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Pennsylvania State Police Traffic Stop Study: 2022 Annual Report January 1 – December 31, 2022

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About the National Policing Institute

The National Policing Institute (formerly the National Police Foundation) is the United States' oldest non-membership, non-partisan police research organization. The Institute was founded in 1970 by the Ford Foundation to advance policing through innovation and science. Today, the Institute builds on its founding concept with the mission to pursue excellence through science and innovation. Through rigorous objective research, detailed independent analysis, and forward-leaning thought leadership, the Institute integrates the work of social scientists and practitioners to advance the policing profession. Institute staff and partners conduct scientific evaluations of policing strategies, organizational assessments, critical incident reviews, and police data projects, and issue timely policing publications important to practitioners and policymakers. The Institute has three organizational focus areas: safety, wellness, and culture; community trust and the legitimacy of policing; and violence and force.

About the Authors

Robin S. Engel, Ph.D., serves as Senior Vice President at the National Policing Institute, following over 25 years in academic positions within higher education institutions. As an award-winning researcher, she has partnered with dozens of police agencies in the U.S. and internationally, served as Principal Investigator for over a hundred research studies and projects, and ranked among the top academics nationally in criminal justice/criminology. From 2015 – 2019, she served as Vice President for Safety and Reform at the University of Cincinnati, where her executive duties included oversight of daily operations and successful implementation of comprehensive police reforms in the aftermath of a fatal police shooting of an unarmed motorist. As a top scholar and trusted leading authority in police science, Dr. Engel oversees the Institute's vast scientific investments designed to translate and integrate research into practice.

Her research includes establishing academic-practitioner partnerships and promoting best practices in policing, with expertise in empirical assessments of police behavior (including traffic stops and use of force), police-minority relations, police supervision and management, criminal justice policies, criminal gangs, and crime reduction strategies. Her work on violence reduction in the City of Cincinnati resulted in several prestigious team awards including the 2008 IACP/Motorola Webber Seavey Award for Excellence in Law Enforcement, the 2009 IACP/West Award for Excellence in Criminal Investigations, and the 2008 National Criminal Justice Association's Outstanding Criminal Justice Program Award. In spring 2017, she was awarded the Distinguished Alumni Award from the School of Criminal Justice at the University at Albany, State University of New York. In 2022, Dr. Engel was awarded the O.W. Wilson Award by the Academy of Criminal Justice Sciences for outstanding and sustained contributions to police education, research and practice. She is also a two-time, governor-appointed member of the Ohio Collaborative Community-Police Advisory Board.

From 2002–2011, she served as the Principal Investigation for the Pennsylvania State Police's *Project on Police Citizen Contacts*. In addition to her work in Pennsylvania, she has also led traffic/pedestrian stop and use of force studies for the Ohio Highway Patrol, Arizona Department of Public Safety, Nebraska State Patrol, State of Vermont, and American Civil Liberties Union, along with local police departments in Cincinnati (OH), Seattle (WA), Tulsa (OK), Oklahoma City (OK), Aurora (CO), Boulder (CO), Colorado Springs (CO), and Fairfax County (VA). She has also published extensively on the topics of traffic stop and use of force data analyses within the top academic peer-reviewed journals in the field, has served as an expert on invited panels and conferences, and provided expert testimony in criminal and civil cases.

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Murat Yildirim, M.S., joined the National Policing Institute as a Research Data Manager in January 2023. Previously, he worked as a Research Associate for the IACP/UC Center for Police Research and Policy. He graduated from the National Police Academy of Turkey in 1997 with a B.A. and earned his Master of Science in Forensic Science from the University of Ankara in Ankara, Turkey, in 2002. He worked as a senior police officer and taught classes and courses at the National Police Academy of Turkey between 1997 and 2011. His work includes the acquisition, collection, cleaning/preparation, analysis, visualization, and mapping of crime data.

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EXECUTIVE SUMMARY

In 2002, the Pennsylvania State Police (PSP) was one of the first state police agencies to initiate traffic stop data collection voluntarily. The current data collection effort is based on foundational work conducted with the same research team for more than a decade, beginning with initial planning in 1999. After discontinuing the data collection program in 2011, the PSP renewed its traffic stop data collection effort in 2021, which now continues in partnership with the National Policing Institute (the Institute). Given the variety of factors involved in police stop and enforcement decisions, it is beneficial for agencies to identify and better understand trends and patterns to enhance their ability to interact with the public safely and fairly. The voluntary collection and analysis of traffic stop data is consistent with recommended best practice, demonstrates dedication to transparency and accountability to the public, and continues the PSP's commitment to evidence-based policing practices.

This report documents the findings from statistical analyses of data collected during all member-initiated traffic stops by the PSP from January 1, 2022 – December 31, 2022. These data are reported by individual troopers after each member-initiated traffic stop, gathered and compiled by the PSP, and transmitted weekly to the Institute's research team. Throughout each section of this report, information is presented at multiple organizational levels, reflecting the PSP's organizational structure consisting of four Areas, 16 Troops, and 88 Stations. Presenting information in this manner illustrates differences and similarities across organizational units. It permits the identification of organizational and geographic groups that may appear as outliers, providing opportunities for closer examination and focused attention by PSP officials.

Data Collection and Audit

Section 2 of this report describes the PSP data collection effort, which includes fields related to legal reasons for and characteristics of the stop, vehicle, driver, passenger, and trooper. In its initial development and continued refinement throughout 2021 and 2022, the PSP's data collection protocol far exceeds the minimum reporting standards often mandated by state legislation or used by law enforcement agencies voluntarily and includes many data fields that provide important explanatory context for understanding traffic stop outcomes.

These data were subjected to a two-phase data audit, with results showing that the PSP now exceeds recommended industry standards for minimizing missing data and logical inconsistencies by auto-populating data fields and using validation rules embedded within the data collection system.

- The Phase I data audit demonstrated a 96.8% match across the two data sources (CDR and CAD), exceeding industry-recommended best practice.
- The Phase II data audit demonstrated that most of the data fields examined have either no missing or invalid data or less than 0.005%, also exceeding industry-recommended best practice.

The PSP has also quickly responded to previous Institute team recommendations for adjustments when data quality issues were identified. The primary purpose of traffic stop data collection is to provide the means for performing rigorous and robust analyses to understand better the factors that influence officers' stop initiation and post-stop enforcement decision-making. The favorable results of this data audit provide confidence that the conclusions drawn from this research are based on reliable and valid data. Overall, the data audit findings suggest that PSP has one of the most comprehensive and accurate traffic stop data collection systems in the country.

Description of Traffic Stop Data

Section 3 reports basic frequency distributions across organizational units to describe the traffic stop data collected by PSP troopers throughout 2022. The purpose of descriptive statistics is to document the general trends in traffic stops, but these analyses cannot explain differences in these trends. Considerable variation is reported in stop characteristics, reasons for the stop, and driver characteristics across PSP organizational units. These differences are expected due to variations in the geography, roadways, jurisdiction, traffic flow, and demographic makeup of residents and travelers across the state. Department trends in these descriptive findings are summarized below.

- Across the PSP, most traffic stops occurred on a weekday (69%), during the daytime (66%), and on a state highway (53%) or an interstate (34%).
- Most stops lasted between 1-15 minutes (88%), involved vehicles registered in Pennsylvania (80%), and without passengers (80%).
- The most frequent stop reason was speeding (40%), with an average of 21.4 mph over the posted speed limit.
- Most drivers stopped were male (67%), Pennsylvania residents (81%), and displayed civil behavior towards the PSP trooper (98%).
- In terms of drivers' race and ethnicity:
    - Race: White (78.5%), Black (14.4%), American Indian or Alaskan Native (0.3%), Asian or Pacific Islander (1.8%), unknown (5.0%).
    - Ethnicity: Hispanic (8.2%), not Hispanic (85.6%), unknown (6.2%).
        - The percentage of non-Hispanic White drivers stopped was 71.1%.
    - PSP issued guidance clarifying the collection of race and ethnicity on August 12, 2022, and the average percentages of unknown race and ethnicity dropped in half.

Often racial/ethnic percentages of stopped drivers are compared to an external data source purported to represent the "expected" population of drivers. Unfortunately, the only readily available external benchmark is residential population data, which has been routinely demonstrated as seriously flawed in its ability to capture a reliable benchmark for drivers stopped for traffic offenses. Research has shown that drivers' risk of being stopped for a traffic offense can be influenced by a host of factors, including driving location, time, frequency, and quality, along with vehicle conditions, traffic conditions, and police organizational and temporal priorities. No benchmark can adequately account for all these conditions. Therefore, due to the inherent methodological limitations of all benchmark analyses, this statistical technique is not conducted. As with previous reports examining PSP traffic stops, this report instead focuses on examining the patterns and trends associated with trooper decision-making resulting in post-stop outcomes.

Traffic Stop Outcomes

Section 4 documents the research team's analyses of post-stop outcomes (e.g., verbal warnings, written warnings, citations, and arrests), including the use of descriptive statistics (frequency of stop outcomes), bivariate analyses examining the association between only drivers' race/ethnicity and post-stop outcomes, and multivariate analyses that consider multiple factors that could predict the likelihood of stop outcomes.

- The frequency of post-stop outcomes (i.e., % of stopped drivers who are warned, cited, and arrested) varies considerably across PSP Areas, Troops, and Stations.
- Across the department:
    - 56.8% of stops resulted in a verbal (18.5%) or written warning (38.3%) being issued to the driver.
    - 57.0% resulted in a citation being issued to the driver.
    - 4.6% of stops resulted in the arrest of the driver.
    - The sum of these percentages exceeds 100% because motorists can receive more than one stop outcome in a single stop.
- At the department level, statistically significant bivariate differences by drivers' race/ethnicity and gender were noted for all outcomes.
    - % of stopped drivers issued a verbal warning:
        - 17.7% of White drivers
        - 21.2% of Black drivers
        - 19.7% of Hispanic drivers
    - % of stopped drivers issued written warnings:
        - 39.4% of White drivers
        - 36.7% of Black drivers
        - 36.1% of Hispanic drivers
    - % of stopped drivers issued citations:
        - 57.3% of White drivers
        - 54.3% of Black drivers
        - 55.1% of Hispanic drivers
    - % of stopped drivers arrested:
        - 4.3% of White drivers
        - 6.6% of Black drivers
        - 5.8% of Hispanic drivers
    - Reported differences by drivers' race/ethnicity varied across organizational units.

Because bivariate analyses do not control for alternative factors that could impact the relationship between stop outcomes and drivers' race/ethnicity or gender, multivariate statistical models were estimated to provide a more thorough and accurate interpretation of the data.

- Binary logistic regression analyses predicting verbal warnings, written warnings, citations, and arrests show that:
  - Legal variables (e.g., reason for the stop, multiple violations, evidence seized) are the strongest predictors of all post-stop outcomes.
  - Once other driver, vehicle, and situational characteristics are taken into account, there are no detectable substantive racial/ethnic differences in warnings, citations, and arrests.
  - PSP members' characteristics were also not substantively strong predictors of stop outcomes, other than assignment to patrol, which was negatively related to verbal and written warnings, but positively related to citations.

Search and Seizure

Vehicle and person searches, along with contraband seized, were examined separately. Section 5 documents the research team's analyses of discretionary searches and seizures conducted by PSP troopers in 2022.

- PSP troopers initiated 12,236 discretionary searches during 2.8% of all member-initiated traffic stops. Discretionary searches are those based on reasonable suspicion, probable cause, or consent.
  - The research team excluded 3,065 searches required by policy or law (i.e., mandatory searches) from these analyses for two reasons.
    - First, a technical issue with data validation rules led to some mandatory searches (incident to arrest) being undercounted.
    - Second, the "outcome test" examining seizures during searches is only appropriate for searches that involve troopers' discretion to initiate a search.
- Binary logistic regression analyses predicting discretionary searches show:
  - The strongest predictors of discretionary searches were the various legal factors related to the stops (e.g., reason for stop, multiple violations).
  - Black and Hispanic drivers were 1.9 and 1.3 times more likely, respectively, to be searched for discretionary reasons than White drivers.
  - The predicted probabilities for discretionary searches indicated that the likelihood of being searched after considering other factors was 2.7% for Black drivers, 2.1% for Hispanic drivers, and 1.4% for White drivers.
    - Although there are differences in the likelihood of being searched across racial/ethnic groups, the overall likelihood of being searched across all racial/ethnic groups is quite low.
  - Discretionary searches are the only post-stop outcome with statistically significant and substantively small or moderate findings of racial and ethnic disparities that are not explained with available measures.

- The most common reason for discretionary searches was verbal and/or written consent (72.7%); searches based on reasonable suspicion or probable cause occurred approximately 27% of the time.
    - These differences are partially explained by Pennsylvania case law, which does not permit motor vehicle searches based on probable cause without a search warrant or exigent circumstances.
- Of the 12,236 stops involving discretionary searches, 53.6% (n=6,561 stops) resulted in the documented seizure of contraband.
    - Contraband was seized in 74.0% of traffic stops involving searches based on probable cause/reasonable suspicion.
    - Contraband was seized in 45.9% of searches based solely on motorists' consent (verbal or written).
    - These seizure rates are considerably higher than those reported for most other agencies nationwide, along with PSP's historical data.
    - The most common types of contraband seized department-wide included drugs (46.1% of seizures) and drug paraphernalia (38.6%).
- Seizure rates for both types of discretionary searches (probable cause / reasonable suspicion and consent) are significantly different across drivers' race and ethnicity.
    - For probable cause / reasonable suspicion (Type II) searches:
        - 75.8% of searches during stops with White drivers result in contraband seizures
        - 73.5% of searches during stops with Black drivers result in contraband seizures
        - 65.1% of searches during stops with Hispanic drivers result in contraband seizures
    - For consent only (Type III) searches:
        - 52.4% of searches during stops with White drivers result in contraband seizures
        - 41.5% of searches during stops with Black drivers result in contraband seizures
        - 32.9% of searches during stops with Hispanic drivers result in contraband seizures
    - Data limitations restricted the research team's ability to further examine the relationship between drivers' race/ethnicity and contraband seizures.
- Traffic stop data cannot address the legality of individual searches or if racial/ethnic disparities are due to racial/ethnic bias or discrimination.
    - Disparities in police agencies often persist after considerable training, increased supervision, and data collection improvements.

    - Suggests there are more complex explanations (e.g., organizational culture, policies, societal factors) for disparities beyond individual trooper/officer bias.
- Given the limitations of quantitative traffic stop data for understanding the complex decision-making in searching a vehicle, the PSP invited the research team to observe two PSP criminal interdiction training classes to provide context for the CDR data analyses and enhanced understanding of the specialized training related to search and seizure activity.
    - Training provided to troopers emphasizes:
        - Professionalism
        - Protection of civil rights
        - Totality of the circumstances
        - Behavioral indicators of possible criminal activity rather than individuals' characteristics.

Recommendations

Informed by the traffic stop data analyses, the Institute research team provides four broad recommendations designed to improve data collection, further examine the patterns and trends in traffic stop enforcement documented in this report, identify opportunities to enhance training, and strengthen accountability. Within each of these recommendations, a series of more specific suggestions are provided for consideration in Section 6.

Recommendation 1: The PSP should continue to refine traffic stop data collection.

As data collection continues, the PSP should maintain periodic evaluation of default settings, validation rules, and error warnings in the TraCS data collection system and seek to build additional data fields as needed.

Recommendation 2: The PSP should continue to examine differences in traffic stop patterns and trends across the agency.

Across virtually all descriptive and bivariate findings in this report, there is wide variation across organizational units in patterns related to stops. Several possible explanations for this variation exist. Despite this expected variation, supervisors across the organization need to consider if any patterns appear unusual for these specific units or geographic areas, and if so, they should be immediately addressed.

Recommendation 3: The PSP should continue to explore the content and impact of search and seizure training, particularly SHIELD criminal interdiction training.

The research team is unaware of any police agency in the country that has conducted an independent, comprehensive assessment of criminal interdiction training. By allowing the Institute's research team access to examine the content and impact of PSP's criminal interdiction training, the PSP sets a national standard for evidence-based training. PSP should continue engaging with the research team to examine changes in trainees' knowledge, perceptions, and self-reported behaviors. This work can assist the PSP in identifying opportunities for enhancements to training content and delivery. The PSP should also consider measuring behavioral differences for those troopers receiving SHIELD training.

Recommendation 4: The PSP should continue to enhance accountability mechanisms and oversight of trooper conduct during traffic stops, particularly for stops that result in consent searches.

The findings of the statistical models examining post-stop outcomes demonstrate that legal variables most strongly predict warnings, citations, arrests, and discretionary searches, and there is no statistical evidence showing substantive differences across racial/ethnic groups in these stop outcomes. Despite these efforts, some unexplained racial/ethnic disparities in consent searches and seizures remain. Just as analyses of traffic stop data cannot indicate that police bias *is* the reason for racial/ethnic disparities in outcomes, they also cannot exclude the possibility that bias is a factor. The research team recommends that PSP administrators review the current practices and identify opportunities to enhance the following: investigation of complaints of biased behavior, compliance with the consent waiver process, supervisory oversight of consent searches, and specialized criminal interdiction training.

Conclusion

As demonstrated by PSP's ongoing data collection and analysis and their responsiveness to the Institute research team's recommendations from previous reports, PSP officials remain committed to the data collection effort and the larger goals of reducing racial/ethnic disparities in traffic stops and post-stop outcomes. It is evident that the PSP seeks to provide legitimate and unbiased policing services to citizens of the Commonwealth of Pennsylvania.

It is important to note that none of the analyses presented in this report can be used to determine whether unexplained racial/ethnic disparities are due to trooper bias or whether troopers otherwise acted in a biased manner toward motorists. Even the most comprehensive data collection effort and rigorous statistical analyses cannot be used for these purposes. Collecting and analyzing data on traffic stops does, however, provide opportunities for PSP administrators to understand better the factors that influence troopers' traffic stop enforcement and to assess patterns and trends across the agency and within organizational units. Continually monitoring traffic stops also offers valuable information to enhance training, policy, and supervision within the organization while simultaneously institutionalizing a culture that inspires fair and impartial policing.

SECTION 1: INTRODUCTION

Given the variety of factors involved in police stop and enforcement decisions, it is beneficial for agencies to identify and better understand trends and patterns to enhance their ability to interact with the public safely and fairly. The Pennsylvania State Police (PSP) renewed their traffic stop data collection effort in 2021 (Engel & Cherkauskas, 2022).[1] There are several goals for this renewed data collection effort and associated research, including: 1) identifying patterns and trends in traffic stops and stop outcomes with a focus on documenting racial/ethnic disparities, 2) using data analyses to enhance effective and equitable law enforcement practices designed to improve public and traffic safety, 3) building public trust through transparent documentation of traffic stop data and related findings, and 4) identifying opportunities for improvement in PSP policies, training, and supervisory oversight related to traffic stops. The PSP's voluntary collection and analysis of traffic stop data is consistent with best practices (Pryor et al., 2020), demonstrates dedication to transparency and accountability to the community it serves, and continues its commitment to evidence-based policing practices.

Historical Context of PSP Traffic Stop Data Collection

The current data collection effort was based on foundational work conducted with the same research team over the course of more than a decade.[2] After initial discussions beginning as early as 1999, in January 2002, the *Police/Citizen Contact Policy Committee*, composed of PSP administrators and the Principal Investigator (Engel), developed the original Contact Data Report (CDR), a paper-based Scantron form completed by PSP troopers during all member-initiated traffic stops. After pilot testing and modifications, the department-wide data collection process began in May 2002. The information collected included the: (1) stop –e.g., date/time, location, duration, roadway type, and reasons for the stop; (2) driver – e.g., gender, age, race/ethnicity, and residency; (3) vehicle – e.g., state of registration, number of passengers; (4) stop outcome – e.g., citation, written warning, arrest, search, property seized during the search; and (5) the troopers' assigned station and employee identification number.

Initially, the completed CDRs were collected at the station level and mailed weekly to the research team. These forms were scanned by project personnel using the Scantron machine purchased by the PSP. Once scanned, the forms were stored securely until the electronic datasets were collated, audited, and considered ready for analysis, at which time the actual scan forms were destroyed through shredding.

In addition to analyses of the PSP stop data, the research team also conducted independent observations of roadway usage and speeding behaviors to provide alternative benchmark

[1] The research team completed the initial work on this project (i.e., the 2021 annual report and two quarterly reports for 2022) under our affiliation at the University of Cincinnati. The research team moved to the National Policing Institute in September 2022; the PSP and the Institute executed a new contract to complete the remaining original deliverables.
[2] This brief overview of the previous work was described in the *2021 Traffic Stop Study* but is repeated here for context.

comparisons for the stop data. Three quarterly reports and one final year report based on these data were delivered to PSP administrators in January 2004 for the first year of data collection (May 1, 2002 – April 30, 2003). The data collection was extended for an additional year (May 1, 2003 – April 30, 2004), and a final report for Year 2 was issued in March 2005. These reports documented trends in PSP-initiated traffic stops and post-stop outcomes, including warnings, citations, searches, and arrests.

The research team collected data for a third year (May 1, 2004 – April 30, 2005); however, a final report was not delivered due to inaccuracies in the data collected initially discovered during focus groups with troopers and confirmed through an internal data audit. Corrections to the data collection process were implemented in September 2005. The Year 3 data was compared to data collected in the fourth year (May 1, 2005 – April 30, 2006) to determine the level of inaccuracy. Based on these findings, a report combining Year 3 and Year 4 data was issued in 2006, representing data collected during calendar years 2004 and 2005.

A new contractual relationship in 2006 and an extension in 2009 allowed for collecting and analyzing five additional years of data (2006 – 2010). The PSP developed and implemented a new electronic data collection system, the CDR-Xpress, in 2006. This allowed for the data to be transmitted electronically to the UC team. Reports documenting the existence of any racial/ethnic disparities in post-stop outcomes during these five years were provided to PSP officials annually, with the final report of data collected in 2010 was issued in 2011. After 2010, data collection during PSP member-initiated traffic stops was discontinued.

The main findings of the data collection from 2002-2010 can be summarized as follows:

- Initial Traffic Stop
    - There was no consistent evidence to suggest that PSP troopers disproportionately stopped minority motorists.
    - Although large racial/ethnic disparities existed between stops and Census-based benchmarks when stop data was compared to benchmarks that better capture roadway usage and driving behavior, these reported disparities were significantly reduced and, in some cases, eliminated.
- Post-Stop Outcomes
    - The reason for stop and other legally relevant characteristics were, substantively, the strongest predictors of all post-stop outcomes (e.g., warnings, citations, arrests, searches).
    - After some initial reporting of disparities, later years demonstrated no statistically significant differences in warnings or citations for Black, Hispanic, or drivers of other races when multiple explanatory factors were simultaneously considered.
    - Black drivers were significantly more likely to be arrested only in Year 1; no racial/ethnic differences in arrests were found to be statistically significant in subsequent reports.
    - Data fields added in 2010 (e.g., criminal history, impairment) strongly predicted arrests and searches during traffic stops.

- Hispanic and Black motorists were significantly more likely to be searched for discretionary reasons compared to Whites but less likely to have contraband seized during searches.
  - Racial/ethnic differences in searches and seizures persisted even after additional training, increased supervision, and improvements in data collection.

2021 Report Summary

The renewed data collection effort was designed to examine patterns and trends regarding PSP members' initiation and outcomes of traffic stops. The *2021 Pennsylvania State Police Traffic Stop Study* describes the PSP's new data collection process, the data fields included, and the Institute's two-phase data audit of the CDR data collected in 2021 (Engel & Cherkauskas, 2022). As is often the case with a statewide data collection effort of this size and scope, the research team identified several data integrity issues that made it impossible to conduct substantive analyses of the 2021 data. Detailed information is provided in the *2021 Pennsylvania State Police Traffic Stop Study*. As these issues were discovered, the PSP implemented several modifications to the data collection process that improved the reliability and validity of the data. As a result of these significant improvements, data collected between January 1 and December 31, 2022, was the second full year of data collected but the first full year of data that the research team analyzed.

2022 Report Outline

This report documents the findings from statistical analyses of data collected during all member-initiated traffic stops by the Pennsylvania State Police (PSP) from January 1, 2022 – December 31, 2022. The remainder of Section 1 provides an overview of the current report, which is divided into six sections: 1) introduction, 2) description of 2022 traffic stop data collection and data audit, 3) description of traffic stop data, 4) bivariate and multivariate analyses of 2022 post-stop outcomes, 5) searches and seizures, including a qualitative assessment of PSP's criminal interdiction training, and 6) discussion and recommendations. Throughout each section of the report, information is presented at multiple organizational levels, reflecting PSP's organizational structure of four Areas, 16 Troops, and 88 Stations. Presenting information in this manner illustrates differences and similarities across organizational units and permits the identification of organizational and geographic groups that may appear as outliers, providing opportunities for closer examination and focused attention by PSP officials.

The content of Sections 2 - 6 is described below.

Section 2

Section 2 first describes the traffic stop data collection system, followed by the methods and results of a two-phase data audit of the 2022 PSP traffic stop data. The primary purpose of traffic stop data collection is to provide the means for performing rigorous and robust analyses to understand better the factors that influence officers' stop initiation and enforcement decision-making and to assess whether the results of these decisions are equitable. To draw such conclusions, one must ensure that the data are reliable, valid, and error-free (Loken & Gelman, 2017). Regardless of the sophistication of the statistical analyses used by researchers, the study is only meaningful if the traffic stop data itself is valid.

Section 3

Section 3 reports basic frequency distributions to describe the traffic stop data collected by PSP troopers throughout 2022. Specifically, it provides information derived from the traffic stop data, such as the number of stops, and how often specific characteristics of the stops, reasons for the stops, and driver characteristics were reported in the data. Reported drivers' characteristics include age, gender, residency, behavior during the stop, and race and ethnicity. The purpose of descriptive statistics is to document the general trends in traffic stops, but these analyses do not provide an explanation for these trends.

Section 4

The analyses of post-stop outcomes (e.g., verbal warnings, written warnings, citations, and arrests) are documented in Section 4. First, descriptive statistics about the frequency of different stop outcomes are provided. Second, driver differences, based on race/ethnicity and gender, are examined for all post-stop outcomes. These initial bivariate analyses examine the association between drivers' race/ethnicity and post-stop outcomes and provide a basic understanding of the relationships, but do not consider any other factors that could predict the likelihood of stop outcomes. Finally, several multivariate analyses that isolate factors associated with officer decision-making regarding traffic stop outcomes are presented. Specifically, Section 4 documents whether these outcomes differ significantly based on a multitude of factors, including: legal variables, driver characteristics, vehicle characteristics, stop characteristics, and trooper characteristics.

Section 5

Section 5 focuses specifically on discretionary search and seizure activity of the PSP. Discretionary searches exclude searches conducted for mandatory reasons (e.g., required based on policy or law) but rather include those conducted based on reasonable suspicion, probable cause, and/or consent. The discretionary search rates for Black and Hispanic drivers are compared to White drivers across multiple organization levels at the bivariate level. Thereafter, a multivariate model predicting discretionary searches is presented that controls for numerous factors. Comparisons of seizure rates for probable cause/reasonable suspicion seizure and consent searches are made and explored by drivers' race/ethnicity. To provide further insight into some of the specialized training that PSP troopers receive related to search and seizure activity, the PSP invited the research team to observe criminal interdiction training classes and survey trainees. This section also documents the independent observations of the research team regarding this training.

Section 6

Section 6 summarizes the major findings from the Institute's comprehensive analyses of 441,329 traffic stops related to the Institute's recommendations. Specifically, the research team provides recommendations for consideration by PSP officials designed to improve data collection, further examine the patterns and trends in traffic stop enforcement documented in this report, identify opportunities to enhance training, and enhance accountability.

Note that the findings reported in this document must be interpreted cautiously. The data collected and presented in this report cannot be used to determine whether or not PSP troopers have individually or collectively engaged in discriminatory or biased policing practices or otherwise acted in a biased manner toward motorists. In addition, the legality of individual traffic stops cannot be assessed with these data. Even the most comprehensive data collection effort and rigorous statistical analyses cannot be used for these purposes. This is a well-documented limitation of traffic stop data collection and analyses (Engel & Calnon, 2004a; Fridell, 2004; Pryor et al., 2020; Tillyer et al., 2010).

Collecting and analyzing data on traffic stops does, however, provides an opportunity for PSP administrators to assess patterns and trends across the agency and within organizational units. Exploring patterns and trends can be utilized for advances in training, policy, practice, and supervision. It assists the agency in its effort to be self-learning and continuously improving by regularly assessing internal operations and better understanding the factors that influence troopers' traffic stop enforcement decisions.

SECTION 2: DATA COLLECTION AND AUDIT

The PSP developed the current data collection effort in partnership with the Institute research team. This process was informed by the previous PSP traffic stop studies conducted from 2002 to 2010 and current best practices in the field. Throughout 2021 and 2022, the PSP has refined and improved the content and quality of the data collection protocol. Section 2 describes the data collection process and the data fields included for analysis. It also provides the results of the research team's two-phase data audit of the PSP data.

Data Collection

PSP troopers must complete Contact Data Reports (CDR) for all member-initiated traffic stops *regardless of the stop's outcome*. Troopers enter data electronically through mobile data terminals (MDTs) in a software system called TraCS (Traffic and Criminal Software). Some data fields are auto-populated from other PSP electronic forms to minimize redundancy and maximize efficiency. Table 2.1 below documents the information included on the CDR during 2022 and contains a brief description of how each variable is measured. The PSP data collection includes comprehensive data fields that capture information about the characteristics of the stop, including the date, time, and location and other relevant context about the stop and stopped vehicle, reason(s) for the stop, driver characteristics, enforcement outcomes, presence of passengers, and identification number of the trooper who made the stop. The PSP's data collection protocol is considerably more comprehensive that far exceeds the minimum reporting standards associated with many state mandated data collection efforts and includes many data fields that provide important explanatory context for understanding traffic stop outcomes.

Note that, as described in the *2021 Traffic Stop Study Report*, the gender and racial/ethnic characteristics of drivers are determined by officers' perceptions rather than asking drivers to identify their gender, race, or ethnicity (Engel & Cherkauskas, 2022). This method is consistent with the guidance of best practice guides regarding traffic stop data collection; identifying drivers' race/ethnicity based on officers' perceptions is the recommended data collection method for examining racially biased policing (Fridell et al., 2001; Pryor et al., 2020; Ramirez et al., 2000). Officers may incorrectly perceive the driver's actual race or ethnicity. This possible misperception, however, is irrelevant for data collection analyses that seek to explain officer-decision making.[3] Troopers gathered other information about the driver (e.g., year of birth) from the driver's license.

[3] Concerns regarding racial, ethnic, and gender profiling are often based on the presumption that officers treat motorists differently due to their personal bias. Therefore, proper data collection efforts must identify officers' *perceptions* of the race/ethnicity of the driver, which may or may not accurately represent the driver's actual race/ethnicity. It is officers' perception that are relevant in these inquiries.

Table 2.1. Summary of 2022 Contact Data Report Fields

Category	Data Fields Captured	Details
Stop Characteristics	Location	County & municipality code/name, latitude/longitude
	Stop Time	24-hour; HH:MM
	Stop Date	MM/DD/YYYY
	Roadway Type	Interstate, state highway, county/local road, other
	Vehicle Registration State	Format: AA, Two alpha characters
	Duration of stop	In minutes: 1 – 15, 16 – 30, 31 – 60, 61+
Reason	Reason(s) for stop	Equipment/inspection, license, other moving violation, registration, speeding
	Speeding information	Posted speed limit, Driver speed, MPH over limit
Special Enforcement	Special enforcement team	Yes/No
	Dedicated enforcement team	Yes/No
	MCSAP	Yes/No (Motor Carrier Safety Assistance program)
Driver	Date of Birth	MM/DD/YYYY
	Gender	Female, Male, Unknown
	Race	White, Black, American Indian/Alaskan Native, Asian/Pacific Islander, Unknown
	Ethnicity	Hispanic Origin, Not of Hispanic Origin, Unknown
	Limited English proficiency (LEP)	Yes/No. If yes, the type of language assistance utilized: Bilingual Department personnel, Propio (phone interpretation), Administrative Office of Pennsylvania Courts Interpreter, Other
	Driver Behavior	Civil, Disrespectful, Non-compliant, Verbally Resistant, Physically Resistant (select all that apply)
	Zip Code of Residency	5-digit zip code, 99999 used for international
Stop Result	Warning Type	None, Verbal Warning, Written Warning
	Number of Warnings	Enter the number of warnings
	Number of Citations	Select number of driver citations
	Driver Arrested	Yes/No
	Search Initiated	Yes - Roadside during the traffic stop, Yes - Towed from stop and searched elsewhere, No
	Searched	Select all that apply: Driver, Passenger, Vehicle
	Search Reason	Incident to arrest, inventory, officer safety (Terry search), plain view contraband, probable cause + exigency, search warrant, consent (written, verbal)
	Property Seized	None, Alcohol, Cash, Drugs, Drug Paraphernalia, Stolen Property, Vehicle, Weapons, Other
	K-9 Utilized	Yes/No
Passenger	Number of passengers	Select number of passengers
	Asked Passenger for ID	Yes/No
	Passenger ID Type	State, federal, county/municipal, or foreign issued ID, other, none
	Passenger ID Justification	Safety concern, reasonable suspicion, assume driving responsibility, other
	Passenger Race & Ethnicity	Same as drivers' race and ethnicity response options
	Limited English proficiency	Yes/No. If yes, same as driver LEP response options
	Stop Outcomes	Number of warnings, citations, or whether arrested
Employee / PSP Member Information	Location Code	Assigned Station
	Gender	Male/Female
	Race/Ethnicity	Black, Hispanic, White, American Indian/Alaskan Native, Hawaiian/Pacific Islander, Asian
	Length of Service	Number of Years of Service
	Assignment	Job Code (e.g., Patrol, Canine, Drugs)
	Rank	Trooper, Corporal, Sergeant, Lieutenant, Captain, Major

Table 2.2 below documents the data fields that were updated or added to the PSP data collection protocol during 2022.[4] Some of these changes were designed to address data integrity issues identified during quarterly reports by the research team. Other changes add potentially relevant explanatory factors that will assist the Institute team in analyzing post-stop outcomes. Follow-up changes to the data collection system were made via Departmental Bulletins from the PSP Director of the Bureau of Communication and Information Services.

Table 2.2. Summary of Changes to Data Collection Protocol throughout 2022

Type of Change	Related Data Field(s)	Description of Change	Reason for Change	Effective Date
Addition	Limited English Proficiency; LEP language assistance	New field to document whether driver had LEP, and if yes, the type of language assistance employed.	Assist in possibly explaining the duration of certain traffic stops.	1/11/2022
Addition	Multiple passenger-related fields	New fields to document passenger race, ethnicity, ID requested, ID type, justification for ID request, LEP, and if yes, the type of language assistance.	Assist in possibly explaining the duration of certain traffic stops.	1/11/2022
Addition	Type of Search Performed	New field to document type(s) of search(es) conducted: Driver, Passenger, and/or Vehicle.	Assist in examining differences in search success rates by search target.	1/11/2022
Update	Multiple passenger-related fields	Number of passenger warnings, citations, and arrests data fields relocated on the CDR form to relate to each specific passenger.	Assist in examining outcomes related to each passenger.	1/11/2022
Update	Passenger data elements	Extract can contain multiple values comma separated for passenger data elements.	Assist in providing more data on each passenger.	1/11/2022
Update	Dedicated Enforcement Team	Form updated to default response option to "Yes," if User is part of a SHIELD or Canine Unit.	Assist in minimizing data entry errors, missing data, and/or logical inconsistencies.	9/6/2022; 10/13/2022

Data Audit

Data auditing is an important mechanism to assess data integrity before engaging in statistical analyses. It is the systematic process of evaluating the reliability and validity of the collected data. **Data reliability** refers to the measured items' stability or consistency (i.e., is the variable measured consistently across cases). Having reliable data is vital to be confident in reporting that any observed changes in the data reflect reality rather than changes in the data collection. **Data validity** refers to the overall accuracy of the measure (i.e., does it measure what it is supposed to be measuring). Establishing the validity of data collection measures is also essential to ensure the

[4] Table 2.2 does not include changes that went into effect on 12/28/2022 for the 2023 data collection because these changes were not examined in this report. The 2023 Annual Report will describe these in detail but, briefly summarized, they include: 1) New reason for stop-stop conducted but determined no violation, 2) Property seized renamed to "result of search" with new response options to document other criminal activity detected, 3) If "equipment/inspection" is the reason for stop, added a data field for window tint, 4) Added a response option of "Two or More Races" for Drivers' race, and 5) changes in validation rules to minimize missing data on search-related data fields.

quality of scientific research. Data collection efforts must strive to be both reliable and valid to establish confidence in any statistical analyses performed.

No data collection is perfect, but minimizing measurement errors (i.e., the difference between observed and actual values) is critical because they can lead to biased or incorrect conclusions drawn from data analyses. It is imperative to mitigate systematic measurement error. Random measurement error is an error that tends to naturally find its way into a database due to chance factors; because it is inconsistent and unpredictable, its impact on conclusions is likely to be minor, given that random errors are assumed to cancel each other out in an analysis (Singleton & Straits, 2005). Systematic measurement error, on the other hand, is an error in a database that produces a bias in the data because the error is consistent across all cases of the measure. Data that are inaccurately or inconsistently collected in a consistent manner may not affect the measure's reliability, but validity will likely be severely impacted (Singleton & Straits, 2005).

Data Preparation

The Institute received 482,261 CDRs in weekly extracts transmitted by the PSP to the research team between January 3, 2022, to January 23, 2023. Stops that occurred in 2021 or 2023 were excluded from the current analyses (n=37,997). Of the 444,264 CDRs recorded in 2022, 1.2% included a duplicate document number (n=5,378). Of these, 2,734 duplicate entries with matching stop date, time, location, driver characteristics, stop reason, and outcomes were excluded. In addition, of the 444,264 CDRs for 2022, 3.4% included a duplicate Computer Aided Dispatch (CAD) number (n=15,092). Most of these CDRs reflected different stops mistakenly assigned to the same CAD number. Only 201 duplicates identified by CAD number were excluded based on matching stop date, time, location, and driver characteristics.

As a result of these exclusions, the final dataset for 2022 CDR analyses includes 441,329 stops for which PSP troopers collected data between January 1, 2022, and December 31, 2022. The remainder of this section summarizes the results of a two-phase data audit of the CDR data collected in 2022.

Data Audit—Phase 1

Description

Phase 1[5] examines the data accuracy by comparing the number of stops in the electronic CDR data to the number of stops in an independent source of information to assess whether all stops recorded in the external source of information are represented in the CDR data. This type of audit determines the extent to which troopers complete data collection forms as required and addresses data validity; that is, whether CDR data represents all member-initiated traffic stops, regardless of the outcome.

An external data source that records the same eligible traffic stops is necessary to determine whether the information is recorded for all stops. Typical comparison data sources include CAD, citation, written warning, videotapes, or other departmental data (Fridell, 2004; Ramirez et al., 2000). In 2004, the Police Executive Research Forum, a police research and policy organization,

[5] In the 2021 report, the data audit phases were presented in the opposite order. Therefore, a comparison between the two reports should compare the 2022 Phase 1 to 2021 Phase 2 and the 2022 Phase 2 to 2021 Phase 1.

published a comprehensive guide for analyzing data from traffic stops that remains a resource for law enforcement agencies nearly two decades later. This guide recommends a 90% or greater match between data sources (Fridell, 2004).

Based on discussions with PSP personnel, the research team determined that the most appropriate and comprehensive comparison data would be CAD calls coded as traffic stop incidents provided by the PSP.[6] The reporting standards are almost identical between the two datasets; however, some exclusions were made from the CAD data to ensure an "apples-to-apples" comparison.[7]

Results

Table 2.3 below compares the aggregate number of traffic stops included in CAD calls (coded as traffic stops) with the total number of traffic stops included in the CDR data for the PSP overall and at the Station level.[8] The table provides a percent difference for each organizational unit, representing the percentage of traffic stops that do not match across the two data sources. The percent difference is calculated as follows, where the "observed value" equals the count of stops in the CDR data and the "true value" equals the count of stops in the CAD data:

$$\text{Percent Difference} = \frac{V_{\text{observed}} - V_{\text{true}}}{V_{\text{true}}}$$

A positive difference rate indicates the percentage of stops that appear in the CDR data but not in the CAD records. Conversely, a negative difference rate indicates the percentage of stops that appear in the CAD records but not in the CDR data.

Overall, the results in Table 2.3 show that the percent difference between the two datasets at the department level is –3.2%, indicating that 96.8% of records match across the two data sources. This percentage exceeds the PERF-recommended correspondence of 90% or more between two sources of information (Fridell, 2004). Department-wide, the number of traffic stops in the CAD records was slightly greater than the number of traffic stops in CDR.

Additionally, using this same standard of 10% difference, the results of this audit are favorable at the station level. Only seven of the 88 stations (and neither specialized unit) had difference rates of 10% or greater. Four of these seven stations were in Troop A (Ebensburg, Greensburg, Kiski Valley, and Somerset). No other Troop had more than one station that exceeded a 10%

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[6] It is important to note that CAD codes for other types of traffic stops that are not trooper-initiated are coded differently (e.g., when a dispatcher receives a report of a traffic violation like an erratic driver and assigns it to a trooper for response). This is important because these stops can be distinguished from the CAD incidents when a trooper initiates a traffic stop and self-generates a call number. Therefore, minor discrepancy between these data sources should be expected and does not necessarily reflect undercounting of traffic stops using the CDR forms.

[7] Specifically, to ensure that the comparison includes only trooper-initiated stops in the CAD data, 5,896 motor carrier enforcement-related stops and 627 disabled motorist-related stops were excluded as these are not CDR-required stops. Further, to guarantee that each CAD incident is only counted once, 969 duplicate incidents were excluded. Finally, to ensure that CAD incidents resulted in a stop that would generate a CDR, 160 CAD incidents that involved a pursuit without apprehension and 533 canceled CAD incidents were excluded since they did not result in the stop of an individual.

[8] PSP members assigned to Highspire Station (Troop T), the Turnpike Commission Building, conducted less than 100 stops for the entire year in 2022. Therefore, this station is excluded from this table.

difference rate. Note that Ebensburg and Greensburg stations had difference rates of nearly –20%, by far the largest difference rates in any station.

Only 11 stations and the Canine unit had positive difference rates. In comparison, the remaining 77 stations and the SHIELD unit had a negative difference rate or no difference, indicating that the number of traffic stops in CAD was higher than the number of traffic stops in CDR.

The *2021 Traffic Stop Study Report* noted that the PSP developed an internal audit dashboard for PSP members and supervisors. This process involves automating the comparison of completed CDR forms with TraCS warning and citation forms to ensure members complete a CDR for every required contact.

The PSP also designed a CDR duplicate detection process to identify and correct any duplicate CDRs before PSP provides data to the Institute research team. By using rules in the TraCS system, the program can analyze data quickly and effectively to detect when a CDR with the same document (CDR) number *or* the same CAD/Case number was already submitted and accepted in the system. In the event of a duplicate, the program will change the status of a CDR to *Duplicate* and exclude those CDRs with a *Duplicate* status from the transmitted data. Each CDR identified as having the same CDR/document number or sharing a CAD number with an already submitted CDR is sent back to the PSP member who submitted it for corrective action. This automated validation process runs daily, immediately preceding the data extraction for submission to the Institute research team, which should eliminate the potential for duplicate records.

Continual supervisory oversight and regular data audits – like the systems in use by the PSP – are critical components for ensuring the continued accuracy and validity of these data.

Table 2.3: Comparison of Number of Stops in CDR and CAD Data Sets for Area I, 2022

	Traffic Stops in CDR	Traffic Stops in CAD	Percent Difference
Troop B			
Belle Vernon	5,066	5,222	-3.0%
Pittsburgh	7,168	6,761	6.0%
Uniontown	11,505	11,662	-1.3%
Washington	4,272	4,326	-1.2%
Waynesburg	2,429	2,502	-2.9%
Troop C			
Clarion	2,652	2,770	-4.3%
Clearfield	3,999	4,129	-3.1%
Dubois	3,110	3,187	-2.4%
Lewis Run	4,054	4,213	-3.8%
Marienville	2,467	2,554	-3.4%
Punxsutawney	3,483	3,483	0.0%
Ridgway	2,802	2,969	-5.6%
Troop D			
Beaver	3,619	3,874	-6.6%
Butler	6,182	6,253	-1.1%
Kittanning	7,941	8,291	-4.2%
Mercer	3,292	3,463	-4.9%
New Castle	2,637	2,706	-2.5%
Troop E			
Corry	2,919	3,028	-3.6%
Erie	9,196	9,512	-3.3%
Franklin	2,115	2,305	-8.2%
Girard	6,321	6,533	-3.2%
Meadville	3,658	4,273	-14.4%
Warren	2,876	3,006	-4.3%

Table 2.3: Comparison of Number of Stops in CDR and CAD Data Sets for Area II, 2022

	Traffic Stops in CDR	Traffic Stops in CAD	Percent Difference
Troop A			
Ebensburg	1,984	2,462	-19.4%
Greensburg	4,745	5,917	-19.8%
Indiana	6,626	7,134	-7.1%
Kiski Valley	1,337	1,511	-11.5%
Somerset (A)	3,351	3,881	-13.7%
Troop G			
Bedford	5,065	5,334	-5.0%
Hollidaysburg	4,276	4,362	-2.0%
Huntingdon	3,899	4,078	-4.4%
Lewistown	4,069	4,574	-11.0%
McConnellsburg	3,441	3,562	-3.4%
Rockview	7,609	8,033	-5.3%
Troop H			
Carlisle	11,184	10,304	8.5%
Chambersburg	12,462	12,876	-3.2%
Gettysburg	8,551	9,430	-9.3%
Harrisburg	9,536	9,632	-1.0%
Lykens	2,890	2,979	-3.0%
Newport	3,741	3,965	-5.6%
Troop T			
Bowmansville	4,197	4,782	-12.2%
Everett	6,570	6,425	2.3%
Gibsonia	5,174	5,315	-2.7%
King of Prussia	5,395	5,436	-0.8%
New Stanton	7,126	7,245	-1.6%
Newville	4,054	4,142	-2.1%
Pocono	4,371	4,476	-2.3%
Somerset (T)	5,411	5,459	-0.9%

Table 2.3: Comparison of Number of Stops in CDR and CAD Data Sets for Area III, 2022

	Traffic Stops in CDR	Traffic Stops in CAD	Percent Difference
Troop F			
Coudersport	2,738	2,941	-6.9%
Emporium	1,267	1,310	-3.3%
Lamar	5,398	5,957	-9.4%
Mansfield	2,464	2,608	-5.5%
Milton	7,771	8,151	-4.7%
Montoursville	5,867	5,967	-1.7%
Selinsgrove	3,643	3,846	-5.3%
Stonington	2,048	2,163	-5.3%
Troop N			
Bloomsburg	2,992	3,115	-3.9%
Fern Ridge	5,781	5,903	-2.1%
Hazleton	6,140	6,239	-1.6%
Lehighton	2,395	2,388	0.3%
Stroudsburg	12,900	13,085	-1.4%
Troop P			
Laporte	2,070	2,076	-0.3%
Shickshinny	2,067	2,109	-2.0%
Towanda	4,527	4,854	-6.7%
Tunkhannock	1,928	2,060	-6.4%
Wilkes-Barre	4,711	4,824	-2.3%
Troop R			
Blooming Grove	4,896	4,880	0.3%
Dunmore	3,136	3,068	2.2%
Gibson	3,973	3,829	3.8%
Honesdale	2,938	2,848	3.2%

Table 2.3: Comparison of Number of Stops in CDR and CAD Data Sets for Area IV and Specialized Units, 2022

	Traffic Stops in CDR	Traffic Stops in CAD	Percent Difference
Troop J			
Avondale	8,890	8,905	-0.2%
Embreeville	7,267	7,402	-1.8%
Lancaster	6,788	6,942	-2.2%
York	9,222	9,356	-1.4%
Troop K			
Media	11,759	12,446	-5.5%
Philadelphia	10,538	10,523	0.1%
Skippack	4,726	4,713	0.3%
Troop L			
Frackville	2,915	3,087	-5.6%
Hamburg	2,605	2,551	2.1%
Jonestown	4,885	5,153	-5.2%
Reading	4,157	4,378	-5.0%
Schuylkill Haven	5,039	5,135	-1.9%
Troop M			
Belfast	3,846	3,948	-2.6%
Bethlehem	4,497	4,557	-1.3%
Dublin	3,907	3,942	-0.9%
Fogelsville	5,956	6,060	-1.7%
Trevose	4,409	4,656	-5.3%
Specialized Units			
SHIELD	4,429	4,568	-3.0%
Canine	2,232	2,303	3.1%

Data Audit—Phase 2

Description

Phase 2 of the audit for 2022 data assesses the degree to which the data captured by PSP troopers are complete and error-free. This assessment involves examining missing data (i.e., no information entered by the officer), logical inconsistencies (i.e., fields with missing and/or incorrect entries that contradict other fields), and the reliability of the data collected. The fields analyzed in this data audit were assessed based on whether they conform with the *CDR Data Dictionary Codebook* guidelines.

Results

Table 2.4 below reports the percentage of missing data and conflicting information for the 2022 CDR data. As noted previously, the PERF recommended missing data rate (based on a guide published in 2004) is less than 10%. However, based on advances in the quality and consistency of data collection systems, our research team recommends a more stringent standard of less than a 5% error rate, with 2% as the goal. Based on these higher standards, the results of this portion of the data audit demonstrate that the PSP's data collection processes are strong.

As shown in Table 2.4, most of the variables examined have either no or very little missing or invalid data. Overall, the data validation built into the TraCS system, and the revisions made throughout 2021 and 2022, have minimized the error rates. The only field with an error rate that exceeds the recommended threshold – Dedicated Enforcement Team – has already been addressed by the PSP in response to quarterly reports identifying the issue.[9]

Finally, two other data fields have issues related to data integrity that are not described by this data audit. First, although drivers' race and ethnicity are not missing any data, there is wide variation in the reported percentage of unknown racial/ethnic characteristics. Section 3 addresses this issue in greater detail. Second, as documented in 2022 quarterly reports, the PSP discovered a technical issue in September 2022 with the search reason data field that likely resulted in incident to arrest searches being underreported. It was quickly addressed but likely still impacted the reliability of PSP troopers reporting mandatory searches. Section 5 describes this issue and the research team's resolution in greater detail.

[9] If a trooper selects "yes" to indicate a Dedicated Enforcement Team assignment, they are prompted to select their assigned DET. In some cases, the number of stops for the selected DET does not match the location or station code for the same enforcement team. For example, 3,893 stops reported SHIELD as the DET, but there are 4,429 stops with a SHIELD location code; 1,367 stops reported Canine as DET, but there are 2,232 stops with a Canine location code. As noted in the Quarter 3 Report, the DET data field was adjusted to default to "yes" for troopers assigned to the SHIELD and Canine units in response to similar discrepancies. Due to the timing of this update in Quarter 4, the overall percentage for 2022 appears problematic. However, examining just the last two months of 2022 reveals a significant improvement to between 4 and 6% inconsistencies between the DET and location code data fields. The research team will continue to monitor this in 2023 quarterly audits. See page 6 of the Quarter 3 Report for further explanation.

Table 2.4: Missing and Invalid Data from Member-Initiated Traffic Stops (n=441,329) Jan-Dec 2022

	% Missing	% Invalid
Stop Characteristics		
Date of Contact	0.00%	0.00%
Time of Contact	0.00%	0.00%
Location of Stop[10]	0.00%	0.00%
Roadway Type	<0.00%	0.00%
Duration of Stop	<0.00%	0.00%
Reason for the Stop[11]	<0.00%	0.00%
Special Traffic Enforcement	<0.00%	0.00%
Dedicated Enforcement Team	0.04%	21.03%
MCSAP Related	0.01%	0.00%
Outcome of the Stop		
Warning Type	0.12%	0.00%
Number of Driver Warnings	0.00%	0.02%
Number of Driver Citations	<0.00%	0.00%
Driver Arrest	<0.00%	0.00%
Valid Search[12]	0.04%	0.72%
Driver Characteristics		
Year of Birth	0.00%	0.06%[13]
Gender	0.00%	0.00%
Race	0.00%	0.00%
Ethnicity	0.00%	0.00%
LEP[14]	0.04%	0.00%
Behavior/Demeanor	<0.01%	0.00%
Zip Code	0.00%	0.61%[15]
Vehicle Characteristics		
Vehicle State of Registration	0.00%	0.00%
Number of Passengers	<0.00%	0.00%
Trooper Characteristics[16]		
Gender	0.00%	0.00%
Race	0.00%	0.00%
Years of Service	0.00%	0.00%
Rank	0.00%	0.00%
Assigned Station Code	0.00%	0.00%

Note: <0.00 reflects less than 0.005% missing or invalid data.

