Pennsylvania State Police Traffic Stop Study: 2023 Annual Report January 1 – December 31, 2023

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Robin S. Engel, Ph.D.
Jennifer Calnon Cherkauskas, Ph.D.
Nicholas Corsaro, Ph.D.
Michael Zidar, Ph.D.

Submitted to:
Colonel Christopher Paris
Commissioner, Pennsylvania State Police

Please direct all correspondence regarding this report to RA-PSPCOMM@pa.gov.

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EXECUTIVE SUMMARY

Studying traffic stops is critical to promoting equitable treatment and enhancing community trust in law enforcement. Traffic stops are the most common public contact with police, and officers wield significant discretion in stopping decisions and subsequent enforcement actions. Given the variety of factors involved in police stops and enforcement decisions, it is beneficial for agencies to identify patterns and trends to enhance their ability to interact with the public safely and fairly. The Pennsylvania State Police (PSP) renewed its traffic stop data collection effort in 2021. This work is based on the development of a voluntary traffic stop data collection system by the PSP in 2000 that was implemented from 2001- 2010, with annual studies conducted by members of the current research team. The PSP's voluntary collection and analysis of traffic stop data is consistent with best practice, demonstrates dedication to transparency and accountability to the public, and advances the PSP's commitment to evidence-based policing practices.

This report documents the findings from statistical analyses of data collected during all PSP member-initiated traffic stops from January 1, 2023 – December 31, 2023 (n=449,047). The main body of this report includes department-wide trends and analysis across PSP's four patrol Areas and 16 Troops. To streamline the annual report, analyses for PSP's 88 stations and two specialized units are provided in Appendix A. Information is presented across organizational units to provide PSP officials an opportunity to examine similarities and differences across the department more closely.

Data and Methods

The primary purpose of traffic stop data collection is to provide a mechanism for performing rigorous statistical analyses examining the factors influencing officers' decisions to conduct traffic stops and their associated enforcement outcomes. Of particular public interest is information regarding any differential police enforcement across racial/ethnic groups. To perform analyses examining traffic stops, the data must be reliable, valid, and error-free. Section 2 of this report describes the PSP traffic stop data collection system, which includes fields related to legal reasons for and characteristics of the stop, vehicle, driver, passenger, and trooper. The reintroduction of traffic stop data collection in 2021 required an organizational commitment to ensure its accuracy, With feedback and adjustments throughout 2021 and 2022, the PSP's data collection protocol now far exceeds the minimum reporting standards often mandated by state legislation or voluntarily used by law enforcement agencies. It includes additional data fields that provide important explanatory context for understanding traffic stop outcomes.

Section 2 also provides the methods and results of the research team's two-phase data audit of the PSP data collected in 2023. The results show 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 demonstrates a 96.4% match across the two data sources (Contact Data Report and Computer Aided Dispatch).
- The Phase II data audit demonstrates that most of the data fields examined have either no missing or invalid data or less than 0.005%.

Overall, the data audit findings show that PSP continues to lead the nation with one of the most comprehensive and accurate traffic stop data collection systems. The strength of the data collection process and the quality of the data add confidence regarding the accuracy of the statistical findings reported using these data.

Finally, Section 2 concludes with an in-depth description of the research methods and quantitative statistical analyses the research team uses for this report, which includes descriptive statistics, bivariate analyses, Veil of Darkness analyses, multivariate regression analyses, predicted probabilities, and outcome test analyses.

Description of Traffic Stop Data

Section 3 reports basic summary information describing the 449,047 traffic stops conducted by PSP Troopers throughout 2023. The purpose of descriptive statistics is to document the general trends in traffic stops, but these analyses cannot test various explanations for the trends observed. Considerable variation is reported in stop characteristics, reasons for the stop, and driver characteristics across PSP organizational units. Some 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 occur on a weekday (68%), during the daytime (67%), and on a state highway (55%) or an interstate (34%).
- Most stops last between 1-15 minutes (90%), involve vehicles registered in Pennsylvania (80%), and do not involve passengers (82%).
- The most frequent stop reason is speeding (40%), with an average of 21.5 mph over the posted speed limit. Approximately 9% of drivers are stopped for two or more reasons.
- Most drivers stopped are male (67%), Pennsylvania residents (81%), and display civil behavior towards the PSP Trooper (98%).
- Most drivers stopped are Non-Hispanic White (71.5%), followed by Black (14.9%), Hispanic White (8.8%), Asian or Pacific Islander (2.1%), American Indian or Alaskan Native (0.4%), two or more races (<0.1%), and unknown race and ethnicity 2.3%.

Some traffic stop reports compared the racial/ethnic percentages of stopped drivers to an external data source (or benchmark) 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 capturing factors that influence drivers' likelihood of being stopped. Therefore, this statistical technique is not conducted due to the inherent lack of reliability and validity of all traffic-stop benchmark analyses.

Instead, the research team uses other techniques, including the Veil of Darkness approach, as an alternative to benchmark analysis. This technique uses a subset of stops occurring during the inter-twilight period when natural variation in daylight occurs throughout the year (n=71,919 stops) to explore whether differences exist in the odds of Black or Hispanic drivers being stopped in daylight versus darkness. These analyses reveal that controlling for only PSP Troop, day of the week, time of day, and seasonality, Blacks and Hispanics are only slightly (1.1 times) more likely to be stopped during daylight than during darkness. Despite its statistical significance, this is not a substantively meaningful difference, indicating a lack of evidence that

Black and Hispanic motorists are more likely to be stopped when conditions are more conducive to viewing drivers' characteristics.

Second, there are sometimes concerns raised that certain types of low-level, non-moving violations are disproportionately used against drivers of color for "pretextual" purposes. Although we take no position on whether stops for violations related to equipment, registration, and inspection are being used for pretextual purposes by the PSP or any other law enforcement agency, we explore whether racial/ethnic differences exist across different reasons for the stop. While some statistically significant bivariate differences are noted, substantively, the racial/ethnic differences in stops for violations related to registration, equipment, and inspection are very small.

Based on the analyses conducted using multiple techniques, no substantive racial /ethnic disparities are detected for the initial traffic stop decision,

Traffic Stop Enforcement Outcomes

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

- Across the department:
    - 56.1% of stops resulted in warnings (18.5% verbal, 38.3% written)
    - 58.7% of stops resulted in citations
    - 3.3% of stops resulted in arrests
    - 2.2% of stops resulted in discretionary searches (i.e., searches based on probable cause, reasonable suspicion, or consent, but excluding searches conducted for mandatory reasons, including incident to arrest and inventory for impounded vehicles)
    - The sum of these percentages exceeds 100% because motorists can receive more than one enforcement outcome during a single stop.
- At the department level, substantively small bivariate differences by drivers' race/ethnicity are noted for all outcomes:
    - Warnings are issued to 56.3% of White drivers, 57.3% of Black drivers, and 54.7% of Hispanic drivers stopped
    - Citations are issued to 59.4% of White drivers, 54.7% of Black drivers, and 56.4% of Hispanic drivers stopped
    - Arrests are made of 3.1% of White drivers, 4.8% of Black drivers, and 3.9% of Hispanic drivers stopped
    - Discretionary searches are conducted for: 1.7% of White drivers, 4.2% of Black drivers, and 3.1% of Hispanic drivers stopped

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 are estimated to provide a more thorough and accurate interpretation of the data. Binary logistic regression analyses predicting warnings, citations, arrests, and discretionary searches show that:

- **No substantive differences across racial/ethnic groups of drivers are found for the odds of receiving warnings, citations, or arrests once other explanatory factors are considered.**
- Legal factors (e.g., the reason for the stop, multiple violations, whether evidence is seized, criminal history) are the strongest predictors of whether a traffic stop results in warnings, citations, arrests, or discretionary searches.
- PSP members' demographic characteristics (e.g., Troopers' race/ethnicity, gender) are also not substantively strong predictors of stop outcomes.
- **Discretionary searches are slightly more likely for Black drivers than White and Hispanic drivers.**
    - Once criminal histories are accounted for, Black drivers are 1.46 times more likely to be subject to a discretionary search (a substantively small effect size). There are no significant differences between White and Hispanic drivers' odds of being subject to a discretionary search.
    - The likelihood of being searched is very small across all racial/ethnic groups. Being searched during a traffic stop with a PSP Trooper is a rare event, regardless of drivers' race/ethnicity. The predicted probabilities for discretionary searches indicate that the likelihood of being searched after considering other factors is 1.4% for Black drivers, compared to 0.9% for White drivers and 1.0% for Hispanic drivers. Again, this demonstrates that while there are slight differences in the likelihood of being searched across racial/ethnic groups, the differences are of small magnitude, and not all factors predicting searches are captured in the data.
- **Collectively, these results demonstrate that troopers' decision-making regarding post-stop enforcement outcomes is most strongly based on legal factors and not the characteristics of drivers or troopers, including their race/ethnicity.**

Contraband Seizures

Section 5 focuses on the PSP's seizure activity for discretionary searches conducted during traffic stops in 2023.

- PSP members conducted a total of 19,042 searches during 2023. Of these, 6,531 resulted in the seizure of contraband, which is an overall seizure rate of 34.3%.
- Nearly half of the 19,042 searches are based solely on mandatory reasons for search (i.e., incident to arrest or inventory). Since PSP members have no discretion over whether to conduct those searches, the analyses reported in Section 5 focus on the 9,745 remaining searches involving troopers' discretion (i.e., searches based on probable cause, reasonable suspicion, or consent). In 2023, discretionary searches occurred during 2.2% of all member-initiated traffic stops.
- **The PSP has a very high rate of discretionary searches that result in seizures.** Of the 9,745 discretionary searches, 5,417 resulted in the seizure of contraband – a discretionary

search seizure rate of 55.6% across the department, representing a slight increase from 53.6% of the discretionary searches conducted in 2022.

  - The most common types of contraband seized department-wide include drugs (48.2% of seizures) and drug paraphernalia (30.1%).

- Contraband is seized in 64.4% of traffic stops involving searches based on probable cause/reasonable suspicion and 51.6% of searches based on motorists' consent (verbal or written) without probable cause.
- **Comparisons of seizure rates across racial/ethnic groups show no substantive disparities for searches based on probable cause or reasonable suspicion.**
  - Seizure rates for probable cause / reasonable suspicion searches (n=3,003) demonstrated that searched Hispanic motorists are slightly *less* likely to be found in possession of contraband (58.3%) compared to White (63.5%) and Black (68.6%) drivers, who have similar seizure rates. The difference for Hispanic drivers is of small substantive magnitude. The outcome test analysis used does not consider other factors that may impact contraband detection.
- **Racial/ethnic disparities in seizure rates remain for consent searches of medium effect size.** The racial/ethnic disparities found in consent search seizure rates are significantly lower than historical analyses from 2002 – 2010, indicating PSP's continued improvement in reducing disparities.
  - Seizure rates for consent searches demonstrate that searched Black and Hispanic motorists are *less* likely to be found in possession of contraband (44.1% and 32.4%, respectively) compared to White drivers (61.4%). The differences across racial/ethnic groups are of medium substantive magnitude. This analysis does not account for other factors that may impact contraband detection.
  - Data and methodological limitations restrict the research team's ability to further examine the relationship between drivers' race/ethnicity and contraband seizures.
- These traffic stop data analyses do not 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, suggesting more complex explanations for disparities beyond individual trooper/officer bias.

Recommendations

Informed by the 2023 traffic stop data analyses, the research team provides three broad recommendations designed to improve data collection, further examine the patterns and trends in traffic stop enforcement documented in this report, and identify opportunities to enhance training and strengthen accountability.

Recommendation 1: The PSP should continue to enhance the traffic stop data collection system and analyses.

The PSP has one of the country's most reliable, valid, and comprehensive data collection systems. This is a direct result of the PSP's regular evaluation of the TraCS system's settings and validation rules, the department's responsiveness to data integrity issues that arose in 2021 and 2022, and the department's consideration of research team recommendations for adding new data fields. Therefore, we recommend that the PSP continue these efforts and collaborate with the research team to enhance our analyses to be more relevant and robust for the PSP's traffic enforcement operations, including the possible incorporation of examining traffic accident patterns.

Recommendation 2: Consider additional opportunities for accountability and oversight for impartial treatment during traffic enforcement.

The statistical models' findings examining post-stop enforcement outcomes demonstrate that legal variables most strongly predict warnings, citations, arrests, and discretionary searches. There is no statistical evidence showing substantive differences across racial/ethnic groups for warnings, citations, and arrests. This finding is consistent with extensive literature that finds legal variables to be the strongest predictors of police behaviors.

Some unexplained racial/ethnic disparities remain for discretionary searches and seizure rates during consent searches. Just as analyses of traffic stop data cannot indicate that police bias *is* the reason for racial/ethnic disparities in outcomes, they also cannot eliminate the possibility that bias is a factor. The research team recommends that PSP administrators continue current accountability and oversight practices, particularly routine and specific MVR and BWC footage reviews. The PSP should identify opportunities to enhance or focus accountability and oversight practices even further on requests for consent to search, compliance with the consent waiver process, and trooper behavior and compliance with PSP regulations during consent searches. The PSP is to be commended for its commitment to using BWCs in addition to their in-car recording systems, which are already in place. Research demonstrates that BWC usage during traffic stops improves officer compliance with data collection mandates, procedurally just treatment during encounters, and public perceptions of police legitimacy.

Recommendation 3: The PSP should continue collaborating with the research team to review related training and policies.

The PSP has already voluntarily engaged with the research team in an ongoing evaluation of its criminal interdiction training, which has led to data collection updates, improvements to training, and greater context for the quantitative data analyses. Therefore, the research team recommends that the PSP further collaborate with the research team to review academy training, policies, and procedures related to traffic enforcement, search and seizure, implicit bias, and other topics relevant to traffic stops to identify opportunities to enhance guidance regarding discretionary decision-making.

Conclusion

As demonstrated by PSP's ongoing data collection and analysis and their responsiveness to the research team's recommendations from previous reports, PSP officials remain committed to providing professional and unbiased policing services to the Commonwealth of Pennsylvania's residents and visitors. This report shows that racial and ethnic disparities in traffic stops and post-stop enforcement outcomes are infrequent within the PSP. This is likely due to several factors: 1) heightened scrutiny of traffic stops, 2) improved training, 3) a strong organizational emphasis on fair treatment, 4) enhanced field supervisory oversight, and 5) more reliable and valid traffic stop data. Although some unexplained racial and ethnic disparities in seizure rates from consent searches warrant further examination, these patterns align with those seen in many jurisdictions nationwide. This suggests that some disparities may be driven by broader societal or organizational factors rather than individual biases of police officers or troopers. Researchers and practitioners across the country continue to explore these issues, with the PSP leading in this important research.

1. INTRODUCTION

Studying traffic stops is critical to promoting equitable treatment and enhancing community trust in law enforcement. Traffic stops are the most common public contact with police, and officers wield significant discretion in stopping decisions and subsequent enforcement actions (Schafer & Mastrofski, 2005; Tapp & Davis, 2022). Given the variety of factors involved in police stops and enforcement decisions, it is beneficial for agencies to identify patterns and trends to enhance their ability to interact with the public safely and fairly. The Pennsylvania State Police (PSP) renewed its traffic stop data collection effort in 2021 (Engel & Cherkauskas, 2022). This work was based on the development of a voluntary traffic stop data collection system by the PSP in 2000 that was implemented from 2001- 2010, with annual studies conducted by members of the current research team.[1]

There are several goals for the renewed traffic stop data collection 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 communities it serves, and advances its commitment to evidence-based policing practices.

About the Pennsylvania State Police

The PSP is a full-service law enforcement agency formed in 1905 (PSP, n.d.). They engage in uniform patrol (including interstate and state highway traffic enforcement), vehicle crash investigations, criminal investigations, numerous specialized functions (e.g., emergency response, forensics, aviation, explosives, etc.), and provide primary law enforcement and public safety services in over 1,200 municipalities throughout the state without existing law enforcement agencies (PATrooper.com, n.d.). Colonel Christopher Paris is the current Commissioner of the PSP, leading approximately 4,565 sworn PSP members.

According to the U.S. Census Bureau (Quickfacts, 2023), PSP serves a state-wide population of 12,961,683 residents with a jurisdiction spanning 46,055 square miles. The largest racial/ethnic residential group in the Pennsylvania Commonwealth is White non-Hispanics (74.1%), followed by Blacks or African Americans (12.3%), Hispanic or Latino 8.9%, 4.2% Asian, 2.4% two or more races, 0.5% American Indian and Alaska Native, and 0.1% Native Hawaiian or other

[1] This earlier work was described in the two previous annual reports available here: PSP Contact Data Reporting.

Pacific Islander. Across the Commonwealth's 67 counties, there is tremendous variation in residents' racial/ethnic characteristics (PSDC, 2022). For example, in Philadelphia County, 43.0% of the residents are Black or African American, followed by 23.9% in Delaware County, and 19.1% in Dauphin County 11.1%. On the other hand, several counties have less than 1% Black or African American residents (e.g., 0.5% in Jefferson County, 0.6% in Elk County, and 0.8% in Bedford County).

2022 Report Summary and PSP Response

The *2022 Pennsylvania State Police Traffic Stop Study* documented the findings of descriptive, bivariate, and multivariate statistical analyses of 441,329 stops initiated by PSP members between January 1 and December 31, 2022 (Engel et al., 2023). Descriptive statistics revealed variation in stop characteristics, reasons for the stop, driver characteristics, and stop outcomes across PSP organizational units. Some differences are expected due to variations in the geography, roadways, jurisdiction, traffic flow, and demographic makeup of residents and travelers across the state. Multivariate statistical analyses demonstrated that legal variables (e.g., reason for the stop, multiple violations, evidence seized) were the strongest predictors of all post-stop outcomes. Once other driver, vehicle, and situational characteristics were taken into account, there were no detectable substantive racial/ethnic differences in warnings, citations, and arrests. Unexplained racial/ethnic disparities remain in searches but have decreased compared to analyses between 2002 and 2010. Overall seizure rates have increased, but consent searches had the lowest seizure rates and moderate unexplained disparity by race/ethnicity.

Informed by the 2022 traffic stop data analyses, the research team provided four broad recommendations designed to improve data collection.

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.

> PSP Response: The PSP implemented new validation rules and data fields in response to the 2022 recommendations.

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.

> PSP Response: PSP leadership discussed the findings of the 2022 report with area and troop commanders at the semi-annual command conference held in Bedford,

PA from September 25th to 27th, 2023, and issued guidance for commander to review the provided findings for their specific organizational units.

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 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.

> PSP Response: PSP has continued to voluntarily administer pre-, post-, and follow-up surveys to members who attend criminal interdiction training courses. This allows the research team to continue evaluating trainees' perceptions, knowledge, and self-reported behavior related to the training and identify any potential areas for improvement.

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. 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.

> PSP Response: The PSP currently has several robust accountability mechanisms in place, including: (1) investigation of all complaints of biased behavior, (2) required random supervisory reviews of mobile video recordings (MVR) and body worn camera (BWC) footage, (3) supervisory review of documentation related to consent searches (via audio, video, or written form), and (4) annual training to related to biased-based policing.
>
> Several recent enhancements to these processes are noted below.
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> - February 2023: The PSP required the submission of the Contact Data Report to be completed by a supervisor when a vehicle and/or person is searched, property is seized, or an arrest is made stemming from a

member-initiated traffic stop. This requirement helps immediately bring all searches (including both those with and without contraband seized) to the attention of the relevant supervisors who ensure compliance with PSP policies.

- June 2023: The reporting manual 7-4 was updated with a new form specific to vehicle searches to ensure that the consenting motorists are more fully aware of the specific actions that the PSP may take to search their vehicle if consent is given.
- July 2023 to April 2025: The ongoing rollout of the department's body worn cameras (BWC) continues with eight of the 16 Troops with complete integration. Of importance for traffic stops, BWC technology provides greater insight into the process of requesting and obtaining motorists' consent to search.
- May 2024: A Special Order provided guidance for BWC use and requires monthly supervisor reviews of BWC footage to ensure compliance with applicable regulations.
- An increased number of Internal Affairs Division supervisors have been tasked with BWC review related to evaluating all complaints.
- The PSP agrees that *Operation SHIELD* training and other criminal interdiction classes have a positive effect on interdiction efforts while maintaining positive police-community relations. The department continues to provide as many training opportunities as possible, including slight increases in class sizes to accommodate agency needs. Note, however, that given the hands-on approach and experiential learning embedded within the curriculum, the PSP is appropriately reluctant to expand class sizes any further at the risk of reducing quality instruction.

As demonstrated by PSP's ongoing data collection and analysis and overall responsiveness to the research team's recommendations from previous reports, PSP officials remain committed to providing legitimate and unbiased policing services to citizens of the Commonwealth of Pennsylvania.

2023 Report Outline

This report documents the findings from statistical analyses of data collected during all PSP member-initiated traffic stops from January 1, 2023 – December 31, 2023. The remainder of Section 1 provides an overview of the current report, which is divided into six sections: 1) introduction, 2) description of 2023 traffic stop data collection and data audit, 3) description of traffic stop data, 4) bivariate and multivariate analyses of 2023 post-stop outcomes, 5) seizures during searches, and 6) discussion and recommendations. Each report section presents information at multiple organizational levels, reflecting PSP's patrol organizational structure of four Areas, 16 Troops[2], and 88 Stations.[3] To streamline the annual report, analyses for PSP's 88 stations and two specialized units are provided in Appendix A. Information is presented across organizational units to provide PSP officials an opportunity to examine similarities and differences across the department more closely.

The content of Sections 2 - 6 is described below.

Section 2

Section 2 describes the traffic stop data collection system and the methods and results of a two-phase data audit of the 2023 PSP traffic stop data. The primary purpose of traffic stop data collection is to provide a mechanism for performing rigorous statistical analyses examining the factors influencing officers' decisions to conduct traffic stops and their associated enforcement outcomes. Of particular public interest is information regarding any differential police enforcement across racial/ethnic groups. To conduct analyses examining traffic stops, the data must be reliable, valid, and error-free to ensure accurate analyses. Regardless of the sophistication of the statistical analyses researchers use, the study is only meaningful if the traffic stop data itself is valid. Section 2 concludes with an in-depth description of the research methods and quantitative statistical analyses used by the research team for this report.

Section 3

Section 3 reports basic summary information describing the traffic stops conducted in 2023. Specifically, it provides information derived from the Contact Data Report (CDR), including the number of stops and the frequency of specific characteristics of the stops, including the reasons for the stops and driver characteristics. 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 cannot test various explanations for the trends observed.

Section 4

The analyses of post-stop outcomes (e.g., warnings, citations, arrests, and discretionary searches) are documented in Section 4. First, descriptive statistics are provided, including the frequency of

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[2] A Troop is an administrative boundary containing all the stations in a geographical area spanning several counties. Troops are named with a letter designation. Troop T is a special group of stations whose personnel patrol the PA Turnpike and its related highways (PSP Troop Directory, n.d.).

[3] As of March 2024, a new station called Jefferson Hills has been added to Troop T, bringing the current total number of PSP Stations to 89. However, for the year 2023, there were only 88 stations.

different stop outcomes. Second, differences in drivers' characteristics are summarized for all post-stop outcomes. These initial bivariate analyses demonstrate the association between drivers' race/ethnicity and post-stop outcomes. They are included to describe any differences noted, but they do not consider any other factors that impact the likelihood of stop outcomes. To do this, several multivariate analyses that isolate factors associated with officer decision-making regarding traffic stop outcomes are presented. Section 4 documents whether traffic stop outcomes differ significantly across many factors, including legal variables, driver characteristics, vehicle characteristics, stop characteristics, and trooper characteristics.

Section 5

Section 5 focuses on the PSP's seizure activity during discretionary searches. Discretionary searches include searches based on probable cause / reasonable suspicion and consent but exclude mandatory searches based on policy (e.g., searches incident to arrest or the result of an impounded vehicle). Comparisons of seizure rates (the percentage of searches that result in a contraband seizure) for probable cause/reasonable suspicion searches and consent searches are reported across driver racial/ethnic groups.

Section 6

Section 6 summarizes the main findings from analyses of the 2023 traffic stop data and provides several recommendations designed to continually improve the data collection system and analyses, identify opportunities to continue to enhance accountability and oversight for continued reductions of racial/ethnic disparities, and collaboratively review the training and policies related to traffic enforcement, search and seizure, and implicit bias to ensure equitable enforcement actions during traffic stops.

Appendix A

Appendix A includes station-level tables for Sections 2-5 to permit PSP Area, Troop, and Station Commanders to review the findings documented in this report at the smallest organizational unit.

2. DATA AND METHODS

The PSP developed the current data collection effort in partnership with Drs. Engel and Cherkauskas of the research team. This process was informed by the previous PSP traffic stop studies conducted from 2002 – 2010 and current best practices in the field. Throughout 2021 and 2022, the PSP 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. The results of the research team's two-phase data audit are also included. Finally, Section 2 concludes with an in-depth description of the research methods and quantitative statistical analyses employed by the research team, the findings of which are reported in Sections 3 – 5.

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 2023 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, location, and other relevant context about the stop and vehicle, reason(s) for the stop, driver characteristics, enforcement outcomes, presence of passengers, and characteristics of the PSP member who made the stop. In response to a recommendation in the 2022 report, the PSP added data fields to indicate whether criminal history is queried, and if yes, whether a criminal history is detected. The PSP also added a manual entry data field, as recommended, to capture the reason for the stop when "Other" reason is selected. Of note, the data fields updated or added to the PSP data collection protocol on August 17, 2023 are included in Table 2.1 but are not available for the full year.

Table 2.1 Summary of 2023 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, other (specify in text entry)
	Speeding information	If reason for stop is speeding: Posted speed limit, Driver speed, MPH over limit
	Window Tint	If reason for stop is equipment: window tint Yes/No
Special Enforcement	Special enforcement team	Yes/No
	Dedicated enforcement team	Yes/No (If yes, the Trooper is prompted to select or confirm, if autopopulated, that they are assigned to a troop-dedicated enforcement team, SHIELD, or Canine t
	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, Two or More Races, Unknown
	Ethnicity	Hispanic Origin, Not of Hispanic Origin, Unknown
	Limited English proficiency	Yes/No (If yes, the type of language assistance utilized)
	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, Yes – Towed, 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
	Criminal History Queried and Criminal History Detected	Query: Yes/No, Detected: Yes/No *These fields were introduced in data collection on 8/17/2023.*
	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

Data Audit

Data auditing is important for assessing 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 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 quality of scientific research. Data collection efforts must strive to be both reliable and valid to establish confidence in any statistical analyses performed (Loken & Gelman, 2017).

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 both systematic measurement error (i.e., consistent mistakes within the data collection system) and random measurement error. Random errors naturally find their 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).

The final dataset for 2023 CDR analyses includes 449,047 stops for which PSP Troopers collected data between January 1, 2023, and December 31, 2023. The next section summarizes the results of a two-phase data audit of the CDR data collected in 2023.

Data Audit—Phase 1

Description

Phase 1 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 enforcement 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 Computer Aided Dispatch (CAD), citations, written warnings, video recordings, or other departmental data (Fridell, 2004; Ramirez et al., 2000). In 2004, the Police Executive Research Forum, a police research and policy organization, 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.[4] The reporting standards are almost identical between the two datasets; however, some exclusions are made from the CAD data to ensure an "apples-to-apples" comparison.[5]

Results

The Phase 1 data audit 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 agency-wide and at the Station level. The percent difference represents 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:

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

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

Overall, the results in Table 2.2 show that the percent difference between the two datasets at the department level is –3.6%, indicating that 96.4% 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 is slightly larger 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. **None** of the 88 stations (or specialized units) have differences of 10% or greater; this is an improvement from 2022, where seven stations exceeded a 10% difference. The station-level findings are available in Appendix A.

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[4] 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.

[5] Specifically, to ensure that the comparison includes only trooper-initiated stops in the CAD data, 4,223 motor carrier enforcement-related stops and 423 disabled motorist-related stops are excluded as these are not CDR-required stops. Further, to guarantee that each CAD incident is only counted once, 919 duplicate incidents are excluded. Finally, to ensure that CAD incidents resulted in a stop that would generate a CDR, 200 CAD incidents that involved a pursuit without apprehension and 356 canceled CAD incidents are excluded since they did not result in the stop of an individual.

Data Audit—Phase 2

Phase 2 of the audit for 2023 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 are assessed based on whether they conform to the *CDR Data Dictionary Codebook* guidelines.

Table 2.2 below reports the percentage of missing data and conflicting information for the 2023 CDR data. As noted previously, PERF recommended in its 2004 guide that the missing data rate should be 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 robust. As shown in Table 2.2, all the variables examined do not include or have minimal missing or invalid data. Overall, the data validation built into the TraCS system and the revisions made throughout 2021 and 2022 have minimized error rates.

Table 2.2. Missing and Invalid Data from Member-Initiated Traffic Stops (n=449,047) Jan-Dec 2023

	% Missing	% Invalid
Stop Characteristics		
Date of Contact	<0.01%	0.00%
Time of Contact	0.00%	0.00%
Location of Stop[6]	0.00%	0.00%
Roadway Type	<0.01%	0.00%
Duration of Stop	<0.01%	0.00%
Reason for the Stop[7]	<0.01%	0.00%
Special Traffic Enforcement	<0.01%	0.00%
Dedicated Enforcement Team	<0.01%	0.00%
MCSAP Related	<0.01%	0.00%
Outcome of the Stop		
Warning Type	0.06%	0.00%
Number of Driver Warnings	0.00%	<0.01%
Number of Driver Citations	<0.01%	0.00%
Driver Arrest	<0.01%	0.00%
Valid Search	0.00%	0.00%
Driver Characteristics		
Year of Birth	0.00%	0.06%[8]
Gender	0.00%	0.00%
Race	0.00%	0.00%
Ethnicity	0.00%	0.00%
LEP	<0.01%	0.00%
Behavior/Demeanor	<0.01%	0.00%
Zip Code	0.01%	0.50%[9]
Vehicle Characteristics		
Vehicle State of Registration	0.00%	0.00%
Number of Passengers	<0.01%	0.00%
Trooper Characteristics[10]		
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: <0.01% reflects less than 0.005% missing or invalid data.

[6] 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.

[7] 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.

[8] There were 296 CDRs with dates of birth before 1/1/1921 or after 1/1/2011.

[9] There were 2,226 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.

[10] 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.

Further Exploration of Unknown Drivers' Race, Ethnicity, and Gender

In addition to missing and invalid data, three other data fields have data integrity issues that are not captured in Phase 2 of the data audit. First, although drivers' race, ethnicity, and gender have no missing data, they each have a percentage of stops for which the trooper reported one or more of these characteristics as "unknown." Note that, as described in the previous annual reports, 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; Engel et al., 2023). Identifying drivers' race/ethnicity based on officers' perceptions is the recommended data collection method for examining racially biased policing and is consistent with best practice guides (Fridell et al., 2001; Pryor et al., 2020; Ramirez et al., 2000). Although officers may incorrectly perceive the driver's actual characteristics, this is irrelevant for data collection analyses that seek to explain officer-decision making.[11]

In response to quarterly reports in 2022 showing large variations in the percentage of "unknown" drivers' race and ethnicity, the PSP, based on recommendations from the research team, provided clarification to its members on August 12, 2022.[12] The percentages of unknown race and ethnicity significantly declined after the PSP directive, from an average of 6.0% to 3.4% for unknown race pre-post directive, and an average of 7.6% to 3.9% for unknown ethnicity pre-post directive. With the addition of "Two or More Races" as a response option for 2023, we expected that the percentages of unknown race and ethnicity would continue to decrease as troopers have an additional option for reporting their perceptions of drivers' race and ethnicity.

Figure 2.1 compares the average percentage of drivers with unknown race and ethnicity reported before and after the August 12th, 2022 directive with the percentages reported throughout 2023. As shown, the percentages of unknown race reported on the CDR forms continued to decrease from an average of 6.0% for the eight months before the August 12th, 2022 directive to an average of 3.4% across the department for the remainder of 2022 and an average of 2.5% for

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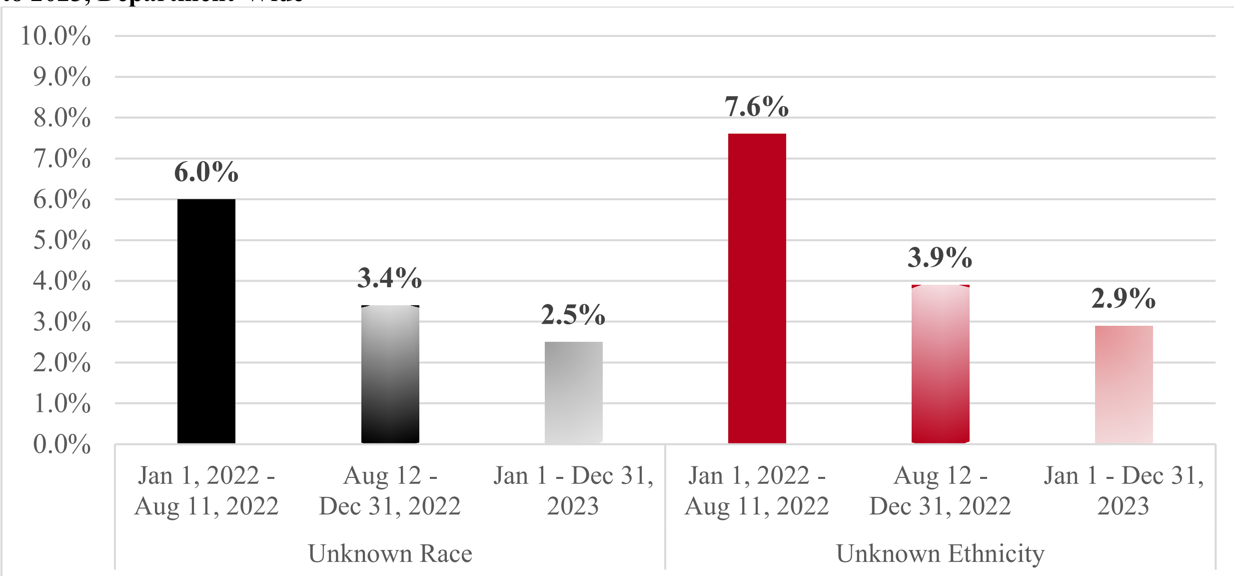
[11] Concerns regarding racial, ethnic, and gender profiling are often based on the presumption that officers treat motorists differently due to their personal bias. Therefore, proper data collection efforts must identify officers' *perceptions* of the race/ethnicity of the driver, which may or may not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

[12] 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."

2023. Similarly, the percentage of reported unknown ethnicity decreased from 7.6% to 3.9% before and after the directive in 2022 and declined further to 2.9% in 2023.

Figure 2.1. Percent Unknown Race/Ethnicity of Drivers Before & After PSP Directive in 2022 in Comparison to 2023, Department-Wide



As shown in Table 2.3, at the Area level, declines in the average percentage of CDRs with unknown race and ethnicity are also reported across all four Areas after the August 12th, 2022 directive. At the Troop level, 15 of the 16 troops have less than 5.0% unknown race (Troop T=5.2%). Additionally, the percentage of unknown drivers' ethnicity for all Troops is now below 10%, and 14 of 16 Troops reported 5.0% or lower unknown drivers' ethnicity.

A table displaying the average percentages of unknown race and ethnicity across PSP stations is included in Appendix A. Four stations remain over 10% of stops with reported unknown driver race and/or ethnicity: Belle Vernon (10.3% race, 11.9% ethnicity), Pittsburgh (16.0% ethnicity—up from 10.1% in 2nd half of 2022), Everett (12.2% race, 11.1% ethnicity), and Somerset (T) (14.1% race and 13.2% ethnicity, though these represent improvements from over 20% in 2022). Overall, this is an improvement from 2022, when seven stations exceeded 10% in the second half of 2022).

Table 2.3. Percent Unknown Race/Ethnicity by Department, Area, and Troop, 2022 compared to 2023

	Unknown Race			Difference between Aug-Dec 22 and 2023	Unknown Ethnicity			Difference between Aug-Dec 22 and 2023
	1/1/22-8/11/22	8/12/22-12/31/22	2023		1/1/22-8/11/22	8/12/22-12/31/22	2023	
PSP Dept.	**6.0%**	**3.4%**	**2.5%**	**-0.9%**	**7.6%**	**3.9%**	**2.9%**	**-1.0%**
AREA I	**5.4%**	**2.8%**	**2.4%**	**-0.4%**	**6.4%**	**3.5%**	**3.2%**	**-0.3%**
Troop B	6.0%	4.5%	4.1%	-0.4%	9.0%	6.3%	6.7%	0.4%
Troop C	7.2%	3.9%	2.3%	-1.6%	6.9%	3.6%	1.7%	-1.9%
Troop D	5.4%	2.1%	2.2%	0.1%	5.7%	3.1%	3.4%	0.3%
Troop E	2.7%	1.0%	0.9%	-0.1%	3.6%	1.0%	0.9%	-0.1%
AREA II	**6.5%**	**4.1%**	**2.7%**	**-1.4%**	**7.5%**	**4.2%**	**2.9%**	**-1.3%**
Troop A	1.9%	0.8%	1.2%	0.4%	2.9%	0.8%	1.1%	0.3%
Troop G	4.5%	3.1%	2.2%	-0.9%	4.6%	2.9%	1.9%	-1.0%
Troop H	3.6%	1.7%	1.0%	-0.7%	3.9%	1.6%	0.9%	-0.7%
Troop T	13.0%	9.0%	5.2%	-3.8%	15.2%	9.8%	6.1%	-3.7%
AREA III	**8.0%**	**3.3%**	**2.8%**	**-0.5%**	**10.8%**	**3.9%**	**2.9%**	**-1.0%**
Troop F	3.7%	1.8%	2.3%	0.5%	4.3%	1.9%	2.3%	0.4%
Troop N	13.4%	4.1%	3.4%	-0.7%	18.0%	4.5%	3.3%	-1.2%
Troop P	2.8%	2.1%	2.7%	0.6%	3.1%	2.9%	3.1%	0.2%
Troop R	11.3%	6.0%	2.8%	-3.2%	17.8%	8.6%	3.4%	-5.2%
AREA IV	**4.3%**	**3.1%**	**2.1%**	**-1.0%**	**6.3%**	**4.0%**	**2.6%**	**-1.4%**
Troop J	1.7%	1.0%	0.9%	-0.1%	2.9%	1.5%	1.0%	-0.5%
Troop K	5.8%	5.3%	3.4%	-1.9%	9.1%	6.9%	4.1%	-2.8%
Troop L	3.7%	2.4%	1.6%	-0.8%	5.1%	3.1%	2.3%	-0.8%
Troop M	6.6%	4.2%	3.0%	-1.2%	8.7%	5.1%	3.8%	-1.3%
Specialized Units								
SHIELD	1.3%	0.6%	0.4%	-0.2%	7.3%	1.0%	0.3%	-0.7%
Canine	3.4%	3.1%	1.2%	-1.9%	3.1%	3.4%	2.9%	-0.5%

Methodology and Statistical Analyses

Examining racial/ethnic disparities, discrimination, and bias in criminal justice outcomes has a long-standing and unresolved controversy regarding appropriate methods and measures (Engel & Swartz, 2014; Mears et al., 2016; Sampson & Lauritsen, 1997). This is particularly true for traffic stops, where the population at risk of being stopped by police is unknown, and the ability of different benchmarks to serve as proxy measures estimating that population is limited (Engel & Calnon, 2004a; Fridell, 2004; Ridgeway & MacDonald, 2010). It is critical that analyses of disparities in traffic stops and stop enforcement outcomes include a series of methodological and statistical techniques for a holistic assessment that acknowledges the strengths and limitations of each approach. Other recent statewide studies have similarly employed multiple approaches to measure disparities (Wolfe et al., 2021; Ross & Barone, 2024). As described below, the statistical analyses used in this report include basic descriptive statistics, bivariate analyses, Veil of Darkness analyses, multivariate analyses, and the outcome test.

