Rule of Law or Luck of the Draw? Extraneous Factors in NC Traffic Stops

By

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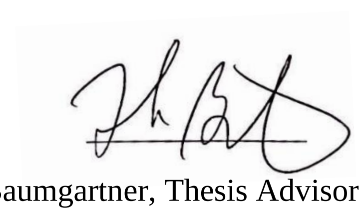

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Abstract

This paper examines the most common interaction an American has with the criminal justice system – the traffic stop. It begins with a discussion of the “Rule of Law” and questions whether North Carolina traffic enforcement meets the standard. I then present a novel theoretical model describing the decision-making function of the “bureaucrat” under various levels of discretion based on Kaufman’s seminal exploration of bureaucratic discretion. Next, I explore the impact of factors extraneous to the outcome of a traffic stop. I do so first through a series of visualizations detailing the extent to which these extra-legal factors correlate with lenient outcomes. Then, I utilize maximum likelihood estimation methods to determine how much of the variance in outcomes is explained by each. The differences across departments are estimated to determine 34% of the variance accounted to extraneous inputs, when controlling for other factors. Officer effects account for nearly 67%. Next, I create simulations of hypotheticals to estimate the impact of an individual officer’s preferences. I find that, on average, NC officers individual preferences account for between 35% and 40% of the variance in outcome. Finally, I use a novel technique to compare a department or officer’s year-to-year consistency to a hypothetical world in which they are making random choices that amount to the same total leniency for the violation in question. This approach shows that larger departments are more consistent, that the Highway Patrol outperforms the state average, and that more serious crimes are treated with less extraneous input, or “noise.” The results validate that North Carolina officers are acting with high levels of bureaucratic discretion in this setting and cast serious doubt on whether the “Rule of Law” is predominant in this facet of the criminal justice system. The study introduces novel approaches to the field, which could be used in other investigations of bureaucratic discretion.

Acknowledgements

Foremost, I owe thanks to Dr. Baumgartner, both for his expertise and encouragement on this project. Moreover, he has informed my trajectory by demonstrating how to put the tools of social science to their best use. I also extend my sincere gratitude to Dr. Hartlyn whose enthusiasm and patience our class could not have done without.

Second, I would like to recognize the “Sunset Surfers,” for their dauntless enthusiasm in the face of overwhelming graphs and tables. Their companionship made the late nights enjoyable. You light my candle.

Finally, and most important, my parents, who have taught me to approach the world with a mind open to new questions and skeptical of answers.

This work is dedicated to Mark Cain.

I. Introduction

An analysis can have two types of error. The first is bias – a clustering not around the true value but around some erroneous result. Bias is discussed extensively in political science literature and has been found to exist in countless settings. Some of the most striking examples occur in the realm of criminal justice, where race, age, gender, and other demographic factors weigh heavily in decisions including arrest and conviction. The more subtle error is that of variation, or “noise,” in outcomes. This issue constitutes a much smaller subset of the field, but its implications can be monumental. A scenario with 50% probability of being excellent and a 50% probability of being terrible would result in a neutral outcome “in expectation,” but under either outcome, the result is far from neutral. This is a very generalized case of extreme noise. This analysis focuses on a routine yet significant experience of noise – traffic stops in North Carolina (NC).

From the perspective of a hypothetical driver, extraneous factors like officer preferences, department preferences, time effects, and others seem like random “noise” surrounding and influencing a decision that is ideally made based on a “signal,” relevant traffic law. This “noise” from extra-legal factors makes the application of law feel arbitrary. Bias in a specific direction makes it seem that the state is opposed to a specific type of person. Impressions of both caprice and prejudice are threats to political legitimacy and the just application of law. This work investigates the former.

An audit of noise in policing has not been conducted in any academic setting before. Bias, especially racial bias, has been analyzed in countless studies, but noise has gone unnoticed. Because of the relative invisibility of this type of error in the literature, I begin my literature review with a justification for this line of research. I provide motivation for my research by briefly surveying the role of noise in the concept of "Rule of Law," and its place in the western political tradition. From there I discuss noise in other contexts. I also reference the theory of Bureaucratic Discretion – the ability of officials to make decisions free from protocol and supervision – to explain noise in traffic stops.

Of key importance in this study is the concept of probable cause. An officer cannot pull over a driver unless they "believe that a traffic violation has occurred," a standard articulated in the 1996 Supreme Court case *Whren v.US* (Whren v. United States, 517 U.S. 806 (1996) n.d.). Because drivers are apt to leave the scene of any violation, an officer cannot obtain a warrant to investigate a potential crime, hence the standard. In every traffic stop, the officer must believe a violation has occurred. Of course, nobody can be correct all the time, and officers will err. Since officers cannot perfectly follow an algorithm, extraneous (extra-legal) factors will enter the decision of whether to end the interaction with a lenient outcome. This discretion based on extraneous factors (e.g., day of the week) represents noise entering the calculation, substituting the "Rule of Law" (applying statutes identically regardless extraneous factors) for the rule of discretionary bureaucrats *through* law (pursuing one's own preferences with the law as justification).

Figure J1 is the first page of the form an officer fills out when completing a traffic stop in NC. The main dataset used in this analysis is a compilation of all these forms from the years 2002 to 2020 in the state of North Carolina, compiled by the North Carolina (NC) Administrative Office of the Courts (AOC). A series of statistical figures on each of the form's aspects is available in *Suspect Citizens* (Baumgartner, Epp, and Shoub 2018). At the less impactful end of the traffic code violation spectrum are stops related to crimes like failure to wear a seatbelt, which has an associated maximum penalty of $25.50, court costs of $135.50, and no points against the driver's license (NC DPS: Seat Belts n.d.). On the opposite end, driving while impaired (DWI) carries a maximum penalty of a $1,000 fine and 6 months in jail. This is the maximum for "Level III" violations, which have no aggravating factors (NC DPS: Driving While Impaired n.d.). Even the most trivial traffic violation can, when multiplied by the millions of occurrences within a state like North Carolina, sum to a very significant amount of time and money transferred. These interactions also help form the basis for one's impression of the criminal justice system and may influence the perceived legitimacy of the entire legal system. The stakes of any individual stop are small, but those of the practice writ large are hard to overstate.

The rest of the paper is organized as follows: First, I discuss the relevant literature. This section is comprised of three parts: Framing the question in the tradition of "Rule of Law," a brief survey of other "noise audits," and a discussion of bureaucratic discretion in other realms. I then formalize the role of bureaucratic discretion in a theoretical model and draw from it 5 testable hypotheses. Next, I present the data sets that I use in the analysis of these hypotheses. Primarily, I use the NC AOC data, but I expand my analysis with more detailed data from Charlotte. I then present a series of visual and descriptive statistics. Additionally, I use the Charlotte dataset to estimate the effect of officer experience on leniency. Next, I use a new maximum likelihood estimation technique to attribute the variation in police traffic stops among different extraneous factors in relative terms, then use a simulation to provide a frame of reference in absolute terms. I then use a novel method of analysis to compare variance over time, an indicator for discretion, between different departments, officers, and across different traffic offenses. Finally, I conclude with an evaluation of my hypotheses and the implications of this research for NC policing and other areas of bureaucratic discretion.

II. Literature Review

The Rule of Law

The concept of the “Rule of Law,” that the law is applied equally to all cases, is as fundamental to western governance as almost any idea. The concept dates back at least to Aristotle, who grappled with the idea in *Politics,* asking whether it was better to be ruled by man or laws, setting up the dichotomy that others have explored for centuries. In *Rhetoric*, he laid out a fundamental argument for the “Rule of Law,” that thoughtful debate and discussion between participants create more just decisions than individual judges under time pressure (Rhetoric 1354b) (Waldron 2020).

Locke points to another benefit of the “Rule of Law” in his work discussing the “state of nature” from which societies emerge. In his view, the uncertainty and arbitrary nature of living by another’s will is something that people long to escape (Locke 1689: §137). “Rule of Law” allows for stability and certainty, under which people can flourish. Montesquieu takes this argument into the economic realm, arguing that arbitrary use of the law may incur negative financial consequences – that businesses require predictable outcomes to judge the expected benefits and costs of their actions (Montesquieu 1748: Bk. V, Ch. 14, p. 61) (Waldron 2020). Beazer posits an especially apt account of how this economic argument might come true through the unpredictability of the modern bureaucracy (Beazer 2012).

In *The Anglo-American Conception of the Rule of Law*, Nedzel and Capaldi make a strong case for the differentiation between “Rule of Law” and “Rule thru Law” by revisiting English thinkers and their European counterparts (Nedzel and Capaldi 2019). They make a distinction that earlier thinkers neglected – whether law was being followed neutrally by its enforcers or used by them to their own ends. They highlight the English thinker Dicey and his distinction, that “Rule of Law” requires “equality before the law” (Nedzel and Capaldi 2019). In other traditions, the law *can* apply to anyone, but does not always. For the law to rule, it *must* apply in all cases. The benefits Aristotle imagined from careful planning and the benefits Locke and Montesquieu highlight in the stability and certainty of law are lost if the legal standard is primarily used as a justification for, and minor check on, bureaucrat’s will. The societal benefits are realized when “no man is above the law [and] every man, whatever be his rank or condition, is subject to the ordinary law of the realm and amenable to the jurisdiction of the ordinary tribunals” (Nedzel and Capaldi 2019). This sentiment was translated into the American political system by Thomas Paine in the phrase “in America, Law is King” (Papke 1998). The “Rule of Law” is foundational to western governance.

Noise

Noise, variability, and randomness undermine the benefits promised by the “Rule of Law.” When a law exists but may or may not apply to one’s case depending on factors outside of one’s control, the aims of the philosophers are lost. This flaw has been shown to be problematic in a wide array of settings. The archetypical case was presented by Danziger et al. when, in an analysis of 1,112 judicial decisions from Israeli parole hearings they showed that judges gave dramatically more favorable rulings (a near 65 percentage point increase) just after breaks, including lunch (Danziger, Levav, and Avnaim-Pesso 2011). This jump did not appear to be a bias towards or against specific groups, but a result of their levels of mental fortitude and hunger. It seemed that “wretches hang that Jury-men may dine” (Pope 1714). This would constitute a high level of noise in reference to the legal standard – a change in the likelihood of an event unrelated to the relevant factors as purported by that standard. Parole decisions were, it seemed, being made based on the status of the judges' stomachs.

Anderson et al. found a 17% difference in the sentencing lengths of typical judges under conditions where they are not constrained by guidelines. Some judges displayed much greater variance (Anderson, Kling, and Stith 1999). Other noisy decision-making processes have been studied within the financial and business sectors, including stock and real estate appraisal, job performance evaluation, and the auditing of financial statements (Adair et al. 1996; Colbert 1988; Fogliato, G'Sell, and Chouldechova 2020).

While noise seems ubiquitous, the sensational findings of Danziger et al. and others are in doubt. In particular, the Israeli parole study has faced issues in replicability and critiques from multiple sources. Weinshall-Margel and Shapard, upon reinvestigating the phenomenon, found that defendants without lawyers were often scheduled right before breaks, and it is these unrepresented defendants that are unlikely to receive parole (Weinshall-Margel and Shapard 2011). It is unclear whether this mechanism accounts for all the effect Danziger et al. found, or whether the system is noisy even controlling for this factor. Even studies fundamental to the field are open to debate, and noise in governance is largely unexplored territory. There are no accounts of noise in policing in circulation, leaving a gaping hole in the literature.

Bureaucratic Discretion

Noise can enter at both the individual and institutional levels. The fundamental theory underlying noise is that some agents hold a high level of bureaucratic discretion. The archetypical example is the forest ranger. In his work under the same title, Kaufman describes the decisions of these bureaucrats as being generally unobservable, surrounded by dozens of miles of wilderness. Their superiors are far removed, the effects of their decisions are difficult to observe, and few individual decisions are so important as to be worthy of much scrutiny (Kaufman 1960).

The theories laid forth in this work have been demonstrated in many empirical studies, both quantitative and qualitative. In Scott's "Assessing Determinants of Bureaucratic Discretion: An Experiment in Street-Level Decision Making," it became clear that "organizational control and client characteristics played an influential role in the awarding of benefits and services to clients seeking public assistance" (Scott 1997). Keiser et al. show that, under high levels of bureaucratic discretion, race acts as a determinant of welfare distribution, when the original aim was for a race-blind application of the program (Keiser, Mueser, and Choi 2004; Keiser and Soss 1998). Racial discrimination is also prevalent in instructions given by election officials operating with high bureaucratic independence. Hunold and Peter argue that bureaucratic discretion is increasing due to " the volume and complexity of rulemaking activity" (Hunold and Peter 2008).

Obviously, the criminal justice system is not as far removed from observing eyes as a forest ranger, and its members make decisions that directly impact others. However, police officers do act on a high degree of discretion. Minor cases, including most traffic infractions, may be under minimal scrutiny. In a work related to the discretion of judges, Anderson et al. found a significant decrease in sentencing variance as a result of the Sentencing Reform Act of 1984 – a set of guidelines that constrained judicial discretion and created a standard by which judges could be scrutinized (Anderson, Kling, and Stith 1999). A similar imposition on officers would likely make the process of determining the outcome of a stop more algorithmic and less "noisy."

III. Theoretical Model

I now present a model to assess the level of bureaucratic discretion exercised by the NC police officers. This model formalizes the utility of the officer as defined

$$U_{it}(M, D, O) = (1 - \lambda)(M + D_{it}) + \lambda(O_{it}) \quad (1)$$

where U_{it} is utility, M is the fulfillment of the bureaucrat's appointed mission, D_{it} is a function of department preferences, and O_{it} is a function of officer preference. λ is a measure of discretion such that $0 \leq \lambda \leq 1$. λ is determined exogenously by the factors Kaufman describes in *The Forest Ranger*. This model is simple and generalizable; it could be applied to a wide variety of contexts, (e.g., the EPA's approach to litigation) while creating interesting and testable implications.

The O_{it} function is typically hidden and is entirely dependent on the agent's preferences. These might include a preference towards certain identity factors of drivers (race, age, gender), the time of day, or any other set of factors that would influence the officer's evaluation of the driver. Officer preferences are assumed to be heterogenous and unobservable. Since the officer faces some level of training and oversight by their department, one would expect that the goals of the department (D_{it}) would enter the agent's utility function, modified by λ. Department preferences are also heterogenous. Both O and D vary by officer i and time t.

These hypotheses are only evaluable if the "M" term remains constant. Otherwise, variation in outcomes could reflect evolution in the bureaucracy's mission. While there have been minor changes in the legal standards by which traffic stops are conducted over the time period 2002 to 2020, the categories of infractions have not changed, and the overarching goal of creating a safe driving environment has not either. I assume "M" is constant across time and officer.

My hypotheses follow from this model and are informed by the existing literature. The police officer is high-discretion bureaucrat in their traffic-enforcement role, and therefore experiences a high λ value. Hence, individual officer leniency preferences "O_{it}" will enter the utility function at high levels, and

H1: There will be high variation in leniency dependent on officer.

Since "O_{it}" is likely to change over time t as the model officer's leniency preferences do,

H2: Individual officers will exhibit high year-to-year variation in leniency.

Oversight, and therefore discretion (λ), is largely determined by individual police departments. Therefore,

H3: There will be high department-to-department variation in leniency

Since larger departments can dedicate more resources to training and oversight,

H4: Larger departments will exhibit lower variation in leniency.

Finally, since infractions with higher associated penalties are more serious and more likely to be challenged in court, officers are under more oversight when conducting stops for these offenses, and therefore

H5: Offenses with higher punishments have lower variance in outcomes.

IV. Data

To evaluate these hypotheses, I use a dataset collected by the AOC and cleaned by Frank Baumgartner and others for their work on the book *Suspect Citizens* (Baumgartner, Epp, and Shoub 2018). The dataset is comprehensive of all North Carolina stops from 2002 until 2020 and contains entries for all the aspects of the NC Traffic Stop Report form (figure J1).

The variable I hope to evaluate is the outcome of a traffic stop. There are 5 options available to police: “No Action,” “Verbal Warning,” “Written Warning,” “Citation Issued,” and “Arrested”. The first three correspond to no material punishment, while citations can include fines and often result in increases to insurance rates. Arrests are obviously materially impactful. I group verbal and written warnings, as well as “No Action” as “Lenient” results, and the rest as “Severe.” Table 1 displays the total number of stops and leniency rate by stop type. The disparate rates of leniency even at this level of distinction are important. Because each stop is predicated on probable cause, it seems that officers are mistaken about the criminal status of drivers’ actions at different rates depending on the suspected violation. Only 11% of seatbelt violation stops result in a lenient outcome, while 70.25% of vehicle equipment stops do.

Table 1

Stop Purpose	Stops	% Of Total Stops	Number Lenient	% Lenient
Speed Limit	10,478,769	41.95	2,374,107	22.66
Stop Light/Sign	1,246,413	4.99	603,079	48.39
Driving Impaired	198,646	0.8	38,196	19.23
Safe Movement	1,442,082	5.77	885,187	61.38
Vehicle Equipment	2,346,627	9.39	1,648,490	70.25
Vehicle Regulatory	4,431,263	17.74	1,701,570	38.40
Seat Belt	2,052,828	8.22	225,338	10.98
Investigation	1,623,228	6.5	732,550	45.13
Other Vehicle	1,160,921	4.65	475,582	40.97
Total	24,980,777	100	8,684,099	34.76

The dataset includes three types of explanatory variable: Identity, temporal, and agent. The literature, including Baumgartner's own work, focuses almost exclusively on outcomes of identity. To capture this, I will use the race of the driver, the age, and the gender of the driver. The temporal variables include time of day, day of week, month of year, and year. Agents include the investigating department, which is defined by geographic bounds, and the officer. None of these variables are legally relevant, so any impact they have is "noise" in the fulfillment of the officer's legal duty. I investigate the impact of these factors as a whole, but also do so separately across all infraction types. Appendices A-I are repositories for these infraction-specific analyses.

In addition, I also make use of a dataset specific to Charlotte, NC. This dataset is useful because, unlike the NC-wide set, it contains officer characteristics including years of experience. This dataset was used in Baumgartner et al.’s *Intersectional Encounters: Representative Bureaucracy and the Routine Traffic Stop* (Baumgartner et al. 2021). The dataset contains the action of the officer as well as the 9 possible traffic stops reasons, allowing for direct comparison with NC-wide data. I will investigate the correlation between officer experience and leniency, controlling for a variety of other factors. The summary of Charlotte stop types is reported below in table 2.

Table 2

Charlotte Stop Types			
Stop Reason	Freq.	Percent	Cumulative Percent
Checkpoint	311	0.35	0.35
Driving While Impaired	121	0.14	0.49
Investigation	2,001	2.27	2.76
Other	2,061	2.34	5.1
Safe Movement	5,650	6.42	11.52
Seatbelt	931	1.06	12.58
Speeding	23,039	26.16	38.74
Stop Light/Sign	9,063	10.29	49.03
Vehicle Equipment	10,078	11.44	60.48
Vehicle Regulatory	34,801	39.52	100
Total	88,056		

Note*:* I remove the checkpoint observations as they have no analog in the full NC dataset.

V. Descriptive Statistics

First, I display a series of descriptive visualizations that shed light on the extent to which traffic stop outcomes are dependent on each factor. Each visualization has been created both for the entirety of the data and for each of the 9 stop types individually. These are available in the same order under the relevant appendix. They are broadly grouped into the impacts of the investigator (officer and department), those of the identity characteristics of the driver (race, gender, age), and those of temporal aspects (time of day, day-of-week (DOW), and year). None of these factors have a place in the legal standards being addressed.

Agent

Figure 1 shows the leniency rate of each officer in the dataset for those with more than 5 total stops over the time period. The officers are ordered from least to most lenient. There are some with near 0% leniency rate and some at every level of leniency, up to and including 100%. A perfectly consistent police force would have a vertical leniency rate at the state average over the period. A police force that is making a random choice at each stop would display a downward-sloping linear trend. The state as a whole looks more like the latter, while the officer leniency spread for equipment violations (figure C1) is the closest to the former description.

Officers are not acting identically – something, external or internal, is affecting how they conduct their stops. Figure J2 displays the same visualization for officers with over 100 stops. Even with the law of large numbers minimizing the chance of a series of flukes for each officer, the spread is still very wide. In fact, the distribution appears almost identical to the full set. Figure 2 displays the spread for NC's Highway Patrol (HWP) – a group dedicated exclusively to policing the roadways of the state. This group also demonstrates a high variance in leniency rate. One's investigating officer is highly correlated with the outcome of a traffic stop.

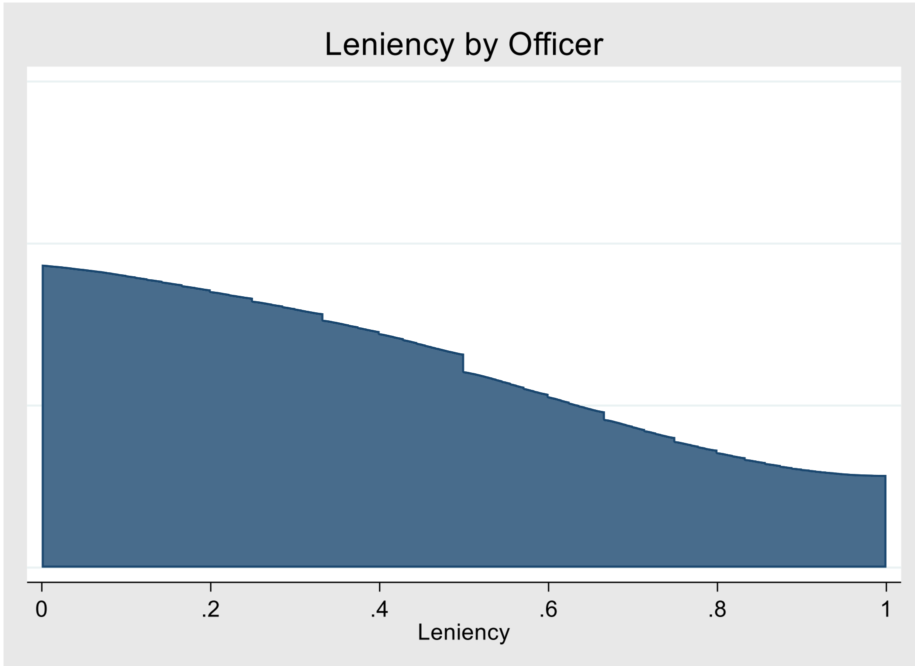

Figure 1

Note: Each point on the vertical axis corresponds to a different officer. Officers with fewer than 5 stops are omitted.

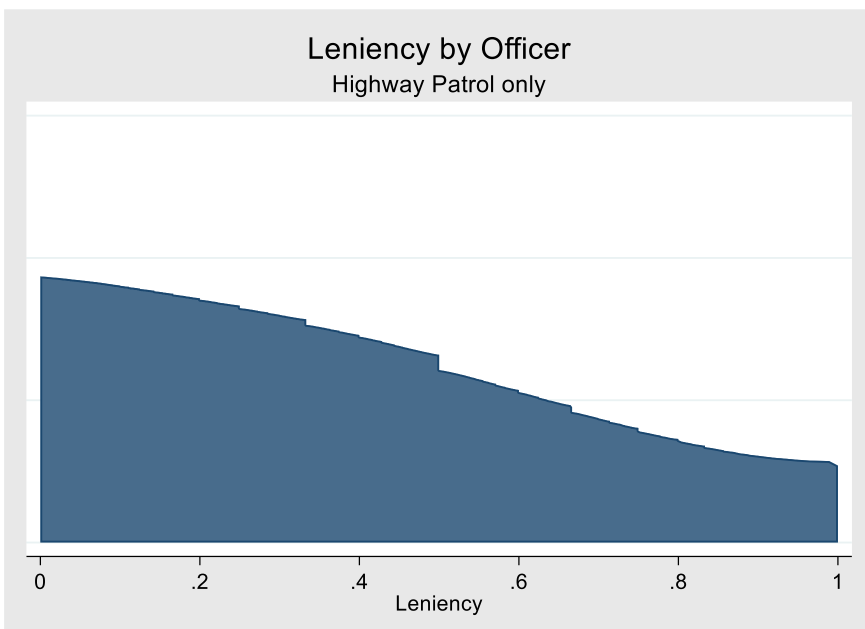

Figure 2

Note: Each point on the vertical axis corresponds to a different officer in the highway patrol. Officers with fewer than 5 stops are omitted.

Figure 3 shows the same analysis by department. Here, the leniency rates are less evenly spread over the horizontal axis, revealing a moderate level of variance. Still, there are departments with very extreme leniency rates compared to the state average. Driving from one jurisdiction to another results in a vastly different expression of the (State-wide) law. The most striking example of a break in the "Rule of Law" might be the difference in expectation when driving on the highway. Though the relevant traffic laws are identical between jurisdictions, many are cautioned to be more careful driving on the highways. To visualize this break, figure 4 shows the "onramp effect," the change in leniency rate that occurs as one enters the Highway Patrol's jurisdiction. For the vast majority of departments, the effect is negative, showing a massive increase in leniency as compared to the Highway Patrol's 18.86% leniency rate. Many of the individual violation types' "onramp" graph appears similar, but some, like DWI and seatbelt violations, have many more departments reporting positive effects, relaying that they are less lenient than the HWP (figures B4 and H4).

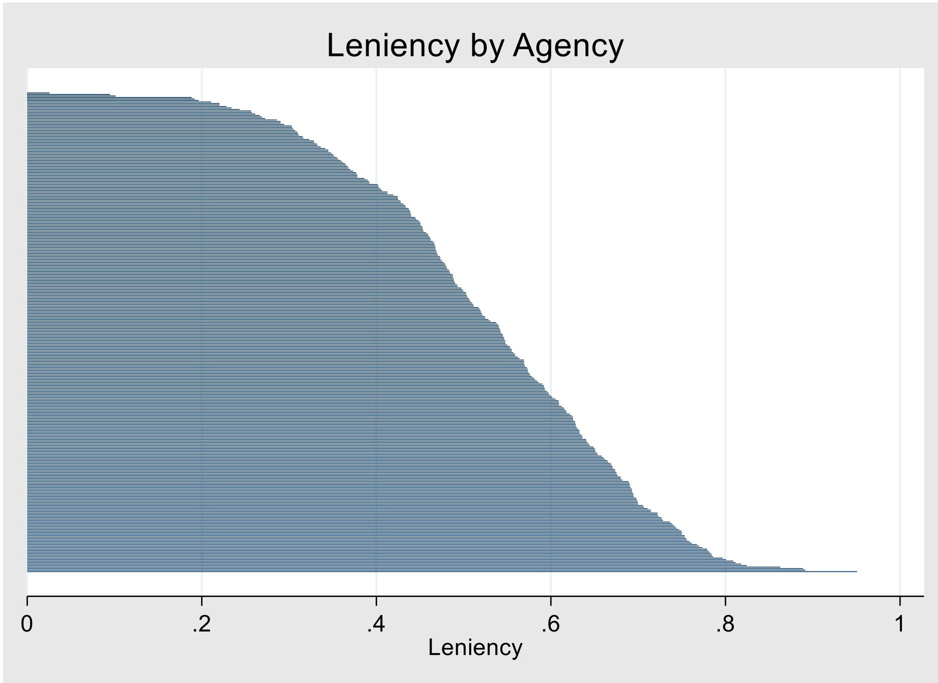

Figure 3

Note: Each point on the vertical axis corresponds to a different department.

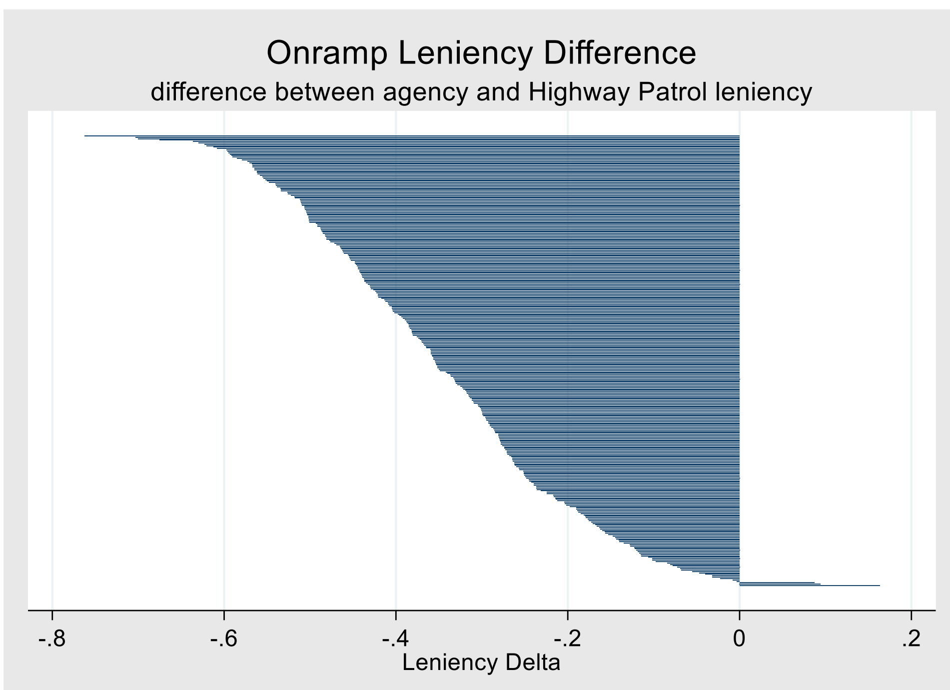

Figure 4

Note: Each point on the vertical axis corresponds to a different department. A leniency delta of 0 would indicate average leniency rate equal to that of the HWP.

Identity

Next, I report on some of the other factors that may be influencing leniency besides the officer and the department. First, the identity traits of the driver. Drivers are marked as “White,” “Black,” “Hispanic,” and “Other” in the state’s form, and as either “Male” or “Female.” These distinctions are limiting and do not account for intersections of race and ethnic identity or non-binary gender identification. An ANOVA test reports a large degree of variance between the race/ethnicity groups at p-values approaching 0 (table 3). It also reports a statistically significant difference between each category and each other. The racial/ethnic differences are smaller than the literature around racial bias would imply, likely because the decision to pull over a driver and the decision to be lenient would be influenced in opposite directions by racial/ethnic bias. While there is always a statistically significant difference between leniency rates experienced by different racial/ethnic categories, this effect is much larger for some stop purposes than others. White people receive especially lenient outcomes as compared to Black people in equipment, investigation, and other vehicle stops (figures C5, D5, and F5), and as compared to Hispanics in stop light/sign, DWI, equipment, investigation, movement, other vehicle, regulatory, seatbelt and speeding violations (figures A5, C5, D5, E5, F5, G5, H5, and I5). The racial effects are most pronounced in investigation stops.

Table 3

	Black	Hispanic	Other
Hispanic	-0.104		
p-value	0.000		
Other	-0.061	0.0423	
p-value	0.000	0.000	
White	-0.037	0.067	0.024
p-value	0.000	0.000	0.000

***Note**:* The intersection of a column and row reports the difference (row minus column) between mean leniency rates applied to each race/ethnicity. P-values are reported below.

Gender is another source of extraneous input into the decision-making process of the officer. A T-test between male and female groups reports a similar but statistically distinct average level of lenience (at the 95% confidence interval). Also of note, the number of males being pulled over across the period and state is 1.72 times the number of females. This may be a result of officer bias, which would be consistent with previous findings (Baumgartner, Epp, and Shoub 2018). It may also have to do with the base rate of drivers on NC roads or the rate at which males break the law.

Table 4

Group	Observations	Mean	Std. Err.	Std. Dev.	95% Conf. Interval	
Female	9152143	0.358	0.0002	0.479	0.357	0.358
Male	15828622	0.342	0.0001	0.474	0.342	0.342
Combined	24980765	0.348	0.0001	0.476	0.347	0.348
Difference		0.016	0.0002		0.016	0.016

Note: Mean refers to the leniency rate across the subgroup.

Next, I review the effect of the age of the driver. An increased age correlates with a much higher level of leniency. Figure 5 displays a scatterplot of average leniency rate for every recorded age in the dataset (in years), overlayed by a local polynomial regression line to approximate the trend. The result is a large and clear trend of increasing leniency with age, with ranges from .3 to .7 average leniency rates. The effect is quasilinear, and reverses at the upper extreme of driving age. This trend implies a sizable preference for acting leniently towards older drivers. Figure 6 relays the same analysis but applied to the HWP. The trend here is much more linear and leniency rates are lower (between .1 and .5 for all ages), but the trend is largely upward-sloping. This is the case for all stop purposes except for investigation (figure D6,), which indicates a parabolic trend with drivers in their late fifties experiencing the maximum leniency.

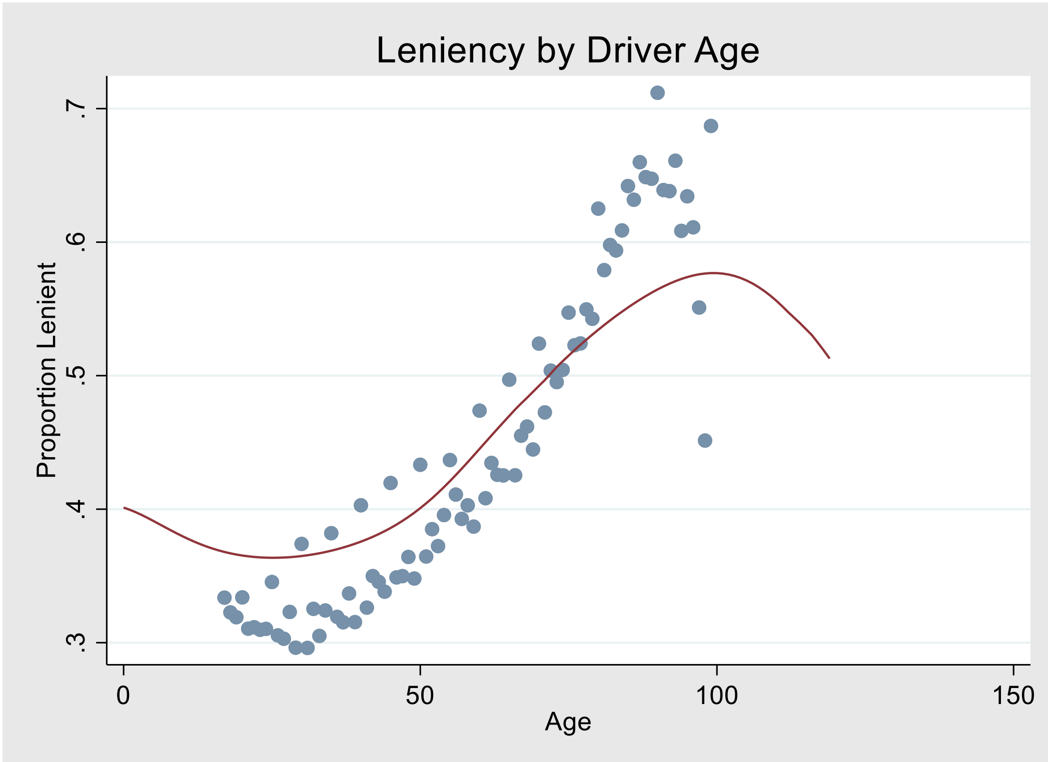

Figure 5

Note: Each point on the plot corresponds to an age on the horizontal axis and a leniency rate on the vertical. The trend line is a "lowess" regression, estimating the trend via the plotted points.

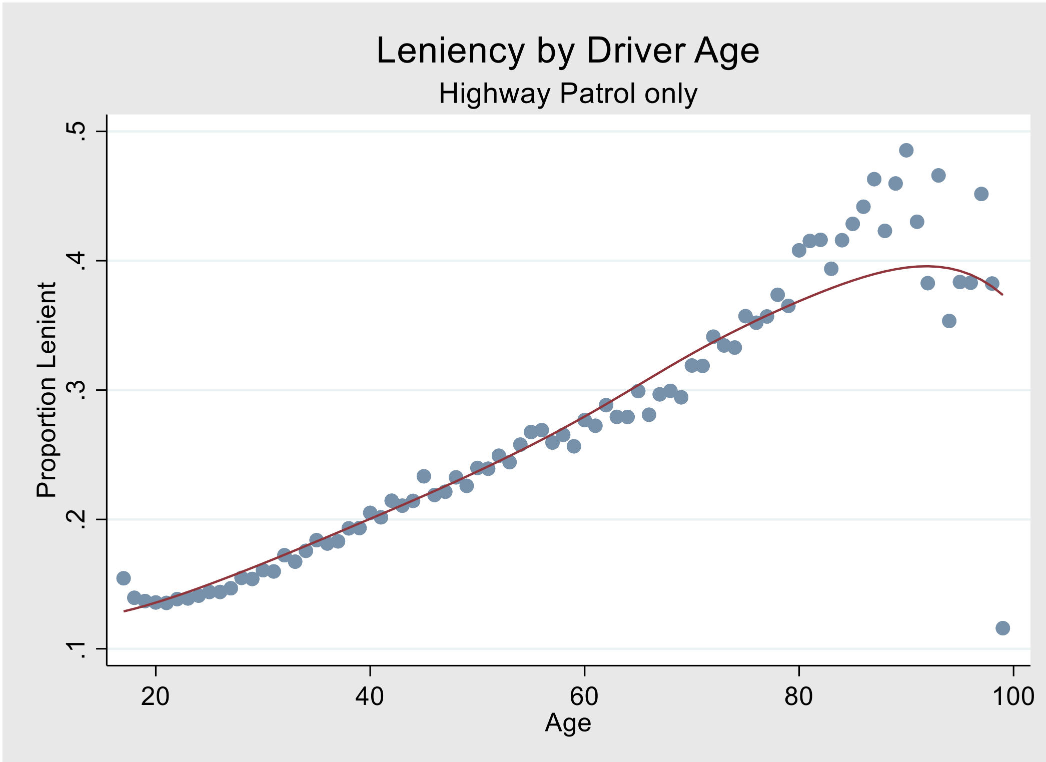

Figure 6

Note: Each point on the plot corresponds to an age on the horizontal axis and a leniency rate on the vertical. The trend line is a "lowess" regression, estimating the trend via the plotted points. This analysis is restricted to HWP stops only.

Temporal

I now consider time trends. First, the hour of day is strongly correlated with the leniency rate. Figure 7 shows the hours of the day from 0 (midnight) to 23 (11:00pm) and the corresponding average leniency rate. There exists a 15-percentage point difference between the minimum leniency stop time (early morning) and maximum (late evening). Whether this swing is due to ambient conditions, such as light, affecting the accuracy of "reasonable suspicion" or officers' preferences shifting over the course of the day is beyond the scope of this analysis. Suffice it to say that there is a real penalty for being stopped during daylight hours. There is a much less dramatic change in leniency rate by day of week. There is less than a 2-percentage point difference in leniency between the weekly minimum, Monday, and maxima, Wednesday, and Thursday (Figure 8). The HWP follows an uncannily similar trend, though at a lower level of overall leniency and a greater percentage point change (Figure 9).

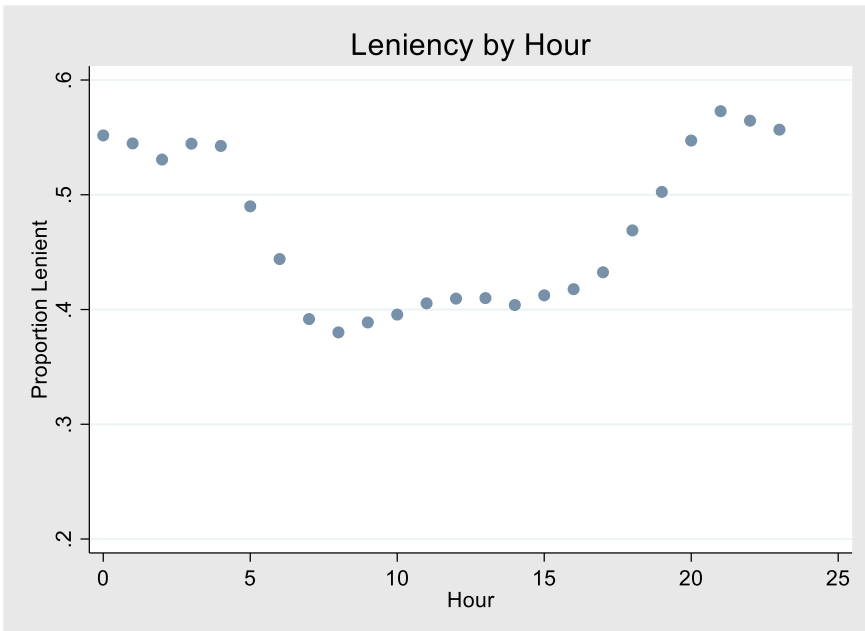

Figure 7

Note*:* Each point on the corresponds to an hour (0-23) on the horizontal axis and a leniency rate on the vertical. 0 corresponds to midnight and 23 to 11:00PM.

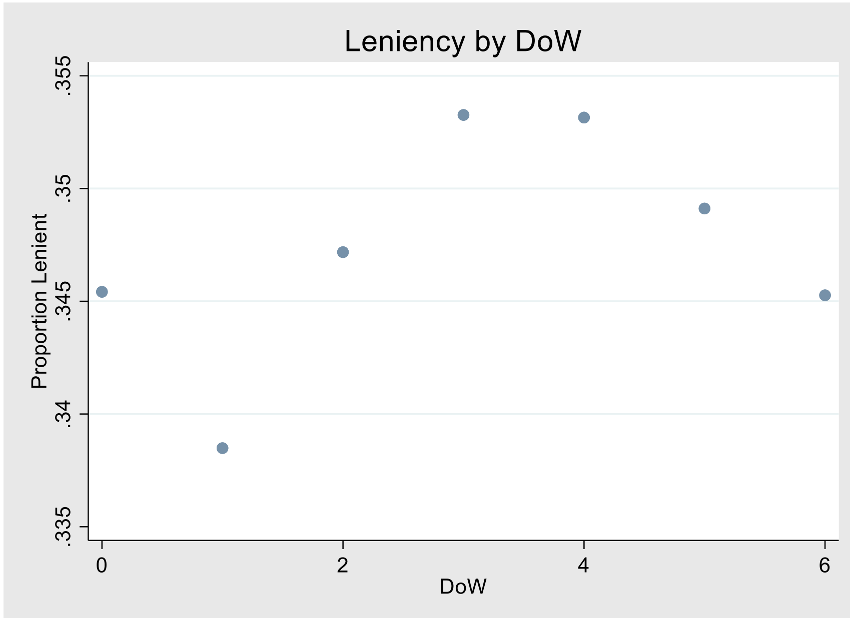

Figure 8

Note*:* Each point on the corresponds to a day of the week on the horizontal axis and a leniency rate on the vertical. 0 corresponds to Sunday, 6 to Saturday.

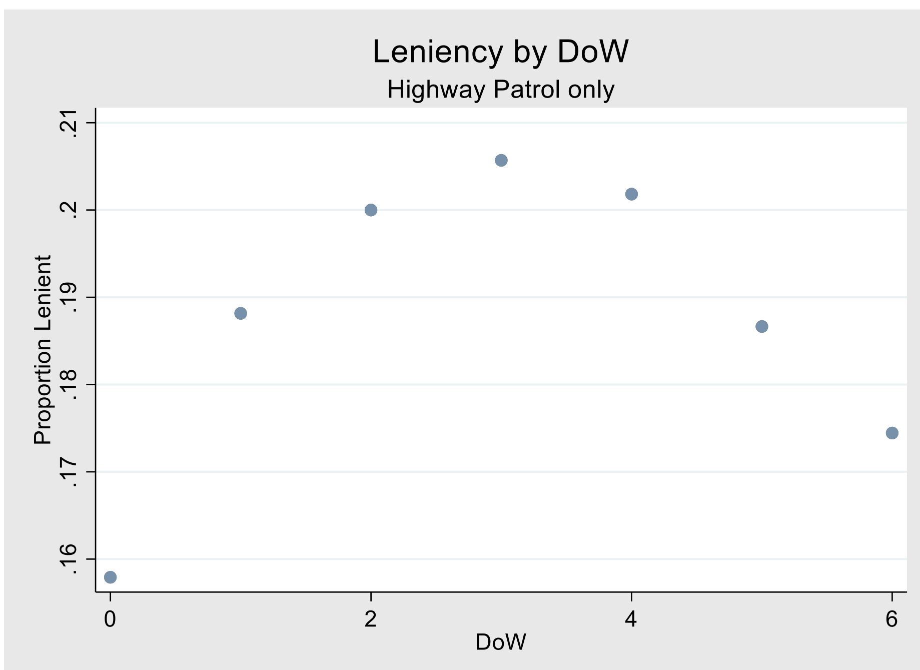

Figure 9

Note*:* Each point on the corresponds to a day of the week on the horizontal axis and a leniency rate on the vertical. 0 corresponds to Sunday, 6 to Saturday. This visualization is restricted to only HWP stops.

Finally, and most strikingly, there is a substantial increase in average leniency rate over the time period. Figure 10 shows the overall trend while figure 11 displays the trend of each stop type. A more detailed treatment of each stop-type's leniency over the time period can be found in the relevant appendices. Only DWI leniency decreases (Figure B11) over time, and only slightly. DWI accounts for a small proportion of the total stops. The rest are constant or increasing (some, like stop sign/light increase dramatically, figure A11) over time. Average leniency across stop types is up nearly 150% since the start of the time period in 2002. The application of the law is obviously not constant over time.

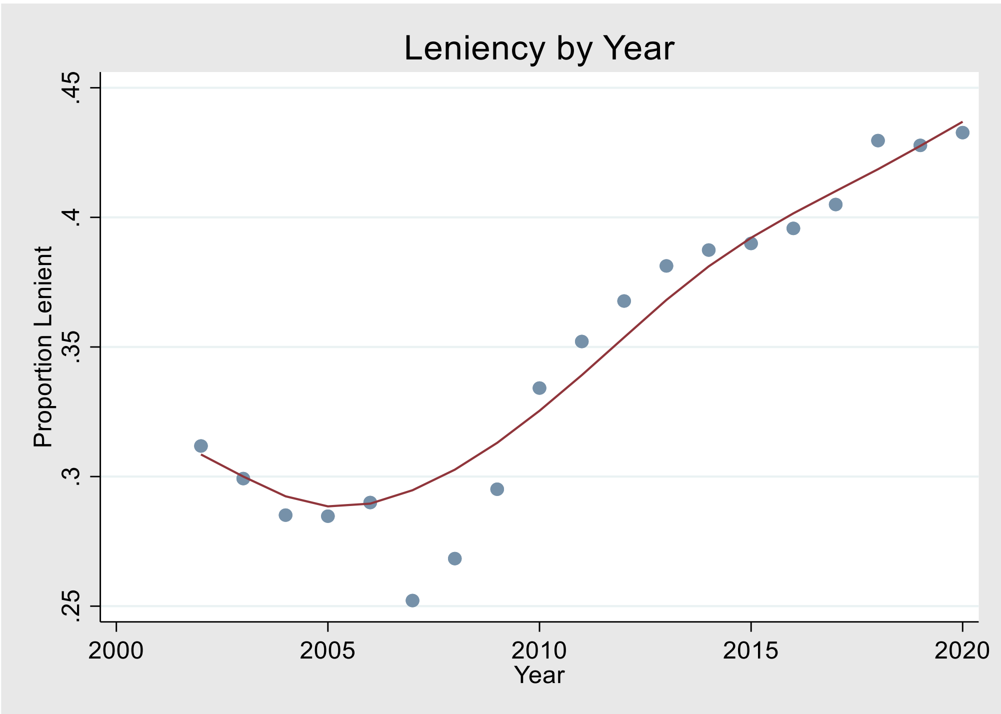

Figure 10

Note*:* Each point on the corresponds to a year (2002-2020) on the horizontal axis and a leniency rate on the vertical. A "lowess" regression estimates the trend via the data points.

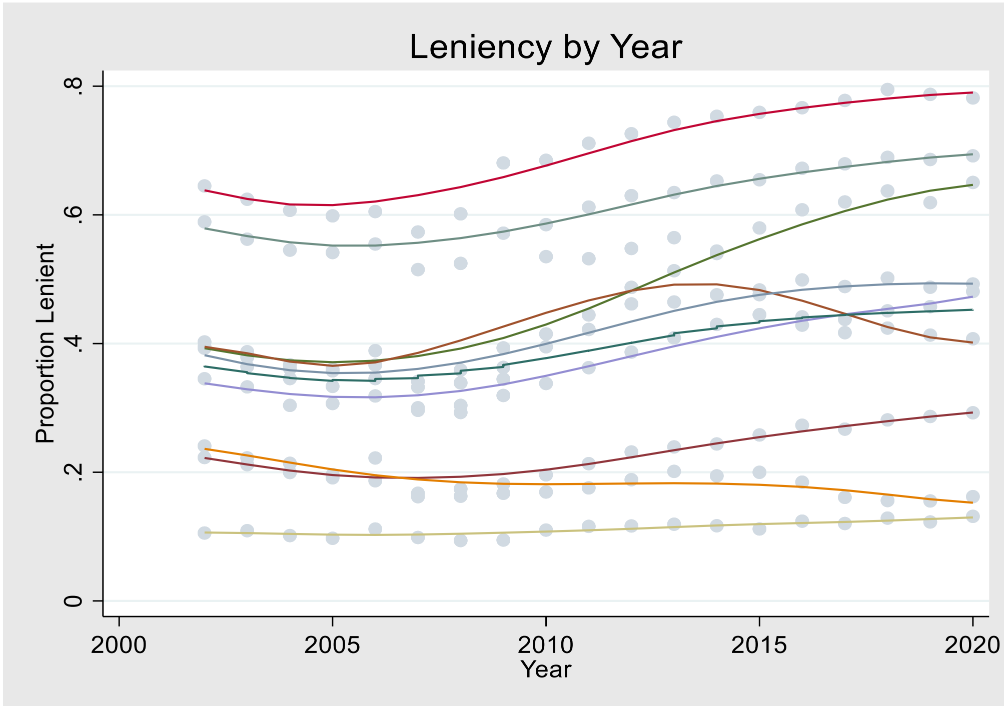

Figure 11

***Note**:* Each point on the corresponds to a year on the horizontal axis and a leniency rate on the vertical. Each stop type is represented by its own lowess regression. For a more detailed display of each trend over time, vide figure 11 in each appendix.

In sum, there is clearly lots of variance input into each traffic stop decision. The law is not constant across the investigating officer or department, the driver's characteristics, or the time of the stop. Most interesting is the massive increase in leniency over the time period, with the highest leniency stop types increasing by the most. Next, I conduct a more rigorous analysis of the relative importance of these extra-legal factors on the leniency outcome.

VI. Years of Experience

To analyze the effect of officer experience on leniency requires the Charlotte dataset, which contains 88,506 observations across all stop types and years 2016-2017. The data also include the number of years an officer has been on the force at the time of the stop, along with useful control variables. I am able to estimate the marginal effect of years of extra time on the force on leniency. Formula (2) describes a maximum likelihood estimation model that I use to do so.

$$P({y_{it}}^{*} = 1|X) = \phi(\beta_0 + F + \beta_1 A + \beta_2 OR + \beta_3 DR + \beta_4 A^2 + \beta_5 OG + \beta_6 DG + \beta_7 S + \varepsilon_{i,t}) \quad (2)$$

Where y* is outcome leniency,

$\phi(\,)$ is the cumulative normal distribution, used to model a binary outcome

F is years on the force fixed effects,

A driver age,

OR is officer race,

DR is driver race,

OG is officer gender,

DG is driver gender,

S is subdivision,

And ε is the error term.

I then report the marginal effect of F on leniency and present them in figure 12. The figure also displays the 95% confidence intervals surrounding the marginal effects. There is a slight decrease in the leniency of an officer as they serve longer on the force. Whether this is explained by experience, lower oversight for more senior officers, a better assessment of reasonable suspicion, or another mechanism, not all officers punish equally. Figure J3 reports the full regression, and marginal effects are reported by stop type in the relevant appendices. Interestingly equipment, regulatory, and speeding violations show declining (figures C13, G13, I13) trends and stop lights/signs, DWI, investigation, movement, other vehicle, seatbelt violations, show ambiguous or flat trends (figures A13, B13, D13, E13, F13, H13). The experience level of the investigating officer seems to matter, but not equally across different stop purposes.

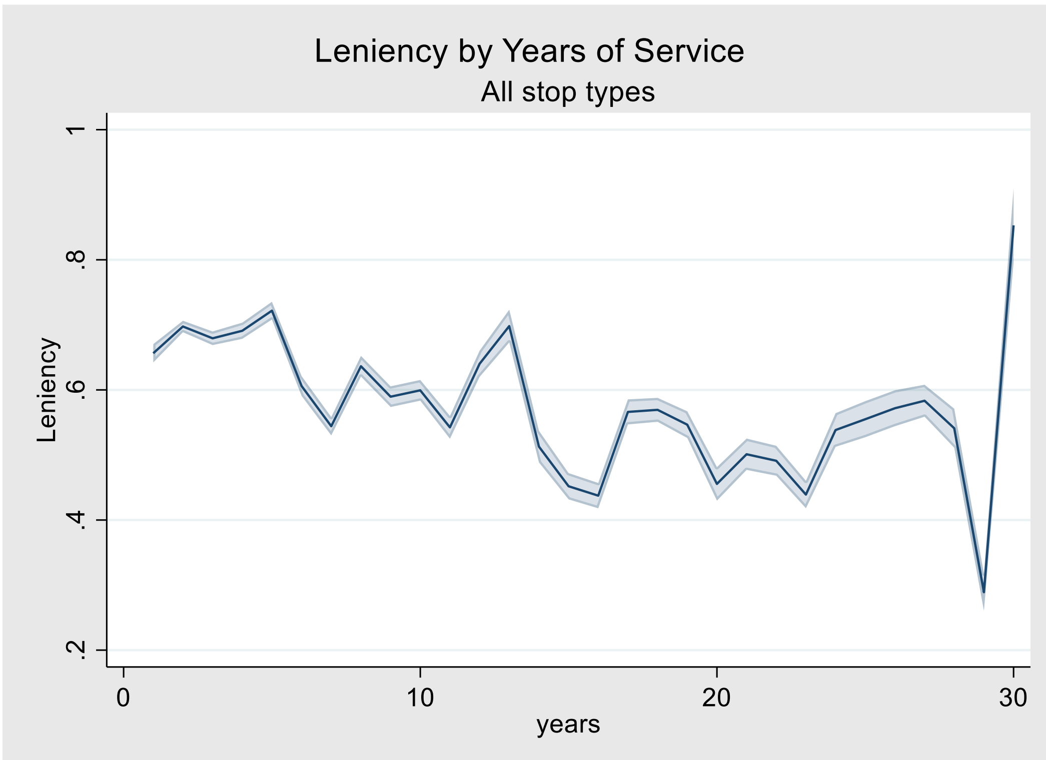

Figure 12

Note*:* The figure displays the predicted leniency rate at each number of years of experience, as determined by formula (2). The results are reported in figure J3, and are broken down by stop type in figure 12 of each appendices A-I.

VII. Variance Attribution

Relative

I now turn to an original type of analysis that utilizes maximum likelihood estimation to account for sources of variance in an outcome. I use the functional form

$P({y_{it}}^* = 1|X) = \phi(\beta_0 + H + W + M + Y + D + O + \beta_1 G_i + \beta_2 (R_i * G_i) + \beta_3 E_i + \beta_4 E_i^2 + \varepsilon_{i,t})$ (3)

Where y* is outcome leniency,

$\phi(\ )$ is the cumulative normal distribution, used to model a binary outcome

H is hour fixed effects,

W is day of the week fixed effects,

M is month fixed effects,

Y is year fixed effects,

D is department fixed effects,

O is officer fixed effects,

G is driver gender,

R is driver race/ethnicity,

E is driver age,

And ε is the error term.

y* is a binary, 1 if lenient, 0 if not. Hour is reported 0 (midnight) through 23 (11:00pm). Day of week is reported 0 (Sunday) through 6 (Saturday). Month is reported 0-11, reflecting January through December. Year is from 2002 through 2020. Department is reported as a unique identifier for each police department. Officer is likewise reported as a unique identifier. Gender is reported as a binary, 1 for male 0 for female. Race is a categorical variable described as “White” “Black” “Hispanic” or “Other.” Driver age is reported in years.