[10] A "valid location of stop" exists if troopers enter county and municipality codes ***and/or*** provide latitude and longitude coordinates. Latitude and longitude are auto-populated from various TraCS forms (e.g., warning, citation), while county and municipality codes are auto-filled from the location selected in the TraCS Location Tool (TLT). Missing data appears if it is missing in the original forms.

[11] These percentages reflect the inclusion of valid data for posted speed limit, actual speed, and amount over speed limit only for stops made based on speeding violations.

[12] The % missing for valid search reflects the stops without a valid entry for the data field indicating whether a search was conducted (1,848 out of 441,329), while the % invalid reflects 110 stops out of 15,301 where a search was indicated but search reason and/or contraband seized were missing a required entry.

[13] There were 261 CDRs with dates of birth before 1/1/1921 or after 1/1/2011.

[14] LEP was missing for 10,061 CDRs, largely because this data field was not included in the data collection until January 11, 2022. The percent missing in Table 2.4 reflects only the 173 CDRs missing LEP after adding the field.

[15] There were 2,695 CDRs that include zip codes with five digits not in the US Zip Code Database and not equal to 99999, the PSP codebook designation for international addresses.

[16] The CDR form requires an employee ID number, which links to an external personnel database and auto-populates the CDR data with information regarding these characteristics.

Section Summary

Between January 1, 2022, and December 31, 2022, information was collected by PSP troopers for 441,329 member-initiated traffic stops. The PSP data collection includes fields related to legal reasons for the stop and characteristics of the stop, vehicle, driver, passenger, and trooper. In its initial development and continued refinement throughout 2021 and 2022, the PSP data collection effort includes several data fields that provide important explanatory context for traffic stops.

The Phase I data audit examined data accuracy by comparing the number of stops in the electronic CDR and CAD data. Overall, the percent difference between the two datasets at the department level is –3.2%, indicating that 96.8% of records match across the two data sources. This percentage exceeds the PERF-recommended correspondence of 90% or more between two sources of information (Fridell, 2004). At the station level, 81 of 88 stations fell within the desired parameter of a 10% difference in either dataset.

The Phase II data audit assessed the missing data and logical inconsistencies within the electronic data for all traffic stops. Most of the variables examined have either no missing or invalid data or less than 0.005%. This measure is well within the 2% or less standard the Institute team recommends. Overall, the data validation checks and auto-population of data fields built into TraCS have minimized the errors related to missing and invalid data.

In summary, this audit suggests that the PSP has one of the country's most comprehensive and high-quality traffic stop data collection efforts.

SECTION 3: DESCRIPTION OF TRAFFIC STOP DATA

PSP troopers engaged in 441,329 traffic stops with the public between January and December 2022. This section describes the characteristics of traffic stops and drivers encountered by troopers during those stops. Information in all reports produced by the research team is presented for the PSP department, Area, Troop, and Station levels[17], as well as two specialized units that routinely conduct traffic stops, [18] to illustrate differences across organizational units. Several possible explanations for variation across organizational units exist, including differences in roadway types, traffic volume, posted speed limits, population density, the demographic makeup of residents and travelers, and motorists' driving and law-violating behavior.

Traffic Stop Characteristics

Table 3.1 provides the total number of traffic stops across all organizational units and the temporal breakdown of traffic stops (by month). As shown, there was wide variation in traffic stop activity across PSP Areas, Troops, and Stations. For example, Area II accounted for the most traffic stops at the Area level (n= 137,170). Similarly, Troops H and T, within Area II, reported the most traffic stops at the Troop level. Conversely, Troops P and R, within Area III, reported the fewest traffic stops.

At the department level, the month of May accounted for the greatest percentage of stops (12.5%), followed by September (10.8%) and November (10.0%). Although this trend was consistent across most of the lower organizational levels, some differences in the percentage of stops made each month are illustrated in Table 3.1. There are several reasons to expect that traffic patterns, and thus officer activity, will vary by month, including weather, seasonal tourism, holidays, road construction, and school-related traffic.

[17] The sum of the stops conducted by the four Area commands and specialized units does not equal the total of stops conducted department-wide because a small number of stops (<0.1%) are made by PSP organizational units outside of the Area commands or specialized SHIELD and Canine units.

[18] An examination of specialized units is critical to understanding racial/ethnic disparities in traffic stop outcomes because the activities of these specialized units and the individuals with whom they have contact are often different than those of typical patrol troopers. SHIELD is the Safe Highways Initiative through Effective Law Enforcement and Detection program and involves PSP members who are specially trained to interdict criminal activity occurring on major highways. One of the primary objectives of Canine teams focused on narcotics detection is to pursue highway interdiction activity through contacts with field personnel and aiding with traffic stops. Additionally, the narcotics detection teams take a proactive stance by providing traffic enforcement while patrolling the highways and creating a safe highway atmosphere with their visibility.

Table 3.1: Monthly Breakdown of Traffic Stops by Department, Area, Troop, & Station, January – December 2022

	Total # of Stops	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
PSP Dept.	**441,329**	**6.6%**	**7.2%**	**9.1%**	**8.2%**	**12.5%**	**7.4%**	**7.5%**	**7.9%**	**10.8%**	**6.1%**	**10.0%**	**6.6%**
AREA I	**103,889**	**6.9%**	**7.1%**	**9.8%**	**8.6%**	**13.3%**	**7.0%**	**7.3%**	**7.7%**	**11.0%**	**5.8%**	**9.7%**	**5.8%**
Troop B	**30,443**	**6.8%**	**7.1%**	**10.4%**	**7.7%**	**13.2%**	**7.2%**	**6.3%**	**7.1%**	**12.3%**	**6.6%**	**9.8%**	**5.5%**
Belle Vernon	5,066	6.3%	6.7%	9.3%	8.0%	14.2%	8.2%	5.7%	7.6%	13.9%	3.6%	11.7%	5.0%
Pittsburgh	7,168	4.7%	5.8%	13.5%	7.0%	14.1%	8.6%	8.0%	5.6%	12.0%	6.4%	10.5%	3.7%
Uniontown	11,505	7.3%	7.5%	9.6%	8.5%	12.4%	7.1%	6.4%	7.7%	10.9%	8.6%	7.8%	6.2%
Washington	4,272	8.3%	7.4%	7.7%	7.5%	12.1%	3.8%	5.0%	8.1%	15.8%	6.5%	11.1%	6.7%
Waynesburg	2,429	8.9%	9.1%	11.8%	6.1%	14.7%	7.5%	5.1%	6.3%	10.9%	3.6%	10.1%	6.0%
Troop C	**22,567**	**8.4%**	**9.3%**	**9.9%**	**8.3%**	**13.4%**	**7.2%**	**6.7%**	**8.2%**	**9.5%**	**5.2%**	**9.6%**	**4.2%**
Clarion	2,652	10.3%	7.2%	12.1%	10.0%	14.0%	4.7%	7.4%	4.9%	11.8%	3.6%	11.5%	2.4%
Clearfield	3,999	6.1%	11.0%	10.2%	8.5%	15.0%	7.9%	7.4%	7.8%	9.3%	4.5%	9.7%	2.8%
Dubois	3,110	7.0%	9.4%	10.8%	9.8%	15.7%	8.0%	5.1%	7.4%	8.2%	3.9%	9.2%	5.4%
Lewis Run	4,054	9.8%	7.8%	10.5%	7.2%	10.1%	6.4%	6.2%	9.4%	11.2%	6.8%	10.0%	4.6%
Marienville	2,467	8.7%	8.8%	7.6%	7.9%	12.6%	7.9%	5.9%	8.2%	10.8%	7.3%	10.3%	4.1%
Punxsutawney	3,483	9.4%	10.1%	9.1%	6.5%	11.9%	6.9%	7.3%	10.9%	8.4%	4.4%	9.3%	5.8%
Ridgway	2,802	7.6%	10.3%	9.0%	8.8%	15.0%	9.1%	7.7%	7.9%	6.8%	6.4%	7.5%	3.9%
Troop D	**23,671**	**7.0%**	**7.3%**	**11.3%**	**9.3%**	**13.4%**	**8.0%**	**9.1%**	**6.6%**	**9.5%**	**5.1%**	**8.3%**	**5.0%**
Beaver	3,619	3.5%	4.1%	12.5%	9.8%	16.6%	7.1%	10.3%	7.7%	8.6%	4.8%	12.1%	2.9%
Butler	6,182	10.5%	9.1%	11.8%	10.2%	12.0%	7.4%	7.7%	5.5%	10.3%	5.4%	4.3%	5.9%
Kittanning	7,941	7.5%	8.1%	11.2%	8.2%	12.6%	8.1%	10.1%	6.8%	9.9%	4.9%	8.0%	4.5%
Mercer	3,292	4.0%	8.3%	11.0%	8.0%	17.2%	8.9%	8.3%	7.7%	8.9%	4.9%	9.1%	3.6%
New Castle	2,637	6.1%	4.1%	9.5%	11.6%	10.2%	9.0%	8.8%	5.7%	8.7%	5.3%	12.0%	8.9%
Troop E	**27,208**	**5.6%**	**5.2%**	**7.7%**	**9.3%**	**13.0%**	**5.7%**	**7.2%**	**8.9%**	**11.9%**	**6.2%**	**11.1%**	**8.1%**
Corry	2,919	7.0%	6.2%	11.6%	12.0%	12.8%	6.3%	5.3%	9.6%	6.9%	4.8%	8.6%	8.9%
Erie	9,196	6.0%	4.3%	6.3%	8.7%	10.6%	4.9%	8.5%	10.6%	15.3%	7.8%	10.1%	6.9%
Franklin	2,115	5.6%	7.6%	10.4%	10.8%	18.3%	4.4%	6.1%	5.8%	7.8%	4.0%	9.8%	9.6%
Girard	6,321	4.9%	5.3%	7.5%	9.8%	14.6%	6.8%	6.8%	7.5%	9.7%	5.3%	12.1%	9.6%
Meadville	3,658	2.9%	5.7%	6.9%	7.7%	11.9%	5.3%	6.8%	8.7%	14.0%	6.5%	14.8%	8.7%
Warren	2,876	7.6%	4.9%	7.4%	7.8%	15.1%	7.1%	7.0%	8.5%	11.2%	6.1%	10.9%	6.4%

Table 3.1: Monthly Breakdown of Traffic Stops by Department, Area, Troop, & Station, January – December 2022

	Total # of Stops	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
AREA II	**137,170**	**6.1%**	**6.9%**	**8.8%**	**7.6%**	**12.4%**	**8.1%**	**7.9%**	**8.2%**	**10.6%**	**6.5%**	**9.7%**	**7.1%**
Troop A	**18,043**	**4.9%**	**4.7%**	**10.7%**	**7.3%**	**15.4%**	**8.7%**	**7.9%**	**7.0%**	**10.7%**	**4.6%**	**10.1%**	**8.0%**
Ebensburg	1,984	5.2%	2.5%	7.3%	9.0%	15.9%	10.2%	5.1%	5.2%	9.6%	1.9%	15.8%	12.4%
Greensburg	4,745	4.5%	5.1%	8.8%	6.5%	12.7%	9.4%	7.4%	8.0%	11.7%	5.9%	10.8%	9.3%
Indiana	6,626	4.1%	3.9%	13.7%	8.1%	15.2%	9.9%	8.1%	8.5%	9.5%	4.5%	6.1%	8.3%
Kiski Valley	1,337	6.2%	3.4%	11.3%	7.1%	13.8%	5.7%	8.5%	6.7%	15.0%	3.7%	13.6%	4.9%
Somerset (A)	3,351	6.1%	7.3%	9.3%	6.2%	20.2%	5.5%	9.3%	3.8%	10.7%	5.2%	12.3%	4.1%
Troop G	**28,359**	**6.8%**	**7.7%**	**8.2%**	**8.1%**	**11.8%**	**6.4%**	**6.3%**	**7.0%**	**13.5%**	**6.0%**	**12.2%**	**6.0%**
Bedford	5,065	7.3%	9.5%	8.8%	7.6%	10.7%	6.3%	5.9%	7.2%	9.3%	7.2%	11.8%	8.3%
Hollidaysburg	4,276	7.4%	9.0%	9.2%	7.0%	11.2%	7.8%	5.2%	7.1%	12.7%	6.6%	11.0%	5.7%
Huntingdon	3,899	7.4%	6.3%	7.6%	8.4%	8.7%	6.3%	4.7%	6.0%	14.4%	7.0%	15.6%	7.8%
Lewistown	4,069	6.8%	7.8%	8.0%	9.9%	14.5%	6.5%	4.9%	5.7%	14.1%	5.2%	9.7%	6.9%
McConnellsburg	3,441	7.6%	6.3%	9.7%	6.8%	13.0%	5.3%	7.5%	7.9%	12.2%	3.3%	14.4%	6.0%
Rockview	7,609	5.4%	7.2%	6.9%	8.6%	12.6%	6.2%	8.1%	7.5%	16.7%	5.8%	11.7%	3.2%
Troop H	**48,365**	**6.5%**	**7.1%**	**9.1%**	**6.1%**	**11.0%**	**8.7%**	**9.2%**	**9.1%**	**9.7%**	**5.9%**	**9.2%**	**8.4%**
Carlisle	11,184	6.9%	7.6%	11.2%	6.6%	10.8%	8.4%	9.3%	7.5%	6.7%	5.2%	10.9%	9.0%
Chambersburg	12,462	6.0%	7.6%	8.7%	4.4%	11.4%	9.1%	7.7%	10.9%	11.3%	5.9%	8.5%	8.5%
Gettysburg	8,551	6.2%	7.3%	6.7%	6.3%	9.1%	7.5%	10.4%	9.5%	12.1%	7.8%	8.9%	8.3%
Harrisburg	9,536	8.0%	7.7%	9.3%	6.9%	10.6%	8.8%	10.7%	9.4%	7.7%	5.7%	8.1%	7.2%
Lykens	2,890	6.7%	6.0%	8.9%	6.1%	12.1%	10.2%	8.7%	8.7%	10.7%	4.3%	8.9%	8.7%
Newport	3,741	3.2%	3.5%	9.3%	8.4%	14.4%	10.3%	7.6%	7.0%	11.9%	5.7%	9.8%	8.8%
Troop T	**42,403**	**5.8%**	**7.0%**	**8.2%**	**9.1%**	**13.0%**	**8.3%**	**7.5%**	**8.4%**	**9.7%**	**8.3%**	**8.6%**	**6.1%**
Bowmansville	4,197	4.6%	7.1%	9.5%	7.4%	12.8%	8.1%	6.6%	8.5%	9.5%	8.5%	10.9%	6.4%
Everett	6,570	7.0%	7.8%	7.6%	8.6%	10.9%	7.8%	6.8%	7.6%	10.1%	10.5%	9.7%	5.9%
Gibsonia	5,174	6.2%	4.9%	8.0%	13.0%	15.0%	9.9%	9.3%	7.6%	7.5%	6.3%	6.8%	5.7%
Highspire	96	0.0%	1.0%	0.0%	0.0%	10.4%	4.2%	13.5%	25.0%	26.0%	2.1%	8.3%	9.4%
King of Prussia	5,395	3.7%	7.2%	8.0%	8.3%	12.2%	8.6%	8.5%	7.7%	8.6%	8.6%	11.2%	7.5%
New Stanton	7,126	5.6%	6.5%	7.1%	9.3%	13.4%	9.0%	6.9%	10.7%	11.7%	8.2%	7.3%	4.3%
Newville	4,054	6.3%	8.7%	8.0%	9.3%	11.8%	5.6%	8.9%	6.8%	12.1%	7.0%	5.9%	9.4%
Pocono	4,371	7.9%	7.7%	10.0%	8.6%	13.7%	9.2%	7.6%	7.6%	8.1%	6.4%	7.6%	5.6%
Somerset (T)	5,411	5.6%	6.5%	8.3%	8.3%	14.2%	7.6%	6.2%	9.6%	8.8%	9.9%	9.3%	5.7%

Table 3.1: Monthly Breakdown of Traffic Stops by Department, Area, Troop, & Station, January – December 2022

	Total # of Stops	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
AREA III	**91,658**	**6.9%**	**6.6%**	**8.9%**	**10.0%**	**13.5%**	**7.4%**	**7.0%**	**7.1%**	**10.6%**	**5.7%**	**10.7%**	**5.6%**
Troop F	**31,196**	**6.1%**	**5.2%**	**8.1%**	**8.9%**	**14.2%**	**7.1%**	**7.6%**	**7.6%**	**10.8%**	**5.9%**	**12.5%**	**6.0%**
Coudersport	2,738	6.6%	7.0%	9.5%	7.2%	14.4%	9.1%	7.1%	5.6%	10.0%	8.5%	9.5%	5.5%
Emporium	1,267	4.2%	5.8%	11.2%	9.1%	12.6%	5.8%	7.9%	9.9%	11.4%	9.8%	10.3%	2.1%
Lamar	5,398	4.2%	3.7%	9.0%	11.3%	14.8%	7.0%	8.3%	7.1%	10.9%	7.2%	11.1%	5.3%
Mansfield	2,464	6.5%	5.3%	6.6%	7.7%	14.5%	6.2%	7.6%	10.6%	13.4%	5.2%	11.7%	4.7%
Milton	7,771	6.3%	5.6%	8.1%	10.2%	14.4%	6.9%	6.5%	7.2%	11.5%	3.8%	13.4%	6.0%
Montoursville	5,867	5.1%	4.9%	6.9%	7.6%	15.7%	7.1%	7.4%	8.7%	9.8%	5.6%	13.3%	7.8%
Selinsgrove	3,643	8.2%	5.3%	7.6%	6.8%	9.4%	7.5%	10.4%	7.8%	10.2%	6.7%	12.4%	7.7%
Stonington	2,048	9.1%	4.7%	7.2%	9.7%	16.9%	7.0%	5.6%	5.1%	8.6%	4.9%	16.3%	5.0%
Troop N	**30,213**	**7.3%**	**7.1%**	**9.0%**	**9.6%**	**13.8%**	**7.0%**	**6.2%**	**6.1%**	**11.4%**	**6.0%**	**11.0%**	**5.5%**
Bloomsburg	2,992	8.1%	10.6%	9.7%	10.7%	14.3%	6.4%	6.9%	6.6%	12.8%	5.3%	5.5%	3.0%
Fern Ridge	5,781	7.5%	5.5%	6.6%	10.0%	17.9%	5.6%	4.4%	3.6%	13.4%	5.5%	14.1%	6.0%
Hazleton	6,140	4.6%	3.9%	9.6%	10.4%	15.5%	7.6%	6.7%	5.7%	11.4%	5.8%	14.6%	4.2%
Lehighton	2,395	4.7%	5.2%	7.2%	9.0%	12.9%	6.9%	6.7%	3.5%	12.2%	7.6%	12.9%	11.3%
Stroudsburg	12,900	8.7%	9.0%	9.9%	8.8%	11.3%	7.5%	6.4%	7.8%	10.1%	6.3%	8.8%	5.5%
Troop P	**15,306**	**7.3%**	**8.6%**	**10.0%**	**11.9%**	**12.7%**	**8.6%**	**6.7%**	**7.2%**	**9.1%**	**4.7%**	**7.9%**	**5.3%**
Laporte	2,070	8.4%	7.7%	10.6%	13.1%	13.2%	6.3%	6.5%	7.1%	9.7%	4.2%	7.1%	6.2%
Shickshinny	2,067	6.0%	5.9%	9.4%	10.9%	11.7%	6.4%	7.4%	6.0%	9.7%	7.8%	11.9%	6.8%
Towanda	4,527	9.3%	9.3%	7.8%	12.7%	12.9%	11.0%	5.9%	6.1%	6.9%	4.7%	7.8%	5.6%
Tunkhannock	1,928	6.4%	10.9%	10.9%	11.0%	11.2%	9.0%	6.6%	9.2%	10.4%	4.6%	5.3%	4.5%
Wilkes-Barre	4,711	6.0%	8.6%	11.6%	11.3%	13.2%	8.2%	7.5%	7.9%	10.1%	3.5%	7.6%	4.4%
Troop R	**14,943**	**7.3%**	**6.6%**	**9.5%**	**10.9%**	**12.4%**	**7.4%**	**7.7%**	**7.8%**	**10.4%**	**5.3%**	**9.3%**	**5.3%**
Blooming Grove	4,896	6.9%	5.6%	9.7%	9.4%	12.3%	6.5%	7.2%	6.8%	12.1%	7.2%	10.4%	5.9%
Dunmore	3,136	5.5%	3.7%	8.9%	9.3%	14.0%	9.4%	9.8%	7.6%	8.7%	4.5%	13.1%	5.6%
Gibson	3,973	8.7%	9.2%	12.1%	12.2%	11.9%	7.6%	6.9%	7.9%	9.0%	4.3%	5.9%	4.4%
Honesdale	2,938	7.9%	7.9%	6.5%	13.1%	11.4%	6.8%	7.8%	9.6%	11.4%	4.5%	8.3%	4.9%

Table 3.1: Monthly Breakdown of Traffic Stops by Department, Area, Troop, & Station, January – December 2022

	Total # of Stops	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
AREA IV	**101,444**	**6.8%**	**8.1%**	**8.7%**	**6.8%**	**11.5%**	**6.7%**	**7.4%**	**8.4%**	**11.0%**	**6.1%**	**10.4%**	**7.9%**
Troop J	**32,167**	**6.8%**	**7.7%**	**10.0%**	**7.0%**	**10.9%**	**7.0%**	**7.2%**	**8.2%**	**10.6%**	**6.0%**	**10.0%**	**8.7%**
Avondale	8,890	6.8%	7.3%	9.2%	5.7%	9.3%	7.6%	6.7%	9.1%	12.5%	5.5%	10.5%	9.9%
Embreeville	7,267	6.5%	9.3%	12.2%	7.1%	10.8%	6.6%	6.4%	8.4%	7.8%	6.4%	10.7%	7.7%
Lancaster	6,788	6.0%	7.4%	10.6%	6.1%	10.0%	6.2%	8.2%	8.5%	10.1%	5.7%	10.4%	10.7%
York	9,222	7.5%	7.1%	8.5%	8.8%	13.0%	7.2%	7.5%	7.1%	11.3%	6.5%	8.5%	7.0%
Troop K	**27,061**	**8.1%**	**8.9%**	**8.4%**	**5.5%**	**10.0%**	**7.7%**	**8.2%**	**9.5%**	**10.9%**	**6.9%**	**9.3%**	**6.6%**
Media	11,759	9.0%	8.9%	9.2%	6.0%	9.8%	7.1%	8.5%	9.0%	10.5%	6.4%	8.5%	7.0%
Philadelphia	10,538	7.0%	9.3%	7.4%	4.5%	8.7%	7.6%	8.0%	11.0%	11.1%	7.8%	10.8%	6.7%
Skippack	4,726	8.5%	7.7%	8.9%	6.3%	13.7%	9.2%	8.0%	7.3%	10.9%	6.1%	8.2%	5.4%
Troop L	**19,601**	**4.9%**	**7.5%**	**8.0%**	**7.7%**	**14.3%**	**5.0%**	**6.8%**	**7.8%**	**12.3%**	**5.2%**	**12.3%**	**8.4%**
Frackville	2,915	2.8%	5.1%	7.0%	12.0%	13.2%	5.1%	8.7%	6.8%	10.7%	7.4%	12.7%	8.3%
Hamburg	2,605	2.8%	7.9%	13.2%	9.6%	19.0%	4.4%	5.0%	6.7%	8.7%	3.6%	11.3%	7.8%
Jonestown	4,885	5.9%	8.8%	8.6%	7.3%	13.1%	5.5%	7.9%	9.8%	12.6%	4.4%	10.2%	6.0%
Reading	4,157	5.2%	8.0%	7.9%	4.3%	13.4%	4.0%	6.8%	7.7%	13.3%	4.0%	12.6%	12.7%
Schuylkill Haven	5,039	5.9%	6.9%	5.2%	7.5%	14.4%	5.7%	5.5%	7.0%	13.9%	6.4%	14.3%	7.4%
Troop M	**22,615**	**7.1%**	**8.2%**	**7.9%**	**7.5%**	**11.8%**	**6.8%**	**7.3%**	**7.9%**	**10.9%**	**6.1%**	**10.6%**	**7.9%**
Belfast	3,846	5.8%	6.7%	8.0%	9.9%	11.9%	6.1%	4.9%	5.7%	12.7%	4.6%	12.9%	10.7%
Bethlehem	4,497	6.6%	9.4%	7.6%	9.0%	11.0%	4.4%	6.6%	7.5%	9.4%	7.8%	11.1%	9.6%
Dublin	3,907	8.2%	8.3%	7.0%	6.6%	10.0%	6.4%	11.9%	9.3%	10.4%	6.7%	8.3%	6.9%
Fogelsville	5,956	7.1%	7.7%	6.9%	6.4%	13.0%	8.5%	7.5%	8.9%	10.6%	5.4%	11.7%	6.4%
Trevose	4,409	7.7%	8.9%	10.4%	6.3%	12.3%	7.9%	6.0%	7.7%	11.6%	6.1%	8.5%	6.8%
Specialized Units													
SHIELD	4,429	7.7%	7.6%	13.6%	8.2%	6.4%	7.5%	11.2%	7.5%	14.7%	6.4%	6.2%	3.0%
Canine	2,232	6.8%	9.1%	7.5%	8.2%	8.0%	8.2%	14.5%	11.7%	9.4%	5.6%	6.6%	4.4%

Table 3.2 documents, at the PSP Department, Area, and Troop level, the average percent of stops that occurred on weekdays, during the day, and on various roadway types; the percent of vehicles with a Pennsylvania registration or the presence of passengers; and the stop duration. Table 3.3 displays the same information at the PSP Station level.

As shown in Table 3.2, department-wide, the majority of traffic stops were made on weekdays (69.4%) and during daylight hours (65.9%).[19] State highways (52.7%) and interstates (33.8%) were the most frequent locations for traffic stops. In addition, 80% of vehicles stopped were registered in Pennsylvania, and 20.0% had at least one passenger. Most traffic stops department-wide (87.8%) were conducted in 15 minutes or less.

Traffic stop characteristics varied somewhat by PSP Area and Troop (reported in Table 3.2) and Station (reported in Table 3.3). For example, Area IV made fewer traffic stops during daylight hours (57.5% of stops) than the department average. Similarly, at the Troop level, 76.1% of traffic stops by Troop R were made during daylight hours, compared to 50.3% of traffic stops by Troop J.

In terms of roadway types, there were several noticeable variations. For example, 83.2% of stops made by Troop T occurred on interstates, which is consistent with their primary area of responsibility on the Pennsylvania Turnpike. The percentage of stops made on interstates was considerably lower in other Troops (e.g., Troop A), with fewer miles of interstate roadways. Less variation is evident in the average percent of stops involving vehicles with a Pennsylvania registration, stops with passengers, and the average stop duration, with only a few outliers. For example, Troop R stopped considerably more drivers with out-of-state vehicle registrations.

There is also significant variation in the traffic stop characteristics for the SHIELD and Canine specialized units. For example, only 23.7% of SHIELD and 37.5% of Canine traffic stops involved vehicles with Pennsylvania registration, compared to the department-wide average of 80.0%.

[19] The creation of day and night variables from the time of stop data field were roughly adjusted by month to align with the shift in sunrise and sunset throughout the year.

Table 3.2: Traffic Stop Descriptives by Department, Area, & Troop, January - December 2022

	Total #of Stops	Weekday	Daytime	Roadway Type				PA Regist. Vehicle	Vehicles with Passengers	Duration of Stop (minutes)			
				Inter	State	Local	Other			1-15	16-30	31-60	61+
PSP Dept.	**441,329**	**69.4%**	**65.9%**	**33.8%**	**52.7%**	**12.6%**	**0.9%**	**80.0%**	**20.0%**	**87.8%**	**8.6%**	**2.4%**	**1.1%**
AREA I	**103,889**	**67.2%**	**62.4%**	**24.5%**	**57.4%**	**17.6%**	**0.5%**	**86.6%**	**18.8%**	**90.6%**	**7.1%**	**1.5%**	**0.8%**
Troop B	30,443	69.7%	59.3%	30.6%	44.1%	24.4%	0.9%	88.3%	16.8%	91.0%	6.6%	1.6%	0.8%
Troop C	22,567	64.6%	63.8%	19.0%	68.8%	12.0%	0.3%	80.1%	21.9%	90.6%	7.0%	1.4%	1.0%
Troop D	23,671	69.9%	65.9%	23.0%	60.5%	15.9%	0.5%	90.6%	17.4%	90.7%	6.5%	1.6%	1.1%
Troop E	27,208	64.0%	61.6%	23.6%	60.1%	15.9%	0.3%	86.6%	19.5%	89.9%	8.2%	1.4%	0.5%
AREA II	**137,170**	**70.3%**	**71.0%**	**41.7%**	**47.7%**	**9.1%**	**1.5%**	**77.5%**	**20.9%**	**89.0%**	**8.1%**	**2.2%**	**0.7%**
Troop A	18,043	69.1%	74.4%	1.4%	87.1%	11.3%	0.2%	91.4%	17.1%	89.2%	7.5%	2.4%	0.9%
Troop G	28,359	68.3%	73.6%	27.6%	63.0%	8.9%	0.5%	81.2%	19.0%	93.5%	5.0%	1.0%	0.4%
Troop H	48,365	70.1%	58.6%	28.7%	56.1%	14.8%	0.3%	79.5%	19.3%	86.6%	9.1%	3.3%	1.0%
Troop T	42,403	72.3%	82.2%	83.2%	11.0%	1.5%	4.2%	66.6%	25.6%	88.6%	9.1%	1.8%	0.5%
AREA III	**91,658**	**67.7%**	**69.6%**	**29.5%**	**56.6%**	**13.3%**	**0.6%**	**77.8%**	**21.0%**	**86.7%**	**9.1%**	**2.9%**	**1.4%**
Troop F	31,196	65.8%	68.3%	20.0%	66.8%	13.0%	0.2%	78.3%	24.1%	92.2%	5.7%	1.4%	0.6%
Troop N	30,213	64.9%	66.3%	41.0%	40.4%	17.7%	0.8%	76.0%	19.5%	85.0%	9.7%	3.6%	1.6%
Troop P	15,306	70.9%	72.4%	9.2%	78.8%	11.0%	0.9%	90.0%	17.3%	91.0%	6.3%	1.7%	1.0%
Troop R	14,943	73.8%	76.1%	47.0%	45.2%	7.2%	0.7%	67.8%	21.4%	73.8%	17.8%	5.7%	2.7%
AREA IV	**101,444**	**70.4%**	**57.5%**	**32.9%**	**54.3%**	**12.2%**	**0.5%**	**82.2%**	**18.5%**	**85.2%**	**10.1%**	**2.9%**	**1.7%**
Troop J	32,167	70.5%	50.3%	15.8%	71.1%	12.3%	0.8%	82.9%	18.4%	85.9%	8.7%	3.0%	2.4%
Troop K	27,061	70.6%	55.4%	59.1%	29.8%	10.6%	0.5%	80.8%	16.7%	85.7%	9.8%	2.8%	1.7%
Troop L	19,601	72.5%	69.3%	24.6%	60.0%	15.2%	0.2%	85.7%	20.3%	86.8%	10.4%	2.3%	0.5%
Troop M	22,615	68.0%	60.2%	33.3%	54.8%	11.3%	0.6%	79.8%	19.1%	82.4%	12.4%	3.3%	1.9%
Specialized Units													
SHIELD	4,429	96.2%	96.3%	97.8%	1.6%	0.7%	0.0%	23.7%	30.3%	78.7%	12.2%	6.2%	2.9%
Canine	2,232	91.9%	88.2%	74.8%	13.3%	11.7%	0.1%	37.5%	32.7%	78.3%	15.4%	4.8%	1.5%

Table 3.3: Area I Traffic Stop Descriptives by Station, January - December 2022

	Total #of Stops	Weekday	Daytime	Roadway Type: Inter	State	Local	Other	PA Regist. Vehicle	Vehicles with Passengers	Duration of Stop (minutes): 1-15	16-30	31-60	61+
Troop B	30,443	69.7%	59.3%	30.6%	44.1%	24.4%	0.9%	88.3%	16.8%	91.0%	6.6%	1.6%	0.8%
Belle Vernon	5,066	74.3%	71.4%	27.2%	50.5%	21.8%	0.6%	88.6%	23.9%	89.0%	7.7%	2.3%	1.0%
Pittsburgh	7,168	69.1%	60.3%	68.4%	19.9%	11.3%	0.5%	84.8%	10.9%	93.3%	5.2%	1.2%	0.3%
Uniontown	11,505	70.6%	49.0%	3.5%	61.6%	33.5%	1.5%	93.5%	14.6%	90.8%	7.1%	1.5%	0.7%
Washington	4,272	66.2%	62.4%	47.2%	16.9%	35.2%	0.7%	85.1%	19.1%	88.6%	7.3%	2.7%	1.4%
Waynesburg	2,429	63.6%	74.4%	25.6%	67.8%	6.5%	0.2%	78.8%	25.5%	93.2%	4.4%	0.9%	1.5%
Troop C	22,567	64.6%	63.8%	19.0%	68.8%	12.0%	0.3%	80.1%	21.9%	90.6%	7.0%	1.4%	1.0%
Clarion	2,652	63.5%	61.1%	41.4%	52.4%	6.0%	0.2%	74.5%	24.7%	88.7%	9.2%	1.1%	0.9%
Clearfield	3,999	65.8%	66.0%	41.4%	52.4%	5.9%	0.4%	69.5%	9.6%	93.7%	4.4%	1.1%	0.8%
Dubois	3,110	62.3%	66.8%	42.6%	46.7%	10.3%	0.5%	70.2%	24.0%	92.2%	5.7%	0.9%	1.2%
Lewis Run	4,054	65.4%	52.1%	2.2%	65.6%	32.0%	0.1%	82.0%	23.8%	89.9%	7.7%	1.4%	1.0%
Marienville	2,467	59.6%	75.1%	1.2%	96.6%	2.1%	0.1%	88.5%	31.4%	92.6%	5.6%	1.1%	0.7%
Punxsutawney	3,483	67.7%	54.7%	1.3%	88.8%	9.4%	0.4%	95.0%	27.4%	86.5%	9.1%	2.8%	1.6%
Ridgway	2,802	65.9%	78.2%	1.3%	87.6%	11.0%	0.2%	82.7%	16.5%	90.8%	7.7%	1.1%	0.5%
Troop D	23,671	69.9%	65.9%	23.0%	60.5%	15.9%	0.5%	90.6%	17.4%	90.7%	6.5%	1.6%	1.1%
Beaver	3,619	71.5%	74.6%	47.3%	27.0%	24.9%	0.8%	86.9%	13.4%	92.1%	6.6%	1.1%	0.1%
Butler	6,182	66.0%	56.3%	12.1%	65.3%	22.0%	0.7%	92.8%	16.5%	91.8%	5.7%	1.6%	0.9%
Kittanning	7,941	70.4%	61.9%	0.9%	88.2%	10.7%	0.2%	95.3%	16.8%	88.7%	7.4%	1.9%	2.0%
Mercer	3,292	69.5%	77.8%	57.7%	36.7%	4.7%	0.9%	81.3%	21.8%	93.7%	4.8%	0.9%	0.6%
New Castle	2,637	76.1%	73.8%	38.5%	41.8%	19.1%	0.6%	88.0%	21.7%	88.7%	7.7%	2.6%	1.0%
Troop E	27,208	64.0%	61.6%	23.6%	60.1%	15.9%	0.3%	86.6%	19.5%	89.9%	8.2%	1.4%	0.5%
Corry	2,919	66.4%	65.6%	0.9%	84.2%	14.8%	0.1%	93.8%	19.2%	93.7%	4.9%	1.1%	0.3%
Erie	9,196	61.6%	51.0%	17.7%	57.2%	24.7%	0.4%	86.2%	17.2%	89.7%	8.8%	1.2%	0.3%
Franklin	2,115	60.8%	64.5%	10.0%	72.9%	16.0%	1.1%	87.3%	19.8%	84.4%	10.3%	3.1%	2.2%
Girard	6,321	65.3%	72.6%	55.8%	36.2%	7.8%	0.2%	82.4%	25.0%	89.0%	9.8%	0.8%	0.4%
Meadville	3,658	67.7%	63.6%	25.3%	60.1%	14.3%	0.3%	86.8%	20.7%	88.6%	8.2%	2.5%	0.8%
Warren	2,876	62.7%	61.8%	1.1%	90.6%	8.3%	0.0%	89.5%	14.0%	94.2%	4.2%	1.2%	0.4%

Table 3.3: Area II Traffic Stop Descriptives by Station, January - December 2022

	Total #of Stops	Weekday	Daytime	Roadway Type				PA Regist. Vehicle	Vehicles with Passengers	Duration of Stop (minutes)			
				Inter	State	Local	Other			1-15	16-30	31-60	61+
Troop A	18,043	69.1%	74.4%	1.4%	87.1%	11.3%	0.2%	91.4%	17.1%	89.2%	7.5%	2.4%	0.9%
Ebensburg	1,984	68.3%	79.2%	0.7%	93.6%	5.6%	0.1%	87.3%	30.7%	92.2%	6.8%	0.7%	0.3%
Greensburg	4,745	67.0%	64.8%	3.0%	77.2%	19.5%	0.3%	95.5%	24.7%	80.2%	13.4%	4.4%	2.0%
Indiana	6,626	70.2%	78.4%	1.0%	91.3%	7.4%	0.3%	89.2%	10.2%	93.5%	3.6%	2.4%	0.5%
Kiski Valley	1,337	67.6%	77.7%	0.4%	88.1%	11.1%	0.3%	93.5%	15.2%	89.5%	7.9%	1.7%	0.9%
Somerset (A)	3,351	70.9%	75.8%	0.8%	88.3%	10.8%	0.1%	91.3%	12.7%	91.7%	6.9%	1.0%	0.4%
Troop G	28,359	68.3%	73.6%	27.6%	63.0%	8.9%	0.5%	81.2%	19.0%	93.5%	5.0%	1.0%	0.4%
Bedford	5,065	66.8%	73.5%	25.7%	67.6%	6.1%	0.6%	75.8%	20.6%	93.6%	4.8%	0.9%	0.7%
Hollidaysburg	4,276	66.4%	72.1%	34.6%	43.1%	21.9%	0.5%	88.8%	13.8%	93.2%	5.0%	1.5%	0.3%
Huntingdon	3,899	68.8%	76.9%	1.1%	93.5%	5.2%	0.2%	94.1%	10.8%	89.5%	9.4%	0.8%	0.3%
Lewistown	4,069	69.3%	74.2%	1.8%	90.3%	7.8%	0.1%	91.5%	30.4%	94.7%	4.4%	0.6%	0.3%
McConnellsburg	3,441	63.7%	73.2%	47.7%	45.5%	6.7%	0.1%	59.6%	31.6%	95.2%	3.1%	1.3%	0.4%
Rockview	7,609	71.6%	72.7%	43.3%	48.8%	7.2%	0.8%	78.3%	13.4%	94.3%	4.2%	1.1%	0.5%
Troop H	48,365	70.1%	58.6%	28.7%	56.1%	14.8%	0.3%	79.5%	19.3%	86.6%	9.1%	3.3%	1.0%
Carlisle	11,184	74.8%	59.5%	42.4%	33.1%	23.9%	0.6%	77.6%	20.7%	79.7%	14.0%	4.7%	1.6%
Chambersburg	12,462	70.9%	63.3%	25.4%	58.7%	15.6%	0.2%	80.7%	18.0%	92.1%	5.7%	1.7%	0.5%
Gettysburg	8,551	66.9%	53.6%	2.4%	88.9%	8.6%	0.1%	73.7%	13.6%	93.8%	4.4%	1.0%	0.8%
Harrisburg	9,536	68.7%	54.6%	58.1%	32.6%	8.8%	0.5%	77.2%	21.7%	79.8%	12.1%	6.5%	1.6%
Lykens	2,890	68.9%	59.9%	2.0%	84.4%	13.5%	0.1%	93.9%	26.0%	93.4%	5.4%	0.8%	0.4%
Newport	3,741	65.2%	60.3%	3.8%	79.8%	16.0%	0.4%	89.8%	21.1%	84.3%	12.2%	3.2%	0.3%
Troop T	42,403	72.3%	82.2%	83.2%	11.0%	1.5%	4.2%	66.6%	25.6%	88.6%	9.1%	1.8%	0.5%
Bowmansville	4,197	71.6%	76.9%	91.8%	4.7%	1.7%	1.8%	77.3%	29.7%	90.0%	7.3%	1.7%	1.0%
Everett	6,570	73.7%	76.1%	96.4%	1.0%	0.3%	2.3%	50.0%	27.9%	89.7%	7.5%	2.3%	0.4%
Gibsonia	5,174	71.8%	87.0%	94.6%	3.9%	1.4%	0.1%	69.3%	23.5%	88.5%	9.2%	1.2%	1.0%
Highspire	96	92.7%	57.3%	81.3%	12.5%	1.0%	5.2%	74.0%	33.3%	79.2%	15.6%	4.2%	1.0%
King of Prussia	5,395	73.0%	80.0%	94.1%	2.0%	0.4%	3.4%	80.1%	20.4%	75.1%	23.1%	1.5%	0.3%
New Stanton	7,126	73.3%	89.2%	51.9%	28.7%	5.0%	14.4%	81.8%	25.5%	91.8%	6.3%	1.4%	0.5%
Newville	4,054	68.5%	79.4%	94.5%	0.6%	0.1%	4.8%	55.5%	34.6%	87.4%	10.7%	1.4%	0.5%
Pocono	4,371	73.9%	80.6%	56.1%	43.8%	0.0%	0.0%	72.5%	33.6%	96.9%	2.3%	0.6%	0.2%
Somerset (T)	5,411	71.0%	85.7%	93.6%	2.0%	1.9%	2.5%	45.8%	13.4%	89.9%	6.4%	3.5%	0.3%

Table 3.3: Area III Traffic Stop Descriptives by Station, January - December 2022

	Total #of Stops	Weekday	Daytime	Roadway Type				PA Regist. Vehicle	Vehicles with Passengers	Duration of Stop (minutes)			
				Inter	State	Local	Other			1-15	16-30	31-60	61+
Troop F	31,196	65.8%	68.3%	20.0%	66.8%	13.0%	0.2%	78.3%	24.1%	92.2%	5.7%	1.4%	0.6%
Coudersport	2,738	67.0%	71.0%	0.4%	90.1%	9.5%	0.1%	85.5%	25.0%	88.2%	10.7%	0.5%	0.5%
Emporium	1,267	72.8%	71.0%	0.9%	90.2%	8.5%	0.3%	89.2%	28.5%	97.2%	2.1%	0.6%	0.1%
Lamar	5,398	61.5%	72.3%	49.4%	36.3%	14.2%	0.1%	64.0%	26.0%	93.7%	4.1%	1.7%	0.5%
Mansfield	2,464	58.4%	68.8%	4.4%	90.1%	5.4%	0.0%	62.2%	20.3%	95.7%	3.2%	0.6%	0.5%
Milton	7,771	67.6%	72.5%	23.6%	66.8%	9.5%	0.1%	76.1%	22.1%	95.3%	3.1%	1.1%	0.5%
Montoursville	5,867	69.7%	64.1%	26.5%	55.1%	18.0%	0.4%	85.4%	24.2%	87.7%	9.5%	1.8%	1.1%
Selinsgrove	3,643	67.7%	61.8%	0.9%	87.0%	12.1%	0.1%	84.2%	27.9%	92.0%	6.0%	1.4%	0.7%
Stonington	2,048	59.3%	60.0%	0.8%	71.4%	27.7%	0.1%	95.9%	20.0%	88.6%	7.4%	3.3%	0.7%
Troop N	30,213	64.9%	66.3%	41.0%	40.4%	17.7%	0.8%	76.0%	19.5%	85.0%	9.7%	3.6%	1.6%
Bloomsburg	2,992	63.1%	58.3%	63.7%	28.3%	7.8%	0.2%	69.8%	18.1%	92.0%	3.4%	2.1%	2.5%
Fern Ridge	5,781	59.9%	79.8%	61.3%	33.2%	5.0%	0.5%	60.2%	27.6%	86.1%	10.6%	2.4%	0.9%
Hazleton	6,140	68.6%	70.5%	44.6%	40.8%	14.1%	0.5%	80.9%	20.7%	88.1%	8.2%	2.6%	1.1%
Lehighton	2,395	64.5%	71.1%	4.5%	72.7%	21.6%	1.1%	90.2%	23.0%	82.6%	9.5%	3.8%	4.1%
Stroudsburg	12,900	65.9%	59.2%	31.8%	40.3%	26.6%	1.3%	79.4%	15.1%	81.9%	11.5%	4.9%	1.6%
Troop P	15,306	70.9%	72.4%	9.2%	78.8%	11.0%	0.9%	90.0%	17.3%	91.0%	6.3%	1.7%	1.0%
Laporte	2,070	66.1%	64.5%	3.4%	79.1%	17.4%	0.0%	87.8%	24.0%	92.4%	5.7%	1.5%	0.3%
Shickshinny	2,067	67.4%	74.1%	5.6%	86.3%	3.0%	5.1%	92.5%	14.8%	93.4%	5.1%	0.6%	0.9%
Towanda	4,527	75.5%	67.4%	0.8%	88.9%	10.0%	0.3%	89.1%	15.2%	91.8%	5.5%	1.8%	0.9%
Tunkhannock	1,928	71.5%	72.3%	1.1%	92.0%	6.8%	0.1%	94.8%	12.8%	92.3%	6.3%	0.9%	0.5%
Wilkes-Barre	4,711	70.0%	79.9%	24.9%	60.3%	14.4%	0.4%	88.9%	19.2%	88.1%	7.8%	2.5%	1.6%
Troop R	14,943	73.8%	76.1%	47.0%	45.2%	7.2%	0.7%	67.8%	21.4%	73.8%	17.8%	5.7%	2.7%
Blooming Grove	4,896	72.9%	68.2%	54.3%	34.1%	10.8%	0.8%	62.7%	22.4%	75.4%	16.5%	5.1%	3.0%
Dunmore	3,136	74.7%	75.4%	54.3%	40.0%	5.0%	0.7%	75.7%	22.9%	57.3%	31.3%	8.3%	3.1%
Gibson	3,973	72.2%	83.4%	62.4%	33.6%	4.0%	0.1%	51.5%	22.6%	74.6%	14.8%	7.0%	3.6%
Honesdale	2,938	76.7%	80.0%	6.2%	84.9%	7.8%	1.2%	89.8%	16.5%	87.5%	9.7%	2.3%	0.5%

Table 3.3: Area IV Traffic Stop Descriptives by Station, January - December 2022

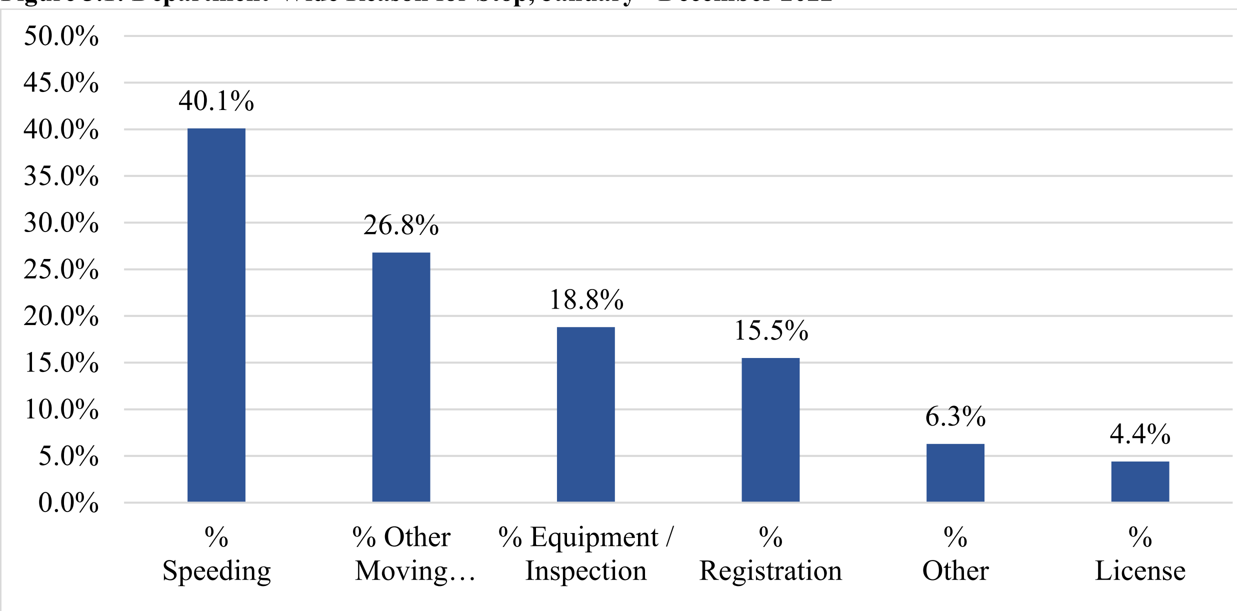
	Total #of Stops	Weekday	Daytime	Roadway Type: Inter	Roadway Type: State	Roadway Type: Local	Roadway Type: Other	PA Regist. Vehicle	Vehicles with Passengers	Duration of Stop (minutes): 1-15	Duration of Stop (minutes): 16-30	Duration of Stop (minutes): 31-60	Duration of Stop (minutes): 61+
Troop J	32,167	70.5%	50.3%	15.8%	71.1%	12.3%	0.8%	82.9%	18.4%	85.9%	8.7%	3.0%	2.4%
Avondale	8,890	71.1%	45.1%	0.9%	86.4%	11.0%	1.7%	76.0%	20.3%	86.6%	8.8%	3.2%	1.4%
Embreeville	7,267	71.4%	61.4%	0.9%	90.6%	8.2%	0.2%	90.1%	16.7%	85.1%	10.1%	1.9%	2.9%
Lancaster	6,788	70.3%	52.4%	2.3%	88.0%	9.3%	0.3%	90.4%	18.6%	83.8%	10.2%	3.1%	2.9%
York	6,417	69.6%	44.9%	51.7%	28.5%	19.0%	0.8%	78.4%	17.7%	87.3%	6.6%	3.7%	2.4%
Troop K	27,061	70.6%	55.4%	59.1%	29.8%	10.6%	0.5%	80.8%	16.7%	85.7%	9.8%	2.8%	1.7%
Media	11,759	71.6%	45.6%	63.8%	31.2%	4.8%	0.2%	72.85	16.9%	87.1%	8.3%	3.1%	1.4%
Philadelphia	10,538	71.6%	63.9%	76.7%	7.9%	15.1%	0.4%	84.4%	18.8%	83.5%	11.8%	2.6%	2.0%
Skippack	4,726	65.7%	60.4%	8.0%	75.6%	14.9%	1.4%	92.9%	11.5%	87.7%	8.3%	2.4%	1.6%
Troop L	19,601	72.5%	69.3%	24.6%	60.0%	15.2%	0.2%	85.7%	20.3%	86.8%	10.4%	2.3%	0.5%
Frackville	2,915	75.1%	74.8%	37.2%	49.0%	13.5%	0.3%	84.5%	25.5%	89.2%	9.7%	1.0%	0.2%
Hamburg	2,605	75.2%	78.9%	39.8%	48.5%	11.6%	0.0%	77.9%	21.8%	78.9%	15.7%	4.7%	0.7%
Jonestown	4,885	72.2%	66.9%	42.8%	40.5%	16.6%	0.2%	77.3%	20.3%	85.3%	11.5%	2.5%	0.7%
Reading	4,157	72.6%	60.6%	11.3%	66.8%	21.6%	0.3%	91.5%	13.3%	89.4%	8.1%	1.9%	0.6%
Schuylkill Haven	5,039	69.8%	70.7%	2.9%	85.6%	11.4%	0.1%	93.8%	22.2%	88.9%	8.8%	2.1%	0.2%
Troop M	22,615	68.0%	60.2%	33.3%	54.8%	11.3%	0.6%	79.8%	19.1%	82.4%	12.4%	3.3%	1.9%
Belfast	3,846	66.5%	59.4%	26.5%	62.4%	11.0%	0.2%	73.5%	22.3%	83.2%	11.4%	4.1%	1.2%
Bethlehem	4,497	71.6%	57.1%	2.7%	91.2%	5.9%	0.2%	89.5%	16.8%	83.7%	11.1%	2.8%	2.4%
Dublin	3,907	64.8%	56.2%	2.3%	85.4%	11.5%	0.8%	92.5%	15.0%	83.1%	12.6%	2.9%	1.4%
Fogelsville	5,956	70.0%	57.0%	45.3%	35.4%	18.3%	1.0%	76.5%	19.9%	80.6%	14.3%	3.5%	1.6%
Trevose	4,409	65.9%	71.7%	81.8%	10.1%	7.6%	0.5%	68.8%	21.2%	82.3%	11.8%	3.0%	2.9%

Reason for the Stop

Tables 3.4 & 3.5 report the reasons for the stops initiated by PSP troopers, including speeding, other moving violations, equipment violations, registration, license, and other. These tables also report the average speed over the limit observed for traffic stops involving speeding violations. The PSP data collection protocol indicates that troopers should select all applicable reasons. Almost 10% of stops involved two or more reasons for the stop; as a result, the percentages reported in Figure 3.1, Table 3.4, and Table 3.5 sum to more than 100%.

