	204	0.10%
20	Credit Card/Atm Fraud	1995	125	0.06%
21	Embezzlement	1995	56	0.03%
22	Forcible Sodomy	1995	52	0.03%
23	Pornography/Obscene Material	1995	34	0.02%
24	Purse-Snatching	1995	23	0.01%
25	Theft From Building	1994	478	0.24%
26	Kidnapping/Abduction	1994	99	0.05%
27	All Other Larceny	1993	1,670	0.84%
28	Drug/Narcotic Violations	1993	862	0.43%
29	Theft From Motor Vehicle	1993	642	0.32%
30	Shoplifting	1993	521	0.26%
31	Weapon Law Violations	1993	289	0.14%
32	Theft of Motor Vehicle Parts/Accessories	1993	174	0.09%
33	Counterfeiting/Forgery	1993	165	0.08%
34	Forcible Fondling - Indecent Liberties/Child Molest	1993	142	0.07%
35	Motor Vehicle Theft	1992	401	0.20%
36	Destruction of Property/Vandalism	1991	62,502	31.30%
37	Intimidation	1991	59,750	29.92%
38	Simple Assault	1991	39,035	19.55%
39	Aggravated Assault	1991	22,213	11.12%
40	Robbery	1991	3,748	1.88%
41	Burglary/Breaking And Entering	1991	3,363	1.68%
42	Arson	1991	1,224	0.61%
43	Theft-Other	1991	796	0.40%
44	Murder/Non-Negligent Manslaughter	1991	265	0.13%
45	Forcible Rape	1991	242	0.12%

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Agencies that report to the FBI's National Incident-Based Reporting System (NIBRS) can also report bias motivations for their crimes, and these reports are included in this dataset. One tricky thing is that the crimes included are different depending on if the agency reported through NIBRS or to the dataset directly, and are not NIBRS reporting agencies. The above table shows all crimes included, but agencies who report directly can only submit a subset of crimes. These crimes are the same as in the Offenses Known and Clearances by Arrest dataset that is detailed in Chapter @ref(offenses\_known) as well as vandalism/destruction of property and human trafficking.

### 7.2.3 The location of the crime

This data is interesting because it includes the location - in categories for types of places, not actual location in the city - of the incident. This is important since the type of location can be a factor in whether the incident is classified as a hate crime. For example, spray paint on a synagogue or a mosque is much more likely to be a hate crime than spray paint on a wall of an abandoned building. Table ?? shows the locations of hate crimes sorted by the year that location was first included in the data and then by frequency of hate crimes. Each hate crime incident can have multiple locations since each offense can have its own incident, but in most cases (96.6%) a hate crime only has a single location.

As with the crime and the bias motivation, the available locations have increased as time went on, though these newer locations are relatively uncommon. One important change in location is that starting in 2010 the location of school/college was split to have one location be for elementary and high schools and another location be for colleges and universities. The majority of hate crimes occur in the victim's home (30%), on a road or alley (19%), in an unknown location (13.6%), and in a parking lot or parking garage. All other locations occur in fewer than 5% of hate crimes.

\begin{figure}

Show 100 entries Search:

	Location	First Year Reported	# of Incidents	% of Incidents
1	Military Installation	2015	3	0.00%
2	Community Center	2013	75	0.04%
3	Dock/Wharf/Freight/Modal Terminal	2012	14	0.01%
4	Shelter - Mission/Homeless	2011	68	0.03%
5	Rest Area	2011	44	0.02%
6	Arena/Stadium/Fairgrounds/Coliseum	2011	35	0.02%
7	Auto Dealership New/Used	2011	34	0.02%
8	Abandoned/Condemned Structure	2011	31	0.02%
9	Daycare Facility	2011	23	0.01%
10	Farm Facility	2011	16	0.01%
11	Amusement Park	2011	14	0.01%
12	Atm Separate From Bank	2011	9	0.00%
13	Tribal Lands	2011	6	0.00%
14	School - Elementary/Secondary	2010	1,748	0.88%
15	School - College/University	2010	1,248	0.63%
16	Park/Playground	2010	646	0.32%
17	Shopping Mall	2010	142	0.07%
18	Industrial Site	2010	65	0.03%
19	Camp/Campground	2010	23	0.01%
20	Gambling Facility/Casino/Race Track	2010	21	0.01%
21	Residence/Home	1991	59,606	29.86%
22	Highway/Road/Alley	1991	37,988	19.03%
23	Other/Unknown	1991	27,178	13.61%
24	School/College	1991	17,249	8.64%
25	Parking Lot/Garage	1991	11,440	5.73%
26	Church/Synagogue/Temple	1991	7,530	3.77%
27	Commercial/Office Building	1991	4,502	2.25%
28	Restaurant	1991	3,978	1.99%
29	Bar/Nightclub	1991	3,549	1.78%
30	Government/Public Building	1991	2,894	1.45%
31	Convenience Store	1991	2,561	1.28%
32	Specialty Store - Tv, Fur, Etc.	1991	2,375	1.19%
33	Air/Bus/Train Terminal	1991	1,931	0.97%
34	Field/Woods	1991	1,917	0.96%
35	Service/Gas Station	1991	1,830	0.92%
36	Grocery/Supermarket	1991	1,628	0.82%
37	Department/Discount Store	1991	1,516	0.76%
38	Drug Store/Doctors Office/Hospital	1991	1,448	0.73%
39	Jail/Prison	1991	1,262	0.63%
40	Hotel/Motel	1991	1,214	0.61%
41	Construction Site	1991	507	0.25%
42	Bank/Savings And Loan	1991	418	0.21%
43	Liquor Store	1991	346	0.17%
44	Lake/Waterway	1991	326	0.16%
45	Rental Storage Facility	1991	188	0.09%

Showing 1 to 45 of 45 entries Previous 1 Next

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### 7.2.4 Number and race of offenders

There are two variables that have information about the people who commit the hate crime: the number of offenders and the race of the offenders (as a single value with the race of the group if all are of the same race or it will say a “multi-racial” group). Unfortunately, important information like the age of the offenders, their criminal history, their relationship to the victim, their gender, or whether they are arrested are completely unavailable in this dataset.

When the police do not have any information about the number of offenders (which is common in cases of property crimes such as vandalism but rare in violent crimes), this data considers that to have zero offenders. The zero is just a placeholder that means that the police have no idea how many offenders there are, not that they think there were actually no offenders. Figure 7.8 shows the percent of hate crimes from 1991-2018 that have each number of offenders recorded. In the actual data it says the actual number of offenders, with the largest group in the current data going to 99 offenders - in this graph I group 10 or more offenders together for simplicity. I also relabel zero offenders as “Unknown” offenders in the graph since that’s more accurate. The most common number of offenders per hate crime is one offender, at about 46% of hate crimes from 1991-2018 having only one offender. This drops sharply to 9% of hate crimes having 2 offenders and continues to drop as the number of offenders increase. However, about a third (36.8%) of hate crimes have an unknown number of offenders.

