Security Without Equity?
The Effect of Secure Communities on Racial Profiling by Police

Jack Willoughby

Professor Frank Sloan, Faculty Advisor

Honors Thesis submitted in partial fulfillment of the requirements for Graduation with Distinction in Economics in Trinity College of Duke University.

Duke University
Durham, North Carolina
2015

Acknowledgements

I would like to acknowledge the guidance and insight of my thesis advisor, Dr. Frank Sloan, without whom this paper would not be possible. I would like to thank the North Carolina State Bureau of Investigation for making the data used publically available, and Sabrina McCutchan for assisting me in accessing the data. I would also like to thank my parents for their support throughout the production of this thesis. Finally, I would like to thank the Duke Endowment for the AB Duke Scholarship that has afforded me a world-class Duke education.

Abstract

Anecdotal and circumstantial evidence suggest that the implementation of Secure Communities, a federal program that allows police officers to more easily identify illegal immigrants, has increased racial bias by police. The goal of this analysis is to empirically evaluate the effect of Secure Communities on racial bias by police using motor vehicle stop and search data from the North Carolina State Bureau of Investigation. This objective differs from most previous research, which has largely attempted to quantify racial profiling for a moment in time rather than looking at how an event influences racial profiling. I examine the effects of Secure Communities on police treatment of Hispanics vs. whites with an expanded difference-in-difference approach that looks at outcomes in motor vehicle search success rate, search rate conditional on a police stop, stop rate, and police action conditional on stop. Statistical analyses yield no evidence that the ratification of Secure Communities increased racial profiling against Hispanics by police. This finding is at odds with the anecdotal and circumstantial evidence that has led many to believe that the ratification of Secure Communities led to a widespread increase in racial profiling by police, a discrepancy that should caution policy makers about making decisions driven by stories and summary statistics.

JEL classification: J15; K42; K37; K14

Keywords: Racial Policing; Bias; Immigration Law; Secure Communities

1 Introduction

Secure Communities, a federal program that allows local police to quickly and easily identify illegal immigrants, has come under intense scrutiny since its inception in 2008. Under Secure Communities, all arrested individuals who receive a criminal background check are cross-referenced against an FBI database to identify if they have violated immigration laws. In response, police may be arbitrarily arresting individuals whom they suspect to be illegal immigrants in order to initiate deportation proceedings. The idea that police may be engaging in racial profiling against Hispanics is reinforced by anecdotal and circumstantial evidence. For example, Latinos comprise 93% of all people arrested through Secure Communities while they only make up 77% of the U.S. undocumented population[1]. While these arguments are effective at generating national attention, they lack the statistical robustness necessary to assert that Secure Communities has, in fact, precipitated an increase in racial profiling against Hispanics by police. This analysis will attempt to empirically test the effect of Secure Communities on racial profiling.

Previous literature related to the economic analysis of racial profiling has overwhelmingly attempted to quantify racial profiling at a given moment in time, rather than to evaluate how an event may have influenced racial profiling. The theory developed in this paper builds on literature that attempts to differentiate justifiable statistical discrimination from unproductive racial bias in its development of a model to identify the effects of Secure Communities on racial profiling. The resulting models indicate what inferences of racial profiling can be drawn from differential changes in four outcome variables associated with motor vehicle stops: the change for whites vs. Hispanics from before to after the implementation of Secure Communities in 1) rate of possession of contraband conditional on search, 2) rate of search conditional on stop, 3) rate of stop, and 4) police action taken against stopped motorists.

[1] Kohli, Markowitz, & Chavez (2011).

The empirical analysis will build on previous work in two subsets of existing literature. First, it will utilize an expanded difference-in-difference methodology similar to two previous empirical attempts to determine how events affected racial profiling. Second, it will employ empirical tests developed in the subset of previous studies that also had access to microdata, rather than merely summary data. The models will be fit with data from the North Carolina State Bureau of Investigation to quantify the effect of Secure Communities on racial profiling. Statistical analyses yield no evidence that the ratification of Secure Communities increased racial profiling against Hispanics by police. This finding is at odds with the anecdotal and circumstantial evidence that has led many to believe that the ratification of Secure Communities led to a widespread increase in racial profiling by police, a discrepancy that should caution policy makers about making decisions driven by stories and summary statistics.