Figure 3.1 displays the stop reasons at the department level. As shown, speeding was the most frequent reason for a stop (40.1%). The next most common reasons were other moving violations (26.8%), equipment violations/inspection (18.8%), and registration violations (15.5%).

Figure 3.1: Department-Wide Reason for Stop, January - December 2022



Like the department-level trends, speeding was the most frequent reason for a stop across most Areas and Troops except for Area IV, Troop J, Troop K, and Troop M, where the most frequent reason was other moving violations. The percentage of stops for speeding varied by Area, with a high of 51.7% in Area II and a low of 30.7% in Area IV. The Troops ranged in their percentage of traffic stops for speeding, from a high of 71.4% (Troop T) to a low of 24.2% (Troop K).

At the department level, the average amount over the posted speed limit recorded for speeding stops was 21.4 miles per hour. However, this ranged from a low of 20.3 miles per hour over the limit in Areas I and III to a high of 24.1 in Area IV. Troop-level variation was also evident, with a low of 17.8 miles per hour over the limit in Troop C to a high of 27.4 miles per hour in Troop M.

Other moving violations were the second most common reason for stops across the department at 26.8%. Areas varied in the percentage of stops based on other moving violations, from 38.2% in

Area IV to 21.1% in Area II. Other moving violations were the most frequent reason for stops in Troop J (39.5%), Troop K (49.3%), and Troop M (36.4%), which are all in Area IV. The percentage of stops for other moving violations varied from 49.3% in Troop K to 15.9% in Troop T. See Table 3.4 for additional reasons for stops across Areas and Troops.

For specialized units, the reasons for traffic stops had similar patterns in both units. The most common traffic stop reason by SHIELD and Canine was other moving violations (43.4% and 58.6%, respectively). The second most common stop reason was for equipment/inspection (34.0% and 22.7%). Finally, speeding was the third most common reason for specialized units (17.8% and 14.7%). Both units demonstrated a lower average amount over the speed limit during speeding stops (11.4 and 12.7 mph) compared to the departmental average of 21.4 mph.

Table 3.5 shows that traffic stop reasons varied dramatically across Stations. On average, speeding is the most frequent reason for a stop, but it ranges from 91.1% in Pocono Station to 13.2% in Philadelphia Station. The average miles per hour over the limit ranged from 32.3 in Trevose Station to 16.4 in Clarion Station. The second most common reason for a stop is other moving violations; however, its prevalence ranges from a high of 53.3% in Philadelphia Station to a low of 8.2% in Pocono Station. On average, equipment or inspection violations were the third most common stop reason, but this varied across Stations, from 46.2% in Honesdale Station to 1.6% in Pocono Station.

Table 3.4: Reason for Stop by Department, Area, & Troop, January – December 2022

	Total # of Stops	Speeding	Avg. Amount Over Limit (MPH)	Other Moving Violation	Equipment/ Inspection	Registration	License	Other
PSP Department	**441,329**	**40.1%**	**21.4**	**26.8%**	**18.8%**	**15.5%**	**4.4%**	**6.3%**
AREA I	**103,889**	**34.4%**	**20.3**	**23.9%**	**23.3%**	**16.3%**	**5.1%**	**7.8%**
Troop B	30,443	30.0%	22.9	30.8%	18.9%	16.4%	6.5%	11.9%
Troop C	22,567	42.3%	17.8	18.0%	25.2%	13.6%	3.0%	4.8%
Troop D	23,671	33.6%	22.0	24.7%	21.9%	17.7%	5.6%	8.1%
Troop E	27,208	33.7%	19.0	20.2%	27.7%	17.3%	4.9%	5.6%
AREA II	**137,170**	**51.7%**	**21.6**	**21.1%**	**16.4%**	**13.9%**	**3.5%**	**5.7%**
Troop A	18,043	53.1%	22.4	17.5%	16.2%	14.6%	3.8%	5.8%
Troop G	28,359	53.6%	21.1	17.0%	16.0%	14.3%	3.2%	4.6%
Troop H	48,365	32.6%	21.1	29.5%	22.4%	16.0%	4.6%	4.7%
Troop T	42,403	71.4%	22.4	15.9%	9.9%	11.0%	2.3%	7.5%
AREA III	**91,658**	**41.1%**	**20.3**	**24.5%**	**20.6%**	**14.4%**	**4.7%**	**5.5%**
Troop F	31,196	50.9%	19.1	20.4%	17.6%	12.2%	3.4%	3.2%
Troop N	30,213	35.5%	21.2	31.1%	18.1%	14.1%	5.7%	7.7%
Troop P	15,306	35.5%	21.8	17.5%	25.6%	19.0%	5.4%	5.5%
Troop R	14,943	37.7%	20.5	26.7%	27.0%	14.7%	4.7%	5.6%
AREA IV	**101,444**	**30.7%**	**24.1**	**38.2%**	**15.1%**	**17.9%**	**4.9%**	**5.8%**
Troop J	32,167	28.5%	23.7	39.5%	15.5%	17.7%	4.7%	4.6%
Troop K	27,061	24.2%	25.8	49.3%	11.1%	18.5%	3.9%	7.5%
Troop L	19,601	44.0%	20.6	23.0%	16.9%	16.2%	5.8%	4.3%
Troop M	22,615	30.2%	27.4	36.4%	17.6%	18.9%	5.8%	6.9%
Specialized Units								
SHIELD	4,429	17.8%	11.4	43.4%	34.0%	12.8%	1.3%	9.2%
Canine	2,232	14.7%	12.7	58.6%	22.7%	12.1%	2.3%	15.5%

Table 3.5: Area I Reason for Stop by Station, January - December 2022

	Total # of Stops	Speeding	Avg. Amount Over Limit (MPH)	Other Moving Violation	Equipment/ Inspection	Registration	License	Other
Troop B	30,443	30.0%	22.9	30.8%	18.9%	16.4%	6.5%	11.9%
Belle Vernon	5,066	27.7%	22.0	19.5%	23.2%	25.4%	9.5%	16.0%
Pittsburgh	7,168	45.9%	25.5	25.1%	16.6%	14.3%	5.3%	8.7%
Uniontown	11,505	21.5%	20.3	39.0%	14.5%	15.2%	6.6%	13.9%
Washington	4,274	19.7%	23.8	35.6%	31.1%	14.3%	6.6%	11.7%
Waynesburg	2,429	46.4%	21.2	24.4%	16.1%	13.2%	3.1%	3.7%
Troop C	22,567	42.3%	17.8	18.0%	25.2%	13.6%	3.0%	4.8%
Clarion	2,652	43.9%	16.4	22.3%	18.6%	13.8%	3.1%	4.5%
Clearfield	3,999	56.3%	17.2	17.5%	15.8%	8.4%	2.0%	3.8%
Dubois	3,110	41.4%	18.5	21.2%	21.0%	16.4%	3.5%	5.8%
Lewis Run	4,054	24.3%	17.3	17.0%	41.0%	17.0%	3.3%	2.6%
Marienville	2,467	55.5%	18.3	10.4%	21.5%	12.8%	1.7%	6.1%
Punxsutawney	3,483	27.4%	18.0	22.5%	34.1%	14.7%	4.7%	8.4%
Ridgway	2,802	54.5%	18.9	13.3%	19.0%	11.9%	2.1%	3.3%
Troop D	23,671	33.6%	22.0	24.7%	21.9%	17.7%	5.6%	8.1%
Beaver	3,619	31.9%	26.0	22.7%	15.7%	19.2%	6.8%	9.5%
Butler	6,182	27.8%	21.8	33.0%	22.2%	14.4%	3.7%	10.3%
Kittanning	7,941	30.9%	21.5	25.0%	26.4%	18.3%	6.8%	4.9%
Mercer	3,292	44.6%	19.9	15.5%	20.4%	18.9%	3.5%	11.1%
New Castle	2,637	43.8%	21.7	18.6%	18.3%	19.6%	7.2%	7.1%
Troop E	27,208	33.7%	19.0	20.2%	27.7%	17.3%	4.9%	5.6%
Corry	2,919	34.6%	17.0	14.3%	28.9%	20.9%	2.6%	7.5%
Erie	9,196	15.3%	21.4	28.0%	33.2%	21.8%	7.5%	6.8%
Franklin	2,115	34.8%	18.4	22.7%	21.3%	20.3%	6.1%	6.7%
Girard	6,321	48.6%	19.6	13.8%	26.9%	11.1%	3.6%	3.3%
Meadville	3,658	36.9%	18.1	19.4%	23.9%	17.2%	3.7%	5.8%
Warren	2,876	51.9%	17.4	15.0%	20.9%	11.9%	2.6%	4.0%

Table 3.5: Area II Reason for Stop by Station, January - December 2022

	Total # of Stops	Speeding	Avg. Amount Over Limit (MPH)	Other Moving Violation	Equipment/ Inspection	Registration	License	Other
Troop A	18,043	53.1%	22.4	17.5%	16.2%	14.6%	3.8%	5.8%
Ebensburg	1,984	77.7%	23.1	10.2%	7.1%	9.0%	2.5%	3.6%
Greensburg	4,745	33.8%	22.4	25.7%	22.4%	21.0%	7.2%	5.3%
Indiana	6,626	63.7%	22.9	12.1%	11.2%	11.1%	1.7%	4.0%
Kiski Valley	1,337	31.5%	24.8	32.6%	23.2%	15.4%	6.2%	7.7%
Somerset (A)	3,351	53.7%	20.5	14.7%	20.2%	15.7%	2.9%	10.5%
Troop G	28,359	53.6%	21.1	17.0%	16.0%	14.3%	3.2%	4.6%
Bedford	5,065	54.0%	19.5	14.1%	17.0%	16.2%	2.1%	3.0%
Hollidaysburg	4,276	31.8%	21.3	20.9%	22.8%	23.1%	5.8%	7.9%
Huntingdon	3,899	57.7%	19.4	14.3%	12.6%	12.4%	3.9%	8.2%
Lewistown	4,069	61.3%	20.7	14.3%	14.7%	11.8%	3.2%	4.9%
McConnellsburg	3,441	57.9%	25.3	21.2%	12.6%	11.0%	1.2%	2.1%
Rockview	7,609	57.5%	21.1	17.5%	15.4%	12.0%	2.9%	2.9%
Troop H	48,365	32.6%	21.1	29.5%	22.4%	16.0%	4.6%	4.7%
Carlisle	11,184	31.6%	20.1	26.2%	27.8%	12.5%	3.7%	7.5%
Chambersburg	12,462	35.5%	18.9	25.1%	23.0%	20.7%	4.4%	2.8%
Gettysburg	8,551	27.1%	19.8	32.9%	25.8%	13.0%	5.9%	2.3%
Harrisburg	9,536	30.5%	21.7	42.4%	11.6%	15.0%	4.5%	7.4%
Lykens	2,890	36.0%	19.8	14.7%	28.4%	22.3%	5.8%	2.9%
Newport	3,741	41.7%	20.6	24.7%	19.5%	15.7%	4.0%	3.5%
Troop T	42,403	71.4%	22.4	15.9%	9.9%	11.0%	2.3%	7.5%
Bowmansville	4,197	62.7%	21.7	12.5%	9.4%	16.7%	3.1%	5.9%
Everett	6,570	79.6%	22.1	17.1%	8.9%	8.4%	1.8%	7.1%
Gibsonia	5,174	73.8%	19.0	26.8%	14.9%	10.7%	2.5%	11.7%
Highspire	96	50.0%	22.3	18.8%	34.4%	8.3%	1.0%	3.1%
King of Prussia	5,395	60.5%	24.4	18.8%	14.8%	11.9%	2.7%	8.0%
New Stanton	7,126	61.4%	21.3	14.8%	15.5%	15.5%	3.1%	8.4%
Newville	4,054	71.4%	24.0	16.3%	4.0%	9.4%	2.1%	5.5%
Pocono	4,371	91.1%	24.3	8.2%	1.6%	2.3%	1.0%	1.1%
Somerset (T)	5,411	74.7%	23.1	11.5%	4.7%	11.4%	1.9%	10.6%

Table 3.5: Area III Reason for Stop by Station, January – December 2022

	Total # of Stops	Speeding	Avg. Amount Over Limit (MPH)	Other Moving Violation	Equipment/ Inspection	Registration	License	Other
Troop F	31,196	50.9%	19.1	20.4%	17.6%	12.2%	3.4%	3.2%
Coudersport	2,738	40.1%	17.7	12.8%	32.4%	12.7%	2.0%	2.4%
Emporium	1,267	59.7%	17.5	16.2%	15.4%	13.7%	3.1%	3.6%
Lamar	5,398	51.9%	19.4	22.9%	16.4%	10.4%	2.7%	3.5%
Mansfield	2,464	53.1%	17.5	22.3%	12.1%	11.1%	1.9%	3.1%
Milton	7,771	53.5%	19.9	22.5%	13.3%	11.0%	4.5%	3.0%
Montoursville	5,867	52.1%	18.3	18.4%	18.7%	13.8%	3.3%	2.8%
Selinsgrove	3,643	49.6%	21.8	20.2%	18.3%	16.9%	4.9%	2.3%
Stonington	2,048	43.7%	17.4	22.8%	21.2%	9.0%	3.0%	5.9%
Troop N	30,213	35.5%	21.2	31.1%	18.1%	14.1%	5.7%	7.7%
Bloomsburg	2,992	43.3%	19.7	19.2%	15.3%	12.6%	3.6%	12.5%
Fern Ridge	5,781	48.3%	20.6	29.3%	18.7%	9.0%	2.9%	4.9%
Hazleton	6,140	40.5%	21.5	32.0%	13.0%	13.4%	9.4%	8.4%
Lehighton	2,395	34.2%	21.9	24.9%	21.8%	16.0%	5.1%	9.3%
Stroudsburg	12,900	25.7%	21.9	35.5%	20.2%	16.7%	5.8%	7.2%
Troop P	15,306	35.5%	21.8	17.5%	25.6%	19.0%	5.4%	5.5%
Laporte	2,070	32.2%	19.4	14.5%	19.3%	26.0%	6.9%	8.1%
Shickshinny	2,067	47.9%	20.6	16.2%	15.7%	17.9%	7.6%	2.5%
Towanda	4,527	21.6%	19.6	19.6%	30.0%	21.6%	5.2%	8.7%
Tunkhannock	1,928	38.1%	19.9	11.4%	30.7%	21.2%	3.4%	3.1%
Wilkes-Barre	4,711	43.8%	24.8	19.7%	26.3%	13.0%	4.7%	3.7%
Troop R	14,943	37.7%	20.5	26.7%	27.0%	14.7%	4.7%	5.6%
Blooming Grove	4,896	32.7%	17.7	37.8%	22.5%	13.0%	3.9%	3.7%
Dunmore	3,136	44.5%	24.2	24.5%	21.1%	17.1%	5.3%	4.6%
Gibson	3,973	48.9%	19.9	22.4%	23.1%	13.1%	5.7%	8.8%
Honesdale	2,938	23.6%	20.8	16.3%	46.2%	17.3%	3.8%	5.6%

Table 3.5: Area IV Reason for Stop by Station, January - December 2022

	Total # of Stops	Speeding	Avg. Amount Over Limit (MPH)	Other Moving Violation	Equipment/ Inspection	Registration	License	Other
Troop J	32,167	28.5%	23.7	39.5%	15.5%	17.7%	4.7%	4.6%
Avondale	8,890	27.8%	23.8	48.0%	11.2%	15.4%	4.4%	5.4%
Embreeville	7,267	34.1%	26.6	33.8%	18.0%	17.6%	5.0%	4.2%
Lancaster	6,788	29.1%	20.7	37.2%	14.0%	18.6%	5.6%	4.7%
York	9,222	24.2%	23.1	37.5%	18.8%	19.2%	3.9%	4.0%
Troop K	27,061	24.2%	25.8	49.3%	11.1%	18.5%	3.9%	7.5%
Media	11,759	30.5%	25.2	45.5%	9.5%	17.7%	3.9%	6.0%
Philadelphia	10,538	13.2%	29.5	59.3%	9.9%	21.0%	4.2%	10.3%
Skippack	4,726	33.4%	24.1	36.4%	18.1%	14.3%	3.4%	5.0%
Troop L	19,601	44.0%	20.6	23.0%	16.9%	16.2%	5.8%	4.3%
Frackville	2,915	41.5%	20.3	15.3%	22.5%	20.2%	6.6%	3.3%
Hamburg	2,605	59.5%	19.9	21.7%	11.0%	12.1%	3.8%	2.3%
Jonestown	4,885	41.4%	19.7	29.5%	15.1%	13.4%	3.7%	7.7%
Reading	4,157	36.2%	24.2	31.6%	17.6%	16.7%	7.7%	3.7%
Schuylkill Haven	5,039	46.2%	19.8	14.9%	17.8%	18.3%	6.8%	3.2%
Troop M	22,615	30.2%	27.4	36.4%	17.6%	18.9%	5.8%	6.9%
Belfast	3,846	38.6%	26.1	28.3%	23.1%	13.5%	5.4%	5.3%
Bethlehem	4,497	21.5%	26.6	42.7%	15.5%	17.9%	5.5%	6.7%
Dublin	3,907	21.8%	27.3	33.6%	26.3%	20.9%	6.3%	9.6%
Fogelsville	5,956	32.2%	24.9	41.4%	13.7%	18.9%	6.4%	3.7%
Trevose	4,409	36.6%	32.3	32.7%	12.4%	22.8%	5.1%	10.5%

Driver Characteristics

The characteristics of the drivers stopped by PSP troopers in 2022 are presented in a series of tables. First, driver age, gender, behavior during the stop, and residency are described at the Department, Area, and Troop levels in Table 3.6 and the Station level in Table 3.7. The race and ethnicity of drivers stopped by PSP troopers in 2022 are listed at the Department, Area, and Troop levels in Table 3.8 and the Station level in Table 3.9.

Driver Age & Gender

As shown in Table 3.6, department-wide, the average age of drivers stopped by troopers was 37.9 years, which is similar to the averages at the Area, Troop, and Station levels. The largest difference in the average age of drivers occurred at the Station level (see Table 3.7). For instance, the average age of drivers stopped by troopers in the Marienville Station was 42.2 years, compared to 34.3 years in Pocono Station.

At the department level, 66.8% of stopped drivers were male; likewise, males were more likely than females to be stopped across organizational units within the department. The lowest percentage of male drivers stopped occurred in Area I (64.2%), specifically Troop B (62.9%). At the station level, the highest percentage of male drivers stopped occurred in Newville Station (72.8%), while the lowest percentage occurred in Uniontown Station (59.3%).

Driver Behavior

Tables 3.6 and 3.7 also provide information about driver behavior, including whether they were civil, disrespectful, non-compliant, verbally resistant, or physically resistant toward troopers during traffic stops. Troopers are instructed to select all that apply as behavior may change throughout the stop, so there are a small number of cases where drivers were reported to be civil and one of the other categories (n=800, 0.2%).[20] At the department level, 97.9% of drivers were reported as only civil, while 1.1% were disrespectful. Non-compliant or resistant drivers were rare, making up 0.5% and 1.1% of drivers, respectively. These findings were consistent at the Area and Troop levels. There is slightly more variation across Stations, but the lowest reported percentage of civil behavior is still only 94.9% at Gettysburg Station.

Driver Residency

Finally, Tables 3.6 and 3.7 provide information regarding driver residency status as determined by driver zip code. Department-wide, 81.3% of drivers stopped by troopers in 2022 were in-state residents. Similar percentages are seen across the four Areas, albeit with some variation. For example, 87.5% of drivers stopped in Area I were in-state residents, while 78.7% of drivers

[20] In this table, the percent "civil" reflects stops where that was the only behavior category selected by the trooper. If a trooper selected civil and at least one other behavior category, they are reported in the percent for the other categories. As a result, the sum of these percentages slightly exceeds 100% due to a small percentage of drivers that were reported to have displayed behavior consistent with more than one of the following categories: disrespectful, non-compliant, verbally resistant, or physically resistant. Overall, in 99.4% of traffic stops, troopers selected only one category for this data field.

stopped in Area III were in-state residents. At the Troop level, there is much more variation. For example, 92.5% of drivers stopped by Troop A resided in-state, while only 68.5% of drivers stopped by Troop T resided in-state.

Similar trends can be seen at the Station level, as there is a wide range in the percentages of stopped drivers that are in-state residents. The highest percentage of in-state drivers stopped occurred in Stonington Station (96.7%), while the lowest percentage of in-state drivers stopped occurred in Somerset (T) Station (48.3%).

The greatest difference is seen with the SHIELD and Canine units. While 87.5% of drivers stopped at the department level were in-state residents, only 28.4% of drivers stopped by the SHIELD unit, and only 42.6% of drivers stopped by the Canine unit were in-state residents.

Table 3.6: Characteristics of Drivers Stopped by Department, Area & Troop, January - December 2022

		Age	Gender	Behavior				Residency
	Total # of Stops	Average (years)	Male	Civil	Dis-respectful	Non-compliant	Verbal or Phys Resistant	In-State
PSP Dept.	**441,329**	**37.9**	**66.8%**	**97.9%**	**1.1%**	**0.5%**	**1.1%**	**81.3%**
AREA I	**103,889**	**38.8**	**64.2%**	**98.0%**	**1.0%**	**0.5%**	**0.9%**	**87.5%**
Troop B	30,443	38.6	62.9%	97.3%	1.4%	0.8%	1.1%	89.1%
Troop C	22,567	39.8	67.4%	98.4%	0.9%	0.3%	0.7%	80.8%
Troop D	23,671	37.8	63.3%	98.2%	1.0%	0.5%	0.9%	91.9%
Troop E	27,208	38.9	63.8%	98.2%	0.8%	0.5%	1.1%	87.6%
AREA II	**137,170**	**37.7**	**66.7%**	**98.1%**	**1.0%**	**0.4%**	**0.9%**	**78.9%**
Troop A	18,043	38.1	65.5%	98.5%	0.8%	0.3%	0.7%	92.5%
Troop G	28,359	38.1	63.9%	98.5%	0.9%	0.2%	0.6%	82.3%
Troop H	48,365	37.7	67.2%	97.2%	1.5%	0.7%	1.4%	80.9%
Troop T	42,403	37.2	68.5%	98.8%	0.5%	0.2%	0.7%	68.5%
AREA III	**91,658**	**38.2**	**66.9%**	**98.1%**	**1.0%**	**0.5%**	**0.9%**	**78.7%**
Troop F	31,196	38.4	64.9%	98.5%	0.7%	0.4%	0.8%	79.5%
Troop N	30,213	37.4	67.9%	97.8%	1.2%	0.6%	1.0%	76.5%
Troop P	15,306	38.6	66.1%	98.0%	1.1%	0.4%	0.9%	90.9%
Troop R	14,943	39.2	69.7%	97.8%	1.3%	0.6%	1.0%	68.9%
AREA IV	**101,444**	**37.1**	**68.7%**	**97.2%**	**1.3%**	**0.7%**	**1.5%**	**83.7%**
Troop J	32,167	37.2	66.5%	97.3%	1.5%	0.7%	1.3%	83.8%
Troop K	27,061	36.9	70.4%	96.5%	1.7%	0.9%	2.0%	83.3%
Troop L	19,601	37.3	67.3%	98.5%	0.7%	0.4%	0.8%	86.6%
Troop M	22,615	37.1	70.9%	97.0%	1.3%	0.9%	1.7%	81.4%
Specialized Units								
SHIELD	4,429	38.2	85.4%	98.7%	0.5%	0.3%	0.8%	28.4%
Canine	2,232	37.1	74.9%	97.0%	1.9%	0.5%	1.0%	42.6%

Table 3.7: Area I Characteristics of Drivers Stopped by Station, January - December 2022

		Age	Gender	Behavior				Residency
	Total # of Stops	Average (years)	Male	Civil	Dis-respectful	Non-compliant	Verbal or Phys Resistant	In-State
Troop B	**30,443**	**38.6**	**62.9%**	**97.3%**	**1.4%**	**0.8%**	**1.1%**	**89.1%**
Belle Vernon	5,066	39.4	64.4%	97.3%	1.8%	0.6%	1.2%	89.8%
Pittsburgh	7,168	37.5	67.0%	96.1%	1.6%	1.6%	1.3%	86.4%
Uniontown	11,505	38.8	59.3%	97.5%	1.5%	0.6%	1.0%	94.1%
Washington	4,272	39.3	64.0%	97.8%	0.8%	0.6%	1.2%	85.0%
Waynesburg	2,429	38.3	63.2%	98.8%	0.5%	0.5%	0.7%	79.5%
Troop C	**22,567**	**39.8**	**67.4%**	**98.4%**	**0.9%**	**0.3%**	**0.7%**	**80.8%**
Clarion	2,652	37.9	67.3%	98.8%	0.5%	0.2%	0.6%	75.3%
Clearfield	3,999	38.9	68.1%	98.2%	1.1%	0.4%	0.8%	69.2%
Dubois	3,110	39.4	68.0%	98.0%	1.3%	0.5%	0.6%	71.2%
Lewis Run	4,054	39.6	65.4%	98.7%	0.8%	0.3%	0.5%	83.2%
Marienville	2,467	42.2	71.3%	98.7%	0.5%	0.2%	0.7%	89.5%
Punxsutawney	3,483	40.7	65.4%	97.9%	1.3%	0.2%	0.9%	95.9%
Ridgway	2,802	40.3	67.6%	98.9%	0.7%	0.1%	0.5%	83.5%
Troop D	**23,671**	**37.8**	**63.3%**	**98.2%**	**1.0%**	**0.5%**	**0.9%**	**91.9%**
Beaver	3,619	37.6	62.4%	97.7%	1.7%	0.3%	0.6%	87.8%
Butler	6,182	37.8	63.7%	98.0%	1.1%	0.6%	0.9%	94.1%
Kittanning	7,941	38.0	64.7%	98.5%	0.7%	0.5%	0.8%	96.3%
Mercer	3,292	36.9	62.5%	98.6%	0.8%	0.2%	0.7%	82.5%
New Castle	2,637	38.7	60.1%	97.7%	0.8%	0.5%	1.5%	90.6%
Troop E	**27,208**	**38.9**	**63.8%**	**98.2%**	**0.8%**	**0.5%**	**1.1%**	**87.6%**
Corry	2,919	39.4	65.3%	98.7%	0.7%	0.3%	0.7%	95.0%
Erie	9,196	38.7	64.3%	97.7%	1.0%	0.7%	1.5%	87.1%
Franklin	2,115	39.7	63.8%	98.2%	1.0%	0.5%	0.8%	88.7%
Girard	6,321	38.1	60.9%	98.7%	0.6%	0.3%	0.8%	83.3%
Meadville	3,658	38.5	64.6%	97.9%	1.0%	0.5%	1.2%	88.9%
Warren	2,876	40.4	66.3%	98.9%	0.7%	0.4%	0.5%	89.6%

Table 3.7: Area II Characteristics of Drivers Stopped by Station, January - December 2022

		Age	Gender	Behavior				Residency
	Total # of Stops	Average (years)	Male	Civil	Dis-respectful	Non-compliant	Verbal or Phys Resistant	In-State
Troop A	**18,043**	**38.1**	**65.5%**	**98.5%**	**0.8%**	**0.3%**	**0.7%**	**92.5%**
Ebensburg	1,984	36.6	63.0%	99.0%	0.5%	0.1%	0.8%	89.5%
Greensburg	4,745	39.9	65.3%	98.1%	1.0%	0.3%	1.0%	96.4%
Indiana	6,626	36.8	65.3%	99.0%	0.5%	0.2%	0.5%	90.5%
Kiski Valley	1,337	40.1	68.7%	97.5%	1.7%	0.7%	0.7%	93.8%
Somerset (A)	3,351	38.1	66.3%	98.3%	0.8%	0.2%	0.8%	92.2%
Troop G	**28,359**	**38.1**	**63.9%**	**98.5%**	**0.9%**	**0.2%**	**0.6%**	**82.3%**
Bedford	5,065	37.9	63.6%	98.8%	0.7%	0.2%	0.4%	76.3%
Hollidaysburg	4,276	37.2	60.6%	98.4%	1.1%	0.3%	0.6%	89.3%
Huntingdon	3,899	40.1	65.1%	98.9%	0.4%	0.1%	0.6%	95.0%
Lewistown	4,069	38.0	61.3%	98.3%	0.9%	0.4%	0.7%	92.5%
McConnellsburg	3,154	38.9	67.4%	97.8%	1.3%	0.2%	1.0%	60.7%
Rockview	7,609	36.9	65.0%	98.6%	0.9%	0.2%	0.6%	80.1%
Troop H	**48,365**	**37.7**	**67.2**	**97.2%**	**1.5%**	**0.7%**	**1.4%**	**80.9%**
Carlisle	11,184	37.7	70.7%	97.6%	1.2%	0.7%	1.1%	79.1%
Chambersburg	12,462	38.2	63.8%	98.0%	0.9%	0.4%	1.1%	81.5%
Gettysburg	8,551	36.8	66.9%	94.9%	3.4%	1.6%	2.2%	75.9%
Harrisburg	9,536	38.1	69.4%	97.3%	1.3%	0.7%	1.5%	78.7%
Lykens	2,890	37.4	64.5%	98.4%	0.9%	0.5%	0.8%	94.8%
Newport	3,741	37.2	65.1%	97.9%	0.8%	0.5%	1.3%	90.2%
Troop T	**42,403**	**37.2**	**68.5%**	**98.8%**	**0.5%**	**0.2%**	**0.7%**	**68.5%**
Bowmansville	4,197	36.3	68.2%	98.9%	0.3%	0.1%	0.8%	78.4%
Everett	6,570	36.6	69.2%	99.1%	0.4%	0.2%	0.4%	53.6%
Gibsonia	5,174	38.9	66.9%	99.2%	0.6%	0.1%	0.2%	70.6%
Highspire	96	37.2	71.9%	100.0%	0.0%	0.0%	0.0%	78.1%
King of Prussia	5,395	36.3	69.7%	97.9%	0.8%	0.2%	1.4%	80.8%
New Stanton	7,126	38.6	65.8%	98.6%	0.4%	0.3%	0.9%	82.8%
Newville	4,054	36.1	72.8%	98.5%	0.7%	0.2%	0.8%	59.0%
Pocono	4,371	34.3	64.6%	98.7%	1.0%	0.2%	0.3%	74.4%
Somerset (T)	5,411	39.3	71.7%	99.3%	0.2%	0.1%	0.5%	48.3%

Table 3.7: Area III Characteristics of Drivers Stopped by Station, January - December 2022

		Age	Gender	Behavior				Residency
	Total # of Stops	Average (years)	Male	Civil	Dis-respectful	Non-compliant	Verbal or Phys Resistant	In-State
Troop F	**31,196**	**38.4**	**64.9%**	**98.5%**	**0.7%**	**0.4%**	**0.8%**	**79.5%**
Coudersport	2,738	41.3	68.3%	98.4%	1.0%	0.5%	0.2%	85.7%
Emporium	1,267	41.4	67.5%	99.5%	0.4%	0.0%	0.2%	90.3%
Lamar	5,398	37.7	66.9%	98.5%	0.6%	0.3%	0.8%	65.2%
Mansfield	2,464	38.7	63.1%	97.5%	1.2%	0.5%	1.2%	63.3%
Milton	7,771	37.6	64.7%	99.0%	0.5%	0.2%	0.6%	77.7%
Montoursville	5,867	37.9	63.3%	98.0%	0.8%	0.5%	1.2%	87.2%
Selinsgrove	3,643	37.9	63.9%	98.9%	0.5%	0.2%	0.4%	84.7%
Stonington	2,048	39.0	62.5%	97.5%	1.4%	0.6%	1.3%	96.7%
Troop N	**30,213**	**37.4**	**67.9%**	**97.8%**	**1.2%**	**0.6%**	**1.0%**	**76.5%**
Bloomsburg	2,992	35.7	66.0%	98.6%	0.8%	0.5%	0.6%	70.6%
Fern Ridge	5,781	38.2	71.9%	98.6%	0.7%	0.3%	0.7%	60.4%
Hazleton	6,140	36.6	68.2%	97.1%	1.8%	0.6%	1.3%	81.4%
Lehighton	2,395	37.1	68.4%	97.8%	1.3%	1.0%	0.8%	90.4%
Stroudsburg	12,900	38.0	66.4%	97.5%	1.2%	0.6%	1.3%	80.2%
Troop P	**15,306**	**38.6**	**66.1%**	**98.0%**	**1.1%**	**0.4%**	**0.9%**	**90.9%**
Laporte	2,070	40.2	66.7%	98.4%	0.8%	0.2%	0.7%	88.5%
Shickshinny	2,067	39.0	67.0%	98.9%	0.6%	0.3%	0.7%	93.5%
Towanda	4,527	38.2	65.8%	97.8%	1.5%	0.4%	0.8%	90.1%
Tunkhannock	1,928	40.1	65.1%	97.4%	1.6%	0.5%	1.2%	95.1%
Wilkes-Barre	4,711	37.4	66.1%	98.1%	0.8%	0.5%	0.9%	89.8%
Troop R	**14,943**	**39.2**	**69.7%**	**97.8%**	**1.3%**	**0.6%**	**1.0%**	**68.9%**
Blooming Grove	4,896	40.4	69.2%	97.8%	1.3%	0.5%	1.0%	64.5%
Dunmore	3,136	37.4	70.0%	96.9%	2.0%	0.6%	1.1%	76.5%
Gibson	3,973	38.0	71.3%	97.8%	1.1%	0.9%	1.5%	52.1%
Honesdale	2,938	40.7	68.1%	98.7%	0.7%	0.4%	0.3%	91.1%

Table 3.7: Area IV Characteristics of Drivers Stopped by Station, January - December 2022

		Age	Gender	Behavior				Residency
	Total # of Stops	Average (years)	Male	Civil	Dis-respectful	Non-compliant	Verbal or Phys Resistant	In-State
Troop J	**32,167**	**37.2**	**66.5%**	**97.3%**	**1.5%**	**0.7%**	**1.3%**	**83.8%**
Avondale	8,890	37.8	66.7%	97.0%	1.9%	0.8%	1.4%	76.1%
Embreeville	7,267	37.3	66.5%	97.6%	1.3%	0.7%	1.3%	91.9%
Lancaster	6,788	36.5	68.8%	97.6%	1.2%	0.5%	1.1%	90.6%
York	9,222	36.8	64.6%	97.3%	1.4%	0.7%	1.5%	79.8%
Troop K	**27,061**	**36.9**	**70.4**	**96.5%**	**1.7%**	**0.9%**	**2.0%**	**83.3%**
Media	11,759	37.4	69.4%	97.1%	1.4%	0.7%	1.4%	75.4%
Philadelphia	10,538	35.7	72.6%	95.8%	2.0%	1.3%	2.6%	87.2%
Skippack	4,726	38.0	68.2%	96.5%	1.7%	0.5%	1.8%	94.3%
Troop L	**19,601**	**37.3**	**67.3**	**98.5%**	**0.7%**	**0.4%**	**0.8%**	**86.6%**
Frackville	2,915	38.3	66.6%	99.1%	0.5%	0.1%	0.4%	85.4%
Hamburg	2,605	37.6	69.3%	98.8%	0.4%	0.4%	0.7%	78.9%
Jonestown	4,885	37.0	65.1%	98.2%	0.7%	0.4%	1.0%	77.5%
Reading	4,157	36.0	69.7%	97.5%	1.3%	0.8%	1.1%	92.7%
Schuylkill	5,039	38.0	66.9%	98.9%	0.5%	0.3%	0.8%	95.0%
Troop M	**22,615**	**37.1**	**70.9**	**97.0%**	**1.3%**	**0.9%**	**1.7%**	**81.4%**
Belfast	3,846	37.0	71.7%	95.9%	1.8%	0.8%	1.8%	75.3%
Bethlehem	4,497	36.8	68.2%	96.7%	1.5%	1.0%	1.9%	90.3%
Dublin	3,907	38.3	68.6%	95.6%	1.6%	1.6%	2.9%	93.2%
Fogelsville	5,956	37.6	72.5%	98.3%	0.6%	0.5%	1.0%	78.4%
Trevose	4,409	35.7	72.6%	97.6%	1.2%	0.7%	1.3%	71.5%

Drivers' Race & Ethnicity

Drivers' race and ethnicity are captured in separate fields on the CDR form. As described in Section 2, drivers' racial/ethnic characteristics are determined by officers' perceptions rather than asking drivers to self-identify. This is consistent with best practice guides regarding traffic stop data collection (Fridell et al., 2001; Pryor et al., 2020; Ramirez et al., 2000). The available response options for each are:

- Race: White, Black, American Indian/Alaskan Native, Asian/Pacific Islander, and Unknown
- Ethnicity: Hispanic Origin, Not of Hispanic Origin, and Unknown

Figure 3.2 below displays the perceived race and ethnicity of drivers stopped by troopers department-wide. As shown, most drivers stopped (78.5%) were White, followed by 14.4% Black, 1.8% Asian, and 0.3% American Indian or Alaskan Native. In the ethnicity field, 8.2% of stopped drivers were reported to be Hispanic.[21]

Figure 3.2: Department-Wide Racial/Ethnic Characteristics of Drivers Stopped, January - December 2022

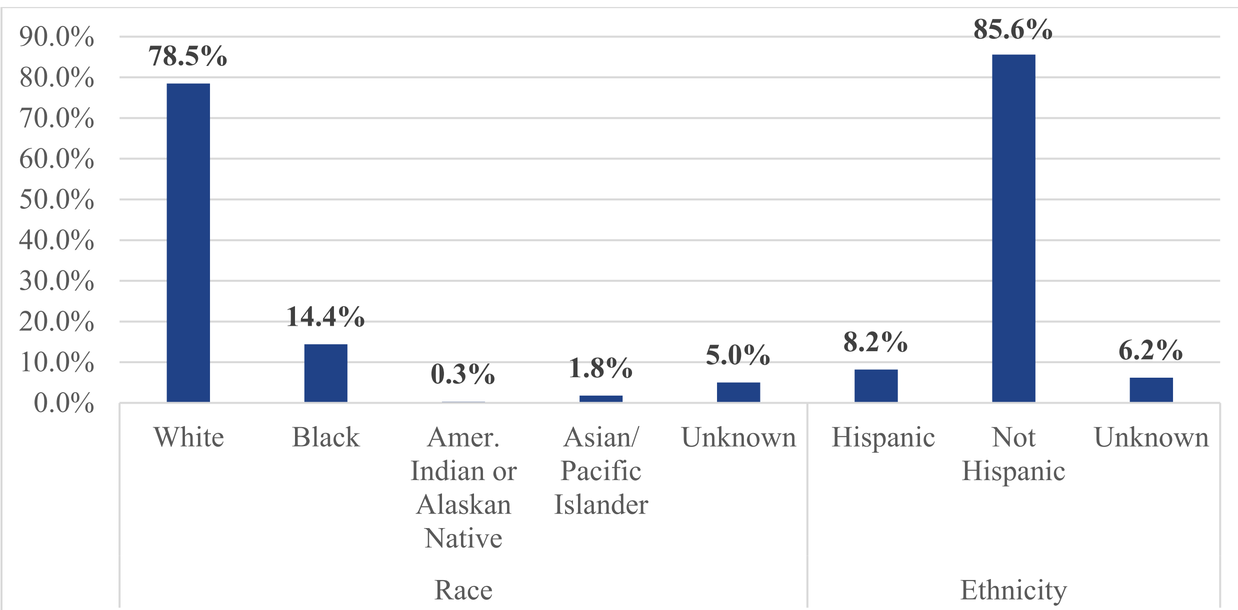


Table 3.8 displays the perceived race and ethnicity of drivers stopped by the Department, Areas, Troops, and specialized units, while Table 3.9 displays the same information at the Station level. These tables demonstrate large variations in the race/ethnicity of drivers stopped across

[21] Most individuals perceived to be Hispanic were White (89.7%). Therefore, the % White displayed in Figure 3.2 and Tables 3.8 and 3.9 includes some individuals perceived to be Hispanic because race and ethnicity are captured separately. The percentage of non-Hispanic White drivers stopped in 2022 was 71.1%. In later analyses in Section 4, the research team combines race and ethnicity. This coding process is described in Section 4.

organizational units. Some variation is expected based on geographic, demographic, and roadway type differences across the Commonwealth.

As shown in Figure 3.2, PSP troopers indicated they could not identify the drivers' race in 5.0% of all traffic stops or identify the drivers' ethnicity during 6.2% of stops. In 85.4% of the cases with unknown drivers' race, the drivers' ethnicity was also reported as unknown. In 68.5% of the cases with unknown drivers' ethnicity, the drivers' race was also unknown. Other observational and traffic studies have reported the difficulties of identifying drivers' race and ethnicity, particularly distinguishing Hispanic drivers from White drivers (Alpert et al., 2004b; Lange et al., 2001; Smith & DeFrances, 2003).

At the Area level, the highest percentage of unknown race was reported in Area III (6.2% of stops) and the lowest in Area IV (3.8%). Across Troops, the highest percentage of unknown race occurred in Troop T (11.5%) and the lowest in Troop J (1.4%). As shown in Table 3.7, of the 88 Stations, 11 reported 1% or fewer stops with unknown drivers' race,[22] and 10 reported 1% or fewer stops with unknown drivers' ethnicity.[23] Conversely, 13 Stations reported 10% or more stops with unknown drivers' race,[24] and 20 Stations with 10% or more with drivers' ethnicity unknown.[25] This issue is explored in more detail below.

[22] Stations with 1% or fewer stops with unknown drivers' race include: Punxsutawney, Corry, Warren, Greensburg, Kiski Valley, Somerset (A), Lykens, Emporium, Stonington, Towanda, Avondale, and Lancaster.
[23] Stations with 1% or fewer stops with unknown drivers' ethnicity include: Punxsutawney, Kittanning, Corry, Greensburg, Kiski Valley, Somerset (A), Emporium, Stonington, and Towanda.
[24] Stations that reported 10% or more stops with unknown drivers' race include: Dubois, Ridgway, Everett, King of Prussia, Somerset (T), Bloomsburg, Hazleton, Lehighton, Blooming Grove, Gibson, Bethlehem, Dublin, and Trevose.
[25] Stations that reported 10% or more stops with unknown drivers' ethnicity include: Belle Vernon, Pittsburgh, Dubois, Ridgway, Franklin, Everett, Gibsonia, King of Prussia, New Stanton, Somerset (T), Bloomsburg, Hazleton, Lehighton, Stroudsburg, Blooming Grove, Gibson, Philadelphia, Skippack, Bethlehem, and Dublin.

Table 3.8: Race and Ethnicity of Drivers Stopped by Department, Area & Troop, Jan - Dec 2022

		Race					Ethnicity	
	Total # of Stops	White	Black	Amer. Indian or Alaskan Native	Asian/Pac. Islander	Unknown	Hispanic	Unknown
PSP Dept.	**441,329**	**78.5%**	**14.4%**	**0.3%**	**1.8%**	**5.0%**	**8.2%**	**6.2%**
AREA I	**103,889**	**84.3%**	**10.1%**	**0.2%**	**1.1%**	**4.4%**	**1.8%**	**5.3%**
Troop B	30,443	78.6%	14.8%	0.1%	1.0%	5.4%	1.5%	7.9%
Troop C	22,567	89.0%	3.7%	0.2%	1.0%	6.0%	1.7%	5.7%
Troop D	23,671	83.6%	11.3%	0.1%	0.7%	4.3%	1.2%	4.9%
Troop E	27,208	87.3%	8.9%	0.2%	1.5%	2.0%	2.6%	2.5%
AREA II	**137,170**	**79.3%**	**12.7%**	**0.3%**	**2.1%**	**5.5%**	**6.0%**	**6.2%**
Troop A	18,043	90.6%	7.2%	0.1%	0.6%	1.5%	1.3%	2.1%
Troop G	28,359	86.4%	7.4%	0.4%	1.9%	3.9%	2.9%	3.9%
Troop H	48,365	80.6%	14.5%	0.3%	1.7%	2.8%	9.4%	3.0%
Troop T	42,403	68.2%	16.6%	0.4%	3.3%	11.5%	6.1%	13.1%
AREA III	**91,658**	**81.0%**	**11.1%**	**0.3%**	**1.4%**	**6.2%**	**9.5%**	**8.2%**
Troop F	31,196	86.7%	8.5%	0.3%	1.5%	3.0%	4.2%	3.3%
Troop N	30,213	71.9%	16.3%	0.3%	1.6%	9.9%	17.6%	12.9%
Troop P	15,306	89.2%	7.6%	0.1%	0.4%	2.6%	5.8%	3.0%
Troop R	14,943	79.3%	9.3%	0.2%	1.8%	9.4%	8.2%	14.5%
AREA IV	**101,444**	**69.7%**	**23.8%**	**0.4%**	**2.3%**	**3.8%**	**15.6%**	**5.3%**
Troop J	32,167	76.2%	19.9%	0.5%	2.0%	1.4%	14.5%	2.4%
Troop K	27,061	50.2%	40.9%	0.5%	2.8%	5.6%	9.0%	8.2%
Troop L	19,601	84.6%	10.8%	0.2%	1.3%	3.1%	19.9%	4.2%
Troop M	22,615	70.9%	20.2%	0.5%	2.9%	5.6%	21.5%	7.2%
Specialized Units								
SHIELD	4,429	71.3%	16.4%	1.3%	10.0%	1.1%	30.1%	5.2%
Canine	2,232	73.6%	19.2%	0.4%	3.5%	3.3%	14.7%	3.2%

Table 3.9: Area I Race and Ethnicity of Drivers Stopped by Station, January - December 2022

	Total # of Stops	Race					Ethnicity	
		White	Black	Amer. Indian or Alaskan Native	Asian/ Pacific Islander	Unknown	Hispanic	Unknown
Troop B	**30,443**	**78.6%**	**14.8%**	**0.1%**	**1.0%**	**5.4%**	**1.5%**	**7.9%**
Belle Vernon	5,066	74.9%	15.6%	0.1%	0.9%	8.4%	1.7%	11.8%
Pittsburgh	7,168	68.3%	25.0%	0.3%	2.3%	4.1%	2.2%	12.9%
Uniontown	11,505	83.4%	11.3%	0.0%	0.3%	4.9%	0.8%	4.5%
Washington	4,272	82.4%	11.4%	0.2%	1.0%	5.0%	2.4%	4.8%
Waynesburg	2,429	87.5%	5.7%	0.1%	0.4%	6.2%	0.9%	6.7%
Troop C	**22,567**	**89.0%**	**3.7%**	**0.2%**	**1.0%**	**6.0%**	**1.7%**	**5.7%**
Clarion	2,652	85.4%	7.1%	0.0%	1.7%	5.8%	3.7%	5.1%
Clearfield	3,999	87.2%	5.4%	0.2%	1.4%	5.9%	1.9%	6.0%
Dubois	3,110	80.0%	6.3%	0.2%	1.7%	11.9%	3.1%	10.8%
Lewis Run	4,054	91.6%	3.0%	0.3%	0.7%	4.4%	1.1%	3.7%
Marienville	2,467	95.5%	1.8%	0.0%	0.4%	2.2%	0.7%	2.6%
Punxsutawney	3,483	98.2%	1.1%	0.1%	0.3%	0.3%	0.6%	0.2%
Ridgway	2,802	84.0%	1.6%	0.5%	1.1%	12.8%	1.1%	12.9%
Troop D	**23,671**	**83.6%**	**11.3%**	**0.1%**	**0.7%**	**4.3%**	**1.2%**	**4.9%**
Beaver	3,619	74.1%	20.3%	0.1%	0.4%	5.2%	1.3%	8.3%
Butler	6,182	85.9%	6.4%	0.1%	0.7%	6.9%	1.0%	7.2%
Kittanning	7,941	87.4%	11.0%	0.1%	0.3%	1.2%	0.9%	1.0%
Mercer	3,292	82.1%	7.9%	0.2%	1.9%	8.0%	1.7%	8.3%
New Castle	2,637	81.5%	15.5%	0.2%	0.8%	2.0%	2.0%	2.0%
Troop E	**27,208**	**87.3%**	**8.9%**	**0.2%**	**1.5%**	**2.0%**	**2.6%**	**2.5%**
Corry	2,919	96.9%	2.5%	0.0%	0.4%	0.3%	0.5%	0.3%
Erie	9,196	82.9%	13.9%	0.3%	1.8%	1.1%	4.4%	1.3%
Franklin	2,115	87.1%	4.2%	0.1%	1.0%	7.6%	1.4%	13.0%
Girard	6,321	84.2%	10.9%	0.2%	2.4%	2.0%	3.3%	2.0%
Meadville	3,658	89.1%	6.3%	0.1%	1.3%	3.1%	1.0%	2.9%
Warren	2,876	96.7%	2.0%	0.1%	0.4%	0.8%	0.5%	1.2%

Table 3.9: Area II Race and Ethnicity of Drivers Stopped by Station, January - December 2022

		Race					Ethnicity	
	Total # of Stops	White	Black	Amer. Indian or Alaskan Native	Asian/ Pacific Islander	Unknown	Hispanic	Unknown
Troop A	**18,043**	**90.6%**	**7.2%**	**0.1%**	**0.6%**	**1.5%**	**1.3%**	**2.1%**
Ebensburg	1,984	86.1%	6.9%	0.4%	0.9%	5.8%	1.8%	6.1%
Greensburg	4,745	91.1%	7.7%	0.1%	0.4%	0.6%	1.3%	0.5%
Indiana	6,626	89.1%	8.8%	0.0%	0.7%	1.3%	1.4%	2.8%
Kiski Valley	1,337	91.8%	6.6%	0.1%	0.7%	0.7%	1.4%	0.7%
Somerset (A)	3,351	94.7%	3.8%	0.1%	0.5%	0.9%	0.8%	0.9%
Troop G	**28,359**	**86.4%**	**7.4%**	**0.4%**	**1.9%**	**3.9%**	**2.9%**	**3.9%**
Bedford	5,065	88.6%	7.5%	0.4%	2.1%	1.4%	2.2%	1.4%
Hollidaysburg	4,276	86.2%	6.8%	0.3%	1.4%	5.4%	2.5%	5.4%
Huntingdon	3,899	90.9%	2.8%	0.0%	0.4%	5.9%	0.7%	5.7%
Lewistown	4,069	90.3%	6.1%	0.3%	1.7%	1.6%	4.0%	1.8%
McConnellsburg	3,154	77.4%	11.7%	0.2%	2.4%	8.4%	3.4%	8.3%
Rockview	7,609	84.8%	8.9%	0.7%	2.9%	2.8%	3.8%	2.8%
Troop H	**48,365**	**80.6%**	**14.5%**	**0.3%**	**1.7%**	**2.8%**	**9.4%**	**3.0%**
Carlisle	11,184	79.0%	16.8%	0.3%	1.8%	2.1%	9.0%	2.4%
Chambersburg	12,462	85.5%	11.9%	0.2%	0.9%	1.8%	8.5%	2.2%
Gettysburg	8,551	84.6%	12.0%	0.6%	1.4%	1.4%	11.8%	1.2%
Harrisburg	9,536	65.7%	22.9%	0.6%	3.4%	7.5%	12.5%	7.6%
Lykens	2,890	91.8%	6.4%	0.1%	0.8%	1.0%	4.9%	1.0%
Newport	3,741	90.0%	7.2%	0.1%	1.6%	1.2%	3.5%	1.3%
Troop T	**42,403**	**68.2%**	**16.6%**	**0.4%**	**3.3%**	**11.5%**	**6.1%**	**13.1%**
Bowmansville	4,197	68.9%	22.7%	0.5%	4.0%	4.0%	11.7%	6.2%
Everett	6,570	56.3%	18.2%	0.5%	4.4%	20.5%	5.2%	19.7%
Gibsonia	5,174	80.6%	12.8%	0.3%	2.3%	4.0%	3.0%	10.1%
Highspire	96	71.9%	18.8%	0.0%	5.2%	4.2%	13.5%	5.2%
King of Prussia	5,395	61.3%	21.7%	0.6%	3.7%	12.6%	8.5%	17.2%
New Stanton	7,126	81.3%	7.9%	0.1%	0.8%	9.9%	1.6%	11.1%
Newville	4,054	68.1%	21.0%	0.4%	5.2%	5.3%	7.8%	5.1%
Pocono	4,371	74.6%	19.0%	1.0%	3.5%	1.9%	10.9%	2.0%
Somerset (T)	5,411	55.1%	14.3%	0.3%	3.5%	26.9%	4.2%	27.0%