Descriptive statistics (e.g., frequencies) summarize quantitative data with counts and percentages. The purpose of descriptive statistics is to summarize and describe the features of numerical data (e.g., the general trends in traffic stops), but these analyses cannot explain differences in these trends. Often, differences are expected due to variations in the geography, roadways, jurisdiction, traffic flow, and demographic makeup of residents and travelers across the state. Descriptive statistics are used in Section 3 to describe traffic stops and drivers, in Section 4 to describe stop outcomes, and in Section 5 to describe searches and seizures.

Bivariate analyses assess the relationship between two variables, which provides an initial understanding of the relationship between a set of variables. However, this approach does not consider any other factors that might influence that relationship. Bivariate analyses in this report are largely based on the Chi-square statistical test that assesses whether the associations 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.

Further, these statistical tests are influenced by sample size and even substantively small differences may be found to be statistically significant in large samples. To assess the substantive significance or strength of statistically significant findings, we rely on the Cramer's V measure of association, which ranges from zero (no association) to one (perfect association). The general rule of thumb for this measure of association is that Cramer's V values of 0.07 to 0.20 are small effects, 0.21 to 0.34 are medium size effects, and 0.35 and up are large effects (Cohen, 1988; Sheskin, 2011). Bivariate analyses are used in Section 3 to examine racial/ethnic differences in reasons for the stop, in Section 4 to examine the association between drivers' race/ethnicity and post-stop outcomes, and in Section 5 to examine the association between drivers' race/ethnicity and seizure rates during discretionary searches.

Examining Disparities in Traffic Stops

Although understanding troopers' initial stopping decisions is of high interest to PSP executives 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 across racial/ethnic groups. However, 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. Residential population data, however is not a valid measure of drivers' risk of being stopped, which is influenced by where they drive, when they drive, how often they drive, what they drive, how they drive, and possibly their demographic characteristics (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. **Due to the inherent methodological limitations of all benchmark analyses, including the lack of reliable and valid comparison data, benchmark analyses are not included in this traffic stop study.** [13]

To provide an alternative exploration of the impact of drivers' race/ethnicity on the initial decision to make a traffic stop, this report incorporates three alternative methods to enable a more holistic assessment of initial traffic stop decisions. First, descriptive statistics of the information included on the CDR are reported at multiple PSP organizational units (Area, Troop, and Station) to provide an opportunity for PSP leaders to assess differences in patterns and determine if there are explanations for these differences. Note that this is just the first step for understanding the complexities surrounding racial/ethnic disparities; it is necessary but not sufficient. Next year, the PSP will have three years of traffic stop data that can be used to examine differences in trends over time. This will provide the opportunity to conduct time series analyses that will be more instructive for an initial examination of racial/ethnic disparities.

Second, this study uses the Veil of Darkness (VOD) technique, developed by Grogger & Ridgeway (2006) as an alternative to benchmark analysis. The VOD statistical technique uses a subset of traffic stops that occur during the "inter-twilight period," where natural variation in daylight occurs throughout the year to assess relative differences in the ratio of minority to non-minority stops that occur in daylight compared to darkness. The VOD approach does not assume it is impossible to identify drivers' characteristics at night, or that it is always possible during the day; it simply assumes it is more difficult to identify drivers' characteristics when dark (Grogger & Ridgeway, 2006; Knode et al., 2024). The primary strength of the VOD is that it relies upon a natural experiment of the seasonal variation in daylight hours to identify whether officers are more likely to stop Black drivers in daylight hours versus darkness hours. The primary limitation

[13] 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 our determination in the 2004-2005 Report that it was not a valid approach to continue (Engel et al., 2007). The remaining annual reports through 2010 focused on stop trends and enforcement outcomes over time.

of this approach is that it is limited to a small subset of all traffic stops that occur primarily during a single PSP shift.

Third, many jurisdictions nationwide have enacted new statutory or policy regulations on officers' traffic enforcement based on the perception that certain types of low-level, non-moving violations are disproportionately used against drivers of color for "pretextual" purposes (Holder, 2023). Though we take no position on whether stops for violations related to equipment, registration, and inspection are being used for pretextual purposes (which is legal under *Whren v. U.S.*, 1996) by the PSP or any other law enforcement agency, we explore whether racial/ethnic differences exist across different reasons for the stop. The primary limitation of this approach is that it is limited to bivariate comparisons, which, as described above, do not account for other factors that may impact that relationship. Nevertheless, an initial finding of substantive bivariate differences in pretextual stops across racial/ethnic groups may indicate that additional consideration of these differences is warranted.

Predicting Stop Outcomes

A major advantage of examining post-stop enforcement 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). As a result, more rigorous statistical and methodological techniques can be applied to understanding any racial/ethnic disparities in post-stop outcomes. The following analyses answer the question: What factors predict the odds of being warned, cited, arrested, or searched?

Multivariate Regression Models

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 shown to influence post-stop enforcement outcomes. Multivariate analyses examine the independent effect of these predictor variables while controlling for (i.e., statistically holding constant) the predictive power and influence of the other variables. Using this approach, the independent effects of race/ethnicity on the likelihood of stop outcomes (e.g., warnings, citations, arrests, searches) are estimated once other available predictor variables are considered. Whether specific stop enforcement outcomes occur or do not occur during 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 =do not occur, 1= do occur).

There are three components to consider when interpreting multivariate regression models. First, the models provide information about the relative strength of the observed relationship with two related values for each independent variable in the model: 1) the coefficient, or predicted log-odds, and 2) the odds ratio. 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 enforcement outcome is less likely). If the coefficient has no sign (i.e., is a positive number), this indicates the influence of that variable is positive, and the enforcement outcome is more likely. In logistic regressions, the results are presented as "odds ratios" representing the association between two events.[14] Odds ratios greater than 1.0 are a positive correlation, whereas odds ratios less than 1.0 are a negative correlation. A formula (1/(Exp(B)) is used to convert an odds ratio less than 1.0 to a positive odds ratio. Odds ratios are interpreted as a change in the likelihood of the enforcement outcome occurring because of the 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, 1.6 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, **when determining the influence particular factors have over the post-stop enforcement outcomes, 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**.[15]

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[14] 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.

[15] 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 (Raudenbush & Bryk, 2002). The research team conducted sensitivity tests related to PSP station and county-level variation in predicting PSP stop outcomes. Ultimately, over 90% of the variation in the outcomes can be explained using level-1 predictors (i.e., stops). Thus,

Third, 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 traffic stop data collection system. Therefore, while researchers can be more confident in multivariate results, the findings should be interpreted with this fundamental limitation in mind.

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 warnings, citations, arrests, or searches occur during traffic stops). However, as with all goodness of fit statistics, the specification accuracy of the models is critical. For example, if there are omitted variables (e.g., related factors that go unmeasured and/or unincluded in the analyses), the goodness-of-fit has a ceiling due to full model specification error. 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, arrests, and discretionary searches during traffic stops. This is a common presumption of all quantitative regression analyses.

Predicted Probabilities

Additional findings are presented to better understand the potential impact of drivers' race/ethnicity on post-stop outcomes. The results of each regression analysis will show whether drivers' race/ethnicity have some degree of association with the odds of given enforcement outcomes. The "odds" are the chances in favor of an outcome, where the range is from zero to infinity, and "1" represents an equal chance. The probability, however, is the likelihood of an outcome occurring. It ranges from zero (impossible) to one (certain). We rely on **predicted probabilities** to more precisely estimate the true impact of race and ethnicity on stop outcomes. 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

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for parsimony and efficiency, we constrain the analyses presented in this section to the individual level (i.e., logistic regressions). The full Hierarchical Generalized Linear Models (HGLM) are available from the authors upon request.

precise risk estimation than the general outcome percentage (when the models are accurate and predictive). [16]

Calculating the probabilities for White, Black, and Hispanic drivers across various situational and legal characteristics of stops makes it possible to compare the estimations between drivers of different racial and ethnic backgrounds in their *probability* of being warned, cited, arrested, or searched all else equal (i.e., all other measures in the models are set to their mean values). [17]

Predicting Contraband Seizures

Discovering contraband during person and vehicle searches is an important outcome when examining potential racial/ethnic disparities. Often referred to as search "success rates" or "hit rates" (i.e., the percent of searches conducted that produce contraband), some researchers use the "outcome test" to identify racial and ethnic disparities by examining differential outcomes in search success rates (Knowles et al., 2001; Ayres, 2001). Racial/ethnic comparisons of seizure rates are calculated by dividing the percent of searches in which officers seize 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 et al., 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 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, there are limitations to 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

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[16] 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.

[17] 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. This is a more noticeable issue when we have rare events.

criterion, the outcome test is only appropriate for analyzing traffic stops that result in a probable cause/reasonable suspicion search. Mandatory searches should not be considered because troopers must 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 consent searches are conducted (Fridell, 2004; Engel, 2008). That is, motorists have the right to refuse search requests, and if the trooper has no probable cause to 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. Other limitations of the outcome test include the problematic assumptions that officers do not consider motorists' behaviors when deciding whether to search, that officers are monolithic in their search decisions, and that the only reason to search is to find contraband.

Notwithstanding the outcome test's limitations, it provides an alternative method to assess post-stop enforcement 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 should be used only for internal comparisons and training. Therefore, although we use the outcome test methodology, we are more circumspect in interpreting the findings for consent searches. *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.

Limitations of Data Analyses

In summary, it is important to note that the statistical findings in this report must be interpreted cautiously. The data collected and presented 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, provide 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 continuously improve by regularly assessing internal operations and better understanding the factors that influence troopers' traffic stop enforcement decisions.

Section Summary

Between January 1, 2023, and December 31, 2023, PSP Troopers collected information for 449,047 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, 96.4% of the 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, **all** 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. All the variables used in the analyses have either no missing or invalid data (less than 0.005%). This measure is well within the 2% or less standard the research 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 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, 2022 directive. After this directive, the average percentages of unknown race and ethnicity significantly decreased. These percentages continued to decrease in 2023, with only 2.5% unknown race and 2.9% unknown ethnicity.

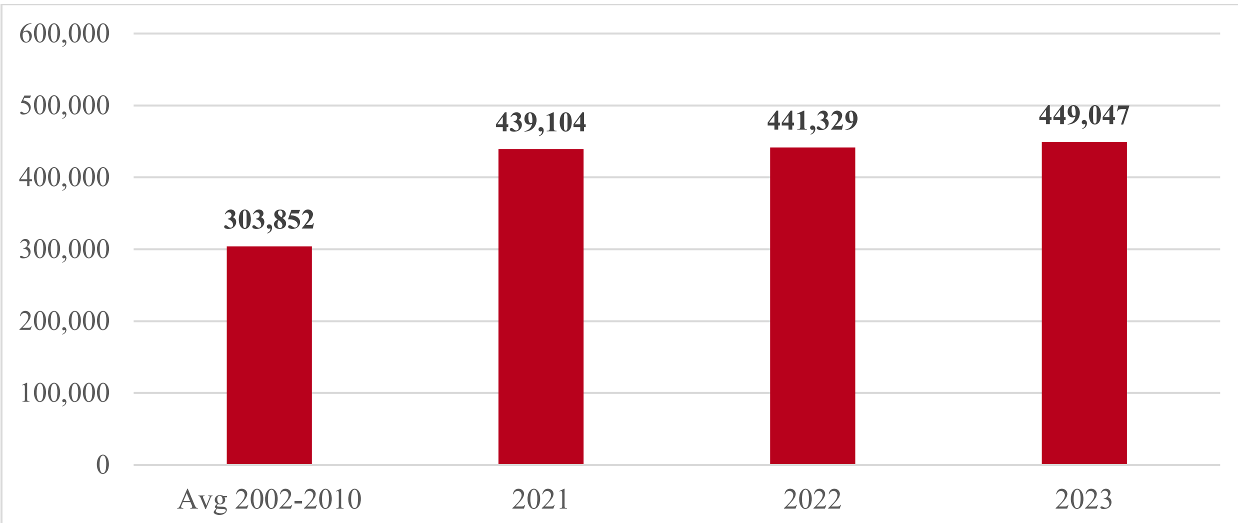
This audit suggests that the PSP has one of the country's most comprehensive and high-quality traffic stop data collection processes.

The research team uses multiple statistical analyses to examine the impact of race/ethnicity on PSP stops and stop outcomes, including descriptive statistics, bivariate analyses, multivariate analyses, the Veil of Darkness technique, and the outcome test for seizures during searches. Each has strengths and limitations that collectively contribute to a comprehensive assessment in which we can be more confident. It cannot be determined with these data and the statistical analyses available if any reported findings of racial/ethnic disparities in traffic stops or post-stop enforcement are the result of individual trooper or organizational racial bias or discrimination.

3. DESCRIPTION OF TRAFFIC STOP DATA

From January 1 to December 31, 2023, PSP Troopers made 449,047 traffic stops. As shown in Figure 3.1, the number of stops in 2023 continued to increase from previous years, with a 47.9% increase from the 2002 – 2010 average, a 2.4% increase from 2021, and a 1.8% increase from 2022.

Figure 3.1. Traffic Stop Volume Over Time



Traffic Stop Characteristics

Table 3.1 provides the total number of traffic stops across all organizational units and the temporal breakdown of traffic stops organized by month. As shown, there is wide variation in traffic stop activity across PSP Areas and Troops. For example, Area II accounts for the most traffic stops at the Area level (n=145,297). Troops H and T, within Area II, report the most traffic stops at the Troop level. Conversely, Troops P and R, within Area III, report the fewest traffic stops.

At the department level, the month of May accounts for the greatest percentage of stops (12.7%), followed by September (10.0%), and April and July (both 9.6%). This trend is consistent across most of the lower organizational levels, but Table 3.1 illustrates differences in the percentage of stops made each month. There are several reasons to expect that traffic patterns and officer activity will vary by month, including weather, seasonal tourism, holidays, road construction, and school-related traffic.

Table 3.1 Monthly Breakdown of Traffic Stops by Department, Area, & Troop, & Station, January – December 2023

	Total # of Stops	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
PSP Dept.	**449,047**	**7.5%**	**7.5%**	**8.9%**	**9.6%**	**12.7%**	**7.0%**	**9.6%**	**7.1%**	**10.0%**	**4.2%**	**8.8%**	**7.1%**
AREA I	98,932	6.5%	6.9%	8.5%	9.6%	13.9%	6.0%	9.6%	6.3%	12.1%	4.0%	10.2%	6.5%
Troop B	25,288	7.2%	7.2%	8.3%	7.5%	15.8%	5.8%	9.9%	5.1%	11.5%	4.2%	11.1%	6.4%
Troop C	26,227	5.2%	6.8%	7.8%	9.8%	13.2%	6.4%	10.0%	6.6%	13.6%	4.3%	10.8%	5.6%
Troop D	22,359	6.1%	6.3%	9.0%	10.8%	14.4%	6.3%	10.1%	8.1%	11.3%	3.5%	8.9%	5.3%
Troop E	25,058	7.3%	7.2%	9.1%	10.3%	12.1%	5.5%	8.5%	5.8%	11.7%	4.0%	9.9%	8.5%
AREA II	145,297	7.7%	7.8%	8.9%	9.8%	12.4%	7.5%	9.2%	7.5%	9.0%	4.9%	8.2%	7.2%
Troop A	18,559	7.3%	5.7%	8.7%	11.6%	12.9%	6.3%	9.6%	5.3%	10.4%	4.6%	11.6%	6.2%
Troop G	28,688	7.9%	8.7%	9.3%	10.4%	13.2%	5.6%	7.7%	5.7%	12.5%	3.2%	9.8%	5.9%
Troop H	49,172	8.7%	8.2%	8.9%	8.3%	11.0%	8.4%	9.7%	8.2%	7.1%	4.7%	8.2%	8.7%
Troop T	48,878	6.6%	7.6%	8.7%	10.4%	13.0%	8.3%	9.3%	8.6%	8.4%	6.3%	5.8%	6.9%
AREA III	90,445	7.5%	7.5%	9.1%	10.0%	14.4%	6.8%	10.1%	6.3%	9.9%	3.6%	8.8%	6.1%
Troop F	35,128	7.5%	7.7%	9.3%	9.9%	14.1%	6.6%	10.3%	7.1%	9.8%	3.4%	8.8%	5.5%
Troop N	28,033	8.5%	7.6%	9.2%	8.7%	14.9%	5.5%	9.7%	5.0%	10.4%	4.2%	9.8%	6.4%
Troop P	15,059	6.1%	7.8%	8.5%	11.3%	13.5%	9.1%	10.3%	6.8%	10.0%	2.6%	7.4%	6.6%
Troop R	12,225	7.2%	6.1%	9.1%	11.4%	15.3%	7.3%	10.0%	6.3%	9.0%	4.1%	8.0%	6.2%
AREA IV	108,251	8.2%	7.9%	8.9%	9.0%	11.1%	7.3%	9.9%	7.5%	9.4%	3.9%	8.4%	8.4%
Troop J	36,152	8.5%	7.0%	8.4%	9.1%	9.8%	7.9%	10.1%	7.7%	9.2%	4.6%	8.0%	9.7%
Troop K	26,711	7.0%	7.0%	9.2%	7.8%	11.1%	7.8%	9.5%	8.8%	11.3%	3.4%	7.7%	9.5%
Troop L	22,302	9.0%	10.0%	9.2%	9.0%	12.0%	5.9%	9.9%	6.9%	8.5%	3.3%	10.3%	5.9%
Troop M	23,086	8.6%	8.1%	9.1%	10.1%	12.4%	7.1%	10.1%	6.5%	8.3%	4.1%	8.1%	7.6%
Specialized Units													
SHIELD	3,833	6.2%	6.9%	8.7%	8.9%	7.9%	12.9%	9.1%	17.2%	8.7%	5.2%	4.4%	4.0%
Canine	1,853	3.9%	9.4%	12.1%	7.9%	7.3%	8.6%	8.4%	13.8%	11.7%	7.3%	5.5%	4.1%

Table 3.2 documents the average percent of stops on weekdays, during the day, and on various roadway types at the PSP Department, Area, and Troop levels. It also notes the percentage of vehicles with a Pennsylvania registration, the presence of passengers, and the stop duration.

As shown in Table 3.2, the majority of traffic stops department-wide are made on weekdays (67.7%) and during daylight hours (67.1%).[18] State highways (54.5%) and interstates (33.7%) are the most frequent locations for traffic stops. In addition, 79.8% of vehicles stopped are registered in Pennsylvania, and 18.5% have at least one passenger. Most traffic stops department-wide (90.0%) are conducted in 15 minutes or less.

Traffic stop characteristics vary somewhat by PSP Area and Troop. For example, Area IV makes fewer traffic stops during daylight hours (58.0% of stops) than the department average. At the Troop level, 81.3% of traffic stops by Troop T are made during daylight hours, compared to 51.8% of traffic stops by Troop J.

In terms of roadway types, there are several noticeable variations. For example, 84.1% of stops made by Troop T occur on interstates, which is consistent with their primary area of responsibility on the Pennsylvania Turnpike. The percentage of stops made on interstates is considerably lower in other Troops with fewer miles of interstate roadways (e.g., Troop A). There is less location-based variation 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, Troops T and R stop smaller percentages of drivers with in-state vehicle registrations.

[18] The creation of day and night variables from the time of stop data field are 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 2023

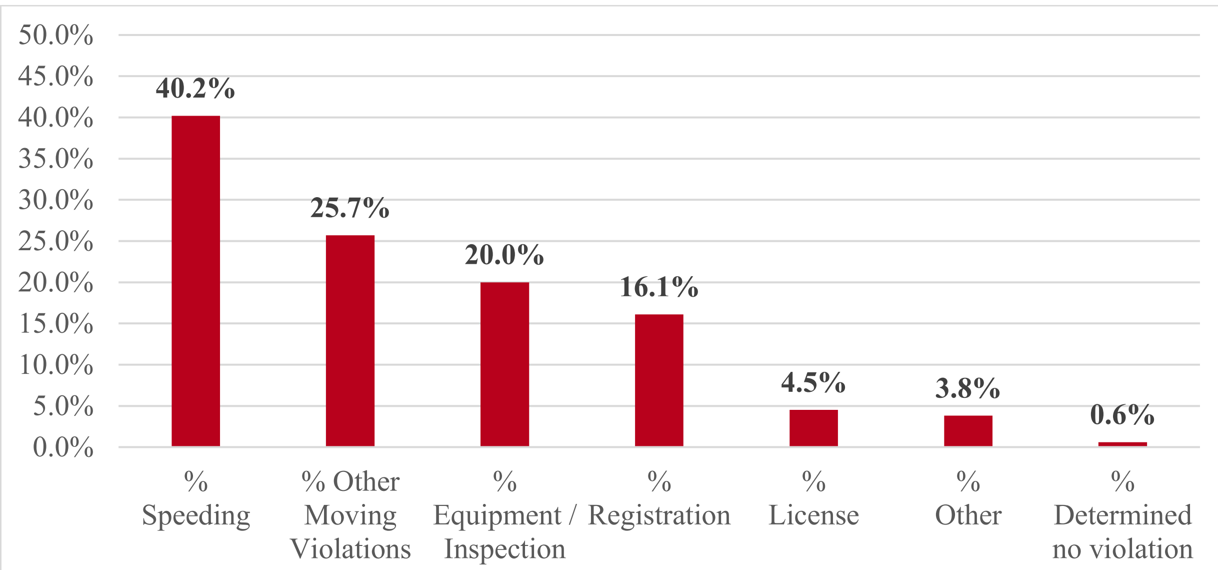
	Total #of Stops	Weekday	Daytime	Roadway Type				PA Regist. Vehicle	Vehicles w/ Passengers	Duration of Stop (minutes)			
				Inter	State	Local	Other			1-15	16-30	31-60	61+
PSP Dept.	**449,047**	**67.7%**	**67.1%**	**33.7%**	**54.5%**	**11.1%**	**0.7%**	**79.8%**	**18.5%**	**90.0%**	**7.2%**	**1.9%**	**1.0%**
AREA I	**98,932**	**64.2%**	**67.3%**	**24.9%**	**59.4%**	**15.2%**	**0.5%**	**85.4%**	**18.2%**	**92.5%**	**5.6%**	**1.1%**	**0.8%**
Troop B	25,288	66.8%	69.0%	32.7%	46.7%	19.8%	0.8%	88.0%	18.7%	92.8%	5.3%	1.2%	0.7%
Troop C	26,227	61.8%	66.1%	18.3%	72.2%	9.3%	0.2%	78.1%	20.6%	93.1%	5.1%	1.0%	0.8%
Troop D	22,359	67.1%	70.9%	22.6%	62.5%	14.4%	0.6%	90.4%	16.4%	92.3%	5.0%	1.4%	1.3%
Troop E	25,058	61.4%	63.8%	26.1%	56.1%	17.4%	0.5%	85.8%	16.7%	91.8%	7.0%	0.9%	0.3%
AREA II	**145,297**	**69.1%**	**69.9%**	**42.6%**	**48.1%**	**8.0%**	**1.2%**	**77.2%**	**19.6%**	**90.1%**	**7.4%**	**1.7%**	**0.8%**
Troop A	18,559	66.2%	76.1%	1.5%	85.0%	13.3%	0.2%	91.6%	16.2%	91.2%	6.7%	1.3%	0.8%
Troop G	28,688	65.3%	69.6%	24.0%	66.1%	9.7%	0.2%	81.1%	16.9%	93.8%	4.9%	0.7%	0.6%
Troop H	49,172	68.8%	56.3%	27.8%	59.9%	12.0%	0.3%	77.3%	17.7%	87.8%	7.9%	3.0%	1.3%
Troop T	48,878	72.8%	81.3%	84.1%	11.7%	1.1%	3.1%	69.4%	24.3%	89.8%	8.5%	1.2%	0.5%
AREA III	**90,445**	**65.4%**	**71.6%**	**28.6%**	**59.8%**	**11.2%**	**0.3%**	**77.4%**	**19.5%**	**90.2%**	**6.7%**	**2.1%**	**1.0%**
Troop F	35,128	63.9%	69.2%	22.0%	67.9%	9.8%	0.2%	76.1%	21.9%	93.8%	4.0%	1.7%	0.5%
Troop N	28,033	63.7%	71.1%	39.4%	44.9%	15.4%	0.3%	76.2%	19.4%	89.3%	7.2%	2.2%	1.3%
Troop P	15,059	68.8%	72.8%	8.9%	81.0%	9.8%	0.4%	89.5%	13.2%	91.3%	6.8%	1.3%	0.6%
Troop R	12,225	69.7%	78.5%	47.4%	44.6%	7.7%	0.4%	69.1%	20.4%	80.5%	13.2%	4.1%	2.2%
AREA IV	**108,251**	**69.4%**	**58.0%**	**31.0%**	**56.6%**	**11.9%**	**0.5%**	**82.6%**	**15.8%**	**87.8%**	**8.5%**	**2.3%**	**1.3%**
Troop J	36,152	69.6%	51.8%	17.9%	70.5%	10.9%	0.7%	82.4%	15.0%	88.2%	7.5%	2.7%	1.5%
Troop K	26,711	70.0%	56.5%	56.8%	32.2%	10.5%	0.5%	81.1%	14.3%	87.9%	8.8%	2.1%	1.2%
Troop L	22,302	70.3%	70.6%	24.1%	61.2%	14.6%	0.1%	85.3%	18.1%	89.3%	8.0%	1.9%	0.7%
Troop M	23,086	67.6%	57.3%	28.4%	58.8%	12.4%	0.4%	82.1%	16.5%	85.9%	10.0%	2.3%	1.7%

Reason for the Stop

Figure 3.2 and Table 3.3 report the reasons for the stops initiated by PSP Troopers, including speeding (as well as the average mph over the limit), other moving violations, equipment violations, registration, license, and other. The PSP data collection protocol indicates that troopers should select all applicable reasons; as a result, 8.6% of stops involved multiple reasons for the stop. Therefore, the percentages reported in Figure 3.2 and Table 3.3 sum to more than 100%.

Figure 3.2 displays the stop reasons at the department level. As shown, speeding is the most frequent reason for a stop (40.2%). The next most common reasons are other moving violations (25.7%), equipment violations/inspection (20.0%), and registration violations (16.1%).

Figure 3.2. Department-Wide Reason for Stop, January - December 2023



As shown in Table 3.3, speeding is the most frequent reason for a stop across most Areas and Troops except for Area IV and Troops H, J, K, and M, where the most frequent reason is other moving violations. The percentage of stops for speeding varies by Area, with a high of 50.0% in Area II and a low of 29.1% in Area IV. The Troops range in their percentage of traffic stops for speeding, from a high of 68.0% (Troop T) to a low of 24.9% (Troop K).

At the department level, the average amount over the posted speed limit recorded for speeding stops is 21.5 miles per hour (mph). However, this ranges from a low of 20.3 mph over the limit in Areas I and III to a high of 24.0 in Area IV. Troop-level variation is also evident, with a low of 17.9 mph over the limit in Troop C to a high of 27.0 miles per hour in Troop M.

Other moving violations are the second most common reason for stops across the department at 25.7%. Areas vary in the percentage of stops based on other moving violations, from 37.3% in Area IV to 20.4% in Area I. Other moving violations are the most frequent reason for stops in Troop J (39.0%), Troop K (45.0%), and Troop M (39.4%), which are all located in Area IV, and

Troop H (31.7%). The percentage of stops for other moving violations varies from 45.0% in Troop K to 13.0% in Troop T. See Table 3.3 for additional reasons for stops across Areas and Troops.

Table 3.3. Reason for Stop by Department, Area, & Troop, January – December 2023

	Total # of Stops	Speeding	Avg. Amt. Over Limit (MPH)	Other Moving Violation	Equipment/ Inspection	Registration	License	Other
PSP Department	**449,047**	**40.2%**	**21.5**	**25.7%**	**20.0%**	**16.1%**	**4.5%**	**3.8%**
AREA I	98,932	**37.1%**	**20.3**	**20.4%**	**25.7%**	**16.7%**	**5.0%**	**3.9%**
Troop B	25,288	31.5%	22.4	24.7%	26.8%	18.3%	6.7%	5.7%
Troop C	26,227	44.6%	17.9	16.4%	26.0%	12.8%	3.1%	3.1%
Troop D	22,359	35.4%	22.8	21.8%	23.8%	18.4%	6.1%	4.2%
Troop E	25,058	36.3%	19.3	18.9%	25.8%	17.5%	4.5%	2.5%
AREA II	145,297	**50.0%**	**21.7**	**20.9%**	**17.0%**	**15.8%**	**3.6%**	**3.9%**
Troop A	18,559	50.2%	22.5	16.1%	18.9%	16.4%	4.7%	3.1%
Troop G	28,688	50.6%	20.9	18.8%	17.6%	13.6%	3.2%	2.8%
Troop H	49,172	31.6%	20.3	31.7%	22.4%	15.6%	4.5%	2.8%
Troop T	48,878	68.0%	22.4	13.0%	10.5%	16.9%	2.6%	5.8%
AREA III	**90,445**	**42.8%**	**20.3**	**23.9%**	**20.9%**	**13.1%**	**4.4%**	**3.5%**
Troop F	35,128	52.0%	19.0	20.9%	17.6%	10.9%	3.0%	1.9%
Troop N	28,033	37.6%	22.0	29.4%	20.2%	12.7%	5.4%	4.6%
Troop P	15,059	33.9%	21.5	19.5%	25.9%	18.6%	6.1%	4.3%
Troop R	12,225	39.2%	20.4	25.4%	25.9%	13.9%	4.1%	4.8%
AREA IV	**108,251**	**29.1%**	**24.0**	**37.3%**	**16.9%**	**18.7%**	**5.5%**	**3.6%**
Troop J	36,152	25.0%	22.9	39.0%	19.3%	18.3%	4.9%	2.8%
Troop K	26,711	24.9%	25.9	45.0%	10.9%	21.9%	4.4%	4.9%
Troop L	22,302	41.5%	21.5	23.1%	18.9%	16.4%	6.1%	3.4%
Troop M	23,086	28.1%	27.0	39.4%	18.3%	18.0%	6.9%	3.6%

Driver Characteristics

Two tables present the characteristics of the drivers stopped by PSP Troopers in 2023. First, Table 3.4 describes the driver's age, gender, behavior during the stop, and residency at the Department, Area, and Troop levels. Table 3.5 lists the race and ethnicity of drivers stopped by PSP Troopers in 2023 at the Department, Area, and Troop levels.

Driver Age & Gender

As shown in Table 3.4, the average age of drivers stopped by troopers department-wide is 38.6 years, similar to the averages at the Area and Troop levels. At the department level, 67.2% of stopped drivers are male; likewise, males are more likely than females to be stopped across organizational units within the department.

Driver Behavior

Table 3.4 also provides information about driver behavior, including whether they are civil, disrespectful, non-compliant, verbally resistant, or physically resistant toward troopers during traffic stops. PSP 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 are reported to be civil and one of the other categories (n=800, 0.2%).[19] At the department level, 98.3% of drivers are reported as only civil, while 0.9% are disrespectful. Non-compliant (0.4%) or resistant (0.9%) drivers are rare. These findings are consistent at the Area and Troop levels.

Driver Residency

Finally, Table 3.4 provides information regarding driver residency status (determined by driver zip code). Department-wide, 81.1% of drivers stopped by troopers in 2023 are in-state residents. Similar percentages are seen across the four Areas, albeit with some variation. For example, 86.5% of drivers stopped in Area I are in-state residents, while 78.3% of drivers stopped in Area III are in-state residents. There is more variation at the Troop level. For example, 92.8% of drivers stopped by Troop A reside in-state, while 69.7% and 71.0% of drivers stopped by Troops R and T, respectively, reside in-state.

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[19] In this table, the percent "civil" reflects stops where that is 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 are reported to have displayed behavior consistent with more than one of the following categories: disrespectful, non-compliant, verbally resistant, or physically resistant. Overall, in 99.5% of traffic stops, troopers selected only one category for this data field.

Table 3.4. Characteristics of Drivers Stopped by Department, Area & Troop, January - December 2023

		Age	Gender	Behavior				Residency
	Total # of Stops	Average (years)	Male	Civil	Dis-respectful	Non-compliant	Verbal or Phys Resistant	In-State
PSP Dept.	**449,047**	**38.6**	**67.2%**	**98.3%**	**0.9%**	**0.4%**	**0.9%**	**81.1%**
AREA I	**98,932**	**39.6**	**65.3%**	**98.3%**	**0.9%**	**0.4%**	**0.8%**	**86.5%**
Troop B	25,288	39.1	64.2%	97.6%	1.3%	0.6%	1.0%	89.2%
Troop C	26,227	40.6	67.8%	98.6%	0.8%	0.3%	0.6%	78.8%
Troop D	22,359	38.8	63.7%	98.5%	0.8%	0.3%	0.8%	91.8%
Troop E	25,058	39.7	64.4%	98.5%	0.6%	0.3%	0.9%	87.2%
AREA II	**145,297**	**38.3**	**66.8%**	**98.4%**	**0.9%**	**0.4%**	**0.9%**	**78.7%**
Troop A	18,559	38.8	64.5%	98.5%	0.8%	0.3%	0.7%	92.8%
Troop G	28,688	38.7	64.1%	98.8%	0.6%	0.2%	0.6%	82.6%
Troop H	49,172	38.2	67.2%	97.5%	1.5%	0.9%	1.5%	78.8%
Troop T	48,878	38.0	68.5%	98.9%	0.5%	0.2%	0.7%	71.0%
AREA III	**90,445**	**39.0**	**67.1%**	**98.6%**	**0.8%**	**0.3%**	**0.7%**	**78.3%**
Troop F	35,128	39.2	65.8%	99.1%	0.6%	0.2%	0.4%	77.3%
Troop N	28,033	38.1	68.3%	98.3%	0.9%	0.4%	0.8%	76.8%
Troop P	15,059	39.4	66.9%	98.3%	1.0%	0.3%	0.8%	90.4%
Troop R	12,225	39.9	68.6%	98.0%	1.1%	0.5%	1.0%	69.7%
AREA IV	**108,251**	**37.8**	**68.5%**	**97.8%**	**1.1%**	**0.6%**	**1.2%**	**84.3%**
Troop J	36,152	38.0	67.0%	98.1%	1.0%	0.5%	1.0%	83.8%
Troop K	26,711	37.3	71.0%	97.2%	1.5%	0.7%	1.3%	84.2%
Troop L	22,302	38.2	66.7%	98.4%	0.6%	0.4%	1.0%	86.1%
Troop M	23,086	37.6	69.8%	97.5%	1.1%	0.8%	1.4%	83.4%

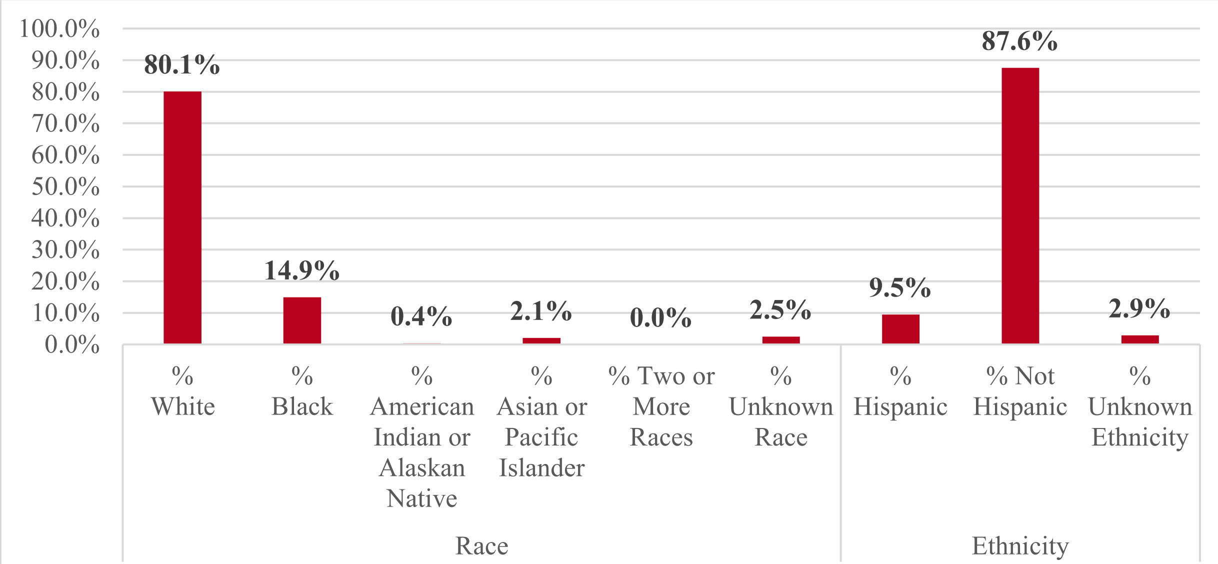
Drivers' Race & Ethnicity

Drivers' race and ethnicity are captured in separate fields on the CDR form and are based on 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, Two or More Races, and Unknown
- Ethnicity: Hispanic Origin, Not of Hispanic Origin, and Unknown

Figure 3.3 below displays the perceived race and ethnicity of drivers stopped by troopers department-wide. Most drivers stopped (80.1%) are perceived as White, followed by 14.9% Black, 2.1% Asian, 0.4% American Indian or Alaskan Native, and less than 0.01% two or more races.[20] In the ethnicity field, 9.5% of stopped drivers are reported to be Hispanic. Most of the 42,632 individuals perceived to be of Hispanic ethnicity are perceived to be of White race (90.2%). Therefore, the percentage of Whites displayed in Figure 3.3 and Table 3.5 includes some individuals perceived as Hispanic because race and ethnicity are captured separately. The percentage of non-Hispanic White drivers stopped in 2023 is 71.5%.[21]

Figure 3.3. Department-Wide Racial/Ethnic Characteristics of Drivers Stopped, January - December 2023



[20] Although the percentage of individuals identifying as two or more races has rapidly increased, this racial identity may be more difficult for PSP members to accurately assess during a traffic stop (Chavez, 2021).