The data also includes the race of the offenders as a group, though not the ethnicity (Hispanic or not) of the offenders. In cases where there are multiple races among offenders, that will be classified as a “multi-racial group”. As shown in Figure 7.8 The most common racial group is “unknown” since the police do not know the race of the offenders. Then are White offenders at nearly 40% of hate crimes followed by Black offenders at nearly 13% of hate crimes. The remaining racial groups are rare with about 2% of hate crimes being committed by a multi-racial group of offenders and

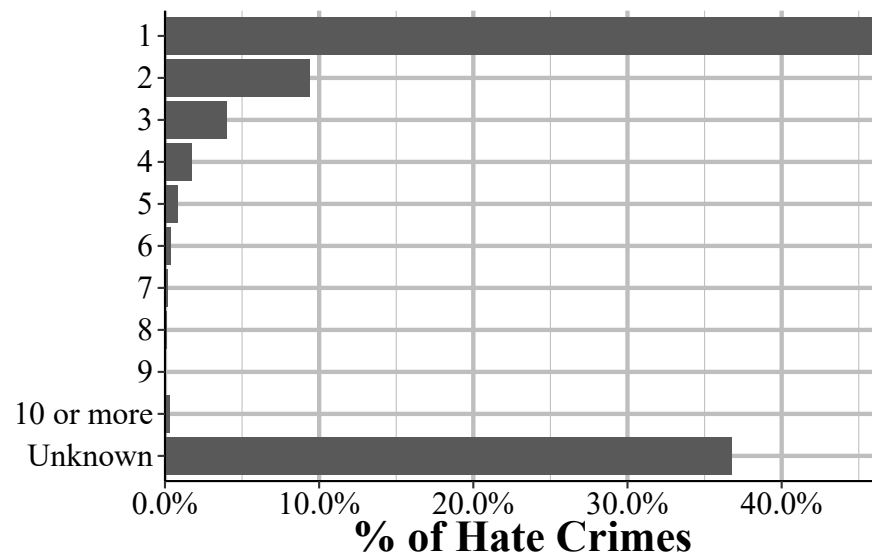


Figure 7.8: The race of offenders, as a group, for hate crime incidents, 1991-2018.

0.72% of hate crimes committed by Asian or Pacific Islander offenders and 0.54% committed by American Indian or Native Alaskan offenders.



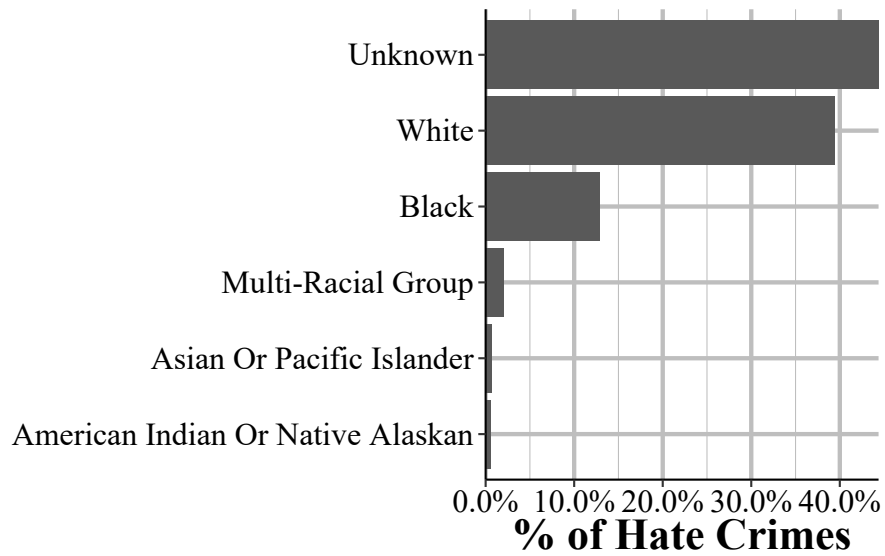


Figure 7.9: The race of offenders, as a group, for hate crime incidents, 1991-2018.



## Chapter 8

# Property Stolen and Recovered (Supplement to Return A)

The Property Stolen and Recovered data - sometimes called the Supplement to Return A (Return A being another name for the Offenses Known and Clearances by Arrest dataset, the “crime” dataset) - provides monthly information about property-related offenses (theft, motor vehicle theft, robbery, and burglary), including the location of the offense (in broad categories like “gas station” or “residence), what was stolen (e.g. clothing, livestock, firearms), and how much the stolen items were worth.<sup>1</sup> The “recovered” part of this dataset covers the type and value of property recovered so you can use this, along with the type and value of property stolen, to determine what percent and type of items the police managed to recover. Like other UCR datasets this is at the agency-month level so you can, for example, learn how often burglaries occur at the victim’s home during the day, and if that rate changes over the year or differs across agencies.

The data, however, provides no information about the offender or the victim (other than if the victim was an individual or a commercial business

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<sup>1</sup>It also includes the value of items stolen during rapes and murders, if anything was stolen.

[based on the location of the incident - “bank”, “gas station”, etc]). The value of the property stolen is primarily based on the victim’s estimate of how much the item is worth (items that are decreased in value once used - such as cars - are supposed to be valued at the current market rate, but the data provides no indication of when it uses the current market rate or the victim’s estimate) so it should be used as a very rough estimate of value.

Before getting into the details of this data, let’s look at one example of how this data can measure property crime in a few different ways. This data is highly useful to use as a rough measure of the cost of crime. This cost is limited to just the value of the property stolen - so excludes things like injuries, mental health effects of victimization, etc. - but is still better than nothing. Since this data includes, for some types of property stolen, both the number of offenses per month (broken down by type of theft and items stolen) and the value of the stolen property, we can also see if the average value of these thefts change over time.

We’ll look at home burglaries that occur during the day in Philadelphia. First, we can look at the number of these kinds of burglaries each month or year. Figure 8.1 shows the annual number of daytime home burglaries and in recent years it has declined sharply into having the fewest on record in 2019. So citywide, Philadelphia has never been safer when it comes to daytime home burglaries. But when considering the cost of crime, we also want to know the actually monetary cost of that incident. This encompasses a lot of different values including physical and emotional harm to the victim (including harm to structures such as broken doors and windows) and changes in people’s behavior (e.g. quit job to avoid going to a certain part of town). With this data we only have the value of the physical items stolen, so while it is still a cost of crime it’s a rather shallow one.

Figure 8.2 measures this cost of crime by showing the annual sum of the value of the property stolen for daytime home burglaries in Philadelphia.

The trend here is different than the previous graph which showed undulations in the number of burglaries but not major trend changes until the 2010s; here is a steady increase, though with varying speed of increase,

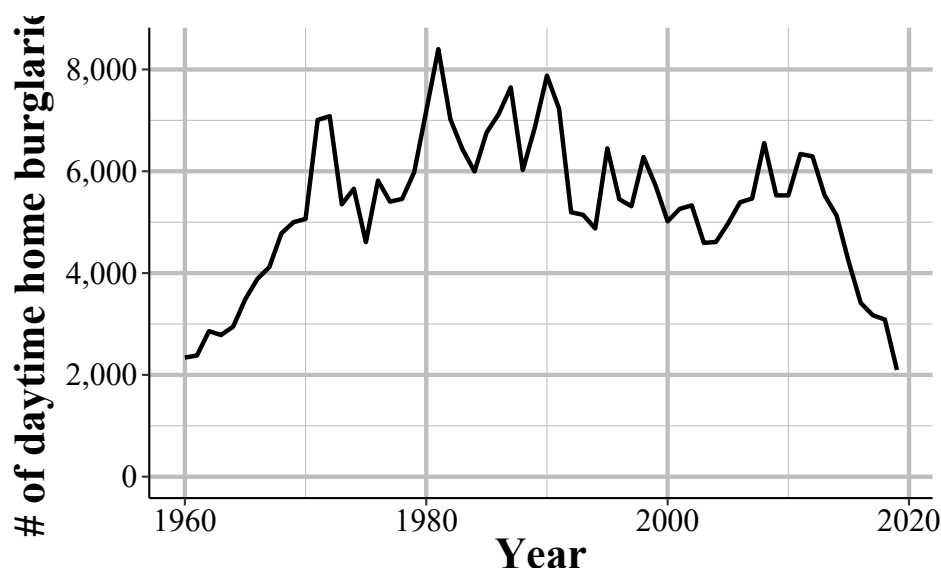


Figure 8.1: The annual number of daytime home burglaries reported in Philadelphia, PA, 1960-2019.

until it peaked in the late 2000s/early 2010s before declining substantially in recent years. While the number of burglaries peaked in the early 1980s, the total value of burglaries didn't peak until the early 2010s, so the cost of this crime (even this very narrow measure of cost) can't be ascertained from knowing the number of burglaries alone. From this measure we can say that daytime home burglaries were worse in the early 2010s and are substantially better currently.

