Crime Reporting Standards and Reported Crimes

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Abstract

Since 1930, the FBI has been publishing the Uniform Crime Report (UCR), the gold standard for understanding crime trends in the United States. It had been published in the form of the Summary Reporting System (SRS). In the 1990s, agencies started transitioning from the SRS to the National Incident-Based Reporting System (NIBRS) to synthesize more detailed data. This data is then converted to an SRS-compatible format (hereafter referred to as "synthetic SRS") for historical comparison. This paper aims to ask whether there is any data discrepancy between the UCR before and after the adoption of the NIBRS. I use a staggered event study design where the event date is the year in which the agency changed from the SRS to the NIBRS. With this design, I find two factors that contribute to a large and statistically significant increase in reported crime for agencies that have adopted the NIBRS compared with agencies that have not: 1) the conversion of assault data, and 2) a change in reporting practices. When I convert the data from NIBRS to synthetic SRS myself, I observe a smaller and statistically insignificant effect for Assault. However, this alternative conversion does not improve the difference-in-differences (DiD) effects for total crime, murder, robbery, burglary, and theft, indicating that the change in reporting practices also plays a role.

Keywords: Crime reporting, UCR, SRS, NIBRS.

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1 Introduction

The Uniform Crime Report (UCR) has been the gold standard for crime data in the United States for over 90 years. It was devised in the 1920s by the International Association of Chiefs of Police (FBI, 2012*a*) and it has been used extensively by researchers[1], government agencies[2], news reports[3], and private sector entities[4] alike to explore crime-related topics. According to the Inter-University Consortium for Political and Social Research (ICPSR), as of August 2022, there were 3,768 publication citations using UCR data (2,149 of which were journal articles). From its inception in 1930 (Poggio et al., 1985), the UCR has been collected and published in the format of the Summary Reporting System (SRS), which reports monthly counts of the 10 most serious types of Group A offenses. In 1988, to meet popular demand, the FBI introduced the National Incident-Based Reporting System (NIBRS), which reports detailed information about each incident for 52 types of Group A offenses (SEARCH, 1997). However, to maintain historical continuity, the FBI converts the NIBRS data into SRS-compatible format to continue publishing the UCR series (see Figure 1 for an illustration of this process). I will refer to the converted data as "synthetic SRS." The NIBRS collects data in a different format than the SRS does, so when it is converted to the synthetic SRS, the conversion process can be prone to errors. There has been no formal assessment as to whether there are any discontinuities between the SRS and the synthetic SRS.

This paper explores the historical continuity of the UCR series after the introduction of the NIBRS. For Law Enforcement Agencies that have not started reporting to the NIBRS, the UCR is in SRS format. For agencies that have started reporting to the NIBRS, the UCR is constructed as a combination of the SRS (before the agency starts reporting to the NIBRS) and the synthetic SRS (after the agency starts reporting to the NIBRS) (FBI, 2012*b*). The conversion process is complex and it can be subject to discrepancies. Specifically, the conversion includes the application of the hierarchy rule, which retains the most serious offense for each incident. Therefore, the conversion may introduce discrepancies that result in an increase in reported crime for agencies

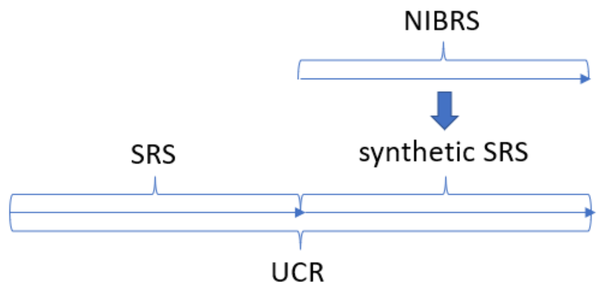
[1] The 2021 American Economic Review, for example, published 115 peer-reviewed studies, 2 of which used the UCR data, which makes up 1.74% of the articles.

[2] For example, https://www.sanfranciscopolice.org/stay-safe/crime-data/crime-dashboard (accessed March 1, 2022).

[3] For example, https://www.cnn.com/2021/09/27/politics/uniform-crime-report-2020/index.html (accessed March 1, 2022).

[4] For example, https://spotcrimebrit.com/2020/09/20/the-spotcrime-open-crime-standard-socs/ (accessed March 1, 2022).

Figure 1: UCR Diagram



Notes: This is an illustrative example of a reporting agency that has switched from the SRS to the NIBRS. After the switch, NIBRS data is converted to SRS-compatible format and merged into the UCR series.

that have adopted the NIBRS compared to agencies that have not adopted it. To check if any discrepancies exist, I perform the conversion based on the set of rules and compared the resulting data series (the alternative UCR) with the existing data series (the existing UCR). Another threat to the historical continuity is that the NIBRS includes a mechanism to check the completion and accuracy of the data. Moreover, the NIBRS reporting system can be integrated with the Record Management System of the police, which can help agencies report to the NIBRS in a more timely manner (Strom and Smith, 2017). The aforementioned technological advances create additional upward pressure for reported crime counts in the UCR for agencies that have adopted the NIBRS. I test whether there are any differences between reporting standards by using a staggered event study design on both the existing UCR data and the alternative UCR data that I construct.

FBI (2015*a*) concludes that there are only small differences between the NIBRS and the synthetic SRS. However, they do not evaluate the historical continuity between the SRS and the synthetic SRS. FBI (2012*b*) and GBI (2021) detail methods for converting the NIBRS to an SRS-compatible format, but they do not report any results related to continuity between the SRS and the synthetic SRS. This paper is the first to evaluate the historical continuity of the UCR after the NIBRS has been introduced. Discontinuities in the UCR can cause an assortment of issues for relevant parties. For academic research, not taking the NIBRS start date into account could generate biased results if the NIBRS start date variable is correlated with the variable whose impact is being evaluated. For reports by government agencies, the discontinuity may affect performance evaluations, policy decisions, and funding decisions, among other things. For news coverage of crime, the discontinuity may present the wrong picture of the crime environment to the general public. For private sector entities, their data accuracy can be compromised and reputations affected. Therefore, this research is very important on many levels.

Crime data comes from the UCR (Kaplan, 2020*b*) and the NIBRS (Kaplan, 2020*a*). NIBRS start date data comes from the FBI (FBI, 2021). I construct an alternative UCR dataset based on the instructions in FBI (2012*b*) and GBI (2021). The data spans from 1994 to 2016 to exclude the early adopters (1990 - 1993) and late adopters (2017 - 2021). Data is at the reporting agency level, and the total number of observations is 331,844 covering 14,428 reporting agencies that continually report to the FBI each month. Since then, there are a number of agencies that adopt the NIBRS each year. Different agencies also choose different months to make the change, although more than half of all agencies make the change in January. Therefore, the best method for evaluating the impact of the change on reported crime is an event study with staggered adoption. I aggregate all the agencies that make the change in the same year at the yearly level and compute the mean and the confidence interval for the effect of the change on different types of crime for the years before and after. In other words, for each group, I compute the Average Treatment Effect on the Treated (ATT) by the NIBRS start year for each year in the data. Then I aggregate the ATT between all the groups to obtain the difference-in-differences (DiD) results and event study results. I use Callaway and Sant'Anna (2020)'s `did` package for the empirical analysis. The crimes that I explore are index crimes covered by the UCR: murder, rape, robbery, burglary, larceny, aggravated assault, assault, and total crime[5].

After the change from the SRS to the synthetic SRS, total reported crime increases by 135.97 in the first year on average and remains large and statistically significantly more than the control group for more than five years. This is a very large increase considering that the mean annual crime count by the agency is 54.86 for the period between 1994 and 2016. Reported rape count does not see a statistically significant change, but reported murder count, assault count, aggravated assault count, robbery count, burglary count, and larceny count all have a large and statistically significant ATT. Two factors contribute to the increase: 1) differences in crime reporting standards between the SRS and the NIBRS 2) differences in crime reporting practices between the SRS and the NIBRS. One factor that is unlikely to contribute to the large increase is the underlying crime environment.

[5]Total crime includes the following categorthe ies: murder, rape, robbery, assault, burglary, larceny, arson, and motor vehicle theft.

In order to test the differences in reporting standards between SRS and synthetic SRS, I examine the NIBRS and convert it to synthetic SRS based on guidelines detailed in FBI (2012*b*) and GBI (2021). The resulting ATT in total crime count is still higher than baseline, but the results are not statistically significant, and the magnitude drops to 71.93 for the first year after the change. This is a 47.10% drop in the discrepancy compared with that in the original UCR. Differences almost all come from assault count. Assuming that the reporting standards between synthetic SRS for the other categories of crime and that of the actual SRS are similar, the rest of the discrepancy comes from differences in crime reporting practices between the SRS and the NIBRS. Again, this means that the NIBRS improves the completion, accuracy, and timeliness of reporting.

The rest of the paper are arranged as follows: Section 2 offers a background of the UCR and its changes over the years. Section 3 reviews the relevant literature. Sections 4 and 5 describe the data. Section 6 details the empirical models. Section 7 presents the results. Section 8 discusses policy implications, and Section 9 concludes.

