ILLINOIS

TRAFFIC AND PEDESTRIAN STOP STUDY

2022 ANNUAL REPORT

TRAFFIC STOP ANALYSIS

SUBMITTED BY

THE MOUNTAIN-WHISPER-LIGHT: STATISTICS AND DATA SCIENCE

The Mountain-Whisper-Light

SC-B CONSULTING

Achieving Innovative Solutions Together

Illinois Traffic and Pedestrian Stop Study

2022 ANNUAL REPORT: TRAFFIC STOP ANALYSIS

Part I Executive Summary and Appendices

Prepared for the Illinois Department of Transportation

By

The Mountain-Whisper-Light: Statistics & Data Science

In Cooperation with SC-B Consulting, Inc.

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Executive Summary

I. Background

In October 2019, The Mountain-Whisper-Light, Inc., aka The Mountain-Whisper-Light: Statistics & Data Science was awarded a contract to conduct a statistical study of the traffic and pedestrian stop data provided by law enforcement agencies to the Illinois Department of Transportation, pursuant to Illinois Vehicle Code 625 ILCS 5/11-212 Traffic and Pedestrian Stop Statistical Study. TMWL is carrying out the project in cooperation with SC-B Consulting, Inc., an Illinois firm. Reports have already been issued on 2019, 2020 and 2021 traffic and pedestrian stops in Illinois and are available online at https://www.idot.illinois.gov/transportation-system/local-transportation-partners/law-enforcement/illinois-traffic-stop-study.

According to the IDOT website, "On July 18, 2003, Senate Bill 30 was signed into law to establish a four-year statewide study of data from traffic stops to identify racial bias. The study began on January 1, 2004, and was originally scheduled to end December 31, 2007. However, the legislature extended the data collection several times, and also expanded the study to include data on pedestrian stops. Public Act 101-0024, which took effect on June 21, 2019, eliminated the study's scheduled end date of July 1, 2019, and extended the data collection."

Under that provision of the Illinois Vehicle Code, IDOT is responsible for providing a standardized law enforcement data compilation form (see Appendix A), analyzing the data and submitting a report of the previous year's findings to the governor, General Assembly, Racial Profiling Prevention and Data Oversight Board, and each law enforcement agency no later than July 1 of each year. In May 2023, TMWL and SC-B, in cooperation with IDOT's Bureau of Data Collection, provided copies of statistical tables for 794 law enforcement agencies in the state of Illinois, based on data collection provided by the respective agencies on traffic and pedestrian stops. These 794 agencies reported at least one traffic or pedestrian stop. Among the 794 agencies, 793 reported on traffic stops or on both traffic stops and pedestrian stops. One agency reported only on pedestrian stops. The agencies were invited to review and comment on the tables. Some agencies did provide comments and those comments are included with their tables in Part II of this report. We have responded to some comments with additional information, and the readers of this report may wish to peruse the agency comments and our responses. Twelve agencies provided comments on traffic tables or both traffic and pedestrian tables. We have provided responses to comments from the Glencoe Department of Public Safety, Gurnee Police Department and Normal Police Department on their traffic stops tables, and we have provided a response to comments from the Gurnee Police on their pedestrian stops tables. Comments on the traffic stops tables (or general comments) and comments on the pedestrian stops tables are included in the Part II traffic or pedestrian tables, respectively.

We are pleased to submit this 2022 annual report for the Illinois Traffic and Pedestrian Stop Study. The Executive Summary in this document covers the traffic stops study and a companion volume with a similar format contains an Executive Summary for the pedestrian stops study.

II. Introduction

How is this report structured?

The report is presented in two parts. **Part I** is this Executive Summary, which includes appendices with detailed technical information on the statistical methodology and analysis. **Part II** includes extensive tables (one set of tables for each law enforcement agency that collected data for all stops conducted in 2022). The tables show stop rates for each racial group, along with other statistics that cover activity during the stops, such as citations or warnings, searches and contraband found.

To obtain the greatest benefit from this report, readers are encouraged to read the full Executive Summary. In addition to the information on data collection, we have provided a sample Traffic Table and a Guide to Using Traffic Tables that includes definitions of statistical terms used in this report and an explanation of the data presented in each panel of the tables. We also include an Interpretation section with additional details on the numeric results presented in the tables and a plain-language description of how the analysis was implemented. Finally, the section on Selected Findings highlights some statewide results. The Appendices include technical material that describes the statistical methods and calculations in detail. The information in the appendices is provided for readers who wish to have a deeper understanding of the methodology.

What is the source of the data?

As noted above, per Illinois law, officers from law enforcement agencies are required to fill in a report when they stop a driver or a pedestrian. Separate templates are provided for traffic and pedestrian stops.

To follow the convention of previous reporting on the Illinois Traffic and Pedestrian Stop Study, we are submitting two separate reports, the Illinois **Traffic** Stop Study and the Illinois **Pedestrian** Stop Study. The above-mentioned data collection templates (known as Traffic Stop or Pedestrian Stop Data Forms) are shown in Appendix A of the ITSS and IPSS. There is an instruction manual that accompanies the traffic stops data collection form — available online at http://www.idot.illinois.gov/Assets/uploads/files/Transportation-System/Pamphlets-&-Brochures/Safety/2012TrafficStopDataSheetInstructions.pdf.

How were the data analyzed?

The results of the data collection are that 793 agencies generated data on 2,012,182 traffic stops. Among the 793 agencies, 550 agencies provided data on traffic stops only and 243 agencies provided data on both traffic and pedestrian stops. Only 58 traffic stops (0.003% of traffic stops) were missing the race designation. Further analysis was carried out to provide statistics that may be helpful in determining if there is potential bias against minorities in initiating a stop or in the activities that occur during a stop.

As specified by the Illinois statute for this study, the tables report on the stops and subsequent experience of individuals stopped. The stopped individuals are classified into one of six racial groups. The law enforcement officer filling in the data collection form must use their judgment to classify an individual into one of the following groups.

- Black or African American
- Hispanic or Latino

- Asian
- American Indian or Alaska Native
- Native Hawaiian or Other Pacific Islander
- White

The data collection forms are extensive. There are more than 60 data items listed for traffic stops and more than 20 data items listed for pedestrian stops. Some items are left blank unless there are further actions beyond a stop, such as a search.

Data collected by local agencies for traffic stops include:

- Information about the driver (including race) and the officer
- The location of the stop (using location designations developed by each agency)
- Reason for the stop
- Outcome of the stop
- Search activity and search findings of contraband

III. Guide to Using Traffic Tables

While many readers of this report previously reviewed traffic and pedestrian stop tables for their respective jurisdictions, here are some brief explanations of the statistics presented in the tables of this report for those who may not be familiar with them.

Table 1 is included as an example to show stop rates, along with certain percentages and ratios. A ratio compares either a rate or a percentage for a minority to the corresponding rate or percentage for Whites. The ratios are intended to make it easier to determine the possibility of racial profiling. The word "possibility" is very important, because racial profiling cannot be proved by the numeric results in this report. Some of the inherent uncertainties and limitations of the statistics are explained later.

The following section includes an example of traffic tables and offers a guide to the numbers in the tables, explained panel by panel. The table reproduced here (Table 1) refers to all traffic stops reported in 2022 from law enforcement agencies in the state of Illinois. The counts, rates, percentages and ratios are for purposes of illustration only and are <u>not</u> tied to any individual agency.

Before using the tables: Following the tables there is an important section on interpretation of the rates, ratios, percentages and 95% confidence intervals. Understanding that section is important for readers of this report to make a proper assessment of what the numbers represent.

Rates, percentages and ratios: The terms "rate," "percentage" and "ratio" are used throughout this report. A brief explanation of the terms is provided here.

A **<u>rate</u>** in this context is the number of individuals (such as the number of individuals stopped) divided by the population the individuals came from, also known in this report as the "benchmark," a term that will be used repeatedly. For example, in Illinois in 2022 there were 383,729 traffic stops of individuals whom the officer assigned to the category "Hispanic or Latino." The estimated benchmark population of Hispanic or Latino drivers in Illinois in 2022 was 1,884,763. Dividing the 383,729 by 1,884,763 yields the stop rate of 0.2036. That is, there was an average of 0.2036 stops per driving member of the Hispanic or Latino population. The decimal value 0.2036 does <u>not</u> mean that 20.36% of Hispanic or Latino drivers had a stop. Some drivers may have been stopped more than once.

A **percentage** in this context has the usual meaning. For example, in Illinois in 2022 there were 926,479 stops of drivers whom the officer assigned to the category “White.” There were 590,885 of those stops with a citation for a moving violation. The number of stops with citations (590,885) divided by the number of stops (926,479) yields the decimal fraction 0.638. That fraction represented as a percentage is 63.8%. In Illinois in 2022, 63.8% of stops of drivers assessed as being White resulted in a citation of the driver.

The **ratio** used in this report is either the ratio of a minority rate to a White rate or the ratio of a minority percentage to a White percentage. If the ratio is 2.0, for example, it means that the minority rate (or percentage) is twice the White rate (or percentage).

Table 1 shows the Illinois statewide results for illustration of traffic stop reporting. Following is a guide to each panel of the table.

> **Panel 1** (shaded rows) presents the traffic stops, benchmark, and stop rate by racial group, and stop rate ratio for each minority group compared to White drivers. Ninety-five percent confidence intervals are shown (in parentheses) for rates and rate ratios. The 95% confidence interval is a “margin of error,” and it is explained in a short section with that heading, below.
>
> **Panel 2** shows the number, percentage (in parentheses) and 95% confidence interval [in square brackets, like this] for selected reasons for traffic stops (moving violation, equipment, licensing/registration and commercial vehicle) for each racial group. The label for the panel includes the note “Percentage of All Stops for the Racial Group with the Noted Reason for Stop.” This tells us that the number of stops for a given reason, such as “Moving Violation,” is divided by the total number of stops for the racial group to convert it to a percentage (after multiplication by 100%). For example, drivers assessed as being Asian had 47,909 stops noted by the officer as “Moving Violation,” and the Asian category had 72,996 total stops in 2022, hence the percentage of stops noted as “Moving Violation” for drivers classified as Asian was 100% x (47,909/72,996) = 65.7% (rounded).
>
> **Panel 3** shows the outcomes of traffic stops including written warning, verbal warning and citation for each racial group. The number, percentage (in parentheses) and 95% confidence interval [in brackets] are shown for each outcome. The ratio and 95% confidence interval (in parentheses) comparing each minority group to White drivers are shown for citations, the most serious outcome recorded for the stop on the traffic data collection form.
>
> **Panel 4** shows vehicle searches and outcomes of vehicle searches during traffic stops, including consent searches, all searches and whether contraband was found during any search for each racial group. The number, percentage (in parentheses) and 95% confidence interval [in brackets] are shown for each outcome. The label for each row shows the basis for calculation of the percentages. The contraband-found percentage is calculated based on all vehicle searches. The ratio and 95% confidence interval (in parentheses) comparing each minority group to White drivers are shown for contraband-found for all vehicle searches. (Note: Searches following a dog sniff are not included in Panel 4. See Panel 6 for the statistics on stops with a dog sniff.)
>
> **Panel 5** shows driver and passenger searches and outcomes of these searches during traffic stops including consent searches, all searches and whether contraband was found during any search for each racial group. The number, percentage (in parentheses) and 95% confidence interval [in brackets] are shown for each outcome. The label for each row shows the basis for calculation of the

percentages. The contraband found percentage is calculated based on all driver or passenger searches. The ratio and 95% confidence interval (in parentheses) comparing each minority group to White drivers are shown for contraband found for all driver or passenger searches. (Note: Searches following a dog sniff are not included in Panel 5. See Panel 6 for the statistics on stops with a dog sniff.)

Panel 6 shows dog sniffs, searches and outcomes of these searches during traffic stops, including dog alerts during a dog sniff, vehicle searches after a dog sniff and whether contraband was found after any vehicle search for each racial group. The number, percentage (in parentheses) and 95% confidence interval [in brackets] are shown for each outcome. The label for each row shows the basis for calculation of the percentages. The percentage of dog sniffs with a dog alert and the percentage of vehicle searches after a dog sniff are calculated based on all dog sniffs. The percentage for contraband found after a vehicle search is calculated based on all vehicle searches after a dog sniff, and the ratio and 95% confidence interval (in parentheses) are shown for contraband found for all vehicle searches after a dog sniff.

The top-right corner of the table indicates the type of benchmark used. Crash-based benchmarks utilize Illinois crash report data and distance-based benchmarks combine population statistics from surrounding ZIP codes while accounting for distance of the ZIP code area to the agency. The note at the bottom left of the table indicates the type of benchmark (crash-based or distance-based) and, if the benchmark is crash-based, the note states the number of crashes that were utilized. The note also lists the primary area of the benchmark, which captures the jurisdiction of the agency. These areas can be one or more cities (or towns or villages), counties or the state of Illinois. All traffic benchmarks also include areas outside of the primary area. The percentage of the benchmark which comes from ZIP codes within the primary area is provided, and an indication of the overall area of the benchmark is provided by a radius around the primary area (in miles). Section V on benchmarks provides more information on how the benchmarks were constructed.

A ratio of 1.0 for Whites: For all rows showing comparisons of minority groups to Whites, a value of 1.0 is shown in the White racial group column, the reference group. In this column for Whites, the Whites are being compared to themselves, so the ratio of rates must be 1.0. The column is included to make it clear that the Whites are the reference group to which each minority is compared.

Zero stops or zero benchmark: For some agencies, the number of stops or the benchmark value or the number of outcomes may be zero for a racial group. When it is not possible to calculate a rate, percentage or ratio and an associated 95% confidence interval because of zero stops or zero benchmarks or zero outcomes, an “NA” is reported in the table. When reporting information such as searches following stops or contraband found, there are cases when all racial groups have entries of zero in the row. That is, there were no searches of any racial group, or no contraband found for any racial group. In that case, the row is omitted. Similarly, when making comparisons to Whites, if all minorities have counts of zero or the Whites have a count of zero, the ratios comparing each minority to Whites cannot be computed and the row of ratios is omitted.

Table 1. Example of a table of traffic stops: Counts, Rates, Percentages and Ratios

Summary of Traffic Stops for 2022 - ILLINOIS STATEWIDE RESULTS						Benchmark: Crash-based*
	White	**Black or African American**	**Hispanic or Latino**	**Asian**	**American Indian or Alaska Native**	**Native Hawaiian or Other Pacific Islander**
Panel: 1 Summary of Traffic Stops, Rates and Rate Ratios with 95% Confidence Intervals. Total stops: 2,012,124. Total benchmark population: 9,481,015.						
Stops (% of Total)	926,479 (46%)	614,772 (31%)	383,729 (19%)	72,966 (3.6%)	8,164 (0.4%)	6,014 (0.3%)
Benchmark (% of Total)	5,047,912 (53%)	1,975,167 (21%)	1,884,763 (20%)	539,009 (5.7%)	29,113 (0.3%)	5,051 (0.05%)
Stop Rate (95% Confidence Interval)	0.1835 (0.1832 - 0.1839)	0.311 (0.31 - 0.312)	0.2036 (0.203 - 0.2042)	0.135 (0.134 - 0.136)	0.28 (0.27 - 0.29)	1.19 (1.16 - 1.22)
Stop Rate Ratio vs White (95% Confidence Interval)	1.0	***1.7 (1.68 - 1.71)***	***1.11 (1.1 - 1.12)***	0.735 (0.728 - 0.743)	***1.51 (1.48 - 1.55)***	***6.5 (6.3 - 6.7)***
Panel: 2 Summary of Reason for Stop - Number (Percentage of All Stops for the Racial Group with the Noted Reason for Stop) [95% Confidence Interval]						
Moving Violation	590,885 (63.8%) [63.6% - 63.9%]	279,448 (45.5%) [45.3% - 45.6%]	199,691 (52%) [51.8% - 52.3%]	47,909 (65.7%) [65.1% - 66.3%]	4,904 (60%) [58% - 62%]	3,789 (63%) [61% - 65%]
Equipment	164,057 (17.7%) [17.6% - 17.8%]	147,426 (24%) [23.9% - 24.1%]	98,423 (25.7%) [25.5% - 25.8%]	14,905 (20.4%) [20.1% - 20.8%]	1,914 (23%) [22% - 25%]	1,119 (19%) [18% - 20%]
Licensing/Registration	163,804 (17.7%) [17.6% - 17.8%]	184,874 (30.1%) [29.9% - 30.2%]	80,912 (21.1%) [20.9% - 21.2%]	9,879 (13.5%) [13.3% - 13.8%]	1,304 (16%) [15% - 17%]	1,047 (17%) [16% - 18%]
Commercial Vehicle	7,724 (0.83%) [0.82% - 0.85%]	2,948 (0.48%) [0.46% - 0.5%]	4,683 (1.22%) [1.19% - 1.26%]	270 (0.37%) [0.33% - 0.42%]	42 (0.51%) [0.37% - 0.7%]	59 (0.98%) [0.75% - 1.3%]
Panel: 3 Summary of Outcome of Stop - Number (Percentage of All Stops for the Racial Group with the Noted Outcome of Stop) [95% Confidence Interval]						
Verbal Warning	252,244 (27.2%) [27.1% - 27.3%]	357,197 (58.1%) [57.9% - 58.3%]	183,794 (47.9%) [47.7% - 48.1%]	30,646 (42%) [41.5% - 42.5%]	4,075 (50%) [48% - 51%]	3,424 (57%) [55% - 59%]
Written Warning	362,320 (39.1%) [39% - 39.2%]	121,025 (19.7%) [19.6% - 19.8%]	89,845 (23.4%) [23.3% - 23.6%]	22,743 (31.2%) [30.8% - 31.6%]	2,111 (26%) [25% - 27%]	1,169 (19%) [18% - 21%]
Citation	311,915 (33.7%) [33.5% - 33.8%]	136,550 (22.2%) [22.1% - 22.3%]	110,090 (28.7%) [28.5% - 28.9%]	19,577 (26.8%) [26.5% - 27.2%]	1,978 (24%) [23% - 25%]	1,421 (24%) [22% - 25%]
Citation Ratio vs White (95% Confidence Interval)	1.0	0.66 (0.656 - 0.664)	0.852 (0.846 - 0.858)	0.8 (0.79 - 0.81)	0.72 (0.69 - 0.75)	0.7 (0.67 - 0.74)
Panel: 4 Summary of Vehicle Search Events - Number (Percentage for the Racial Group) [95% Confidence Interval]						
Consent Search (% of Stops)	8,451 (0.91%) [0.89% - 0.93%]	7,628 (1.24%) [1.21% - 1.27%]	4,442 (1.16%) [1.12% - 1.19%]	397 (0.54%) [0.49% - 0.6%]	108 (1.3%) [1.1% - 1.6%]	47 (0.78%) [0.57% - 1%]
All Searches (% of Stops)	53,195 (5.74%) [5.69% - 5.79%]	32,432 (5.28%) [5.22% - 5.33%]	16,394 (4.27%) [4.21% - 4.34%]	1,126 (1.54%) [1.45% - 1.64%]	247 (3%) [2.7% - 3.4%]	140 (2.3%) [2% - 2.7%]
Contraband Found (% of All Searches)	11,319 (21.3%) [20.9% - 21.7%]	13,534 (41.7%) [41% - 42.4%]	5,623 (34%) [33% - 35%]	268 (24%) [21% - 27%]	78 (32%) [25% - 39%]	41 (29%) [21% - 40%]

Summary of Traffic Stops for 2022 - ILLINOIS STATEWIDE RESULTS						Benchmark: Crash-based*
	White	**Black or African American**	**Hispanic or Latino**	**Asian**	**American Indian or Alaska Native**	**Native Hawaiian or Other Pacific Islander**
Contraband Found Ratio vs White (95% Confidence Interval)	1.0	***1.96 (1.91 - 2.01)***	***1.61 (1.56 - 1.66)***	1.1 (0.99 - 1.3)	***1.5 (1.2 - 1.9)***	1.4 (0.99 - 1.9)
Panel: 5 Summary of Driver or Passenger Search Events - Number (Percentage for the Racial Group) [95% Confidence Interval]						
Consent Search (% of Stops)	6,073 (0.66%) [0.64% - 0.67%]	5,844 (0.95%) [0.93% - 0.98%]	3,180 (0.83%) [0.8% - 0.86%]	177 (0.24%) [0.21% - 0.28%]	83 (1%) [0.81% - 1.3%]	32 (0.53%) [0.36% - 0.75%]
All Searches (% of Stops)	33,148 (3.58%) [3.54% - 3.62%]	23,856 (3.88%) [3.83% - 3.93%]	13,173 (3.43%) [3.37% - 3.49%]	716 (0.98%) [0.91% - 1.1%]	160 (2%) [1.7% - 2.3%]	99 (1.6%) [1.3% - 2%]
Contraband Found (% of All Searches)	3,430 (10.3%) [10% - 10.7%]	3,151 (13.2%) [12.8% - 13.7%]	1,044 (7.9%) [7.5% - 8.4%]	42 (5.9%) [4.2% - 7.9%]	10 (6.2%) [3% - 11%]	6 (6.1%) [2.2% - 13%]
Contraband Found Ratio vs White (95% Confidence Interval)	1.0	***1.28 (1.22 - 1.34)***	0.77 (0.71 - 0.82)	0.57 (0.41 - 0.77)	0.6 (0.29 - 1.1)	0.59 (0.21 - 1.3)
Panel: 6 Summary of Dog Sniff Events - Number (Percentage for the Racial Group) [95% Confidence Interval]						
Dog Sniff (% of Stops)	2,143 (0.23%) [0.22% - 0.24%]	960 (0.16%) [0.15% - 0.17%]	558 (0.15%) [0.13% - 0.16%]	58 (0.079%) [0.06% - 0.1%]	6 (0.073%) [0.027% - 0.16%]	4 (0.067%) [0.018% - 0.17%]
Dog Alert after Dog Sniff (% of Dog Sniffs)	1,705 (80%) [76% - 83%]	727 (76%) [70% - 81%]	398 (71%) [64% - 79%]	48 (83%) [61% - 100%]	5 (83%) [27% - 100%]	2 (50%) [6.1% - 100%]
Vehicle Search after Dog Sniff (% of Dog Sniffs)	1,624 (76%) [72% - 80%]	696 (72%) [67% - 78%]	375 (67%) [61% - 74%]	42 (72%) [52% - 98%]	4 (67%) [18% - 100%]	2 (50%) [6.1% - 100%]
Contraband Found (% of Vehicle Searches, preceding row)	995 (61%) [58% - 65%]	470 (68%) [62% - 74%]	163 (43%) [37% - 51%]	15 (36%) [20% - 59%]	3 (75%) [15% - 100%]	0 (0%) [0% - 100%]
Contraband Found Ratio vs White (95% Confidence Interval)	1.0	1.1 (0.99 - 1.2)	0.71 (0.6 - 0.84)	0.58 (0.33 - 0.97)	1.2 (0.25 - 3.6)	0 (0 - 3)

***Benchmark Definition**
Benchmark Type: Crash-based (153,445 crash reports used).
Primary Benchmark Area (State): Illinois.
93.4% of the benchmark comes from zip codes within the primary area.
95.1% of the benchmark comes from zip codes within 12 miles of the primary area, including the primary area.

IV. Interpretation of Traffic Tables

95% Confidence Interval

Table 1 presents a "95% confidence interval" for each rate, percentage or ratio. The 95% confidence interval reflects uncertainty in estimating the rate, percentage or ratio due to sampling variability. The 95% confidence interval provides a range of plausible values. The "95%" figure means that when various studies include such an interval, 95% of the studies, on average, will include the *true* value in the interval. Because there is an element of chance involved in being stopped, being searched, etc., the true value of a rate or percentage or ratio is not known. The 95% confidence interval uses widely accepted methods and expresses some of the uncertainty in the estimated rate, percentage or ratio. The uncertainty is often due to small numbers of stops or a small benchmark population in the geographic area used to calculate rates, percentages or ratios.

Ratios

A ratio of rates or percentages with a value of 1.0 indicates that the rates or percentages are equal between the minority group and Whites. Ratios above or below 1.0 show greater or lesser stop activity with minorities, respectively. Comparisons of minority groups to White drivers or White pedestrians where the 95% confidence interval lies above 1.0 are **bolded** in the stops tables. One can say that the value of 1.0 does not fall within the 95% confidence interval of the estimated ratio. These **bolded** ratios are statistical deviations and may be the basis for further consideration of potential racial disparities related to stops. A **bolded** ratio does not prove that there is racial profiling but may be taken as the basis for further inquiry. In addition to whether or not a ratio is **bolded**, the absolute magnitude of the ratio should be considered. For example, a **bolded** ratio of 5.0 is a higher priority to investigate than a small, bolded ratio of 1.2. A larger ratio implies that the potential impact on individuals is larger, and it is less likely that the elevated ratio is only due to limitations of the chosen benchmark than when the ratio is closer to 1.0.

Limitations

There is a limitation in the use of ratios to determine potential racial disparities. The 95% confidence intervals for stop rates and stop rate ratios do not consider the error in estimating the driver and pedestrian benchmark populations. (The population of drivers or pedestrians who are considered the source of the persons stopped in a given jurisdiction are a population, and that population is referred to as the "benchmark" for the jurisdiction.) Note that each law enforcement agency has a "jurisdiction," which is the geographic area that the agency is responsible for policing. In this report "agency" and "jurisdiction" are sometimes used interchangeably.

The benchmarks attempt to estimate the actual driving population within the jurisdiction of each agency using a combination of data sources, including surveys by the U.S. Census Bureau, Illinois crash reports (collected by IDOT), and Illinois driver license counts (provided by the office of the Secretary of State of Illinois). But these data can only approximate the driving populations and necessarily rely on particular assumptions, which may not always be accurate. Thus, the benchmarks may have some errors, and the extent of the error is unknown. If it were possible to estimate this error as it affects rates and rate ratios, the 95% confidence intervals would be wider and, thus, confidence intervals for some ratios might then include 1.0 (a ratio of 1.0 may indicate no racial disparity). A confidence interval overlapping 1.0 would not prompt bolding and the need for further inquiry. (The section labeled "**Benchmarks**," below, describes the methods used to estimate the population from which stopped individuals originated.)

Another limitation that may affect the rates, percentages and ratios is the designation of race by the law enforcement officer conducting the stop. That designation of race might not correspond to the driver's or pedestrian's own racial identity. The possibility of errors by the officer in assigning a race is considered in a later section of this report. In addition, the stop rate for a racial group will depend on (a) the assignment of beats (geographic surveillance area) to officers in a jurisdiction and (b) the degree of overlap of those beats to the residential area of each racial group. If there is higher (or lower) surveillance of an area with a high residential concentration of a racial group, then that can lead to a higher (or lower) stop rate for the racial group, compared to areas where surveillance is constant across all racial groups.

Statistics based on stops only

The percentages and ratios of percentages in the tables are based on stop counts and stop activity only. The percentages and ratios of percentages do not depend on the estimated benchmark population, and they do not have the potential benchmark error noted above. Percentages based on stops will be a resource for any inquiry about potential racial profiling.

It is important to note that the percentages are calculated with reference to a specific activity. For example, in the traffic tables, the percentage of searches for a racial group is a percentage of *stops* leading to a search. The percentage of contraband found in a vehicle is the percentage of *vehicle searches* leading to contraband found. For percentages, each row label (or the heading for the panel) indicates the basis for the percentage.

Can stop rates be compared across years?

The methodology used for calculating stop rates in this study, using a population benchmark, differs from studies of stops in 2019-2020 and in 2018 and earlier. The methodology is largely the same as used for the 2021 stops report. See Section V below for specific details on the benchmarks. While the new methodology provides more accurate estimates of the racial composition of the driving population, the changes impact comparisons of results from the 2022 stops analysis to the analyses in 2019-2020 and to the analyses in years prior to 2019. Comparisons of 2022 to 2019-2020 are easier than comparisons of 2021 to 2004-2018 because the table formats are very similar even though there are some underlying methodological differences.

These and other changes have improved the estimate of the benchmark populations and the accuracy of stop rate ratios. Thus, any difference in rate ratios between 2021-2022 stops reports and earlier stops reports (2019-2020 and 2004-2018) may be at least partly due to a change in statistical methods used in this report rather than to a real change in stop rates. The new methods are intended to estimate the benchmark population more accurately. Another factor making it difficult to compare 2022 stop rates to 2018 rates (and earlier) is that the 2022 report presents rates, percentages and rate ratios separately for each of the six individual races — rather than with all minorities combined into one category, as used in the 2018 and earlier reports. Perusal of tables in Part II of this report will show the reader that the five minority races do have different stop rates. The statewide rates in Table 1, Panel 1, above, show a diversity of stop rates among the six races, and, also, among the five minority races. The 2019-2020 reports also reported results separately for each individual race, making comparisons of 2019-2020 to 2021-2022 more straightforward.

