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Are you going to get a ticket or a warning for speeding? An autologistic regression analysis in Burlington, VT

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Abstract

Law enforcement is critical for improving traffic safety. However, disputes on the equity in law enforcement have continuously exacerbated the distrust between the public and the law enforcement agencies in the United States in the past decades. This study explores this issue by identifying factors influencing outcomes of traffic stops - the most common scenarios where people need to deal with law enforcement agencies. To exclude possible confounding factors, this study specifically focuses on speeding traffic stops leading to tickets or warnings in Burlington, Vermont from 2012 to 2017. The Euclidean distance-based autologistic regression model is adopted due to the presence of spatial correlations of traffic stops. It is found that with the increasing speeding severity, a speeding traffic stop is more likely to lead to a ticket. Speeding of 20 mph over the speed limit significantly influences the penalty type. Young drivers, male drivers and minority drivers are found to be more likely to be issued tickets, which suggests the possible presence of some inherent biases against these groups. In addition, time of day and month are also found to influence the likelihood of receiving speeding tickets. These findings are expected to help both the public and law enforcement agencies to better understand the characteristics of law enforcement and take appropriate measures to eliminate possible biases.

Keywords

Law enforcement, Bias, Speeding traffic stop, Autologistic regression, Ticket, Warning

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A B S T R A C T

Law enforcement is critical for improving traffic safety. However, disputes on the equity in law enforcement have continuously exacerbated the distrust between the public and the law enforcement agencies in the United States in the past decades. This study explores this issue by identifying factors influencing outcomes of traffic stops - the most common scenarios where people need to deal with law enforcement agencies. To exclude possible confounding factors, this study specifically focuses on speeding traffic stops leading to tickets or warnings in Burlington, Vermont from 2012 to 2017. The Euclidean distance-based autologistic regression model is adopted due to the presence of spatial correlations of traffic stops. It is found that with the increasing speeding severity, a speeding traffic stop is more likely to lead to a ticket. Speeding of 20 mph over the speed limit significantly influences the penalty type. Young drivers, male drivers and minority drivers are found to be more likely to be issued tickets, which suggests the possible presence of some inherent biases against these groups. In addition, time of day and month are also found to influence the likelihood of receiving speeding tickets. These findings are expected to help both the public and law enforcement agencies to better understand the characteristics of law enforcement and take appropriate measures to eliminate possible biases.

1. Introduction

Traffic crash is a major source of deaths and fatalities in the United States. Law enforcement is critical for preventing crashes by stopping and penalizing traffic violations. Drivers are usually pulled over by police officers when suspected of violating traffic rules. The outcome of a traffic stop may be no action, a warning, a ticket, a search, or an arrest, with warnings and tickets being the two primary results. A warning usually means no monetary penalty or no criminal record, whereas a ticket might lead to a penalty of hundreds of dollars and a criminal record. Due to the huge differences of outcomes and discretion of officers in law enforcement, factors influencing traffic violation outcomes are critical and sensitive. A common argument is the presence of racial profiling (Harris, 1999), i.e. law enforcement discrimination against people by their races. Some studies support this claim (Baumgartner et al., 2017a, 2017b; C. Regoeczi and Kent, 2014; Geiger-Oneto and Phillips, 2003; Helfers, 2016; Lundman and Kaufman, 2003; Miller, 2008; Novak and Chamlin, 2012; Roh and Robinson, 2009; Ryan, 2016; Vito et al., 2017; Warren et al., 2006; Withrow, 2004), some not (Lange et al., 2005; Pickerill et al., 2009; Ritter, 2017; Tillyer and Engel, 2013), and some others got mixed results (Meehan and Ponder, 2002; Novak and Chamlin, 2012), i.e. racial profiling only existed in some specific scenarios. These inconsistent conclusions imply that racial profiling in traffic law enforcement is a complex issue and might be highly location-dependent. Thus, it is unreasonable to generalize findings from one jurisdiction to others. Another common observation is the so-called weekly or monthly effects (Auerbach, 2017), i.e. police officers are more likely to issue tickets at some specific time points, such as the end of the month. In addition, driver gender, driver age, and many other factors have been shown to possibly influence the law enforcement outcome (Pickerill et al., 2009; Quintanar, 2017; Ryan, 2016). Debates on these controversies have continued to increase the distrust between the public and police (Horowitz, 2007). This study proposes to detect the presence of any inherent bias in law enforcement or not. It will focus on identifying factors affecting the determination of issuing a ticket vs. a warning to a traffic stop and figuring out if driver demographic and temporal factors influence the decision making of the police of the studied region.