The study proceeds as follows: Section 2 discusses relevant background information, Section 3 provides a brief summary of background literature, section 4 builds a theoretical model, section 5 introduces the data used, section 6 explains the empirical model, section 7 describes the results of analysis, section 8 elaborates on a potential challenge to the results, and section 9 concludes.

2 Background Information

Secure Communities is a federal program designed to involve local police in the Department of Homeland Security's (DHS) fight against immigration violations. Prior to its implementation the identification of illegal immigrants was time and resource intensive, and usually required on-site interviews by federal Immigration and Customs Enforcement (ICE) officers.[2] When police arrest individuals, standard procedure is to take the fingerprint of the arrestee and

[2]This and the following descriptions of Secure Communities and 287(g) come from *http://www.ice.gov*, the subset of the DHS website devoted to ICE.

submit it to the Federal Bureau of Investigation (FBI) for a criminal background check; Secure Communities mandates that all fingerprints sent to the FBI for criminal background checks are forwarded to the DHS, where they are run through a database that flags known violators of immigration laws. A flagged individual's identity is then sent to ICE for review, after which ICE determines whether it wants to issue a detainer on the arrestee. Detainers result in the arrestee being held in jail for up to 48 hours, during which an ICE officer will interview the individual and determine if he/she will be deported. The individual does not need to be found guilty of the crime for which he/she was arrested in order to be deported, and deportation verdicts are often found prior to the conclusion of parallel proceedings through the criminal justice system; through May 2013, 63,665 of the 306,662 people (21%) deported under secure communities had a spotless criminal record.[3] If ICE deems the individual deportable, he/she is placed in a detaining facility until the event of his/her deportation. Secure Communities was gradually rolled out in all local police jurisdictions in the USA from 2008 to 2013.

Prior to the implementation of Secure Communities, local police officers from select jurisdictions could aid in immigration enforcement through provisions outlined in section 287(g) of the Immigration and Nationality Act enacted in 1996 (287g). Under 287g, local police jurisdictions and the Federal Government may enter agreements that allow police officers, after a baseline level of training and under the supervision of trained ICE officers, to identify and detain illegal immigrants they encounter while on duty. Jurisdictions that had previously enacted 287g were still mandated to implement Secure Communities, but the ease with which they could identify illegal immigrants increased less than in jurisdictions that had not previously enacted 287g. While considerable literature exists on the effect of Secure Communities and 287g on crime, citizens' rights, and police relations with their local community,[4] to my knowledge, no formal economic model has been built to quantify the

[3]Immigration and Customs Enforcement (2013).

[4]Examples include Kohli, Markowitz, & Chavez (2011), Weinstein (2012), Kang (2012), Gill (2013), Cox

effect of Secure Communities on racial bias police.

3 Literature Review

Two prevailing, competing definitions of racial discrimination have emerged in previous literature: 1) racial discrimination is the use of race as an input in police' decisions, and 2) racial discrimination is the use of race as an input in police' decisions that results in suboptimal decision-making. There is a subtle but important distinction between the two that lies in the acknowledgment of statistical discrimination as a positive force. Under the assumption that racial discrimination is undesirable, the first definition advocates that police should be color-blind at all times, regardless of its effect on their ability to do their jobs, while the second advocates that police do their jobs to the best of their abilities independent of race. This analysis will subscribe to the second definition, which parallels the notion of taste-based discrimination first introduced by Becker (1957). This will allow for statistical discrimination in which police can use information about race as they would other signals, like age, gender, type of car being driven, location, etc., to improve their performance as police officers.