Since I am interested in accounting for variance, not the size of any one effect, I do not report the values associated with covariates or their marginal effects. Instead, I will use a measure of explained variance, similar to Residual Sum of Squares from OLS estimation, to determine the importance of each factor. Unfortunately, MLE regression models cannot report a true RSS value, but there are many options for estimating this value. For the rest of the paper, I will use McFadden's R^2 (MC R^2), which is estimated as per (4) (Domencich and McFadden 1977). The estimator prioritizes relaying information about the total amount of explained variance. I then compute the change in R^2 as a percentage of the original R^2, to make comparisons between disparate datasets and models.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2}$$

(4)

The method will proceed as follows: First, I estimate the fully saturated model and report the total R^2. From there, I iterate through each variable/group of variables, removing them and recording the change in R^2. I take the ratio of the change in R^2 and the measure from the saturated model to return the percent change in explanatory power of the new model. From there, I can compare the percent change between different iterations to observe the relative importance of different factors. Due to computational limitations, I cannot include every officer in the computation. For this reason, I compute the model twice, once with all observations and without officer fixed effects, and the second with the highest-stop officers. I compute each version of the analysis separately for each of the 9 stop purposes. For computational ease, I calculate these results on a random sample of 5% of the original dataset. This amounts to 1,248,846 observations. Due to restrictions to the maximum number of variables in a regression, I limit the specification that includes officers to officers with > 8000 total stops and draw a random sample of 5% of the available observations. This still leaves 207,570 total observations. An important assumption is that these high-stop officers are representative of the entire class.

Table 5 reports the changes in R^2 at each iteration of the model. The variable or variable group in the leftmost column corresponds to what is being left out of the saturated model. The left group displays the results for the no-officer specification, while the right reports results for the restricted sample with only the highest-stop officers. It does not report department fixed effects since they are always 0 in this specification; the effect of the department is nested within the officer fixed effect. Department and officer fixed effects have the highest explanatory power, followed by identity factors and the hour of the day. For all the time and attention identity factors have received in regard to criminal justice, the combined impact of age, race, and gender of the driver is only an 8.1-9.5% change from the saturated model.

Table 5

	No Officer			Officer		
	Total	Change	% Change	Total	Change	% Change
Saturated	0.116	0	0	0.148	0	0
Identity	0.105	0.011	9.483	0.136	0.012	8.108
Year	0.107	0.009	7.759	0.145	0.003	2.027
Month	0.116	0	0	0.148	0	0
Day	0.116	0	0	0.148	0	0
Hour	0.106	0.01	8.620	0.147	0.001	0.676
Department	0.076	0.04	34.483	N/A		
Officer	N/A			0.056	0.092	62.162

Notes: The table reports the MF R^2 value (4) when each covariate or collection of covariates is removed from model (3). It then reports the absolute value of the change and the percentage of the saturated model's R^2 represented by the change. It is split into a section without officer fixed effects drawing from the full dataset, and one with officer effects over the subset with high-stop officers.

Once again, this analysis has been completed at the level of each individual stop type, tables of which are available in the relevant appendices. A summary of these results is reported in table 6. The table contains the percentage of McFadden's R^2 accounted for by department and officer fixed effects, and the combined value of the identity aspects (age, gender, and race). The effect of department is largest in movement, DWI, speeding, stop light/sign and regulatory investigations. Officer effects are largest in seatbelt and other vehicle infractions. Identity is most impactful in speeding, seatbelt, and other vehicle stops. Identity factors are uniformly the least impactful of the three. Officer fixed effects are more impactful than department, but this is to be expected since the former fixed effect is included in the latter in each case, adding no new explanatory power.

Table 6

% Of MF R2			
	Department	Officer	Identity
Stop Light/Sign	41.748	46.465	6.061
DWI	44.872	63.544	3.055
Equipment	37.5	51.056	5.282
Investigation	25	60.677	2.604
Movement	47.059	51.172	5.469
Other Vehicle	33.333	73.460	9.005
Regulatory	41.573	56.111	3.333
Seatbelt	26.601	72.289	10.241
Speeding	42.3088	61.798	10.112

Notes: The table reports the percent of MF R^2 value (4) attributed to the columns (department, officer, and identity effects) across all stop types as determined by formula (3). The department stops come from the version without officer fixed effects drawn from the full dataset, and the officer effect from the subset with only high-stop officers. The values reported here can be found in figure 14 in appendices A-I.

Simulated

While this analysis gives a strong sense of the relative importance of each extraneous factor, it does little to clarify their absolute relevance. To that end, I have developed another new technique. I use the R^2 value obtained from the partial sample with only high-stop officers. I then create a variable for each stop, drawn randomly from a uniform distribution between 0 and 1. I then attach an officer-specific term (L) to each officer to represent their leniency bias. This leniency-bias term is another random draw at the officer level. If, for example, $\lambda_i = .1$, then the leniency-bias term is drawn at random from a uniform distribution of $-.1 < L < .1$. This would represent the assumption that officers have leniency biases up to 10% of the total leniency calculation. I then sum the random draw and leniency-bias term. If the total is less than the mean leniency rate, that stop is considered a "simulated lenient" at the "λ_i" level .

Formally,

$$y* = \begin{cases} 1 \text{ if } L + R < M \\ 0 \text{ if } L + R \geq M \end{cases} \quad (5)$$

Where y* is the simulated outcome of the stop, 1 for lenient, 0 for not lenient

L is the Leniency bias term = $U(-\lambda_i, \lambda_i)$,

λ_i is a term in the vector $\langle .1, .15, .2, .25, .3, .35, .4, .45, .5 \rangle$,

R is the random outcome of the stop = U(0, 1),

And M is the true mean leniency rate for the population.

From there, I compute a series of regressions at each level of λ of the form:

$$P(y_{it}^* = 1|X) = \phi(\beta_0 + 0 + \varepsilon_{i,t}) \quad (6)$$

Where y* is outcome leniency,

$\phi(\,)$ is the cumulative normal distribution, used to model a binary outcome, O is officer fixed effect,

And ε is random error.

I take the McFadden's R^2 value (4) from each of these regressions and compare them to the difference in McFadden's R^2 value found by dropping the officer fixed effects from the fully saturated model (3). This creates a direct comparison between simulated leniency-biases and the real leniency bias of the officers, controlled for all the other terms in the saturated model. Note that the effect of the real officer bias is .129 (table 7), which indicates an officer bias between the simulated biases λ_i = .25 and λ_i = .4. On average, within this group, officers' leniency biases equal to between 35% and 40% of the total determination. Even taking the conservative end of this range represents a high level of officer discretion.

Table 7

	λ_i	MF R^2
Simulated	0.1	0.022
	0.15	0.057
	0.2	0.094
	0.25	0.102
	0.3	0.094
	0.35	0.11
	0.4	0.138
	0.45	0.137
	0.5	0.16
Real		0.129

Observations: 582,866

Note: The table reports the MF R^2 (4) at each level of λ_i derived from (5) and (6). The "Real" value comes from the R^2 effect reported from using (3) on the same dataset. The models were estimated using the subset of data with officers that conducted >6500 stops in the time frame. The data is subset again to a random sample of 5% of the observations.

VIII. Average Yearly Delta

In a third analytical method, I create a term called average yearly delta (AYD). This term measures the average year-to-year change in leniency rate and can be applied to officers or their departments. Formally,

$$AYD = \frac{\sum_{t=1}^{T} |(L_t - L_{t-1})|}{T}$$

(7)

Where AYD is average yearly delta,

t is time period,

L is leniency rate,

and T is the total number of time periods.

Next, I estimate the AYD for each department for each stop type. I also compute the metric for the HWP. Figure 13 shows the average AYD for non-HWP departments and for the HWP. Across the board, non-HWP departments have much higher AYDs. It also seems that both DWI and seatbelt violations have high AYD, disputing H5, which would predict DWI to be significantly higher. However, AYDs are susceptible to the law of large numbers. The more stops for any given stop type, the lower a department's year-to-year variance and so lower the state-wide average. To correct for this statistical fact, I create a simulated AYD and compare it to the real one.

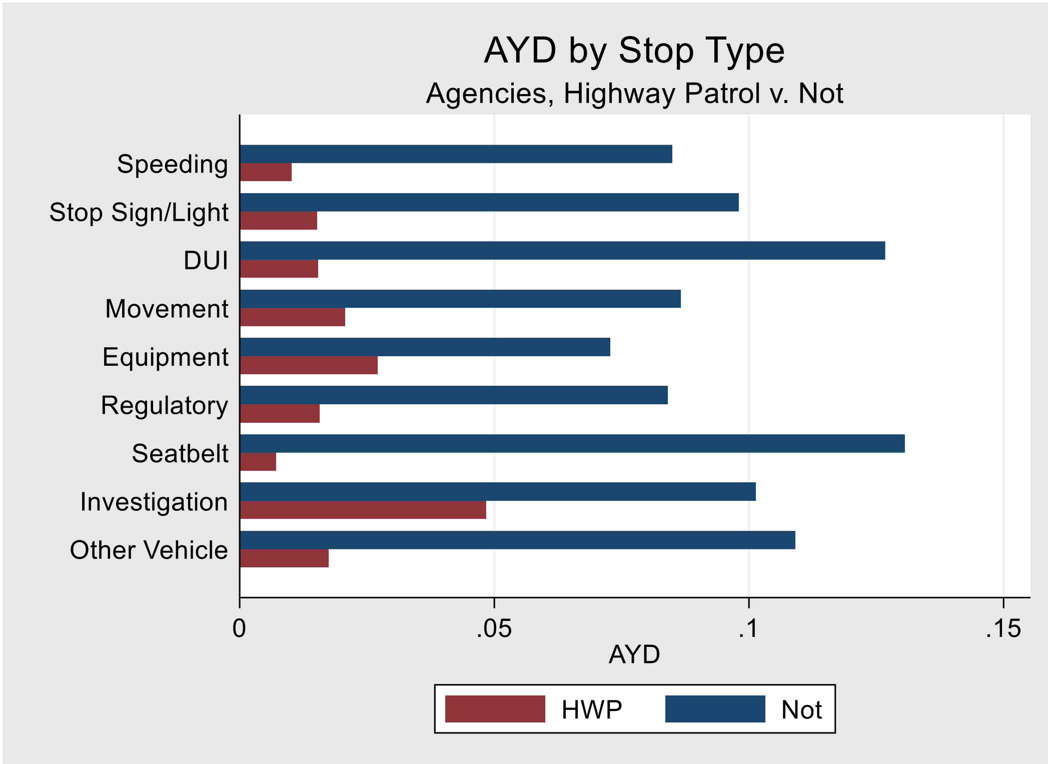

Figure 13

Notes: The figure displays the average yearly delta (7) by stop type, broken down into HWP and the average of all other departments. An AYD of .1 indicates that average leniency changes by .1 year-to-year on average. For more detailed information on AYD by stop type, vide figure 15 in appendices A-I.

To create a simulated AYD, I take the average leniency rate for a stop type over the entire time period. Then, for each real stop, I then take a random draw from the uniform interval between 0 and 1. If the draw is lower than the mean leniency rate, this is a simulated lenient outcome. Otherwise, it is a simulated non-lenient. Formally,

$$y* = \begin{cases} 1 \; if \; R < M \\ 0 \; if \; R \geq M \end{cases} \quad (8)$$

Where y* is the simulated outcome of the stop,

R is the random outcome of the stop = U(0, 1), And M is the true mean leniency rate for the population.

I then apply the AYD formula (7) to the simulated outcomes. This creates a simulated AYD that corresponds to the hypothetical world in which officers make mistakes in their probable cause decisions at random at a rate equal to the total leniency rate of the real world. I then subtract the simulated department AYD from the true one and report results in figure 14. This controls for the downward effect of larger sample sizes on variability. In this estimation, seatbelt and speeding violations have the largest positive difference between real and simulated AYD. The group of other departments still tend to have larger differenced AYDs than highway patrol. HWP actually has negative AYD in speeding, stop sign/light, and regulatory violations, outperforming the "random draw" world.

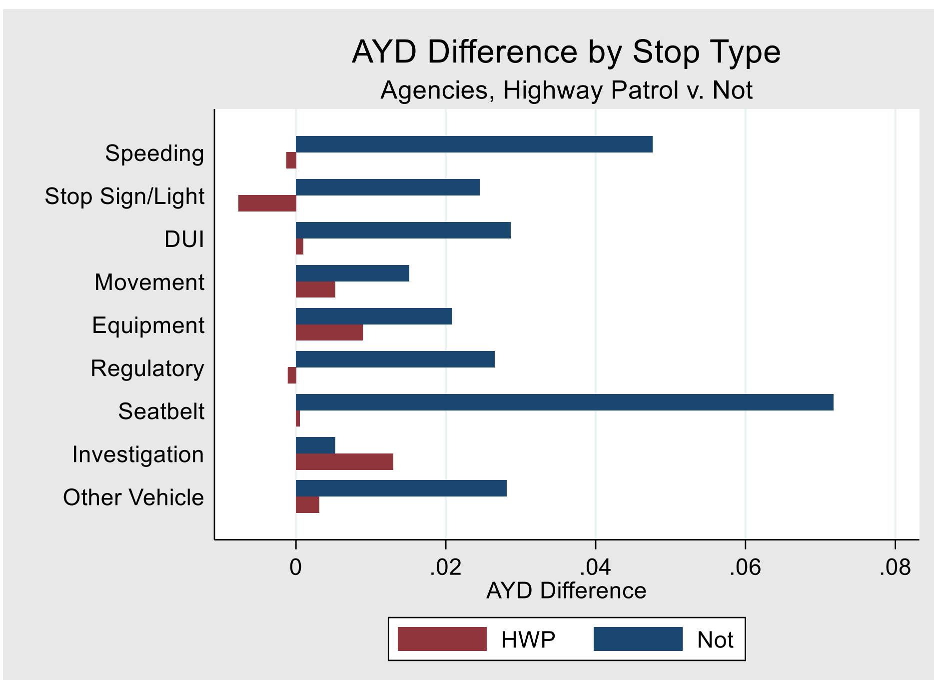

Figure 14

Notes: The figure displays the difference between average yearly delta (7) and the simulated AYD (8) by stop type, broken down into HWP and the average of all other departments. A differenced AYD of .1 indicates that average leniency changes by .1 more than simulated from random draws year-to-year on average. For more detailed information on AYD by stop type, vide figure 15 in appendices A-I.

I then apply the same analysis at the officer level, again averaging AYD within each stop type and subtracting the averaged, simulated, AYD. Doing so reveals that the average officer is more consistent year-by-year than one drawing at random. It also shows that, in most cases, the HWP is a more consistent group (figure 15). Speeding and seatbelt are once again the two largest differenced AYDs and DWI is the smallest, supporting hypothesis 5.

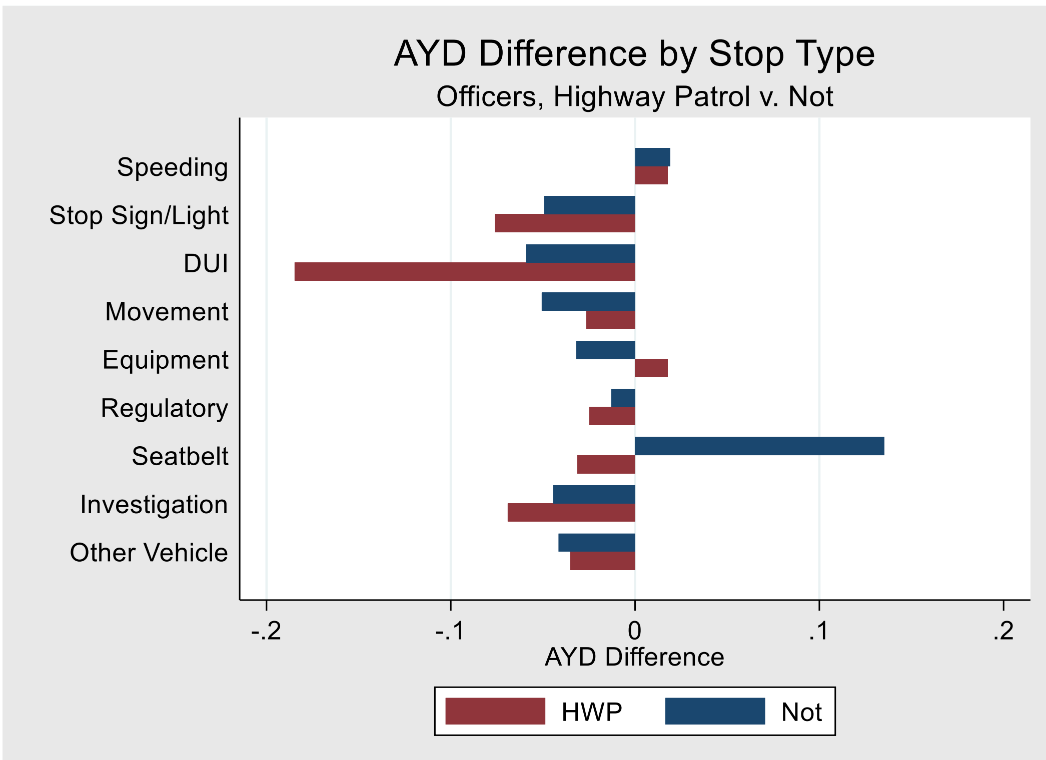

Figure 15

Notes: The figure displays the difference between average yearly delta (7) and the simulated AYD (8) for officers by stop type, broken down into officers in the HWP and the average of all other officers. A differenced AYD of .1 indicates that average leniency changes by .1 more than simulated from random draws year-to-year on average. For more detailed information on AYD by stop type, vide figure 16 in appendices A-I.

Next, I plot the AYD difference against the total number of stops within the department, a proxy for department size (e.g., figure A 15). I then construct a local polynomial regression for each stop type. Figure 16 displays the trend between AYD difference and total number of stops, reported in log terms, for two different stop types. At every level of stops, seatbelt violations have a higher AYD difference than DWI stops, lending even more support to H5. Figure 17 displays local polynomial regressions for all stop types plotted against the total number of stops. The propensity for downward trends amongst all stop types strongly supports H4, since larger departments are more consistent in their year-to-year leniency rates, even controlling for department size.

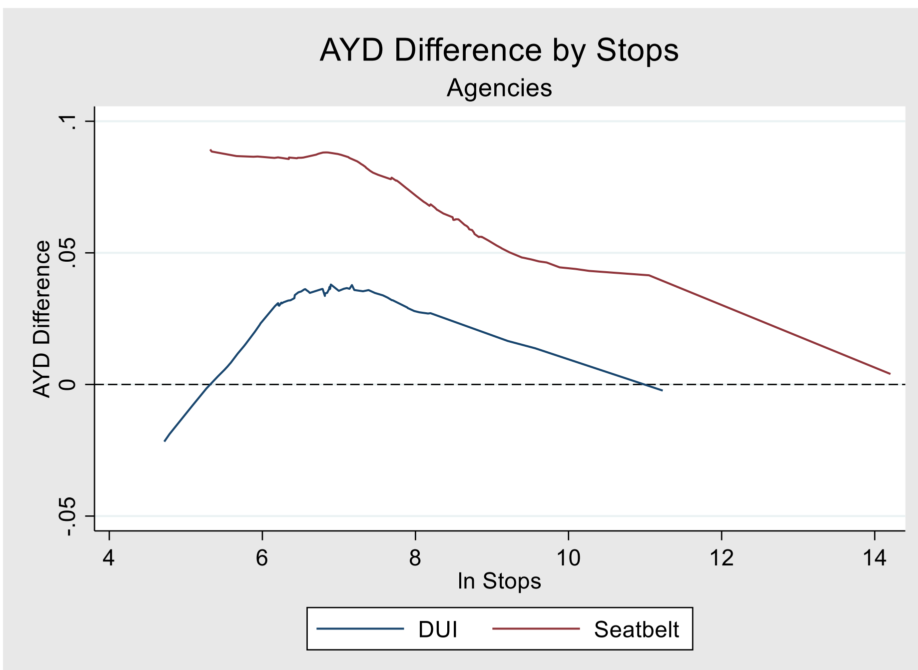

Figure 16

Notes: The figure displays the difference between average yearly delta (7) and the simulated AYD (8) for departments with different numbers of stops, reported in ln terms. Each point used to estimate the "lowess" regression represents a department, with a number of stops and an AYD difference. I include regression lines for both DWI and Seatbelt AYD differences. A 0 AYD difference indicates that the department at that number of stops is performing at a yearly variance equal to that simulated in (8).

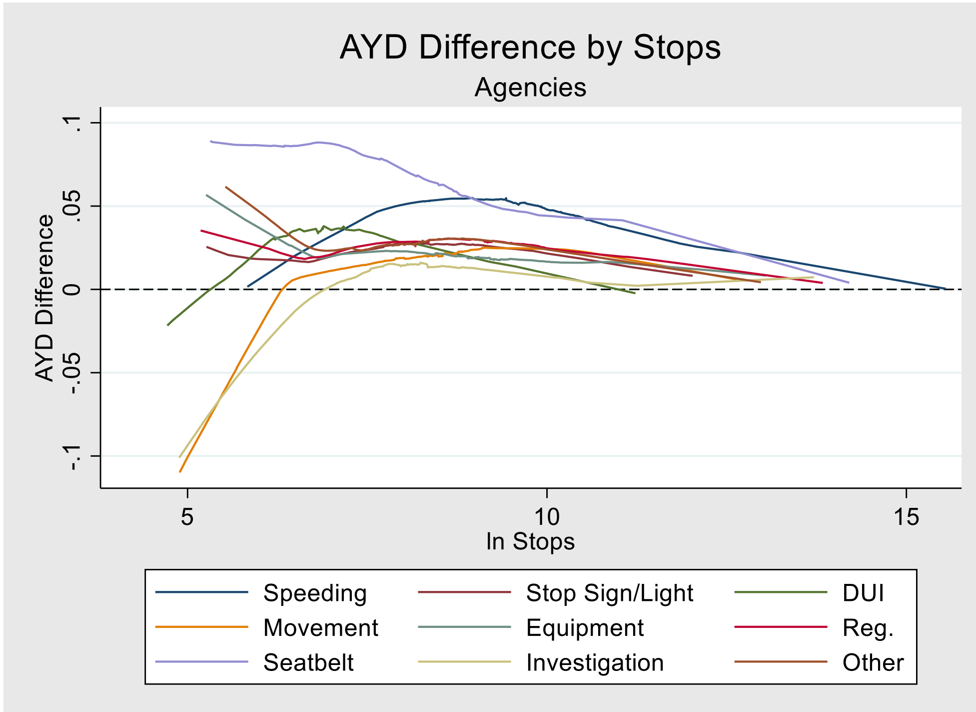

Figure 17

Notes: The figure displays the difference between average yearly delta (7) and the simulated AYD (8) for departments with different numbers of stops, reported in ln terms. Each point used to estimate the "lowess" regression represents a department, with a number of stops and an AYD difference. I include regression lines for all stop types. A 0 AYD difference indicates that the department at that number of stops is performing at a yearly variance equal to that simulated in (8).

Figure 18 is identical to 16 but applied to individual officers. It is clear here that officers are monotonically more consistent year-to-year in DWI stops than in seatbelts. Figure 19 reports all stop types. The lack of downward trend shows that it is department size, not total number of stops (which could be an indicator for experience) that leads to greater consistency. This resolves an alternative explanation for the trends observed in figure 14 and further supports H3.

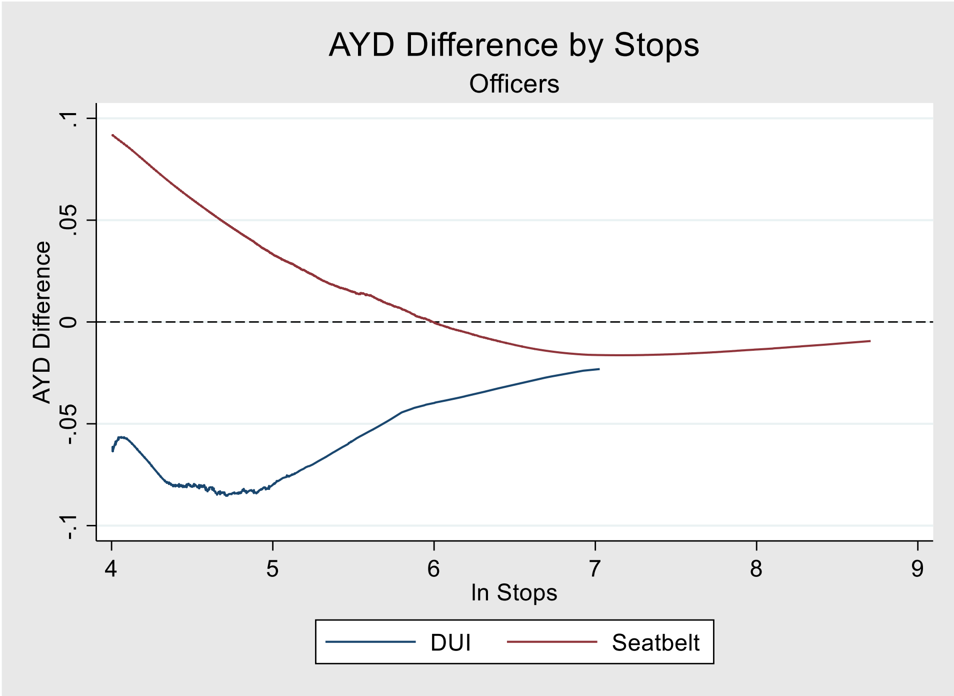

Figure 18

Notes: The figure displays the difference between average yearly delta (7) and the simulated AYD (8) for officers with different numbers of stops, reported in ln terms. Each point used to estimate the "lowess" regression represents a department, with a number of stops and an AYD difference. I include regression lines for both DWI and Seatbelt AYD differences. A 0 AYD difference indicates that the department at that number of stops is performing at a yearly variance equal to that simulated in (8).

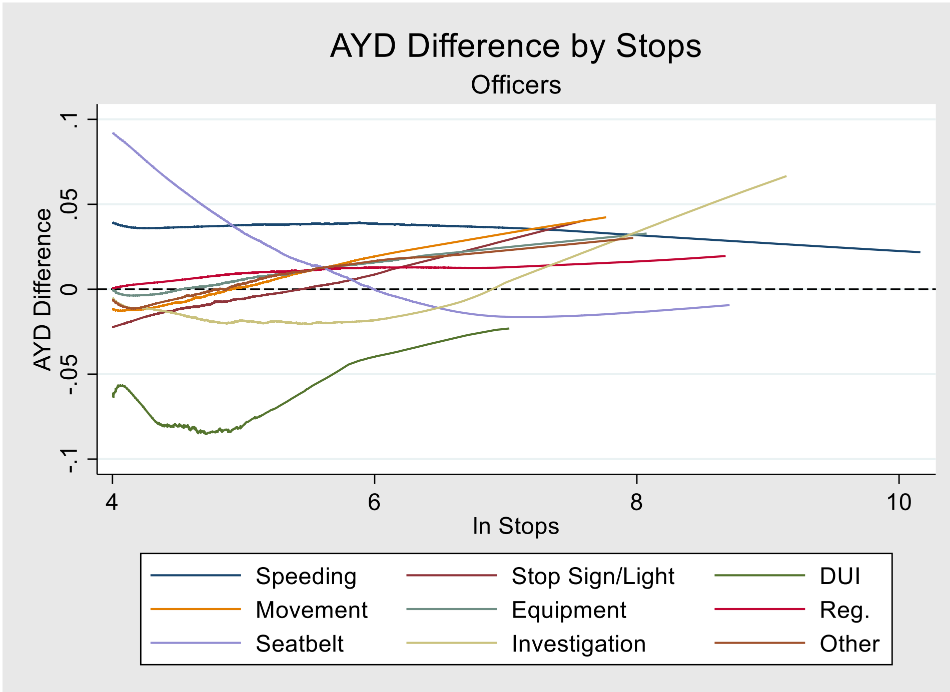

Figure 19

Notes: The figure displays the difference between average yearly delta (7) and the simulated AYD (8) for officers with different numbers of stops, reported in ln terms. Each point used to estimate the "lowess" regression represents a department, with a number of stops and an AYD difference. I include regression lines for all stop types. A 0 AYD difference indicates that the department at that number of stops is performing at a yearly variance equal to that simulated in (8).

IX. Conclusion

There is a high level of variance in the outcomes of NC traffic stop outcomes. Leniency rates vary widely across department and officer, but less within HWP. Going from one jurisdiction to another creates a major difference in expected outcome of a traffic stop, and officers are far from following the law algorithmically, evincing H1 and H3. There is a slight negative correlation between years on the force and leniency, controlling for several relevant factors. Leniency is affected by race, gender, and age of the driver, and the correlation is strong in all settings and has a large impact in some. The day of week, time of day, and year all have strong correlations with leniency but seem to account for little of the observed variance when controlling for other inputs (similar to the results from the Israeli parole boards). Wednesdays and Thursdays, recent years, and late evenings correlate with the most leniency, all else being equal. The trend in leniency rates over time is steadily increasing across the different stop purposes. The trend is less pronounced among the HWP.

Through the variance attribution approach, this study confirms that department and especially officer fixed effects are very impactful in predicting the variance in leniency outcomes. While identity factors certainly matter, they are not as impactful in accounting for variance as the other inputs. Additionally, the amount of variance explained by officer discretion is commensurate with a simulated discretion rate between 35% and 40% of the leniency decision.

Finally, through the use of AYD and simulated AYD techniques, it is clear that crimes with lower potential penalties like seatbelt violations have a much higher level of variance, even controlling for expectations based on the law of large numbers (H5). The highway patrol outperforms "random draw" simulations both as a department and on an individual level whereas the average police department and officer do not. Finally, larger departments are closer to meeting their AYD expectations than are smaller ones, across all stop types (H4). The same is not true for officers with more arrests. Department size is negatively correlated with variance in leniency, while total number of stops does not.

The theory and methodologies developed for this study can be applied easily to other contexts. AYD and variance attribution scores could be used to assess to a wide variety of bureaucrats. Even within policing, this analysis falls short of investigating variance in search and arrest rates, or any police action outside of traffic stops. These tools and the theoretical model they assess could be applied to judicial decisions, school administrators, welfare distributors, among a plethora of other bureaucrats. The final confirmation of Kaufman's premise would be a ranking of different types of bureaucrats' discretion via a single method, such as those presented here.

The lack of consistency indicates that police officers are high-discretion bureaucrats in general, though there is variation within the profession and across the law being enforced. This implies that their preferences, including bias based on identities, but also a wide array of other extraneous personal inputs, enter what one might expect to be a consistent process defined by law. In the arena of NC traffic stops, the concept of the "Rule of Law" is subsumed by the rule *through* law. In an environment where trust in the legitimacy of the criminal justice system and other institutions is at a premium, a roll of the dice is a costly way to determine the outcome of even a traffic stop.

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Appendix A: Stop Signs and Stop Lights

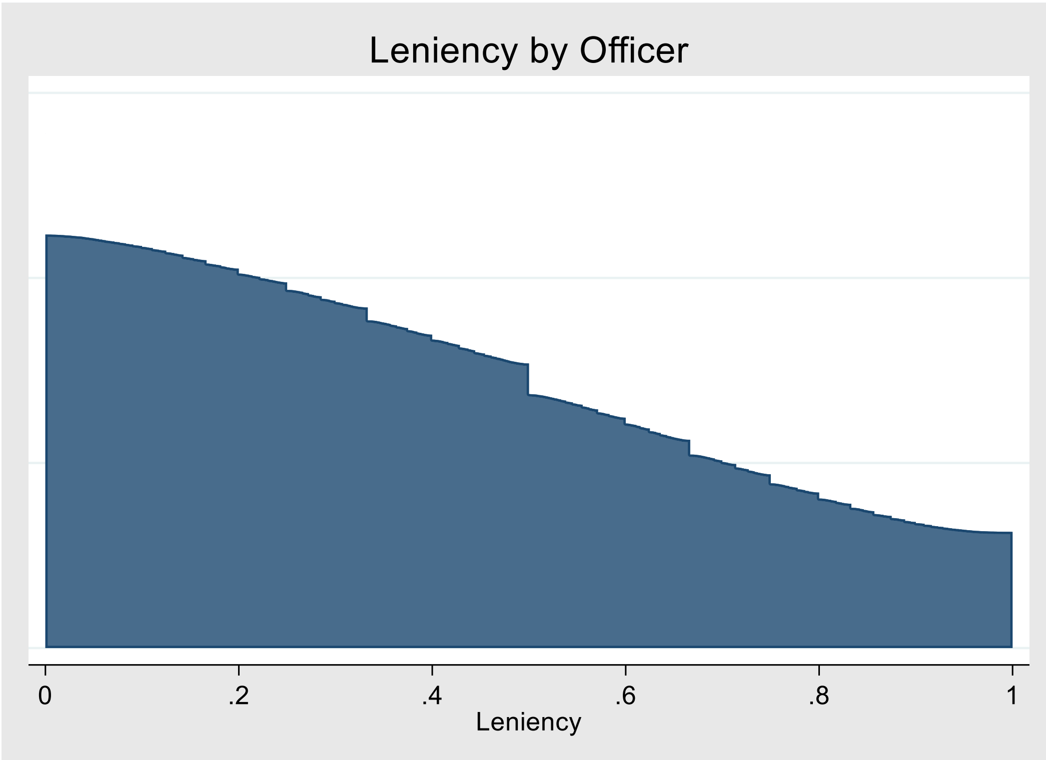


Figure A 1

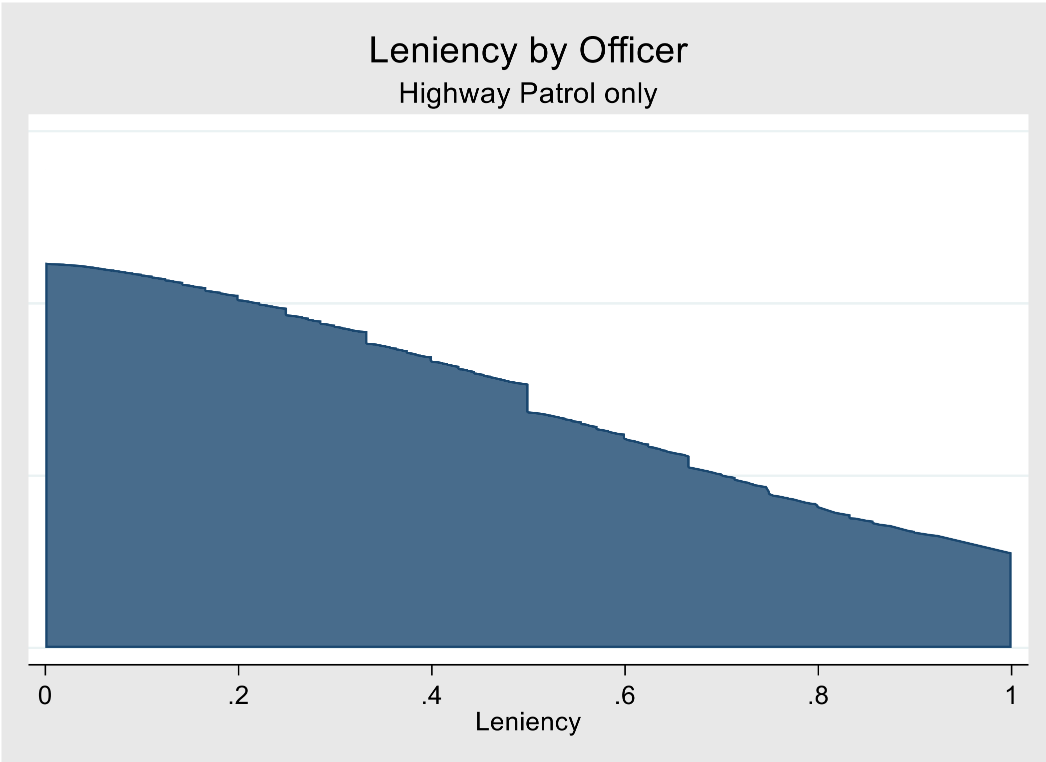


Figure A 2

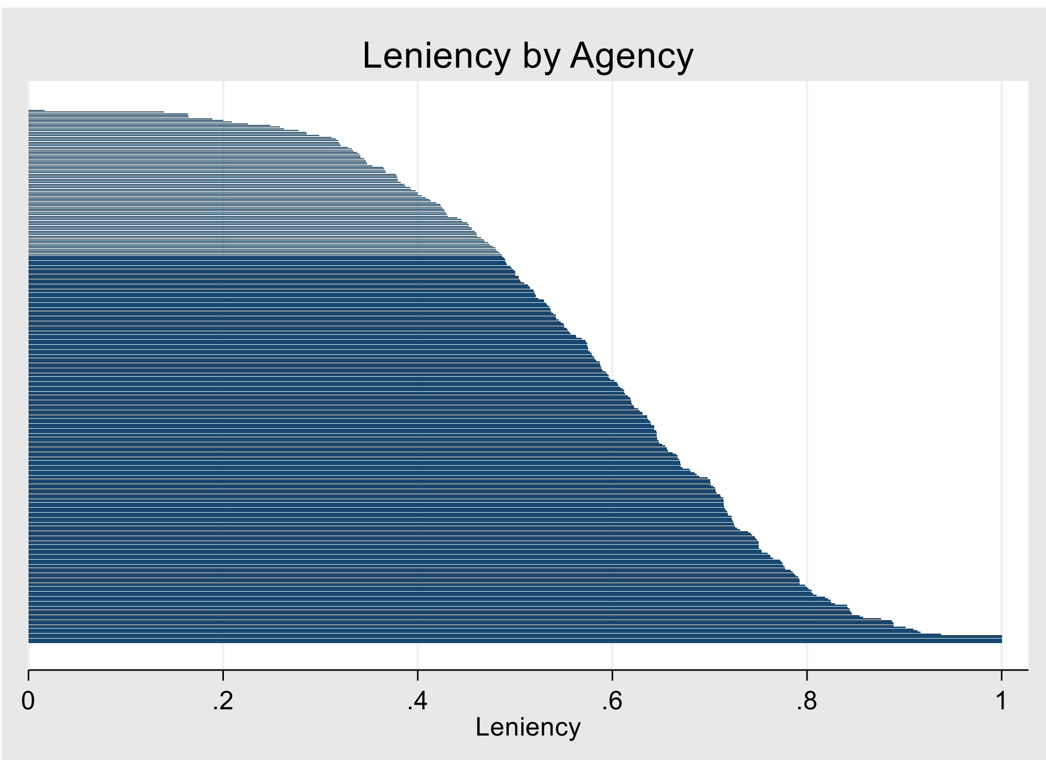


Figure A 3

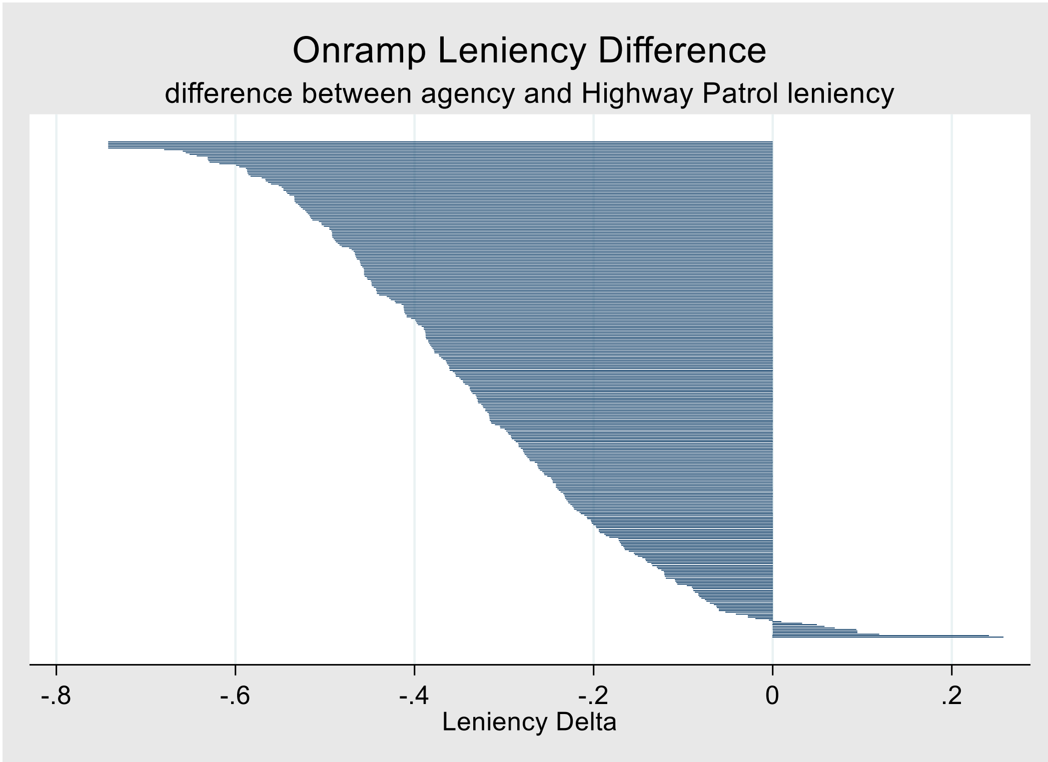


Figure A 4

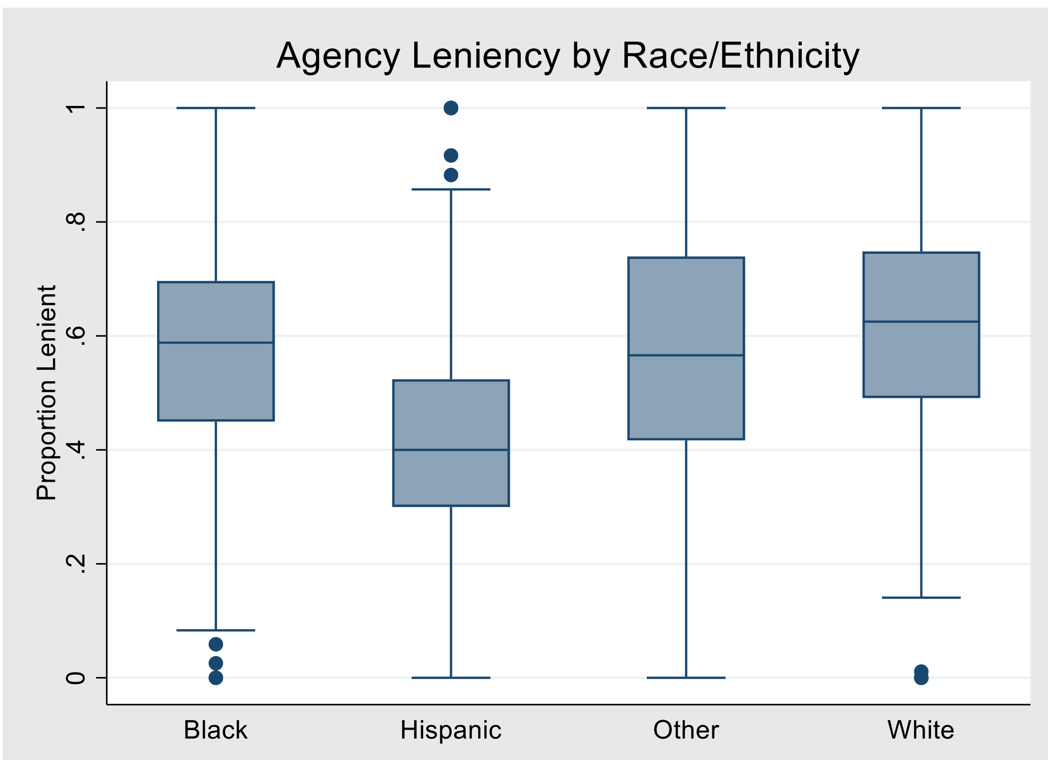


Figure A 5

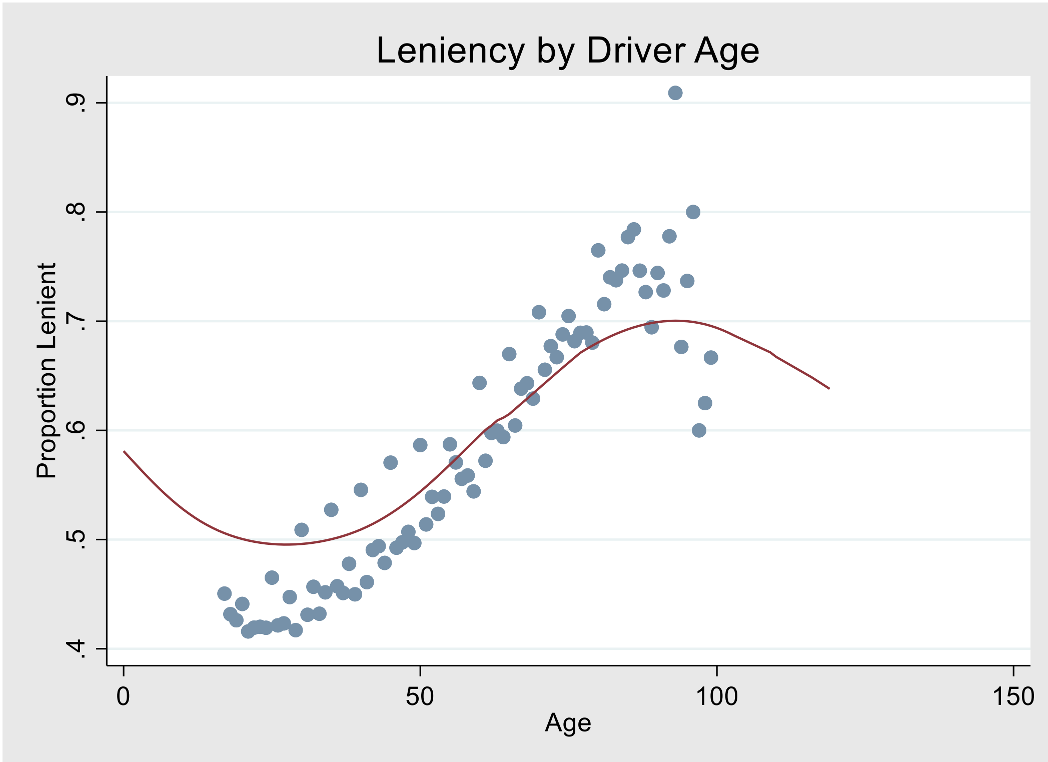


Figure A 6

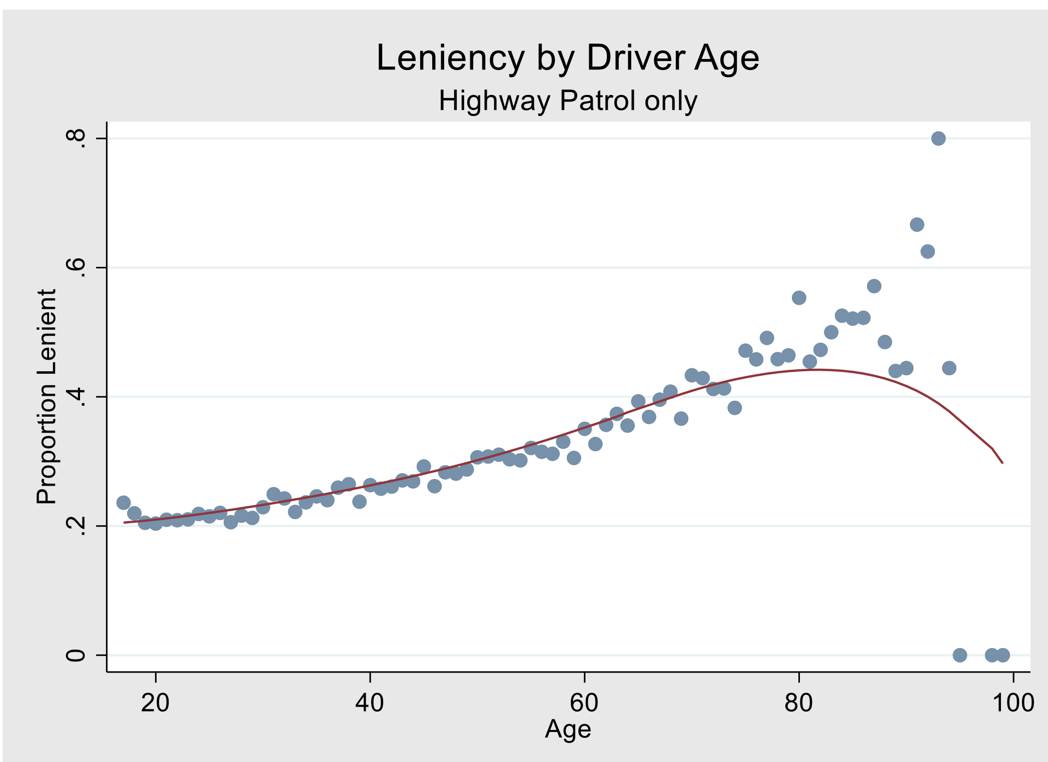


Figure A 7

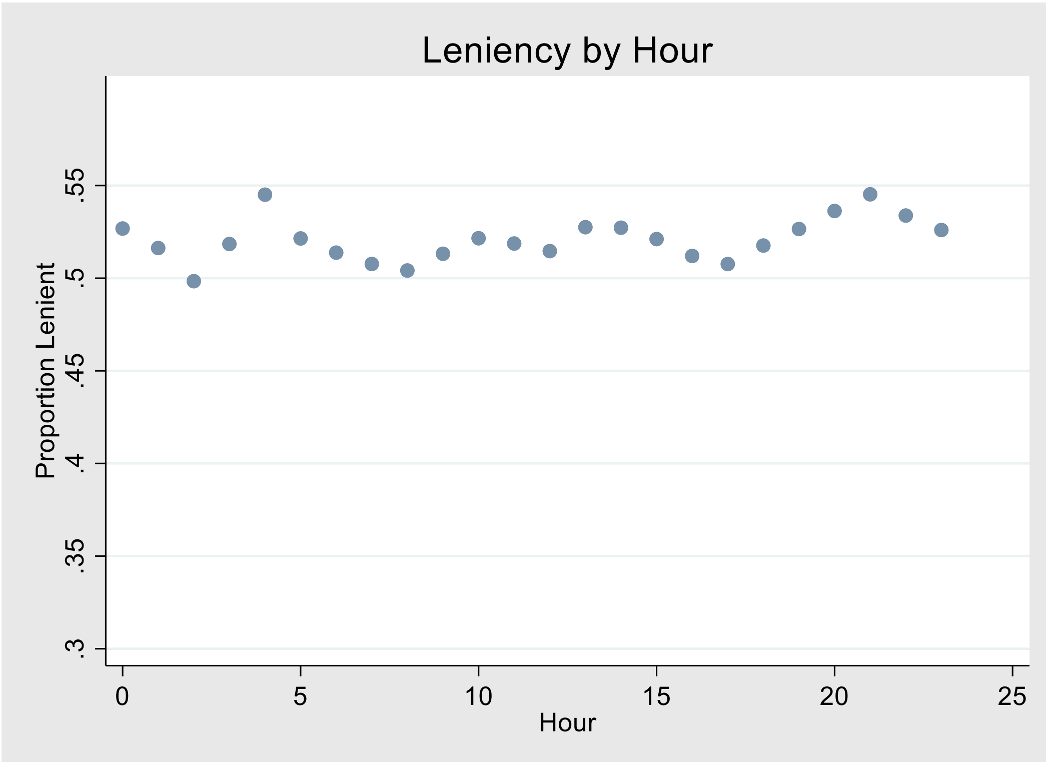


Figure A 8

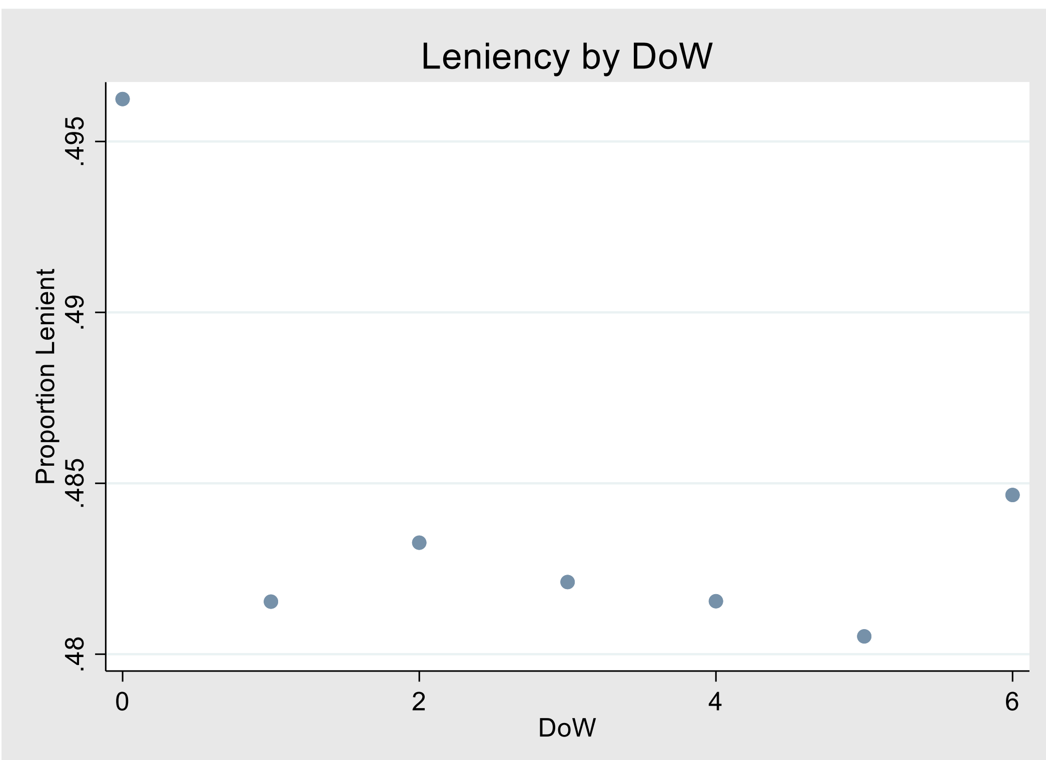


Figure A 9

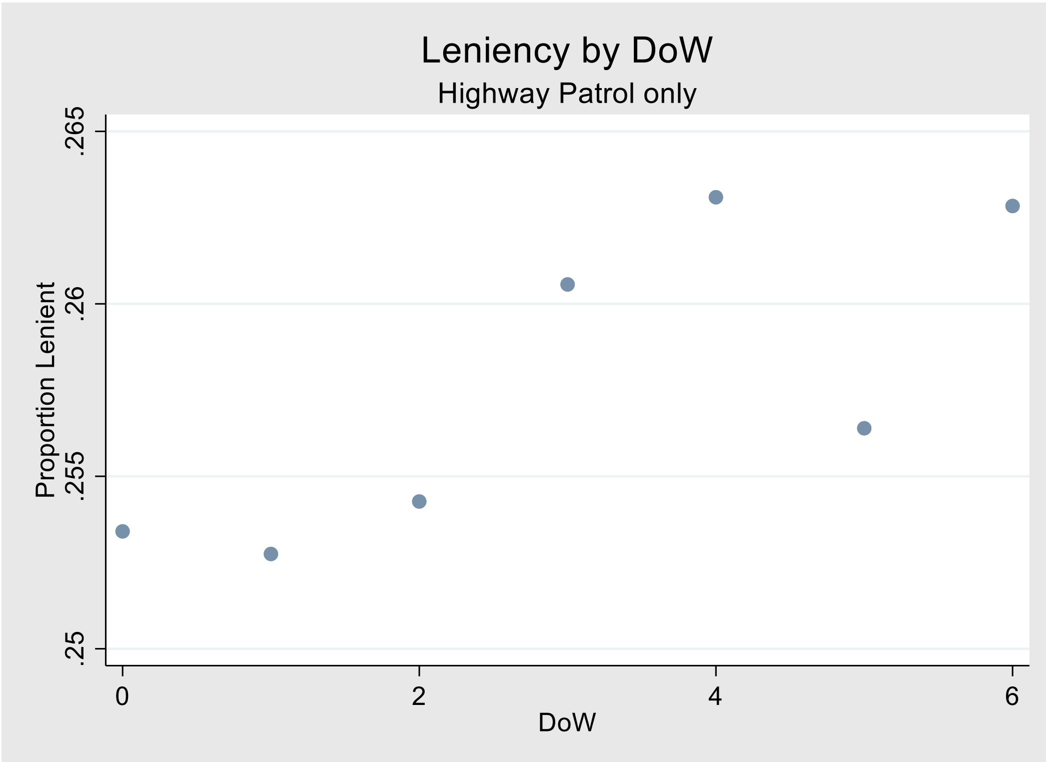


Figure A 10

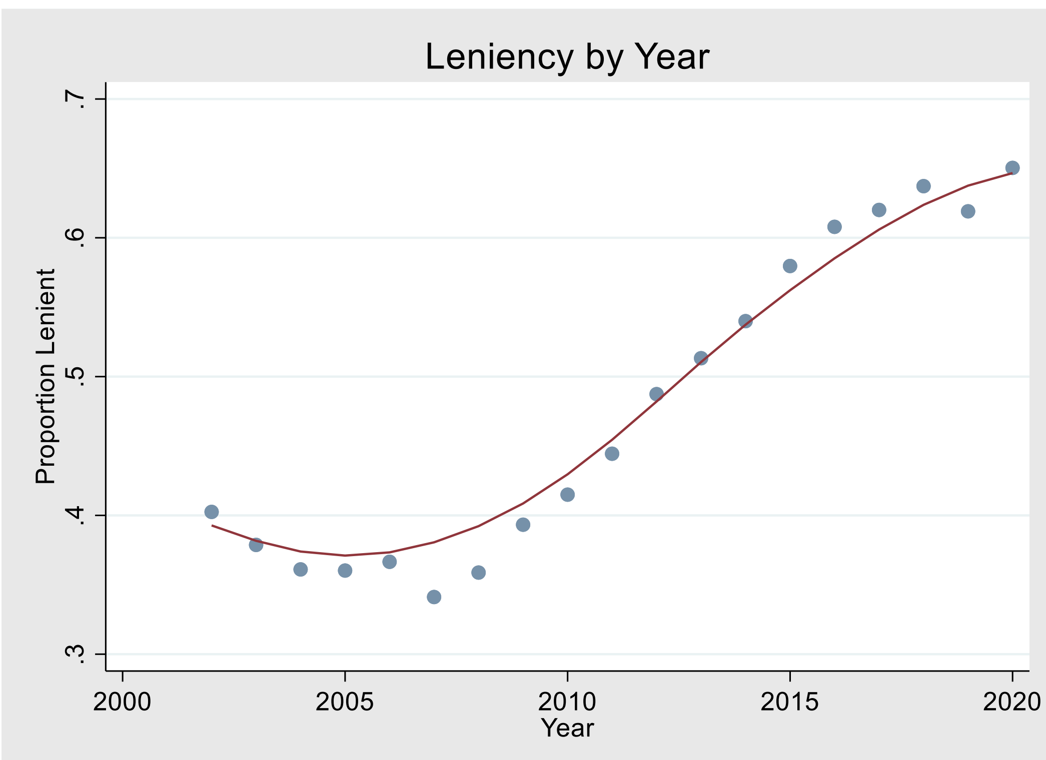


Figure A 11

VARIABLES	Stop Reason Stop Sign/Light
years = 2	0.106
years = 3	0.231***
years = 4	0.132
years = 5	0.398***
years = 6	0.0413
years = 7	0.0868
years = 8	0.179*
years = 9	-0.100
years = 10	-0.0875
years = 11	-0.136
years = 12	0.0479
years = 13	0.0855
years = 14	-0.0405
years = 15	-0.123
years = 16	-0.170*
years = 17	0.256**
years = 18	0.220**
years = 19	0.138
years = 20	-0.284**
years = 21	-0.106
years = 22	0.330**
years = 23	0.250**
years = 24	-0.190
years = 25	-0.0377
years = 26	0.0645
years = 27	-0.00204
years = 28	-0.00422
years = 29	-0.0215
years = 30	0.446
years = 35, omitted	-
Driver_Age	0.00408
CMPD_Division = 2, Eastway Division	-0.171**
CMPD_Division = 3, Freedom Division	-0.160
CMPD_Division = 4, Hickory Grove Division	0.0701
CMPD_Division = 5, Independence Division	0.0292
CMPD_Division = 6, Metro Division	-0.192**
CMPD_Division = 7, North Division	0.0817
CMPD_Division = 8, North Tryon Division	0.0794