Table 3.9: Area III Race and Ethnicity of Drivers Stopped by Station, January - December 2022

	Total # of Stops	Race					Ethnicity	
		White	Black	Amer. Indian or Alaskan Native	Asian/ Pacific Islander	Unknown	Hispanic	Unknown
Troop F	**31,196**	**86.7%**	**8.5%**	**0.3%**	**1.5%**	**3.0%**	**4.2%**	**3.3%**
Coudersport	2,738	95.8%	1.0%	0.1%	0.8%	2.4%	0.8%	2.3%
Emporium	1,267	97.2%	1.5%	0.2%	0.2%	0.9%	0.6%	0.9%
Lamar	5,398	82.4%	10.0%	0.6%	2.6%	4.4%	5.3%	4.4%
Mansfield	2,464	81.8%	7.3%	0.6%	2.7%	7.5%	2.3%	7.3%
Milton	7,771	85.7%	10.1%	0.5%	1.6%	2.1%	7.0%	2.4%
Montoursville	5,867	83.6%	12.4%	0.2%	1.3%	2.5%	2.3%	2.6%
Selinsgrove	3,643	89.0%	7.2%	0.0%	1.2%	2.7%	4.2%	5.1%
Stonington	2,048	93.2%	6.0%	0.0%	0.1%	0.7%	4.8%	0.7%
Troop N	**30,213**	**71.9%**	**16.3%**	**0.3%**	**1.6%**	**9.9%**	**17.6%**	**12.9%**
Bloomsburg	2,992	74.5%	12.2%	0.1%	2.0%	11.1%	8.7%	12.8%
Fern Ridge	5,781	78.9%	15.3%	0.3%	1.9%	3.6%	15.6%	4.6%
Hazleton	6,140	70.6%	10.7%	0.1%	1.2%	17.4%	32.7%	17.6%
Lehighton	2,395	79.9%	6.7%	0.1%	0.4%	12.8%	12.1%	15.2%
Stroudsburg	12,900	67.2%	22.2%	0.4%	1.8%	8.3%	14.5%	13.9%
Troop P	**15,306**	**89.2%**	**7.6%**	**0.1%**	**0.4%**	**2.6%**	**5.8%**	**3.0%**
Laporte	2,070	90.5%	6.7%	0.2%	0.4%	2.2%	3.7%	2.7%
Shickshinny	2,067	88.7%	8.6%	0.1%	0.4%	2.2%	8.5%	2.0%
Towanda	4,527	96.9%	1.8%	0.1%	0.2%	0.9%	1.3%	1.0%
Tunkhannock	1,928	91.6%	3.2%	0.1%	0.3%	4.9%	3.4%	6.1%
Wilkes-Barre	4,711	80.4%	15.1%	0.2%	0.7%	3.6%	10.8%	4.2%
Troop R	**14,943**	**79.3%**	**9.3%**	**0.2%**	**1.8%**	**9.4%**	**8.2%**	**14.5%**
Blooming Grove	4,896	78.6%	7.8%	0.1%	1.3%	12.1%	8.4%	22.9%
Dunmore	3,136	78.7%	14.8%	0.3%	1.6%	4.5%	11.4%	9.9%
Gibson	3,973	73.2%	11.6%	0.4%	3.5%	11.2%	10.0%	11.4%
Honesdale	2,938	89.2%	2.8%	0.0%	0.5%	7.5%	2.1%	9.6%

Table 3.9: Area IV Race and Ethnicity of Drivers Stopped by Station, January - December 2022

	Total # of Stops	Race					Ethnicity	
		White	Black	Amer. Indian or Alaskan Native	Asian/ Pacific Islander	Unknown	Hispanic	Unknown
Troop J	**32,167**	**76.2%**	**19.9%**	**0.5%**	**2.0%**	**1.4%**	**14.5%**	**2.4%**
Avondale	8,890	80.9%	16.2%	0.4%	1.8%	0.7%	20.7%	1.2%
Embreeville	7,267	69.1%	24.8%	0.9%	3.0%	2.2%	10.5%	2.5%
Lancaster	6,788	81.4%	16.0%	0.3%	1.4%	0.8%	16.2%	1.6%
York	9,222	73.4%	22.6%	0.3%	1.8%	1.9%	10.5%	3.8%
Troop K	**27,061**	**50.2%**	**40.9%**	**0.5%**	**2.8%**	**5.6%**	**9.0%**	**8.2%**
Media	11,759	50.4%	43.0%	0.7%	3.1%	2.8%	7.3%	2.7%
Philadelphia	10,538	40.4%	47.2%	0.3%	2.8%	9.3%	11.3%	11.5%
Skippack	4,726	71.5%	21.4%	0.5%	2.1%	4.4%	8.3%	14.4%
Troop L	**19,601**	**84.6%**	**10.8%**	**0.2%**	**1.3%**	**3.1%**	**19.9%**	**4.2%**
Frackville	2,915	84.2%	9.8%	0.1%	0.8%	5.1%	15.8%	5.9%
Hamburg	2,605	82.6%	14.0%	0.4%	1.5%	1.5%	20.8%	3.1%
Jonestown	4,885	82.9%	10.3%	0.3%	2.0%	4.5%	20.2%	5.7%
Reading	4,157	81.6%	13.7%	0.1%	1.2%	3.4%	32.5%	5.3%
Schuylkill Haven	5,039	90.1%	7.7%	0.1%	0.8%	1.4%	11.0%	1.4%
Troop M	**22,615**	**70.9%**	**20.2%**	**0.5%**	**2.9%**	**5.6%**	**21.5%**	**7.2%**
Belfast	3,846	70.1%	24.6%	0.3%	2.9%	2.1%	21.5%	2.8%
Bethlehem	4,497	70.4%	16.7%	0.2%	1.4%	11.3%	27.7%	11.7%
Dublin	3,907	78.9%	9.2%	0.3%	1.7%	10.0%	9.4%	11.0%
Fogelsville	5,956	74.6%	19.8%	0.7%	2.4%	2.5%	28.7%	5.4%
Trevose	4,409	59.9%	30.2%	0.7%	6.1%	3.1%	16.1%	5.6%

Further Exploration of Unknown Drivers' Race and Ethnicity

The 2022 Quarter 1 and 2 reports showed large variations in the percentage of unknown responses for the drivers' race and ethnicity fields. In response, the PSP provided additional guidance to its members based on recommendations from the Institute research team. On August 12, 2022, the Director of the Bureau of Communication and Information Services (BCIS) released a PSP Postmaster Communication. This directive reiterated that when completing the race and ethnicity fields, "members are reminded that they **shall** report their perceptions of occupants' race/ethnicity." Further guidance indicated:

> "Unknown" should only be used in the rare circumstance that a member is unable to perceive the race and/or ethnicity. For the purposes of the CDR form, the occupant's actual race/ethnicity is irrelevant as the information we are collecting is based on the members' perception. For the same reason, members shall not ask occupants to identify their actual race/ethnicity.

The directive also noted that because there is no response option for more than one race, "Members may select 'unknown' when they encounter someone they perceive to be biracial. To the extent that is the case, please select the race/ethnicity that most closely aligns to your perception whenever possible." Of note, the PSP added "Two or More Races" as a response option for the 2023 data collection. As a result, we expect that the percentages of unknown race and ethnicity will continue to decrease as troopers have an additional option for reporting their perceptions of drivers' race and ethnicity.

In a similar manner to the Quarter 3 report, we compare the average percentage of drivers with unknown race and ethnicity reported before and after the August 12th directive. Tables 3.10 and 3.11 display the average percentages of unknown race and ethnicity for the PSP Department, Areas, Troops, Stations, and specialized units for two time periods: January 1 – August 11 (before the directive) compared to August 12 – December 31 (after the directive). This information is also displayed graphically for the department (Figure 3.3) and Areas (Figure 3.4).

As shown, the percentage of unknown race reported on the CDR forms decreased from an average of 6.0% for the eight months before the August 12th directive to an average of 3.4% across the department after the directive; similarly, the percentage of reported unknown ethnicity decreased from 7.6% to 3.9%. Both represent statistically significant declines using a t-test comparison of means analysis. At the Area level, declines in the average percentage of CDRs with unknown race and ethnicity were also reported across all four Areas after the August 12th directive.

Figure 3.3: Comparison of Percent Unknown Race/Ethnicity of Drivers Before and After PSP Directive, Department-Wide

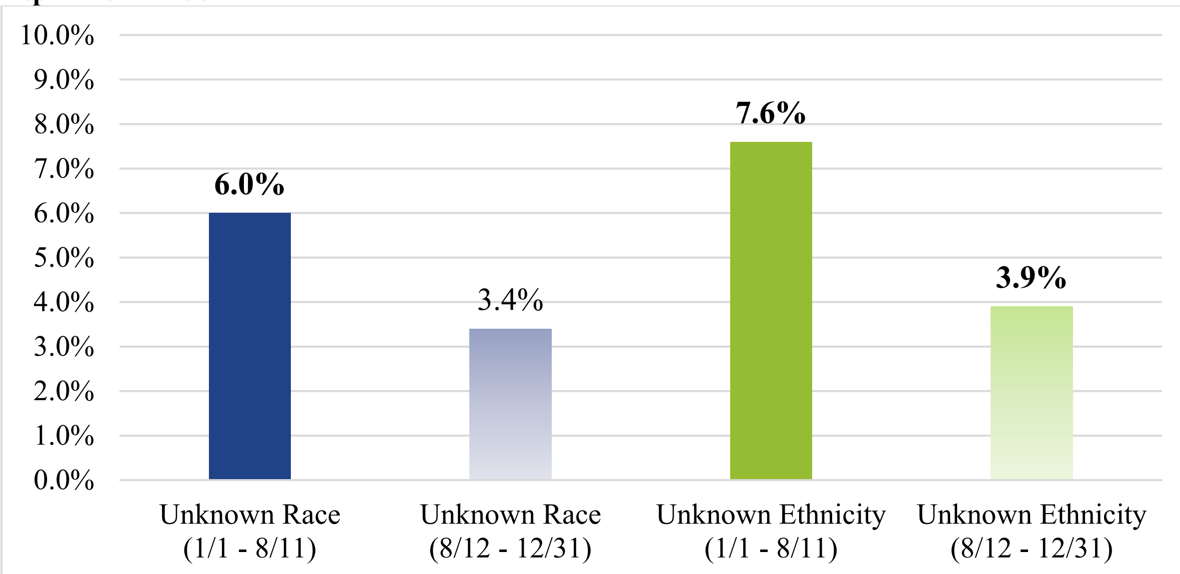
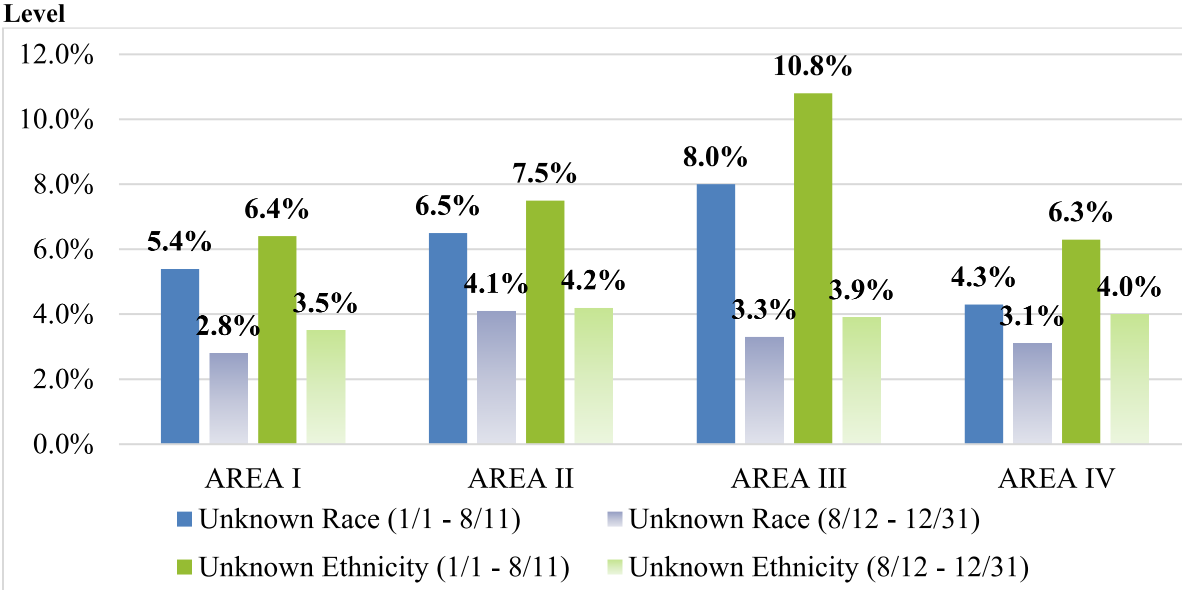


Figure 3.4: Comparison of Percent Unknown Race/Ethnicity of Drivers Before and After PSP Directive, Area Level



As shown in Table 3.10, at the Troop level, lower percentages of unknown drivers' race were reported by all Troops following the directive. Notably, the percentage of unknown drivers' race for all Troops is now below 10%. All Troops except T, R, K, and M reported 5.0% or lower unknown drivers' race. Additionally, the percentage of unknown drivers' ethnicity for all Troops is now below 10%, and 11 of 16 Troops reported 5.0% or lower unknown drivers' ethnicity.

Table 3.10: Percent Unknown Race/Ethnicity of Drivers Stopped by Department, Area, & Troop, 2022

	Total # of Stops	Unknown Race	Unknown Race	Difference	Unknown Ethnicity	Unknown Ethnicity	Difference
		1/1-8/11	8/12-12/31		1/1-8/11	8/12-12/31	
PSP Dept.	**441,329**	**6.0%**	**3.4%**	**-2.6%**	**7.6%**	**3.9%**	**-3.7%**
AREA I	**103,889**	**5.4%**	**2.8%**	**-2.6%**	**6.4%**	**3.5%**	**-2.9%**
Troop B	30,443	6.0%	4.5%	-1.5%	9.0%	6.3%	-2.7%
Troop C	22,567	7.2%	3.9%	-3.3%	6.9%	3.6%	-3.3%
Troop D	23,671	5.4%	2.1%	-3.3%	5.7%	3.1%	-2.6%
Troop E	27,208	2.7%	1.0%	-1.7%	3.6%	1.0%	-2.6%
AREA II	**137,170**	**6.5%**	**4.1%**	**-2.4%**	**7.5%**	**4.2%**	**-3.3%**
Troop A	18,043	1.9%	0.8%	-1.1%	2.9%	0.8%	-2.1%
Troop G	28,359	4.5%	3.1%	-1.4%	4.6%	2.9%	-1.7%
Troop H	48,365	3.6%	1.7%	-1.9%	3.9%	1.6%	-2.3%
Troop T	42,403	13.0%	9.0%	-4.0%	15.2%	9.8%	-5.4%
AREA III	**91,658**	**8.0%**	**3.3%**	**-4.7%**	**10.8%**	**3.9%**	**-6.9%**
Troop F	31,196	3.7%	1.8%	-1.9%	4.3%	1.9%	-2.4%
Troop N	30,213	13.4%	4.1%	-9.3%	18.0%	4.5%	-13.5%
Troop P	15,306	2.8%	2.1%	-0.7%	3.1%	2.9%	-0.2%
Troop R	14,943	11.3%	6.0%	-5.3%	17.8%	8.6%	-9.2%
AREA IV	**101,444**	**4.3%**	**3.1%**	**-1.2%**	**6.3%**	**4.0%**	***-2.3%***
Troop J	32,167	1.7%	1.0%	-0.7%	2.9%	1.5%	-1.4%
Troop K	27,061	5.8%	5.3%	-0.5%	9.1%	6.9%	-2.2%
Troop L	19,601	3.7%	2.4%	-1.3%	5.1%	3.1%	-2.0%
Troop M	22,615	6.6%	4.2%	-2.4%	8.7%	5.1%	-3.6%
Specialized Units							
SHIELD	4,429	1.3%	0.6%	-0.7%	7.3%	1.0%	-6.3%
Canine	2,232	3.4%	3.1%	-0.3%	3.1%	3.4%	+0.3%

As shown in Table 3.11, at the station level, decreased percentages of unknowns were reported in 77 of 88 stations (drivers' race), and 83 of 88 stations (drivers' ethnicity) following the August 12th directive. Some stations experienced 10% or more reductions in unknown drivers' race, including King of Prussia, Bloomsburg, Hazleton, Lehighton, and Blooming Grove. Likewise, the following stations reported 10% or more reductions in unknown drivers' ethnicity: Franklin, King of Prussia, Bloomsburg, Hazelton, Lehighton, Stroudsburg, Blooming Grove, and Dunmore.

Despite the issued directive, a small number of stations (2 of 88) showed notable *increases* (difference of 3% or more) in the percentage of reported unknown drivers' race/ethnicity: Hollidaysburg (race and ethnicity) and Honesdale (race only). Further, seven stations remain over 10% of stops with reported unknown drivers' race and/or ethnicity: Belle Vernon, Pittsburgh, Everett, Somerset (T), Blooming Grove, Honesdale, and Skippack. Both these trends warrant further examination by PSP officials.

Table 3.11: Area I Percent Unknown Race/Ethnicity of Drivers Stopped by Station, 2022

	Total # of Stops	Unknown Race	Unknown Race	Difference	Unknown Ethnicity	Unknown Ethnicity	Difference
		1/1-8/11	8/12-12/31		1/1-8/11	8/12-12/31	
Troop B	**30,443**	**6.0%**	**4.5%**	**-1.5%**	**9.0%**	**6.3%**	**-2.7%**
Belle Vernon	5,066	7.8%	9.6%	+1.8%	11.6%	12.2%	+0.6%
Pittsburgh	7,168	4.7%	3.2%	-1.5%	14.5%	10.1%	-4.4%
Uniontown	11,505	5.6%	3.8%	-1.8%	5.2%	3.5%	-1.7%
Washington	4,272	6.8%	2.8%	-4.0%	6.7%	2.5%	-4.2%
Waynesburg	2,429	7.5%	3.8%	-3.7%	8.2%	4.1%	-4.1%
Troop C	**22,567**	**7.2%**	**3.9%**	**-3.3%**	**6.9%**	**3.6%**	**-3.3%**
Clarion	2,652	7.5%	2.5%	-5.0%	6.2%	2.9%	-3.3%
Clearfield	3,999	6.4%	4.8%	-1.6%	6.7%	4.4%	-2.3%
Dubois	3,110	14.4%	6.8%	-7.6%	13.5%	5.3%	-8.2%
Lewis Run	4,054	3.6%	5.6%	+2.0%	2.8%	5.0%	+2.2%
Marienville	2,467	3.1%	0.7%	-2.4%	3.9%	0.6%	-3.3%
Punxsutawney	3,483	0.5%	0.2%	-0.3%	0.3%	0.2%	-0.1%
Ridgway	2,802	15.5%	6.6%	-8.9%	15.3%	7.0%	-8.3%
Troop D	**23,671**	**5.4%**	**2.1%**	**-3.3%**	**5.7%**	**3.1%**	**-2.6%**
Beaver	3,619	6.6%	2.3%	-4.3%	8.1%	8.7%	+0.6%
Butler	6,182	8.7%	2.7%	-6.0%	9.0%	3.2%	-5.8%
Kittanning	7,941	1.3%	0.9%	-0.4%	1.1%	0.8%	-0.3%
Mercer	3,292	9.8%	4.2%	-5.6%	10.3%	3.9%	-6.4%
New Castle	2,637	2.2%	1.6%	-0.6%	2.4%	1.4%	-1.0%
Troop E	**27,208**	**2.7%**	**1.0%**	**-1.7%**	**3.6%**	**1.0%**	**-2.6%**
Corry	2,919	0.4%	0.1%	-0.3%	0.3%	0.5%	+0.2%
Erie	9,196	1.7%	0.6%	-1.1%	2.0%	0.7%	-1.3%
Franklin	2,115	10.7%	1.7%	-9.0%	18.5%	2.5%	-16.0%
Girard	6,321	2.2%	1.8%	-0.4%	2.3%	1.5%	-0.8%
Meadville	3,658	4.5%	1.7%	-2.8%	4.7%	1.1%	-3.6%
Warren	2,876	1.0%	0.6%	-0.4%	1.5%	0.8%	-0.7%

Table 3.11: Area II Percent Unknown Race/Ethnicity of Drivers Stopped by Station, 2022

	Total # of Stops	Unknown Race	Unknown Race	Difference	Unknown Ethnicity	Unknown Ethnicity	Difference
		1/1-8/11	8/12-12/31		1/1-8/11	8/12-12/31	
Troop A	**18,043**	1.9%	0.8%	**-1.1%**	2.9%	0.8%	**-2.1%**
Ebensburg	1,984	9.0%	1.8%	-7.2%	9.5%	1.9%	-7.6%
Greensburg	4,745	0.6%	0.7%	+0.1%	0.6%	0.5%	-0.1%
Indiana	6,626	1.7%	0.6%	-1.1%	3.8%	0.7%	-3.1%
Kiski Valley	1,337	0.7%	0.9%	+0.2%	0.7%	0.9%	+0.2%
Somerset (A)	3,351	0.9%	0.8%	-0.1%	1.0%	0.8%	-0.2%
Troop G	**28,359**	**4.5%**	**3.1%**	**-1.4%**	**4.6%**	**2.9%**	**-1.7%**
Bedford	5,065	1.8%	0.8%	-1.0%	1.8%	0.7%	-1.1%
Hollidaysburg	4,276	4.0%	7.3%	+3.3%	4.0%	7.3%	+3.3%
Huntingdon	3,899	7.1%	4.7%	-2.4%	7.1%	4.4%	-2.7%
Lewistown	4,069	2.4%	0.5%	-1.9%	2.5%	0.6%	-1.9%
McConnellsburg	3,441	10.6%	5.3%	-5.3%	10.9%	4.8%	-6.1%
Rockview	7,609	3.7%	1.6%	-2.1%	3.9%	1.3%	-2.6%
Troop H	**48,365**	**3.6%**	**1.7%**	**-1.9%**	**3.9%**	**1.6%**	**-2.3%**
Carlisle	11,184	2.4%	1.7%	-0.7%	2.8%	1.6%	-1.2%
Chambersburg	12,462	2.2%	1.1%	-1.1%	3.0%	1.0%	-2.0%
Gettysburg	8,551	1.9%	0.8%	-1.1%	1.7%	0.5%	-1.2%
Harrisburg	9,536	9.1%	4.7%	-4.4%	9.1%	4.7%	-4.4%
Lykens	2,890	1.2%	0.7%	-0.5%	1.3%	0.6%	-0.7%
Newport	3,741	1.6%	0.8%	-0.8%	1.6%	0.8%	-0.8%
Troop T	**42,403**	**13.0%**	**9.0%**	**-4.0%**	**15.2%**	**9.8%**	**-5.4%**
Bowmansville	4,197	4.9%	2.7%	-2.2%	7.9%	3.6%	-4.3%
Everett	6,570	23.3%	16.5%	-6.8%	22.6%	15.5%	-7.1%
Gibsonia	5,174	4.6%	2.6%	-2.0%	11.6%	6.8%	-4.8%
Highspire	96	3.1%	4.7%	+1.6%	6.3%	4.7%	-1.6%
King of Prussia	5,395	17.0%	6.3%	-10.7%	22.5%	9.6%	-12.9%
New Stanton	7,126	11.9%	6.5%	-5.4%	13.5%	7.3%	-6.2%
Newville	4,054	5.1%	5.6%	+0.5%	5.4%	4.7%	-0.7%
Pocono	4,371	2.2%	1.2%	-1.0%	2.3%	1.3%	-1.0%
Somerset (T)	5,411	29.5%	22.9%	-6.6%	30.0%	22.5%	-7.5%

Table 3.11: Area III Percent Unknown Race/Ethnicity of Drivers Stopped by Station, 2022

	Total # of Stops	Unknown Race	Unknown Race	Difference	Unknown Ethnicity	Unknown Ethnicity	Difference
		1/1-8/11	8/12-12/31		1/1-8/11	8/12-12/31	
Troop F	**31,196**	**3.7%**	**1.8%**	**-1.9%**	**4.3%**	**1.9%**	**-2.4%**
Coudersport	2,738	2.3%	2.5%	+0.2%	2.2%	2.3%	+0.1%
Emporium	1,267	1.4%	0.2%	-1.2%	1.3%	0.2%	-1.1%
Lamar	5,398	5.2%	3.1%	-2.1%	5.6%	2.5%	-3.1%
Mansfield	2,464	11.0%	3.0%	-8.0%	11.1%	2.4%	-8.7%
Milton	7,771	2.5%	1.5%	-1.0%	2.8%	1.7%	-1.1%
Montoursville	5,867	3.6%	0.9%	-2.7%	3.8%	1.1%	-2.7%
Selinsgrove	3,643	3.1%	2.1%	-1.0%	6.5%	3.2%	-3.3%
Stonington	2,048	0.6%	0.7%	+0.1%	0.8%	0.5%	-0.3%
Troop N	**30,213**	**13.4%**	**4.1%**	**-9.3%**	**18.0%**	**4.5%**	**-13.5%**
Bloomsburg	2,992	14.7%	3.5%	-11.2%	17.0%	3.6%	-13.4%
Fern Ridge	5,781	4.8%	1.8%	-3.0%	6.5%	2.0%	-4.5%
Hazleton	6,140	24.0%	7.3%	-16.7%	24.7%	6.8%	-17.9%
Lehighton	2,395	20.3%	4.4%	-15.9%	24.3%	4.9%	-19.4%
Stroudsburg	12,900	10.8%	3.6%	-7.2%	19.0%	4.6%	-14.4%
Troop P	**15,306**	**2.8%**	**2.1%**	**-0.7%**	**3.1%**	**2.9%**	**-0.2%**
Laporte	2,070	2.6%	1.3%	-1.3%	3.2%	1.5%	-1.7%
Shickshinny	2,067	2.3%	2.0%	-0.3%	2.0%	2.0%	-0.0%
Towanda	4,527	0.9%	1.1%	+0.2%	0.8%	1.6%	+0.8%
Tunkhannock	1,928	6.0%	2.5%	-3.5%	7.6%	2.8%	-4.8%
Wilkes-Barre	4,711	3.8%	3.3%	-0.5%	3.8%	5.2%	+1.4%
Troop R	**14,943**	**11.3%**	**6.0%**	**-5.3%**	**17.8%**	**8.6%**	**-9.2%**
Blooming Grove	4,896	18.2%	3.3%	-14.9%	31.7%	10.3%	-21.4%
Dunmore	3,136	5.5%	2.7%	-2.8%	13.7%	3.5%	-10.2%
Gibson	3,973	11.8%	9.7%	-2.1%	12.7%	8.5%	-4.2%
Honesdale	2,938	5.8%	10.8%	+5.0%	8.6%	11.5%	+2.9%

Table 3.11: Area IV Percent Unknown Race/Ethnicity of Drivers Stopped by Station, 2022

	Total # of Stops	Unknown Race	Unknown Race	Difference	Unknown Ethnicity	Unknown Ethnicity	Difference
		1/1-8/11	8/12-12/31		1/1-8/11	8/12-12/31	
Troop J	**32,167**	**1.7%**	**1.0%**	**-0.7%**	**2.9%**	**1.5%**	-1.4%
Avondale	8,890	0.9%	0.3%	-0.6%	1.8%	0.5%	-1.3%
Embreeville	7,267	2.5%	1.8%	-0.7%	3.2%	1.4%	-1.8%
Lancaster	6,788	0.9%	0.7%	-0.2%	1.8%	1.4%	-0.4%
York	9,222	2.2%	1.3%	-0.9%	4.5%	2.9%	-1.6%
Troop K	**27,061**	**5.8%**	**5.3%**	**-0.5%**	**9.1%**	**6.9%**	**-2.2%**
Media	11,759	2.9%	2.6%	-0.3%	2.9%	2.4%	-0.5%
Philadelphia	10,538	9.8%	8.6%	-1.2%	13.2%	9.3%	-3.9%
Skippack	4,726	5.1%	3.3%	-1.8%	15.5%	12.6%	-2.9%
Troop L	**19,601**	**3.7%**	**2.4%**	**-1.3%**	**5.1%**	**3.1%**	**-2.0%**
Frackville	2,915	5.6%	4.5%	-1.1%	6.2%	5.5%	-0.7%
Hamburg	2,605	1.8%	0.9%	-0.9%	3.7%	2.2%	-1.5%
Jonestown	4,885	5.2%	3.5%	-1.7%	6.8%	4.2%	-2.6%
Reading	4,157	4.5%	2.1%	-2.4%	7.2%	3.3%	-3.9%
Schuylkill	5,039	1.6%	1.1%	-0.5%	1.9%	1.0%	-0.9%
Troop M	**22,615**	**6.6%**	**4.2%**	**-2.4%**	**8.7%**	**5.1%**	**-3.6%**
Belfast	3,846	2.2%	2.0%	-0.2%	3.0%	2.6%	-0.4%
Bethlehem	4,497	13.5%	8.5%	-5.0%	13.9%	8.7%	-5.2%
Dublin	3,907	12.8%	5.6%	-7.2%	14.0%	6.3%	-7.7%
Fogelsville	5,956	2.7%	2.2%	-0.5%	6.0%	4.5%	-1.5%
Trevose	4,409	3.2%	2.8%	-0.4%	7.0%	3.2%	-3.8%

Limitations of Traffic Stop Data Analyses

Although understanding troopers' initial stopping decisions are of high interest to PSP administrators and the public, the collected traffic stop data cannot address all the factors that influence this decision-making. Previous research has attempted to compare the percentage of drivers stopped by race/ethnicity against various benchmark estimates of the "expected" population of drivers, but this line of inquiry is inherently limited. Unfortunately, the only readily available external benchmark is residential population data, which we know to be seriously flawed for this purpose. It does not capture the difference in drivers' risk of being stopped that is influenced by where they drive, when they drive, how often they drive, what they drive, how they drive, and who they are (Alpert et al., 2004a; Engel & Calnon, 2004a; Fridell, 2004). Other studies have used accident data as an alternate estimate of the driving population (Alpert et al., 2004a; Lovrich et al., 2007; Withrow & Williams, 2015), but collision reports in Pennsylvania do not include drivers' race or ethnicity.

Given these limitations, when the PSP originally initiated traffic stop data collection in 2002, they also contracted with the research team to conduct independent roadway observations of the motoring public's roadway usage and speeding behavior at sampled locations across the Commonwealth to provide alternative benchmark comparisons for the stop data. This observational research demonstrated that it was inaccurate to assume that the residential population was similar to the driving population or the population committing speeding violations, particularly in counties with significant interstate travel. Furthermore, although large racial/ethnic disparities existed between stops and Census-based benchmarks, when stop data was compared to benchmarks that better capture roadway usage and driving behavior, these reported disparities were significantly reduced and, in some cases, eliminated. There was no consistent evidence to suggest that PSP troopers made stopping decisions based on drivers' race/ethnicity.

Due to the inherent methodological limitations of all benchmark analyses, the research team decided not to employ this technique and focus instead on examining the patterns and trends in post-stop outcomes. In addition, as data collection continues over time, patterns and trends in traffic stops and post-stop outcomes will be examined from year to year to determine whether any significant differences are evident.[26]

Section Summary

Section 3 described the characteristics of traffic stops and stopped drivers across PSP organizational units based on data collected during 441,329 stops from January 1 to December 31, 2022. Considerable variation is reported in stop characteristics, reasons for the stop, and driver characteristics across PSP organizational units. This is to be expected due to differences in

[26] This decision is consistent with our research team's previous work with the PSP. After the first two years of stop data were compared to residential population statistics, observations of roadway usage, and speeding behavior, the research team reported in the 2004-2005 Report our determination that it was not a valid approach to continue (Engel et al., 2007). The remaining annual reports produced at that time focused on trends in stops over time and stop outcomes.

the geography, roadways, jurisdiction, traffic flow, and demographic makeup of residents and travelers across the state.

Department trends in these descriptive findings are summarized below.

- Across the department, the majority of traffic stops had the following characteristics:
    - Occurred on a weekday (69.4%)
    - Occurred during the daytime (65.9%)
    - Occurred on a state highway (52.7%) or an interstate (33.8%)
    - Involved a vehicle registered in Pennsylvania (80%)
    - Involved vehicles without passengers (80%)
    - Lasted between 1-15 minutes (87.8%)

- Across the department, the most frequent reason for a stop was speeding (40.1%), with an average of 21.4 mph over the posted speed limit, followed by other moving violations (26.8%), equipment violations/inspections (18.8%), and registration violations (15.5%).

- Across the department, the characteristics of the drivers include:
    - Average age of 37.9 years
    - 66.8% male
    - Driver behavior was overwhelmingly civil (97.9%), with only a small percentage of stops reported to involve disrespectful, non-compliant, or resistant drivers
    - 81.3% Pennsylvania residents
    - White (78.5%), Black (14.4%), Hispanic (8.2%), Asian (1.8%), American Indian or Alaskan Native (0.3%), unknown race (5.0%), unknown ethnicity (6.2%)
        - In response to the wide variation in the percentage of unknown drivers' race and ethnicity in the first two quarterly reports, the PSP provided additional guidance to its members on completing these fields with an August 12th directive.
    - After the August 12th directive, the average percentage of unknown race decreased from 6.0% to 3.4% across the department; similarly, the percentage of unknown ethnicity decreased from 7.6% to 3.9%.

SECTION 4: TRAFFIC STOP OUTCOMES

This section reports the outcomes that resulted from member-initiated traffic stops conducted in 2022. Initially, we document the percentage of stops resulting in verbal or written warnings, citations, or arrests of the motorists, including basic descriptive statistics at the Department, Area, Troop, and Station levels. Building on the descriptive statistics, this section also reports the results of significance testing on statistical models predicting the likelihood that traffic stops resulted in warnings, citations, and arrests.

A major advantage of examining post-stop outcomes is that, unlike the initial stop decision, where the comparison population of who is eligible to be stopped is unknown and can only be poorly estimated, the comparison population for post-stop outcomes is known (i.e., all stopped drivers). In the following analyses, we answer the question: Of all the drivers stopped, what factors predict the likelihood of being issued a warning or citation or arrested? Benchmark comparisons are unnecessary when information is collected on all stopped drivers, regardless of the outcomes they received. Because the comparison population (other stopped drivers) is known, more rigorous statistical and methodological techniques can be applied to understanding any racial/ethnic disparities in post-stop outcomes.

Two sets of analyses are the focal point of this section: 1) bivariate analyses examining the relationship between traffic stop outcomes and driver characteristics, and 2) more sophisticated multivariate analyses that model the strength of the factors predicting whether or not warnings, citations, and arrests are made.

Description of Traffic Stop Outcomes

The disposition of traffic stops (e.g., warnings, citations, and arrests) is reported at the Department, Area, and Troop levels in Table 4.1 and the Station level in Table 4.2. These tables below report the total number and percentage of stops resulting in a driver warning, citation, and/or arrest. The reported percentages exceed 100% because drivers may experience one or more post-stop outcomes (e.g., a driver may be warned and cited during the same stop).

Figure 4.1 and Table 4.1 below report the post-stop outcomes for drivers during the 441,329 stops initiated by PSP troopers in 2022. As shown, 57.0% of drivers were issued citations, while 56.8% received verbal or written warnings (18.5% and 38.3%, respectively). Driver arrests were rare, occurring in only 4.6% of traffic stops.

Figure 4.1: Department-Wide Post-Stop Outcomes, January - December 2022

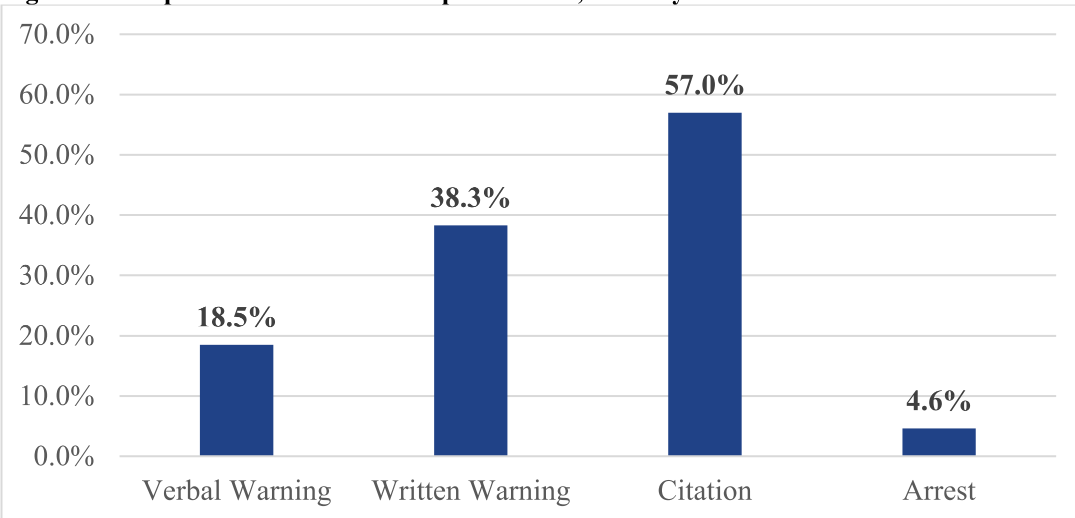
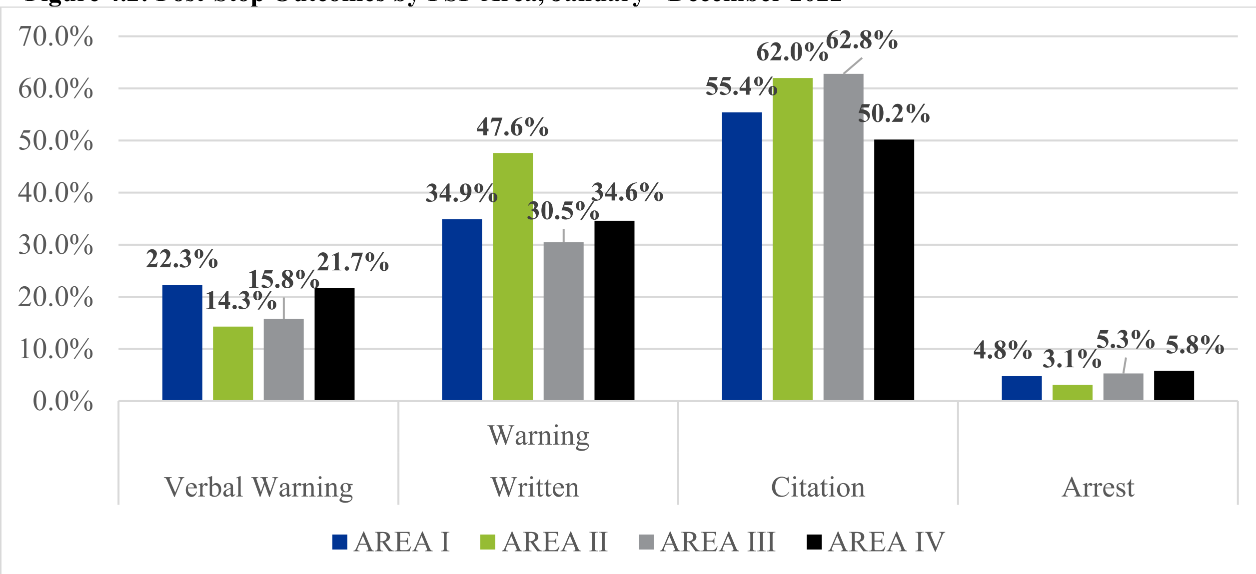


Table 4.1: Drivers' Post-Stop Outcomes by Department, Area & Troop, Jan – Dec 2022

	Total # of Stops	Verbal Warning	Written Warning	Citation	Arrest
PSP Dept.	**441,329**	**18.5%**	**38.3%**	**57.0%**	**4.6%**
AREA I	**103,889**	**22.3%**	**34.9%**	**55.4%**	**4.8%**
Troop B	30,443	33.3%	20.1%	52.7%	4.5%
Troop C	22,567	10.0%	52.9%	59.6%	4.4%
Troop D	23,671	18.0%	41.4%	51.6%	6.9%
Troop E	27,208	23.9%	30.8%	58.4%	3.9%
AREA II	**137,170**	**14.3%**	**47.6%**	**62.0%**	**3.1%**
Troop A	18,043	10.4%	39.2%	68.8%	4.6%
Troop G	28,359	16.0%	43.1%	60.2%	3.8%
Troop H	48,365	18.9%	51.9%	44.4%	4.5%
Troop T	42,403	9.5%	49.4%	80.3%	0.6%
AREA III	**91,658**	**15.8%**	**30.5%**	**62.8%**	**5.3%**
Troop F	31,196	15.8%	32.5%	60.1%	5.0%
Troop N	30,213	15.9%	27.6%	64.0%	7.0%
Troop P	15,306	17.7%	31.9%	60.3%	3.5%
Troop R	14,943	13.5%	31.0%	68.5%	4.6%
AREA IV	**101,441**	**21.7%**	**34.6%**	**50.2%**	**5.8%**
Troop J	32,167	26.4%	35.6%	43.4%	6.3%
Troop K	27,061	24.9%	31.0%	47.3%	5.8%
Troop L	19,601	15.8%	31.6%	61.9%	5.2%
Troop M	22,615	16.4%	39.9%	53.3%	5.6%
Specialized Units					
SHIELD	4,429	15.7%	82.8%	0.5%	2.3%
Canine	2,232	60.9%	32.9%	4.9%	3.7%

As reported in Table 4.1 above and graphically displayed in Figure 4.2 below, post-stop outcomes differed across PSP Areas. For example, troopers assigned to Area II issued the most warnings to drivers (14.3% verbal and 47.6% written warnings), while troopers in Area III issued the least (15.8% verbal, 30.5% written warnings). Drivers in Areas II and III were the most likely to be cited (62.0% and 62.8%, respectively), while drivers in Area IV were the least likely to be issued citations (50.2%). Troopers in Area II arrested the smallest percentage of stopped drivers (3.1%), while Area IV reported the highest percentage of drivers arrested (5.8%).

Figure 4.2: Post-Stop Outcomes by PSP Area, January - December 2022



Troops ranged in issuing warnings from a high of 70.8% of stopped motorists in Troop H to a low of 43.5% in Troop N. For citations, Troop T had the highest percentage of drivers cited (80.3%), while Troop J had the lowest (43.4%). Traffic stops resulting in driver arrests ranged from a high of 7.0% of stops in Troop N to a low of 0.6% in Troop T.

As for specialized units, the SHIELD unit issued a very high percentage of warnings (15.7% verbal, 82.8% written warnings). The Canine unit also issued warnings during 93.8% of stops but had a higher percentage of verbal warnings (60.9%) than the SHIELD unit. In addition, both units infrequently cited drivers. Finally, the SHIELD unit arrested 2.3% of stopped drivers, while the Canine unit arrested slightly more, with 3.7% of all stopped drivers.

Table 4.2 reports post-stop outcomes at the Station level. There is considerable variability across Stations for all stop outcomes. The highest percentage of warnings were issued at New Stanton Station, with 14.8% verbal warnings and 69.7% written warnings (84.5% total), and the fewest at Beaver Station, with 15.0% verbal warnings and 16.9% written warnings (31.9% total). Troopers assigned to Pocono Station had the highest citation rate (88.3%), while Gettysburg Station had the lowest (29.5%). The stations that reported the largest percentage of drivers who were arrested include Selinsgrove Station (13.0%), Lehighton (12.2%,) and Stonington (10.8%). In contrast, in all nine stations in Troop T, drivers were arrested in 1.0% or less of all stops.

Table 4.2: Area I Drivers' Post-Stop Outcomes by Station, January - December 2022

	Total # of Stops	Verbal Warning	Written Warning	Citation	Arrest
Troop B	30,443	33.3%	20.1%	52.7%	4.5%
Belle Vernon	5,066	27.3%	23.6%	59.6%	4.0%
Pittsburgh	7,168	23.4%	18.1%	69.0%	3.4%
Uniontown	11,505	47.2%	19.4%	37.7%	5.0%
Washington	4,272	29.0%	22.3%	47.1%	6.0%
Waynesburg	2,429	16.3%	18.5%	71.3%	3.0%
Troop C	22,567	10.0%	52.9%	59.6%	4.4%
Clarion	2,652	7.1%	41.8%	65.6%	4.3%
Clearfield	3,999	9.7%	34.2%	63.9%	4.1%
Dubois	3,110	13.2%	63.5%	67.8%	3.7%
Lewis Run	4,054	8.6%	67.8%	47.3%	5.7%
Marienville	2,467	9.0%	44.1%	71.3%	2.8%
Punxsutawney	3,483	9.8%	58.7%	49.7%	6.0%
Ridgway	2,802	12.9%	56.9%	58.7%	2.9%
Troop D	23,671	18.0%	41.4%	51.6%	6.9%
Beaver	3,619	15.0%	16.9%	70.3%	6.2%
Butler	6,182	28.4%	40.5%	45.3%	7.5%
Kittanning	7,941	12.3%	55.0%	42.1%	7.1%
Mercer	3,292	20.4%	32.2%	63.5%	6.4%
New Castle	2,637	11.4%	48.0%	54.3%	6.2%
Troop E	27,208	23.9%	30.8%	58.4%	3.9%
Corry	2,919	11.3%	46.5%	60.6%	2.5%
Erie	9,196	34.3%	23.9%	50.1%	5.2%
Franklin	2,115	14.3%	37.3%	61.8%	6.0%
Girard	6,321	18.7%	23.9%	67.4%	2.5%
Meadville	3,658	25.2%	37.9%	57.7%	4.3%
Warren	2,876	19.8%	39.2%	60.7%	2.0%

Table 4.2: Area II Drivers' Post-Stop Outcomes by Station, January - December 2022

	Total # of Stops	Verbal Warning	Written Warning	Citation	Arrest
Troop A	18,043	10.4%	39.2%	68.8%	4.6%
Ebensburg	1,984	11.3%	32.0%	83.3%	2.1%
Greensburg	4,745	7.3%	53.8%	62.4%	5.2%
Indiana	6,626	12.6%	30.6%	67.1%	5.4%
Kiski Valley	1,337	15.3%	28.2%	69.0%	3.7%
Somerset (A)	3,351	7.7%	44.1%	72.4%	3.8%
Troop G	28,359	16.0%	43.1%	60.2%	3.8%
Bedford	5,065	14.2%	51.5%	63.0%	2.8%
Hollidaysburg	4,276	27.1%	36.9%	49.6%	5.9%
Huntingdon	3,899	15.0%	33.9%	67.1%	3.4%
Lewistown	4,069	7.8%	51.1%	63.3%	3.9%
McConnellsburg	3,441	16.7%	50.5%	57.3%	2.9%
Rockview	7,609	15.7%	37.9%	60.4%	3.7%
Troop H	48,365	18.9%	51.9%	44.4%	4.5%
Carlisle	11,184	9.3%	60.7%	46.5%	3.9%
Chambersburg	12,462	21.9%	48.7%	50.5%	2.4%
Gettysburg	8,551	23.4%	54.7%	29.5%	5.1%
Harrisburg	9,536	27.6%	41.4%	41.1%	6.0%
Lykens	2,890	8.8%	61.5%	61.1%	3.7%
Newport	3,741	13.3%	49.3%	47.8%	8.5%
Troop T	42,403	9.5%	49.4%	80.3%	0.6%
Bowmansville	4,197	12.1%	26.0%	78.3%	0.6%
Everett	6,570	7.8%	73.1%	80.0%	0.8%
Gibsonia	5,174	4.8%	74.4%	84.6%	0.7%
Highspire	96	16.7%	41.7%	54.2%	1.0%
King of Prussia	5,395	11.9%	24.5%	84.6%	0.5%
New Stanton	7,126	14.8%	69.7%	69.5%	0.8%
Newville	4,054	9.0%	29.7%	73.3%	0.4%
Pocono	4,371	6.6%	24.9%	88.3%	0.4%
Somerset (T)	5,411	6.8%	47.4%	87.2%	0.4%

Table 4.2: Area III Drivers' Post-Stop Outcomes by Station, January - December 2022

	Total # of Stops	Verbal Warning	Written Warning	Citation	Arrest
Troop F	31,196	15.8%	32.5%	60.1%	5.0%
Coudersport	2,738	11.5%	47.5%	55.1%	2.3%
Emporium	1,267	6.4%	63.7%	50.6%	1.5%
Lamar	5,398	24.6%	15.7%	60.3%	3.4%
Mansfield	2,464	16.3%	36.4%	63.0%	3.4%
Milton	7,771	13.5%	26.1%	63.4%	3.0%
Montoursville	5,867	23.3%	26.6%	57.5%	4.6%
Selinsgrove	3,643	5.1%	48.1%	65.9%	13.0%
Stonington	2,048	10.2%	45.7%	54.3%	10.8%
Troop N	30,213	15.9%	27.6%	64.0%	7.0%
Bloomsburg	2,992	13.2%	24.8%	68.9%	4.8%
Fern Ridge	5,781	14.5%	19.6%	75.1%	4.0%
Hazleton	6,140	14.5%	21.3%	76.6%	5.9%
Lehighton	2,395	15.6%	24.6%	72.2%	12.2%
Stroudsburg	12,900	17.9%	35.3%	50.3%	8.3%
Troop P	15,306	17.7%	31.9%	60.3%	3.5%
Laporte	2,070	21.3%	29.6%	56.9%	3.2%
Shickshinny	2,067	17.9%	21.7%	72.5%	3.8%
Towanda	4,527	26.7%	35.0%	45.9%	3.4%
Tunkhannock	1,928	8.9%	55.2%	51.6%	3.6%
Wilkes-Barre	4,711	11.0%	24.8%	73.7%	3.5%
Troop R	14,943	13.5%	31.0%	68.5%	4.6%
Blooming Grove	4,896	14.6%	35.5%	56.0%	6.5%
Dunmore	3,136	12.3%	29.9%	77.8%	3.3%
Gibson	3,973	13.7%	25.2%	76.1%	5.0%
Honesdale	2,938	12.8%	32.8%	69.3%	2.0%

Table 4.2: Area IV Drivers' Post-Stop Outcomes by Station, January - December 2022

	Total # of Stops	Verbal Warning	Written Warning	Citation	Arrest
Troop J	32,167	26.4%	35.6%	43.4%	6.3%
Avondale	8,890	33.8%	35.6%	38.3%	5.3%
Embreeville	7,267	16.0%	40.9%	56.3%	5.0%
Lancaster	6,788	25.3%	33.4%	43.9%	7.0%
York	9,222	28.2%	33.2%	37.9%	7.7%
Troop K	27,061	24.9%	31.0%	47.3%	5.8%
Media	11,759	21.0%	32.5%	46.3%	6.1%
Philadelphia	10,538	31.3%	27.2%	49.1%	5.5%
Skippack	4,726	20.4%	35.8%	45.9%	5.8%
Troop L	19,601	15.8%	31.6%	61.9%	5.2%
Frackville	2,915	22.7%	24.2%	60.7%	3.7%
Hamburg	2,605	12.9%	31.4%	72.2%	2.7%
Jonestown	4,885	17.6%	34.0%	58.1%	6.1%
Reading	4,157	13.5%	36.5%	56.4%	8.6%
Schuylkill Haven	5,039	13.6%	29.7%	65.6%	3.6%
Troop M	22,615	16.4%	39.9%	53.3%	5.6%
Belfast	3,846	17.4%	30.0%	59.7%	4.2%
Bethlehem	4,497	14.1%	36.9%	56.8%	5.9%
Dublin	3,907	13.5%	52.6%	44.9%	7.9%
Fogelsville	5,956	16.3%	38.1%	52.3%	5.5%
Trevose	4,409	20.9%	42.9%	53.0%	4.8%

Post-Stop Outcomes by Severity

The previous section reported the percentage of traffic stops resulting in each disposition independently. The total percentages across outcomes exceeded 100% because drivers could receive multiple outcomes. An alternative way to examine these data is to use a severity index, where only the most severe outcome for each traffic stop is reported. A severity index was created using warnings, citations, and arrests.[27] The rank ordering is as follows (from least severe to most severe):

- Level 1: Warning
- Level 2: Citation
- Level 3: Arrest

For example, if a driver received both a warning and a citation, they would be included only in the citation category. In the case of a citation and an arrest, the traffic stop would be categorized as resulting in an arrest.