The absence of racial discrimination yields an equilibrium in which the marginal motorist of all races should have an equal probability of being guilty, which here is defined as carrying contraband, conditional on being searched. Unfortunately, data only provide each race's average probability of carrying contraband conditional on search, which is known as its "hit rate." The challenge that most relevant previous literature attempts to address is how to extrapolate from average to marginal hit rates, which is known as the "infra-marginality problem." Knowles, Persico, & Todd (2001) address this problem with a model that describes an equilibrium in which all motorists will have the same probability of carrying contraband. This work paved the way for continued research that attempts to differentiate between

& Miles (2014).

statistical and taste-based discrimination, similar to the model built in this paper. While this analysis will rely on a theoretical model that parallels and builds on Knowles, Persico & Todd (2001), it will not be subject to their key assumptions, because the goal of this analysis differs from most previous literature. Previous literature has overwhelmingly focused on identifying the presence of racial discrimination by police at a given moment in time, but this analysis seeks to identify how an event affected racial discrimination by police.[5].

At least two other studies, to my knowledge, have similarly attempted to determine how an event effects racial profiling rather than to assess the existence of racial profiling at a given point in time. Warren & Tomaskovic-Devey (2009) sought to determine if increased social and political scrutiny on racial profiling affected racial profiling levels of police. Using data from the North Carolina Highway Traffic Study, Warren & Tomaskovic-Devey examined whether the timing of changes in search and hit rates is correlated with media references and legislative changes. They do not, however, include a control group, which subjects their analysis to potential confounding.

Heaton (2010) extends their study to assess the effects of police agency or government programs aimed at reducing racial bias by police. Heaton focuses on the state police department of New Jersey, which experienced a racial profiling scandal in 1998-9 in which white police officers shot four African-American and Hispanic motorists on the NJ Turnpike. The scandal precipitated an investigation that identified racial profiling by NJ state police officers and implemented reforms to decrease racial profiling. Heaton uses an expanded difference-in-difference specification that controls for location and crime type in its evaluation of how motor vehicle crime rates changed for whites vs. minorities from before to after the scandal. He uses data from neighboring states as a control to evaluate changes in racial profiling specific to New Jersey. While Heaton's methodology provides a good starting point, he only

[5]For generalizations and extensions of the Knowles, Persico & Todd (2001) model, see Hernández-Murillo & Knowles (2004), Dharmapala & Ross (2004), Dominitz & Knowles (2006), Anwar & Fang (2006), Persico & Todd (2006), Bjerk (2007), Antonovics & Knight (2009), and Sanga (2009).

has access to summary data that provide yearly averages of crimes by race and location, and therefore cannot control for individual level observables, like gender and time of day, that are available in microdata.

Another aspect of previous literature that relates to the current study is empirical research based on microdata rather than summary data. Pickerill, Mosher, & Pratt (2009) provide a good explanation of the importance of using microdata in quantifying racial bias. They argue that the outcomes that suggest racial inequality may not be indicative of intentional racial bias if there exist observable signals, like gender or time of day of the stop, that correlate with the race of a motorist and a police officer's decision to stop or search the person. Many studies fail to account for these signals in their use of summary data. Pickerill, Mosher, & Pratt use microdata from the state of Washington to control for observable motorist characteristics and attempt to isolate the racial bias that is truly due to race. They control for characteristics of the driver, police officer, and the stop in general. Importantly, they differentiate between the amount of discretion that officers have in different types of stops and searches, arguing that searches precipitated by a high level of police discretion are more prone to intentional racially motivated bias than those in which the police officer has no choice in whether or not to make the search.