Traffic stops can be divided into two categories by violation type: non-moving violations, such as parking in prohibited areas and broken headlights, and moving violations, such as driving under influence and speeding. These violations might lead to very different outcomes and penalties by their risks. For example, speeding might be more likely to receive a ticket than a broken headlight. Thus, it is reasonable to analyze traffic stop data separately by violation type in law enforcement analysis to exclude possible confounding effects. Typically, most existing studies analyze all traffic stop data together (Baumgartner et al., 2017a, 2017b;

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Blalock et al., 2007; C. Regoeczi and Kent, 2014; Factor, 2018; Lange et al., 2005; Roh and Robinson, 2009; Ryan, 2016; Tillyer and Engel, 2013; Withrow, 2004), and only a few recent studies are aimed at specific traffic stops (Goncalves and Mello, 2018; Quintanar, 2017). Speeding is one of the most dangerous and common violations contributing to traffic accidents. In 2015, 27% of traffic fatalities were related to speeding crashes in the United States (National Center for Statistics and Analysis, 2017a), and the number of speeding-related fatalities kept increasing from 2014 to 2016 (National Center for Statistics and Analysis, 2017a, 2017b). This study will specifically focus on analyzing speeding traffic stops. Quintanar (2017) compared speeding tickets issued by police and automated cameras in Lafayette, Louisiana from Oct 2007 to Feb 2008. They found that women were more likely to be issued speeding tickets by police officers, whereas race was not systematically considered by police officers in issuing speeding tickets, although it might not be completely ignored. Goncalves and Mello (2018) analyzed speeding citations of Florida Highway Patrol from 2005 to 2015 and concluded that minorities were less likely to receive the jump of charged speeds than white drivers. These two researches imply that the factors influencing speeding outcomes might also be highly location-dependent, thus it might be difficult to generalize existing research findings to other places.

In terms of methodology, unobserved heterogeneity is often an issue in crash analysis due to the unavailability of many crash-related factors (Mannering et al., 2016), where spatial correlations have been proved to play important roles in many studies (Aguero-Valverde and Jovanis, 2006; Liu and Sharma, 2017, 2018; Song et al., 2006; Wang and Kockelman, 2013; Yu et al., 2019). Both traffic stop data and traffic crash data are collected by law enforcement agencies in the U.S., and they share many common features. For example, traffic stop data often accompany with spatial information, either macroscopic regional data or microscopic geographic coordinates, thus spatial correlations might not be ignored either for traffic stop analysis. A case study of red light running citations and crashes in Lincoln, Nebraska indicated that both of them showed clustering trends in space (Liu et al., 2015). However, most existing studies of traffic stop analysis did not explicitly consider spatial correlations (Baumgartner et al., 2017a, 2017b; Blalock et al., 2007; C. Regoeczi and Kent, 2014; Factor, 2018; Goncalves and Mello, 2018; Lange et al., 2005; Quintanar, 2017; Roh and Robinson, 2009; Ryan, 2016; Tillyer and Engel, 2013; Withrow, 2004), whereas the study of Roh and Robinson (2009) demonstrated the presence of spatial dependence of traffic stops across police beats for the Houston Police Department, Texas. It should be noted that compared to macroscopic regional data, such as police beat, geographic coordinates could provide more accurate location information of individual observations. Thus, when geographic coordinates are available, the geographic coordinates-based spatial analysis is expected to provide more insights of individuals.

The study focuses on exploring the law enforcement equity with six years' speeding traffic stop data from Burlington, Vermont (VT), by identifying factors influencing their outcomes, where spatial dependency is explicitly taken into account. The following paper is organized as follows. Section 2 describes the data collection and preprocess. Section 3 illustrates the methodology. Section 4 shows the estimation results. Section 5 gives conclusions and discussions.

2. Materials

Burlington is the most populous city with a population of 42,260 in Vermont, United States. The Burlington Police Department (BPD) is the main local law enforcement agency.[1] Traffic stop data of BPD from 01/01/2012 to 12/31/2017 were collected from its website (Burlington Police Department, 2018). Most data was accompanied with geographic coordinates and time information. There were totally 33,874 traffic stop records, including 4653 speeding traffic stops. According to the recorded speeding range types, these data can be divided into five categories: 0–10 mph over speed limit, 11–20 mph over speed limit, 21–30 mph over speed limit, 30 or more mph over speed limit, and unreasonable and imprudent speed. It should be noted that to the best knowledge of the authors, there is no explicit definition of "unreasonable and imprudent speed" in Vermont, thus it is difficult to figure out the real speeding ranges of these traffic stops. The outcome of a traffic stop might be no action, a warning, a ticket, an arrest on warrant, an arrest, or unknown for the studied dataset. To exclude possible confounding effects, this study will only focus on analyzing the moving violation-based speeding traffic stops leading to tickets or warnings with no search conducted, no arrest or no accident, and no contraband evidence. Finally, to identify factors influencing the outcomes of speeding by regression analysis, 4089 speeding traffic stop records with known driver age (≥ 16), driver gender (male or female), driver race (Asian, African American, Hispanics, others, or White), speeding range (excluding "unreasonable and imprudent speed"), and geographic coordinates will be used in this study. These data occupy 87.9% of total speeding traffic stops. A summary of these data can be seen in Table 1.