The final way we can measure daytime home burglaries is to put the previous variables together to look at the cost per burglary. This will give us the average amount of property stolen from each burglary victim. Figure 8.3 shows the cost average cost per burglary for each year of data available.

Now we have a different story than the other graphs. Even though the number of daytime home burglaries declined substantially over the last decade and the total cost is around the level seen in the 1980s, the cost per burglary remains at record highs in recent years, though down from the peak in the mid-2010s. This suggests that while burglaries are down, the

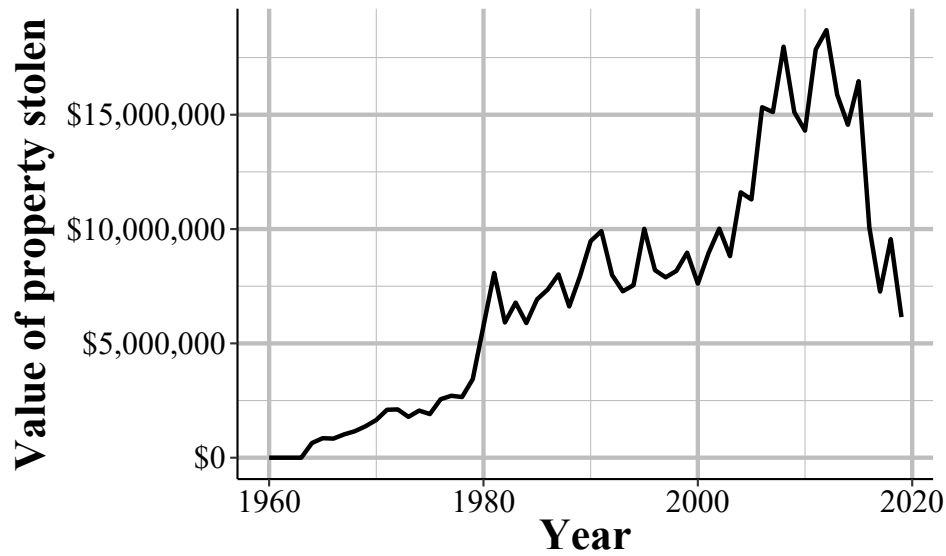


Figure 8.2: The total annual cost of daytime home burglaries in Philadelphia.

burden on each burglary victim has continued to grow.

Part of this - and part of the long-term increase seen in Figure 8.2 - is simply due to inflation. \$1 in 1963, the first year we have data on the value of burglaries, is worth \$8.28 in 2019, according to the Bureau of Labor Statistics. The values in this data are *not* adjusted for inflation so you need to do that adjustment yourself before any analyses, otherwise your results will be quite a bit off.

When we adjust all values to 2019 dollars, as shown in Figure 8.4, the trend becomes changes a bit. There's still a steady increase in cost per burglary over time but it is far more gradual than in Figure 8.3. And now the difference from the cost in early years and late years are far smaller.

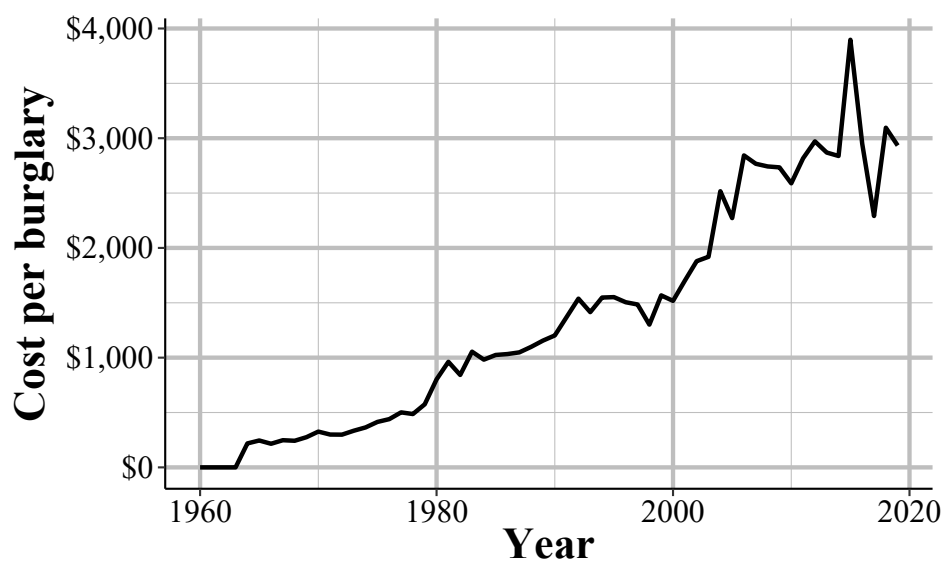


Figure 8.3: The annual number of burglaries and cost per burglary for daytime home burglaries in Philadelphia, 1960-2019.

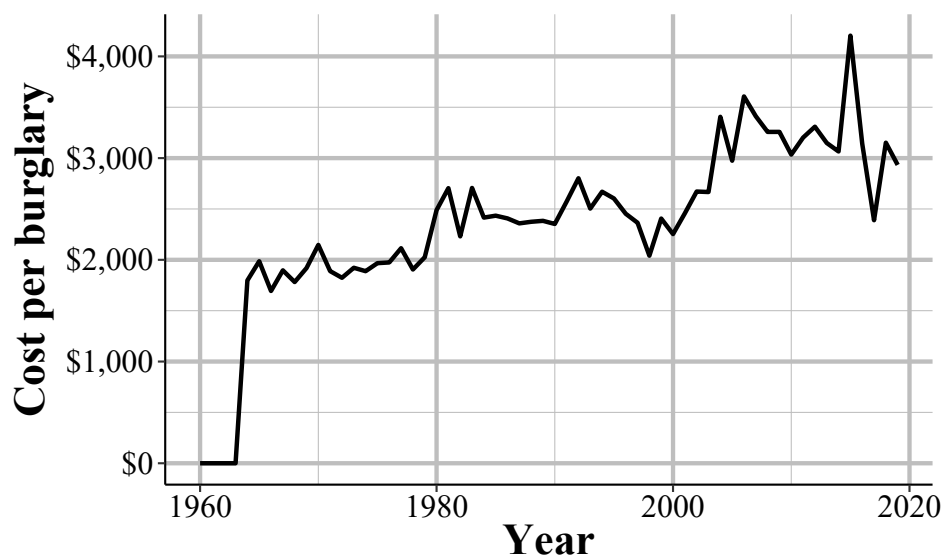


Figure 8.4: The inflation-adjusted annual number of burglaries and cost per burglary for daytime home burglaries in Philadelphia, 1960-2019.

## 8.1 Agencies reporting

We'll start by looking at which agencies report. The data is available from 1960 through 2019 though the columns about the value of the property only begin in 1964. Figure 8.5 show the number of agencies each year that reported at least one month during that year. In the first several years of data barely any agencies reported data and then it spiked around 1966 to over 6,000 agencies per year then grew quickly until over 12,000 agencies reported data in the late 1970s. From here it actually gradually declined until fewer than 12,000 agencies in the late 1990s before reversing course again and growing to about 15,000 agencies by 2019 - down several hundred agencies from the peak a few years earlier.