[21] In later analyses in Section 4, the research team combines race and ethnicity by coding individuals who are perceived to be White (race) or Unknown (race) and Hispanic (ethnicity) as Hispanic. The 7.8% of individuals perceived to be Hispanic and another race (e.g., Black, Asian) are coded as their race.

Table 3.5 displays the perceived race and ethnicity of drivers stopped by the Department, Areas, and Troops. These tables demonstrate large variations in the race/ethnicity of drivers stopped across organizational units. Some variation is expected based on geographic, demographic, and roadway type differences across the Commonwealth. For example, Troop K in the Philadelphia area report Black drivers in 43.2% of its stops, whereas troops in more rural areas report less than 10% of their stops are Black drivers. Similar trends are noted for Hispanic drivers.

As shown in Figure 3.3 and Table 3.5, PSP Troopers indicate they cannot identify the drivers' race and ethnicity in 2.5% and 2.9% of all traffic stops, respectively. In 76.0% of the cases with unknown drivers' race, the drivers' ethnicity is also reported as unknown. In 65.4% of the cases with unknown drivers' ethnicity, the drivers' race is also unknown. Other observational and traffic studies have reported difficulty identifying drivers' race and ethnicity, particularly distinguishing Hispanic drivers from White drivers (Alpert et al., 2004b; Lange et al., 2001, 2005; Smith & DeFrances, 2003).

Table 3.5. Race and Ethnicity of Drivers Stopped by Department, Area & Troop, Jan - Dec 2023

		Race						Ethnicity	
	Total # of Stops	White	Black	Amer. Indian or Alaskan Native	Asian/Pac. Islander	Unknown	Two or More Races	Hispanic	Unknown
PSP Dept.	**449,047**	**80.1%**	**14.9%**	**0.4%**	**2.1%**	**2.5%**	**<0.1%**	**9.5%**	**2.9%**
AREA I	**98,932**	**86.2%**	**9.8%**	**0.3%**	**1.3%**	**0.0%**	**<0.1%**	**2.1%**	**3.2%**
Troop B	25,288	80.0%	14.8%	0.2%	0.9%	4.1%	<0.1%	1.8%	6.7%
Troop C	26,227	91.1%	4.6%	0.4%	1.6%	2.3%	<0.1%	2.6%	1.7%
Troop D	22,359	84.8%	11.9%	0.2%	0.9%	2.2%	<0.1%	1.4%	3.4%
Troop E	25,058	88.5%	8.5%	0.2%	1.8%	0.9%	0.1%	2.6%	0.9%
AREA II	**145,297**	**80.8%**	**13.6%**	**0.5%**	**2.4%**	**2.7%**	**<0.1%**	**6.9%**	**2.9%**
Troop A	18,559	90.2%	7.7%	0.1%	0.7%	1.2%	<0.1%	1.4%	1.1%
Troop G	28,688	87.6%	7.6%	0.5%	2.1%	2.2%	<0.1%	3.4%	1.9%
Troop H	49,172	80.3%	16.1%	0.4%	2.1%	1.0%	<0.1%	10.9%	0.9%
Troop T	48,878	73.6%	17.0%	0.5%	3.6%	5.2%	0.1%	6.8%	6.1%
AREA III	**90,445**	**83.9%**	**11.2%**	**0.4%**	**1.7%**	**2.8%**	**<0.1%**	**11.5%**	**2.9%**
Troop F	35,128	87.0%	8.5%	0.5%	1.8%	2.3%	<0.1%	4.9%	2.3%
Troop N	28,033	77.3%	16.6%	0.5%	2.2%	3.4%	<0.1%	23.0%	3.3%
Troop P	15,059	88.9%	7.7%	0.1%	0.6%	2.7%	<0.1%	6.0%	3.1%
Troop R	12,225	84.3%	10.6%	0.4%	1.9%	2.8%	0.0%	10.4%	3.4%
AREA IV	**108,251**	**71.0%**	**24.1%**	**0.4%**	**2.3%**	**2.1%**	**<0.1%**	**17.2%**	**2.6%**
Troop J	36,152	76.1%	20.5%	0.5%	2.0%	0.9%	<0.1%	15.8%	1.0%
Troop K	26,711	49.9%	43.2%	0.5%	3.0%	3.4%	0.0%	10.1%	4.1%
Troop L	22,302	85.3%	11.5%	0.2%	1.3%	1.6%	<0.1%	21.1%	2.3%
Troop M	23,806	73.8%	19.9%	0.5%	2.8%	3.0%	0.1%	23.8%	3.8%

Examining Disparities in Traffic Stops

Some traffic stop reports compare the racial/ethnic percentages of stopped drivers are compared to an external data source (or benchmark) 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 factors that influence a drivers' likelihood of being stopped, 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, this statistical technique is not conducted due to the inherent lack of reliability and validity of all traffic-stop benchmark analyses.

Instead, the research team uses other techniques, including the Veil of Darkness (VOD) approach as an alternative to benchmark analyses. As described in Section 2, this technique uses a subset of stops occurring during the inter-twilight period when natural variation in daylight occurs throughout the year to explore whether differences exist in the odds of Black or Hispanic drivers being stopped in daylight versus darkness. This subsample includes 71,919 stops (16.0% of all 2023 stops) that occur in the time period from the earliest dusk to the latest sunset (5:01 pm to 9:02 pm).[22] The research team estimates two regression models that independently predict stops of Black and Hispanic drivers that also include the daylight variable of interest and control variables for PSP Troop, day of the week, time of the day, and seasonality.[23]

The full regression results are provided in Appendix A. In summary, the variable of interest – daylight – shows that Black and Hispanic drivers are only slightly (1.1 times) more likely to be stopped during daylight than during darkness. Despite its statistical significance, this is not a substantively meaningful difference. As noted in Section 2, Generally speaking, odds ratios from 1.0 to 1.5 are considered substantively small (Chen et al., 2010). This indicates a lack of evidence that Black and Hispanic motorists are more likely to be stopped when conditions are more conducive to viewing drivers' characteristics.

Several VOD analyses examining traffic stop data from other state police agencies have reported similar findings—either null or small statistically significant differences (see for example, Knode et al., 2024; RIPA Board, 2020, 2021, 2022; Ross & Barone, 2024; Wolfe et al., 2021). Future VOD analyses conducted for the PSP using 2024 data will explore incorporating additional control variables, examining stops during the early morning inter-twilight period, and combining multiple years of data.

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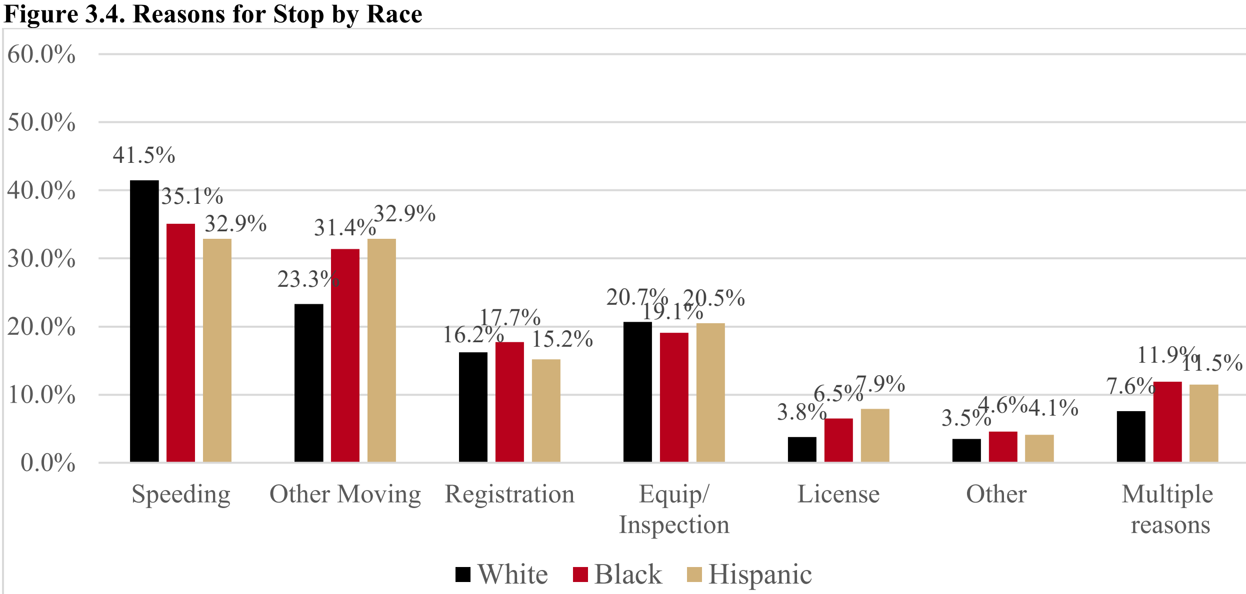
[22] Stops occurring between sunset and dusk, when it is neither daylight or dark, are excluded in accordance with recent guidance (Knode et al., 2024).

[23] A quasibinomial link function accounts for the error distribution of our dichotomous outcome (Knode et al., 2024).

An additional method to measure possible racial/ethnic disparities in traffic stops is to examine the reason for stops. As noted in Section 2, many jurisdictions nationwide have enacted new statutory or policy regulations on officers' traffic enforcement based on the concern that certain low-level, non-moving violations are disproportionately used against drivers of color for "pretextual" purposes (Holder, 2023). Although we take no position on whether stops for violations related to equipment, registration, and inspection are being used for pretextual purposes (which is legal under *Whren v. U.S.*, 1996) by the PSP or any other law enforcement agency, we explore whether racial/ethnic differences exist across different reasons for the stop that may warrant further examination.

Figure 3.4 displays bivariate comparisons between race/ethnicity and reasons for PSP traffic stops. While some statistically significant differences are noted for all reasons for the stop, substantively, the racial/ethnic differences for stops for violations related to registration, equipment, and inspection are substantively very small (as measured by the Cramer's V statistic).

Figure 3.4. Reasons for Stop by Race



Section Summary

Section 3 described the characteristics of traffic stops and stopped drivers across PSP organizational units based on data collected during 449,047 stops from January 1 to December 31, 2023. Considerable variation is reported in stop characteristics, reasons for the stop, and driver characteristics across PSP organizational units. Some differences are to be expected due to differences 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 department, the majority of traffic stops have the following characteristics:
    - Occurred on a weekday (67.7%)

- Occurred during the daytime (67.1%)
- Occurred on a state highway (54.5%) or an interstate (33.7%)
- Involved a vehicle registered in Pennsylvania (79.8%)
- Involved vehicles without passengers (81.5%)
- Lasted between 1-15 minutes (90.0%)

- Across the department, the most frequent reason for a stop is speeding (40.2%), with an average of 21.5 mph over the posted speed limit, followed by other moving violations (25.7%), equipment violations/inspections (20.0%), and registration violations (16.1%).

- Across the department, the characteristics of the drivers include:
  - Average age of 38.6 years
  - 67.2% male
  - Driver behavior is overwhelmingly civil (98.3%), with only a small percentage of stops reported to involve disrespectful, non-compliant, or resistant drivers
  - 81.1% Pennsylvania residents
  - White not Hispanic (71.5%), Black (14.9%), Hispanic White (8.8%), Asian (2.1%), American Indian or Alaskan Native (0.4%), unknown race and ethnicity (2.3%)

- **Regarding the initial traffic stop decision, no substantive racial/ethnic disparities are detected using multiple analytical techniques.**

  - Using the Veil of Darkness approach (an alternative to benchmark analysis), this analysis reveals that Blacks and Hispanics are 1.1 times more likely to be stopped during daylight compared to darkness, which is not a substantively meaningful difference despite its statistical significance.
  - There is a public perception that certain types of low-level, non-moving violations are disproportionately used against drivers of color for "pretextual" purposes. The research team explores whether racial/ethnic differences exist across different reasons for the stop. Although statistically significant bivariate differences are noted, substantively, the racial/ethnic differences for stops for violations related to registration, equipment, and inspection are very small.

4. TRAFFIC STOP ENFORCEMENT OUTCOMES

Section 4 reports the enforcement outcomes of member-initiated traffic stops conducted in 2023. Initially, the percentage of stops resulting in warnings, citations, arrests, and discretionary searches of the motorists, including basic descriptive statistics at the Department, Area, and Troop levels are documented. 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, arrests, and discretionary searches. 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 regression analyses that model the strength of the factors predicting whether warnings, citations, arrests, and searches occur.

Description of Traffic Stop Outcomes

Overview

Between January 1 and December 31, 2023, PSP Troopers initiated 449,047 traffic stops that could result in one or more post-stop enforcement outcomes for drivers (e.g., a driver may be warned and cited during the same stop).[24] Slightly over one-fifth (21.1%) of the drivers stopped (n=94,587) received more than one enforcement action (warning, citation, or arrest).

In 2023, PSP Troopers issued 251,598 total warnings to drivers, 74.6% of which are written warnings (n=187,637) compared to 25.4% verbal warnings (n=63,961). When written warnings are issued, the number of warnings is captured. Approximately three-quarters of the stops involving written warnings (75.7%) resulted in a single written warning, 16.0% in two written warnings, and 8.3% in three or more written warnings. In 2023, PSP Troopers issued citations to 263,633 drivers. Of these drivers, 74.7% are issued a single citation, 9.2% are issued two citations, and 5.7% have three or more citations issued. In 2023, PSP Troopers arrested 14,982 drivers.

An alternative way to think about enforcement outcomes 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 (verbal or written), citations, and arrests, with warnings as least severe and arrests as most severe. For example, if a driver receives both a warning and a citation, they are included only in the citation category. Across the department, 37% of all traffic stops result in issuing a warning to the driver as the most severe disposition. Over half of all traffic stops result in a

[24] PSP captures stop outcomes for passengers as well as drivers. However, because only 18.5% of the stops involved passengers and enforcement outcomes for passengers are extremely rare (less than 0.5% of all stops and about 2% of stops with passengers), this report focuses exclusively on enforcement actions involving drivers.

citation as the most severe outcome (56.6%), while only 3.3% of all traffic stops result in a driver's arrest.

In 2023, PSP Troopers conducted a total of 19,042 total searches, representing 4.2% of all traffic stops. This represents a 3.5% increase compared to the reported searches in 2022. However, as documented in the 2022 annual report (Engel et al. 2023), there was evidence that a technical issue with the data collection system (corrected in September 2022) likely resulted in an undercounting of incident to arrest searches. Therefore, the number of searches overall in 2022 was underreported.[25] As shown in Figure 4.1, the most common reason for searches during traffic stops in 2023 was incident to arrest (66.4%),[26] followed by verbal consent (36.1%). However, PSP Troopers are instructed to select all reasons for traffic stop searches that apply. Almost 31% of stops with searches involved more than one reason for the search. Tables in Appendix A display the reasons for all searches at the Area, Troop, and Station levels. Nearly all searches are conducted roadside (96.9%); the remainder are of vehicles towed and searched elsewhere. Approximately 43% of searches are of only the driver, 29% of the driver and vehicle, 17.5% of the vehicle only, and 7% of the driver, vehicle, and at least one passenger.

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). Therefore, the remainder of this report focuses analyses exclusively on "discretionary" searches, which the research team defines as a search that is *not* based solely on a mandatory reason (i.e., required by law or department policy). Therefore, the 9,297 searches based only on incident to arrest and/or inventory searches are excluded from further analyses because they do not involve officers' discretionary choices to initiate a search. If a search was conducted based on both discretionary *and* mandatory reasons, it was retained in the analyses of discretionary searches because the research team is interested in examining searches that involved any discretionary decision-making. **This results in 9,745 discretionary searches (2.2% of all stops, approximately 51% of all searches) that are based on probable cause, reasonable suspicion, and drivers' consent.**

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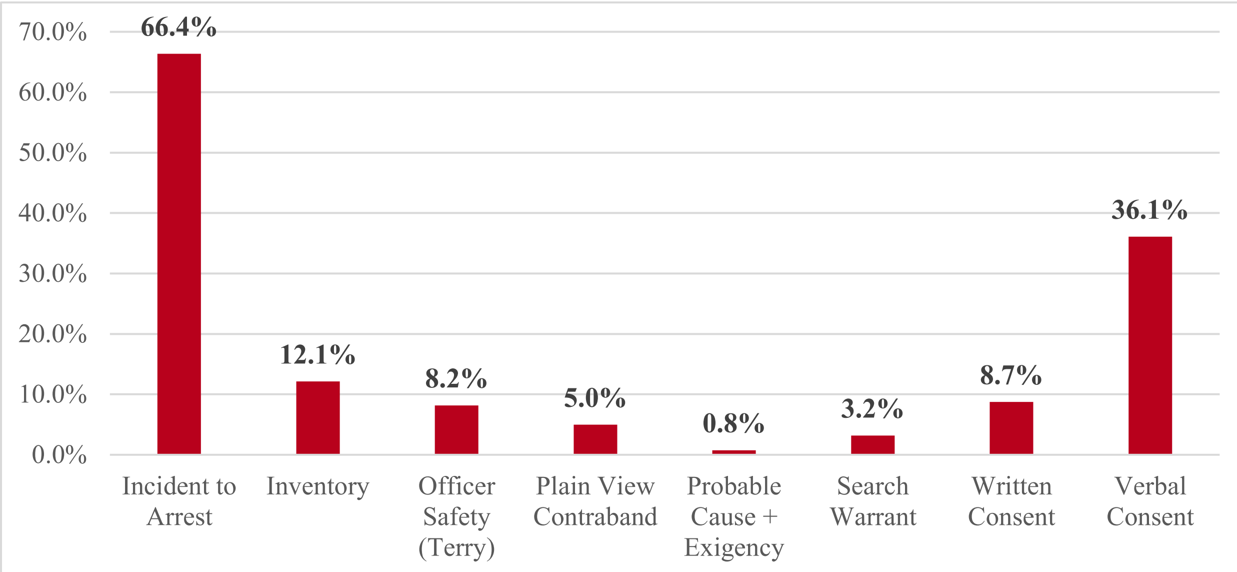
[25] As described in the *2021 Pennsylvania State Police Traffic Stop Study,* the values for categories of search reasons changed mid-year in 2021, with some reasons eliminated, others added, and the numeric codes for all categories differing from the previous CDR form to the updated form (Engel & Cherkauskas, 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.

[26] The percent of searches that were incident to arrest in 2022 was 36%, which provides further evidence that these searches were previously undercounted.

Figure 4.1. Reasons for Traffic Stop Searches in 2023 (n=19,042 searches)



Stop Outcomes by Organizational Units

The disposition of traffic stops (e.g., warnings, citations, arrests, and discretionary searches) is reported at the Department, Area, and Troop levels in Table 4.1 and graphically displayed in Figure 4.2. As noted above, the reported percentages exceed 100% because drivers may experience more than one enforcement outcomes during a single sto. As shown, 58.7% of drivers are issued citations, while 56.1% receive verbal or written warnings (14.3% and 41.8%, respectively). Driver arrests and discretionary searches are rare, occurring in only 3.3% and 2.2% of traffic stops, respectively.

Figure 4.2. Department-Wide Post-Stop Outcomes, January - December 2023

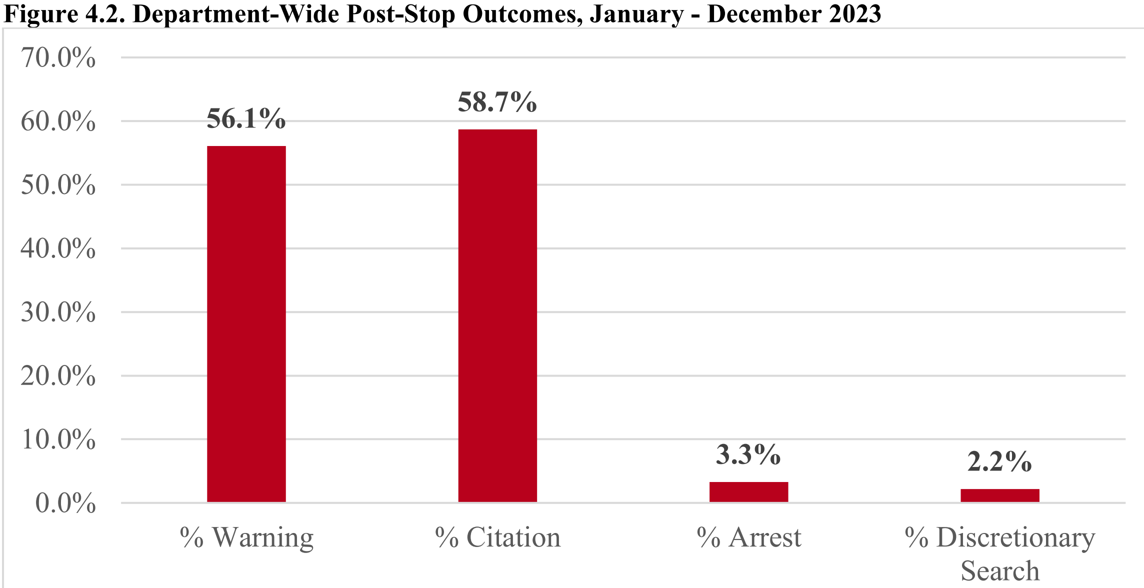


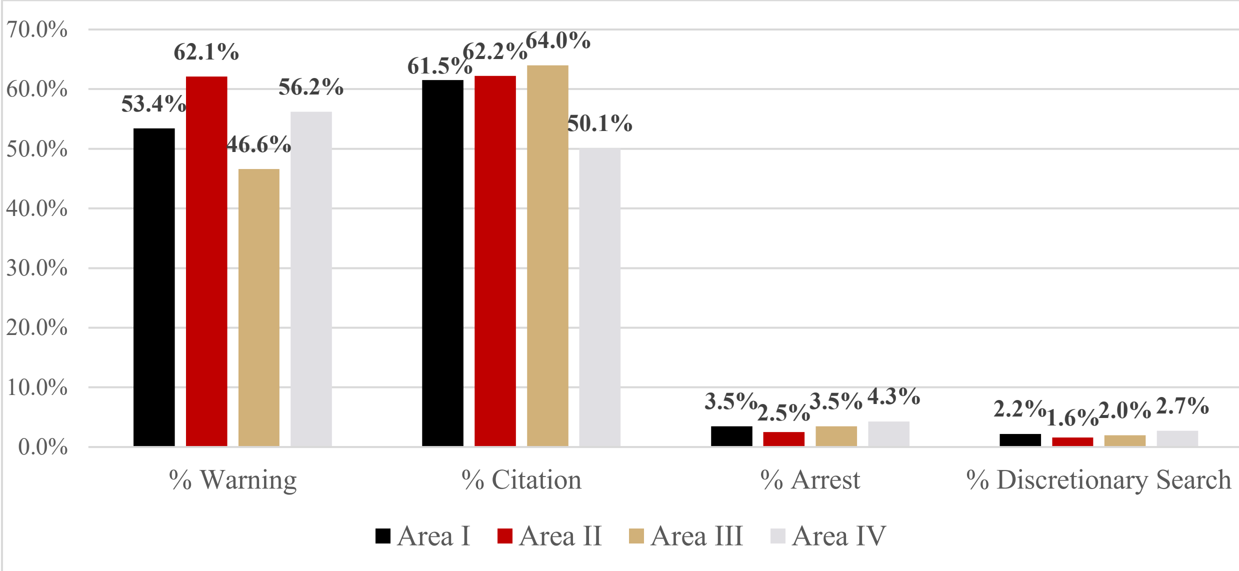
Table 4.1. Drivers' Post-Stop Outcomes by Department, Area & Troop, January – December 2023

	Total # of Stops	Warning	Citation	Arrest	Discretionary Search
PSP Dept.	449,047	56.1%	58.7%	3.3%	2.2%
AREA I	98,932	53.4%	61.5%	3.5%	2.2%
Troop B	25,288	43.3%	65.8%	3.4%	2.7%
Troop C	26,227	60.8%	61.2%	3.0%	1.6%
Troop D	22,359	52.3%	59.7%	5.1%	3.2%
Troop E	25,058	56.8%	58.9%	2.9%	1.3%
AREA II	145,297	62.1%	62.2%	2.5%	1.6%
Troop A	18,559	54.1%	66.6%	3.3%	1.8%
Troop G	28,688	58.9%	62.0%	3.0%	2.1%
Troop H	49,172	71.0%	43.0%	4.0%	2.5%
Troop T	48,878	57.9%	80.0%	0.3%	0.2%
AREA III	90,4455	46.6%	64.0%	3.5%	2.0%
Troop F	35,128	50.5%	61.4%	2.5%	1.3%
Troop N	28,033	40.4%	67.5%	5.0%	2.3%
Troop P	15,059	52.1%	59.0%	2.8%	1.9%
Troop R	12,225	43.2%	69.8%	3.7%	3.3%
AREA IV	108,251	56.2%	50.1%	4.3%	2.7%
Troop J	36,152	62.4%	41.7%	4.5%	2.5%
Troop K	26,711	53.5%	49.9%	4.3%	3.3%
Troop L	22,302	47.3%	62.6%	3.6%	2.4%
Troop M	23,086	57.8%	51.3%	4.6%	2.3%

As reported in Table 4.1 above and graphically displayed in Figure 4.3 below, post-stop outcomes differed across PSP Areas. For example, troopers assigned to Area II issued the most warnings to drivers (62.1%), while troopers in Area III issued the least (46.6%). Drivers in Area III are the most likely to be cited (64.0%), while drivers in Area IV are the least likely to be issued citations (50.1%). Troopers in Area II arrest and search the smallest percentage of stopped drivers (2.5% and 1.6%, respectively), while Area IV reports the highest percentage of drivers arrested and searched (4.3% and 2.7%, respectively).

Troops range in their frequency of issuing warnings from a high of 71.0% of stopped motorists in Troop H to a low of 40.4% in Troop N. Troop T has the highest percentage of drivers cited (80.0%), while Troop J has the lowest (41.7%). Traffic stops resulting in driver arrests range from a high of 5.1% of stops in Troop D to a low of 0.3% in Troop T.

Figure 4.3. Post-Stop Outcomes by PSP Area, January - December 2023



Bivariate Analyses of Traffic Stop Outcomes

As described in Section 2, bivariate analyses examine the association between only two variables – in this case, drivers' race/ethnicity and post-stop outcomes – and do not control for alternative factors that could impact the relationship between the two. Bivariate analyses are based on two comparisons. First, drivers' race/ethnicity is analyzed in relation to all traffic stop outcomes. Drivers' race/ethnicity is represented by White, Black, and Hispanic categories. Given the relatively small number of traffic stops involving drivers perceived to be American Indian or Alaskan Native, Asian or Pacific Islander, Two or More Races, or unknown, analyses of these stops are not reported. Second, the relationship between driver gender and stop outcomes is examined. Analyses involving drivers' gender reflect all traffic stops in which drivers' gender is recorded.[27] Appendix A includes Area, Troop, and Station-level tables reporting the total number of stops for each race/ethnicity and gender group and the percentage of drivers from each group who are warned, cited, arrested, or searched for discretionary reasons. Only the department-level differences are graphically displayed and discussed here.

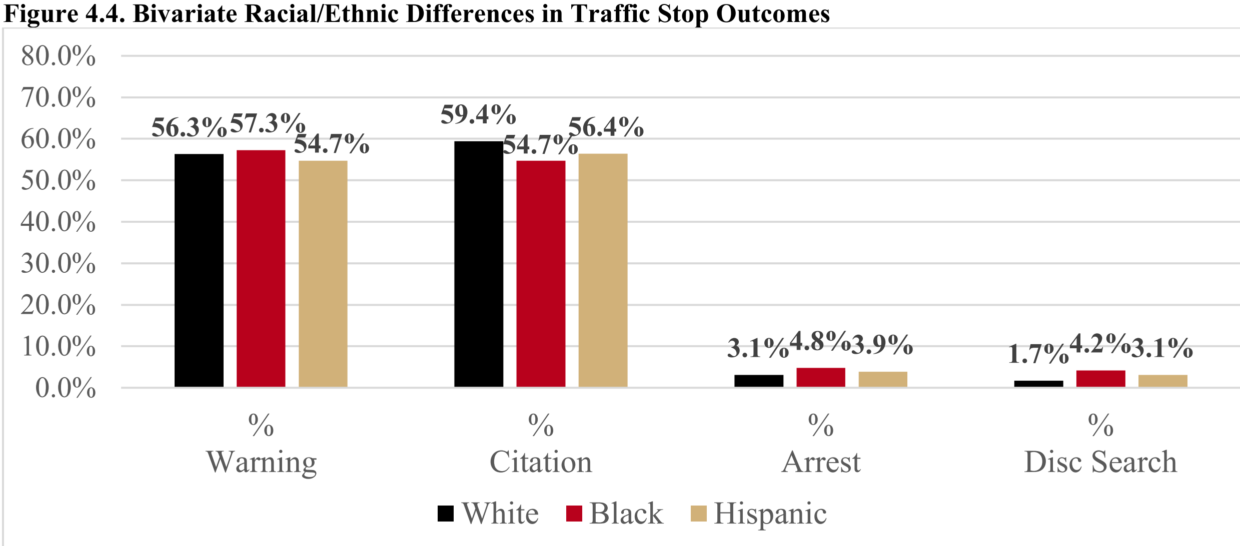
Figures 4.4 and 4.5 illustrate the variation in post-stop outcomes (i.e., warnings, citations, arrests, and discretionary searches) by drivers' race/ethnicity and gender, respectively. Across the department, there are statistically significant bivariate differences in the rate of all traffic stop outcomes depending on drivers' race/ethnicity. Hispanic motorists are least likely to receive warnings. White drivers are significantly more likely to receive a citation (59.4%) than Black and Hispanic drivers (54.7% and 56.4%, respectively). Black and Hispanic drivers are

[27] It excludes the 955 cases (0.2%) where driver gender is reported to be unknown.

significantly more likely than White drivers to be arrested (4.8% and 3.9%, respectively, compared to 3.1%) and they are significantly more likely to be subject to a discretionary search than White drivers (4.2% and 3.1%, respectively, compared to 1.7%). Based on the Cramer's V statistic for effect sizes, these all represent substantively small differences.

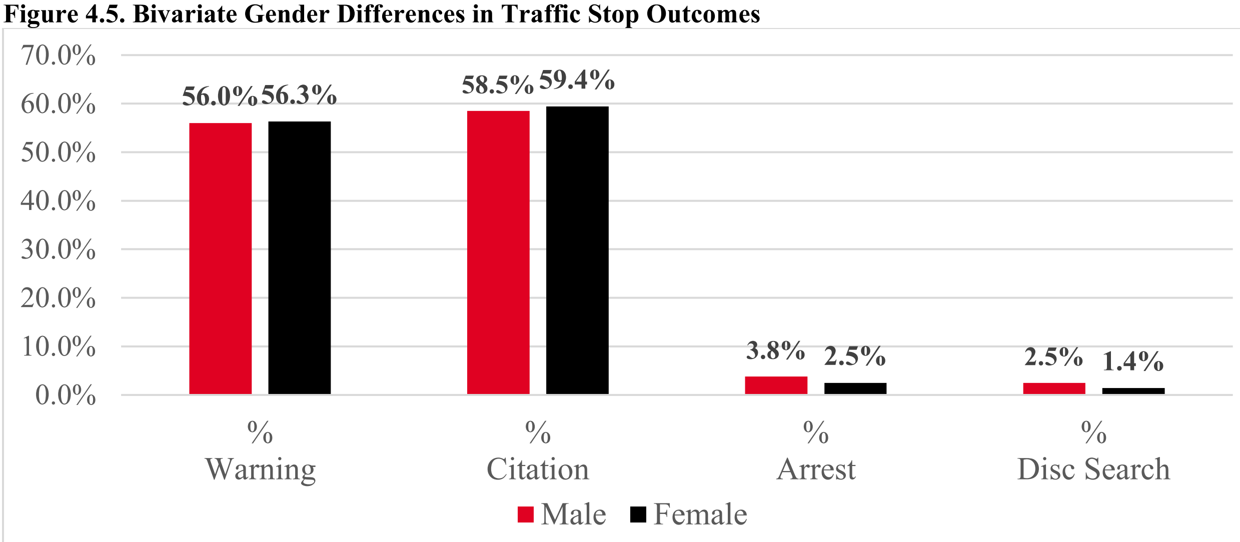
Figure 4.5 displays differences in the frequency of traffic stop outcomes based on driver gender. There are no statistically significant differences for warnings. Female drivers are slightly more likely to be cited, while male drivers are more likely to be arrested or searched. Based on the Cramer's V statistic for effect sizes, these all represent substantively small differences.

Figure 4.4. Bivariate Racial/Ethnic Differences in Traffic Stop Outcomes



NOTE: These are all statistically significant bivariate relationship at p value < .001

Figure 4.5. Bivariate Gender Differences in Traffic Stop Outcomes



NOTE: The gender differences for warnings are not statistically significant. The remainder are statistically significant bivariate relationship at p value < .001.

It is important to reiterate that the bivariate relationships reported in these figures and the tables in Appendix A do not statistically control for other relevant legal and extralegal factors that might influence officer decision-making. This information is included solely to provide details to PSP administrators regarding differences in post-stop outcomes at various organizational levels and cannot be used to assess whether racial/ethnic or gender differences in outcomes 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

As described in Section 2, multivariate analyses are statistical estimation methods that simultaneously account for independent predictors of a given outcome. Given that traffic stop enforcement actions are measured as dichotomous (0=did not happen or 1=happened) for 1) warnings, 2) citations, 3) arrests, or 4) discretionary searches, binary logistic regression is used to account for the impact of various factors, including driver, vehicle, situational, trooper characteristics and legal variables. The statistical models isolate what individual factors, given similar situations, predict enforcement outcomes.

Descriptive Statistics

For each of the multivariate models reported below, numerous independent variables are included that could influence the enforcement outcomes that drivers receive. A description of these variables is included below.

- **Legal variables:**
  - **Reason for the stop** – measured as six dichotomous variables, where 0 = no and 1 = yes, for each individual reason for the stop (speeding, equipment only, license only, moving only, registration only, and "other" violations); speeding is treated as the reference category (excluded) in the analyses
  - **Multiple reasons for the stop** – measured as a dichotomous variable, where 0 = single reason for stop and 1 = two or more reasons for stop
  - **Special Traffic Enforcement** – measured as a dichotomous variable for stops associated with specific PSP initiative or program, where 0 = no and 1 = yes
  - **Evidence** – measured as a dichotomous variable, where 0 = no and 1 = yes, for contraband discovered during a search
  - **Criminal history –** measured as a dichotomous variable, where 0 = no and 1 = yes, for queries that show driver has a criminal history

- **<u>Driver Characteristics</u>**:
  - **Race** – measured as four dichotomous variables, where 0 = no and 1 = yes for White, Black, Other (including American Indian or Alaska Native, Asian or Pacific Islander, Two or More Races) and Unknown[28]
  - **Ethnicity** – measured as a dichotomous variable, where 0 = Not Hispanic and 1 = Hispanic)[29]
  - **Gender** – measured as a dichotomous variable, where 0 = female and 1 = male[30]
  - **Driver Age** – recorded as a dichotomous variable for "young driver", where driver age 25 or older = 0 and 1 = under 25
  - **Civil behavior** – measured as a dichotomous variable, where 0 = disrespectful, non-compliant, vebally, or physically resistant, and 1 = civil
  - **Limited English Proficiency** – measured as a dichotomous variable, where 0 = no and 1 = yes

- **<u>Vehicle characteristics</u>:**
  - **PA vehicle registration** – measured as a dichotomous variable, where 0 = out of state registration and 1 = PA registration
  - **Passengers** – measured as a dichotomous variable, where 0 = no passengers, and 1 = one or more passengers in the vehicle

- **<u>Situational characteristics</u>:**
  - **Daytime** – measured as a dichotomous variable, where 0 = nighttime and 1 = daytime
  - **Weekday** – measured as a dichotomous variable, where 0 = weekend and 1 = weekday
  - **Summer Month**– measured as a dichotomous variable, where 0 = Jan – May & Sept – Dec and 1 = June, July & August
  - **Interstate** – measured as a dichotomous variable, where 0 = state road, county road, other and 1 = interstate

- **<u>PSP Member characteristics</u>:**
  - **Gender** – measured as a dichotomous variable, where 0 = female and 1 = male
  - **Race/ethnicity** – measured as a dichotomous variable, where 0 = White and 1 = Non-White

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[28] 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.
[29] The research team estimated multiple logistic regression models, with cases of unknown ethnicity excluded and also with unknown ethnicity recoded as "Not Hispanic" to retain these cases in the analyses. There are no substantive differences in the regression models. The regression models with unknown ethnicity coded as "Not Hispanic" are presented in this report. The regression models with unknown ethnicity excluded from the analyses are available from the authors upon request.
[30] Although driver gender is not missing for any cases, for 955 cases it is reported as "unknown." These cases are excluded from the final dataset for multivariate analyses.

- **Experience** – measured as a dichotomous variable, where 0=>3 years and 1 = <3 years with the PSP
- **Patrol Assignment** – measured as a dichotomous variable, where 0 = non-Patrol and 1 = Patrol
- **Trooper Rank** – measured as a dichotomous variable, where 0 = Corporal and above and 1 = Trooper

Addition of Criminal History

In response to one of the recommendations in the 2022 report, the PSP added two fields related to driver criminal history to the CDR system on August 17, 2023. First, there is a yes/no question about whether the PSP member queried criminal history, and second, if there is a query, whether criminal history is detected (as measured by arrests, charges, and dispositions).

From August 17 to December 31, 2023, there were 111,901 stops conducted (24.9% of all 2023 stops). Of these, 5.5% resulted in a criminal history query by troopers, and of those queries, 56.5% resulted in the detection of the driver's criminal history. Because the data fields are unavailable for the entire year, the criminal history variable cannot be included in the main logistic regression models examining data for the whole year. However, separate models for the period where criminal history is available (August 17 – December 31, 2023) are presented and demonstrate that the addition of this field is substantively important for the findings.

Table 4.2 provides the summary statistics for the variables in the final datasets used for multivariate analyses, including the statistical model based on the full year of data (Models A) and the limited sample model examining the quarter of the data that measures criminal history (Models B).[31] Comparisons of Models A and B show extremely similar univariate distributions for the independent and dependent variables across all regression models. Therefore, there does not appear to be any bias in examining the restricted sample. Indeed, including the criminal history measure in the analyses considerably improves model fit, suggesting the methods are vastly improved with their inclusion.

[31] The measures with missing data overlap, so the final total of cases for analysis equates to 99.7% of the total distribution of stops. Also, the warning model is based on 447,539 stops instead of 447,821 due to a small amount of missing data on just warnings (n=288). The descriptive statistics, however, do not substantively vary between the two samples.