2 Background

In 1920, with the goal of improving crime data reliability, the SSRC and the FBI devised a uniform standard for crime to be reported by the local agencies (Skogan, 1975). The standard is called the Uniform Crime Report (UCR). Since then, the UCR has been the gold standard for crime reporting at the national level. It collects four categories of violent crime (murder, rape, robbery, and aggravated assault) and four categories of property crime (burglary, theft, motor vehicle theft, and arson) and reports monthly count to the FBI under its Summary Reporting System (SRS). Table 1 provides an example that illustrates the format of the SRS. It includes crime numbers for a list of Group A offenses per month for each reporting agency. However, it does not collect data on the circumstances under which crimes occur (Skogan, 1975) even though information on crime circumstances can help with crime prevention and mitigation, among other goals. Luckily, digitization has made it easier for police agencies to record more detailed data. Since the late 1980s, the FBI has begun to encourage crime reporting agencies to switch from the SRS to the more detailed National Incidence-Based Reporting system (NIBRS) (FBI, 2004). In 2016, the FBI made the decision to replace the SRS with the NIBRS as the national standard by January 2021

(FBI, 2016).

Table 1: SRS Reporting Format

ORI Number	Agency Name	State	Year	Month	Actual Murder	...	Actual All Crimes
EX1234567	Example Agency	Example State	2000	January	5	...	200
EX1234567	Example Agency	Example State	2000	February	2	...	40

Notes: ORI Number is the code for the reporting agency, where EX is the state. The SRS reporting format has monthly count for 10 different types of Group A offenses, but it does not have details for each offense.

One key difference between the SRS and the NIBRS is that the SRS requires agencies to report monthly numbers of eight categories of crime to the FBI every year. The NIBRS, on the other hand, requires agencies to report details on each offense. For example, if there are five murders that happened in the agency's jurisdiction within a six-month period, the agency is required to report the dates of the murders, the characteristics of the murders, the characteristics of the victims, and the characteristics of the offenders. The NIBRS also reports up to 10 offenses per incident, as opposed to SRS, which usually reports only one offense per incident. Instead of reporting only eight categories of the Group A offenses, the NIBRS covers 52 of them. Table 2 provides an example for the format of the NIBRS. The ORI Number is the reporting agency code, and the Age of Victim is not filled in because the Type of Victim is Society/Public. The switch from the SRS to the NIBRS happened after the *Blueprint for the Future of the Uniform Crime Reporting Program (The Blueprint)* (Poggio et al., 1985) was published. *The Blueprint* mentioned increasing accuracy as a reason for switching, arguing that tabulations can be computerized and edit checks can be more sound.

Table 2: NIBRS Reporting Format

ORI Number	Incident Number	Incident Date	UCR Offense Code	...	Type of Victim	Age of Victim	Location Type
EX1234567	A1B2C3D4E5F6	2000-05-10	Intimidation	...	Individual	50	Construction Site
EX1234567	A1B2C3D4E5F6	2000-05-10	Drug/Narcotic Violations	...	Society/Public		Construction Site

Notes: The NIBRS has details on each incident, where the same incident number can cover multiple offenses. The information includes location, demographics of the victim, demographics of the offender, whether there is firearm involved, etc. The NIBRS covers 52 Group A offenses. ORI Number is the reporting agency code (e.g. police station).

Another key difference between the SRS and the NIBRS is the hierarchy rule. The SRS is subject to the hierarchy rule, which means that among the offenses associated with each incident, the most serious offense is reported (FBI, 2012*b*). For example, if an incident has two offenses: one murder and one rape, only the murder would be reported. Even though only the most serious offense is reported, if the offense is crime against person (murder, rape, and assault), the count reported equals to the number of victims. For example, if an incident has two offenses: two murders and two rapes, the two murders are reported. The exception to the hierarchy rule is arson - all counts of arson are reported. For example, if an incident has two offenses: two murders and two arsons, both murders and both arsons are reported. The NIBRS is not as restricted by the hierarchy rule and the top ten offenses are reported.

Due to the difference in reporting standards, the NIBRS is published as its own series. The FBI plans to keep publishing UCR data as monthly counts, which means that it has been converting the NIBRS data into SRS format, what we'll call "synthetic SRS" in this paper. For agencies that never joined the NIBRS, their data would come from the SRS consistently. However, for agencies that join the NIBRS, their data in the UCR consist of the SRS before they join the NIBRS and synthetic SRS after. Instead of examining the difference between the NIBRS and the synthetic SRS, this paper focuses on the consistency between the actual SRS and the synthetic SRS.

3 Literature Review

The literature has detailed methods to convert the NIBRS to SRS format (synthetic SRS). It has also assessed the difference between the NIBRS and the synthetic SRS after the conversion. However, there is a lack of work on assessing the historical continuity between the SRS and the synthetic SRS. This section opens with a list of economics papers that use the NIBRS, the SRS, or synthetic SRS to motivate the necessity of good conversion of the NIBRS to synthetic SRS.

There are many economics papers that use SRS, synthetic SRS, and NIBRS data: Foley (2011) uses SRS alongside NIBRS data. The data series themselves should be internally consistent because the paper uses the NIBRS whenever it is available, so results should not be affected by synthetic SRS conversion. Dahl and DellaVigna (2009), Card and Dahl (2011), Heaton (2012), Yörük (2014), Doleac and Sanders (2015), Doleac (2017), Lindo, Siminski and Swensen (2018) and Lindo, Swensen and Waddell (2022) use NIBRS data only, so their analysis also does not involve time series comparison before and after the NIBRS. Chalfin, Danagoulian and Deza (2019) supplements the NIBRS with incident-based reporting from other sources, so the historical consistency of the synthetic SRS conversion also should not affect the results. Moreno-Medina (2021) supplements SRS data with NIBRS data, though they look at the relationship between church attendance and crime with rain as the instrumental variable. It is unlikely that church attendance instrumented by rain is correlated with the switch from the SRS to the NIBRS. It does, though, provide an example of a paper that uses both SRS and NIBRS in a time series, which is potentially subject to inconsistencies.

FBI (2012*b*) and GBI (2021) have detailed how to convert the NIBRS to the SRS. FBI (2012*b*) includes a detailed description of the hierarchy rule and instructions on how each category of offense should be handled. GBI (2021) explained exceptions to the hierarchy rule in detail, and presented many examples to enhance understanding of the procedure.

Although literature has not covered the historical comparison between the SRS and the synthetic SRS, there has been some work that compare the NIBRS and synthetic SRS. FBI (2015*b*) saw a 2.1% overall difference between the NIBRS and the synthetic SRS, with Larceny being the category with the largest difference of 2.6%. A 2019 update of the document, FBI (2019) also saw small differences between the NIBRS and synthetic SRS. The category with the largest difference is Motor Vehicle Theft, which has the NIBRS being 4.5% higher than that of the synthetic SRS, and Burglary being 2.2% lower than that of the synthetic SRS.

4 Data

Crime data come from the UCR and the NIBRS. I use Jacob Kaplan's concatenated files for the UCR that was hosted on the Inter-university Consortium for Political and Social Research (ICPSR) platform (Kaplan, 2020*b*). The data is available by the year at the monthly level for each reporting agency. The years that I am interested in are between 1994 and 2016, so the data from these years are concatenated together. The reason why I picked data from these years is because the first agency to start reporting to the NIBRS joined in 1990 (see Table 3 and Figure 2 for the information), and by 1994, around 5% of the agencies have joined the NIBRS. This ensures that I am excluding the early adopters from the analysis, those who have very good record keeping to start with. Also, I am excluding those who enter in 2016-2021 to exclude the late adopters who may have worse than average record keeping. The crime types examined include murder, manslaughter, rape, robbery, assault, aggravated assault, burglary, theft, motor vehicle theft, grand arson, and all crimes.