Grogger & Ridgeway (2006) similarly argue that intentional racially motivated bias will be more prevalent during daylight hours when police can more easily identify the race of a motorist. They test their hypothesis by examining the difference in discrepancies in the rate at which police stop whites vs. blacks for stops that occur during the day vs. after sundown. Finally, Antonovics & Knight (2009) recognize that if racial inequality is due purely to statistical discrimination, then levels of racial inequality should not vary depending on the race of the police officer for a given group of motorists (e.g., white police officers should search black motorists at the same success rate as black police officers search black motorists). Unfortunately, the data used in this analysis does not contain information on the race of the police officer, so this test is not presently feasible, which is a limitation in the analysis. This analysis will, however, borrow the insight of Pickerill, Mosher, & Pratt (2009) and Grogger & Ridgeway (2006) and incorporate the time of day and discretion level of a stop and search, respectively, into its empirical model.

4 Theoretical Methodology

4.1 Overall Theory and Assumptions

A. Convergence of expected value of making a search

Assume that the goal of a police officer is to optimize the officer's ability to protect and serve his/her community under the police officer's time and financial constraints. Therefore, the value of a motor vehicle search is the extent to which the search aligns with police objectives to protect and serve a community. Next, define a loss function that police use to quantify the extent to which any given action advances their ability to protect and serve their jurisdiction, where greater loss corresponds to less productive officer actions. To maximize the value of his/her searches, each police officer chooses the basket of searches that minimizes his/her loss function, which is a weighted average of type 1 and type 2 errors. Given the premise of innocent until proven guilty, the police judges suspects under the null hypothesis of innocence, making type 1 error the negative value of wrongly searching an innocent motorist, and type 2 error the negative value of failing to search a guilty motorist. Therefore, the loss function for making a search for police officer i:

$$Loss_i = \mathrm{Pr}(Innocent) \times \mathrm{U}_i(Error_1) - \mathrm{Pr}(Guilty) \times \mathrm{U}_i(Error_2)$$

where $\mathrm{U}_i(Error_1)$ is the utility police officer i receives from wrongly searching an innocent person, and $\mathrm{U}_i(Error_2)$ is the utility the police officer receives from failing to search a guilty person, with $max(\mathrm{U}(Error_1), \mathrm{U}(Error_2)) < 0$. Each police officer subjectively evaluates the probability of guilt for a motorist, which he/she then combines with his/her loss function to make a search decision. The police search individuals for whom the expected value of a search exceeds the expected value of not searching, based on the police officer's perception of the value of searching the stopped individual. Assume that before a search police cannot perceive which motorists, if carrying contraband, would be carrying relatively more contraband, and therefore there is no differentiation between the severity of crimes in a police officer's loss function. The loss of not searching an individual can be set to equal 0, yielding an equilibrium in which officer i searches an individual if:

$$\Pr(Guilty) > \alpha_i \times \Pr(Innocent)$$

where $\alpha_i = \mathrm{U}_i(Error_1)/\mathrm{U}_i(Error_2)$ indicates the weight that a police officer i places on type 1 vs. type 2 error.

Regardless of the weight a police officer's loss function places on the two error types, a police officer would minimize his/her loss function by first searching motorists whom he/she perceives have the highest probability of guilt, and proceeding with searches in descending order of probability of guilt. The results are therefore robust to competing arguments about how racially unbiased police make decisions, assuming only that police act to maximize their ability to serve their jurisdiction. The breakeven perceived search probability, above which police search a motorist and below which police do not search, would vary by police officer depending on his/her individual-specific α_i. Officers who search stopped motorists more frequently place a higher importance on reducing type 2 error relative to type 1, and officers who search less frequently value the converse. Furthermore, the loss function of non-racially biased police will value the error types of Hispanics and whites equally, so that in equilibrium, the expected value of searching Hispanics and whites are equal on the margin.

Mathematically, the value of a search is the product of its probability of finding contraband and its value conditional on a contraband finding. The probability of a search yielding contraband is inferred by the police officer based on the signals he/she observes when stopping a motorist, and is therefore only partially represented in the data. Some of the these observed signals are known to the data analyst and the police officer, like the gender, race and age of the driver, or the time of day, while others are known only to the officer, like the shiftiness of the drivers eyes or the smell of the car. All probabilities used in building theory will be conditional on the signals observable to the police officer unless otherwise noted.