Drivers are divided into three age categories, i.e. young (≤25), middle (>25 and <65), and old (≥65), and most drivers are young or middle-aged. Male drivers are involved in nearly double speeding traffic stops than are female drivers, although the female population is actually slightly larger than the male population in Burlington (50.9% vs 49.1%) (United States Census Bureau, 2018). Additionally, 88.0% of speeding

Table 1
Summary of variables used in modeling outcomes of speeding traffic stops.

Variable	Definition	Values
Outcome	The outcome of a speeding traffic stop	1226, 1 for ticket; 2863, 0 for warning.
Age	Age of the driver	1357, young if the driver age ≥16 and <25; 2548, middle if the driver age > 25 and <65, ***baseline***; 184, old if the driver age ≥65.
Gender	Gender of the driver	2554, 1 if the driver is male; 1535, 0 if the driver is female.
Minority	Race of the driver	492, 1 if the driver is not White; 3597, 0 if the driver is White.
Speeding	Speeding range over the posted speed limit	2025, 1–10 mph over speed limit, ***baseline***; 1942, 11–20 mph over speed limit; 122, 21 or more mph over speed limit.
Hour	Hour of day when the traffic stop occurred:	267, 0; 190, 1; 86, 2; 38, 3; 40, 4; 133, 5; 175, 6; 173, 7; 124, 8; 177, 9; 172, 10; 200, 11; 151, 12, ***baseline***; 136, 13; 136, 14; 145, 15; 104, 16; 77, 17; 202, 18; 244, 19; 293, 20; 257, 21; 265, 22; 304, 23.
Day of week	Day of week when the traffic stop occurred	634, Monday, ***baseline***; 524, Tuesday; 563, Wednesday; 536, Thursday; 664, Friday; 664, Saturday; 504, Sunday.
Month	Month of year when the traffic stop occurred	519, January; 290, February; 364, March; 301, April, ***baseline***; 382, May; 302, June; 293, July; 355, August; 381, September; 257, October; 306, November; 339, December.

[1] Note: other law enforcement agencies include the University of Vermont Police, the Chittenden County Sheriff, and the Vermont State Police.

traffic stops involved White drivers, which is consistent with the proportion of White people in total population in Burlington (88.0%) (United States Census Bureau, 2018). Considering the non-White driver records are very limited (153 Asians, 233 African Americans, 38 Hispanics, and 68 others), they are merged as" minority" in the following analysis. In terms of speeding range, the data includes 2025 records of "0–10 mph over speed limit", 1942 records of "11–20 mph over speed limit", 109 records of "21–30 mph over speed limit", and 13 records of "30 or more mph over speed limit". Most speeding violations are <20 mph over speed limit, whereas only very few ones are >20 mph over speed limit. Since the number of "30 or more mph over speed limit" is too small, they are merged with the "21–30 mph over speed limit" to become "21 or more mph over speed limit". In addition, time of day, day of week and month of year information are also considered to explore whether any hourly, weekly or monthly effects exist.

3. Methodology

The ordinary logistic model is often used for analyzing binary outcome data. However, considering traffic stops might have some underlying spatial correlations, an autologistic model is adopted in this study (Besag, 1974). Compared to the ordinary logistic model, the autologistic model introduces an autocovariate to cover spatial correlations of traffic stops, as shown in the following equations, where the autocovariate is calculated as a Euclidean distance weighted sum of the dependent variable. It means that for locations with events occurring in their neighborhood, the probabilities of events occurring in these locations are also high, and vice versa. The autologistic model has been used widely in agriculture (Besag, 1974; Gumpertz et al., 1997), ecology (Augustin et al., 1996; Huffer and Wu, 1998), and public health (Bo et al., 2014), but not as much in transportation. The key point of autologistic analysis is to determine the neighborhood structure. Although the autologistic model was initially proposed for lattice data analysis (Besag, 1974), it is also effective for point data analysis by setting the appropriate neighborhood. In this study, whenever the distance of two traffic stops is shorter than a predefined threshold distance, they are thought to be neighbors. Otherwise, they are not neighbors. The threshold distance is determined by making sure that every data has at least one neighbor in this study.