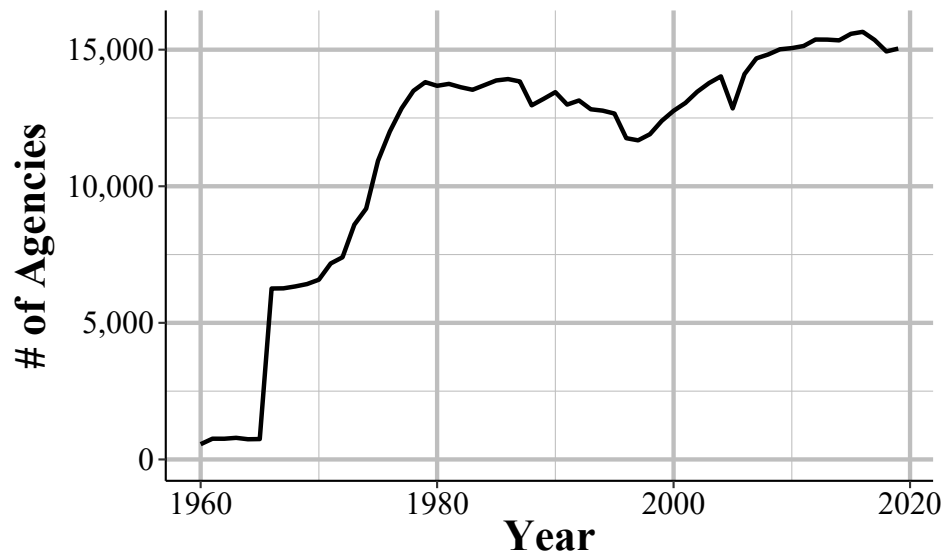


Figure 8.5: The annual number of police agencies that report at least month of data that year.

Since this data is called the “Supplement to Return A” we would expect that the agencies that report here are the same as the ones that report to the Offenses Known and Clearances by Arrest data, which is also called the Return A dataset. Figure 8.6 shows the percent of agencies in this dataset



that are also in the Return A data. Except for the first several years of data in the 1960s, we can see that most years have nearly all agencies reporting to both, though this has declined in recent years. Since the late 1970s nearly 90% of agencies that report to the Offenses Known data also report to this dataset.

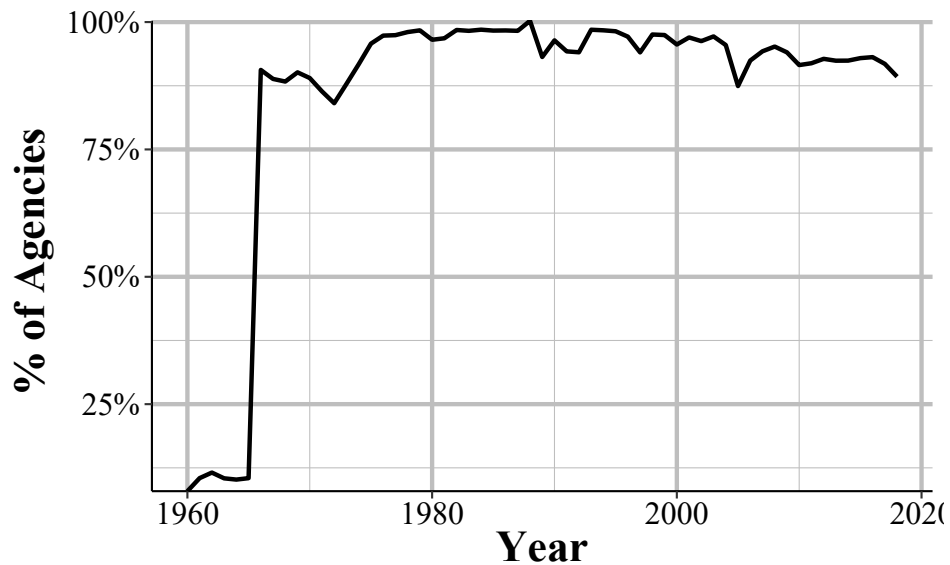


Figure 8.6: The percent of agencies in the Supplement to Return A data that are also in the Offenses Known and Clearances by Arrest (Return A) data in that year, 1960-2019.

## 8.2 Important variables

This data can really be broken into two parts: the monthly number of property (including robbery) crimes that occur that are more detailed than in the Offenses Known data, and the value of the property stolen (and recovered) from these crimes.<sup>2</sup> For each category I present the complete

<sup>2</sup>I'm really not sure why this data isn't just merged with the Offenses Known data, especially the first part where it's just counts of crimes.

breakdown of the available offenses/items stolen and describe some of the important issues to know about them. Like other UCR data, there are also variables that provide information about the agency - ORI codes, population under jurisdiction - the month and year that the data covers, and how many months reported data.

### 8.2.1 A more detailed breakdown of property (and robbery) crimes

The first part of this data is just a monthly (or yearly in the annual data that I've released - the FBI, however, only releases data monthly so I just aggregated the months together) number of crimes of each type reported to the police (and that a police investigation discovered actually happened.

For more on this process, please see Chapter 3.3.1). There are six crimes and their subsets included here: burglary, theft, robbery, and motor vehicle theft. The remaining two are rape and murder, but they don't break down these crimes into any subcategories and are only available starting in 1974.

Burglary is reported based on whether the building burgled was the victim's residence or not, and also the time of the burglary. Time is either during the day (6am-5:59pm) or night (6:pm-5:59am) or if the time is unknown. Data is available since 1960 for both the day and night burglaries, but only since 1964 for the unknown time burglaries. For robbery, the subcategories are based on where the robberies occurred such as if it happened in a bank, a gas station, or a street.

Theft is divided into two groups. The first group is based on the value of items stolen: less than \$50, \$50-\$199, and \$200 and up. The second group of thefts is broken into the type of theft such as a shoplifting or stealing from someone's car. All theft variables begin in 1960 other than thefts from a coin machine and from a building which start in 1964 and the miscellaneous "All other thefts" variable that has data starting in 1961.

Finally, motor vehicle theft is broken into where the stolen vehicle was stolen and found: stolen in the reporting agency's jurisdiction and found by

the same agency, stolen in the reporting agency's jurisdiction and found by a different agency, and stolen in a different agency's jurisdiction and found by the reporting agency.

The complete list of each subsection and a brief definition for the non-obvious ones are presented below.

- Burglary
  - Home/residence during the day (6:00am - 5:59pm)
  - Home/residence during the night (6:00pm - 5:59am)
  - Home residence at unknown time
  - Non-residence (i.e. all buildings other than victims home) during the day (6:00am - 5:59pm)
  - Non-residence (i.e. all buildings other than victims home) during the night (6:00pm - 5:59am)
  - Non-residence (i.e. all buildings other than victims home) at unknown time
- Theft/larceny (excluding of a motor vehicle)
  - <\$50
  - \$50-\$199
  - \$200 and up
  - Pick pocket
  - Purse snatching
  - Shoplifting
  - Stealing from a car (but not stealing the car itself)
  - Stealing parts of a car, such as the car battery or the tires
  - Stealing a bicycle
  - Stealing from a building where the offender is allowed to be in (and is not counted already as shoplifting)
  - Stealing from a “coin operated machine” which is mainly vending machines
  - All other thefts

- Robbery
  - Highway - This is an old term to say a place is outside and in generally accessible and visible areas. This includes robberies on public streets and alleys.
  - Commercial building - This is robberies in a business other than ones stated below. Includes restaurants, stores, hotels, bars.
  - Gas station
  - Chain/convenience store - a neighborhood store that generally is open late and sells food
  - Home/residence
  - Bank
  - Miscellaneous/other - This is all other robberies not already covered.
- Motor vehicle theft
  - Stolen in current agency jurisdiction and found by that agency
  - Stolen in current agency jurisdiction and found by another agency
  - Stolen in another agency's jurisdiction and recovered by current agency
- Murder
- Rape

### 8.2.2 The value of property stolen in property (and robbery) crimes

The next set of variables is the value of the property stolen in each crime, as well as the value of property stolen broken down by the type of property (e.g. clothing, electronics, etc.). To be clear, this is *only* the value of the property stolen during the crime. The cost of any injuries (mental or physical) or any lasting cost to the victim, their family, and society for these crimes are not included. This, of course, vastly underestimates the

cost of these crimes so please understand that while this is a measure of the cost of crime, it is only a narrow slice of the true cost.