Certain percentages will be comparable across years, because the percentages are based on stops data only, and percentages are calculated in the same manner as in previous years. However, to compare a percentage based on 2022 stops data to a percentage reported in a year prior to 2019, some additional calculations will be needed. This 2022 stops report and the 2019-2020 stops reports present results for each racial group, whereas reports prior to 2019 combined five races into one group: all minorities. To calculate a percentage for 2022 stops of all minorities, the user will need to add together (across the five minority racial groups) all of the numerators and, separately, all of the denominators and then divide the numerator sum by the denominator sum, then multiply by 100% to get the all-minority percentages. As noted earlier, this report presents results for each racial group separately, since the minority groups do have differing rates, percentages and ratios in some jurisdictions.

V. Benchmarks

The number of stops for each racial group and each agency is compared to a "benchmark" in order to calculate the agency's stop rate for the racial group. The benchmark provides an estimated population count for each of the six racial groups. These population counts are then compared to the traffic stop counts of each racial group to assess and compare the stop rates (stops per unit of population) of each racial group. See Appendix C of this report, Technical Notes on Benchmarks, for a detailed discussion of benchmarks and associated calculations, including important limitations.

The methods for calculating the benchmark for each agency for this report are similar to the methods used for the report on 2021 stops. Briefly, traffic stop benchmarks are based on the U.S. Census Bureau's most recent American Community Survey population statistics tabulated at the ZIP code level. For agencies with a sufficient number of crash reports available in their jurisdiction, the Illinois traffic crash report data (based on 2019-2020 SR 1050 crash reports[1]) were used to build the traffic stop crash-based benchmarks. For the other agencies (without sufficient crash reports) the traffic stop benchmarks were constructed by combining ZIP code data from the surrounding area, weighted by the distance from the agency's jurisdiction (distance-based benchmarks). Both types of benchmarks (crash-based and distance-based) combined populations from ZIP codes directly associated with an agency (e.g., the ZIP codes of a city for a city police agency) as well as populations from ZIP codes from the surrounding area (see Section C.6). Note that the traffic stop and pedestrian stop benchmark methodologies differ because of the different data sources available to generate them. Thus, it is not unusual for there to be notable differences between the traffic and pedestrian benchmarks for the same agency.

VI. Determining Race of Each Driver Stopped

How race is determined and reported for each driver stopped is mentioned in previous reports, but it has not been covered analytically by our team prior to this report on 2022 stops. We previously noted that one of the sources of uncertainty in stops rates and rate ratios is that the race of the driver (or a pedestrian, for pedestrian stops) is assessed by the officer — without instructions or guidance provided

[1] https://www.idot.illinois.gov/Assets/uploads/files/Transportation-System/Manuals-Guides-&-Handbooks/Safety/Illinois%20Traffic%20Crash%20Report%20SR%201050%20Instruction%20Manual%202019.pdf (last accessed May 5th, 2022).

along with the data collection form. The officer's designation of race — selected from six options provided on the data collection form — is the designation that is used for all subsequent analyses of the stops data. This approach to data collection supports the assumption that errors in the designation of driver race are likely to occur.

We used a statistical technique to analyze how accurately officers report the race of each driver that is stopped. The technique is similar to techniques used by the U.S. Census Bureau. As noted in a report on racial disparities in the use of force by the Office of the Inspector General of the City of Chicago[1] one of the limitations of the data on race is that it is generated by the officers, not by the driver whose race is being reported. Our goal in this analysis was to determine if the data collected on the Traffic Stops Data Collection Form (Appendix A) supports the officer-designated race or can be used to identify problems in accurately noting race. Accuracy can be improved in the future by changing the way in which the race of the driver is determined and reported. At this stage, the analysis is preliminary and limited in the sense that our research could not show that agencies are accurately reporting race, and we did not find clear evidence on misreporting for most agencies. We did find evidence that some agencies are likely not accurately reporting race.

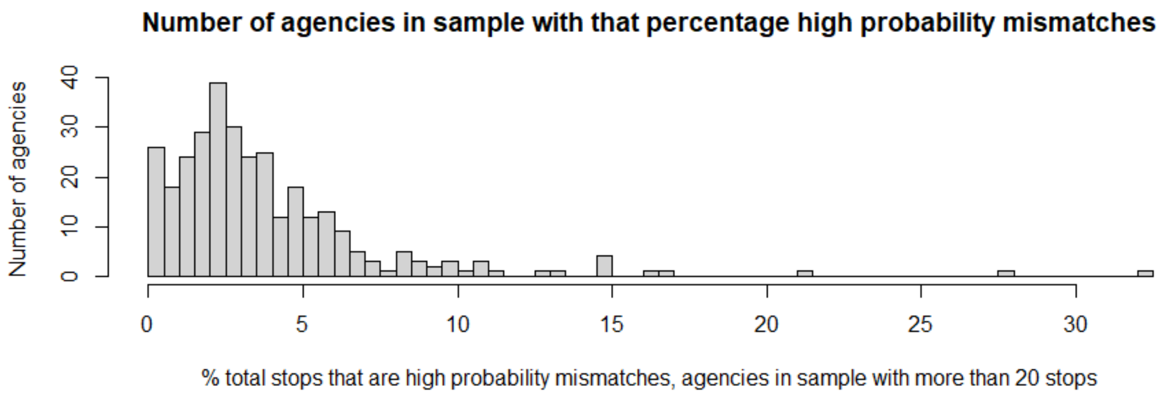
The technique that we used requires access to the individual components of a name, including clear and separate identification of the first name and the last name. Specific first names (given names) and last names (surnames) both occur with different frequencies within each of the six race options, so names may be reliable indicators of an individual's race. However, the driver-name data that is collected by the officers is reported as a full name and entered into the database in a single text field with no separation of name components. We encountered 29 different patterns of handling first and last name and other name components. We used statistical software to separately extract the first and last names from the multiple ways that names were recorded in the database (see Appendix D).

Next, we used an established algorithm, Bayesian Improved Surname Geocoding, to predict the probable race of each driver. The algorithm uses the name components in conjunction with demographic data from the recorded ZIP code of the driver's residence. For each of the six race options mandated for this study, the algorithm calculated an estimated probability that the stopped driver is of a given race — a process that yields one probability for each of the race options. We compared the most probable race to the race reported by the officer at the time of the stop. In a sample of 238,950 drivers in the 2022 dataset, the BISG analysis shows 12,660 drivers (5.3%) as highly probable mismatches. A "highly probable" mismatch is defined as (1) a BISG-calculated probability of ≥ 95% that the predicted race of a driver is correct, and (2) the predicted race is different than the race recorded by the officer.

It is important to note that highly probable mismatches were concentrated in specific agencies and ZIP codes. For this analysis of stops 465 (59%) of the 793 agencies that reported traffic stops in 2022 were included in this agency-level analysis; excluded were agencies reporting fewer than 20 traffic stops. Of the 465 agencies, over 100 had zero or 1% of their total stops classified as highly probably mismatches, while other agencies had varying mismatch percentages, ranging up to 39% of their total stops (see Figure 1 of this section). Highly probable mismatches were most common when officers reported a driver's race as White and the BISG algorithm designated the same driver as Hispanic. This scenario includes 7,062 driver stops (56%) of the 12,660 highly probable mismatches. A factor that may play a role in mismatching of rates relates to how individuals identify as or define "Hispanic." In terms of measurement, Hispanic is often considered an ethnicity and not a race (such as by the U.S. Census

Bureau and the National Institutes of Health). However, the lived experience of what it means to be Hispanic may not concur with formal measures.

Figure 1. Agency percentage of stops for which officer-designated race and predicted race do not match. Limited to stops with high confidence (= or > 95%) in predicted race.



We carried out an analysis of stops for which our BISG algorithm provides high confidence (= or > 95%) that the race predicted by BISG is correct. This analysis is based on stops where the driver's name — as presented from data collection — followed a simple and standard order of first and last name and other regularizing rules. The results in Table 1, below, show the agreement percentage (boxed cells) between the officer's choice of race and the predicted race. The agreement is quite good when the officer recorded a driver's race as White, Black or Hispanic and less accurate for API and AIAN — two minority groups encountered less often. (Asian, Native Hawaiian, Pacific Islander were combined as API for this analysis.) Other analyses show a lower agreement rate between the officer's designation and the predicted race when the presentation of names is less standard.

Table 1. Accuracy of officer's recorded race for a driver compared to predicted race of the driver (based on driver's name and zip code demographics). Results from a sample of 209,945 traffic stops.

	PREDICTED				
	WHITE	BLACK	HISP	API	AIAN
OFFICER DESIGNATED: WHITE	94%	0.7%	5%	0.6%	0
OFFICER DESIGNATED: BLACK	5%	94%	0.6%	0.1%	0
OFFICER DESIGNATED: HISP	2%	0.3%	97%	0.3%	0
OFFICER DESIGNATED: API	11%	2%	5%	83%	0
OFFICER DESIGNATED: AIAN	8%	3%	5%	84%	0.8%

Notes to Table 1. Row percentages add to 100% except for rounding. Based on a sample of 209,945 stops with stopped drivers' names provided in a standard and readily useable format ("pattern 10" — see Appendix D) and with high confidence (= or > 95%) that the predicted race is correct. Abbreviations: HISP: Hispanic or Latino; API: Asian, Native Hawaiian, Pacific Islander combined; AIAN: American Indian or Alaska Native. Count of stops by row: White, 138,018; Black, 48,200; Hispanic/Latino, 20,468; API, 2,865; AIAN, 394.

Considerations and limitations

There are several points to consider when determining drivers' races, especially in an increasingly multi-ethnic, multi-racial society.

1) The Traffic Stops Data Collection Form (Appendix A)
    - does not indicate whether officers may select multiple races and does not provide an "other" option where they can provide supporting data or additional racial categories, if needed.
    - lists "Hispanic or Latino" as a racial category, which likely fosters inaccuracy (see item 4, below).
2) The electronic data entry system for traffic stop data could permit the entry of multiple race options to increase the accuracy of race-related data.
3) BISG algorithms may present a bias against…
    - individuals who are adopted, married women or other individuals who changed their names for any reason. For example, a person from Asia adopted by a White family and given an American name would likely be mis-designated as White; a White woman who changed her surname upon marriage to a black man might be mis-designated as Black — by the methods used here.
    - individuals who do not originate from their current zip codes. For example, a Smith raised in rural Idaho may be mis-designated as a race consistent with Smiths located in the current zip code of residence in urban Chicago.
    - Individuals whose address/zip code on their driver licenses are not current.
4) Illinois defines "Hispanic or Latino" as "a person of Cuban, Mexican, Puerto Rican, South or Central American, or other Spanish culture or origin, regardless of race"[2] and instructs officers to select Hispanic even if the driver could also be classified as another race. Many Hispanic "race" (BISG-estimated) to White race (officer-reported) mismatches are substantial within some agencies. We cannot make claims about whether the mis-designation of race is accidental or intentional but mis-designations of Hispanics as White will result in agency stop rate ratios that inaccurately show fewer minority stops. Emphasizing the correct reporting procedures and monitoring this kind of potential mis-designation in future reports may help correct these situations.

References (for Section VI)

1. City of Chicago Office of the Inspector General. (2021, March 1) *Report on Race and Ethnicity-Based Disparities in the Chicago Police Department's Use of Force*, p.26 Global Data Limitations.

2. Illinois Traffic Stop Study; 2012 Traffic Stop Data Sheet Explanation of Required Data Elements, p.4.

VII. Selected Findings

This section of the report shows some tables and figures that present results on the agencies and their stops from the entire State of Illinois for 2022. Some results are contrasted with their corresponding 2021 values.

Coronavirus Disease (COVID-19): 2019 and later

The COVID-19 pandemic in the United States continued to have a substantial impact on the number of stops made in 2021 and some in 2022, as is apparent from multiple figures shown below. The first confirmed case of COVID-19 was detected in Illinois on Jan. 23, 2020[2]. On March 16 and 17, 2020, the Illinois State government closed bars, restaurants, and schools[3] and ultimately executed a statewide stay-at-home order starting March 21, 2020[4].

Agency reporting status

Among the 1,005 agencies that could submit stops data to IDOT, 78.9% of the agencies had stops and provided complete stops data for 2022 to IDOT (Table 2, top numeric row), which is a substantial increase compared to 72.6% in 2021, and nearly a return to the 81.8% of 2020. A total of 24 agencies had no traffic stops (2.4%) and 20.8% of agencies collected stops data for less than a year ("incomplete") or had stops but did not submit any stops data ("Noncompliant"), which is a substantial decrease compared to 27.1% in 2021.

[2] Ghinai I, McPherson TD, Hunter JC, et al. First known person-to-person transmission of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) in the USA. *Lancet*. 2020;395(10230):1137-1144. doi:10.1016/S0140-6736(20)30607-3.

[3] Chicago Tribune. Mar 13, 2020. *Governor cancels Illinois schools statewide until March 30 to slow the spread of coronavirus.*

[4] Chicago Channel 5 website. Published March 20, 2020. Updated on March 20, 2020, at 10:42 pm. *Illinois Governor Issues Stay-at-Home Order*. Accessed on June 1, 2021, at https://www.nbcchicago.com/news/local/illinois-governor-expected-to-issue-stay-at-home-order-sources/2241118/.

Table 2. Agency status on reporting. **Illinois, all agencies, Traffic stops, 2021 and 2022.**

Status of Agency	2021		2022	
	Number of agencies	Percent of agencies	Number of agencies	Percent of agencies
Complete reporting[a]	730	72.6%	793	78.9%
Zero stops[b]	3	0.3%	24	2.4%
Incomplete[c]	55	5.5%	21	2.1%
Noncompliant[d]	217	21.6%	188	18.7%
All agencies combined	1,005	100%	1,005	100%

[a]Agency with one or more stops that were completely reported.
[b]Agency performed no stops over the year.
[c]Agency submitted some but not all of their stops for the year.
[d]Agency made stops, but no stops data was submitted.

Number of stops

The total number of reported traffic stops in 2022 was 2,012,182. The number of stops per agency was generally substantial. Hundreds of agencies (about 76%) had over 100 stops during 2022 (Table 3).

Table 3. Number of Traffic stops for agencies with at least one stop. Illinois, all agencies, Traffic stops, 2021 and 2022.

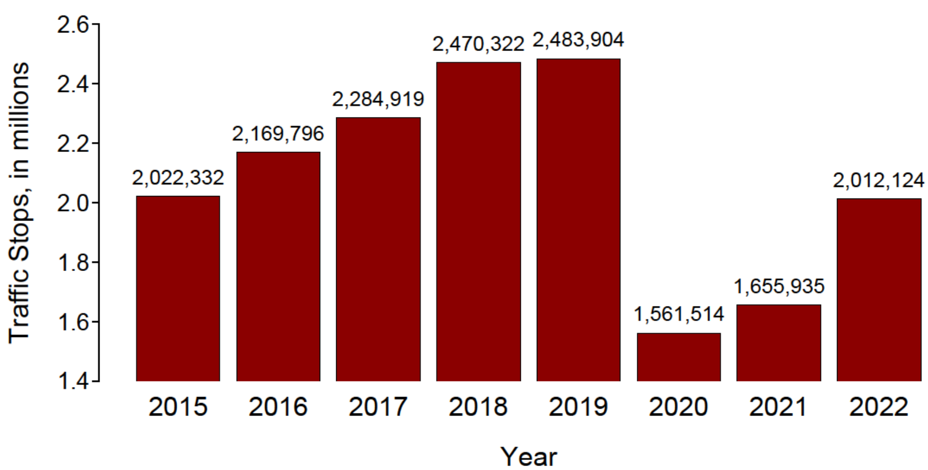
Number of stops	2021		2022	
	Number of agencies	Percent of agencies	Number of agencies	Percent of agencies
1-10	64	8.8%	55	6.9%
11-100	123	16.8%	138	17.4%
101-1,000	281	38.5%	299	37.7%
1,001-10,000	253	34.7%	282	35.6%
10,001-100,000	7	1.0%	17	2.1%
More than 100,000	2	0.3%	2	0.3%
All compliant agencies with ≥ 1 stop	730	100%	793	100%

Notes:
(1) Includes only agencies with at least one stop, and includes all agencies with either complete or incomplete reporting of 2022 stops.
(2) Chicago Police: 377,870 in 2021; 511,738 in 2022. (Chicago is also represented in the Table above.)

Stops that were reported with missing information about the race of the driver were excluded from this report and were not considered as “reported stops.” In 2021 there were 30 such stops, and in 2022 there were 58 such stops.

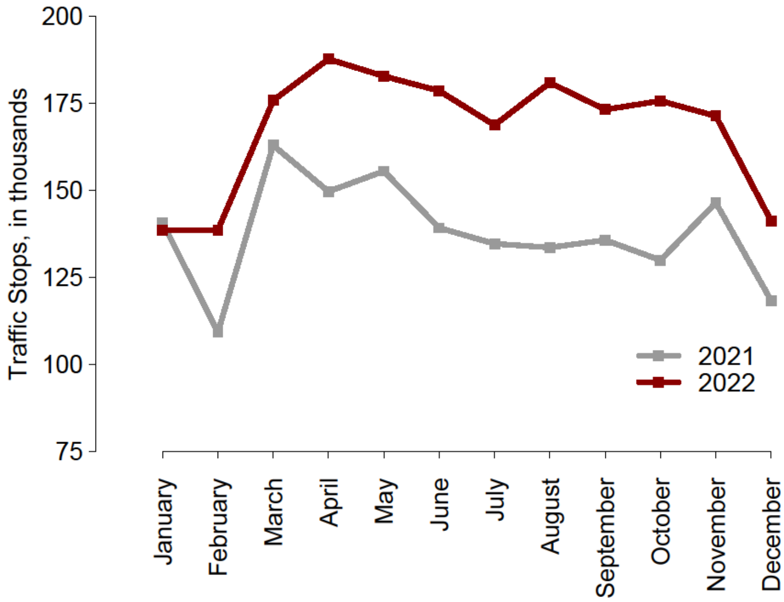
The number of reported stops per year grew each year since 2015 (Figure 1a) until there was a sharp decrease in 2020. There was a 23% increase in the number of stops reported to IDOT from 2015 to 2019; in 2020, the number of reported stops sharply decreased 37% from 2019. In 2021, this number increased a moderate 6% from 2020. In 2022, it increased 22% from 2021, reaching very close to the 2015 number. This suggests that the effects of the COVID-19 pandemic were still present in 2022.

Figure 1a. Illinois, number of traffic stops, 2015-2022.



The monthly pattern of stops reveals that the number of stops per month remained somewhat steady throughout 2022 (Figure 1b). Except for January, each month of 2022 has had more stops than the corresponding month in 2021. However, the 2022 stop numbers have not fully recovered to their pre-COVID-19 level.

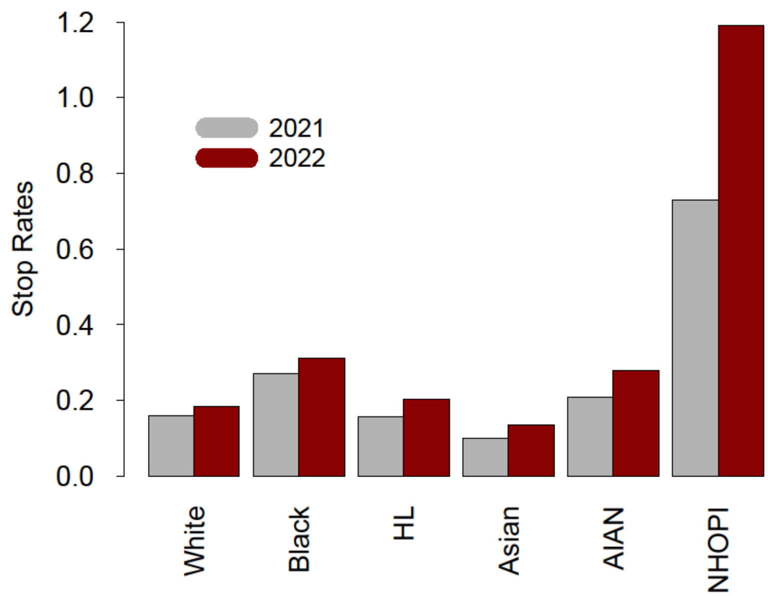
Figure 1b. Illinois, number of Traffic stops per month, 2021 (gray line) and 2022 (dark red line).



Stop rates

The statewide stop rates are diverse among the six racial groups (Figure 2). Of interest, the smallest minority group (Native Hawaiian or Other Pacific Islander) had the highest stop rates. This is, potentially, an anomaly due to a persisting mismatch between the officer-identified race of stopped individuals and the self-identified race reported in the U.S. census survey data used as part of the benchmark calculations in this study. Also, stops rates for all racial groups have increased in 2022 as compared to 2021.

Figure 2. Stop rates for each racial group, 2021 (gray bars) and 2022 (dark red bars). Illinois, Traffic stops, 2021 and 2022.



Abbreviations for racial groups: Black = "Black or African American," HL = "Hispanic or Latino," AIAN = "American Indian or Alaska Native," NHOPI = "Native Hawaiian or Other Pacific Islander."

Distribution of stop rate ratios

Table 4.a shows the numbers of comparisons of stops rates of a minority racial group and Whites carried out in the traffic stops study. Any comparison yields a rate ratio — the minority stop rate divided by the White stop rate. Each agency might contribute up to five such comparisons (five minority groups, each compared to Whites on their stop rates)[5].

The first column under "A" in Table 4.a illustrates all comparisons: each minority/White rate ratio from each agency has been compiled across all agencies. Table 4.a then categorizes the rate ratios by their magnitude and shows the percentage distribution across categories. The columns under "B" restrict the comparisons to those based on at least 50 White stops and 50 stops of the minority group compared. The 50 stops would provide a more precise rate ratio than a smaller number of stops. The large percentage of stops in the category "<0.25" in panel A for both 2021 and 2022 is due to the presence of many small agencies that have a small number of stops and zero stops for one or more minorities.

We note a drastic reduction — more than 4-fold from Panel A to Panel B — in the total number of rate ratios, from 3,940 (all comparisons) down to 887 (more precise comparisons). From the more precise comparisons (Panel B, based on 50 or more stops of Whites and 50 or more stops of the minority group compared) we estimate that in 76.3% of these rate ratios, minority drivers were stopped at a higher rate

[5] For this analysis there were fewer than five comparisons when White drivers had zero stops or when a benchmark population value was zero for either a minority racial group or Whites, thus making some comparison rate ratios numerically undefined.

than White drivers (rate ratio > 1). This suggests (as a possibility but does not prove) that racial profiling was a factor in a number of traffic stops.

The overall distribution of rate ratios seems roughly similar from 2021 and 2022. The 95% confidence intervals provided in the tables of Part II should be used as a guide to the precision of rates, percentages and rate ratios when interpreting the numeric results for a specific agency.

***Table 4.a Distribution of stop rate ratios*. (Each Non-White racial group compared to Whites for an agency). Illinois, Traffic stops, 2021 and 2022.**

	A. All agencies and racial groups*		B. Agencies and racial groups with at least 50 stops**	
Stop rate ratios	2021	2022	2021	2022
<0.25	37.1%	35.0%	0.6%	1.2%
0.25 to <0.5	7.9%	8.0%	5.3%	4.6%
0.5 to <1.0	14.7%	14.0%	19.1%	17.8%
1.0 to <2.0	16.8%	18.5%	33.1%	33.6%
2.0 to <4.0	13.9%	14.6%	30.9%	32.2%
≥4.0	9.6%	9.9%	10.9%	10.5%
All ratios***	100%	100%	100%	100%

* All comparisons of Whites and a racial group for all agencies. Excludes ratios from agencies with zero stops of White drivers or a benchmark population value of zero for either a minority racial group or Whites.

** All comparisons of Whites and a racial group for all agencies; all comparisons must have at least 50 stops of Whites and 50 stops of the compared racial group. Excludes undefined rate ratios, or where either Whites or the compared racial group have less than 50 stops.

***The number of ratios that were included in the analysis in columns A and B respectively, were 3,640 and 789 in 2021; 3,940 and 887 in 2022. Each ratio involves a comparison of one non-White racial group vs. Whites for one agency.

Table 4.b shows the distribution of stop rate ratios in 2022 among the three most populous minority groups. Since each agency provides only a single stop rate ratio for a single minority group compared to Whites, then a proportion of stop ratios equates to a proportion of agencies. From the more precise comparisons (Panel B) we estimate that in 93.8% of agencies with at least 50 stops for both Whites and Blacks, Black drivers are stopped at a higher rate than White drivers (rate ratio > 1). For Hispanic drivers, this value is 79.5%. Similar to the note on Table 4.a, this suggests (as a possibility but does not prove) that racial profiling was a factor in a number of traffic stops. This finding does not occur among stopped Asian drivers, who are stopped at a higher rate than White drivers in only 18.9% of agencies with at least 50 stops for both Whites and Asians.

Table 4.b Distribution of stop rate ratios for Blacks, Hispanic and Asian drivers. **(Each noted non-White racial group compared to Whites for an agency). Illinois, Traffic stops, 2022.**

	A. All agencies and racial groups			B. Agencies and racial groups with at least 50 stops*		
Stop rate ratios	Black	Hispanic	Asian	Black	Hispanic	Asian
<0.25	9.9%	17.1	40.0%	0	2.2%	2.7%
0.25 to <0.5	5.5%	8.2	18.4%	0.3%	3.7%	18.9%
0.5 to <1.0	11.5%	19.7	25.6%	5.9%	14.6%	59.5%
1.0 to <2.0	24.0%	36.9	10.8%	22.7%	55.6%	16.9%
2.0 to <4.0	35.0%	15.2	3.3%	53.6%	22%	2.0%
≥4.0	14.1%	2.8	1.9%	17.5%	1.9%	0
All ratios	100%	100%	100%	100%	100%	100%

*All comparisons of Whites and a racial group for all agencies; all comparisons must have at least 50 stops of Whites and 50 stops of the compared racial group. Excludes undefined rate ratios, or where either Whites or the compared racial group have less than 50 stops.

Table 4.c shows the distribution of citation ratios among the three minority groups, and all the racial groups collectively, in 2022. Here we estimate that in 74.4% of all agencies with at least 50 stops for both Whites and Blacks, Black drivers are receiving citations at a higher rate than White drivers (citation ratios > 1). For Hispanic drivers, this value is 85.7%. Similar to the note on Table 4.a, this suggests (as a possibility but does not prove) that racial profiling was a factor in a number of citations. This finding does not occur among Asian drivers, whose citation rate is higher than among White drivers in only 44.6% of all agencies with at least 50 stops for both Whites and Asians. Overall, in 72.1% of all citation ratios minority drivers are getting citations at a higher rate than White drivers.

***Table 4.c Distribution of citation ratios*. (Each ratio that enters into the computation involves each noted non-White racial group compared to Whites for an agency). Illinois, Traffic stops, 2022.**

Cit. rate ratios*	Black	Hispanic	Asian	All racial groups
<0.25	0.3%	0.3%	0	0.2%
0.25 to <0.5	0	0.3%	3.4%	1.5%
0.5 to <1.0	25.4%	13.7%	52.0%	26.2%
1.0 to <2.0	70.5%	83.2%	44.6%	69.3%
2.0 to <4.0	3.9%	2.5%	0	2.7%
≥4.0	0	0	0	0
All ratios**	100%	100%	100%	100%

*All comparisons of Whites and a racial group for all agencies; all comparisons must have at least 50 stops of Whites and 50 stops of the compared racial group. Excludes undefined ratios, or ratios where either Whites or the compared racial group have less than 50 stops.
**The number of ratios that were included in the analysis for 2022 stops is 884. Each ratio that enters into the computation involves a comparison of one non-White racial group to Whites for one agency.

Table 4.d shows the distribution of contraband found ratios in vehicle searches among the three more populous minority groups, and all the racial groups collectively, in 2022. Here we estimate that in 51.5% of all agencies with at least 50 stops for both Whites and Blacks, contraband is found in Black drivers' vehicle searches at a higher rate than in White drivers (ratio > 1). For Hispanic drivers, this value is 41.1%, for Asian drivers it is 36.4%, and the overall percentage for all racial groups is 45.3%. Given that about half or fewer of citation ratios (comparing a minority to Whites) are greater than 1.0, this result neither suggest nor excludes a presence of racial profiling related to this aspect of traffic stops.

***Table 4.d Distribution of contraband found ratios in vehicle searches*. (Each ratio that enters into the *computation* involves each noted non-White racial group compared to Whites for an agency). Illinois, Traffic stops, 2022.**

Cont. rate ratios*	Black	Hispanic	Asian	All racial groups
<0.25	5.7%	10.6%	33.3%	12.0%
0.25 to <0.5	5.7%	5.7%	7.1%	5.8%
0.5 to <1.0	37.0%	42.6%	23.2%	36.9%
1.0 to <2.0	44.3%	36.2%	29.3%	38.7%
2.0 to <4.0	5.7%	4.5%	6.1%	5.6%
≥4.0	1.5%	0.4%	1.0%	1.0%
All ratios**	100%	100%	100%	100%

*All comparisons of Whites and a racial group for all agencies; all comparisons must have at least 50 stops of Whites and 50 stops of the compared racial group. Excludes undefined ratios, or ratios where either Whites or the compared racial group have less than 50 stops.
**The number of ratios that were included in the analysis for 2022 stops is 718. Each ratio that enters into the computation involves a comparison of one non-White racial group to Whites for one agency.