CMPD_Division = 9, Providence Division	0.229***
CMPD_Division = 10, South Division	0.279***
CMPD_Division = 11, Steele Creek Division	-0.256***
CMPD_Division = 12, University City Division	-0.358***
CMPD_Division = 13, Westover Division	-0.00788
Officer_Race = 2, omitted	-
Officer_Race = 3, American Indian/Alaska Native	-0.116
Officer_Race = 4, Asian / Pacific Islander	-0.606**
Officer_Race = 5, Black/African American	-0.384
Officer_Race = 6, Hispanic/Latino	-0.327
Officer_Race = 8, Not Specified	-0.231
Officer_Race = 9, White	-0.183
driver_age_sqr	7.12e-05
Driver_Gender	-0.153***
Officer_Gender	0.106**
Driver_Race = 2, Black	-0.0524
Driver_Race = 3, Native American	-0.321
Driver_Race = 4, Other/Unknown	-0.163
Driver_Race = 5, White	-0.0586
Constant	0.630*
Observations	8,965

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure A 12

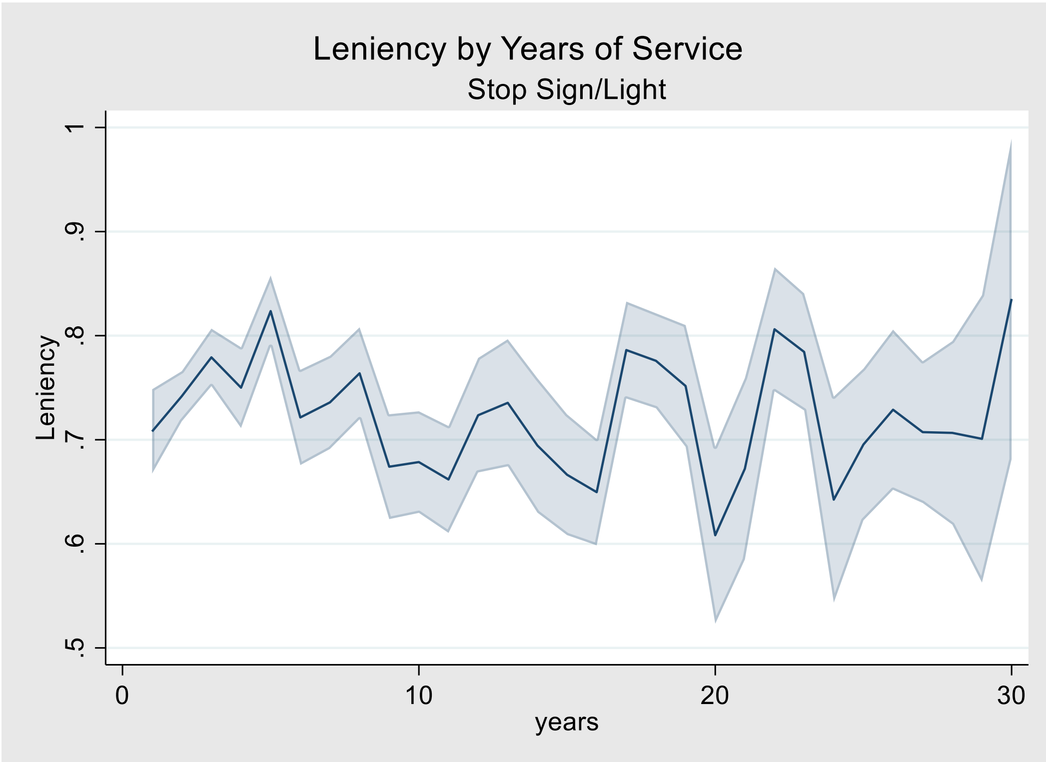


Figure A 13

	No Officer			Officer		
	Total	Change	% Change	Total	Change	% Change
Saturated	0.103	0	0	0.297	0	0
Identity	0.086	0.017	16.505	0.279	0.018	6.061
Year	0.077	0.026	25.243	0.28	0.017	5.724
Month	0.103	0	0	0.297	0	0
Day	0.103	0	0	0.297	0	0
Hour	0.101	0.002	1.942	0.295	0.002	0.673
Department	0.06	0.043	41.748	N/A		
Officer	N/A			0.159	0.138	46.465

Stops Cutoff: 300

Figure A 14

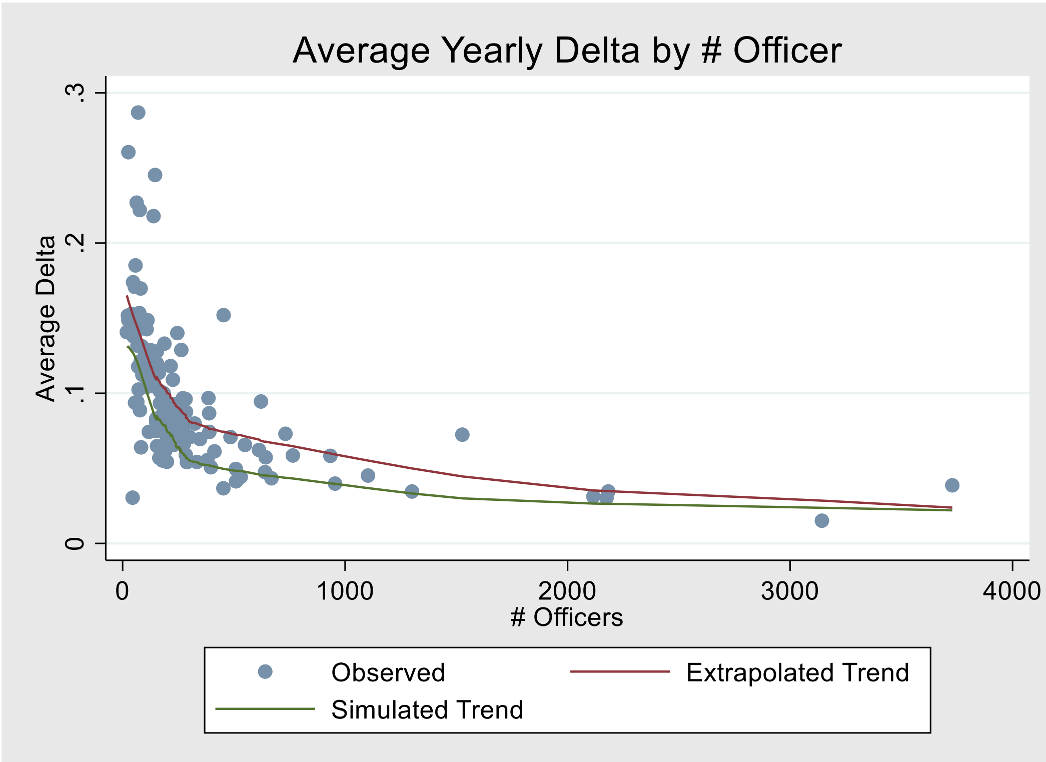


Figure A 15

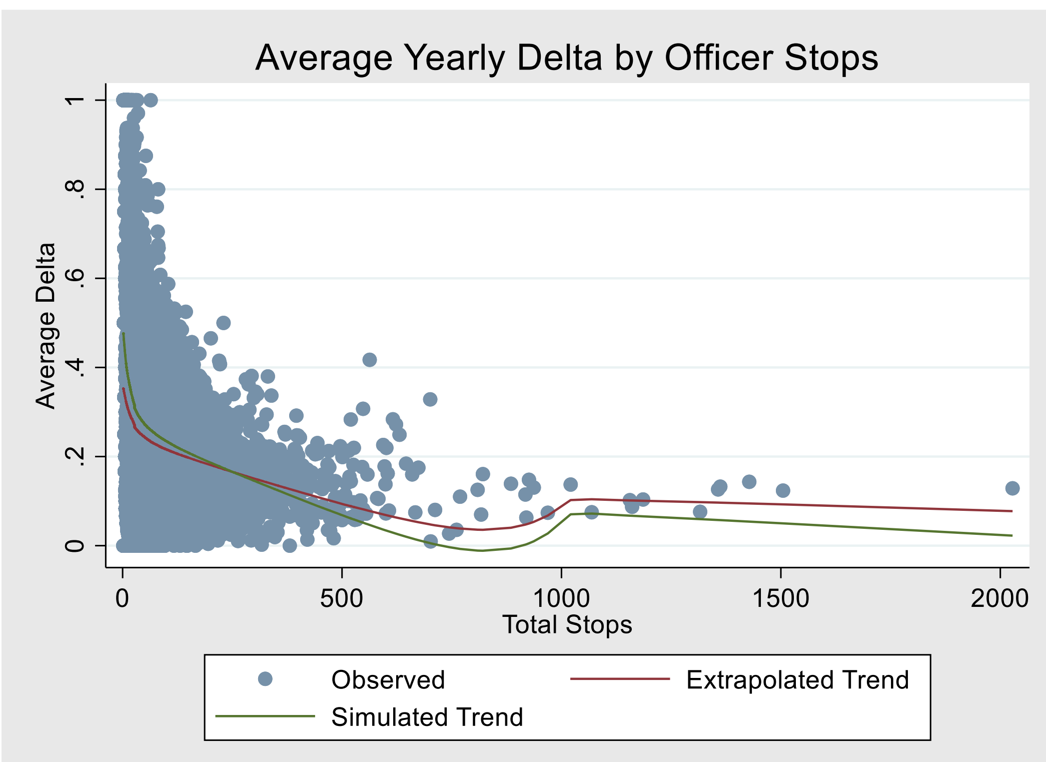


Figure A 16

Appendix B: Driving While Intoxicated

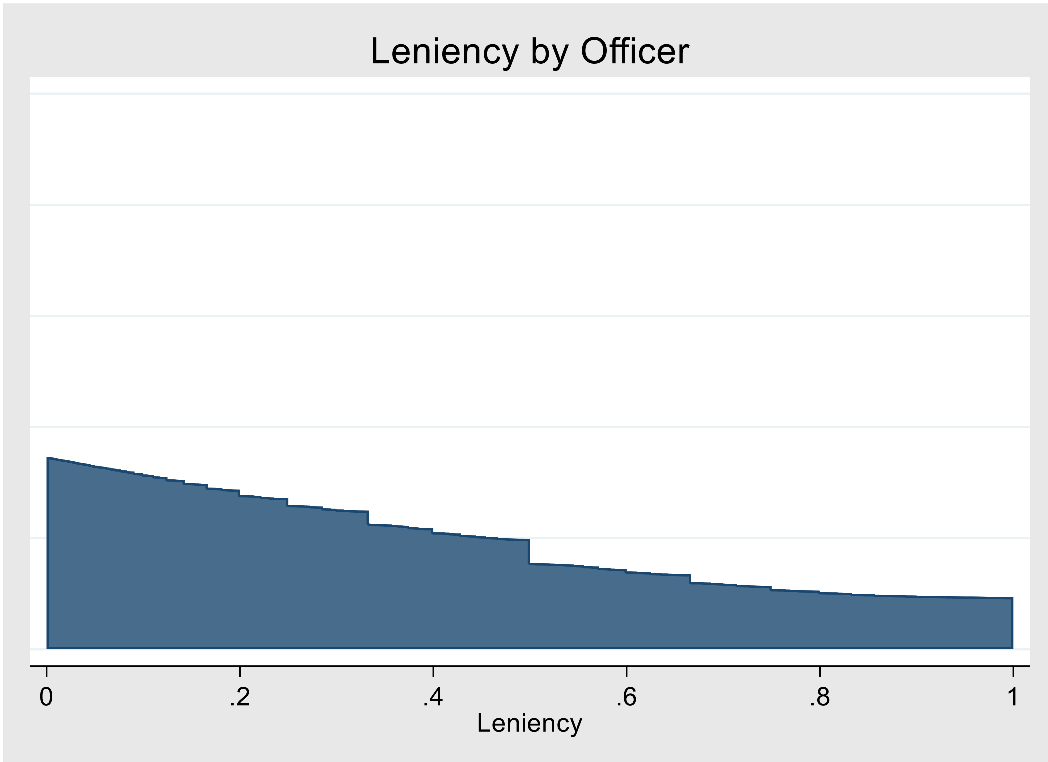


Figure B 1

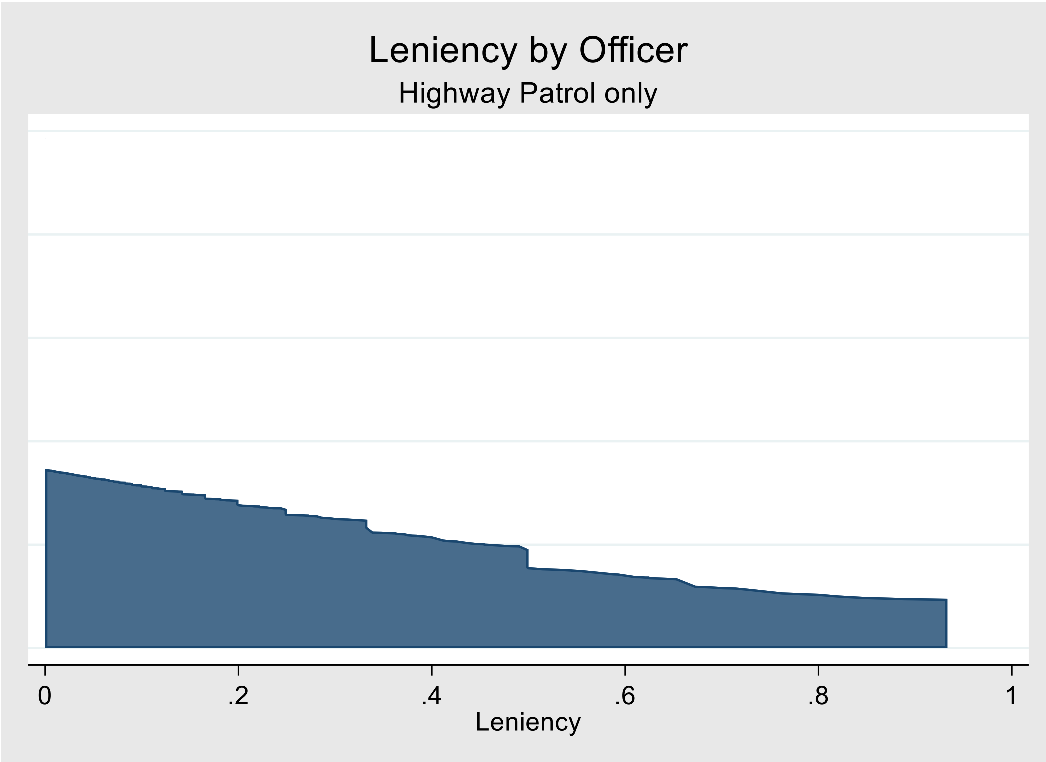


Figure B 2

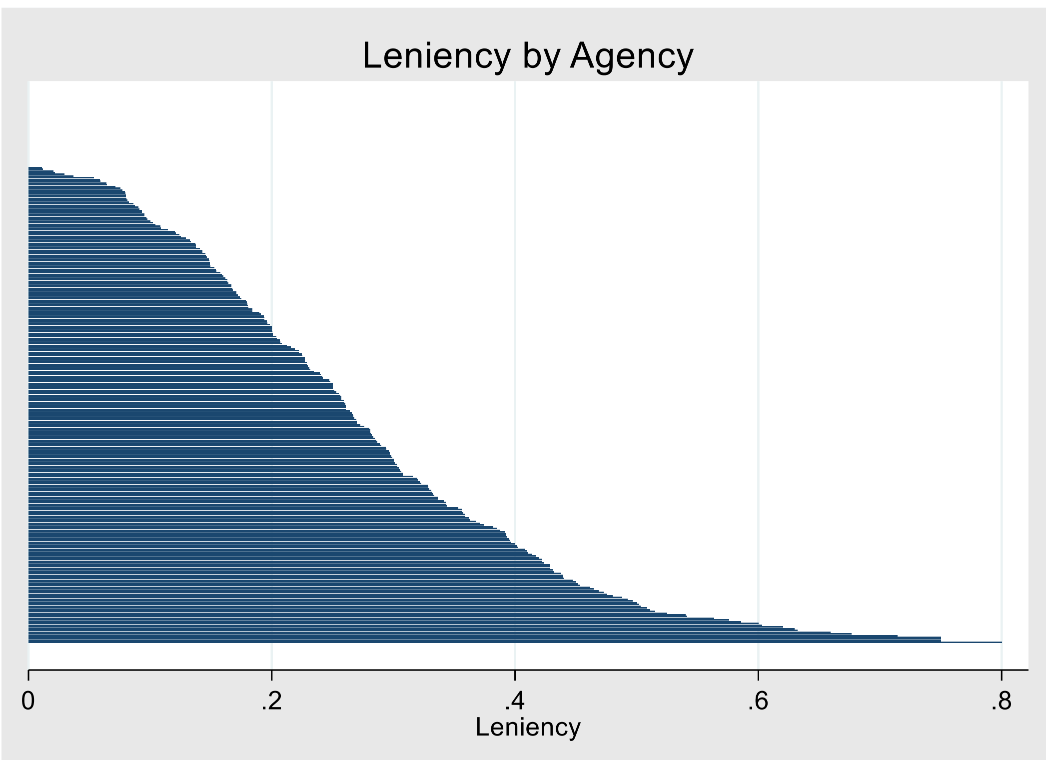


Figure B 3

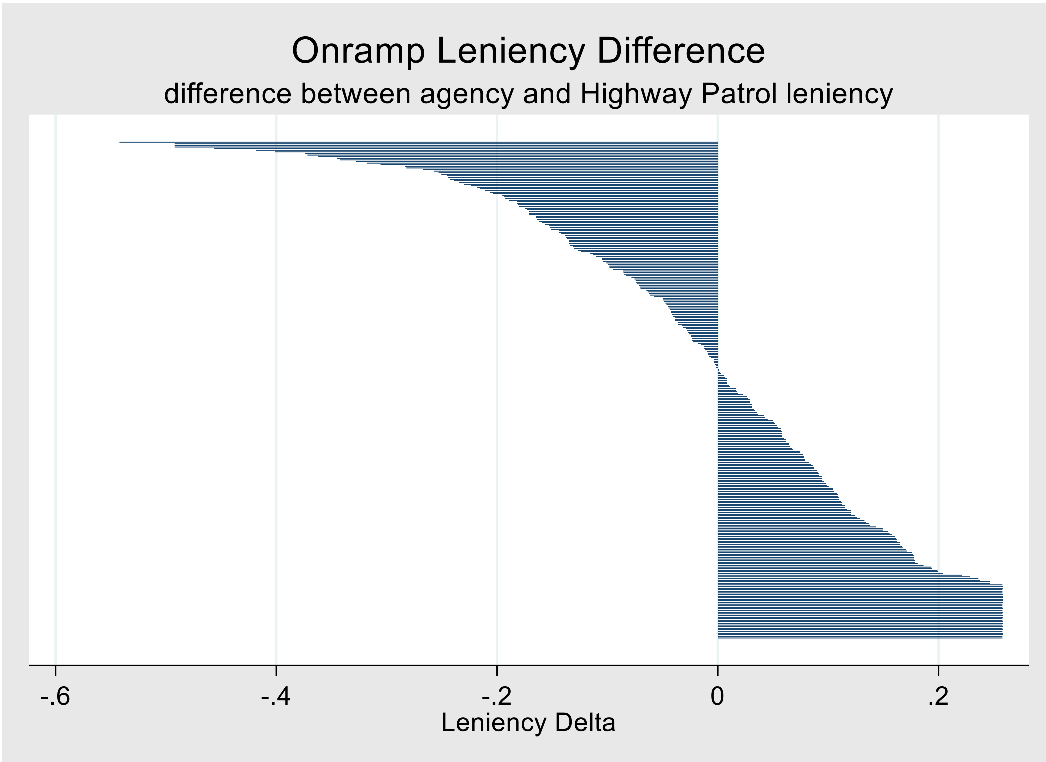


Figure B 4

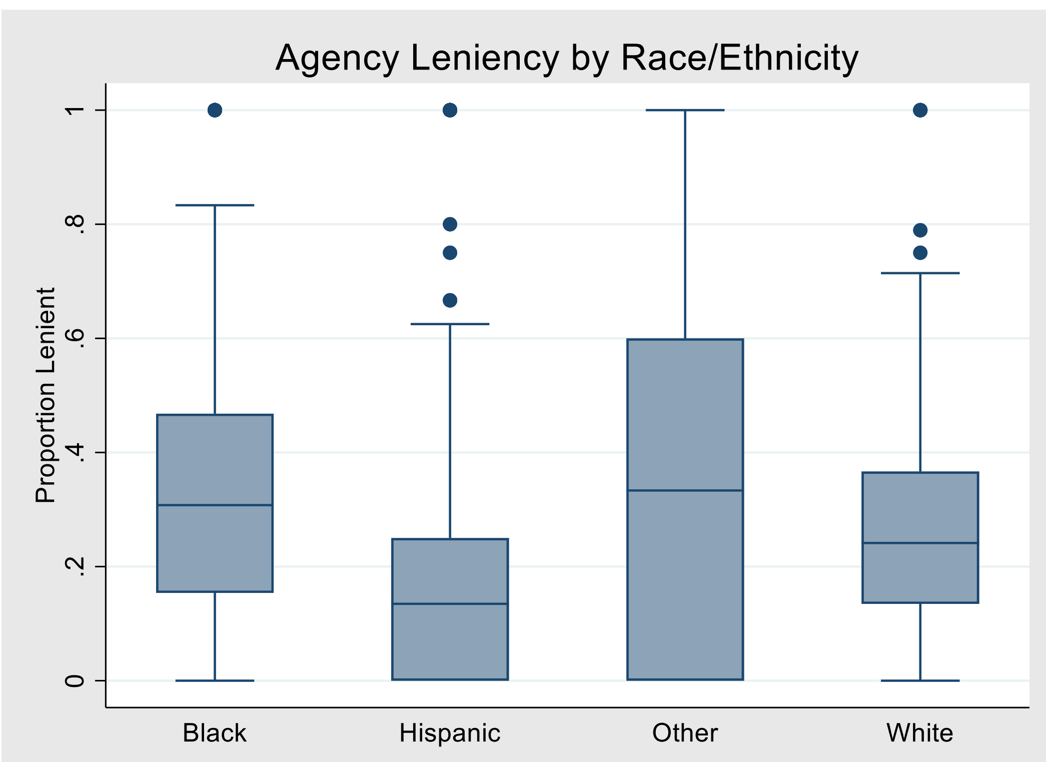


Figure B 5

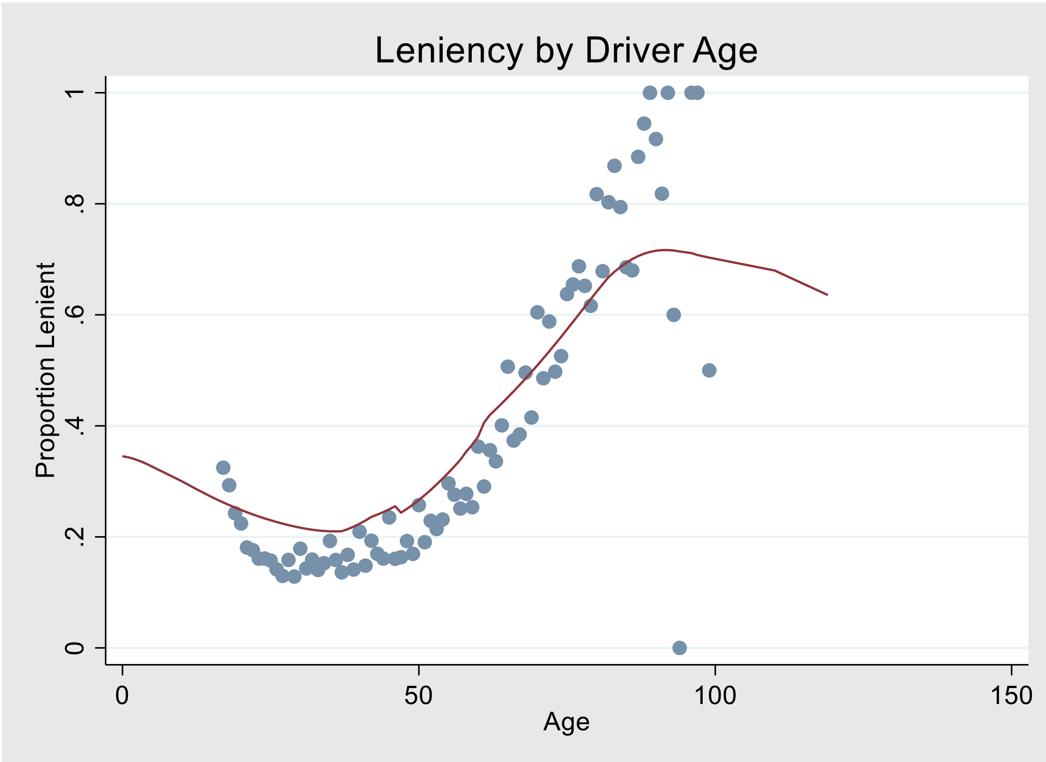
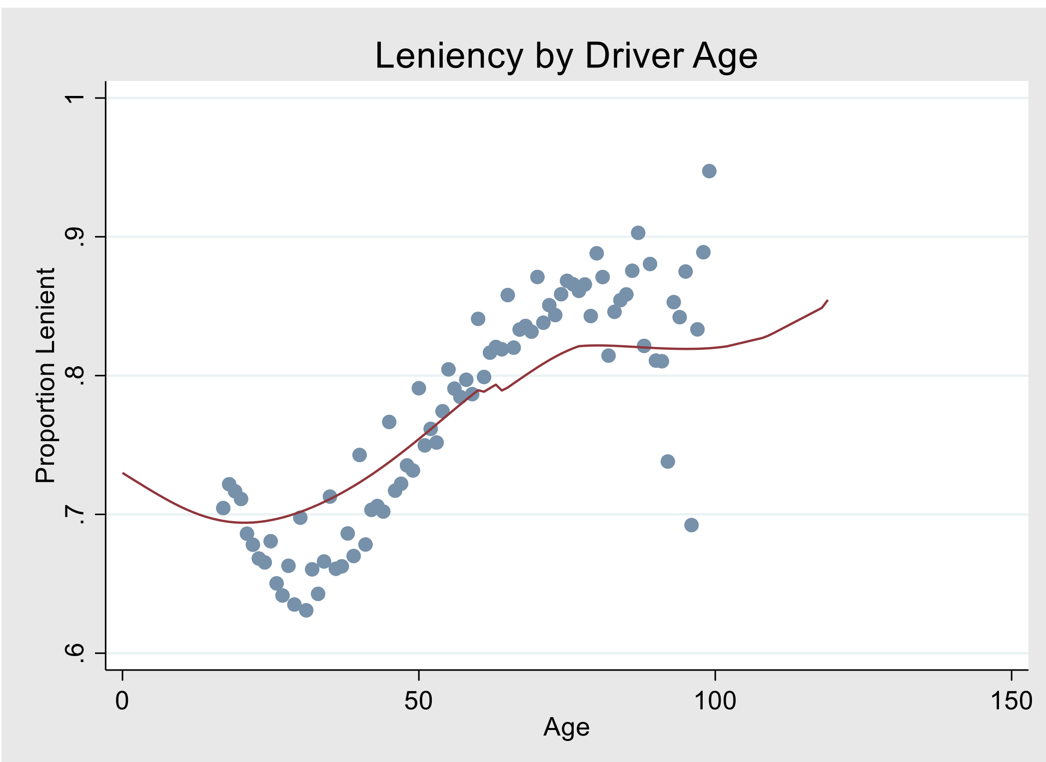

Leniency by Driver Age
Proportion Lenient
0
.2
.4
.6
.8
1
0
50
100
150
Age

Figure B 6


Leniency by Driver Age
Proportion Lenient
.6
.7
.8
.9
1
0
50
100
150
Age

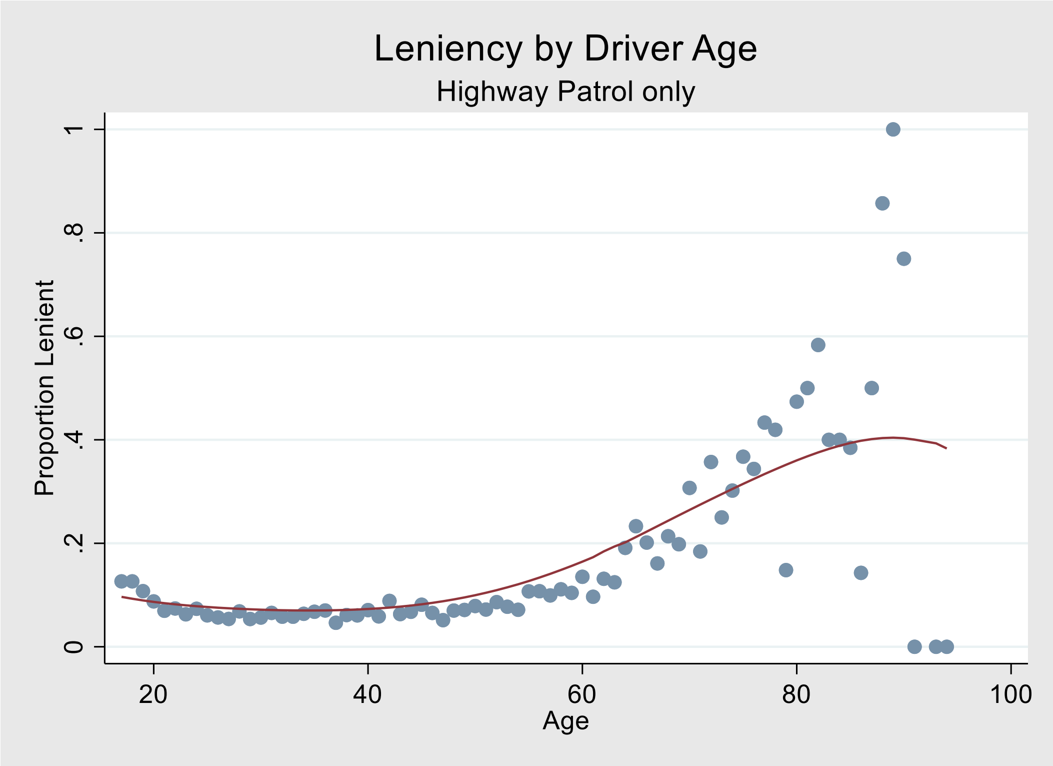


Figure B 7

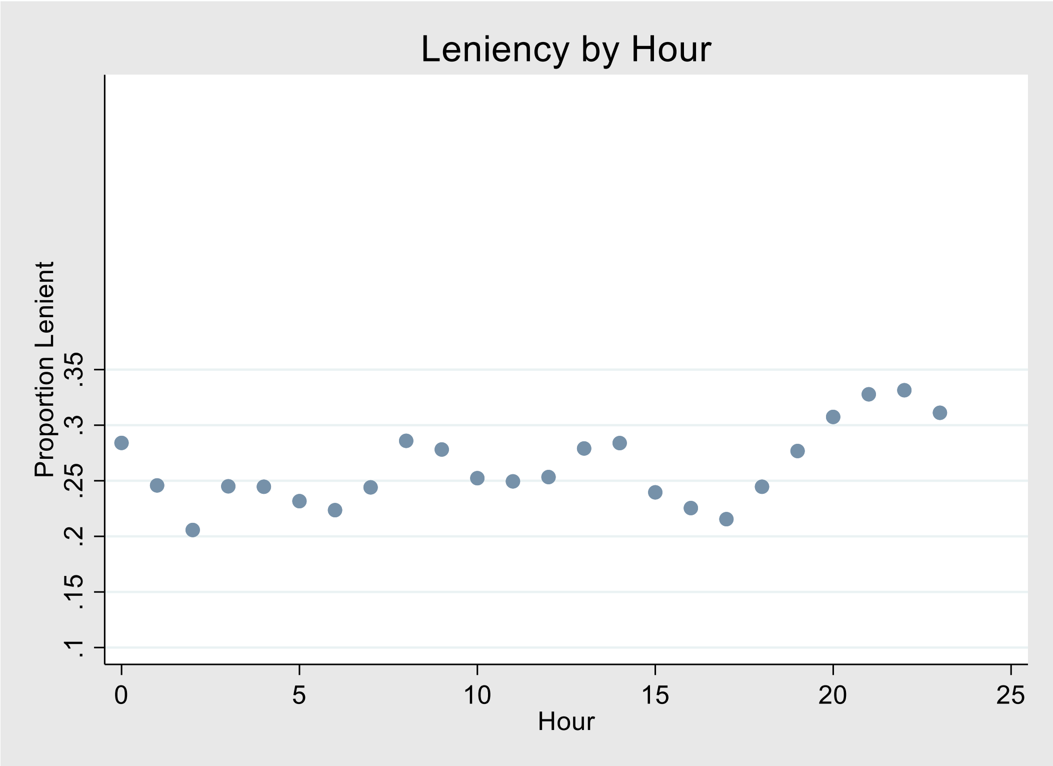


Figure B 8

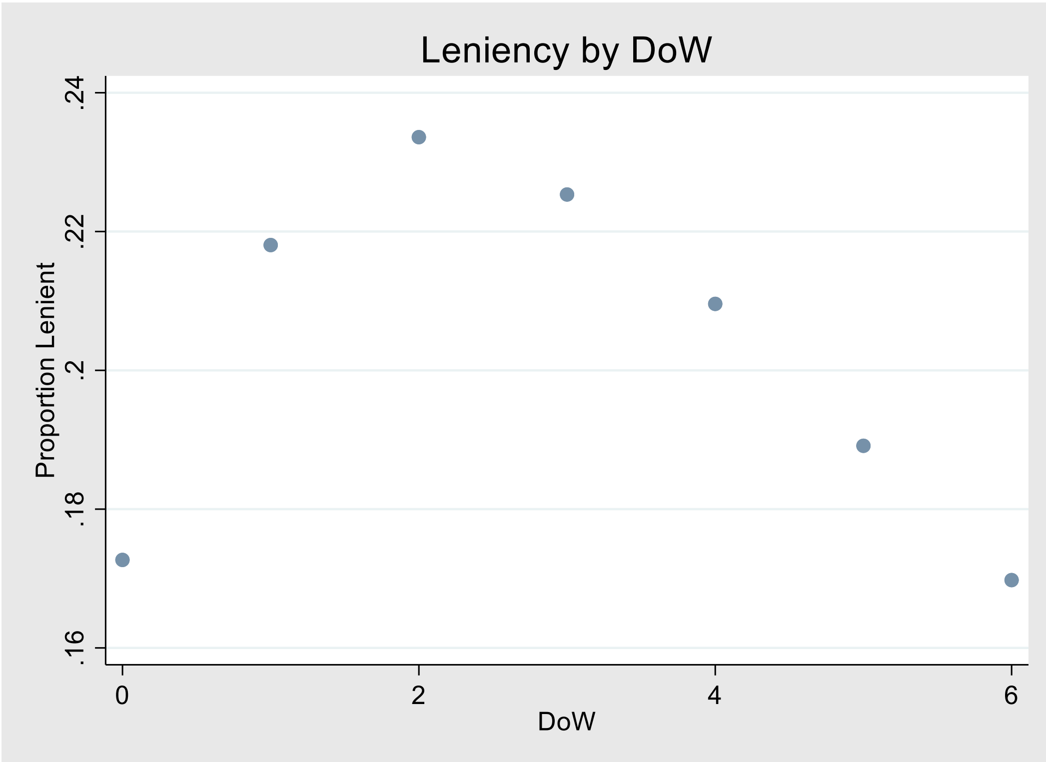


Figure B 9

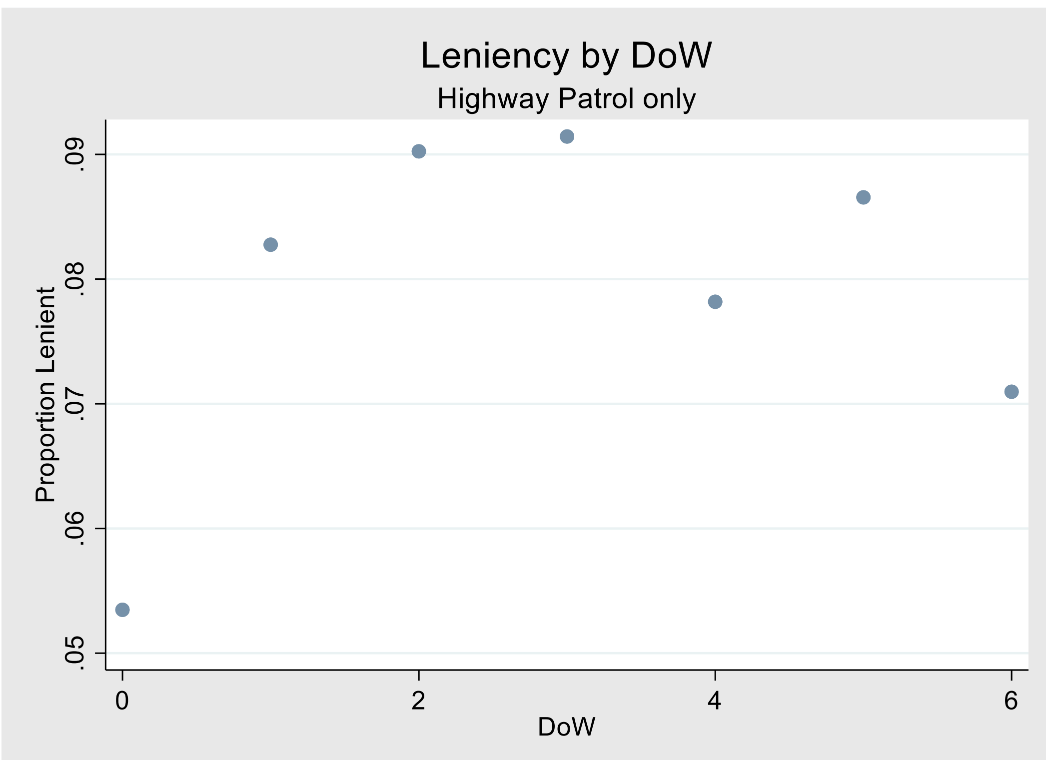


Figure B 10

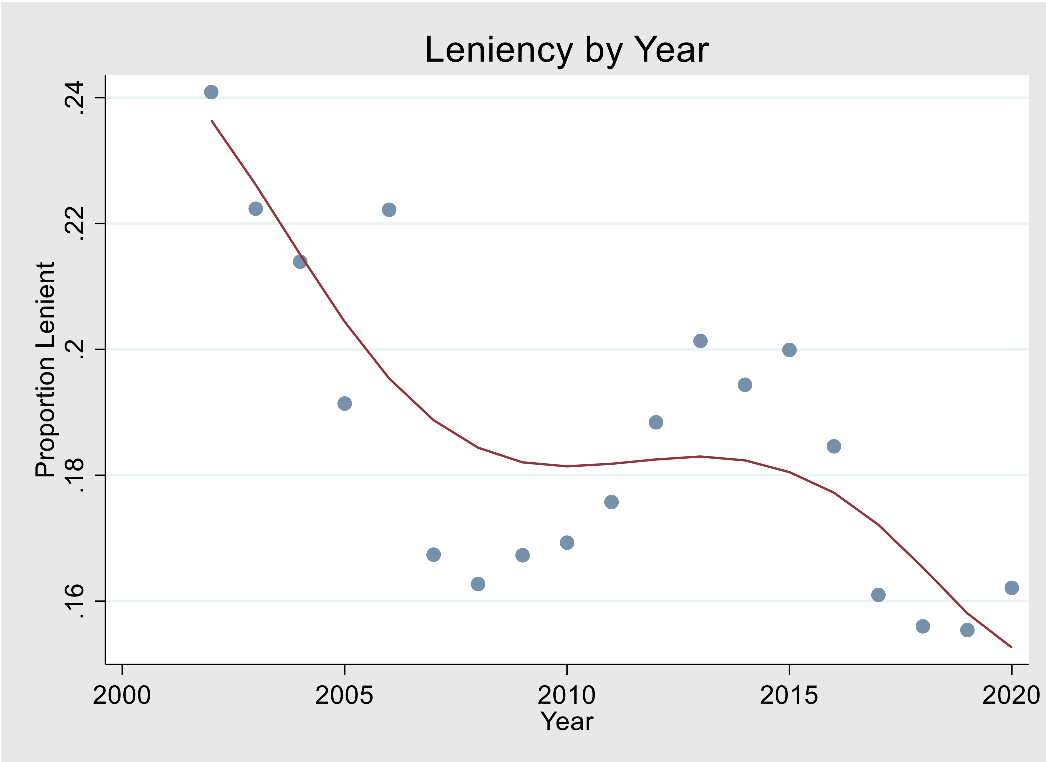


Figure B 11

VARIABLES	Stop Reason DWI
years = 2	-0.405
years = 3	-0.848
years = 4	-0.737
years = 5	-0.385
years = 6, omitted	-
years = 7, omitted	-
years = 8	-0.969
years = 10, omitted	-
years = 11, omitted	-
years = 12, omitted	-
years = 14, omitted	-
years = 15, omitted	-
years = 16, omitted	-
years = 18, omitted	-
years = 19, omitted	-
years = 20, omitted	-
years = 21	0.133
years = 22	0.522

years = 23	0.498
years = 27, omitted	-
Driver_Age	-0.00855
driver_age_sqr	0.000110
Driver_Gender	-0.425
Officer_Gender	-0.559
Constant	1.764
Observations	57

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure B 12

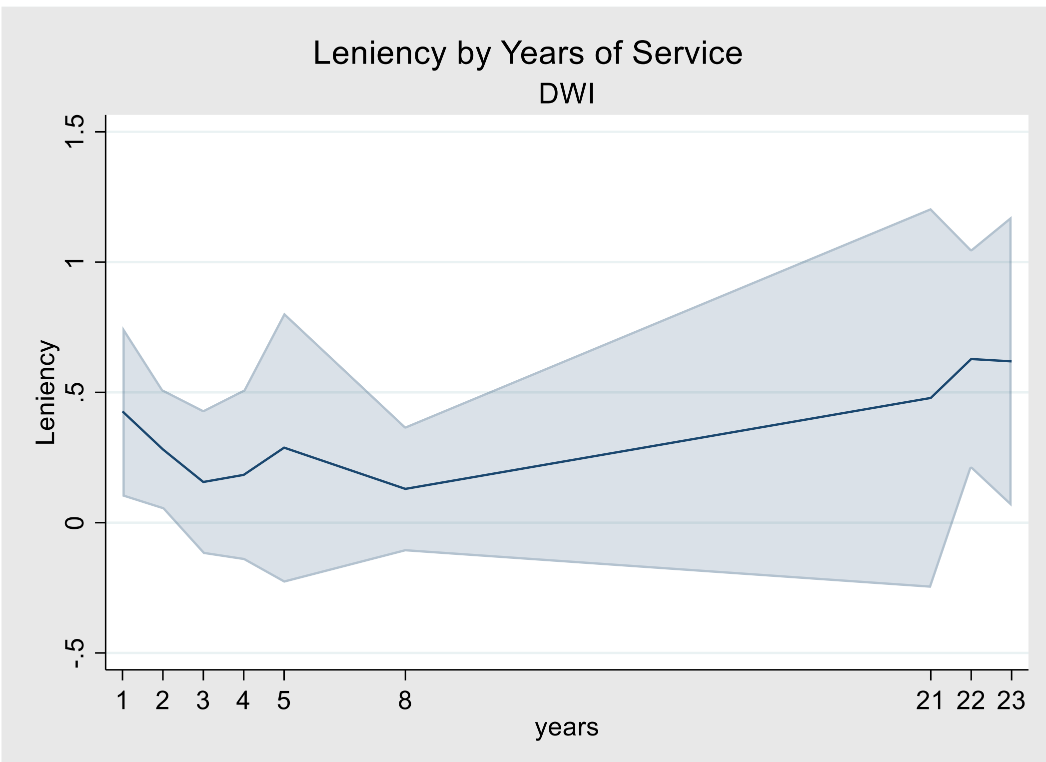


Figure B 13

	No Officer			Officer		
	Total	Change	% Change	Total	Change	% Change
Saturated	0.156	0	0	0.491	0	0
Identity	0.114	0.042	26.923	0.476	0.015	3.055
Year	0.152	0.004	2.564	0.48	0.011	2.240
Month	0.155	0.001	0.641	0.49	0.001	0.204
Day	0.154	0.002	1.282	0.491	0	0
Hour	0.152	0.004	2.564	0.487	0.004	0.815

Department	0.086	0.07	44.872	N/A		
Officer	N/A			0.179	0.312	63.544

Stops Cutoff: 100

Figure B 14

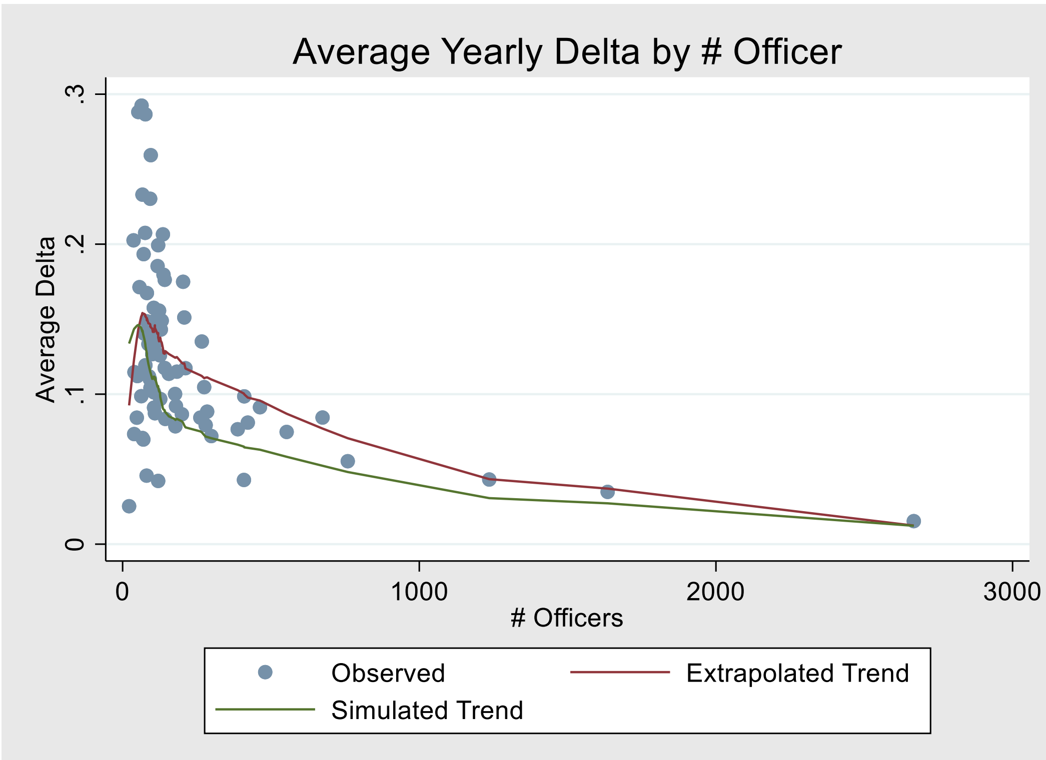
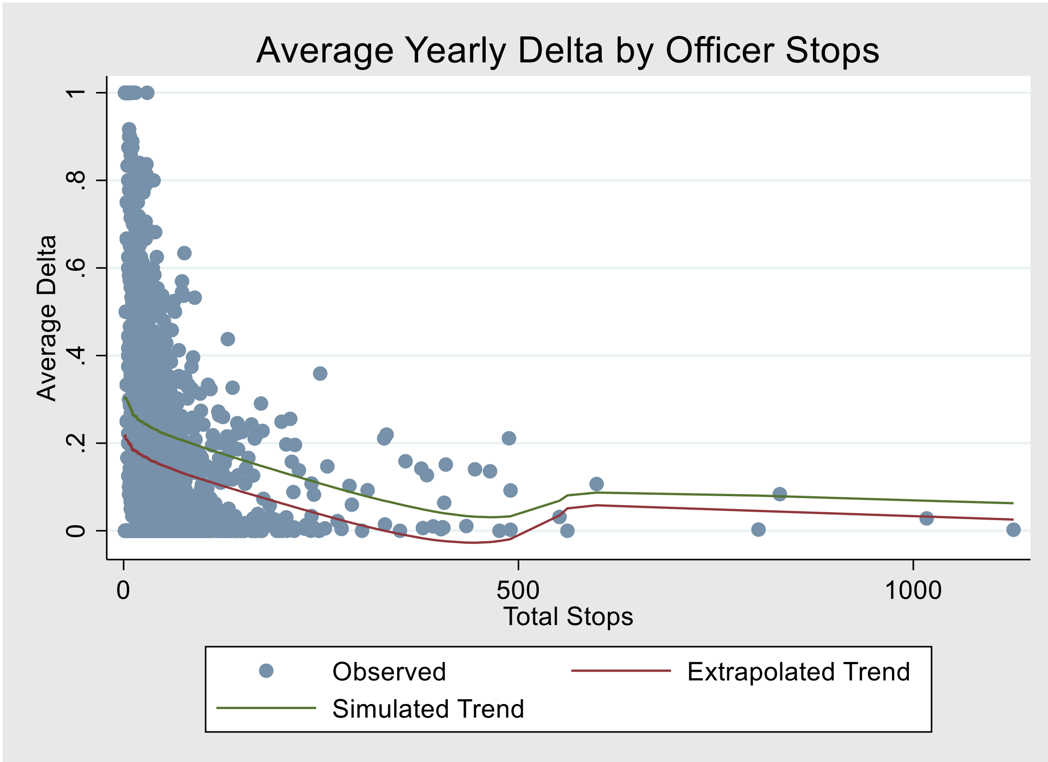


Figure B 15



Average Yearly Delta by Officer Stops
Average Delta
0
.2
.4
.6
.8
1
0
500
1000
Total Stops
Observed
Extrapolated Trend
Simulated Trend