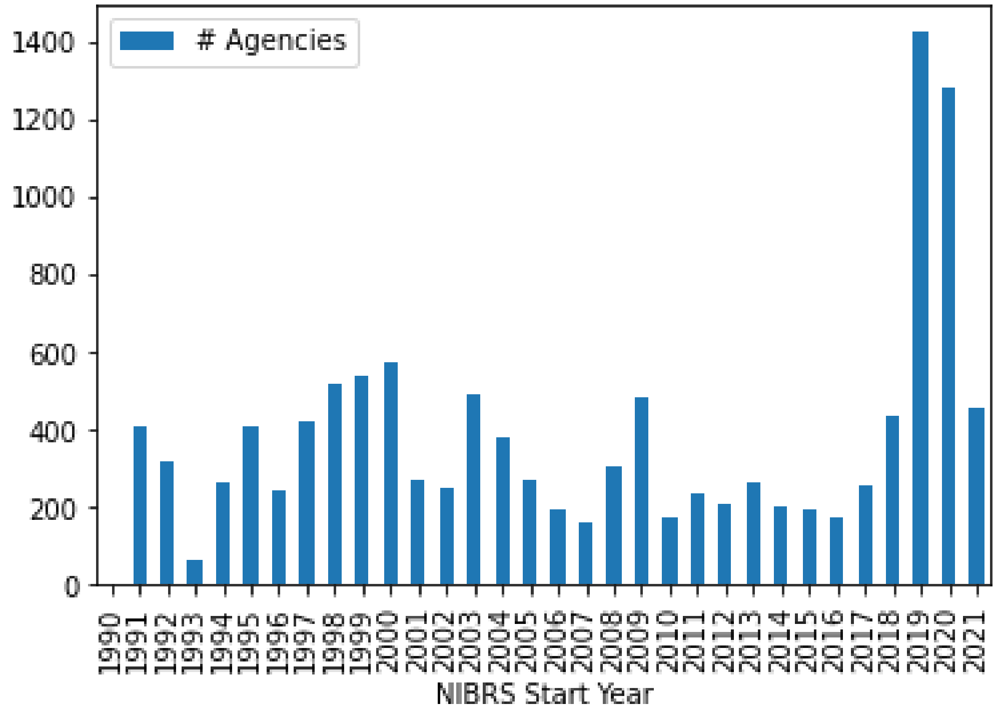
Table 3: Number of Agencies that Start NIBRS in Each Year

NIBRS Start Year	# Agencies	Population	% Agencies	% Population
1990	1	186445	0.0%	0.07%
1991	405	4767813	1.65%	1.67%
1992	316	3484042	1.28%	1.22%
1993	63	1127230	0.26%	0.39%
1994	266	3565378	1.08%	1.25%
1995	411	4978344	1.67%	1.74%
1996	240	3697959	0.97%	1.29%
1997	425	5822776	1.73%	2.03%
1998	520	5294258	2.11%	1.85%
1999	536	7284988	2.18%	2.54%
2000	577	8025402	2.34%	2.8%
2001	269	2975926	1.09%	1.04%
2002	253	2687548	1.03%	0.94%
2003	491	5307283	1.99%	1.85%
2004	379	4817793	1.54%	1.68%
2005	270	4509985	1.1%	1.58%
2006	195	2163360	0.79%	0.76%
2007	158	2165346	0.64%	0.76%
2008	302	2271107	1.23%	0.79%
2009	486	3677349	1.97%	1.28%
2010	172	2145998	0.7%	0.75%
2011	235	2408688	0.95%	0.84%
2012	209	2781024	0.85%	0.97%
2013	265	1268016	1.08%	0.44%
2014	204	1170070	0.83%	0.41%
2015	196	2986958	0.8%	1.04%
2016	177	3103889	0.72%	1.08%
2017	255	2117140	1.04%	0.74%
2018	438	11137127	1.78%	3.89%
2019	1426	24495174	5.79%	8.55%
2020	1281	17106333	5.2%	5.97%
2021	458	5440597	1.86%	1.9%
Never entered	12741	131364554	51.75%	45.88%

Notes: The data has 24,620 reporting agencies that are index in year 2000 nationally. 11,879 have started reporting to the NIBRS by 2021, making up 48.25% of the data. They cover 54.12% of the population.

Agencies not only switch to the NIBRS in different years, but the switches do not all happen at the beginning of the year. According to Table 4, 55.09% of the agencies make the switch in

Figure 2: Number of Agencies that Switched to the NIBRS by the Year



Notes: There were 24,620 reporting agencies that were indexed in 2000. 12,741 of them have not switched to NIBRS by 2021. Of the 11,879 that switched, 1,426 started reporting to the NIBRS in 2019.

January, but each year sees between 3% and 5% of the agencies make the switch. From Figure 3, we can see that this variability in the month of adoption exists in every year. However, the majority of the switching happens at the beginning of the year.

According to Table 5, from 1994 to 2016, Theft makes up almost half of all crimes in the UCR and Assault makes up around one third. Aggravated assault makes up around one fifth of total Assault. Murder, Manslaughter, and Arson make up the smallest proportion of total crime. Rape, Robbery, Burglary, and Motor Vehicle Theft are in the middle.

NIBRS data also comes from the ICPSR (Kaplan, 2020*a*). The segment I use is the victim segment because of hierarchy rule exceptions. For each offense, all victims are counted for crimes against persons (murder, rape, assault). Therefore, information is needed from the victim segment for NIBRS to synthetic SRS conversion.

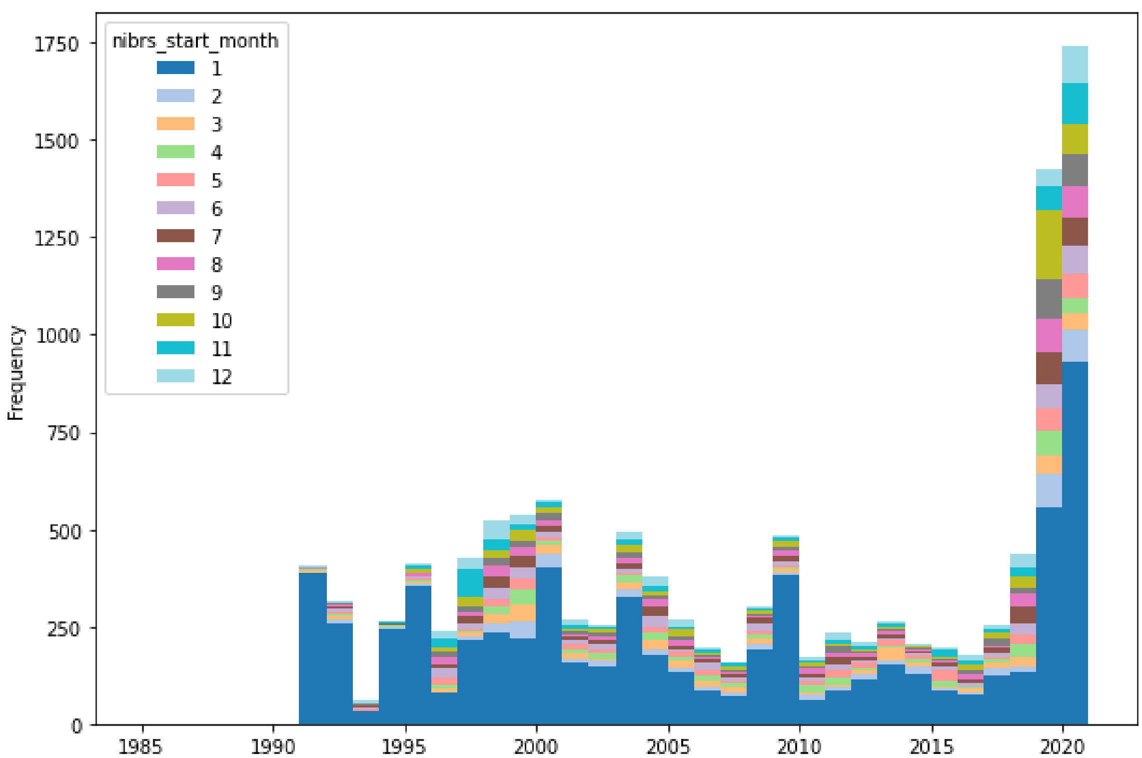
Synthetic SRS data is constructed using the NIBRS victim segment. Table 6 is a made-up example of one incident that has four offenses associated with it. I reorganize the data by the offense, count the number of victims under each offense, and keep the most serious offense for

Table 4: Number of Agencies that Start NIBRS in Each Month

NIBRS Start Month	Number of Agencies	Percentage
1	6544	55.09%
2	526	4.43%
3	442	3.72%
4	456	3.84%
5	436	3.67%
6	464	3.91%
7	515	4.34%
8	480	4.04%
9	434	3.65%
10	560	4.71%
11	511	4.3%
12	511	4.3%
Total	11,879	100%

Notes: January is the most popular month for agencies to start reporting to the NIBRS, but there are agencies that start reporting in each month of the year.

Figure 3: NIBRS Start Month within Each Year



Notes: although the majority of reporting agencies start reporting to the NIBRS in January, a number of them will start reporting in a different month almost every year.

Table 5: Mean Annual Crime Count at Agency Level (1994-2016)

Crime	Mean
Actual Murder	0.07
Actual Manslaughter	0.00
Actual Rape Total	0.36
Actual Assault Total	14.29
Actual Robbery Total	1.67
Actual Assault Aggravated	3.39
Actual Burg Total	8.24
Actual Theft Total	25.78
Actual Mtr Veh Theft Total	4.17
Actual Arson Grand Total	0.28
Actual All Crimes	54.86

Notes: The mean annual crime count at the agency level is 54.86 for years 1994 - 2016. The largest component is Theft, then Assault, Burglary, and Motor Vehicle Theft.