Table 4.e shows the distribution of contraband found ratios in searches of individual drivers or passengers among three minority groups individually, and all the racial groups collectively in 2022. Here we estimate that in 41.6% of all agencies with at least 50 stops for both Whites and Blacks, contraband is found while searching Black drivers or their passengers at a higher rate than in White drivers or their passengers (ratio > 1). For Hispanic drivers or their passengers, this number is 31.9%, for Asian drivers it is 16.7%, and the overall percentage for all racial groups is 33.6%. This result does not suggest a presence of racial profiling related to this aspect of traffic stops.

***Table 4e. Distribution of contraband found ratios from searches of individuals: driver or passengers*. (Each ratio that enters into the computation involves each noted non-White racial group compared to Whites for an agency). Illinois, Traffic stops, 2022.**

Rate ratios*	Black	Hispanic	Asian	All minority racial groups
<0.25	21.1%	32.9%	73.8%	34.6%
0.25 to <0.5	6.1%	10.2%	0	6.5%
0.5 to <1.0	31.2%	25.0%	9.5%	25.4%
1.0 to <2.0	29.7%	18.5%	2.4%	21.0%
2.0 to <4.0	8.2%	9.7%	9.5%	8.8%
≥4.0	3.6%	3.7%	4.8%	3.7%
All ratios**	100%	100%	100%	100%

*All comparisons of Whites and a racial group for all agencies; all comparisons must have at least 50 stops of Whites and 50 stops of the compared racial group. Excludes undefined ratios, or ratios where either Whites or the compared racial group have less than 50 stops.
**The number of ratios that were included in the analysis for 2022 stops is 599. Each ratio that enters into the computation involves a comparison of one non-White racial group to Whites for one agency.

Reason for Stop

The reason for each stop is summarized in Figure 3a. The percentage of stops for each reason varied substantially by racial group (Figure 3b).

Figure 3a. Percentage of stops by reason for stop. Illinois, Traffic stops, 2022.

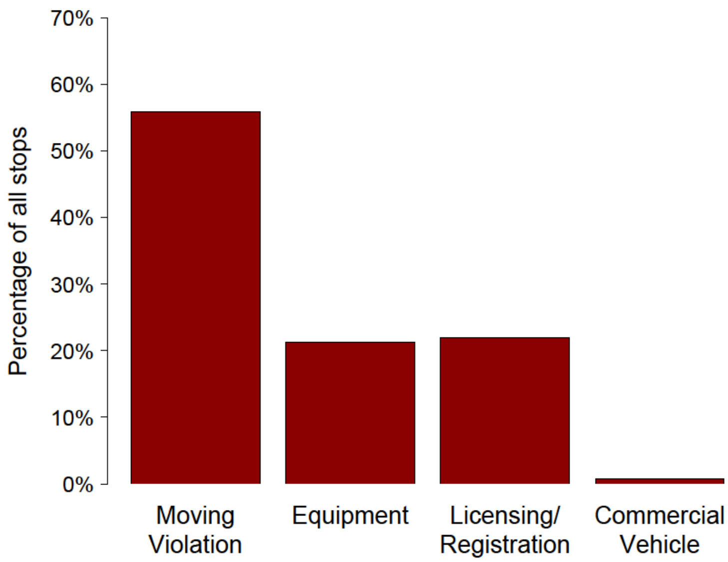
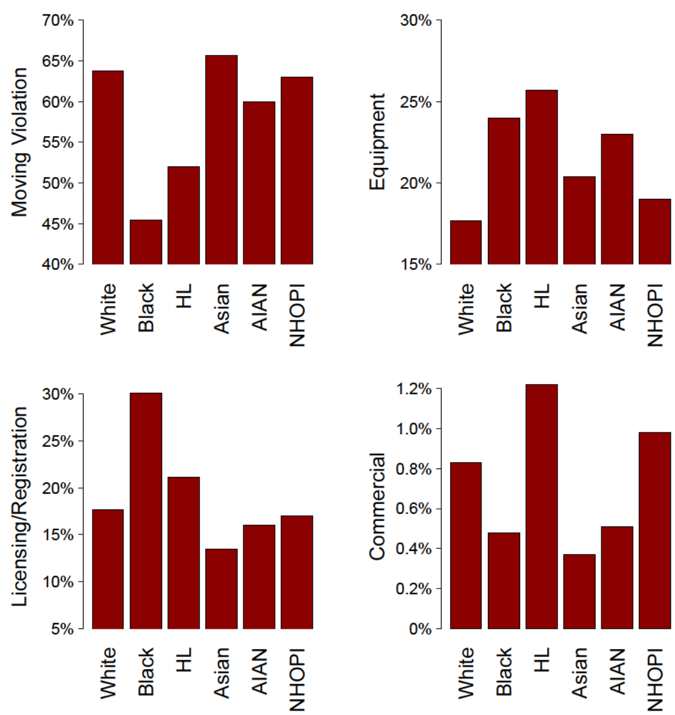


Figure 3b. Percentage of stops for the noted reason, by race. **For each race, the percentages sum to 100% across the four noted reasons. Note that the upper and lower limits of the y-axis vary across the four panels. Illinois, Traffic stops, 2022.**

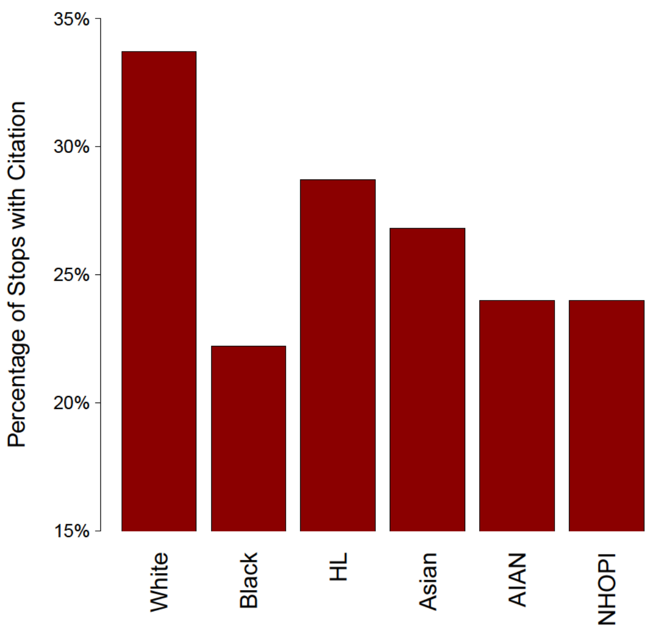


Abbreviations for racial groups: Black = "Black or African American," HL = "Hispanic or Latino," AIAN = "American Indian or Alaska Native," NHOPI = "Native Hawaiian or Other Pacific Islander."

Outcome of stop: citation

Similar to the results in Figure 3b, the six racial groups have diverse percentages receiving a citation as the outcome of the stop (Figure 4). “Citation” is the most serious result of the three outcomes recorded on the traffic stop data collection form: citation, written warning or verbal warning/stop card.

Figure 4. Percentage of stops with a citation, by race. Illinois, Traffic stops, 2022.

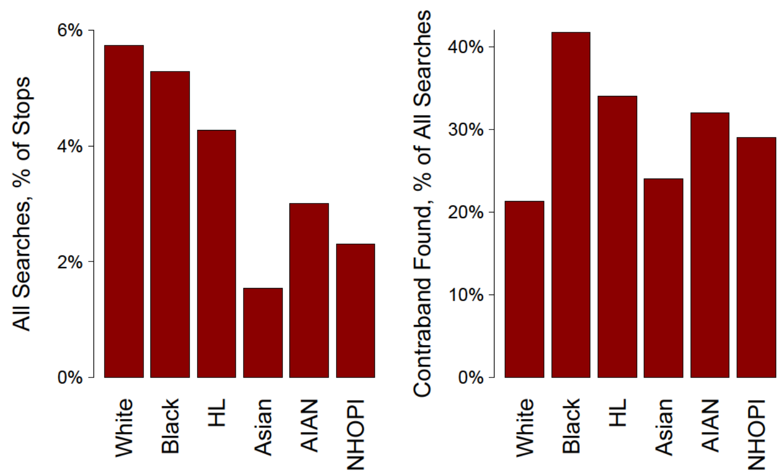


Abbreviations for racial groups: Black = “Black or African American,” HL = “Hispanic or Latino,” AIAN = “American Indian or Alaska Native,” NHOPI = “Native Hawaiian or Other Pacific Islander.”

Searches

Figure 5a shows that the vehicle search rate was moderately low for all of the racial groups (approximately 2-6% of stops, left panel), but given a vehicle search, the contraband yield was not low (21-42% of searches, right panel). As noted in other figures, there is variation among the races’ percentages in both panels.

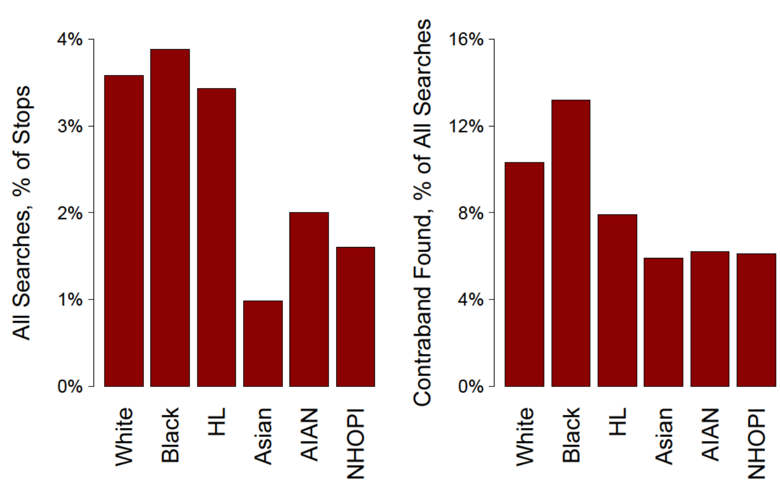
Figure 5a. Percentage of stops with vehicle searches; percentages of vehicle searches with Contraband Found, by race. **Note that the upper and lower limits of the vertical axis vary across the two panels. Illinois, Traffic stops, 2022.**



Abbreviations for racial groups: Black = "Black or African American," HL = "Hispanic or Latino," AIAN = "American Indian or Alaska Native," NHOPI = "Native Hawaiian or Other Pacific Islander."

Figure 5b shows that the driver or passenger search rate (searching an individual) was low for all of the racial groups (approximately 1-4% of stops, left panel), and given a driver or passenger search, the contraband yield was somewhat higher (3-14% of searches, right panel). As noted in other figures, there is variation among the races' percentages in both panels.

Figure 5b. Percentage of stops with driver or passenger searches; percentages of vehicle searches with Contraband Found, by race. Note that the upper and lower limits of the vertical axis vary across the two panels. Illinois, Traffic stops, 2022.



Dog sniffs

While there were thousands of dog sniffs performed statewide (3,729 in 2022), it was still relatively rare compared to the total number of stops by Illinois law enforcement agencies. The rate for all stops combined is that only one in 540 stops in 2022 had a dog sniff. Not all agencies conduct dog sniffs, because the trained dogs are not available in each agency. While the frequency of dog sniffs is low statewide (0.07%-0.23% of stops across the six racial groups), the finding of contraband following a vehicle search after a dog sniff is substantial, at 36-75% of vehicle searches across the four racial groups, excluding the American Indian and Native Hawaiian/Pacific Islander groups, which have numbers of stops with dog sniffs (6 and 4 stops with dog sniffs, respectively) too small to be reliable for inference.

Table 5. Number of stops with a dog sniff and their percentage among all stops. Given that a dog sniff occurred, number and percentage of stops with contraband found. Illinois, Traffic stops, 2022.

Racial Group	Stops with Dog Sniff		Contraband Found	
	Number	Percentage of stops	Number	Percentage of vehicle searches*
White	2,143	0.23%	995	61%
Black or African American	960	0.16%	470	68%
Hispanic or Latino	558	0.15%	163	43%
Asian	58	0.08%	15	36%
American Indian or Alaska Native	6	0.07%	3	75%
Native Hawaiian or Other Pacific Islander	4	0.07%	0	0
All groups combined	3,729	0.19%	1,646	60.0%

*The vehicle search occurred after a dog sniff.

VIII. Some General Comments

A considerable number of agencies have a relatively small number of stops for one or more of the racial groups. The limited stop counts yield a wide 95% confidence interval, which means high uncertainty in the corresponding rate, percentage or ratio. The uncertainty from potential benchmark issues (discussed earlier) or race classification issues (also discussed earlier) add to the uncertainty implied by the confidence intervals. Any investigation of racial profiling that is initiated based on this report should consider all of the sources of uncertainty.

In Part II of this report (agency tables) each agency has ratios of rates or ratios of percentages. Some of them are bolded as a "statistical deviation." The bolded ratios and their meaning and interpretation are topics covered elsewhere in this report. In addition to whether or not a ratio is bolded, the absolute magnitude of the ratio should be considered when interpreting the results, as discussed earlier.

If a ratio is not bolded, it does not prove that there is no racial profiling in the agency. It is worth looking at the upper and lower bound of the 95% confidence interval to see what the uncertainty is. That interval quantifies the uncertainty and shows the largest ratio and the smallest ratio that are reasonably plausible, given the data.

For example**,** consider a ratio of ***1.0*** for a specific minority percentage of stops with a search, compared to the corresponding White percentage of stops with a search — in a particular agency. The ratio of 1.0 indicates that the percentage of stops with a search was the same for both the Whites and for the specific minority group. However, the counts of searches are very small in this example, and the 95% confidence interval for the ratio is ***0.025*** up to ***5.8***. (This is very similar to an actual agency result.) That is, it is plausible that the true search percentage of the minority group is anywhere from one-fortieth of the White percentage up to almost six times the White percentage.

Clearly, in a case like the one described above, we do not know enough about the ratio to draw any conclusion except that we are uncertain. Thus, a confidence interval for a ratio that includes 1.0 and is very wide (encompassing values well above the calculated ratio and also well below the ratio) usually means that presence or absence of potential racial profiling cannot be determined from the data in hand.

Lastly, while there is a considerable focus on the stop rate ratios reported in Panel 1 of the tables in Part II of this report (detailed tables), the other panels provide valuable complementary information on the outcomes of stops and how the outcome statistics compare between racial groups. As noted earlier, the stop outcome results are compared among individuals that were stopped and do not rely on any external population benchmark. This avoids some limitations of benchmarks. Ultimately, stop results for an agency should be interpreted holistically, considering all panels together; different panels may suggest different interpretations when viewed individually.

IX. Looking Ahead

TMWL is continuing to review the current statistical methodology and consider refinements and improvements. In our analysis of 2021 stops we made a major update to our benchmarking approach. Our striving for ever-more accurate benchmarks will continue as relevant datasets become available. We now have access to traffic volume data for a very large number of road and highway segments in Illinois. We may be able to use this data to identify large traffic flows in or near police agency jurisdictions. This will be complex geographic data to use, but it may serve as a way to refine or check on our benchmarks.

The Illinois statute establishing the profiling study mandates a study evaluating individual officers for presence or absence of racial profiling in stops. A possible approach to that legally mandated endeavor is currently under review and may appear in a subsequent report.

Appendix A. Traffic Stop Data Collection Form In Use During 2022

Illinois Department of Transportation

Traffic Stop Data Sheet

Agency Code

****Section A - Traffic Stop Information****

Date of Stop (MM/DD/YYYY) | **Time of Stop (Military Time)** | **Duration of Stop (Minutes)**

Officer Name | **Officer Badge Number**

Name of Driver

Address | **City** | **State** AL | **Zip Code**

Vehicle Make | **Vehicle Year** | **Driver's Year of Birth (ex: 1957)**

Driver Sex
1 ☐ Male 2 ☐ Female

Driver Race
1 ☐ White 2 ☐ Black or African American 3 ☐ American Indian or Alaska Native 4 ☐ Hispanic or Latino 5 ☐ Asian
6 ☐ Native Hawaiian or Other Pacific Islander

Reason for Stop
1 ☐ Moving Violation 2 ☐ Equipment 3 ☐ License Plate / Registration 4 ☐ Commercial Vehicle

If Moving, Type of Violation
1 ☐ Speed 2 ☐ Lane Violation 3 ☐ Seat Belt 4 ☐ Traffic Sign or Signal 5 ☐ Follow too Close 6 ☐ Other

Result of Stop
1 ☐ Citation 2 ☐ Written Warning 3 ☐ Verbal Warning / Stop Card

Beat of Location Stop

****Section B - Searches****

	Consent Search Requested?	Consent Given?	Search Conducted?	Search Conducted By?
Vehicle	1 ☐ Yes 2 ☐ No	1 ☐ Yes 2 ☐ No	1 ☐ Yes 2 ☐ No	1 ☐ Consent 2 ☐ Other

If yes, what was found: 1 ☐ Drugs 2 ☐ Drug Paraphernalia 3 ☐ Alcohol 4 ☐ Weapon 5 ☐ Stolen Property 6 ☐ Other

If a search of the Vehicle was conducted, was contraband found? 1 ☐ Yes 2 ☐ No

If the contraband found was drugs, what was the amount? 1 ☐ < 2 grams 2 ☐ 2-10 grams 3 ☐ 11-50 grams 4 ☐ 51-100 grams 5 ☐ > 100 grams

	Consent Search Requested?	Consent Given?	Search Conducted?	Search Conducted By?
Driver	1 ☐ Yes 2 ☐ No	1 ☐ Yes 2 ☐ No	1 ☐ Yes 2 ☐ No	1 ☐ Consent 2 ☐ Other
Passenger(s)	1 ☐ Yes 2 ☐ No	1 ☐ Yes 2 ☐ No	1 ☐ Yes 2 ☐ No	1 ☐ Consent 2 ☐ Other

If a search of the Driver or Passenger(s) was conducted, was contraband found? 1 ☐ Yes 2 ☐ No

If yes, what was found: 1 ☐ Drugs 2 ☐ Drug Paraphernalia 3 ☐ Alcohol 4 ☐ Weapon 5 ☐ Stolen Property 6 ☐ Other

If the contraband found was drugs, what was the amount? 1 ☐ < 2 grams 2 ☐ 2-10 grams 3 ☐ 11-50 grams 4 ☐ 51-100 grams 5 ☐ > 100 grams

****Section C - Police Dog Sniff Searches****

Did a police dog perform a sniff of the vehicle? 1 ☐ Yes 2 ☐ No

If a police dog performed a sniff of the vehicle, did the dog alert to the presence of contraband? 1 ☐ Yes 2 ☐ No

If an alert occurred, was the vehicle searched? 1 ☐ Yes 2 ☐ No

If the vehicle was searched, was contraband found? 1 ☐ Yes 2 ☐ No

If yes, what was found: 1 ☐ Drugs 2 ☐ Drug Paraphernalia 3 ☐ Alcohol 4 ☐ Weapon 5 ☐ Stolen Property 6 ☐ Other

If the contraband found was drugs, what was the amount? 1 ☐ < 2 grams 2 ☐ 2-10 grams 3 ☐ 11-50 grams 4 ☐ 51-100 grams 5 ☐ > 100 grams

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Appendix B. Technical Notes on Rates, Percentages and Ratios

B.1. Overview

This technical appendix includes a detailed explanation of the rate, post-stop outcomes and ratio calculations used in constructing the statewide and agency tables that appear in Part II of this report. We explain how comparisons of each minority group to White drivers or pedestrians are carried out. We also explain how the confidence interval is calculated based on known sources of uncertainty in the data.[6] Further, this section describes how an agency may be designated (by a bold font in the tables) as potentially standing out beyond an assumption of no racial profiling. An agency that is designated as standing out might use this report as a basis for further inquiry. As stated elsewhere and repeated here, there is nothing in this report that proves an agency is practicing racial profiling. We provide some limitations for interpreting the findings based on the available data and methods.

B.2. Stop rates, post-stop outcomes and ratio calculations

We performed all calculations for the entire state of Illinois and for each agency.

B.2.1 Stop rates and rate ratios

We calculated stop rates separately for each racial group by dividing the number of stops in the racial group by the benchmark estimate of the driving population in the racial group. A description of the methods used to estimate the benchmark populations is included in Appendix C.

We assumed the number of stops followed a Poisson distribution, used in previous examination of racial disparities in traffic stops (Gelman et al. 2007, Ridgeway 2007) and calculated 95% confidence intervals for the rates using exact methods (Garwood 1936). When the benchmark estimate of the population was zero, no rate or confidence interval could be calculated. A benchmark population of zero for a specific minority group happens when the census population estimate for the minority is zero.

We compared each minority group to White drivers or pedestrians using the ratio of the minority group stop rate to the White group stop rate. We calculated a 95% confidence interval for each rate ratio by conditioning on the sum of the numbers of stops in the two racial groups being compared. Assuming the number of stops in each group followed a Poisson distribution, conditioning on the sum of the number of stops creates a binomial variable. For distance-based benchmarks, an exact confidence was calculated using binomial methods (Lehmann and Romano 2005). If it was impossible to calculate a rate because of a zero benchmark, or if the number of stops in the White group was zero, no rate ratio or confidence interval was reported.

We calculated the 95% confidence intervals for rate ratios from crash-based benchmarks in a different way than for distance-based benchmarks in order to incorporate the number of crashes used in the benchmark (see Appendix C for how crash-based and distance-based benchmarks were defined and calculated). For each minority group, the proportion of minority stops out of the sum of the minority and White stops (p_{stops}) and the proportion of the minority group in the benchmark population out of the minority and White groups ($p_{benchmark}$) were calculated. The rate ratio can be calculated from

[6] The estimated benchmark population is an example of a component of the methodology that has uncertainty that could not be quantified for this study.

these proportions using the following formula: $\left(p_{stops}/\left(1-p_{stops}\right)\right)/\left(p_{benchmark}/\left(1-p_{benchmark}\right)\right)$. However, the corresponding 95% confidence interval for the rate ratios requires the effective sample sizes (the numerator and denominator) corresponding to $p_{benchmark}$, which is related to the number of crashes used in the benchmark.

The stops proportion was treated as a binomial variable, as above. The benchmark proportion was initially treated as an over- or under-dispersed binomial with the number of crashes used as the denominator. The variance of the benchmark proportion was estimated using the parametric bootstrap, where the number of crashes per ZIP code was drawn from a multinomial distribution for each bootstrap iteration. The dispersion parameter of the benchmark proportion was estimated as the ratio of the bootstrap variance divided by the variance that is estimated assuming a standard binomial proportion (i.e., using the classic formula p[1-p]/N, where p is the benchmark proportion and N is the number of crashes). The dispersion parameter indicates how much more variable (dispersion > 1) or less variable (dispersion < 1) the proportion is than expected for a standard binomial variable if the denominator was the number of crashes. The effective denominator for the benchmark proportion, which is the denominator that would produce the same variance as expected using the standard binomial formula, was then calculated as the number of crashes divided by the dispersion parameter. Similarly, the effective numerator of the benchmark proportion was calculated as the benchmark proportion times the effective denominator. Using the number of minority stops, White stops, effective benchmark numerator, and effective benchmark denominator, the 95% confidence of the rate ratio was calculated using exact binomial methods as carried out above for distance-based benchmarks. This method of calculating 95% confidence intervals tends to produce wider intervals than if they were calculated the same way as for distance-based benchmarks, because the effective benchmark numerator and denominator based on the number of crashes are each less than the corresponding benchmark population counts. This methodology is used in order to account for additional variability in the benchmark population estimates related to the number of crashes, which is generally smaller than the number of stops.

A rate ratio of 1.0 indicates the minority group and White drivers or pedestrians had equal rates of stops. If the 95% confidence interval lies entirely above 1.0, the rate ratio is statistically significantly greater than 1.0 and may require agency inquiry. These statistically significant rate ratios are bolded in the summary tables. These bolded ratios are statistical deviations and the basis for further consideration of potential racial disparities. Comparisons of minority groups to White drivers or pedestrians where the 95% confidence lies below 1.0 (one) are not bolded because the intent of this study is to identify potential racial profiling that discriminates against minority drivers or pedestrians.

B.2.2 Post-stop outcomes

For all calculations, we assumed the benchmark accurately captured the population of drivers or pedestrians. The benchmark used to calculate each rate is itself an estimate of the population of drivers or pedestrians for a racial group. Confidence intervals of rates and rate ratios assumed only sampling error and thus do not account for this additional source of error in benchmark estimates. Accounting for benchmark error would increase the width of the confidence intervals reported for rates and rate ratios and would likely reduce the number of agencies that appear to stand out as needing further inquiry.

We calculated post-stop outcome percentages separately for each racial group. Table B1 shows the type of numerator and denominator used to calculate each percentage shown in the traffic tables.

Table B1. Numerators and denominators for traffic stop outcomes.

Category	Outcome	Numerator	Denominator
Reasons for Stop			
	Moving Violation	Number of moving violation stops	Number of stops
	Equipment	Number of equipment stops	Number of stops
	Licensing/Registration	Number of licensing/registration stops	Number of stops
	Commercial Vehicle	Number of commercial vehicle stops	Number of stops
Outcomes of Stop			
	Verbal Warning	Number of verbal warnings	Number of stops
	Written Warning	Number of written warnings	Number of stops
	Citation	Number of citations	Number of stops
Vehicle Searches			
	Consent Search	Number of consent searches	Number of stops
	All Searches	Number of searches	Number of stops
	Contraband Found	Number of searches where contraband was found	Number of searches
Driver or Passenger Searches			
	Consent Search	Number of stops with a consent search*	Number of stops
	All Searches	Number of stops with a driver or passenger search*	Number of stops
	Contraband Found	Number of stops with a driver or passenger search where contraband was found*	Number of stops with a driver or passenger search*
Dog Sniff Searches			
	Dog Sniff	Number of dog sniffs	Number of stops
	Dog Alert after Dog Sniff	Number of dog alerts	Number of dog sniffs
	Vehicle Search after Dog Sniff	Number of vehicle searches after a dog sniff	Number of dog sniffs
	Contraband Found after Vehicle Search	Number of vehicle searches after a dog sniff, where contraband was found	Number of vehicle searches following a dog sniff

* Although a stop may result in the search of more than one individual (e.g., both the driver and a passenger are searched), multiple individuals searched (from one vehicle) are counted here as one stop with a driver or passenger search or both.

We assumed that percentages follow a binomial distribution and can be approximated by a Poisson distribution (Serfling 1978), and we calculated confidence intervals for the rates using exact methods (Garwood 1936). When the denominator of the percentage was zero (for example, an agency had a benchmark of zero for a specific racial group), no percentage or confidence interval could be calculated.

For selected outcomes we compared each minority group to White drivers, using the ratio of the minority group percentage to the White group percentage. We calculated a 95% confidence interval for each ratio using exact methods (Lehmann and Romano 2005). If it was impossible to calculate a percentage because of a zero denominator, or if the numerator of the White group percentage was zero, no ratio or confidence interval was reported.

B.3 Durations

We calculated the median durations of stops separately for each racial group. The median represents the value such that about half of stops have a shorter duration than the median and half of stops have a longer duration than the median.

B.4 Limitations

For all calculations, we assumed that the driver or pedestrian was assigned to the correct racial group. However, an officer's assessment of the race of a driver may be in error. Because police officers made the racial group assignment, there is a potential misclassification bias of drivers or pedestrians. If misclassification resulted in a minority driver or pedestrian frequently being categorized in a different minority group, the stop rates of some minority groups may be underestimated, while others are overestimated. Consequently, the rate ratios of some minority groups may be underestimated, while others are overestimated. This is a limitation that would be difficult to correct based on the available information. Section IV of this report consider—in more detail— the issue of determining race of drivers.

Some of the alerts to rate ratios (**bolded font** in the tables) may be "false positives." This can happen as follows. Within the statewide or individual agency tables for traffic and pedestrian stops, we calculated five minority group comparisons with the White group. There were five of these comparisons for each ratio analysis. For example, there are five ratios comparing the stop rate for each of the five minorities to the stop rate for Whites[7]. Thus, we constructed five 95% confidence intervals — one each for the five stop-rate ratios. That is, each agency was checked for profiling in each of five minority groups. For each minority comparison with White drivers or pedestrians there was the potential to make a type I error. That is, we may have, by chance, incorrectly indicated the potential need for inquiry for profiling. While we set a 5% type I error rate for each minority comparison, the multiple comparisons inflate the possibility of making such an error overall to more than 5%. We chose not to correct for these multiple comparisons, viewing each minority comparison to Whites as an independent examination of profiling.

References (for Appendix B)

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Gelman, A, Fagan, J, and Kiss, A (2007). An analysis of the New York City Police Department's 'stop-and-frisk' policy in the context of claims of racial bias. Journal of the American Statistical Association, Vol. 102, No. 479, 813–823.

Lehmann, EL, and Romano, JP (2005). Testing Statistical Hypotheses, Third edition. Springer: New York.

[7] There may be fewer than five ratios depending on the occurrence of zero stops for Whites or zero benchmark for a minority. These are cases where a ratio cannot be calculated.