Figure B 16

Appendix C: Equipment

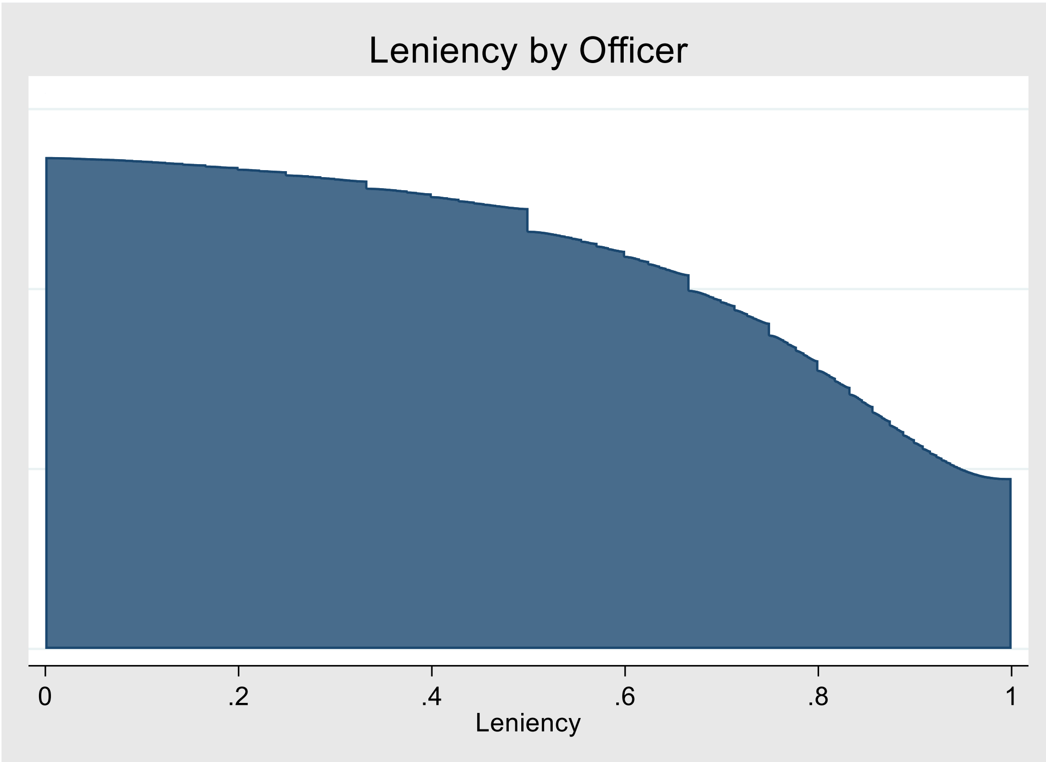


Figure C 1

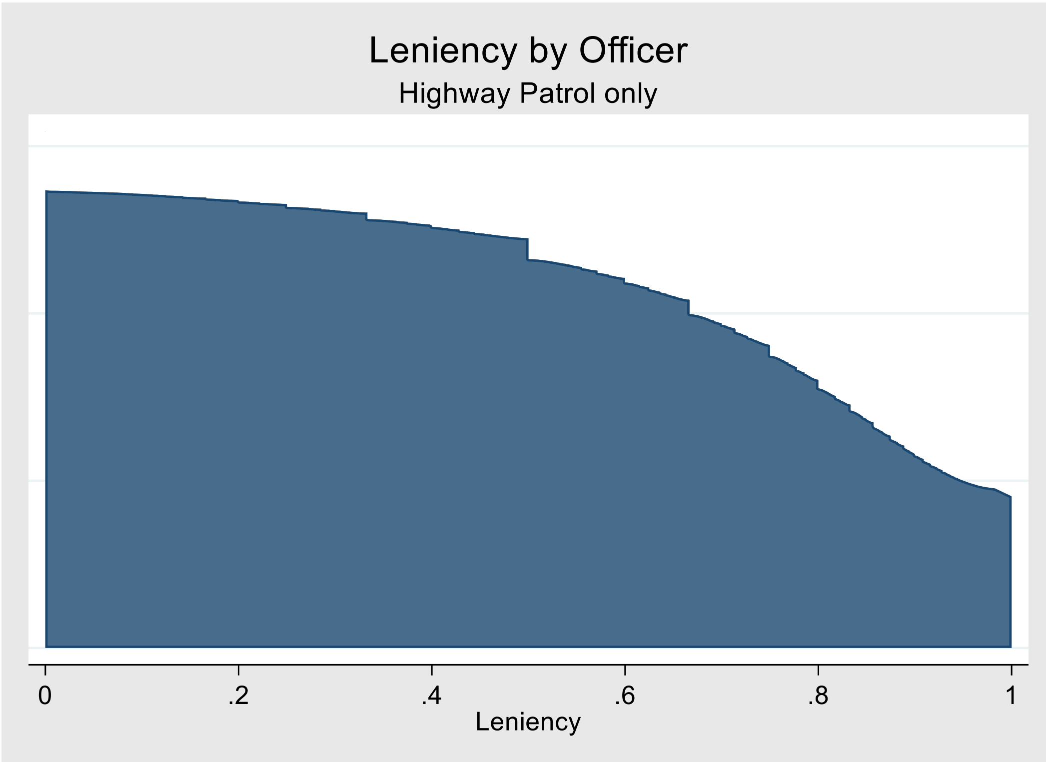


Figure C 2

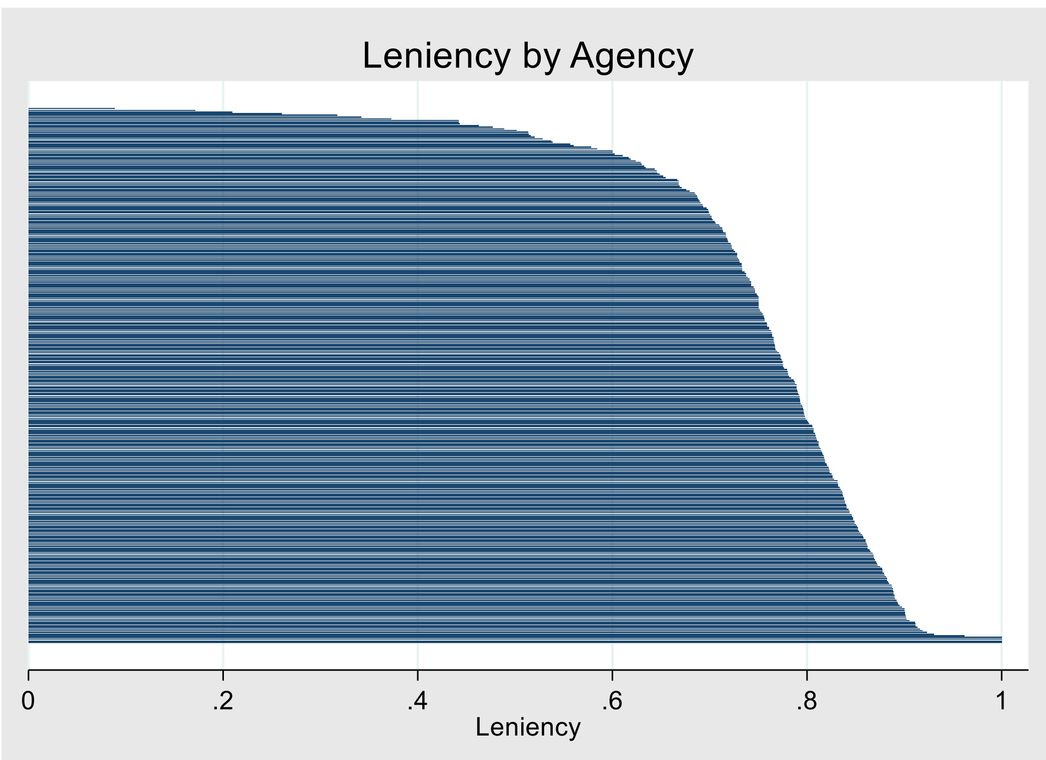


Figure C 3

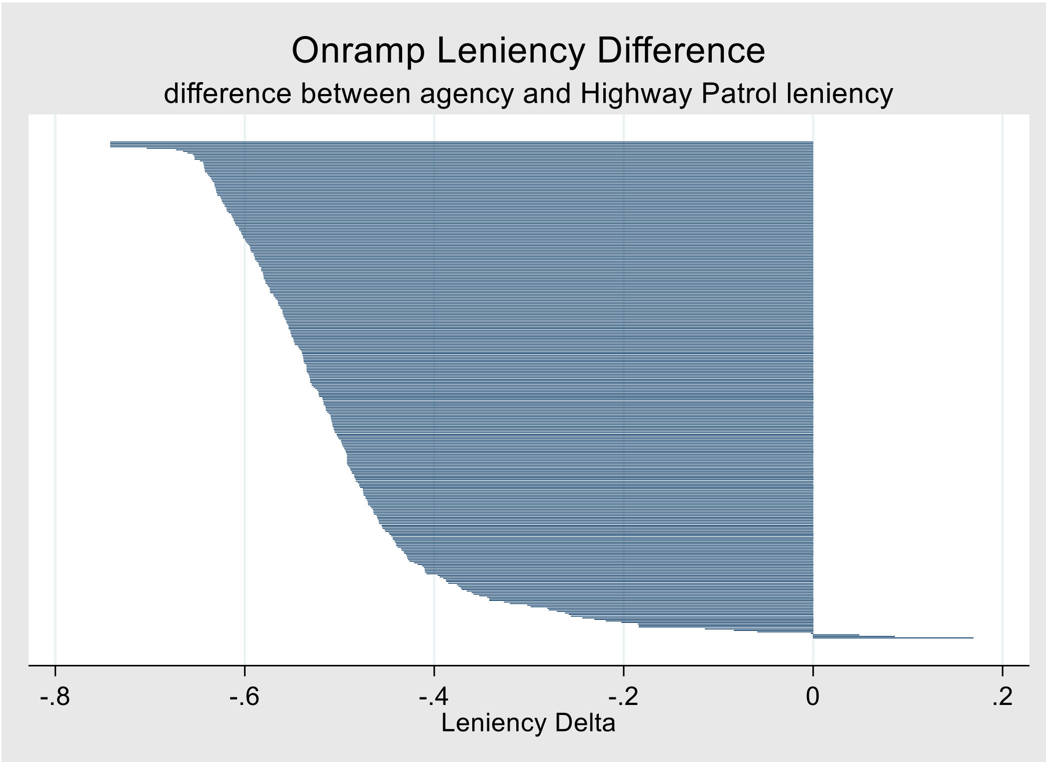


Figure C 4

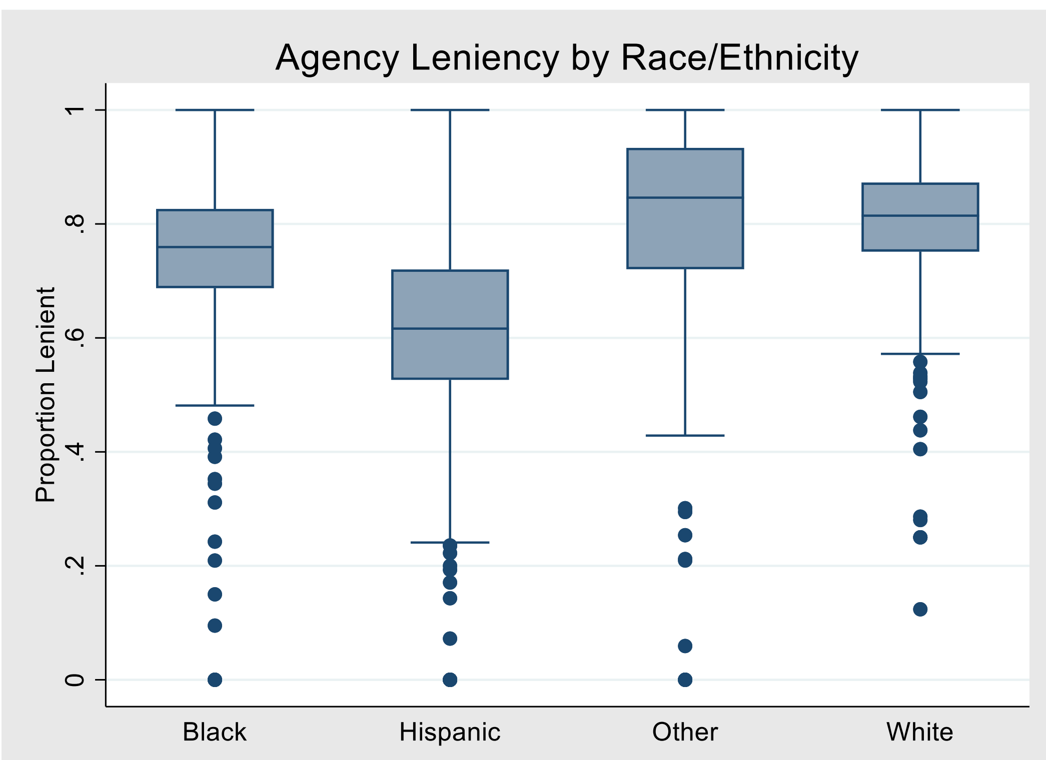


Figure C 5

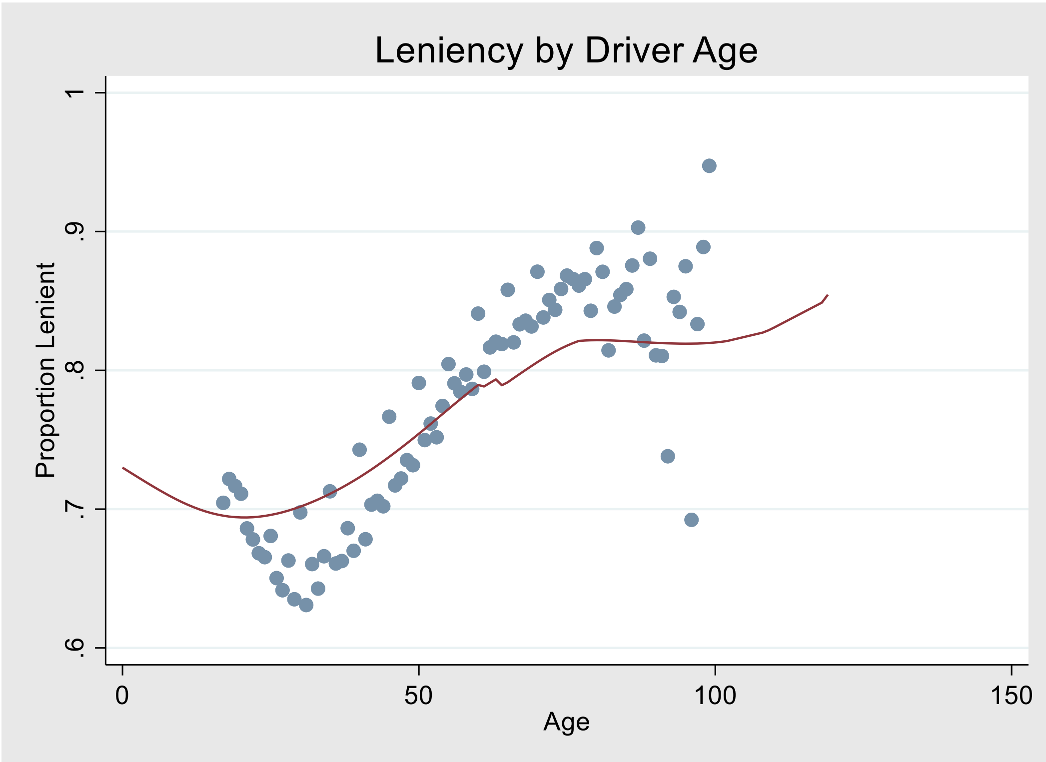


Figure C 6

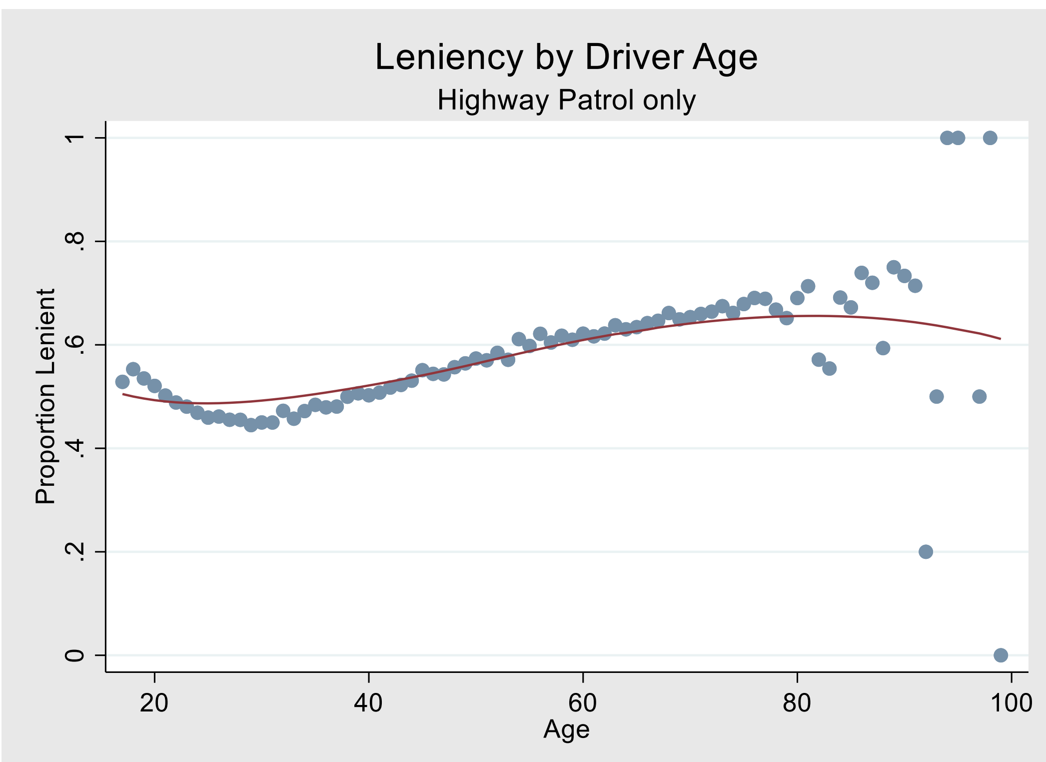


Figure C 7

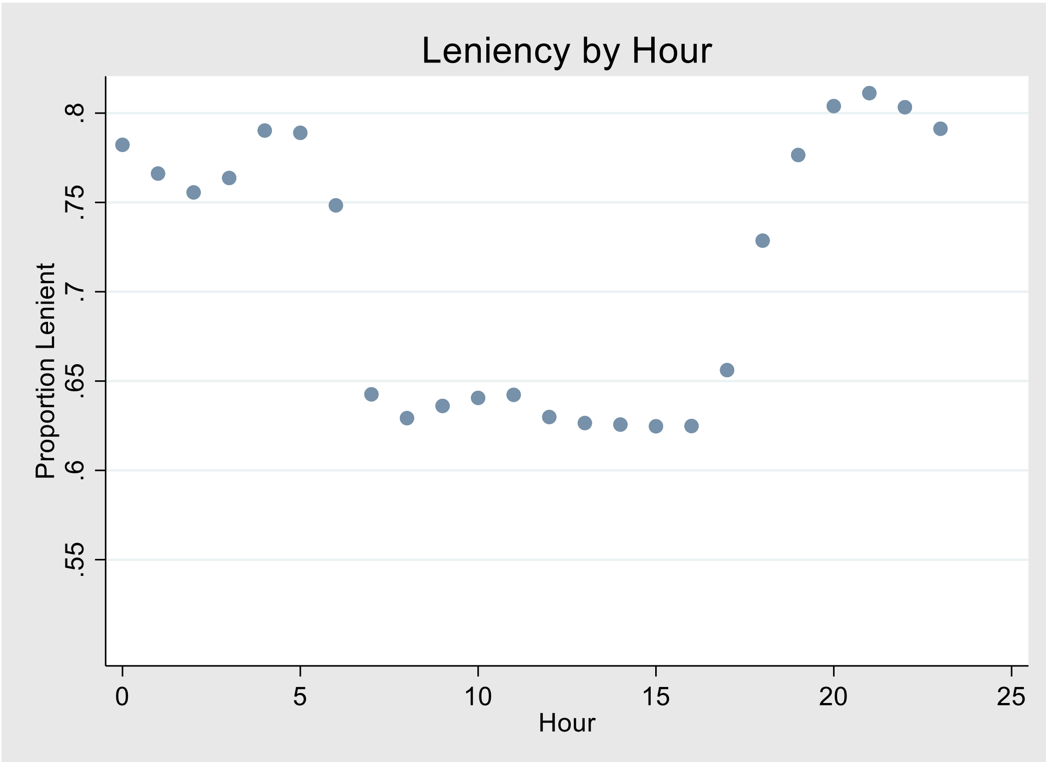

Leniency by Hour
Proportion Lenient
.55
.6
.65
.7
.75
.8
0
5
10
15
20
25
Hour

Figure C 8

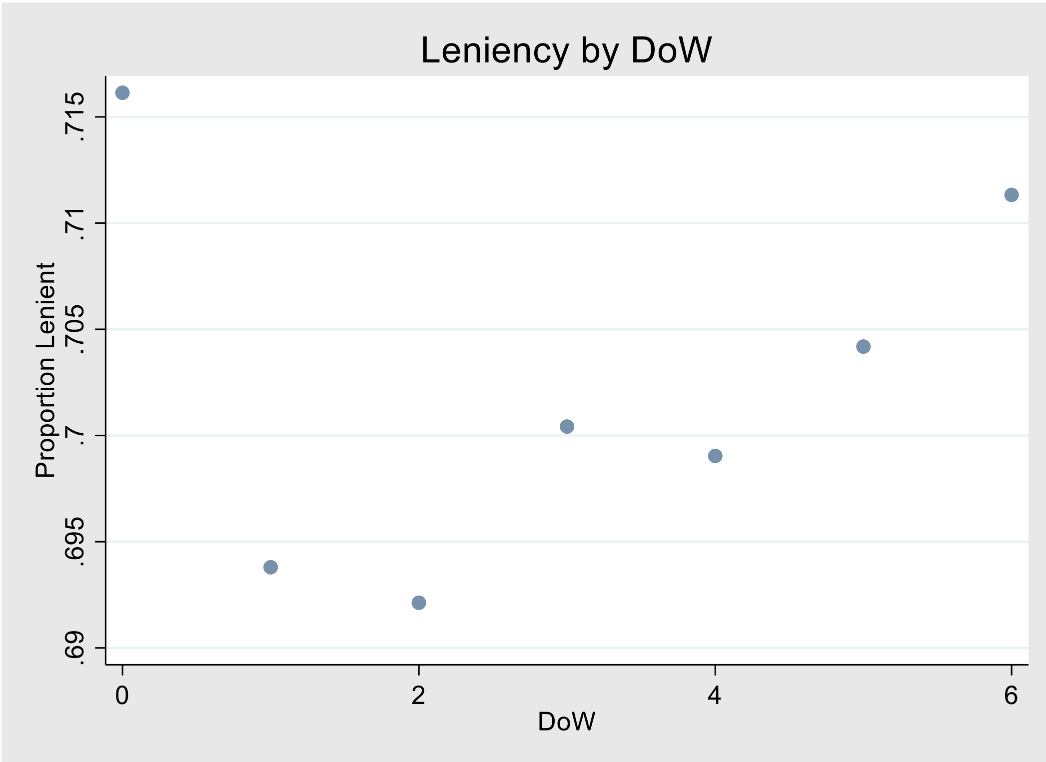


Figure C 9

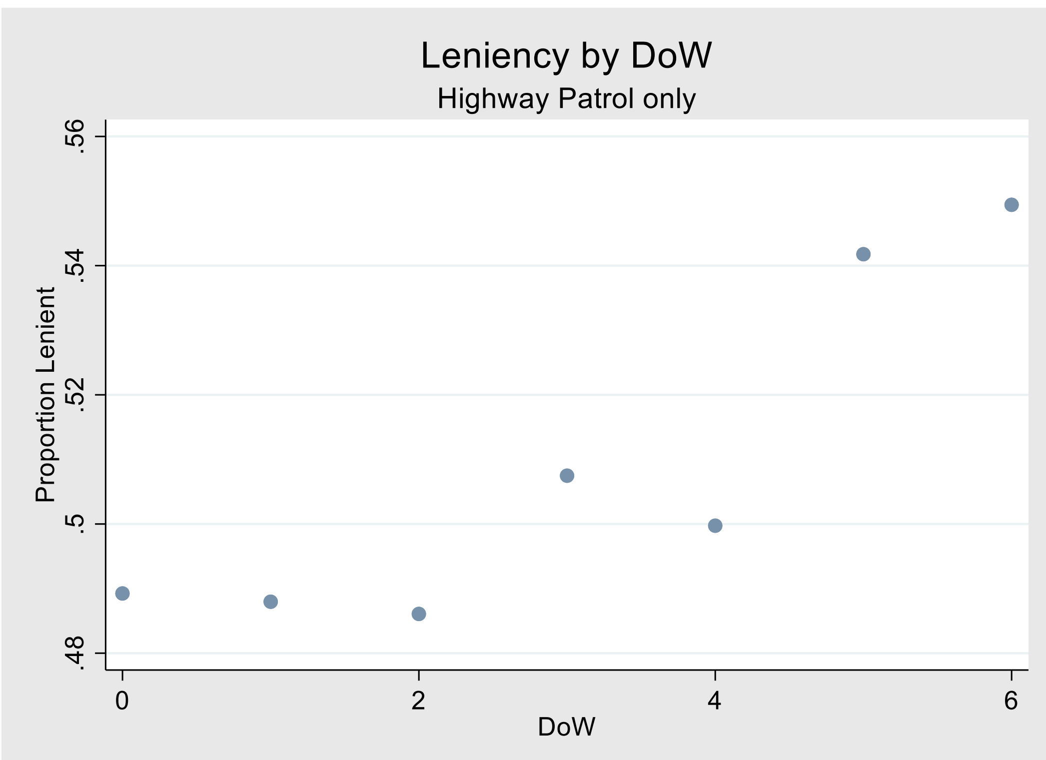


Figure C 10

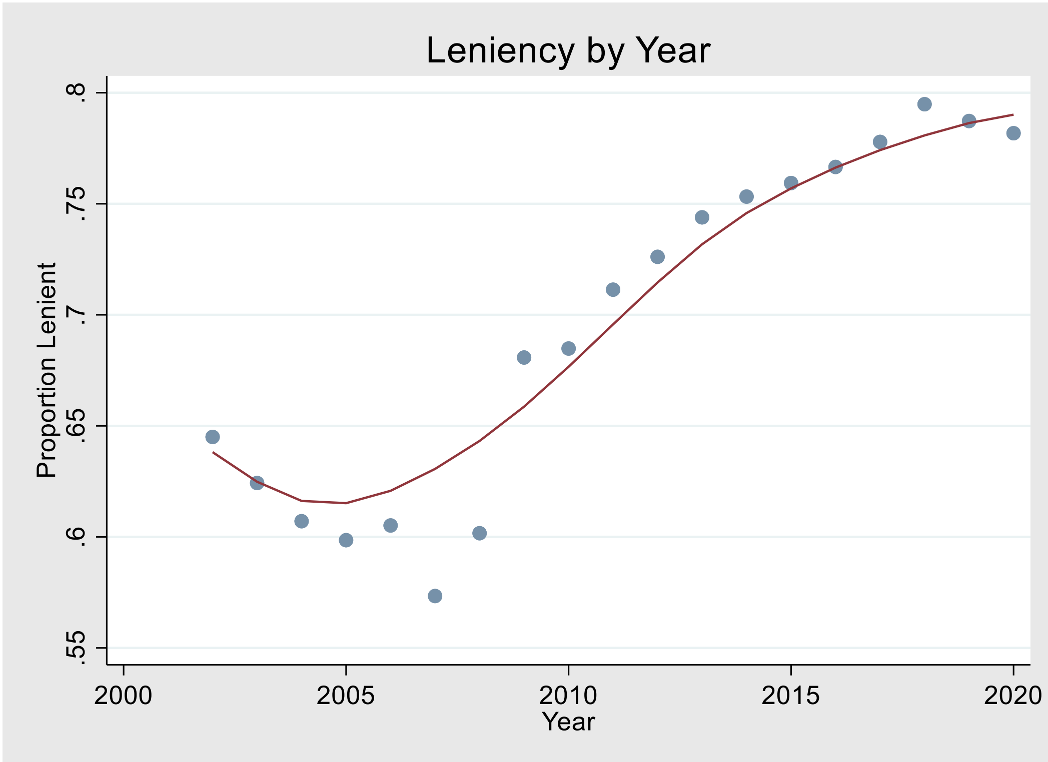


Figure C 11

VARIABLES	Stop Reason Equipment
years = 2	-0.023
years = 3	0.092
years = 4	0.032
years = 5	-0.001
years = 6	0.056
years = 7	-0.033
years = 8	0.159*
years = 9	0.004
years = 10	0.203**
years = 11	0.037
years = 12	0.193*
years = 13	-0.152
years = 14	-0.371***
years = 15	-0.250**
years = 16	-0.274**
years = 17	-0.143
years = 18	-0.182*
years = 19	0.045
years = 20	-0.032

years = 21	-0.071
years = 22	-0.464***
years = 23	-0.826***
years = 24	-0.413*
years = 25	0.162
years = 26	0.068
years = 27	-0.577***
years = 28	-0.736***
years = 29	-1.271***
years = 30, omitted	-
Driver_Age	-0.015*
CMPD_Division = 2, Eastway Division	-0.132*
CMPD_Division = 3, Freedom Division	0.003
CMPD_Division = 4, Hickory Grove Division	0.043
CMPD_Division = 5, Independence Division	0.040
CMPD_Division = 6, Metro Division	-0.172*
CMPD_Division = 7, North Division	0.127
CMPD_Division = 8, North Tryon Division	-0.065
CMPD_Division = 9, Providence Division	0.170*
CMPD_Division = 10, South Division	0.298***
CMPD_Division = 11, Steele Creek Division	-0.066
CMPD_Division = 12, University City Division	-0.230**
CMPD_Division = 13, Westover Division	0.107
Officer_Race = 2, omitted	-
Officer_Race = 3, American Indian/Alaska Native	0.259
Officer_Race = 4, Asian / Pacific Islander	0.361
Officer_Race = 5, Black/African American	0.395
Officer_Race = 6, Hispanic/Latino	0.442
Officer_Race = 7, Native Hawaiian/Oth Pac Island	0.900
Officer_Race = 8, Not Specified	0.942**
Officer_Race = 9, White	0.452
driver_age_sqr	0.000***
Driver_Gender	-0.159***
Officer_Gender	-0.044
Driver_Race = 2, Black	-0.530***
Driver_Race = 3, omitted	-
Driver_Race = 4, Other/Unknown	-0.416**
Driver_Race = 5, White	-0.446***
Constant	1.438***
Observations	9,943

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure C 12

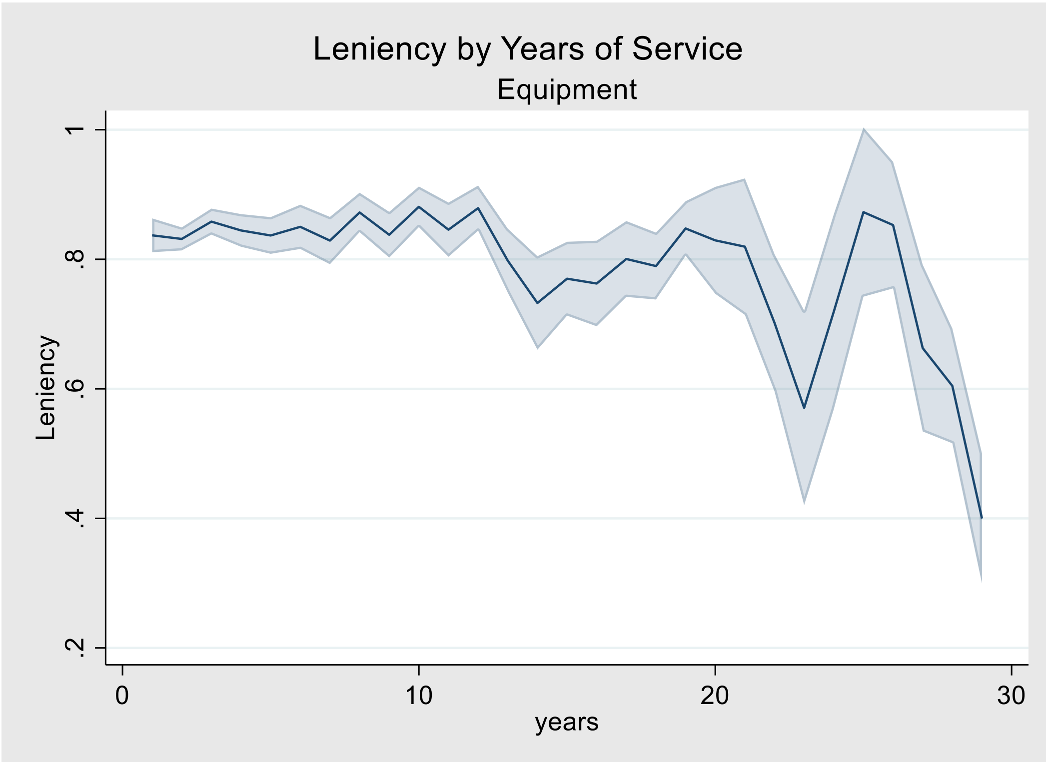


Figure C 13

	No Officer			Officer		
	Total	Change	% Change	Total	Change	% Change
Saturated	0.104	0	0	0.284	0	0
Identity	0.085	0.019	18.269	0.269	0.015	5.282
Year	0.095	0.009	8.654	0.281	0.003	1.056
Month	0.104	0	0	0.284	0	0
Day	0.104	0	0	0.284	0	0
Hour	0.093	0.011	10.577	0.283	0.001	0.352
Department	0.065	0.039	37.5	N/A		
Officer	N/A			0.139	0.145	51.056