Table 4.3 below reports the severity index for all member-initiated traffic stops in 2022 at the Department, Area, and Troop levels. Across the department, 38.4% of all traffic stops resulted in issuing a warning to the driver as the most severe disposition. Over half of all traffic stops resulted in a citation as the most severe outcome (54.0%), while only 4.6% of all traffic stops resulted in a driver's arrest.

Area IV reported the largest percentage of traffic stops resulting in warnings as the most severe outcome (43.9%) and the highest percentage of stops resulting in arrest as the most severe outcome (5.8%). Area II was responsible for the highest percentage of stops that resulted in a citation as the most severe outcome (60%), followed closely by Area II (59.2%).

At the Troop level, more than half the stops conducted in Troops H and J resulted in a warning as the most severe outcome (50.7% and 50.3%, respectively). Troop T reported citation as the most serious outcome for 79.8% of traffic stops. Stops in Troops N and D resulted in arrest as the most serious outcome 7.0% and 6.9% of the time, respectively. In the Shield and Canine units, most stops result in warnings as the most severe outcome (96.6% and 90.3%, respectively.

[27] Verbal and written warnings are combined for the purposes of this analysis.

Table 4.3: 2022 Most Severe Driver Outcomes by Department, Area, Troop, & Specialized Units

	Total # of Stops	% No Enforcement Outcome	% Warning	% Citation	% Arrest
PSP	**441,329**	**3.0%**	**38.4%**	**54.0%**	**4.6%**
AREA I	**103,889**	**3.5%**	**39.5%**	**52.1%**	**4.8%**
Troop B	30,443	3.5%	42.1%	49.9%	4.5%
Troop C	22,567	2.7%	36.7%	56.2%	4.4%
Troop D	23,671	3.9%	42.4%	46.8%	6.9%
Troop E	27,208	3.9%	36.4%	55.8%	3.9%
AREA II	**137,170**	**2.2%**	**34.6%**	**60.0%**	**3.1%**
Troop A	18,043	1.7%	28.5%	65.3%	4.6%
Troop G	28,359	2.8%	35.8%	57.7%	3.8%
Troop H	48,365	2.8%	50.7%	42.0%	4.5%
Troop T	42,403	1.4%	18.2%	79.8%	0.6%
AREA III	**91,658**	**3.2%**	**32.3%**	**59.2%**	**5.3%**
Troop F	31,196	3.2%	35.2%	56.6%	5.0%
Troop N	30,213	3.3%	30.4%	59.3%	7.0%
Troop P	15,306	3.3%	35.0%	58.2%	3.5%
Troop R	14,943	2.8%	27.2%	65.5%	4.6%
AREA IV	**101,441**	**3.4%**	**43.9%**	**46.8%**	**5.8%**
Troop J	32,167	3.5%	50.3%	39.9%	6.3%
Troop K	27,061	4.8%	45.4%	43.8%	5.8%
Troop L	19,601	2.2%	33.8%	58.8%	5.2%
Troop M	22,615	2.6%	42.0%	49.7%	5.6%
Specialized Units					
SHIELD	4,429	0.8%	96.6%	0.4%	2.3%
Canine	2,232	2.3%	90.3%	3.6%	3.7%

Table 4.4 below provides the most severe outcomes for all member-initiated traffic stops at the station level for 2022. Washington Station reported the largest percentage of stops that resulted in no enforcement outcome (10.2%). In Gettysburg Station, 62.6% of all traffic stops resulted in issuing a warning to the driver as the most severe disposition. Pocono Station reported the highest percentage of stops resulting in a citation as the most severe outcome, with 88.0%, and stops in Selinsgrove resulted in the highest percentage of arrests as the most serious outcome (13.0%).

Table 4.4: Area I 2022 Most Severe Driver Outcomes by Station

	Total # of Stops	% No Enforcement Outcome	% Warning	% Citation	% Arrest
Troop B					
Belle Vernon	5,066	1.1%	38.2%	56.7%	4.0%
Pittsburgh	7,168	1.5%	28.5%	66.6%	3.4%
Uniontown	11,505	3.8%	56.3%	34.9%	5.0%
Washington	4,272	10.2%	39.7%	44.0%	6.0%
Waynesburg	2,429	1.1%	27.2%	68.6%	3.0%
Troop C					
Clarion	2,652	1.4%	31.8%	62.5%	4.3%
Clearfield	3,999	5.4%	29.7%	60.8%	4.1%
Dubois	3,110	1.0%	30.7%	64.6%	3.7%
Lewis Run	4,054	3.4%	48.0%	42.9%	5.7%
Marienville	2,467	2.1%	26.1%	69.0%	2.8%
Punxsutawney	3,483	2.0%	46.9%	45.1%	6.0%
Ridgway	2,802	2.1%	38.7%	56.3%	2.9%
Troop D					
Beaver	3,619	8.2%	18.2%	67.3%	6.2%
Butler	6,182	4.0%	49.0%	39.5%	7.5%
Kittanning	7,941	1.0%	54.5%	37.4%	7.1%
Mercer	3,292	1.9%	33.7%	58.0%	6.4%
New Castle	2,637	8.8%	34.5%	50.4%	6.2%
Troop E					
Corry	2,919	3.9%	34.2%	59.4%	2.5%
Erie	9,196	4.1%	44.2%	46.4%	5.2%
Franklin	2,115	2.5%	32.9%	58.5%	6.0%
Girard	6,321	4.0%	27.6%	65.9%	2.5%
Meadville	3,658	3.1%	37.6%	54.8%	4.3%
Warren	2,876	5.0%	33.7%	59.2%	2.0%

Table 4.4: Area II 2022 Most Severe Driver Outcomes by Station

	Total # of Stops	% No Enforcement Outcome	% Warning	% Citation	% Arrest
Troop A					
Ebensburg	1,984	0.8%	15.7%	81.4%	2.1%
Greensburg	4,745	1.9%	34.1%	58.7%	5.2%
Indiana	6,626	1.9%	29.8%	62.8%	5.4%
Kiski Valley	1,337	2.8%	27.5%	66.0%	3.7%
Somerset (A)	3,351	0.9%	25.8%	69.5%	3.8%
Troop G					
Bedford	5,065	1.1%	35.0%	61.1%	2.8%
Hollidaysburg	4,276	4.6%	45.0%	44.4%	5.9%
Huntingdon	3,899	5.8%	26.3%	64.4%	3.4%
Lewistown	4,069	1.4%	33.9%	60.8%	3.9%
McConnellsburg	3,441	1.9%	38.8%	56.4%	2.9%
Rockview	7,609	2.4%	35.6%	58.3%	3.7%
Troop H					
Carlisle	11,184	1.8%	50.6%	43.7%	3.9%
Chambersburg	12,462	2.1%	46.4%	49.0%	2.4%
Gettysburg	8,551	4.2%	62.6%	28.1%	5.1%
Harrisburg	9,536	4.4%	51.8%	37.8%	6.0%
Lykens	2,890	2.1%	36.1%	58.2%	3.7%
Newport	3,741	1.8%	46.6%	43.1%	8.5%
Troop T					
Bowmansville	4,197	3.2%	18.2%	78.0%	0.6%
Everett	6,570	1.1%	18.8%	79.3%	0.8%
Gibsonia	5,174	1.3%	14.1%	84.0%	0.7%
Highspire	96	2.1%	43.8%	53.1%	1.0%
King of Prussia	5,395	1.5%	13.8%	84.2%	0.5%
New Stanton	7,126	0.9%	29.5%	68.9%	0.8%
Newville	4,054	2.3%	24.2%	73.0%	0.4%
Pocono	4,371	0.7%	10.8%	88.0%	0.4%
Somerset (T)	5,411	1.0%	11.6%	87.0%	0.4%

Table 4.4: Area III 2022 Most Severe Driver Outcomes by Station

	Total # of Stops	% No Enforcement Outcome	% Warning	% Citation	% Arrest
Troop F					
Coudersport	2,738	2.0%	42.5%	53.2%	2.3%
Emporium	1,267	1.3%	47.6%	49.6%	1.5%
Lamar	5,398	3.8%	34.3%	58.4%	3.4%
Mansfield	2,464	5.5%	30.0%	61.1%	3.4%
Milton	7,771	3.4%	31.9%	61.7%	3.0%
Montoursville	5,867	3.4%	36.5%	55.4%	4.6%
Selinsgrove	3,643	2.0%	31.7%	53.4%	13.0%
Stonington	2,048	1.8%	42.1%	45.3%	10.8%
Troop N					
Bloomsburg	2,992	1.4%	27.3%	66.5%	4.8%
Fern Ridge	5,781	1.8%	22.3%	71.9%	4.0%
Hazleton	6,140	2.2%	20.0%	71.8%	5.9%
Lehighton	2,395	1.6%	22.5%	63.6%	12.2%
Stroudsburg	12,900	5.2%	41.1%	45.3%	8.3%
Troop P					
Laporte	2,070	2.9%	39.4%	54.4%	3.2%
Shickshinny	2,067	1.6%	24.0%	70.5%	3.8%
Towanda	4,527	5.4%	47.4%	43.8%	3.4%
Tunkhannock	1,928	2.7%	44.2%	49.4%	3.6%
Wilkes-Barre	4,711	2.3%	22.3%	71.8%	3.5%
Troop R					
Blooming Grove	4,896	4.3%	36.8%	52.4%	6.5%
Dunmore	3,136	0.9%	20.8%	75.0%	3.3%
Gibson	3,973	1.3%	21.3%	72.4%	5.0%
Honesdale	2,938	4.2%	26.0%	67.8%	2.0%

Table 4.4: Area IV 2022 Most Severe Driver Outcomes by Station

	Total # of Stops	% No Enforcement Outcome	% Warning	% Citation	% Arrest
Troop J					
Avondale	8,890	3.2%	56.9%	34.6%	5.3%
Embreeville	7,267	2.3%	39.3%	53.4%	5.0%
Lancaster	6,788	3.4%	48.9%	40.6%	7.0%
York	9,222	4.9%	53.5%	33.9%	7.7%
Troop K					
Media	11,759	4.9%	46.1%	42.5%	6.1%
Philadelphia	10,538	3.4%	45.3%	45.8%	5.5%
Skippack	4,726	7.6%	43.8%	42.8%	5.8%
Troop L					
Frackville	2,915	1.9%	35.4%	59.0%	3.7%
Hamburg	2,605	0.9%	26.4%	70.0%	2.7%
Jonestown	4,885	2.3%	37.5%	54.1%	6.1%
Reading	4,157	1.8%	38.5%	51.1%	8.6%
Schuylkill Haven	5,039	3.1%	29.5%	63.8%	3.6%
Troop M					
Belfast	3,846	4.2%	34.0%	57.5%	4.2%
Bethlehem	4,497	2.6%	37.8%	53.7%	5.9%
Dublin	3,907	2.4%	49.4%	40.3%	7.9%
Fogelsville	5,956	1.8%	44.6%	48.1%	5.5%
Trevose	4,409	2.7%	43.3%	49.2%	4.8%

Bivariate Analyses of Traffic Stop Outcomes

Descriptive statistics like those presented in Tables 4.1 – 4.4 above tell us how often stop outcomes occur but do not explain the factors that contribute to these outcomes. We now turn to analyses that can better understand the factors associated with these outcomes. First, bivariate analyses, presented in Tables 4.5 – 4.7 to follow, provide an initial understanding of the relationships between variables.

The analyses presented here are based on the chi-square test that assesses whether the correlations between two variables have significantly different values than expected. When we refer to *statistical significance*, this is the confidence level that the observed differences are not due to random chance and/or sampling error and is identified with a p-value. The social sciences traditionally rely upon a confidence level of 95% (indicating that the finding is 5% or less due to random chance and/or sampling error). This represents the degree of confidence associated with the relationship or the extent to which the relationship is not due to chance. Statistically significant results reported in these tables are reported at the .05, .01, and .001 levels, which indicates that the observed racial/ethnic and gender differences reflect a true statistical difference between the groups and are not due to chance 95%, 99%, or 99.9% of the time.

It is important to recognize that the chi-square statistic used only compares two variables – one predictor variable and one outcome variable. In the analyses below, the variables considered are drivers' characteristics (e.g., race/ethnicity) and the outcome received (e.g., warning, citation, and arrest), but the bivariate analyses do not consider any additional factors that may impact officer decision making. In other words, the chi-square test does not measure other factors potentially associated with the likelihood of receiving post-stop outcomes (e.g., legal reason for the stop); instead, it only considers the race/ethnicity of the driver. Further, these statistical tests are influenced by the large sample size, where even substantively minor differences may be statistically significant. Consequently, the results of these analyses should be interpreted with caution, and the multivariate models (reported later in this section) should be examined for a more comprehensive understanding of the relationship between drivers' race/ethnicity and post-stop outcomes. As a reminder, the information provided in these tables also cannot be used to assess whether differences in outcomes across racial/ethnic and gender groups are due to trooper bias.

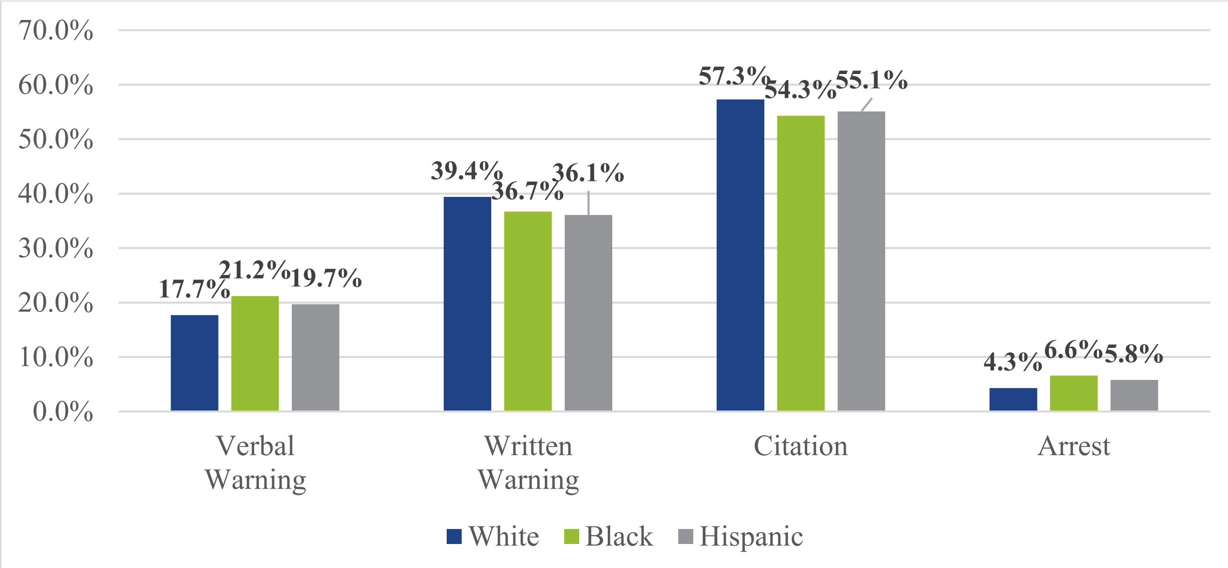
All bivariate analyses were based on two comparisons. First, drivers' race/ethnicity was analyzed in relation to all traffic stop outcomes. Drivers' race/ethnicity is represented by White, Black, and Hispanic categories.[28] Given the relatively small number of traffic stops involving drivers identified as American Indian/Alaskan Native, Asian/Pacific Islander, unknown, or missing, analyses of these stops are not reported. Second, the relationship between driver gender and stop outcomes was examined. Analyses involving drivers' gender reflect all traffic stops in which drivers' gender was recorded.[29] For each organizational unit, the tables report the total number of stops for each race/ethnicity and gender group and the percentage of drivers from each group that were warned, cited, or arrested. Statistically significant relationships are indicated with an asterisk.[30]

Table 4.5 below illustrates the variation in post-stop outcomes (i.e., verbal warnings, written warnings, citations, and arrests) by drivers' race/ethnicity and gender for the department and Area levels. Across the department, there were statistically significant bivariate differences in the

[28] As noted in Section 2 and 3, drivers' race and ethnicity are captured separately on the CDR. Therefore, to accurately capture individuals considered to be drivers of racial/ethnic minority groups, we need to isolate non-Hispanic Whites. Therefore, race and ethnicity are combined by the research team. Individuals who were perceived to be White (race) and Hispanic (ethnicity) are coded as Hispanic for analytical purposes. The small percent (7.4%) of individuals perceived to be Hispanic and another race (e.g., Black, Asian) were coded as their race.
[29] It excludes the 2,736 cases (0.6%) where driver gender was reported to be unknown.
[30] The asterisk is only included in the first group of the comparison. For example, if the relationship between racial/ethnic groups (i.e., White, Black, and Hispanic drivers) and warnings was statistically significant, an asterisk is placed beside the rate of warning for White drivers. The correct interpretation of this result is that the rate of warnings significantly differs between the three races/ethnicities, and the actual rate of warnings for each group should be consulted for the rank order of the groups. For each group, the number of asterisks indicates the degree of statistical significance as described at the bottom of all tables in this section. Statistical significance is reported at the 0.05, 0.01, and 0.001 levels.

rate of all traffic stop outcomes depending on drivers' race/ethnicity. These differences are also first graphically displayed in Figure 4.3.

Figure 4.3. Bivariate Racial/Ethnic Differences in Traffic Stop Outcomes



As shown above, Hispanic and Black motorists were significantly more likely to receive verbal warnings (19.7% and 21.2%, respectively) than White drivers (17.7%). Conversely, Hispanic and Black drivers were significantly less likely to receive written warnings (36.1% and 36.7%, respectively) than White drivers (39.4%). White drivers were significantly more likely to receive a citation (57.3%) than Black and Hispanic drivers (54.3% and 55.1%, respectively). Black and Hispanic drivers were significantly more likely (6.6% and 5.8%, respectively) than White drivers (4.3%) to be arrested.

When considering gender, Table 4.5 shows statistically significant differences for male and female drivers for each post-stop outcome at the 0.001 P-level. Female drivers were significantly more likely to be given written warnings (39.3%) and citations (57.8%) compared to stopped male drivers (38.2% and 57.0%, respectively). Conversely, of all the male drivers stopped, 5.1% were arrested, compared to 3.6% of all female drivers stopped. As with the racial differences reported above, these results do not consider the impact of any other factors.

Area-level data differences in traffic stop outcomes based on racial/ethnic characteristics are also displayed in Table 4.5. Analyses of warnings indicate racial/ethnic differences in all Areas. At least one minority group received proportionately more verbal warnings in each Area, while White drivers consistently received proportionately more written warnings in each Area. All Areas besides Area I demonstrated statistically significant racial/ethnic differences in rates of citations. No clear trend can be discerned from these results as the statistical significance level and rank ordering of the racial/ethnic groups varied by Area. For arrests, all four Areas reported statistically significant differences across racial/ethnic groups. In all four Areas, minority drivers received proportionately higher rates of arrest.

Analyses of drivers' gender also demonstrated statistically significant differences. As demonstrated in Table 4.5, Area I reported statistically significant differences across gender for every post-stop category except verbal warnings, and Area II indicated statistically significant differences for every category except citations. Statistically significant differences across gender groups were also evident in all Areas for written warnings, and arrests. In all Areas, male drivers were arrested disproportionately more than female drivers. Conversely, female drivers were given written warnings disproportionately more than male drivers in all Areas. Although these general patterns held across Areas, specific differences in the rates across Areas are reported in Table 4.5.

Table 4.5 2022 Stop Outcomes by Race and Gender for Department and Areas

	Drivers	Total # of stops	% verbal warning	% written warning	% citation	% arrest
PSP Dept	White	313,870	17.7%***	39.4%***	57.3%***	4.3%***
	Black	63,455	21.2%	36.7%	54.3%	6.6%
	Hispanic	33,658	19.7%	36.1%	55.1%	5.8%
	Male	294,969	18.5%***	38.2%***	57.0%***	5.1%***
	Female	143,624	17.8%	39.3%	57.8%	3.6%
AREA I	White	86,004	21.3%***	36.7%***	55.4%	4.7%***
	Black	10,462	26.3%	27.7%	56.0%	7.7%
	Hispanic	1,689	27.5%	27.7%	57.7%	5.5%
	Male	66,706	21.6%	34.9%***	56.4%***	5.4%***
	Female	36,070	22.1%	36.0%	55.3%	3.9%
AREA II	White	101,494	14.0%***	48.3%***	61.2%***	3.1%***
	Black	17,447	15.4%	46.7%	62.0%	4.8%
	Hispanic	7,542	16.9%	44.8%	57.8%	3.6%
	Male	91,485	14.4%***	47.4%***	62.1%	3.6%***
	Female	45,112	13.7%	48.6%	62.4%	2.3%
AREA III	White	66,532	15.4%***	31.8%***	62.4%***	5.3%***
	Black	10,150	17.2%	31.8%	59.7%	7.1%
	Hispanic	8,043	15.3%	26.8%	68.0%	6.0%
	Male	61,296	15.9%***	30.0%***	63.2%	5.8%***
	Female	29,719	15.0%	32.2%	63.0%	4.4%
AREA IV	White	56,230	20.7%***	35.2%***	50.7%***	5.2%***
	Black	24,154	24.3%	33.9%	48.2%	7.4%
	Hispanic	14,786	22.2%	33.5%	52.0%	7.0%
	Male	69,673	22.1%***	34.2%***	49.9%***	6.5%***
	Female	31,429	20.8%	35.9%	51.1%	4.3%

NOTE: Asterisks identify statistically significant chi-square associations. * p < .05 ** p<.01 *** p<.001

Table 4.6 displays differences in traffic stop outcomes by drivers' race/ethnicity and gender at the Troop level. Ten of the 16 Troops experienced statistically significant racial/ethnic differences in verbal and written warnings. In Troops with statistically significant differences in verbal warnings, all ten Troops had at least one minority group with the highest rate of warnings. Regarding written warnings, two Troops had at least one minority group with the highest rate of written warnings. In comparison, in the other eight Troops, White drivers received disproportionately more written warnings. For citations, ten of the 16 Troops reported a statistically significant difference between racial/ethnic groups. Of the ten Troops with statistically significant differences, five reported at least one minority group with the highest rate of citations. For arrests, 14 of 16 Troops reported statistically significant differences across racial/ethnic groups, with minority drivers ranking highest in the rate of arrest in these Troops.

Table 4.6 also reports differences in traffic stop outcomes by drivers' gender at the troop level. Eight of the 16 Troops reported statistically significant differences in verbal warnings, while 12 of the 16 Troops reported statistically significant differences in written warnings. In all cases, the percentage of male drivers who received verbal warnings was significantly larger than female drivers, while the opposite was true for written warnings. For citations, four of the 16 Troops indicated statistically significant differences in the citation rate between male and female drivers. Male drivers received disproportionately more citations in two of the four Troops with statistically significant differences. Finally, all 16 Troops demonstrated statistically significant gender differences in rates of arrest, with male drivers arrested more frequently than female drivers in all 16 Troops.

Table 4.6: 2022 Stop Outcomes by Race and Gender for Troops in Area I and II

	Drivers	Total # of stops	% verbal warning	% written warning	% citation	% arrest
Area I, Troop B	White	23,536	32.2%***	20.9%	53.3%	4.2%***
	Black	4,514	36.0%	20.3%	51.8%	6.9%
	Hispanic	435	32.9%	20.9%	56.8%	4.6%
	Male	19,158	32.1%	20.3%	54.2%*	5.1%***
	Female	10,667	33.1%	20.9%	52.9%	3.5%
Area I, Troop C	White	19,775	9.9%	54.5%***	57.7%***	4.6%
	Black	846	8.0%	43.9%	71.3%	4.8%
	Hispanic	356	9.8%	39.6%	76.1%	4.5%
	Male	15,204	9.9%	51.9%***	60.7%***	4.9%***
	Female	7,304	10.2%	55.4%	57.9%	3.2%
Area I, Troop D	White	19,550	17.2%***	43.5%***	51.7%***	6.7%***
	Black	2,670	13.8%	36.5%	57.4%	9.9%
	Hispanic	252	21.8%	38.5%	49.6%	7.9%
	Male	14,977	17.4%	41.6%*	52.2%	7.4%***
	Female	8,334	16.4%	43.0%	52.5%	6.0%
Area I, Troop E	White	23,143	23.3%***	31.8%***	58.7%***	3.5%***
	Black	2,432	28.4%	26.2%	56.9%	7.7%
	Hispanic	646	35.8%	21.4%	51.2%	5.7%
	Male	17,367	24.0%	30.4%*	58.6%	4.5%***
	Female	9,765	23.7%	31.8%	58.3%	2.8%
Area II, Troop A	White	16,132	10.5%	39.3%	68.7%	4.5%*
	Black	1,299	9.5%	37.3%	70.0%	5.6%
	Hispanic	217	14.4%	35.8%	63.6%	7.8%
	Male	11,820	11.0%***	38.5%**	68.7%	5.3%***
	Female	6,214	9.2%	40.5%	68.9%	3.3%
Area II, Troop G	White	23,761	15.7%***	43.6%	60.2%***	3.8%***
	Black	2,105	18.3%	42.9%	59.2%	6.3%
	Hispanic	771	22.3%	41.4%	53.3%	3.4%
	Male	18,110	16.8%***	42.4%***	60.4%	4.3%***
	Female	10,043	14.5%	45.1%	60.9%	2.9%
Area II, Troop H	White	34,855	17.9%***	52.6%*	45.1%***	3.9%***
	Black	7,017	21.8%	51.2%	40.2%	7.8%
	Hispanic	4,246	20.4%	51.0%	44.0%	4.9%
	Male	32,500	18.8%	52.1%	44.0%***	5.1%***
	Female	15,742	18.8%	52.0%	45.7%	3.3%
Area II, Troop T	White	26,746	9.7%	52.2%***	78.4%***	0.4%***
	Black	70,271	9.3%	45.0%	83.2%	1.2%
	Hispanic	2,308	9.0%	35.3%	84.2%	1.0%
	Male	29,055	9.2%	49.0%***	80.6%	0.7%***
	Female	13,113	9.1%	51.2%	80.7%	0.4%

NOTE: Asterisks identify statistically significant chi-square associations. * p < .05 ** p<.01 *** p<.001

Table 4.6: 2022 Stop Outcomes by Race and Gender for Troops in Area III and IV

	Drivers	Total # of stops	% verbal warning	% written warning	% citation	% arrest
Area III, Troop F	White	25,831	15.4%***	32.9%	61.0%***	4.9%***
	Black	2,660	20.8%	32.4%	52.2%	6.7%
	Hispanic	1,244	17.1%	31.7%	54.6%	5.7%
	Male	20,241	16.4%***	32.1%*	59.9%	5.4%***
	Female	10,856	14.7%	33.5%	60.8%	4.1%
Area III, Troop N	White	16,996	15.2%*	29.6%***	62.8%***	7.5%
	Black	4,931	16.8%	31.2%	59.9%	7.9%
	Hispanic	4,906	15.5%	24.8%	70.3%	6.9%
	Male	20,526	15.8%*	27.0%***	64.5%	7.4%***
	Female	9,361	14.8%	29.9%	64.6%	5.9%
Area III, Troop P	White	12,953	17.8%	33.0%***	59.2%***	3.4%***
	Black	1,168	16.2%	28.9%	65.8%	5.4%
	Hispanic	747	16.1%	26.2%	69.2%	4.6%
	Male	10,113	18.1%*	31.0%***	60.4%	4.0%***
	Female	51,584	16.7%	33.8%	60.3%	2.6%
Area III, Troop R	White	10,752	12.9%	31.2%**	69.2%	5.0%**
	Black	1,391	12.8%	35.3%	68.4%	6.3%
	Hispanic	1,146	12.3%	30.6%	72.3%	3.6%
	Male	104,163	13.2%	30.8%	69.7%	4.9%*
	Female	4,344	13.8%	31.8%	68.4%	4.0%
Area IV, Troop J	White	20,133	25.3%***	36.8%***	43.5%***	5.1%***
	Black	6,409	27.5%	36.2%	41.4%	8.9%
	Hispanic	4,450	30.2%	31.1%	45.0%	8.3%
	Male	21,389	26.9%**	34.8%***	43.1%	7.1%****
	Female	10,742	25.3%	37.4%	44.1%	4.6%
Area IV, Troop K	White	11,416	22.8%***	32.5%***	47.1%	5.5%***
	Black	11,064	26.5%	30.6%	47.7%	6.9%
	Hispanic	2,262	27.3%	28.9%	48.5%	5.8%
	Male	19,056	25.7%***	30.8%*	46.6%***	6.5%***
	Female	7,855	23.0%	32.3%	49.9%	4.3%
Area IV, Troop L	White	13,046	15.5%	31.6%	62.0%	4.6%***
	Black	2,114	15.5%	32.7%	63.2%	6.8%
	Hispanic	3,601	17.1%	32.0%	60.6%	7.1%
	Male	13,198	16.3%**	31.1%**	61.6%	6.1%***
	Female	6,296	14.7%	33.0%	62.7%	3.4%
Area V, Troop M	White	11,635	16.3%***	39.3%	53.9%	5.7%*
	Black	4,567	18.9%	39.3%	52.2%	6.8%
	Hispanic	4,473	15.8%	39.3%	53.7%	6.2%
	Male	16,030	16.4%	39.8%	53.5%	5.9%**
	Female	6,536	16.6%	40.6%	53.1%	5.0%

NOTE: Asterisks identify statistically significant chi-square associations. * $p < .05$ ** $p<.01$ *** $p<.001$

Table 4.6: 2022 Stop Outcomes by Race and Gender for Specialized Units

	Drivers	Total # of stops	% verbal warning	% written warning	% citation	% arrest
SHIELD	White	1,913	14.5%*	84.3%**	0.5%	1.3%***
	Black	725	18.5%	79.3%	0.4%	4.1%
	Hispanic	1,248	14.0%	84.3%	0.8%	3.1%
	Male	3,781	15.5%	82.8%	0.5%	2.4%
	Female	638	16.0%	83.1%	0.6%	1.6%
Canine	White	1,335	66.2%***	27.7%***	5.7%	2.9%***
	Black	428	49.1%	43.5%	4.2%	7.7%
	Hispanic	314	52.7%	41.2%	4.5%	2.9%
	Male	1,672	58.9%*	34.6%	4.9%	3.7%
	Female	506	64.4%	30.6%	5.5%	3.8%

NOTE: Asterisks identify statistically significant chi-square associations. * p < .05 ** p<.01 *** p<.001

Table 4.7 presents the results of bivariate analyses between drivers' race/ethnicity and traffic stop outcomes at the station level for 2022.[31] In contrast to information provided in Tables 4.5 and 4.6, the racial/ethnic categories presented in Table 4.7 are restricted to White and non-White because the number of stops of some racial/ethnic groups is too small for individual comparisons at the station level. The "non-White" category includes Black, Hispanic, American Indian/Alaskan Native, and Asian or Pacific Islander drivers.

Four stations (Uniontown, Lamar, York, and Media) displayed significant differences for each of the outcomes, while an additional 21 stations had significant differences for all but one outcome. Of the 88 stations, 35 showed statistically significant differences for verbal warnings, 34 showed statistically significant differences for written warnings, 46 showed statistically significant differences for citations, and 40 showed statistically significant differences for arrests.

Of the stations with significant differences, Whites were less likely than Non-Whites to receive verbal warnings but were more likely than Non-Whites to receive written warnings. Furthermore, Non-Whites were more likely than Whites to receive a citation and to be arrested.

[31] Analyses examining the relationship between drivers' gender and traffic stop outcomes at the station level are not reported but are available from the authors upon request.

Table 4.7: 2022 Stop Outcomes by Race for Stations in Area I

	Drivers	Total # of Stops	% verbal warning	% written warning	% citation	% arrest
AREA I, Troop B						
Belle Vernon	White	3,718	26.4%***	25.3%	59.8%***	4.0%**
	Non-White	929	33.1%	25.0%	52.1%	6.0%
Pittsburgh	White	4,754	22.1%***	17.8%	69.7%	2.5%***
	Non-White	2,128	25.6%	19.1%	67.6%	5.6%
Uniontown	White	9,521	44.8%***	20.2%*	39.8%***	4.9%**
	Non-White	1,428	54.2%	17.8%	29.9%	6.8%
Washington	White	3,434	28.6%*	23.1%	48.2%	5.5%***
	Non-White	634	32.9%	23.1%	50.2%	10.1%
Waynesburg	White	2,106	13.7%	19.6%	73.7%	3.2%
	Non-White	173	14.5%	16.3%	75.1%	4.0%
AREA I, Troop C						
Clarion	White	2,177	7.6%***	43.8%***	63.0%***	4.5%
	Non-White	325	2.8%	32.6%	78.5%	3.4%
Clearfield	White	3,426	10.3%*	35.5%***	62.7%***	4.5%*
	Non-White	344	6.1%	22.4%	79.9%	1.7%
Dubois	White	2,408	12.4%***	68.6%***	62.1%***	4.3%
	Non-White	346	6.4%	59.5%	85.3%	3.2%
Lewis Run	White	3,687	8.2%***	68.7%***	46.5%	5.7%
	Non-White	204	18.6%	52.9%	45.6%	8.8%
Marienville	White	2,342	8.9%	44.2%	71.1%	2.6%***
	Non-White	74	10.8%	48.6%	68.9%	9.5%
Punxsutawney	White	3,402	9.7%*	58.8%	49.8%	6.0%
	Non-White	71	17.1%	62.9%	45.1%	7.0%
Ridgway	White	2,333	12.9%	59.4%	56.3%	3.2%
	Non-White	113	15.0%	54.9%	63.7%	4.4%

NOTE: Asterisks identify statistically significant chi-square associations. * p < .05 ** p<.01 *** p<.001

Table 4.7: 2022 Stop Outcomes by Race for Stations in Area I

	Drivers	Total # of Stops	% verbal warning	% written warning	% citation	% arrest
AREA I, Troop D						
Beaver	White	2,647	13.4%	18.9%***	70.6%*	5.6%***
	Non-White	791	13.8%	12.6%	75.2%	9.5%
Butler	White	5,255	26.6%	42.7%	47.9%*	7.6%
	Non-White	503	25.8%	44.1%	42.1%	9.9%
Kittanning	White	6,882	12.7%	55.4%	41.0%***	6.8%***
	Non-White	965	10.5%	52.5%	48.7%	9.8%
Mercer	White	2,649	18.9%	33.0%	64.9%	6.6%
	Non-White	385	16.4%	33.2%	66.0%	7.3%
New Castle	White	2,117	11.2%	50.4%***	55.6%**	5.9%
	Non-White	471	12.6%	38.0%	47.3%	8.1%
AREA I, Troop E						
Corry	White	2,814	11.3%	46.6%	60.9%	2.5%
	Non-White	97	14.4%	44.3%	51.5%	3.1%
Erie	White	7,257	33.7%***	24.1%*	49.9%	4.4%***
	Non-White	1,845	38.0%	21.8%	50.1%	8.5%
Franklin	White	1,822	13.7%	37.6%	62.8%	6.0%
	Non-White	137	14.6%	41.6%	59.1%	10.2%
Girard	White	5,156	18.3%*	24.7%*	68.2%***	2.3%*
	Non-White	1,047	21.3%	21.5%	62.5%	3.4%
Meadville	White	3,234	25.8%	38.7%*	56.9%	4.4%
	Non-White	317	22.9%	32.8%	62.5%	5.4%
Warren	White	2,769	20.1%	39.1%	61.0%**	1.9%**
	Non-White	84	16.7%	42.9%	46.4%	6.0%

NOTE: Asterisks identify statistically significant chi-square associations. * p < .05 ** p<.01 *** p<.001

Table 4.7: 2022 Stop Outcomes by Race for Stations in Area II

	Drivers	Total # of Stops	% verbal warning	% written warning	% citation	% arrest
AREA II, Troop A						
Ebensburg	White	1,678	11.6%	30.8%	84.0%	2.1%
	Non-White	195	12.3%	28.7%	86.2%	3.6%
Greensburg	White	4,267	7.3%	53.9%	62.7%	5.1%
	Non-White	450	7.6%	54.7%	58.4%	6.7%
Indiana	White	5,826	12.9%	30.7%	66.6%	5.3%
	Non-White	717	11.6%	29.3%	70.2%	6.8%
Kiski Valley	White	1,213	15.7%	28.3%	69.1%	3.6%
	Non-White	114	12.3%	27.2%	69.3%	4.4%
Somerset (A)	White	3,148	7.7%	44.4%	72.3%	3.9%
	Non-White	174	8.0%	40.2%	71.8%	2.9%
AREA II, Troop G						
Bedford	White	4,386	13.7%***	52.4%***	62.4%	2.5%***
	Non-White	614	18.8%	43.8%	64.8%	5.5%
Hollidaysburg	White	3,595	27.1%*	38.5%	51.4%	6.1%
	Non-White	457	32.5%	37.3%	47.0%	7.2%
Huntingdon	White	3,523	15.8%	33.5%	66.1%	3.4%*
	Non-White	147	11.6%	39.5%	72.1%	6.8%
Lewiston	White	3,517	7.7%	51.9%*	62.0%**	3.7%*
	Non-White	489	9.2%	46.1%	68.9%	5.7%
McConnellsburg	White	2,552	16.1%	52.1%**	54.0%***	3.1%
	Non-White	604	14.4%	46.0%	68.2%	3.1%
Rockview	White	6,188	14.9%***	38.0%	61.8%***	3.8%
	Non-White	1,216	20.6%	38.1%	52.1%	3.9%

NOTE: Asterisks identify statistically significant chi-square associations. * p < .05 ** p<.01 *** p<.001

Table 4.7: 2022 Stop Outcomes by Race for Stations in Area II

	Drivers	Total # of Stops	% verbal warning	% written warning	% citation	% arrest
AREA II, Troop H						
Carlisle	White	7,920	9.0%	60.3%	47.0%	3.3%***
	Non-White	3,080	9.7%	61.9%	45.8%	5.6%
Chambersburg	White	9,697	21.7%	48.5%**	51.3%***	2.0%***
	Non-White	2,569	20.7%	51.4%	47.7%	4.0%
Gettysburg	White	6,299	22.1%***	56.5%***	28.1%***	4.9%
	Non-White	2,151	26.0%	50.8%	32.9%	5.9%
Harrisburg	White	5,170	27.0%**	40.6%	42.1%***	4.6%***
	Non-White	3,675	30.0%	41.0%	36.9%	8.9%
Lykens	White	2,526	8.4%	61.5%	61.7%	3.7%
	Non-White	342	11.4%	61.7%	56.4%	4.1%
Newport	White	3,242	12.7%**	50.4%**	47.4%	8.2%
	Non-White	454	17.4%	43.7%	48.9%	10.8%
Area II, Troop T						
Bowmansville	White	2,487	11.6%	26.7%	75.8%***	0.4%*
	Non-White	1,549	13.4%	24.8%	81.9%	1.0%
Everett	White	3,428	8.2%	72.0%	77.7%**	0.7%*
	Non-White	1,816	6.8%	74.0%	81.4%	1.4%
Gibsonia	White	4,045	4.6%	75.3%	84.7%	0.4%***
	Non-White	930	4.0%	72.7%	86.1%	1.7%
Highspire	White	57	15.8%	45.6%	49.1%	1.8%
	Non-White	35	20.0%	34.3%	62.9%	0.0%
King of Prussia	White	2,906	10.4%	25.1%	85.0%	0.4%
	Non-White	1,830	12.0%	24.2%	86.0%	0.8%
New Stanton	White	5,695	15.2%	69.6%	68.9%	0.6%
	Non-White	737	14.4%	67.7%	72.3%	1.1%
Newville	White	2,475	9.0%	31.6%***	72.0%***	0.2%***
	Non-White	1,370	7.8%	26.3%	78.7%	0.9%
Pocono	White	2,857	6.3%	27.8%***	86.6%***	0.1%***
	Non-White	1,453	6.0%	19.7%	92.0%	1.0%
Somerset (T)	White	2,790	9.1%**	53.5%	83.0%***	0.4%
	Non-White	1,193	6.5%	53.6%	89.4%	0.8%

NOTE: Asterisks identify statistically significant chi-square associations. * $p < .05$ ** $p<.01$ *** $p<.001$

Table 4.7: 2022 Stop Outcomes by Race for Stations in Area III

	Drivers	Total # of Stops	% verbal warning	% written warning	% citation	% arrest
AREA III, Troop F						
Coudersport	White	2,606	11.6%	47.4%	54.9%	2.3%
	Non-White	70	10.0%	48.6%	62.9%	4.3%
Emporium	White	1,225	6.0%	63.6%	51.2%	1.6%
	Non-White	30	13.3%	70.0%	36.7%	0.0%
Lamar	White	4,199	26.5%***	14.7%***	60.4%*	3.9%**
	Non-White	983	21.1%	20.9%	56.6%	2.1%
Mansfield	White	1,963	17.0%*	38.7%***	62.3%***	3.7%
	Non-White	317	12.0%	27.8%	74.1%	1.9%
Milton	White	6,131	12.5%***	25.0%***	65.4%***	2.9%
	Non-White	1,473	17.7%	32.1%	53.5%	3.7%
Montoursville	White	4,784	21.8%***	26.3%	60.2%***	3.8%***
	Non-White	941	31.6%	28.6%	42.4%	9.5%
Selinsgrove	White	3,108	5.1%	48.4%	65.4%	12.9%
	Non-White	447	5.6%	46.6%	67.3%	10.7%
Stonington	White	1,815	10.1%	45.2%	55.7%***	10.4%*
	Non-White	221	11.8%	50.2%	43.4%	14.9%
AREA III, Troop N						
Bloomsburg	White	2,008	14.3%	26.5%	65.9%*	5.1%
	Non-White	657	12.3%	24.7%	70.2%	5.6%
Fern Ridge	White	3,708	15.1%*	20.1%	73.4%***	4.0%
	Non-White	1,876	13.0%	20.1%	77.8%	3.9%
Hazelton	White	2,635	14.2%*	26.9%***	70.4%***	6.4%
	Non-White	2,525	16.4%	19.8%	80.3%	7.4%
Lehighton	White	1,653	15.5%*	27.8%***	69.4%*	13.7%
	Non-White	451	20.4%	20.0%	74.7%	10.6%
Stroudsburg	White	6,988	15.8%	36.9%	51.8%	8.9%
	Non-White	4,902	17.1%	36.3%	51.0%	8.3%

NOTE: Asterisks identify statistically significant chi-square associations. * p < .05 ** p<.01 *** p<.001

Table 4.7: 2022 Stop Outcomes by Race for Stations in Area III

	Drivers	Total # of Stops	% verbal warning	% written warning	% citation	% arrest
AREA III, Troop P						
Laporte	White	1,811	19.7%***	30.1%	58.0%*	2.9%*
	Non-White	217	30.6%	28.7%	48.4%	6.0%
Shickshinny	White	1,746	18.5%	22.2%	71.1%***	4.2%*
	Non-White	287	15.4%	19.6%	81.2%	1.7%
Towanda	White	4,333	26.1%*	35.3%	46.3%	3.4%
	Non-White	154	34.6%	32.7%	39.6%	4.5%
Tunkhannock	White	1,710	8.6%**	57.9%***	50.1%	3.7%
	Non-White	129	15.5%	40.3%	58.9%	4.7%
Wilkes-Barre	White	3,351	10.4%	24.4%*	75.1%**	3.0%***
	Non-White	1,212	12.2%	27.8%	70.9%	5.4%
AREA III, Troop R						
Blooming Grove	White	3,487	12.8%	35.8%	58.4%	7.5%
	Non-White	824	14.2%	38.6%	55.2%	6.2%
Dunmore	White	2,148	12.1%	31.2%	75.9%***	2.9%*
	Non-White	860	12.9%	28.1%	82.0%	4.8%
Gibson	White	2,556	14.3%*	23.7%***	76.2%*	6.1%**
	Non-White	999	11.4%	31.7%	72.9%	3.8%
Honesdale	White	2,561	12.2%	32.5%	71.1%	2.1%
	Non-White	158	15.2%	32.3%	72.8%	1.9%

NOTE: Asterisks identify statistically significant chi-square associations. * $p < .05$ ** $p<.01$ *** $p<.001$

Table 4.7: 2022 Stop Outcomes by Race for Stations in Area IV

	Drivers	Total # of Stops	% verbal warning	% written warning	% citation	% arrest
AREA IV, Troop J						
Avondale	White	5,380	32.4%***	37.3%***	38.1%	4.2%***
	Non-White	3,452	36.1%	33.0%	38.6%	6.9%
Embreeville	White	4,332	15.4%	42.3%**	55.3%*	3.9%***
	Non-White	2,804	16.8%	38.8%	58.2%	6.8%
Lancaster	White	4,477	23.8%***	33.7%	45.1%**	6.3%***
	Non-White	2,261	28.2%	33.1%	41.1%	8.5%
York	White	5,944	27.2%**	34.6%**	38.4%*	6.0%***
	Non-White	3,132	30.5%	31.5%	36.0%	11.1%
AREA IV, Troop K						
Media	White	5,143	19.6%**	31.6%**	49.1%***	4.8%***
	Non-White	6,297	21.9%	34.0%	45.0%	7.4%
Philadelphia	White	3,242	31.4%	29.9%***	44.8%***	5.8%
	Non-White	6,398	31.1%	25.8%	51.4%	5.9%
Skippack	White	3,018	19.1%*	31.3%	46.0%	6.4%*
	Non-White	1,507	21.9%	32.0%	47.1%	4.9%
AREA IV, Troop L						
Frackville	White	2,055	24.1%	25.2%*	57.3%***	4.2%
	Non-White	726	21.3%	20.4%	67.2%	2.8%
Hamburg	White	1,666	12.4%	31.3%	70.4%**	1.9%***
	Non-White	906	13.4%	31.7%	75.7%	4.4%
Jonestown	White	3,124	15.8%***	34.7%	59.4%**	5.2%***
	Non-White	1,542	20.1%	36.1%	54.5%	8.6%
Reading	White	2,161	13.4%	36.2%	57.4%	7.8%*
	Non-White	1,880	13.7%	36.6%	55.8%	9.8%
Schuylkill Haven	White	4,040	13.4%	30.2%	65.3%	3.7%
	Non-White	944	14.5%	28.2%	66.0%	3.5%
AREA IV, Troop M						
Belfast	White	1,972	17.4%	27.2%***	62.4%***	3.5%*
	Non-White	1,799	17.7%	33.9%	56.2%	5.2%
Bethlehem	White	2,026	15.0%	33.7%	58.5%	5.9%
	Non-White	1,985	14.9%	33.7%	59.2%	7.3%
Dublin	White	2,742	13.5%	52.9%	43.7%	8.4%
	Non-White	793	15.8%	50.0%	43.8%	9.2%
Fogelsville	White	2,911	16.1%	35.9%***	55.8%***	5.0%
	Non-White	2,919	16.1%	41.3%	48.6%	6.0%
Trevose	White	1,984	21.0%	43.3%	52.1%	4.7%
	Non-White	2,302	20.2%	43.3%	54.0%	5.1%

NOTE: Asterisks identify statistically significant chi-square associations. * p < .05 ** p<.01 *** p<.00

Tables 4.5 – 4.7 illustrate the wide variation in traffic stop outcomes across drivers' racial/ethnic and gender groups across PSP organizational units for 2022. It is important to reiterate, however, that the relationships reported in the previous tables are bivariate and thus do not statistically control for other relevant legal and extralegal factors that might influence officer decision-making. The information reported in Tables 4.5 – 4.7 is included in this report solely to provide details to PSP administrators regarding differences in post-stop outcomes at the Area, Troop, and Station levels. The information in these tables cannot be used to assess whether differences in outcomes across racial/ethnic and gender groups are due to trooper bias. It is plausible that racial/ethnic and gender differences in post-stop outcomes exist due to legal and extralegal reasons other than race/ethnicity and gender. More advanced statistical analyses that control for other legally relevant variables are presented below to explore these possibilities.

Multivariate Binary Logistic Regressions

Many factors may influence troopers' decision-making once a traffic stop is made. For example, driver characteristics, vehicle characteristics, stop characteristics, reasons for the stop, other legal variables, and trooper characteristics have all been hypothesized to influence post-stop outcomes. Multivariate analyses examine the independent effect of these predictor variables while controlling for, or statistically holding constant, the predictive power and influence of the other variables.

Although multivariate statistical modeling is a more robust analytical strategy than bivariate analysis, the critical weakness of multivariate statistical analysis is that it can only statistically control for those variables that are measured. This is called "model specification error" or the error in a statistical model due to the inability to specify all factors that influence the outcome. Every relevant factor that might explain stop outcomes cannot be realistically gathered in a systematic data collection system. Therefore, while researchers can be more confident in multivariate results, the findings should be interpreted with this fundamental limitation in mind.

Whether specific stop outcomes occurred or did not occur (e.g., warning, citation, arrest, etc.) within a stop means the outcome of interest in each event is binary. The appropriate statistical modeling technique for a binary outcome is logistic regression, as the outcome is dichotomous (0 or 1; did or did not occur).

Two components are the most important to consider when interpreting multivariate regression models. First, the models provide information about the relative strength of the observed relationship in two related values: 1) the coefficient, or predicted log-odds, and 2) the odds ratio for each independent variable in the model. The coefficient represents an additive expression of a particular variable. If a negative sign accompanies the coefficient, the direction of the relationship is negative, i.e., the influence of the variable means the outcome is less likely. If the coefficient has no sign (i.e., is a positive number), this indicates that the influence of that variable is positive, and the outcome is more likely. In logistic regressions, the results are presented as "odds ratios" representing the association between two events.[32] Odds ratios greater than 1.0 are a positive relationship, and odds ratios less than 1.0 are a negative correlation. We use the formula (1/(Exp(B)) to convert an odds ratio less than 1.0 to a positive odds ratio (which we then multiply by -1.0 to maintain consistency on a standard scale of comparison). Odds ratios are interpreted as a change in the likelihood of the outcome occurring because of a specific variable. One of the most important considerations is the amount of influence of a particular variable, or the strength of its relationship with the dependent variable (represented by the size of the odds ratio). Generally speaking, an odds ratio of 1.0 to 1.5 may be considered substantively small, 1.5 to 2.5 as moderate, and 2.6 or greater as large (Chen et al., 2010).

Second, when findings are reported to be significant, this refers to *statistical significance*, or the confidence level that the observed differences are not due to random chance and/or sampling error. Sometimes differences across the coefficients exist, but they are not statistically significant. This means we cannot be confident that the difference is not due to random chance. For each variable in the model, a threshold of statistical significance is identified with a p-value. The social sciences traditionally rely upon a confidence level of 95% (indicating that the finding is 5% or less due to random chance and/or sampling error). This represents the degree of confidence associated with the relationship or the extent to which the relationship is not due to chance. However, significance testing in large samples can be more sensitive to very small or artifactual relationships between variables, thus detecting statistically significant differences that are not substantively or practically significant (Allison, 1999). For this reason, we have increased the significance threshold to 0.1% for our analyses that rely on large sample sizes (i.e., only one time in 1,000 is the observed relationship due to chance).