To formalize, let $\{$contraband $= C$, search $= S$, punishment $= P$, race $= R$, white $= W$, and Hispanic $= H\}$. As articulated above, absent racial profiling, the expected value of the marginal search for a police officer should be equal for all races:

$$\Pr(C \mid S, W) \times \mathrm{E}[P \mid C, W] = \Pr(C \mid S, H) \times \mathrm{E}[P \mid C, H]$$

Assume for now that the expected value to an unbiased police officer on finding contraband is equal for white and Hispanic motorists:[6]

$$\mathrm{E}[P \mid C, W] = \mathrm{E}[P \mid C, H] \quad (1)$$

Assumption 1 implies that absent racial profiling and on the margin, the probability of finding contraband, which can be defined as the "hit rate," will converge across races:

$$\Pr(C \mid S, W) = \Pr(C \mid S, H) \quad (2)$$

[6]The implications of relaxing this assumption will be explored in section 8

B. Expected value of carrying contraband

The expected profit of carrying contraband (π) to a motorist depends on: the motorist's expected benefit if not caught with contraband (b); the cost (c), which is a sum of financial costs (e.g., gas, tolls), opportunity costs (e.g., forgone wages at a legitimate job), and the mental anguish associated with transporting contraband; and the expected value of the penalty of being caught. The expected penalty of being caught while carrying contraband equals the product of the probability of being searched (p_1), the probability of a police officer finding contraband conditional on search and its presence (p_2), and the expected penalty conditional on being searched and contraband found. The expected penalty conditional on being caught with contraband is a weighted average of expected penalty issued by the criminal justice system conditional on a finding of contraband and no deportation (j), which includes fines and jail time, and the negative value placed on being deported conditional on deportation (d), weighted by the probability of being deported conditional on contraband being found ($q \mid C$). For U.S. citizens, $(q \mid C) = 0$. The expected value of committing a crime is:

$$\pi = (1 - p_1 \times p_2) \times b - c - p_1 \times p_2 \times ((1 - (q \mid C)) \times j + (q \mid C) \times d) \tag{3}$$

After implementation of Secure Communities, the expected value of carrying contraband would change:

$$\Delta\pi = \Delta\left((1 - p_1 \times p_2) \times b\right) - \Delta c - \Delta\left(p_1 \times p_2 \times (j + (q \mid C) \times (d - j))\right) \tag{4}$$

Assume that for the subset of crimes included in the analysis, which is confined to the presence of contraband in a motor vehicle, deportation is viewed by illegal immigrants as worse than prosecution through the judicial system, so that $d - j > 0$. Also assume that the implementation of Secure Communities does not affect the expected benefit or costs associated with carrying contraband, the probability of a search finding contraband conditional on its presence, or the expected judiciary outcome or negative value people place on deportation conditional on the presence of contraband.[7] Therefore, $\Delta b = \Delta c = \Delta p_2 = \Delta j = \Delta d = 0$. Equation 4 simplifies to:

$$\begin{aligned}\Delta\pi &= -\, b \times p_2 \times \Delta p_1 - p_2 \times (d - j) \times \Delta\left(p_1 \times (q \mid C)\right) - j \times p_2 \times \Delta p_1 \\ &= -\,(b + j) \times p_2 \times \Delta p_1 - p_2 \times (d - j) \times \Delta\left(p_1 \times (q \mid C)\right)\end{aligned}$$