The cost is the cost for the victim to replace the stolen item. So the current market price for that item (though factoring in the current state the item is in, e.g. if it's already damaged) and, for businesses, the cost to buy that item and *not* the cost they sell it for. While the police can ask the victim how much the property was worth, they aren't required to use the exact amount given as victim's may exaggerate the value of items. This is not an exact science so I recommend only interpreting these values are estimates - and potentially rough estimates.

The value of the property stolen is broken into two overlapping categories: by crime type, and by type of property that was stolen. These are the exact same categories as covered in Section 8.2.1 but now is the dollar amount of the items stolen from those types of crimes. The second group is what type of items, based on several discrete categories, was stolen. Please note that multiple items can be stolen in each category - i.e. there is no Hierarchy Rule used here (for more in the Hierarchy Rule that is used in other UCR data, please see Section 3.1.1). And it counts the property stolen for each crime type *as well as* for each item type. So if you sum up all of the crime variables and all of the item type variables together you'll overcount the value of property stolen. Each of the item types and their definitions - some categories include or exclude things that you may not expect them to - are detailed below.

Though this data starts in 1960, not all variables are available then. 1963 and 1964 saw many new variables added - the values in these variables are reported as 0 in previous years - and in 1974 and 1975 even more variables are added. In 1963 the value of burglaries where the time of the burglary was known, thefts broken down categories based on the value of property taken, from of car parts, theft from cars, shoplifting, and "other" thefts was added to the data. In the following year this data began including the value of property stolen from burglaries where the time of the burglary was unknown was added as well as thefts of bicycles, from "coin operated

machines” (i.e. vending machines), purse snatching, and pick pocketing. The value of property stolen during rapes and murders was first reported in 1974. Finally, 1975 was the last year with near variables, with this year including consumable goods, stolen guns, household goods, livestock, office equipment and electronics, and sound and picture equipment.

- Burglary
  - Home/residence during the day (6:00am - 5:59pm)
  - Home/residence during the night (6:00pm - 5:59am)
  - Home residence at unknown time
  - Non-residence (i.e. all buildings other than victims home) during the day (6:00am - 5:59pm)
  - Non-residence (i.e. all buildings other than victims home) during the night (6:00pm - 5:59am)
  - Non-residence (i.e. all buildings other than victims home) at unknown time
- Murder
- Rape
- Robbery
  - Highway - This is an old term to say a place is outside and in generally accessible and visible areas. This includes robberies on public streets and alleys.
  - Commercial building - This is robberies in a business other than ones stated below. Includes restaurants, stores, hotels, bars.
  - Gas station
  - Chain/convenience store - a neighborhood store that generally is open late and sells food
  - Home/residence
  - Bank
  - Miscellaneous/other - This is all other robberies not already covered.

- Theft/larceny (excluding of a motor vehicle)
  - Pick pocket
  - Purse snatching
  - Shoplifting
  - Stealing from a car (but not stealing the car itself)
  - Stealing parts of a car, such as the car battery or the tires
  - Stealing a bicycle
  - Stealing from a building where the offender is allowed to be in (and is not counted already as shoplifting)
  - Stealing from a “coin operated machine” which is mainly vending machines
  - All other thefts
- Currency
  - This includes all money and signed documents that can be exchanged for money (e.g. checks). Blank checks and credit and debit cards are not included (they are in the Miscellaneous/other category)
- Jewelry and “previous metals”
  - Only metals that are considered high value are included here. Metals that are generally worth little are counted in the Miscellaneous/other category.
- Clothing and fur
  - This also includes items that you take with you when leaving the house (except for your phone): wallet, shoes, purse, backpacks.
- Motor vehicle stolen in current agency jurisdiction
  - This includes only vehicles than can be driven on wheels so excludes trains and anything on water or that can fly.
- Office equipment and electronics

- This includes “typewriters” and “magnetic tapes” but is essentially any kind of equipment needed to run a business. So printers, computers, cash registers, computer equipment like a monitor or a mouse, and computer software. These items do not have to be stolen from a commercial building to be included in this category.
- Sound and picture equipment
  - This is a kind of odd category that is a product of its time. Anything that produces noise or pictures (including the fancy motion pictures) is included. This includes TVs, cameras, projectors, radios, MP3 players (but not phones that can play music) and (since again, this is a very old dataset) VHS cassettes.
- Guns
  - This includes all types of firearms other than toys or BB/pellet/paintball guns.
- Home furniture
  - This includes all of the “big things” in a house: beds, chairs, AC units, washer/dryer units, etc. However, items that are in the “Office equipment and electronics” category do not apply.
- Consumable goods
  - This is anything that can be consumed such as food, drinks, and drugs, or anything you use in the bathroom.
- Livestock
  - This is all animals other than ones that you would consider a pet
- Miscellaneous/other
  - Anything that is not part of the above categories would fall in here. Cell phones and credit cards are included.



### 8.2.3 Value of recovered property by type of item stolen

For the below subset of items stolen, this data includes the value of the items that were recovered. This is a subset of the section above - the value of property stolen. I don't know why but this data has more values for the property stolen than for property recovered. For example, we know how much was stolen during bank robberies but not how much was recovered from bank robberies. The only info we have for the value of recovered property is for the breakdown in the items themselves - not breakdowns of crimes such as robbery or burglary. So we can know the value of guns recovered, but not if those guns were taken from a burglary, a robbery, a theft, etc.

While this dataset began in 1960, the recovered property variables begin later, and in different years. For clothing and fur, currency, jewels and precious metals, motor vehicles, Miscellaneous/other, and the variable that sums up all of the recovered property variables, the first year with data was 1961. The remaining variables - consumable goods, guns, household goods/home furniture, livestock, office equipment and electronics, and sound and picture equipment - began in 1975.

Another issue is that it uses the value of the property as it is recovered, not as it is stolen. For example, if someone steals a laptop that's worth \$1,000 and then the police recover it damaged and it's now worth only \$200, we'd see \$1,000 for the stolen column for "office equipment and electronics" and only \$200 for the recovered column for that category. So an agency that recovers 100% of the items that were stolen can appear to only recover a fraction of them since the value of recovered items could be substantially lower than the value of stolen items - and there's no way to know how many items are actually recovered, we must rely on the value of stolen and recovered.<sup>3</sup>

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<sup>3</sup>Even if we look at the Offenses Known and Clearances by Arrest data, that only says if there was an arrest or exceptional clearance in the case, not if the property stolen was

The full list of items recovered and their definitions are below:

- Currency
  - This includes all money and signed documents that can be exchanged for money (e.g. checks). Blank checks and credit and debit cards are not included (they are in the Miscellaneous/other category)
- Jewelry and “previous metals”
  - Only metals that are considered high value are included here. Metals that are generally worth little are counted in the Miscellaneous/other category.
- Clothing and fur
  - This also includes items that you take with you when leaving the house (except for your phone): wallet, shoes, purse, backpacks.
- Motor vehicle stolen in current agency jurisdiction
  - This includes only vehicles than can be driven on wheels so excludes trains and anything on water or that can fly.
- Office equipment and electronics
  - This includes “typewriters” and “magnetic tapes” but is essentially any kind of equipment needed to run a business. So printers, computers, cash registers, computer equipment like a monitor or a mouse, and computer software. These items do not have to be stolen from a commercial building to be included in this category.
- Sound and picture equipment
  - This is a kind of odd category that is a product of its time. Anything that produces noise or pictures (including the fancy motion

pictures) is included. This includes TVs, cameras, projectors, radios, MP3 players (but not phones that can play music) and (since again, this is a very old dataset) VHS cassettes.