Ridgeway, G. (2007). Analysis of Racial Disparities in the New York Police Department's Stop, Question, and Frisk Practices. Santa Monica, CA: RAND Corporation. https://www.rand.org/pubs/technical_reports/TR534.html

Serfling, RJ (1978). Some elementary results on Poisson approximation in a sequence of Bernoulli trials. SIAM Review, Vol. 20, No. 3, 567-579.

Appendix C. Technical Notes on Benchmarks

C.1. Overview

In the analysis to detect racial profiling, the number of stops by each agency of each racial group is compared to a "benchmark" population of the racial group. The rate of stops per benchmark population for the racial group can be compared to the same rate for Whites. The benchmark provides an expected racial distribution of the population and would be an expected percentage racial distribution of the stops if the stops were conducted in a uniform way, blind to the race of the driver. That is, the stop rates calculated using an ideal benchmark would be approximately constant across all racial groups if there were no profiling.

Details on the data sources used for benchmarks, how racial categories were defined, how benchmark regions were determined, and other benchmark calculations are covered below. In addition, differences in benchmark methodology employed this year compared with prior years is described in **Section C.7** and limitations and strengths of the methodology are described in **Section C.8**.

C.2. Data Sources

Multiple data sources were combined to calculate benchmarks, including multiple datasets provided by the U.S. Census Bureau, Illinois Department of Transportation, and Illinois Secretary of State. The U.S. Census Bureau datasets used include those from the decennial census, the American Community Survey (ACS), and Gazetteer files, depending on the year and type of benchmark (traffic stops or pedestrian stops).

C.2.1. Data from the U.S. Census Bureau

The ACS is an ongoing survey conducted by the U.S. Census Bureau that collects information on the U.S. population in all 50 states, the District of Columbia and Puerto Rico[8]. The information collected is similar to that collected by the U.S. decennial census, but the ACS results are released on an annual basis rather than every 10 years. Another difference between the ACS and census is that the ACS is based on a random sample of about 3.5 million individuals while the census attempts to reach every person living in the U.S. and its territories.

Besides the 1-year (1Y) ACS releases, there are also 5-year (5Y) releases. These 5Y releases combine 5 consecutive years, primarily to increase the sample size of relatively small areas or groups of individuals. It would be challenging to estimate the population of small communities reliably with only one survey-year of data. In addition to standard tabulations, the ACS also provides individual-level data, referred to as the public use microdata sample (PUMS). The PUMS data allows more

[8] https://www.census.gov/programs-surveys/acs. Last accessed 5/15/22.

detailed and complex analyses involving multiple variables. Due to privacy concerns, there are restrictions on the level of geographic identification provided with each type of release of ACS data.

The Gazetteer files provide geographic information, such as geographic area, latitude, and longitude, for different relevant regions in the U.S., including ZIP codes, places (a city, town, or village, referred to simply as city hereafter), counties, and states. These files are updated annually.

The U.S. Census Bureau approximates ZIP codes (defined by the U.S. Postal Service) with ZIP code tabulation areas (ZCTAs)[9]. Throughout this report, the term "ZIP code" will be used to refer both to ZCTAs and U.S. Postal Service ZIP code for simplicity.

Table C.1 lists the U.S. Census Bureau datasets used for different purposes, for both the traffic and pedestrian stop benchmarks. More detail on pedestrian stop benchmarks can be found in the corresponding Illinois pedestrian stops study report, 2022 stops, Part I. Of note, as can be seen from the table, different datasets were used for traffic and pedestrian benchmarks, which is different than in past years. The primary reason is that pedestrian benchmarks are based on city-, county-, or state-level population statistics, while the traffic stop benchmarks are based on ZIP-code-level population statistics.

The reader who compares this appendix to the corresponding appendix in the 2022 pedestrian stops report will note that the decennial 2020 census data is not used for this traffic analysis, whereas it is used for the 2022 pedestrian stops analysis. The reason is that the traffic benchmark analysis requires ZIP-code-level population data, which, at the time of this writing, was not available from the 2020 decennial census. The ACS survey data for ZIP codes was fully adequate to complete the traffic benchmark analysis.

[9] https://www.census.gov/programs-surveys/geography/guidance/geo-areas/zctas.html. Last accessed 5/21/22.

Table C.1. U.S. Census Bureau datasets used for benchmarks.

Information Needed	Traffic Stop Benchmarks	Pedestrian Stop Benchmarks
Age distribution in Illinois	1Y ACS PUMS 2021	N/A
Age distribution by race/ethnicity*	5Y ACS PUMS 2017-2021	5Y ACS PUMS 2017-2021
Individual race groups to reallocate residents with more than one race*	5Y ACS PUMS 2017-2021	DEC 2020
Population counts for each race/ethnicity		
By ZIP code†	5Y ACS 2017-2021	5Y ACS 2017-2021‡
By city	N/A	DEC 2020
By county	N/A	DEC 2020
For Illinois	N/A	DEC 2020
Geographic area of each city in Illinois	Gazetteer Files 2022	N/A
Geographic area of each county in Illinois	Gazetteer Files 2021§	N/A
Latitude and longitude of each ZIP code	Gazetteer Files 2022	N/A

1Y = 1-year; 5Y = 5-year; ACS = American Community Survey; DEC = decennial census; PUMS = public-use microdata sample; *Includes Illinois and 24 states within 400 miles of Illinois; †ZIP codes approximated using ZIP code tabulation areas (ZCTAs) defined by the U.S. Census Bureau; ‡ZIP-code-level data was used for Chicago Police District benchmarks; §2021 county area data was used before 2022 was not available online at the time Gazetteer files were downloaded (2/11/2023).

For this report, multiple ACS releases were used, all corresponding to 2021 as the most recent year of data available. The first was the 2021 1Y PUMS, which was used to estimate the age distribution of the entire population of Illinois in 2021. The second release used was the 2017-2021 5Y PUMS, which was used to 1) estimate the state-level age distribution for each racial group and 2) estimate reallocation factors for individuals reporting multiple races (see **Section C.4**). The 5Y release was used instead of the 1Y release to achieve a larger sample size for those racial groups which had fewer individuals in Illinois. The third release used was the 2017-2021 5Y detailed table of race and ethnicity for each ZIP code in Illinois or any of 24 surrounding states within 400 miles of Illinois (Alabama, Arkansas, Georgia, Indiana, Iowa, Kansas, Kentucky, Louisiana, Michigan, Minnesota, Mississippi, Missouri, Nebraska, North Carolina, Ohio, Oklahoma, Pennsylvania, South Carolina, South Dakota, Tennessee, Texas, Virginia, West Virginia, and Wisconsin). In general, the 2021 ACS datasets were used for the traffic stop benchmarks instead of the 2020 decennial census because individual-level data (PUMS) and race and ethnicity data by ZIP code were not publicly released by the time this report was being prepared. However, the pedestrian stop benchmarks used city-, county-, and state-level race and ethnicity data primarily, rather than ZIP-code-level, so the pedestrian benchmarks were mainly based on 2020 census data.

C.2.2. Data from Illinois Traffic Crash Reports

On behalf of this study, the Bureau of Data Collection, Office of Planning & Programming, Illinois Department of Transportation (IDOT), provided a report of data extracted from Illinois SR 1050 traffic crash reports from 2019-2020[10]. These crash reports are required to be filed for crashes in Illinois that resulted in bodily injury or death of any person or that damage to the property of any one person in excess of $1,500 (or $500 if any driver does not have insurance). Information in the crash reports included the date and time of the crash, the location of the crash (latitude, longitude, city, and county), the number of vehicles involved, the ZIP code of each driver's address, the type of roadway on which the crash occurred, and the type of law enforcement agency filing the report. As described in **Section C.6** ("Calculating Agency Benchmarks"), this information was used to estimate driver benchmark populations for agencies with a sufficient number of usable reports available. In particular, the crash data were used to estimate the proportion of drivers originating from each ZIP code directly associated with an agency's jurisdiction as well as ZIP codes from the surrounding area.

C.2.3. Data from the Illinois Secretary of State

On behalf of this study, the Bureau of Data Collection, Office of Planning & Programming, IDOT requested and received a report from the Office of the Illinois Secretary of State, a report with counts of licensed drivers in Illinois for each single year of age. The report was run on March 31, 2022. This was combined with ACS estimates of the population count of each age in Illinois (2021 1Y PUMS) to determine the proportion of individuals who are potential drivers based on having a driver's license as a function of age. This is described in more detail in **Section C.4**.

C.3. Racial Categories

The U.S. decennial census and ACS collect self-identified race and ethnicity information based on the U.S. Census Bureau's definitions. The primary racial categories provided by the census are White alone, Black or African American alone, American Indian and Alaska Native alone, Asian alone, Native Hawaiian and Other Pacific Islander alone, some other race alone, and two or more races. The primary ethnicity categories provided by the census are "Hispanic or Latino" and "Not Hispanic or Latino." Race and ethnicity are collected using two separate questions and the respondent can select any racial group along with any ethnicity.

From Illinois Public Act 101-0024, the law enabling this study, the following racial categories are collected based on the police officer's subjective determination of the race of the person being stopped. These include American Indian and Alaska Native, Asian, Black or African American, Hispanic or Latino, Native Hawaiian or Other Pacific Islander, or White. Only a single race may be selected.

Besides the difference between the census/ACS's self-identified race and the Illinois law's officer-identified race, there are other differences between the census/ACS and Illinois law's categories. The primary differences are 1) in the census/ACS, Hispanic or Latino is an ethnicity instead of the Illinois law's designation of Hispanic or Latino as a race; 2) the census/ACS allows for multiple races to be

[10] https://www.idot.illinois.gov/Assets/uploads/files/Transportation-System/Manuals-Guides-&-Handbooks/Safety/Illinois%20Traffic%20Crash%20Report%20SR%201050%20Instruction%20Manual%202019.pdf. Last accessed 5/21/22.

selected while the Illinois law does not; and 3) the census/ACS allows the "some other race" option while the Illinois law does not.

To make the different racial categories compatible between the census/ACS data used for benchmarks and the stops data using the Illinois racial categories, we made three major adjustments. The first adjustment was to use Hispanic or Latino as the assigned race for benchmarking if the census/ACS ethnicity was listed as Hispanic or Latino, regardless of race. The second adjustment was to reallocate the "multiple races" group into multiple single race groups using equal fractions fractional allocation[11]. For example, an individual who self-identified as White, American Indian or Alaska Native, and Asian would be treated as 1/3 White, 1/3 American Indian or Alaska Native, and 1/3 Asian for the purpose of calculating total race/ethnicity distributions. The 2021 5Y ACS PUMS race and ethnicity table for Illinois was used to calculate state-level reallocation factors, as shown in **Table C.2**. The third adjustment was that individuals listing some other race alone (a race not among those listed) in the census/ACS data were excluded from the process of defining a benchmark population. In the 2021 5Y ACS sample, 310,527/12,806,821 (2.4%) of Illinois residents self-identified as not Hispanic or Latino and more than one race and were fractionally reallocated to multiple single race categories. Additionally, 34,562 (0.3%) identified as not Hispanic or Latino and some other race and were excluded from benchmark calculations.

Table C.2. Equal fractions fractional reallocation factors for Illinois residents who self-identify as not Hispanic or Latino and more than one race, based on the 2021 5Y ACS PUMS. The factors were used to calculate the effective number of individuals with a single race category as a proportion of the multiple race category, e.g., single race count = (single race fraction) x multiple race count. The fractions sum to 1 so all multiple race individuals are included.

Race/Ethnicity	Fraction
Not Hispanic or Latino White	0.500
Not Hispanic or Latino Black	0.222
Not Hispanic or Latino American Indian or Alaska Native	0.085
Not Hispanic or Latino Asian	0.181
Not Hispanic or Latino Native Hawaiian or Other Pacific Islander	0.013

C.4. Adjusting for Age and Driver's Licenses

Population counts by race from the census/ACS were adjusted to reflect the number of potential legal drivers by considering three datasets: (a) the number of driver's licenses by age (each year of age separately) — a file provided by the Illinois Secretary of State's office through IDOT, (b) the number of individuals in Illinois based on the 2021 1Y ACS PUMS, and (c) the age distribution by race across Illinois based on the 2021 5Y ACS PUMS. The adjustments were based on the following formulas for the probability of being a driver (having a driver's license) based on race and age:

[11] Parker JD and Makuc DM. Methodologic implications of allocating multiple-race data to single-race categories. *Health Services Research*. 2002;37(1):201-213.

$$
\begin{aligned}
Pr(Driver|Race) &= \sum_{Age} Pr(Driver|Race, Age)Pr(Age|Race) \\
&\cong \sum_{Age} Pr(Driver|Age)Pr(Age|Race).
\end{aligned}
$$

The first equality is exact based on standard laws of probability. The probability of being a driver by race and age was then approximated by the probability of being a driver by age, or symbolically, $Pr(Driver|Race, Age) \cong Pr(Driver|\ Age)$. We made this approximation because data available from IDOT allowed us to estimate the probability of being a driver by age but not by race.

$Pr(Driver|Age)$ was estimated in two steps. First, for each age, the number of licenses from the IDOT database was divided by the number of individuals of that age living in Illinois, based on the 2020 1Y ACS PUMS. Ages > 90 were grouped due to sparsity of data in that age range. Second, to reduce variability in the estimates, ages 17 and over were smoothed using a cubic smoothing spline (**Figure C.1**). Ages < 17 were not smoothed due to the rapid changes from <15 to 15 to 16 that would be overly smoothed by a spline. The curve shown in **Figure C.1** with smoothing applied was used to represent $Pr(Driver|Age)$ in the benchmark calculations. The smoothed curve is reasonably representative of the proportion of population with a driver's license, one dot for each year of age. The curve shown in **Figure C.1** was also used to approximate the proportion of drivers by age for the states surrounding Illinois.

Figure C.1. Smoothed estimates of the proportion of driver's licenses out of the Illinois state population for each single year of age. The black points represent the original raw estimates before smoothing (red curve) to reduce variability.

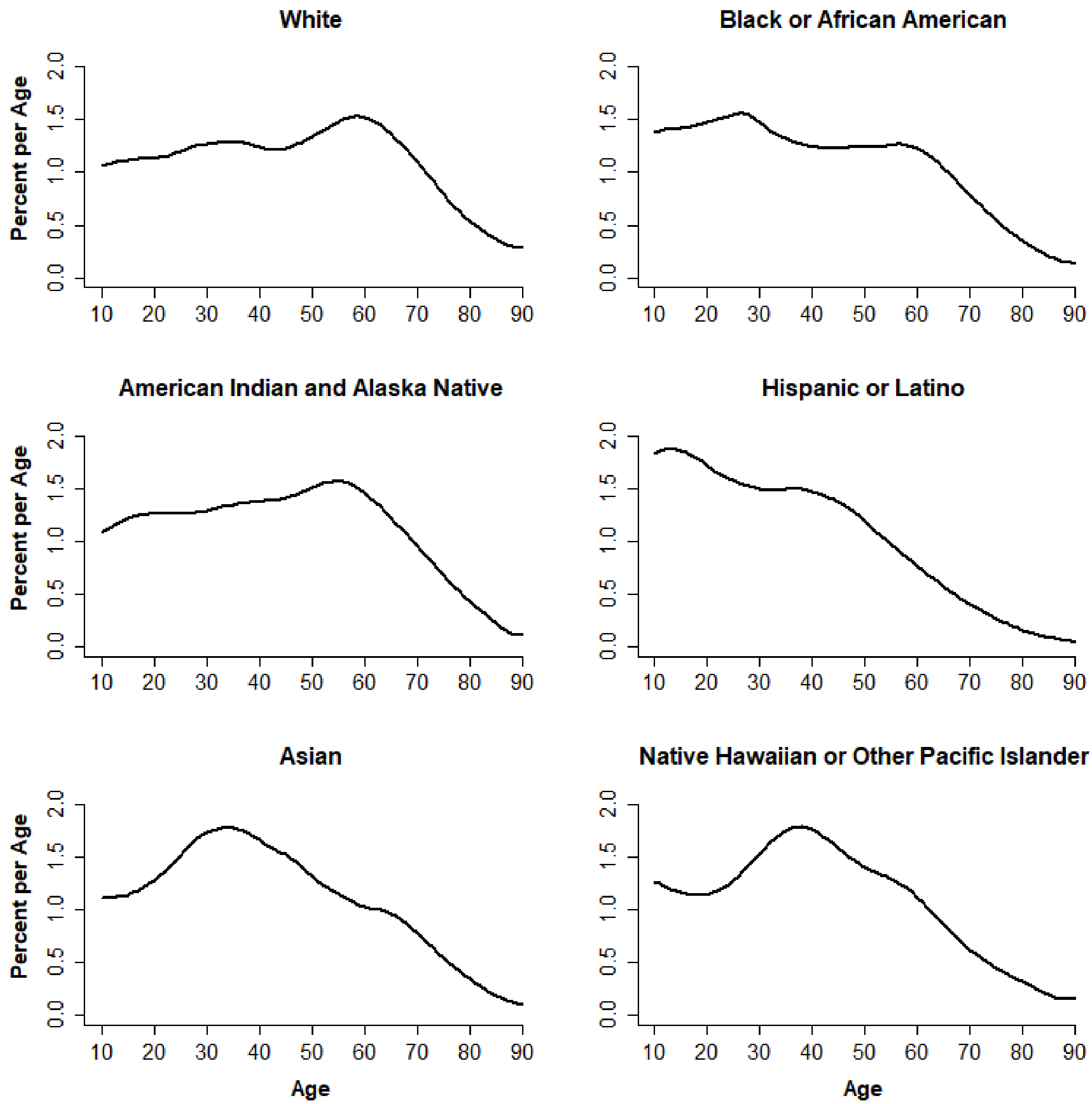
The second quantity needed was $Pr(Age|Race)$. This was estimated by smoothing the estimated age distributions in Illinois for each racial group separately. These estimates are shown in **Figure C.2.** The estimates are shown for age 10 and up, but only the smoothed curve values for ages 15 and over are used in the analysis. The ages under 15 are represented in the plot because the smoothing method works on a span of data surrounding the age for which a smoothed value is needed, similar to the methodology used in a moving average. The estimates from **Figure C.1** and **Figure C.2** were combined using the formula above to estimate $Pr(Driver|Race)$ for each race, summarized in **Table C.3**. The age adjustment was performed by multiplying the population count for each race by the factor in **Table C.3.**

Table C.3. Estimated probability of being a driver in Illinois by race across all ages based on IDOT and ACS data.

Race	Drivers*
White	0.72
Black or African American	0.69
Hispanic or Latino	0.63
Asian	0.72
American Indian and Alaska Native	0.73
Native Hawaiian or Other Pacific Islander	0.70

*Estimated proportion of state population with a driver's license. This estimate is strongly influenced by the proportion of the population <15, an age group that is not eligible for a license.

Figure C.2. Smoothed estimates of the percent of the population of Illinois at each age for each racial group.



C.5. Estimating ZIP Code Population Sizes

The starting point for estimating regional population sizes was the 2021 5Y ACS race and ethnicity tables for the ZIP codes in Illinois and the surrounding states, as described in **Section C.2**. As described in **Section C.4**, these population sizes for the ZIP codes were adjusted for age and the number of driver's licenses by multiplying by a factor derived for each racial group, $Pr(Driver|Race)$. (See the equation in **Section C.4.**) The adjusted population counts per ZIP code formed the building blocks for the agency benchmark calculations, described in the next section.

C.6. Calculating Agency Benchmarks

The population sizes of each ZIP code estimated in **Section C.5** were combined in various ways to derive a benchmark for each agency. There were two major types of benchmarks generated, referred to as crash-based and distance-based benchmarks. Both types of benchmarks combined populations from ZIP codes directly associated with an agency (e.g., the ZIP codes of a city for a city police agency) as well as populations from ZIP codes from the surrounding area. The primary areas chosen for each agency are listed at the end of this appendix in **Table C.5**.

Crash-based benchmarks were generated using traffic crash reports (see **Section C.2.2**) for agencies with a sufficient number of usable crashes. The crash reports include the ZIP codes of the drivers, which were used to determine which ZIP codes to include in the benchmark and how much weight to give each ZIP code. Distance-based benchmarks also combined ZIP codes in a weighted fashion but used a mathematical formula to determine how much weight to give each ZIP code as a function of its distance from the agency, where the weight always decreased with increasing distance. The crash data from similar and nearby agencies was used to determine the distance-based weighting formula for a given agency.

The methodology used for each type of benchmark is covered in the subsections below.

C.6.1. Crash reports

Crash reports are expected to provide a better estimate of the driving population than census-based data on local residents for multiple reasons[12]. In particular, crash reports provide direct information on drivers in an area—not just residents of that area—including relative frequency of drivers from the area and from outside the area. The crash reports include the driver's ZIP code, so the contributions of drivers from different locations inside and outside the area are available as well, including from locations far away. Crash-based benchmarks also reflect driving frequency, as an individual who is on the road more often, all else being equal, is more likely to be in a crash. Similarly, greater driving frequency also increases exposure to the risk of a traffic stop.

The not-at-fault driver indicated in crash reports from two-vehicle collisions were used for benchmark calculations[13]. The not-at-fault driver is expected to be representative of the driving population in the area as if they were being randomly sampled by the crash. For each agency, only reports of crashes which occurred within the primary area of that agency were used (e.g., the corresponding city of a city police agency or the corresponding county of a county sheriff agency). The specific reports used also varied by the agency type, as described below. Crash reports did not directly include the driver's race but included the ZIP code of the driver's address. As described below, racial distributions were based on ZIP code population statistics. Crash reports which were missing driver ZIP code, had an invalid ZIP code (the string provided in the ZIP code field did not match a ZIP code within the set of U.S. Census Bureau ZCTAs), or had a ZIP code outside of Illinois

[12] Withrow BL and Williams H. Proposing a benchmark based on vehicle collision data in racial profiling research. *Criminal Justice Review*. 2015;40(4):449-469.

[13] Alpert GP, Smith MR, Dunham RG. Towards a better benchmark: Assessing the utility of not-at-fault traffic crash data in racial profiling research. *Justice Research and Policy*. 2004;6(1):43-69.

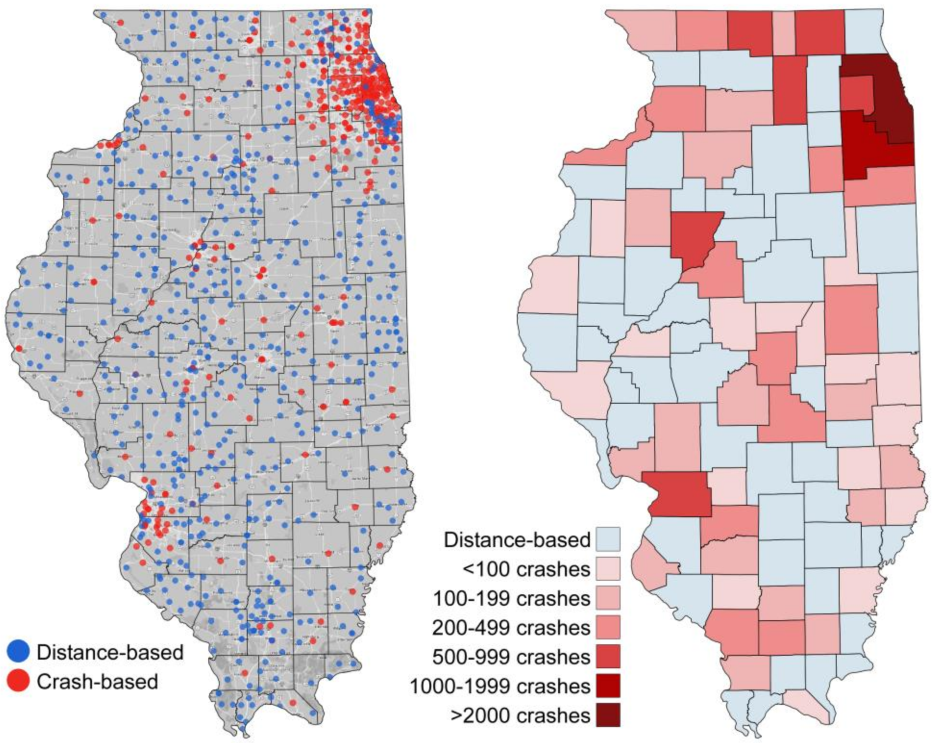
and the 24 states within 400 miles of Illinois (see **Section C.2**) were considered not usable and were excluded.

Crash-based benchmarks were generated for agencies with at least 50 usable crash reports and where at least 70% of their crash reports were considered usable. The former requirement was imposed so there would be a minimum amount of coverage of the ZIP codes of drivers in the area. The latter requirement was imposed because the greater the fraction of crash reports that area excluded, the greater the risk that the remaining reports will be non-representative of the ZIP codes of drivers. **Figure C.3** shows the locations of city police and county sheriff agencies with sufficient crashes for crash-based benchmarks. The usable crash data is concentrated in more urban areas, especially in the Chicago metropolitan area in Northeastern Illinois, though there is some coverage across the entire state.

Statewide crash report data was available for the years 2019-2021. For each agency, the years of crash data used for the benchmark was selected based on the number of crash reports per year. If a large number of crash reports were available based on only the most recent year or two years, only those years were used for a given agency. It was assumed that using more recent crash data would correspond better to current driving conditions than using all years of crash data available. However, for smaller agencies with fewer crash reports, all years were still used to achieve a large enough number of crashes to estimate benchmarks.

If an agency had at least 1500 usable crash reports in the most recent year available, then only the most recent year of crash data was used. This corresponds to a worst-case margin-of-error of ± 2.5% in the estimated proportion of crashes with a given driver ZIP code (based on driver's residential address). If an agency had at least 500 usable crash reports in the most recent two years, then only those two years of crash data were used (worse-cast margin-of-error: ± 5%). If neither of the first two conditions were met, the most recent years of crash data were included up until there were at least 100 crash reports (worst-case margin of error: ± 10%) or there were no more years of crash data available. As noted above, crash data was only used if at least 50 usable crash reports were available and all above conditions also required at least 70% of crash reports to be usable.

Figure C.3. Locations of city police and county sheriff agencies with sufficient crash data for crash-based benchmarks. **The left panel shows city police agencies, and the right panel shows county sheriff agencies. The black lines on both panels indicate county boundaries. Crash-based benchmarks were generated for agencies with at least 50 usable crash reports and where at least 70% of their crash reports were considered usable, indicated with red points or regions. The shade of red indicates the number of usable crashes for county sheriff agencies. Distance-based benchmarks were generated for all other agencies, indicated with blue points or regions.**



C.6.2. Types of agencies

Crash reports were further selected based on the type of agency to better approximate drivers within each agency's jurisdiction. Each crash report contained the type of agency that completed the report (city police, county sheriff, or state police) and the type of roadway, in particular whether it was an interstate or not. The benchmark for the State of Illinois as a whole was based on all usable crash reports, regardless of agency or roadway type. For the Illinois State Police, crash reports completed by the state police, or which occurred on an interstate anywhere in Illinois were included. For other state-level agencies, all crash reports not used for the state police were included. For county sheriff agencies, the inclusion criteria for reports were as follows: the crash occurred in the corresponding county, the report was completed by a county sheriff agency, and the crash did not occur on an interstate. For other county-level agencies, all reports of crashes which occurred in the corresponding county or counties and not used for the state police were included. Lastly, for all other agencies, where the primary area of jurisdiction was one or a small number of cities, the inclusion criteria were: the crash occurred in the corresponding city or cities, the report was completed by a city police agency, and the crash did not occur on an interstate.

C.6.3. Chicago

Due to its size, multiple benchmarks were produced for Chicago. Crash reports from the entire city of Chicago were used for the primary benchmark of the Chicago Police. In addition, separate benchmarks were generated corresponding to each of the 22 Chicago Police Districts[14]. These benchmarks were generated from crash reports the same way as for city police agencies, except for how the crashes were selected, as they each needed to correspond to only part of the city of Chicago. The crash reports included the latitude and longitude of the crash, and these coordinates were used to identify crashes that occurred within each Chicago Police District's boundaries[15]. For each district, crashes were selected that met both the criteria in **Section C.6.2** for the city of Chicago as well as being located within the district's boundaries.

C.6.4. Crash-based benchmarks

For agencies with a sufficient number of crashes (see **Section C.6.1**), crash-based benchmarks were generated as follows. After selecting usable crash reports as described above, the proportion of crashes out of all usable was calculated for each ZIP code, based on the not-at-fault driver's ZIP code. Each proportion represents an estimated probability of a not-at-fault individual being involved in a traffic accident being from that ZIP code. This was used as a surrogate for the probability of a driver in the area being from that ZIP code, symbolically $Pr(ZIP|Driver)$. These proportions were used to determine how much weight to give each ZIP code in the calculations.

The second step involved calculating the proportion of the total driver population of each ZIP code (see **Section C.5**) that belongs to each racial group. Each of these proportions represents an estimated probability that a driver from that ZIP code is of a particular race, symbolically $Pr(Race|ZIP, Driver)$. The estimated probability of a driver in the area being of a particular race was then calculated as the sum of these proportions over all ZIP codes, each weighted by the proportion of crashes involving drivers from that ZIP code. The formula for this calculation was:

$$Pr(Race|Driver) = \sum_{ZIP} Pr(Race|ZIP, Driver) \times Pr(ZIP|Driver).$$

A highly simplified example of these calculations involving two ZIP codes and two races is as follows. If 70% of crashes were from ZIP code A (10% Black) and 30% were from ZIP code B (50% black), the proportion above would be (0.7 x 10%) + (0.3 x 50%) = 22% Black.