Since $0 \leq p_2 \leq 1$; $0 \leq \min\{b,\, c,\, d,\, j\}$, the values of p_2, d, b, c, and j affect the magnitude of the change in motorists' incentives to commit crimes, but the values cannot change its sign. Decomposing by whites (W) and Hispanics (H), the theoretical changes in propensity to commit a crime are:

$$\begin{aligned}\Delta\pi^W &= -[\gamma \times \Delta p_1^W + \delta \times \Delta\left(p_1^W \times (q \mid C)^W\right))] \\ \Delta\pi^H &= -[\gamma \times \Delta p_1^H + \delta \times \Delta\left(p_1^H \times (q \mid C)^H\right))]\end{aligned}$$

where $\gamma = (b + j) \times p_2$ and $\delta = p_2 \times (d - j)$ are positive constants. The primary effect of Secure Communities is to increase the probability of being deported conditional on contraband being found, or $\Delta(q \mid C) > 0$. Since there is a much higher fraction of Hispanics than whites who are in the USA illegally,[8] $\Delta(q \mid C)^H > \Delta(q \mid C)^W$. Next, police would require some time, even if only a very brief amount, to realize that Hispanics are no longer committing as many crimes and update their statistical discrimination. Therefore, the most likely change in

[7] The validity of this assumption is a potential limitation of the study. It is conceivable that after the ratification of Secure Communities, the contraband carrying market will adjust and a new general equilibrium will arise in which carrying contraband is costlier to illegal immigrants but more well compensated due to the increased risk, so that the the value of carrying contraband increases, or $\Delta b > 0$. For simplicity, assume that there is an inelastic enough supply of contraband carriers that their compensation does not change after the ratification of Secure Communities.

[8] Pew Hispanic Center (2006) estimates that approximately 78% of undocumented people in the U.S. are Hispanic, while the CIA Fact Book estimates that the total population of the U.S. is only 15.1% Hispanic

p_1^R that may result from the implementation of Secure Communities is a perceived increase in expected value of punishment conditional on finding contraband by searching more Hispanics, so that $\Delta p_1^H \geq 0$. Taken together, theory indicates that $\Delta\pi^H < 0$, $\Delta\pi^H < \Delta\pi^W$, and that $\Delta\pi^W$ is theoretically ambiguous since there is a small effect on punishment $\Delta\left(q \mid C\right)^W > 0$ which may be counteracted by a shift in police resources from searching whites to Hispanics, or $\Delta p_1^W < 0$. In plain language, the implementation of Secure Communities yields an equilibrium in which Hispanics are incentivized to commit fewer crimes, both absolutely and relative to whites.

4.2 Methods and method specific theory

<u>Method 1: Hit rates</u>

As explained in section 4.1, part A, when the expected value conditional on finding contraband is equal for both races of motorists, the marginal searched white and Hispanic motorists will have the same probability of carrying contraband, or hit rates of marginal motorists will be equal:

$$\Pr\left(C \mid S, W\right) = \Pr\left(C \mid S, H\right)$$

This marginal rate is unknown to the data analyst, however, since only the average hit rate is deducible from recorded statistics. Furthermore, looking simply at the observed average hit rates fails to account for the infra-marginality problem, which acknowledges the potential difference between average and marginal hit rates. While hit rates should be equal across races on the margin, if there exist strong signals that indicate the presence of contraband more reliably for one race compared to another, so that the probability of carrying contraband is higher for non-marginal individuals of one race, then the average hit rates will not be equal absent racial profiling. As the goal of this analysis is to determine how an exogenous event affects racial profiling, rather than to quantify the level of racial discrimination in a community at a point in time, it has the unique ability to use difference-in-difference to remedy the infra-marginality problem without requiring stronger claims about the convergence of behavior at equilibrium.

Police officers' searches can be ordered by their perceived probability of success, which is known by the police but not by the analyst, in order to establish which searches should be considered "on the margin." Define that the α percentile of searches with the lowest perceived success rate are on the margin, and the $(1-\alpha)$ percentile of searches with the highest probability are not on the margin, with $(1-\alpha) >> \alpha$. The average success rate for the non-marginal searches is θ, and the average success rate for the marginal searches is λ, with $\theta \geq \lambda$. The observed contraband hit rate, X, for race R is a weighted average of θ and λ:

$$X^R = (1-\alpha) \times \theta^R + \alpha \times \lambda^R$$

The difference in marginal probability of carrying contraband conditional on search between Hispanics, H, and whites, W, must be calculated using data that contain only the difference in average hit rates:

$$\begin{aligned} X^H - X^W &= (1-\alpha) \times \theta^H + \alpha \times \lambda^H - \left((1-\alpha) \times \theta^W + \alpha \times \lambda^W\right) \\ &= (1-\alpha) \times \left(\theta^H - \theta^W\right) + \alpha \times \left(\lambda^H - \lambda^W\right) \end{aligned}$$