$$Y_i \tilde{} Binomial(p_i) \tag{1}$$

$$log\left(\frac{p_i}{1-p_i}\right)=\beta_0+\beta_1*X_{1i}+\ldots+\beta_m*X_{mi}+\gamma*Autocov_i \tag{2}$$

$$Autocov_i=\frac{\sum_{j=1}^{n_i}w_{ij}Y_j}{\sum_{j=1}^{n_i}w_{ij}} \tag{3}$$

$$w_{ij}=\frac{1}{d_{ij}} \tag{4}$$

where, $i = 1, 2, \ldots, 4089$, is the index of traffic stops; Y_i is the outcome of traffic stop i, 1 if ticket, 0 if warning; p_i is the probability of Y_i being a ticket; $X_{1i}, \ldots, X_{mi}$ are the covariates of traffic stop i; $\beta_0, \ldots, \beta_m$ are the regression coefficients of covariates; $Autocov_i$ is the autocovariate of traffic stop i to represent spatial effects; γ is the regression coefficient of autocovariate; n_i is the number of neighbors of data i; w_{ij} is the spatial weight between data i and j, equal to the inverse of Euclidean distance between data i and j, d_{ij}.

As a comparison, an ordinary logistic regression model is also built and estimated. Both models are estimated in R (R Core Team, 2016) with the "spatialEco" package (Evans, 2017).

Table 2
Likelihood ratio test of the ordinary logistic regression model and the autologistic regression model.

Model	Degree of freedom	Loglikelihood	Degree of freedom difference	Chi-square value	P-value
Ordinary logistic	52.454	−2326.8			
Autologistic	53.417	−2299.8	0.963	54.1	<0.001

Table 3
Confusion matrices of the ordinary logistic regression model and the autologistic regression model.

Observation	Ordinary logistic		Autologistic	
	Warning	Ticket	Warning	Ticket
Warning	2770	93	2743	120
Ticket	1050	176	992	234

4. Results

4.1. Model evaluation

Performance of the ordinary logistic regression model and the autologistic regression model are checked with the likelihood ratio test, where the latter performs significantly better than the former as shown in Table 2. The confusion matrixes of the two models are shown in Table 3. The total prediction accuracies of the autologistic regression model is slightly higher than the ordinary logistic regression model (72.8% vs. 72.0%). Besides, the autologistic regression model could more accurately predict tickets, the minority class of outcomes. This is extremely important in practice, as imbalanced data is common in transportation.

In addition, Moran's I statistic is used to check the spatial correlations of residuals of the two models (Anselin, 1988), and the results are shown in Table 4. The residuals of the ordinary logistic model show significant spatial correlations, but not the autologistic model. That is, the autologistic regression model does cover spatial correlations of traffic stops well. As a summary, it concludes that the autologistic regression model is preferred than the ordinary logistic regression model for traffic stop outcome analysis in this case.

4.2. Estimated results analysis

The estimated results of the autologistic regression model with all covariates are shown in Table 5. In addition to driver age, driver gender and driver race, their interaction terms are also included in the model. To identify significant variables, the model is re-estimated after excluding insignificant variables until all the variables are significant. Table 6 shows the estimated results of the final model with all variables significant. The estimated coefficients in Tables 5 and 6 are generally consistent. It should be noted that "Hour = 11" is insignificant in the final model and thus removed.

It can be found:

1) All speeding indicators show significantly positive effects. The odds ratios of speeding 11–20 over speed limit and speeding 21 or more mph over speed limit leading to tickets are 1.944 and 9.650 times of speeding 1–10 mph over speed limit, respectively. That is, speeding traffic stops are more likely to be issued tickets rather than warnings

Table 4
Moran's I statistics of residuals of the ordinary logistic regression model and the autologistic regression model.

Model	Moran's I statistic	P-value
Ordinary logistic	0.038	<0.001
Autologistic	−0.021	0.999

Table 5
Estimation results of the autologistic regression model with all covariates.