Stops Cutoff: 450

Figure C 14

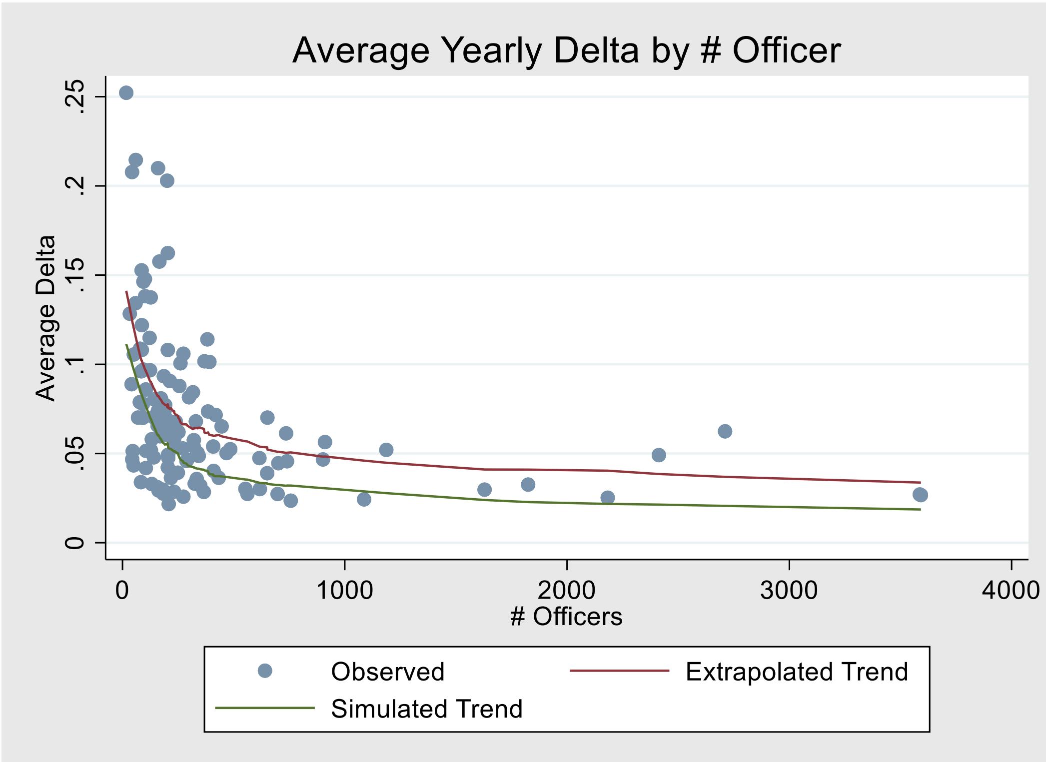


Figure C 15

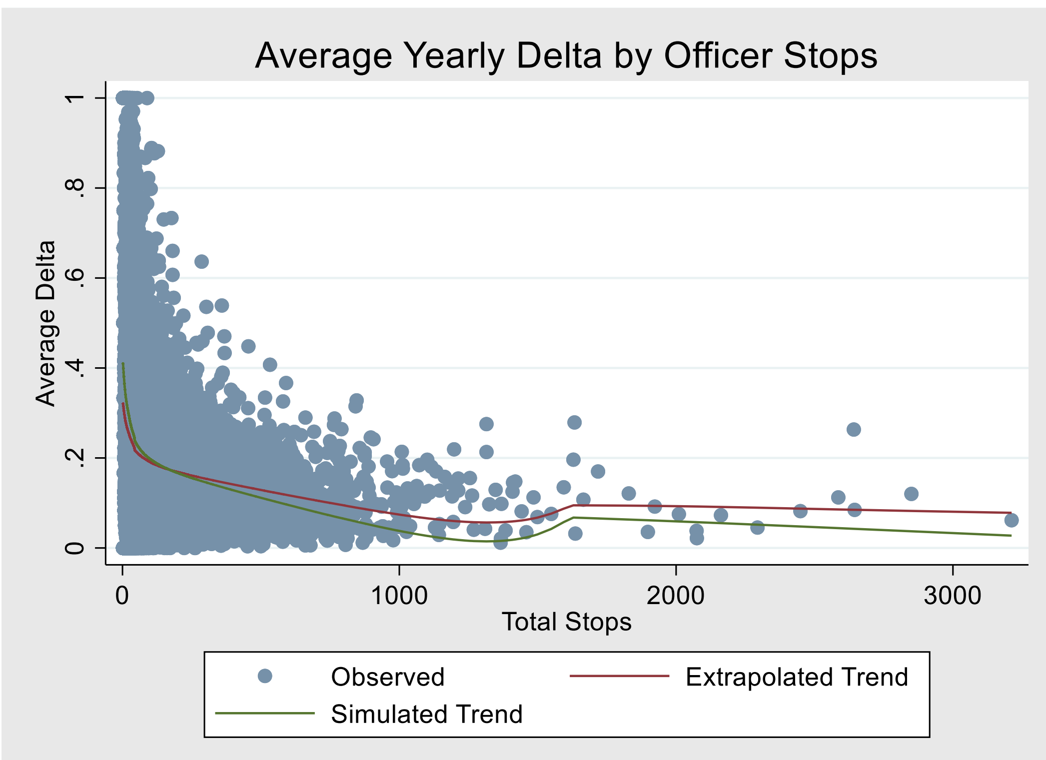


Figure C 16

Appendix D: Investigation

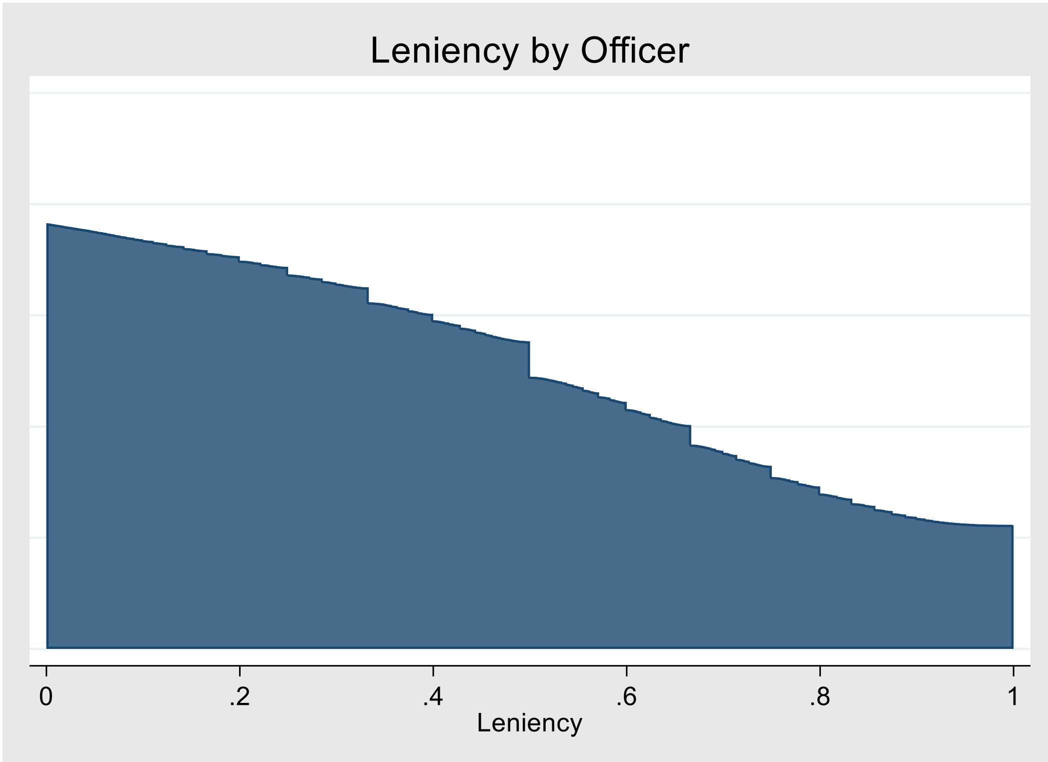


Figure D 1

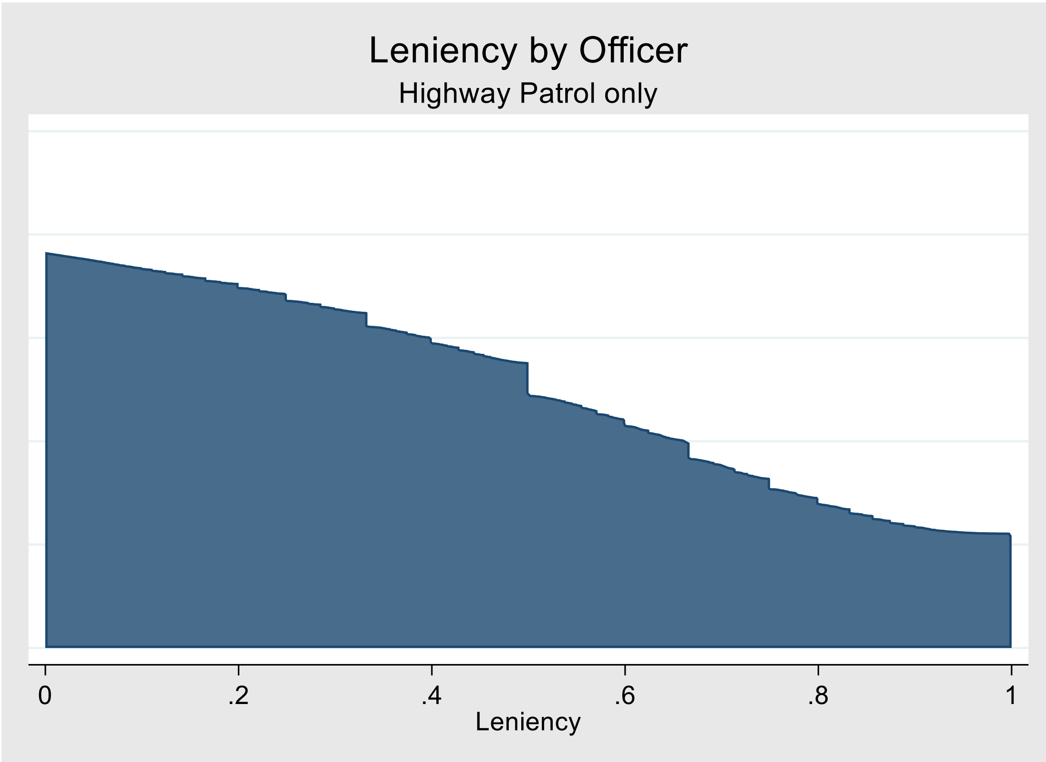


Figure D 2

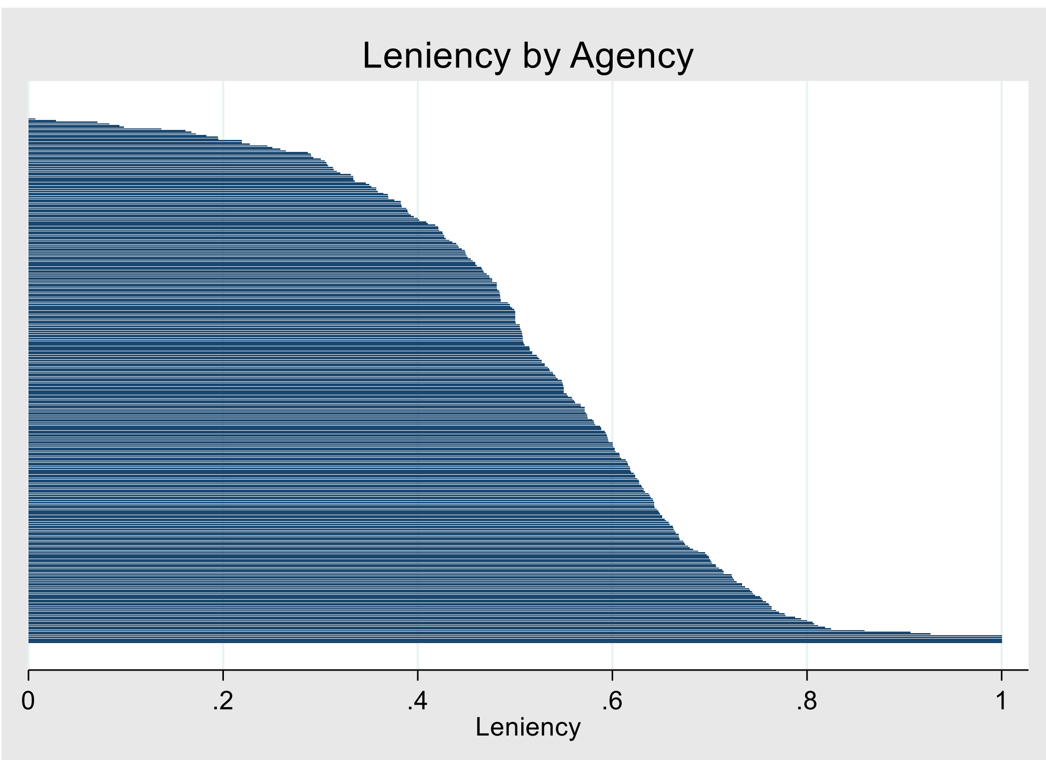


Figure D 3

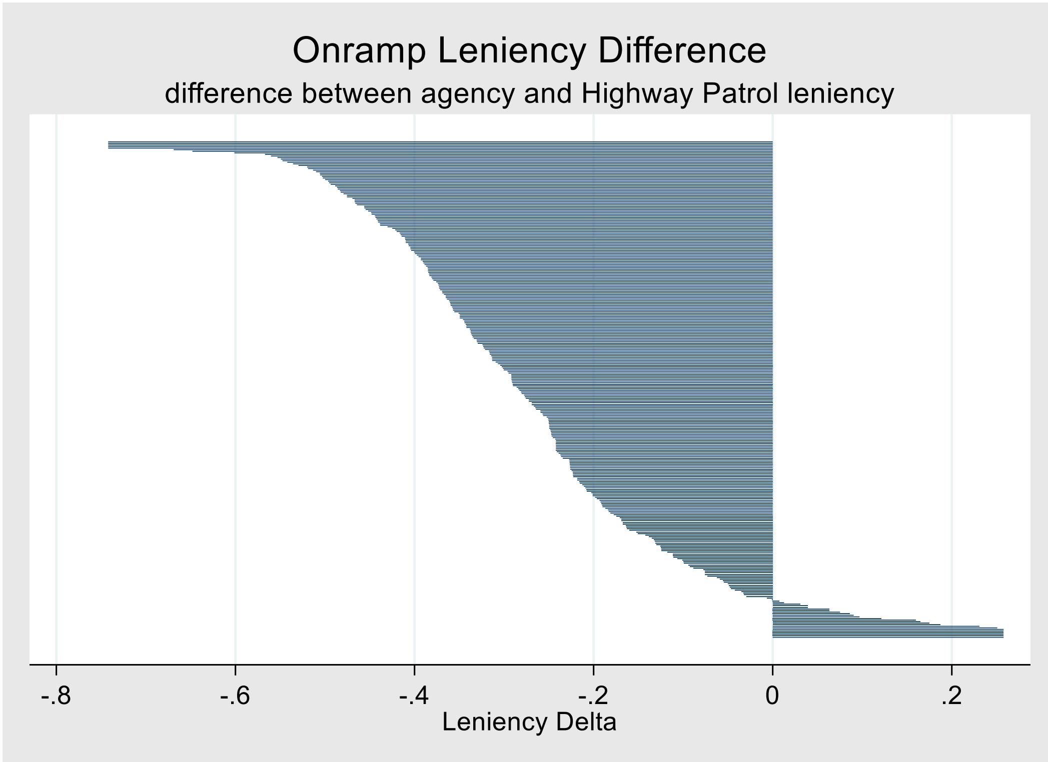


Figure D 4

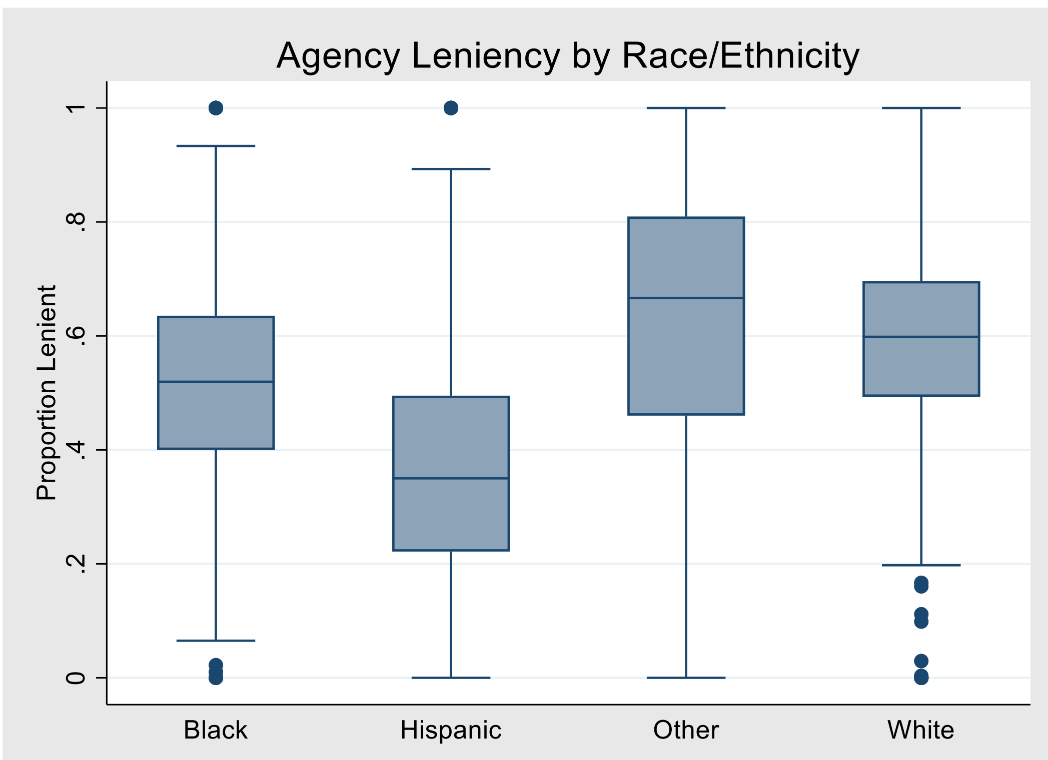


Figure D 5

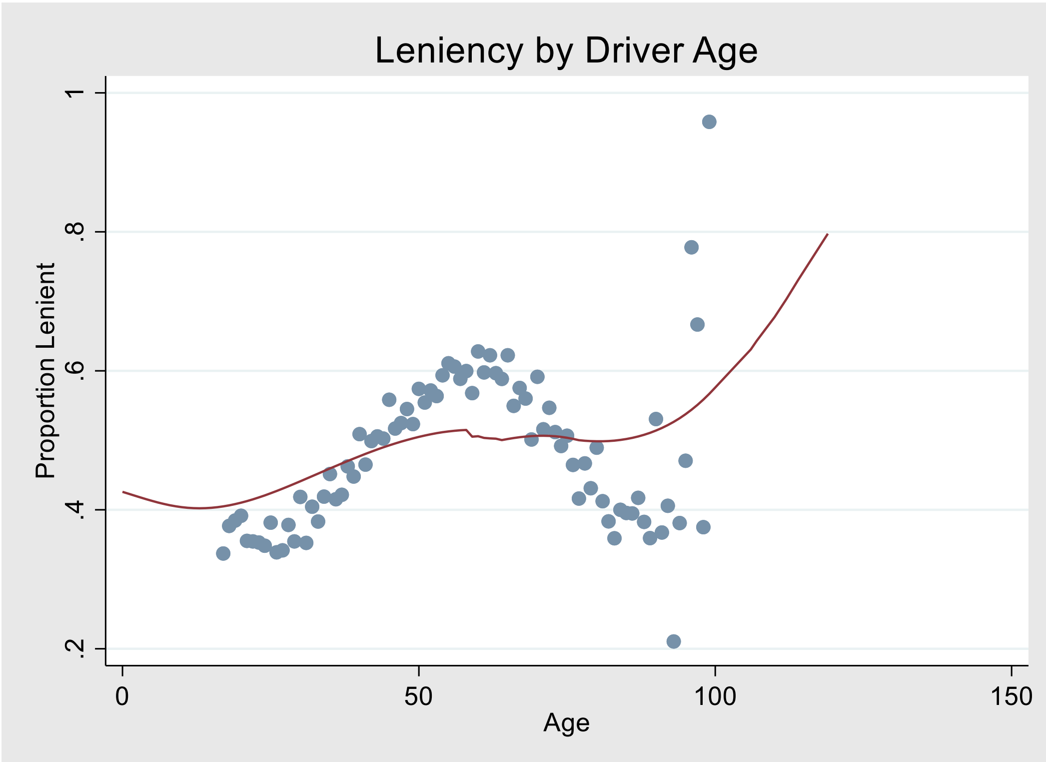


Figure D 6

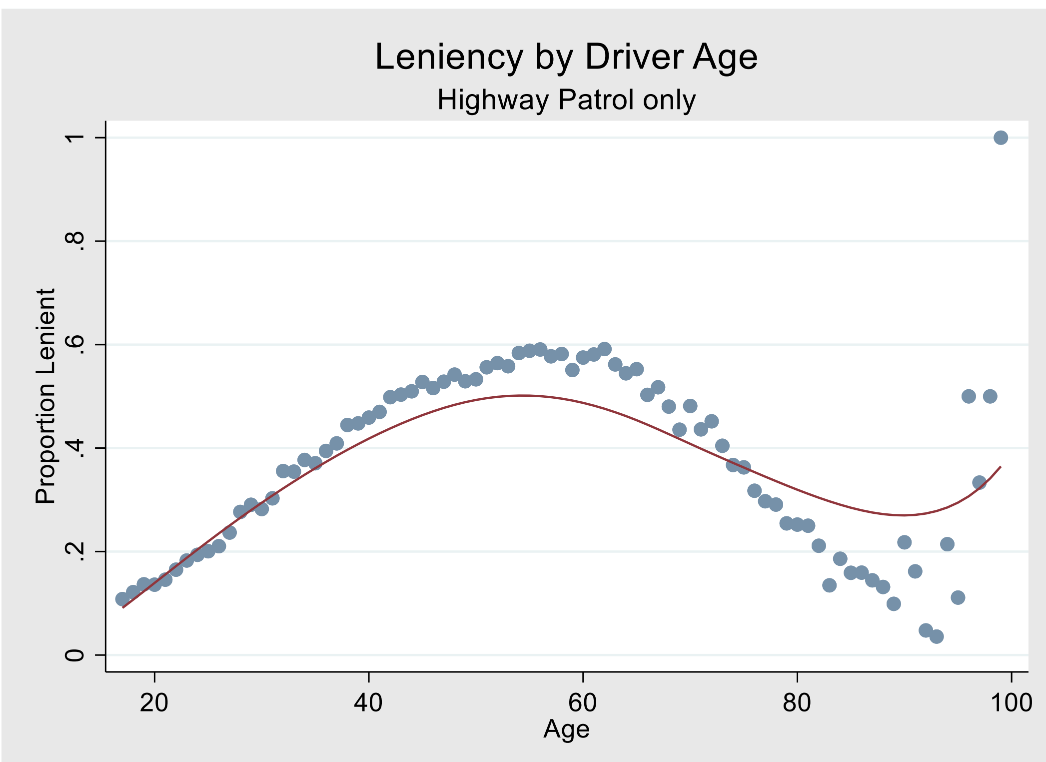


Figure D 7

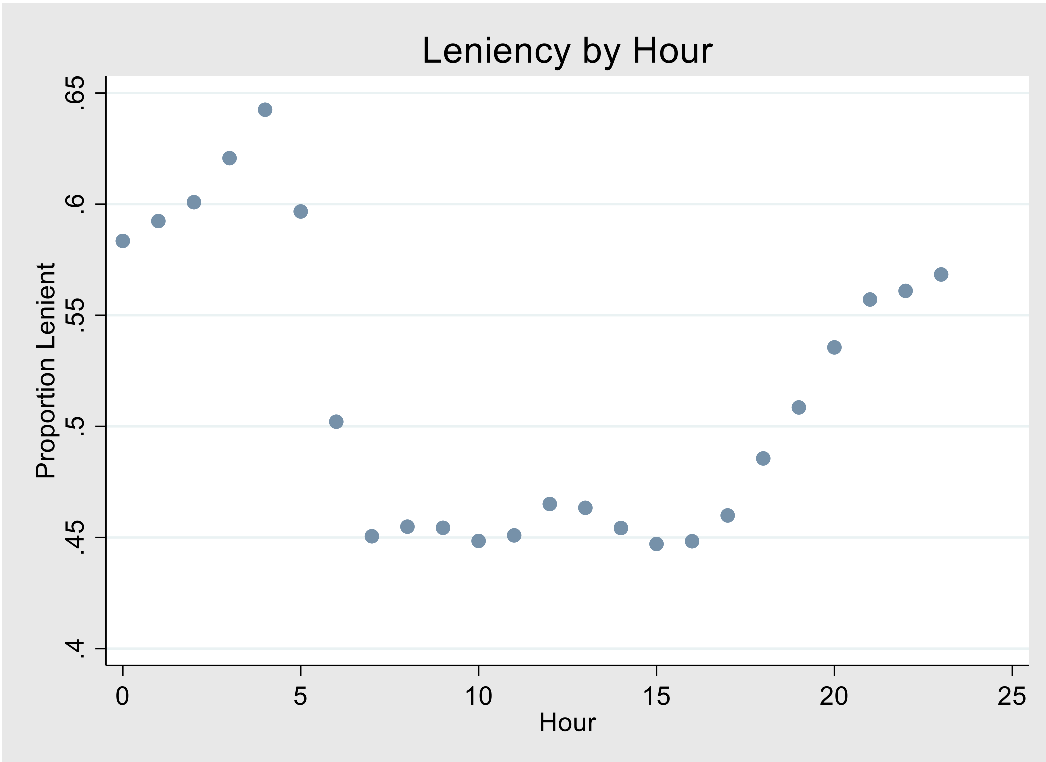


Figure D 8

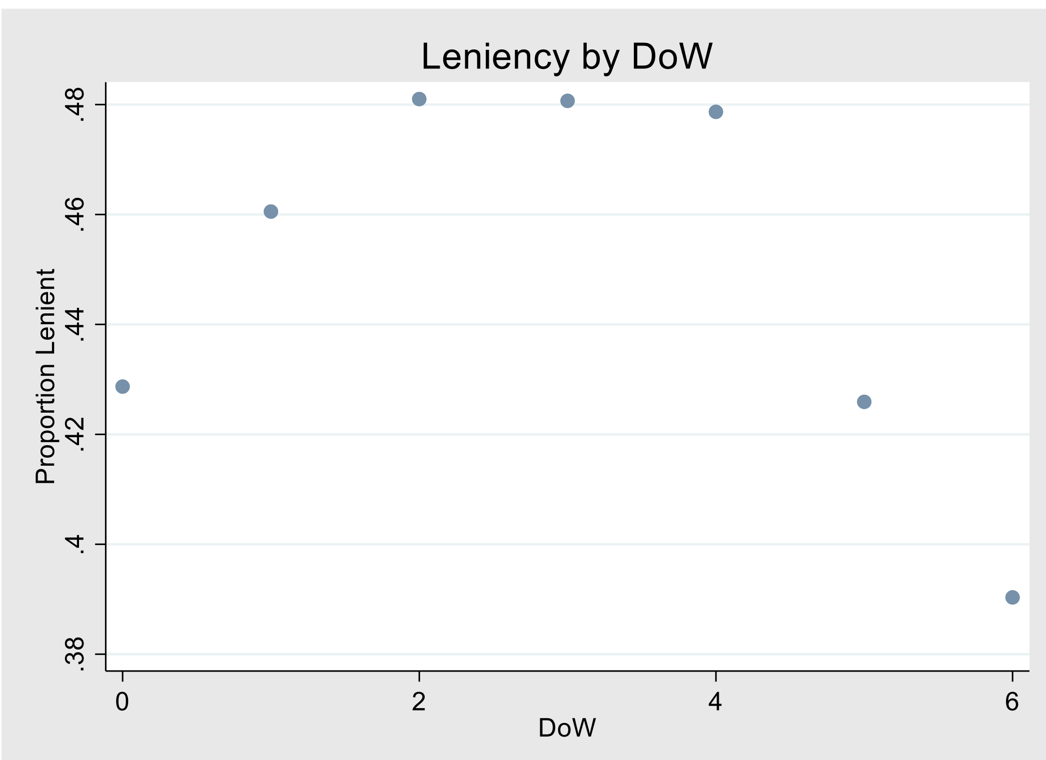


Figure D 9

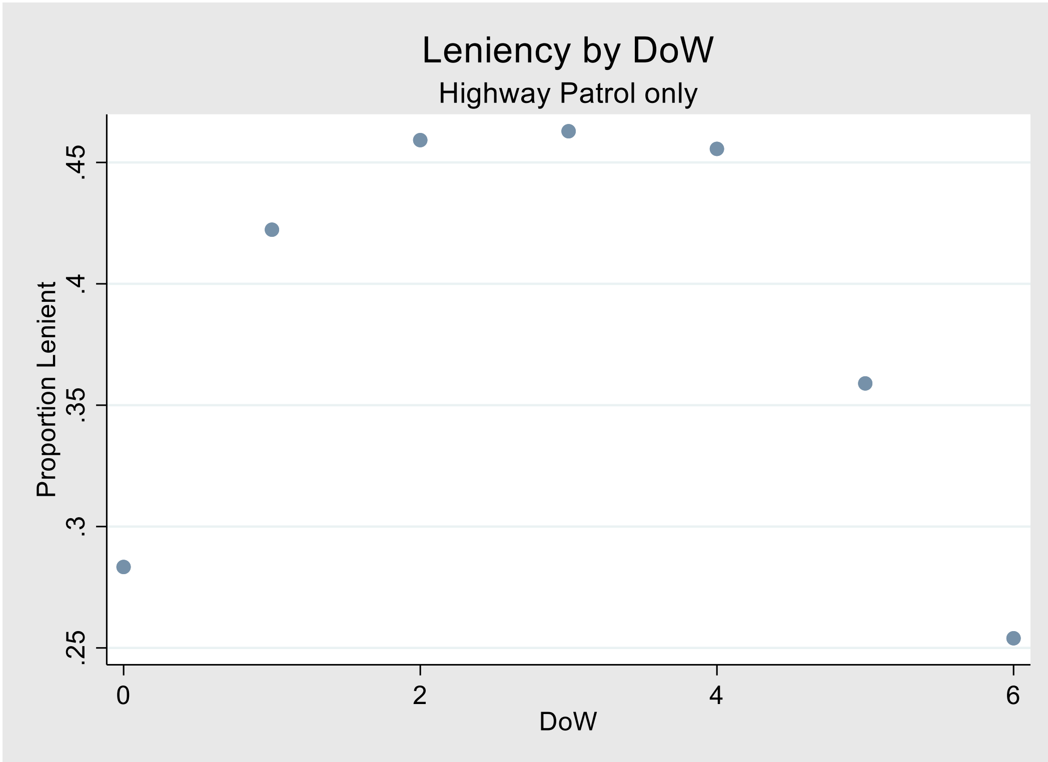


Figure D 10

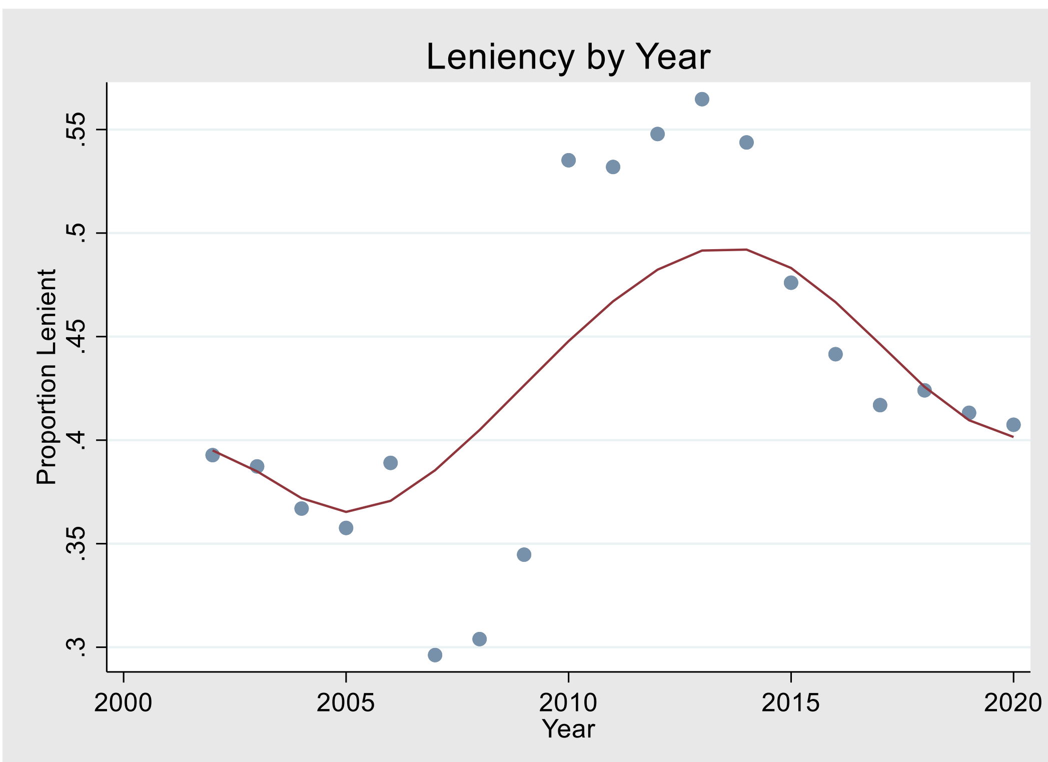


Figure D 11

VARIABLES	Stop Reason Investigation
years = 2	0.125
years = 3	0.103
years = 4	0.195
years = 5	0.058
years = 6	0.097
years = 7	-0.157
years = 8	0.017
years = 9	0.083
years = 10	0.261
years = 11	-0.096
years = 12	-0.106
years = 13	-0.065
years = 14	0.144
years = 15	-0.070
years = 16	-0.446*
years = 17	0.082
years = 18	0.128
years = 19	-0.432**
years = 20	-1.221***
years = 21	-0.698***
years = 22	-0.395
years = 23	-0.288
years = 24	0.134
years = 25	0.468**
years = 26	0.270
years = 27	-0.580**
years = 28	-0.122
years = 29	0.228
Driver_Age	0.008
CMPD_Division = 2, Eastway Division	-0.330
CMPD_Division = 3, Freedom Division	-0.132
CMPD_Division = 4, Hickory Grove Division	0.059
CMPD_Division = 5, Independence Division	0.061
CMPD_Division = 6, Metro Division	0.032
CMPD_Division = 7, North Division	-0.0176
CMPD_Division = 8, North Tryon Division	0.001
CMPD_Division = 9, Providence Division	-0.225
CMPD_Division = 10, South Division	0.337

CMPD_Division = 11, Steele Creek Division	-0.681***
CMPD_Division = 12, University City Division	0.013
CMPD_Division = 13, Westover Division	-0.121
Officer_Race = 2, omitted	-
Officer_Race = 3, omitted	-
Officer_Race = 4, Asian / Pacific Islander	-0.105
Officer_Race = 5, Black/African American	0.256***
Officer_Race = 6, Hispanic/Latino	0.639***
Officer_Race = 7, omitted	-
Officer_Race = 8, Not Specified	0.599*
Officer_Race = 9, omitted	-
driver_age_sqr	-1.72e-05
Driver_Gender	-0.121*
Officer_Gender	0.068
Driver_Race = 2, Black	-0.109
Driver_Race = 3, omitted	-
Driver_Race = 4, Other/Unknown	-0.236
Driver_Race = 5, White	-0.199
Constant	0.227
Observations	1,959

sStandard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure D 12

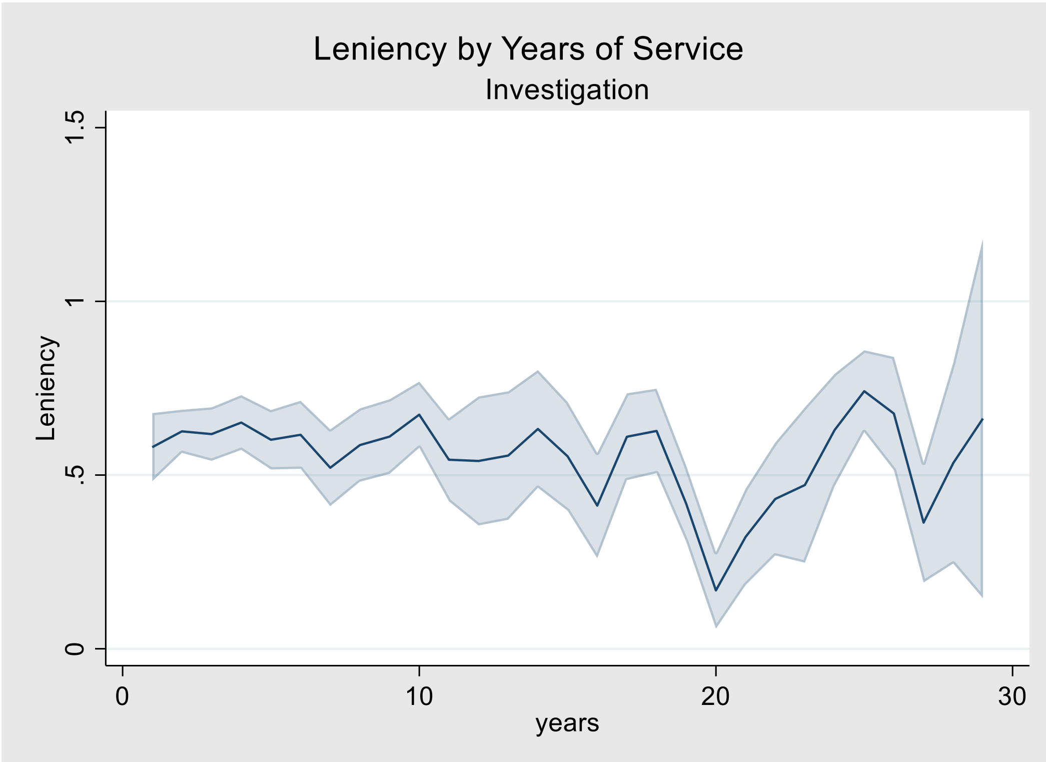


Figure D 13

	No Officer			Officer		
	Total	Change	% Change	Total	Change	% Change
Saturated	0.108	0	0	0.384	0	0
Identity	0.069	0.039	36.111	0.374	0.01	2.604
Year	0.086	0.022	20.370	0.370	0.014	3.646
Month	0.108	0	0	0.383	0.001	0.260
Day	0.106	0.002	1.852	0.383	0.001	0.260
Hour	0.103	0.005	4.630	0.383	0.001	0.260
Department	0.081	0.027	25	N/A		
Officer	N/A			0.151	0.233	60.6771

Stops Cutoff: 500

Figure D 14

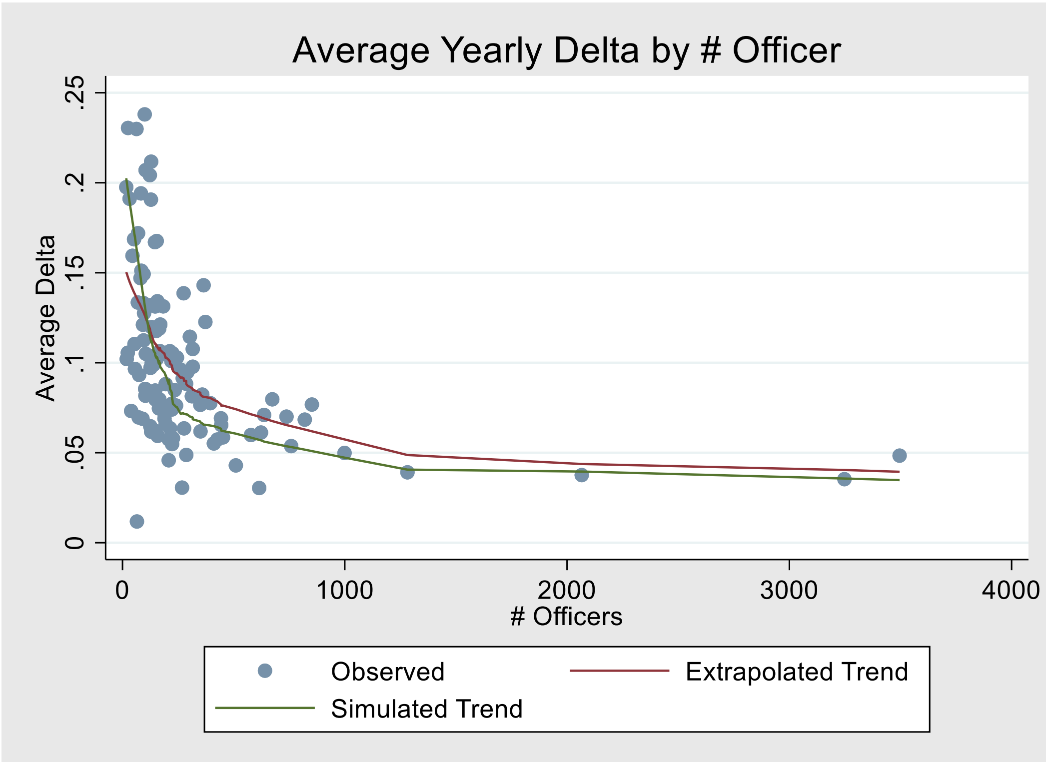


Figure D 15

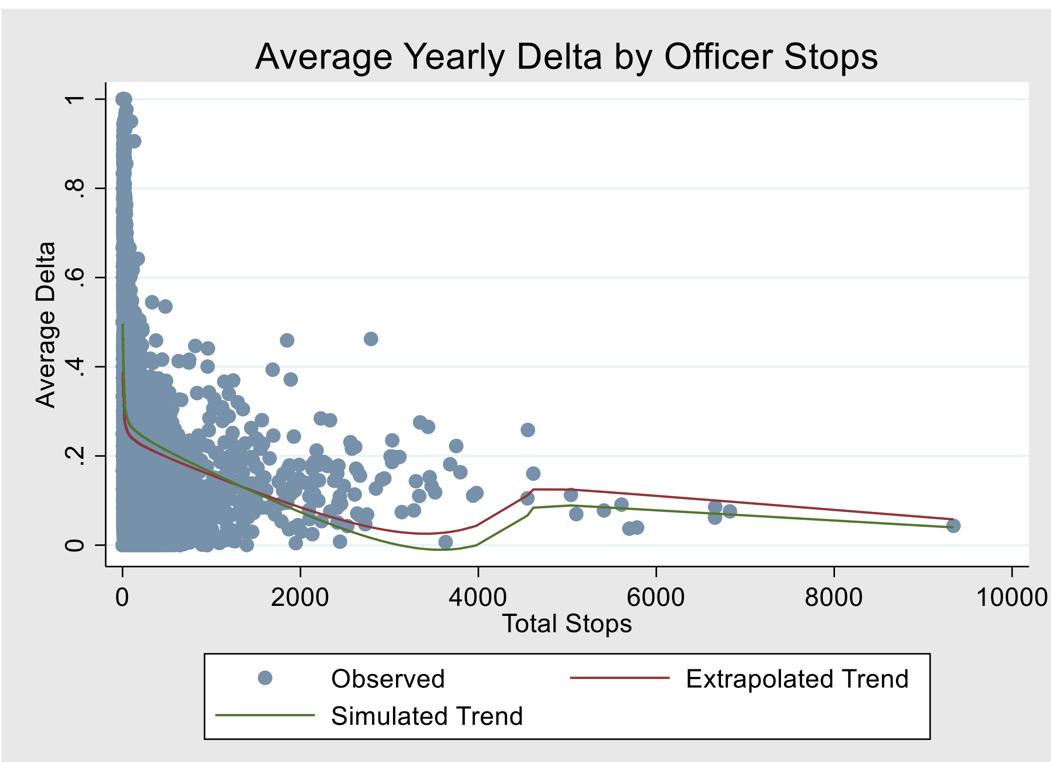


Figure D 16

Appendix E: Movement

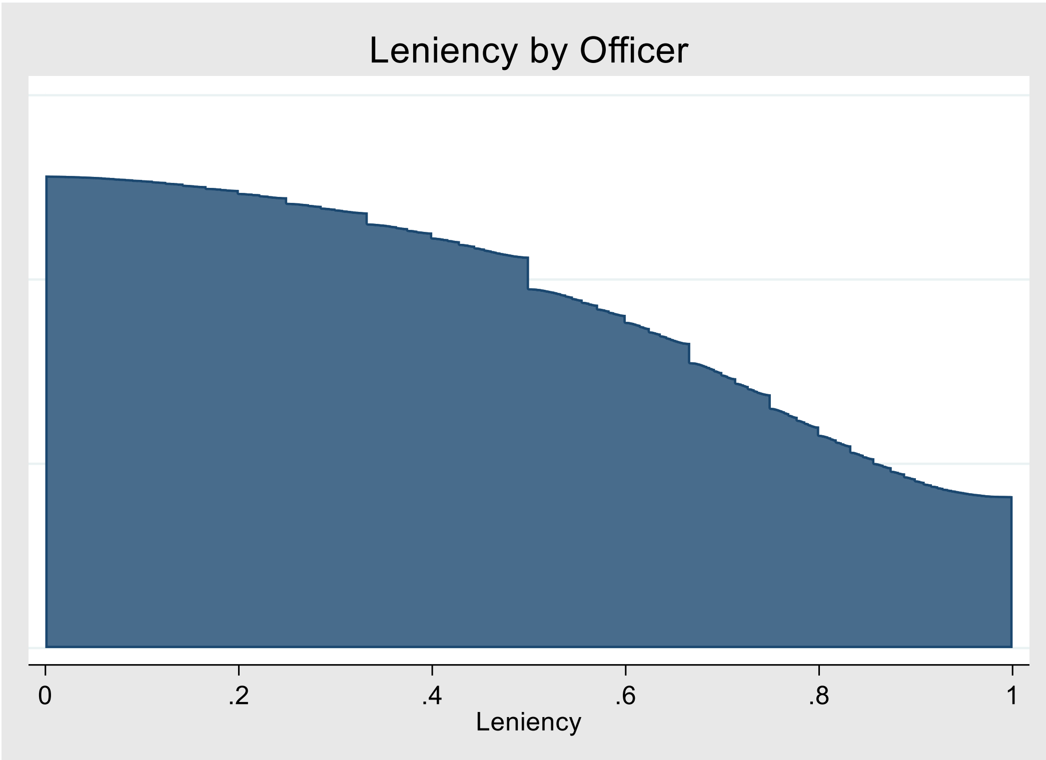


Figure E 1

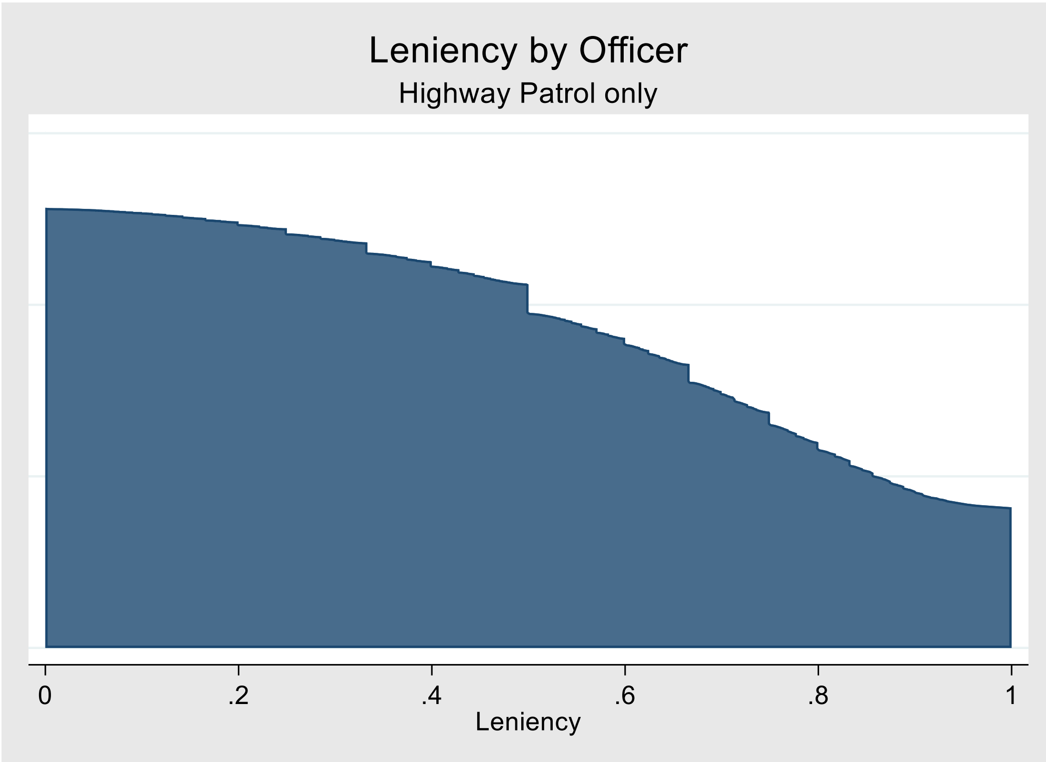


Figure E 2

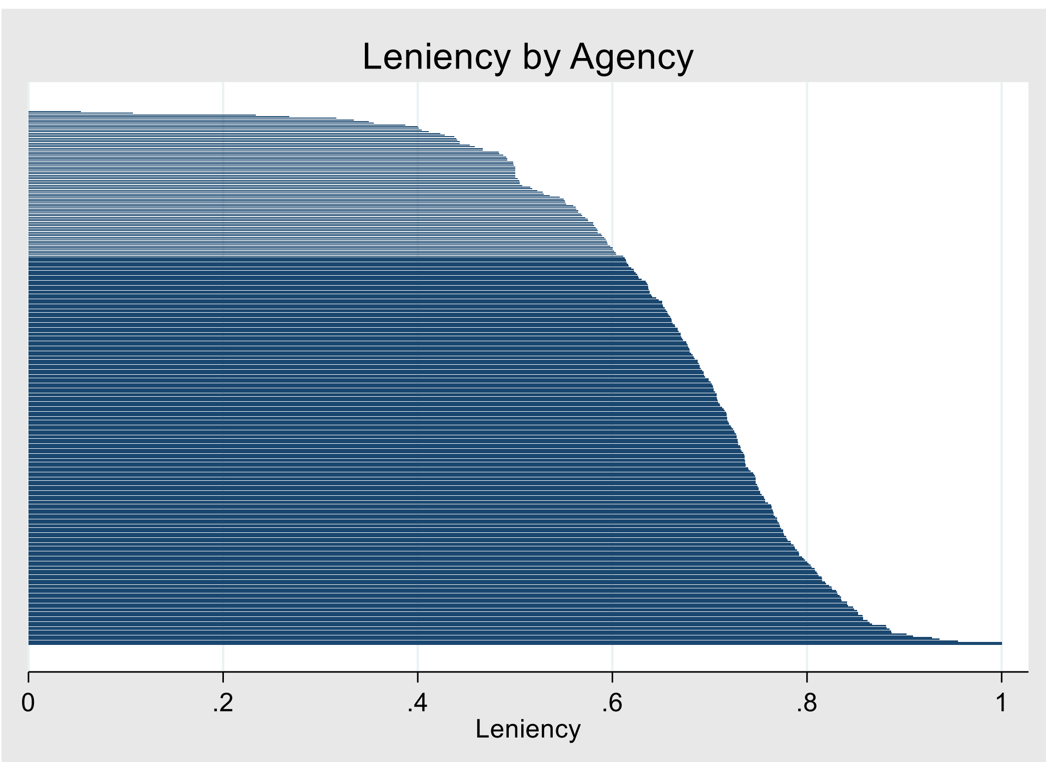


Figure E 3

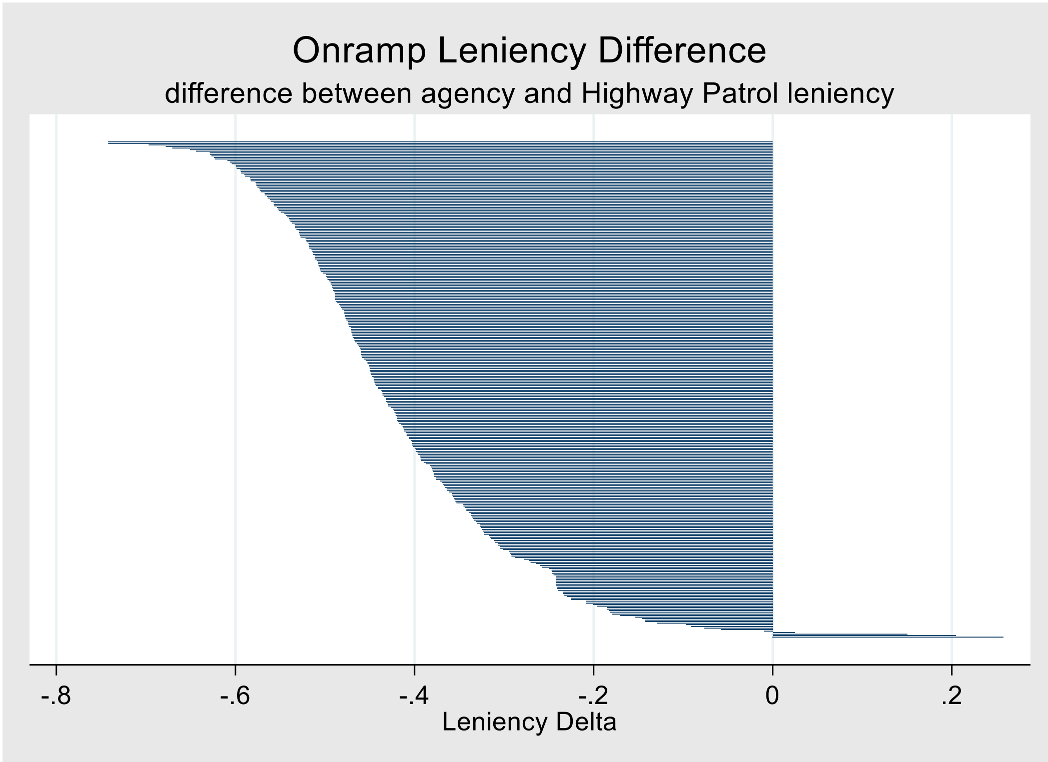


Figure E 4

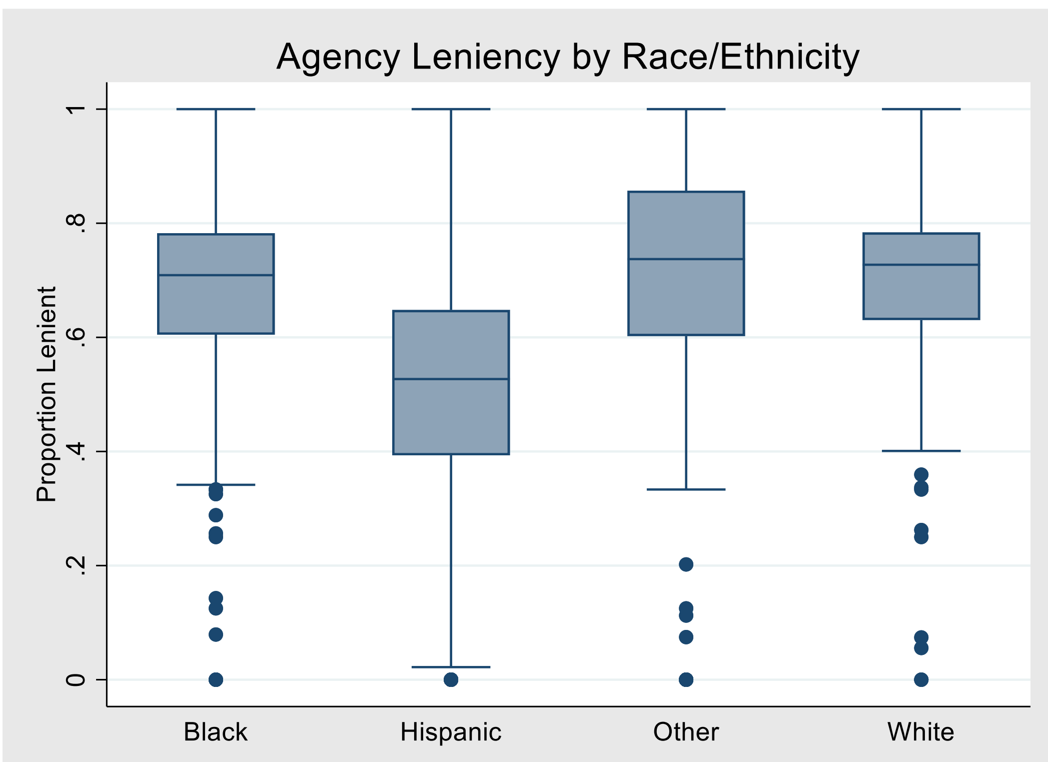


Figure E 5

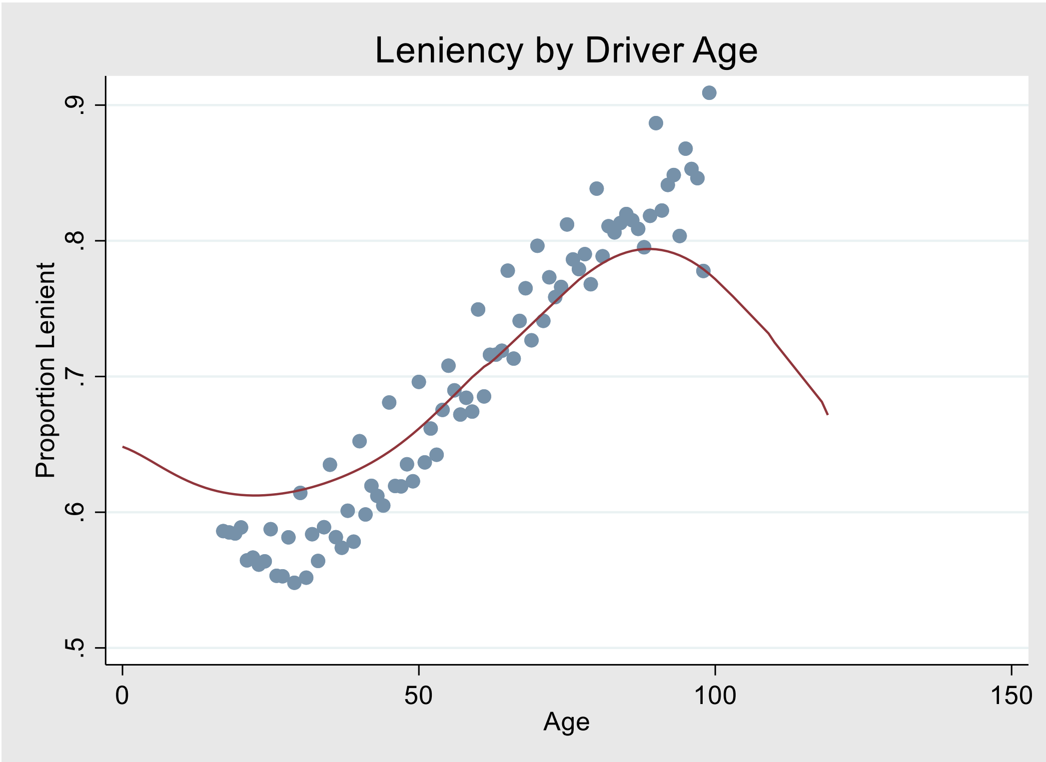


Figure E 6

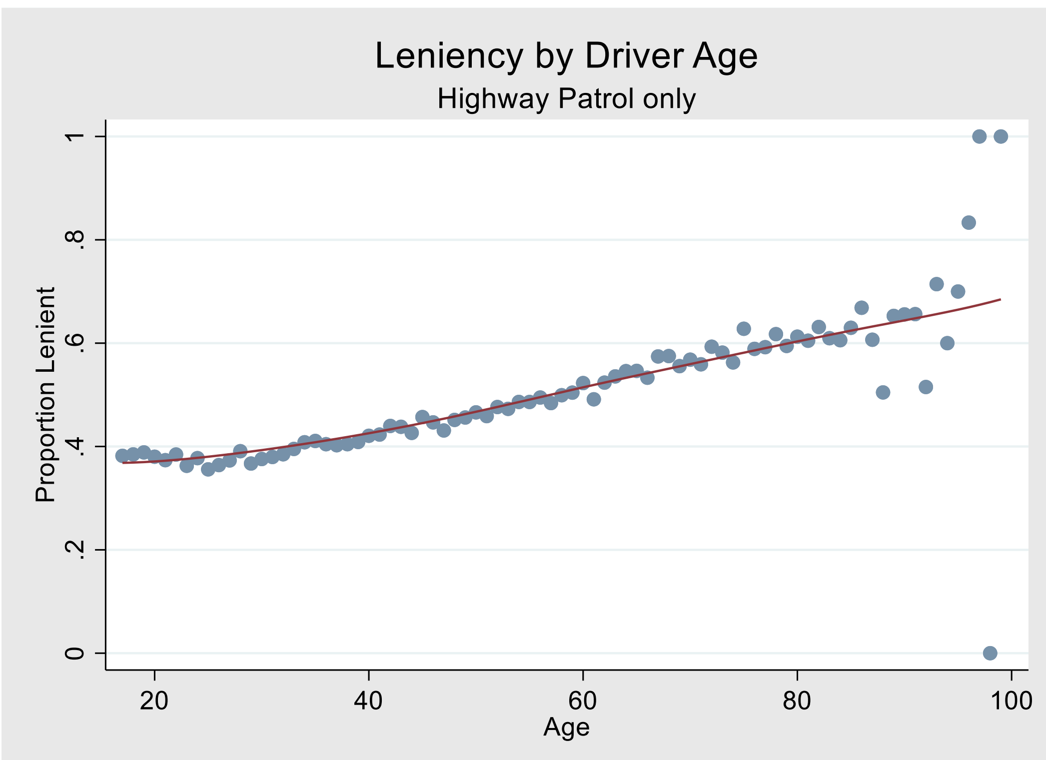


Figure E 7

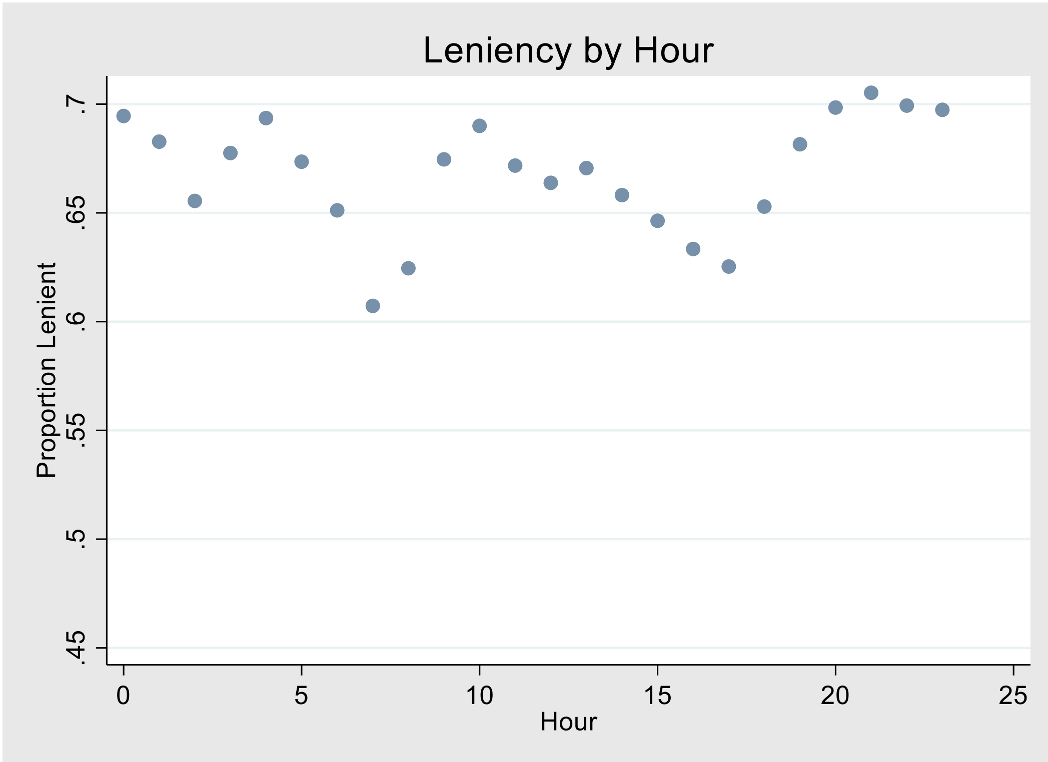


Figure E 8

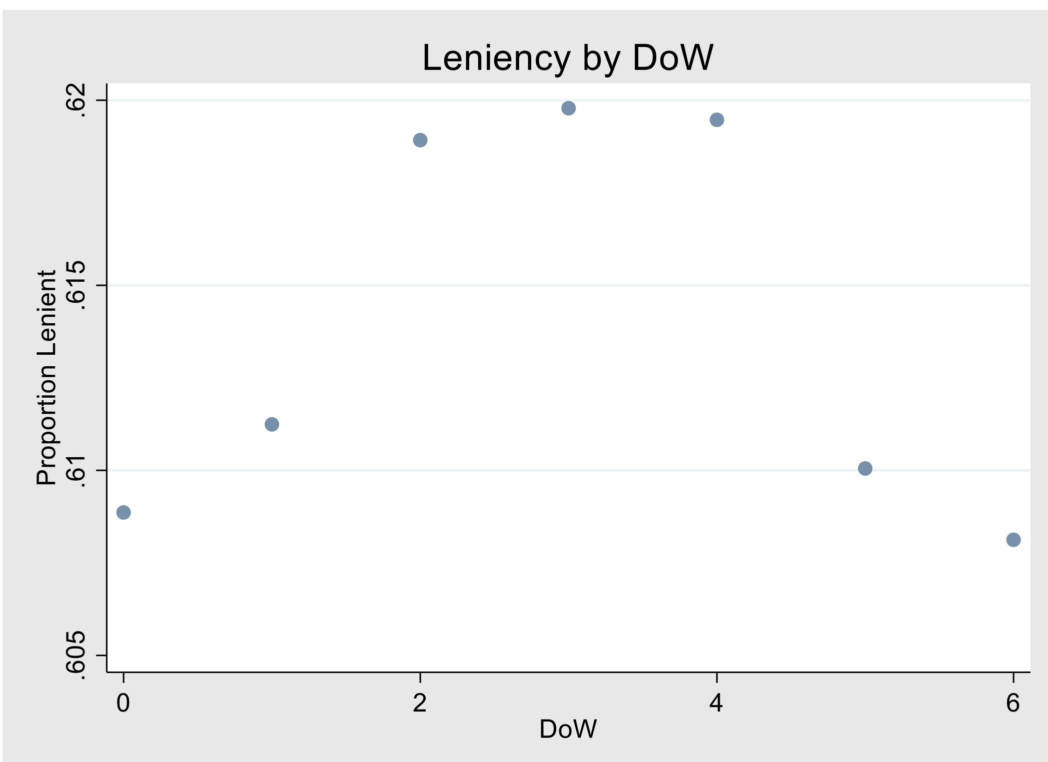


Figure E 9

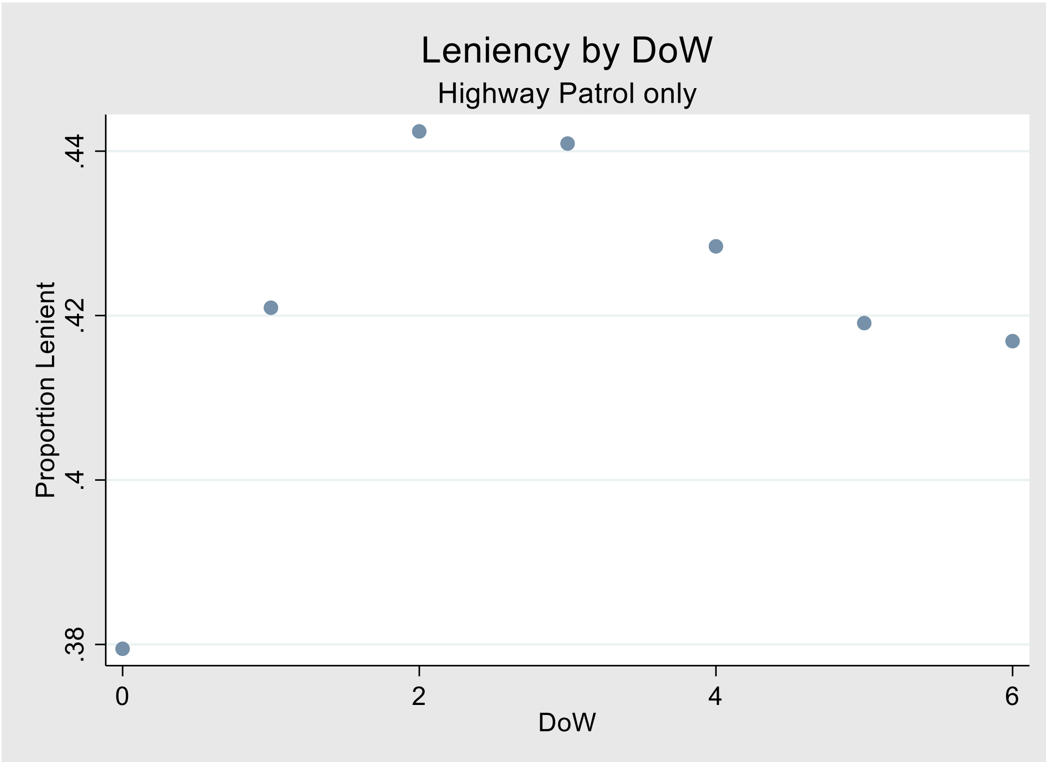


Figure E 10

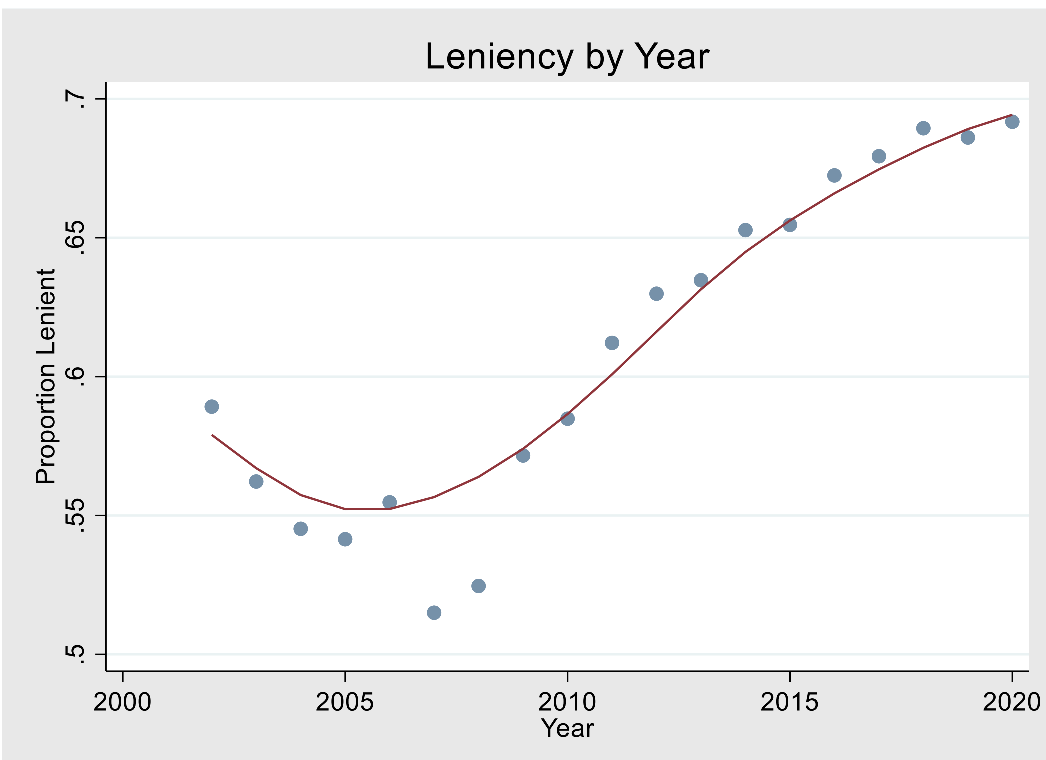


Figure E 11

VARIABLES	Stop Reason Movement
years = 2	-0.0295
years = 3	0.120
years = 4	0.0443
years = 5	0.0133
years = 6	-0.263**
years = 7	-0.638***
years = 8	-0.125
years = 9	-0.169
years = 10	-0.0776
years = 11	-0.151
years = 12	0.169
years = 13	-0.246
years = 14	-0.0870
years = 15	-0.505***
years = 16	-0.534***
years = 17	-0.159
years = 18	0.333**
years = 19	0.214
years = 20	0.115
years = 21	-0.0782
years = 22	-0.281
years = 23	0.000514
years = 24	0.151
years = 25	-0.106
years = 26	-0.0619
years = 27	0.0418
years = 28	-0.215
years = 29	0.520
years = 30, omitted	-
Driver_Age	-0.00303
CMPD_Division = 2, Eastway Division	-0.133
CMPD_Division = 3, Freedom Division	-0.0457
CMPD_Division = 4, Hickory Grove Division	-0.399***
CMPD_Division = 5, Independence Division	-0.228**
CMPD_Division = 6, Metro Division	-0.222**
CMPD_Division = 7, North Division	-0.380***
CMPD_Division = 8, North Tryon Division	-0.300***
CMPD_Division = 9, Providence Division	0.0745
CMPD_Division = 10, South Division	0.000430

CMPD_Division = 11, Steele Creek Division	-0.505***
CMPD_Division = 12, University City Division	-0.309***
CMPD_Division = 13, Westover Division	-0.199**
Officer_Race = 2, 2 or More	-0.880
Officer_Race = 3, American Indian/Alaska Native	-0.533
Officer_Race = 4, Asian / Pacific Islander	0.106
Officer_Race = 5, Black/African American	-0.414
Officer_Race = 6, Hispanic/Latino	-0.153
Officer_Race = 8, Not Specified	0.113
Officer_Race = 9, White	-0.0445
driver_age_sqr	0.000185*
Driver_Gender	-0.0884**
Officer_Gender	-2.12e-05
Driver_Race = 2, Black	-0.198
Driver_Race = 3, Native American	-0.669
Driver_Race = 4, Other/Unknown	-0.316*
Driver_Race = 5, White	-0.294**
Constant	1.353***
Observations	5,559

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure E 12

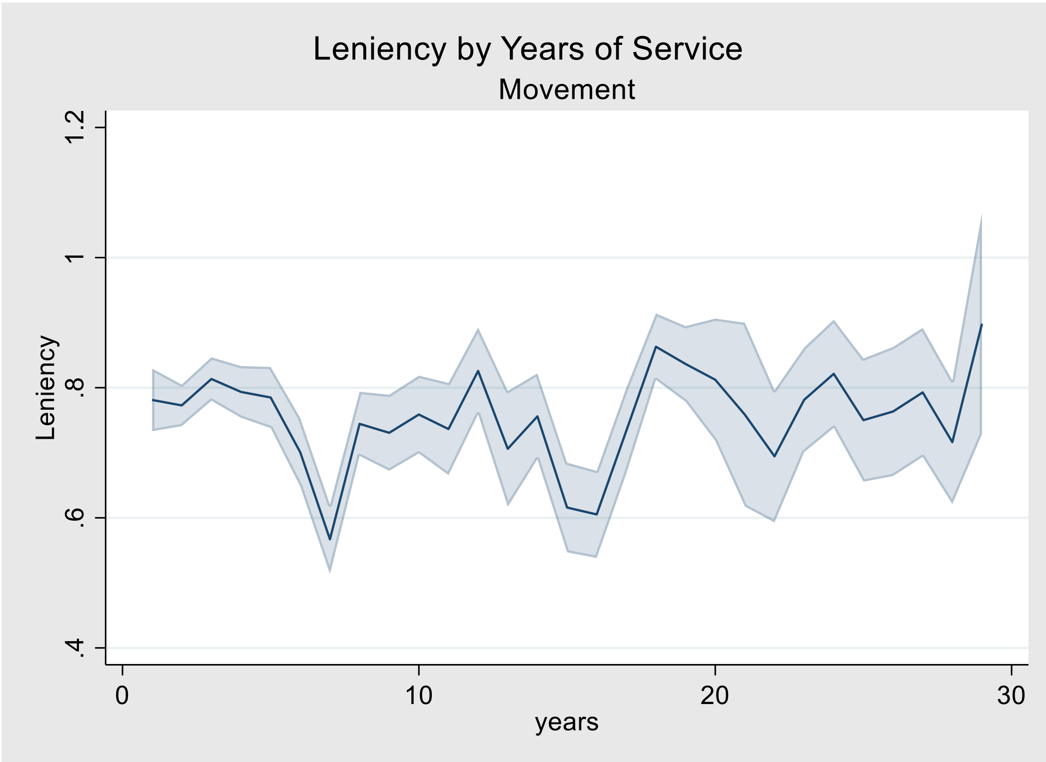


Figure E 13

	No Officer			Officer		
	Total	Change	% Change	Total	Change	% Change
Saturated	0.085	0	0	0.256	0	0
Identity	0.068	0.017	20	0.242	0.014	5.469
Year	0.078	0.007	8.235	0.252	0.004	1.563
Month	0.085	0	0	0.256	0	0
Day	0.085	0	0	0.256	0	0
Hour	0.082	0.003	3.529	0.254	0.002	0.781
Department	0.045	0.04	47.059	N/A		
Officer	N/A			0.125	0.131	51.171875