- Guns
  - This includes all types of firearms other than toys or BB/pellet/paintball guns.
- Household goods/Home furniture
  - This includes all of the “big things” in a house: beds, chairs, AC units, washer/dryer units, etc. However, items that are in the “Office equipment and electronics” category do not apply.
- Consumable goods
  - This is anything that can be consumed such as food, drinks, and drugs, or anything you use in the bathroom.
- Livestock
  - This is all animals other than ones that you would consider a pet
- Miscellaneous/other
  - Anything that is not part of the above categories would fall in here. Cell phones and credit cards are included.

## 8.3 Data errors

This dataset comes with a considerable number of data errors - basically enormous valuations for stolen property. Some of the values are so big that

it is clearly an error and not just something very expensive stolen.

However, this gets tricky since there can in fact simply be very expensive items stolen and make it look like an error. Some of the stolen property include variables for both the number of items of that type stolen and the

total value of the items. From this we can make an average value per item stolen which can help our understanding of what was stolen. However, some items only have the value of the property stolen and the value of property recovered so we actually don't know how many of those items were stolen. These cases makes it even harder to believe that a large value is true and not just a data error since we don't know if the number of these thefts increased, causing the increase in the value reported. We'll look at a couple examples of this and see how difficult it can be to trust this data.

First, we'll look at the value of livestock thefts in New York City. Livestock is one of the variables where we know the value stolen and recovered but not how many times it happened. Being a major urban city, we might expect that there are not many livestock animals in the city so the values should be low. Figure 8.7 shows the annual value of livestock thefts in NYC. There are two major issues here. First, In all but two years they report \$0 in livestock thefts. This is likely wrong since even New York City has some livestock (even just the police horses and the horse carriages tourists like) that probably got stolen. The second issues is the massive spike of reported livestock theft value in 1993 with over \$15 million stolen (the only other year with reported thefts is 1975 with \$87,651 stolen). Clearly NYC didn't move from \$0 in thefts for decades to \$15 million in a year and then \$0 again so this is a blatant data error.

It gets harder to determine when a value is a mistake when it is simply a big spike - or drop - in reported value in a dataset that otherwise looks correct. Take, for example, the annual value of stolen clothing and fur in Philadelphia from 1960-2019, shown in Figure 8.8. The annual value of these stolen items more than doubled in 1989 compared to the previous year and then declined rapidly in the following year. Is this real? Is it a data error? It's really hard to tell. Here we don't know how many clothing/fur thefts there were, only the value of the total thefts that month (which is aggregated annually here). It continues a multi-year trend of increasing value of thefts but it larger than previous increases in value. And while the spike is very large in percent terms, it's not so extraordinarily huge that we

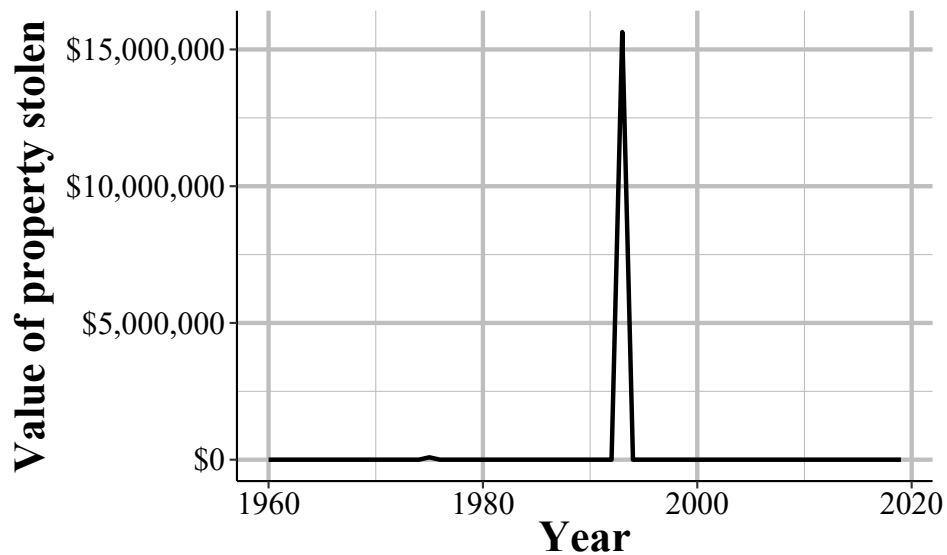


Figure 8.7: The annual value of stolen livestock in New York City, 1960-2019.

immediately think it's an error - though some outlier detection methods may think so if it's beyond the expected value for that year.

It's also important to have some understanding of what the data *should* look like when trying to figure out what data point may be incorrect. In this figure we see a huge spike in 1989. If we know, for example, that a ring of fur thieves were active this year, then that makes it far more likely that the data is real. This may be a rather odd example, but it is helpful to try to understand the context of the data to better understand when the “weird” data is an error and when it's just “weird but correct”.

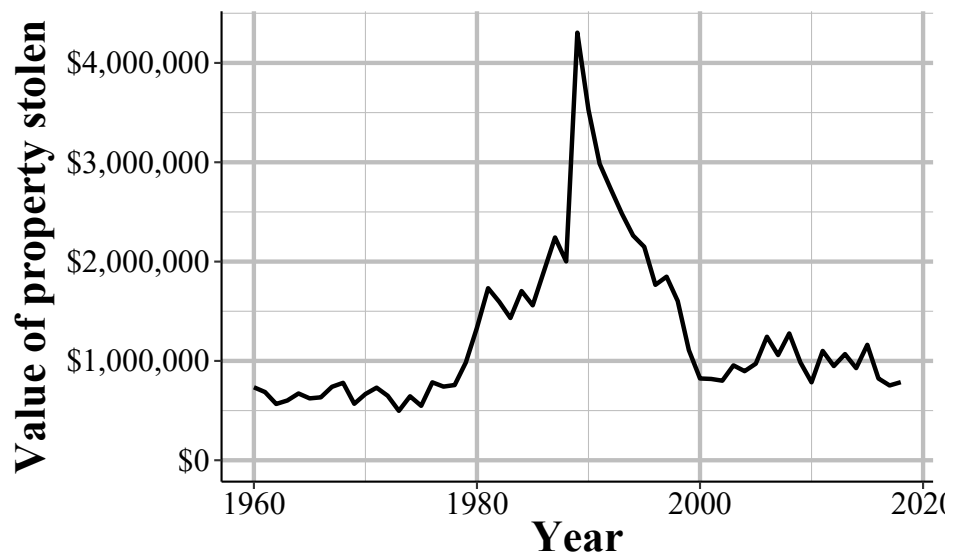


Figure 8.8: The annual value of stolen clothing and fur in Philadelphia, PA, 1960-2019

# Chapter 9

## Arson

The arson dataset provides monthly counts at the police agency-level for arsons that occur, and includes a breakdown of arsons by the type of arson (e.g. arson of a person's home, arson of a vehicle, arson of a community/public building) and the estimated value of the damage caused by the arson. This data includes all arsons reported to the police or otherwise known to the police (e.g. discovered while on patrol) and also has a count of arsons that lead to an arrest (of at least one person who committed the arson) and reports that turned out to not be arsons (such as if an investigation found that the fire was started accidentally).

For each type of arson it includes the number of arsons where the structure was uninhabited or otherwise not in use, so you can estimate the percent of arsons of buildings which had the potential to harm people. This measure is for structures where people normally did not inhabit the structure - such as a vacant building where no one lives. A home where no one is home *at the time of the arson* does not count as an uninhabited building.