Next, the difference-in-difference is calculated by subtracting the difference in hit rates for Hispanics vs. whites from before to after implementation of Secure Communities. The percentile at which "the margin" has been defined is held constant, so $\Delta\alpha = 0$. The difference-in-difference of hit rates will be:

$$\Delta\left(X^H - X^W\right) = (1-\alpha) \times \left(\Delta\theta^H - \Delta\theta^W\right) + \alpha \times \left(\Delta\lambda^H - \Delta\lambda^W\right)$$

To determine if Secure Communities affected racial bias by police requires determination of $\Delta\lambda^W - \Delta\lambda^H$). Section 4.1, part B, showed that $\Delta\theta^H < \Delta\theta^W$, and by definition $0 < \alpha < (1-\alpha) < 1$. The above relationship can be rewritten:

$$\Delta\left(X^H - X^W\right) = \alpha \times \left(\Delta\lambda^H - \Delta\lambda^W\right) + \tau$$

where $\tau = (1-\alpha) \times \left(\Delta\theta^H - \Delta\theta^W\right) > 0$. Racial profiling exists against Hispanics only if the marginal searched Hispanic motorist is of lower probability of success than the marginal searched white motorist, or $\Delta\lambda^H < \Delta\lambda^W$. An observation of $\Delta\left(X^H - X^W\right) > 0$ would necessarily occur absent racial profiling against Hispanics, or when $\Delta\lambda^H \geq \Delta\lambda^W$, but could also occur in conjunction with racial profiling if the decrease in the probability of the non-marginal motorists is sufficiently high, or $\alpha \times \left(\Delta\lambda^H - \Delta\lambda^W\right) < \tau = (1-\alpha) \times (\Delta\theta H - \Delta\theta W)$. Therefore, a finding of $\Delta\left(X^H - X^W\right) > 0$ is inconclusive, while a finding of $\Delta\left(X^H - X^W\right) < 0$ indicates the presence of racial bias against Hispanics. Therefore, in order to reject that racial bias exists, it is necessary but not sufficient that $\Delta\left(X^H - X^W\right) > 0$.

Method 2: Search given stop rates

Define {contraband = C, search = S, punishment = P, race = R, white = W, and Hispanic = H}. Here, a model will be built to infer racial bias from police' decision to search a motorist given a stop has already occurred. In determining which motorists to search given a stop, police maximize the value of their actions under time and financial constraints, as outlined in section 4.1, part A. Section 4.1, part A shows that when the expected value conditional on finding contraband is equal for both races of motorists, the marginal searched white and Hispanic motorists have the same probability of carrying contraband, or the hit rate of the marginal motorists is equal:

$$\Pr(C \mid S, W) \,/\, \Pr(C \mid S, H) = 1 \tag{5}$$

By Bayes Rule:

$$\begin{aligned}\Pr(C \mid S, R) &= [\Pr(S, R \mid C) \times \Pr(C)] \,/\, \Pr(S, R) \\ &= [\Pr(R \mid C) \times \Pr(C)] \,/\, [\Pr(R \mid S) \times \Pr(S)]\end{aligned} \tag{6}$$

since $\Pr(S \mid C) = 1$, or search is a prerequisite for finding contraband. Using this relationship to simplify equation 5 yields:

$$\begin{aligned}&\Pr(C \mid S, W)/\Pr(C \mid S, H) = 1 \\ &\quad = [[\Pr(W \mid C) \times \cancel{\Pr(C)}] \,/\, [\Pr(W \mid S) \times \cancel{\Pr(S)}]] \,/ \\ &\quad\quad [[\Pr(H \mid C) \times \cancel{\Pr(C)}] \,/\, [\Pr(H \mid S) \times \cancel{\Pr(S)}]] \\ &\quad = [\Pr(W \mid C) \,/\, \Pr(W \mid S)] \,/\, [\Pr(H \mid C) \,/\, \Pr(H \mid S)]\end{aligned}$$