In sum, due to the large sample size, even if the observed relationship between variables is statistically significant, it may not be substantively important. Therefore, we focus on the magnitude of the regression coefficients and the odds ratios (which indicate the strength of the relationship) rather than just their statistical significance when determining the amount of influence particular factors have over the post-stop outcomes.[33]

Descriptive Statistics

For each of the multivariate models reported below, numerous independent variables were included that could potentially influence enforcement outcomes that drivers receive. All possible

[32] Technically, this odds ratio is a form of log-odds, but the interpretation of this value is not intuitively straightforward; therefore, this type of coefficient is usually exponentiated to allow for interpretation in terms of odds (Liao, 1994). The odds ratio represents this antilog transformation of the coefficient into the multiplicative odds of the outcome variable based on the predictor variable, all else being equal.

[33] It is important to note that regular multivariate analyses are based on one level of data and reflect a one-to-one ratio between variables at that level. That is, variables in most data are independent of other variables. The PSP stop data, however, do not conform to this rule because stops occur within and across 88 PSP stations and within and across 67 counties within the Commonwealth. Thus, the shared characteristics between events within these organizational or geographical units are not independent of one another. The research team conducted sensitivity tests related to PSP station and county-level variation in predicting PSP stop outcomes. This information is provided in Appendix A. Ultimately, over 90% of the variation in the outcomes can be explained using level-1 predictors (i.e., stops) in all but one of the outcome models (verbal warnings). Thus, for parsimony and efficiency, we constrain the analyses presented in this section to the individual level (i.e., logistic regressions). The full HGLM models are available from the authors upon request.

explanatory variables must be statistically controlled to examine the variables of interest (i.e., drivers' race/ethnicity). Table 4.8 provides the summary statistics for the variables (described below) in the final dataset used for multivariate analyses.[34]

- Legal variables:
  - Reason for the stop is a series of dichotomous variables where 0=speeding, the reference category; and 1=each of the other reasons for the stop (equipment only violation, license only violation, moving only violation, registration only violation, and "other" violations)
  - Multiple Reasons for the Stop (0=single reason for stop; 1=2 or more reasons for stop)
  - Stop associated with a Special Traffic Enforcement program (0=no; 1=yes)
  - Evidence found during a search (0=no; 1=yes)

- Driver characteristics (values for each variable are in parentheses):
  - Race (five dichotomous variables: White, Black, American Indian, or Alaska Native, Asian/Pacific Islander, and Unknown Race[35]
  - Ethnicity (0=Not Hispanic; 1=Hispanic)
  - Gender (0=female; 1=male)
  - Age (in years)
  - Behavior (0=disrespectful, non-compliant, verbally or physically resistant; 1=civil)
  - Limited English Proficiency (0=no; 1=yes) [36]

- Vehicle characteristics:
  - Vehicle registration (1=PA registration; 0=out-of-state registration)
  - Whether any passengers in the vehicle (0=no; 1=yes)

- Situational characteristics:
  - Daytime (0=nighttime; 1=daytime)
  - Weekday (0=weekend; 1=weekday)
  - Summer (0=Jan – May & Sept – Dec; 1=June, July & August)
  - Interstate (0=state road, county road, other; 1=interstate)

- PSP Member characteristics:

[34] The measures that have missing data have some overlap, so the final total of cases for analysis equates to 99.3% of the total distribution of the total 441,329 stops.
[35] White is the excluded comparison category in the analyses. Therefore, the effects of race/ethnicity variables reported in the models are *in comparison to* Whites. For examples, the odds ratio represents the likelihood of a Black driver being issued a citation compared to a White driver.
[36] For the measure *Limited English Proficiency*, originally 10,061 records were coded as missing because the measure did not become a part of the data collection efforts of PSP until January 11, 2022. Our research team faced a dilemma regarding this measure: a) exclude it (and all other cases during the pre-measurement period of collection), or b) recode the missing measures as zeros. We chose the latter for two reasons. First, we would have lost roughly 2.3% of all cases in our regressions due to this one missing measure, which had a total distribution of 0.5% (i.e., 1 out of 190 cases where data was collected). Second, we ran the analyses each way (excluded and coded as zeros) and the results were virtually identical for this and all other measures. We were most concerned with having a representative (and holistic) sample of the data in our final analyses.

- Gender (0=female; 1=male)[37]
- Race/ethnicity (0=White; 1=Non-White)
- Experience (0=>3 years; 1=<3 years)
- Assignment (0=non-Patrol; 1=Patrol)
- Rank (0=Corporal and above; 1=Trooper)

[37] Although driver gender was not missing for any cases, for 2,736 cases it was reported as "unknown." These cases have been excluded from the final dataset for multivariate analyses.

Table 4.8: Descriptive Statistics for Final Dataset Used for Multivariate Analyses (n=438,300)

Dependent Variables	Mean (%)	SD	Min	Max	# Missing in Final Analysis
Verbal Warning	.18	.38	0	1	--
Written Warning	.39	.48	0	1	--
Any Warning	.57	.49	0	1	--
Citation	.57	.49	0	1	--
Arrested	.05	.21	0	1	--
Independent Variables					--
Legal Measures					
Speeding (Reference)	.40	.49	0	1	--
Equipment Only Violation	.14	.34	0	1	--
License Only Violation	.02	.14	0	1	--
Moving Only Violation	.22	.42	0	1	--
Registration Only Violation	.11	.31	0	1	--
Other Only Violation	.04	.20	0	1	--
Multiple Reasons (2 or more violations)	.10	.29	0	1	--
Special Traffic Enforcement	.17	.37	0	1	--
Evidence Seized in Stop	.02	.12	0	1	--
Driver Characteristics					
White (Reference)	.79	.40	0	1	--
Black	.14	.35	0	1	--
American Indian or Alaska Native	.00	.05	0	1	
Asian/Pacific Islander	.02	.13	0	1	--
Race Unknown	.04	.20	0	1	--
Hispanic Ethnicity	.08	.27	0	1	--
Male	.67	.47	0	1	2,736
Age (Years)	37.9	14.8	12	99	302
Driver Behavior Civil	.98	.14	0	1	--
Limited English Proficiency	.01	.07	0	1	
Vehicle Characteristics					
Pennsylvania Plate Registration	.80	.39	0	1	--
Passengers Present	.20	.39	0	1	--
Situational Characteristics					
Daytime	.66	.47	0	1	--
Weekday (Mon-Thurs)	.70	.45	0	1	--
Summer Months (June-August)	.23	.42	0	1	--
Interstate	.34	.47	0	1	--
PSP Member Characteristics					
Male Trooper	.96	.20	0	1	--
Non-White Trooper	.08	.27	0	1	--
3 Years Less Experience	.36	.47	0	1	--
Patrol Assignment	.95	.21	0	1	16
Trooper Rank	.90	.30	0	1	--

Verbal Warnings

Table 4.9 below reports the binary logistic regression model examining verbal warnings as the outcome in the stops (compared to all other outcomes). The results show that the largest and most salient predictors of verbal warnings were associated with legal measures (specifically equipment, moving, and other violations relative to speeding). The odds ratios were consistently medium-to-large, indicating these legal factors were vitally important. Stops performed as part of a special traffic enforcement program were also significantly less likely to result in a verbal warning (1.9 less likely to be issued a verbal warning when compared to all other stop outcomes). If evidence was seized, the likelihood of a verbal warning was far less likely (3.8 times less likely).

Driver demographic characteristics were either not statistically significant or not substantively important predictors of verbal warnings. For example, Hispanic drivers were not significantly different from White drivers in their odds of receiving a verbal warning. Similarly, gender was not statistically significant. For example, Black and American Indian/Alaska Native drivers were slightly more likely than White drivers (i.e., the reference category) to be issued a verbal warning (odds ratios of 1.17 and 1.15 accordingly). When the driver’s race was unknown, the driver's likelihood of being issued a verbal warning was slightly less (1.18 times less likely).

If drivers were reported as having been civil during the encounter, they were 1.74 times more likely to be given a verbal warning. If passengers were present in the encounter, the stop was 1.48 times less likely to result in a verbal warning. Additionally, daytime stops were significantly less likely (by 1.82 times) to result in a verbal warning than were nighttime stops (the reference category).

Troopers’ characteristics were neither powerful nor salient predictors of verbal warnings, given the low odds ratios observed in the estimates (typically less than 1.3). The lone exception to the impact of trooper characteristics on verbal warnings was that troopers assigned to patrol were 1.7 less likely than all other troopers to end the stop with a verbal warning.

Table 4.9: Binary Logistic Regression Analyses Predicting VERBAL WARNINGS during traffic stops in 2022

	VERBAL WARNINGS (n=438,300)		
	Coefficient	**St. Error**	**Odds Ratio**
Intercept	-1.55*	.048	--
Legal Measures			
Equipment Only Violation	0.74*	.014	2.09
License Only Violation	0.62*	.028	1.86
Moving Only Violation	1.24*	.012	3.45
Registration Only Violation	0.57*	.015	1.77
Other Only Violation	1.38*	.019	3.96
Multiple Reasons	0.37*	.017	1.45
Special Traffic Enforcement	-0.65*	.014	-1.92
Evidence Seized in Stop	-1.35*	.047	-3.86
Driver Characteristics			
Black	0.15*	.012	1.17
Asian/Pacific Islander	-0.02	.032	--
American Indian or Alaska Native	0.14	.070	--
Race Unknown	-0.17*	.022	-1.18
Hispanic Ethnicity	0.04	.015	--
Male	-0.18	.009	--
Age (Years)	0.01*	.000	1.00
Driver Behavior Civil	0.55*	.032	1.74
Limited English Proficiency	0.04	.058	--
Vehicle Characteristics			
Pennsylvania Plate Registration	-0.09*	.011	-1.10
Passengers Present	-0.39*	.012	-1.48
Situational Characteristics			
Daytime	-0.60*	.009	-1.82
Weekday (Mon-Thurs)	-0.08*	.009	-1.08
Summer Months (June-August)	0.24*	.009	1.28
Interstate	-0.04*	.010	-1.04
PSP Member Characteristics			
Male Trooper	0.05	.020	--
Non-White Trooper	0.07*	.014	1.08
3 Years Less Experience	0.23*	.009	1.26
Patrol Assignment	-0.52*	.018	-1.68
Trooper Rank	-0.24*	.015	1.26
Model Fit Statistics			
Nagelkerke R-Square	.133		

* = p < .001 Only odds ratios for statistically significant estimates are presented.
Odds Ratios for negative coefficients are calculated as 1/Exp(B), which equates to a value > 1.0, which we include as a negative odds ratio (-). This odds ratio can be interpreted as 'less likely' with the binary outcome.

Written Warnings

Table 4.10 reports the binary logistic regression model examining written warnings as the outcome compared to all other stop outcomes. The strongest predictor of written warnings was if evidence was seized during the stop, with an odds ratio of -12.0. This means that if evidence was seized, the odds of the stop resulting in a written warning were 12 times *less* likely. In short, a written warning was much less likely to occur if evidence was seized. The results show multiple strong predictors of verbal warnings associated with legal measures (specifically equipment and registration violations relative to speeding, the reference category). The odds ratios were consistently medium-to-large, indicating that compared to speeding, equipment violations were 2.2 times more likely to result in a written warning; likewise, registration violations were 1.8 times more likely to result in a written warning. Conversely, if a driver was stopped for a license violation (again, when compared to speeding), they were 1.5 times less likely to receive a written warning.

Black drivers were 1.1 times less likely to receive a written warning relative to White drivers; the same is true of Hispanic drivers (odds ratio = -1.2). When the driver's race was unknown, the likelihood the driver would be issued a verbal warning was also slightly less (1.1 times less likely) than were White drivers. These are not substantively important differences. Despite statistically significant relationships, no other demographic characteristics (age or gender) were associated with noteworthy differences in the likelihood of receiving a written warning. If drivers were reported as having been civil during the encounter, they were 2.3 times more likely to be given a written warning.

None of the vehicle or situational characteristics were substantively important predictors of a written warning. Stops conducted by PSP members at the trooper rank were 1.1 times more likely to result in written warnings than stops performed by Corporals and above. Additionally, stops that occurred by PSP members assigned to patrol were 1.4 less likely to result in written warnings.

The research team also examined a combined model of any warning (verbal or written), and it showed very similar findings.

Table 4.10: Binary Logistic Regression Analyses Predicting WRITTEN WARNINGS during traffic stops in 2022

	WRITTEN WARNINGS (n=438,300)		
	Coefficient	**St. Error**	**Odds Ratio**
Intercept	-1.38*	.038	--
Legal Measures			
Equipment Only Violation	0.77*	.010	2.16
License Only Violation	-0.44*	.025	-1.54
Moving Only Violation	0.29*	.009	1.34
Registration Only Violation	0.56*	.011	1.76
Other Only Violation	-0.23*	.018	-1.26
Multiple Reasons	0.83*	.011	2.30
Special Traffic Enforcement	0.10*	.008	1.11
Evidence Seized in Stop	-2.49*	.052	-12.05
Driver Characteristics			
Black	-0.10*	.009	-1.11
Asian/Pacific Islander	-0.06	.024	--
American Indian or Alaska Native	0.04	.056	--
Race Unknown	-0.11*	.016	-1.11
Hispanic Ethnicity	-0.17*	.012	-1.18
Male	-0.07*	.007	-1.07
Age (Years)	0.00*	.000	1.00
Driver Behavior Civil	0.82*	.026	2.27
Limited English Proficiency	-0.18*	.047	-1.19
Vehicle Characteristics			
Pennsylvania Plate Registration	-0.12*	.009	-1.12
Passengers Present	0.16*	.008	1.18
Situational Characteristics			
Daytime	-0.06*	.007	-1.06
Weekday (Mon-Thurs)	0.17*	.007	1.18
Summer Months (June-August)	-0.03*	.008	-1.03
Interstate	0.04*	.007	1.05
PSP Member Characteristics			
Male Trooper	-0.11*	.015	-1.11
Non-White Trooper	-0.17*	.012	-1.18
3 Years Less Experience	0.01	.007	--
Patrol Assignment	-0.31*	.015	-1.37
Trooper Rank	0.11*	.011	1.12
Model Fit Statistics			
Nagelkerke R-Square	.061		

* = p < .001 Only odds ratios for statistically significant estimates are presented.
Odds Ratios for negative coefficients are calculated as 1/Exp(B), which equates to a value > 1.0, which we include as a negative odds ratio (-). This odds ratio can be interpreted as 'less likely' with the binary outcome.

Citations

The binary logistic regression model showing the estimates of driver citations as the outcome is reported in Table 4.11 below. The strongest and most consistent predictor of driver citations were legal factors (i.e., types of violation). The reference category, speeding, is the point of comparison for all measures based on the reason for stop. Each reason for the stop variable was statistically significant ($p < .001$) and negative in direction. For example, stops for equipment violations were four times *less* likely to result in a citation than were stops for speeding violations; stops for other moving violations were six times less likely to result in a citation than speeding, and stops for "other" violations were six times less likely to yield a citation than were speeding violations. In short, this means that being stopped for speeding was clearly the strong predictor of receiving a citation compared with all other reasons. Furthermore, if the stop occurred as part of a special traffic enforcement program, the odds of the stop resulting in a citation were 2.0 times more likely when compared to all other stops.

The odds of a stop resulting in a citation were virtually indistinguishable between Black and White drivers stopped. Black drivers were slightly less likely (nearly -1.1 compared with 1.0 as the baseline) to receive a citation relative to White drivers. There was no statistically significant difference between the odds of a Hispanic driver receiving a citation compared to White drivers. When the driver's race was unknown, they were 1.7 times more likely to receive a citation than White drivers. None of the other demographic characteristics (age or gender) were associated with any noteworthy differences in the likelihood of receiving a driver citation. Drivers coded as behaving civilly were 2.7 times *less* likely to have the stop result in a citation.

Daytime stops were 2.7 times more likely to result in a citation when compared with all other stops. Drivers of vehicles with Pennsylvania registration were 1.4 times more likely to receive a citation than drivers of out-of-state vehicles, while drivers with passengers were 1.3 times more likely to receive a citation than drivers traveling alone.

Finally, traffic stops performed by PSP members assigned to patrol were about 2.9 times more likely to result in a citation compared to other trooper assignments. The impact of other trooper characteristics was minimal.

Table 4.11: Binary Logistic Regression Analyses Predicting DRIVER CITATIONS during traffic stops in 2022

	DRIVER CITATIONS (n=438,300)		
	Coefficient	**St. Error**	**Odds Ratio**
Intercept	0.644*	.039	--
Legal Measures			
Equipment Only Violation	-1.54*	.011	-4.67
License Only Violation	-0.61*	.023	-1.84
Moving Only Violation	-1.81*	.010	-6.10
Registration Only Violation	-1.15*	.012	-3.15
Other Only Violation	-1.91*	.018	-6.71
Multiple Reasons	-0.21*	.013	-1.23
Special Traffic Enforcement	0.68*	.010	1.97
Evidence Seized in Stop	0.30*	.027	1.35
Driver Characteristics			
Black	-0.08*	.010	-1.08
Asian/Pacific Islander	-0.03	.027	--
American Indian or Alaska Native	-0.26*	.063	-1.30
Race Unknown	0.54*	.018	1.72
Hispanic Ethnicity	-0.03	.013	--
Male	0.09*	.008	1.10
Age (Years)	-0.01*	.000	-1.01
Driver Behavior Civil	-0.98*	.026	-2.67
Limited English Proficiency	0.27*	.050	1.31
Vehicle Characteristics			
Pennsylvania Plate Registration	0.32*	.010	1.38
Passengers Present	0.27*	.009	1.31
Situational Characteristics			
Daytime	0.99*	.008	2.70
Weekday (Mon-Thurs)	-0.02	.008	--
Summer Months (June-August)	-0.26*	.008	-1.30
Interstate	0.15*	.008	1.16
PSP Member Characteristics			
Male Trooper	-0.10*	.017	-1.11
Non-White Trooper	0.09*	.013	1.10
3 Years Less Experience	-0.32*	.008	-1.37
Patrol Assignment	1.06*	.017	2.89
Trooper Rank	0.04*	.019	1.04
Model Fit Statistics			
Nagelkerke R-Square	.306		

* = p < .001 Only odds ratios for statistically significant estimates are presented.
Odds Ratios for negative coefficients are calculated as 1/Exp(B), which equates to a value > 1.0, which we include as a negative odds ratio (-). This odds ratio can be interpreted as 'less likely' with the binary outcome.

Arrests

Table 4.12 reports the binary logistic regression model results estimating the likelihood of the driver being arrested during a traffic stop. One measure in particular, evidence seized, was correlated extremely strongly with the odds of an arrest, which equated to an enhanced 170 times greater likelihood of an arrest where evidence was seized. Certainly, it is worth noting the cross-correlation of these measures in reality: When an arrest is decided, evidence seizure may lead to an arrest, but it can also be a response to an arrest. The CDR does not capture the sequencing of events during traffic stops. Therefore, the relationship between evidence seized and arrest cannot be interpreted causally because we do not have information about the temporal order of events (Engel & Calnon, 2004b).[38]

The patterns associated with the legal reasons for the stop and the likelihood of arrests starkly contrast to the pattern with citations (which was clearly highest for speeding, given the negative odds ratios for that model compared to all other legal measures). For arrests, each measure was statistically significant in a positive direction, meaning that a stop involving speeding was significantly *less* likely to result in an arrest compared to other reasons for the stop. For example, other moving violations (4.8 times more likely than speeding), multiple reason violations (4.1 times more likely than speeding), and other moving violations (3.0 times more likely than speeding) were among the strongest correlates of stops resulting in arrests. While statistically significant, equipment and registration violations were only slightly more likely to result in arrests (in terms of effect size) compared to stops for speeding.

The odds of stopped Black and White drivers being arrested were very similar, net of all measures included in this model. Black drivers were only slightly more likely (1.1 times) to be arrested in a stop relative to White drivers. Likewise, Hispanic drivers were slightly more likely (1.2 times) to be arrested in a stop than White drivers. When drivers' race was unknown, they were 2.7 times *less* likely to be arrested than White drivers. The odds ratios for race, ethnicity, and gender are all substantively small, suggesting only inconsequential or no racial/ethnic disparities detected in arrests during traffic stops.

Slight differences in drivers' likelihood of arrest were observed by gender, with male drivers 1.4 times more likely to be arrested during stops compared to female drivers. Stops where drivers were coded as behaving civilly were 5.9 times *less* likely to result in arrests (meaning that when a driver was coded as disrespectful, non-compliant, or verbally or physically resistant, the stops were 5.9 times *more* likely to result in an arrest). Also, stops involving drivers with limited English proficiency were nearly two times more likely to result in arrests.

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[38] We ran the arrest analysis with the inclusion and exclusion of evidence seized. The bivariate correlation between the evidence and arrest measures was -.452, which suggests that while the two measures are related, they are not capturing the same phenomenon (i.e., arrests are made without evidence seized, and, probably less likely, seizures are occurring without arrests). Additionally, the model that excluded evidence was weaker in its predictability (i.e., the Nagelkerke r-square value was reduced from .35 to .16). Finally, the estimates for race were very similar across both sets of models (e.g., the race odds ratio for Black arrestees was 1.12 where evidence was included and 1.29 where evidence was excluded; the odds ratios for Hispanic ethnicity was 1.17 with evidence and 1.14 without evidence). In sum, the arrest model that included evidence was the more uniform and parsimonious model and is included in the report.

Some situational factors were significantly and substantively related to the odds of an arrest occurring, including daytime and day of the week. Daytime stops were 2.9 times less likely than nighttime stops to result in an arrest (conversely, this means nighttime stops were 2.9 times more likely than daytime stops to yield an arrest). Weekday stops were 1.6 times less likely to result in an arrest, meaning that weekend stops were 1.6 more likely to result in an arrest.

Finally, two trooper characteristics demonstrated minor influence over the likelihood of arrest. Specifically, stops performed by PSP members assigned to patrol were roughly 1.3 times more likely to result in an arrest. And finally, male troopers were 1.5 times *less* likely than female troopers to arrest motorists when other factors were held constant.

Table 4.12: Binary Logistic Regression Analyses Predicting DRIVER ARRESTS during traffic stops in 2022

	DRIVER ARRESTS (n=438,300)		
	Coefficient	**St. Error**	**Odds Ratio**
Intercept	-1.72*	.086	--
Legal Measures			
Equipment Only Violation	0.16*	.036	1.17
License Only Violation	0.94*	.053	2.56
Moving Only Violation	1.11*	.028	3.03
Registration Only Violation	0.27*	.038	1.31
Other Only Violation	1.57*	.037	4.82
Multiple Reasons	1.40*	.031	4.05
Special Traffic Enforcement	-0.26*	.027	-1.30
Evidence Seized in Stop	5.14*	.038	170.09
Driver Characteristics			
Black	0.11*	.023	1.12
Asian/Pacific Islander	-0.47*	.086	-1.61
American Indian or Alaska Native	-1.37*	.278	-3.93
Race Unknown	-1.00*	.068	-2.71
Hispanic Ethnicity	0.16*	.029	1.17
Male	0.30*	.019	1.35
Age (Years)	-0.01*	.001	-1.01
Driver Behavior Civil	-1.77*	.031	-5.85
Limited English Proficiency	0.68*	.088	1.97
Vehicle Characteristics			
Pennsylvania Plate Registration	0.29*	.026	1.34
Passengers Present	0.21*	.021	1.24
Situational Characteristics			
Daytime	-1.05*	.019	-2.86
Weekday (Mon-Thurs)	-0.44*	.018	-1.55
Summer Months (June-August)	0.18*	.020	1.20
Interstate	-0.57*	.023	-1.76
PSP Member Characteristics			
Male Trooper	-0.42*	.037	-1.52
Non-White Trooper	-0.22*	.033	-1.25
3 Years Less Experience	-0.18*	.018	-1.19
Patrol Assignment	0.28*	.051	1.33
Trooper Rank	0.16*	.033	1.17
Model Fit Statistics			
Nagelkerke R-Square	.352		

* = $p < .001$ Only odds ratios for statistically significant estimates are presented.
Odds Ratios for negative coefficients are calculated as 1/Exp(B), which equates to a value > 1.0, which we include as a negative odds ratio (-). This odds ratio can be interpreted as 'less likely' with the binary outcome.

Model Effects and Estimated Effect Sizes of the Race of Driver Across Outcomes

A series of additional findings are presented below to better understand the potential impact of drivers' race/ethnicity on post-stop outcomes. First, the Nagelkerke r-square statistic for each model is included in the outcome-specific tables. This metric, specific to binary logistic regression, provides a broad perspective of model goodness-of-fit. The generalized rule of thumb within the social sciences is that a model < .10 is a poorly fitting model; a model between .10 and .20 is a weak-to-solid fitting model; and a model > .20 is a robust fitting model (Muijs, 2012). The model fit describes if the factors collectively are considered strong predictors of the outcomes (in this case, do all the factors measured using the CDR data collection forms provide information that strongly predicts whether or not warnings, citations, or arrests are made during traffic stops). While we are confident in our estimate-comparisons (i.e., within each model, which specific factors have the strongest association with the post-stop outcomes), we also acknowledge many *unmeasured factors* could explain the likelihood of warnings, citations, or arrests during traffic stops.

Using this criterion, the written warning regression model is considered a poor-fitted model (Nagelkerke r-square = .061). The verbal warning regression model is moderately fitted (with a value of .133). Finally, driver citations (.306) and driver arrests (.352) were the best-fitting models. This means that we have more confidence in the findings predicting the likelihood of citations and arrests during traffic stops compared to written or verbal warnings.

The results of each regression analysis show that drivers' race/ethnicity have some degree of association with the likelihood of given outcomes, but their effect sizes are typically in the marginal to small range, net of other control variables (i.e., all else equal). Table 4.8 previously displayed the raw percentage for each outcome. However, that descriptive percentage takes no additional information into account. Once additional information is accounted for, the baseline likelihood of an event changes.[39] We rely on predicted probabilities to estimate the true impact of race and ethnicity more precisely on stop outcom*es*. Following Liao (1994:12), we converted the logistic regression coefficients in our models to predicted probabilities. For the stop outcomes, the predicted probabilities estimate the likelihood of an event for the average person/stop accounting for all the factors in the models. It is a more precise risk estimation than the general outcome percentage (when the models are accurate and predictive).

Using predicted probabilities allows us to compare estimations for different racial and ethnic groups, net of these other important factors. Calculating the probabilities for White, Black, and Hispanic drivers across various situational and legal characteristics of stops makes it possible to estimate more precisely the difference between drivers of different racial and ethnic backgrounds

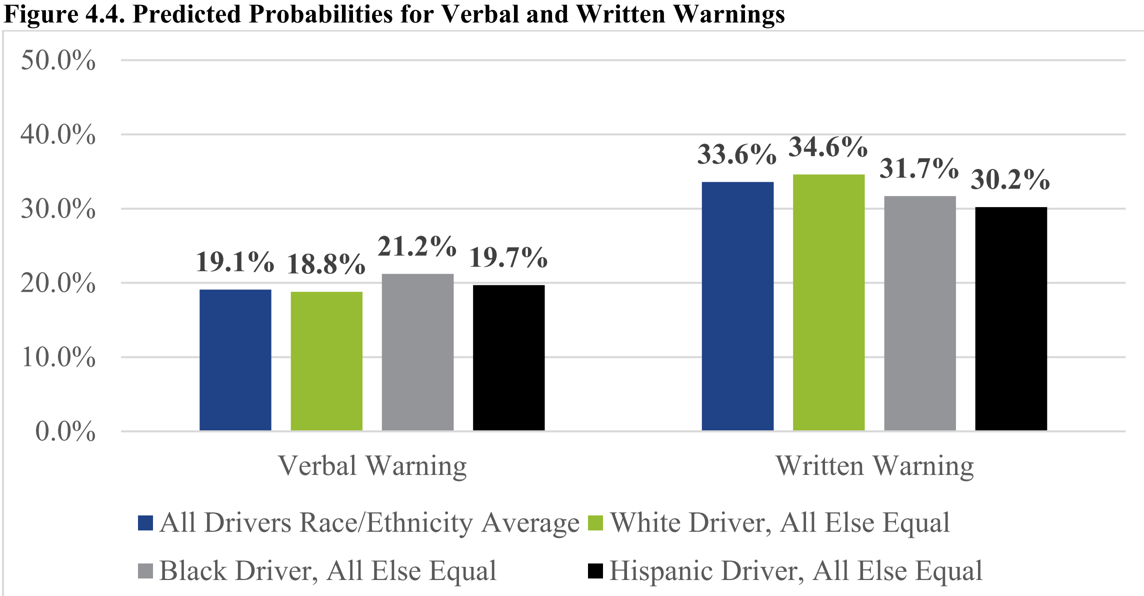
[39] To draw a parallel, the CDC (2022) reported the likelihood of COVID-related death in 2020 was 0.5% to 1%. However, for age groups 60-69, the likelihood was 3.6%; for 70-79, the likelihood was 8.0%; and for 80+ the likelihood was 14.8%. The more detail that we have, the more precise our estimation is of an event occurring to that (or any other) group. Absent that information, we typically rely on the overall percentage of the outcome for everyone.

in their probability of being warned, cited, or arrested, all else equal (i.e., all other measures in the models were set to their mean values).[40]

Figure 4.4 displays the predicted probabilities for verbal and written warnings. It shows that all else equal (i.e., under the same measured conditions), Whites had an 18.8% likelihood of a verbal warning, Hispanics had a 19.7% likelihood, and Black drivers had a 21.2% likelihood. As a point of comparison, any driver with an equipment violation had a 30.4% chance of a verbal warning. Among stops, the race/ethnicity of drivers had little bearing on verbal warnings as the outcome.

Figure 4.4 below shows that net of all other factors, White drivers were 34.6% likely to receive a written warning, compared to Black drivers (31.7%) and Hispanic drivers (30.2%). Thus, all else equal, where the driver was White, the stop resulted in a written warning roughly 3 more times per every 100 stops relative to a Black driver where a written warning was the outcome of the stop, and roughly four more times per every 100 stops (where a written warning was given) relative to Hispanics.[41]

Figure 4.4. Predicted Probabilities for Verbal and Written Warnings



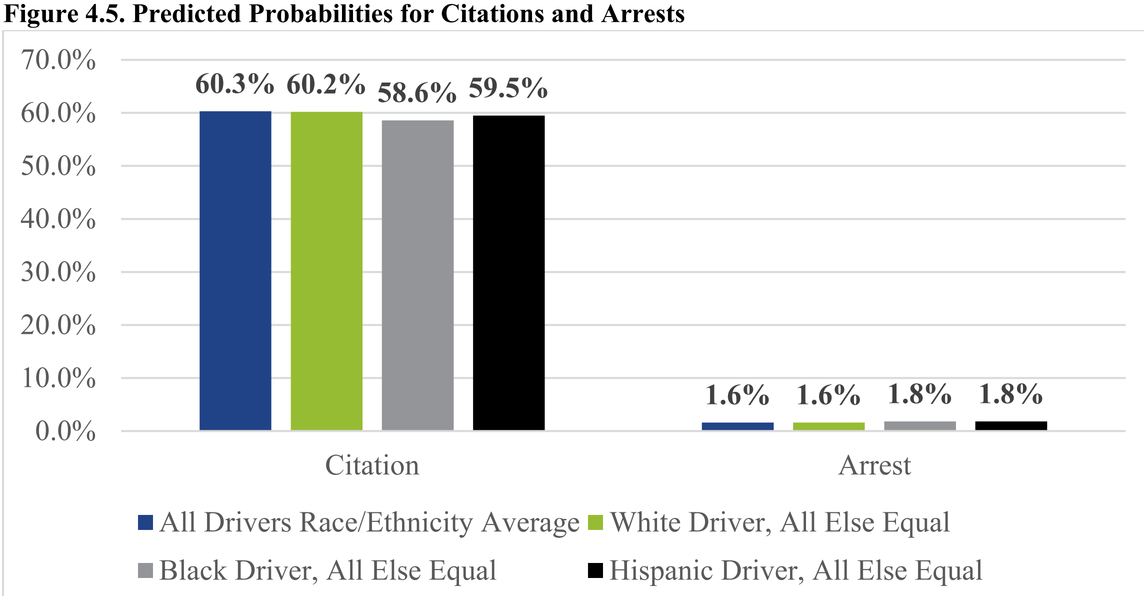
[40] The predicted probabilities are a prediction of an outcome, and the ability to predict accurately is based on a full and complete regression model. A model with omitted variable bias (i.e., factors that are important but go unmeasured/unaccounted for) will not fully and accurately predict an outcome. In the case where the events occur more than the predictions, the predictions are predicated on the estimates, and not the distribution of outcomes. Thus, while arrests occur 4.6% in the total distribution of cases, our model's accuracy is only at 2%, meaning that we cannot predict the outcomes half of the time because we do not have all the factors that are relevant to the outcomes). This is a more noticeable issue when we have rare events (something that happens 4.6% of the time, versus 30% of the time).

[41] It is also worth noting that the largest racial/ethnic difference among all outcomes observed in Figures 4.4 – 4.6 was for written warnings, which had the lowest acceptable threshold of model fit (via the Nagelkerke r-square statistic). In short, the poorest fitting model with the greatest likelihood of omitted variable bias yielded the largest percentage difference among the race/ethnicity of the drivers.

Likewise, Figure 4.5 below displays the predicted probabilities for citations and arrests. *Regarding citations as the outcome, net of all other measured factors, White, Black, and Hispanic drivers had virtually the same likelihood of receiving a citation* (White=60.2%; Black=58.6%; Hispanic=59.5%). As a point of reference, any driver pulled over for a speeding violation had a 78.1% likelihood of receiving a citation, net of all other factors.

Figure 4.5 also displays the predicted probabilities for arrests. The likelihood of an arrest occurring, controlling for all the factors in our models, was 1.6%. Additional analyses show that *White, Black, and Hispanic drivers had virtually the same likelihood of being arrested during a traffic stop* net of all other measured factors (White=1.6%; Black=1.8%; Hispanic=1.8%). By comparison, if a driver of any race/ethnicity was pulled over for multiple reasons, the likelihood that the stop would result in an arrest was 5.6%.

Figure 4.5. Predicted Probabilities for Citations and Arrests



Section Summary

This section described the post-stop outcomes resulting from traffic stops conducted by PSP troopers throughout 2022. Post-stop outcomes varied considerably by PSP Area, Troop, and Station, but traffic stop outcomes across the department were:

- 56.8% of stops resulted in a warning issued to the driver (18.5% verbal, 38.3% written)
- 57.0% of stops resulted in a citation issued to the driver
- 4.6% of stops resulted in the arrest of the driver

Building on the descriptive statistics, this section also reported the results of bivariate and multivariate statistical analyses conducted on stop outcomes to understand better the impact of drivers' race/ethnicity.

Bivariate Analysis

- At the department level, statistically significant bivariate differences by drivers' race/ethnicity and gender were noted for all outcomes:
  - Verbal warnings of drivers: 17.7% White, 21.2% Black, 19.7% Hispanic
  - Written warnings of drivers: 39.4% White, 36.7% Black, 36.1% Hispanic
  - Citations of drivers: 57.3% White, 54.3% Black, 55.1% Hispanic
  - Arrests of drivers: 4.3% White, 6.6% Black, 5.8% Hispanic.
- Statistically significant gender differences were observed for all outcomes, but the differences for warnings and citations were negligible, while male drivers were significantly more likely to be arrested than female drivers.
- These patterns and trends by drivers' race/ethnicity and gender varied at the Area level and more so at the troop and station levels.
- Bivariate analyses do not control for alternative factors that could impact the relationship between stop outcomes and drivers' race/ethnicity or gender.

Multivariate Analyses

Multivariate statistical models take multiple factors into account when attempting to explain traffic stop outcomes, providing a more thorough and accurate interpretation of the data. Unlike a bivariate model, they allow an examination of the impact of drivers' race/ethnicity once other explanatory factors measured by the PSP data collection system are considered. As a reminder, one of the most important considerations in multivariate models is the strength of an independent variable's relationship with the dependent variable. Generally speaking, odds ratios of 1.0 to 1.5 are substantively small, 1.5 to 2.5 are moderate, and 2.6 or greater are large (Chen et al., 2010).

- Across all stop outcomes, the most substantive predictors of whether the stop results in a warning, citation, or arrest are legal factors
  - Reasons for stop, whether there were multiple violations, and whether evidence was seized robustly predict all post-stop outcomes.
  - Odds ratios for these legal variables were consistently moderate to large predictors.
- No substantive differences across racial/ethnic groups exist for warnings, citations, and arrests once other explanatory factors are taken into account.
- Some other driver, vehicle, and situational characteristics have moderate to large effects on some stop outcomes.
  - Civil driver behavior was positively related to warnings but negatively related to citations and arrests.
  - Stops conducted during the day were positively related to citations but negatively related to arrests.
- Drivers' gender did not substantively predict warnings or citations, but male drivers were 1.4 times more likely to be arrested.
- PSP members' characteristics were not substantively strong predictors of stop outcomes, other than assignment to patrol, which was negatively related to verbal and written warnings, but positively related to citations.

Collectively, these results demonstrate that troopers' decision-making regarding post-stop outcomes is most strongly based on legal factors and not the characteristics of drivers or troopers, including their race/ethnicity.

Finally, the multivariate analyses are better suited to make substantive claims about the impact of drivers' race/ethnicity on post-stop outcomes due to their simultaneous consideration of multiple explanatory factors, but they are limited by the type and amount of data collected. Here we acknowledge the potential for model misspecification (i.e., pertinent predictors of post-stop outcomes that are unmeasured cannot be included in the statistical models). Thus, multivariate analyses can only demonstrate whether racial/ethnic disparities exist after statistically controlling for the factors measured with these data. None of the analyses presented in this report, including these multivariate analyses, can be used to determine whether unexplained racial/ethnic disparities are due to trooper bias. Based on the analyses of these data, however, we can conclude there is no statistical evidence demonstrating substantive differences across racial/ethnic groups in issuing warnings or citations or conducting arrests during traffic stops conducted by the PSP.

SECTION 5: SEARCH AND SEIZURE

The material presented in this section focuses specifically on motor vehicle and person searches conducted by PSP troopers during traffic stops. Information is provided at the Department, Area, Troop, and Station level on search rates, comparisons of who is searched by race/ethnicity, reasons for the search, the rate of contraband or evidence seized during searches, and seizure rates by race/ethnicity. This section concludes with a summary of the main findings on the PSP's search and seizure rates.

Focus on Discretionary Searches

Troopers reported conducting searches during 3.5% of traffic stops, with 15,301 searches conducted across the department in 2022. Note, however, that as described in 2022 quarterly reports, the PSP informed the research team of a reporting issue discovered on September 5, 2022, with the "incident to arrest" response option for the "reason for search" data field.[42] As noted in the previous quarterly reports, it is unknown how frequently this issue may have occurred before it was discovered, and there is no method for either the PSP or the research team to determine how troopers reported search information within these specific circumstances. The PSP instituted a rule change within the data collection system to correct the possible reporting errors on September 30, 2022. At that time, the research team determined that it would evaluate this data integrity issue and its implications for search and seizure analyses in this 2022 Annual Report.

Although 36% of all searches recorded on the CDR forms indicated incident to arrest as a reason for search, there is evidence that the technical issue described above likely resulted in a significant undercounting of this particular reason for search and, therefore, the number of searches overall. For example, of the 20,290 drivers arrested during traffic stops, only 46% were reported to have been searched incident to arrest. Furthermore, a *t*-test comparison of means before and after the rule correction indicated a significant increase in the percent of searches reported based on incident to arrest.

Based on this known undercounting of mandatory searches in 2022, the research team determined that the most appropriate way to examine PSP searches is to focus analyses exclusively on what we term "discretionary" searches. For the purposes of this report, a

[42] As described in the *2021 Pennsylvania State Police Traffic Stop Study,* the values for categories of search reasons changed mid-year in 2021, with some reasons eliminated, others added, and the numeric codes for all categories differing from the previous CDR form to the updated form (Engel & Cherkauskas, 2022). Previously "0" indicated that the search reason was "not applicable" and "incident to arrest" was "1". The "not applicable" option, however, was eliminated on the updated form because the search reason does not open as a field for completion if no search is initiated, and "incident to arrest" was subsequently assigned the value "0". When the update was made, however, it appears that an old validation rule inadvertently was not removed; specifically, if the search initiated is yes, search reason cannot be "not applicable." This issue was discovered when a member tried to select "0" for "incident to arrest" as a search reason. The system warned them it was not a valid response when search initiated was yes.

discretionary search is one that is not based on a mandatory reason (i.e., required by law or department policy). For example, both inventory searches and searches incident to arrest are required by PSP policy (i.e., they are considered mandatory searches) and therefore do not measure officers' discretionary choices to initiate a search. Focusing specifically on discretionary searches is widely considered best practice for traffic stop studies, as this is the most instructive way to consider racial/ethnic disparities in searches (Fridell, 2004; Tillyer & Klahm, 2015; Tillyer et al., 2012). And as further described below, scholars have routinely recognized that mandatory searches should be excluded from analyses using the "outcome test" (Engel, 2008; Engel & Tillyer, 2008).[43]

Of the 15,301 reported searches, 3,065 searches have been eliminated from further analyses because they were based on: 1) only incident to arrest, 2) only vehicle inventory, 3) incident to arrest *and* inventory, or 4) that were missing a search reason are excluded from further analyses. If a search was conducted based on both discretionary *and* mandatory reasons, it was retained in the analyses of discretionary searches. This results in **12,236 discretionary searches (2.8% of all stops)** on which the remaining statistical analyses are based.

Discretionary Search Rates

Compared to historical PSP data from 2006 to 2010[44], a greater percentage of stops in 2022 resulted in discretionary searches. Combined with the overall increase in traffic stops, considerably more searches were conducted in 2022 compared to historic levels. Over the last decade, the PSP has made a concerted effort to expand criminal interdiction training and enforcement activity in response to increasing concerns about violent crime, drug trafficking, and gun violence. For example, the Safe Highways Initiative through Effective Law Enforcement and Detection (SHIELD) section was established in 2013. It involves PSP members specially trained to interdict or prevent criminal activity on major highways. In addition to the daily work of the SHIELD Section, the members of SHIELD also provide training to selected troopers through two training opportunities. This training is further described in the final part of Section 5.

Table 5.1 below displays information related to traffic stops that resulted in discretionary searches at the Department, Area, and Troop levels and for specialized units. Specifically, this table reports the percentage of stops resulting in discretionary searches and the total number of discretionary searches conducted either on the roadside or after a vehicle was towed. The prevalence of discretionary searches varied across PSP Areas, with Area II having the lowest percentage of stops that resulted in discretionary searches (1.9%) and Area IV having the highest (3.7%). Similarly, there is variation in the rates of traffic stops resulting in discretionary searches

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[43] Annual reports produced for PSP for data collected from 2006-2010 did not examine seizure rates by race/ethnicity for searches conducted for mandatory reasons for this reason.

[44] Significant data quality issues were discovered for stops that resulted in searches and arrests from 2002-2005. Therefore, our historical comparison data only includes search data for 2006-2010 after the errors were resolved. The highest search rate between 2006 and 2010 was 1.9%, and most years were between 1.1% and 1.3% -- including mandatory searches. Even with the known undercounting of mandatory searches, 3.5% of traffic stops resulted in searches in 2022.

at the Troop level. For example, 0.3% of stops conducted in Troop T resulted in a discretionary search, compared to 4.4% in Troop K. Of note, all Troops within Area IV averaged a similar or higher percentage of stops resulting in discretionary searches than the department-wide average of 2.8%. Finally, given the mission of the specialized units, their average discretionary search rate was considerably higher than the department-wide average. Specifically, discretionary searches were conducted during 12.1% of traffic stops made by the SHIELD unit and 10.6% by the Canine unit.

Table 5.1 below also illustrates the different search reasons across the Department, Areas, Troops, and the specialized units. As shown, most discretionary searches conducted department-wide secured motorists' verbal consent (71.6%), while 20.2% were based on written consent. Less common reasons include plain view (11.3%), officer safety (10.0%), search warrant (7.2%), and probable cause with exigent circumstances (2.1%).

PSP troopers' heavy reliance on the use of consent searches is due, in part, to the unique case law in Pennsylvania guiding vehicular searches, which does not allow searches based on probable cause without a search warrant unless exigent circumstances exist (*Commonwealth v. Alexander*, 2020 Pa. LEXIS 6439). In this decision, the Supreme Court of Pennsylvania ruled that a provision of the Commonwealth's Constitution (Article I, Section 8) provides greater privacy protections to drivers in Pennsylvania than the Fourth Amendment of the U.S. Constitution. In Pennsylvania, troopers are permitted to hold a vehicle during the immediate application for a search warrant.

As shown, the reasons for search differ across Areas and Troops. For example, 79.4% of discretionary searches conducted in Area I included verbal consent, compared to 59.0% in Area IV. In Area I, written consent accounted for just 8.2% of discretionary searches, while it accounted for 29.8% of discretionary searches in Area IV.

Notable differences also exist in how motorists consent to searches at the Troop level. For instance, only 4.3% of discretionary searches by Troop D involve written consent, while 81.6% involve verbal consent. Conversely, 49.5% of discretionary searches by Troop J involve written consent, while only 44.0% involve verbal consent. Finally, most discretionary searches by the SHIELD and Canine units involved verbal consent from motorists; 63.4% of SHIELD searches were also based on written consent.

At the Area and Troop level, there was substantial variability in reported frequencies of each search reason besides written or verbal consent. For example, in Areas II and III, the third most common reason for a search was for plain view contraband (9.4%, and 11.1%, respectively). In Area I and IV, however, the third most common reason for a search was officer safety, accounting for 10.4% and 15.3% of discretionary searches in these Areas, respectively. At the troop level, there is even more variability for search reasons. For example, Troop K reported that almost a fifth of their stops were due to officer safety (19.8%), while Troops G and F reported that this accounted for less than 5% of their discretionary searches.

While examining the specific reasons for searches is instructive, this information is better analyzed when collapsed into discrete categories or types of searches. For the analyses reported in the remainder of Section 5, the research team divided searches into three categories based on the presumed level of officer discretion for different situations. Type I searches – **mandatory** – are searches that are required by PSP policy (e.g., incident to arrest, vehicle inventory), and as previously noted, have been excluded from all further analyses because of their known undercounting. While searches based solely on a mandatory reason are excluded from these analyses, if a search was conducted for a non-mandatory reason *and* one of the mandatory reasons, it was retained in the analyses of discretionary searches and classified based on the other reason. Type II searches include those that are based on the development of **reasonable suspicion or probable cause**. Specifically, Type II searches include those based on officer safety (*Terry)*, plain view searches, probable cause plus exigency, and a search warrant. Type III searches include those discretionary searches that are based **solely on consent** (whether written, verbal, or both). Within the discretionary reasons, if a search was based on multiple reasons (i.e., both a Type II and Type III reason), it was assigned to the search category with the least officer discretion (Type II). Therefore, the analyses below examining the search and seizure rates by type of search are based on mutually exclusive categories.

Table 5.1 below displays the distribution of discretionary searches by search types at the Department, Area, Troop, and Specialized Unit level. Across the department, 72.7% of discretionary searches were Type III searches, while 27.3% were Type II searches. At the Area level, Type III searches were the most common category of discretionary searches for all four Areas. Overall, Type II searches were the least common category across all four Areas, ranging from 22.3% to 33.8%.

Type III searches were the most common in all sixteen troops. Similar to patterns at the department-wide and at the Area level, Type II searches were the least common type of discretionary search in each of the sixteen troops. The vast majority of discretionary searches in the SHIELD and Canine units were Type III searches (90.1% and 80.1%, respectively).

Table 5.1: Discretionary Searches and Search Reasons by Department, Area, Troop, and Specialized Units 2022

	% of Stops Resulting in Disc Search	Total # of Disc. Searches	Officer Safety (Terry)	Plain View	Prob Cause + Exigency	Search Warrant	Written Consent	Verbal Consent	Type II (RS/PC)	Type III (Consent-Only)
PSP Dept.	**2.8%**	**12,236**	**10.0%**	**11.3%**	**2.1%**	**7.2%**	**20.2%**	**71.6%**	**27.3%**	**72.7%**
AREA I	**2.7%**	**2,775**	**10.4%**	**14.5%**	**3.5%**	**5.8%**	**8.2%**	**79.4%**	**29.9%**	**70.1%**
Troop B	3.5%	1,059	8.6%	11.2%	4.1%	5.4%	4.6%	82.7%	25.5%	74.5%
Troop C	1.6%	354	10.5%	17.5%	1.7%	8.8%	16.1%	72.6%	34.7%	65.3%
Troop D	3.9%	935	11.0%	16.1%	3.0%	5.0%	4.3%	81.6%	30.4%	69.6%
Troop E	1.6%	427	13.3%	16.2%	4.7%	6.3%	19.0%	72.1%	35.6%	64.4%
AREA II	**1.9%**	**2,545**	**8.1%**	**9.4%**	**2.1%**	**7.0%**	**14.2%**	**76.5%**	**24.0%**	**76.0%**
Troop A	1.9%	338	9.2%	11.5%	2.4%	6.5%	14.2%	73.7%	26.9%	73.1%
Troop G	2.3%	648	3.5%	8.5%	2.6%	6.5%	24.5%	74.4%	19.0%	81.0%
Troop H	3.0%	1,446	9.5%	8.6%	1.7%	6.8%	9.3%	79.5%	24.3%	75.7%
Troop T	0.3%	113	14.2%	18.6%	3.5%	12.4%	18.6%	60.2%	40.7%	59.3%
AREA III	**2.6%**	**2,387**	**6.1%**	**11.1%**	**1.8%**	**5.4%**	**15.6%**	**77.9%**	**22.3%**	**77.7%**
Troop F	1.5%	475	4.8%	11.4%	0.6%	7.6%	11.2%	81.5%	22.5%	77.5%
Troop N	3.0%	906	6.8%	12.4%	2.9%	5.3%	8.4%	79.0%	24.8%	75.2%
Troop P	2.6%	391	6.9%	8.2%	1.5%	5.6%	37.1%	63.4%	21.0%	79.0%
Troop R	4.1%	615	5.5%	10.9%	1.1%	3.7%	15.9%	82.8%	19.3%	80.7%
AREA IV	**3.7%**	**3,743**	**15.3%**	**11.5%**	**1.6%**	**9.5%**	**29.8%**	**59.0%**	**33.8%**	**66.2%**
Troop J	3.8%	1,224	15.3%	13.0%	1.1%	10.1%	49.5%	44.0%	35.5%	64.5%
Troop K	4.4%	1,178	19.8%	10.3%	1.4%	13.7%	8.7%	65.6%	40.6%	59.4%
Troop L	3.2%	635	12.1%	8.3%	2.8%	2.8%	35.3%	67.4%	23.8%	76.2%
Troop M	3.1%	706	10.9%	13.9%	1.6%	7.2%	26.1%	66.3%	28.5%	71.5%
Specialized Units										
SHIELD	12.1%	535	0.9%	2.1%	0.0.%	7.5%	63.4%	63.0%	9.9%	90.1%
Canine	10.6%	236	1.7%	14.0%	0.4%	5.5%	22.9%	84.3%	19.9%	80.1%

Table 5.2 details discretionary searches at the Station level.[45] Across stations, there is considerably more variability in stops that result in discretionary searches. Twenty-one stations conducted discretionary searches during 1% or fewer traffic stops, with the highest proportion of stops resulting in discretionary searches occurring in Blooming Grove (6.0%).

At the station level, there is also variability in the reasons for discretionary searches. Although specific information regarding the reason for the search is provided at the station level in Table 5.2, due to the small number of discretionary searches conducted in many stations, these percentages need to be interpreted with caution. Across most stations, verbal consent was more likely to be given than written consent (80 of 87 stations), and 11.5% of stations reported zero discretionary searches based on written consent (10 of 87 stations). Besides consent, several other reasons for discretionary searches were provided and the frequency of each being reported varied widely.

[45] PSP Members assigned to Highspire Station in Troop T, which is the Turnpike Commission Building, did not conduct any searches in 2022. Therefore, Highspire Station is excluded from all station-level tables throughout Section 5.