Covariate	Coefficient	Std. error	Wald	P-value
Intercept	−2.361	0.254	−9.301	<0.001*
Male	0.360	0.106	3.404	0.001*
Young	0.506	0.134	3.771	<0.001*
Old	−0.488	0.336	−1.452	0.146
Minority	0.722	0.222	3.259	0.001*
Male: young	−0.133	0.167	−0.792	0.429
Male: old	0.387	0.413	0.937	0.349
Male: minority	−0.395	0.272	−1.454	0.146
Young: minority	−0.154	0.422	−0.366	0.714
Old: minority	−2.902	8.505	−0.341	0.733
Young: male: minority	−0.083	0.506	−0.165	0.869
Old: male: minority	1.735	8.558	0.203	0.839
Speeding = 11−20 mph	0.656	0.075	8.732	<0.001*
Speeding = 21 or more mph	2.259	0.214	10.537	<0.001*
Hour = 0	0.333	0.237	1.406	0.160
Hour = 1	−0.123	0.264	−0.468	0.640
Hour = 2	0.291	0.310	0.938	0.348
Hour = 3	0.144	0.397	0.363	0.716
Hour = 4	−0.695	0.467	−1.488	0.137
Hour = 5	−0.039	0.296	−0.133	0.894
Hour = 6	0.113	0.269	0.422	0.673
Hour = 7	0.165	0.265	0.621	0.534
Hour = 8	0.588	0.274	2.147	0.032*
Hour = 9	0.378	0.257	1.469	0.142
Hour = 10	0.402	0.258	1.560	0.119
Hour = 11	0.488	0.248	1.968	0.049*
Hour = 13	0.365	0.270	1.353	0.176
Hour = 14	0.513	0.270	1.903	0.057
Hour = 15	0.445	0.265	1.678	0.093
Hour = 16	0.355	0.290	1.226	0.220
Hour = 17	0.415	0.309	1.343	0.179
Hour = 18	0.027	0.256	0.106	0.915
Hour = 19	0.276	0.242	1.138	0.255
Hour = 20	0.006	0.239	0.023	0.982
Hour = 21	0.174	0.241	0.722	0.470
Hour = 22	0.212	0.239	0.887	0.375
Hour = 23	−0.114	0.238	−0.481	0.631
Tuesday	−0.276	0.142	−1.942	0.052
Wednesday	−0.052	0.136	−0.387	0.699
Thursday	−0.140	0.140	−0.998	0.318
Friday	0.101	0.129	0.784	0.433
Saturday	0.171	0.127	1.347	0.178
Sunday	−0.121	0.139	−0.867	0.386
January	0.097	0.156	0.619	0.536
February	0.085	0.181	0.467	0.641
March	−0.135	0.175	−0.772	0.440
April	−0.072	0.181	−0.396	0.692
June	−0.081	0.184	−0.441	0.659
July	−0.150	0.181	−0.831	0.406
August	0.309	0.167	1.853	0.064
September	0.206	0.164	1.262	0.207
October	−0.147	0.191	−0.767	0.443
November	0.074	0.175	0.422	0.673
December	0.380	0.169	2.253	0.024*
Autocovariate	1.381	0.188	7.357	<0.001*

Note:
* Significant at 95% confidence interval.

with the increase of speeding magnitude. In addition, 20 mph over speed limit seems a threshold of greatly influencing the penalty, as traffic stops with speeding 21 or more mph over speed limit are much more likely to receive tickets.

2) Male drivers show significantly positive effects. The odds ratio of a male driver receiving a ticket is 1.262 times of that of a female driver in a speeding traffic stop under the same scenario. As is shown in Table 7, males committed many more speeding violations, especially speeding 21 or more mph over speed limit, than females, although the male population is actually slightly smaller than the female population (49.1% versus 50.9%) in Burlington (United States Census Bureau, 2018). Therefore, males are generally much more likely to commit aggressive speeding than females, which might lead law enforcement officials to have some inherent biases to them.

Table 6
Estimation results of the autologistic regression model with only significant covariates.

Covariate	Coefficient	Std. error	Wald	P-value	Odds ratio
Intercept	−2.092	0.101	−20.758	<0.001*	0.123
Male	0.233	0.075	3.122	0.002*	1.262
Young	0.383	0.074	5.156	<0.001*	1.467
Minority	0.355	0.106	3.365	0.001*	1.426
Speeding = 11−20 mph	0.665	0.073	9.088	<0.001*	1.944
Speeding = 21 or more mph	2.267	0.213	10.628	<0.001*	9.650
Hour = 8	0.412	0.197	2.088	0.037*	1.510
December	0.337	0.123	2.745	0.006*	1.401
Autocovariate	1.431	0.183	7.806	<0.001*	4.183

Note:
* Significant at 0.95 confidence interval.

3) The regression coefficient of young drivers is significantly positive, whereas the regression coefficient of old drivers is insignificant. Thus, young drivers are more likely to get tickets than middle-aged and old drivers for the same speeding traffic stops. The odds ratio of young drivers receiving a ticket is 1.467 times of that of other drivers. Table 8 shows the composition of speeding traffic stops by speeding type and driver age. Although young drivers are only involved in 33.2% of total traffic stops, they committed 40.2% of traffic stops of 21 or more mph over speed limit, which might lead law enforcement officials to have some inherent biases.
4) Driver race shows significantly positive effects, where minority drivers are 42.6% more likely to receive tickets than White drivers under the same speeding scenario. The result implies that there might be the presence of racial profiling in speeding law enforcement of BPD, which is kind of consistent with former studies also targeting traffic stop data of Vermont (Seguino et al., 2012; Seguino and Brooks, 2017, 2018), where African Americans and Hispanics were found to be more likely to be stopped, searched, and arrested than Whites and Asians. Although this study does not differentiate the races of minority drivers due to the data size limitation, it still provides some insights on the role of the race of the driver in influencing the enforcement decisions.
5) None of the interaction terms of driver age, driver gender or driver race show significant effects in this case. It should be noted that the limited sample sizes for some interaction terms might influence the results, thus similar analysis with enough samples for all interaction terms are recommended to be conducted in the future to verify the findings of this study. To strengthen the study further, anonymous questionnaires to police officers are strongly suggested to gauge whether there is really any inherent bias in speeding law enforcement, in terms of driver demographic features.
6) For time indicators, hour 8 is significantly positive, which means speeding traffic stops are more likely to be issued tickets at 8 AM than other hours; none of the day of week indicators is found to be significant. Besides, December is significantly positive, which means speeding traffic stops are more likely to be issued tickets in December than other months. These findings imply that there might be some hourly and monthly effects in speeding law enforcement of BPD.
7) The autocovariate shows significant positive effects, which means that the speeding traffic stops with larger autocovariates are more