These proportions were used to define the *relative* distribution of each race for the crash-based benchmarks. That is, the percentage of the benchmark associated with each race rather than the total number of drivers of each race. To estimate the number of drivers per race, first the total number of drivers was estimated ($Drivers_{Total}$). The number of drivers of each race was then calculated as $Drivers_{Total} \times Pr(Race|Driver)$. The total number of drivers was estimated by summing up the populations of surrounding ZIP codes (all races combined) but weighted according

[14] https://home.chicagopolice.org/about/police-districts/. Last accessed 5/15/22.

[15] https://data.cityofchicago.org/Public-Safety/Boundaries-Police-Districts-current-/fthy-xz3r. Last accessed 5/21/22.

to distance from the primary area of the agency, in the same way as for distance-based benchmarks (see **Section C.6.8**). Those calculations are described in more detail below.

C.6.5. Calculation of the distance between ZIP codes

All other benchmark calculations involved using the distance between ZIP codes within the primary area of an agency and ZIP codes outside of that primary area to determine how much weight that outside ZIP code should be given. ZIP codes further away from the agency's primary area were given less weight to represent the lower likelihood of a driver from that ZIP code being within the agency's jurisdiction.

To calculate the distance between any pair of ZIP codes, first the boundaries of each ZIP code were extracted from the choroplethrZip software package for the statistical software "R." The centroid of each ZIP code was calculated (in terms of latitude and longitude) and the geodesic distance between them was calculated using standard formulas that account for the curvature of the Earth.

For pairs of ZIP codes with a centroid-to-centroid distance less than or equal to 20 miles, the distance was recalculated using a more accurate method that better accounts for the shape of each ZIP code, which can be highly irregular and variable between ZIP codes. That method involved first randomly selecting a point within the boundaries of the first ZIP code and randomly selecting another point within the boundaries of the second ZIP code. The geodesic distance between this random pair of points within the two ZIP codes was calculated in the same way as for the centroid-to-centroid distance. This selection of random pairs of points was repeated to produce a total of 100,000 pairs of points and their corresponding distances for each pair of ZIP codes. These differences were averaged to produce the average distance between the two ZIP codes. The results of these two distance calculation methods (centroid-to-centroid distance and average random point-to-point distance) became more similar to each other as the distance between ZIP codes increased. The cutoff of 20 miles ensured that there was at most a difference of 5% (less than 1 mile) in the worst case between the two methods.

The above calculations apply to the distance between two individual ZIP codes. However, many agencies had a primary area that included more than one ZIP code, e.g., any large city, a county, or the state of Illinois. The calculations were then extended to allow the calculation of a distance between a set of one or more ZIP codes within the primary area (Set A) and an individual ZIP code, either inside or outside of the primary area (ZIP code B). The first step was to calculate the pairwise distance between each ZIP code within Set A and ZIP code B using the method described above. The distance between a ZIP code and itself was defined as 0, so if Set A contained ZIP code B, one of the distances calculated would be 0. The second step was to calculate the *minimum* value of these distances between ZIP codes in Set A and ZIP code B. This minimum distance was defined as the distance between Set A and ZIP code B.

This definition means that the distance calculated corresponds approximately to the average distance one would have to drive in order to enter the primary area of an agency from a particular ZIP code, assuming the shortest (straight-line) route was taken (and ignoring details like curving roads and natural boundaries). Drivers who already live in the primary area do not need to travel at all to reach the primary area (hence a distance of 0). A driver who lives south of Cook County would only need to drive as far as the closest ZIP code on the southern boundary of Cook County to enter that area, so the extent of Cook County to the north is not relevant for that driver for the purpose of distance calculations. By contrast, a driver who lives north of Cook County would have their distance measured to the northern boundary of Cook County instead for the same reason.

C.6.6. Weighting ZIP codes according to their distance from an agency

As noted above, ZIP codes were combined in a weighted fashion to generate distance-based benchmarks. The weight given to each ZIP code decreases with increasing distance from the agency, with distance calculated as in the previous section. For example, ZIP codes within the primary area are given full weight (weight = 1) in the benchmark (i.e., ZIP codes with distance = 0). A ZIP code outside the primary area should have a weight below 1 because a random driver from that ZIP code would not spend as much time within the agency's jurisdiction as a random driver from the primary area. But a ZIP code just outside of the primary area may have weight not far below 1 because of proximity but a ZIP code 20 miles away would have a much lower weight, as a random driver from that ZIP code would be much less likely to be within the agency's jurisdiction than a random driver from a closer ZIP code.

Distance-based benchmarks were generated for agencies without sufficient crash reports to generate crash-based benchmarks (see **Section C.6.1**). However, crash reports from similar agencies and nearby agencies were used to determine how much weight to give to ZIP codes as a function of distance. Two different types of weighing functions were used, each of which appeared to work better for certain types of agencies (see **Figure C.4** and **Section C.6.7**). The first type of weighting function is called the log-linear model. It is shown below before and after log-transformation:

$$\begin{aligned} weight &= e^{decay \times distance} \\ \ln(weight) &= decay \times distance. \end{aligned}$$

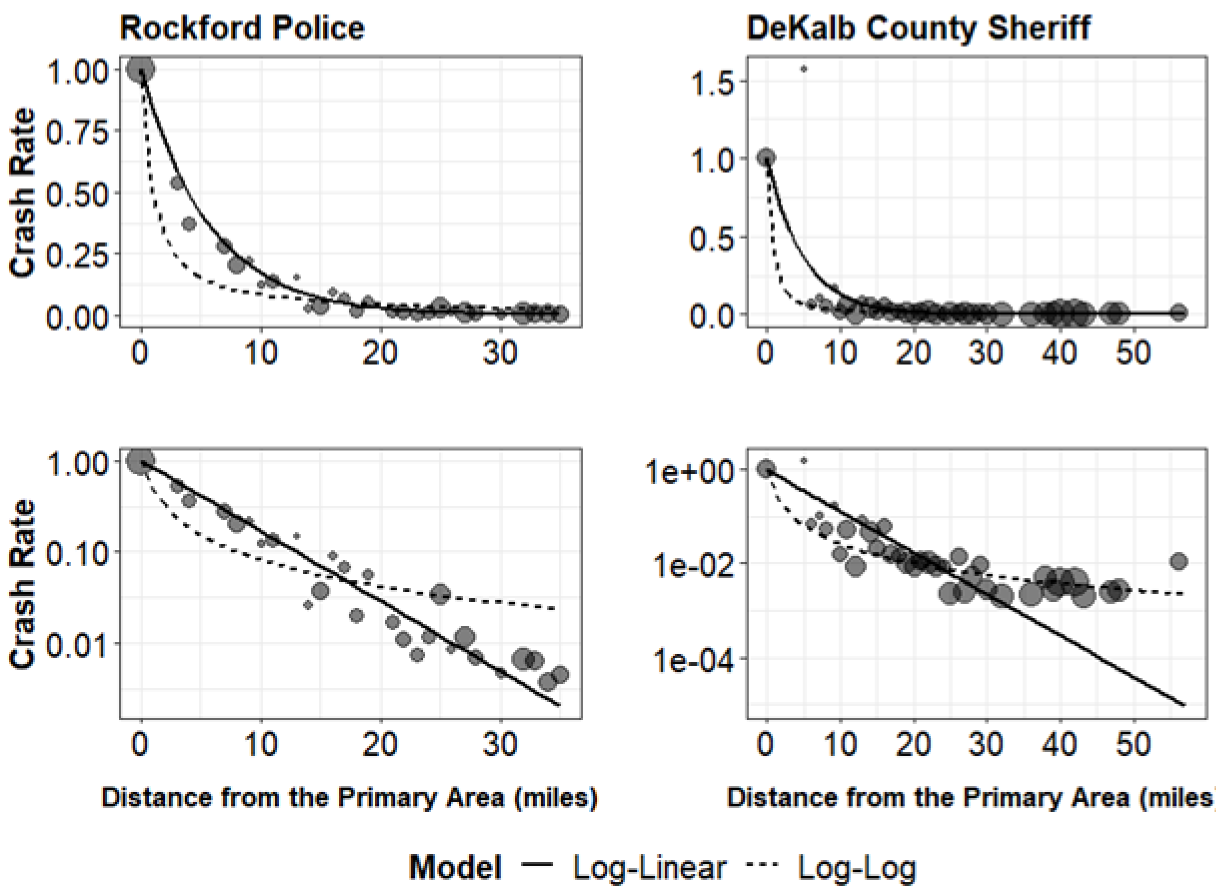
When distance = 0, the weight = 1. The decay parameter, always less than 0, controls how quickly the weight decreases with increasing distance. It is called the log-linear model because the log of the weight changes linearly with distance. This is also called an exponential decay model.

The second formula is called the log-log model, shown again before and after log-transformation:

$$\begin{aligned} weight &= (1 + distance)^{decay} \\ \ln(\text{weight}) &= decay \times \ln(1 + distance). \end{aligned}$$

The distance is in units of miles. As with the log-linear formula, when distance = 0, the weight = 1. The decay parameter is also always less than 0 and controls how quickly weight decreases with increasing distance. It is called the log-log model because the log of the weight changes logarithmically with distance. Qualitatively, the two functions are similar but result in somewhat different weight-distance curves. The log-log model results in a relatively rapid decrease in weight for short distances away from the agency, but this rate of decrease slows down with increasing distances and results in a longer "tail," which allows much farther away locations to be included. By contrast, the log-linear model has a slower initial rate of decrease, but that rate is the same for shorter and longer distances away from the agency. Relative to the log-log model, the log-linear model will give less weight to far away locations. **Figure C.4** shows examples of these two formulas for two different agencies.

Figure C.4. Normalized crash rates in each ZIP code for two agencies. **The left panels are for Rockford Police and the right panels are for DeKalb County Sheriff. Each point represents the crash rate in a single ZIP code (number of crashes divided by the number of drivers), with the crash rate normalized to be equal to 1 for ZIP codes within the primary area of the agency (where distance = 0). Larger points indicate a larger driver population in the ZIP code, normalized for each agency separately. The top and bottom rows show the same data, but the bottom row uses a logarithmic scale for the crash rate (y-axis). All panels show how the log-linear model (solid curve) and log-log model (dashed curve) fit the crash data. As can be seen, the log-linear model fits Rockford crash rates better and the log-log fits DeKalb County crash rates better, i.e., the crash rate data points follow one of the curves more closely than the other curve. Note, data shown are from the 2021 stops report.**



C.6.7. Training models for ZIP-code weight as a function of distance from an agency

To generate distance-based benchmarks, crash reports from similar agencies and nearby agencies were used to determine how much weight to give to ZIP codes as a function of distance from the agency. The only types of agencies that needed distance-based benchmarks were city police agencies and county sheriff agencies, as all other county-level and state-level agencies had sufficient crash reports available for crash-based benchmarks.

This section is very technical. As a high-level summary, this section describes 1) how the decay rate parameters needed to calculate ZIP-code weights were first estimated from the crash data (see **Figure C.4**), 2) how these decay rates were related to driver density and degree of urbanization, and 3) how these factors were used to predict an appropriate decay rate for agencies without sufficient crash data. These decay rates were used to calculate the ZIP-code weights used in the section below to calculate distance-based benchmarks. The rest of this section can be skipped without impacting the understanding of subsequent sections.

For each city police agency and county sheriff agency with a crash-based benchmark, both the log-linear and log-log models were fit to their crash data to estimate the corresponding decay parameters for those agencies. The unit of analysis was the ZIP code, with the number of crashes and number of drivers per ZIP code. Poisson regression was used to fit the crash rate per 1000 drivers based on the log-linear and log-log models. For each agency, between 95-98% of the crashes closest to the city or county were included in the analysis, to avoid excessive influence from a small number of drivers from very far away locations. **Figure C.4** shows how well the log-linear and log-log models fit the crash data for two different agencies.

For each agency, Akaike's information criterion (AIC) was calculated for the log-linear and log-log models. AIC is a standard metric for comparing how well two or more models fit the data. Based on the AIC, the log-linear model fits the crash data better than the log-log model for most city police agencies. In contrast, the log-log model fits the crash data better than the log-linear model most county sheriff agencies. Because of this, the log-linear model was selected to use for city police agencies and the log-log model was selected to use for county sheriff agencies when calculating distance-based benchmarks.

After selecting the type of model (log-linear or log-log), additional models were needed to predict the decay rate needed for an agency that did not have sufficient crash data to estimate the decay rate directly. The model training sets consisted of the city police agencies and county sheriff agencies with crash-based benchmarks. The outcome variable to predict was the decay rate estimated from crash data. Two factors from the 2010 decennial census were used as potential predictors: the density of drivers (drivers per square mile) of the city or county and the percentage of the county population located in urban areas (percent urban). These factors were not yet available from the 2020 census. Non-linear transformations of driver density and percent urban based on restricted cubic splines (RCS) with three knots were assessed. Knots were selected at the 10^{th}, 50^{th}, and 90^{th} percentiles. Predictors and their transformations were included if they increased the apparent adjusted R-squared statistic and their corresponding regression coefficients were statistically significantly different from zero ($p < 0.05$). The final decay rate prediction models are shown in **Table C.4**.

Table C.4. Linear regression models to predict the weight decay rate for the log-linear model (used for city police agencies) and log-log model (used for county sheriff agencies). The model training sets consisted of the city police agencies and county sheriff agencies with crash-based benchmarks.

Variable	RCS Transformation*	City Police (log-linear) β	SE	P-value	County Sheriff (log-log) β	SE	P-value
Intercept		-0.040	0.070	0.57	-1.008	0.088	<0.001
Log2(Driver density (drivers per sq. mile))	Linear	-0.014	0.007	0.031			
	Non-linear	-0.027	0.010	0.005			
Percent urban (%)	Linear	0.013	0.045	0.77	-0.383	0.204	0.067
	Non-linear	-0.240	0.053	<0.001	1.029	0.257	<0.001

β = regression coefficient, corresponding to the change in the predicted decay rate per 1-unit change in predictor; SE = standard error; RCS = restricted cubic spline.

*Any predictor with an RCS transformation (based on three knots) has two coefficients, one corresponding to the linear portion and the other corresponding to the non-linear deviation off of that linear portion. The knots used for log2[driver density] were 9.37, 10.5, and 11.8 for the city police model. The knots used for percent urban were 53.9%, 95.8%, and 99.96% for the city police model and 28.1%, 55.4%, and 89.7% for the county sheriff model.

The city police decay rate model included both driver density and percent urban with non-linear transformations. The regression coefficients were all negative, indicating that the predicted decay rate decreases (gets more negative) with increasing driver density and percent urban, and that this relationship gets stronger for highly dense and highly urban areas. Decay rates which are more negative imply the weight given to surrounding ZIP codes decreases faster with increasing distance. The final R-squared estimate for this model, calculated using leave-one-out cross-validation, was 48%.

The county sheriff decay rate model included only percent urban because driver density did not significantly improve the model fit (p = 0.18). Percent urban also had a non-linear transformation, with negative and positive coefficients for the linear and non-linear portions, respectively. This indicates that the decay rate was the largest (least negative) for areas with the lowest driver density and the highest driver density. Decay rates which are less negative imply the weight given to surrounding ZIP codes decreases slower with increasing distance. The final R-squared estimate for this model, calculated using leave-one-out cross-validation, was 43%.

These decay rate models, trained using crash data, were used to predict the decay rate for the ZIP code weights needed for distance-based benchmarks, described next.

C.6.8. Distance-based benchmarks

The last few sections have described how the distance between the primary area of an agency and another ZIP code was calculated, how ZIP codes were weighted as a function of their distance from an agency, and how the weighting function was individualized per agency by considering the driver density, percent urban of the county, and nearby agencies. This section describes how the weighting function was used to combine ZIP codes for distance-based benchmarks.

For a given agency, the following steps were performed to determine the weighting function, or function that assigns a weight to a ZIP code based on its distance from the agency:

1) The type of weighting function was determined using the agency type (see **Section C.6.6**)
    a. The log-linear model was used for city police agencies.
    b. The log-log model was used for county sheriff agencies as well as other county-level and state-level agencies.
2) The decay rate parameter was then determined (see **Sections C.6.6** and **C.6.7**)
    a. If the agency had sufficient crash data (see **Section C.6.1**), the decay rate was estimated directly from the crash data (see **Section C.6.7**).
    b. Otherwise, the decay rate was predicted using the driver density, percent urban, and nearby agencies using one of the models in **Table C.4**, according to step 1) above.

Once the weighting function was determined for a given agency, then all ZIP codes within 400 miles of the agency's primary area were given a weight using that function. The weight was always 1 for the primary area (e.g., city for a city police agency or county for a county sheriff agency) and decreases with increasing distance away from the agency's primary area. The weight was most often essentially zero much closer than 400 miles away, but that depends on the decay rate selected in step 2 above.

After the weights have been assigned to all ZIP codes, the benchmark population was calculated using the driver population counts estimated in **Section C.5**:

$$\begin{aligned} Drivers_{Race} &= \sum_{ZIP} Weight_{ZIP} \times Drivers_{Race,ZIP} \\ Drivers_{Total} &= \sum_{Race} Drivers_{Race}. \end{aligned}$$

Note that the absolute number of drivers was calculated for each race. The percentage of each race in the benchmark population was thus calculated as

$$100\% \times Drivers_{Race}/Drivers_{Total}.$$

Another implication of these calculations based on absolute numbers of drivers is that the benchmarks are also effectively weighted by population size of each ZIP code. For example, consider a hypothetical agency for a small city that also has a large neighboring city. The weight for the smaller city's ZIP codes would be 1, as always. The weight for the neighboring city's ZIP codes could be 0.5 on average, indicating those ZIP codes are given half the weight in the calculations above. But if the neighboring city is 5 times larger than the smaller city, after weighting by 0.5, the weighted driver counts from that city would still be 2.5 times larger than the driver counts for the smaller city, and the race percentages would effectively be more weighted towards the larger city than the smaller city. This happened because while a single random resident of the larger city is less likely to be driving in the smaller city than a single random resident of the smaller city, the larger city had so many more residents total than the smaller city that they may still constitute a majority of the drivers within the smaller city.

C.6.9. Comparison of crash-based and distance-based benchmarks

Crash-based benchmarks are expected to be more accurate representations of the driving population for a given agency than the corresponding distance-based benchmarks, as crash-based benchmarks are based directly on empirical data about drivers in the area. Distance-based benchmarks are only used for agencies where an insufficient number of crash reports was available (see **Section C.6.1**), though over time more crash data will become available and usable for benchmarks. However, the distance-based benchmarks were designed to approximate the patterns observed in the crash data, such as the decreasing relationship between crash rates and distance from the agency.

One advantage of the crash-based benchmarks is that they do not assume a particular type of model for weighting the ZIP codes. Rather, the proportion of crashes of not-at-fault drivers from the ZIP code are used for each weight. Not being constrained by a model allows crash-based benchmarks to capture complex driving patterns, such as if many drivers from a ZIP code on the west side of a city tend to drive through the city while disproportionately fewer drivers from a ZIP code on the east side of a city drive through the city, despite each ZIP code being the same distance from the city. That type of pattern could be apparent in the crash data of the city in the middle, which would have a disproportionate number of crashes from the western ZIP code compared to the eastern ZIP code. Distance-based benchmarks on the other hand, lacking the rich empirical data on drivers in the area, instead rely on a model that depends primarily on the distance from the agency, which imposes radial symmetry in the ZIP code weights around the agency.

Despite these limitations of the distance-based benchmarks, they do appear to be reasonable approximations to the crash-based benchmarks, as summarized below, based on data from the 2021 stops report. This assessment was based on agencies with sufficient crash data, where both crash-based and distance-based benchmarks could be calculated as described above. The percentage of each race was calculated for each benchmark for comparison.

Overall, the correlation coefficients (r) between the crash-based and distance-based race percentage ranged from 0.95 (Black or African American) to 0.97 (Asian), except for American Indian or Alaska Native (r = 0.89) and Native Hawaiian or Other Pacific Islander (r = 0.71). On average, distance-based benchmarks had only a 1% lower White percentage (absolute difference) than crash-based benchmarks, and only a 0.5% higher percentage for Blacks and Asians, with even smaller differences for the other groups. The root mean squared difference in the race percentage between the two benchmarks (a measure of the total error in either direction) was 5% for White drivers, 4% for Black drivers, 3% for Hispanic drivers, 1% for Asian drivers, and 0.05% for American Indian or Alaska Native and Native Hawaiian or Other Pacific Islander drivers. This shows that the methodology for distance-based benchmarks can achieve similar benchmarks as the crash-based methodology, without much bias in either direction (over- or underrepresenting any particular race) relative to the crash-based benchmarks, which is assumed to be the more accurate method.

C.6.10. Other benchmarks

Starting in the 2022 stops report, some changes were made in how the benchmark for Round Lake Park Police Department was calculated. Round Lake Park is a village in Lake County with a total population under 8,000. The village boundaries intersect with two ZIP codes, 60073 and 60030. Both of these ZIP codes include multiple cities, villages or towns and are much bigger than Round Lake Park itself. Furthermore, the village boundaries include an area that is outside of the traffic stop jurisdiction of the police department and has different demographics from the rest of Round Lake Park. To address this, we made the following modifications to the general benchmark methodology described above:

1) The Round Lake Park traffic jurisdiction area was approximated using a smaller geographic unit, called a block group.

2) All ZIP codes within 15 miles of Round Lake Park were replaced with block groups.

3) Population statistics for block groups were extracted from the 2020 decennial census and adjusted as described above for ZIP-code-based population statistics.

4) Distance-based benchmarks were calculated as described above except distances were measured between block groups for the region within 15 miles of Round Lake Park.

Block groups are standard U.S. census geographic units that are smaller than census tracts and ZIP codes. The six block groups used to approximate the area of Round Lake Park Police Department's traffic stop jurisdiction, as identified by the last 5 digits, were: 14043, 14042, 14022, 14041, 14032, and 14044. The common prefix for these block groups was 1500000US1709786 (e.g., 1500000US170978614043 is the complete code identifying the first block group listed). Population statistics for the block groups were extracted from the 2020 decennial census instead of the 2017-2021 ACS dataset to achieve better estimates of demographics within the small areas represented by the block groups.

In this case, block groups were able to provide a better approximation to the smaller jurisdiction of Round Lake Park Police Department than ZIP codes. This block-group-based approach may be used in the future for other smaller agencies.

C.7. Methodological Differences with Past Reports for Stops in 2019-2020

While the methodology used for this report and the 2021 stops report has some similarities with the 2019-2020 stops reports, there are a number of important differences. These must be considered when comparing this report to past reports for stops from 2019-2020. The methodology used in this report is the same as the report of 2021 stops except where noted above. The 2019 and 2020 stops reports also describe differences with their methodologies compared with reports from 2004-2018.

The biggest difference is that in this report, ZIP-code-level population counts were combined in a weighted fashion to generate benchmarks while the 2019-2020 stops reports (and the 2004-2018 stops reports) used city-, county-, or state-level population counts. The weights given to each ZIP code in the current benchmarks were determined using Illinois traffic crash reports (see **Section C.6**.), so they are able to better reflect actual driving patterns. The previous benchmarks most often used county-level population counts to include both the agency jurisdiction as well as the surrounding area. The new approach utilizing crash reports allows the benchmarks to be more individualized to each agency and incorporate both nearby populations and populations farther away, without being constrained by city, county, or state lines. The new benchmarks are expected to be a more accurate representation of the driving population within each agency's jurisdiction because the crash reports provide empirical data on the drivers in the area.

Another important difference is that, in this report and the 2021 stops report, individuals who reported multiple races on the census/ACS were reallocated into single race groups, while in past reports (2004-2020 stops), those with multiple races were excluded from benchmark calculations. In past years, the multiple race group was less than 2% of Illinois's population. Now this group is 2.4% of Illinois's population based on the 2020 5Y ACS and 3.3% of the population based on the 2021 decennial census. Furthermore, while the absolute percentage is still relatively low, the multiple race group disproportionately includes residents who identify as American Indian/Alaska Native or Native Hawaiian/Other Pacific Islander as one of their races. After reallocating the multiple races as described in **Section C.3.**, the number of American Indian or Alaska Native residents of Illinois (based on the 2021 5Y ACS) increased from 10,357 (0.1% of the population) to 36,630 (0.3% of the population) and the number of Native Hawaiian or Other Pacific Islander increased from 3,048 (0.02% of the population) to 7,227 (0.06% of the population). These groups are now better represented in the benchmarks than in past years (2004-2020 stops reports), which should lead to better estimates of their stop rates.

C.8. Limitations

While the current benchmarks which utilize traffic crash reports improve upon benchmarks from prior years (2020 stops and earlier), there remain limitations to consider while interpreting the results. The not-at-fault drivers in two vehicle crashes are intended to be representative of the driving population, but that may not be the case for a variety of reasons[16,17]. For example, while the potential for traffic accidents tends to increase with increased driving frequency, this may not be a linear relationship and may be affected by other factors including time of day, ambient light, travel speed, and type of roadway. Furthermore, driver race was not collected as part of the crash report, but the race distribution was inferred from the driver's ZIP code and ZIP-code-level population counts from the ACS/census. In particular, this means that drivers traveling from a given ZIP code are assumed to have the same racial distribution as the residents of that ZIP code, which may not be accurate. As can be seen in **Figure C.3**, more crash report data are available in urban areas, so the observed travel patterns may be less applicable to the benchmarks of more rural areas. We used driver density and degree of urbanization as factors when calculating benchmarks to mitigate this issue to some degree.

Another limitation is that ZIP-code-level demographics may be less accurate for small localities that do not align well with the ZIP code boundaries, and where there is substantial variation in racial

[16] Withrow BL and Williams H. Proposing a benchmark based on vehicle collision data in racial profiling research. *Criminal Justice Review*. 2015;40(4):449-469.

[17] Alpert GP, Smith MR, Dunham RG. Towards a better benchmark: Assessing the utility of not-at-fault traffic crash data in racial profiling research. *Justice Research and Policy*. 2004;6(1):43-69.

distributions between neighboring areas sharing the same ZIP code. In addition, while we adjust population statistics to reflect the number of licensed drivers, this misses drivers who drive illegally without a license or overcounts individuals who no longer drive because of a suspended license or another reason and whose license has not expired.

Despite these limitations, the benchmarking method we have used has a number of strengths. Traffic crash reports, while likely not exactly representing the driving population, improve upon the common approach of relying on local resident populations counted by the census or ACS[18,19]. Furthermore, there are close to 1,000 law enforcement agencies in Illinois, each with their unique situation. The combination of traffic crash reports and ZIP-code-level ACS data provides detailed and relatively contemporary data in a uniform fashion across the state. Our methodology is able to use this data in a systematic and consistent way across a large number of agencies while alternative methods would require a tremendous amount of resources to acquire specialized data to construct a customized benchmark for each agency. New Illinois traffic crash data and ACS is released annually, so the underlying data for all agencies is able to remain relatively current and reflect demographic composition. In addition, for smaller agencies with fewer crash reports per year, over time, more years of crash data will be combined to increase the number of benchmarks that can be based directly on crash reports (crash-based benchmarks) rather than indirectly by inferring the traffic pattern based on similar agencies (distance-based benchmarks).

Besides the general limitations of the methodology described above, there are some other important limitations to consider when interpreting the benchmarks and stop rate ratios. Most importantly, the benchmarks are based on census or ACS tabulations of race, which are provided by the respondent. Illinois stop data used race as recorded by the police officer, which may differ from what the individual being stopped would report. Therefore, some differences between the racial distribution of the stop data and the corresponding racial distribution of the benchmark may be due to racial misclassification.

Another challenge is that the census and ACS collect race in a different way than defined by the Illinois state law for the stops study, so some adjustments had to be made for compatibility, as described in Section **C.3**, above. This approach may have induced some differences in racial distributions between the stops (with race assigned by the officer) and corresponding benchmarks (based on self-assigned race). Lastly, the ACS data is based on a survey which takes a random sample of the population. There is some error in survey estimates due simply to sampling variability. In particular, this can impact estimates of population counts of smaller groups. For example, the number of American Indian or Alaska Native and Native Hawaiian or Other Pacific Islanders were relatively small in a number of regions, so these counts may be more uncertain for some jurisdictions. Improvements in counting those groups were made starting with the 2021 stops report, but the equal fractions fractional allocation method that was used for handling "multiple races" is only a pragmatic approximation that could still differ from both self-identified and officer-identified primary race. Thus, while the study has strengths, there are some limitations as well. Thus, the narrative in this report emphasizes that if a ratio comparing a racial group

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[18] Fridell, L. A. (2004). By the numbers: A guide for analyzing race data from vehicle stops. Washington, DC: Police Executive Research Forum. https://www.ncjrs.gov/App/Publications/abstract.aspx?ID=209827 . Last accessed 5/25/21.