Stops Cutoff: 300

Figure E 14

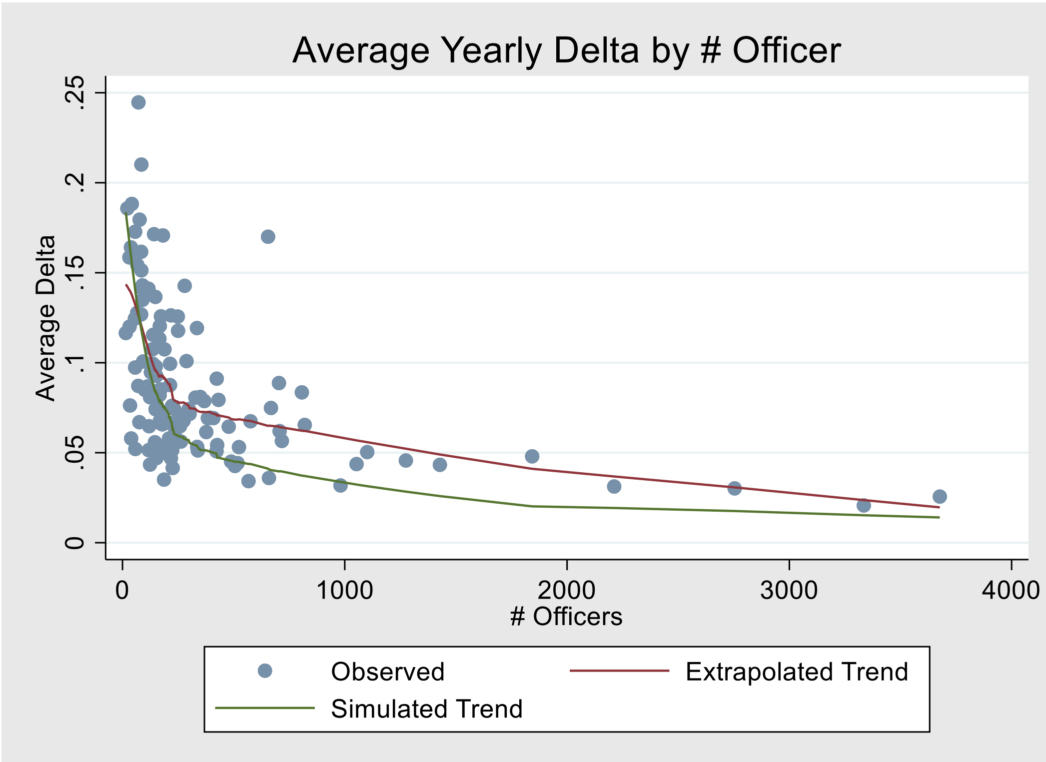


Figure E 15

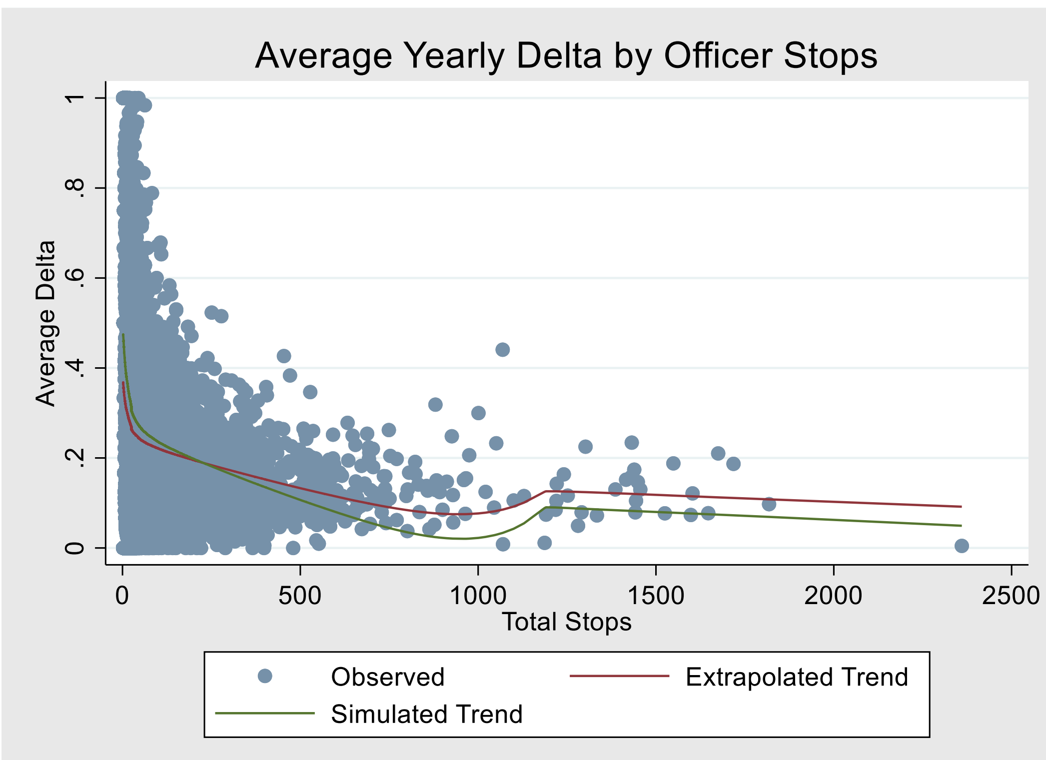


Figure E 16

Appendix F: Other Vehicle

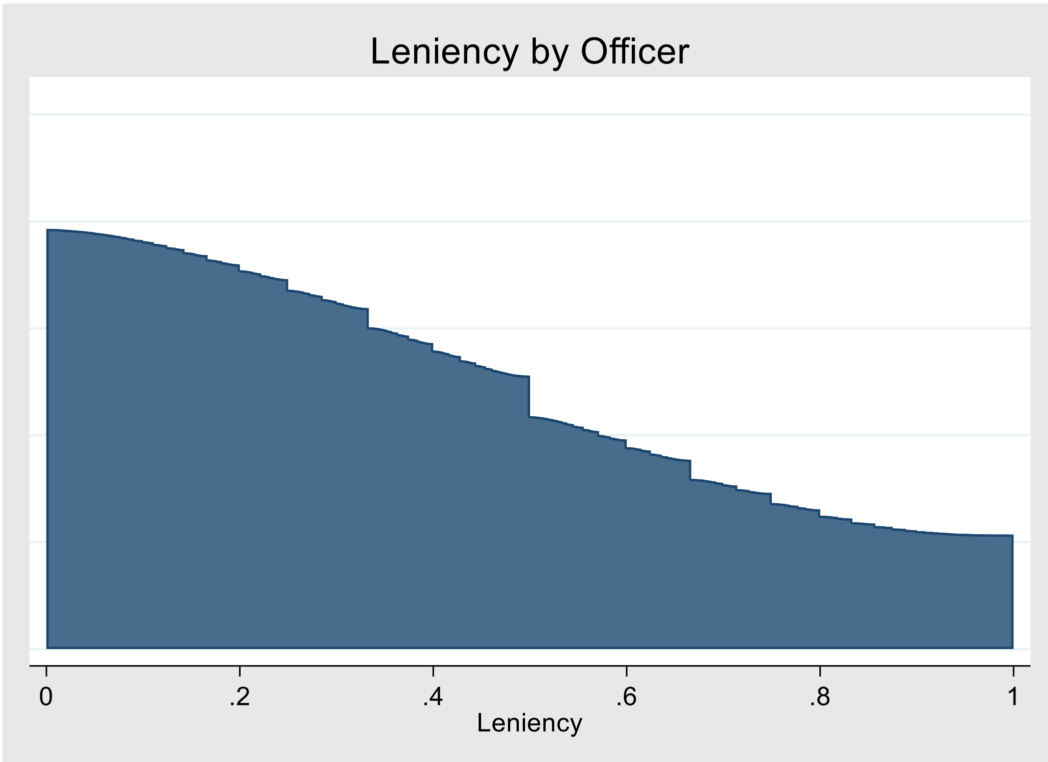


Figure F 1

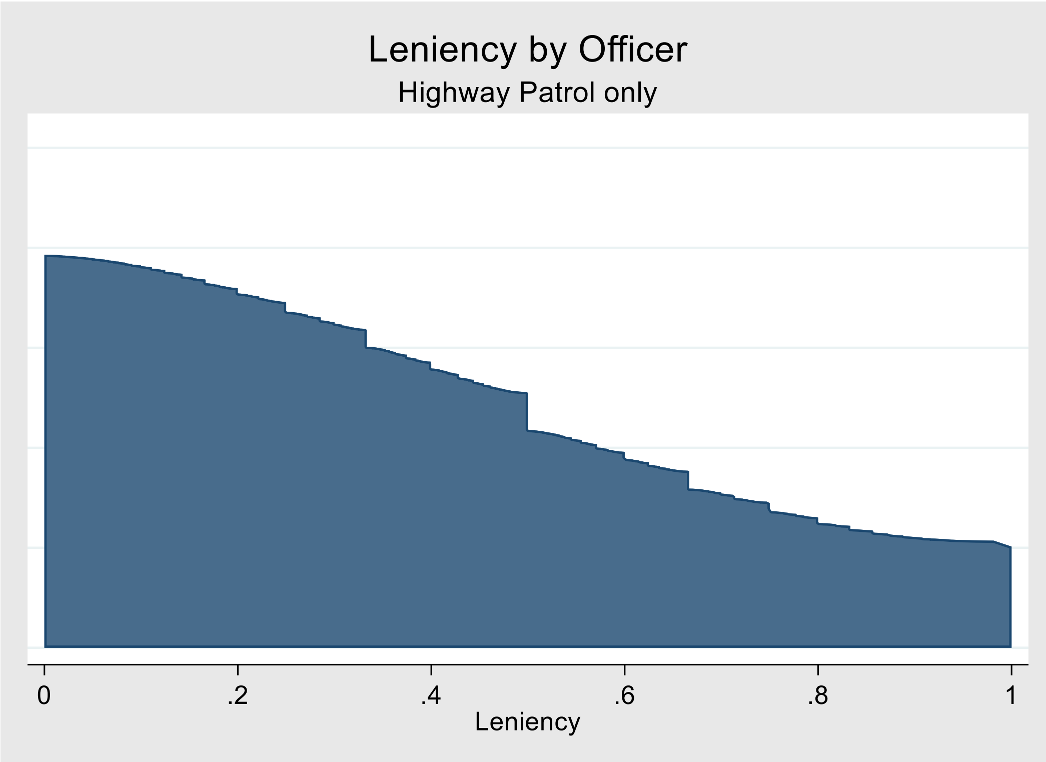


Figure F 2

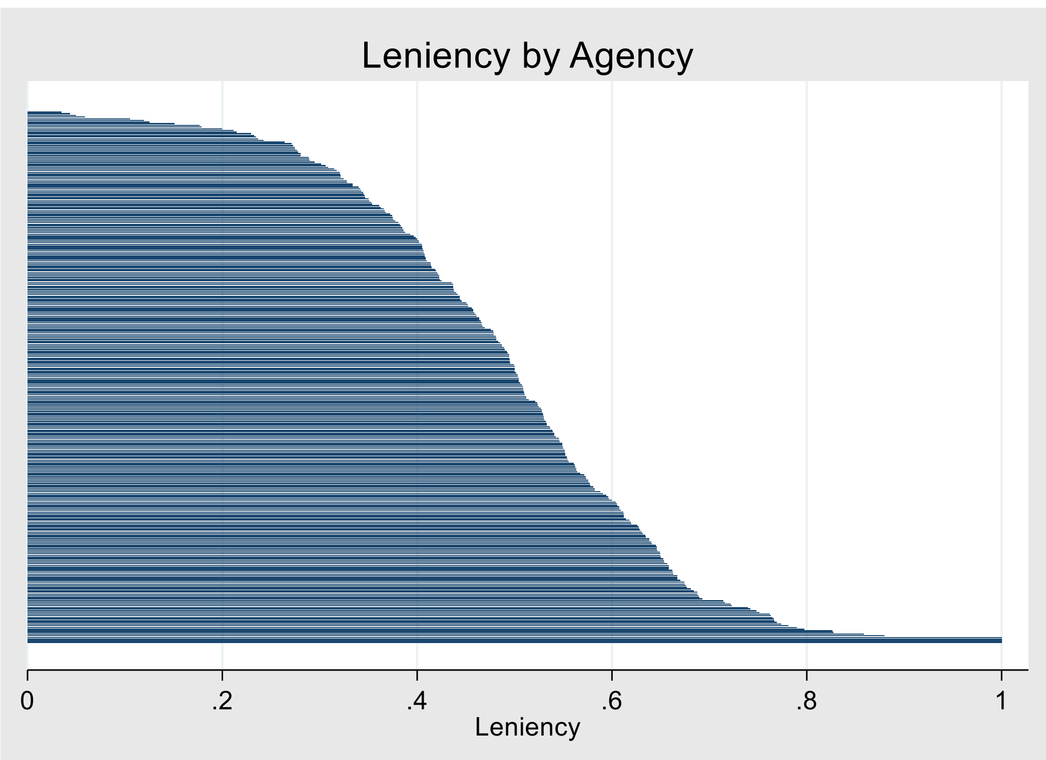


Figure F 3

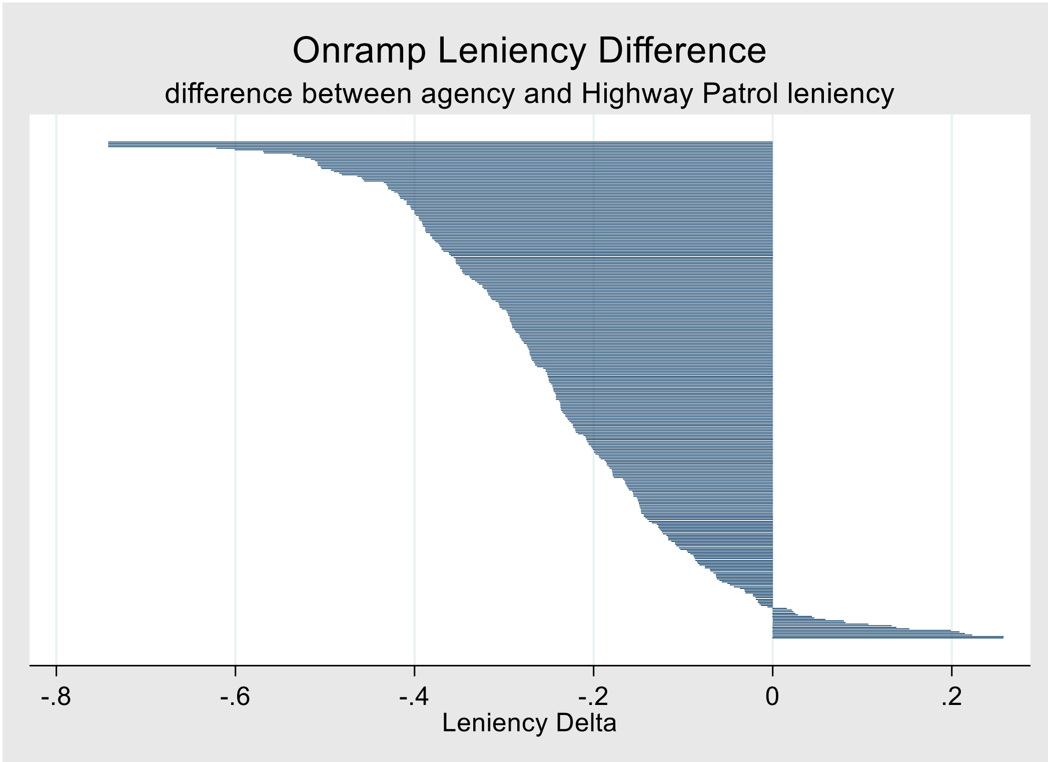


Figure F 4

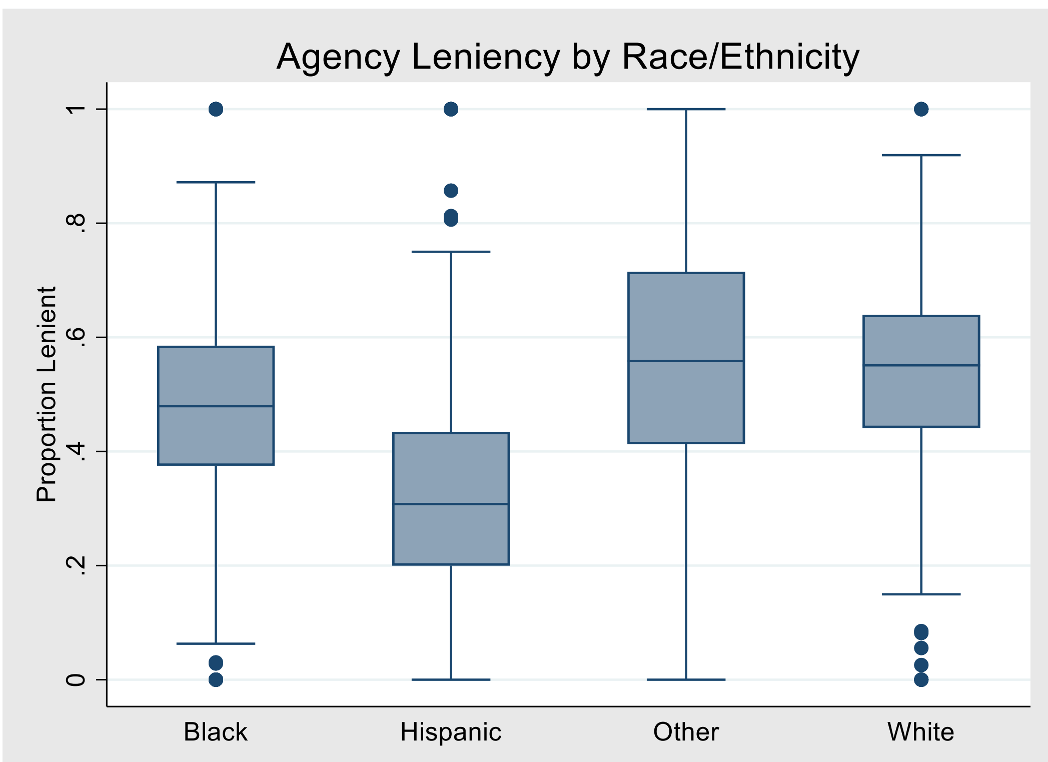


Figure F 5

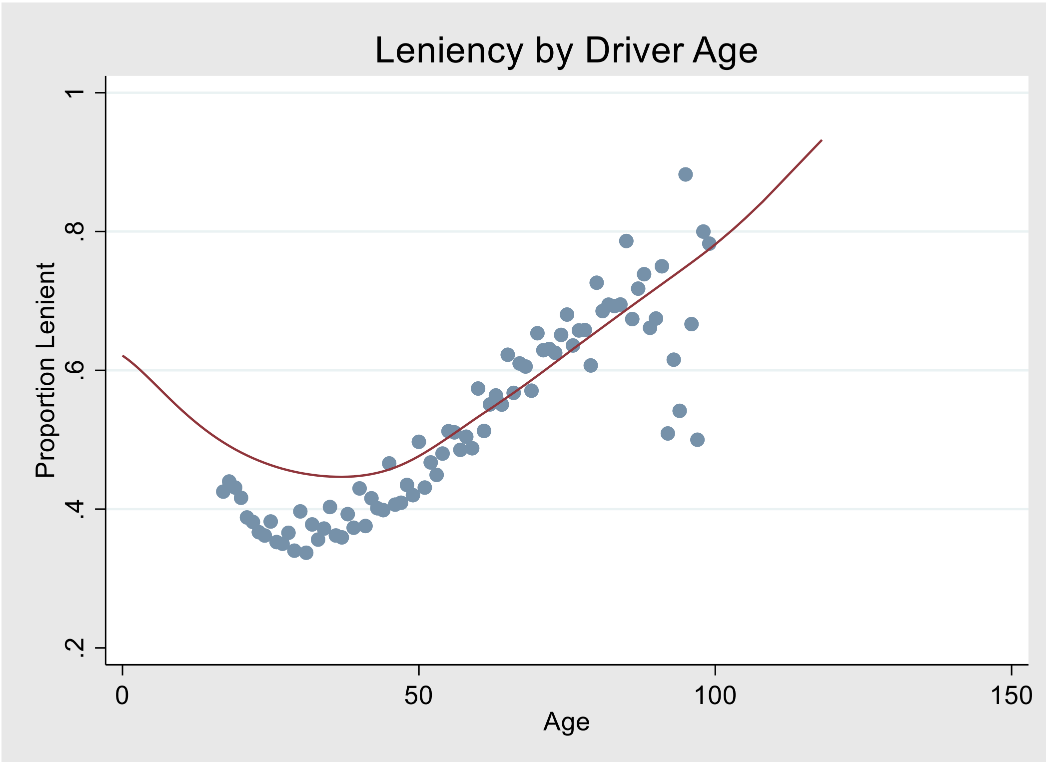


Figure F 6

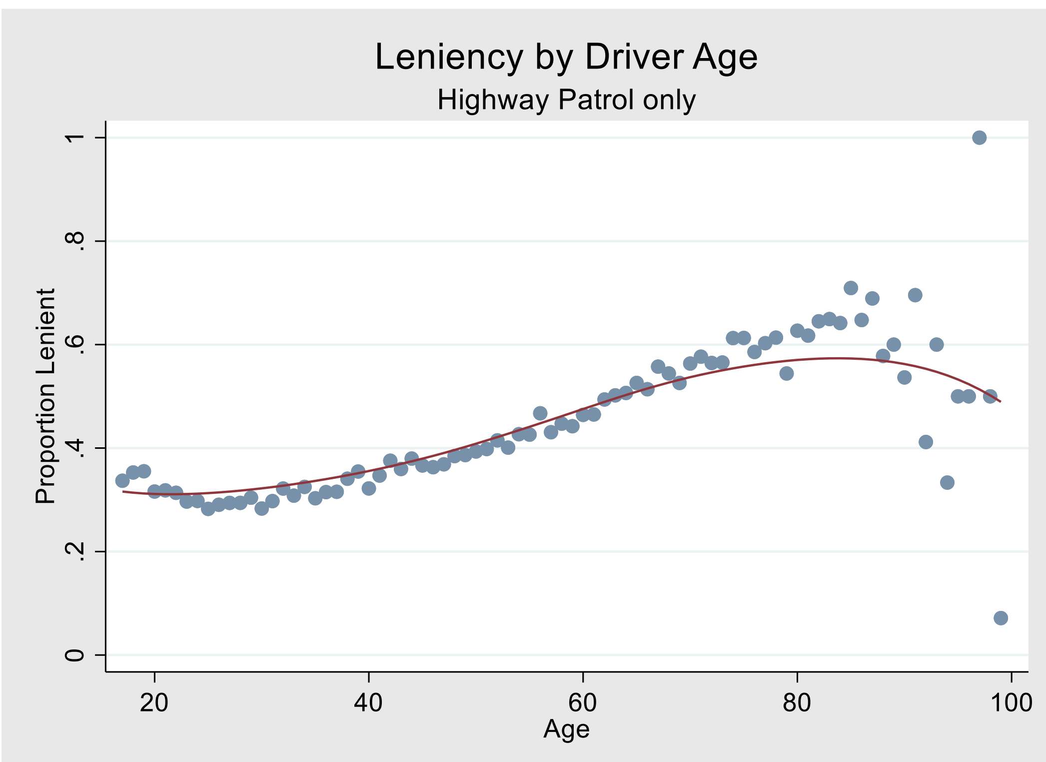


Figure F 7

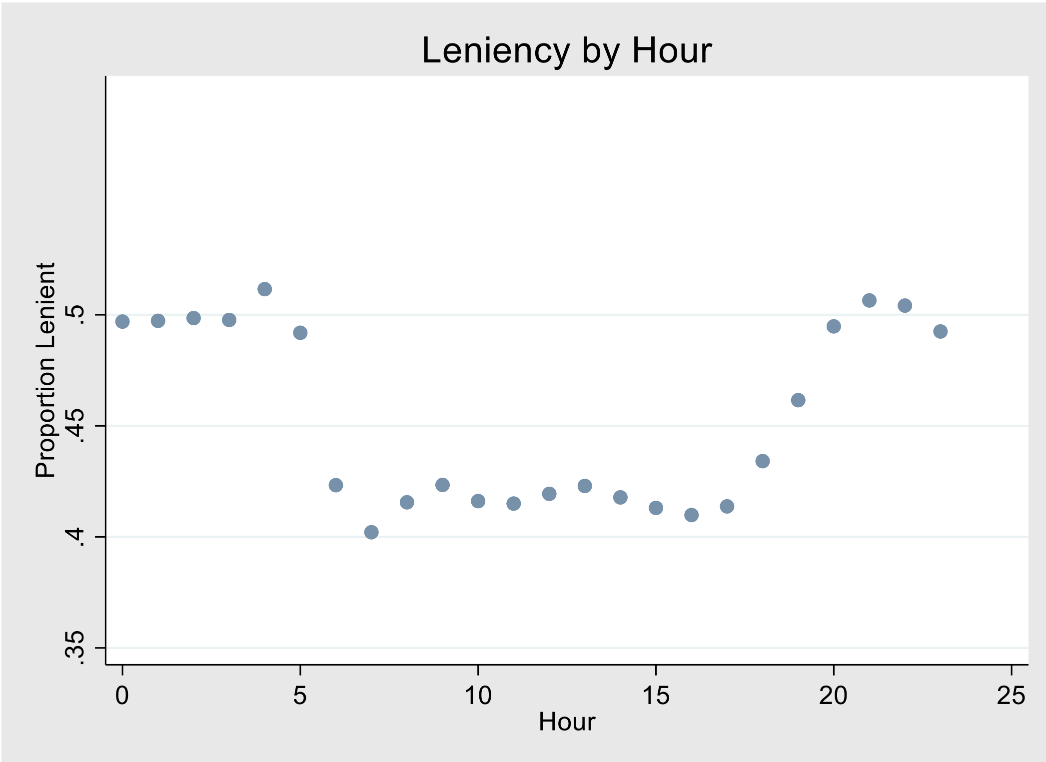


Figure F 8

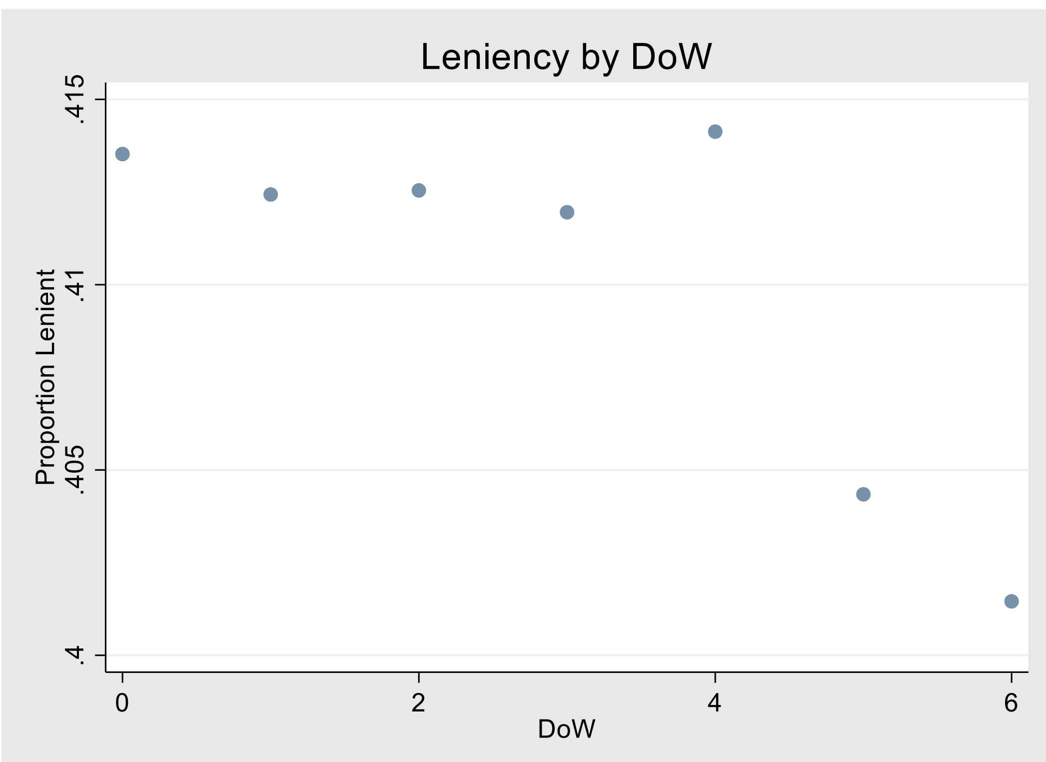


Figure F 9

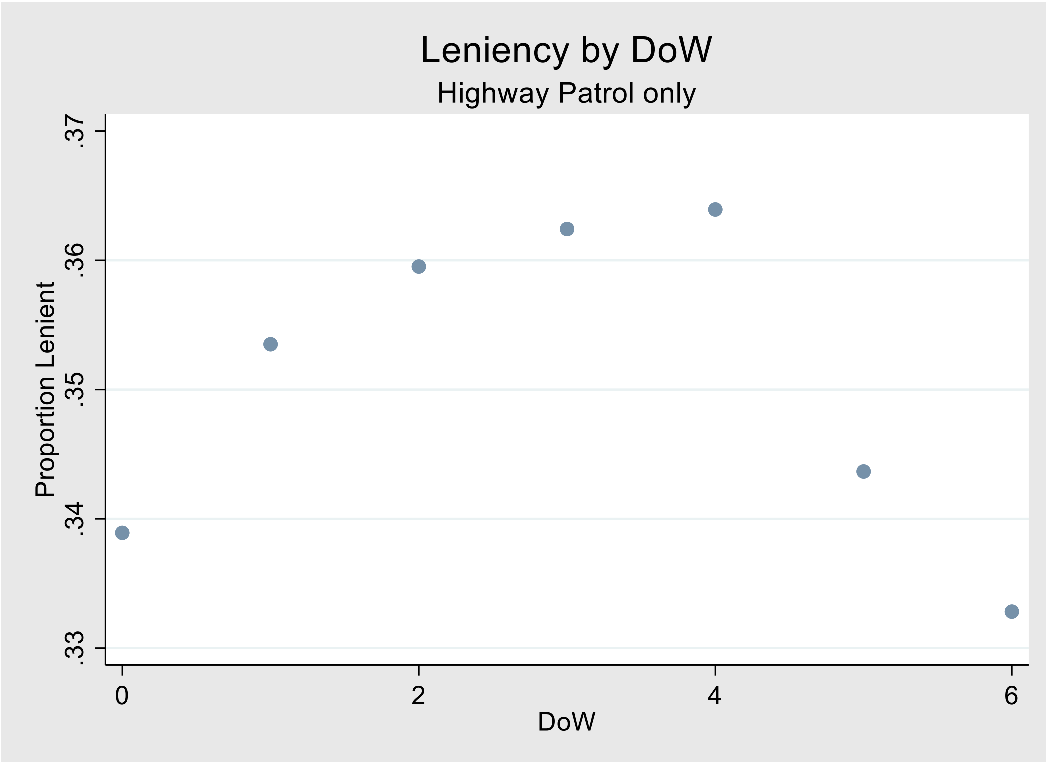


Figure F 10

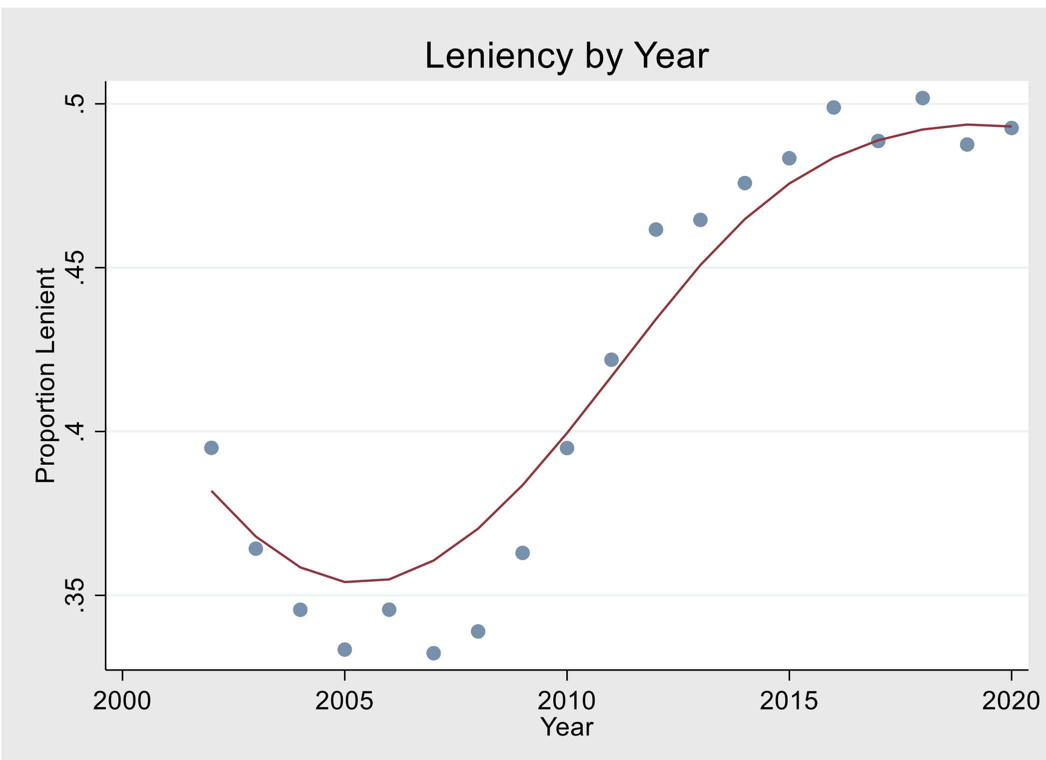


Figure F 11

VARIABLES	Stop Reason Other Vehicle
years = 2	0.473**
years = 3	0.512**
years = 4	0.636***
years = 5	-0.052
years = 6	-0.042
years = 7	0.471**
years = 8	0.233
years = 9	0.431**
years = 10	0.235
years = 11	-0.119
years = 12	0.078
years = 13	0.509
years = 14	0.011
years = 15	-0.224
years = 16	-0.519**
years = 17	-0.023
years = 18	0.306
years = 19	0.552**
years = 20	0.493*
years = 21	0.040
years = 22	0.678***
years = 23	0.445*
years = 24	0.546**
years = 25	0.580**
years = 26	0.629**
years = 27	0.440**
years = 28	0.327
years = 29	0.489*
years = 30	0.973**
years = 35, omitted	-
Driver_Age	-0.041***
CMPD_Division = 2, Eastway Division	0.461***
CMPD_Division = 3, Freedom Division	0.110
CMPD_Division = 4, Hickory Grove Division	0.171
CMPD_Division = 5, Independence Division	0.308
CMPD_Division = 6, Metro Division	-0.019
CMPD_Division = 7, North Division	0.487***
CMPD_Division = 8, North Tryon Division	-0.120

CMPD_Division = 9, Providence Division	0.079
CMPD_Division = 10, South Division	0.121
CMPD_Division = 11, Steele Creek Division	-0.017
CMPD_Division = 12, University City Division	-0.617***
CMPD_Division = 13, Westover Division	0.114
Officer_Race = 3, omitted	-
Officer_Race = 4, Asian / Pacific Islander	-0.245
Officer_Race = 5, Black/African American	-0.227
Officer_Race = 6, Hispanic/Latino	-0.317
Officer_Race = 8, Not Specified	-0.046
Officer_Race = 9, White	-0.0211
driver_age_sqr	0.001***
Driver_Gender	-0.162**
Officer_Gender	-0.221*
Driver_Race = 2, Black	-0.805***
Driver_Race = 3, omitted	-
Driver_Race = 4, Other/Unknown	-0.981***
Driver_Race = 5, White	-0.755**
Constant	2.122**
Observations	2,035

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure F 12

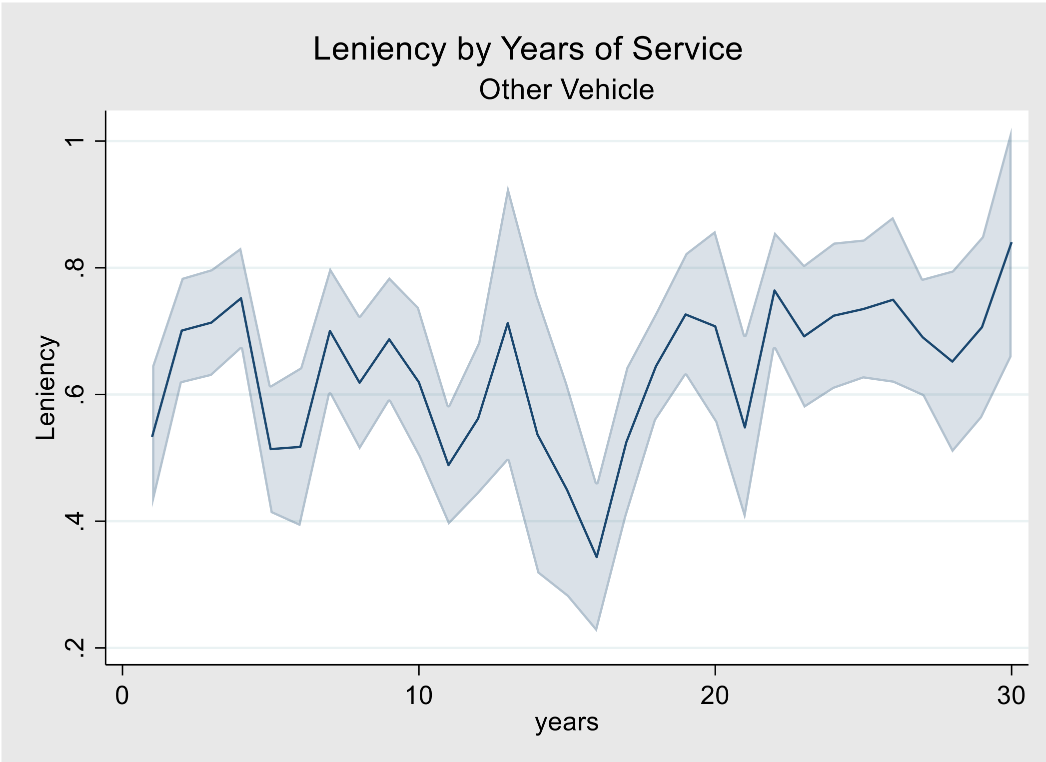


Figure F 13

	No Officer			Officer		
	Total	Change	% Change	Total	Change	% Change
Saturated	0.063	0	0	0.211	0	0
Identity	0.041	0.022	34.921	0.192	0.019	9.005
Year	0.056	0.007	11.111	0.209	0.002	0.948
Month	0.063	0	0	0.211	0	0
Day	0.063	0	0	0.211	0	0
Hour	0.06	0.003	4.762	0.209	0.002	0.9479
Department	0.042	0.021	33.333	N/A		
Officer	N/A			0.056	0.155	73.460