Table 6: Example of an Incident that Corresponds with Multiple Offenses

State Code	ORI Number	Incident ID	Date	Victim Sequence Number	Offense Code
65	MS1234567	1A234BCD56 7	20000101	1	13A
65	MS1234567	1A234BCD56 7	20000101	1	220
65	MS1234567	1A234BCD56 7	20000101	2	13A
65	MS1234567	1A234BCD56 7	20000101	2	220

Notes: the state code in this table corresponds to a made-up state called "Made-up State" which has a made-up state code of 65. "ORI Number" identifies the Law Enforcement Agency (LEA) that reports the crime, whereas Incident ID is asequence number representing the incident. Date is an eight digit number that represents the year, month, and date of the incident, and Offense Code is the code that represents the NIBRS crime category. In this example, the offense code of 13A corresponds to Aggravated Assault and 220 corresponds to Burglary/Breaking and Entering.

each incident. In the above example, the offense code 13A is kept with a victim count of 2. For crimes against persons, I keep the victim count without changing it. For crimes against property (robbery, burglary, larceny, and motor vehicle theft), I normalize the victim count to one. Since the NIBRS has more detailed categorization of crime than the SRS, I convert the relevant categories of crime from the NIBRS to the SRS ones following guidelines in Table 7. Then I replace the original synthetic SRS from the UCR series with the alternatively constructed synthetic SRS to create an alternative UCR series.

NIBRS start date data is obtained from the FBI's Crime Data Explorer (FBI, 2021). The files include data from 1960 to 2020. For each year, it lists the Law Enforcement Agencies that exist during that year, their NIBRS certification date and their NIBRS start date, among other information.

Table 7: Aggregation from NIBRS Categories to UCR Categories

NIBRS	UCR
Murder/Nonnegligent Manslaughter (09A)	Actual Murder
Forcible Rape (11A)	Actual Rape Total
Robbery (120)	Actual Robbery Total
Burglary/Breaking and Entering (220)	Actual Burglary Total
Larceny/Theft Offenses (23A - 23H)	Actual Larceny Total
Aggravated Assault (13A)	Actual Assault Aggravated
Assault (13A - 13C)	Actual Assault Total

Notes: The NIBRS data categories come from the NIBRS Data Collection Guidelines (FBI, 2000). The UCR data categories come from Jacob Kaplan's concatenated files at the monthly level (Kaplan, 2020*b*). "Actual" contrasts with "unfounded" and it rules out false or baseless complaints (FBI, 2004).

I used data from 2000.

5 Preliminary Data Analysis

In total, there are 24,620 reporting agencies in the nation. They are represented by their Originating Agency Identifiers (ORI) (NACJD, n.d.). Table 8 gives an example of the types of agencies that have ORIs. In the Detroit area, there are four agencies: the municipal police, the Drug Enforcement Agency, the state police covering the urban portion of Detroit, and the state police covering the suburban portion of it. Each of these agencies has an ORI. Other types of agencies with an ORI include county police, airport police, park police, and campus police.

Table 8: Example of Originating Agency Identifier (ORI)

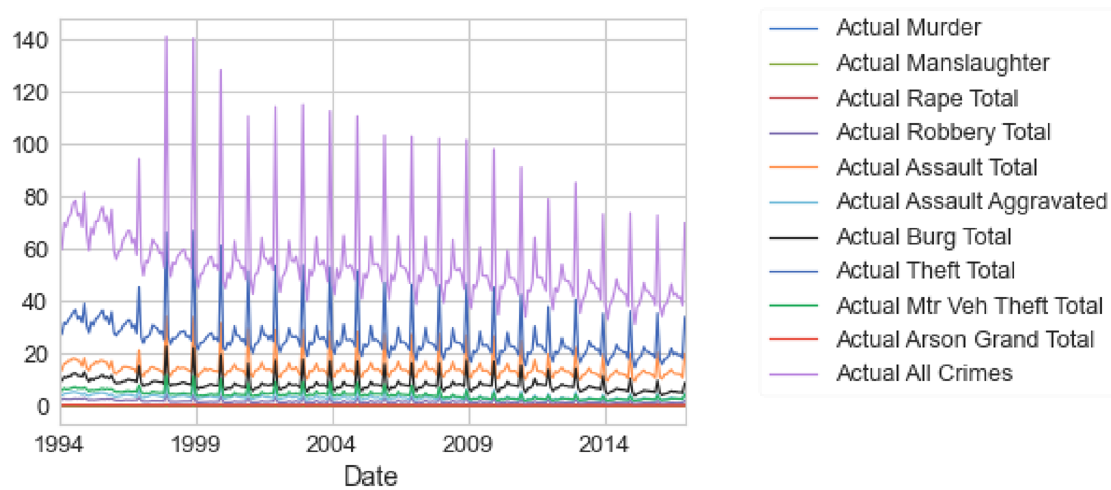
ORI	UCR Agency Name	NIBRS Start Date	Population
MIDEA0100	DEA, DETROIT	N/A	0
MI8234900	DETROIT	2005-01-01	663502
MI8202000	STATE POLICE, DETROIT	2019-01-01	0
MI8202900	STATE POLICE, DETROIT	N/A	0

Notes: there are four agencies that have the word "Detroit" in their names. One of them is the Detroit Drug Enforcement Agency. Another one is the municipal police. The two other ORIs represent different departments within the state police. MI8202000 represents the urban division and MI8202900 represents the suburban division.

Summary statistics of crimes is given in Table 5. Among 24,620 originating agencies spanning 23 years from 1994 to 2016, the mean for Theft is the highest among all the crimes. The next highest is Assault, Burglary, Motor vehicle theft, Aggravated assault, Robbery, Rape, Arson and

Murder. The time series for the different categories of crime (including all crimes) is in Figure 4. Crime count decreases over 1994-2016 in general, though it is stagnant between 2000 and 2008. The month with the highest crime count is December, and the second peak is in the summer.

Figure 4: Time series for different categories of crime



Notes: X axis has the months between January 1994 and December 2016. Y axis consists of 11 data series of means between originating agencies, including Actual All Crimes on the top and Actual Manslaughter on the bottom. Overall, crime count decreases over time, stagnating between 2000 and 2008.

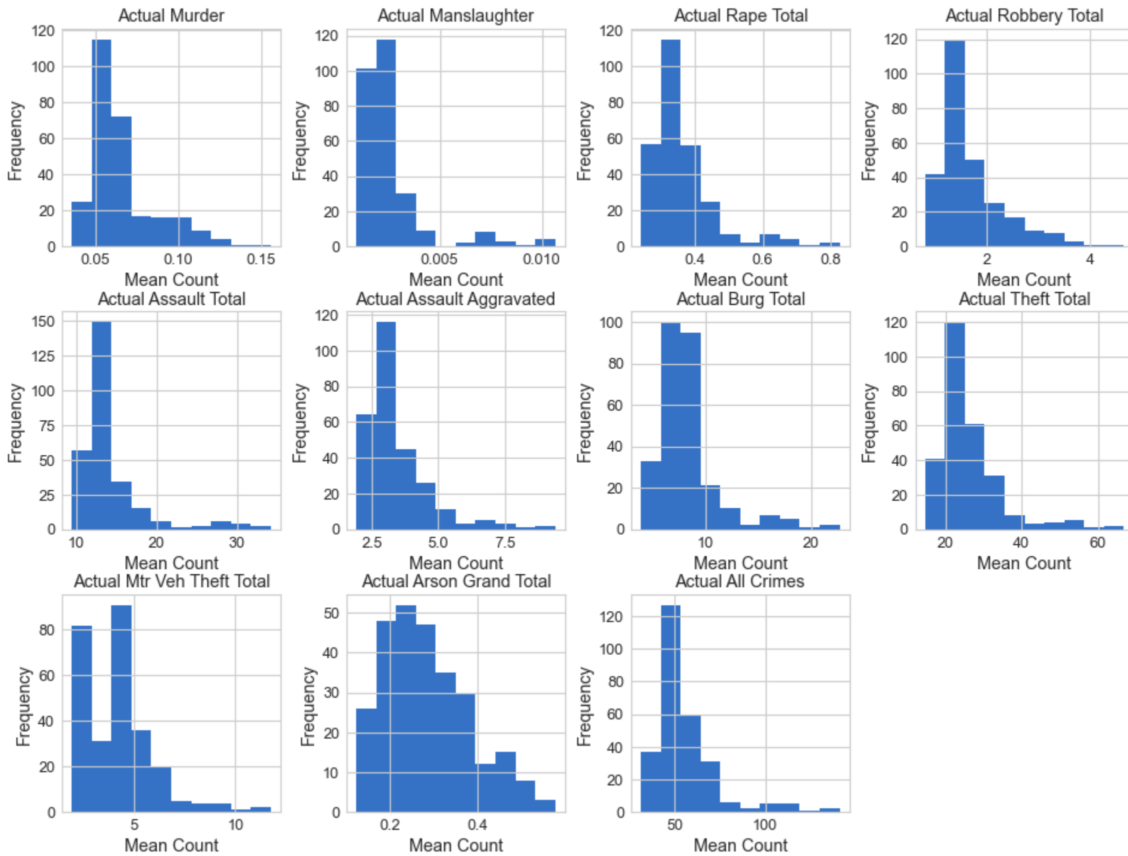
Histograms are plotted for each category of crime in Figure 5 over the 23 years between 1994 and 2016 at the monthly level. All of the distributions are approximately normal with large outliers. The date the maximum are achieved are in Table 9. Most of the crimes are the highest in December of 1997 or December of 1998. Manslaughter is the highest in December of 2005.