[19] Alpert G.P., Dunham R.G., Smith M.R. (2007). Investigating Racial Profiling by the Miami-Dade Police Department: A Multimethod Approach. *Criminology & Public Policy*;6(1):25-56. https://www.ncjrs.gov/App/Publications/abstract.aspx?ID=239772 . Last accessed 5/25/21.

to Whites differs substantially from 1.0 (that is, differs from racial equality) that may be the basis for further inquiry but does not prove that there is racial profiling.

Table C.5. Geographic region or regions used in the Traffic Study for each agency that made stops and completely or partially reported them. All benchmarks include the population within the primary area as well as populations from the surrounding area. Places outside of the primary area are given a lower weight that decreases with distance. The "% within Primary Area" indicates how much of the benchmark population comes from ZIP codes within the primary area. The "Benchmark Radius" indicates how far the benchmark extends beyond the primary area to capture at least 95% of the included population, weighted by distance. Populations beyond that radius are also included but with much lower weight that adds up to <5% of the final benchmark population. See Section C.6 for more detail on how benchmarks were calculated from ZIP-code-level population counts.

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Abingdon Police	13462	Distance-based	N/A	City: Abingdon	41.7%	21
Adams County Sheriff	13054	Distance-based	N/A	County: Adams	81.4%	221
Addison Police	13245	Crash-based	572	City: Addison	33.4%	27
Albany Police	13929	Distance-based	N/A	City: Albany	3.7%	26
Albion Police	13284	Distance-based	N/A	City: Albion	44.4%	33
Aledo Police	13664	Crash-based	52	City: Aledo	57.7%	25
Alexander County Sheriff	13059	Distance-based	N/A	County: Alexander	45.6%	337
Alexis Police	13663	Distance-based	N/A	City: Alexis	13.8%	32
Algonquin Police	13566	Crash-based	546	City: Algonquin	24.3%	31
Alpha Police	13367	Distance-based	N/A	City: Alpha	11.6%	26
Alsip Police	13213	Crash-based	781	City: Alsip	17.2%	400
Altamont Police	13288	Distance-based	N/A	City: Altamont	40.8%	24
Alton and Southern Railway Police	14143	Crash-based	190	City: East St. Louis	47.6%	31
Alton Police	13626	Crash-based	976	City: Alton	49.6%	35
Amboy Police	13528	Distance-based	N/A	City: Amboy	22.6%	43
Anna Police	13883	Crash-based	209	City: Anna	38.6%	89
Annawan Police	13366	Distance-based	N/A	City: Annawan	8.5%	38

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Antioch Police	13463	Distance-based	N/A	City: Antioch	36.8%	17
Arcola Police	13243	Distance-based	N/A	City: Arcola	34.7%	30
Arlington Heights Police	13212	Crash-based	629	City: Arlington Heights	31.7%	27
Armington Police	13878	Distance-based	N/A	City: Armington	5.2%	28
Arthur Police	13242	Distance-based	N/A	City: Arthur	38.3%	30
Ashland Police	13098	Distance-based	N/A	City: Ashland	18.2%	27
Assumption Police	13120	Distance-based	N/A	City: Assumption	17.9%	35
Athens Police	13656	Distance-based	N/A	City: Athens	19.3%	22
Atkinson Police	13365	Distance-based	N/A	City: Atkinson	11.0%	34
Auburn Police	13829	Distance-based	N/A	City: Auburn	28.4%	18
Aurora Police	13413	Crash-based	2517	City: Aurora	58.5%	28
Avon Police	13324	Distance-based	N/A	City: Avon	28.2%	30
Bannockburn Police	13464	Crash-based	60	City: Bannockburn	7.9%	266
Barrington Hills Police	13466	Crash-based	384	City: Barrington Hills	22.9%	30
Barrington Police	13465	Crash-based	707	City: Barrington	31.2%	31
Barry Police	13725	Distance-based	N/A	City: Barry	34.4%	27
Bartlett Police	13211	Crash-based	560	City: Bartlett	26.4%	28
Bartonville Police	13712	Crash-based	136	City: Bartonville	35.3%	39
Batavia Police	13414	Crash-based	452	City: Batavia	30.2%	32
Beardstown Police	13097	Crash-based	97	City: Beardstown	64.9%	79
Beckemeyer Police	13135	Distance-based	N/A	City: Beckemeyer	7.2%	32
Bedford Park Police	13210	Crash-based	671	City: Bedford Park	1.3%	102
Beecher Police	13956	Distance-based	N/A	City: Beecher	21.7%	22
Belleville Police	13795	Crash-based	938	City: Belleville	61.9%	22
Bellwood Police	13209	Crash-based	538	City: Bellwood	28.3%	31

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Belvidere Police	13069	Distance-based	N/A	City: Belvidere	50.1%	21
Bensenville Police	13247	Crash-based	630	City: Bensenville	20.9%	29
Benton Police	13311	Distance-based	N/A	City: Benton	49.7%	23
Berkeley Police	13208	Crash-based	90	City: Berkeley	26.7%	25
Berwyn Police	13207	Crash-based	1276	City: Berwyn	36.5%	21
Bethalto Police	13625	Crash-based	247	City: Bethalto	41.7%	31
Bethany Police	13695	Distance-based	N/A	City: Bethany	17.2%	29
Bloomingdale Police	13248	Crash-based	558	City: Bloomingdale	16.0%	23
Bloomington Police	13581	Crash-based	1717	City: Bloomington	59.7%	101
Blue Island Police	13206	Crash-based	286	City: Blue Island	28.6%	23
Blue Mound Police	13590	Distance-based	N/A	City: Blue Mound	16.0%	26
Bluffs Police	13836	Distance-based	N/A	City: Bluffs	19.4%	31
Bolingbrook Police	13955	Crash-based	1132	City: Bolingbrook	43.1%	35
Bond County Sheriff	13067	Crash-based	66	County: Bond	66.7%	52
Boone County Sheriff	13068	Crash-based	162	County: Boone	69.8%	42
Bourbonnais Police	13447	Crash-based	388	City: Bourbonnais	45.4%	42
Bradley Police	13446	Crash-based	682	City: Bradley	21.9%	45
Bradley University Police	13711	Crash-based	2833	City: Peoria	67.9%	37
Braidwood Police	13954	Distance-based	N/A	City: Braidwood	29.7%	24
Breese Police	13134	Crash-based	86	City: Breese	51.2%	27
Bridgeport Police	13522	Distance-based	N/A	City: Bridgeport	30.8%	27
Bridgeview Police	13204	Crash-based	811	City: Bridgeview	11.7%	44
Brighton Police	13592	Distance-based	N/A	City: Brighton	14.4%	31
Broadview Police	14006	Crash-based	422	City: Broadview	15.5%	34
Brookfield Police	14065	Crash-based	393	City: Brookfield	31.8%	27
Brooklyn Police	13794	Distance-based	N/A	City: Brooklyn	0.3%	16
Brown County Sheriff	13071	Distance-based	N/A	County: Brown	43.9%	336

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Buda Police	13084	Distance-based	N/A	City: Buda	9.6%	41
Buffalo Grove Police	13467	Crash-based	662	City: Buffalo Grove	25.6%	31
Bull Valley Police	13565	Distance-based	N/A	City: Bull Valley	31.0%	27
Bunker Hill Police	13602	Distance-based	N/A	City: Bunker Hill	12.0%	34
Burbank Police	13200	Crash-based	764	City: Burbank	33.0%	20
Bureau County Sheriff	13083	Crash-based	177	County: Bureau	75.8%	48
Bureau Police	14136	Distance-based	N/A	City: Bureau	1.1%	47
Burnham Police	13199	Distance-based	N/A	City: Burnham	5.4%	15
Burr Ridge Police	13249	Crash-based	221	City: Burr Ridge	19.7%	32
Bushnell Police	13544	Distance-based	N/A	City: Bushnell	35.9%	28
Byron Police	13703	Distance-based	N/A	City: Byron	18.6%	29
Cahokia Heights Police	13793	Crash-based	432	City: Cahokia Heights	50.1%	44
Calhoun County Sheriff	13086	Distance-based	N/A	County: Calhoun	11.3%	332
Calumet Park Police	13197	Crash-based	314	City: Calumet Park	19.2%	54
Cambria Police	13970	Distance-based	N/A	City: Cambria	1.2%	19
Cambridge Police	13364	Distance-based	N/A	City: Cambridge	19.5%	29
Camp Point Police	13055	Distance-based	N/A	City: Camp Point	30.2%	30
Campton Hills Police	14114	Distance-based	N/A	City: Campton Hills	33.1%	18
Canton Police	13321	Distance-based	N/A	City: Canton	70.0%	26
Carbondale Police	13387	Distance-based	N/A	City: Carbondale	61.3%	19
Carlinville Police	13601	Crash-based	103	City: Carlinville	64.4%	59
Carlyle Police	13133	Distance-based	N/A	City: Carlyle	42.8%	35
Carmi Police	13919	Crash-based	133	City: Carmi	60.4%	43
Carol Stream Police	13250	Crash-based	525	City: Carol Stream	32.4%	24

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Carpentersville Police	13415	Distance-based	N/A	City: Carpentersville	35.8%	14
Carrier Mills Police	13801	Distance-based	N/A	City: Carrier Mills	22.5%	26
Carroll County Sheriff	13092	Distance-based	N/A	County: Carroll	45.2%	304
Carrollton Police	13334	Distance-based	N/A	City: Carrollton	40.5%	41
Carterville Police	13969	Distance-based	N/A	City: Carterville	28.8%	18
Carthage Police	13348	Distance-based	N/A	City: Carthage	50.6%	31
Cary Police	13564	Crash-based	296	City: Cary	50.8%	25
Casey Police	13126	Distance-based	N/A	City: Casey	45.1%	32
Caseyville Police	13792	Crash-based	78	City: Caseyville	20.5%	38
Cass County Sheriff	13096	Crash-based	62	County: Cass	67.7%	52
Catlin Police	13898	Distance-based	N/A	City: Catlin	15.2%	24
Cedar Point Police	13517	Distance-based	N/A	City: Cedar Point	1.0%	43
Cedarville Police	13854	Distance-based	N/A	City: Cedarville	3.6%	32
Central City Police	13634	Distance-based	N/A	City: Central City	80.4%	18
Centralia Police	13633	Distance-based	N/A	City: Centralia	76.4%	20
Champaign County Sheriff	13112	Crash-based	451	County: Champaign	78.5%	56
Champaign Police	13111	Crash-based	1410	City: Champaign	53.9%	105
Channahon Police	13953	Crash-based	108	City: Channahon	43.1%	40
Charleston Police	13143	Crash-based	430	City: Charleston	58.8%	156
Chatham Police	13828	Crash-based	169	City: Chatham	53.3%	18
Chenoa Police	13580	Distance-based	N/A	City: Chenoa	29.9%	27
Cherry Police	13082	Distance-based	N/A	City: Cherry	2.7%	31
Cherry Valley Police	13981	Crash-based	162	City: Cherry Valley	13.0%	37
Chester Police	13751	Distance-based	N/A	City: Chester	62.3%	35

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Chicago Metra Police	13195	Crash-based	98038	County: Cook, Lake, McHenry, Kane, DuPage, Kendall, Will	94.7%	5
Chicago Police	13194	Crash-based	43067	City: Chicago	71.7%	29
Chicago Police (1st District - Central)	13194.01	Crash-based	2255	City: Chicago 1st District (Central)	10.7%	193
Chicago Police (2nd District - Wentworth)	13194.02	Crash-based	1700	City: Chicago 2nd District (Wentworth)	30.4%	39
Chicago Police (3rd District - Grand Crossing)	13194.03	Crash-based	1733	City: Chicago 3rd District (Grand Crossing)	24.9%	36
Chicago Police (4th District - South Chicago)	13194.04	Crash-based	2000	City: Chicago 4th District (South Chicago)	48.6%	32
Chicago Police (5th District - Calumet)	13194.05	Crash-based	2136	City: Chicago 5th District (Calumet)	37.5%	31
Chicago Police (6th District - Gresham)	13194.06	Crash-based	2267	City: Chicago 6th District (Gresham)	35.8%	36
Chicago Police (7th District - Englewood)	13194.07	Crash-based	1706	City: Chicago 7th District (Englewood)	24.8%	31
Chicago Police (8th District - Chicago Lawn)	13194.08	Crash-based	3660	City: Chicago 8th District (Chicago Lawn)	50.4%	24
Chicago Police (9th District - Deering)	13194.09	Crash-based	2267	City: Chicago 9th District (Deering)	40.1%	30
Chicago Police (10th District - Ogden)	13194.1	Crash-based	1844	City: Chicago 10th District (Ogden)	30.8%	34
Chicago Police (11th District - Harrison)	13194.11	Crash-based	2217	City: Chicago 11th District (Harrison)	28.7%	34
Chicago Police (12th District - Near West)	13194.12	Crash-based	2708	City: Chicago 12th District (Near West)	20.9%	40
Chicago Police (14th District - Shakespeare)	13194.14	Crash-based	1505	City: Chicago 14th District (Shakespeare)	22.2%	46
Chicago Police (15th District - Austin)	13194.15	Crash-based	2889	City: Chicago 15th District (Austin)	31.7%	31
Chicago Police (16th District - Jefferson Park)	13194.16	Crash-based	2659	City: Chicago 16th District (Jefferson Park)	42.3%	29
Chicago Police (17th District - Albany Park)	13194.17	Crash-based	1795	City: Chicago 17th District (Albany Park)	45.5%	31
Chicago Police (18th District - Near North)	13194.18	Crash-based	2003	City: Chicago 18th District (Near North)	13.0%	225
Chicago Police (19th District - Town Hall)	13194.19	Crash-based	1719	City: Chicago 19th District (Town Hall)	29.9%	121

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Chicago Police (20th District - Lincoln)	13194.2	Crash-based	1448	City: Chicago 20th District (Lincoln)	39.3%	35
Chicago Police (22nd District - Morgan Park)	13194.22	Crash-based	1893	City: Chicago 22nd District (Morgan Park)	34.4%	24
Chicago Police (24th District - Rogers Park)	13194.24	Crash-based	2044	City: Chicago 24th District (Rogers Park)	45.7%	34
Chicago Police (25th District - Grand Central)	13194.25	Crash-based	2401	City: Chicago 25th District (Grand Central)	48.0%	23
Chicago Ridge Police	13193	Crash-based	153	City: Chicago Ridge	16.0%	27
Chillicothe Police	13710	Distance-based	N/A	City: Chillicothe	39.4%	18
Chrisman Police	13281	Distance-based	N/A	City: Chrisman	34.6%	29
Christian County Sheriff	13119	Crash-based	161	County: Christian	69.8%	62
Christopher Police	13309	Distance-based	N/A	City: Christopher	12.7%	21
Cicero Police	13191	Crash-based	2337	City: Cicero	41.3%	25
Clarendon Hills Police	13251	Crash-based	65	City: Clarendon Hills	20.0%	42
Clifton Police	13374	Distance-based	N/A	City: Clifton	19.5%	39
Clinton County Sheriff	13132	Crash-based	258	County: Clinton	78.4%	36
Clinton Police	13237	Crash-based	152	City: Clinton	64.3%	72
Coal City Police	13339	Crash-based	85	City: Coal City	55.3%	30
Coal Valley Police	13766	Distance-based	N/A	City: Coal Valley	10.3%	16
Coffeen Police	13679	Distance-based	N/A	City: Coffeen	7.5%	43
Colchester Police	13543	Distance-based	N/A	City: Colchester	32.4%	31
Coles County Sheriff	13142	Crash-based	199	County: Coles	79.5%	30
Colfax Police	13579	Distance-based	N/A	City: Colfax	20.7%	24
College of DuPage Police	13252	Crash-based	799	City: Glen Ellyn	28.3%	23
College of Lake County Police	13468	Crash-based	1597	City: Grayslake, Waukegan, Vernon Hills	60.8%	18
Collinsville Police	13624	Crash-based	528	City: Collinsville	50.0%	32
Colona Police	13363	Distance-based	N/A	City: Colona	11.9%	18

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Columbia Police	13670	Crash-based	244	City: Columbia	43.4%	35
Cook County Forest Preserve Police	13189	Crash-based	69467	County: Cook	87.8%	15
Cook County Sheriff	13188	Crash-based	2580	County: Cook	79.4%	20
Cortland Police	13234	Distance-based	N/A	City: Cortland	8.0%	31
Coulterville Police	13750	Distance-based	N/A	City: Coulterville	24.8%	38
Country Club Hills Police	13187	Crash-based	465	City: Country Club Hills	27.0%	23
Countryside Police	13186	Crash-based	466	City: Countryside	23.1%	30
Cowden Police	13843	Distance-based	N/A	City: Cowden	16.6%	32
Crainville Police	13968	Distance-based	N/A	City: Crainville	28.5%	18
Crawford County Sheriff	13218	Crash-based	154	County: Crawford	74.0%	73
Crest Hill Police	13952	Crash-based	695	City: Crest Hill	19.8%	28
Crestwood Police	13185	Crash-based	755	City: Crestwood	14.2%	400
Crete Police	14000	Crash-based	169	City: Crete	35.3%	29
Creve Coeur Police	13877	Crash-based	131	City: Creve Coeur	23.7%	34
Crystal Lake Park District Police	14010	Crash-based	671	City: Crystal Lake	38.2%	37
Crystal Lake Police	13563	Crash-based	671	City: Crystal Lake	38.2%	37
CSX Transportation Railroad Police	14147	Crash-based	190	City: East St. Louis	47.6%	31
Dallas City Police	13347	Distance-based	N/A	City: Dallas City	14.1%	33
Dana Police	14151	Distance-based	N/A	City: Dana	3.5%	36
Danvers Police	13578	Distance-based	N/A	City: Danvers	9.7%	23
Danville Police	13897	Distance-based	N/A	City: Danville	84.1%	13
Darien Police	13253	Crash-based	587	City: Darien	23.9%	24
Decatur Park District Police	13589	Crash-based	1901	City: Decatur	76.2%	41
Decatur Police	13588	Crash-based	1901	City: Decatur	76.2%	41
Deer Creek Police	13876	Distance-based	N/A	City: Deer Creek	2.2%	21

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Deerfield Police	13469	Crash-based	535	City: Deerfield	25.0%	59
DeKalb County Sheriff	13223	Crash-based	647	County: DeKalb	65.8%	38
DeKalb Police	13233	Crash-based	580	City: DeKalb	59.0%	53
Delavan Police	13875	Distance-based	N/A	City: Delavan	19.4%	29
DePue Police	13081	Distance-based	N/A	City: DePue	44.9%	28
Des Plaines Police	13184	Crash-based	1303	City: Des Plaines	39.3%	26
DeSoto Police	13966	Distance-based	N/A	City: DeSoto	11.8%	20
DeWitt County Sheriff	13236	Crash-based	90	County: DeWitt	57.8%	94
Divernon Police	13825	Distance-based	N/A	City: Divernon	9.9%	20
Dixmoor Police	13183	Distance-based	N/A	City: Dixmoor	14.3%	13
Dixon Police	13526	Crash-based	404	City: Dixon	64.0%	64
Donnellson Police	13066	Distance-based	N/A	City: Donnellson	2.7%	43
Downers Grove Police	13254	Crash-based	949	City: Downers Grove	29.7%	24
Downs Police	13577	Distance-based	N/A	City: Downs	7.9%	20
Du Quoin Police	13715	Distance-based	N/A	City: Du Quoin	45.3%	28
DuPage County Forest Preserve Police	14043	Crash-based	8882	County: DuPage	66.8%	20
DuPage County Sheriff	13255	Crash-based	766	County: DuPage	71.6%	14
Dupo Police	13790	Distance-based	N/A	City: Dupo	2.4%	18
Durand Police	13980	Distance-based	N/A	City: Durand	15.5%	21
Dwight Police	13532	Distance-based	N/A	City: Dwight	35.7%	41
East Alton Police	13623	Distance-based	N/A	City: East Alton	11.3%	22
East Carondelet Police	13789	Distance-based	N/A	City: East Carondelet	1.0%	19
East Dubuque Police	13406	Distance-based	N/A	City: East Dubuque	15.0%	20
East Dundee Police	13416	Crash-based	229	City: East Dundee	12.6%	36

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
East Hazel Crest Police	13181	Distance-based	N/A	City: East Hazel Crest	7.6%	15
East Moline Police	13764	Crash-based	336	City: East Moline	37.6%	40
East Peoria Police	13874	Crash-based	590	City: East Peoria	28.9%	68
East St. Louis Park District Police	13788	Crash-based	190	City: East St. Louis	47.6%	31
Eastern Illinois University Police	13141	Crash-based	430	City: Charleston	58.8%	156
Easton Police	13647	Distance-based	N/A	City: Easton	9.6%	36
Edinburg Police	13118	Distance-based	N/A	City: Edinburg	11.5%	25
Edwards County Sheriff	13283	Distance-based	N/A	County: Edwards	18.3%	370
Edwardsville Police	13622	Crash-based	607	City: Edwardsville	38.9%	70
Effingham County Sheriff	13287	Distance-based	N/A	County: Effingham	77.9%	228
Effingham Police	13286	Crash-based	783	City: Effingham	46.0%	182
Elburn Police	13417	Distance-based	N/A	City: Elburn	19.9%	21
Elgin Community College Police	13418	Crash-based	1505	City: Elgin	60.2%	23
Elgin Police	13419	Crash-based	1505	City: Elgin	60.2%	23
Elizabeth Police	13405	Distance-based	N/A	City: Elizabeth	26.1%	34
Elizabethtown Police	13352	Distance-based	N/A	City: Elizabethtown	23.2%	41
Elk Grove Village Police	13180	Crash-based	763	City: Elk Grove Village	19.3%	36
Elmhurst Police	13256	Crash-based	635	City: Elmhurst	24.9%	34
Elmwood Park Police	13179	Crash-based	434	City: Elmwood Park	48.6%	17
Elmwood Police	13709	Distance-based	N/A	City: Elmwood	30.9%	24
Elsah Police	13397	Distance-based	N/A	City: Elsah	1.0%	28
Elwood Police	13950	Crash-based	90	City: Elwood	12.0%	400
Energy Police	13965	Distance-based	N/A	City: Energy	3.3%	19
Erie Police	13928	Distance-based	N/A	City: Erie	17.0%	28

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Essex Police	13445	Distance-based	N/A	City: Essex	3.7%	44
Eureka Police	13985	Crash-based	62	City: Eureka	52.4%	42
Evanston Police	13178	Crash-based	680	City: Evanston	42.8%	30
Evergreen Park Police	13177	Crash-based	545	City: Evergreen Park	15.1%	24
Fairbury Police	13531	Distance-based	N/A	City: Fairbury	53.2%	30
Fairfield Police	13913	Crash-based	218	City: Fairfield	63.8%	44
Fairmont City Police	13786	Distance-based	N/A	City: Fairmont City	2.2%	19
Fairmount Police	13896	Distance-based	N/A	City: Fairmount	9.8%	25
Fairview Heights Police	13785	Crash-based	682	City: Fairview Heights	21.7%	47
Fairview Police	13318	Distance-based	N/A	City: Fairview	2.6%	39
Farmer City Police	13235	Distance-based	N/A	City: Farmer City	15.6%	29
Farmington Police	13317	Distance-based	N/A	City: Farmington	21.8%	26
Fayette County Sheriff	13293	Distance-based	N/A	County: Fayette	65.6%	270
Findlay Police	13842	Distance-based	N/A	City: Findlay	11.4%	31
Fithian Police	13895	Distance-based	N/A	City: Fithian	4.9%	23
Flora Police	13127	Distance-based	N/A	City: Flora	64.4%	29
Flossmoor Police	13176	Distance-based	N/A	City: Flossmoor	7.7%	15
Fondulac Park District Police	14017	Crash-based	590	City: East Peoria	28.9%	68
Ford County Sheriff	13300	Crash-based	54	County: Ford	63.0%	50
Forest City Police	13646	Distance-based	N/A	City: Forest City	3.9%	36
Forest Park Police	13174	Crash-based	605	City: Forest Park	15.6%	30
Forest Preserve District of Will County Police	13932	Crash-based	6461	County: Will	78.4%	22
Forest View Police	13173	Crash-based	154	City: Forest View	23.1%	32

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Forreston Police	13702	Distance-based	N/A	City: Forreston	18.4%	32
Fox Lake Police	13470	Crash-based	345	City: Fox Lake	21.1%	37
Fox River Grove Police	13562	Distance-based	N/A	City: Fox River Grove	5.1%	17
Frankfort Police	13949	Crash-based	627	City: Frankfort	32.1%	27
Franklin County Sheriff	13307	Crash-based	139	County: Franklin	71.6%	49
Franklin Grove Police	13525	Distance-based	N/A	City: Franklin Grove	18.4%	31
Franklin Park Police	13172	Crash-based	546	City: Franklin Park	18.6%	29
Freeburg Police	13783	Crash-based	84	City: Freeburg	38.1%	32
Freeport Police	13852	Crash-based	329	City: Freeport	76.3%	35
Fulton County Sheriff	13316	Distance-based	N/A	County: Fulton	71.8%	233
Fulton Police	13927	Crash-based	53	City: Fulton	46.3%	42
Galena Police	13404	Crash-based	99	City: Galena	58.0%	149
Galesburg Police	13459	Crash-based	675	City: Galesburg	69.0%	49
Gallatin County Sheriff	13328	Distance-based	N/A	County: Gallatin	29.7%	355
Galva Police	13362	Distance-based	N/A	City: Galva	24.9%	36
Geneseo Police	13361	Crash-based	98	City: Geneseo	58.2%	37
Geneva Police	13421	Crash-based	525	City: Geneva	21.8%	34
Genoa Police	13232	Crash-based	64	City: Genoa	40.6%	36
Germantown Police	14026	Distance-based	N/A	City: Germantown	7.5%	36
Gibson City Police	13299	Distance-based	N/A	City: Gibson City	38.7%	32
Gifford Police	13109	Distance-based	N/A	City: Gifford	14.9%	22
Gilberts Police	13422	Distance-based	N/A	City: Gilberts	8.2%	20
Gillespie Police	13599	Distance-based	N/A	City: Gillespie	28.9%	33
Girard Police	13598	Distance-based	N/A	City: Girard	34.2%	28
Glasford Police	13708	Distance-based	N/A	City: Glasford	11.1%	20

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Glen Carbon Police	13621	Distance-based	N/A	City: Glen Carbon	17.2%	21
Glen Ellyn Police	13258	Crash-based	799	City: Glen Ellyn	28.3%	23
Glencoe Dept. of Public Safety	13171	Distance-based	N/A	City: Glencoe	5.7%	16
Glendale Heights Police	13259	Crash-based	582	City: Glendale Heights	38.4%	22
Glenview Police	13170	Crash-based	880	City: Glenview	32.5%	26
Glenwood Police	13169	Distance-based	N/A	City: Glenwood	6.0%	15
Golf Police	14035	Distance-based	N/A	City: Golf	0.1%	14
Goreville Police	13410	Distance-based	N/A	City: Goreville	15.6%	30
Grafton Police	13396	Distance-based	N/A	City: Grafton	1.6%	33
Grand Ridge Police	13515	Distance-based	N/A	City: Grand Ridge	8.2%	35
Grandview Police	13824	Distance-based	N/A	City: Grandview	51.9%	7
Granite City Police	13620	Crash-based	581	City: Granite City	61.5%	39
Grant Park Police	13444	Distance-based	N/A	City: Grant Park	4.4%	38
Grantfork Police	14045	Distance-based	N/A	City: Grantfork	58.3%	24
Granville Police	13738	Distance-based	N/A	City: Granville	14.5%	26
Grayslake Police	13471	Crash-based	716	City: Grayslake, Hainesville	26.8%	25
Grayville Police	13916	Distance-based	N/A	City: Grayville	24.4%	35
Greenfield Police	13332	Distance-based	N/A	City: Greenfield	26.3%	45
Greenup Police	13220	Distance-based	N/A	City: Greenup	36.9%	27
Greenview Police	13655	Distance-based	N/A	City: Greenview	11.2%	32
Greenville Police	13065	Crash-based	68	City: Greenville	55.9%	68
Grundy County Sheriff	13338	Crash-based	319	County: Grundy	68.5%	53
Gurnee Police	13473	Crash-based	1010	City: Gurnee	19.8%	40