In cases where the arson led to a death, that death would be recorded as a murder on the Offenses Known and Clearances by Arrest dataset - but not indicated anywhere on this dataset. If an individual who responds to the arson dies because of it, such as a police officer or a firefighter, this is not

considered a homicide (though the officer death is still included in the Law Enforcement Officers Killed and Assaulted data) unless the arsonists intended to cause their deaths. Even though the UCR uses the Hierarchy Rule, where only the most serious offense that occurs is recorded, all arsons are reported - arson is exempt from the Hierarchy Rule.

## 9.1 Agencies reporting

Figure 9.1 shows the annual number of police agencies that reported at least one month that year. With data starting in 1979, there were a little over 12,000 agencies reporting a year until the early 2000s where it recovered from a sharp drop in agencies to steadily increase to about 16,000 a year. While arson data is available through 2019, this graph only shows data through 2018.

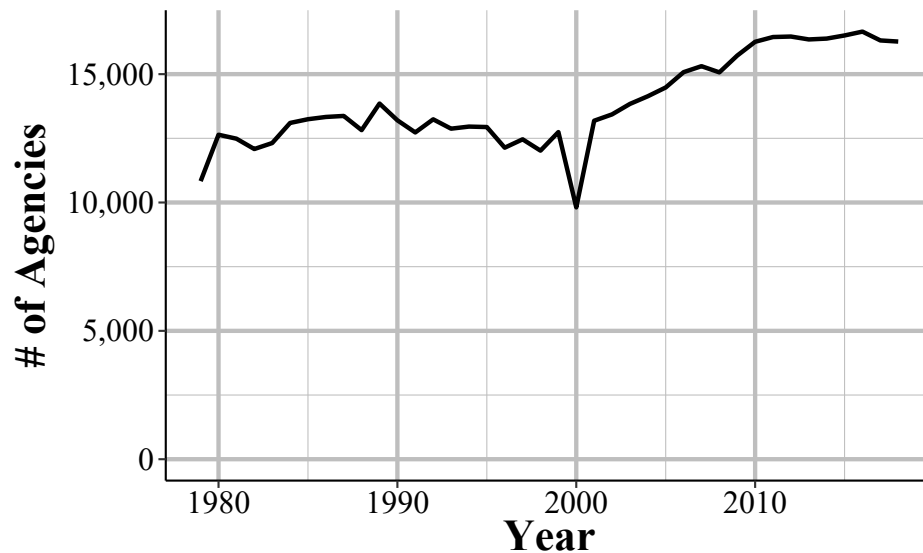


Figure 9.1: The annual number of police agencies that report at least month of data that year.



## 9.2 Important variables

Similar to the Offenses Known and Clearances by Arrest data, which is covered in Chapter @ref(offenses\_known), this data shows the monthly number of crimes - in this case only arsons - reported or discovered by the police, the number found by police to be unfounded, and the number cleared by the police. In addition, it includes the number of arsons in structures that were uninhabited, and the estimated cost of the damage caused by the arsons. For each variable, the arsons also broken into several categories of arsons, which we'll talk about in Section 9.3. Like other UCR data, there are also variables that provide information about the agency - ORI codes, population under jurisdiction - the month and year that the data covers, and how many months reported data.

### 9.2.1 Actual arsons

This variable includes the number of arsons either reported to the police or otherwise known to the police in that month and that the police determine to actually be arsons - that is, reports that are not unfounded. This is based only on the police's determination that an arson occurred, not the decision of other groups like a court or the conviction of someone for the crime.

### 9.2.2 Unfounded arsons

This variable shows the number of arsons reports that the police determined to not actually be arsons. For example, if a house burns down and police think it was arson but later determine that it was an accident, it would be an unfounded arson.

### 9.2.3 Reported arsons

This variable is the sum of actual arsons and unfounded arsons - it is the total number of arsons that were reported or known to the police, even if a later investigation found that it wasn't actually an arson. Since this is the sum of two already present variables - and is less informative than the two variables are as separate variables - I'm not exactly sure why it's included.

### 9.2.4 Cleared arsons

This shows the number of arsons where at least one offender is arrested or when an arrest cannot be made for some reason but the police know who the offender is - the latter option is called "exceptional clearances" or "clearances by exceptional means." There is no way to tell if an clearance is due to an arrest or due to exceptional means.<sup>1</sup>.

For exceptional clearances, police must have identified the offender, have sufficient evidence to arrest that offender, know where they are (so they can actually be apprehended) and only then be unable to make the arrest.

Exceptional clearances include cases where the offender dies before an arrest (by any means, including suicide, accidental, illness, killed by someone including a police officer) or when the police are unable to arrest the person since they are already in custody by another jurisdiction (including out of the country or in custody of another agency) and extradition is denied. Two other potential causes of exceptional clearance is when prosecution of the case cannot go forward because the district attorney refuses to prosecute the case, for reasons other than lack of evidence, or when a victim refuses to assist the prosecution in the case.

Please note that this data is at the incident-level which means that having multiple people arrested for an incident still only is a clearance for that single incident. Clearances are also reported in the month they occur, not

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<sup>1</sup>NIBRS data does tell more information about the type of arrest, but UCR data does not

in the month that the initial crime happened. This can lead to cases where there are more clearances than crimes, incorrectly leading to the conclusion that police solve  $>100\%$  of crimes.

Figure 9.2 shows the number of actual arsons (reports that are founded) and clearances for single-family home arsons in League City, Texas, a city of about 100,000 outside of Houston. In most years there were fewer clearances than arsons, but in four years (1982, 1981, 1992, and 2007) there were more clearances than arsons. This is simply because clearances are reported in the month they occur, regardless of when the arson they are clearance occurred.

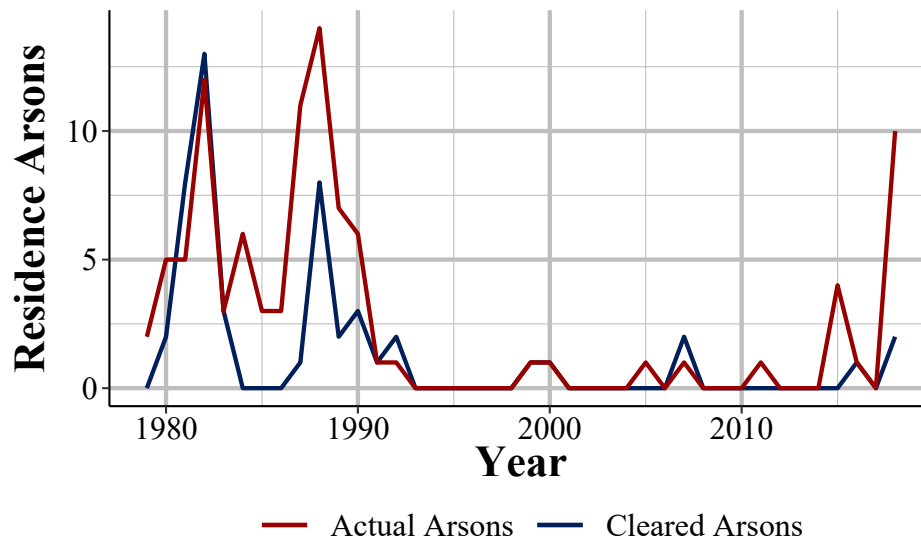


Figure 9.2: The annual number of single-family home arsons and clearances in League City, Texas.

It is rare that there are more clearances than crimes in a given month though this is partially just due to few cases every being cleared. According to the 2019 NIBRS, it takes on average 7 days between the incident and the arrest (median = 0 days) for all crimes, and an average of 11.6 days from incident to arrest for arsons specifically (median = 0 days) for offenders who get arrested. This means that most clearances will be for crimes

committed that month, though certainly not all. Therefore, use caution when trying to use this variable to measure crime clearance rates.