6 Empirical Models

The empirical model is the group-time treatment effects. In order to obtain the aggregated effects, Equation 1 will be aggregated across time periods for each group and then aggregate across groups. It will be aggregated across groups to obtain the event study effects. The notation follows that of Callaway and Sant'Anna (2020). Identification for the group-time treatment effects uses the following formula:

$$ATT^{ny}_{unc}(g,t) = \mathbb{E}\left[Y_t - Y_{g-1} | G_g = 1\right] - \mathbb{E}\left[Y_t - Y_{g-1} | D_t = 0, G_g = 0\right] \tag{1}$$

Figure 5: Histograms for different categories of crime



Notes: X axis denotes the mean of the crime counts between the originating agencies. Y axis tallies the frequency of the occurrences in each bin. There are outliers on the right side in each of the categories of crime.

Table 9: Month When Maximum is Reached

Crime Type	Date
Actual Murder	12/1997
Actual Manslaughter	12/2005
Actual Rape Total	12/1998
Actual Robbery Total	12/1997
Actual Assault Total	12/1997
Actual Assault Aggravated	12/1998
Actual Burg Total	12/1997
Actual Theft Total	12/1998
Actual Mtr Veh Theft Total	12/1997
Actual Arson Grand Total	12/1998
Actual All Crimes	12/1997

Notes: The highest monthly count is reached in December of 1997 or December 1998 for most types of crime. It is reached in December 2005 for manslaughter.

where the left hand side has the average treatment effect on the treated for the group g and time t. ny stands for not-yet-treated, and unc stands for unconditional. I use the unconditional treatment effect under the assumption that the time of switch is uncorrelated with characteristics of reporting agencies that affect the level of crime. Y_t is the reported crime in time t, and Y_{g-1} is the reported crime in time $g-1$. $G_g = 1$ for the group that made the switch in time g, and $D_t = 0$ indicates that the agency had not made the switch in time t.

Two factors contribute to the sign of the ATT. One is the consistency of the synthetic SRS to the SRS, and the other is the changes in reporting practices. I expect the synthetic SRS to be consistent with the SRS, whereas the reporting practices to be more detailed. Therefore, I expect the sign of the aggregated ATT to be positive. As reporting practices perfect over time, I expect the event study ATT to grow over time and steady at some point.

6.1 DiD Specification

The aggregation for each group uses the following formula:

$$\theta_{sel}(g) = \frac{1}{\tau - g + 1} \sum_{t=g}^{\tau} ATT(g,t) \tag{2}$$

The $ATT(g,t)$ are obtained from Formula 1. Formula 2 puts less weight on groups that made the switch earlier, and more weight on groups that made the switch later to mitigate bias. The aggregation across groups uses the following formula:

$$\theta_{sel}^{O} = \sum_{g \in \mathcal{G}} \theta_{sel}(g) P(G = g | G \leq \tau) \tag{3}$$

Formula 3 puts more weight on groups that include more reporting agencies and smaller weight on groups that include fewer reporting agencies. The estimation of these parameters are obtained via the doubly robust method, and the comparison is made with the "not-yet-switched" groups, including those that never made the switch.

Inference for the parameter θ_{sel}^{O} uses simultaneous confidence intervals that involve a bootstrapping procedure. The procedure accounts for multiple parameters of interests, in this case multiple g's and multiple e's.

6.2 Event Study

One thing I would like to know is how the effect of the switch changes over time. Therefore, the jump in crime rates should last for a long time, while the effect size should become smaller over time.

For the event study, I aggregate the group-time treatment effect into a treatment effect that is calculated based on time elapsed after treatment, which is captured by the letter e

$$\theta_{es}(e) = \sum_{g \in \mathscr{G}} \mathbf{1}(g+e \leq \tau) P(G=g|G+e \leq \tau) ATT(g, g+e) \tag{4}$$

$\theta_{es}(e)$ denotes the size of the treatment effect e periods after the switch. It consists of group-time treatment effects for all groups that have a treatment effect in period $g+e$. The more agencies there are in the group, the higher is the weight for this group. $\mathscr{G}$ is the set that includes all groups, G is an indicator variable that denotes whether a reporting agency belongs to the group g, whereas τ denotes the very last time period.

6.3 Identification Assumptions

One of the identification assumptions of this approach is parallel trends. Parallel trends assumption specifies that the treated group and the control group would have followed parallel paths in the absence of treatment. According to Freyaldenhoven et al. (2021) and Roth et al. (2022), one way to determine if the parallel trends assumption holds is to examine the pre-treatment section of the event study figure. If the pre-treatment "event study" figure looks randomly distributed and not significantly different than 0, the parallel trends assumption holds.

7 Results

This section includes results from the difference-in-difference regressions between the agencies that have made the switch and agencies that have yet to make the switch. It also includes results from the event study. The event study includes total crime count and the different categories of crime: Murder, Rape, Robbery, Aggravated Assault, Assault, Burglary, and Theft. Then I discuss the results.

7.1 DiD

The DiD results are shown in Table 10 for both the original UCR and the alternative UCR. For the original UCR, the coefficients are positive on all crime types and statistically significant on Total Crime, Murder, Robbery, Assault, Aggravated Assault, and Burglary. Compared with Table 5, which is the mean crime count at the agency level over the years 1994 and 2016, the DiD coefficients are much larger.

Table 10: DiD Results

	Total Crime	Murder	Rape	Robbery	Assault	Aggravated Assault	Burglary	Theft
				Original UCR				
DiD	184.95	0.19	0.96	7.44	79.51	15.60	25.69	54.71
SE	55.53	0.04	0.67	1.80	21.68	4.17	10.01	40.73
				Alternative UCR				
DiD	122.72	0.21	0.67	7.45	23.89	9.26	22.73	53.84
SE	56.98	0.05	0.70	1.86	19.10	4.17	10.60	38.26

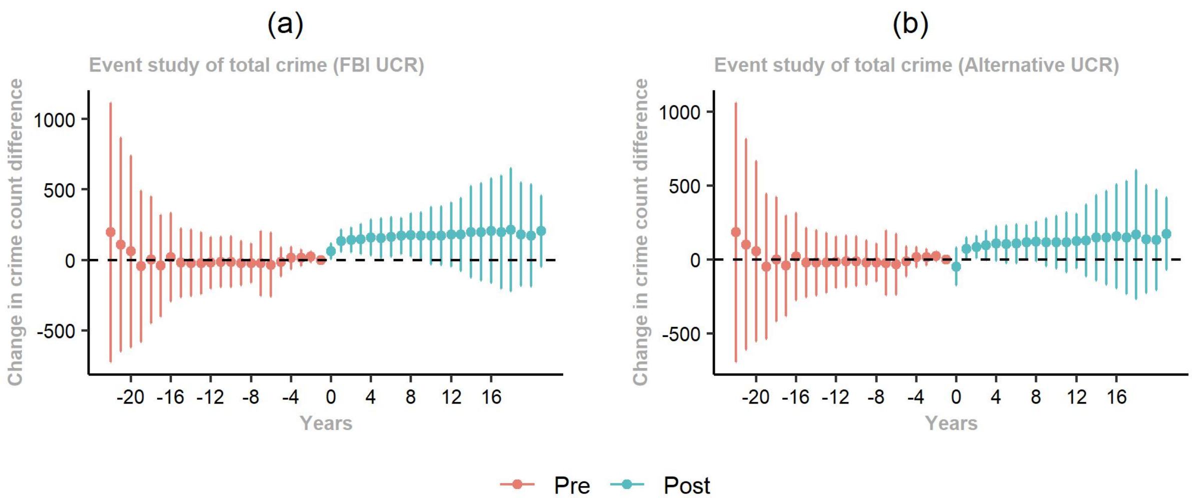
Notes: For the original UCR, the coefficients on Total Crime, Murder, Robbery, Assault, Aggravated Assault, and Burglary are statistically significant. For the alternative UCR, the coefficient on Assault dropped considerably and became statistically insignificant.

These results convey two insights: 1) there are statistically and economically significant increases in almost all crime categories. 2) The alternative UCR mitigates the increase in the original UCR moderately in most of the crime categories and greatly in Assault.

7.2 Event Study

Figure 6 shows the event study results for total reported crime count. Panel (a) captures the treatment effect in the FBI UCR. The difference between the control group and the treatment group of total reported crime count jumps up during the year when the switch happens, though not as high as the subsequent years, possibly because reporting agencies don't all make the switch on January 1st. Therefore, for some reporting agencies, data from the year of the switch also captures some variations from before the switch. However, after the first year, crime count is consistently higher than benchmark, and stays statistically significant for ten years. Panel (b) displays results from alternative UCR. During the year of the switch, many offenses are categorized under the same incidents, so the difference between the crime count in the treatment group and the control group drops, though not significantly. After that, the difference in crime count becomes statistically significantly higher than that at the baseline for two years. Table 11 shows the change in reported crime count in the treatment group compared with the control group. Change in the FBI UCR is an increase of around 150 in the five years after the switch, which is statistically significant throughout the five years. Changes in the alternative UCR is an increase of around 100 in the five years after the switch.