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Hamel Police	13619	Distance-based	N/A	City: Hamel	2.8%	28
Hamilton County Sheriff	13341	Distance-based	N/A	County: Hamilton	55.6%	321
Hampshire Police	13423	Crash-based	88	City: Hampshire	44.3%	43
Hampton Police	13763	Distance-based	N/A	City: Hampton	3.0%	13
Hancock County Sheriff	13345	Crash-based	80	County: Hancock	65.0%	70
Hanover Park Police	13168	Crash-based	572	City: Hanover Park	29.3%	23
Hanover Police	14048	Distance-based	N/A	City: Hanover	17.7%	34
Harper College Police	13167	Crash-based	939	City: Palatine	41.5%	24
Harrisburg Police	13798	Crash-based	309	City: Harrisburg	53.1%	38
Hartford Police	13618	Crash-based	62	City: Hartford	6.5%	162
Harvard Police	13561	Crash-based	196	City: Harvard	65.3%	54
Harwood Heights Police	13165	Crash-based	434	City: Harwood Heights	20.3%	19
Havana Police	13645	Crash-based	82	City: Havana	58.5%	39
Hawthorn Woods Police	14020	Crash-based	195	City: Hawthorn Woods	31.5%	27
Hazel Crest Police	13164	Distance-based	N/A	City: Hazel Crest	10.3%	14
Henderson County Sheriff	13355	Distance-based	N/A	County: Henderson	41.6%	342
Henning Police	13893	Distance-based	N/A	City: Henning	1.2%	40
Henry County Sheriff	13360	Distance-based	N/A	County: Henry	76.1%	142
Henry Police	13639	Distance-based	N/A	City: Henry	29.6%	30
Herrin Police	13963	Crash-based	339	City: Herrin	47.4%	26
Herscher Police	13443	Distance-based	N/A	City: Herscher	8.8%	42
Heyworth Police	13575	Distance-based	N/A	City: Heyworth	20.9%	24
Hickory Hills Police	13163	Distance-based	N/A	City: Hickory Hills	7.5%	14
Highland Park Police	13474	Crash-based	539	City: Highland Park	29.2%	43
Highland Police	13617	Crash-based	258	City: Highland	67.8%	24

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Highwood Police	13475	Distance-based	N/A	City: Highwood	8.0%	15
Hillsboro Police	13676	Crash-based	107	City: Hillsboro	48.1%	41
Hillside Police	13162	Crash-based	415	City: Hillside	13.8%	34
Hinckley Police	13231	Distance-based	N/A	City: Hinckley	10.0%	29
Hinsdale Police	13260	Crash-based	650	City: Hinsdale	25.5%	23
Hodgkins Police	13049	Distance-based	N/A	City: Hodgkins	8.2%	16
Hoffman Estates Police	13048	Crash-based	768	City: Hoffman Estates	28.3%	24
Homer Police	13108	Distance-based	N/A	City: Homer	18.7%	20
Hometown Police	13047	Crash-based	69	City: Hometown	14.5%	198
Homewood Police	13046	Distance-based	N/A	City: Homewood	15.0%	13
Hoopeston Police	13892	Distance-based	N/A	City: Hoopeston	59.9%	33
Hopedale Police	13872	Distance-based	N/A	City: Hopedale	8.7%	26
Hudson Police	13574	Distance-based	N/A	City: Hudson	10.8%	15
Huntley Police	13558	Crash-based	377	City: Huntley	36.2%	37
Hutsonville Police	13217	Distance-based	N/A	City: Hutsonville	13.8%	32
Illinois Central College Police	13871	Crash-based	590	City: East Peoria	28.9%	68
Illinois Commerce Commission Police	13995	Crash-based	127519	State: Illinois	95.7%	400
Illinois Department of Natural Resources Police	13823	Crash-based	127519	State: Illinois	95.7%	400
Illinois State Police	13991	Crash-based	25926	State: Illinois	82.2%	325
Illinois State University Police	13573	Crash-based	863	City: Normal	38.8%	119
Ina Police	14117	Distance-based	N/A	City: Ina	17.7%	30
Indian Head Park Police	13045	Distance-based	N/A	City: Indian Head Park	14.4%	14
Indianola Police	13891	Distance-based	N/A	City: Indianola	3.0%	33

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Inverness Police	14121	Crash-based	51	City: Inverness	42.6%	400
Iroquois County Sheriff	13372	Distance-based	N/A	County: Iroquois	55.0%	227
Island Lake Police	13476	Crash-based	144	City: Island Lake	28.5%	20
Itasca Police	13261	Crash-based	226	City: Itasca	16.8%	30
Iuka Police	14019	Distance-based	N/A	City: Iuka	21.4%	30
Jackson County Sheriff	13383	Crash-based	296	County: Jackson	69.0%	121
Jacksonville Police	13687	Crash-based	541	City: Jacksonville	68.6%	38
Jasper County Sheriff	13390	Crash-based	71	County: Jasper	67.6%	33
Jefferson County Sheriff	13393	Distance-based	N/A	County: Jefferson	83.0%	220
Jerome Police	13820	Distance-based	N/A	City: Jerome	55.1%	7
Jersey County Sheriff	13395	Crash-based	185	County: Jersey	66.5%	30
Jerseyville Police	13394	Crash-based	283	City: Jerseyville	59.9%	31
Jo Daviess County Sheriff	13402	Crash-based	139	County: Jo Daviess	60.7%	122
John A Logan College Police	13961	Distance-based	N/A	City: Carterville	28.8%	18
Johnsburg Police	13557	Distance-based	N/A	City: Johnsburg	18.8%	23
Johnson County Sheriff	13409	Distance-based	N/A	County: Johnson	34.6%	361
Joliet Junior College Police	13946	Crash-based	1856	City: Joliet	53.8%	29
Joliet Police	13945	Crash-based	1856	City: Joliet	53.8%	29
Justice Police	14056	Distance-based	N/A	City: Justice	6.8%	14
Kane County Forest Preserve Police	13424	Crash-based	4450	County: Kane	79.4%	21
Kane County Sheriff	13425	Distance-based	N/A	County: Kane	67.9%	129
Kankakee County Sheriff	13441	Crash-based	340	County: Kankakee	81.6%	21
Kankakee Police	13440	Crash-based	833	City: Kankakee	60.0%	45
Kansas Police	13279	Distance-based	N/A	City: Kansas	13.1%	34
Kaskaskia College Police	14161	Distance-based	N/A	City: Centralia	76.4%	20

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Kendall County Sheriff	13453	Distance-based	N/A	County: Kendall	61.4%	158
Kenilworth Police	13044	Distance-based	N/A	City: Kenilworth	1.4%	13
Kewanee Police	13359	Crash-based	290	City: Kewanee	75.2%	36
Kildeer Police	13477	Crash-based	129	City: Kildeer	30.2%	33
Kincaid Police	13117	Distance-based	N/A	City: Kincaid	7.3%	24
Kingston Police	13230	Distance-based	N/A	City: Kingston	6.9%	33
Kirkland Police	13229	Distance-based	N/A	City: Kirkland	6.7%	32
Knox County Sheriff	13458	Crash-based	140	County: Knox	73.8%	43
Knoxville Police	13457	Distance-based	N/A	City: Knoxville	28.2%	30
La Grange Park Police	13043	Crash-based	195	City: La Grange Park	18.3%	37
La Grange Police	14013	Distance-based	N/A	City: La Grange	17.4%	13
La Salle Police	13513	Distance-based	N/A	City: La Salle	37.5%	29
Ladd Police	13080	Distance-based	N/A	City: Ladd	6.2%	25
LaHarpe Police	13344	Distance-based	N/A	City: LaHarpe	27.3%	30
Lake Bluff Police	13478	Crash-based	148	City: Lake Bluff	29.5%	51
Lake County Forest Preserve Police	13479	Crash-based	5576	County: Lake	82.1%	21
Lake County Sheriff	13480	Distance-based	N/A	County: Lake	68.7%	131
Lake Forest Police	13481	Crash-based	194	City: Lake Forest	25.3%	51
Lake in the Hills Police	13556	Crash-based	420	City: Lake in the Hills	32.4%	25
Lake Land College Police	13140	Crash-based	560	City: Mattoon	63.5%	55
Lake Villa Police	13482	Distance-based	N/A	City: Lake Villa	34.3%	16
Lake Zurich Police	13483	Crash-based	584	City: Lake Zurich	29.7%	31
Lakemoor Police	13484	Crash-based	197	City: Lakemoor	22.9%	61
Lakewood Police	13555	Crash-based	108	City: Lakewood	22.0%	35

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Lamoille Police	13079	Distance-based	N/A	City: Lamoille	10.3%	37
Lansing Police	13041	Crash-based	540	City: Lansing	40.8%	22
LaSalle County Sheriff	13514	Distance-based	N/A	County: LaSalle	70.2%	157
Lawrence County Sheriff	13521	Crash-based	64	County: Lawrence	63.1%	63
Lawrenceville Police	13520	Distance-based	N/A	City: Lawrenceville	57.0%	25
Lebanon Police	13782	Distance-based	N/A	City: Lebanon	14.9%	22
Lee County Sheriff	13524	Crash-based	196	County: Lee	72.7%	113
Leland Grove Police	13819	Distance-based	N/A	City: Leland Grove	49.1%	7
Leland Police	13512	Distance-based	N/A	City: Leland	11.2%	35
Lemont Police	13944	Crash-based	328	City: Lemont	35.6%	23
Lena Police	13851	Distance-based	N/A	City: Lena	31.1%	38
LeRoy Police	13572	Distance-based	N/A	City: LeRoy	31.7%	24
Lewis University Police	14131	Crash-based	932	City: Romeoville	31.8%	34
Lexington Police	13571	Distance-based	N/A	City: Lexington	20.0%	20
Libertyville Police	13485	Crash-based	249	City: Libertyville	16.7%	34
Lincoln Land Community College Police	13818	Crash-based	2024	City: Springfield	70.8%	72
Lincoln Police	13536	Crash-based	382	City: Lincoln	69.0%	60
Lincolnshire Police	13486	Crash-based	173	City: Lincolnshire	10.9%	48
Lincolnwood Police	13040	Crash-based	610	City: Lincolnwood	15.1%	34
Lindenhurst Police	13487	Crash-based	143	City: Lindenhurst	58.3%	27
Lisle Police	13262	Distance-based	N/A	City: Lisle	17.1%	15
Litchfield Police	13674	Crash-based	190	City: Litchfield	52.1%	50
Livingston County Sheriff	13530	Distance-based	N/A	County: Livingston	69.7%	166
Livingston Police	13616	Distance-based	N/A	City: Livingston	4.7%	31

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Loami Police	13817	Distance-based	N/A	City: Loami	7.5%	19
Lockport Park District Police	14087	Crash-based	615	City: Lockport	36.4%	28
Lockport Police	13943	Crash-based	615	City: Lockport	36.4%	28
Logan County Sheriff	13535	Crash-based	66	County: Logan	71.2%	32
Lombard Police	13263	Crash-based	883	City: Lombard	32.5%	29
Lostant Police	13518	Distance-based	N/A	City: Lostant	4.5%	39
Loves Park Police	13979	Crash-based	546	City: Loves Park	21.6%	28
Lovington Police	13694	Distance-based	N/A	City: Lovington	18.3%	30
Loyola University Police	13039	Crash-based	3160	City: Chicago 24th District (Rogers Park), Chicago 18th District (Near North)	30.8%	133
Lynwood Police	13358	Crash-based	237	City: Lynwood	34.7%	31
Machesney Park Police	14156	Distance-based	N/A	City: Machesney Park	27.7%	13
Mackinaw Police	13870	Distance-based	N/A	City: Mackinaw	20.0%	21
Macomb Police	13542	Crash-based	292	City: Macomb	55.6%	180
Macon County Sheriff	13587	Crash-based	337	County: Macon	73.2%	109
Macoupin County Sheriff	13597	Crash-based	127	County: Macoupin	85.0%	15
Madison County Sheriff	13615	Crash-based	726	County: Madison	81.5%	20
Mahomet Police	13106	Crash-based	73	City: Mahomet	65.8%	33
Manhattan Police	13942	Distance-based	N/A	City: Manhattan	28.7%	24
Manito Police	13643	Distance-based	N/A	City: Manito	18.8%	25
Manteno Police	13439	Crash-based	148	City: Manteno	49.3%	110
Maple Park Police	13426	Distance-based	N/A	City: Maple Park	9.7%	26
Marengo Police	13554	Crash-based	73	City: Marengo	51.4%	166
Marine Police	13613	Distance-based	N/A	City: Marine	6.4%	26
Marion County Sheriff	13630	Distance-based	N/A	County: Marion	78.2%	231
Marion Police	13959	Crash-based	516	City: Marion	52.1%	86

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Marissa Police	13780	Distance-based	N/A	City: Marissa	14.4%	37
Maroa Police	13586	Distance-based	N/A	City: Maroa	19.2%	22
Marquette Heights Police	13869	Distance-based	N/A	City: Marquette Heights	47.2%	11
Marseilles Police	13511	Distance-based	N/A	City: Marseilles	25.4%	42
Marshall County Sheriff	13637	Distance-based	N/A	County: Marshall	38.0%	315
Marshall Police	13124	Crash-based	77	City: Marshall	53.2%	153
Martinsville Police	13123	Distance-based	N/A	City: Martinsville	29.0%	33
Maryville Police	13612	Crash-based	134	City: Maryville	25.9%	46
Mascoutah Police	13779	Distance-based	N/A	City: Mascoutah	33.0%	26
Mason City Police	13642	Distance-based	N/A	City: Mason City	44.9%	31
Mason County Sheriff	13641	Distance-based	N/A	County: Mason	41.3%	327
Massac County Sheriff	13650	Crash-based	89	County: Massac	58.2%	383
Matteson Police	13036	Crash-based	580	City: Matteson	24.4%	30
Mattoon Police	13139	Crash-based	560	City: Mattoon	63.5%	55
Maywood Police	13035	Crash-based	738	City: Maywood	26.9%	27
Mazon Police	13337	Distance-based	N/A	City: Mazon	12.0%	34
McCook Police	13034	Crash-based	232	City: McCook	6.0%	24
McCullom Lake Police	14139	Distance-based	N/A	City: McCullom Lake	36.1%	20
McDonough County Sheriff	13541	Distance-based	N/A	County: McDonough	65.4%	301
McHenry County College Police	14127	Crash-based	671	City: Crystal Lake	38.2%	37
McHenry County Conservation District Police	14004	Crash-based	2233	County: McHenry	74.2%	26
McHenry County Sheriff	13553	Crash-based	859	County: McHenry	69.3%	27
McHenry Police	13552	Crash-based	558	City: McHenry	51.9%	29
McLean County Sheriff	13570	Distance-based	N/A	County: McLean	74.3%	229

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
McLean Police	13569	Distance-based	N/A	City: McLean	7.4%	29
McLeansboro Police	13340	Distance-based	N/A	City: McLeansboro	59.0%	32
McNabb Police	13739	Distance-based	N/A	City: McNabb	4.2%	34
Melrose Park Police	13033	Crash-based	1095	City: Melrose Park	29.3%	30
Mendota Police	13510	Crash-based	85	City: Mendota	68.2%	28
Mercer County Sheriff	13661	Distance-based	N/A	County: Mercer	53.0%	278
Meredosia Police	13689	Distance-based	N/A	City: Meredosia	22.2%	31
Merrionette Park Police	14024	Distance-based	N/A	City: Merrionette Park	10.5%	13
Metamora Police	13984	Distance-based	N/A	City: Metamora	28.7%	20
Metro Water Reclamation District Police	13031	Crash-based	69467	County: Cook	87.8%	15
Metropolis Police	13649	Crash-based	128	City: Metropolis	60.3%	400
Metropolitan Airport Authority	13760	Crash-based	1365	City: Moline, East Moline, Rock Island	66.0%	41
Midlothian Police	13030	Crash-based	494	City: Midlothian	26.6%	25
Milan Police	13761	Distance-based	N/A	City: Milan	22.8%	15
Milford Police	13371	Distance-based	N/A	City: Milford	48.1%	34
Milledgeville Police	14071	Distance-based	N/A	City: Milledgeville	14.4%	27
Millikin University Police	14142	Crash-based	1901	City: Decatur	76.2%	41
Millstadt Police	13778	Crash-based	66	City: Millstadt	50.0%	27
Minier Police	13868	Distance-based	N/A	City: Minier	11.4%	25
Minooka Police	13336	Crash-based	173	City: Minooka	42.2%	69
Mokena Police	13941	Distance-based	N/A	City: Mokena	20.2%	19
Moline Police	13759	Crash-based	864	City: Moline	40.0%	41
Momence Police	13438	Distance-based	N/A	City: Momence	20.8%	35
Monee Police	13940	Crash-based	111	City: Monee	13.4%	219

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Monmouth Police	13903	Crash-based	191	City: Monmouth	68.8%	60
Monroe County Sheriff	13668	Crash-based	114	County: Monroe	75.4%	21
Montgomery County Sheriff	13673	Distance-based	N/A	County: Montgomery	75.6%	193
Montgomery Police	13436	Crash-based	229	City: Montgomery	27.8%	33
Monticello Police	13717	Crash-based	62	City: Monticello	64.5%	26
Moody Bible Institute Police Department	14153	Crash-based	2003	City: Chicago 18th District (Near North)	13.0%	225
Moraine Valley Community College Police	13029	Distance-based	N/A	City: Palos Hills	10.4%	14
Morgan County Sheriff	13686	Distance-based	N/A	County: Morgan	72.2%	244
Morris Police	13335	Crash-based	555	City: Morris	50.6%	72
Morrison Police	13925	Distance-based	N/A	City: Morrison	45.5%	30
Morrisonville Police	13116	Distance-based	N/A	City: Morrisonville	14.9%	31
Morton College Police	14027	Crash-based	2337	City: Cicero	41.3%	25
Morton Grove Police	13027	Crash-based	643	City: Morton Grove	19.5%	30
Morton Police	13867	Crash-based	254	City: Morton	54.3%	40
Mounds Police	13730	Distance-based	N/A	City: Mounds	15.0%	32
Mount Carmel Police	13901	Crash-based	99	City: Mount Carmel	73.3%	35
Mount Olive Police	13596	Distance-based	N/A	City: Mount Olive	20.0%	33
Mount Prospect Police	13026	Distance-based	N/A	City: Mount Prospect	28.9%	13
Mount Pulaski Police	13533	Distance-based	N/A	City: Mount Pulaski	17.9%	27
Mount Vernon Police	13392	Crash-based	470	City: Mount Vernon	56.0%	80
Mount Zion Police	13585	Distance-based	N/A	City: Mount Zion	26.3%	13
Moweaqua Police	13841	Distance-based	N/A	City: Moweaqua	21.5%	31
Mundelein Police	13488	Crash-based	629	City: Mundelein	34.9%	28
Murphysboro Police	13382	Distance-based	N/A	City: Murphysboro	54.9%	25

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Murrayville Police	13690	Distance-based	N/A	City: Murrayville	16.7%	35
Naperville Police	13264	Crash-based	2200	City: Naperville	41.4%	29
Naplate Police	14052	Distance-based	N/A	City: Naplate	82.4%	18
Nauvoo Police	13343	Distance-based	N/A	City: Nauvoo	9.1%	35
Neoga Police	13219	Distance-based	N/A	City: Neoga	28.9%	24
New Athens Police	13777	Distance-based	N/A	City: New Athens	19.9%	29
New Baden Police	13130	Distance-based	N/A	City: New Baden	23.7%	27
New Lenox Police	13939	Crash-based	737	City: New Lenox	41.3%	28
Newman Police	13244	Distance-based	N/A	City: Newman	11.2%	30
Newton Police	13389	Distance-based	N/A	City: Newton	65.1%	25
Niles Police	13025	Distance-based	N/A	City: Niles	11.6%	11
Nokomis Police	13672	Distance-based	N/A	City: Nokomis	44.0%	32
Normal Police	13568	Crash-based	863	City: Normal	38.8%	119
Norridge Police	13024	Crash-based	696	City: Norridge	22.2%	22
Norris City Police	13915	Distance-based	N/A	City: Norris City	38.2%	36
North Aurora Police	13427	Crash-based	380	City: North Aurora	22.3%	32
North Pekin Police	13866	Crash-based	65	City: North Pekin	56.9%	36
North Riverside Police	13023	Crash-based	614	City: North Riverside	10.3%	25
North Utica-Utica Police	13509	Distance-based	N/A	City: North Utica	7.7%	42
Northbrook Police	13022	Crash-based	621	City: Northbrook	38.2%	27
Northeastern Illinois University Police	13021	Crash-based	1795	City: Chicago 17th District (Albany Park)	45.5%	31
Northern Illinois University Police	13227	Crash-based	580	City: DeKalb	59.0%	53
Northfield Police	13020	Distance-based	N/A	City: Northfield	9.2%	16
Northlake Police	13019	Crash-based	631	City: Northlake	21.3%	114

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Northwestern University Police	13018	Crash-based	2382	City: Evanston, Chicago 18th District (Near North)	18.4%	201
O'Fallon Police	13776	Crash-based	636	City: O'Fallon	36.8%	45
Oak Brook Police	13265	Crash-based	623	City: Oak Brook	7.9%	131
Oak Forest Police	13016	Distance-based	N/A	City: Oak Forest	18.5%	14
Oak Lawn Police	13015	Crash-based	1426	City: Oak Lawn	28.9%	27
Oak Park Police	13014	Crash-based	1082	City: Oak Park	23.6%	31
OakBrook Terrace Police	13266	Crash-based	346	City: Oakbrook Terrace	10.8%	122
Oakton Community College Police	13013	Crash-based	1506	City: Des Plaines, Skokie	39.0%	25
Oakwood Hills Police	13551	Distance-based	N/A	City: Oakwood Hills	18.8%	19
Oakwood Police	14008	Distance-based	N/A	City: Oakwood	13.9%	25
Oblong Police	13216	Distance-based	N/A	City: Oblong	41.1%	34
Ogle County Sheriff	13699	Distance-based	N/A	County: Ogle	80.3%	67
Oglesby Police	13508	Distance-based	N/A	City: Oglesby	20.9%	31
Okawville Police	13907	Distance-based	N/A	City: Okawville	11.7%	41
Olney Police	13754	Crash-based	223	City: Olney	58.5%	98
Olympia Fields Police	13012	Crash-based	492	City: Olympia Fields	7.3%	30
Oreana Police	14149	Distance-based	N/A	City: Oreana	12.9%	15
Oregon Police	13698	Crash-based	59	City: Oregon	44.1%	91
Orion Police	13357	Distance-based	N/A	City: Orion	9.9%	20
Orland Hills Police	14077	Crash-based	171	City: Orland Hills	23.3%	29
Orland Park Police	13011	Crash-based	1262	City: Orland Park	31.4%	29
Oswego Police	13451	Crash-based	710	City: Oswego	31.1%	34
Ottawa Police	13507	Crash-based	735	City: Ottawa	62.6%	47
Palatine Police	13010	Crash-based	939	City: Palatine	41.5%	24
Palestine Police	13215	Distance-based	N/A	City: Palestine	27.9%	27

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Palmyra Police	13595	Distance-based	N/A	City: Palmyra	14.7%	42
Palos Heights Police	13009	Distance-based	N/A	City: Palos Heights	7.2%	15
Palos Hills Police	13008	Distance-based	N/A	City: Palos Hills	10.4%	14
Palos Park Police	13007	Crash-based	189	City: Palos Park	14.1%	21
Pana Police	13115	Crash-based	95	City: Pana	70.5%	72
Paris Police	13278	Crash-based	144	City: Paris	64.6%	41
Park City Police	13490	Crash-based	210	City: Park City	55.7%	48
Park Forest Police	13006	Crash-based	416	City: Park Forest	40.8%	26
Park Ridge Police	13005	Crash-based	530	City: Park Ridge	26.0%	30
Parkland College Police	13105	Crash-based	1410	City: Champaign	53.9%	105
Pawnee Police	13814	Distance-based	N/A	City: Pawnee	25.9%	17
Paxton Police	13298	Distance-based	N/A	City: Paxton	41.3%	25
Payson Police	13056	Distance-based	N/A	City: Payson	13.8%	18
Pearl City Police	13849	Distance-based	N/A	City: Pearl City	19.7%	35
Pecatonica Police	13978	Distance-based	N/A	City: Pecatonica	28.5%	21
Pekin Park District Police	13865	Crash-based	691	City: Pekin	61.7%	34
Pekin Police	13864	Crash-based	691	City: Pekin	61.7%	34
Peoria County Sheriff	13707	Crash-based	558	County: Peoria	72.6%	35
Peoria Heights Police	13706	Crash-based	57	City: Peoria Heights	26.3%	55
Peoria Park District Police	13705	Crash-based	2833	City: Peoria	67.9%	37
Peoria Police	13704	Crash-based	2833	City: Peoria	67.9%	37
Peotone Police	13938	Crash-based	65	City: Peotone	30.8%	40
Perry County Sheriff	13714	Crash-based	81	County: Perry	67.9%	31
Peru Police	13506	Crash-based	302	City: Peru	33.7%	48
Petersburg Police	13653	Distance-based	N/A	City: Petersburg	45.9%	27
Phoenix Police	13004	Distance-based	N/A	City: Phoenix	11.3%	14
Piatt County Sheriff	13716	Crash-based	68	County: Piatt	66.2%	24

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Pike County Sheriff	13723	Crash-based	73	County: Pike	73.0%	200
Pinckneyville Police	13713	Distance-based	N/A	City: Pinckneyville	57.8%	32
Pingree Grove Police	14093	Crash-based	114	City: Pingree Grove	36.5%	35
Pittsfield Police	13722	Crash-based	75	City: Pittsfield	60.0%	116
Plainfield Police	13937	Crash-based	1049	City: Plainfield	46.3%	32
Plainville Police	14124	Distance-based	N/A	City: Plainville	5.8%	24
Plano Police	13450	Crash-based	169	City: Plano	53.8%	23
Pleasant Plains Police	13813	Distance-based	N/A	City: Pleasant Plains	11.6%	21
Plymouth Police	13350	Distance-based	N/A	City: Plymouth	23.6%	36
Polo Police	13697	Distance-based	N/A	City: Polo	31.9%	31
Pontiac Police	13529	Distance-based	N/A	City: Pontiac	76.7%	30
Pontoon Beach Police	14054	Crash-based	179	City: Pontoon Beach	47.0%	318
Pope County Sheriff	13727	Distance-based	N/A	County: Pope	48.4%	340
Posen Police	13003	Crash-based	228	City: Posen	13.4%	74
Prairie du Rocher Police	13746	Distance-based	N/A	City: Prairie du Rocher	5.2%	40
Prairie Grove Police	14068	Distance-based	N/A	City: Prairie Grove	35.9%	23
Princeton Police	13077	Crash-based	169	City: Princeton	61.5%	30
Prophetstown Police	13924	Distance-based	N/A	City: Prophetstown	28.5%	31
Prospect Heights Police	13002	Crash-based	168	City: Prospect Heights	15.5%	23
Pulaski County Sheriff	13729	Distance-based	N/A	County: Pulaski	21.7%	381
Putnam County Sheriff	13736	Distance-based	N/A	County: Putnam	26.0%	327
Quincy Police	13058	Crash-based	1046	City: Quincy	71.1%	44
Rantoul Police	13104	Crash-based	259	City: Rantoul	69.2%	30
Richland Community College Police	14159	Crash-based	1901	City: Decatur	76.2%	41
Richland County Sheriff	13753	Crash-based	108	County: Richland	59.1%	278

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Richmond Police	13550	Distance-based	N/A	City: Richmond	5.9%	28
Richton Park Police	13001	Crash-based	390	City: Richton Park	27.6%	28
Ridge Farm Police	13889	Distance-based	N/A	City: Ridge Farm	7.0%	38
River Forest Police	13000	Crash-based	316	City: River Forest	14.2%	29
River Grove Police	12999	Crash-based	725	City: River Grove	12.6%	22
Riverdale Police	12998	Distance-based	N/A	City: Riverdale	10.6%	14
Riverside Police	12997	Crash-based	259	City: Riverside	21.1%	26
Riverton Police	13812	Distance-based	N/A	City: Riverton	17.9%	17
Riverwoods Police	13491	Crash-based	114	City: Riverwoods	19.1%	26
Robbins Police	12996	Distance-based	N/A	City: Robbins	2.2%	14
Robinson Police	13214	Crash-based	125	City: Robinson	65.4%	42
Rochelle Police	13696	Crash-based	176	City: Rochelle	65.0%	80
Rochester Police	13811	Crash-based	56	City: Rochester	37.5%	28
Rock Falls Police	13923	Crash-based	234	City: Rock Falls	47.9%	56
Rock Island County Sheriff	13757	Crash-based	310	County: Rock Island	60.3%	83
Rock Island Police	13756	Crash-based	671	City: Rock Island	49.2%	49
Rock Valley College Police	13977	Crash-based	2671	City: Rockford	73.4%	29
Rockdale Police	13936	Distance-based	N/A	City: Rockdale	18.2%	19
Rockford Police	13975	Crash-based	2671	City: Rockford	73.4%	29
Rockton Police	13974	Distance-based	N/A	City: Rockton	25.8%	18
Rolling Meadows Police	12995	Crash-based	310	City: Rolling Meadows	21.9%	33
Romeoville Police	13935	Crash-based	932	City: Romeoville	31.8%	34
Roodhouse Police	13331	Distance-based	N/A	City: Roodhouse	38.1%	37
Roscoe Police	13973	Crash-based	254	City: Roscoe	37.0%	46
Roselle Police	13267	Crash-based	482	City: Roselle	28.8%	21
Rosemont Police	12994	Crash-based	357	City: Rosemont	11.8%	95
Round Lake Beach Police	13492	Crash-based	338	City: Round Lake Beach	58.8%	24