Table 4.2. Descriptive Statistics for Final Dataset Used for Multivariate Analyses

	Model A (Jan 1 – Dec 31 2023) N=447,821				Model B (Aug 17 – Dec 31, 2023) N=111,633			
Dependent Variables	Mean (%)	SD	Min	Max	Mean (%)	SD	Min	Max
Any Warning	.561	.496	0	1	.565	.496	0	1
Citation	.588	.492	0	1	.573	.495	0	1
Arrest	.033	.180	0	1	.040	.196	0	1
Discretionary Search	.022	.146	0	1	.024	.152	0	1
Independent Variables								
Legal Measures								
Speeding Only (Reference category)	.366	.482	0	1	.369	.483	0	1
Equipment Only Violation	.158	.365	0	1	.139	.346	0	1
License Only Violation	.026	.158	0	1	.027	.161	0	1
Moving Only Violation	.217	.412	0	1	.236	.425	0	1
Registration Only Violation	.123	.329	0	1	.034	.121	0	1
Other Only Violation	.024	.152	0	1	.015	.121	0	1
Multiple Reasons (2+ violations)	.086	.281	0	1	.081	.272	0	1
Special Traffic Enforcement	.164	.370	0	1	.201	.400	0	1
Evidence Seized in Stop	.015	.120	0	1	.017	.129	0	1
Criminal History Detected	--	--	--	--	.031	.174	0	1
Driver Characteristics								
White (Reference)	.802	.398	0	1	.801	.399	0	1
Black	.149	.356	0	1	.153	.360	0	1
Other Race	.025	.157	0	1	.024	.153	0	1
Race Unknown	.023	.150	0	1	.022	.147	0	1
Hispanic Ethnicity	.095	.293	0	1	.096	.295	0	1
Male	.672	.469	0	1	.674	.469	0	1
Young Driver	.199	.399	0	1	.212	.409	0	1
Driver Behavior Civil	.983	.131	0	1	.982	.133	0	1
Limited English Proficiency	.005	.070	0	1	.005	.069	0	1
Vehicle Characteristics								
Pennsylvania Plate Registration	.798	.402	0	1	.798	.401	0	1
Passengers Present	.185	.388	0	1	.171	.376	0	1
Situational Characteristics								
Daytime	.672	.470	0	1	.575	.494	0	1
Weekday (Mon-Thurs)	.677	.468	0	1	.670	.470	0	1
Summer Months (June-August)	.238	.426	0	1	.009	.097	0	1
Interstate	.337	.473	0	1	.331	.471	0	1
PSP Member Characteristics								
Male Trooper	.952	.214	0	1	.950	.219	0	1
Non-White Trooper	.087	.282	0	1	.088	.284	0	1
3 Years Less Experience	.315	.465	0	1	.304	.460	0	1
Patrol Assignment	.959	.199	0	1	.954	.209	0	1
Trooper Rank	.877	.329	0	1	.869	.337	0	1

Warnings

Table 4.3 below reports the binary logistic regression model examining warnings as the outcome in the stops (compared to all other outcomes). This model has a Nagelkerke r-square value of .130, which indicates moderate model fit.

The most important, consistent, and robust predictors of warnings are legal measures. Specifically, each of the eight variables are statistically significant cross-correlates of warnings. The vast majority of the odds ratios are medium to large sized in magnitude (suggesting a moderate to strong association with receiving a warning). Stops with equipment only violations (odds ratio = 2.98) are those most likely to result in a warning, relative to all other stops. Moving only violations (odds ratio = 2.77) are also considerably more likely to result in warnings, net of all other factors. Stops with 'multiple reasons' are 2.64 times less likely to result in a warning than stops for single violations (meaning that, if there are multiple reasons for a stop, a warning is a less-likely outcome, all else equal). Additionally, registration only stops are 2.13 times less likely to result in a warning. Finally, the largest and most robust effect size relative to all other factors is whether evidence is seized. If evidence is seized in the stop, the stop is 19.9 times less likely to result in a warning. The limited sample model (Model B) revealed no statistically significant impact of criminal history on the odds of a driver receiving a warning. Therefore, for parsimony, only the main model for the full year is presented.

The characteristics of the drivers, including demographics, behavior, and English proficiency, are also accounted for in the models. If the officer codes the driver's behavior as civil, the stop is 2.46 times more likely to result in a warning, net of all other factors. It is also noteworthy that the only statistically insignificant predictor is if the driver is Black (relative to White drivers, which are the reference category). In sum, Black and White drivers are similarly likely to receive a warning. If the driver race is unknown, the stop is 1.34 times less likely to result in a warning, all else equal. The remaining driver characteristic odds ratios are below 1.3 (and thus the effect sizes are not salient or meaningful).

Additionally, daytime stops are significantly less likely (by 1.67 times) to result in a warning than nighttime stops (the reference category).

Given the low odds ratios observed in the estimates (typically less than 1.3), troopers' characteristics are neither powerful nor salient predictors of warnings. The lone exception to the impact of trooper characteristics on warnings is that troopers assigned to patrol are 1.6 less likely than all other troopers to end the stop with a warning.

Table 4.3. Binary Logistic Regression Analyses Predicting WARNINGS during traffic stops in 2023 (n=447,539)

	Coefficient	St. Error	Odds Ratio
Intercept	-0.348	0.036	--
Legal Measures			
Equipment Only Violation	1.09*	0.010	2.98
License Only Violation	-0.16*	0.021	1.17
Moving Only Violation	1.02*	0.009	2.77
Registration Only Violation	0.75*	0.010	2.13
Other Only Violation	0.44*	0.021	1.56
Multiple Reasons	0.97*	0.012	2.64
Special Traffic Enforcement	-0.14*	0.009	1.15
Evidence Seized in Stop	-2.99*	0.045	19.96
Driver Characteristics			
Black	-0.02	0.009	--
Other Race	-0.09*	0.020	1.09
Race Unknown	-0.30*	0.021	1.34
Hispanic Ethnicity	-0.18*	0.011	1.20
Male	-0.06*	0.007	1.07
Age (Years)	-0.04*	0.008	1.04
Driver Behavior Civil	0.90*	0.025	2.46
Limited English Proficiency	-0.16*	0.046	1.17
Vehicle Characteristics			
Pennsylvania Plate Registration	-0.20*	0.009	1.23
Passengers Present	0.00	0.008	--
Situational Characteristics			
Daytime	-0.51*	0.007	1.67
Weekday (Mon-Thurs)	0.13*	0.007	1.13
Summer Months (June-August)	0.12*	0.008	1.13
Interstate	-0.05*	0.007	1.05
PSP Member Characteristics			
Male Trooper	-0.06*	0.015	1.06
Non-White Trooper	-0.24*	0.011	1.27
3 Years Less Experience	0.01	0.007	--
Patrol Assignment	-0.51*	0.017	1.66
Trooper Rank	0.29*	0.010	1.34
Nagelkerke R-Square	.130		

* = $p < .001$ 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

Table 4.4 below reports the binary logistic regression model showing the estimates of driver citations as the outcome. This model has a Nagelkerke r-square value of .271, which indicates robust model fit. This means there is more confidence in the findings predicting the likelihood of citations during traffic stops than warnings.

The legal measures in the models are the strongest and most consistent significant predictors of the stop ending in a citation. Specifically, moving-only violations are 5.8 times less likely to result in a citation when compared to speeding (the reference category). Similarly, equipment-only violations are almost 4.5 times less likely to result in a citation than drivers stopped for speeding violations. Other violations are 5.4 times less likely to end in a citation (when compared with stops due to speeding). Finally, registration violations are 3.1 times less likely to result in a citation when contrasted with speeding violations. In short, this means that being stopped for speeding is a strong predictor of receiving a citation compared to all other reasons. Furthermore, if the stop occurs as part of a special traffic enforcement program, it is 1.7 times more likely to result in a citation compared to all other stops. Drivers with evidence seized are also 1.7 times more likely to receive a citation compared to drivers with no seizure.

Model B (not shown) revealed that drivers with criminal histories are 1.8 times less likely to receive a citation. The addition of criminal history does not substantively impact any of the other model effects and has a negligible impact on the model fit; therefore, for parsimony, only the main model for the full year is presented.

Most driver demographic characteristics do not consistently predict whether stops result in citations. The odds of a stop resulting in a citation are virtually indistinguishable between Black and White drivers stopped. Black drivers are slightly less likely (-1.1 compared with 1.0 as the baseline) to receive a citation relative to White drivers. There is no statistically significant difference between the odds of a Hispanic driver or a driver of another race receiving a citation compared to White drivers. When the driver's race is unknown, they are 1.8 times more likely to receive a citation than White drivers, net of other factors in the model. Neither driver's age nor gender is associated with any substantively important differences in the odds of receiving a driver citation. Drivers coded as behaving civilly are 2.4 times *less* likely to have the stop result in a citation.

Some situational and PSP member characteristics predict whether stops result in citations. Specifically, daytime stops are 2.7 times more likely to result in a citation than nighttime stops. Stops involving patrol officers are 2.4 times more likely to end in a citation than stops involving troopers with other assignments. The impact of other trooper characteristics is minimal.

Table 4.4. Binary Logistic Regression Analyses Predicting CITATIONS during traffic stops in 2023 (n=447,821)

	Coefficient	St. Error	Odds Ratio
Intercept	0.463	0.039	--
Legal Measures			
Equipment Only Violation	-1.502*	0.010	4.49
License Only Violation	-0.658*	0.021	1.93
Moving Only Violation	-1.773*	0.010	5.89
Registration Only Violation	-1.141*	0.011	3.13
Other Only Violation	-1.694*	0.022	5.44
Multiple Reasons	-0.193*	0.014	1.21
Special Traffic Enforcement	0.534*	0.010	1.71
Evidence Seized in Stop	0.534*	0.028	1.71
Driver Characteristics			
Black	-0.095*	0.010	1.10
Other Race	0.041	0.023	--
Race Unknown	0.567*	0.025	1.76
Hispanic Ethnicity	0.036	0.012	--
Male	0.053*	0.007	1.05
Age (Years)	0.141*	0.009	1.15
Driver Behavior Civil	-0.876*	0.028	2.40
Limited English Proficiency	0.097	0.049	1.10
Vehicle Characteristics			
Pennsylvania Plate Registration	0.350*	0.009	1.42
Passengers Present	0.162*	0.009	1.18
Situational Characteristics			
Daytime	0.995*	0.007	2.71
Weekday (Mon-Thurs)	-0.081*	0.007	1.09
Summer Months (June-August)	-0.175*	0.008	1.19
Interstate	0.185*	0.008	1.20
PSP Member Characteristics			
Male Trooper	-0.121*	0.016	1.13
Non-White Trooper	0.059*	0.012	1.06
3 Years Less Experience	-0.230*	0.008	1.26
Patrol Assignment	0.890*	0.017	2.44
Trooper Rank	-0.112*	0.011	1.12
Nagelkerke R-Square	.271		

* = 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 4.5 reports two binary logistic regressions predicting driver arrests during traffic stops in 2023. Model A is for all stops in 2023 without missing data (n=447,821). Model B is the time-restricted model that includes only stops from August 17 – December 31, 2023 (n=111,633) with the estimated impact of the criminal history included.[32] The Nagelkerke r-square value for each arrest model demonstrates a robust fit (Model A = .493 and Model B = .504), indicating we can have strong confidence in their findings.

As a first step, we examine the findings in Model A given that this model includes the full data range (January 1, 2023 -- December 31, 2023). Evidence seized correlates extremely strongly with the odds of an arrest, equating to 489 times greater odds of an arrest when evidence is seized compared to no seizure of evidence. It is important to note the cross-correlation of these measures in real-world applications. There is no sequential ordering to these measures. For example, evidence seizure may lead to an arrest, but it can also be a response to a search conducted incident to arrest. Therefore, the relationship between any two measures, such as evidence seized and arrest, cannot be interpreted causally because we do not have information about the temporal order of events (Engel & Calnon, 2004b).[33] This caveat aside, the findings presented in Table 4.5 below illuminate several noteworthy associations.

Model A shows that the legal measures explain the greatest variation in PSP traffic stops resulting in arrests. Specifically, each legal measure is statistically significant and positive – meaning that the legal violations are the strongest predictors of arrests compared to other factors such as driver, vehicle, situational, and PSP member characteristics. Within the legal measures, we observe that stops that occur for other reasons beyond speeding (the reference category), with equipment, license, and moving violations being most likely to result in the driver being arrested.

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[32] We also conducted a separate analysis to examine the congruence between the full sample (Model A) and the time-restricted sample without the criminal history variable. There are no substantively significant deviations between Models A and B (absent the criminal history variable), indicating that the full- and restricted-time frames do not lead to different findings across the covariates that are similar in both analyses. Also, given that Model B is constrained to the period between August 17 and December 31, 2023, we do not include the temporal controls (e.g., the measure for summer because it has a value of 0 in 99% of the cases in the limited sample). For brevity, these analyses are not included in this report, however, are available from the authors upon request.

[33] The bivariate correlation between the evidence and arrest measures is .575, 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). We ran the arrest analysis by including and excluding "evidence seized". The model that excluded evidence is weaker in its predictability (i.e., the Nagelkerke r-square value for Model 1 is reduced from .493 to .264). Finally, the estimates for race are similar across both sets of models (e.g., the race odds ratio for Black arrestees is 1.2 where evidence is included and 1.4 where evidence is excluded in Model 1; the odds ratios for Hispanic ethnicity is 1.17 with evidence and 1.07 without evidence). In sum, the arrest model that included evidence is the more uniform and parsimonious model and is included in the report.

Additionally, stops with moving violations are 5.5 times more likely to result in an arrest (relative to speeding, the reference group). License-only violations are 3.9 times more likely to result in a driver's arrest. Likewise, if a stop has multiple reasons, the odds of the stop ending in a driver's arrest are 6.1 times more likely than drivers stopped for a single reason.

Regarding situational factors, daytime stops are 4.0 times less likely to result in an arrest than nighttime stops. Stops on the interstate are 2.1 times less likely to result in an arrest than other roadway types. PSP member characteristics are also significant predictors of arrest in Model 2. Stops made by patrol officers are 2.0 times more likely to result in arrest, while stops made by troopers (compared to PSP members of other ranks) are 5.7 times less likely to result in arrest.

In Model A, Black drivers are about 1.2 times more likely to be arrested than White drivers, holding all else equal. This is a substantively small effect size. Hispanic drivers' odds of being arrested are not significantly different from White drivers. Other demographic characteristics that retain a degree of statistical association with arrests are driver gender and age. Male drivers are 1.4 times more likely than female drivers to be arrested, net of all other factors. Also, drivers under 25 years old are 1.4 times more likely to be arrested than drivers 25 years old or older. Civil drivers are 5.7 times less likely to be arrested than drivers engaging in disrespectful, noncompliant, or resistant behavior. Stops involving drivers with limited English proficiency are almost two times more likely to result in arrests.

Moving to Model B, which includes the impact of accounting for criminal history, we observe several empirical phenomena. First, the model fit (Nagelkerke R-square value) is higher, indicating less model error (.504 in Model A compared to .475 in Model B). Additionally, the coefficient for criminal history is positive and statistically significant, indicating drivers with criminal histories are 9.4 times more likely to be arrested than drivers without a criminal history, net of all other factors.

In addition, there are statistically significant and substantive reductions in the other model estimates once the analyses accounted for criminal history. Many of the odds ratios for the same estimates in Model B are smaller than in Model A (e.g., the odds ratio associated with evidence seized during the stop is reduced to 292 times higher in Model B from 489 times higher in Model A), suggesting that evidence seized odds are slightly overestimated when failing to account for the driver's criminal history.

Most notably, the odds of Black drivers being arrested are no longer statistically significantly different than White drivers once prior criminal history is considered. Likewise, driver age is not statistically significant in Model B. In short, several driver characteristics significantly associated with the odds of arrest are no longer significantly associated with arrests once the model improved because an important factor (driver's criminal history) is included in the regressions.

The effects of vehicle, situational, and PSP member characteristics in Models A and B are similar, suggesting the impact of accounting for drivers' criminal history is contained within legal measures and driver characteristics. In summary, the fact that PSP began accounting for driver's criminal history significantly improves the validity of the model predicting arrests.

Table 4.5. Binary Logistic Regression Analyses Predicting DRIVER ARRESTS during traffic stops in 2023

	Model A (n=447,821)			Model B (n=111,633)		
	Coefficient	**St. Error**	**Odds Ratio**	**Coefficient**	**St. Error**	**Odds Ratio**
Intercept	-1.367	0.101	--	-1.813	0.185	--
Legal Measures						
Equipment Only Violation	0.58*	0.047	1.79	0.55*	0.086	1.73
License Only Violation	1.37*	0.068	3.92	1.27*	0.121	3.55
Moving Only Violation	1.71*	0.038	5.55	1.64*	0.069	5.14
Registration Only Violation	0.56*	0.052	1.75	0.37*	0.096	1.44
Other Only Violation	2.49*	0.053	12.10	2.29*	0.114	9.91
Multiple Reasons	1.81*	0.044	6.11	1.62*	0.082	5.06
Special Traffic Enforcement	-0.57*	0.038	1.77	-0.70*	0.065	2.02
Evidence Seized in Stop	6.19*	0.049	489.74	5.68*	0.093	292.99
Criminal History Detected	--	--	--	2.24*	0.063	9.39
Driver Characteristics						
Black	0.18*	0.029	1.20	0.08	0.054	--
Other Race	-0.42*	0.090	1.52	-0.40	0.165	--
Race Unknown	-0.51*	0.103	1.67	-0.17	0.173	--
Hispanic Ethnicity	0.15*	0.035	1.17	0.10	0.065	--
Male	0.36*	0.025	1.43	0.29*	0.046	1.34
Driver Under 25 Years Old	-0.38*	0.029	1.46	-0.15	0.051	--
Driver Behavior Civil	-1.74*	0.042	5.72	-1.36*	0.085	3.91
Limited English Proficiency	0.66*	0.108	1.93	0.70*	0.206	2.02
Vehicle Characteristics						
Pennsylvania Plate Registration	0.31*	0.033	1.36	0.23*	0.060	1.26
Passengers Present	0.06	0.028	--	0.03	0.053	--
Situational Characteristics						
Daytime	-1.57*	0.026	4.83	-1.40*	0.050	4.07
Weekday (Mon-Thurs)	-0.53*	0.022	1.70	-0.60*	0.041	1.82
Summer Months (June-August)	0.14*	0.025	1.16	--	--	--
Interstate	-0.75*	0.030	2.11	-0.87*	0.057	2.39
PSP Member Characteristics						
Male Trooper	-0.21*	0.046	1.23	-0.27*	0.082	1.31
Non-White Trooper	-0.13*	0.040	1.14	-0.21	0.075	--
3 Years Less Experience	-0.23*	0.028	1.26	-0.27*	0.052	1.31
Patrol Assignment	0.54*	0.063	1.72	0.85*	0.117	2.34
Trooper Rank	-1.87*	0.026	6.49	-1.84*	0.048	6.28
Nagelkerke R-Square	.493			.504		

* = 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.

Predicting Discretionary Searches

Table 4.6 below reports two binary logistic regression models examining *discretionary searches* as the outcome compared to stops without discretionary searches. We employed the same process used in the arrest analyses where Model A includes data for the full year of 2023 while Model B includes stop data from August 17 – December 31, 2023.[34] The Nagelkerke R-square for Model A (.164) indicates a moderate fit. Once criminal history is included in Model B, the model fit for discretionary searches improves to a robust fitting model (Nagelkerke r-square=.280).

Using Model A (all data in 2023) as the onset point of discussion, each legal measure is a statistically significant correlate of discretionary search outcomes. Stops for other violations, license-only violations, moving violations, and equipment violations (compared to speeding, the reference category) are 7.3 times, 5.9 times, 4.0, and 3.9 times more likely to result in discretionary searches, respectively. Multiple reason stops are 5.6 times more likely to end in discretionary searches. Stops associated with special traffic enforcement programs are 1.7 times less likely to result in discretionary searches.

Stops with passengers are 2.6 times more likely to result in discretionary searches than stops with only drivers. The PSP member characteristics significantly associated with discretionary searches in Model A are related to officer assignment and rank. Patrol officers are 2.4 times less likely to conduct discretionary searches, while troopers are 4.0 times less likely to conduct discretionary searches than PSP members that are corporals or higher rank, net of other factors.

Black drivers, in Model A, are 2.0 times more likely to experience discretionary searches than White drivers (the reference group). Drivers of unknown race are 1.4 times more likely than Whites to have discretionary searches, while Hispanic drivers are 1.3 times more likely than Whites, all else equal. After accounting for criminal history, in Model B, several driver characteristic measures either are no longer statistically significant, or the effect sizes reduced from moderate to small. Hispanic drivers and drivers with unknown race are no longer significantly different than White drivers in their likelihood of having a discretionary search performed. Black drivers' odds of experiencing a discretionary search reduce from 2.0 (a moderate effect size) in Model A to 1.46 (a small effect size) in Model B relative to White drivers.

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[34]The Clogg z-coefficient difference tests comparing the estimates in Model A with the same time-restriction (as Model B), but without criminal history, show very few significant deviations over time. The only differences are for legal measures and driver characteristic, including PA registration (odds ratio=1.49 in Model A and is 1.68 in this time-restricted analysis), weekday likelihood of association (odds ratio=1.21 in Model A, but is statistically insignificant in the time-restricted analysis), and patrol assignment (odds ratio=2.48 in Model A and is 1.94 in the time-restricted analysis). These effect sizes are marginal to small and not likely to influence any interpretation of the data.

Model B also demonstrates that drivers with a criminal history are 18.9 times more likely to experience a discretionary search than those without. This is the strongest predictor of the odds of a stop resulting in a discretionary search. All other legal measures retain their level of statistical significance in Model B. However, the magnitude of each estimate is marginally to moderately smaller (e.g., the odds ratio for other violations reduced to 5.6 in Model B from nearly 7.4 in Model A). All other remaining estimates remain similar between Models A and B.

Table 4.6. Binary Logistic Regression Analyses Predicting Discretionary Searches during traffic stops in 2023

	Model A (n=447,821)			Model B (n=111,901)		
	Coefficient	**St. Error**	**Odds Ratio**	**Coefficient**	**St. Error**	**Odds Ratio**
Intercept	-1.655	0.085	--	-1.880	0.171	--
Legal Measures						
Equipment Only Violation	1.37*	0.040	3.94	1.09	0.080	2.96
License Only Violation	1.78*	0.061	5.92	1.22	0.124	3.39
Moving Only Violation	1.40*	0.037	4.06	1.12	0.072	3.05
Registration Only Violation	1.12*	0.045	3.05	0.79	0.088	2.21
Other Only Violation	2.00*	0.055	7.38	1.72	0.126	5.60
Multiple Reasons	1.73*	0.041	5.64	1.35	0.082	3.84
Special Traffic Enforcement	-0.55*	0.036	1.73	-0.55	0.066	1.74
Criminal History Detected	--	--	--	2.94	0.052	18.89
Driver Characteristics						
Black	0.70*	0.025	2.02	0.38*	0.053	1.46
Other Race	-0.28*	0.082	1.33	-0.33	0.173	--
Race Unknown	-0.39*	0.097	1.47	-0.63	0.232	--
Hispanic Ethnicity	0.23*	0.033	1.26	0.11	0.068	--
Male	0.46*	0.026	1.59	0.28*	0.052	1.32
Driver Under 25 Years Old	0.10*	0.026	1.11	0.29*	0.053	1.34
Driver Behavior Civil	-1.37*	0.041	3.92	-1.07*	0.086	2.90
Limited English Proficiency	0.44*	0.093	1.56	0.30	0.208	--
Vehicle Characteristics						
Pennsylvania Plate Registration	-0.40*	0.027	1.49	-0.48*	0.054	1.61
Passengers Present	0.96*	0.023	2.62	0.87*	0.047	2.40
Situational Characteristics						
Daytime	-0.63*	0.023	1.87	-0.32*	0.046	1.37
Weekday (Mon-Thurs)	0.19*	0.024	1.21	0.03	0.047	--
Summer Months (June-August)	-0.05	0.025	--	--	--	--
Interstate	-0.27*	0.026	1.31	-0.54*	0.054	1.72
PSP Member Characteristics						
Male Trooper	-0.13	0.046	--	-0.28	0.092	--
Non-White Trooper	-0.16*	0.039	1.18	-0.15	0.077	--
3 Years Less Experience	0.08	0.027	--	-0.01	0.055	--
Patrol Assignment	-0.91*	0.035	2.48	-0.52*	0.076	1.68
Trooper Rank	-1.39*	0.025	4.03	-1.46*	0.052	4.33
Nagelkerke R-Square	.164			.280		

*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.

Estimated Effect Sizes of Driver Race/Ethnicity for Arrests and Discretionary Searches

As described in Section 2, we rely on predicted probabilities to estimate the impact of race and ethnicity more precisely on stop outcomes. Table 4.3 previously displayed the raw percentage for each enforcement outcome. However, that descriptive percentage takes no additional information into account. Once other factors are accounted for, the baseline likelihood of an event changes. Calculating the predicted 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 in their probability of being arrested or searched (based on probable cause, reasonable suspicion, or consent), all else equal (i.e., all other measures in the models are set to their mean values). The predicted probabilities reported below are based on the Model B estimates that include criminal history.[35]

Figure 4.6 displays the predicted probabilities for arrests and discretionary searches based on Model B presented in Tables 4.6 and 4.7. The likelihood of an arrest occurring, controlling for all the factors in our models, is 0.9% (i.e., a rare event). Additional analyses show that *White, Black, and Hispanic drivers have virtually the same likelihood of being arrested during a traffic stop* net of all other measured factors (White=0.8%; Black=0.9%; Hispanic=0.9%). By comparison, if a driver of any race/ethnicity has a criminal history, the probability that the stop would result in an arrest is 7.4%.

The likelihood of any driver being involved in a discretionary search based on the estimated regression is 1.0%, which is also quite low. However, some minor variations exist across racial/ethnic groups. Specifically, the predicted probabilities show the likelihood of a discretionary search for White drivers is 0.9%, compared to 1.4% for Black drivers, and 1.0% for Hispanic drivers. By comparison, if a driver of any race/ethnicity has a criminal history, the probability that the stop would result in a discretionary search is 14.9%. This demonstrates that other factors have a much stronger impact on the likelihood of discretionary searches during traffic stops compared to the effect of drivers' race/ethnicity.

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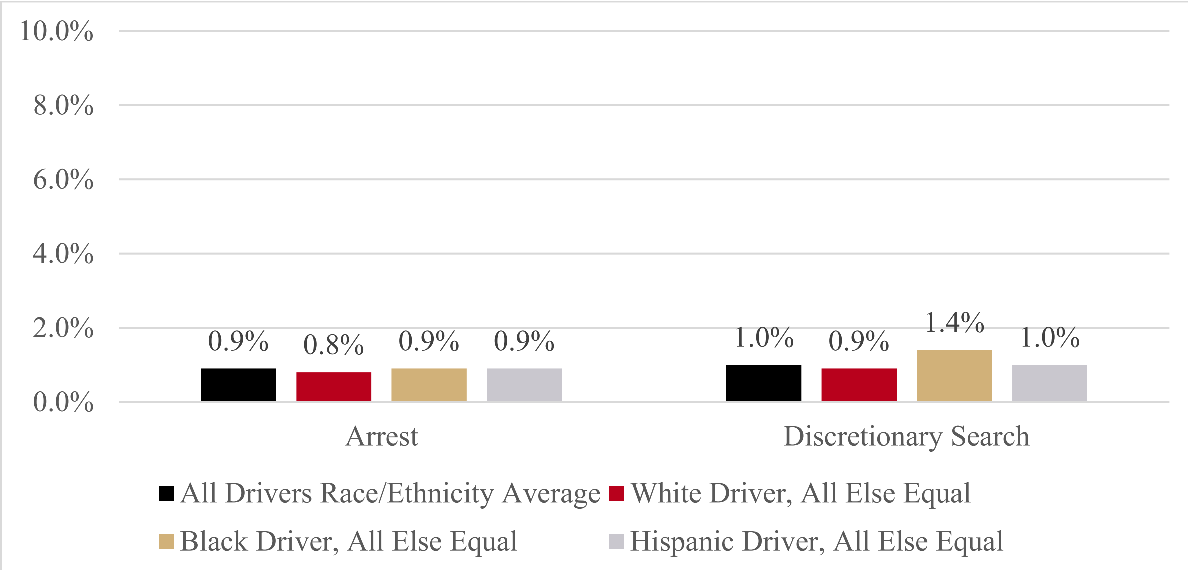
[35] Predicted probabilities for Model A estimates are available from the authors upon request.

Figure 4.7. Predicted Probabilities for Arrests and Discretionary Searches



Section Summary

This section described the post-stop enforcement outcomes of traffic stops conducted by PSP Troopers throughout 2023. Across the department:

- 56.1% of stops resulted in warnings (18.5% verbal, 38.3% written)
- 58.7% of stops resulted in citations
- 3.3% of stops resulted in arrests
- 2.2% of stops resulted in discretionary searches

These enforcement actions varied across PSP Areas, Troops, and Stations (see Appendix A).

Bivariate Analysis

- At the department level, substantively small differences by drivers' race/ethnicity are noted for all outcomes:
  - Warnings are issued to: 56.3% of White drivers, 57.3% of Black drivers, and 54.7% of Hispanic drivers stopped
  - Citations are issued to: 59.4% of White drivers, 54.7% of Black drivers, and 56.4% of Hispanic drivers stopped
  - Arrests are made of: 3.1% of White drivers, 4.8% of Black drivers, and 3.9% of Hispanic drivers stopped
  - Discretionary searches are conducted for: 1.7% of White drivers, 4.2% of Black drivers, and 3.1% of Hispanic drivers stopped
- Substantively small gender differences are also observed for all outcomes except warnings. Female drivers are slightly more likely to be cited, while male drivers are more likely to be arrested or searched.

- Bivariate analyses do not control for alternative factors that could impact the relationship between stop outcomes and drivers' race/ethnicity or gender.

Building on the descriptive and bivariate statistics, Section 4 also reported results of multivariate statistical analyses conducted on stop enforcement outcomes to understand better the impact of drivers' race/ethnicity and other factors.

Multivariate Analyses

Multivariate statistical models consider multiple factors when explaining 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.

Table 4.7 summarizes the findings from the multivariate statistical models.

- Legal factors (e.g., reasons for the stop, multiple violations, whether evidence is seized, and whether the driver has a criminal history) are the strongest predictors of whether a traffic stop results in warnings, citations, arrests, or discretionary searches.
- PSP members' demographic characteristics (e.g., Troopers' race/ethnicity, gender) are not substantively strong predictors of traffic stop enforcement outcomes.
- No substantive differences across racial/ethnic groups of drivers are found for the odds of receiving warnings, citations, or arrests once other explanatory factors are considered.
- Discretionary searches are slightly more likely for Black drivers compared to White and Hispanic drivers.
    - Once criminal histories are accounted for, Black drivers are 1.46 times more likely to be subject to a discretionary search (a substantively small effect size).

Predicted Probabilities

The results of each regression analysis show whether drivers' race/ethnicity have some degree of association with the odds of given enforcement outcomes. The "odds" are the chances in favor of an outcome, where the range is from zero to infinity, and "1" represents an equal chance. The probability, however, is the likelihood of an outcome occurring. It ranges from zero (impossible) to one (certain). We rely on predicted probabilities to estimate the likelihood of an event (arrest or discretionary search) more precisely for drivers of each race/ethnicity by setting all other measures in the models to their mean values; this is particularly useful for rare events.

- The predicted probability (or likelihood) of being arrested is nearly equivalent across racial/ethnic groups, net of other factors.
    - All else equal, the likelihood of a White driver being arrested during a traffic stop is 0.8% compared to 0.9% for Black and Hispanic drivers.

- The likelihood of being searched is very small across all racial/ethnic groups. That is, being searched during a traffic stop with a PSP Trooper is a rare event, regardless of drivers' race/ethnicity.
    - The predicted probabilities for discretionary searches indicate that the likelihood of being searched after considering other factors is 1.4% for Black drivers, compared to 0.9% for White drivers and 1.0% for Hispanic drivers.
    - This demonstrates that while there are slight differences in the likelihood of being searched across racial/ethnic groups, the differences are of small magnitude, and not all factors predicting searches are captured in the data.

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

Finally, as noted in prior reports, multivariate analyses are empirical methods particularly well 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. However, these methods are limited by the type and amount of data collected. Here we acknowledge the potential for model misspecification (i.e., unmeasured pertinent predictors of post-stop outcomes that cannot be included in the statistical models). Including drivers' criminal histories makes this point particularly obvious: once criminal histories are accounted for, the effects of driver characteristics are lessened or eliminated. Due to specification error, none of the analyses presented in this report, including multivariate analyses, can be used to determine whether unexplained racial/ethnic disparities are due to trooper bias.

Table 4.7. Summary of Findings from Multivariate Analyses of Stop Outcomes

	Warnings	Citations	Arrests	Discretionary Searches
Percent of Stops (n=449,047)	**56.1%**	**58.7%**	**3.3%**	**2.2%**
Multivariate Regression Model - Strongest Predictors	Reason for stop Multiple reasons Evidence seized (-) Civil behavior	Reason for stop Spec Traffic Enf Evidence seized Civil behavior (-)	Reason for stop Multiple reasons Evidence seized Civil behavior (-) Criminal history	Reason for stop Multiple reasons Civil behavior (-) Passengers Criminal history
Racial/Ethnic Differences	No substantive differences across racial/ethnic groups	No substantive differences across racial/ethnic groups	No substantive differences across racial/ethnic groups	No substantive differences for Hispanic drivers Substantively small differences for Black drivers

5. CONTRABAND SEIZURES

The material presented in Section 5 focuses specifically on contraband seizures that occurred during motor vehicle and person searches conducted by PSP Troopers during traffic stops. Sometimes referred to as search "success rates" or "hit rates," seizure rates are the percentage of searches conducted that result in the discovery of contraband. The seizure rates during searches are provided at the Department, Area, and Troop levels and explored by race/ethnicity. Due to the small number of searches conducted in many stations, there are no station-level tables for seizures in Appendix A.

PSP members conducted a total of 19,042 searches during 2023. Of these, 6,531 resulted in contraband seizure, constituting an **overall seizure rate for any search (regardless of reason) of 34.3%**. This rate was not available in 2022 due to a known undercounting of searches incident to arrest. As noted in Section 4, nearly half of the 2023 searches are based solely on mandatory reasons for search. Since PSP members have no discretion over whether to conduct those searches, the remainder of Section 5 focuses on the 9,745 searches based on discretionary reasons. Discretionary searches include those conducted for these reasons: *Terry* (officer safety), search warrant, plain view, probable cause plus exigency, and verbal and/or written consent.

Discretionary Searches Resulting in Seizures

Table 5.1 below shows that, of the 9,745 discretionary searches conducted in 2023, 5,417 resulted in contraband seizures, for a **department-wide discretionary search seizure rate of 55.6%**. This is considerably higher than seizure rates reported for many other agencies across the country (ranging from 18% to 40%), including PSP's historical data (Baumgartner et al., 2016; Missouri AGO, 2022; Texas DPS, 2023). Several agencies noted that overall seizure rates during searches have recently increased, indicating a possible improvement in officers' detection skills or simply a reduction in officers' willingness to conduct searches that are unlikely to be fruitful.

The seizure rates for discretionary searches vary across Areas, from a high of 63.4% of searches in Area I to a low of 51.8% in Area IV. Area IV has the highest percentage of stops that result in a discretionary search but the lowest seizure rate. Troop G has the highest percentage of discretionary searches resulting in seizures of evidence/contraband (77.8%), while Troop K has the lowest (39.8%).

Table 5.1 below also documents the types of evidence and/or contraband seized during PSP's discretionary searches. The trends displayed at the department level are, with few exceptions, consistent across Areas and Troops. The majority of contraband seized department-wide is drugs (48.2%) and drug paraphernalia (30.1%), followed distantly by weapons (4.4%), cash (1.6%), and alcohol (1.0%). Note that a single search could produce multiple types of contraband seized; therefore, the sum of percentages in the various categories in Table 5.1 may exceed 100%.

Table 5.1. Types of Evidence Seized by Department, Area, Troop, and Specialized Units during Discretionary Searches (n=9,745)

	Total # of Discretionary Searches	% Disc. Searches w/ Seizure	# of Seizures	% Cash	% Drugs	% Vehicle	% Weapons	% Stolen Prop.	% Alcohol	% Drug-Paraphernalia	% Other
PSP	**9,745**	**55.6%**	**5,417**	**1.6%**	**48.2%**	**0.8%**	**4.4%**	**0.7%**	**1.0%**	**30.1%**	**1.6%**
AREA I	**2,150**	**63.4%**	**1,364**	**1.3%**	**54.5%**	**0.7%**	**4.0%**	**0.4%**	**1.8%**	**39.2%**	**2.1%**
Troop B	684	54.7%	374	1.6%	46.2%	0.9%	4.8%	0.6%	1.0%	30.3%	1.2%
Troop C	429	74.8%	321	0.7%	61.1%	0.9%	3.3%	0.0%	3.5%	51.3%	6.8%
Troop D	711	67.4%	479	2.0%	60.6%	0.4%	5.1%	0.3%	1.5%	40.4%	0.3%
Troop E	326	58.3%	190	0.0%	49.7%	0.6%	0.9%	0.6%	1.5%	39.3%	1.8%
AREA II	**2,284**	**59.6%**	**1,362**	**1.7%**	**52.1%**	**0.5%**	**4.0%**	**0.7%**	**1.1%**	**32.6%**	**1.1%**
Troop A	332	53.3%	177	1.8%	44.3%	0.6%	3.0%	0.6%	1.5%	25.0%	1.2%
Troop G	616	77.8%	479	1.6%	67.9%	0.0%	3.9%	0.6%	1.1%	40.7%	0.8%
Troop H	1232	52.8%	650	1.7%	46.7%	0.5%	4.5%	0.6%	0.8%	31.3%	1.1%
Troop T	104	53.8%	56	1.0%	48.1%	3.8%	1.9%	1.9%	2.9%	25.0%	2.9%
AREA	**1,815**	**59.0%**	**1,071**	**1.4%**	**50.9%**	**0.6%**	**3.0%**	**0.7%**	**0.8%**	**32.3%**	**1.4%**
Troop F	471	59.9%	282	1.3%	49.5%	0.0%	4.5%	0.8%	0.8%	31.4%	0.8%
Troop N	656	59.1%	388	1.5%	52.7%	0.6%	3.4%	0.9%	0.9%	32.5%	1.8%
Troop P	290	52.4%	152	1.0%	41.7%	1.0%	2.4%	0.3%	1.0%	28.6%	1.4%
Troop R	398	62.6%	249	1.8%	56.3%	1.0%	1.3%	0.5%	0.5%	35.9%	1.5%
AREA	**2,871**	**51.8%**	**1,486**	**1.6%**	**45.4%**	**1.0%**	**6.3%**	**1.1%**	**0.8%**	**24.8%**	**1.5%**
Troop J	908	64.1%	582	1.4%	58.6%	0.4%	3.9%	1.0%	1.1%	30.7%	1.4%
Troop K	882	39.8%	351	2.4%	32.2%	1.4%	10.8%	1.7%	0.3%	14.7%	0.9%
Troop L	542	54.2%	294	0.9%	47.4%	1.3%	4.4%	0.7%	0.6%	29.2%	1.7%
Troop	539	48.1%	259	1.3%	42.5%	1.3%	5.0%	0.6%	1.3%	27.1%	2.4%

Table 5.2 below summarizes information regarding the seizure rates of different discretionary search types. As shown, **searches based on probable cause/reasonable suspicion have a seizure rate of 64.4%, while searches based on consent without probable cause have a seizure rate of 51.6%.** Again, these seizure rates are among the highest reported across the country.