Table 5.2: Area I Search Reasons by Station, 2022

	% of Stops Resulting in Disc Search	Total # of Disc. Searches	Officer Safety (Terry)	Plain View	Prob Cause + Exigency	Search Warrant	Written Consent	Verbal Consent	Type II (RS/PC)	Type III (Consent-Only)
Troop B										
Belle Vernon	5.6%	285	9.8%	9.1%	1.8%	6.3%	3.5%	88.4%	23.2%	76.8%
Pittsburgh	1.5%	105	7.6%	25.7%	13.3%	3.8%	3.8%	74.3%	43.8%	56.2%
Uniontown	4.1%	473	6.1%	8.0%	2.5%	3.6%	6.6%	85.8%	17.8%	82.2%
Washington	3.5%	148	6.1%	14.2%	8.1%	8.8%	2.0%	78.4%	31.8%	68.2%
Waynesburg	2.0%	48	35.4%	14.6%	0.0%	10.4%	2.1%	50.0%	56.3%	43.8%
Troop C										
Clarion	0.2%	6	16.7%	16.7%	16.7%	16.7%	0.0%	83.3%	33.3%	66.7%
Clearfield	1.6%	63	7.9%	9.5%	3.2%	11.1%	6.3%	84.1%	30.2%	69.8%
Dubois	0.5%	15	6.7%	20.0%	0.0%	20.0%	20.0%	40.0%	46.7%	53.3%
Lewis Run	3.2%	129	3.9%	26.4%	0.0%	4.7%	19.4%	74.4%	32.6%	67.4%
Marienville	0.9%	23	0.0%	17.4%	4.3%	8.7%	21.7%	82.6%	26.1%	73.9%
Punxsutawney	2.8%	97	24.7%	9.3%	0.0%	11.3%	15.5%	66.0%	41.2%	58.8%
Ridgway	0.7%	21	4.8%	23.8%	9.5%	4.8%	23.8%	66.7%	33.3%	66.7%
Troop D										
Beaver	1.9%	70	2.9%	2.9%	1.4%	5.7%	1.4%	92.9%	12.9%	87.1%
Butler	4.6%	285	23.2%	28.1%	3.2%	7.4%	4.9%	67.0%	51.9%	48.1%
Kittanning	4.8%	378	4.5%	12.4%	1.9%	4.5%	2.6%	87.3%	21.7%	78.3%
Mercer	1.5%	48	16.7%	20.8%	6.3%	6.3%	16.7%	81.3%	37.5%	62.5%
New Castle	5.8%	154	6.5%	7.8%	5.2%	1.3%	4.5%	89.6%	17.5%	82.5%
Troop E										
Corry	0.8%	23	4.3%	8.7%	0.0%	21.7%	13.0%	60.9%	30.4%	69.6%
Erie	1.4%	132	15.9%	22.7%	1.5%	6.8%	13.6%	70.5%	43.2%	56.8%
Franklin	2.7%	58	3.4%	20.7%	5.2%	12.1%	70.7%	62.1%	34.5%	65.5%
Girard	0.8%	52	17.3%	15.4%	15.4%	3.8%	11.5%	55.8%	46.2%	53.8%
Meadville	4.2%	154	14.9%	7.8%	4.5%	2.6%	8.4%	86.4%	24.7%	75.3%
Warren	0.2%	7	0.0%	71.4%	0.0%	0.0%	0.0%	42.9%	71.4%	28.6%

Table 5.2: Area II Search Reasons by Station, 2022

	% of Stops Resulting in Disc Search	Total # of Disc. Searches	Officer Safety (Terry)	Plain View	Prob Cause + Exigency	Search Warrant	Written Consent	Verbal Consent	Type II (RS/PC)	Type III (Consent-Only)
Troop A										
Ebensburg	0.5%	9	22.2%	33.3%	11.1%	0.0%	0.0%	44.4%	55.6%	44.4%
Greensburg	2.8%	132	15.9%	12.1%	3.0%	4.5%	21.2%	68.9%	31.8%	68.2%
Indiana	1.6%	109	1.8%	7.3%	0.9%	7.3%	3.7%	83.5%	16.5%	83.5%
Kiski Valley	1.4%	19	5.3%	26.3%	5.3%	10.5%	26.3%	57.9%	36.8%	63.2%
Somerset (A)	2.1%	69	7.2%	10.1%	1.4%	8.7%	15.9%	75.4%	27.5%	72.5%
Troop G										
Bedford	2.1%	104	3.8%	5.8%	0.0%	4.8%	30.8%	68.3%	13.5%	86.5%
Hollidaysburg	2.9%	124	0.8%	6.5%	1.6%	4.0%	18.5%	85.5%	12.9%	87.1%
Huntingdon	1.1%	43	7.0%	16.3%	0.0%	14.0%	7.0%	79.1%	32.6%	67.4%
Lewistown	1.4%	58	5.2%	24.1%	10.3%	10.3%	6.9%	75.9%	43.1%	56.9%
McConnellsburg	2.4%	83	3.6%	4.8%	0.0%	1.2%	16.9%	85.5%	8.4%	91.6%
Rockview	3.1%	236	3.8%	6.8%	3.8%	8.1%	35.2%	66.1%	19.9%	80.1%
Troop H										
Carlisle	2.7%	298	15.4%	10.4%	2.7%	8.4%	13.8%	73.8%	31.9%	68.1%
Chambersburg	1.2%	155	7.1%	14.8%	1.9%	5.8%	8.4%	80.0%	27.7%	72.3%
Gettysburg	2.7%	234	6.4%	7.7%	2.1%	0.9%	3.4%	88.5%	16.2%	83.8%
Harrisburg	5.4%	518	3.9%	6.0%	0.6%	9.3%	11.2%	78.0%	18.5%	81.5%
Lykens	2.7%	79	12.7%	15.2%	1.3%	6.3%	1.3%	84.8%	27.8%	72.2%
Newport	4.3%	162	21.6%	6.2%	2.5%	6.2%	8.0%	78.4%	35.2%	64.8%
Troop T										
Bowmansville	0.1%	3	33.3%	0.0%	0.0%	0.0%	0.0%	66.7%	33.3%	66.7%
Everett	0.4%	27	0.0%	25.9%	0.0%	29.6%	40.7%	44.4%	40.7%	59.3%
Gibsonia	0.1%	6	33.3%	0.0%	16.7%	0.0%	0.0%	50.0%	50.0%	50.0%
King of Prussia	0.1%	8	37.5%	50.0%	0.0%	0.0%	0.0%	62.5%	75.0%	25.0%
New Stanton	0.2%	13	46.2%	15.4%	7.7%	7.7%	0.0%	53.8%	53.8%	46.2%
Newville	0.6%	23	13.0%	21.7%	4.3%	8.7%	34.8%	60.9%	47.8%	52.2%
Pocono	0.2%	9	0.0%	11.1%	0.0%	0.0%	0.0%	88.9%	11.1%	88.9%
Somerset (T)	0.4%	24	4.2%	8.3%	4.2%	12.5%	8.3%	70.8%	25.0%	75.0%

Table 5.2: Area III Search Reasons by Station, 2022

	% of Stops Resulting in Disc Search	Total # of Disc. Searches	Officer Safety (Terry)	Plain View	Prob Cause + Exigency	Search Warrant	Written Consent	Verbal Consent	Type II (RS/PC)	Type III (Consent-Only)
Troop F										
Coudersport	1.4%	38	7.9%	21.1%	0.0%	2.6%	18.4%	73.7%	28.9%	71.1%
Emporium	0.6%	8	25.0%	12.5%	0.0%	0.0%	0.0%	100.0%	37.5%	62.5%
Lamar	1.7%	93	1.1%	11.8%	0.0%	11.8%	4.3%	77.4%	23.7%	76.3%
Mansfield	0.8%	19	10.5%	10.5%	0.0%	15.8%	5.3%	84.2%	36.8%	63.2%
Milton	1.2%	97	3.1%	5.2%	0.0%	4.1%	12.4%	84.5%	10.3%	89.7%
Montoursville	2.4%	141	5.7%	12.1%	1.4%	6.4%	13.5%	83.0%	24.1%	75.9%
Selinsgrove	1.0%	37	8.1%	18.9%	0.0%	13.5%	16.2%	75.7%	32.4%	67.6%
Stonington	2.1%	42	2.4%	7.1%	2.4%	7.1%	9.5%	85.7%	19.0%	81.0%
Troop N										
Bloomsburg	2.5%	74	2.7%	10.8%	0.0%	9.5%	18.9%	73.0%	23.0%	77.0%
Fern Ridge	1.9%	112	3.6%	25.0%	5.4%	3.6%	19.6%	61.6%	33.9%	66.1%
Hazleton	1.9%	114	4.4%	12.3%	10.5%	3.5%	7.0%	85.1%	22.8%	77.2%
Lehighton	5.3%	128	5.5%	14.8%	0.0%	7.8%	3.1%	81.3%	26.6%	73.4%
Stroudsburg	3.7%	477	9.2%	9.0%	1.7%	4.8%	5.9%	82.0%	23.1%	76.9%
Troop P										
Laporte	2.7%	55	7.3%	5.5%	0.0%	3.6%	14.5%	89.1%	14.5%	85.5%
Shickshinny	2.3%	47	0.0%	2.1%	8.5%	0.0%	42.6%	61.7%	8.5%	91.5%
Towanda	3.6%	162	9.9%	6.8%	1.2%	8.0%	51.2%	50.6%	24.7%	75.3%
Tunkhannock	2.8%	54	3.7%	13.0%	0.0%	3.7%	24.1%	70.4%	20.4%	79.6%
Wilkes-Barre	1.5%	73	6.8%	13.7%	0.0%	6.8%	28.8%	68.5%	26.0%	74.0%
Troop R										
Blooming	6.0%	294	6.1%	7.5%	1.4%	2.7%	10.2%	83.0%	16.3%	83.7%
Dunmore	2.0%	63	14.3%	41.3%	3.2%	4.8%	73.0%	68.3%	54.0%	46.0%
Gibson	5.8%	232	1.7%	6.0%	0.0%	4.7%	9.5%	86.6%	11.6%	88.4%
Honesdale	0.9%	26	11.5%	19.2%	3.8%	3.8%	0.0%	80.8%	38.5%	61.5%

Table 5.2: Area IV Search Reasons by Station, 2022

	% of Stops Resulting in Disc Search	Total # of Disc. Searches	Officer Safety (Terry)	Plain View	Prob Cause + Exigency	Search Warrant	Written Consent	Verbal Consent	Type II (RS/PC)	Type III (Consent-Only)
Troop J										
Avondale	3.5%	312	20.2%	14.7%	0.6%	7.1%	42.3%	41.7%	36.9%	63.1%
Embreeville	2.3%	170	14.7%	8.2%	2.4%	9.4%	24.1%	70.0%	29.4%	70.6%
Lancaster	3.8%	260	10.0%	15.4%	1.2%	5.8%	53.5%	50.4%	28.8%	71.2%
York	5.2%	482	15.1%	12.2%	1.0%	14.7%	61.0%	33.0%	40.5%	59,5%
Troop K										
Media	4.1%	483	13.5%	12.0%	0.8%	15.5%	15.3%	67.2%	36.6%	63.4%
Philadelphia	5.0%	527	29.8%	10.1%	1.7%	12.7%	4.9%	59.4%	49.3%	50.7%
Skippack	3.4%	163	6.7%	6.1%	1.8%	11.7%	1.8%	79.8%	25.2%	74.8%
Troop L										
Frackville	2.5%	74	1.4%	12.2%	5.4%	0.0%	6.8%	81.1%	18.9%	81.1%
Hamburg	0.5%	12	8.3%	8.3%	0/0%	33.3%	25.0%	41.7%	50.0%	50.0%
Jonestown	4.4%	213	14.1%	5.6%	1.9%	3.3%	34.3%	84.0%	23.0%	77.0%
Reading	3.8%	156	17.3%	13.5%	1.9%	2.6%	40.4%	56.4%	31.4%	68.6%
Schuylkill Haven	3.6%	180	10.0%	5.6%	3.9%	1.7%	44.4%	53.3%	18.3%	81.7%
Troop M										
Belfast	4.7%	181	12.7%	7.2%	1.1%	6.1%	8.8%	80.7%	22.7%	77.3%
Bethlehem	1.3%	59	15.3%	20.3%	3.4%	8.5%	55.9%	40.7%	39.0%	61.0%
Dublin	2.0%	80	27.5%	31.3%	1.3%	12.5%	38.8%	36.3%	56.3%	43.8%
Fogelsville	3.4%	204	7.8%	9.8%	2.5%	1.5%	15.2%	78.9%	20.1%	79.9%
Trevose	4.1%	182	3.8%	15.4%	0.5%	12.1%	40.1%	59.3%	28.0%	72.0%

Search Rates by Drivers' Race/Ethnicity

Descriptive statistics like those presented in Tables 5.1 – 5.2 above tell us how often discretionary searches occur but do not explain the factors that predict when searches are conducted. We now turn to analyses that can better understand the factors associated with discretionary searches. First, bivariate analyses, presented in Tables 5.3 – 5.5 to follow, provide initial descriptions of the relationships between discretionary searches and drivers' race/ethnicity and gender. As noted in Section 4, it is important to recognize that the chi-square statistic used in the analyses below only compares two variables – one predictor variable (drivers' race/ethnicity or gender) and one outcome variable (discretionary search). The bivariate analyses do not consider additional factors that may impact trooper decision-making.

Table 5.3 below demonstrates there were significant differences found across racial/ethnic groups for discretionary searches. Of all Black and Hispanic drivers stopped, 5.5% and 4.6%, respectively, were subject to discretionary searches, compared to 2.2% of White drivers stopped. There were also significant gender differences for discretionary searches, with male drivers significantly more likely to be searched (3.2%) than female drivers (1.9%).

Table 5.3: 2022 Discretionary Searches by Race and Gender for Department and Areas

	Drivers	Total # of stops	% Discretionary search
PSP Dept	White	313,870	2.2%***
	Black	63,455	5.5%
	Hispanic	33,658	4.6%
	Male	294,969	3.2%***
	Female	143,624	1.9%
AREA I	White	86,004	2.4%***
	Black	10,462	5.9%
	Hispanic	1,689	4.3%
	Male	66,706	2.9%***
	Female	36,070	2.2%
AREA II	White	101,494	1.4%***
	Black	17,447	4.7%
	Hispanic	7,542	3.5%
	Male	91,485	2.2%***
	Female	45,112	1.2%
AREA III	White	66,532	2.3%***
	Black	10,150	4.8%
	Hispanic	8,043	3.1%
	Male	61,296	2.9%***
	Female	29,719	1.9%
AREA IV	White	56,230	2.8%***
	Black	24,154	5.7%
	Hispanic	14,786	4.5%
	Male	69,673	4.4%***
	Female	31,429	2.2%

NOTE: Asterisks identify statistically significant chi-square associations. * p < .05 ** p<.01 *** p<.001

As shown in Table 5.3 above, all PSP Areas also demonstrated statistically significant racial/ethnic differences in discretionary search rates, with Black and Hispanic drivers consistently searched at higher rates compared to White drivers. In all PSP Areas, male drivers were also significantly more likely than female drivers to be subject to discretionary searches. These racial/ethnic differences in discretionary searches at the department and Area level are also graphically displayed in Figure 5.1 below.

Figure 5.1: 2022 Percentage of Stopped Drivers Searched, by Race and Gender, for PSP Department and Areas

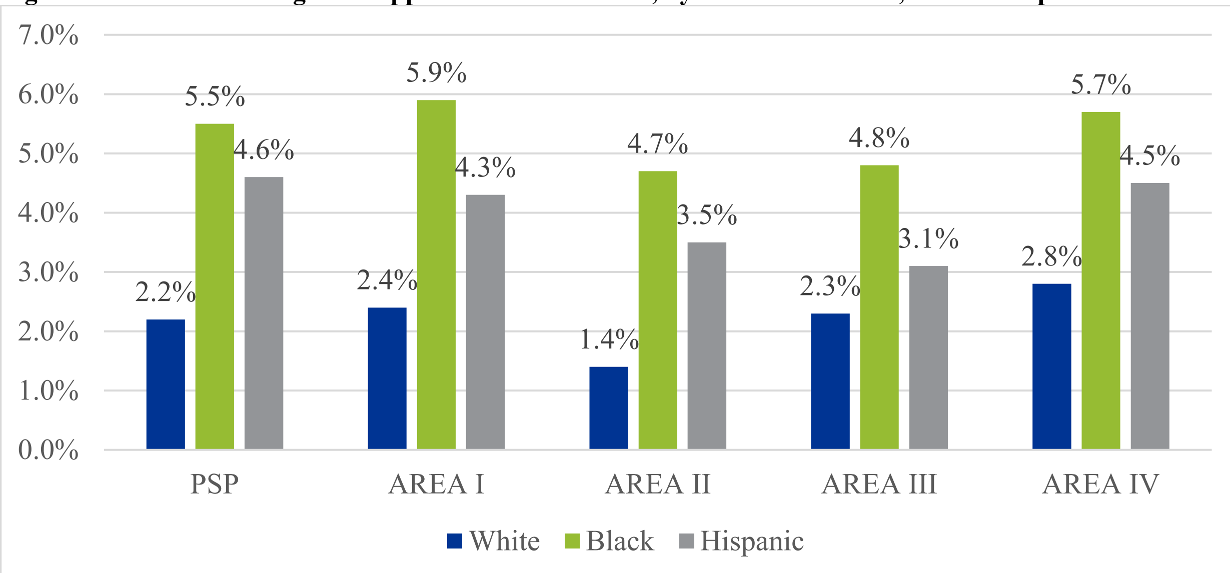


Table 5.4 below documents the differences in discretionary searches across racial/ethnic and gender groups for PSP Troops and specialized units. All 16 Troops and the two specialized units demonstrated statistically significant racial/ethnic differences in the rate of discretionary searches, and in all cases, Black and Hispanic drivers experienced disproportionately more discretionary searches than White drivers. Fifteen of the 16 Troops also indicated statistically significant differences in discretionary search rates for male and female drivers. In all these Troops, male drivers were significantly more likely than female drivers to be subject to discretionary searches.

Table 5.4: 2022 Discretionary Searches by Race and Gender for Troops in Areas I and II

	Drivers	Total # of stops	% search
Area I, Troop B	White	23,536	3.1%***
	Black	4,514	6.6%
	Hispanic	435	4.4%
	Male	19,158	3.8%***
	Female	10,667	3.1%
Area I, Troop C	White	19,775	1.5%***
	Black	846	3.3%
	Hispanic	356	2.5%
	Male	15,204	1.7%
	Female	7,304	1.4%
Area I, Troop D	White	19,550	3.5%***
	Black	2,670	7.7%
	Hispanic	252	7.9%
	Male	14,977	4.3%***
	Female	8,334	3.4%
Area I, Troop E	White	23,143	1.3%***
	Black	2,432	3.5%
	Hispanic	646	3.7%
	Male	17,367	1.9%***
	Female	9,765	1.0%
Area II, Troop A	White	16,132	1.6%***
	Black	1,298	3.9%
	Hispanic	217	10.1%
	Male	11,820	2.2%***
	Female	6,214	1.3%
Area II, Troop G	White	23,761	1.8%***
	Black	2,105	7.5%
	Hispanic	771	4.9%
	Male	18,110	2.7%***
	Female	10,043	1.7%
Area II, Troop H	White	34,855	1.9%***
	Black	7,017	7.9%
	Hispanic	4,246	4.5%
	Male	32,500	3.6%***
	Female	15,742	1.7%
Area II, Troop T	White	26,746	0.2%***
	Black	7,027	0.7%
	Hispanic	2,308	0.5%
	Male	29,055	0.3%**
	Female	13,113	0.2%

NOTE: Asterisks identify statistically significant chi-square associations.
* p < .05 ** p<.01 *** p<.001

Table 5.4: 2022 Discretionary Searches by Race and Gender for Troops in Areas III and IV, SHIELD, and Canine

	Drivers	Total # of stops	% search
Area III, Troop F	White	25,831	1.1%***
	Black	2,660	4.9%
	Hispanic	1,244	4.3%
	Male	20,241	1.8%***
	Female	10,856	1.0%
Area III, Troop N	White	16,996	3.2%***
	Black	4,931	3.9%
	Hispanic	4,906	2.5%
	Male	20,526	3.4%***
	Female	9,361	2.2%
Area III, Troop P	White	12,953	2.4%***
	Black	1,168	5.1%
	Hispanic	747	2.3%
	Male	10,113	2.9%***
	Female	5,158	1.9%
Area III, Troop R	White	10,752	3.6%***
	Black	1,391	7.6%
	Hispanic	1,146	5.2%
	Male	10,416	4.5%**
	Female	4,344	3.4%

	Drivers	Total # of stops	% search
Area IV, Troop J	White	20,133	2.8%***
	Black	6,409	6.9%
	Hispanic	4,450	4.4%
	Male	21,389	4.4%***
	Female	10,742	2.7%
Area IV, Troop K	White	11,416	3.7%***
	Black	11,064	5.3%
	Hispanic	2,262	5.5%
	Male	19,056	5.3%***
	Female	7,855	2.1%
Area IV, Troop L	White	13,046	2.7%***
	Black	2,114	4.4%
	Hispanic	3,601	5.0%
	Male	13,198	3.8%***
	Female	6,296	2.0%
Area IV, Troop M	White	11,635	2.2%***
	Black	4,567	5.3%
	Hispanic	4,473	3.8%
	Male	16,030	3.6%***
	Female	6,536	1.9%

	Drivers	Total # of stops	% search
SHIELD	White	1,913	6.6%***
	Black	725	14.8%
	Hispanic	1,248	19.1%
	Male	3,781	12.8%***
	Female	638	7.7%

NOTE: Asterisks identify statistically significant chi-square associations. * p < .05 ** p<.01 *** p<.001

	Drivers	Total # of stops	% search
Canine	White	1,335	6.9%***
	Black	428	17.8%
	Hispanic	314	19.4%
	Male	1,672	11.8%*
	Female	506	7.7%

Table 5.5 below presents the results of bivariate analyses between drivers' race/ethnicity and discretionary searches at the station level for 2022.[46] As with the bivariate analyses presented in Section 4, the racial/ethnic categories presented in Table 5.5 are restricted to White and non-White because the number of stops of some racial/ethnic groups is too small for individual comparisons at the station level. The "non-White" category includes Black, Hispanic, American Indian/Alaskan Native, and Asian or Pacific Islander drivers.

Of the 88 stations, 57 showed statistically significant differences for discretionary searches. Of the stations with significant differences, Non-Whites were more likely than Whites to be searched for discretionary reasons.

[46] Analyses examining the relationship between drivers' gender and traffic stop outcomes at the station level are not reported but are available from the authors upon request.

Table 5.5: 2022 Discretionary Searches by Race and Gender for Stations in Area I

	Drivers	Total # of Stops	% search
AREA I, Troop B			
Belle Vernon	White	3,718	5.1%***
	Non-White	929	10.2%
Pittsburgh	White	4,754	0.9%***
	Non-White	2,128	2.8%
Uniontown	White	9,521	3.8%***
	Non-White	1,428	7.6%
Washington	White	3,434	2.6%***
	Non-White	634	8.4%
Waynesburg	White	2,106	2.0%
	Non-White	173	3.5%
AREA I, Troop C			
Clarion	White	2,177	0.3%
	Non-White	325	0.0%
Clearfield	White	3,426	1.6%
	Non-White	344	1.5%
Dubois	White	2,408	0.5%
	Non-White	346	0.9%
Lewis Run	White	3,687	2.8%***
	Non-White	204	10.3%
Marienville	White	2,342	0.8%
	Non-White	74	2.7%
Punxsutawney	White	3,402	2.7%*
	Non-White	71	7.0%
Ridgway	White	2,333	0.6%***
	Non-White	113	3.5%

NOTE: Asterisks identify statistically significant chi-square associations.
* p < .05 ** p<.01 *** p<.001

	Drivers	Total # of Stops	% search
AREA I, Troop D			
Beaver	White	2,647	1.4%***
	Non-White	791	3.9%
Butler	White	5,255	4.1%***
	Non-White	503	12.1%
Kittanning	White	6,882	4.4%***
	Non-White	965	8.0%
Mercer	White	2,649	1.1%***
	Non-White	385	4.2%
New Castle	White	2,117	5.2%***
	Non-White	471	9.1%
AREA I, Troop E			
Corry	White	2,814	0.8%
	Non-White	97	1.0%
Erie	White	7,257	1.0%***
	Non-White	1,845	3.3%
Franklin	White	1,822	2.2%***
	Non-White	137	8.8%
Girard	White	5,156	0.7%
	Non-White	1,047	1.2%
Meadville	White	3,234	4.0%**
	Non-White	317	7.3%
Warren	White	2,769	0.2%
	Non-White	84	1.2%

Table 5.5: 2022 Discretionary Searches by Race and Gender for Stations in Area II

	Drivers	Total # of Stops	% search
AREA II, Troop A			
Ebensburg	White	1,678	0.4%*
	Non-White	195	1.5%
Greensburg	White	4,267	2.3%***
	Non-White	450	7.3%
Indiana	White	5,826	1.4%***
	Non-White	717	3.6%
Kiski Valley	White	1,213	1.2%**
	Non-White	114	4.4%
Somerset (A)	White	3,148	1.9%**
	Non-White	174	5.2%
AREA II, Troop G			
Bedford	White	4,386	1.6%***
	Non-White	614	5.7%
Hollidaysburg	White	3,595	2.3%***
	Non-White	457	9.0%
Huntingdon	White	3,523	1.1%
	Non-White	147	1.4%
Lewiston	White	3,517	1.0%***
	Non-White	489	4.7%
McConnellsburg	White	2,552	2.3%
	Non-White	604	3.6%
Rockview	White	6,188	2.3%***
	Non-White	1,216	7.3%

NOTE: Asterisks identify statistically significant chi-square associations.
*p<.05 ** p<.01 *** p<.001

	Drivers	Total # of Stops	% search
AREA II, Troop H			
Carlisle	White	7,920	1.5%***
	Non-White	3,080	5.6%
Chambersburg	White	9,697	0.8%***
	Non-White	2,569	3.1%
Gettysburg	White	6,299	2.0%***
	Non-White	2,151	4.7%
Harrisburg	White	5,170	3.0%***
	Non-White	3,675	9.8%
Lykens	White	2,526	2.5%*
	Non-White	342	4.7%
Newport	White	3,242	3.8%***
	Non-White	454	8.6%
AREA II, Troop			
Bowmansville	White	2,487	0.0%
	Non-White	1,549	0.1%
Everett	White	3,428	0.2%***
	Non-White	1,816	1.0%
Gibsonia	White	4,045	0.0%*
	Non-White	930	0.3%
King of Prussia	White	2,906	0.2%
	Non-White	1,830	0.2%
New Stanton	White	5,695	0.2%
	Non-White	737	0.0%
Newville	White	2,475	0.2%***
	Non-White	1,370	1.2%
Pocono	White	2,857	0.0%***
	Non-White	1,453	0.6%
Somerset (T)	White	2,790	0.3%**
	Non-White	1,193	1.1%

Table 5.5: 2022 Discretionary Searches by Race and Gender for Stations in Area III

	Drivers	Total # of Stops	% search
AREA III, Troop F			
Coudersport	White	2,606	1.5%
	Non-White	70	0.0%
Emporium	White	1,225	0.6%
	Non-White	30	3.3%
Lamar	White	4,199	1.4%***
	Non-White	983	3.3%
Mansfield	White	1,963	0.6%
	Non-White	317	1.3%
Milton	White	6,131	0.7%***
	Non-White	1,473	3.5%
Montoursville	White	4,784	1.4%***
	Non-White	941	7.5%
Selinsgrove	White	3,108	0.9%**
	Non-White	447	2.2%
Stonington	White	1,815	1.3%***
	Non-White	221	8.1%
AREA III, Troop N			
Bloomsburg	White	2,008	2.1%**
	Non-White	657	4.4%
Fern Ridge	White	3,708	1.8%
	Non-White	1,876	2.1%
Hazelton	White	2,635	2.3%
	Non-White	2,525	2.0%
Lehighton	White	1,653	5.9%
	Non-White	451	6.0%
Stroudsburg	White	6,988	4.0%
	Non-White	4,902	3.8%

NOTE: Asterisks identify statistically significant chi-square associations.
* p < .05 ** p<.01 *** p<.001

	Drivers	Total # of Stops	% search
AREA III, Troop P			
Laporte	White	1,811	2.3%***
	Non-White	217	6.5%
Shickshinny	White	1,746	2.1%
	Non-White	287	3.8%
Towanda	White	4,333	3.5%
	Non-White	154	5.8%
Tunkhannock	White	1,710	2.7%*
	Non-White	129	6.2%
Wilkes-Barre	White	3,351	1.1%***
	Non-White	1,212	2.9%
AREA III, Troop R			
Blooming Grove	White	3,487	5.2%***
	Non-White	824	9.6%
Dunmore	White	2,148	1.6%**
	Non-White	860	3.1%
Gibson	White	2,556	6.0%
	Non-White	999	6.8%
Honesdale	White	2,561	0.9%
	Non-White	158	1.9%

Table 5.5: 2022 Stop Outcomes by Race for Stations in Area IV

	Drivers	Total # of Stops	% search
AREA IV, Troop J			
Avondale	White	5,380	2.8%***
	Non-White	3,452	4.7%
Embreeville	White	4,332	1.5%***
	Non-White	2,804	3.6%
Lancaster	White	4,477	2.9%***
	Non-White	2,261	5.8%
York	White	5,944	3.7%***
	Non-White	3,132	8.2%
AREA IV, Troop K			
Media	White	5,143	2.8%***
	Non-White	6,297	5.4%
Philadelphia	White	3,242	5.6%
	Non-White	6,398	5.2%
Skippack	White	3,018	3.3%
	Non-White	1,507	3.8%
AREA IV, Troop L			
Frackville	White	2,055	2.6%
	Non-White	726	2.8%
Hamburg	White	1,666	0.1%***
	Non-White	906	1.1%
Jonestown	White	3,124	3.0%***
	Non-White	1,542	7.5%
Reading	White	2,161	2.8%***
	Non-White	1,880	5.1%
Schuylkill Haven	White	4,040	3.5%
	Non-White	944	4.0%
AREA IV, Troop M			
Belfast	White	1,9722	3.0***
	Non-White	1,799	6.7%
Bethlehem	White	2,026	1.0%*
	Non-White	1,985	1.8%
Dublin	White	2,742	1.8%*
	Non-White	793	3.3%
Fogelsville	White	2,911	2.0%***
	Non-White	2,919	4.9%
Trevose	White	1,984	3.6%
	Non-White	2,302	4.7%

NOTE: Asterisks identify statistically significant chi-square associations.
* $p < .05$ ** $p<.01$ *** $p<.001$

Predicting Discretionary Searches

As described in Section 4, many factors may influence troopers' decision-making once a traffic stop is made. Multivariate analyses examine the independent effect of these predictor variables while controlling for, or statistically holding constant, the predictive power and influence of the other variables. In Table 5.6 below, the binary logistic regression model examining *discretionary searches* as the outcome compared to stops without discretionary searches is reported.

Table 5.6: Binary Logistic Regression Analyses Predicting Discretionary Searches during traffic stops in 2022

	DISCRETIONARY SEARCHES (n=438,300)		
	Coefficient	**St. Error**	**Odds Ratio**
Intercept	-3.03	.094	--
Legal Measures			
Equipment Only Violation	1.37	.039	3.93
License Only Violation	1.97	.055	7.18
Moving Only Violation	1.34	.036	3.82
Registration Only Violation	1.28	.042	3.60
Other Only Violation	1.76	.048	5.82
Multiple Reasons	1.91	.037	6.77
Special Traffic Enforcement Stop	-0.39	.031	-1.48
Driver Characteristics			
Black Driver	0.62	.023	1.86
Asian/Pacific Islander Driver	-0.09	.080	--
American Indian	-0.29	.206	--
Driver Race Unknown	-0.46	.132	-1.58
Hispanic Ethnicity	0.29	.030	1.34
Male Driver	0.45	.023	1.57
Age of Driver (Years)	-0.02	.001	-1.02
Driver Behavior Civil	-1.21	.036	-3.36
Driver Limited English Proficiency	0.55	.081	1.73
Vehicle Characteristics			
Pennsylvania Plate Registration	-0.39	.025	-1.47
Passengers Present	0.97	.020	2.63
Situational Characteristics			
Daytime	-0.44	.020	-1.56
Weekday (Mon-Thurs)	0.23	.022	1.26
Summer Months (June-August)	0.08	.022	1.09
Interstate	-0.13	.023	-1.14
PSP Member Characteristics			
Male Trooper	0.23	.053	1.26
Non-White Trooper	-0.19	.036	-1.21
3 Years Less Experience	0.27	.021	1.32
Patrol Assignment	-0.53	.038	-1.70
Trooper Rank	0.12	.037	--
Model Fit Statistics			
Nagelkerke R-Square	.135		

*p < .001 Only odds ratios for statistically significant estimates are presented.
Odds Ratios for negative coefficients are calculated as 1/Exp(B), which equates to a value > 1.0, which we include as a negative odds ratio (-). This odds ratio can be interpreted as 'less likely' with the binary outcome.

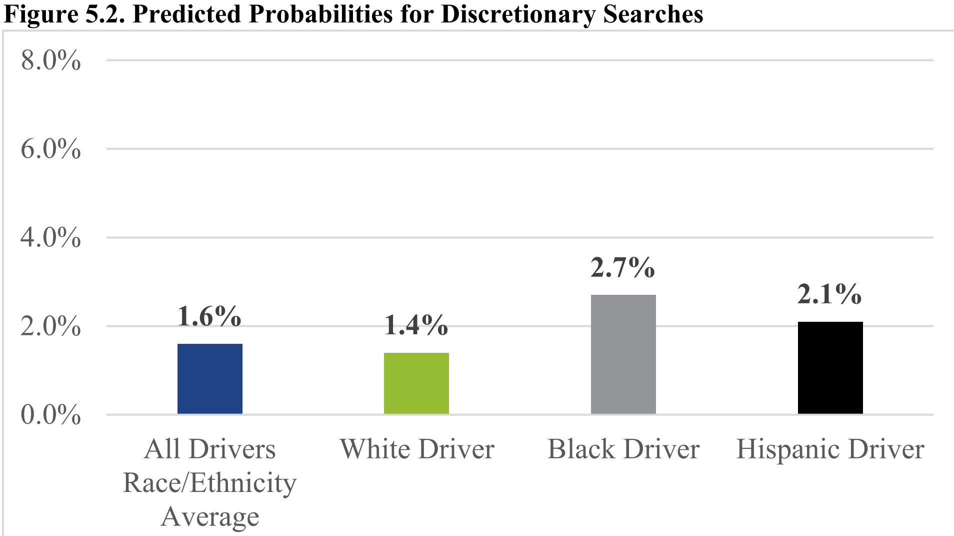
As with warnings, citations, and arrests, the strongest predictors of discretionary searches were the various legal factors related to the stops. Drivers stopped for a license violation were 7.1 times more likely to be searched compared to drivers stopped for speeding. Traffic stops involving multiple violations were 6.7 times more likely to result in a discretionary search compared to stops involving just a speeding violation. Finally, "other" violations were also more likely to result in a discretionary search (5.8 times more likely than stops for speeding).

After statistically controlling for other relevant legal and extralegal factors, Black drivers were 1.9 times more likely to be involved in a discretionary search than White drivers. Also, Hispanic drivers were roughly 1.3 times more likely to be involved in a discretionary search than White drivers. Thus, discretionary searches are the only post-stop outcomes conducted by PSP troopers with statistically significant and substantively moderate findings of racial and ethnic disparities that are not explained with other information measured.

The presence of vehicle passengers increased the odds of a discretionary search by 2.6 times. Pennsylvania registered vehicles were 1.4 times less likely to result in a discretionary search, indicating a higher rate of discretionary searchers for out-of-state drivers. Male troopers were 1.2 times more likely than female troopers to conduct discretionary searches. Stops performed by troopers who had three years or less experience were also 1.3 times more likely to result in a discretionary search outcome.

As with other post-stop outcomes, we also examine the predicted probabilities for discretionary searches (see Figure 5.2 below). The likelihood of any driver being involved in a discretionary search based on the estimated regression was 1.6%, however, there were some differences in this likelihood based on the race/ethnicity of the driver(s). Specifically, the likelihood for Black drivers to be searched was 2.7% after considering other factors. Likewise, the likelihood for Hispanic drivers was 2.1%. By comparison, after controlling for other measured predictors, the likelihood for White drivers to be searched was 1.4%. These findings show there remains some substantive differences in the likelihood of being searched across racial/ethnic groups, but the overall likelihood of being searched across all racial/ethnic groups is quite low.

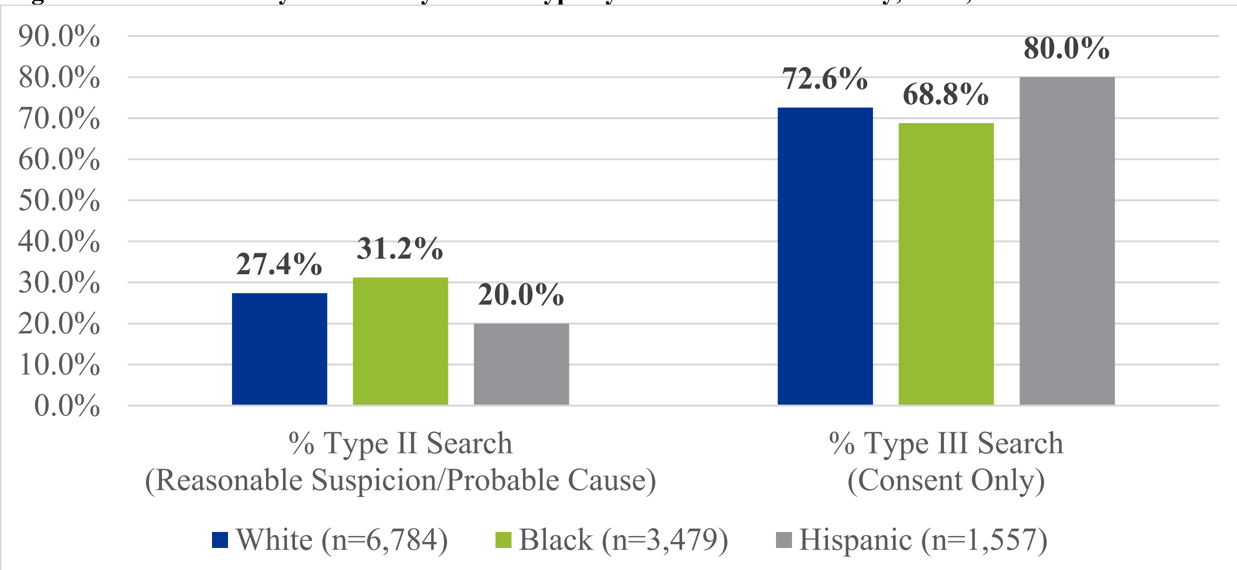
Figure 5.2. Predicted Probabilities for Discretionary Searches



Racial/Ethnic Differences in Discretionary Search Rates by Type of Search

To better understand the racial/ethnic disparities reported for the likelihood of traffic stops resulting in a discretionary search, we now return to a discussion of the types of searches. Specifically, the difference across racial/ethnic groups are examined within the two categories of discretionary searches (Type II – reasonable suspicion/probable cause, and Type III – consent only) are graphically displayed in Figure 5.3 below and reported later in Table 5.7. The results show differences in the percentages of discretionary search types across racial/ethnic groups. Specifically, Black drivers were the most likely to be searched based on reasonable suspicion or probable cause and Hispanic drivers were most likely to be searched based on consent.

Figure 5.3. Discretionary Searches by Search Type by Drivers' Race/Ethnicity, n=12,236



As shown in Table 5.7 below, gender differences were also evident. Across the department, Type II searches were more likely to be conducted on males, while female drivers were significantly more likely than male drivers to be searched based on consent.

At the Area level, significant differences in Type II searches were seen in Areas II, III, and IV, where Black drivers who were searched were more likely to be searched based on probable cause/reasonable suspicion compared to White and Hispanic drivers who were searched. Statistical significance was also seen in Areas II, III, and IV for Type III searches, where Hispanic drivers who were searched were significantly more likely to be searched based solely on consent compared to searched White and Black drivers. No significant racial differences were found in Area I.

Males were more likely than females to be the subjects of Type II searches in Areas I, II, and III, while females were more likely than males to be the subjects of Type III searches in Areas I, II and III. No significant gender differences were found in Area IV.

Within the Canine unit, statistically significant differences were observed for both Type II and Type III searches. Black drivers were most likely to be searched via Type II searches, while

White and Hispanic drivers were more likely than Blacks to be searched based on consent. There were no statistically significant racial/ethnic or gender differences for SHIELD, nor were there significant gender differences for the Canine unit.

Table 5.7: Reasons for Search (by search type) by Driver Characteristics (Department, Area, and Specialized Units), n=12,236[47]

	Drivers	Total # of Discretionary Searches	% Type II Search (Prob Cause/ Reas Susp)	% Type III Search (Consent Only)
PSP Dept	White	6,784	27.4%***	72.6%***
	Black	3,479	31.2%	68.8%
	Hispanic	1,557	20.0%	80.0%
	Male	9,509	28.3%***	71.7%***
	Female	2,707	23.6%	76.4%
AREA I	White	2,027	29.5%	70.5%
	Black	617	32.4%	67.6%
	Hispanic	72	22.2%	77.8%
	Male	1,964	32.2%***	67.8%***
	Female	807	23.9%	76.1%
AREA II	White	1,392	24.0%***	76.0%***
	Black	816	27.3%	72.7%
	Hispanic	263	14.8%	85.2%
	Male	2,009	25.0%*	75.0%*
	Female	535	20.2%	79.8%
AREA III	White	1,538	22.6%*	77.4%*
	Black	491	24.8%	75.2%
	Hispanic	253	16.6%	83.4%
	Male	1,808	23.6%**	76.4%**
	Female	568	17.8%	82.2%
AREA IV	White	1,599	34.1%***	65.9%***
	Black	1,366	36.6%	63.4%
	Hispanic	670	28.1%	71.9%
	Male	3,034	34.3%	65.7%
	Female	706	31.4%	68.6%
SHIELD	White	127	14.2%	85.8%
	Black	107	9.3%	90.7%
	Hispanic	238	8.0%	92.0%
	Male	485	9.5%	90.5%
	Female	49	14.3%	85.7%
Canine	White	92	13.0%***	87.0%***
	Black	76	35.5%	64.5%
	Hispanic	61	13.1%	86.9%
	Male	197	19.8%	80.2%
	Female	39	20.5%	79.5%

NOTE: * p < .05, ** p < .01, *** p < .001

[47] Searches of drivers of other or unknown races (n=416) and unknown gender (n=20) are excluded from these comparisons due to their relative infrequency of occurrence.

Discretionary Searches Resulting in Seizures

It is now instructive to consider the rates of contraband seizures across discretionary searches. As shown in Table 5.8 below, of the 12,236 discretionary searches conducted in 2022, there were 6,561 seizures of contraband. The percentage of discretionary searches that resulted in the seizure of evidence and/or contraband was 53.6% across the department. This seizure rate is considerably higher than rates reported for many other agencies across the country and PSP's historic data. For example, over an almost 20-year period, the North Carolina State Highway Patrol found contraband in 18.1% of searches (Baumgartner et al., 2016). In Texas and Missouri, however, the seizure rate for contraband was 34% and 40%, respectively (Missouri Attorney General's Office, 2022; Texas Department of Public Safety, 2023). In some departments, the seizure rate also varied by race (Sanders et al., 2022; Seguino et al., 2020; Texas Department of Public Safety, 2023). Several states also noted that the overall seizure rates during searches have recently increased across the board, indicating a possible improvement in officer detection.

The seizure rates for discretionary searches varied across PSP Areas, from a high of 59.1% of searches in Area I to a low of 50.4% in Area IV. Of note, Area IV had the highest percentage of stops that resulted in a search, but the lowest seizure rate. At the Troop level, Troop C had the highest percentage of discretionary searches resulting in seizures of evidence/contraband (71.2%), while Troop K had the lowest (39.2%).

Table 5.8 below also documents the types of evidence and/or contraband seized during discretionary searches conducted by PSP troopers. The trends displayed at the department level were, with few exceptions, consistent across Areas and Troops. The majority of contraband seized department-wide was drugs (46.1%) and drug paraphernalia (38.6%), followed distantly by weapons (5.1%), cash (2.1%), and alcohol (1.7%). Note that a single search could produce multiple types of contraband seized; therefore, the sum of percentages in the various categories in Table 5.8 may exceed 100%.

Table 5.8: Types of Evidence Seized by Department, Area, Troop, and Specialized Units (n=6,561)

	Total # of Discretionary Searches	% Disc. Searches w/ Seizure	# of Seizures	% Cash	% Drugs	% Vehicle	% Weapons	% Stolen Prop.	% Alcohol	% Drug-Paraphernalia	% Other
PSP Department	**12,236**	**53.6%**	**6,561**	**2.1%**	**46.1%**	**0.8%**	**5.1%**	**1.0%**	**1.7%**	**38.6%**	**1.4%**
AREA I	**2,775**	**59.1%**	**1,639**	**1.9%**	**50.6%**	**0.8%**	**5.3%**	**1.0%**	**2.2%**	**41.4%**	**0.9%**
Troop B	1,059	50.6%	536	2.1%	43.3%	0.8%	6.4%	0.8%	0.9%	34.6%	0.6%
Troop C	354	71.2%	252	1.4%	56.8%	0.8%	4.0%	1.1%	5.6%	55.9%	2.5%
Troop D	935	63.1%	590	1.8%	54.9%	0.4%	5.0%	1.0%	2.1%	40.4%	0.5%
Troop E	427	61.1%	261	2.3%	54.3%	1.2%	4.0%	1.2%	2.3%	48.5%	0.9%
AREA II	**2,545**	**57.0%**	**1,450**	**2.2%**	**48.5%**	**0.4%**	**5.0%**	**0.8%**	**1.8%**	**42.2%**	**1.5%**
Troop A	338	53.3%	180	2.7%	42.6%	0.0%	4.1%	0.0%	1.5%	35.2%	1.8%
Troop G	648	65.3%	423	1.9%	60.2%	0.2%	3.4%	0.5%	1.7%	54.9%	0.6%
Troop H	1,446	54.7%	791	2.3%	45.1%	0.5%	6.0%	1.0%	1.6%	39.2%	1.7%
Troop T	113	49.6%	56	2.7%	42.5%	1.8%	4.4%	1.8%	6.2%	27.4%	3.5%
AREA III	**2,387**	**58.7%**	**1,401**	**1.7%**	**52.2%**	**0.7%**	**3.9%**	**1.0%**	**1.4%**	**45.1%**	**1.3%**
Troop F	475	58.5%	278	2.5%	50.9%	0.6%	3.8%	1.1%	1.5%	44.8%	1.5%
Troop N	906	59.7%	541	2.1%	53.4%	0.9%	4.3%	0.9%	0.7%	45.6%	1.1%
Troop P	391	50.9%	199	1.0%	45.8%	0.5%	2.8%	1.0%	0.8%	38.1%	1.0%
Troop R	615	62.3%	383	0.8%	55.6%	0.5%	4.2%	1.0%	2.8%	48.9%	1.5%
AREA IV	**3,743**	**50.4%**	**1,887**	**2.0%**	**43.0%**	**1.3%**	**6.4%**	**1.1%**	**1.8%**	**35.7%**	**1.5%**
Troop J	1,224	62.9%	770	1.4%	57.5%	1.0%	4.2%	0.6%	2.5%	49.8%	1.6%
Troop K	1,178	39.2%	462	2.7%	30.9%	1.6%	11.0%	1.7%	1.1%	22.0%	0.9%
Troop L	635	52.0%	330	1.3%	43.9%	0.0%	5.2%	0.8%	1.1%	34.5%	0.9%
Troop M	706	46.0%	325	2.3%	37.0%	2.5%	3.8%	1.6%	2.4%	35.6%	3.0%
Specialized											
SHIELD	535	20.7%	111	5.2%	16.4%	0.6%	2.6%	0.4%	0.0%	7.3%	2.1%
Canine	236	26.7%	63	2.1%	21.6%	0.8%	2.1%	0.8%	0.4%	17.4%	3.0%

Similarly, Table 5.9 below displays seizure rates at the station level. Due to the small number of discretionary searches conducted in many stations, these percentages must be interpreted with caution. The trend present at the department is largely consistent with what is seen across stations. In terms of seizure rates, the highest seizure rates came from Emporium Station (100.0%), Corry Station (91.3%), Pocono (88.9%) and Warren Station (85.7%). There were four stations with seizure rates lower than 40% and two stations with seizure rates lower than 30%. As seen in the Area and Troop level, drugs and drug paraphernalia accounted for the vast majority of evidence/contraband seized at the station level. Drugs were the most likely type of evidence/contraband to be recovered in 66 of the 88 stations.

Like Table 5.8 above, a single search could produce multiple types of contraband seized; therefore, the sum of percentages in the various categories in Table 5.9 may exceed 100%.