Table 7
Composition of speeding traffic stops by speeding type and driver gender.

No	Speeding type	Female	Male
1	1−10 mph over speed limit	714	1311
2	11−20 mph over speed limit	792	1150
3	21 or more mph over speed limit	29	93

Table 8
Composition of speeding traffic stops by speeding type and driver age.

No	Speeding type	Young	Middle	Old
1	1−10 mph over speed limit	645	1291	89
2	11−20 mph over speed limit	663	1189	90
3	21 or more mph over speed limit	49	68	5

likely to be issued tickets rather than warnings. The result confirms the presence of spatial correlations in speeding traffic stops in another view. Besides, since the autocovariates are closely related to geographic locations, it implies that there are some hot areas where speeding traffic stops are more likely to be seriously penalized and there are some cold areas where speeding traffic stops are less likely to be penalized.

4.3. Autocovariate analysis

Fig. 1 shows the histogram of autocovariates, and Fig. 2 shows the geographic distribution of autocovariates over space. Autocovariates are around 0.3 in most locations, whereas there are some hot areas with large autocovariates, which are mainly located in the downtown area and along some major roadways, such as Main Street and Shelburne Road. The presence of autocovariates might be attributed to many unobserved factors, such as terrain, geometric design, officer and speed limit. For example, law enforcement is found to vary greatly by individual officers (Goncalves and Mello, 2018), where some officers might be strict to speeding but others not. Deep investigation is needed to figure out the true reasons for spatial effects. It would be helpful for taking customized measures in the future law enforcement improvement initiatives.

5. Conclusions and discussions

Law enforcement is critical to prevent traffic accidents, however disputes on the equity of law enforcement has become a social issue. This study explores the equity of law enforcement by identifying factors influencing outcomes of speeding traffic stops issued by Burlington Police Department, VT from 2012 to 2017. To exclude possible confounding effects, this study specifically focuses on speeding traffic stops leading to tickets or warnings. The autologistic regression model is adopted to appropriately account for spatial correlations of speeding traffic stops. It is found that with the increase of speeding range, traffic stops are more likely to lead to tickets. For most part, 20 mph over speed limit seems to be a tipping threshold, because speeding violations of 21 or more mph over speed limit are much more likely to be issued tickets rather than warnings. Young drivers, male drivers, and minority drivers are more likely to receive a ticket than a warning in a speeding traffic stop, which implies the possible presence of inherent biases against these groups in law enforcement. In addition, speeding traffic stops occurring in December and at 8 AM are more likely to lead to tickets. Finally, the hot areas of law enforcement, where drivers are more likely to be issued tickets in speeding traffic stops, are identified. These areas are mainly located in the downtown area and along some major roadways.

This research has several advancements compared to existing studies. Firstly, it confirms the significant spatial correlations across traffic stops. Although spatial correlations have been widely studied in traffic crash analysis, they are rarely discussed in traffic stop analysis before. This study demonstrates the importance and necessity of taking spatial correlations into account in similar studies. It also kind of demonstrates that traffic stop data and traffic crash data do share many common features. Secondly, this is one of pioneering studies applying the point-based autologistic regression model into analyzing transportation problems, where the Euclidean distances between points are used to determine their spatial correlations. As a comparison, currently, most transportation researches adopt the area-based spatial regression models to account for spatial correlations of data, where the raw point data, such as crashes or violations, are needed to be aggregated by area first before modeling. However, some important information might be lost in the aggregation process, which would influence the final estimation results. Meanwhile, the autologistic regression model could give quantitative evaluation results by points, i.e. hot points in this study, which could help the related stakeholders locate the problematic objects quickly and precisely. As a comparison, the area-based spatial regression models could also identify the key areas, which however are often too big to identify the specific targets. Thirdly, this study is one of few studies exploring the law enforcement equity with one specific type of traffic