Table 5.2 also documents the seizure rates for the two types of discretionary searches at the Area level. Across all four Areas, probable cause/reasonable suspicion searches are the most likely to result in the seizure of contraband. Area III has the highest probable cause/reasonable suspicion seizure rate (66.8%), while Area I has the highest seizure rate for consent searches without probable cause (62.7%).

Table 5.2. 2023 Seizure Rates by Search Type by Department and Area

	Seizure Rate for All Discretionary Searches	Seizure Rate for Probable Cause/ Reasonable Suspicion Searches	Seizure Rate for Consent without Probable Cause Searches
PSP Dept.	**55.6% (n=9,745)**	**64.4% (n=3,003)**	**51.6% (n=6,742)**
AREA I	63.4% (n=2,150)	64.9% (n=755)	62.7% (n=1,395)
AREA II	59.6% (n=2,284)	60.4% (n=682)	59.3% (n=1,602)
AREA III	59.0% (n=1,815)	66.8% (n=492)	56.2% (n=1,333)
AREA IV	51.8% (n=2,871)	65.2% (n=1,043)	44.1% (n=1,828)

Figure 5.1 compares the seizure rates for discretionary searches conducted in 2023 to those in 2022. The overall seizure rate for discretionary searches slightly increased from 53.6% in 2022 to 55.6% in 2023. The probable cause/reasonable suspicion seizure rate decreased from 74% in 2022 to 64.4% in 2023. Although this percentage declined, there are far fewer probable cause/reasonable suspicion searches than consent searches. Therefore, the overall seizure rate for discretionary searches increased because the consent without probable cause seizure rate increased from 45.9% in 2022 to 51.6% in 2023.

Figure 5.1. Comparison of Discretionary Search Seizure Rates (2002 vs. 2023)

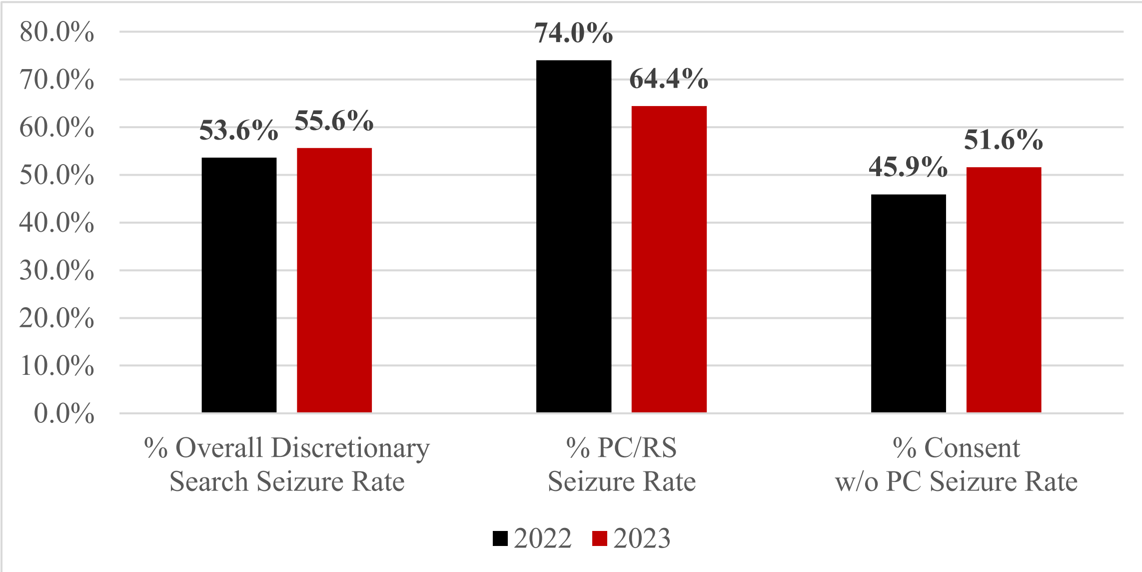


Table 5.3 displays the seizure rates of different discretionary searches at the Troop level. As shown, most Troops have higher seizure rates for probable cause/reasonable suspicion searches (13 of 16 troops) than consent without probable cause searches. Troops with the highest probable cause/reasonable suspicion search seizure rates are Troop R (89.7%), Troop G (84.3%), and Troop C (78.8%). The Troops with the lowest probable cause/reasonable suspicion search seizure rates are Troop E (49.4%) and Troop A (46.8%). Troops with the highest seizure rates for consent searches without probable cause are Troop G (76.1%) and Troop C (71.2%), while the Troops with the lowest rates are Troop K (25.9%) and Troop M (36.7%).

Table 5.3. 2023 Seizure Rates for Discretionary Searches by Reasons for Search for Troops
(%=the percent of discretionary searches resulting in seizures, n=number of discretionary searches)

	Seizure Rate for All Discretionary Searches	Seizure Rate for Probable Cause/ Reasonable Suspicion Searches	Seizure Rate for Consent without Probable Cause Searches
PSP Dept.	**55.6% (n=9,745)**	**64.4% (n=3,003)**	**51.6% (n=6,742)**
AREA I			
Troop B	54.7% (n=684)	60.9% (n=192)	52.2% (n=492)
Troop C	74.8% (n=429)	78.8% (n=203)	71.2% (n=226)
Troop D	67.4% (n=711)	67.3% (n=196)	67.4% (n=515)
Troop E	58.3% (n=326)	49.4% (n=164)	67.3% (n=162)
AREA II			
Troop A	53.3% (n=332)	46.8% (n=126)	57.3% (n=206)
Troop G	77.8% (n=616)	84.3% (n=127)	76.1% (n=489)
Troop H	52.8% (n=1,232)	56.5% (n=386)	51.1% (n=846)
Troop T	53.8% (n=104)	65.1% (n=43)	45.9% (n=61)
AREA III			
Troop F	59.9% (n=471)	69.4% (n=124)	56.5% (n=347)
Troop N	59.1% (n=656)	61.1% (n=211)	58.2% (n=445)
Troop P	52.4% (n=290)	58.2% (n=79)	50.2% (n=211)
Troop R	62.6% (n=398)	89.7% (n=68)	57.0% (n=330)
AREA IV			
Troop J	64.1% (n=908)	71.0% (n=307)	60.6% (n=601)
Troop K	39.8% (n=882)	58.0% (n=381)	25.9% (n=501)
Troop L	54.2% (n=542)	64.1% (n=181)	49.3% (n=361)
Troop M	48.1% (n=539)	71.8% (n=174)	36.7% (n=365)

Seizure Rates and the Outcome Test

The discovery of contraband during searches is an important outcome to consider when examining racial/ethnic disparities in enforcement. The outcome test is a statistical technique used to identify racial and ethnic disparities by examining differential outcomes in seizure rates (Knowles et al., 2001; Ayres, 2001). Section 2 describes this statistical technique in detail.

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 analyzing traffic stops resulting in a probable cause/reasonable suspicion search. Consent searches are more complex.[36] 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). Notwithstanding the limitations of the outcome test, it is a useful alternative method to assess post-stop outcomes. Analyses examining racial/ethnic differences in consent seizure rates and the seizure rates for probable cause/reasonable suspicion searches are provided. This information should be used for internal comparisons and training only to allow the PSP to better understand consent searches and their productivity. *No definitive conclusions about racial bias should be drawn from these comparisons* (for details, see Engel, 2008; Engel & Tillyer, 2008). The outcome test analysis used does not consider other factors that may impact contraband detection.

Figure 5.2 and Table 5.4 below display the seizure rates for discretionary searches conducted by PSP Troopers in 2023. As shown, there are statistically 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 are searched for probable cause/reasonable suspicion reasons are slightly *less* likely to have contraband seized during a discretionary search (58.3%) compared to searched White and Black drivers, whose seizure rates are similar (p-value=.002). The seizure rate for probable cause/reasonable suspicion searches for Black drivers is 68.6% compared to 63.5% for White drivers. This is a substantively small difference based on the Cramer's V statistic for effect sizes (Cramer's V value=.065).

Statistically significant racial/ethnic differences are evident for consent without probable cause searches (p-value=<.001). Hispanic drivers are the least likely to have contraband seized

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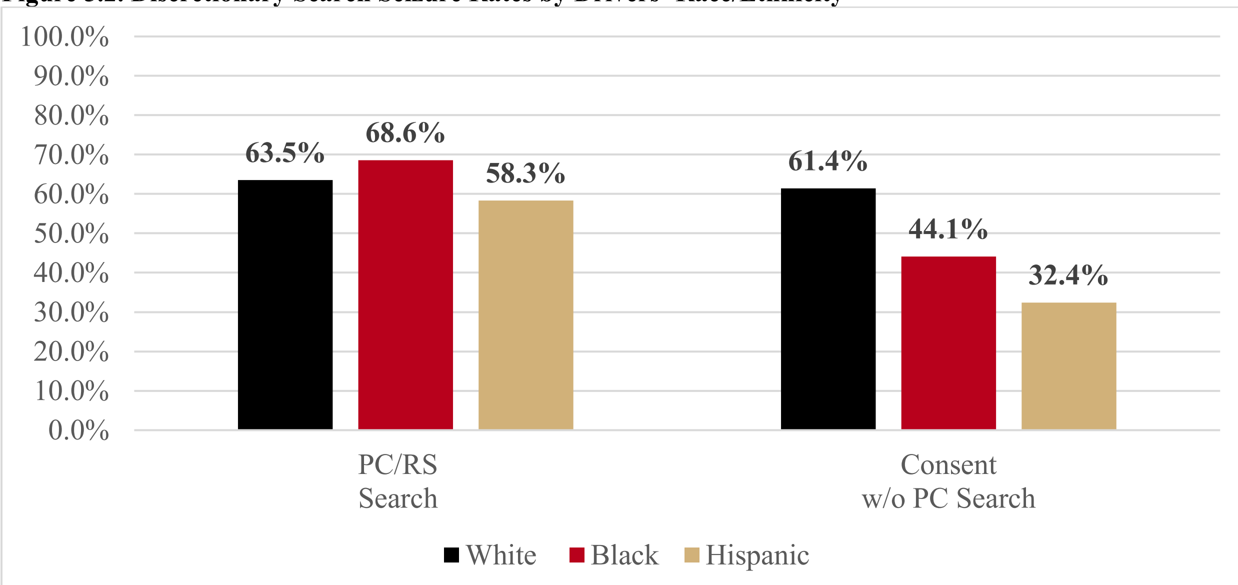
[36] PSP Troopers' heavy reliance on the use of consent searches is due, in part, to the unique case law in Pennsylvania guiding vehicular searches, which does not allow searches based on probable cause without a search warrant unless exigent circumstances exist (*Commonwealth v. Alexander*, 2020 Pa. 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.

(32.4%), while White drivers are the most likely to have contraband seized (61.4%). Of the Black drivers searched based on consent without probable cause, 44.1% of searches result in contraband seizures. This is a substantively medium difference based on the Cramer's V statistic for effect sizes (Cramer's V value=.221). These findings are consistent with results from other state and local police agencies across the country and previous reports issued for the PSP (see for example, Sanders et al., 2022; Seguino et al., 2020; Texas Department of Public Safety, 2023). The racial/ethnic disparities found in consent search seizure rates are significantly lower than historical analyses from 2002 – 2010, indicating PSP's continued improvement in reducing disparities.

Figure 5.2. Discretionary Search Seizure Rates by Drivers' Race/Ethnicity



At the Area level, patterns of racial/ethnic differences in seizure rates are also found but vary by Area. First, for probable cause/reasonable suspicion searches, substantively small (as measured by the Cramer's V statistic) racial/ethnic differences in seizure rates exist for Areas I, II, and IV, during probable cause/reasonable suspicion searches. No statistically significant differences are noted for Area III. In Area I, seizure rates for Black and Hispanic drivers are higher than for White drivers. In Area II, seizure rates for Black drivers are significantly higher than seizure rates for White and Hispanic drivers, who have similar seizure rates. In Area IV, the seizure rates of White and Black drivers are very similar and significantly higher than for Hispanic drivers.

Seizure rates for consent searches without probable cause reported more uniform and statistically significant differences across race/ethnicity. Across all four areas, seizure rates for White drivers are significantly higher than seizure rates for Black and Hispanic drivers. This reflects substantively small differences (as measured by the Cramer's V statistic) for Areas I, II, and IV, and medium differences for Area III. Hispanic drivers are the least likely to have contraband seized in consent searches without probable cause across each Area.

Table 5.4: Discretionary Search Seizure Rates by Driver Race/Ethnicity

	Drivers	Total # of Prob Cause/ Reas Susp Searches	% Prob Cause/ Reas Susp Searches	Total # of Consent w/o Prob Cause Searches	% Consent w/o Prob Cause Searches
PSP Dept	White	1,742	63.5%**	3,720	61.4%***
	Black	900	68.6%	1,900	44.1%
	Hispanic	302	58.3%	910	32.4%
AREA I	White	593	62.7%*	1,023	65.8%***
	Black	144	74.3%	301	56.8%
	Hispanic	10	80.0%	48	41.7%
AREA II	White	414	55.8%***	887	68.1%***
	Black	194	71.6%	493	51.3%
	Hispanic	64	56.3%	182	42.9%
AREA III	White	309	69.3%	883	63.5%***
	Black	105	63.8%	237	42.2%
	Hispanic	52	59.6%	165	38.8%
AREA IV	White	419	67.5%*	772	53.5%***
	Black	433	66.3%	706	39.7%
	Hispanic	168	56.0%	301	34.9%

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

Unfortunately, we are not able to further examine the relationship between drivers' race/ethnicity and seizure as we do with other stop outcomes because the multivariate prediction model is unreliable.[37] 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 impact that race/ethnicity has on the likelihood of contraband seizures during discretionary searches because the statistical models suggest that much stronger factors that predict these outcomes are not measured within the CDR data collection.

Section Summary

For 2023, PSP Troopers conducted 9,745 discretionary searches during 2.2% of all member-initiated traffic stops. In 2023, 55.6% of the 9,745 discretionary searches conducted by PSP Troopers resulted in the seizure of contraband. Searches based on probable cause/reasonable suspicion have a seizure rate of 64.4%, while searches based on consent without probable cause have a seizure rate of 51.6%. This seizure rate is considerably higher than many other agencies

[37] The model predicting whether contraband was seized during discretionary searches is not provided due to several factors: smaller sample size (n=9745), 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.

nationwide, including PSP's historical data from 2002 – 2010. The most common types of contraband seized department-wide are drugs (48.2%) and drug paraphernalia (30.1%), followed distantly by weapons (4.4%).

Seizure rates for probable cause/reasonable suspicion searches demonstrated that searched Hispanic motorists are *less* likely to be found in possession of contraband compared to White and Black drivers, who have similar seizure rates. The difference for Hispanic drivers is of small substantive magnitude, and the analysis does not consider other factors that may impact the detection of contraband.

Seizure rates for consent searches without probable cause demonstrate that searched Black and Hispanic motorists are *less* likely to be found in possession of contraband compared to White drivers. The differences across racial/ethnic groups are of medium substantive magnitude; however, the analysis cannot account for other factors that may impact the detection of contraband.

The research team's observations of PSP's criminal interdiction training, documented in the previous annual report, concluded 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 (Engel et al., 2023). We are optimistic that PSP's continued emphasis on improvements in training will further reduce the disparities in consent search seizure rates.

6. RECOMMENDATIONS

This report documents the findings from statistical analyses of data collected during 449,047 member-initiated traffic stops by the Pennsylvania State Police (PSP) from January 1, 2023 – December 31, 2023. Five key findings are summarized below, followed by three recommendations for PSP officials to consider.

Summary of Key Findings

(1) The PSP has developed a comprehensive data collection system, establishing strong reliability and validity of traffic stop data that exceeds industry standards. The strength of the data collection process and the quality of the data add confidence regarding the accuracy of the statistical findings reported.

(2) Regarding the initial traffic stop decision, no substantive racial /ethnic disparities were detected using multiple analytical techniques.

(3) Regarding post-stop enforcement outcomes, no substantive racial/ethnic disparities were detected in warnings, citations, or arrests using multivariate regression modeling.

(4) Regarding discretionary searches, the initial small to moderate racial/ethnic disparities reported using multivariate regression modeling were reduced to small or no disparities when drivers' criminal history was added to the data collection instrument.

(5) Regarding contraband seizures, the PSP has a very high rate of discretionary searches that result in seizures. Comparisons of seizure rates across racial/ethnic groups show no substantive disparities for searches based on probable cause or reasonable suspicion. However, moderate racial/ethnic disparities in seizure rates remain for consent searches. The disparities in consent search seizure rates are significantly lower than historical analyses from 2002 – 2010, indicating continued improvement.

Recommendations

Informed by the 2023 traffic stop data analyses, the research team provides three broad recommendations designed to improve data collection, further examine the patterns and trends in traffic stop enforcement documented in this report, and identify opportunities to enhance training and strengthen accountability.

Recommendation 1: The PSP should continue to enhance the traffic stop data collection system and analyses.

The PSP has one of the country's most reliable, valid, and comprehensive data collection systems. This is a direct result of the PSP's regular evaluation of the TraCS system's settings and validation rules, the department's responsiveness to data integrity issues that arose in 2021 and 2022, and the department's consideration of research team recommendations for adding new data fields. Therefore, we recommend that the PSP continue these efforts and collaborate with the research team to enhance the statistical analyses further. This collaboration will provide additional consideration of the factors associated with traffic stops, including the possible incorporation of traffic accident patterns into the analyses for the 2024 data.

Recommendation 2: Consider additional opportunities for accountability and oversight for impartial treatment during traffic enforcement.

The findings of the statistical models examining post-stop enforcement outcomes demonstrate that legal variables most strongly predict warnings, citations, arrests, and discretionary searches. There is no statistical evidence showing substantive differences across racial/ethnic groups for warnings, citations, and arrests. This finding is consistent with extensive literature that finds legal variables to be the strongest predictors of police behaviors (Huff, 2021; Mastrofski et al., 1995; Riksheim & Chermak, 1993).

Some unexplained racial/ethnic disparities remain for discretionary searches and seizure rates during consent searches. Just as analyses of traffic stop data cannot indicate that police bias *is* the reason for racial/ethnic disparities in outcomes, they also cannot eliminate the possibility that bias is a factor. The research team recommends that PSP administrators continue current accountability and oversight practices, particularly routine and specific MVR and BWC footage reviews. The PSP should identify opportunities to enhance or focus accountability and oversight practices even further on requests for consent to search, compliance with the consent waiver process, and trooper behavior and compliance with PSP regulations during consent searches. The PSP is to be commended for its commitment to using BWCs in addition to their in-car recording systems, which are already in place. Research demonstrates that BWC usage during traffic stops improves officer compliance with data collection mandates, procedurally just treatment during encounters, and public perceptions of police legitimacy (Braga et al., 2022; Demir et al., 2020a, 2020b).

Recommendation 3: The PSP should continue collaborating with the research team to review related training and policies.

The PSP has already voluntarily engaged with the research team in an ongoing evaluation of its criminal interdiction training, which has led to data collection updates, improvements to training, and greater context for the quantitative data analyses. Therefore, the research team recommends that the PSP further collaborate with the research team to review academy training, policies, and procedures related to traffic enforcement, search and seizure, implicit bias, and other topics relevant to traffic stops to identify opportunities to enhance guidance regarding discretionary decision-making.

Conclusion

As demonstrated by PSP's ongoing data collection and analysis and their responsiveness to the research team's recommendations from previous reports, PSP officials remain committed to providing professional and unbiased policing services to the Commonwealth of Pennsylvania's residents and visitors. This report shows that racial and ethnic disparities in traffic stops and their post-stop enforcement outcomes are infrequent within the PSP. This is likely due to several factors: 1) heightened scrutiny of traffic stops, 2) improved training, 3) a strong organizational emphasis on fair treatment, 4) enhanced field supervisory oversight, and 5) more reliable and valid traffic stop data. Although some unexplained racial and ethnic disparities in seizure rates from consent searches warrant further examination, these patterns align with those seen in many jurisdictions nationwide. This suggests that some disparities may be driven by broader societal or organizational factors rather than individual biases of police officers or troopers. Researchers and practitioners across the country continue to explore these issues, with the PSP leading in this important research.

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APPENDIX A: STATION-LEVEL TABLES

To streamline the annual report, station-level tables are presented here by their corresponding section of the main report.

Section 2 Supplemental Tables: pages 79-84

Section 3 Supplemental Tables: pages 85-105

Section 4 Supplemental Tables: pages 106-124

Table A.1. Comparison of Number of Stops in CDR and CAD Data Sets for Areas I & II, 2023

	Traffic Stops in CDR	Traffic Stops in CAD	Percent Difference
Troop B			
Belle Vernon	4,950	5,200	-4.8%
Pittsburgh	5,592	5,911	-5.4%
Uniontown	7,782	8,282	-6.0%
Washington	4,586	4,669	-1.8%
Waynesburg	2,378	2,538	-6.3%
Troop C			
Clarion	3,012	3,137	-4.0%
Clearfield	4,354	4,511	-3.5%
Dubois	3,651	3,671	-0.5%
Lewis Run	5,409	5,582	-3.1%
Marienville	2,930	3,008	-2.6%
Punxsutawney	3,664	3,785	-3.2%
Ridgway	3,207	3,402	-5.7%
Troop D			
Beaver	3,763	3,820	-1.5%
Butler	4,744	4,827	-1.7%
Kittanning	7,289	7,596	-4.0%
Mercer	3,535	3,754	-5.8%
New Castle	3,018	3,081	-2.0%
Troop E			
Corry	2,858	3,006	-4.9%
Erie	6,941	7,352	-5.6%
Franklin	2,066	2,166	-4.6%
Girard	6,535	6,797	-3.9%
Meadville	4,217	4,538	-7.1%
Warren	2,337	2,434	-4.0%
Troop A			
Ebensburg	2,637	2,674	-1.4%
Greensburg	5,879	6,100	-3.6%
Indiana	5,684	5,925	-4.1%
Kiski Valley	1,609	1,592	1.1%
Somerset (A)	2,750	2,881	-4.5%
Troop G			
Bedford	5,676	5,789	-2.0%
Hollidaysburg	4,404	4,502	-2.2%
Huntingdon	4,227	4,433	-4.6%
Lewistown	4,028	4,222	-4.6%
McConnellsburg	3,236	3,258	-0.7%
Rockview	7,117	7,447	-4.4%
Troop H			
Carlisle	9,191	8,507	8.0%
Chambersburg	12,076	12,456	-3.1%
Gettysburg	10,875	11,307	-3.8%
Harrisburg	9,705	9,892	-1.9%
Lykens	3,357	3,428	-2.1%
Newport	3,968	4,085	-2.9%
Troop T			
Bowmansville	5,840	6,273	-6.9%
Everett	6,150	6,136	0.2%
Gibsonia	5,600	5,911	-5.3%
Highspire	145	159	-8.8%
King of Prussia	6,874	7,328	-6.2%
New Stanton	8,944	9,271	-3.5%
Newville	5,717	6,096	-6.2%
Pocono	4,516	4,706	-4.0%
Somerset (T)	5,060	5,262	-3.8%

Table A.1: Comparison of Number of Stops in CDR and CAD Data Sets for Areas III & IV, 2023

	Traffic Stops in CDR	Traffic Stops in CAD	Percent Difference
Troop F			
Coudersport	4,687	4,871	-3.8%
Emporium	985	996	-1.1%
Lamar	5,258	5,357	-1.8%
Mansfield	3,001	3,063	-2.0%
Milton	7,478	7,668	-2.5%
Montoursville	6,592	6,717	-1.9%
Selinsgrove	4,619	4,826	-4.3%
Stonington	2,508	2,543	-1.4%
Troop N			
Bloomsburg	2,549	2,647	-3.7%
Fern Ridge	4,682	4,779	-2.0%
Hazleton	7,283	7,685	-5.2%
Lehighton	3,019	3,297	-8.4%
Stroudsburg	10,500	10,849	-3.2%
Troop P			
Laporte	1,742	1,768	-1.5%
Shickshinny	2,076	2,134	-2.7%
Towanda	4,479	4,751	-5.7%
Tunkhannock	2,342	2,370	-1.2%
Wilkes-Barre	4,416	4,409	0.2%
Troop R			
Blooming Grove	4,036	4,199	-3.9%
Dunmore	3,435	3,476	-1.2%
Gibson	2,982	3,038	-1.8%
Honesdale	1,771	1,848	-4.2%
Troop J			
Avondale	8,543	8,909	-4.1%
Embreeville	7,031	7,408	-5.1%
Lancaster	9,158	9,803	-6.6%
York	11,420	12,152	-6.0%
Troop K			
Media	12,637	13,195	-4.2%
Philadelphia	9,626	9,930	-3.1%
Skippack	4,425	4,533	-2.4%
Troop L			
Frackville	3,741	3,816	-2.0%
Hamburg	3,268	3,069	6.5%
Jonestown	5,395	5,700	-5.4%
Reading	5,375	5,560	-3.3%
Schuylkill Haven	4,523	4,623	-2.2%
Troop M			
Belfast	3,891	4,024	-3.3%
Bethlehem	6,255	6,464	-3.2%
Dublin	3,321	3,647	-8.9%
Fogelsville	6,146	6,517	-5.7%
Trevose	3,473	3,520	-1.3%
Specialized Units			
SHIELD	3,833	4,035	-5.0%
Canine	1,853	2,035	-5.0%

Table A.2 Area I Percent Unknown Race/Ethnicity of Drivers Stopped by Station, 2022 compared to 2023

	Unknown Race			Difference btw Aug-Dec 22 and 2023	Unknown Ethnicity			Difference btw Aug-Dec 22 and 2023
	1/1/22-8/11/22	8/12/22-12/31/22	2023		1/1/22-8/11/22	8/12/22-12/31/22	2023	
Troop B	**6.0%**	**4.5%**	**4.1%**	**-0.4%**	**9.0%**	**6.3%**	**6.7%**	**0.4%**
Belle Vernon	7.8%	9.6%	10.3%	0.7%	11.6%	12.2%	11.9%	-0.3%
Pittsburgh	4.7%	3.2%	4.7%	1.5%	14.5%	10.1%	16.0%	5.9%
Uniontown	5.6%	3.8%	1.6%	-2.2%	5.2%	3.5%	1.6%	-1.9%
Washington	6.8%	2.8%	2.1%	-0.7%	6.7%	2.5%	0.9%	-1.6%
Waynesburg	7.5%	3.8%	1.9%	-1.9%	8.2%	4.1%	2.2%	-1.9%
Troop C	**7.2%**	**3.9%**	**2.3%**	**-1.6%**	**6.9%**	**3.6%**	**1.7%**	**-1.9%**
Clarion	7.5%	2.5%	3.4%	0.9%	6.2%	2.9%	3.1%	0.2%
Clearfield	6.4%	4.8%	4.1%	-0.7%	6.7%	4.4%	3.9%	-0.5%
Dubois	14.4%	6.8%	2.9%	-3.9%	13.5%	5.3%	1.3%	-4.0%
Lewis Run	3.6%	5.6%	2.1%	-3.5%	2.8%	5.0%	1.6%	-3.4%
Marienville	3.1%	0.7%	0.4%	-0.3%	3.9%	0.6%	0.1%	-0.5%
Punxsutawney	0.5%	0.2%	0.3%	0.1%	0.3%	0.2%	0.1%	-0.1%
Ridgway	15.5%	6.6%	2.9%	-3.7%	15.3%	7.0%	1.5%	-5.5%
Troop D	**5.4%**	**2.1%**	**2.2%**	**0.1%**	**5.7%**	**3.1%**	**3.4%**	**0.3%**
Beaver	6.6%	2.3%	3.8%	1.5%	8.1%	8.7%	8.4%	-0.3%
Butler	8.7%	2.7%	1.7%	-1.0%	9.0%	3.2%	4.1%	0.9%
Kittanning	1.3%	0.9%	2.2%	1.3%	1.1%	0.8%	2.0%	1.2%
Mercer	9.8%	4.2%	2.7%	-1.5%	10.3%	3.9%	2.5%	-1.4%
New Castle	2.2%	1.6%	0.7%	-0.9%	2.4%	1.4%	0.7%	-0.7%
Troop E	**2.7%**	**1.0%**	**0.9%**	**-0.1%**	**3.6%**	**1.0%**	**0.9%**	**-0.1%**
Corry	0.4%	0.1%	0.4%	0.3%	0.3%	0.5%	0.5%	0.0%
Erie	1.7%	0.6%	0.5%	-0.1%	2.0%	0.7%	0.6%	-0.1%
Franklin	10.7%	1.7%	1.6%	-0.1%	18.5%	2.5%	2.0%	-0.5%
Girard	2.2%	1.8%	1.0%	-0.8%	2.3%	1.5%	0.9%	-0.6%
Meadville	4.5%	1.7%	1.4%	-0.3%	4.7%	1.1%	1.1%	0.0%
Warren	1.0%	0.6%	0.6%	0.0%	1.5%	0.8%	0.7%	-0.1%

Table A.2. Area II Percent Unknown Race/Ethnicity of Drivers Stopped by Station, 2022 compared to 2023

	Unknown Race			Difference btw Aug-Dec 22 and 2023	Unknown Ethnicity			Difference btw Aug-Dec 22 and 2023
	1/1/22-8/11/22	8/12/22-12/31/22	2023		1/1/22-8/11/22	8/12/22-12/31/22	2023	
Troop A	**1.9%**	**0.8%**	**1.2%**	**0.4%**	**2.9%**	**0.8%**	**1.1%**	**0.3%**
Ebensburg	9.0%	1.8%	1.2%	-0.6%	9.5%	1.9%	1.9%	0.0%
Greensburg	0.6%	0.7%	0.8%	0.1%	0.6%	0.5%	0.6%	0.1%
Indiana	1.7%	0.6%	1.8%	1.2%	3.8%	0.7%	1.1%	0.4%
Kiski Valley	0.7%	0.9%	1.2%	0.3%	0.7%	0.9%	0.7%	-0.2%
Somerset (A)	0.9%	0.8%	1.1%	0.3%	1.0%	0.8%	1.3%	0.5%
Troop G	**4.5%**	**3.1%**	**2.2%**	**-0.9%**	**4.6%**	**2.9%**	**1.9%**	**-1.0%**
Bedford	1.8%	0.8%	0.9%	0.1%	1.8%	0.7%	0.7%	0.0%
Hollidaysburg	4.0%	7.3%	3.7%	-3.6%	4.0%	7.3%	3.5%	-3.8%
Huntingdon	7.1%	4.7%	5.2%	0.5%	7.1%	4.4%	4.9%	0.5%
Lewistown	2.4%	0.5%	0.8%	0.3%	2.5%	0.6%	0.7%	0.1%
McConnellsburg	10.6%	5.3%	2.5%	-2.8%	10.9%	4.8%	1.6%	-3.2%
Rockview	3.7%	1.6%	1.0%	-0.6%	3.9%	1.3%	0.9%	-0.4%
Troop H	**3.6%**	**1.7%**	**1.0%**	**-0.7%**	**3.9%**	**1.6%**	**0.9%**	**-0.7%**
Carlisle	2.4%	1.7%	1.2%	-0.5%	2.8%	1.6%	0.8%	-0.8%
Chambersburg	2.2%	1.1%	0.5%	-0.6%	3.0%	1.0%	0.5%	-0.5%
Gettysburg	1.9%	0.8%	0.7%	-0.1%	1.7%	0.5%	0.6%	0.1%
Harrisburg	9.1%	4.7%	2.0%	-2.7%	9.1%	4.7%	2.0%	-2.7%
Lykens	1.2%	0.7%	0.5%	-0.2%	1.3%	0.6%	0.6%	0.0%
Newport	1.6%	0.8%	1.1%	0.3%	1.6%	0.8%	1.2%	0.4%
Troop T	**13.0%**	**9.0%**	**5.2%**	**-3.8%**	**15.2%**	**9.8%**	**6.1%**	**-3.7%**
Bowmansville	4.9%	2.7%	2.6%	-0.1%	7.9%	3.6%	3.9%	0.3%
Everett	23.3%	16.5%	12.2%	-4.3%	22.6%	15.5%	11.1%	-4.4%
Gibsonia	4.6%	2.6%	1.8%	-0.8%	11.6%	6.8%	2.6%	-4.2%
Highspire	3.1%	4.7%	6.9%	2.2%	6.3%	4.7%	6.2%	1.5%
King of Prussia	17.0%	6.3%	3.6%	-2.7%	22.5%	9.6%	7.6%	-2.0%
New Stanton	11.9%	6.5%	3.8%	-2.7%	13.5%	7.3%	5.3%	-2.0%
Newville	5.1%	5.6%	2.6%	-3.0%	5.4%	4.7%	3.2%	-1.5%
Pocono	2.2%	1.2%	1.8%	0.6%	2.3%	1.3%	1.8%	0.5%
Somerset (T)	29.5%	22.9%	14.1%	-8.8%	30.0%	22.5%	13.2%	-9.3%

Table A.2. Area III Percent Unknown Race/Ethnicity of Drivers Stopped by Station, 2022 compared to 2023

	Unknown Race			Difference btw Aug-Dec 22 and 2023	Unknown Ethnicity			Difference btw Aug-Dec 22 and 2023
	1/1/22-8/11/22	8/12/22-12/31/22	2023		1/1/22-8/11/22	8/12/22-12/31/22	2023	
Troop F	**3.7%**	**1.8%**	**2.3%**	**0.5%**	**4.3%**	**1.9%**	**2.3%**	**0.5%**
Coudersport	2.3%	2.5%	0.9%	-1.6%	2.2%	2.3%	0.7%	-1.6%
Emporium	1.4%	0.2%	0.3%	0.1%	1.3%	0.2%	0.3%	0.1%
Lamar	5.2%	3.1%	3.9%	0.8%	5.6%	2.5%	4.9%	2.4%
Mansfield	11.0%	3.0%	8.2%	5.2%	11.1%	2.4%	7.2%	4.8%
Milton	2.5%	1.5%	2.2%	0.7%	2.8%	1.7%	2.1%	0.4%
Montoursville	3.6%	0.9%	1.0%	0.1%	3.8%	1.1%	1.2%	0.1%
Selinsgrove	3.1%	2.1%	1.2%	-0.9%	6.5%	3.2%	1.3%	-1.9%
Stonington	0.6%	0.7%	0.9%	0.2%	0.8%	0.5%	1.0%	0.5%
Troop N	**13.4%**	**4.1%**	**3.4%**	**-0.7%**	**18.0%**	**4.5%**	**3.3%**	**-1.2%**
Bloomsburg	14.7%	3.5%	4.9%	1.4%	17.0%	3.6%	5.2%	1.6%
Fern Ridge	4.8%	1.8%	1.0%	-0.8%	6.5%	2.0%	0.7%	-1.3%
Hazleton	24.0%	7.3%	5.2%	-1.9%	24.7%	6.8%	4.4%	-2.4%
Lehighton	20.3%	4.4%	3.7%	-0.7%	24.3%	4.9%	4.2%	-0.7%
Stroudsburg	10.8%	3.6%	2.8%	-0.8%	19.0%	4.6%	2.9%	-1.7%
Troop P	**2.8%**	**2.1%**	**2.7%**	**0.6%**	**3.1%**	**2.9%**	**3.1%**	**0.2%**
Laporte	2.6%	1.3%	0.3%	-1.0%	3.2%	1.5%	0.6%	-0.9%
Shickshinny	2.3%	2.0%	0.8%	-1.2%	2.0%	2.0%	1.0%	-1.0%
Towanda	0.9%	1.1%	2.4%	1.3%	0.8%	1.6%	2.5%	0.9%
Tunkhannock	6.0%	2.5%	0.6%	-1.9%	7.6%	2.8%	0.6%	-2.2%
Wilkes-Barre	3.8%	3.3%	6.0%	2.7%	3.8%	5.2%	7.1%	1.9%
Troop R	**11.3%**	**6.0%**	**2.8%**	**-3.2%**	**17.8%**	**8.6%**	**3.4%**	**-5.2%**
Blooming Grove	18.2%	3.3%	1.5%	-1.8%	31.7%	10.3%	2.3%	-8.0%
Dunmore	5.5%	2.7%	1.5%	-1.2%	13.7%	3.5%	2.1%	-1.4%
Gibson	11.8%	9.7%	7.3%	-2.4%	12.7%	8.5%	7.3%	-1.2%
Honesdale	5.8%	10.8%	0.8%	-10.0%	8.6%	11.5%	1.8%	-9.7%

Table A.2. Area IV Percent Unknown Race/Ethnicity of Drivers Stopped by Station, 2022 compared to 2023

	Unknown Race			Difference btw Aug-Dec 22 and 2023	Unknown Ethnicity			Difference btw Aug-Dec 22 and 2023
	1/1/22-8/11/22	8/12/22-12/31/22	2023		1/1/22-8/11/22	8/12/22-12/31/22	2023	
Troop J	**1.7%**	**1.0%**	**0.9%**	**-0.1%**	**2.9%**	**1.5%**	**1.0%**	**-0.5%**
Avondale	0.9%	0.3%	0.5%	0.2%	1.8%	0.5%	0.5%	0.0%
Embreeville	2.5%	1.8%	1.8%	0.0%	3.2%	1.4%	1.6%	0.2%
Lancaster	0.9%	0.7%	0.5%	-0.2%	1.8%	1.4%	1.0%	-0.4%
York	2.2%	1.3%	2.5%	1.2%	4.5%	2.9%	2.9%	0.0%
Troop K	**5.8%**	**5.3%**	**3.4%**	**-1.9%**	**9.1%**	**6.9%**	**4.1%**	**-2.8%**
Media	2.9%	2.6%	1.3%	-1.3%	2.9%	2.4%	1.5%	-0.9%
Philadelphia	9.8%	8.6%	6.1%	-2.5%	13.2%	9.3%	6.9%	-3.4%
Skippack	5.1%	3.3%	3.4%	0.1%	15.5%	12.6%	5.2%	-7.4%
Troop L	**3.7%**	**2.4%**	**1.6%**	**-0.8%**	**5.1%**	**3.1%**	**2.3%**	**0.8%**
Frackville	5.6%	4.5%	2.0%	-2.5%	6.2%	5.5%	2.9%	-2.6%
Hamburg	1.8%	0.9%	2.4%	1.5%	3.7%	2.2%	3.5%	1.3%
Jonestown	5.2%	3.5%	1.9%	-1.6%	6.8%	4.2%	2.6%	-1.6%
Reading	4.5%	2.1%	1.3%	-0.8%	7.2%	3.3%	2.3%	-1.0%
Schuylkill Haven	1.6%	1.1%	0.6%	-0.5%	1.9%	1.0%	0.8%	-0.2%
Troop M	**6.6%**	**4.2%**	**3.0%**	**-1.2%**	**8.7%**	**5.1%**	**3.8%**	**-1.3%**
Belfast	2.2%	2.0%	2.5%	0.5%	3.0%	2.6%	4.1%	1.5%
Bethlehem	13.5%	8.5%	4.6%	-3.9%	13.9%	8.7%	4.6%	-4.1%
Dublin	12.8%	5.6%	3.1%	-2.5%	14.0%	6.3%	3.4%	-2.9%
Fogelsville	2.7%	2.2%	2.6%	0.4%	6.0%	4.5%	3.6%	-0.9%
Trevose	3.2%	2.8%	1.2%	-1.6%	7.0%	3.2%	2.6%	-0.6%
Specialized Units								
SHIELD	1.3%	0.6%	0.4%	-0.2%	7.3%	1.0%	0.3%	-0.7%
Canine	3.4%	3.1%	1.2%	-1.9%	3.1%	3.4%	2.9%	-0.5%