Stops Cutoff: 400

Figure F 14

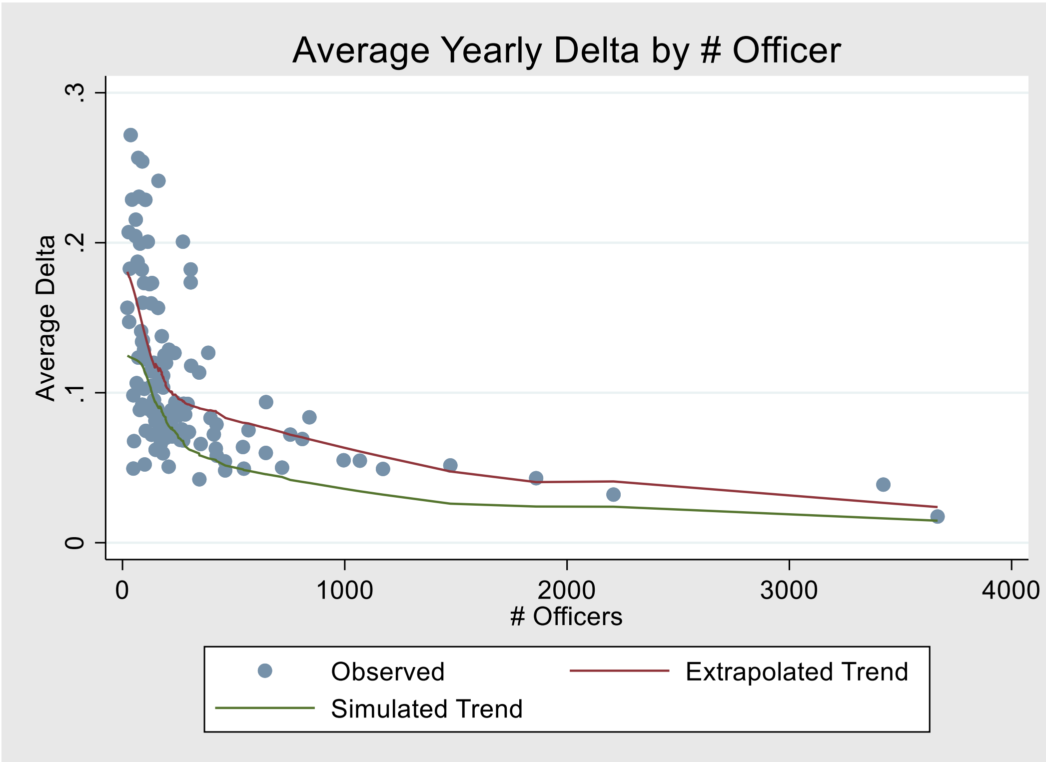


Figure F 15

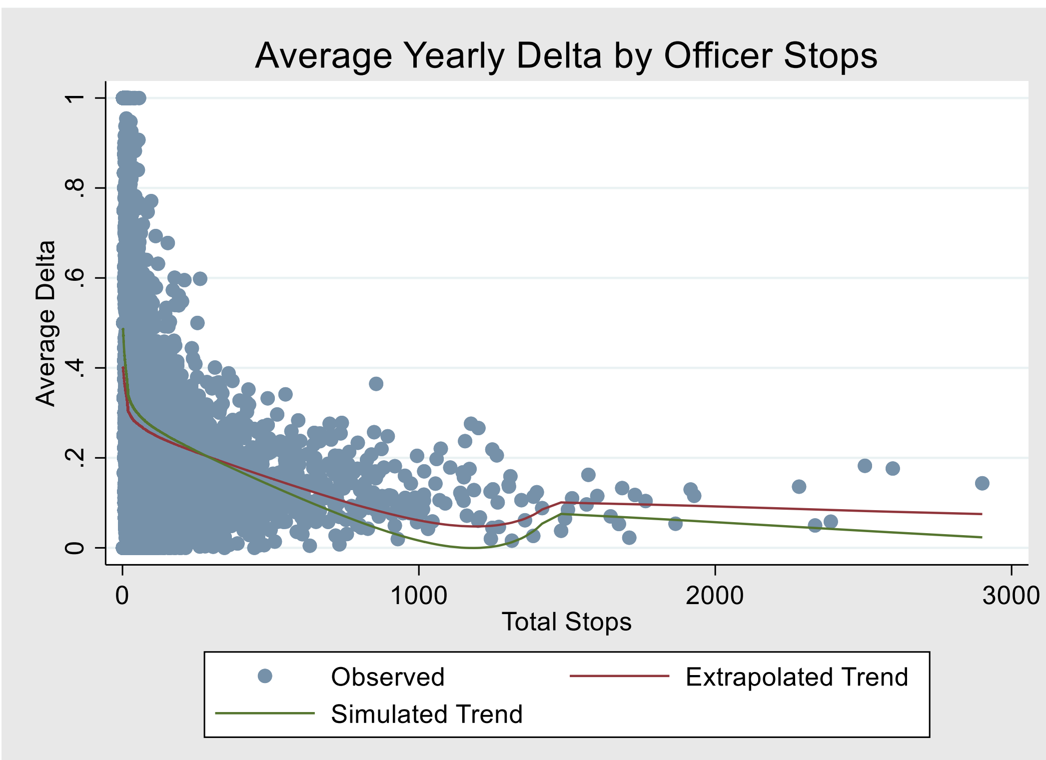


Figure F 16

Appendix G: Regulatory

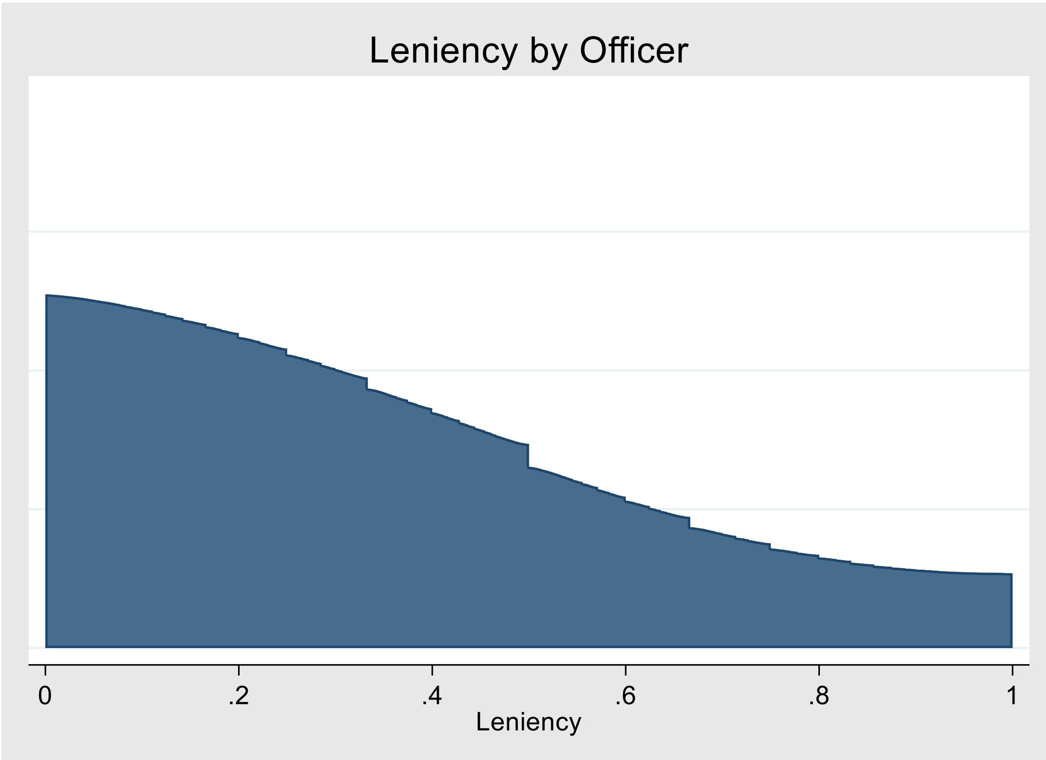


Figure G 1

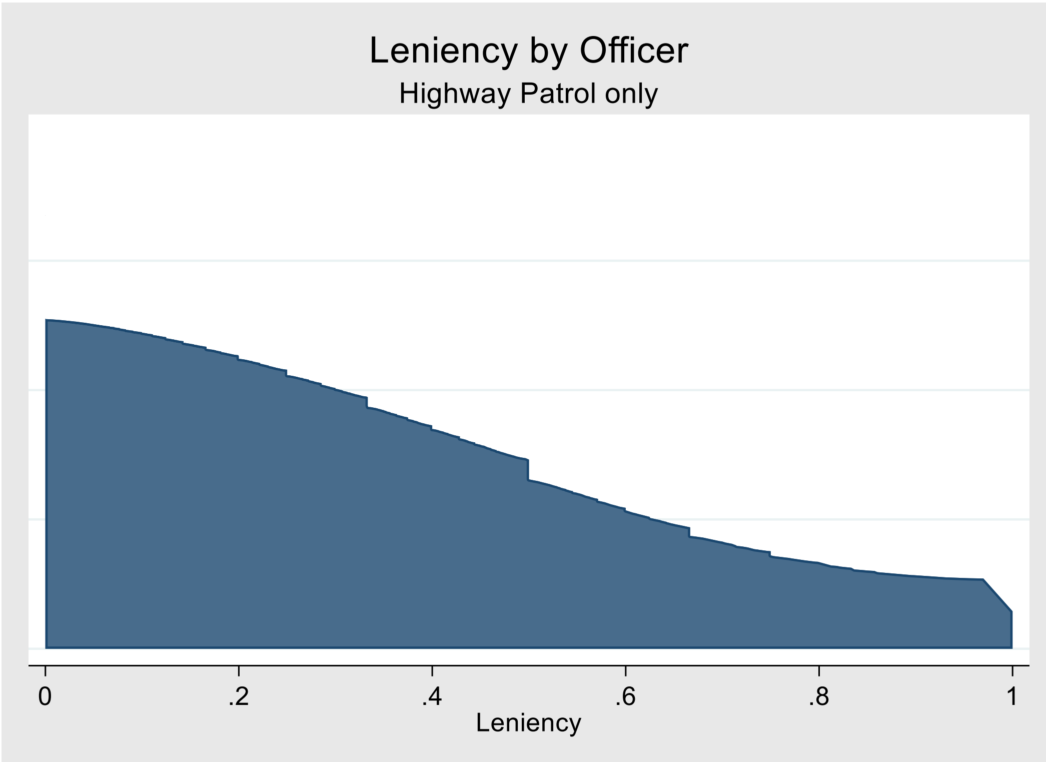


Figure G 2

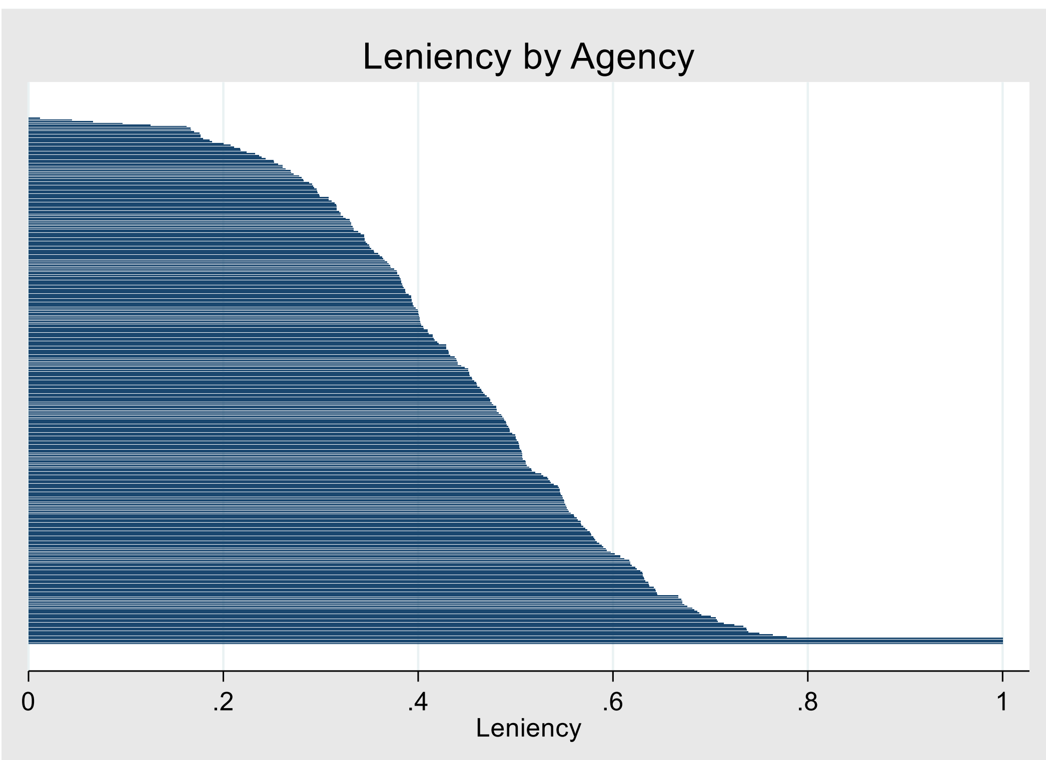


Figure G 3

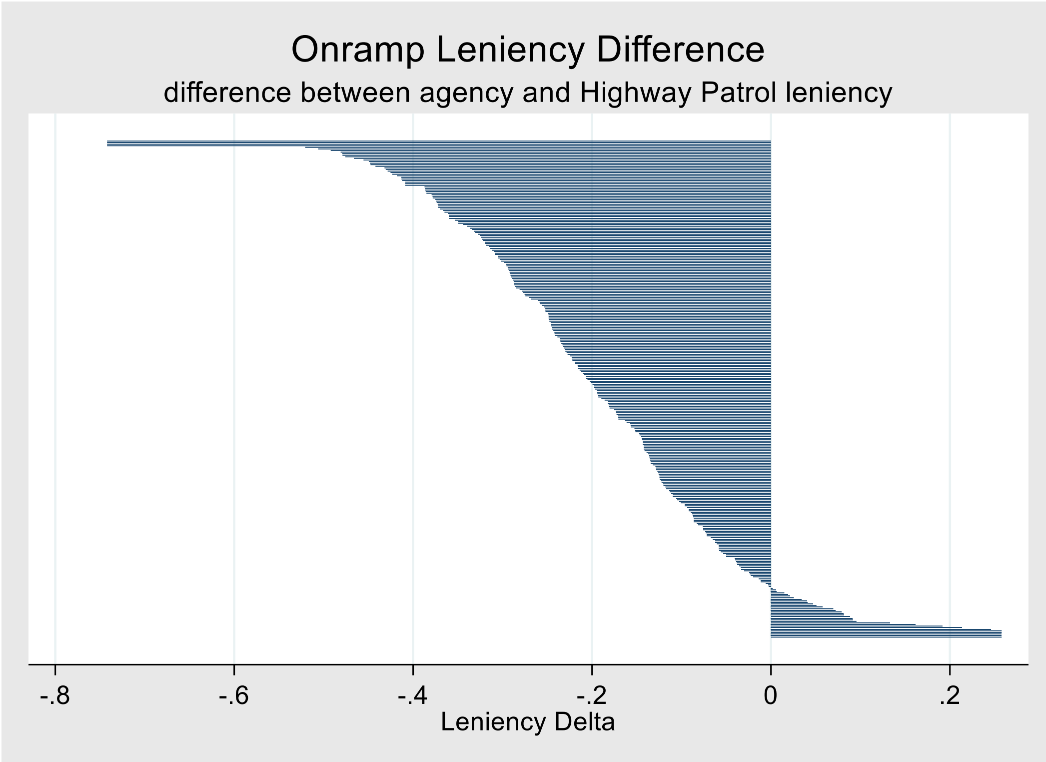


Figure G 4

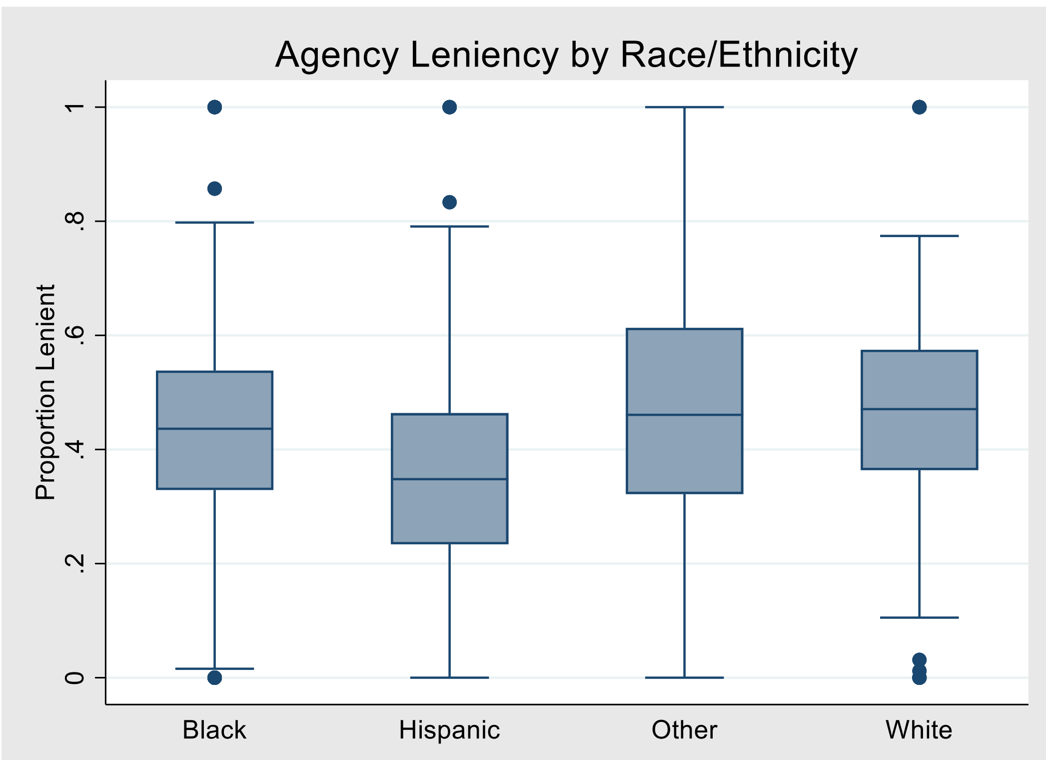


Figure G 5

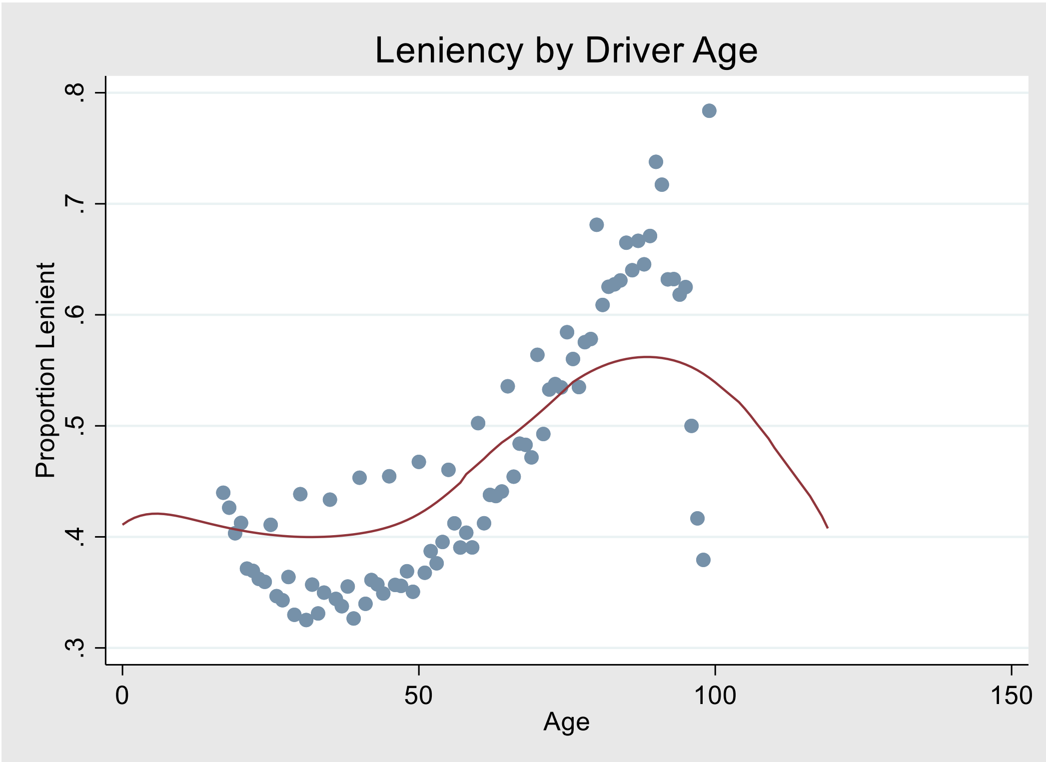


Figure G 6

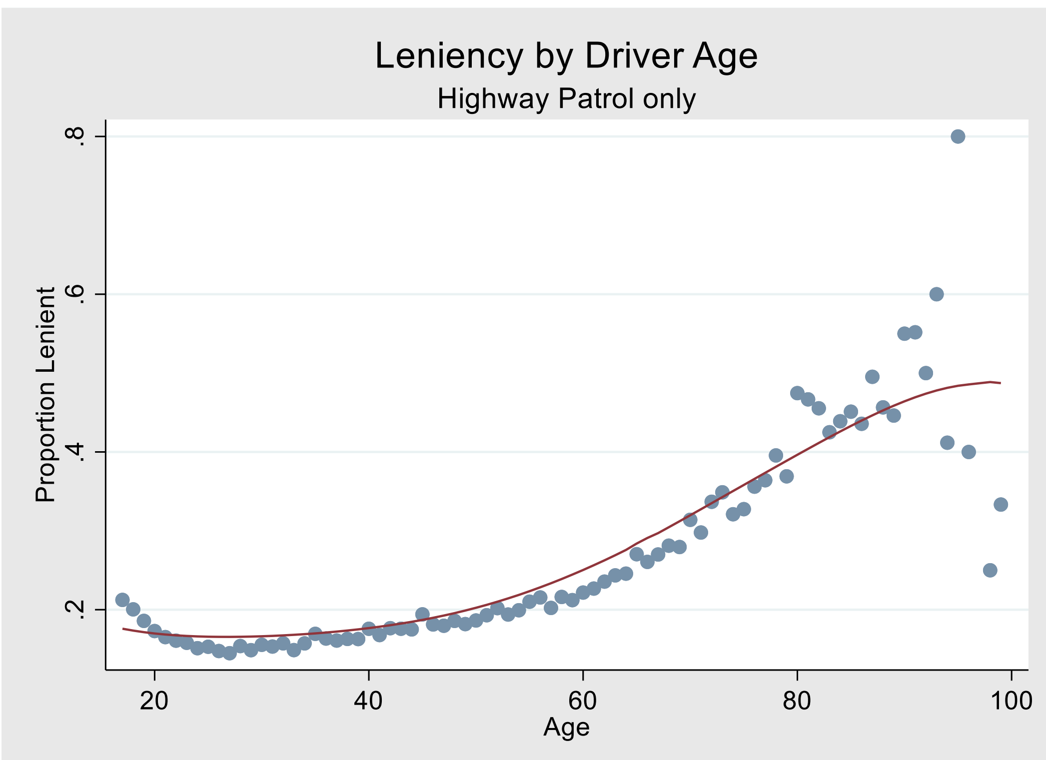


Figure G 7

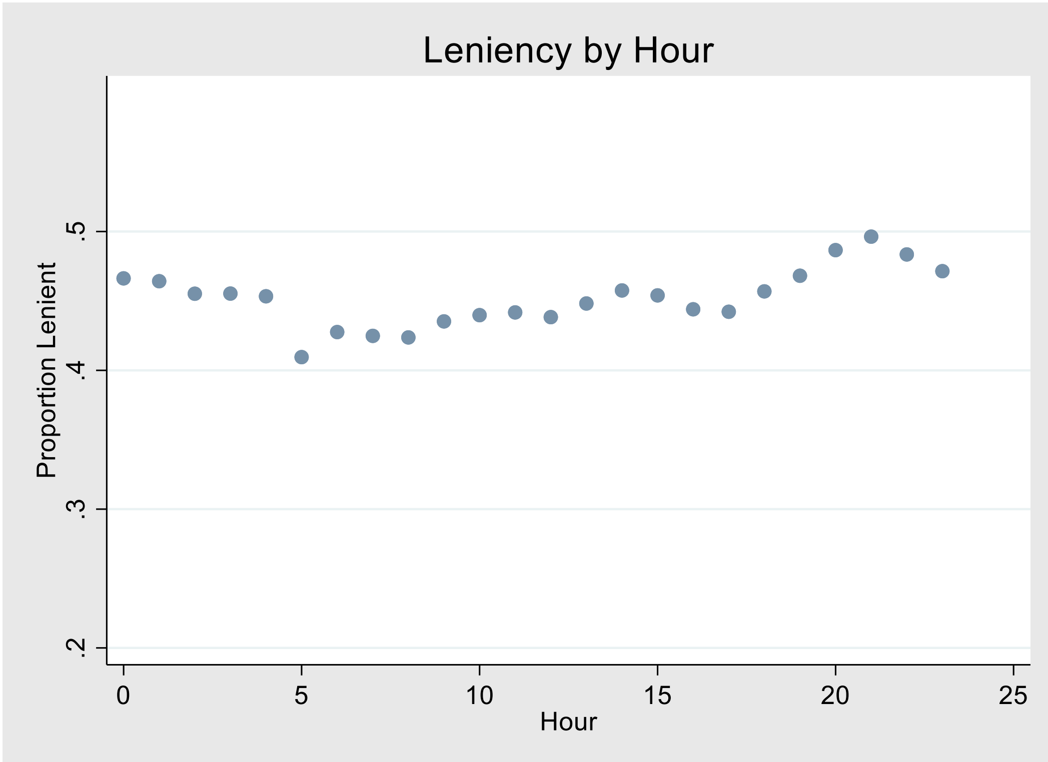


Figure G 8

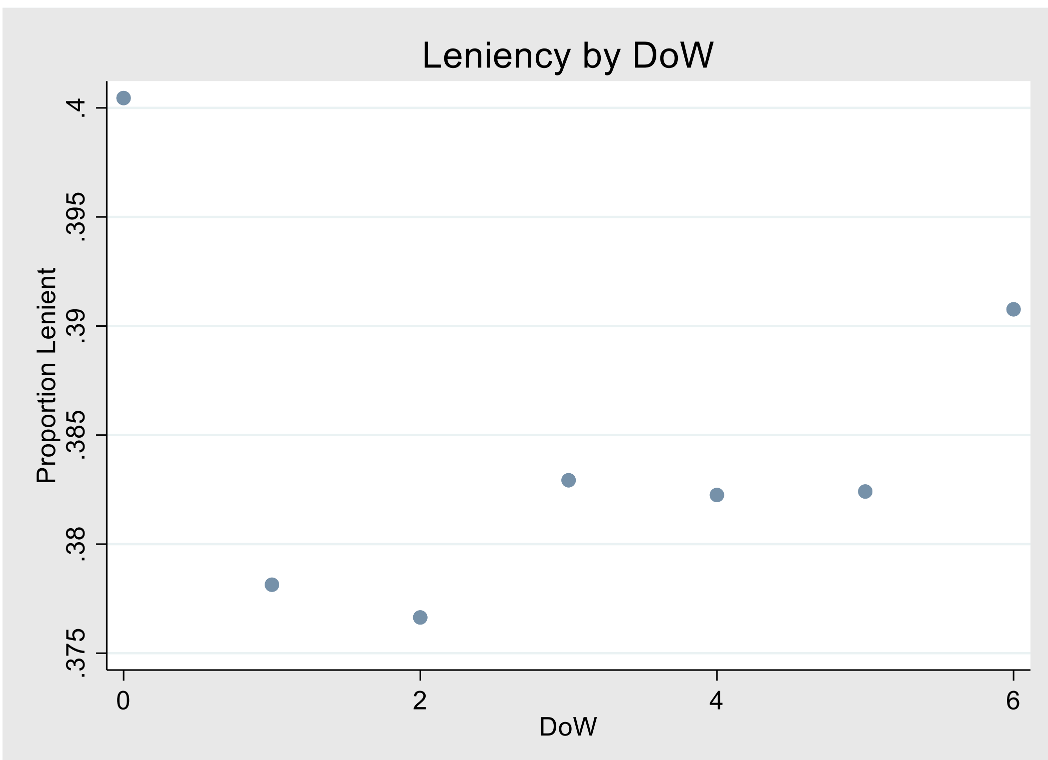


Figure G 9

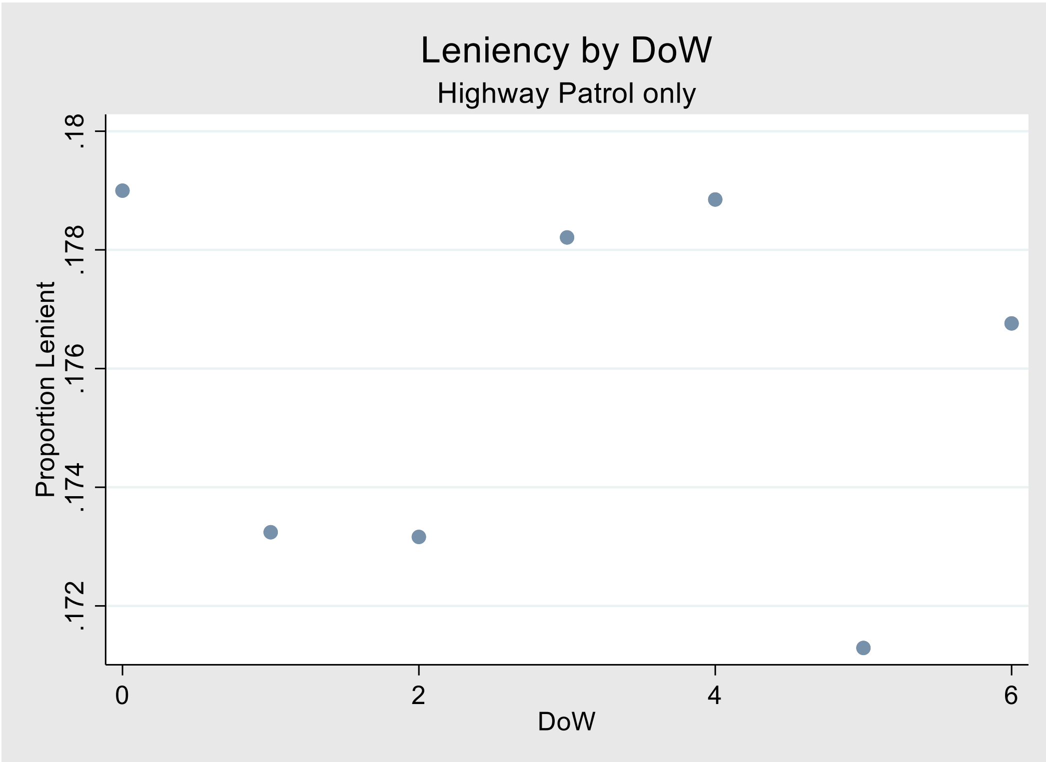


Figure G 10

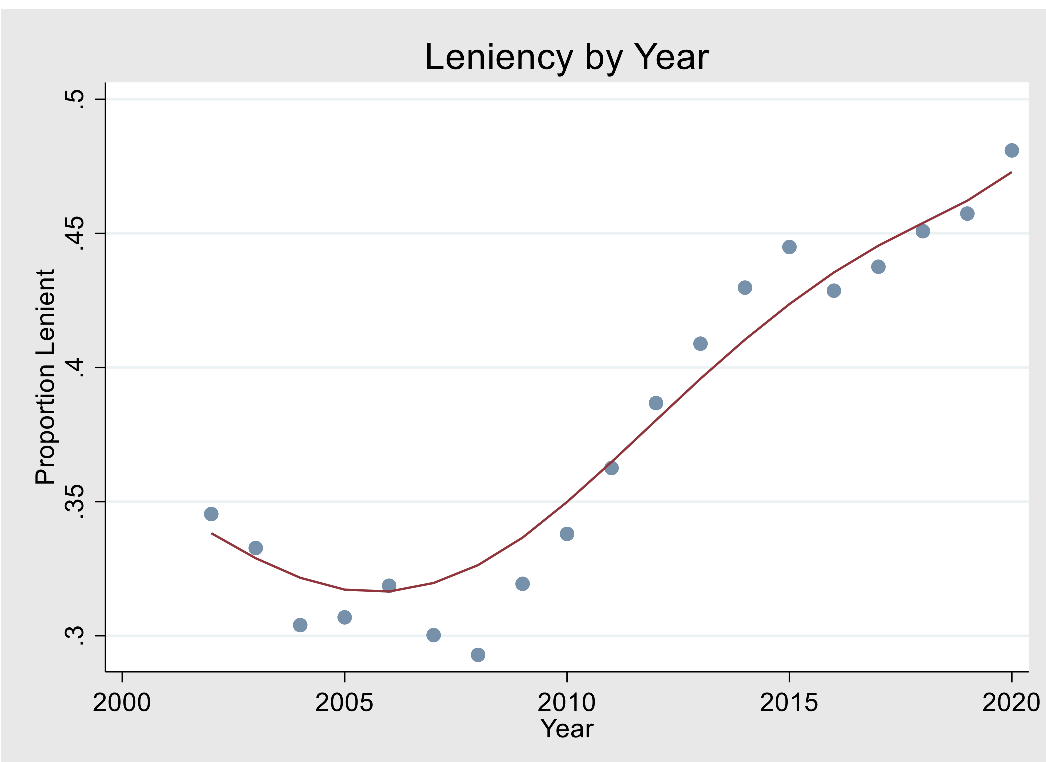


Figure G 11

VARIABLES	Stop Reason Regulatory
years = 2	0.223***
years = 3	0.268***
years = 4	0.253***
years = 5	0.328***
years = 6	0.181***
years = 7	-0.0227
years = 8	0.106**
years = 9	0.118***
years = 10	0.223***
years = 11	0.244***
years = 12	0.163***
years = 13	0.137**
years = 14	0.115*
years = 15	-0.0199
years = 16	-0.288***
years = 17	-0.113**
years = 18	-0.330***
years = 19	-0.442***
years = 20	-0.426***
years = 21	-0.182***
years = 22	-0.087
years = 23	-0.164***
years = 24	-0.097
years = 25	-0.163**
years = 26	-0.086
years = 27	-0.203***
years = 28	-0.342***
years = 29	-0.089
years = 30	-0.013
Driver_Age	-0.010***
CMPD_Division = 2, Eastway Division	0.010
CMPD_Division = 3, Freedom Division	0.092**
CMPD_Division = 4, Hickory Grove Division	0.163***
CMPD_Division = 5, Independence Division	-0.088**
CMPD_Division = 6, Metro Division	0.054
CMPD_Division = 7, North Division	0.060
CMPD_Division = 8, North Tryon Division	0.152***
CMPD_Division = 9, Providence Division	-0.103**
CMPD_Division = 10, South Division	-0.031

CMPD_Division = 11, Steele Creek Division	-0.057
CMPD_Division = 12, University City Division	-0.263***
CMPD_Division = 13, Westover Division	0.356***
Officer_Race = 2, 2 or More	0.129
Officer_Race = 3, American Indian/Alaska Native	0.318
Officer_Race = 4, Asian / Pacific Islander	-0.277*
Officer_Race = 5, Black/African American	-0.103
Officer_Race = 6, Hispanic/Latino	-0.229
Officer_Race = 7, Native Hawaiian/Oth Pac Island	0.032
Officer_Race = 8, Not Specified	0.522***
Officer_Race = 9, White	-0.041
driver_age_sqr	0.002***
Driver_Gender	-0.037***
Officer_Gender	0.061***
Driver_Race = 2, Black	-0.150**
Driver_Race = 3, Native American	-0.635**
Driver_Race = 4, Other/Unknown	-0.158*
Driver_Race = 5, White	-0.186***
Constant	0.457**
Observations	34,448

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure G 12

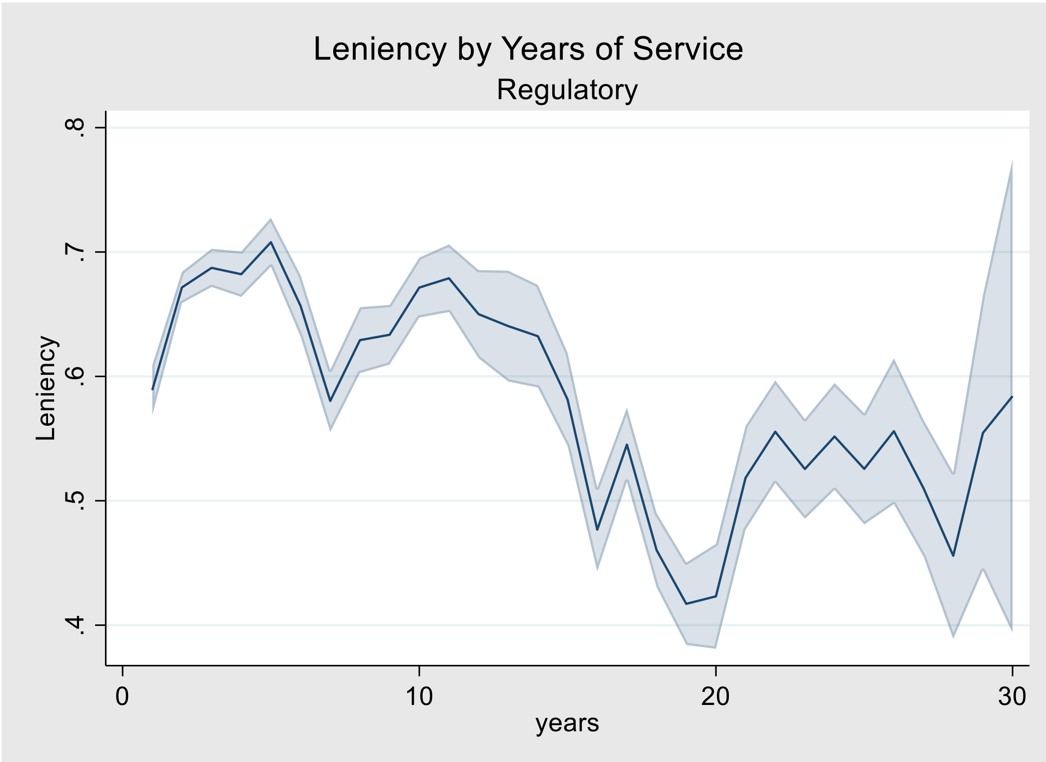


Figure G 13

	No Officer			Officer		
	Total	Change	% Change	Total	Change	% Change
Saturated	0.089	0	0	0.18	0	0
Identity	0.083	0.006	6.742	0.174	0.006	3.333
Year	0.08	0.009	10.112	0.178	0.002	1.111
Month	0.089	0	0	0.18	0	0
Day	0.089	0	0	0.18	0	0
Hour	0.088	0.001	1.124	0.18	0	0
Department	0.052	0.037	41.573	N/A		
Officer	N/A			0.079	0.101	56.111

Stops Cutoff: 950

Figure G 14

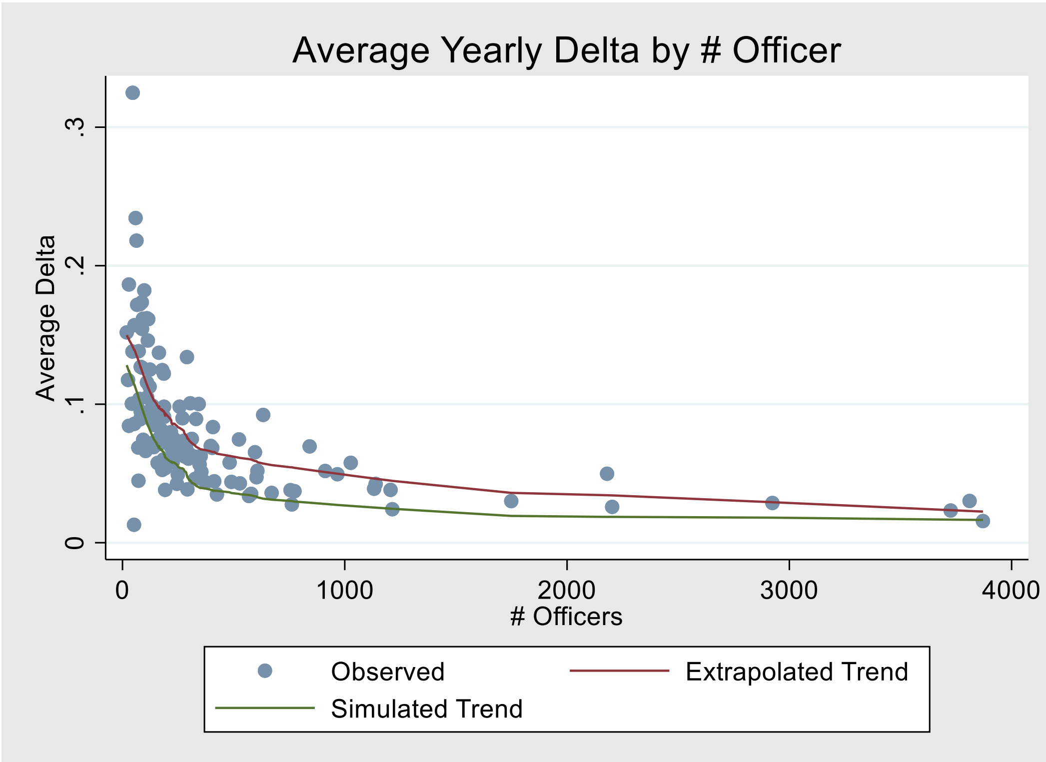


Figure G 15

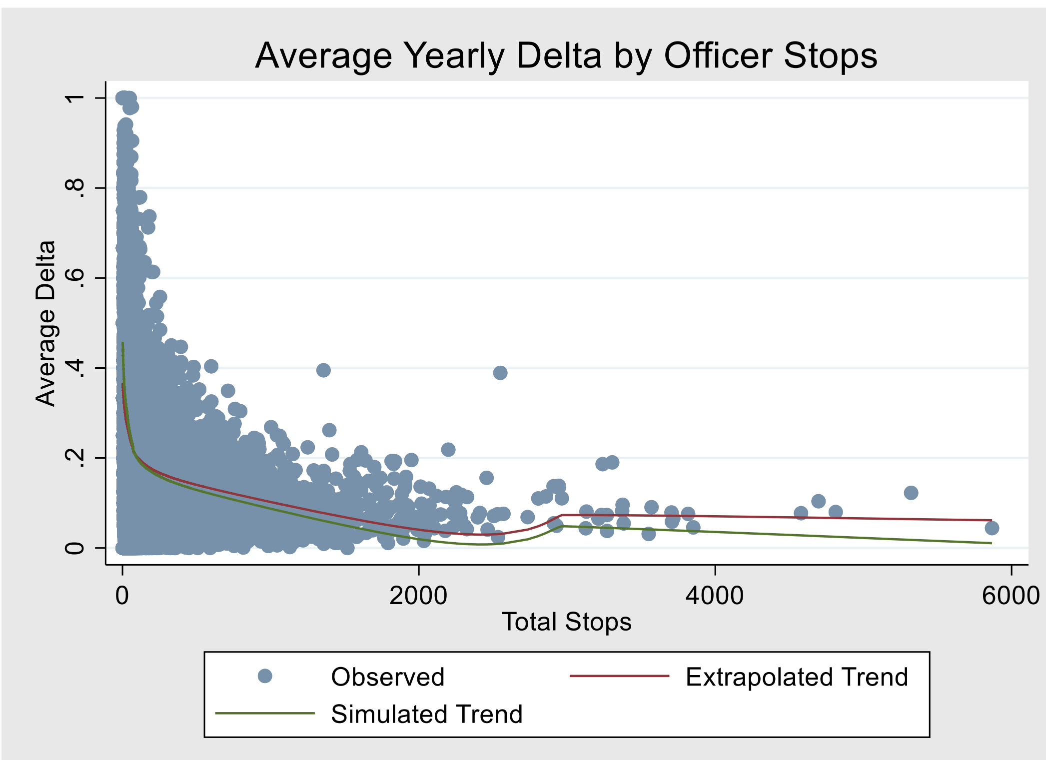


Figure G 16

Appendix H: Seatbelt

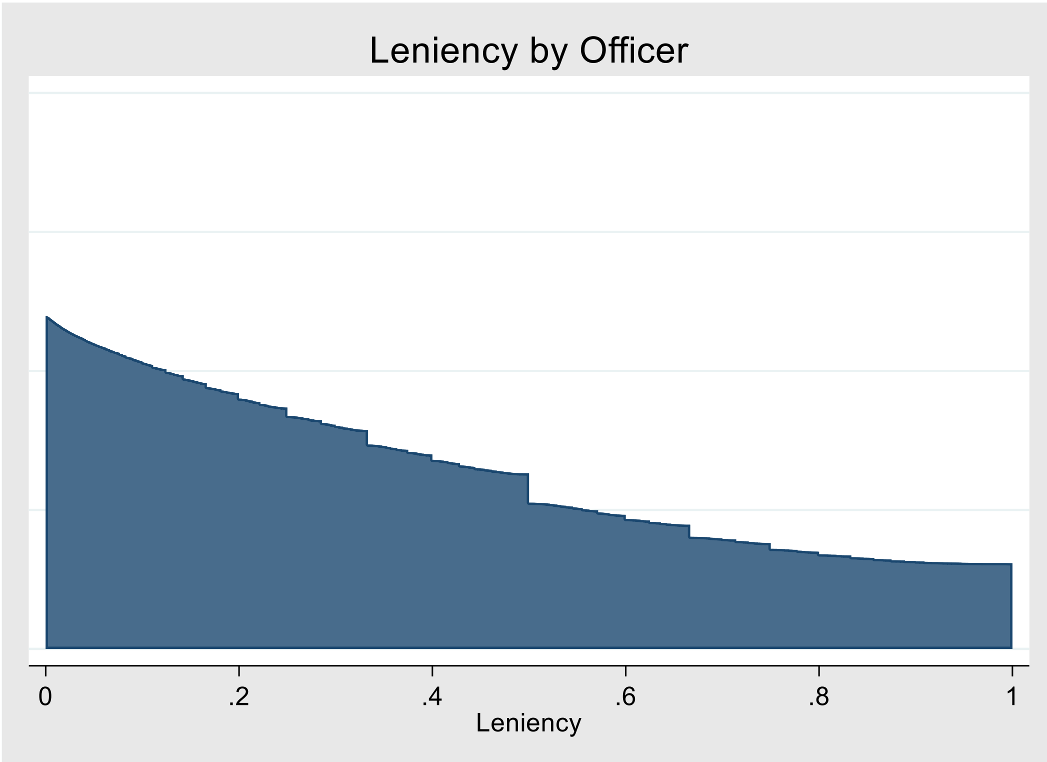


Figure H 1

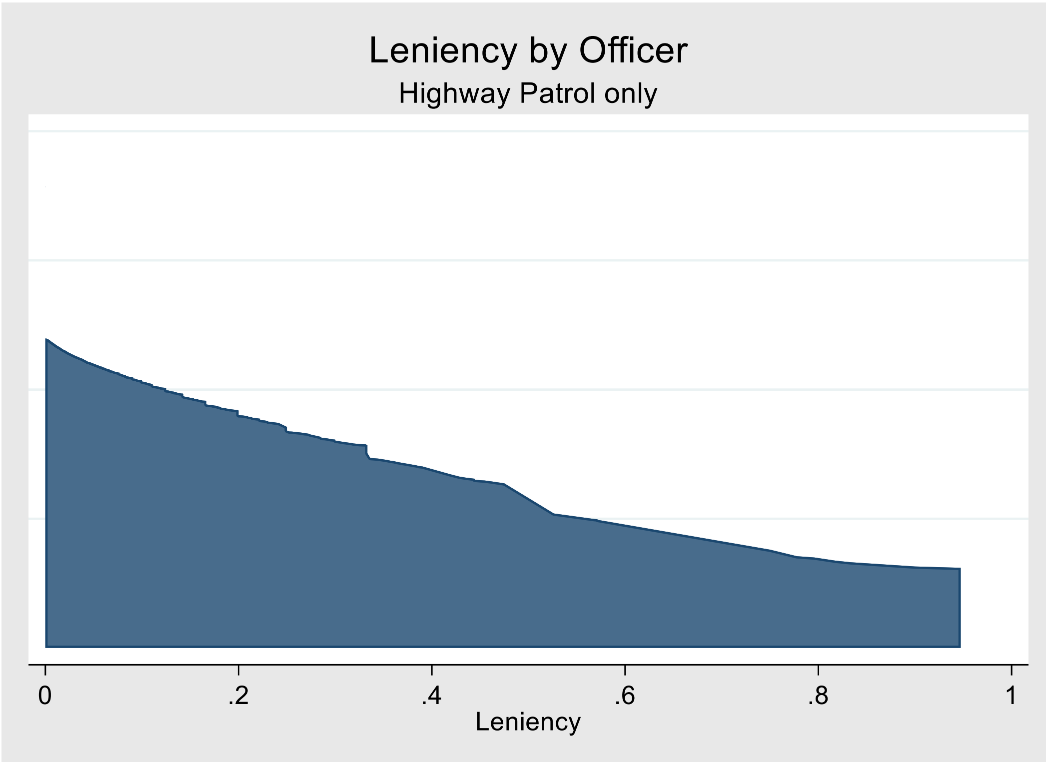


Figure H 2

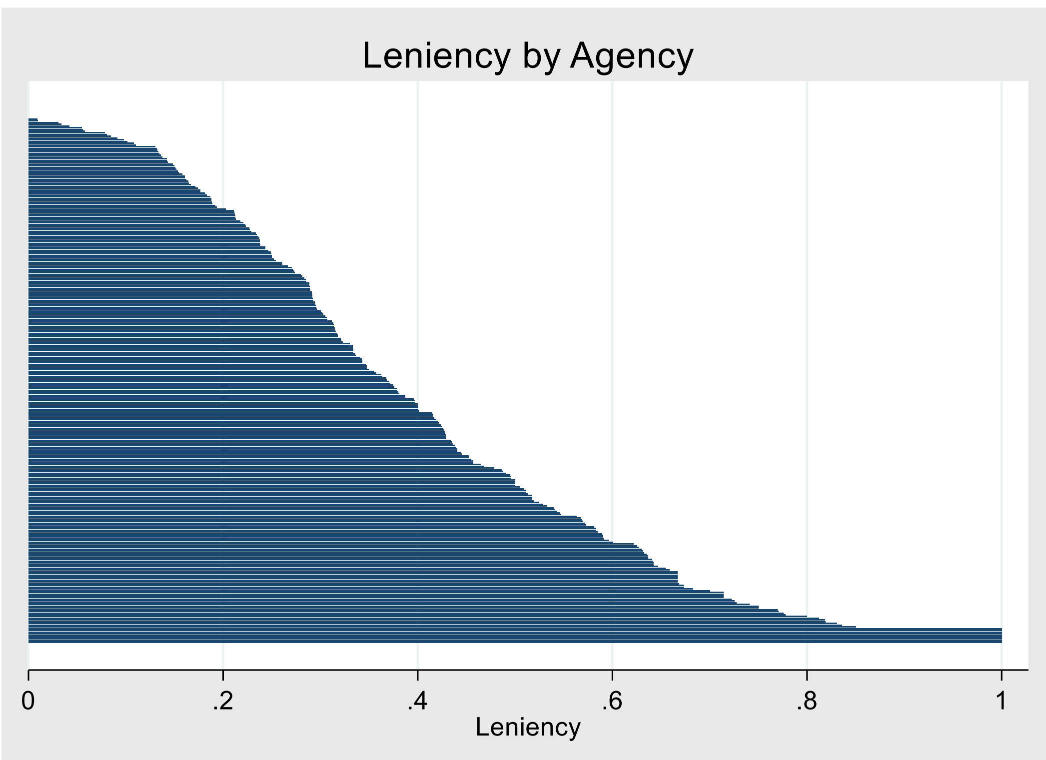


Figure H 3

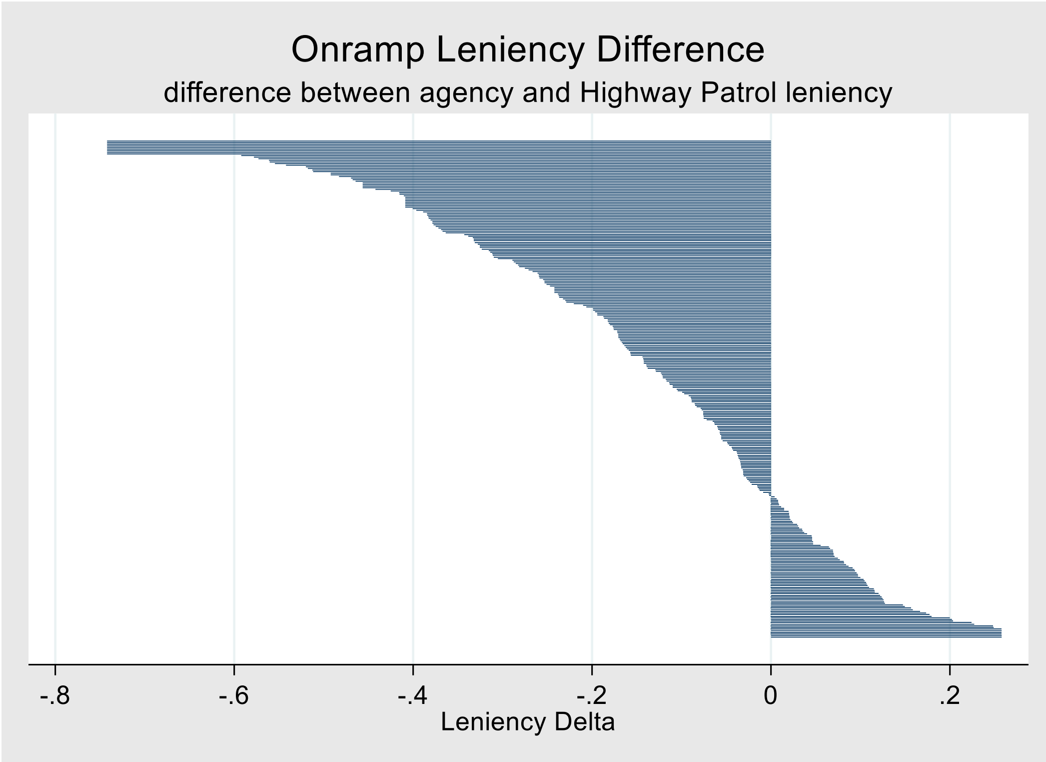


Figure H 4

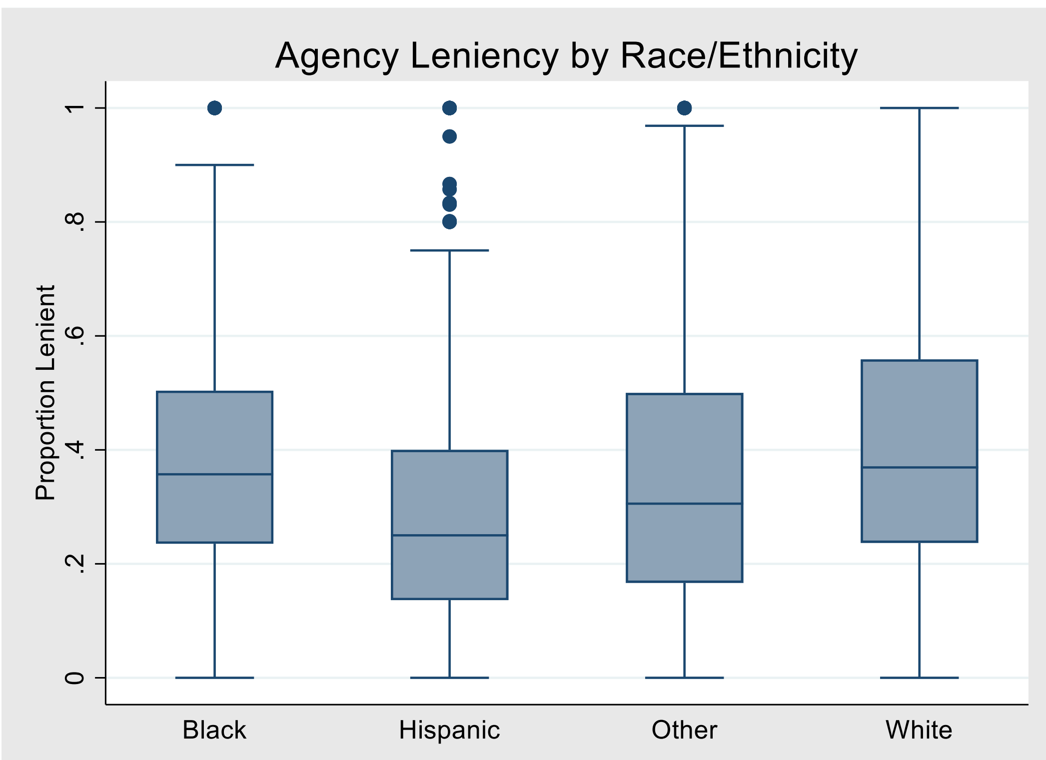


Figure H 5

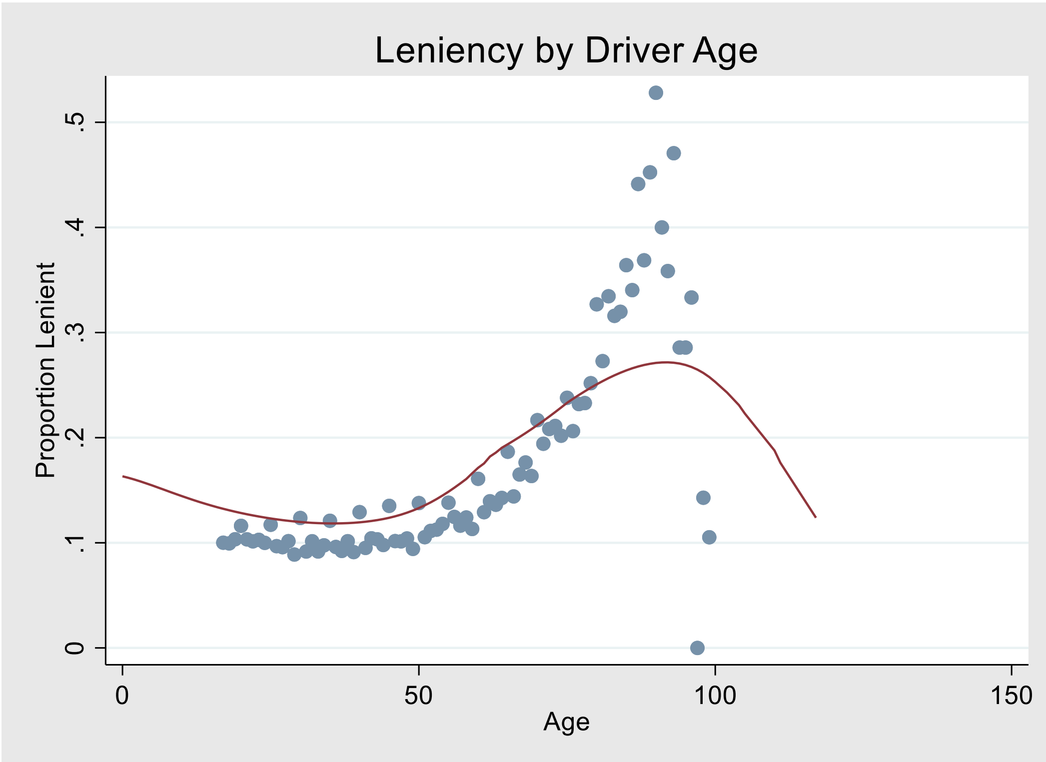


Figure H 6

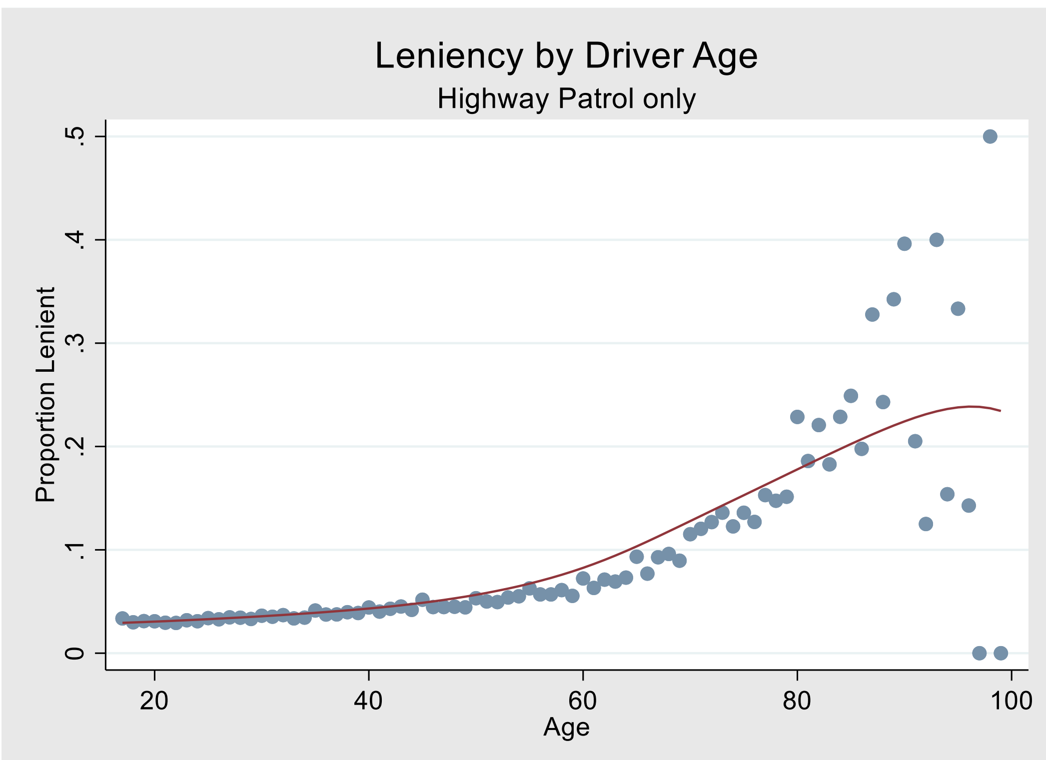


Figure H 7

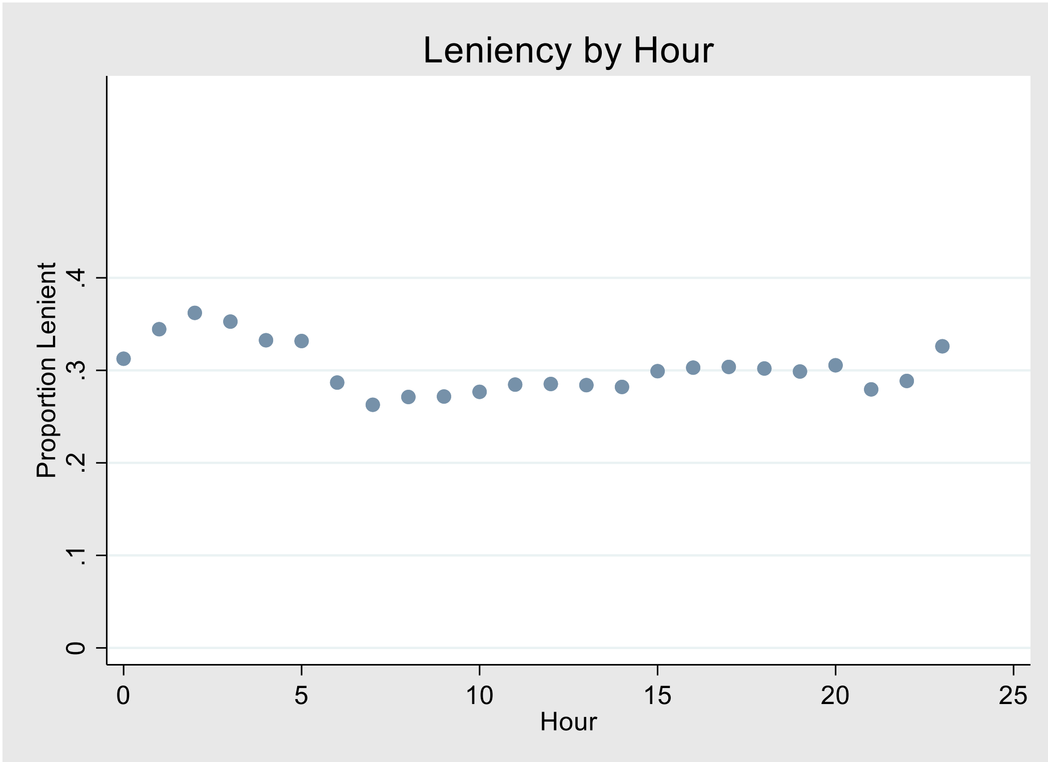


Figure H 8

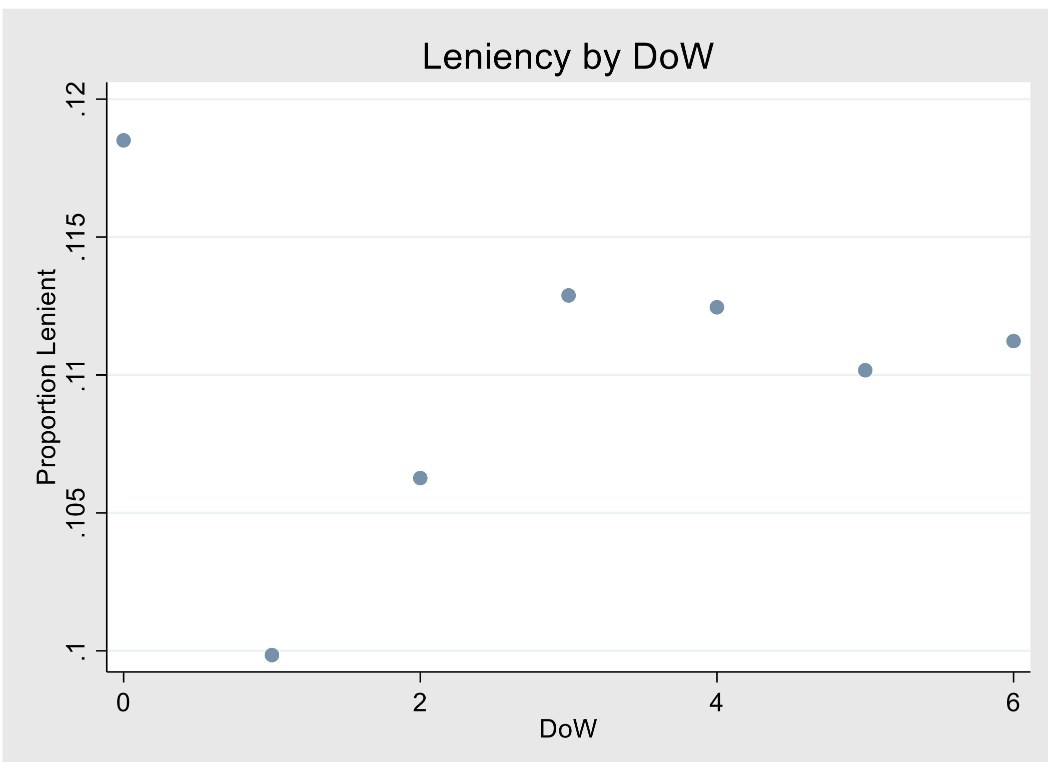


Figure H 9

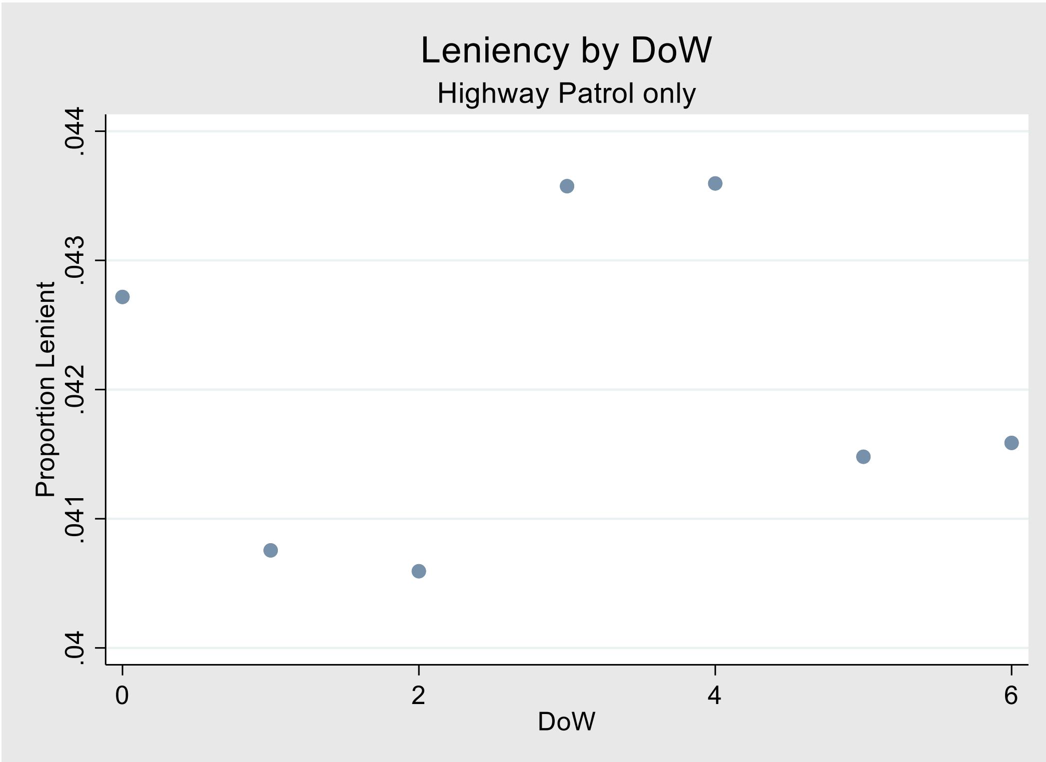


Figure H 10

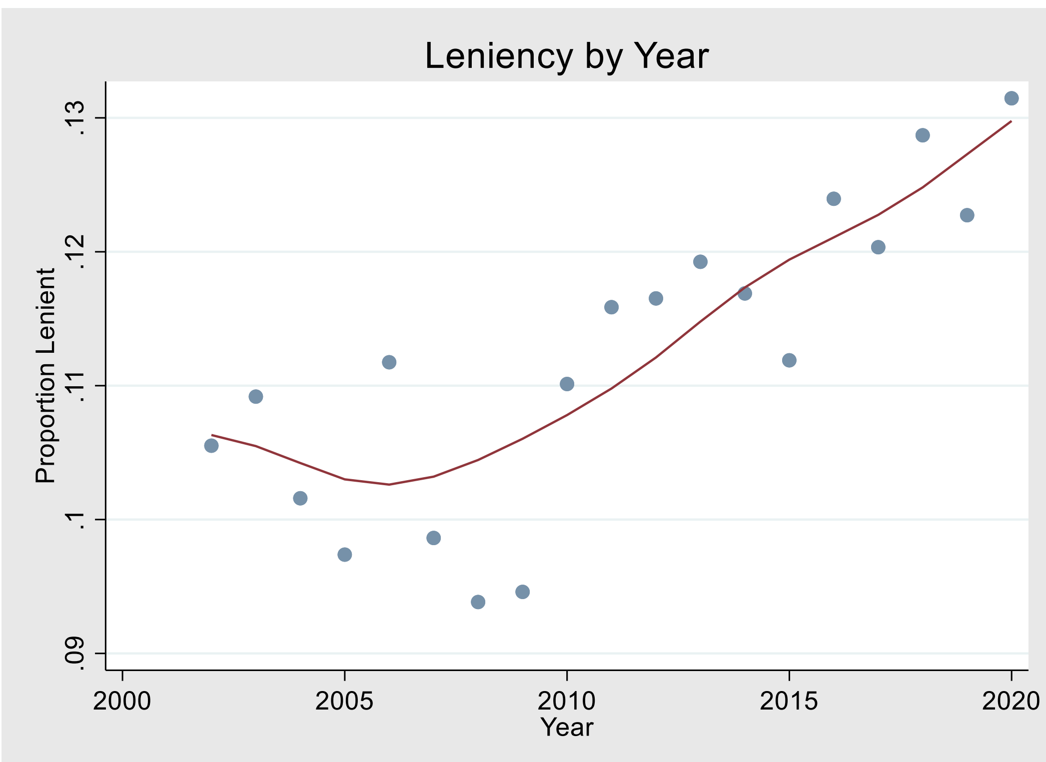


Figure H 11

VARIABLES	Stop Reason Seatbelt
years = 2	0.126
years = 3	-0.00900
years = 4	-0.274
years = 5	-0.330
years = 6	-0.514
years = 7	-0.754**
years = 8	-0.774**
years = 9	-0.593
years = 10	-0.828**
years = 11	-1.846***
years = 12	-0.628
years = 13	-0.357
years = 14	-1.132**
years = 15	-0.977**
years = 16	-0.680*
years = 17	0.197
years = 18	0.131
years = 19	-0.644
years = 20	-1.199**
years = 21	-1.095**
years = 22	-1.854***
years = 23	-0.428
years = 24	-1.961***
years = 25	0.198
years = 26	0.354
years = 27, omitted	-
years = 28	-0.876
years = 29, omitted	-
years = 30, omitted	-
Driver_Age	-0.022
CMPD_Division = 2, Eastway Division	-0.042
CMPD_Division = 3, Freedom Division	-0.183
CMPD_Division = 4, Hickory Grove Division	0.064
CMPD_Division = 5, Independence Division	-0.416
CMPD_Division = 6, Metro Division	-0.039
CMPD_Division = 7, North Division	0.076
CMPD_Division = 8, North Tryon Division	-0.065
CMPD_Division = 9, Providence Division	0.563*

CMPD_Division = 10, South Division	0.026
CMPD_Division = 11, Steele Creek Division	0.193
CMPD_Division = 12, University City Division	-0.582*
CMPD_Division = 13, Westover Division	0.230
Officer_Race = 4, Asian / Pacific Islander	-0.347*
Officer_Race = 5, Black/African American	-0.412***
Officer_Race = 6, Hispanic/Latino	-0.357
Officer_Race = 8, Not Specified	-0.601
Officer_Race = 9, omitted	-
driver_age_sqr	0.000
Driver_Gender	0.132
Officer_Gender	0.363**
Driver_Race = 2, Black	-0.561
Driver_Race = 3, omitted	-
Driver_Race = 4, Other/Unknown	-0.906
Driver_Race = 5, White	-0.604
Constant	0.741
Observations	915