Table 5.9: Types of Evidence Seized by Station in Area I

	Total # of Discretionary Searches	% Disc. Searches w/ Seizure	% of Seizures	% Cash	% Drugs	% Vehicle	% Weapons	% Stolen Prop.	% Alcohol	% Drug Para-phernalia	% Other
Troop B	1,059	50.6%	536	2.1%	43.3%	0.8%	6.4%	0.8%	0.9%	34.6%	0.6%
Belle Vernon	285	44.6%	127	3.2%	35.1%	0.7%	7.4%	0.7%	0.7%	33.0%	0.7%
Pittsburgh	105	65.7%	69	1.9%	61.9%	1.9%	6.7%	1.9%	0.0%	24.8%	1.0%
Uniontown	473	46.7%	221	0.8%	40.2%	0.8%	5.5%	0.8%	0.6%	34.2%	0.6%
Washington	148	65.5%	97	4.7%	59.5%	0.7%	8.1%	0.7%	1.4%	45.9%	0.0%
Waynesburg	48	45.8%	22	0.0%	33.3%	0.0%	4.2%	0.0%	6.3%	33.3%	0.0%
Troop C	354	71.2%	252	1.4%	56.8%	0.8%	4.0%	1.1%	5.6%	55.9%	2.5%
Clarion	6	83.3%	5	16.7%	50.0%	16.7%	0.0%	0.0%	0.0%	66.7%	0.0%
Clearfield	63	61.9%	39	0.0%	42.9%	0.0%	3.2%	1.6%	3.2%	46.0%	1.6%
Dubois	15	73.3%	11	0.0%	60.0%	0.0%	13.3%	0.0%	0.0%	53.3%	6.7%
Lewis Run	129	84.5%	109	0.0%	71.3%	0.0%	3.9%	0.8%	9.3%	67.4%	1.6%
Marienville	23	56.5%	13	4.3%	43.5%	8.7%	4.3%	0.0%	4.3%	47.8%	8.7%
Punxsutawney	97	62.9%	61	3.1%	48.5%	0.0%	4.1%	2.1%	4.1%	51.5%	3.1%
Ridgway	21	66.7%	14	0.0%	61.9%	0.0%	0.0%	0.0%	4.8%	42.9%	0.0%
Troop D	935	63.1%	590	1.%	54.9%	0.4%	5.0%	1.0%	2.1%	40.4%	0.5%
Beaver	70	70.0%	49	1.4%	68.6%	1.4%	1.4%	1.4%	0.0%	50.0%	0.0%
Butler	285	61.8%	176	2.1%	53.0%	0.0%	5.6%	1.4%	1.4%	32.6%	0.0%
Kittanning	378	58.2%	220	1.3%	49.2%	0.8%	6.3%	0.5%	2.1%	40.2%	1.1%
Mercer	48	56.3%	27	0.0%	37.5%	0.0%	4.2%	2.1%	4.2%	33.3%	0.0%
New Castle	154	76.6%	118	3.2%	71.4%	0.0%	2.6%	0.6%	3.9%	53.2%	0.6%
Troop E	427	61.1%	261	2.3%	54.3%	1.2%	4.0%	1.2%	2.3%	48.5%	0.9%
Corry	23	91.3%	21	0.0%	73.9%	4.3%	0.0%	0.0%	4.3%	87.0%	0.0%
Erie	132	53.8%	71	5.3%	47.0%	0.8%	3.8%	1.5%	3.0%	41.7%	1.5%
Franklin	58	70.7%	41	0.0%	63.8%	1.7%	3.4%	0.0%	5.2%	50.0%	1.7%
Girard	52	48.1%	25	1.9%	42.3%	1.9%	5.8%	1.9%	0.0%	38.5%	1.9%
Meadville	154	63.0%	97	1.3%	58.4%	0.6%	4.5%	1.3%	1.3%	50.6%	0.0%
Warren	7	85.7%	6	0.0%	57.1%	0.0%	0.0%	0.0%	0.0%	71.4%	0.0%

Table 5.9: Types of Evidence Seized by Station in Area II

	Total # of Discretionary Searches	% Disc. Searches w/ Seizure	% of Seizures	% Cash	% Drugs	% Vehicle	% Weapons	% Stolen Prop.	% Alcohol	% Drug Para-phernalia	% Other
Troop A	338	53.3%	180	2.7%	42.6%	0.0%	4.1%	0.0%	1.8%	35.2%	1.8%
Ebensburg	9	44.4%	4	0.0%	44.4%	0.0%	0.0%	0.0%	0.0%	22.2%	0.0%
Greensburg	132	45.5%	60	3.0%	34.8%	0.0%	6.1%	0.0%	1.5%	27.3%	2.3%
Indiana	109	64.2%	70	3.7%	51.4%	0.0%	3.7%	0.0%	0.9%	42.2%	0.9%
Kiski Valley	19	42.1%	8	0.0%	31.6%	0.0%	0.0%	0.0%	5.3%	31.6%	0.0%
Somerset (A)	69	55.1%	38	1.4%	46.4%	0.0%	2.9%	0.0%	1.4%	42.0%	2.9%
Troop G	648	65.3%	423	1.9%	60.2%	0.2%	3.4%	0.5%	1.7%	54.9%	0.6%
Bedford	104	51.9%	54	1.0%	45.2%	0.0%	0.0%	0.0%	1.0%	48.1%	1.9%
Hollidaysburg	124	59.7%	74	0.8%	54.0%	0.0%	3.2%	0.0%	0.8%	48.4%	0.0%
Huntingdon	43	55.8%	24	4.7%	51.2%	2.3%	0.0%	0.0%	0.0%	48.8%	2.3%
Lewistown	58	84.5%	49	0.0%	79.3%	0.0%	3.4%	0.0%	1.7%	62.1%	0.0%
McConnellsburg	83	67.5%	56	1.2%	65.1%	0.0%	7.2%	0.0%	1.2%	59.0%	0.0%
Rockview	236	70.3%	166	3.0%	65.3%	0.0%	4.2%	1.3%	3.0%	59.3%	0.4%
Troop H	1,446	54.7%	791	2.3%	45.1%	0.5%	6.0%	1.0%	1.6%	39.2%	1.7%
Carlisle	298	57.0%	170	4.4%	49.7%	1.3%	3.7%	0.7%	2.0%	39.9%	2.3%
Chambersburg	155	55.5%	86	5.2%	44.5%	0.6%	9.7%	2.6%	3.2%	34.2%	2.6%
Gettysburg	234	51.7%	121	0.9%	44.4%	0.0%	4.3%	0.0%	2.1%	32.1%	0.4%
Harrisburg	518	45.4%	235	1.7%	38.2%	0.0%	7.9%	1.4%	0.6%	33.4%	1.4%
Lykens	79	73.4%	58	0.0%	51.9%	1.3%	6.3%	1.3%	3.8%	58.2%	1.3%
Newport	162	74.7%	12	0.6%	56.8%	0.6%	3.1%	0.6%	0.6%	62.3%	2.5%
Troop T	113	49.6%	56	2.7%	42.5%	1.8%	4.4%	1.8%	6.2%	27.4%	3.5%
Bowmansville	3	33.3%	1	0.0%	33.3%	0.0%	0.0%	0.0%	0.0%	33.3%	0.0%
Everett	27	77.8%	21	7.4%	77.8%	0.0%	7.4%	7.4%	3.7%	55.6%	14.8%
Gibsonia	6	33.3%	2	0.0%	33.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
King of Prussia	8	62.5%	5	0.0%	50.0%	0.0%	0.0%	0.0%	25.0%	50.0%	0.0%
New Stanton	13	46.2%	6	7.7%	30.8%	0.0%	7.7%	0.0%	0.0%	23.1%	0.0%
Newville	23	26.1%	6	0.0%	13.0%	8.7%	4.3%	0.0%	8.7%	4.3%	0.0%
Pocono	9	88.9%	8	0.0%	77.8%	0.0%	0.0%	0.0%	11.1%	11.1%	0.0%
Somerset (T)	24	29.2%	7	0.0%	25.0%	0.0%	4.2%	0.0%	4.2%	25.0%	0.0%

Table 5.9: Types of Evidence Seized by Station in Area III

	Total # of Discretionary Searches	% Disc. Searches w/ Seizure	% of Seizures	% Cash	% Drugs	% Vehicle	% Weapons	% Stolen Prop.	% Alcohol	% Drug Para-phernalia	% Other
Troop F	475	58.5%	278	2.5%	50.9%	0.6%	3.8%	1.1%	1.5%	44.8%	1.5%
Coudersport	38	84.2%	32	0.0%	76.3%	0.0%	7.9%	0.0%	0.0%	81.6%	0.0%
Emporium	8	100.0%	8	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	87.5%	0.0%
Lamar	93	54.8%	51	1.1%	46.2%	1.1%	4.3%	0.0%	2.2%	22.6%	3.2%
Mansfield	19	57.9%	11	10.5%	47.4%	0.0%	5.3%	0.0%	0.0%	47.4%	0.0%
Milton	97	49.5%	48	2.1%	46.4%	0.0%	0.0%	2.1%	0.0%	39.2%	0.0%
Montoursville	141	58.9%	83	2.8%	51.8%	1.4%	6.4%	1.4%	2.1%	47.5%	2.8%
Selinsgrove	37	59.5%	22	2.7%	45.9%	0.0%	0.0%	0.0%	2.7%	54.1%	0.0%
Stonington	42	54.8%	23	4.8%	42.9%	0.0%	2.4%	2.4%	2.4%	47.6%	0.0%
Troop N	906	59.7%	541	2.1%	53.4%	0.9%	4.3%	0.9%	0.7%	45.6%	1.1%
Bloomsburg	74	63.5%	47	1.4%	59.5%	0.0%	2.7%	0.0%	0.0%	37.8%	1.4%
Fern Ridge	112	65.2%	73	0.9%	60.7%	0.0%	0.9%	0.0%	1.8%	40.2%	0.9%
Hazleton	114	52.6%	60	1.8%	45.6%	1.8%	7.0%	1.8%	1.8%	46.5%	0.9%
Lehighton	128	65.6%	84	2.3%	58.6%	1.6%	3.9%	0.8%	0.0%	52.3%	0.8%
Stroudsburg	477	57.9%	276	2.5%	51.2%	0.8%	4.8%	1.0%	0.4%	46.1%	1.3%
Troop P	391	50.9%	199	1.0%	45.8%	0.5%	2.8%	1.0%	0.8%	38.1%	1.0%
Laporte	55	52.7%	29	0.0%	47.3%	1.8%	0.0%	0.0%	0.0%	40.0%	0.0%
Shickshinny	47	51.1%	24	0.0%	51.1%	0.0%	2.1%	0.0%	0.0%	42.6%	0.0%
Towanda	162	46.3%	75	1.2%	39.5%	0.0%	1.2%	0.6%	1.2%	36.4%	1.9%
Tunkhannock	54	61.1%	33	0.0%	57.4%	0.0%	1.9%	0.0%	0.0%	51.9%	1.9%
Wilkes-Barre	73	52.1%	38	2.7%	46.6%	1.4%	9.6%	4.1%	1.4%	27.4%	0.0%
Troop R	615	62.3%	383	0.8%	55.6%	0.5%	4.2%	1.0%	2.8%	48.9%	1.5%
Blooming Grove	294	53.7%	158	1.0%	45.2%	0.3%	4.8%	0.7%	1.0%	37.8%	1.4%
Dunmore	63	73.0%	46	0.0%	68.3%	0.0%	7.9%	1.6%	7.9%	58.7%	3.2%
Gibson	232	69.0%	160	0.9%	63.4%	0.4%	3.0%	1.3%	3.0%	58.6%	1.3%
Honesdale	26	73.1%	19	0.0%	73.1%	3.8%	0.0%	0.0%	7.7%	65.4%	0.0%

Table 5.9: Types of Evidence Seized by Station in Area IV

	Total # of Discretionary Searches	% Disc. Searches w/ Seizure	% of Seizures	% Cash	% Drugs	% Vehicle	% Weapons	% Stolen Prop.	% Alcohol	% Drug Para-phernalia	% Other
Troop J	1,224	62.9%	770	1.4%	57.5%	1.0%	4.2%	0.6%	2.5%	49.8%	1.6%
Avondale	312	47.4%	148	1.9%	43.6%	1.6%	3.5%	1.0%	3.2%	40.7%	1.9%
Embreeville	170	70.0%	119	0.0%	63.5%	1.2%	5.9%	1.2%	1.2%	55.3%	0.6%
Lancaster	260	60.8%	158	1.2%	54.6%	1.5%	3.1%	0.8%	2.7%	50.8%	1.5%
York	482	71.6%	345	1.7%	66.0%	0.2%	4.8%	0.0%	2.5%	53.1%	1.9%
Troop K	1,178	39.2%	462	2.7%	30.9%	1.6%	11.0%	1.7%	1.1%	22.0%	0.9%
Media	483	44.9%	217	2.5%	35.0%	2.1%	12.8%	2.7%	1.9%	32.7%	1.7%
Philadelphia	527	33.0%	174	3.0%	25.6%	1.5%	10.1%	0.9%	0.6%	12.1%	0.4%
Skippack	163	42.3%	69	1.8%	35.6%	0.6%	8.0%	1.2%	0.6%	22.1%	0.6%
Troop L	635	52.0%	330	1.3%	43.9%	0.0%	5.2%	0.8%	1.1%	34.5%	0.9%
Frackville	74	40.5%	30	0.0%	32.4%	0.0%	1.4%	0.0%	2.7%	29.7%	2.7%
Hamburg	12	66.7%	8	0.0%	58.3%	0.0%	0.0%	0.0%	16.7%	25.0%	8.3%
Jonestown	213	51.2%	109	0.9%	44.6%	0.0%	3.8%	0.9%	0.5%	40.8%	0.5%
Reading	156	61.5%	96	2.6%	54.5%	0.0%	9.6%	1.3%	0.6%	34.0%	1.3%
Schuylkill	180	48.3%	87	1.1%	37.8%	0.0%	5.0%	0.6%	0.6%	30.0%	0.0%
Troop M	706	46.0%	325	2.3%	37.0%	2.5%	3.8%	1.6%	2.4%	25.6%	3.0%
Belfast	181	40.3%	73	1.1%	33.7%	4.4%	2.2%	2.2%	1.7%	34.3%	2.2%
Bethlehem	59	54.2%	32	0.0%	47.5%	1.7%	5.1%	0.0%	1.7%	37.3%	0.0%
Dublin	80	68.8%	55	0.0%	58.8%	2.5%	3.8%	1.3%	3.8%	58.8%	5.0%
Fogelsville	204	35.8%	73	2.0%	29.4%	1.0%	3.4%	0.5%	1.0%	25.5%	1.0%
Trevose	182	50.5%	92	5.5%	35.7%	2.7%	5.5%	2.7%	4.4%	37.4%	6.0%

Information regarding the seizure rates of different types of discretionary searches is further summarized below. In Table 5.10 below, seizure rates for Type II (reasonable suspicion/probable cause) and III (consent only) searches are displayed. As illustrated in Table 5.10, the department-wide seizure rate for all discretionary searches was 53.6%. Type II searches based on probable cause/reasonable suspicion had a seizure rate of 74.0%, while Type III searches based on consent had a seizure rate of 45.9%. Again, these high seizure rates are among the highest reported across the country.

These high seizure rates were also evident at the Area and Troop levels. Across all four Areas, reasonable suspicion / probable cause searches were the most likely to result in the seizure of contraband. Area III had the highest Type II seizure rate (81.4%) and Type III (consent) seizure rate (52.2%). Area IV had the lowest seizure rate for both types of searches.

At the Troop level, Type II searches had the highest seizure rate in terms of recovering contraband in all sixteen Troops. The Troop with the highest Type II seizure rate was Troop G (87.8%), while the troop with the lowest Type II seizure rate was Troop K (57.5%). Type III searches were the least likely to result in the seizure of contraband in all sixteen Troops; Troop C had the highest Type III seizure rate (64.9%), and Troop K had the lowest (26.7%).

The overall seizure rate for the SHIELD (20.7%) and Canine (26.7%) units were lower than the overall seizure rate for discretionary searches at the department level. For the SHIELD unit, 88.7% of Type II searches resulted in the seizure of contraband but only 13.3% of Type III searches. Alternatively, for the Canine unit, 57.4% of Type II searches result in seizure, compared to 19.0% of Type III searches.

Table 5.10: 2022 Seizure Rates for Discretionary Searches by Reasons for Search by Department, Area & Troop, and Specialized Units

	Total # of Discretionary Searches	Overall Disc. Search Seizure Rate	Type II: Probable Cause/ Reasonable Suspicion Search Seizure Rate	Type III: Consent Search Seizure Rate
PSP Dept.	**12,236**	**53.6%**	**74.0%**	**45.9%**
AREA I	**2,775**	**59.1%**	**76.5%**	**51.6%**
Troop B	1,059	50.6%	75.2%	42.2%
Troop C	354	71.2%	82.9%	64.9%
Troop D	935	63.1%	78.2%	56.5%
Troop E	427	61.1%	70.4%	56.0%
AREA II	**2,545**	**57.0%**	**78.7%**	**50.1%**
Troop A	338	53.3%	72.5%	46.2%
Troop G	648	65.3%	87.8%	60.0%
Troop H	1,446	54.7%	79.5%	46.8%
Troop T	113	49.6%	60.9%	41.8%
AREA III	**2,387**	**58.7%**	**81.4%**	**52.2%**
Troop F	475	58.5%	85.0%	50.8%
Troop N	906	59.7%	79.1%	53.3%
Troop P	391	50.9%	75.6%	44.3%
Troop R	615	62.3%	86.6%	56.5%
AREA IV	**3,743**	**50.4%**	**67.0%**	**41.9%**
Troop J	1,224	62.9%	73.3%	57.2%
Troop K	1,178	39.2%	57.5%	26.7%
Troop L	635	52.0%	70.9%	46.1%
Troop M	706	46.0%	73.1%	35.2%
Specialized Units				
SHIELD	535	20.7%	88.7%	13.3%
Canine	236	26.7%	57.4%	19.0%

As noted above, the seizure rates for discretionary searches conducted in 2022 are much higher than previously reported by the PSP in the data collection period between 2002 and 2010. Due to data quality issues with stops resulting in searches from 2002 – 2005, Figures 5.4 and 5.5 report the current Type II and III seizure rates in comparison to data collected from 2006 to 2010 after the errors were resolved. Figure 5.4 below shows that the highest Type II search rate historically was 48.9% in 2006 in comparison to 74% for 2022. Most years averaged between 35% and 45% seizures for searches based on reasonable suspicion or probable cause. Similarly, Figure 5.5 below shows that the highest Type III search rate historically was 22.5% in 2007 with the normal range of seizures occurring during 18% to 23% of the consent only searches in comparison to nearly 46% in 2022.

Figure 5.4: Percent of Reasonable Suspicion/Probable Cause Searches Resulting in Seizure (2006-2010 compared to 2022)

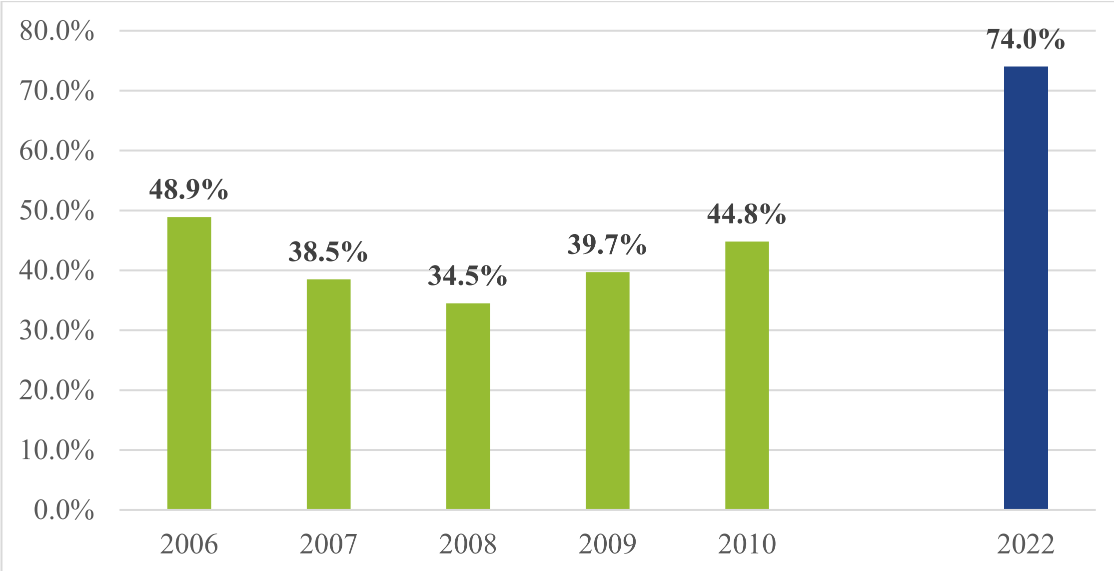
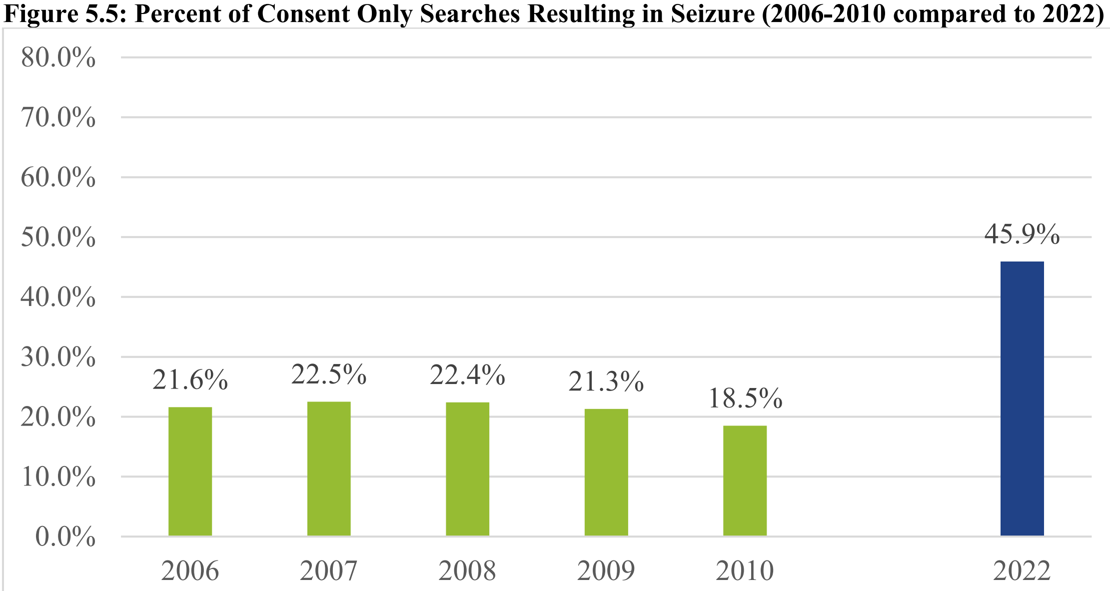


Figure 5.5: Percent of Consent Only Searches Resulting in Seizure (2006-2010 compared to 2022)



Seizure Rates and the Outcome Test

The discovery of contraband during person and vehicle searches is an important outcome to consider when examining potential bias by police officers. Often referred to as search "success rates," or "hit rates" (i.e., the percent of searches conducted that produce contraband and/or resulted in arrest), some researchers use the "outcome test" to identify racial and ethnic disparities by examining differential outcomes in search success rates (Knowles, Persico, & Todd, 2001; Ayres, 2001). Racial/ethnic comparisons of seizure rates are calculated by dividing the percent of searches in which officers seize some type of contraband (e.g., drugs, illegal weapons, etc.) by the number of total searches (Fridell, 2004; Ramirez et al., 2000). Some researchers have suggested that if drivers are searched strictly based on legal factors and suspicions unrelated to race, one would expect similar percentages of searches resulting in seizures across racial groups (Knowles, Persico, & Todd, 2001; Ayres, 2001).

The application of the outcome test to police searches is based on the premise that if officers are profiling minority drivers based on racial prejudice, they will continue to search minorities even when the returns (i.e., the discovery of contraband) are smaller for minorities than the returns for searching Whites (Anwar & Fang, 2006). Conversely, if no bias exists, over a period of time a state of equilibrium will be achieved in which the police will search racial groups proportionate to their actual possession of contraband. The need to include multiple variables (i.e., multivariate model) is removed by reliance on the principle of equilibrium.

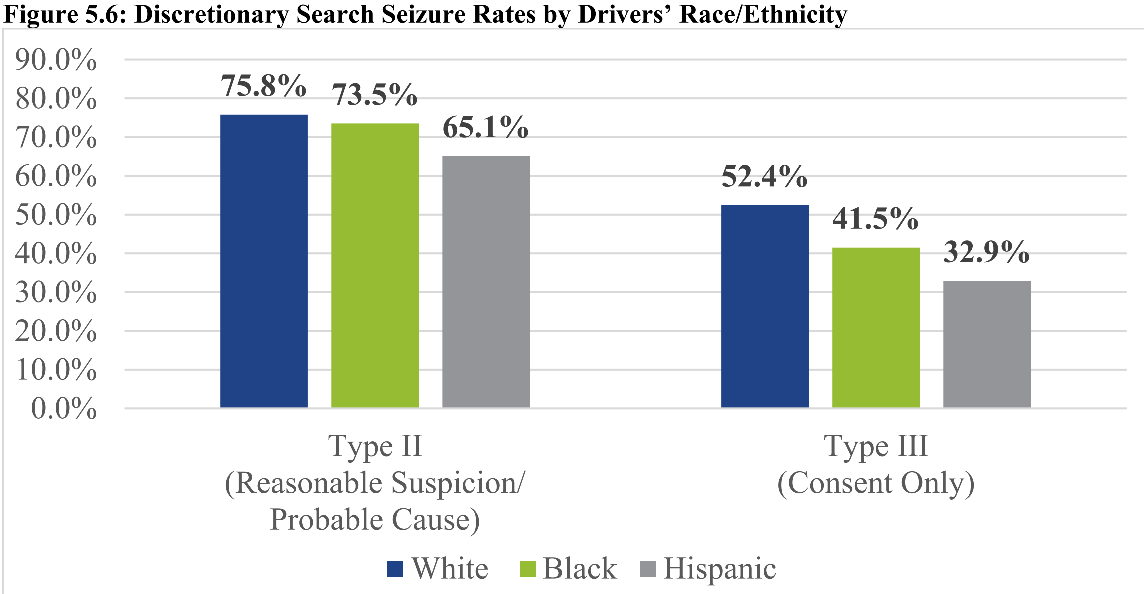
As with other analytical techniques, limitations exist that limit the conclusions that can be drawn from the outcome test (Engel, 2008; Engel & Tillyer, 2008). One of the key assumptions of the outcome test is that officers have full discretion over whether to conduct searches. Using that criterion, the outcome test is only appropriate for an analysis of traffic stops that result in a probable cause/reasonable suspicion search. Mandatory searches should not be considered because troopers are required to perform these searches under certain circumstances. Consent searches are more complex. Although officers initially decide from whom to *request* consent to search, ultimately it is the motorists, not officers, who decide whether or not consent searches are conducted (Fridell, 2004; Engel, 2007). That is, motorists have the right to refuse search requests, and if the trooper has no probable cause to conduct the search, the denial of the request must be honored. Furthermore, previous PSP reports demonstrate that rates for granting consent to search are not equivalent across racial/ethnic groups.

Notwithstanding the limitations of the outcome test, it does provide an alternative method to assess post-stop outcomes. To allow the PSP to better understand consent searches and their productivity, analyses examining racial/ethnic differences in consent seizure rates are provided along with the seizure rates for reasonable suspicion / probable cause searches with the strong caveat that this information be used for purposes of internal comparisons and training only. *No definitive conclusions about racial bias should be drawn from these comparisons* (for details, see Engel, 2008; Engel & Tillyer, 2008). Any racial/ethnic disparities in seizure rates discovered using this method do not necessarily imply trooper bias.

Figure 5.6 and Table 5.11 below display the seizure rates for discretionary searches conducted by PSP troopers in 2022. As shown, there are significant differences in the seizure rates for both types of discretionary searches across drivers' race and ethnicity – with the largest disparities for Hispanic compared to White motorists. The results of the outcome test for race/ethnicity indicate that Hispanic drivers who were searched for probable cause/reasonable suspicion reasons were significantly *less* likely to have contraband seized during a discretionary search compared to searched White and Black drivers, whose seizure rates were similar. Specifically, 75.8% of probable cause/reasonable suspicion searches of White drivers resulted in seizures of contraband, compared to 73.5% for Black drivers and 65.1% for Hispanic drivers.

Similar racial/ethnic differences were evident for consent only searches. Hispanic drivers were the least likely to have contraband seized (32.9%). Further, the difference between White and Black drivers was more pronounced for consent searches compared to the modest differences for reported for reasonable suspicion / probable cause searches. Over half of White drivers subject to consent searches resulted in contraband seized, compared to 41.5% of Black drivers. These findings are consistent with results from other state and local police agencies across the country, as well as previous reports issued for the PSP. Unfortunately, we were not able to further examine the relationship between drivers' race/ethnicity and seizure as we did with other stop outcomes because the multivariate prediction model was unreliable.[48] In short, we do not have good measures of the factors that predict the likelihood of finding contraband during discretionary searches. It is impossible to estimate the true impact that race/ethnicity has on the likelihood of contraband seizures during discretionary searches because stronger factors that predict these outcomes are not measured within the CDR data collection.

Figure 5.6: Discretionary Search Seizure Rates by Drivers' Race/Ethnicity



At the Area level, similar patterns of racial/ethnic differences in seizure rates were also found. Across Areas, modest racial/ethnic and gender differences were reported for probable cause searches; consent only searches reported more pronounced differences across race/ethnicity and gender. Statistically significant racial differences in Type II searches were only found in Area IV, while statistically significant racial differences in Type III searches were found across all four areas. Hispanic drivers were the least likely to have contraband seized in consent-only searches across each Area, while White drivers were the most likely in each Area. In Areas II, III, and IV female drivers were also significantly more likely to have contraband seized in consent-only searches. The SHIELD and Canine units reported only modest contraband seizure

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48 The model predicting whether contraband was seized during discretionary searches is not provided due to several factors: smaller sample size (approximately 12,000), the small Nagelkerke R-Square value (.09), and the instability of the estimates within categories of situational and event characteristics. In short, the model is not robust, is slightly unstable, and does not provide a reliable foundation for estimation.

differences across race/ethnicity and gender of drivers regardless of search type, however these differences were not statistically significant.

Table 5.11: Discretionary Search Seizure Rates by Driver Characteristics

	Drivers	Total # of Discretionary Searches	Total # of Type II Searches	% Type II Search (Prob Cause/ Reas Susp)	Total # of Type III Searches	% Type III Search (Consent Only)
PSP Dept	White	6,784	1,856	75.8%***	4,928	52.4%***
	Black	3,479	1,084	73.5%	2,395	41.5%
	Hispanic	1,557	312	65.1%	1,245	32.9%
	Male	9,509	2,693	73.1%*	6,816	43.8%***
	Female	2,707	639	77.8%	2,068	53.2%
AREA I	White	2,027	597	75.9%	1,430	54.2%***
	Black	617	200	78.5%	417	47.5%
	Hispanic	72	16	62.5%	56	30.4%
	Male	1,964	633	76.5%	1,331	51.3%
	Female	807	193	76.2%	614	52.4%
AREA II	White	1,392	334	78.1%	1,058	55.2%***
	Black	816	223	81.2%	593	45.4%
	Hispanic	263	39	71.8%	224	41.1%
	Male	2,009	502	78.5%	1,507	47.8%***
	Female	535	108	79.6%	427	58.1%
AREA III	White	1,538	347	82.7%	1,191	57.4%***
	Black	491	122	77.0%	369	45.5%
	Hispanic	253	42	81.0%	211	43.6%
	Male	1,808	426	80.0%	1,382	50.2%**
	Female	568	101	88.1%	467	58.0%
AREA IV	White	1,599	545	69.4%*	1,054	48.6%***
	Black	1,366	500	67.8%	866	38.3%
	Hispanic	670	188	59.6%	482	34.2%
	Male	3,034	1,042	65.5%*	1,992	39.6%***
	Female	706	222	74.3%	484	51.7%
SHIELD	White	127	18	88.9%	109	8.3%
	Black	107	10	80.0%	97	11.3%
	Hispanic	238	19	89.5%	219	16.9%
	Male	485	46	89.1%	439	13.2%
	Female	49	7	85.7%	42	14.3%
Canine	White	92	12	75.0%	80	22.5%
	Black	76	27	59.3%	49	24.5%
	Hispanic	61	8	25.0%	53	11.3%
	Male	197	39	59.0%	158	20.3%
	Female	39	8	50.0%	31	12.9%

NOTE: * p < .05, ** p < .01, *** p < .001

SHIELD Training Summary

Given the limitations of quantitative traffic stop data for understanding the complex decision-making in searching a vehicle, the PSP invited the research team to observe training classes to provide context for the CDR data analyses. This allows for an enhanced understanding of the specialized training provided to troopers regarding interdiction of criminal activity on Pennsylvania's roadways.

SHIELD is the *Safe Highways Initiative through Effective Law Enforcement and Detection* program and involves PSP members specially trained to interdict (prevent) criminal activity occurring on major highways. These troopers are strategically deployed across the Commonwealth, emphasizing highway safety through visibility and high-volume traffic stops to identify, disrupt, and dismantle criminal activity and organizations. In addition to the daily work of the SHIELD Section, the members of SHIELD also provide training to PSP members through two training programs. The *Introduction to Criminal Interdiction* training is an 8-hour overview course offered at PSP's regional training centers or the PSP Academy approximately four times per year. *Operation SHIELD* training is a 40-hour comprehensive course provided two to three times per year at the PSP Training Academy. Previous focus groups conducted with PSP troopers in 2005 demonstrated a perceived positive impact of SHIELD training on successful criminal interdiction work (Engel et al., 2007).

The same research team member attended both training classes and observed the delivery of all course content in person. The *Operation SHIELD* training was observed October 17-21, 2022, at the PSP Training Academy, with an off-site half day for scenario practice. A total of 36 participants attended, including four troopers from other state police agencies. The *Introduction to Criminal Interdiction* training was observed March 29, 2023, at PSP's Southeast Regional Training Center. Approximately 40 participants attended, including some local municipal agency officers.

Overview of the Training

A total of 20 instructors delivered the *Operation SHIELD* training throughout the consecutive five-day course, most of whom are current or former SHIELD members. Most training sessions followed a similar format, including PowerPoint-based lectures, group discussions, and video examples. The live-action, scenario-based half-day allowed students to practice skills and apply the knowledge they had gained in the first three days of training. The final day featured a mock suppression hearing with role players.

The training modules include an overview of criminal interdiction, search and seizure case law in Pennsylvania, indicators of possible criminal activity, roadside interviews, conducting consent searches, drug trafficking trends and hidden compartments, commercial motor vehicles, effective report writing, racial profiling awareness, and human trafficking. Students are initially introduced to basic concepts before more advanced material builds upon and reinforce the earlier training content. The *Introduction to Criminal Interdiction* training was delivered by six instructors and addresses most of the same topics in a similar but condensed format, and does not include a scenario-based training component.

Training Evaluation

Although criminal interdiction training is provided to law enforcement across the country, we are not aware of any systematic evaluation of its impact. The PSP invited the Institute research team to examine the impact of PSP's SHIELD training and identify any areas for continued improvement through a mixed-methods approach of direct observation and student surveys. The Institute research team member who observed the training reviewed the provided course materials, took field notes throughout the training delivery, and synthesized her qualitative assessments after the courses concluded. These observations are summarized below.

Qualitative Assessment

The instructors for both training courses were knowledgeable and experienced in a wide range of criminal interdiction topics. They established a good rapport with the troopers in the classroom, and, in turn, the troopers who attended actively participated in group discussions and asked relevant questions. The curricula were organized in a logical sequence that builds upon previous modules and cycles back to earlier training content as context for new material.

The 40-hour course includes a half day of seven role-playing scenarios, with small groups of students cycling through six of the seven scenarios. This training format provided students the opportunity to participate in interactive dialogue and hands-on skill practice in more realistic settings. Each scenario featured an actual vehicle for students to practice searching. The role-play actors maintained their characters and appropriately reacted to trooper questions and behavior throughout the interactions. SHIELD members observed the scenarios and debriefed with students at their conclusion to reinforce various training tenets. Notably, there was at least one video and one role-play scenario where the totality of the stop's circumstances was insufficient for establishing reasonable suspicion to request consent to search. This reinforces the idea that indicators do not always mean criminal activity, and troopers must use their training, roadside interview, and experience to confirm or deny suspicions.

Several recurring themes were emphasized throughout both criminal interdiction training courses. These included:

- Professional, respectful, and friendly treatment of stopped motorists
- Protection of the stopped individuals' legal rights and the case law guiding troopers' conduct of traffic stops
- Behavioral indicators of possible criminal activity, *not* relying on individual characteristics
- Looking beyond the initial traffic stop violation for evidence of any possible criminal activity, not just drug trafficking (i.e., "All Crimes Approach")
- Relying on and articulating the totality of the circumstances
- Establishing a baseline of normal motoring public to identify abnormal activity more easily

Survey Assessment

In addition to the research team's qualitative assessment, the PSP instructors administered in-person paper surveys to training attendees immediately preceding training delivery and at the conclusion of the courses. PSP instructors randomly assigned participants with a numeric code used only to link and compare the pre- and post-training responses to examine changes at the individual level. The survey responses were provided to the research team and later entered into a digital database.

The surveys include questions grouped within eight conceptual areas: views on policing, views on drug enforcement, views on marijuana legalization, perceptions of criminal interdiction, experience with criminal interdiction, openness to training, and perceptions of the specific training attended. Most survey items were designed to measure trooper attitudes, perceptions, and confidence in skills that might be affected by their participation in the training courses. Other survey items were designed to get a baseline measure of attitudes and perceptions that might affect their responses to other survey items, measure their receptivity to training in general, and explore their perceptions of the content, delivery, and impact of the training on their knowledge and confidence. Finally, additional items capturing demographic and job-related characteristics of the survey participants were included.

Preliminary analyses demonstrate the SHIELD training courses are extremely well-received by participants, increase students' knowledge of and confidence with numerous criminal interdiction skills, and effectively dispel stereotypes. Given the small sample size of respondents currently available, however, no detailed analyses are provided in the current report.

A summary presentation was provided to the PSP SHIELD leadership, documenting the qualitative assessment and preliminary analyses. Based on the research team's observations of the 40-hour Operation SHIELD course, some recommendations for improvement were provided, which have already been incorporated into more recent course delivery. These included:

- Identify learning objectives at the beginning of each module and summarize them at the end
- Allow sufficient time for trainees to respond to instructor-posed questions
- Ensure consistency in messaging across all instructors during scenario debriefing
- Keep all presenters' slides up-to-date based on changes in policy, case law, and criminal interdiction trends
- Include a table of contents for the course material provided

At this time, the research team is continuing to collect and analyze survey responses from PSP's ongoing criminal interdiction trainings and will continue to debrief PSP leadership and provide recommendations for training enhancement.

Section Summary

Section 5 documents the research team's analyses of discretionary searches and seizures conducted by PSP troopers in 2022. The research team excluded 3,065 searches required by policy or law (i.e., mandatory searches) from these analyses for two reasons. First, a technical issue with data validation rules led to some mandatory searches (incident to arrest) being undercounted. Second, the "outcome test" examining seizures during searches is only appropriate for searches that involve troopers' discretion to initiate a search.

For the year 2022, PSP troopers conducted 12,236 discretionary searches during 2.8% of all member-initiated traffic stops. The Institute research team used a binary logistic regression model to predict discretionary searches, to isolate the impact of drivers' race/ethnicity controlling for other legal and extralegal factors that are measured by the CDR data collection. We found that the strongest predictors of discretionary searches were the various legal factors related to the stops (e.g., reason for the stop, whether multiple violations were reported). Nevertheless, Black and Hispanic drivers were 1.9 and 1.3 times more likely, respectively, to be involved in a discretionary search than White drivers. Thus, discretionary searches are the only post-stop outcomes conducted by PSP troopers with statistically significant and substantively moderate findings of racial and ethnic disparities that are not explained with other information measured. Although there are significant differences in the odds of discretionary searches across racial/ethnic groups, the overall likelihood of being searched across all racial/ethnic groups is quite low. Specifically, the likelihood for Black drivers to be subject to a discretionary search was 2.7% after considering other factors, compared to 2.1% for Hispanic drivers and 1.4% for White drivers.

Discretionary searches were most commonly based on drivers' verbal and/or written consent (72.7%). Discretionary searches based on reasonable suspicion or probable cause occurred approximately 27% of the time. This is, in part, due to Pennsylvania case law that does not permit motor vehicle searches based on probable cause without a search warrant, unless exigent circumstances apply.

In 2022, 53.6% of the 12,236 discretionary searches conducted by PSP troopers resulted in the seizure of contraband. Type II searches (based on probable cause/reasonable suspicion) had a seizure rate of 74.0%, while Type III searches (based on consent) had a seizure rate of 45.9%. This seizure rate is considerably higher than rates reported for many other agencies across the country and PSP's historic data. The most common types of contraband seized department-wide were drugs (46.1%) and drug paraphernalia (38.6%), followed distantly by weapons (5.1%).

Seizure rates for both types of discretionary searches are significantly different across drivers' race and ethnicity, particularly for Hispanic drivers. Hispanic drivers who were searched for probable cause/reasonable suspicion reasons were significantly *less* likely to have contraband seized during a discretionary search (65.1%) compared to searched White and Black drivers, whose seizure rates were similar (75.8% and 73.5%, respectively).

Similar racial/ethnic differences were evident for consent only searches. Black (41.5%) and Hispanic drivers (32.9%) were significantly less likely than White drivers (52.4%) to have contraband seized. These findings are consistent with results from other state and local police agencies across the country and previous reports issued for the PSP. Unfortunately, data limitations restricted our ability to further examine the relationship between drivers' race/ethnicity and seizure as we did with other stop outcomes. The CDR data collection form cannot measure every factor influencing trooper decision-making and stop outcomes; this is particularly true for predicting the likelihood of finding contraband during discretionary searches. Therefore, we cannot estimate the true impact that race/ethnicity has on the likelihood of contraband seizures during discretionary searches.

Traffic stop data cannot address the legality of individual searches or if statistical disparities are due to racial/ethnic bias or discrimination. PSP patterns of disparities are consistent with several other state police / highway patrol agencies as well as previous reports issued for the PSP. Disparities often persist after considerable training, increased supervision, and data collection improvements, which suggests there are more complex explanations (e.g., organizational culture, policies, societal factors) for disparities than individual trooper or police officer bias.

The research team's observations of PSP criminal interdiction training documents that the training provided to troopers emphasizes professionalism, protection of civil rights, an emphasis on the totality of the circumstances, and behavioral indicators of possible criminal activity rather than individuals' characteristics.

SECTION 6: DISCUSSION & RECOMMENDATIONS

This report documents the findings from statistical analyses of data collected during all member-initiated traffic stops by the Pennsylvania State Police (PSP) from January 1, 2022 – December 31, 2022. It represents the first full year of data collected and substantively analyzed by the research team in over a decade. The final section of this report summarizes how the major findings from the Institute's comprehensive analyses of 441,329 traffic stops relate to the Institute team's recommendations moving forward for consideration by PSP officials.

Recommendations

The Institute research team provides four broad recommendations designed to improve data collection, further examine the patterns and trends in traffic stop enforcement documented in this report, identify opportunities to enhance training, and enhance accountability. Within each of these recommendations, a series of more specific suggestions are provided for consideration.

Recommendation 1: The PSP should continue to refine traffic stop data collection.

The results of the two-phase data audit suggest that the PSP has one of the country's most comprehensive and high-quality traffic stop data collection efforts. The PSP's data collection protocol far exceeds the minimum reporting standards often mandated by state legislation or used by law enforcement agencies voluntarily and includes many data fields that provide important explanatory context for understanding traffic stop outcomes. It also exceeds industry standards for minimizing missing data and logical inconsistencies by auto-populating data fields and using validation rules embedded within the data collection system.

The PSP has quickly responded to previous Institute recommendations for adjustments when data quality issues were identified. For example, several changes have already occurred at the conclusion of 2022 for the 2023 data collection, including adding "Two or More Races" as a response option for the driver race field. The 2023 annual report will examine the impact of this revised field on the percentages of unknown race and ethnicity.

Nevertheless, as data collection continues, the PSP should continue to periodically evaluate the default settings, validation rules, and error warnings in the TraCS data collection system and seek to include additional data fields to continue to enhance the already robust data collection process. Specifically, it is recommended that the PSP:

1.1. Examine the validation rules associated with arrests and searches and ensure proper data collection protocols are followed.

1.2. Adjust the "other" response option for the reason for the stop field to allow manual data entry, as is consistent with best practice recommendations (Pryor et al., 2020). It is important to determine if there is a consistent category within the "other" catchall grouping that could be separately analyzed. This is especially important for the reason for the stop category because:

- 27,730 stops were based on "other" reasons, and 71% of the time, it was the only reason indicated.

- Other reason was a strong predictor of post-stop outcomes, including discretionary searches.
- Troopers may be using this response option when they should be using another response option (i.e., a training issue) or there may be another reason for the stop that should be added (i.e., a data collection issue).

1.3. Consider including additional data fields based on previous PSP data collection and recent best practice recommendations (Pryor et al., 2020). Data fields to consider adding or adjusting include:
- Fields that indicate what was searched – vehicle, driver, and/or passengers.
- Whether consent to search was requested, and if yes, whether it was granted or refused. This information was previously collected by the PSP and demonstrated differences across racial/ethnic groups in their likelihood of giving consent when asked.
- Specify primary and secondary reasons for the stop, or violations observed prior to the stop and subsequent to the stop, to capture the temporal order of events that involve multiple violations.
- Criminal history checked (Yes/No), and if yes, what type of offense (check all that apply = None, Drug, Property, Violent, Traffic/license).

Recommendation 2: The PSP should continue to examine differences in traffic stop patterns and trends across the agency.

The PSP employs over 4,700 troopers and is organized across four Area commands, 16 Troops, and 88 stations. Across virtually all descriptive and bivariate findings in this report, there is wide variation across organizational units in stop characteristics, reasons for the stop, driver characteristics, stop outcomes, and search activity. These differences are to be expected. Several possible explanations for this variation exist, including differences in roadway types, traffic volume, posted speed limits, population density, the demographic makeup of residents and travelers, and motorists' driving and law-violating behavior.

Despite this expected variation, it is important for supervisors at every level within the organization to consider if the patterns and trends identified in this report are consistent with their expectations for these specific units or geographic areas. Any unexplained variations should be immediately addressed.

2.1. PSP Area, Troop, and Station commanders should review the findings documented in this report for the best understanding of trends in racial/ethnic and gender disparities in stop outcomes within their jurisdictions. These commanders' local and organizational knowledge can provide important context to supplement the information provided by the Contact Data Reports.

2.2. Routine supervisory oversight should incorporate information from this report and hold troopers accountable when appropriate.

Recommendation 3: The PSP should continue to explore the content and impact of search and seizure training, particularly SHIELD.

In historical reports to PSP provided between 2002 and 2010, our research team suggested that training designed to reduce individual prejudice would likely not address the core issue of why non-White drivers are disproportionately searched. Instead, it was argued that to change troopers' behavior effectively, the PSP should institute criminal interdiction training related to educating troopers about the complexities of interactions with members of different racial/ethnic groups, conducting more effective roadside interviews, and understanding cultural differences in behavior as they relate to indicators of possible criminal activity.

Based on the research team's independent observations of two specialized criminal interdiction training courses, these previous recommendations have been fully incorporated into PSP's training. The current PSP criminal interdiction training includes a module on racial profiling awareness and mitigating the impact of implicit bias. Throughout the training, instructors emphasize the importance of relying on *behavioral* indicators of possible criminal activity rather than individuals' characteristics. The curriculum also emphasizes the importance of the totality of the circumstances rather than relying on gut instincts or one or two indicators of possible criminal activity. Finally, the training includes a module and scenario-based opportunities for conducting effective roadside interviews.

The research team is unaware of any police agency in the country that has conducted an independent, comprehensive assessment of criminal interdiction training. However, this issue is not unique to criminal interdiction training – generally, police training is rarely systematically evaluated. As noted recently by Skogan and colleagues, "we know virtually nothing about the short- or long-term effects associated with police training of any type" (2015, p. 320). Indeed, this shortcoming has been highlighted by researchers for decades (Buchanan & Perry, 1985; Lum et al., 2016; National Research Council, 2004). Moving forward, it is essential to better understand and systematically assess the impact of police training programs. Strategies based on scientifically grounded research, or evidence, are more likely to successfully achieve the goal of reducing problems in a cost-effective manner (Sherman, 2013).

By allowing the Institute's research team access to examine the content and impact of criminal interdiction training, the PSP is setting a national standard for evidence-based training.

3.1. Continued examination of changes in trainees' knowledge about, perceptions of, attitudes toward, and self-reported use of the tactics and skills taught in criminal interdiction training. This examination should include trainee surveys administered pre-training, immediately post-training, and follow-up after 4-6 months in the field.

- Findings from the data analyses documenting any identified changes pre/post training should be shared directly with SHIELD trainers for continual adjustments and improvements in training content and delivery.

3.2. The PSP should consider examining any observed behavioral differences for those Troopers receiving SHIELD training. For example, examination of traffic stop data for Troopers pre/post training could explore any differences in the volume and rate of traffic stops and post-stop outcomes that would be instructive for training enhancements or modifications.

Recommendation 4: The PSP should continue to enhance accountability mechanisms and oversight of Trooper conduct during traffic stops, particularly for stops that result in consent searches.

The findings of the statistical models examining post-stop outcomes demonstrate that legal variables are the strongest predictors of warnings, citations, arrests, and discretionary searches. This finding is consistent with the larger literature on police behavior that has found legal variables to be the strongest predictors of police behaviors (Huff, 2021; Mastrofski et al., 1995; Riksheim & Chermak, 1993). Furthermore, there is no statistical evidence demonstrating substantive differences across racial/ethnic groups in issuing warnings or citations or conducting arrests during traffic stops conducted by the PSP. This is good news for Commonwealth residents, and the PSP should be applauded for their decades-long efforts to reduce any racial/ethnic disparities.

Despite these efforts, some unexplained racial/ethnic disparities in consent searches and seizures remain. Just as analyses of traffic stop data cannot indicate that police bias *is* the reason for racial/ethnic disparities in outcomes, they also cannot exclude the possibility that bias is a factor. Traffic stop data collection is only one tool for agencies to use to enhance fair and impartial policing practices.

Rather than restrict the practice of consent searches (which yield high rates of contraband seizures across all racial/ethnic groups), the research team recommends that PSP administrators consider the enhancement of the following practices.

4.1. The PSP should continue to investigate complaints of biased behavior, enhance supervision, and ensure that training continues to focus on behavioral indicators of possible criminal activity.

4.2. The PSP should continue to examine trooper compliance with the process for waiver of rights and consent to search form. It is also recommended that PSP executives consider establishing more specific guidelines documenting the circumstances under which it is deemed appropriate for PSP Troopers to request consent to search.

4.3. Field supervisors should be required to routinely examine the situations under which troopers are requesting and conducting searches based solely on consent. For example, a sample of recordings from digital in-car cameras could be reviewed for traffic stops involving person and/or vehicle searches. These recordings could be analyzed to identify patterns in successful and unsuccessful searches to inform future training and policies.

4.4. The PSP should consider expansion of the *Introduction to Criminal Interdiction* and *Operation SHIELD* training where possible. Initial analyses suggest that SHIELD training has positive impacts.

Conclusion

This report has documented that racial and ethnic disparities in traffic stops and post-stop outcomes are rare within the PSP. This is likely due to: 1) increased scrutiny in traffic stops, 2) advances in training, 3) organizational priorities placed on equitable treatment, 4) increased field supervisory oversight, and 5) increased reliability and validity of the traffic stop data itself. While some unexplained racial/ethnic disparities in consent searches remain deserving of further attention, these patterns mirror those reported in many jurisdictions across the country. This suggests that rather than individual police officer or trooper bias, there are larger societal and/or organizational explanations for these disparities. Academics and practitioners around the country are continuing to examine these issues, and the PSP is at the forefront of this critical research.

As demonstrated by their ongoing data collection and analysis and their responsiveness to the Institute research team's recommendations from previous reports, it is clear that PSP officials remain committed to both the data collection effort and the larger goals of reducing racial/ethnic disparities in traffic stops and post-stop outcomes, as well as providing legitimate and unbiased policing services to citizens of the Commonwealth of Pennsylvania. Continual monitoring of traffic stops offers valuable information to the organization while simultaneously institutionalizing a culture that inspires fair and impartial policing.

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APPENDIX A: MULTIVARIATE ANALYSES SENSITIVITY TESTS

As noted in Section 4, regular multivariate analyses are based on one level of data and reflect a one-to-one ratio between variables at that level. That is, variables in most data are independent of other variables. The PSP stop data, however, do not conform to this rule because stops occur within and across 88 PSP stations and within and across 67 counties within the Commonwealth. Thus, the shared characteristics between events within these organizational or geographical units are not independent. Warnings, citations, arrests, and seizures within stops within the same station or county share some characteristics. This scenario is a frequent problem within educational research when trying to assess children's achievements in school independent of school structures (i.e., kids from the same classrooms share the same teacher characteristics; and kids from the same schools share the same school characteristics, etc.). Hierarchical Growth Linear Modeling (HGLM) was specifically designed to handle this shared commonality problem when the outcomes are binary in nature (Raudenbush & Bryk, 2002).

For each outcome examined in this report, we partitioned the outcome variation into individual-level and aggregate-level components consistent with HGLM modeling. The first set of random intercept models indicated the level of variation that existed at the individual and aggregate levels. These results are summarized in Table A.1.

Table A.1. Summary of Sensitivity Tests – Station & County Random Intercept Models

	Sensitivity Test 1: PSP Stations		Sensitivity Test 2: Counties	
Outcome	Individual Level Variation	PSP Station Level Variation	Individual Level Variation	PA County Level Variation
Verbal Warning	81.1%	18.9%	84.9%	15.1%
Written Warning	91.5%	8.5%	94.6%	5.4%
Any Warning	92.2%	7.8%	96.0%	4.0%
Citation	91.1%	8.9%	95.6%	4.4%
Arrest	98.7%	1.3%	99.9%	0.1%
Search	98.4%	1.6%	99.9%	0.1%

The results show that the greatest relative variation at the aggregate levels across each of these outcomes was at the station-level in comparison to the county-level. There was more explained variance at the station than the county level for every outcome modeled, suggesting a greater station than county effect. However, viable station-level measures were unavailable for our analyses. Thus, we chose to conduct HGLM analysis relying on county-level data at level-2 given the large body of evidence that exists in the scholarly literature for these associations.

We drew upon the following county-level data, which were incorporated into all HGLM analyses: total population; % White population; % Black population; % unemployed; % disadvantaged (composite of female headed family households with no husband, % in poverty; # of children per household); at-risk youth population (% 15-24 male)[1]; 2021 crash rates by county[2]; 2021 crime rate by county. None of these measures corresponded with any of the outcomes in any statistically significant, meaningful, or consistent manner, save one relationship. The lone exception was the total population county-verbal warning likelihood (where higher rates of total population at the county-level increased the likelihood that verbal warnings were issued during stops). In all other outcomes, none of these measures mattered in any meaningful way.

The important conclusions about the set of HGLM analyses conducted here is that a) PSP station-level account for more aggregate variation in the outcomes modeled here than do the counties; and b) none of the traditional disadvantage, risk, or crime indicators explains the outcomes of interest in this analysis. At the aggregate level, we truly suffer from model misspecification, which means there are aggregate factors that correspond with the outcomes (e.g., almost 19% of the variation in verbal warnings was observed at the PSP station-level), but that we do not have access to the measures/factors that correspond with these decision-making patterns.

In summary, 81% to 99% of the variation in the various outcomes was at the individual level (i.e., level 1). Indeed, despite the absence of level-2 measures, over 90% of the outcome variation can be explained using level-1 predictors in all but one of the outcomes (verbal warnings). Thus, for parsimony and efficiency we constrain the multivariate analyses in Section 4 to the individual-level (i.e., logistic regressions).