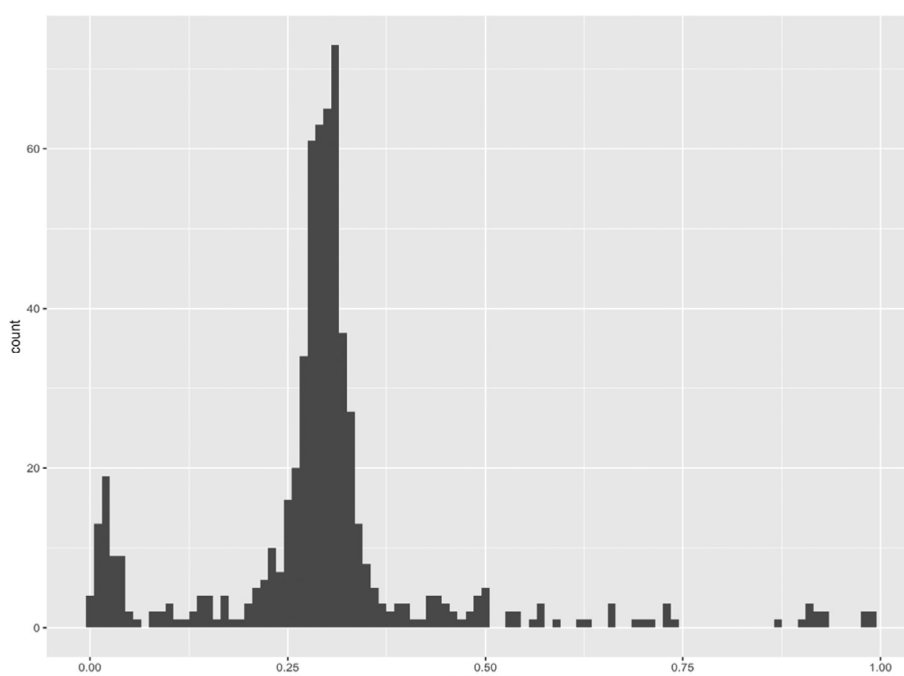

Fig. 1. Histogram of autocovariates from the autologistic regression model with only significant covariates.