Figure 6: Event Study Plot for Total Crime Count



Notes: Numbers on the x-axis are years before and after the switch. Numbers on the y-axis is the comparison of the change in crime count between the control group and the treatment group. Dots are the mean values, and vertical lines are the 95% confidence interval. Panel (a) shows the event study with FBI UCR, and Panel (b) shows the event study with alternative UCR. Total crime increases significantly in the "treatment group" compared to the "control group" for ten time periods in FBI UCR, but increases significantly for two time periods in alternative UCR.

Table 11: Change in Total Crime After Switch in Reporting Standards

Years After Switch	Change (FBI UCR)	SE (FBI UCR)	Change (Alt. UCR)	SE (Alt. UCR)
1	135.97	29.77	71.93	31.04
2	143.92	34.18	83.73	31.25
3	148.04	41.31	96.45	41.70
4	159.97	49.19	107.03	49.09
5	154.35	54.07	101.97	52.38

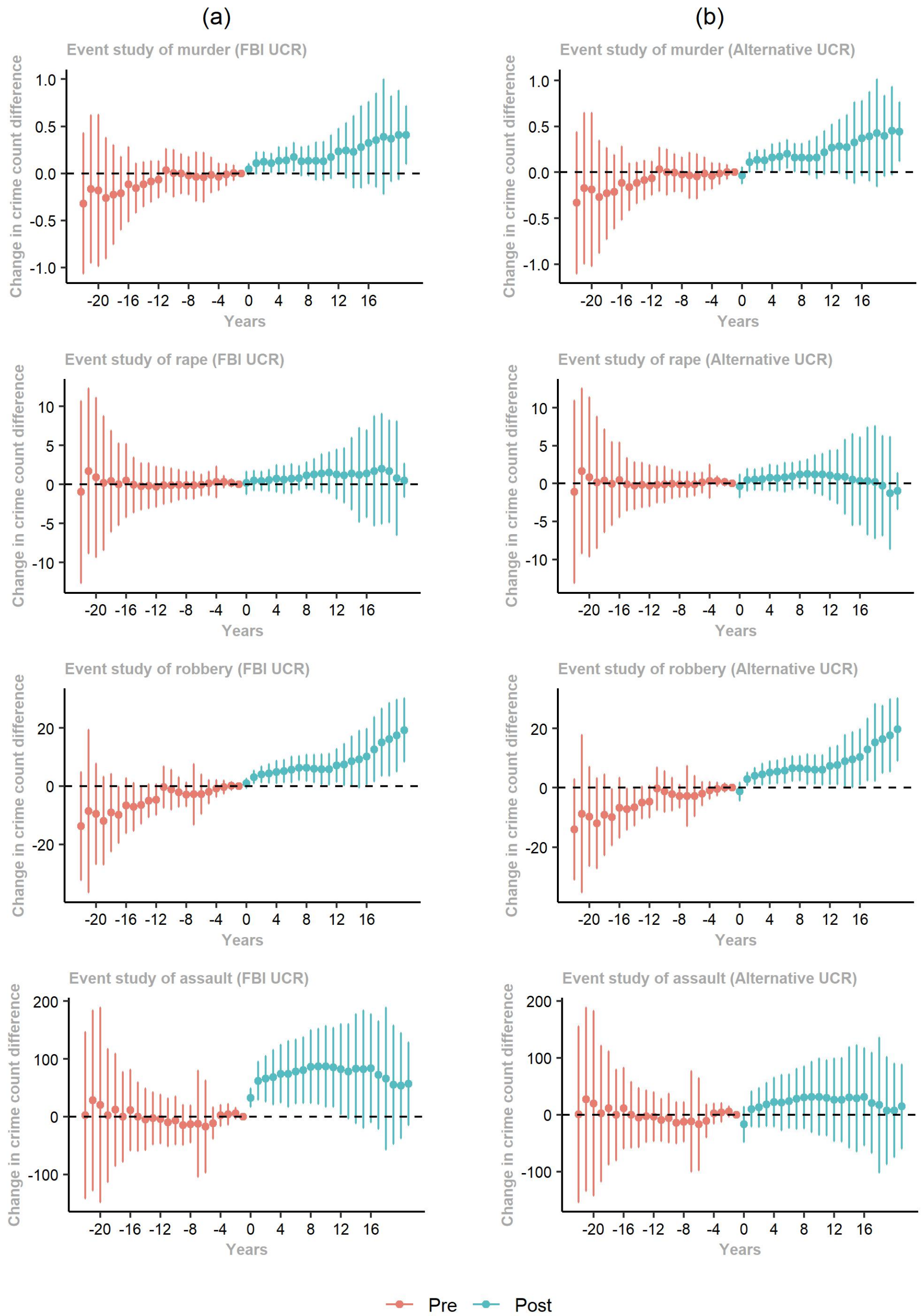
Notes: During the first five years after the switch, the agencies that made the switch reported an increase of approximately 150 in the crime count compared to the agencies that had not made the switch in the FBI UCR. The increase is consistently statistically significant. In the alternative UCR, there is an increase of around 100, and the increase becomes statistically insignificant starting the third year.

The results are counter-intuitive. The UCR uses SRS data from agencies that have not transitioned to the NIBRS. For the agencies that have transitioned, their UCR data from before the transition comes from the SRS. Their UCR data from after the transition comes from a conversion from the NIBRS back to a synthetic SRS, which is in SRS format. Since the underlying crime environment does not change based on whether an agency adopts the NIBRS, there should be no change in the relationship between the control group and the treatment group after the switch. Where does the change occur? Since total crime consists of Murder, Rape, Robbery, Aggravated Assault, Burglary, and Larceny, I examine the six categories separately to see where the "treatment effect" comes from.

Event study results for different crime categories are in Figures 7 and 8. The main difference between the FBI UCR and the alternative UCR comes from Assaults. The FBI UCR has a large and statistically significant jump after the switch. However, the alternative UCR does not. Murder, Robbery, Burglary and Theft all have a statistically significant jump in both the FBI UCR and the alternative UCR. Murder and Robbery have a moderate linear time trend, which may break the parallel trends assumption. Changes in the first five years after the switch are in tables 12 and 13. The magnitude in the FBI UCR is between three times and six times of that in the alternative UCR, though the standard errors are comparable.

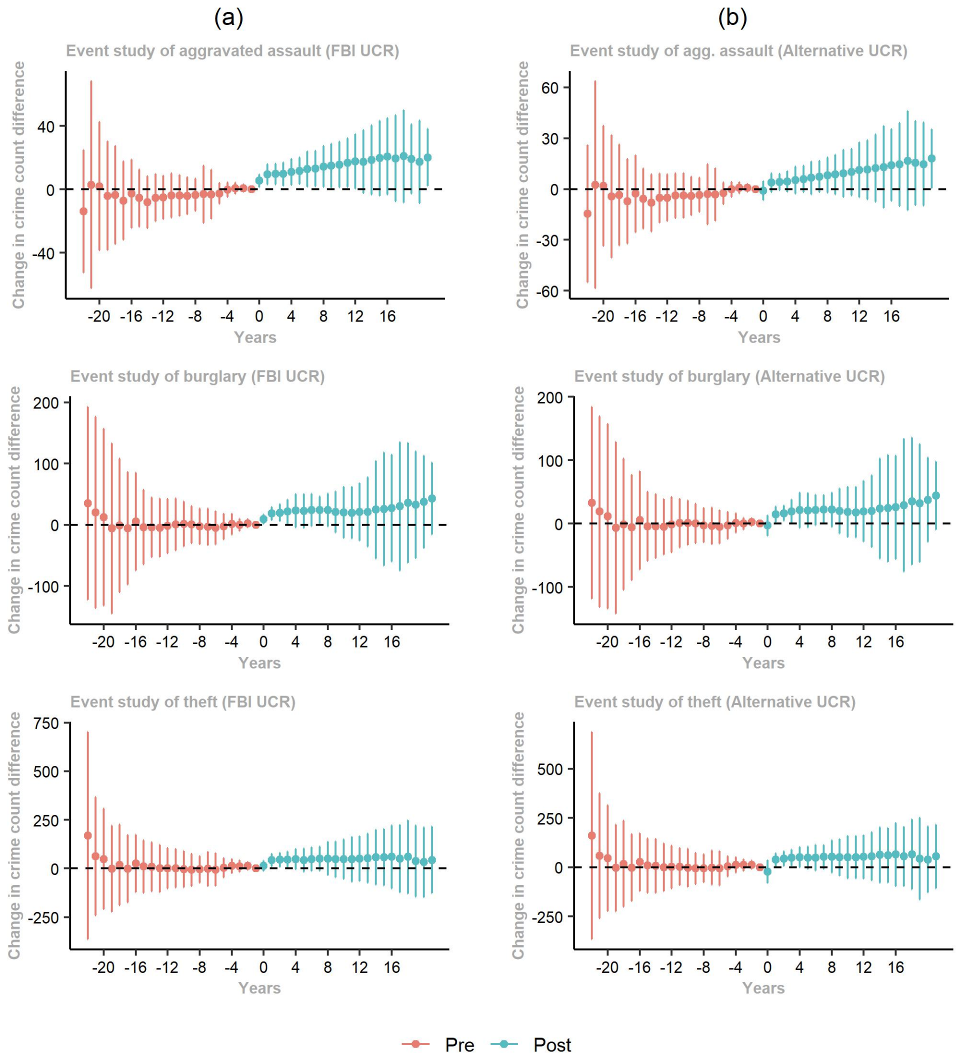
Results have shown that inconsistency in crime reporting standards between the SRS and the synthetic SRS exists. The largest contributing factor comes from Assault. Other categories (Murder, Rape, Robbery, Burglary, and Theft) are consistent between FBI UCR and the alternative UCR. Also, there are inconsistencies in crime reporting practices between the SRS and the NIBRS. Even after the NIBRS has been converted to synthetic SRS, there is still a large and statistically significant jump in almost all categories of crime. Strom and Smith (2017) has mentioned that the NIBRS system has the capacity to connect with the Records Management System where the patrol office enter data on the scene of the crime. Aurora PD (1994) has mentioned that agencies are unable to update the SRS after they submit the data, but they are able to update the NIBRS with new information. Therefore, the NIBRS improves the accuracy of crime reporting over the UCR, which can explain the jump in crime.