Section 3 Supplemental Tables

Table A.3. Monthly Breakdown of Traffic Stops by Department, Area, Troop, & Station, January – December 2023

	Total # of Stops	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
PSP Dept.	**449,047**	**7.5%**	**7.5%**	**8.9%**	**9.6%**	**12.7%**	**7.0%**	**9.6%**	**7.1%**	**10.0%**	**4.2%**	**8.8%**	**7.1%**
AREA I													
Troop B													
Belle Vernon	4,950	4.5%	5.2%	7.5%	8.2%	13.2%	7.8%	9.9%	8.7%	12.2%	5.4%	8.7%	8.7%
Pittsburgh	5,592	5.8%	8.6%	10.1%	4.5%	18.0%	6.0%	8.9%	3.5%	13.1%	2.8%	14.2%	4.5%
Uniontown	7,782	11.6%	9.6%	8.7%	8.0%	16.0%	5.1%	9.7%	4.0%	9.2%	4.1%	8.7%	5.4%
Washington	4,586	5.8%	4.6%	7.5%	10.2%	14.0%	4.9%	10.4%	5.1%	10.9%	4.6%	12.2%	9.7%
Waynesburg	2,378	4.9%	5.3%	6.1%	6.1%	19.0%	4.8%	11.8%	5.3%	14.6%	4.5%	14.3%	3.3%
Troop C													
Clarion	3,012	2.7%	4.5%	5.4%	9.5%	13.3%	3.6%	12.7%	5.4%	18.1%	2.6%	15.7%	6.3%
Clearfield	4,354	3.6%	7.2%	5.8%	10.2%	12.1%	8.5%	11.6%	6.6%	13.7%	4.2%	10.5%	6.0%
Dubois	3,651	6.5%	5.5%	8.4%	9.9%	16.9%	4.9%	9.7%	4.9%	13.3%	3.1%	12.8%	4.0%
Lewis Run	5,409	6.2%	9.2%	9.6%	10.3%	10.9%	6.7%	8.6%	7.5%	10.9%	5.0%	8.9%	6.3%
Marienville	2,930	5.9%	6.2%	8.6%	10.8%	10.9%	6.3%	8.9%	6.5%	13.8%	6.9%	10.6%	4.5%
Punxsutawney	3,664	6.8%	7.1%	9.6%	8.4%	15.9%	6.9%	9.1%	5.6%	14.3%	4.0%	7.7%	4.7%
Ridgway	3,207	4.1%	5.9%	6.1%	9.1%	12.9%	6.8%	9.9%	9.4%	13.1%	4.4%	11.4%	6.7%
Troop D													
Beaver	3,763	7.4%	6.5%	9.3%	10.4%	13.9%	6.3%	8.8%	8.7%	11.6%	2.9%	9.2%	4.9%
Butler	4,744	7.6%	6.8%	8.6%	11.6%	13.5%	7.9%	9.7%	6.3%	11.2%	4.5%	8.6%	3.7%
Kittanning	7,289	5.1%	6.1%	9.9%	9.5%	13.9%	7.1%	11.2%	8.2%	10.6%	3.6%	8.9%	6.0%
Mercer	3,535	4.0%	4.1%	10.0%	12.3%	14.5%	4.2%	9.7%	9.6%	12.5%	2.9%	10.0%	6.3%
New Castle	3,018	6.9%	8.1%	6.0%	11.1%	17.7%	4.5%	10.0%	8.1%	11.4%	3.4%	7.8%	5.0%
Troop E													
Corry	2,858	4.7%	7.0%	9.3%	12.3%	11.5%	3.7%	10.2%	9.5%	10.5%	6.7%	7.7%	7.0%
Erie	6,941	7.3%	5.8%	8.7%	9.2%	12.8%	4.3%	10.7%	6.7%	12.1%	3.7%	12.2%	6.7%
Franklin	2,066	7.6%	6.5%	9.0%	11.5%	13.9%	4.7%	8.3%	5.2%	13.3%	3.2%	9.4%	7.5%
Girard	6,535	9.6%	9.0%	8.0%	9.7%	10.4%	7.4%	7.1%	5.1%	11.8%	3.3%	7.5%	11.2%
Meadville	4,217	6.8%	7.6%	10.7%	12.3%	12.6%	6.5%	5.8%	5.3%	11.3%	3.4%	8.1%	9.5%
Warren	2,337	4.8%	6.5%	10.0%	8.9%	12.4%	5.3%	9.0%	1.9%	11.9%	5.6%	16.0%	7.7%

Table A.3. Monthly Breakdown of Traffic Stops by Department, Area, Troop, & Station, January – December 2023

	Total # of Stops	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
AREA II													
Troop A													
Ebensburg	2,637	7.0%	5.0%	9.0%	11.8%	16.6%	7.0%	10.7%	3.4%	9.4%	2.1%	11.0%	7.2%
Greensburg	5,879	7.4%	5.5%	9.0%	11.0%	12.3%	6.2%	8.3%	5.7%	10.8%	4.0%	13.5%	6.4%
Indiana	5,684	7.4%	6.4%	10.0%	10.8%	11.4%	6.7%	8.5%	5.7%	9.7%	7.4%	10.3%	5.6%
Kiski Valley	1,609	6.8%	5.9%	6.4%	15.0%	12.1%	5.5%	14.3%	3.3%	14.0%	1.7%	10.1%	5.0%
Somerset (A)	2,750	7.2%	4.9%	6.6%	12.4%	14.1%	5.2%	10.8%	6.7%	10.0%	3.9%	11.5%	6.6%
Troop G													
Bedford	5,676	7.8%	8.8%	11.5%	10.4%	11.8%	6.5%	6.7%	4.8%	11.7%	2.9%	11.3%	5.7%
Hollidaysburg	4,404	7.9%	9.8%	8.4%	9.0%	13.5%	6.2%	8.4%	7.1%	12.7%	3.7%	8.5%	4.7%
Huntingdon	4,227	8.6%	9.2%	8.0%	9.0%	11.2%	2.9%	8.6%	4.9%	11.8%	4.8%	11.5%	9.6%
Lewistown	4,028	7.9%	8.2%	10.2%	11.1%	14.3%	5.9%	6.5%	5.5%	13.5%	2.5%	9.2%	5.3%
McConnellsburg	3,236	7.8%	7.7%	8.2%	10.1%	15.0%	5.0%	9.6%	7.0%	13.5%	2.9%	8.1%	5.0%
Rockview	7,117	7.7%	8.4%	8.9%	11.9%	13.8%	6.1%	7.5%	5.4%	12.4%	2.9%	9.6%	5.4%
Troop H													
Carlisle	9,191	11.9%	7.3%	7.7%	8.9%	9.5%	7.8%	11.7%	8.0%	6.3%	4.4%	7.4%	9.1%
Chambersburg	12,076	9.1%	9.0%	8.9%	7.5%	11.1%	7.9%	9.7%	7.6%	6.2%	5.5%	8.1%	9.5%
Gettysburg	10,875	7.0%	8.5%	10.2%	8.2%	11.8%	9.8%	8.2%	7.6%	7.9%	4.4.%	7.4%	9.2%
Harrisburg	9,705	8.2%	7.2%	8.2%	8.5%	8.7%	7.9%	10.1%	9.6%	8.0%	5.5%	9.3%	8.7%
Lykens	3,357	7.1%	7.7%	8.4%	8.8%	13.1%	9.7%	10.2%	9.1%	7.2%	4.1%	9.6%	4.9%
Newport	3,968	7.2%	10.1%	10.2%	8.4%	15.4%	7.5%	8.3%	7.9%	7.2%	2.2%	9.1%	6.6%
Troop T													
Bowmansville	5,840	5.2%	8.4%	11.3%	10.4%	15.2%	8.0%	9.3%	7.1%	5.9%	5.2%	6.5%	7.5%
Everett	6,150	7.6%	8.7%	10.2%	11.4%	12.0%	8.1%	8.3%	9.3%	6.9%	6.9%	5.5%	5.2%
Gibsonia	5,600	5.2%	8.5%	7.4%	10.2%	12.8%	10.2%	8.3%	8.2%	9.8%	5.5%	5.8%	8.1%
Highspire	145	9.7%	14.5%	15.9%	0.7%	9.0%	4.1%	6.2%	19.3%	1.4%	13.1%	5.5%	0.7%
King of Prussia	6,874	8.5%	7.4%	7.3%	9.7%	13.5%	7.0%	8.4%	7.2%	9.7%	7.1%	7.4%	6.8%
New Stanton	8,944	5.8%	6.6%	8.0%	9.7%	12.5%	8.0%	11.3%	10.1%	9.1%	6.2%	5.5%	7.3%
Newville	5,717	6.7%	5.5%	7.3%	12.3%	13.8%	8.8%	8.0%	10.3%	7.6%	6.8%	4.9%	7.9%
Pocono	4,516	7.3%	7.2%	7.9%	10.3%	14.2%	9.5%	10.0%	7.4%	8.4%	6.0%	4.7%	7.2%
Somerset (T)	5,060	6.9%	8.8%	10.8%	9.7%	10.8%	7.7%	10.0%	8.6%	9.3%	5.7%	6.0%	5.8%

Table A.3. Monthly Breakdown of Traffic Stops by Department, Area, Troop, & Station, January – December 2023

	Total # of Stops	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
AREA III													
Troop F													
Coudersport	4,687	6.3%	8.3%	8.5%	10.4%	11.5%	7.2%	11.4%	10.0%	9.0%	3.7%	7.4%	6.2%
Emporium	985	6.6%	9.7%	11.1%	7.0%	18.5%	4.4%	9.2%	6.8%	8.8%	4.1%	9.1%	4.7%
Lamar	5,258	7.6%	4.4%	10.5%	9.3%	16.3%	5.7%	10.5%	5.0%	11.6%	3.4%	10.0%	5.6%
Mansfield	3,001	4.8%	5.6%	7.2%	10.5%	11.5%	6.1%	15.9%	11.2%	10.5%	3.8%	7.6%	5.6%
Milton	7,478	7.8%	10.3%	8.5%	8.9%	14.6%	5.6%	9.8%	6.1%	10.0%	3.8%	8.9%	5.7%
Montoursville	6,592	8.6%	9.4%	10.1%	10.6%	15.1%	8.0%	8.3%	6.4%	8.9%	2.7%	6.6%	5.2%
Selinsgrove	4,619	6.1%	5.2%	11.0%	11.0%	12.8%	8.2%	9.3%	6.2%	10.9%	4.3%	9.4%	5.5%
Stonington	2,508	11.3%	7.9%	6.5%	9.3%	13.8%	5.7%	9.4%	7.2%	7.6%	1.4%	15.0%	4.8%
Troop N													
Bloomsburg	2,549	6.8%	8.9%	12.4%	10.3%	12.8%	7.0%	11.5%	3.8%	9.2%	3.1%	8.8%	5.5%
Fern Ridge	4,682	9.3%	6.4%	9.6%	9.9%	22.6%	3.8%	13.6%	2.8%	9.3%	1.2%	7.6%	3.9%
Hazleton	7,283	6.9%	7.1%	6.8%	8.2%	14.6%	6.0%	11.9%	4.8%	11.5%	4.9%	10.1%	7.2%
Lehighton	3,019	9.2%	8.4%	9.2%	8.2%	11.5%	5.7%	6.4%	4.0%	10.1%	4.7%	13.1%	9.6%
Stroudsburg	10,500	9.5%	7.9%	10.0%	8.2%	13.2%	5.5%	7.1%	6.6%	10.5%	5.2%	9.9%	6.4%
Troop P													
Laporte	1,742	5.9%	8.2%	8.1%	9.1%	15.6%	8.6%	11.5%	9.5%	8.7%	3.0%	5.8%	5.9%
Shickshinny	2,076	6.3%	8.9%	5.2%	11.0%	13.9%	6.6%	12.2%	5.6%	15.0%	1.7%	8.3%	5.3%
Towanda	4,479	10.0%	9.8%	10.7%	10.1%	9.8%	11.6%	8.1%	6.1%	7.5%	2.8%	7.6%	5.8%
Tunkhannock	2,342	3.2%	3.8%	7.4%	16.3%	18.6%	8.1%	11.5%	7.5%	7.4%	2.6%	6.5%	7.1%
Wilkes-Barre	4,416	3.8%	7.2%	8.5%	11.0%	13.4%	8.4%	10.5%	6.6%	12.0%	2.7%	7.9%	8.0%
Troop R													
Blooming Grove	4,036	7.8%	6.1%	8.0%	10.0%	17.3%	8.2%	9.2%	5.7%	7.3%	4.9%	8.1%	7.7%
Dunmore	3,435	7.5%	5.3%	10.5%	11.3%	15.3%	7.4%	11.0%	4.4%	10.2%	3.8%	7.6%	5.7%
Gibson	2,982	4.9%	6.5%	6.7%	12.6%	15.5%	6.5%	11.3%	9.5%	9.4%	3.7%	8.7%	4.7%
Honesdale	1,771	9.1%	6.9%	13.2%	13.0%	10.3%	6.7%	7.8%	5.9%	9.7%	3.5%	7.5%	6.4%

Table A.3. Monthly Breakdown of Traffic Stops by Department, Area, Troop, & Station, January – December 2023

	Total # of Stops	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
AREA IV													
Troop J													
Avondale	8,543	8.6%	8.0%	7.5%	10.5%	11.0%	8.9%	9.3%	7.2%	8.1%	5.7%	7.6%	7.6%
Embreeville	7,031	9.5%	7.8%	10.2%	8.2%	10.1%	10.2%	9.1%	7.1%	7.7%	3.4%	7.1%	9.6%
Lancaster	9,158	7.4%	5.8%	8.2%	11.1%	10.4%	7.3%	10.0%	7.3%	9.4%	4.9%	8.3%	9.9%
York	11,420	8.7%	6.8%	8.0%	7.0%	8.2%	6.1%	11.3%	8.7%	10.8%	4.3%	8.7%	11.3%
Troop K													
Media	12,637	7.4%	6.7%	7.5%	8.7%	10.3%	7.3%	9.9%	10.8%	10.8%	3.4%	7.5%	9.5%
Philadelphia	9,626	7.4%	7.0%	11.1%	7.2%	11.0%	7.9%	8.5%	8.2%	11.1%	3.6%	7.3%	9.7%
Skippack	4,425	4.9%	7.7%	10.1%	6.2%	13.4%	8.8%	10.6%	4.2%	13.1%	3.0%	9.1%	9.0%
Troop L													
Frackville	3,741	8.1%	13.0%	8.3%	9.3%	10.3%	6.2%	10.1%	6.1%	8.2%	4.5%	10.4%	5.6%
Hamburg	3,268	9.3%	10.0%	10.4%	11.0%	13.3%	4.5%	11.0%	5.5%	7.7%	2.6%	9.9%	4.9%
Jonestown	5,395	9.4%	8.9%	7.5%	8.7%	13.3%	6.6%	10.0%	7.5%	7.0%	3.2%	10.1%	8.0%
Reading	5,375	7.7%	8.7%	9.4%	7.6%	9.2%	5.8%	10.8%	8.1%	11.9%	3.7%	11.6%	5.4%
Schuylkill Haven	4,523	10.4%	10.4%	11.2%	9.4%	14.0%	6.0%	8.0%	6.6%	7.4%	2.5%	9.4%	4.9%
Troop M													
Belfast	3,891	8.2%	7.0%	10.6%	11.9%	15.6%	7.6%	9.7%	5.1%	7.5%	3.0%	7.9%	5.9%
Bethlehem	6,255	7.5%	8.5%	9.6%	9.4%	14.3%	7.2%	9.2%	7.6%	8.0%	3.6%	6.6%	8.5%
Dublin	3,321	8.3%	10.4%	8.3%	8.2%	10.6%	7.3%	10.6%	8.2%	8.7%	6.1%	7.3%	6.1%
Fogelsville	6,146	8.9%	6.8%	8.3%	11.2%	10.6%	7.0%	10.7%	6.3%	9.0%	4.3%	8.8%	8.1%
Trevose	3,473	10.6%	8.8%	8.7%	9.1%	10.2%	6.4%	10.5%	5.0%	8.1%	3.6%	10.7%	8.2%
Specialized Units													
SHIELD	3,833	6.2%	6.9%	8.7%	8.9%	7.9%	12.9%	9.1%	17.2%	8.7%	5.2%	4.4%	4.0%
Canine	1,171	5.9%	6.8%	12.8%	8.3%	6.2%	10.5%	8.4%	14.6%	11.2%	5.1%	6.1%	4.1%

Table A.4. Area I Traffic Stop Descriptives by Station, January - December 2023

	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													
Belle Vernon	4,950	72.4%	69.5%	22.5%	55.2%	21.1%	1.2%	90.0%	20.5%	92.8%	5.2%	1.3%	0.8%
Pittsburgh	5,592	65.4%	69.7%	73.0%	17.7%	7.7%	1.7%	86.8%	10.7%	95.6%	3.5%	0.6%	0.3%
Uniontown	7,782	69.4%	65.1%	1.9%	70.6%	27.1%	0.4%	93.1%	19.3%	91.6%	6.0%	1.1%	1.2%
Washington	4,586	61.6%	68.8%	50.5%	21.6%	27.6%	0.3%	84.0%	22.5%	89.9%	7.8%	1.7%	0.6%
Waynesburg	2,378	60.1%	79.6%	25.3%	67.9%	6.7%	0.1%	77.6%	24.2%	95.0%	3.0%	1.3%	0.6%
Troop C													
Clarion	3,012	55.9%	62.4%	39.7%	56.1%	3.7%	0.5%	74.3%	24.0%	93.2%	5.5%	0.6%	0.7%
Clearfield	4,354	63.3%	67.1%	38.4%	57.1%	4.3%	0.3%	72.5%	8.0%	95.2%	3.4%	0.8%	0.5%
Dubois	3,651	58.9%	72.8%	44.8%	47.5%	7.6%	0.2%	68.9%	24.2%	92.6%	4.1%	1.0%	2.3%
Lewis Run	5,409	64.6%	51.2%	2.6%	76.0%	21.2%	0.1%	76.4%	19.9%	92.4%	5.4%	1.4%	0.8%
Marienville	2,930	61.1%	74.7%	0.9%	96.6%	2.6%	0.0%	90.2%	29.9%	94.6%	4.3%	0.7%	0.4%
Punxsutawney	3,664	64.1%	65.9%	3.3%	90.0%	6.6%	0.1%	94.1%	28.2%	87.9%	9.2%	2.0%	1.0%
Ridgway	3,207	62.2%	78.0%	0.2%	87.0%	12.6%	0.1%	73.3%	14.4%	96.3%	3.4%	0.2%	0.0%
Troop D													
Beaver	3,763	67.6%	80.3%	46.5%	30.2%	23.2%	0.0%	88.7%	12.5%	94.2%	5.2%	0.4%	0.2%
Butler	4,744	63.6%	61.8%	10.0%	72.3%	15.5%	2.2%	91.9%	16.0%	92.1%	5.2%	1.7%	1.0%
Kittanning	7,289	65.9%	64.4%	0.5%	89.4%	10.1%	0.1%	95.1%	14.7%	90.6%	5.7%	1.5%	2.1%
Mercer	3,535	68.0%	80.3%	49.1%	44.7%	6.2%	0.1%	82.9%	20.7%	96.0%	3.0%	0.4%	0.6%
New Castle	3,018	73.5%	78.1%	34.7%	43.1%	21.6%	0.6%	87.7%	21.2%	90.2%	5.0%	2.9%	1.9%
Troop E													
Corry	2,858	67.1%	70.7%	0.3%	83.7%	15.9%	0.1%	92.6%	19.5%	97.1%	2.1%	0.6%	0.2%
Erie	6,941	59.0%	52.6%	21.3%	48.3%	30.1%	0.4%	81.9%	10.3%	93.1%	5.9%	0.8%	0.1%
Franklin	2,066	55.9%	66.3%	8.8%	75.2%	14.8%	1.3%	91.9%	18.5%	89.8%	8.3%	1.2%	0.7%
Girard	6,535	57.4%	70.6%	56.9%	32.7%	10.2%	0.2%	84.3%	24.0%	86.7%	12.2%	1.1%	0.1%
Meadville	4,217	67.2%	63.2%	25.3%	57.2%	16.2%	1.2%	86.4%	19.2%	92.2%	6.0%	1.3%	0.5%
Warren	2,337	65.3%	67.4%	0.5%	94.0%	5.5%	0.1%	87.0%	6.2%	96.4%	3.0%	0.4%	0.3%

Table A.4. Area II Traffic Stop Descriptives by Station, January - December 2023

	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 A													
Ebensburg	2,637	58.6%	78.8%	0.9%	92.5%	6.5%	0.0%	90.0%	21.5%	95.1%	3.1%	0.5%	1.3%
Greensburg	5,879	63.4%	68.9%	2.7%	74.9%	22.0%	0.4%	95.1%	21.7%	86.6%	10.6%	1.6%	1.2%
Indiana	5,684	73.4%	81.6%	0.5%	91.0%	8.4%	0.1%	87.5%	8.1%	92.8%	5.1%	1.6%	0.5%
Kiski Valley	1,609	62.3%	77.8%	0.4%	87.1%	12.2%	0.3%	94.5%	17.3%	92.2%	6.0%	1.1%	0.6%
Somerset (A)	2,750	67.2%	76.3%	2.3%	85.8%	11.7%	0.1%	92.1%	15.3%	93.2%	5.3%	1.2%	0.3%
Troop G													
Bedford	5,676	66.1%	72.3%	17.3%	76.0%	6.6%	0.1%	73.6%	21.2%	94.9%	3.2%	0.7%	1.2%
Hollidaysburg	4,404	66.0%	69.2%	30.5%	46.4%	23.0%	0.2%	89.9%	16.7%	90.3%	6.9%	1.8%	1.0%
Huntingdon	4,227	65.6%	74.3%	1.5%	93.7%	4.8%	0.1%	93.4%	10.9%	92.3%	7.1%	0.2%	0.3%
Lewistown	4,028	67.3%	69.6%	1.9%	85.4%	12.6%	0.1%	89.7%	25.7%	94.5%	4.5%	0.6%	0.4%
McConnellsburg	3,236	62.3%	68.0%	49.3%	46.1%	4.5%	0.1%	56.6%	21.5%	94.5%	4.2%	0.9%	0.4%
Rockview	7,117	64.1%	65.7%	39.7%	52.4%	7.4%	0.5%	80.8%	10.3%	95.0%	4.2%	0.4%	0.4%
Troop H													
Carlisle	9,191	71.2%	60.3%	42.1%	37.9%	19.6%	0.4%	78.7%	17.5%	80.9%	13.5%	4.5%	1.1%
Chambersburg	12,076	68.1%	55.1%	27.6%	58.7%	13.5%	0.2%	78.5%	16.6%	93.4%	4.5%	1.5%	0.7%
Gettysburg	10,875	67.8%	56.7%	3.1%	90.8%	6.1%	0.1%	68.0%	14.3%	92.2%	4.0%	1.2%	2.6%
Harrisburg	9,705	68.7%	50.9%	60.3%	29.9%	9.5%	0.3%	75.3%	18.2%	81.5%	10.8%	6.0%	1.7%
Lykens	3,357	67.4%	57.0%	1.4%	85.7%	12.7%	0.1%	95.1%	29.6%	93.1%	5.7%	0.7%	0.4%
Newport	3,968	68.9%	62.0%	6.1%	81.5%	11.6%	0.8%	85.9%	19.4%	85.6%	10.9%	3.1%	0.3%
Troop T													
Bowmansville	5,840	75.6%	78.5%	95.4%	3.4%	1.1%	0.1%	80.2%	27.1%	94.7%	3.8%	0.9%	0.7%
Everett	6,150	72.2%	71.8%	95.3%	1.1%	0.2%	3.5%	49.0%	17.6%	89.2%	6.5%	3.4%	0.9%
Gibsonia	5,600	74.4%	80.1%	93.4%	4.8%	1.7%	0.1%	74.5%	24.4%	87.6%	11.7%	0.4%	0.2%
Highspire	145	93.1%	68.3%	84.8%	5.5%	0.7%	9.0%	77.2%	25.5%	66.9%	28.3%	2.8%	2.1%
King of Prussia	6,874	71.5%	82.8%	96.5%	2.0%	0.4%	1.2%	82.9%	18.7%	82.1%	16.8%	0.7%	0.4%
New Stanton	8,944	72.3%	88.6%	52.3%	33.2%	2.9%	11.6%	79.6%	25.0%	90.4%	7.6%	1.5%	0.5%
Newville	5,717	73.6%	79.7%	99.4%	0.2%	0.0%	0.4%	59.8%	38.7%	87.6%	11.2%	0.8%	0.4%
Pocono	4,516	75.4%	82.6%	56.4%	43.5%	0.0%	0.0%	73.2%	33.0%	95.9%	3.3%	0.5%	0.3%
Somerset (T)	5,060	67.2%	83.8%	93.8%	2.3%	1.3%	2.6%	46.7%	11.7%	94.2%	4.5%	1.0%	0.3%

Table A.4. Area III Traffic Stop Descriptives by Station, January - December 2023

	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 F													
Coudersport	4,687	62.6%	70.0%	0.3%	91.9%	7.7%	0.1%	84.9%	21.3%	92.4%	5.7%	1.7%	0.1%
Emporium	985	70.6%	78.7%	3.2%	92.9%	3.7%	0.2%	86.3%	30.1%	92.0%	4.8%	2.4%	0.8%
Lamar	5,258	60.2%	77.7%	60.4%	30.3%	9.2%	0.1%	55.8%	25.5%	95.8%	3.0%	0.8%	0.4%
Mansfield	3,001	56.6%	70.9%	2.0%	90.9%	7.1%	0.1%	61.5%	17.6%	96.0%	2.6%	0.4%	1.0%
Milton	7,478	63.4%	66.5%	31.5%	63.3%	5.0%	0.2%	71.4%	19.8%	96.6%	1.6%	1.4%	0.3%
Montoursville	6,592	67.2%	65.4%	30.7%	54.9%	13.8%	0.7%	86.0%	23.7%	90.4%	6.0%	2.9%	0.7%
Selinsgrove	4,619	67.8%	68.1%	1.2%	90.0%	8.8%	0.1%	79.1%	25.1%	92.6%	4.7%	1.8%	0.9%
Stonington	2,508	66.0%	64.2%	0.7%	72.4%	26.8%	0.0%	97.4%	13.1%	93.3%	4.6%	2.1%	0.0%
Troop N													
Bloomsburg	2,549	60.8%	67.1%	60.1%	31.3%	8.5%	0.1%	71.3%	19.9%	92.8%	4.3%	1.2%	1.7%
Fern Ridge	4,682	60.6%	80.6%	60.1%	35.5%	4.3%	0.1%	59.4%	22.0%	91.7%	6.5%	1.3%	0.4%
Hazleton	7,283	64.9%	69.2%	42.2%	43.2%	14.0%	0.5%	79.5%	23.0%	90.1%	7.3%	1.9%	0.7%
Lehighton	3,019	66.2%	67.8%	3.6%	76.3%	19.8%	0.3%	91.5%	23.4%	85.4%	8.4%	4.3%	1.9%
Stroudsburg	10,500	64.1%	70.0%	33.5%	44.6%	21.7%	0.3%	78.2%	14.5%	87.9%	7.8%	2.5%	1.9%
Troop P													
Laporte	1,742	65.0%	72.4%	3.2%	87.6%	9.2%	0.1%	84.6%	24.9%	92.8%	5.6%	1.2%	0.5%
Shickshinny	2,076	66.7%	80.5%	5.7%	88.3%	5.9%	0.1%	94.7%	10.3%	90.8%	7.9%	0.8%	0.4%
Towanda	4,479	72.5%	66.9%	0.6%	87.7%	11.4%	0.4%	88.9%	9.2%	91.8%	5.0%	1.9%	1.2%
Tunkhannock	2,342	67.2%	79.2%	1.1%	95.6%	3.3%	0.0%	92.4%	9.4%	94.2%	4.7%	0.9%	0.1%
Wilkes-Barre	4,416	68.3%	72.0%	25.1%	60.4%	13.7%	0.8%	88.1%	15.9%	88.7%	9.7%	1.2%	0.4%
Troop R													
Blooming Grove	4,036	68.0%	72.0%	58.3%	31.3%	9.7%	0.7%	61.4%	21.0%	80.5%	11.9%	4.1%	3.5%
Dunmore	3,435	72.1%	82.5%	41.4%	49.4%	9.1%	0.1%	83.0%	19.3%	72.5%	21.4%	4.6%	1.5%
Gibson	2,982	67.0%	79.1%	64.6%	31.0%	4.3%	0.1%	49.6%	23.7%	82.8%	9.6%	5.4%	2.2%
Honesdale	1,771	73.1%	84.5%	5.3%	88.4%	5.9%	0.5%	92.7%	15.9%	91.8%	6.4%	1.2%	0.6%

Table A.4. Area IV Traffic Stop Descriptives by Station, January - December 2023

	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 J													
Avondale	8,543	66.7%	39.0%	0.7%	86.7%	11.0%	1.6%	76.2%	14.9%	88.2%	5.9%	4.1%	1.8%
Embreeville	7,031	73.6%	66.2%	3.2%	90.8%	5.9%	0.1%	89.7%	15.4%	87.8%	8.7%	1.7%	1.9%
Lancaster	9,158	70.1%	54.3%	3.0%	89.0%	8.0%	0.1%	89.3%	15.6%	87.0%	9.2%	2.6%	1.2%
York	11,420	69.0%	50.5%	51.9%	31.0%	16.3%	0.9%	77.0%	14.3%	89.3%	6.7%	2.6%	1.4%
Troop K													
Media	12,637	70.5%	48.9%	59.2%	35.1%	5.3%	0.3%	75.2%	12.7%	90.2%	6.8%	1.9%	1.1%
Philadelphia	9,626	72.5%	63.4%	77.1%	6.8%	16.0%	0.2%	83.1%	16.7%	84.4%	11.9%	2.3%	1.4%
Skippack	4,425	62.8%	63.1%	5.5%	79.3%	13.6%	1.6%	93.5%	13.6%	89.3%	7.5%	2.3%	0.9%
Troop L													
Frackville	3,741	69.9%	69.3%	27.2%	59.2%	13.6%	0.0%	86.3%	24.1%	90.4%	7.9%	1.0%	0.7%
Hamburg	3,268	71.2%	77.1%	43.6%	46.0%	10.3%	0.1%	72.7%	21.3%	80.4%	14.2%	4.1%	1.3%
Jonestown	5,395	69.3%	69.1%	39.9%	45.4%	14.5%	0.1%	78.0%	13.4%	89.2%	8.8%	1.2%	0.7%
Reading	5,375	68.4%	69.8%	13.2%	68.9%	17.7%	0.2%	90.9%	16.7%	92.8%	5.2%	1.5%	0.5%
Schuylkill Haven	4,523	73.4%	69.8%	1.5%	83.5%	14.9%	0.1%	95.6%	18.3%	90.8%	6.1%	2.3%	0.7%
Troop M													
Belfast	3,891	66.3%	63.7%	26.2%	63.2%	10.5%	0.1%	76.0%	19.5%	89.1%	7.1%	2.2%	1.6%
Bethlehem	6,255	70.3%	53.4%	3.7%	89.7%	6.5%	0.1%	89.6%	14.5%	86.7%	9.5%	2.4%	1.4%
Dublin	3,321	68.9%	54.7%	2.3%	85.9%	11.5%	0.3%	93.2%	12.7%	86.6%	11.0%	1.7%	0.6%
Fogelsville	6,146	68.4%	52.8%	40.3%	35.4%	23.1%	1.2%	78.4%	16.5%	86.7%	9.2%	2.7%	1.3%
Trevose	3,473	61.4%	67.4%	79.0%	13.8%	7.0%	0.2%	71.6%	20.1%	78.8%	14.6%	2.2%	4.4%
Specialized Units													
SHIELD	3,833	98.1%	97.8%	98.1%	1.3%	0.5%	0.1%	25.2%	31.6%	81.2%	10.4%	5.6%	2.8%
Canine	1,853	93.8%	91.2%	76.7%	14.2%	8.9%	0.2%	38.2%	26.5%	81.1%	13.4%	4.3%	1.2%

Table A.5. Area I Reason for Stop by Station, January - December 2023

	Total # of Stops	Speeding	Avg. Amount Over Limit (MPH)	Other Moving Violation	Equipment/ Inspection	Registration	License	Other
Troop B								
Belle Vernon	4,950	25.1%	20.3	23.4%	31.4%	25.8%	8.4%	6.7%
Pittsburgh	5,592	43.1%	25.0	22.5%	25.8%	12.0%	3.5%	4.5%
Uniontown	7,782	24.7%	19.9	29.5%	22.7%	19.6%	8.6%	5.9%
Washington	4,586	26.7%	24.9	23.7%	33.6%	18.6%	7.3%	7.4%
Waynesburg	2,378	49.0%	20.8	18.8%	20.4%	12.6%	3.0%	2.2%
Troop C								
Clarion	3,012	48.9%	17.3	20.1%	15.3%	14.1%	2.5%	3.5%
Clearfield	4,354	51.2%	16.8	15.8%	22.4%	9.7%	2.7%	2.0%
Dubois	3,651	52.4%	18.8	19.4%	17.4%	13.5%	2.8%	4.4%
Lewis Run	5,409	26.3%	17.5	17.7%	42.5%	13.6%	3.0%	1.6%
Marienville	2,930	49.5%	18.0	9.9%	24.3%	15.4%	3.0%	3.3%
Punxsutawney	3,664	36.1%	18.3	19.5%	32.1%	13.6%	4.7%	5.8%
Ridgway	3,207	58.8%	18.8	10.7%	17.7%	10.5%	2.9%	1.8%
Troop D								
Beaver	3,763	25.9%	25.8	21.4%	24.0%	21.7%	8.2%	6.3%
Butler	4,744	34.9%	21.7	28.6%	23.4%	15.2%	4.6%	2.9%
Kittanning	7,289	32.4%	24.3	23.8%	25.0%	17.6%	7.8%	4.3%
Mercer	3,535	48.2%	20.1	13.2%	21.8%	19.0%	3.5%	4.8%
New Castle	3,018	40.2%	22.6	17.0%	23.8%	20.6%	4.9%	2.8%
Troop E								
Corry	2,858	39.6%	17.2	13.6%	21.9%	23.6%	3.5%	2.6%
Erie	6,941	20.8%	22.7	29.8%	25.1%	21.3%	7.5%	2.8%
Franklin	2,066	41.4%	19.4	21.4%	19.2%	18.3%	5.4%	2.8%
Girard	6,535	43.9%	19.8	11.6%	32.8%	11.1%	2.5%	2.0%
Meadville	4,217	31.6%	18.0	20.1%	26.7%	19.8%	4.2%	3.6%
Warren	2,337	58.8%	17.3	9.7%	18.7%	12.7%	2.0%	1.1%

Table A.5. Area II Reason for Stop by Station, January - December 2023

	Total # of Stops	Speeding	Avg. Amount Over Limit (MPH)	Other Moving Violation	Equipment/ Inspection	Registration	License	Other
Troop A								
Ebensburg	2,637	73.9%	23.6	7.5%	10.9%	7.5%	1.8%	1.6%
Greensburg	5,879	34.3%	22.1	21.6%	23.8%	23.5%	7.8%	2.8%
Indiana	5,684	61.7%	22.7	12.5%	12.5%	11.6%	3.0%	2.5%
Kiski Valley	1,609	35.7%	23.8	21.2%	29.6%	16.4%	6.0%	6.5%
Somerset (A)	2,750	46.3%	20.6	17.1%	23.0%	19.4%	3.5%	4.5%
Troop G								
Bedford	5,676	55.0%	20.2	11.3%	19.7%	16.9%	2.3%	2.4%
Hollidaysburg	4,404	30.6%	21.6	22.0%	25.8%	20.6%	4.9%	3.9%
Huntingdon	4,227	53.8%	19.3	19.4%	14.8%	10.7%	3.2%	4.4%
Lewistown	4,028	52.4%	20.6	17.6%	17.4%	12.7%	3.4%	3.4%
McConnellsburg	3,236	51.9%	23.1	24.8%	16.4%	8.4%	1.5%	1.2%
Rockview	7,117	55.9%	21.5	20.5%	13.3%	11.4%	3.5%	1.9%
Troop H								
Carlisle	9,191	26.8%	21.1	27.6%	29.1%	14.7%	3.8%	6.1%
Chambersburg	12,076	32.1%	20.3	27.9%	22.5%	21.1%	4.1%	2.0%
Gettysburg	10,875	34.4%	19.2	31.3%	22.5%	10.2%	4.7%	1.6%
Harrisburg	9,705	26.0%	21.6	47.3%	14.1%	15.1%	5.8%	2.8%
Lykens	3,357	28.1%	19.8	18.7%	35.0%	21.2%	4.0%	1.5%
Newport	3,968	49.6%	19.9	26.5%	16.3%	12.3%	3.6%	2.1%
Troop T								
Bowmansville	5,840	59.5%	22.5	8.8%	7.8%	29.1%	3.2%	3.9%
Everett	6,150	76.0%	22.2	17.8%	7.9%	13.8%	1.6%	3.0%
Gibsonia	5,600	60.7%	19.9	21.1%	18.9%	23.2%	3.7%	15.1%
Highspire	145	43.4%	21.9	13.1%	17.9%	27.6%	5.5%	2.1%
King of Prussia	6,874	53.4%	24.6	13.0%	19.0%	20.3%	3.5%	7.6%
New Stanton	8,944	66.7%	20.1	12.5%	11.8%	13.3%	1.9%	2.6%
Newville	5,717	71.2%	24.5	10.9%	4.9%	18.2%	3.0%	3.2%
Pocono	4,516	85.2%	23.8	11.2%	4.0%	5.5%	2.3%	5.6%
Somerset (T)	5,060	80.6%	23.0	7.7%	5.9%	9.9%	1.8%	8.2%