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure H 12

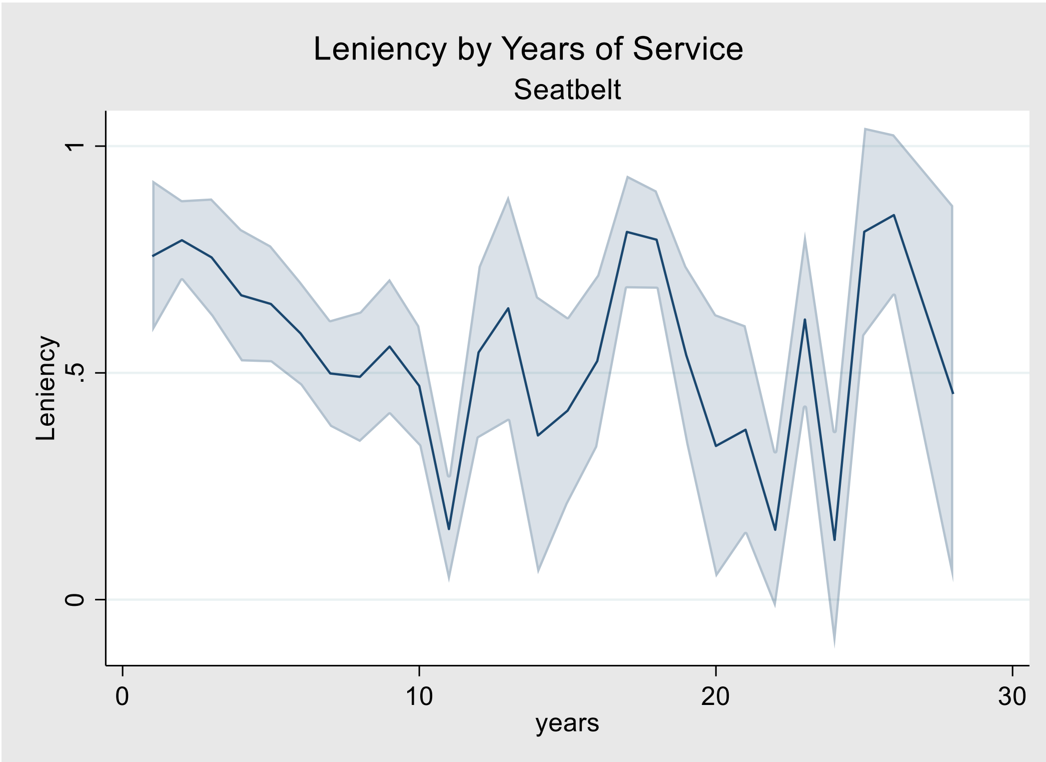


Figure H 13

	No Officer			Officer		
	Total	Change	% Change	Total	Change	% Change
Saturated	0.203	0	0	0.166	0	0
Identity	0.189	0.014	6.897	0.149	0.017	10.241
Year	0.191	0.012	5.911	0.165	0.001	0.602
Month	0.194	0.009	4.434	0.165	0.001	0.602
Day	0.196	0.007	3.448	0.166	0	0
Hour	0.194	0.009	4.434	0.165	0.001	0.602
Department	0.149	0.054	26.601	N/A		
Officer	N/A			0.046	0.12	72.289

Percent Used	25	Stops Cutoff:	750

Figure H 14

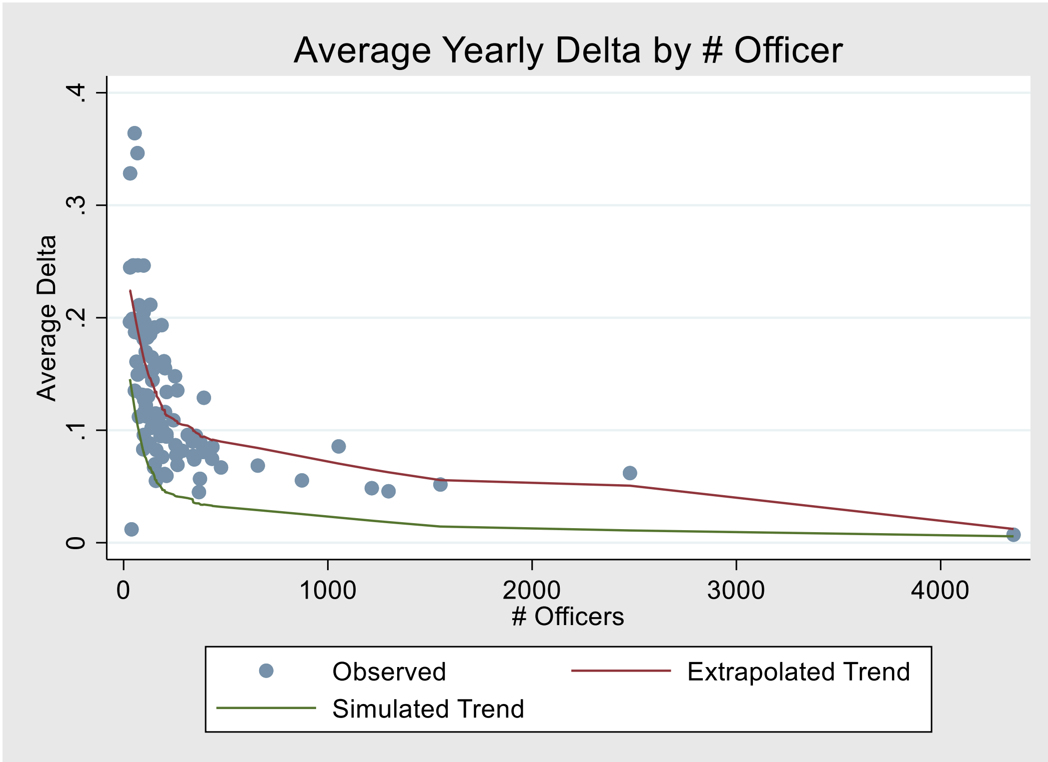


Figure H 15

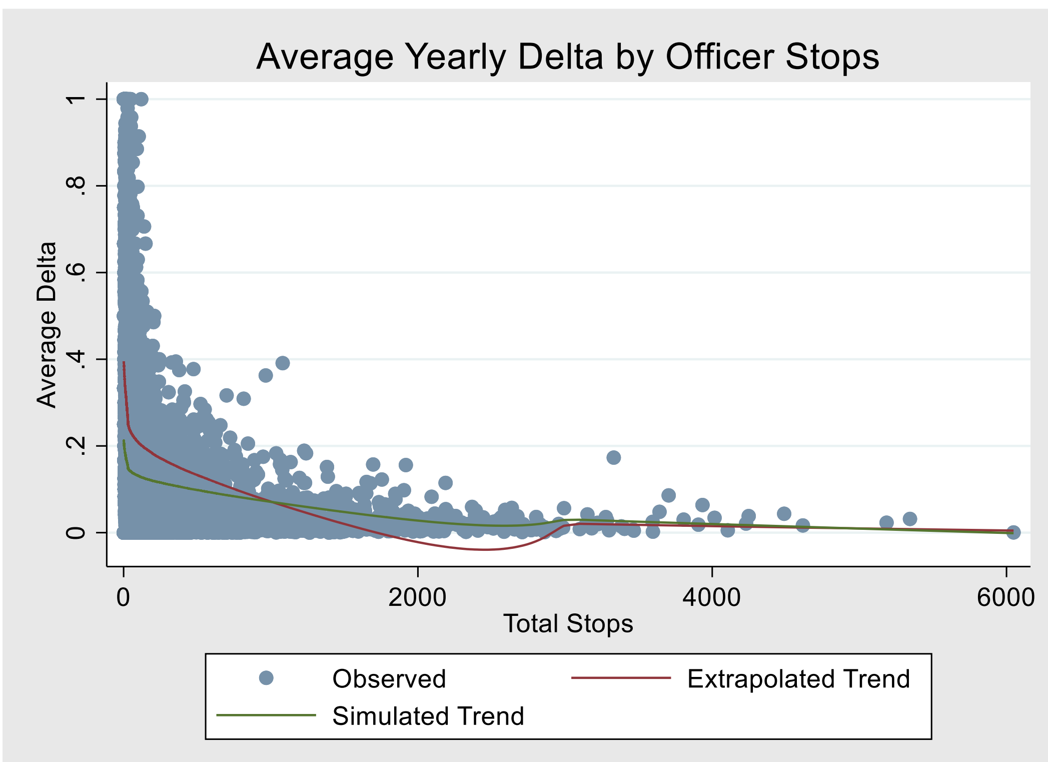


Figure H 16

Appendix I: Speeding

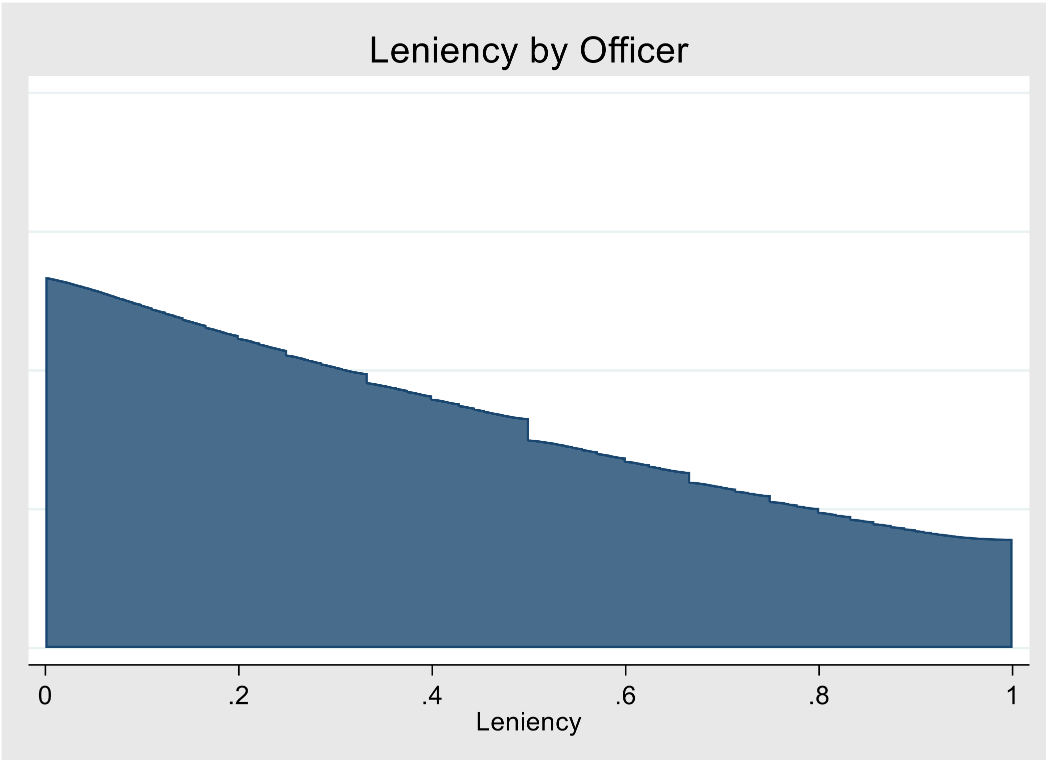


Figure I 1

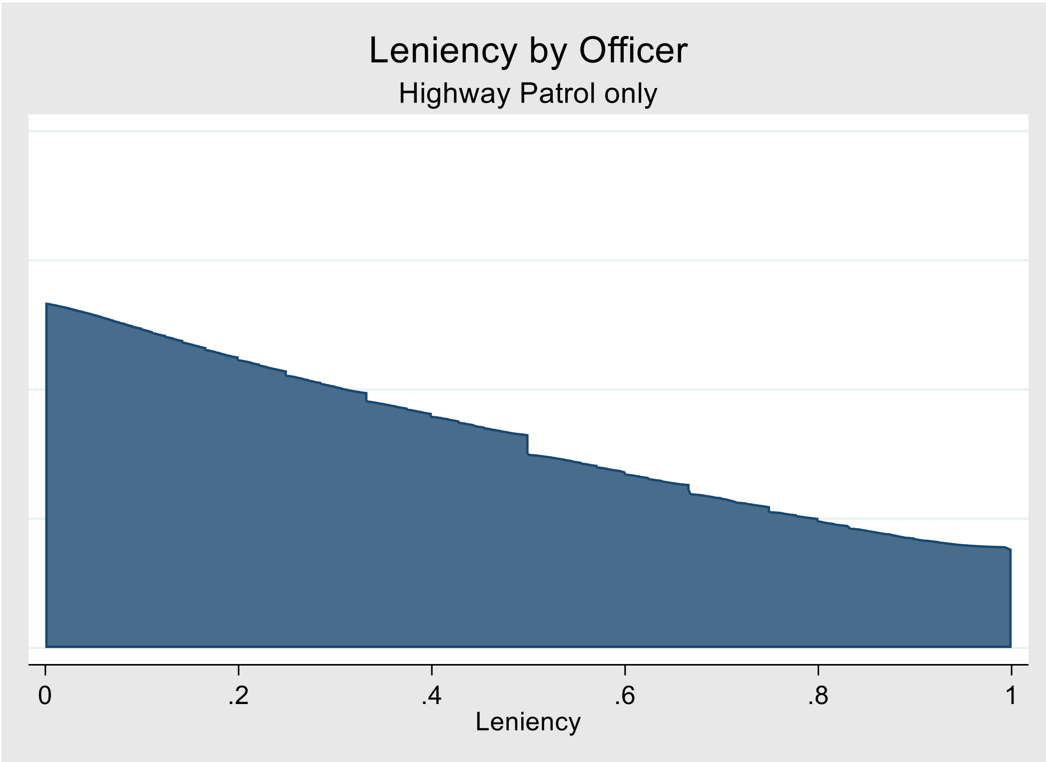


Figure I 2

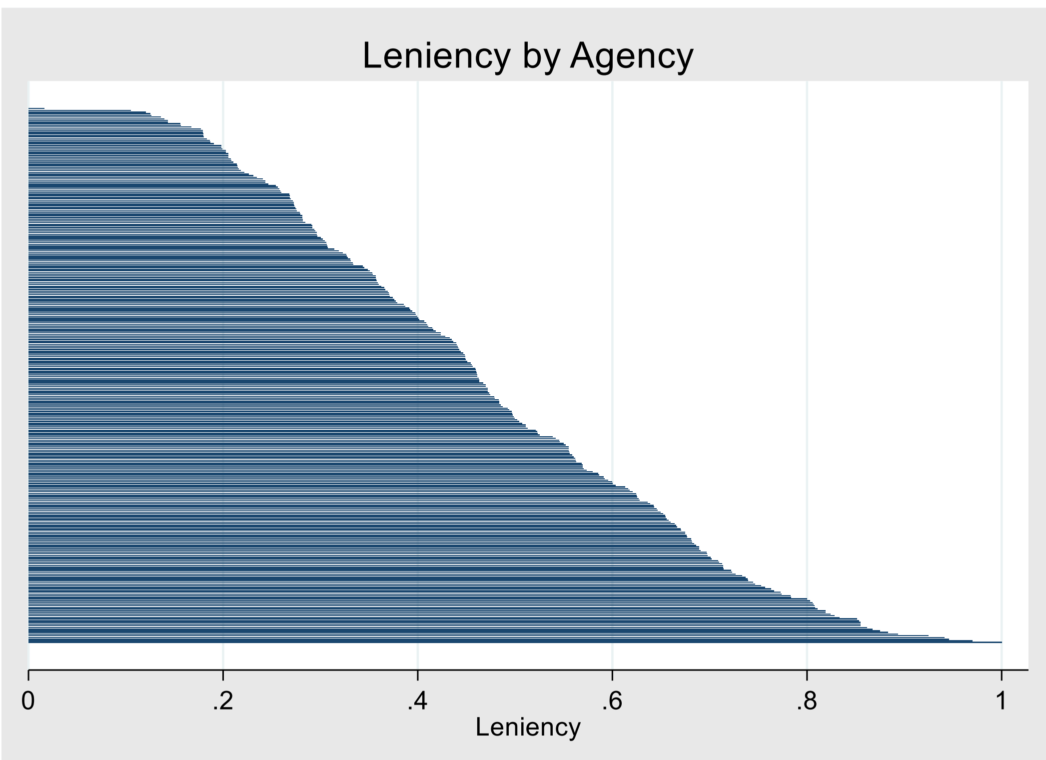


Figure I 3

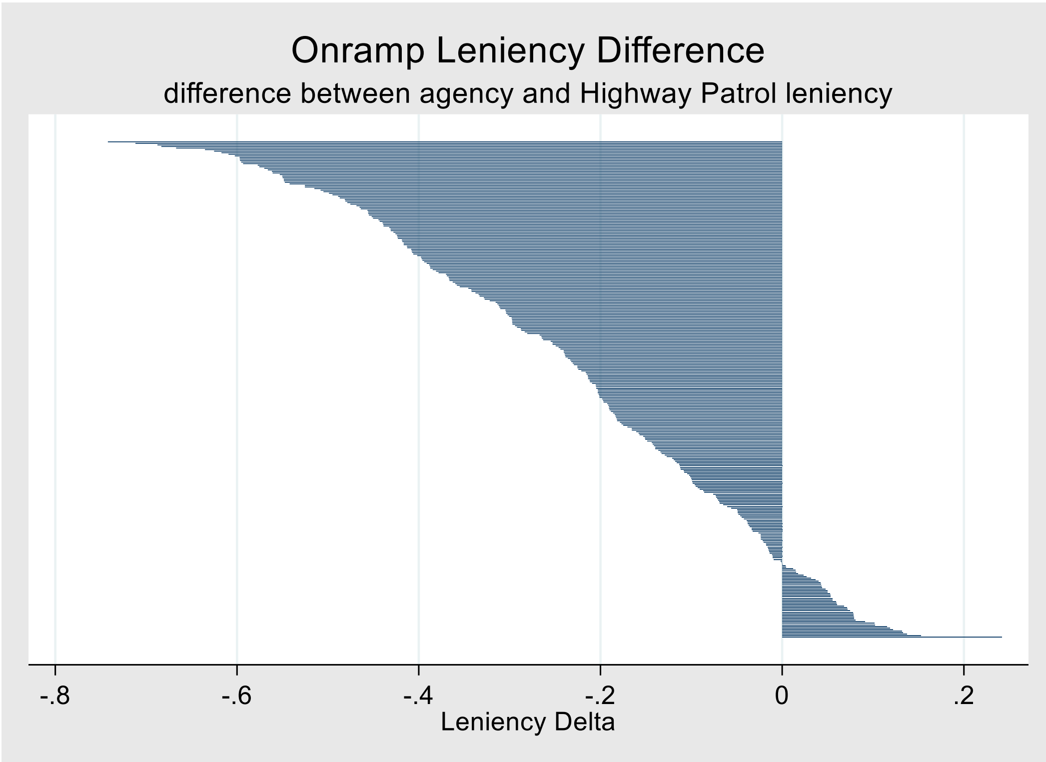


Figure I 4

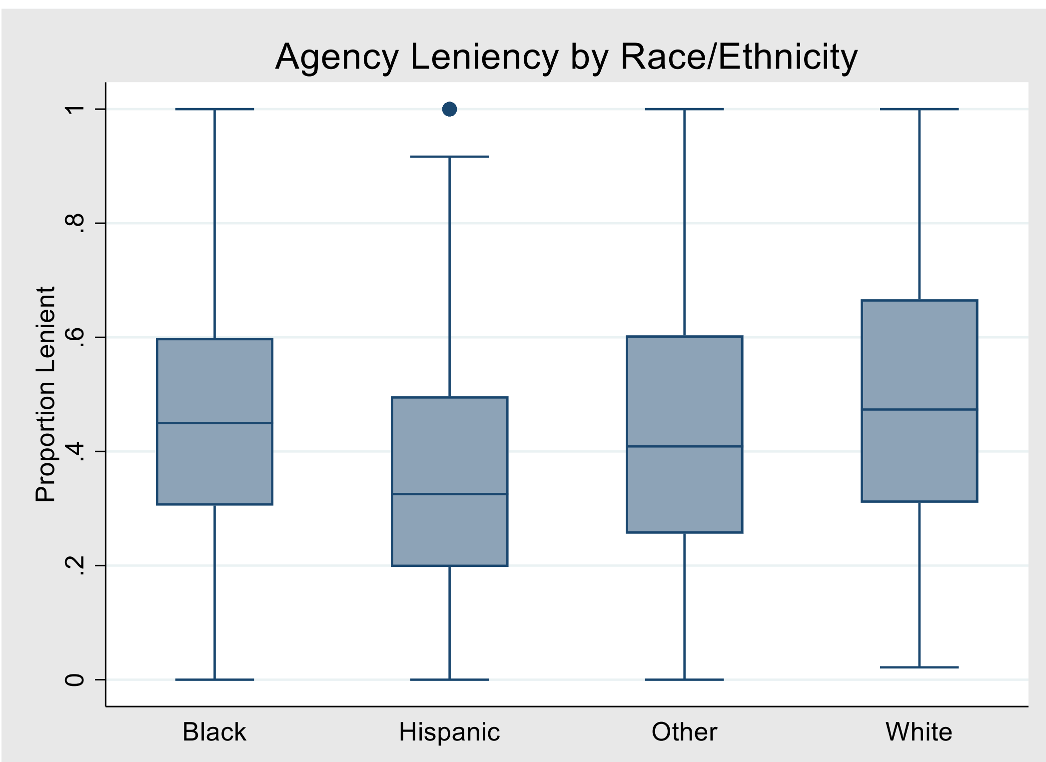


Figure I 5

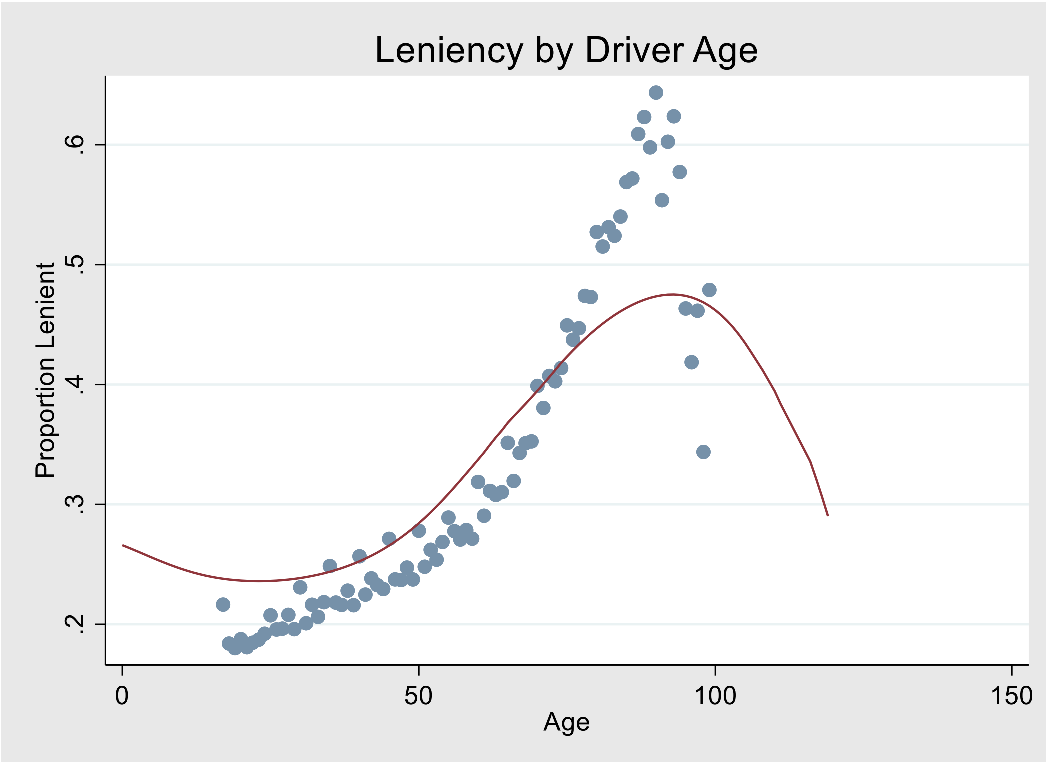


Figure I 6

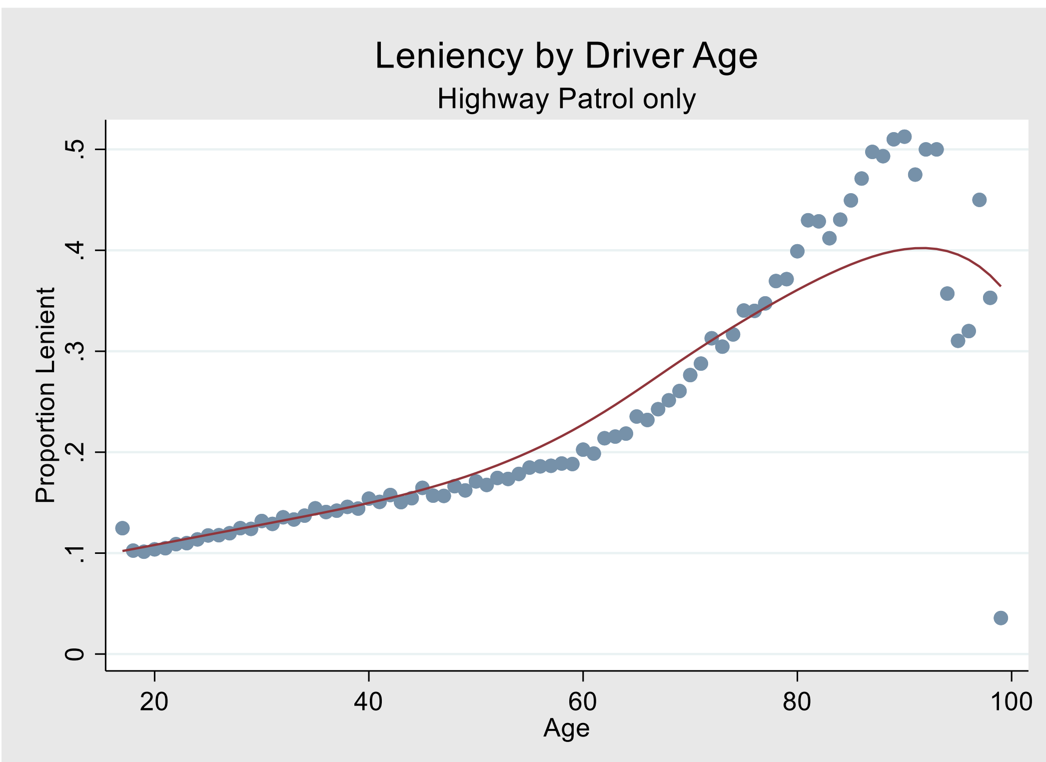


Figure I 7

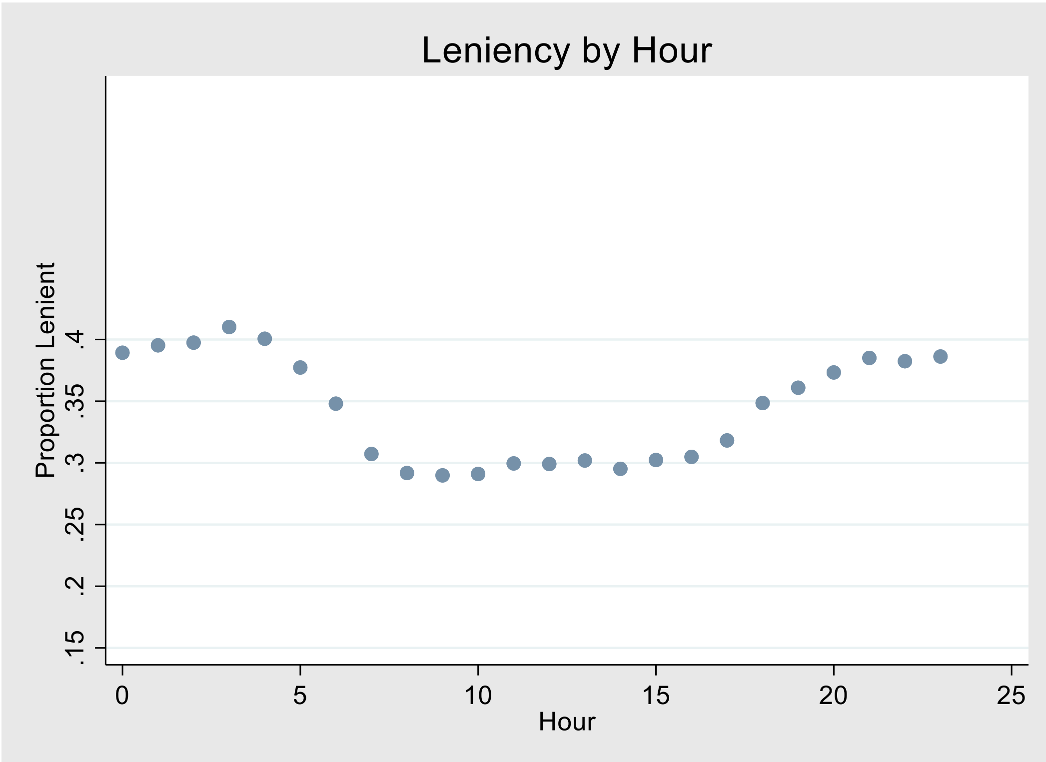


Figure I 8

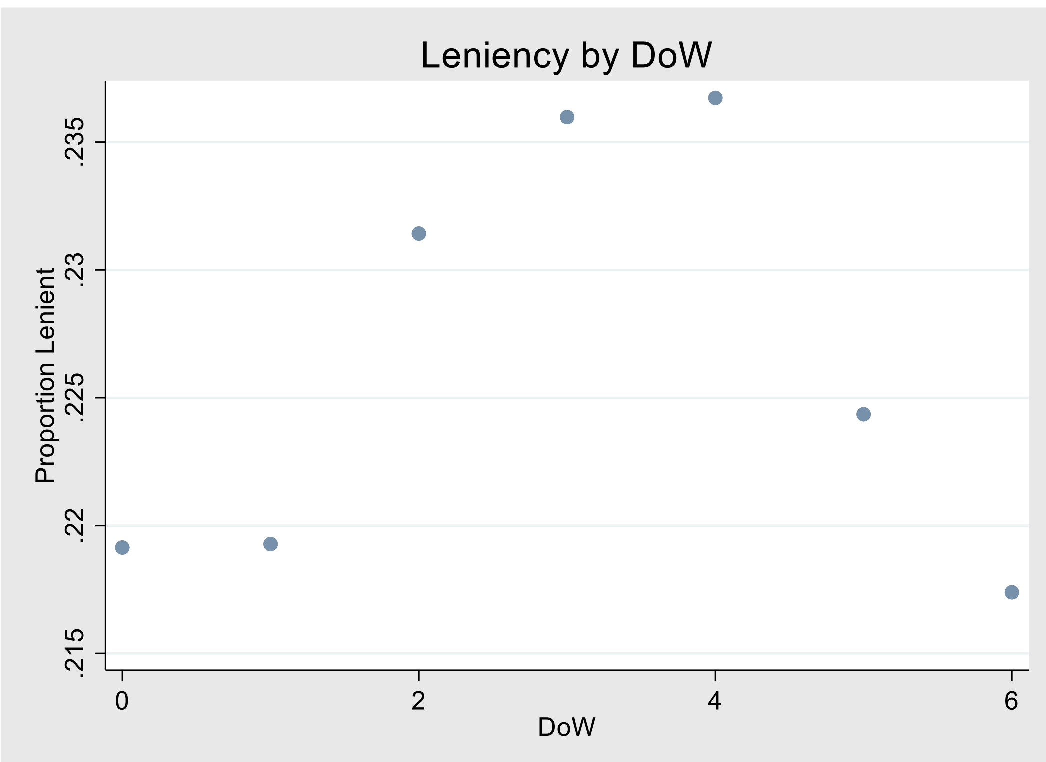


Figure I 9

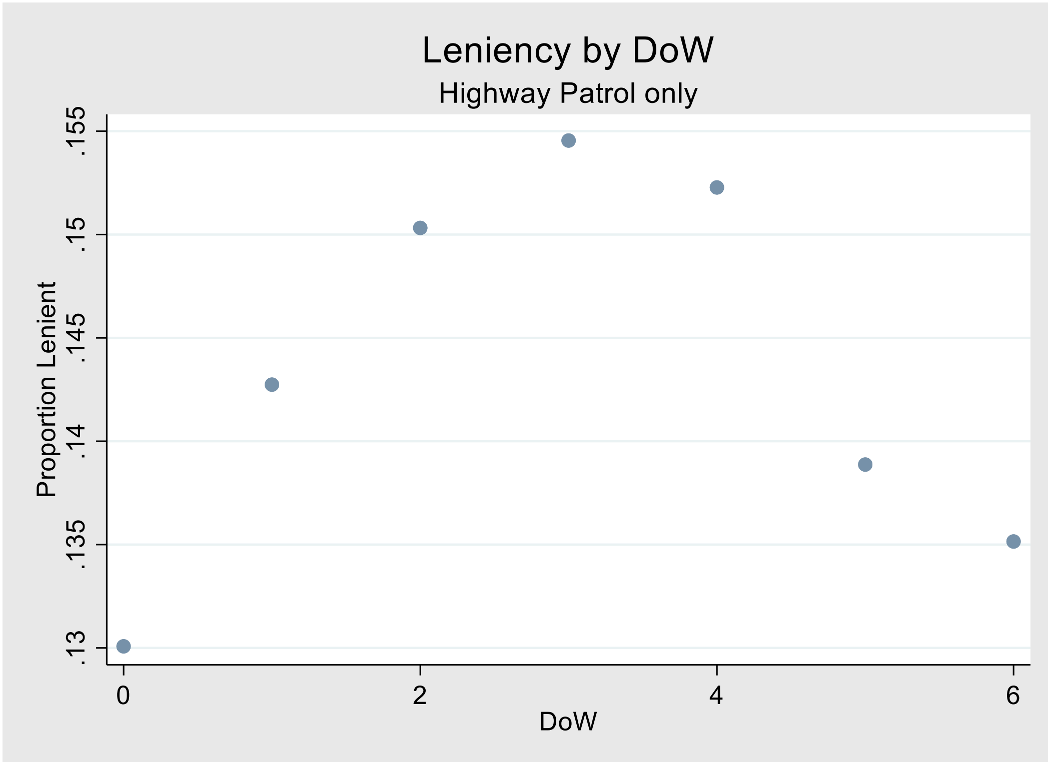


Figure I 10

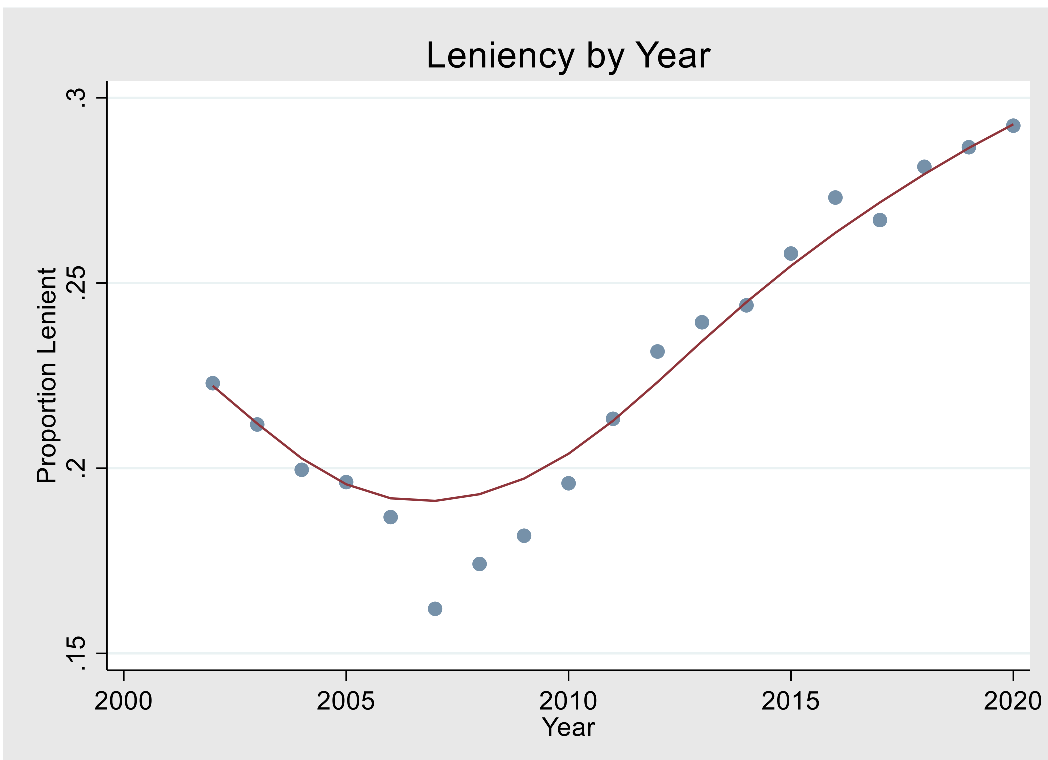


Figure I 11

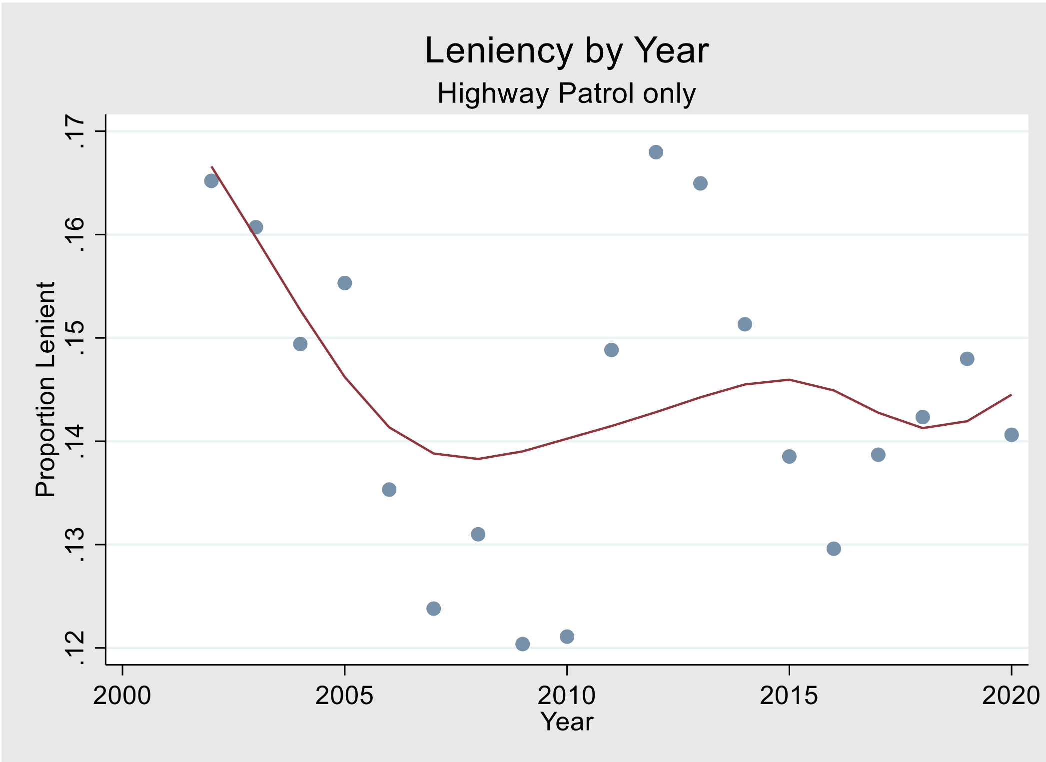


Figure I 12

VARIABLES	Stop Reason Speeding
years = 2	-0.189**
years = 3	-0.751***
years = 4	-0.354***
years = 5	-0.0230
years = 6	-0.468***
years = 7	-0.532***
years = 8	-0.475***
years = 9	-0.662***
years = 10	-0.722***
years = 11	-1.152***
years = 12	-0.802***
years = 13	-0.383***
years = 14	-1.224***
years = 15	-1.211***
years = 16	-1.254***
years = 17	-0.639***
years = 18	-0.374***

years = 19	-0.270***
years = 20	-0.361***
years = 21	-0.319***
years = 22	-0.866***
years = 23	-0.946***
years = 24	-0.462***
years = 25	-0.357***
years = 26	-0.554***
years = 27	-0.422***
years = 28	-0.568***
years = 29	-1.326***
years = 30	0.972***
Driver_Age	-0.012***
CMPD_Division = 2, Eastway Division	-0.087
CMPD_Division = 3, Freedom Division	-0.057
CMPD_Division = 4, Hickory Grove Division	0.132*
CMPD_Division = 5, Independence Division	-0.004
CMPD_Division = 6, Metro Division	0.154**
CMPD_Division = 7, North Division	0.229***
CMPD_Division = 8, North Tryon Division	0.012
CMPD_Division = 9, Providence Division	0.466***
CMPD_Division = 10, South Division	0.433***
CMPD_Division = 11, Steele Creek Division	0.078
CMPD_Division = 12, University City Division	-0.159***
CMPD_Division = 13, Westover Division	0.154**
Officer_Race = 2, omitted	-
Officer_Race = 3, American Indian/Alaska Native	1.719***
Officer_Race = 4, Asian / Pacific Islander	-0.308***
Officer_Race = 5, Black/African American	-0.392***
Officer_Race = 6, Hispanic/Latino	0.402***
Officer_Race = 8, Not Specified	0.719***
Officer_Race = 9, White	0.0318
driver_age_sqr	0.0002***
Driver_Gender	0.011
Officer_Gender	0.261***
Driver_Race = 2, Black	-0.053
Driver_Race = 3, Native American	0.197
Driver_Race = 4, Other/Unknown	-0.154**
Driver_Race = 5, White	-0.042
Constant	-0.241
Observations	22,533

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure I 13

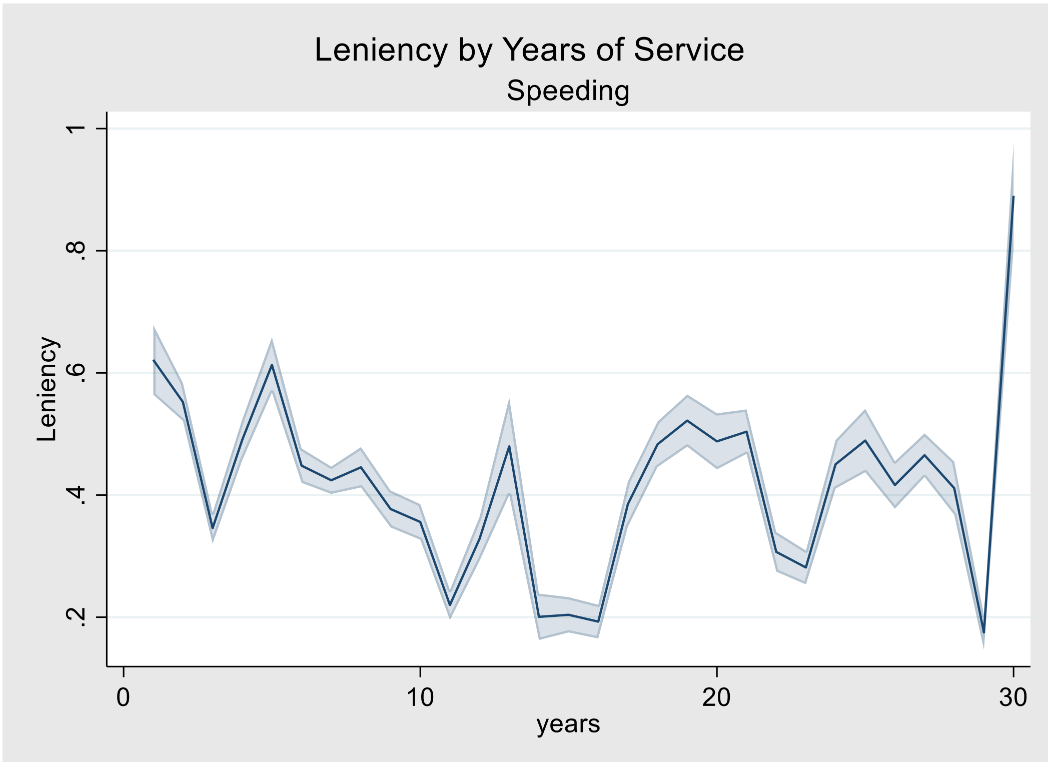


Figure I 14

	No Officer			Officer		
	Total	Change	% Change	Total	Change	% Change
Saturated	0.104	0	0	0.178	0	0
Identity	0.09	0.014	13.462	0.16	0.018	10.112
Year	0.098	0.006	5.769	0.175	0.003	1.685
Month	0.104	0	0	0.177	0.001	0.562
Day	0.104	0	0	0.178	0	0
Hour	0.1	0.004	3.846	0.177	0.001	0.562
Department	0.06	0.044	42.308	N/A		
Officer	N/A			0.068	0.11	61.798

Percent Used	25	Stops Cutoff:	3500

Figure I 15

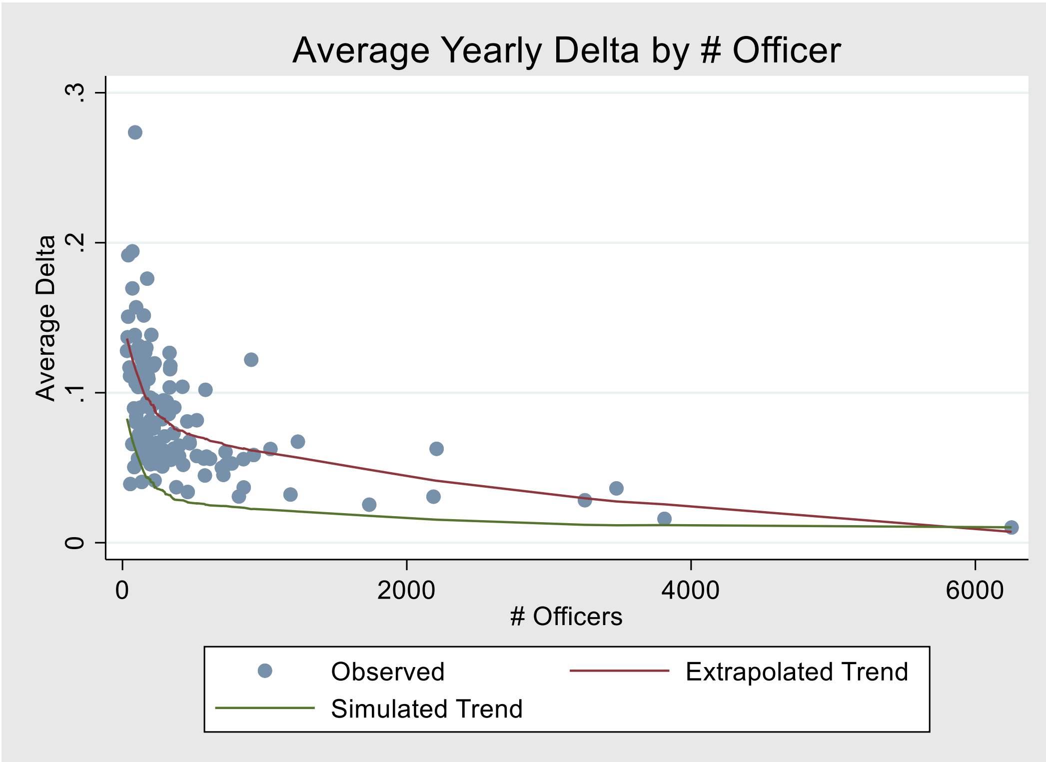


Figure I 16

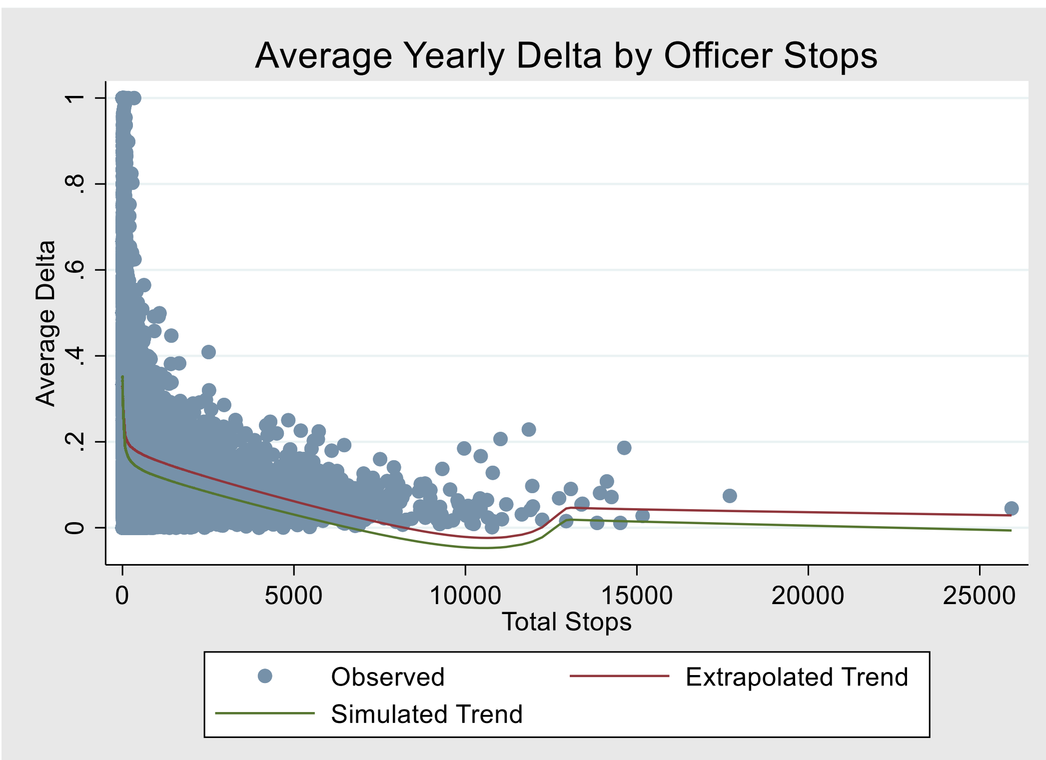


Figure I 17

Appendix J: Other

TRAFFIC STOP REPORT

Agency Name **Date (Month/Day/Year)** **Time**

County of Stop **Officer ID Number**

City of Stop

Part I

Initial Purpose of Traffic Stop *(check only one)*

- ☐ Checkpoint
- ☐ Driving While Impaired
- ☐ Investigation
- ☐ Other Motor Vehicle Violation
- ☐ Safe Movement Violation
- ☐ Seat Belt Violation
- ☐ Speed Limit Violation
- ☐ Stop Light / Sign Violation
- ☐ Vehicle Equipment Violation
- ☐ Vehicle Regulatory Violation

Vehicle Driver Information

Driver's Age ______ **Driver's Race** ☐ White ☐ Black ☐ Native American ☐ Asian ☐ Other

Driver's Sex ☐ Male ☐ Female

Driver's Ethnicity ☐ Non-Hispanic ☐ Hispanic *(Person of Mexican, Puerto Rican, Cuban, Central or South American, or other Spanish Culture)*

Enforcement Action Taken as a Result of the Traffic Stop *(check only one)*

- ☐ Citation Issued
- ☐ No Action Taken
- ☐ On-View Arrest → If arrest made, who was arrested? ☐ Driver ☐ Passenger(s)
- ☐ Verbal Warning
- ☐ Written Warning

Physical Resistance Encountered

Did Officer(s) encounter any physical resistance from Driver and/or Passenger(s)?	☐ Yes	☐ No
Did Officer(s) engage in the use of force against the Driver and/or Passenger(s)?	☐ Yes	☐ No
Did injuries occur to the Officer(s) as a result of the stop?	☐ Yes	☐ No
Did injuries occur to the Driver as a result of the stop?	☐ Yes	☐ No
Did injuries occur to the Passenger(s) as a result of the stop?	☐ Yes	☐ No

Vehicle/Driver/Passenger(s) Search

Was a search initiated subsequent to the traffic stop? ☐ Yes* ☐ No

*If search was initiated, complete Part II

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Figure J 1

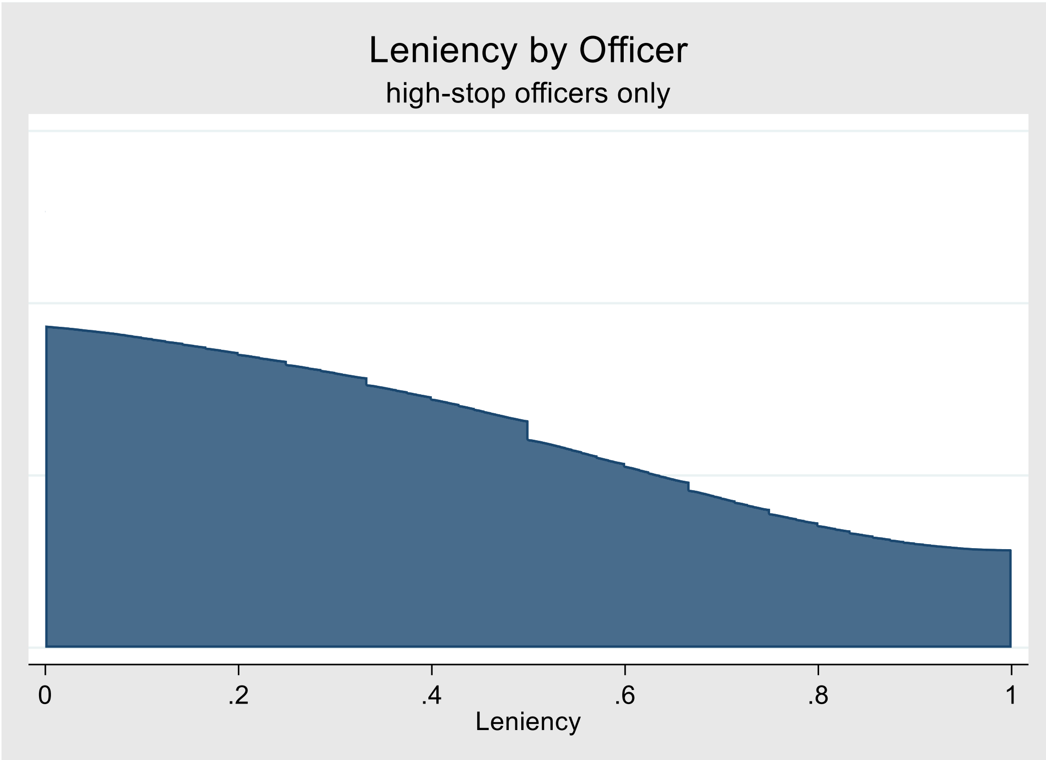

Figure J 2

VARIABLES	lenient
2.years	0.117***
3.years	0.065***
4.years	0.098***
5.years	0.190***
6.years	-0.137***
7.years	-0.298***
8.years	-0.055*
9.years	-0.180***
10.years	-0.154***
11.years	-0.302***
12.years	-0.045
13.years	0.119***
14.years	-0.378***
15.years	-0.535***
16.years	-0.572***
17.years	-0.241***
18.years	-0.233***
19.years	-0.292***

20.years	-0.525***
21.years	-0.408***
22.years	-0.434***
23.years	-0.568***
24.years	-0.313***
25.years	-0.270***
26.years	-0.226***
27.years	-0.196***
28.years	-0.306***
29.years	-0.980***
30.years	0.661***
35o.years	-
driver_age	-0.012***
2.division	-0.066***
3.division	-0.105***
4.division	0.082***
5.division	-0.127***
6.division	-0.066**
7.division	-0.036
8.division	0.0331
9.division	0.014
10.division	-0.033
11.division	-0.279***
12.division	-0.447***
13.division	0.107***
2.o_race	0.076
3.o_race	0.418***
4.o_race	-0.259***
5.o_race	-0.254***
6.o_race	-0.082
7.o_race	0.153
8.o_race	0.461***
9.o_race	-0.041
driver_age_sqr	0.0002***
drive_g	-0.027***
officer_g	0.070***
2.driver_r	-0.124***
3.driver_r	-0.184
4.driver_r	-0.232***
5.driver_r	-0.168***
Constant	0.661***

Observations	86,829

*** p<0.01, ** p<0.05, * p<0.1

Figure J 3