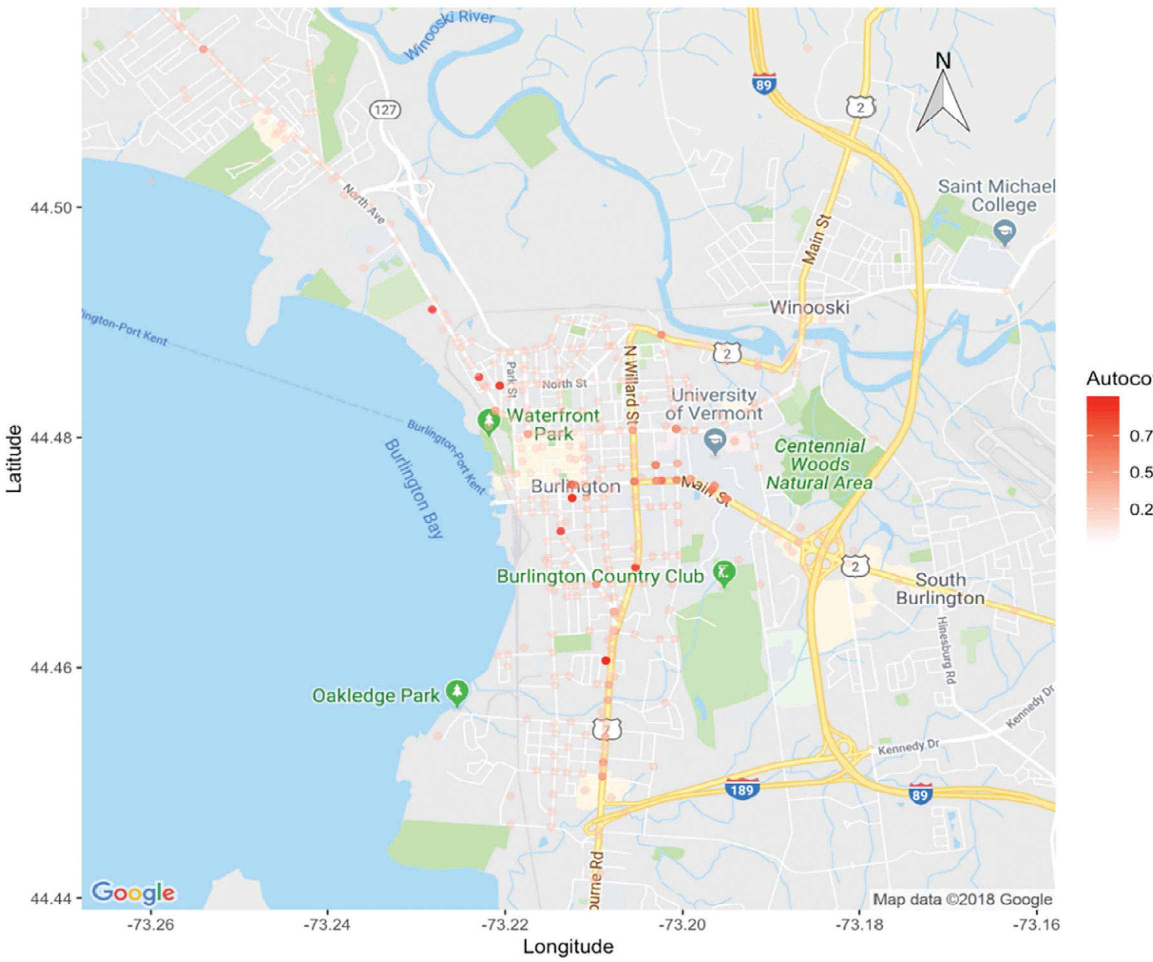

Fig. 2. Geographic distribution of autocovariates from the autologistic regression model with only significant covariates (Source: Google Map).

stop data from one law enforcement agency, which could greatly reduce the confounding effects compared to other studies using all traffic stop data. This is very important for accurately and correctly figuring out the role of concerned factors in law enforcement, as there are many reasons for traffic stops and lots of factors might influence their outcomes. Ignoring those confounders might greatly undermine the credibility of research findings. Therefore, the findings from this study are expected to be more reliable and in accordance with the truth. Fourthly, the 20 mph over speed limit is found to be a tipping point greatly affecting outcomes of speeding traffic stops, which has not been discussed in former studies to the best knowledge of the authors. This information might help the public to recognize features in speeding law enforcement somehow and instruct them to drive carefully to avoid heavy penalties.

5.1. Policy implications

These findings are expected to help locals and law enforcement agencies to better understand the implicit bias in law enforcement and provide many instructive insights to address concerns regarding bias in policing. It should be noted that the findings of this study only show the features of the studied dataset but are not intended to be generalized to any other law enforcement activity or any other law enforcement agency. However, this approach might be adopted in similar studies for exploring trends and biases in law enforcement.

Firstly, the paper indicates the possible presence of implicit bias against specific demographic groups, i.e. young drivers, male drivers and minority drivers, in the speeding law enforcement of BPD. Aiming at the implicit bias, for the in-service officers, customized on-the-job trainings could be developed to help them realize and appreciate this issue and prompt them to enforce laws discreetly and equitably to reduce possible disputes. Besides, a commitment to increase diversity in recruitment, retention and promotion of law enforcement is also critical for increasing mutual trusts between law enforcement agencies and the communities they serve (U.S. Department of Justice and Employee Equal Opportunity Commission, 2016). According to a report in 2016, the BPD is slightly underrepresented by Black and Hispanic officers (Pozo and Fowler, 2016). Thus, it may consider increasing the representation of minority officers.

Secondly, aiming at the detected hot areas of law enforcement, further investigations are suggested to figure out what are the true reasons and thus targeted solutions can be developed. If this is related to some specific units/officers by checking ticketing records, customized trainings to these units/officers would be the key of reducing the biased policing quickly and effectively. If this is related to improper highway geometric designs or traffic control device settings, some transportation engineering solutions might be considered to eliminate hidden troubles.

Thirdly, it is essential to encourage residents to defend themselves by law when they think they might be unfairly treated in law enforcement activities. The findings of this study indicate that people might encounter many different kinds of implicit biases in law enforcement. However, although many people might be unconvinced of tickets, they might not be going to fight for them due to the concerns of time and money costs. It is suggested that the government might consider funding some special programs to support the public by providing legal and other services.

Therefore, the public could protect their legal interests with least costs. Meanwhile, it is believed that this would also prompt officers to further regulate their behaviors in law enforcement activities.

5.2. Future studies

In future, many aspects can be explored for gaining comprehensive data driven insights. Firstly, this study only focuses on speeding traffic stop data, whereas studies targeting other types of traffic stop data are needed to produce comprehensive results. If multiple traffic stop types are analyzed simultaneously, multivariate statistical models might be considered to cover their possible correlations. Secondly, other studies have reported the demeanor and history records of drivers to be correlated to the outcomes of a traffic stop (Kent and Regoeczi, 2015). The demographic features of officers might also impact the enforcement decisions. These information are unavailable in this dataset. However, they should be seriously taken into account to produce more precise estimation results when available. Thirdly, the influences of many factors might change over time. Future studies may explore the dynamic effects of these factors.

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