Table A.5. Area III Reason for Stop by Station, January – December 2023

	Total # of Stops	Speeding	Avg. Amount Over Limit (MPH)	Other Moving Violation	Equipment/ Inspection	Registration	License	Other
Troop F								
Coudersport	4,687	33.6%	16.5	22.9%	29.7%	12.3%	1.9%	2.0%
Emporium	985	62.7%	18.4	8.3%	14.9%	13.6%	3.5%	2.3%
Lamar	5,258	28.8%	19.6	28.8%	16.6%	9.4%	2.5%	1.0%
Mansfield	3,001	56.2%	18.0	19.6%	13.3%	11.0%	1.8%	1.1%
Milton	7,478	54.3%	18.9	20.3%	16.3%	10.4%	4.5%	2.8%
Montoursville	6,592	59.0%	18.6	17.3%	14.6%	11.1%	2.1%	2.2%
Selinsgrove	4,619	58.3%	21.6	18.5%	15.5%	12.2%	3.6%	1.6%
Stonington	2,508	47.6%	18.6	23.2%	19.1%	8.3%	3.5%	1.9%
Troop N								
Bloomsburg	2,549	47.4%	19.6	22.8%	17.7%	14.6%	5.2%	2.9%
Fern Ridge	4,682	46.2%	20.9	31.0%	21.7%	6.5%	2.5%	2.0%
Hazleton	7,283	39.2%	22.2	36.4%	12.9%	9.7%	7.5%	5.8%
Lehighton	3,019	32.0%	22.1	30.4%	22.7%	14.5%	5.2%	4.6%
Stroudsburg	10,500	31.9%	23.5	25.0%	24.5%	16.5%	5.4%	5.4%
Troop P								
Laporte	1,742	29.8%	22.0	12.0%	23.4%	27.9%	9.5%	5.8%
Shickshinny	2,076	44.9%	21.4	12.4%	19.9%	21.3%	5.9%	2.1%
Towanda	4,479	18.2%	19.7	19.0%	35.7%	22.6%	5.7%	4.9%
Tunkhannock	2,342	41.8%	19.7	16.6%	26.0%	15.4%	4.2%	1.7%
Wilkes-Barre	4,416	57.8%	23.9	27.8%	19.6%	11.2%	6.2%	5.7%
Troop R								
Blooming Grove	4,036	39.6%	18.5	32.7%	16.4%	9.8%	3.1%	7.4%
Dunmore	3,435	47.2%	22.3	17.8%	24.1%	17.8%	5.4%	2.2%
Gibson	2,982	41.0%	20.04	30.1%	25.7%	12.8%	4.8%	4.4%
Honesdale	1,771	19.4%	20.8	15.6%	51.7%	17.7%	2.8%	4.3%

Table A.5. Area IV Reason for Stop by Station, January - December 2023

	Total # of Stops	Speeding	Avg. Amount Over Limit (MPH)	Other Moving Violation	Equipment/ Inspection	Registration	License	Other
Troop J								
Avondale	8,543	22.1%	23.6	52.2%	13.7%	13.7%	4.1%	2.6%
Embreeville	7,031	49.5%	26.7	35.1%	19.3%	19.1%	6.7%	3.4%
Lancaster	9,158	29.0%	21.1	31.2%	20.9%	18.7%	5.7%	3.2%
York	11,420	21.4%	21.2	37.9%	22.0%	21.0%	3.8%	2.4%
Troop K								
Media	12,637	29.9%	25.7	44.9%	10.1%	19.4%	4.4%	2.8%
Philadelphia	9,626	11.3%	28.3	52.1%	10.5%	28.6%	4.3%	7.6%
Skippack	4,425	40.5%	25.0	29.9%	14.1%	14.2%	4.7%	4.9%
Troop L								
Frackville	3,741	35.1%	20.1	17.3%	26.1%	20.1%	6.8%	3.1%
Hamburg	3,268	56.2%	21.1	26.0%	12.6%	12.0%	3.0%	1.8%
Jonestown	5,395	45.4%	20.1	24.7%	14.8%	10.8%	3.7%	5.4%
Reading	5,375	43.2%	25.0	28.2%	15.2%	16.0%	7.0%	2.9%
Schuylkill Haven	4,523	29.3%	19.9	17.5%	26.8%	23.5%	9.7%	2.9%
Troop M								
Belfast	3,891	38.5%	24.7	26.7%	23.5%	15.6%	4.8%	3.9%
Bethlehem	6,255	74.8%	26.6	44.1%	16.5%	14.8%	6.6%	2.5%
Dublin	3,321	25.9%	26.7	34.9%	22.4%	20.7%	8.6%	3.2%
Fogelsville	6,146	23.1%	25.0	45.0%	13.8%	21.0%	9.4%	2.4%
Trevose	3,473	32.6%	33.4	39.9%	19.9%	18.6%	3.6%	8.0%
Specialized Units								
SHIELD	3,833	17.5%	11.7	39.7%	42.5%	12.5%	1.6%	5.6%
Canine	1,853	16.1%	13.0	52.5%	37.1%	8.0%	3.2%	3.7%

Table A.6. Area I Characteristics of Drivers Stopped by Station, January - December 2023

		Age	Gender	Behavior				Residency
	Total # of Stops	Average (years)	Male	Civil	Dis-respectful	Non-compliant	Verbal or Phys Resistant	In-State
Troop B								
Belle Vernon	4,950	39.0	98.8%	97.2%	2.0%	0.5%	1.0%	92.3%
Pittsburgh	5,592	38.2	66.2%	97.5%	1.1%	0.7%	1.2%	88.5%
Uniontown	7,782	39.5	61.9%	97.2%	1.6%	0.8%	1.0%	94.0%
Washington	4,586	39.9	63.9%	98.3%	0.7%	0.7%	0.8%	84.4%
Waynesburg	2,378	38.6	64.7%	99.1%	0.4%	0.2%	0.5%	78.4%
Troop C								
Clarion	3,012	39.5	68.5%	99.0%	0.6%	0.2%	0.4%	74.4%
Clearfield	4,354	39.1	67.8%	98.7%	0.8%	0.2%	0.5%	73.1%
Dubois	3,651	39.7	66.4%	98.2%	0.7%	0.7%	0.9%	70.0%
Lewis Run	5,409	40.6	66.5%	98.8%	0.6%	0.5%	0.6%	77.8%
Marienville	2,930	43.7	71.6%	98.6%	0.9%	0.2%	0.6%	90.9%
Punxsutawney	3,664	41.3	67.6%	97.5%	1.3%	0.3%	1.2%	94.7%
Ridgway	3,207	41.1	68.0%	99.4%	0.4%	0.1%	0.2%	73.2%
Troop D								
Beaver	3,763	38.6	60.6%	98.4%	1.1%	0.3%	0.6%	89.4%
Butler	4,744	38.8	65.0%	97.9%	1.0%	0.7%	1.0%	93.7%
Kittanning	7,289	38.3	64.7%	98.6%	0.8%	0.2%	0.6%	96.1%
Mercer	3,535	38.5	65.5%	99.1%	0.6%	0.2%	0.4%	84.3%
New Castle	3,018	40.9	61.2%	98.4%	0.5%	0.2%	1.3%	90.3%
Troop E								
Corry	2,858	41.2	64.6%	99.0%	0.7%	0.3%	0.2%	93.1%
Erie	6,941	39.2	64.5%	98.3%	0.8%	0.4%	1.2%	83.3%
Franklin	2,066	40.7	63.6%	96.9%	0.5%	0.6%	2.6%	92.3%
Girard	6,535	38.8	63.4%	98.7%	0.6%	0.1%	0.8%	85.9%
Meadville	4,217	39.7	64.6%	98.7%	0.6%	0.2%	0.7%	88.6%
Warren	2,337	41.2	67.1%	99.3%	0.5%	0.1%	0.1%	88.9%

Table A.6. Area II Characteristics of Drivers Stopped by Station, January - December 2023

	Total # of Stops	Age	Gender	Behavior				Residency
		Average (years)	Male	Civil	Dis-respectful	Non-compliant	Verbal or Phys Resistant	In-State
Troop A								
Ebensburg	2,637	36.8	63.5%	98.7%	0.7%	0.0%	0.9%	91.1%
Greensburg	5,879	39.7	63.1%	98.1%	0.9%	0.4%	1.0%	96.3%
Indiana	5,684	37.9	64.5%	99.0%	0.6%	0.2%	0.4%	89.1%
Kiski Valley	1,609	39.8	67.6%	98.4%	0.9%	0.5%	0.6%	95.9%
Somerset (A)	2,750	39.9	66.3%	98.4%	0.7%	0.4%	0.9%	92.5%
Troop G								
Bedford	5,676	38.8	65.7%	99.3%	0.4%	0.2%	0.2%	74.5%
Hollidaysburg	4,404	38.0	60.3%	98.5%	0.9%	0.2%	0.8%	91.0%
Huntingdon	4,227	41.0	60.9%	99.0%	0.5%	0.1%	0.5%	94.5%
Lewistown	4,028	38.7	63.1%	98.5%	0.5%	0.4%	0.8%	91.0%
McConnellsburg	3,236	39.7	69.7%	98.2%	0.8%	0.3%	1.0%	59.3%
Rockview	7,117	37.1	65.2%	98.9%	0.5%	0.1%	0.6%	82.4%
Troop H								
Carlisle	9,191	38.7	69.5%	98.3%	0.9%	0.4%	0.7%	80.1%
Chambersburg	12,076	38.1	64.7%	98.2%	0.8%	0.4%	1.0%	80.0%
Gettysburg	10,875	37.5	65.8%	95.9%	3.3%	2.4%	2.8%	69.8%
Harrisburg	9,705	38.7	70.8%	97.4%	1.1%	0.6%	1.4%	77.2%
Lykens	3,357	38.5	65.5%	97.5%	1.5%	0.5%	1.7%	95.6%
Newport	3,968	38.2	66.0%	98.3%	0.7%	0.2%	1.1%	87.1%
Troop T								
Bowmansville	5,840	37.2	67.3%	99.1%	0.3%	0.2%	0.5%	81.2%
Everett	6,150	37.0	71.3%	98.6%	0.8%	0.3%	0.7%	52.0%
Gibsonia	5,600	40.1	66.4%	99.5%	0.3%	0.1%	0.2%	75.6%
Highspire	145	40.6	67.6%	97.9%	1.4%	0.0%	0.7%	75.9%
King of Prussia	6,874	37.1	69.6%	98.4%	0.6%	0.1%	1.1%	83.2%
New Stanton	8,944	39.4	65.5%	98.8%	0.4%	0.2%	0.9%	80.6%
Newville	5,717	37.6	70.3%	98.7%	0.4%	0.2%	1.0%	62.6%
Pocono	4,516	35.6	67.4%	99.2%	0.6%	0.0%	0.1%	74.8%
Somerset (T)	5,060	39.4	71.2%	99.1%	0.2%	0.2%	0.6%	49.7%

Table A.6. Area III Characteristics of Drivers Stopped by Station, January - December 2023

		Age	Gender	Behavior				Residency
	Total # of Stops	Average (years)	Male	Civil	Dis-respectful	Non-compliant	Verbal or Phys Resistant	In-State
Troop F								
Coudersport	4,687	42.9	68.3%	99.1%	0.7%	0.2%	0.2%	85.3%
Emporium	985	43.0	71.6%	99.3%	0.5%	0.1%	0.1%	87.7%
Lamar	5,258	37.8	69.7%	99.4%	0.3%	0.1%	0.3%	57.2%
Mansfield	3,001	39.0	64.8%	98.4%	1.0%	0.2%	0.6%	62.2%
Milton	7,478	38.0	66.3%	99.2%	0.4%	0.1%	0.3%	73.9%
Montoursville	6,592	38.8	63.4%	99.0%	0.6%	0.2%	0.4%	87.0%
Selinsgrove	4,619	38.7	64.5%	99.2%	0.5%	0.3%	0.3%	80.e3%
Stonington	2,508	39.6	59.3%	99.0%	0.6%	0.3%	0.4%	98.1%
Troop N								
Bloomsburg	2,549	36.5	67.9%	98.8%	0.8%	0.4%	0.4%	72.5%
Fern Ridge	4,682	38.3	72.8%	98.8%	0.5%	0.3%	0.7%	59.5%
Hazleton	7,283	37.1	69.4%	98.2%	1.0%	0.5%	0.8%	80.3%
Lehighton	3,019	38.5	66.8%	98.0%	1.1%	0.3%	1.0%	1.0%
Stroudsburg	10,500	39.0	66.1%	98.2%	1.0%	0.4%	0.9%	78.6%
Troop P								
Laporte	1,742	40.9	68.1%	98.0%	0.7%	0.5%	1.4%	85.6%
Shickshinny	2,076	40.6	65.0%	98.8%	0.7%	0.1%	0.5%	95.3%
Towanda	4,479	38.7	65.8%	98.6%	1.0%	0.3%	0.6%	89.3%
Tunkhannock	2,342	40.4	66.7%	98.7%	1.0%	0.2%	0.4%	93.2%
Wilkes-Barre	4,416	38.4	68.4%	97.6%	1.2%	0.5%	1.2%	89.7%
Troop R								
Blooming Grove	4,036	41.4	68.1%	97.3%	1.6%	0.6%	1.4%	62.2%
Dunmore	3,435	38.3	67.5%	97.9%	1.2%	0.3%	1.0%	83.8%
Gibson	2,982	39.0	72.1%	98.4%	0.9%	0.6%	0.8%	49.6%
Honesdale	1,771	41.6	66.0%	99.0%	0.4%	0.2%	0.5%	92.9%

Table A.6. Area IV Characteristics of Drivers Stopped by Station, January - December 2023

		Age	Gender	Behavior				Residency
	Total # of Stops	Average (years)	Male	Civil	Dis-respectful	Non-compliant	Verbal or Phys Resistant	In-State
Troop J								
Avondale	8,543	38.4	67.9%	97.9%	1.0%	0.4%	1.3%	77.7%
Embreeville	7,031	38.3	67.1%	98.1%	1.1%	0.4%	0.9%	91.8%
Lancaster	9,158	37.4	69.2%	98.5%	0.8%	0.4%	0.7%	90.2%
York	11,420	38.1	64.4%	97.9%	1.1%	0.6%	1.0%	78.3%
Troop K								
Media	12,637	38.2	69.4%	97.6%	1.5%	0.6%	1.0%	77.6%
Philadelphia	9,626	35.6	74.9%	97.2%	1.6%	0.7%	1.4%	88.2%
Skippack	4,425	38.2	66.9%	96.2%	1.6%	0.6%	2.2%	94.4%
Troop L								
Frackville	3,741	39.5	65.2%	98.5%	0.7%	0.3%	0.7%	86.7%
Hamburg	3,266	39.2	69.3%	98.8%	0.3%	0.3%	0.8%	73.7%
Jonestown	5,395	37.5	66.1%	98.7%	0.5%	0.3%	0.9%	78.7%
Reading	5,375	36.8	66.9%	97.7%	0.9%	0.6%	1.5%	91.9%
Schuylkill Haven	4,523	38.9	66.7%	98.6%	0.6%	0.3%	0.9%	96.4%
Troop M								
Belfast	3,891	38.2	69.9%	97.3%	1.1%	0.6%	1.5%	76.8%
Bethlehem	6,255	36.5	68.7%	96.6%	1.6%	1.2%	1.8%	90.3%
Dublin	3,321	38.8	66.4%	98.3%	0.7%	0.5%	1.2%	94.2%
Fogelsville	6,146	38.1	69.3%	98.0%	0.8%	0.5%	1.4%	80.5%
Trevose	3,473	36.5	76.0%	97.8%	1.0%	0.9%	1.0%	73.0%
Specialized Units								
SHIELD	3,833	39.3	84.3%	99.4%	0.3%	0.2%	0.3%	30.4%
Canine	1,853	38.2	77.8%	96.4%	2.3%	0.9%	1.8%	43.0%

Table A.7. Area I Race and Ethnicity of Drivers Stopped by Station, January - December 2023

		Race						Ethnicity	
	Total # of Stops	White	Black	Amer. Indian or Alaskan Native	Asian/ Pacific Islander	Unknown	Two or More Races	Hispanic	Unknown
Troop B	**25,288**	**80.0%**	**14.8%**	**0.2%**	**0.9%**	**4.1%**	**<0.1%**	**1.8%**	**6.7%**
Belle Vernon	4,950	71.7%	16.9%	0.1%	0.8%	10.3%	<0.1%	2.1%	11.9%
Pittsburgh	5,592	69.9%	23.4%	0.3%	1.7%	4.7%	<0.1%	2.4%	16.0%
Uniontown	7,782	87.3%	10.6%	0.1%	0.4%	1.6%	0.0%	1.0%	1.6%
Washington	4,586	82.8%	13.8%	0.2%	1.1%	2.1%	0.0%	3.1%	0.9%
Waynesburg	2,378	91.6%	5.7%	0.2%	0.6%	1.9%	<0.1%	1.4%	2.2%
Troop C	**26,277**	**91.1%**	**13.6%**	**0.4%**	**1.6%**	**2.3%**	**<0.1%**	**2.6%**	**1.7%**
Clarion	3,012	87.1%	7.2%	0.3%	2.0%	3.4%	0.1%	4.6%	3.1%
Clearfield	4,354	89.5%	4.4%	0.2%	1.7%	4.1%	<0.1%	3.1%	3.9%
Dubois	3,651	86.4%	7.8%	0.9%	1.9%	2.9%	<0.1%	4.7%	1.3%
Lewis Run	5,409	91.1%	4.5%	0.5%	1.7%	2.1%	0.1%	2.1%	1.6%
Marienville	2,930	96.9%	2.2%	0.1%	0.3%	0.4%	0.0%	0.7%	0.1%
Punxsutawney	3,664	98.1%	1.3%	0.1%	0.3%	0.3%	0.0%	0.8%	0.1%
Ridgway	3,207	89.5%	4.4%	0.4%	2.8%	2.9%	<0.1%	1.8%	1.5%
Troop D	**22,359**	**84.8%**	**11.9%**	**0.2%**	**0.9%**	**2.2%**	**<0.1%**	**1.4%**	**3.4%**
Beaver	3,763	78.5%	17.2%	0.1%	0.4%	3.8%	0.0%	1.8%	8.4%
Butler	4,744	91.1%	6.4%	0.1%	0.7%	1.7%	0.1%	1.2%	4.1%
Kittanning	7,289	83.5%	13.3%	0.3%	0.7%	2.2%	<0.1%	1.2%	2.0%
Mercer	3,535	85.3%	9.4%	0.4%	2.1%	2.7%	0.0%	1.7%	2.5%
New Castle	3,018	85.3%	13.1%	0.2%	0.8%	0.7%	<0.1%	1.8%	0.7%
Troop E	**25,058**	**88.5%**	**13.6%**	**0.5%**	**2.4%**	**2.7%**	**<0.1%**	**6.9%**	**2.9%**
Corry	2,858	98.1%	1.4%	0.0%	0.1%	0.4%	0.0%	0.4%	0.5%
Erie	6,941	81.9%	14.3%	0.6%	2.6%	0.5%	0.1%	4.7%	0.6%
Franklin	2,066	92.9%	4.5%	0.3%	0.7%	1.6%	0.0%	1.7%	2.0%
Girard	6,535	85.8%	10.5%	0.1%	2.6%	1.0%	<0.1%	3.4%	0.9%
Meadville	4,217	90.0%	6.5%	0.2%	1.8%	1.4%	0.1%	1.1%	1.1%
Warren	2,337	97.2%	1.8%	0.0%	0.4%	0.6%	0.0%	0.7%	0.7%

Table A.7. Area II Race and Ethnicity of Drivers Stopped by Station, January - December 2023

		Race						Ethnicity	
	Total # of Stops	White	Black	Amer. Indian or Alaskan	Asian/ Pacific Islander	Unknown	Two or More Races	Hispanic	Unknown
Troop A	**18,559**	**90.2%**	**7.7%**	**0.1%**	**0.7%**	**1.2%**	**<0.1%**	**1.4%**	**1.1%**
Ebensburg	2,637	89.7%	7.4%	0.3%	1.4%	1.2%	0.0%	2.1%	1.9%
Greensburg	5,879	90.6%	8.1%	0.1%	0.4%	0.8%	<0.1%	1.3%	0.6%
Indiana	5,684	87.6%	9.6%	0.1%	0.8%	1.8%	<0.1%	1.3%	1.1%
Kiski Valley	1,609	91.2%	6.8%	0.2%	0.4%	1.2%	0.1%	1.7%	0.7%
Somerset (A)	2,750	94.7%	3.8%	<0.1%	0.4%	1.1%	0.0%	1.1%	1.3%
Troop G	**28,688**	**87.6%**	**7.6%**	**0.5%**	**2.1%**	**2.2%**	**<0.1%**	**3.4%**	**1.9%**
Bedford	5,676	90.1%	6.1%	0.8%	2.1%	0.9%	0.0%	2.9%	0.7%
Hollidaysburg	4,404	86.1%	8.9%	0.2%	1.0%	3.7%	0.0%	1.9%	3.5%
Huntingdon	4,227	91.1%	3.3%	0.1%	0.4%	5.2%	0.0%	0.9%	4.9%
Lewistown	4,028	89.9%	6.3%	0.5%	2.5%	0.8%	<0.1%	5.2%	0.7%
McConnellsburg	3,236	80.1%	13.2%	0.9%	3.3%	2.5%	0.1%	5.2%	1.6%
Rockview	7,117	86.6%	8.6%	0.6%	3.2%	1.0%	<0.1%	4.5%	0.9%
Troop H	**49,172**	**80.3%**	**16.1%**	**0.4%**	**2.1%**	**1.0%**	**<0.1%**	**10.9%**	**0.9%**
Carlisle	9,191	80.1%	16.3%	0.4%	2.1%	1.2%	<0.1%	9.0%	0.8%
Chambersburg	12,076	83.0%	15.1%	0.3%	1.1%	0.5%	<0.1%	12.0%	0.5%
Gettysburg	10,875	83.3%	13.6%	0.6%	1.8%	0.7%	0.1%	12.8%	0.6%
Harrisburg	9,705	66.0%	26.9%	0.7%	4.3%	2.0%	<0.1%	14.4%	2.0%
Lykens	3,357	93.9%	4.9%	0.1%	0.6%	0.5%	0.0%	4.6%	0.6%
Newport	3,968	87.4%	8.8%	0.3%	2.2%	1.1%	<0.1%	4.2%	1.2%
Troop T	**48,878**	**73.6%**	**17.0%**	**0.5%**	**3.6%**	**5.2%**	**0.1%**	**6.8%**	**6.1%**
Bowmansville	5,840	70.9%	21.5%	1.1%	3.9%	2.6%	0.0%	10.7%	3.9%
Everett	6,150	63.2%	18.2%	0.6%	5.4%	12.2%	0.3%	7.6%	11.1%
Gibsonia	5,600	84.1%	11.5%	0.1%	2.6%	1.8%	0.0%	3.1%	2.6%
Highspire	145	65.5%	21.4%	0.0%	6.2%	6.9%	0.0%	9.0%	6.2%
King of Prussia	6,874	68.7%	23.3%	0.4%	3.9%	3.6%	<0.1%	9.7%	7.6%
New Stanton	8,944	84.9%	9.9%	0.1%	1.4%	3.8%	0.0%	2.1%	5.3%
Newville	5,717	71.4%	20.2%	0.8%	5.0%	2.6%	0.0%	7.6%	3.2%
Pocono	4,516	77.1%	17.9%	1.1%	2.1%	1.8%	0.0%	11.6%	1.8%
Somerset (T)	5,060	64.4%	15.7%	0.5%	5.1%	14.1%	0.2%	5.0%	13.2%

Table A.7. Area III Race and Ethnicity of Drivers Stopped by Station, January - December 2023

		Race						Ethnicity	
	Total # of Stops	White	Black	Amer. Indian or Alaskan Native	Asian/ Pacific Islander	Unknown	Two or More Races	Hispanic	Unknown
Troop F	**35,128**	**87.0%**	**8.5%**	**0.5%**	**1.8%**	**2.3%**	**<0.1%**	**4.9%**	**2.3%**
Coudersport	4,687	97.0%	1.1%	0.1%	0.9%	0.9%	0.0%	1.2%	0.7%
Emporium	985	96.2%	2.5%	0.3%	0.6%	0.3%	0.0%	2.6%	0.3%
Lamar	5,258	80.9%	11.7%	0.5%	2.9%	3.9%	0.1%	9.6%	4.9%
Mansfield	3,001	78.7%	8.2%	1.7%	3.2%	8.2%	<0.1%	3.0%	7.2%
Milton	7,478	84.0%	10.9%	0.8%	2.1%	2.2%	<0.1%	6.9%	2.1%
Montoursville	6,592	87.3%	10.3%	0.3%	0.9%	1.0%	0.1%	2.3%	1.2%
Selinsgrove	4,619	87.7%	8.8%	0.3%	2.0%	1.2%	0.0%	5.4%	1.3%
Stonington	2,508	93.4%	5.3%	<0.1%	0.2%	0.9%	<0.1%	5.0%	1.0%
Troop N	**28,033**	**77.3%**	**16.6%**	**0.5%**	**2.2%**	**3.4%**	**<0.1%**	**23.0%**	**3.3%**
Bloomsburg	2,549	79.8%	11.8%	0.3%	3.2%	4.9%	0.0%	10.1%	5.2%
Fern Ridge	4,682	79.3%	15.9%	0.7%	3.1%	1.0%	0.1%	18.9%	0.7%
Hazleton	7,283	80.5%	12.2%	0.2%	1.9%	5.2%	<0.1%	43.7%	4.4%
Lehighton	3,019	86.6%	8.7%	0.2%	0.7%	3.7%	0.0%	11.8%	4.2%
Stroudsburg	10,500	70.9%	23.4%	0.8%	2.1%	2.8%	0.0%	16.9%	2.9%
Troop P	**15,059**	**88.9%**	**7.7%**	**0.1%**	**0.6%**	**2.7%**	**<0.1%**	**6.0%**	**3.1%**
Laporte	1,742	92.7%	5.7%	0.2%	1.1%	0.3%	0.0%	4.1%	0.6%
Shickshinny	2,076	90.2%	8.8%	<0.1%	0.1%	0.8%	0.0%	7.7%	1.0%
Towanda	4,479	94.3%	2.8%	0.1%	0.3%	2.4%	<0.1%	1.6%	2.5%
Tunkhannock	2,342	95.5%	3.4%	0.1%	0.5%	0.6%	0.0%	3.2%	0.6%
Wilkes-Barre	4,416	77.7%	15.3%	0.1%	0.9%	6.0%	<0.1%	11.9%	7.1%
Troop R	**12,225**	**84.3%**	**10.6%**	**0.4%**	**1.9%**	**2.8%**	**0.0%**	**10.4%**	**3.4%**
Blooming Grove	4,036	87.5%	9.3%	0.2%	1.3%	1.5%	0.0%	10.9%	2.3%
Dunmore	3,435	83.3%	13.4%	0.3%	1.5%	1.5%	0.0%	13.0%	2.1%
Gibson	2,982	74.7%	13.3%	1.0%	3.7%	7.3%	0.0%	11.1%	7.3%
Honesdale	1,771	94.7%	3.5%	0.2%	0.7%	0.8%	0.0%	3.2%	1.8%

Table A.7. Area IV Race and Ethnicity of Drivers Stopped by Station, January - December 2023

		Race						Ethnicity	
	Total # of Stops	White	Black	Amer. Indian or Alaskan Native	Asian/ Pacific Islander	Unknown	Two or More Races	Hispanic	Unknown
Troop J	**36,152**	**76.1%**	**20.5%**	**0.5%**	**2.0%**	**0.9%**	**<0.1%**	**15.8%**	**1.0%**
Avondale	8,543	81.6%	15.7%	0.5%	1.7%	0.5%	0.0%	23.3%	0.5%
Embreeville	7,031	67.2%	26.0%	1.0%	4.0%	1.8%	<0.1%	13.0%	1.6%
Lancaster	9,158	81.4%	16.0%	0.4%	1.7%	0.5%	0.1%	17.6%	1.0%
York	11,420	73.1%	24.3%	0.2%	1.3%	1.0%	0.1%	10.4%	1.0%
Troop K	**26,711**	**49.9%**	**43.2%**	**0.5%**	**3.0%**	**3.4%**	**0.0%**	**10.1%**	**4.1%**
Media	12,637	52.0%	42.8%	0.6%	3.3%	1.3%	0.1%	7.7%	1.5%
Philadelphia	9,626	37.4%	53.5%	0.5%	2.5%	6.1%	<0.1%	13.9%	6.9%
Skippack	4,425	71.2%	22.0%	0.6%	2.8%	3.4%	0.0%	8.6%	5.2%
Troop L	**22,302**	**85.3%**	**11.5%**	**0.2%**	**1.3%**	**1.6%**	**<0.1%**	**21.1%**	**2.3%**
Frackville	3,741	88.6%	8.7%	0.0%	0.6%	2.0%	0.0%	19.8%	2.9%
Hamburg	3,268	79.8%	15.2%	0.4%	2.2%	2.4%	0.1%	22.3%	3.5%
Jonestown	5,395	84.9%	11.2%	0.3%	1.6%	1.9%	<0.1%	19.8%	2.6%
Reading	5,375	82.9%	14.2%	0.2%	1.3%	1.3%	<0.1%	31.5%	2.3%
Schuylkill Haven	4,523	89.8%	8.4%	0.3%	1.0%	0.6%	0.0%	10.4%	0.8%
Troop M	**23,806**	**73.8%**	**19.9%**	**0.5%**	**2.8%**	**3.0%**	**0.1%**	**23.8%**	**3.8%**
Belfast	3,891	72.4%	21.5%	0.3%	3.2%	2.5%	0.1%	21.0%	4.1%
Bethlehem	6,255	73.4%	19.7%	0.5%	1.8%	4.6%	<0.1%	28.7%	4.6%
Dublin	3,321	82.8%	11.3%	0.5%	2.3%	3.1%	<0.1%	14.3%	3.4%
Fogelsville	6,146	75.6%	18.5%	0.7%	2.6%	2.6%	0.0%	29.6%	3.6%
Trevose	3,473	63.9%	29.1%	0.4%	5.0%	1.2%	0.3%	16.8%	2.6%
Specialized Units									
SHIELD	3,833	70.8%	17.5%	0.8%	10.4%	0.4%	0.1%	32.4%	0.3%
Canine	1,853	69.7%	24.5%	0.6%	3.5%	1.7%	0.0%	16.6%	2.8%

Table A.8. Veil of Darkness Binary Logistic Regressions Predicting Stops of Black and Hispanic Drivers

	Model A: Stops of Black Drivers			**Model B: Stops of Hispanic Drivers**		
	Coefficient	**Stnd. Error**	**Odds Ratio**	**Coefficient**	**Stnd. Error**	**Odds Ratio**
Intercept	-2.59*	0.11	--	-4.15*	0.18	--
Daylight	**0.14***	**0.03**	**1.15**	**0.12***	**0.04**	**1.13**
Troop B	0.74*	0.08	2.10	0.38	0.18	--
Troop C	-0.98*	0.10	2.66	0.19	0.18	--
Troop D	0.67*	0.08	1.95	-0.16	0.20	--
Troop E	0.00	0.09	--	0.42	0.18	--
Troop F	0.05	0.08	--	1.20*	0.16	3.32
Troop G	-0.06	0.09	--	0.85*	0.17	2.34
Troop H	0.69*	0.08	1.99	2.01*	0.15	7.46
Troop J	0.96*	0.08	2.61	2.32*	0.15	10.18
Troop K	2.28*	0.08	9.78	2.04*	0.15	7.69
Troop L	0.34*	0.09	1.40	2.85*	0.15	17.29
Troop M	1.05*	0.08	2.86	2.96*	0.15	19.30
Troop N	0.86*	0.08	2.36	2.91*	0.15	18.36
Troop P	-0.13	0.10	1.14	1.07*	0.17	2.92
Troop R	0.36*	0.10	1.43	2.01*	0.17	7.46
Troop T	1.04*	0.07	2.83	1.62*	0.15	5.05
Monday	0.08	0.04	--	0.05	0.05	--
Tuesday	-0.03	0.04	--	-0.05	0.05	--
Wednesday	-0.01	0.04	--	-0.13	0.05	--
Thursday	-0.01	0.04	--	-0.15	0.05	--
Saturday	0.10	0.04	--	0.05	0.05	--
Sunday	0.10	0.04	--	0.07	0.05	--
Time Spline 1	-0.10	0.08	--	0.06	0.09	--
Time Spline 2	-0.00	0.11	--	-0.11	0.12	--
Time Spline 3	0.08	0.09	--	-0.01	0.11	--
Time Spline 4	-0.01	0.08	--	0.00	0.11	--
Time Spline 5	-0.01	0.19	--	-0.22	0.22	--
Time Spline 6	0.27	0.11	--	0.17	0.15	--

NOTE: * = 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.
Friday is the reference category for day of the week.

Section 4 Supplemental Tables

Table A.9. Searches and Search Reasons by Department, Area, Troop, and Specialized Units 2023

	% of Stops Resulting in Any Search	Total # of All Searches	Incident to Arrest	Inventory	Officer Safety (Terry)	Plain View	Prob Cause + Exigency	Search Warrant	Written Consent	Verbal Consent
PSP Dept.	**4.2%**	**19,042**	**66.4%**	**12.1%**	**8.2%**	**5.0%**	**0.8%**	**3.2%**	**8.7%**	**36.1%**
AREA I	**4.3%**	**4,225**	**70.2%**	**1.5%**	**9.1%**	**6.7%**	**1.1%**	**2.7%**	**3.9%**	**37.8%**
Troop B	4.7%	1,194	64.7%	2.5%	7.0%	5.9%	1.4%	3.2%	2.3%	46.4%
Troop C	3.4%	899	74.2%	1.6%	9.8%	10.7%	1.1%	3.4%	8.1%	32.1%
Troop D	5.9%	1,322	69.3%	1.1%	7.6%	4.8%	1.0%	2.7%	2.4%	42.6%
Troop E	3.2%	810	75.7%	0.6%	14.0%	6.4%	0.9%	1.0%	3.8%	23.8%
AREA II	**3.0%**	**4,402**	**68.8%**	**3.2%**	**8.5%**	**4.2%**	**0.7%**	**3.2%**	**6.9%**	**36.9%**
Troop A	3.9%	733	73.8%	3.4%	12.0%	3.3%	1.0%	1.2%	6.1%	31.2%
Troop G	3.6%	1,033	61.0%	2.2%	3.2%	5.4%	0.9%	3.9%	9.2%	45.8%
Troop H	4.9%	2,425	71.2%	2.6%	9.6%	3.8%	0.5%	3.3%	5.9%	35.8%
Troop T	0.4%	211	61.6%	14.2%	10.4%	6.6%	1.9%	5.2%	9.5%	26.1%
AREA III	**4.2%**	**3,768**	**70.8%**	**7.0%**	**5.7%**	**4.6%**	**0.6%**	**2.4%**	**5.3%**	**35.9%**
Troop F	3.0%	1,061	68.6%	8.0%	4.6%	4.9%	0.6%	2.5%	4.1%	33.2%
Troop N	5.6%	1,582	79.4%	8.7%	6.7%	3.8%	0.4%	2.7%	3.2%	30.3%
Troop P	3.5%	525	68.2%	3.2%	8.0%	4.8%	1.0%	2.1%	14.5%	35.2%
Troop R	4.9%	600	54.5%	4.3%	2.8%	6.3%	1.0%	1.5%	4.8%	55.7%
AREA IV	**5.5%**	**5,978**	**65.3%**	**30.6%**	**9.6%**	**4.8%**	**0.7%**	**4.1%**	**12.1%**	**29.7%**
Troop J	5.4%	1,963	72.9%	39.6%	8.8%	3.8%	0.5%	4.2%	18.3%	24.9%
Troop K	6.3%	1,672	54.1%	38.0%	13.3%	4.8%	1.2%	6.6%	4.1%	34.4%
Troop L	4.6%	1,016	65.6%	5.9%	10.3%	5.4%	0.7%	2.2%	15.5%	36.8%
Troop M	5.7%	1,327	68.0%	26.9%	5.6%	6.0%	0.3%	2.4%	10.6%	25.2%

Table A.10. Area I Search Reasons by Station, 2023

	% of Stops Resulting in Any Search	Total # of All Searches	Incident to Arrest	Inventory	Officer Safety (Terry)	Plain View	Prob Cause + Exigency	Search Warrant	Written Consent	Verbal Consent
Troop B										
Belle Vernon	4.2%	210	54.3%	1.4%	4.8%	10.0%	1.4%	3.8%	1.4%	56.2%
Pittsburgh	1.8%	103	75.7%	6.8%	6.8%	8.7%	3.9%	1.0%	2.9%	17.5%
Uniontown	7.0%	541	63.4%	1.3%	8.7%	2.4%	0.7%	3.1%	2.2%	51.2%
Washington	5.9%	272	69.1%	1.5%	2.9%	7.4%	1.5%	3.7%	2.9%	39.7%
Waynesburg	2.9%	68	72.1%	13.2%	16.2%	10.3%	2.9%	2.9%	1.5%	48.5%
Troop C										
Clarion	2.6%	79	97.5%	1.3%	1.3%	7.6%	0.0%	2.5%	1.3%	3.8%
Clearfield	2.4%	104	80.8%	1.9%	17.3%	5.8%	0.0%	8.7%	2.9%	24.0%
Dubois	3.0%	108	88.9%	0.9%	2.8%	3.7%	0.0%	2.8%	0.9%	12.0%
Lewis Run	6.5%	350	57.7%	2.0%	14.0%	17.4%	0.9%	2.6%	13.7%	48.6%
Marienville	2.8%	83	75.9%	3.6%	6.0%	7.2%	7.2%	0.0%	7.2%	28.9%
Punxsutawney	4.0%	145	82.8%	0.0%	7.6%	6.9%	0.7%	5.5%	6.2%	32.4%
Ridgway	0.9%	30	83.3%	0.0%	3.3%	10.0%	0.0%	0.0%	16.7%	23.3%
Troop D										
Beaver	3.2%	119	68.9%	0.8%	12.6%	3.4%	0.0%	1.7%	1.7%	33.6%
Butler	7.4%	353	70.0%	2.0%	15.9%	6.5%	2.3%	2.8%	3.4%	39.4%
Kittanning	7.7%	558	74.7%	0.2%	2.0%	4.3%	0.4%	3.6%	1.6%	40.3%
Mercer	2.0%	70	74.3%	4.3%	11.4%	5.7%	0.0%	1.4%	10.0%	37.1%
New Castle	7.4%	222	53.2%	1.4%	4.5%	3.6%	1.4%	1.4%	0.9%	59.9%
Troop E										
Corry	1.6%	46	71.7%	0.0%	4.3%	6.5%	0.0%	0.0%	4.3%	30.4%
Erie	4.4%	307	90.2%	0.7%	7.2%	3.6%	0.3%	0.3%	2.3%	14.7%
Franklin	4.4%	91	89.0%	0.0%	2.2%	7.7%	1.1%	1.1%	14.3%	11.0%
Girard	2.3%	153	77.8%	1.3%	15.7%	5.9%	1.3%	2.0%	4.6%	21.6%
Meadville	4.0%	167	53.9%	0.0%	19.2%	11.4%	1.8%	0.6%	1.2%	52.7%
Warren	1.9%	45	26.7%	2.2%	66.7%	6.7%	0.0%	4.4%	0.0%	6.7%

Table A.10. Area II Search Reasons by Station, 2023

	% of Stops Resulting in Any Search	Total # of All Searches	Incident to Arrest	Inventory	Officer Safety (Terry)	Plain View	Prob Cause + Exigency	Search Warrant	Written Consent	Verbal Consent
Troop A										
Ebensburg	3.1%	83	92.8%	0.0%	10.8%	2.4%	0.0%	0.0%	0.0%	9.6%
Greensburg	4.9%	287	66.2%	3.1%	5.6%	3.8%	0.7%	1.4%	9.8%	40.4%
Indiana	3.4%	191	71.2%	1.0%	25.7%	1.0%	2.1%	1.0%	3.1%	33.5%
Kiski Valley	3.7%	59	79.7%	16.9%	10.2%	5.1%	1.7%	0.0%	0.0%	8.5%
Somerset (A)	4.1%	113	80.5%	3.5%	7.1%	5.3%	0.0%	2.7%	9.7%	31.9%
Troop G										
Bedford	3.6%	202	64.4%	1.5%	4.0%	6.9%	0.5%	3.0%	8.4%	40.6%
Hollidaysburg	4.4%	192	52.6%	0.5%	2.6%	4.2%	0.5%	4.2%	15.1%	48.4%
Huntingdon	1.3%	53	71.7%	1.9%	0.0%	9.4%	1.9%	7.5%	1.9%	34.0%
Lewistown	3.7%	149	58.4%	12.1%	8.1%	7.4%	1.3%	4.0%	4.0%	33.6%
McConnellsburg	4.5%	146	41.1%	0.0%	1.4%	2.1%	0.7%	2.7%	19.9%	61.6%
Rockview	4.1%	291	73.5%	0.0%	2.1%	5.2%	1.0%	4.1%	4.5%	48.1%
Troop H										
Carlisle	3.1%	288	72.9%	1.7%	8.3%	3.8%	1.4%	2.4%	4.9%	34.4%
Chambersburg	3.2%	390	62.8%	1.8%	3.1%	4.1%	0.5%	4.4%	12.1%	30.0%
Gettysburg	5.4%	590	76.6%	2.4%	12.4%	4.7%	0.2%	1.9%	0.8%	32.7%
Harrisburg	7.8%	753	64.5%	3.7%	8.8%	2.4%	0.3%	4.8%	9.7%	43.3%
Lykens	4.7%	158	81.6%	4.4%	28.5%	7.6%	0.6%	3.2%	0.6%	32.3%
Newport	6.2%	246	82.9%	1.2%	4.9%	3.3%	0.4%	2.0%	1.6%	32.9%
Troop T[1]										
Bowmansville	0.5%	30	76.7%	30.0%	6.7%	3.3%	3.3%	0.0%	0.0%	13.3%
Everett	0.6%	36	36.1%	2.8%	2.8%	8.3%	2.8%	13.9%	27.8%	36.1%
Gibsonia	0.3%	17	70.6%	23.5%	41.2%	5.9%	5.9%	5.9%	0.0%	23.5%
King of Prussia	0.2%	17	82.4%	35.3%	5.9%	5.9%	5.9%	5.9%	0.0%	5.9%
New Stanton	0.4%	35	80.0%	0.0%	8.6%	11.4%	0.0%	0.0%	5.7%	17.1%
Newville	0.3%	19	57.9%	26.3%	26.3%	10.5%	0.0%	10.5%	0.0%	21.1%
Pocono	0.6%	28	78.6%	10.7%	10.7%	3.6%	0.0%	3.6%	0.0%	17.9%
Somerset (T)	0.6%	29	24.1%	6.9%	0.0%	3.4%	0.0%	3.4%	27.6%	62.1%

[1] Highspire Station did not report any searches for 2023 so it is excluded from this table.