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Round Lake Heights Police	13493	Distance-based	N/A	City: Round Lake Heights	58.6%	13
Round Lake Park Police	13494	Distance-based	N/A	City: Round Lake Park	10.2%	12
Round Lake Police	13495	Crash-based	614	City: Round Lake	57.6%	19
Roxana Police	13611	Crash-based	87	City: Roxana	8.0%	28
Royalton Police	13306	Distance-based	N/A	City: Royalton	6.1%	20
Ruma Police	13743	Distance-based	N/A	City: Ruma	23.7%	36
Rushville Police	13833	Distance-based	N/A	City: Rushville	70.9%	24
Salem Police	13628	Distance-based	N/A	City: Salem	62.6%	23
Saline County Sheriff	13797	Crash-based	138	County: Saline	78.6%	94
San Jose Police	13640	Distance-based	N/A	City: San Jose	7.0%	36
Sandoval Police	13627	Distance-based	N/A	City: Sandoval	17.7%	28
Sandwich Police	13226	Crash-based	81	City: Sandwich	51.9%	29
Sangamon County Sheriff	13810	Distance-based	N/A	County: Sangamon	76.3%	265
Sauget Police	13225	Distance-based	N/A	City: Sauget	4.7%	20
Sauk Village Police	12993	Distance-based	N/A	City: Sauk Village	37.2%	15
Schaumburg Police	12992	Crash-based	1205	City: Schaumburg	27.3%	24
Schiller Park Police	12991	Crash-based	675	City: Schiller Park	15.9%	40
Schuyler County Sheriff	13832	Distance-based	N/A	County: Schuyler	58.2%	311
Scott County Sheriff	13835	Distance-based	N/A	County: Scott	51.6%	328
Secretary of State Police	13809	Crash-based	127519	State: Illinois	95.7%	400
Shannon Police	13093	Distance-based	N/A	City: Shannon	14.8%	32
Shelby County Sheriff	13840	Crash-based	216	County: Shelby	72.4%	61
Shelbyville Police	13839	Distance-based	N/A	City: Shelbyville	61.1%	28

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Sheldon Police	13369	Distance-based	N/A	City: Sheldon	26.6%	36
Sheridan Police	13504	Distance-based	N/A	City: Sheridan	17.1%	36
Shiloh Police	13775	Crash-based	466	City: Shiloh	56.8%	55
Shorewood Police	13934	Crash-based	517	City: Shorewood	30.3%	33
Silvis Police	13755	Crash-based	164	City: Silvis	23.2%	26
Skokie Police	12990	Crash-based	1300	City: Skokie	35.0%	26
Sleepy Hollow Police	13428	Distance-based	N/A	City: Sleepy Hollow	11.9%	19
Somonauk Police	13224	Distance-based	N/A	City: Somonauk	9.6%	37
South Barrington Police	13061	Crash-based	172	City: South Barrington	19.0%	30
South Beloit Police	14070	Distance-based	N/A	City: South Beloit	25.1%	18
South Chicago Heights Police	12989	Crash-based	329	City: South Chicago Heights	42.9%	30
South Elgin Police	13429	Crash-based	520	City: South Elgin	29.0%	23
South Holland Police	12988	Distance-based	N/A	City: South Holland	11.9%	14
South Jacksonville Police	13685	Distance-based	N/A	City: South Jacksonville	88.5%	21
South Pekin Police	13863	Distance-based	N/A	City: South Pekin	3.5%	19
South Roxanna Police	13610	Distance-based	N/A	City: South Roxana	2.2%	22
South Suburban College Police	12987	Distance-based	N/A	City: South Holland, Oak Forest	18.8%	12
Southern Illinois University Carbondale Police	13381	Distance-based	N/A	City: Carbondale	61.3%	19
Southern Illinois University Edwardsville Police	13609	Crash-based	607	City: Edwardsville	38.9%	70
Southern View Police	13807	Distance-based	N/A	City: Southern View	39.3%	8
Southwestern Illinois College Police	13773	Crash-based	1519	City: Belleville, Granite City	63.2%	26
Sparta Police	13742	Distance-based	N/A	City: Sparta	29.1%	45

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Spillertown Police	13958	Distance-based	N/A	City: Spillertown	65.5%	20
Spring Grove Police	13549	Crash-based	108	City: Spring Grove	25.9%	41
Spring Valley Police	13075	Distance-based	N/A	City: Spring Valley	25.9%	26
Springfield Park District Police	13806	Crash-based	2024	City: Springfield	70.8%	72
Springfield Police	13805	Crash-based	2024	City: Springfield	70.8%	72
St. Anne Police	13437	Distance-based	N/A	City: St. Anne	22.1%	37
St. Charles Police	13430	Distance-based	N/A	City: St. Charles	38.3%	16
St. Clair County Sheriff	13772	Distance-based	N/A	County: St. Clair	69.7%	238
St. Jacob Police	13608	Distance-based	N/A	City: St. Jacob	10.0%	25
Stanford Police	13567	Distance-based	N/A	City: Stanford	4.9%	26
Stark County Sheriff	13846	Distance-based	N/A	County: Stark	38.7%	323
Staunton Police	13594	Distance-based	N/A	City: Staunton	22.7%	34
Steeleville Police	13741	Distance-based	N/A	City: Steeleville	24.2%	37
Steger Police	13161	Crash-based	237	City: Steger	35.0%	23
Stephenson County Sheriff	13848	Crash-based	206	County: Stephenson	67.5%	69
Sterling Police	13922	Crash-based	562	City: Sterling	56.9%	31
Stickney Police	13160	Crash-based	520	City: Stickney	40.5%	27
Stockton Police	13400	Distance-based	N/A	City: Stockton	37.4%	36
Stone Park Police	13159	Distance-based	N/A	City: Stone Park	2.2%	12
Stonington Police	13121	Distance-based	N/A	City: Stonington	7.3%	28
Streamwood Police	13158	Crash-based	514	City: Streamwood	35.8%	30
Sugar Grove Police	13431	Crash-based	153	City: Sugar Grove	22.1%	34
Sullivan Police	13692	Crash-based	68	City: Sullivan	66.2%	51
Summerfield Police	14128	Distance-based	N/A	City: Summerfield	1.0%	27

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Summit Police	13157	Distance-based	N/A	City: Summit	4.2%	13
Sumner Police	13523	Distance-based	N/A	City: Sumner	53.4%	23
Swansea Police	13771	Crash-based	541	City: Swansea	28.2%	29
Sycamore Police	14015	Crash-based	367	City: Sycamore	48.9%	37
Taylorville Police	13114	Crash-based	289	City: Taylorville	60.2%	43
Tazewell County Sheriff	13862	Crash-based	426	County: Tazewell	72.1%	22
Terminal Railroad Association	14041	Crash-based	190	City: East St. Louis	47.6%	31
Teutopolis Police	13285	Distance-based	N/A	City: Teutopolis	30.2%	26
Thayer Police	13804	Distance-based	N/A	City: Thayer	4.3%	21
Thomasboro Police	13103	Distance-based	N/A	City: Thomasboro	5.1%	15
Thornton Police	13156	Crash-based	124	City: Thornton	10.3%	49
Tilton Police	13887	Distance-based	N/A	City: Tilton	5.4%	27
Tinley Park Police	13155	Crash-based	1001	City: Tinley Park	35.4%	31
Tiskilwa Police	13074	Distance-based	N/A	City: Tiskilwa	18.4%	35
Tolono Police	13102	Distance-based	N/A	City: Tolono	19.3%	13
Toluca Police	13636	Distance-based	N/A	City: Toluca	14.3%	33
Toulon Police	13845	Distance-based	N/A	City: Toulon	26.0%	31
Tower Lakes Police	13496	Distance-based	N/A	City: Tower Lakes	32.0%	18
Trenton Police	13129	Distance-based	N/A	City: Trenton	10.8%	32
Tri-County Drug Enforcement Narcotics Team	14126	None	N/A	NA: NA	NA%	NA
Triton College Police	13154	Crash-based	725	City: River Grove	12.6%	22
Troy Police	13607	Crash-based	278	City: Troy	51.1%	292
Tuscola Police	13239	Crash-based	63	City: Tuscola	56.2%	181

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Ullin Police	13733	Distance-based	N/A	City: Ullin	5.7%	36
Union County Sheriff	13879	Crash-based	115	County: Union	70.9%	100
Union Police	13548	Distance-based	N/A	City: Union	2.7%	28
University of Chicago Police	14057	Crash-based	1700	City: Chicago 2nd District (Wentworth)	30.4%	39
University of Illinois Chicago Police	13152	Crash-based	2708	City: Chicago 12th District (Near West)	20.9%	40
University of Illinois Springfield Police	13803	Crash-based	2024	City: Springfield	70.8%	72
University of Illinois Urbana-Champaign Police	13101	Crash-based	2011	City: Champaign, Urbana	67.8%	102
Urbana Police	13100	Crash-based	601	City: Urbana	44.2%	103
Ursa Police	14025	Distance-based	N/A	City: Ursa	9.7%	26
VA Medical Center Police	13886	Distance-based	N/A	City: Danville	84.1%	13
Valmeyer Police	13667	Distance-based	N/A	City: Valmeyer	1.6%	32
Vermilion County Sheriff	13885	Distance-based	N/A	County: Vermilion	73.6%	202
Vernon Hills Police	13497	Distance-based	N/A	City: Vernon Hills	23.6%	15
Vienna Police	13408	Distance-based	N/A	City: Vienna	46.7%	29
Villa Grove Police	13238	Distance-based	N/A	City: Villa Grove	21.9%	28
Villa Park Police	13268	Crash-based	508	City: Villa Park	27.5%	25
Wabash County Sheriff	13900	Distance-based	N/A	County: Wabash	49.0%	343
Walnut Police	13073	Distance-based	N/A	City: Walnut	24.8%	29
Warren County Sheriff	13902	Crash-based	98	County: Warren	57.6%	264
Warren Police	13399	Distance-based	N/A	City: Warren	21.9%	36
Warrensburg Police	14040	Distance-based	N/A	City: Warrensburg	8.8%	18
Warrenville Police	13269	Crash-based	258	City: Warrenville	17.6%	33
Washington County Sheriff	13905	Crash-based	102	County: Washington	57.3%	219

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Washington Police	13860	Crash-based	201	City: Washington	62.7%	26
Waterloo Police	13666	Crash-based	231	City: Waterloo	63.4%	32
Waterman Police	14063	Distance-based	N/A	City: Waterman	8.1%	36
Watseka Police	13379	Distance-based	N/A	City: Watseka	62.8%	28
Waubonsee Community College Police	13432	Crash-based	2560	City: Sugar Grove, Aurora	59.0%	28
Wauconda Police	13498	Crash-based	374	City: Wauconda	24.7%	31
Waukegan Police	13499	Crash-based	2515	City: Waukegan	62.6%	23
Waverly Police	13684	Distance-based	N/A	City: Waverly	16.0%	25
Wayne County Sheriff	13911	Distance-based	N/A	County: Wayne	68.6%	288
Wayne Police	13270	Distance-based	N/A	City: Wayne	1.4%	20
West Chicago Police	13271	Crash-based	601	City: West Chicago	34.9%	28
West City Police	13303	Distance-based	N/A	City: West City	39.8%	27
West Dundee Police	13433	Crash-based	85	City: West Dundee	11.6%	38
West Frankfort Police	13302	Distance-based	N/A	City: West Frankfort	39.7%	20
Western Illinois University Police	13540	Crash-based	292	City: Macomb	55.6%	180
Western Springs Police	13149	Crash-based	230	City: Western Springs	30.2%	17
Westmont Police	13272	Crash-based	534	City: Westmont	24.3%	27
Westville Police	13884	Distance-based	N/A	City: Westville	21.6%	21
Wheaton Police	13273	Crash-based	682	City: Wheaton	35.7%	33
Wheeling Police	13148	Crash-based	730	City: Wheeling	32.8%	27
White Hall Police	13330	Distance-based	N/A	City: White Hall	34.8%	44
Whiteside County Sheriff	13920	Crash-based	294	County: Whiteside	71.0%	76
Will County Sheriff	13931	Crash-based	1173	County: Will	73.2%	21
Williamson County Sheriff	13957	Crash-based	270	County: Williamson	81.8%	60
Williamson Police	14023	Distance-based	N/A	City: Williamson	21.0%	35

Agency	ID	Benchmark Type	Number of Crash Reports Used	Primary Benchmark Area	% within Primary Area	Benchmark Radius (miles)
Williamsville Police	13802	Distance-based	N/A	City: Williamsville	10.5%	21
Willisville Police	14110	Distance-based	N/A	City: Willisville	6.1%	34
Willow Springs Police	13147	Crash-based	266	City: Willow Springs	11.2%	24
Willowbrook Police	13274	Crash-based	374	City: Willowbrook	19.6%	109
Wilmette Police	13146	Crash-based	508	City: Wilmette	31.4%	32
Winchester Police	13834	Distance-based	N/A	City: Winchester	48.0%	25
Winfield Police	13275	Crash-based	249	City: Winfield	17.9%	31
Winnebago County Sheriff	13972	Crash-based	926	County: Winnebago	81.2%	48
Winnebago Police	13971	Distance-based	N/A	City: Winnebago	25.0%	18
Winnetka Police	13145	Crash-based	69	City: Winnetka	22.5%	58
Winthrop Harbor Police	13500	Distance-based	N/A	City: Winthrop Harbor	11.0%	17
Wonderlake Police	14033	Distance-based	N/A	City: Wonder Lake	14.8%	26
Wood Dale Police	13276	Crash-based	351	City: Wood Dale	24.2%	26
Wood River Police	13605	Distance-based	N/A	City: Wood River	13.8%	22
Woodford County Sheriff	13988	Distance-based	N/A	County: Woodford	73.2%	153
Woodland Police	13380	Distance-based	N/A	City: Woodland	3.7%	43
Woodridge Police	13277	Crash-based	767	City: Woodridge	23.9%	35
Woodstock Police	13546	Crash-based	539	City: Woodstock	51.6%	42
Worden Police	14067	Distance-based	N/A	City: Worden	12.1%	28
Worth Police	13144	Crash-based	216	City: Worth	12.8%	35
Wyanet Police	13072	Distance-based	N/A	City: Wyanet	16.3%	37
Yates City Police	13454	Distance-based	N/A	City: Yates City	10.4%	28
Yorkville Police	13449	Crash-based	395	City: Yorkville	35.3%	41
Zion Police	13501	Crash-based	623	City: Zion	53.5%	20

Appendix D. Determining the Race of Each Driver Stopped — Additional Notes and Methods

Literature Review

The Bayesian Improved Surname Geocoding (BISG) technique we used to predict race in this study has been used widely over the last decade. It uses data the United States Federal Census produced in the 2010 Census Surname Table, which lists the most common surnames (last names) and the associated self-reported races and Hispanic origin for each name. Konstantinos Tzioumis created and published a list drawn from mortgage data of given names (first names) showing "the distribution of self-reported race and ethnicity" for 4250 first names of almost 2.5M mortgage applicants in 2007 and 2010, combined across several lenders."[1, 2] (Superscripts in this appendix refer to the references at the end of the appendix.)

In 2009, Marc N. Elliott's team used health plan data to calculate or infer race.[3] They started with surname and zip codes to infer race and compare it to the self-reported race of almost 2 million health plan enrollees with a finding of strong accuracy of prediction. Ioan Voicu argued that including first names improves the race estimation for non-Hispanic Blacks according to his 2018 analysis of mortgage applications and self-reported race.[4]

In August 2022, Ann Haas et al. showed the last name and zip code correlated with self-reported race at least 92% of the time for Medicare beneficiaries.[2] Like Voicu's study, when Haas included first names in her analysis, the correlation improved by 0.2 to 2.3% depending on race and gender.

BISG has also been applied in law enforcement settings. In 2020, Elizabeth Luh used last names and zip codes to estimate race data for drivers and compared them to Texas State Trooper reported races.[5] She compared error rates of race prediction to incidences of vehicle search resulting in officers finding and vehicle searches not finding contraband. Results show that some officers were more frequently misreporting the race of the Hispanic drivers as White when the officers did not find contraband. This pattern biased the rates of contraband found per race.

Formatting and preparing drivers' names for analysis

Our process was more complicated than simply implementing the BISG algorithm because the data we received did not separate first names and last names into 2 fields. We attempted to stratify the names by first and last, manually reviewed samples for errors and then omitted some patterns of names from the analysis as described below.

Splitting full names into first and last names

In the initial dataset, each driver's full name appeared as one field. Common patterns emerged. For example:

John Doe
Doe, John
John Doug Doe
John D. Doe

Despite the IDOT instructions[6] to record drivers' names using the format "Last, First" only 75% of the names included a comma. Other names had multiple commas and some names had up to 8 words. We also found hundreds of names that we believe were recorded incorrectly, as "Last, Last First."

To clean the data, we used regular expressions in R statistical software to extract a set of names that followed the patterns we identified. These patterns took account of features such as presence of a comma, order of first and last name, and multiple other features. We created approximately 30 name patterns. Then, we assigned each word a label based on its location in the pattern and broke the names into columns. For example, "Doe, John" was assigned "Last, First" and split into separate "Last" and "First" names columns. We continued this process for the more than 2 million names reported in 2022 stops.

We removed suffixes like "Junior" and "Senior" from names, as well as obvious typos like multiple consecutive spaces and various symbols or unusual punctuation. We standardized name formatting by eliminating spaces, such as changing Mc Donald (includes a blank space) to McDonald (no space) and de la Cruz to delaCruz in order to match the format of the US Census name list.

Of note, we recognized various cultural patterns for names. For example, some drivers had more than 3 names (first, middle, last), sometimes up to 6 names, separated by spaces or commas. We defined patterns in order to capture and preserve as much of the diversity in the data as possible.

Checking for errors in names

To calculate error rates in our name cleaning process, we manually reviewed a sample of 100 names extracted from each of the 30 patterns. For patterns containing less than 100 names, the full list was reviewed. Some of the most common name patterns are described below along with the error rates we found in this sample.

Table #. Descriptions and Error Rates of Common Name Patterns, 2022.

Pattern Number	Description of Name Patterns	Number of Names Displaying Pattern	Error Rate
1	FirstNameOnly	3035	37.00%
2	First Last	442055	6.00%
3	First M. Last	8925	0.00%
4	First M Last (no period)	33126	0.00%
5	First Middle Last	22604	25.00%
10	Last, First M	191254	0.00%
11	Last First M (no comma)	16500	0.00%
12	Last, First, M (2 commas)	2309	5.00%
13	Last, (only last with comma)	1556	0.00%
23	Last, First First M	1291	40.00%
29	Last, First (separated by comma)	927053	1.00%

Most names were concentrated in a few patterns. For example, Pattern 2 was the largest number of names in 2021 stops data with a count of 442,055[20]. This pattern fits two words without a comma, which we assumed was First Last. We later learned that the instructions to the officer were to report names as “Last, First” and considered revising our assumption. However, the names in that category were predominantly “First Last” when we manually reviewed them. The error rate for this pattern was 6%, mainly when the officer reported the name as “Last First” with no comma between names.

We had more confidence in Pattern 10, the pattern “Last, First M.” This pattern had 191,254 names and 0% error in the sample we reviewed manually. Therefore, we decided to use only names in Pattern 10 for our initial review.

We noted that many errors occurred when the first and last names were reversed. Therefore we limited our first review to Pattern 10 which had 0% errors in our review sample. We are working on a method to calculate the likelihood that the names are correct or reversed.

Second, there were several patterns that seemed to generate extensive typos from the original data. Hundreds of names were reported that had the same first and last name. (Similar to Doe, Doe John.)

At times we used gender data to determine if a name is likely first or last. For example. Franklin could be a first or last name, however, if Driver sex was reported as female, Franklin was more likely the last name.

Analysis

Limitations: Obtaining and Calculating Race Data

We understand that this analysis is limited in a few ways. Specifically, we realize that race is a complex concept and many people may describe themselves as multiracial. We also realize that there are at least four different way the race variable could be designated: The race reported by the officer, race probability (BISG), self-reported race, and the genetic group that the driver may belong to. These four ways to designate race may or may not yield the same response. However, our analysis is strictly limited to available data - officer-reported race and BISG race probability.

We excluded stops that only recorded 1 name because we were not able to accurately label the name as first or last.

Total number of stops reported

There were 2,012,182 traffic stops reported for 2022. We note that some literature showed a decrease in traffic stops across the country during this time period, citing COVID-19.[7] We did not find this trend in the Illinois data since there were 400,000 more stops in 2022 than there were in 2021.

[20] Some initial research was done with 2021 stops data—before 2022 stops data became available.

Selected Results

Highly Probable Mismatches

After predicting race for each driver, we compared predictions to the races designated by the officers and noted whether they were the same. If the comparison did not match, we flagged it as a potential mismatch. Approximately 40,000 drivers' races were mismatched. Most of these mismatches were excluded from analysis when we removed estimates with low probability of accuracy. Over 12,000 high-probability mismatches remained, when the race predictions were greater than 95% probability. We then further analyzed the rates of these high probability mismatch by agency.

Overall, the high probability mismatch rate average was 6% of the sample, but when we looked at rates of those mismatches by agency, the agencies ranged from less than 1% to 39.8%. We were very conservative in this calculation and did not include any low or medium probability mismatches in the mismatch rates by agencies. We calculated the number of high probability mismatches divided by the total number of stops from that agency in our sample.

Given these finding, it is probable that agencies with high proportions of mismatches did not accurately report race data. This could be unintentional, for example, a driver does not display typical physical racial traits or an officer could have difficulty discerning race using only observation. Lack of daylight does not seem to be a factor influencing observation, since the average time of the highly probably mismatches is approximately 2:00pm (ample daylight). A Texas study suggests that officers were intentionally misreporting Hispanic drivers' race to improve their search statistics against minority drivers.[5]

Misreporting of People of Color

As noted earlier, 7,062 (55.8%) of the 12,660 high probability mismatches occurred when an officer reported a driver as White, but we inferred (from BISG) that the driver was Hispanic. There were also smaller trends in high probability mismatches, such as 2,587 drivers reported by officers as Black but we inferred as White; 809 drivers reported as White drivers but we inferred as Asian; and 309 drivers who were reported as Black that we estimated as Hispanic.

Additionally, we found that the 10 most common names among this group of "White or Hispanic" high probability mismatched drivers were of Hispanic origin. According to the US Census Bureau, there is less surname diversity among Hispanics in the United States compared to other racial and ethnic groups.[8] Therefore, Hispanic names are often easily recognized.)

Since we only analyzed Name Pattern 10, which had 0% errors in our manually reviewed sample, and we only used mismatches that had more than an estimated 95% accuracy for the predicted race, we believe this increases the chance that the officer truly mismatched the race. Specifically, it is less likely to be a name categorization error and more likely to truly be a mismatched race.

Male and Female Ratios

Females were 39% of the sample but only 32% of the high probability mismatches. This is important because there were slightly fewer females in the high probability mismatch group than males. This means that the mismatches of females whose married names may not match the race linked to their maiden names are not over-represented and do not likely skew the data. We hope to conduct further analysis to determine if the error rates change based on sex of the driver.

Native American Populations

Because the sample of American Indian/Alaskan Native drivers is small, our analysis may be less accurate in this racial group than for the others. However, it is still important to note that less than 1% of those 394 drivers the officers designated as AI/AN matched the BISG-predicted race. BISG algorithms designated those drivers were Asian or Native Hawaiian/Pacific Islander rather than AI/AN.

Confidence level of the overall analysis

We rigorously cleaned and formatted our dataset to provide us the most accurate predictive race data possible. To ensure that our name separation process accurately matches first and last names correctly, we sampled all of the name patterns and calculated the error rates. For this analysis, we decided to use the largest pattern that had less than 1% error in names. Similarly, we calculated the number of names that matched the corresponding lists. The last names of our sample matched the Census surname list over 90% of the time. Therefore, we have high confidence we assigned the names correctly. We also compared race estimates that had more than 95% confidence of the race estimate to remove low probability matches. This helped to minimize the mismatches with our BISG estimate.

Suggested Improvements to Name-Related Data Collection and Data Entry

Name Fields

With increased accuracy of name data, accurate race estimates provided by the BISG algorithm would also increase. Highly accurate race data permits opportunities for additional analyses.

It was difficult to analyze the data properly when there are high levels of variation how the data are collected and entered into the database. In the future, if names in the dataset are entered into separate fields by first and last name without symbols and extraneous spaces, analysis will improve in accuracy and diversity. Suggestions for cleaner data collection include:

1. Scan the drivers' licenses

Some licenses can be scanned to display identifying information of drivers. Given the amount of time the officers are paid to do paperwork and the number of resulting typos, it could be worth considering automating the process for recording licenses at traffic stops. This would improve both the accuracy of the names reported and reduce the time each officer spends on administrative details.

2. Insert separated name fields

The current data collection form allows officers to enter driver names in any format. To reduce error, offering separate fields for each type of name is essential. Similar to methods used by the US Census, we suggest fields for first name(s), middle name(s) or initials, last name(s) and suffix. Each field could be optional since we saw thousands of names that the officer could only gather 1 name.

Example:

FIRST NAME(S)	**MIDDLE NAME(S) OR INITIALS**	**LAST NAME(S)**	**SUFFIX (Jr., Sr., etc.)**

Suggested Improvements to Race Data Collection

Self-reported race

Self-reported race data is an important part of statistical analyses of traffic stops. In Texas, the laws governing traffic stops changed in 2015 and now require officers ask drivers for their race. Since then, officer reporting has become more accurate.[9]

It would be useful to implement this change in Illinois, but we are acutely aware of some problems that arise from this kind of technique, including:

- some drivers and officers may feel uncomfortable discussing race
- power dynamics and political situations may make it uncomfortable for drivers to provide truthful answers
- adding a question to the officer's traffic stop protocol will lengthen the time a driver is stopped
- the officers may resist changes that add to their workload

We are researching ways to validate our process with a local sample population that includes full names, zip codes and self-reported race.

Update the IDOT race categories to match US Census categories

The race categories we received from IDOT do not match the current US Census categories. For our analysis, we combined the Native Hawaiian or Other Pacific Islander category with the Asian because the Census Surname lists did not have a NHOPI designation.

The new categories in the 2020 Census allow for fine details of race and ethnicity, and there has been an increased number of people self-reporting multiple races.[9] It may be useful to think about how we collect and report race in the future.

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Appendix E. Additional Notes on Illinois Law Concerning the Stops Study

The Illinois General Assembly has promulgated laws that require the collection and analysis of data on traffic stops by law enforcement agencies in the state. The statutes relating to the statistical analysis of traffic and pedestrian stops are found in the Compiled Statutes of the Illinois General Assembly, 625 ILCS 5/11-212, effective 6/21/2019. See also Public Act 101-0024.

Section 11-212 of the Illinois statute authorizes the “Traffic and pedestrian stop statistical study”. This section also requires that when a police officer stops an individual, a specific set of information is to be recorded. This information includes name, address, gender, race (six specific categories: White, Black or African American, Hispanic or Latino, Asian, American Indian or Alaska Native and Native Hawaiian or Other Pacific Islander), the violation, vehicle information, date, time, location, search information, whether contraband was found, disposition of the stop (warning, citation or arrest—arrest recorded only for pedestrian stops[21]) and the name and badge number of the officer. This information is to be obtained whether the police officer makes a traffic stop or a pedestrian stop and either issues a citation or a warning (or arrest for a pedestrian stop). In addition, the length of the contact in minutes is to be recorded for traffic stops. These data items are recorded using the data collection form included in Appendix A. The law further specifies that the collected data are to be sent to the Illinois Department of Transportation by a specific date each year for the stops data collected in the preceding year.

The Illinois Department of Transportation is further directed by statute to analyze the data and submit summary reports to the Governor, the General Assembly, and the Racial Profiling Agency. The Illinois Department of Transportation is authorized to contract with an outside entity for the analysis of the data. That analysis is the purpose of this report. Moreover, the reporting entity is directed to scrutinize the data for evidence of “statistically significant aberrations.” An illustrative list of possible aberrations recorded in the statute include: (1) a higher-than-expected number of minorities stopped, (2) a higher-than-expected number of citations issued to minorities, (3) a higher-than-expected number of minorities stopped by a specific police agency, and (4) a higher-than-expected number of searches conducted on minority drivers or pedestrians.

The relevant statute, 625 ILCS 5/11-212 and subsection (a) provides that the law enforcement officer “…shall record at least the following…”. The statue seems to suggest the current data collection form includes a minimum level of information, and leaves open the possibility of gathering additional information in the future.

There are a few additional data items that could be collected during traffic stops to enhance the analysis effort. Some additional data items might include: (1) arrest for DUI, (2) officer’s race (which has been shown to affect stop rates; see Ba et al. *Science*. 2021 Feb 12:696-702), (3) occurrence of a physical arrest in a traffic stop (the arrest outcome is currently included only in the pedestrian stop data collection form) and (4) latitude and longitude of the stop (which can be used to more precisely determine the benchmark for drivers or pedestrians but might need some technological changes). Additionally, there is

[21] The pedestrian stop data collection form in use during 2021 has provision for recording an arrest. The traffic stop data collection form in use during 2021 does not provide a means of recording an arrest.

a section on this report on accuracy of race designation by the stopping officer. The findings of that research suggest to us that obtaining a self-reported race from the driver may improve accuracy.