Figure 7: Event Study Plot for Different Categories of Crime (1)



Notes: Numbers on the x-axis are years before and after the switch. Numbers on the y-axis are differences in the crime count between the control group and the treatment group compared with the baseline. Vertical bars are the 95% confidence interval. Panel (a) shows the event study with the FBI UCR, and Panel (b) shows the event study with alternative UCR. The main difference between the FBI UCR and the alternative UCR lies in Assault. the FBI UCR has a large jump after the switch, and the increase is statistically significant for 13 years. The alternative UCR does not have a large and statistically significant jump.

Figure 8: Event Study Plot for Different Categories of Crime (2)



Notes: Numbers on the x-axis are years before and after the switch. Numbers on the y-axis are percentage changes in crime rate. Vertical bars are 95% confidence intervals. Panel (a) shows the event study with the FBI UCR, and Panel (b) shows the event study with alternative UCR. Aggravated Assault has a statistically significant increase in the FBI UCR, but not in the alternative UCR. Burglary and Theft have a statistically significant increase in both the FBI UCR and the alternative UCR.

8 Discussion

The findings suggest that researchers who use UCR data should take the NIBRS start date into account when they examine the validity of their results. For example, if the research topic is to evaluate a change in policy, researchers should discuss whether these policy changes coincide with NIBRS start dates. Note that NIBRS participation differs at the reporting agency level. For county level analysis or state level analysis, NIBRS participation can be aggregated with crime counts as

Table 12: Change in Different Categories of Crime After Switch in Reporting Standards

Years After Switch	Change (FBI UCR)	SE (FBI UCR)	Change (Alt. UCR)	SE (Alt. UCR)
		Murder		
1	0.11	0.04	0.11	0.04
2	0.12	0.04	0.14	0.04
3	0.11	0.04	0.13	0.04
4	0.13	0.05	0.16	0.06
5	0.14	0.05	0.17	0.06
		Rape		
1	0.50	0.59	0.48	0.66
2	0.42	0.57	0.50	0.62
3	0.53	0.63	0.61	0.66
4	0.75	0.80	0.79	0.79
5	0.61	0.82	0.71	0.76
		Robbery		
1	3.14	0.81	2.95	0.79
2	4.03	0.99	3.98	1.04
3	4.37	1.19	4.53	1.32
4	4.90	1.41	5.12	1.42
5	5.15	1.42	5.41	1.42
		Assault		
1	62.14	13.34	10.11	12.86
2	65.62	16.18	12.72	14.06
3	68.22	19.32	17.94	15.56
4	74.30	20.35	21.97	17.70
5	74.02	23.21	21.43	20.03

Notes: Among Murder, Rape, Robbery and Assault, FBI UCR and alternative UCR are comparable except for Assault. The variance between FBI UCR and alternative UCR are comparable, but the magnitude in FBI UCR is between three times and six times as large.

weights. Using population to create the weights is not advised because non-local agencies don't have a population associated with them, yet they contribute to 1% - 3% of crime reporting (See Table 14 for more details).

9 Conclusion

This paper examines the continuity of the UCR series for crime reporting during the change from the SRS to the NIBRS. For historical comparison, the NIBRS is converted to the synthetic SRS

Table 13: Change in Different Categories of Crime After Switch in Reporting Standards

Years After Switch	Change (FBI UCR)	SE (FBI UCR)	Change (Alt. UCR)	SE (Alt. UCR)
	Aggravated Assault			
1	9.35	2.47	3.84	2.17
2	9.67	2.51	4.08	1.87
3	9.66	2.88	4.42	2.48
4	10.99	3.20	5.33	3.11
5	11.68	3.27	5.96	3.11
	Burglary			
1	18.70	4.39	14.55	5.07
2	19.84	5.59	16.54	5.02
3	21.56	8.27	19.33	8.06
4	23.31	11.22	21.35	11.82
5	22.51	11.44	20.91	11.55
	Theft			
1	42.33	13.48	37.69	13.41
2	45.01	15.01	43.19	14.78
3	45.11	17.29	47.41	17.15
4	47.88	21.21	50.95	21.12
5	44.14	24.55	47.32	23.19

Notes: Among Aggravated Assault, Burglary, and Theft, Aggravated Assault has the largest difference between the FBI UCR and the alternative UCR, which is consistent with the difference of Assault documented in Table 12. The standard errors are all comparable.

which is concatenated to the SRS series for agencies that have made the change. Then, the converted series are published as a UCR series, alongside other data series from agencies that have not adopted the NIBRS. While the literature has examined the difference between the NIBRS and the synthetic SRS, this work is the first to examine the continuity between SRS and synthetic SRS. The tedious process of converting the NIBRS to synthetic SRS has resulted in some discrepancies. Also, since the NIBRS reports more details than the SRS, the records are more accurate, more timely, and more complete; however, this also means that the number of crimes reported is larger.

Empirical analysis shows that both discrepancies exist: discrepancies resulting from the conversion between the NIBRS and synthetic SRS, and discrepancies resulting from improved reporting practices. The findings strengthen points made in the existing literature. Past work has demonstrated that there are many details to pay attention to when converting the NIBRS to the SRS. Also, literature has pointed out that the NIBRS has edit checks to review the reported data. Therefore,

Table 14: Crime Reported by Non-Local Agencies

	Murder	Proportion	Rape	Proportion	Robbery	Proportion	Assault	Proportion
count	276.00	276.00	276.00	276.00	276.00	276.00	276.00	276.00
mean	23.95	0.02	271.18	0.04	290.98	0.01	6237.92	0.02
std	9.77	0.01	111.49	0.01	91.54	0.00	1521.15	0.00
min	6.00	0.00	112.00	0.01	137.00	0.00	3879.00	0.01
25%	16.75	0.01	183.00	0.03	231.00	0.01	5013.75	0.02
50%	23.50	0.02	248.00	0.03	282.00	0.01	5900.50	0.02
75%	31.00	0.02	313.50	0.05	336.50	0.01	7094.25	0.02
max	60.00	0.05	651.00	0.07	698.00	0.02	12018.00	0.03

	Motor Vehicle Theft	Proportion	Arson	Proportion	Aggravated Assault	Proportion	Burglary	Proportion
count	276.00	276.00	276.00	276.00	276.00	276.00	276.00	276.00
mean	2155.76	0.02	283.26	0.02	1266.77	0.03	2926.94	0.03
std	391.14	0.01	95.78	0.00	279.66	0.00	611.66	0.01
min	1395.00	0.01	94.00	0.01	798.00	0.02	1562.00	0.01
25%	1841.00	0.02	211.75	0.02	1059.00	0.02	2604.00	0.02
50%	2086.50	0.02	267.50	0.02	1201.00	0.03	2863.50	0.03
75%	2457.50	0.02	334.50	0.02	1402.25	0.03	3183.00	0.03
max	3403.00	0.04	644.00	0.02	2341.00	0.03	5192.00	0.04

	Theft	Proportion	All Crimes	Proportion
count	276.00	276.00	276.00	276.00
mean	13375.77	0.05	25575.72	0.02
std	2468.77	0.02	4280.04	0.00
min	8994.00	0.02	19279.00	0.01
25%	11567.50	0.03	22737.00	0.02
50%	12765.00	0.05	24609.00	0.02
75%	14478.25	0.07	27256.00	0.03
max	21531.00	0.12	42610.00	0.03

Notes: Data comes from the years 1994 to 2016 at the monthly level, totalling 276 observations. In the UCR data, there are various types of reporting agencies: local police, county police, state police, drug enforcement agencies, campus police, park police, and airport police. For each type of crime, the proportion reported by non-local police is different across the years. The table reports summary statistics for each crime across the years. We can see from the table that non-local agencies report between 1% to 3% of the crime.

records from the NIBRS are more complete and more accurate.