Table A.10. Area III Search Reasons by Station, 2023

	% of Stops Resulting in Any Search	Total # of All Searches	Incident to Arrest	Inventory	Officer Safety (Terry)	Plain View	Prob Cause + Exigency	Search Warrant	Written Consent	Verbal Consent
Troop F										
Coudersport	3.3%	153	60.8%	0.0%	1.3%	5.9%	1.3%	2.0%	4.6%	36.6%
Emporium	2.1%	21	71.4%	0.0%	42.9%	4.8%	0.0%	9.5%	0.0%	42.9%
Lamar	2.9%	151	48.3%	1.3%	6.0%	2.6%	0.0%	3.3%	12.6%	39.1%
Mansfield	2.3%	69	82.6%	2.9%	4.3%	5.8%	1.4%	1.4%	1.4%	17.4%
Milton	2.6%	198	63.1%	38.4%	8.1%	2.5%	0.5%	3.0%	4.0%	31.8%
Montoursville	3.8%	253	79.4%	1.2%	4.0%	5.5%	0.0%	2.8%	0.4%	29.6%
Selinsgrove	3.4%	156	71.2%	1.3%	0.0%	7.7%	1.3%	1.3%	3.2%	44.9%
Stonington	2.4%	60	88.3%	0.0%	0.0%	5.0%	0.0%	0.0%	5.0%	13.3%
Troop N										
Bloomsburg	4.7%	120	82.5%	10.8%	0.8%	2.5%	0.8%	1.7%	8.3%	20.8%
Fern Ridge	3.1%	147	62.6%	4.8%	0.0%	5.4%	0.0%	3.4%	4.8%	42.2%
Hazleton	4.3%	313	76.4%	13.1%	1.9%	5.1%	0.0%	1.6%	2.9%	24.3%
Lehighton	9.8%	297	81.1%	11.1%	3.0%	5.7%	1.3%	2.0%	6.1%	32.0%
Stroudsburg	6.7%	705	83.0%	6.1%	12.8%	2.3%	0.3%	3.5%	1.0%	31.5%
Troop P										
Laporte	5.0%	87	46.0%	0.0%	16.1%	5.7%	0.0%	1.1%	18.4%	51.7%
Shickshinny	1.5%	31	71.0%	9.7%	6.5%	3.2%	9.7%	3.2%	12.9%	22.6%
Towanda	4.2%	190	75.8%	2.1%	6.3%	5.8%	1.1%	3.7%	24.7%	33.2%
Tunkhannock	1.7%	40	70.0%	12.5%	10.0%	12.5%	0.0%	2.5%	0.0%	35.0%
Wilkes-Barre	4.0%	177	70.1%	2.8%	5.6%	1.7%	0.0%	0.6%	5.1%	31.6%
Troop R										
Blooming Grove	7.6%	308	69.5%	4.9%	3.6%	5.2%	1.0%	0.6%	1.6%	53.6%
Dunmore	1.5%	51	74.5%	9.8%	7.8%	19.6%	2.0%	3.9%	11.8%	21.6%
Gibson	7.2%	214	26.2%	1.4%	0.5%	3.7%	0.5%	2.3%	8.4%	69.6%
Honesdale	1.5%	27	70.4%	11.1%	3.7%	14.8%	3.7%	0.0%	0.0%	33.3%

Table A.10. Area IV Search Reasons by Station and Specialized Units, 2023

	% of Stops Resulting in Any Search	Total # of All Searches	Incident to Arrest	Inventory	Officer Safety (Terry)	Plain View	Prob Cause + Exigency	Search Warrant	Written Consent	Verbal Consent
Troop J										
Avondale	6.4%	551	87.1%	59.0%	11.3%	3.8%	0.2%	2.2%	9.8%	12.0%
Embreeville	4.3%	299	74.2%	29.8%	6.0%	4.3%	0.0%	2.3%	11.4%	30.4%
Lancaster	4.1%	375	70.1%	23.7%	6.7%	1.9%	0.5%	2.4%	24.8%	22.7%
York	6.5%	738	63.3%	37.3%	9.2%	4.5%	0.8%	7.5%	24.1%	33.3%
Troop K										
Media	5.5%	694	58.4%	49.9%	6.2%	7.2%	0.9%	7.6%	5.8%	29.5%
Philadelphia	6.1%	585	39.8%	33.7%	24.3%	3.9%	2.4%	5.8%	4.3%	42.2%
Skippack	8.8%	391	68.3%	23.3%	9.0%	1.8%	0.0%	6.1%	1.0%	31.7%
Troop L										
Frackville	4.3%	162	72.8%	3.7%	3.7%	3.1%	0.0%	1.9%	8.0%	30.2%
Hamburg	1.6%	53	88.7%	18.9%	26.4%	7.5%	0.0%	1.9%	3.8%	22.6%
Jonestown	5.3%	287	55.1%	2.4%	4.2%	7.0%	0.0%	2.8%	19.9%	50.2%
Reading	4.6%	246	71.5%	4.9%	21.1%	5.3%	1.2%	2.0%	5.7%	35.4%
Schuylkill Haven	5.9%	268	62.3%	9.3%	7.8%	4.9%	1.5%	1.9%	26.5%	30.6%
Troop M										
Belfast	5.4%	212	47.2%	25.9%	5.7%	5.2%	0.5%	2.8%	5.7%	45.8%
Bethlehem	5.8%	360	70.3%	29.2%	4.2%	7.2%	0.8%	2.2%	15.8%	15.3%
Dublin	5.9%	195	92.3%	10.8%	3.6%	9.2%	0.0%	1.5%	5.1%	6.2%
Fogelsville	5.7%	349	60.5%	25.5%	9.7%	4.0%	0.0%	1.7%	6.0%	33.5%
Trevose	6.1%	211	74.9%	41.2%	2.8%	5.2%	0.0%	4.3%	19.4%	25.6%
Specialized Units										
SHIELD	10.8%	415	5.8%	1.0%	0.7%	0.2%	0.0%	2.2%	57.3%	80.0%
Canine	14.6%	171	17.0%	0.0%	2.3%	3.5%	0.0%	1.8%	14.6%	84.8%

Table A.11.Area I Drivers' Post-Stop Outcomes by Station, January - December 2023

	Total # of Stops	Warning	Citation	Arrest	Discretionary Search
Troop B					
Belle Vernon	4,950	46.6%	62.6%	2.9%	2.8%
Pittsburgh	5,592	28.4%	82.4%	1.6%	0.6%
Uniontown	7,782	52.9%	55.7%	4.6%	4.3%
Washington	4,586	50.3%	60.0%	4.9%	3.0%
Waynesburg	2,378	26.6%	78.1%	2.2%	1.8%
Troop C					
Clarion	3,012	44.8%	71.8%	2.6%	0.4%
Clearfield	4,354	49.9%	62.6%	2.1%	1.1%
Dubois	3,651	66.8%	70.4%	2.8%	0.6%
Lewis Run	5,409	71.0%	43.2%	5.3%	4.3%
Marienville	2,930	59.3%	68.6%	2.4%	1.1%
Punxsutawney	3,664	60.3%	56.5%	3.5%	2.0%
Ridgway	3,207	68.5%	67.7%	0.9%	0.3%
Troop D					
Beaver	3,763	37.2%	74.1%	2.4%	1.6%
Butler	4,744	58.5%	54.8%	6.3%	4.4%
Kittanning	7,289	55.9%	51.9%	6.8%	3.6%
Mercer	3,535	48.2%	69.2%	1.6%	1.0%
New Castle	3,018	57.9%	57.1%	6.4%	4.8%
Troop E					
Corry	2,858	56.7%	62.1%	1.3%	0.6%
Erie	6,941	57.6%	50.8%	4.1%	1.0%
Franklin	2,066	56.6%	62.0%	4.0%	1.1%
Girard	6,535	48.9%	67.5%	2.0%	1.0%
Meadville	4,217	68.1%	50.7%	3.2%	2.7%
Warren	2,337	56.1%	66.4%	1.8%	1.5%

Table A.11. Area II Drivers' Post-Stop Outcomes by Station, January - December 2023

	Total # of Stops	Warning	Citation	Arrest	Discretionary Search
Troop A					
Ebensburg	2,637	36.4%	80.1%	3.1%	0.7%
Greensburg	5,879	61.0%	61.4%	3.8%	2.4%
Indiana	5,684	54.1%	64.2%	2.8%	2.0%
Kiski Valley	1,609	47.8%	66.9%	3.5%	0.9%
Somerset (A)	2,750	59.9%	69.3%	3.4%	1.7%
Troop G					
Bedford	5,676	63.7%	65.1%	2.9%	1.8%
Hollidaysburg	4,404	56.4%	58.6%	3.1%	2.9%
Huntingdon	4,227	49.6%	67.2%	1.1%	0.6%
Lewistown	4,028	70.1%	61.1%	3.4%	1.8%
McConnellsburg	3,236	66.7%	53.3%	3.3%	3.5%
Rockview	7,117	52.6%	62.9%	3.7%	2.4%
Troop H					
Carlisle	9,191	67.3%	47.1%	2.5%	1.4%
Chambersburg	12,076	69.6%	50.0%	2.6%	1.5%
Gettysburg	10,875	75.9%	31.4%	4.7%	2.6%
Harrisburg	9,705	71.3%	36.9%	5.6%	4.5%
Lykens	3,357	75.4%	57.0%	4.1%	2.8%
Newport	3,968	65.8%	46.9%	5.7%	2.6%
Troop T					
Bowmansville	5,840	38.5%	82.0%	0.4%	0.1%
Everett	6,150	78.5%	82.4%	0.4%	0.4%
Gibsonia	5,600	72.1%	82.2%	0.3%	0.2%
Highspire[2]	145	51.8%	67.6%	0.0%	0.0%
King of Prussia	6,874	41.7%	82.8%	0.2%	0.1%
New Stanton	8,944	79.8%	68.7%	0.4%	0.1%
Newville	5,717	39.9%	76.8%	0.3%	0.2%
Pocono	4,516	44.5%	84.6%	0.6%	0.2%
Somerset (T)	5,060	54.5%	88.9%	0.3%	0.4%

[2] PSP Members assigned to Highspire Station in Troop T, which is the Turnpike Commission Building, did not conduct any searches in 2023.

Table A.11. Area III Drivers' Post-Stop Outcomes by Station, January - December 2023

	Total # of Stops	Warning	Citation	Arrest	Discretionary Search
Troop F					
Coudersport	4,687	62.8%	54.8%	2.5%	1.6%
Emporium	985	65.6%	62.1%	2.1%	1.4%
Lamar	5,258	45.9%	56.9%	1.7%	1.7%
Mansfield	3,001	58.2%	67.5%	2.2%	0.7%
Milton	7,478	47.2%	60.6%	1.9%	1.1%
Montoursville	6,592	45.4%	64.4%	3.5%	1.4%
Selinsgrove	4,619	42.6%	69.0%	3.1%	1.8%
Stonington	2,508	60.1%	56.7%	2.3%	0.5%
Troop N					
Bloomsburg	2,549	41.1%	71.4%	4.0%	1.5%
Fern Ridge	4,682	34.3%	73.7%	2.6%	1.7%
Hazleton	7,283	35.8%	73.8%	3.7%	1.4%
Lehighton	3,019	49.9%	60.6%	8.7%	4.2%
Stroudsburg	10,500	43.2%	61.5%	6.0%	3.0%
Troop P					
Laporte	1,742	60.6%	45.7%	3.0%	3.9%
Shickshinny	2,076	44.8%	74.8%	1.3%	0.7%
Towanda	4,479	61.9%	51.4%	3.7%	2.6%
Tunkhannock	2,342	62.6%	52.4%	1.5%	0.8%
Wilkes-Barre	4,416	36.4%	68.0%	3.1%	1.7%
Troop R					
Blooming Grove	4,036	43.7%	63.4%	6.4%	4.7%
Dunmore	3,435	43.1%	76.5%	1.1%	0.7%
Gibson	2,982	46.2%	68.2%	4.4%	5.8%
Honesdale	1,771	37.1%	74.1%	1.3%	0.6%

Table A.11. Area IV Drivers' Post-Stop Outcomes by Station, January - December 2023

	Total # of Stops	Warning	Citation	Arrest	Discretionary Search
Troop J					
Avondale	8,543	72.3%	34.2%	5.8%	2.0%
Embreeville	7,031	55.7%	54.6%	3.6%	1.7%
Lancaster	9,158	58.7%	47.1%	3.3%	1.9%
York	11,420	62.1%	35.2%	5.0%	3.8%
Troop K					
Media	12,637	48.4%	51.9%	4.1%	2.5%
Philadelphia	9,626	60.6%	45.5%	3.4%	4.0%
Skippack	4,425	52.7%	53.7%	6.9%	4.1%
Troop L					
Frackville	3,741	53.6%	59.3%	3.3%	1.7%
Hamburg	3,268	39.6%	76.2%	1.5%	0.8%
Jonestown	5,395	50.0%	56.6%	3.9%	3.3%
Reading	5,375	43.2%	65.9%	3.7%	2.5%
Schuylkill Haven	4,523	49.3%	58.6%	4.8%	3.1%
Troop M					
Belfast	3,891	50.6%	62.2%	3.7%	3.3%
Bethlehem	6,255	53.8%	52.4%	5.0%	2.0%
Dublin	3,321	67.4%	41.6%	5.5%	1.1%
Fogelsville	6,146	56.9%	47.9%	4.0%	2.8%
Trevose	3,473	65.2%	52.8%	5.0%	2.2%
Specialized Units					
SHIELD	3,833	98.4%	0.3%	1.4%	10.5%
Canine	1,853	89.7%	4.5%	3.5%	13.1%

Table A.12. 2023 Stop Outcomes by Race and Gender for Department and Areas

	Drivers	Total # of stops	% warning	% citation	% arrest	% discretionary search
PSP Dept	White	321,262	56.3%***	59.4%***	3.1%***	1.7%***
	Black	66,932	57.3%	54.7%	4.8%	4.2%
	Hispanic	39,328	54.7%	56.4%	3.9%	3.1%
	Male	301,159	56.0%	58.5%***	3.8%***	2.5%***
	Female	146,933	56.3%	59.4%	2.5%	1.4%
AREA I	White	83,472	12.7%***	60.9%***	3.4%***	1.9%***
	Black	9,715	16.6%	62.1%	5.5%	4.6%
	Hispanic	1,926	17.0%	64.8%	3.6%	3.0%
	Male	64,404	13.4%***	61.8%***	4.0%***	2.4%***
	Female	34,213	12.7%	61.3%	2.8%	1.8%
AREA II	White	108,529	10.3%***	62.1%***	2.2%***	1.2%***
	Black	19,830	14.1%	60.3%	4.0%	3.5%
	Hispanic	9,455	16.4%	58.0%	3.2%	2.7%
	Male	96,882	11.2%	62.1%	2.8%***	1.9%***
	Female	48,151	10.9%	62.5%	1.7%	1.0%
AREA III	White	66,688	12.2%***	63.3%***	3.3%***	1.8%***
	Black	10,086	13.6%	63.1%	4.9%	3.4%
	Hispanic	9,455	12.3%	69.3%	3.4%	2.3%
	Male	60,725	12.7%***	64.0%	3.9%***	2.3%***
	Female	29,507	11.7%	64.5%	2.6%	1.4%
AREA IV	White	59,710	17.1%***	50.9%***	3.9%***	2.0%***
	Black	26,095	25.3%	46.8%	5.2%	4.4%
	Hispanic	17,361	19.8%	52.3%	4.6%	2.7%
	Male	74,167	20.6%***	49.9%*	4.8%***	3.2%***
	Female	33,934	17.4%	50.6%	3.2%	1.5%

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

Table A.13. 2023 Stop Outcomes by Race and Gender for Troops in Area I and II

	Drivers	Total # of stops	% warning	% citation	% arrest	% discretionary search
Area I, Troop B	White	19,827	44.1%**	65.9%***	3.3%***	2.4%***
	Black	3,740	46.0%	63.1%	5.0%	4.6%
	Hispanic	432	49.8%	57.2%	2.5%	3.7%
	Male	16,229	43.2%	66.1%	3.8%***	3.0%***
	Female	8,914	43.8%	66.3%	2.7%	2.2%
Area I, Troop C	White	23,335	62.2%***	59.2%***	3.1%	1.6%***
	Black	1,194	54.7%	72.4%	3.5%	3.6%
	Hispanic	611	46.8%	79.9%	2.9%	2.8%
	Male	17,794	59.9%***	62.1%***	3.3%***	1.7%
	Female	8,410	63.0%	59.4%	2.3%	1.6%
Area I, Troop D	White	18,684	53.0%***	59.8%	4.8%***	2.8%***
	Black	2,650	49.3%	60.5%	7.9%	6.6%
	Hispanic	295	53.9%	58.6%	4.7%	2.7%
	Male	14,246	51.8%**	60.3%	5.8%***	3.5%***
	Female	7,979	53.9%	59.5%	3.9%	2.6%
Area I, Troop E	White	21,606	56.9%	59.0%	2.6%***	1.2%***
	Black	2,131	58.4%	56.5%	4.8%	2.6%
	Hispanic	588	54.1%	58.0%	4.4%	2.9%
	Male	16,135	56.7%	58.5%	3.2%***	1.5%**
	Female	8,910	57.1%	59.6%	2.2%	1.0%
Area II, Troop A	White	16,517	53.9%*	67.1%***	3.2%***	1.5%***
	Black	1,429	55.1%	63.4%	5.2%	4.0%
	Hispanic	252	61.5%	53.2%	4.0%	6.7%
	Male	11,963	54.4%	66.0%*	3.7%***	2.0%
	Female	6,583	53.6%	67.6%	2.5%	1.3%
Area II, Troop G	White	24,237	59.1%**	62.5%***	2.9%***	1.8%***
	Black	2,177	61.8%	55.9%	4.9%	6.0%
	Hispanic	927	63.6%	58.5%	3.8%	4.0%
	Male	18,397	59.0%	61.8%	3.5%***	2.5%***
	Female	10,184	59.5%	62.8%	2.0%	1.6%
Area II, Troop H	White	34,581	70.9%	44.0%***	3.2%***	1.7%***
	Black	7,924	72.0%	37.9%	7.0%	5.7%
	Hispanic	4,975	71.1%	42.2%	4.2%	3.6%
	Male	33,053	71.0%	42.4%***	4.5%***	3.1%***
	Female	16,085	71.0%	44.2%	2.8%	1.4%
Area II, Troop T	White	33,194	60.1%***	78.1%***	0.3%***	0.1%***
	Black	8,300	54.1%	82.2%	0.7%	0.6%
	Hispanic	2,946	47.0%	84.9%	0.8%	0.5%
	Male	33,469	57.1%***	80.3%*	0.4%***	0.3%***
	Female	15,299	59.4%	79.5%	0.1%	0.1%

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

Table A.13. 2023 Stop Outcomes by Race and Gender for Troops in Area III and IV

	Drivers	Total # of stops	% warning	% citation	% arrest	% discretionary search
Area III, Troop F	White	28,954	50.5%***	62.0%***	2.3%***	1.0%***
	Black	2,975	53.4%	56.2%	4.4%	3.4%
	Hispanic	1,635	54.5%	53.9%	2.2%	3.9%
	Male	23,119	50.9%	60.8%***	2.9%***	1.6%***
	Female	11,975	50.0%	62.8%	1.5%	0.8%
Area III, Troop N	White	15,941	41.6%***	66.0%***	5.4%***	2.5%***
	Black	4,651	42.5%	65.5%	5.8%	2.9%
	Hispanic	5,873	36.1%	73.2%	4.0%	1.6%
	Male	19,148	39.8%**	67.8%	5.3%***	2.6%***
	Female	8,754	41.7%	67.8%	4.2%	1.7%
Area III, Troop P	White	12,648	53.7%***	58.4%***	2.7%*	1.9%*
	Black	1,163	46.8%	66.4%	3.9%	2.9%
	Hispanic	764	45.6%	65.7%	2.4%	1.8%
	Male	10,074	52.0%	59.3%	3.2%***	2.2%***
	Female	4,940	52.7%	58.9%	1.9%	1.3%
Area III, Troop R	White	9,145	43.0%**	69.2%*	3.8%	2.9%***
	Black	1,297	47.7%	67.2%	4.1%	5.4%
	Hispanic	1,183	41.5%	73.3%	2.9%	3.9%
	Male	8,384	42.9%	70.0%	3.9%	3.4%
	Female	3,838	43.7%	69.5%	3.3%	2.8%
Area IV, Troop J	White	22,145	62.4%	41.8%***	3.9%***	1.9%***
	Black	7,401	63.5%	39.2%	6.3%	4.8%
	Hispanic	5,421	62.1%	44.3%	4.9%	2.0%
	Male	24,204	62.1%*	41.9%	5.0%***	3.0%***
	Female	11,910	63.3%	41.4%	3.4%	1.6%
Area IV, Troop K	White	10,888	49.8%***	52.7%***	4.6%*	2.4%***
	Black	11,531	57.2%	46.9%	4.4%	4.3%
	Hispanic	2,495	54.2%	51.2%	3.3%	3.6%
	Male	18,955	54.6%***	48.5%***	4.6%***	4.0%***
	Female	7,701	51.2%	53.6%	3.5%	1.6%
Area IV, Troop L	White	14,690	47.7%*	62.1%	3.3%***	2.0%***
	Black	2,574	48.0%	62.7%	4.4%	3.3%
	Hispanic	4,364	45.5%	64.0%	4.5%	3.3%
	Male	14,885	47.1%	62.6%	4.2%***	2.8%***
	Female	7,390	47.8%	62.6%	2.3%	1.6%
Area V, Troop M	White	11,987	57.6%	52.2%*	4.3%***	1.7%***
	Black	4,589	58.9%	49.8%	5.9%	4.3%
	Hispanic	5,081	56.7%	51.2%	5.1%	2.4%
	Male	16,123	57.6%	51.9%*	5.0%***	2.8%***
	Female	6,933	58.4%	50.3%	3.7%	1.3%

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

Table A.14.[3] 2023 Stop Outcomes by Race for Stations in Area I

	Drivers	Total # of	% warning	% citation	% arrest
AREA I, Troop B					
Belle Vernon	White	3,464	49.8%**	62.8%***	2.8%*
	Non-White	981	55.2%	52.5%	4.4%
Pittsburgh	White	3,814	27.6%**	82.2%	1.3%***
	Non-White	1,526	31.9%	81.6%	2.7%
Uniontown	White	6,729	52.6%	57.3%***	4.2%**
	Non-White	933	55.9%	49.0%	6.1%
Washington	White	3,669	50.1%	60.8%**	4.5%***
	Non-White	830	53.0%	54.8%	7.2%
Waynesburg	White	2,151	27.1%	77.7%	2.3%
	Non-White	184	23.9%	79.9%	2.2%
AREA I, Troop C					
Clarion	White	2,517	46.9%***	69.4%***	3.0%*
	Non-White	404	37.1%	83.2%	1.0%
Clearfield	White	3,785	52.0%***	60.0%***	2.4%*
	Non-White	400	31.3%	83.8%	0.5%
Dubois	White	3,008	69.5%***	66.6%***	3.2%**
	Non-White	550	54.8%	87.8%	1.1%
Lewis Run	White	4,830	72.7%***	41.0%***	5.2%
	Non-White	480	63.3%	56.7%	6.9%
Marienville	White	2,819	59.1%	68.9%	2.3%**
	Non-White	100	65.7%	61.0%	7.0%
Punxsutawney	White	3,568	60.2%	56.6%	3.5%
	Non-White	91	67.0%	50.5%	5.5%
Ridgway	White	2,828	68.9%	65.7%***	0.8%*
	Non-White	298	67.1%	80.5%	2.0%

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

[3] There are too few discretionary searches conducted at the station level to present bivariate analyses for this outcome.

Table A.14. 2023 Stop Outcomes by Race for Stations in Area I

	Drivers	Total # of	% warning	% citation	% arrest
AREA I, Troop D					
Beaver	White	2,895	39.3%**	76.3%	2.2%*
	Non-White	730	33.7%	74.7%	3.6%
Butler	White	4,269	58.1%	55.8%***	5.9%***
	Non-White	396	61.1%	47.1%	10.9%
Kittanning	White	6,017	56.4%**	50.8%***	6.5%**
	Non-White	1,119	52.1%	57.6%	9.0%
Mercer	White	2,965	48.4%	69.2%	1.4%*
	Non-White	478	48.5%	66.9%	2.9%
New Castle	White	2,528	57.6%	57.8%*	6.0%*
	Non-White	469	58.8%	51.6%	9.0%
AREA I, Troop E					
Corry	White	2,798	56.8%	62.2%	1.3%
	Non-White	50	59.2%	56.0%	2.0%
Erie	White	5,391	57.6%	50.6%	3.6%***
	Non-White	1,517	58.3%	50.7%	6.1%
Franklin	White	1,896	56.6%	62.1%	3.9%
	Non-White	139	57.6%	59.0%	5.8%
Girard	White	5,416	48.7%*	67.4%	2.0%
	Non-White	1,057	52.1%	66.9%	2.4%
Meadville	White	3,755	68.6%	50.4%	3.1%
	Non-White	403	64.8%	52.4%	3.7%
Warren	White	2,262	56.1%	66.6%	1.9%
	Non-White	63	57.1%	58.7%	0.0%

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

Table A.14. 2023 Stop Outcomes by Race for Stations in Area II

	Drivers	Total # of Stops	% warning	% citation	% arrest
AREA II, Troop A					
Ebensburg	White	2,318	35.6%**	80.2%	2.8%
	Non-White	292	44.5%	78.1%	4.5%
Greensburg	White	5,252	60.6%*	62.2%***	3.6%*
	Non-White	584	65.0%	54.3%	5.3%
Indiana	White	4,922	53.8%	65.0%**	2.6%**
	Non-White	671	55.7%	59.0%	4.6%
Kiski Valley	White	1,449	48.1%	66.7%	3.5%
	Non-White	143	45.5%	69.2%	3.5%
Somerset (A)	White	2,576	60.2%	69.6%	3.3%
	Non-White	146	53.4%	68.5%	5.5%
AREA II, Troop G					
Bedford	White	4,958	64.7%***	64.3%**	2.7%**
	Non-White	672	57.0%	69.3%	4.9%
Hollidaysburg	White	3,717	57.5%	59.6%	3.1%
	Non-White	525	60.6%	57.7%	4.4%
Huntingdon	White	3,819	49.1%*	68.2%***	1.1%
	Non-White	196	57.1%	52.6%	2.6%
Lewiston	White	3,427	70.2%	60.1%**	3.4%
	Non-White	575	69.7%	66.4%	3.0%
McConnellsburg	White	2,443	66.7%	54.8%**	3.0%
	Non-White	725	67.4%	49.2%	4.4%
Rockview	White	5,873	52.1%	63.6%***	3.8%
	Non-White	1,179	55.2%	58.3%	3.5%

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

Table A.14. 2023 Stop Outcomes by Race for Stations in Area II

	Drivers	Total # of	% warning	% citation	% arrest
AREA II, Troop H					
Carlisle	White	6,634	67.1%	47.2%	2.0%***
	Non-White	2,496	67.6%	47.5%	3.9%
Chambersburg	White	8,759	69.5%	51.3%***	2.0%***
	Non-White	3,269	70.6%	46.0%	4.1%
Gettysburg	White	7,736	77.0%***	29.7%***	4.2%***
	Non-White	3,066	73.7%	34.8%	5.8%
Harrisburg	White	5,129	69.8%***	40.1%***	3.8%***
	Non-White	4,406	73.0%	32.5%	7.7%
Lykens	White	3,002	75.6%	56.0%***	3.9%
	Non-White	340	74.1%	65.3%	5.9%
Newport	White	3,321	64.9%	46.7%	5.1%***
	Non-White	606	65.7%	46.9%	9.1%
Area II, Troop T					
Bowmansville	White	3,635	37.2%**	81.0%*	0.3%*
	Non-White	2,072	40.9%	83.5%	0.7%
Everett	White	3,487	78.5%*	81.4%	0.3%*
	Non-White	1,920	75.6%	81.9%	0.7%
Gibsonia	White	4,554	73.0%***	82.2%	0.2%**
	Non-White	951	67.7%	81.9%	0.7%
Highspire	White	84	57.8%	66.7%	100.0%
	Non-White	51	47.1%	68.6%	100.0%
King of Prussia	White	4,200	42.0%	81.9%**	0.2%
	Non-White	2,487	41.0%	84.4%	0.2%
New Stanton	White	7,419	80.4%***	67.5%***	0.4%
	Non-White	1,194	76.2%	74.0%	0.5%
Newville	White	3,704	42.0%***	73.6%***	0.2%*
	Non-White	1,874	37.4%	82.0%	0.6%
Pocono	White	3,022	48.5%***	82.2%***	0.3%**
	Non-White	1,430	36.0%	89.5%	1.0%
Somerset (T)	White	3,068	56.4%	87.0%**	0.2%*
	Non-White	1,305	56.6%	90.3%	0.6%

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

Table A.14. 2023 Stop Outcomes by Race for Stations in Area III

	Drivers	Total # of Stops	% warning	% citation	% arrest
AREA III, Troop F					
Coudersport	White	4,501	62.9%	54.9%	2.4%
	Non-White	151	65.6%	53.6%	4.6%
Emporium	White	926	65.6%	62.1%	2.2%
	Non-White	56	64.3%	62.5%	1.8%
Lamar	White	3,799	45.5%**	58.0%***	1.9%
	Non-White	1,274	50.5%	51.9%	1.3%
Mansfield	White	2,279	60.2%***	64.5%***	2.7%*
	Non-White	483	45.5%	77.4%	0.8%
Milton	White	5,786	45.1%***	63.5%***	1.7%
	Non-White	1,532	57.9%	48.7%	2.0%
Montoursville	White	5,622	44.9%*	65.1%**	3.0%***
	Non-White	909	48.5%	59.7%	6.6%
Selinsgrove	White	3,817	43.2%	68.2%*	2.6%***
	Non-White	750	40.5%	72.3%	5.6%
Stonington	White	2,224	59.0%**	57.7%**	2.1%
	Non-White	262	68.3%	48.5%	3.8%
AREA III, Troop N					
Bloomsburg	White	1,793	42.7%	70.1%	4.4%
	Non-White	635	38.3%	73.5%	3.9%
Fern Ridge	White	2,909	35.4%*	72.9%	2.7%
	Non-White	1,743	32.6%	75.4%	2.6%
Hazelton	White	3,148	38.2%**	69.8%***	3.1%**
	Non-White	3,857	34.6%	76.9%	4.5%
Lehighton	White	2,300	50.7%	59.7%	9.0%
	Non-White	612	49.0%	61.8%	8.3%
Stroudsburg	White	5,791	42.7%	61.7%	7.0%***
	Non-White	4,424	44.0%	61.9%	4.9%

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

Table A.14. 2023 Stop Outcomes by Race for Stations in Area III

	Drivers	Total # of	% warning	% citation	% arrest
AREA III, Troop P					
Laporte	White	1,553	59.9%	45.7%	3.0%
	Non-White	184	65.2%	45.7%	3.3%
Shickshinny	White	1,763	45.1%	74.1%	1.3%
	Non-White	300	44.3%	78.3%	1.7%
Towanda	White	4,162	61.6%	52.1%	3.7%
	Non-White	216	63.9%	51.9%	5.1%
Tunkhannock	White	2,169	63.1%	51.8%	1.4%
	Non-White	159	60.1%	59.1%	3.1%
Wilkes-Barre	White	2,997	37.6%	69.3%	2.8%
	Non-White	1,173	39.0%	69.2%	3.1%
AREA III, Troop R					
Blooming Grove	White	3,132	44.0%	62.1%**	6.4%
	Non-White	853	42.8%	67.6%	4.8%
Dunmore	White	2,461	44.1%	75.1%**	1.0%
	Non-White	929	41.6%	79.5%	1.6%
Gibson	White	1,925	45.1%*	69.4%***	5.1%
	Non-White	849	49.6%	61.6%	3.8%
Honesdale	White	1,627	36.9%	73.9%	1.2%
	Non-White	129	40.3%	76.7%	2.3%

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

Table A.14. 2023 Stop Outcomes by Race for Stations in Area IV and Specialized Units

	Drivers	Total # of Stops	% warning	% citation	% arrest
AREA IV, Troop J					
Avondale	White	5,002	72.6%	33.3%*	5.2%**
	Non-White	3,502	72.1%	35.5%	6.7%
Embreeville	White	3,873	56.4%	53.9%	3.2%*
	Non-White	3,057	55.3%	55.6%	4.2%
Lancaster	White	5,943	57.8%**	48.1%**	3.0%
	Non-White	3,183	60.8%	44.9%	3.7%
York	White	7,327	62.5%	36.0%**	4.1%***
	Non-White	4,007	61.9%	33.4%	6.7%
AREA IV, Troop K					
Media	White	5,685	44.6%***	56.1%***	3.3%***
	Non-White	6,804	51.8%	48.6%	4.8%
Philadelphia	White	2,394	59.2%	45.7%	2.8%
	Non-White	6,674	61.0%	45.6%	3.5%
Skippack	White	2,798	52.4%	51.9%**	8.5%***
	Non-White	1,479	54.0%	56.4%	3.9%
AREA IV, Troop L					
Frackville	White	2,637	55.2%**	57.4%**	3.6%
	Non-White	1,034	50.1%	63.1%	2.8%
Hamburg	White	1,954	40.0%	73.3%***	1.4%
	Non-White	1,249	37.1%	81.8%	1.5%
Jonestown	White	3,596	47.5%***	59.4%***	3.0%***
	Non-White	1,701	55.3%	50.4%	6.1%
Reading	White	2,891	43.4%	66.7%	2.8%***
	Non-White	2,422	42.9%	65.0%	4.8%
Schuylkill Haven	White	3,612	49.8%	58.4%	4.7%
	Non-White	889	48.3%	59.1%	5.3%
AREA IV, Troop M					
Belfast	White	2,099	48.0%***	64.7%***	3.0%**
	Non-White	1,698	54.4%	58.4%	4.7%
Bethlehem	White	2,949	52.6%	53.9%	3.9%***
	Non-White	3,032	52.8%	52.7%	6.6%
Dublin	White	2,301	68.0%	40.3%	6.1%
	Non-White	924	66.7%	42.6%	4.5%
Fogelsville	White	2,958	56.6%	50.9%***	3.6%*
	Non-White	3,042	58.5%	43.5%	4.6%
Trevose	White	1,680	65.9%	52.4%	5.2%
	Non-White	1,755	65.0%	53.1%	4.8%
Specialized Units					
SHIELD	White	1,573	98.7%	0.3%	0.7%**
	Non-White	2,247	98.4%	0.4%	1.9%
Canine	White	996	89.2%	4.8%	2.6%*
	Non-White	833	90.4%	4.3%	4.6%