### **9.2.5 Cleared for arsons where all offenders are under age 18**

This variable is the same for normal clearances but only for arsons where every offender is under the age of 18. In these cases a clearance by arrest can include citing the juvenile offender with an order to go to court to stand trial, even if the juvenile is not actually taken into police custody. As this variable requires that the police know every offender (to be able to determine that they are all under 18), it is likely highly flawed and not a very useful variable to use.

### **9.2.6 Uninhabited building arsons**

This data also includes the number of arsons that occur in uninhabited structures. These structures must be uninhabited in the long-term, not simply having no one inside them when the arson occurs. The FBI defines these are structures that are “uninhabited, abandoned, deserted, or not normally in use.” at the time of the arson. For example, a vacation home whose owners aren’t living in at the time would be “not normally in use” so would be an uninhabited building. A business that is closed when the fire started, but is open during the day, is not an uninhabited building.

### **9.2.7 Estimated damage cost**

The final variable is the estimated cost of the arson. This is how much the police estimates the value (in dollars) of the damaged or destroyed property is. Since this is the value of property damage, injuries to people (including non-physical injuries such as trauma or mental health costs) are not

included. Since this is estimated damage it may be inaccurate to some degree. This variable is the sum of monthly estimated cost so while you can get the average cost by dividing this by the number of actual offenses, this average may be significantly off due to having extremely small or large values in your data. This value may be \$0 since arsons include attempted arsons which may cause little or no damage. Please note that this value is not inflation-adjusted so you will have to adjust the value yourself.

## 9.3 Types of arsons

For each of the arson categories above, this dataset has information for ten different *types* of arson. The type is based on where the arson occurred, not based on how the fire was initiated, how far or fast it spread, or any other information about the arson - nothing is actually known about the arson outcome other than if the arson was cleared and the estimated damage. There are seven arsons types for buildings, two for vehicles, and one as an “other” category that includes arsons of outdoor areas like parks or forests (though this group does not have any subcategories so all you know is the arson is neither of a building or a vehicle). For both the buildings and the vehicle arson types there is also a “total buildings” and “total vehicles” category that is just the sum of each subcategory; there is also a “grant total” variable that sums all building, vehicle, and other arsons.

### 1. Building arsons

- Single occupancy home
- Other residential
- Storage
- Industrial/manufacturing building
- Other commercial building
- Community or public building
- All other structures

## 2. Vehicles

- Motor vehicles
- Other vehicles

## 3. All other arsons

Some arsons can burn down multiple types of structures or cars - fire, after all, tends to spread. This data defines the arson based on where the fire originated. So an arson that starts in someone's house and also burns down their car in the garage would be a single-family home arson, not a vehicle arson. This is true even if the damage is more severe for a type other than where the fire started. So if someone threw a Molotov cocktail at a car parked outside a house and it lightly damaged the car but spread to homes nearby and destroyed those homes, it is still a vehicle arson (though the damage recorded would include the homes burned.)

## 9.4 Data errors

Like the other UCR data, there are some cases where there are obvious data entry errors leading to impossible numbers of reported arsons or the price of an arson. As an example, Figure 9.3 shows the annual number of single-family home arsons in Byron City, Illinois, which has a population of slightly over 3,600 people. Every year with data available there are zero arsons reported until 2003 when 469 arsons are reported. Since it is exceedingly unlikely that suddenly an eighth of the city suddenly burned down, and the city never again had a residence arson, this is almost certainly a data entry error. As arsons are relatively rare, having errors - and especially ones like this - can drastically change the results of your analysis so it is important to check your data carefully for more errors. For those using the data that I have cleaned and concatenated, the complete list of obvious outliers that I removed is available on the data's [page on openICPSR](#).

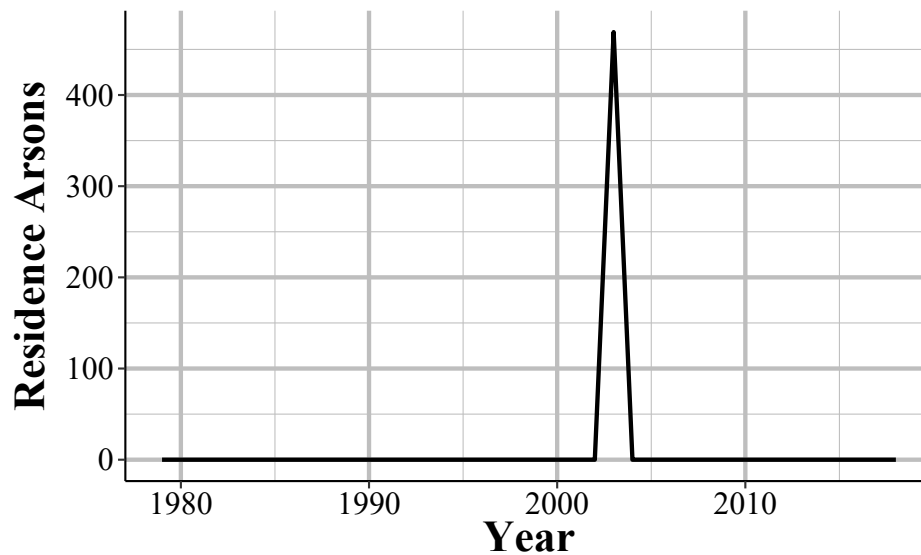


Figure 9.3: Annual single-family home arsons in Byron City, Illinois. The sudden spike to over 400 arsons in a single year is an example of data errors in this dataset.

There are also cases where it is less clear when a value is a data error or is simply due to an outlier - but real - value. For example, Figure 9.4 shows the annual average cost of a single-family home fire in Los Angeles, California. In most years the damage is low - since an arson can damage only part of the house, these low values likely mean that on average only part of the house was damaged, not the entire house. In 2009, however, the average damage is about \$540,000 per arson. Is this a data entry error that simply inputs a damage value that is too high? It's certainly possible. However, it could also be that some extraordinarily expensive homes were destroyed that year. In 2009 Los Angeles only reported 63 single-family home arsons so having one, or a few, super mansions - which LA has plenty of - destroyed could mean that this huge value is real.

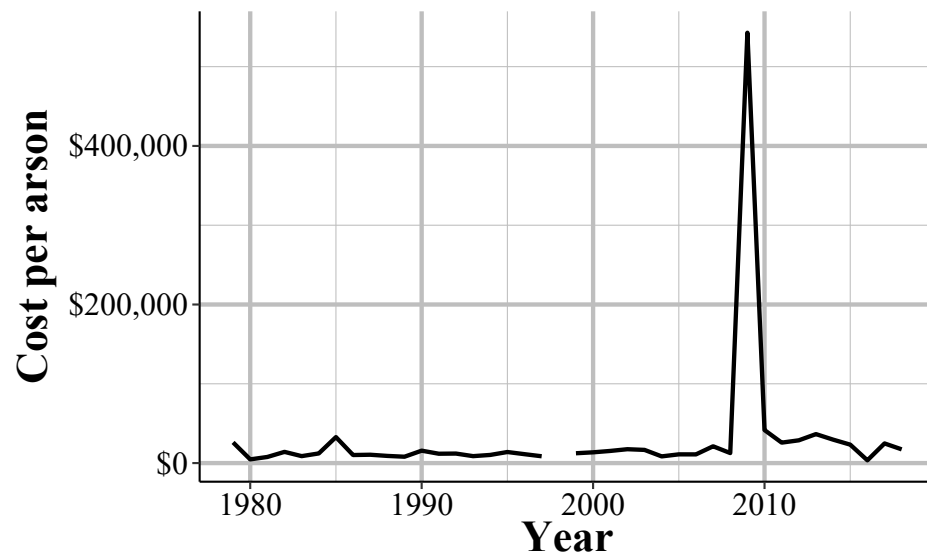


Figure 9.4: The annual average cost per single-family home arson in Los Angeles, California.



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