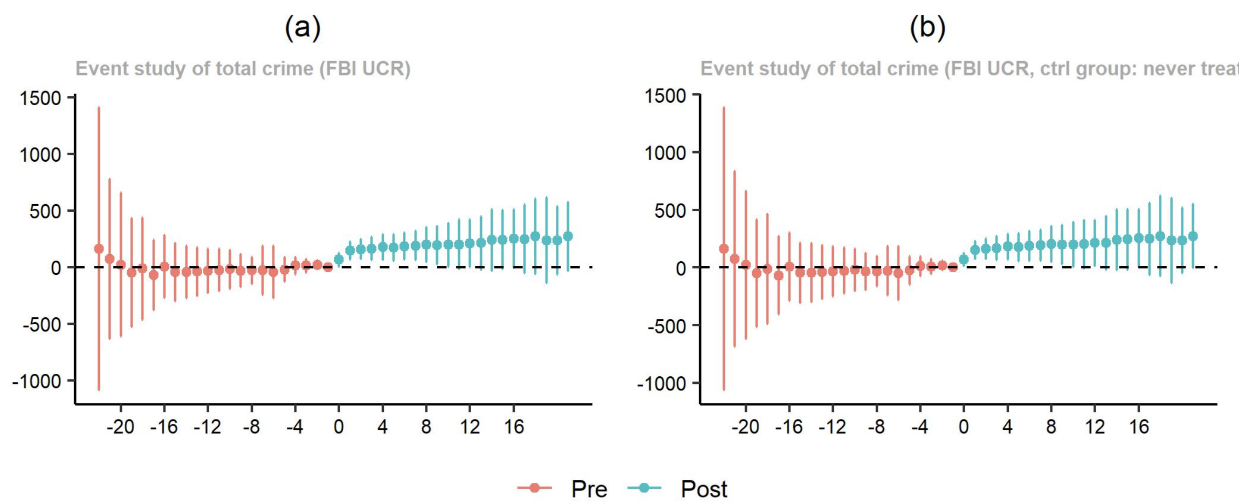
This paper has two policy implications: 1) relevant departments should implement tests similar to the ones conducted in this paper to examine the continuity between the SRS and the synthetic SRS after they adopt the NIBRS. 2) researchers who use the UCR data series should take into account the NIBRS start date when they evaluate the validity of their results. Future work is needed to establish a standard for converting the NIBRS to synthetic SRS and to evaluate the discrepancy between SRS and synthetic SRS.

A Appendix

A.1 Use Never Treated Group as Control Variable

The main specification uses the not-yet-treated group as the control to increase the sample size. However, not-yet-treated units can turn into treated units, which may create bias in small sample. This section of the appendix compares the regression results for total crime between using the not-yet-treated group and the never-treated group as the control. Figure A1 shows a comparison between the event study results using the not-yet-treated group as the control and using the never-treated group as the control. Panel (a) uses the not-yet-treated group as the control, and Panel (b) uses the never-treated group as the control. The two figures are almost identical, meaning that using the not-yet-treated group does not result in bias. Table A1 documents the DiD effect and standard error with the not-yet treated group as the control and the DiD effect and standard error with the never treated group as the control during the first five years after the NIBRS start date. With the never treated group as the control, the DiD effect is slightly larger, but the standard error is also slightly larger.

Figure A1: Event Study Plot for Total Crime Count (using not-yet-treated group and never-treated group as control)



Notes: Numbers on the x-axis are years before and after the switch. Numbers on the y-axis is the comparison of the change in crime count between the control group and the treatment group. Dots are the mean values, and vertical lines are the 95% confidence interval. Panel (a) shows the event study using the not-yet-treated group as the control, and Panel (b) shows the event study with the never-treated group as the control. The two figures are almost identical, indicating that there are no significant difference between the two control groups.

Table A1: Change in crime (not-yet treated control group vs never treated control group)

Years After Switch	Change (not-yet treated)	SE (not-yet treated)	Change (never treated)	SE (never treated)
1	146.83	31.48	151.84	31.79
2	157.48	34.86	161.81	35.96
3	162.76	41.55	167.94	39.95
4	175.66	45.11	181.13	46.72
5	171.02	46.42	176.03	50.62

Notes: The table documents the DiD effect in crime after the UCR switches from the SRS to the synthetic SRS. It offers a comparison between using the not-yet treated group and the never treated group as the controls. The advantage of the not-yet treated control group is that it increases the sample size. The concern is that units switch in and out of the not-yet treated group, which may bias the results in small sample. The first column documents the DiD effect with the not-yet treated group as the control, and the third column documents the DiD effect with the never treated group as the control. Columns 2 and 4 are standard errors. We can see that the mean and the standard errors are slightly different but very comparable.

A.2 Alternative methodology

De Chaisemartin and d'Haultfoeuille (2020) presented an alternative method for computing ATE than the Callaway and Sant'Anna (2020) method. Their method is introduced because the regular two-way fixed effects estimator will assign negative weights to the difference between the group that is already treated and the group that is newly treated. For staggered adoption scenarios with heterogeneous treatment effects between groups and time periods, these negative weights may bias results. My main analysis avoids introducing negative weights by comparing treated units with either not-yet treated units or never treated units. However, it does not provide me with information about exactly how much negative weights affect my main results. Zhang and de Chaisemartin (2021) provides a tool in R, TwoWayFEWeights, which can compute the number of positive weights and negative weights. Table A2 shows that 82.93% of the weights are positive, and the sum of all positive weights is 1.06, compared with the sum of all negative weights, which is -0.06. Therefore, not all of the weights are positive. A small proportion are negative, which may bias my results. Therefore, it was accurate for me to not apply the two-way fixed effects methodology.

The DiD results are presented in Table A3. The De Chaisemartin and d'Haultfoeuille (2020) (CH2020) result is much smaller but still large and statistically significant.

Table A2: Weights for DiD Estimator

	Number	Percentage	Sum
Positive weights	67255	82.93%	1.06
Negative weights	13846	17.07%	-0.06
Total	81101	1	1

Notes: The majority of weights estimated by the DiD estimator are positive, which make up 82.93% of all the weights. The sum of the positive weights is even larger in absolute value compared with the sum of the negative weights.

Table A3: Comparison between DiD results from Callaway and Sant'Anna (2020) (CS2020) and De Chaisemartin and d'Haultfoeuille (2020) (CH2020) methods

CS2020		CH2020	
Mean	SE	Mean	SE
185	55.5	66.7	26.8

Notes: The DiD effect from CH2020 is much smaller than that of CS2021, though still large and statistically significant.

A.3 Other Response Variables

The main specification uses crime numbers as the response variable while some other papers in the Economics of Crime use crime rate as the response variable. The reason why I use crime numbers is because the unit of observation is at the reporting agency level. There are many different types of agencies, and not all of them have a population associated with them, thus it is not possible to compute the crime rate. Table A4 shows that there are nine types of reporting agencies, four of which report to the UCR consistently every month from 1994 to 2016. Of the ones that report consistently, many of them are county police or state police. Crime rate calculated at the city level is not comparable to crime rate at the county level because cities are part of counties, and city crimes are not counted towards crimes recorded by county police.

The other candidate response variable is the percent change in crime numbers. According to Table A5, 25% of the 331844 observations have 3 or fewer crimes. When constructing the time series for computing percent change, the formula of $ln(n+1)$ is applied. When there are a large number of observations with low crime number, the regression coefficient is biased. For example, a increase from 1 to 2 means a 100% change, and an increase from 1 to 3 means a 200% change. These low crime counts introduce bias into the results, therefore, they are not included in the analysis, either.

Table A4: Agency Types and Counts

Agency Type	Count	Count (consistent)
City	14117	11480
County	3137	2865
Federal	388	0
Other	1117	1
Other State Agency	1951	0
State Police	1901	82
Tribal	239	0
University or College	1037	0
Unknown	541	0
Total	24428	14428

Notes: There are nine different types of reporting agencies, four of which have agencies that report to the UCR each month from 1994 to 2016. Crime rate at the city level is not comparable with crime rate at the county level, which is also not comparable than that at the state level, so crime rate is not a good response variable for this research project.

Table A5: Summary Statistics for Crime Numbers

Statistic	Number
Count	331844
Mean	894
Min	0
1st Quartile	3
Median	112
3rd Quartile	476
Max	643545

Notes: Of 331844 data records for annual number of crime, one quarter of them are under 3. However, to construct a percent change variable, I need to apply the formula $ln(n+1)$, which changes greatly at low n values, biasing the final result.

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