Applying Bayes rule once again yields:

$$\begin{aligned}&(\Pr(C \mid W) \times \cancel{\Pr(W)}/\cancel{\Pr(C)}) \,/\, (\Pr(S \mid W) \times \cancel{\Pr(W)}/\cancel{\Pr(S)}) = \\ &(\Pr(C \mid H) \times \cancel{\Pr(H)}/\cancel{\Pr(C)}) \,/\, (\Pr(S \mid H) \times \cancel{\Pr(H)}/\cancel{\Pr(S)})\end{aligned}$$

Simplifying yields that equilibrium absent bias requires a constant "hit rate" across races:

$$\Pr(C \mid W) \,/\Pr(S \mid W) = \Pr(C \mid H) \,/\Pr(S \mid H) \tag{7}$$

Equation 7 can be rewritten:

$$\Pr(C \mid W) \,/\Pr(C \mid H) = \Pr(S \mid W) \,/\Pr(S \mid H)$$

After implementation of Secure Communities, absent racial profiling this relationship yields:

$$\Delta[\Pr(C \mid W)/\Pr(C \mid H)] = \Delta[\Pr(S \mid W)/\Pr(S \mid H)]$$

As demonstrated in section 4.1, part A, theory predicts that Secure Communities will cause Hispanics to decrease their propensity to carry contraband more than it will for whites:

$$\Delta[\Pr(C \mid W)/\Pr(C \mid H)] > 1$$

which implies that absent racial bias,

$$\Delta[\Pr(S \mid W)/\Pr(S \mid H)] > 1$$

Equivalently, the rate of search conditional on stop should decrease for Hispanics relative to whites absent racial bias by police, which is empirically testable. Furthermore, $\Delta[\Pr(S \mid W)/\Pr(S \mid H)]$ should increase as time passes after implementation of Secure Communities if police update their beliefs regarding $\Delta[\Pr(C \mid W)/\Pr(C \mid H)]$ with a lag. Finally, search costs do not enter the model because they are independent of Secure Communities and will therefore be negated in the difference-in-difference methodology.

Method 3: Stop rates

Now let {stop = T, being viewed by the police = V, and guilt = G}. Being viewed by the police is a prerequisite for being stopped by the police:

$$\Pr(T \mid R) = \Pr(V \mid R) \times \Pr(T \mid V, R) \tag{8}$$

Unlike a successful motor vehicle search, defined as finding contraband the motorist is carrying, a successful stop catches a guilty motorist more generally. Regardless of the source of guilt, police determine whom to stop based on the expected value of the stop to society. Extending that model gives:

$$\mathrm{E}[T \mid R] = \Pr(G \mid T, R) \times \mathrm{E}[P \mid G, R]$$

As above, assuming $\mathrm{E}[P \mid G, W] = \mathrm{E}[P \mid G, H]$, police maximize the value of their searches by maximizing the probability of a finding of guilt conditional on stop. Therefore, each individual police officer will stop those whom they believe have the highest probability of being guilty first, and then proceed in their stops in descending order of perceived guilt up to some threshold guilt value. All motorists above the threshold value will be stopped, and all below the breakeven value will not be stopped. Since for each individual, an officer can only choose either to stop someone or not, each officer will have a probability of stopping an individual motorist $\Pr(T \mid V, R) = \{0, 1\}$ depending on where the motorist lands relative to the police officer's personal threshold value. However, because the threshold value plausibly differs by police officer, there is a monotonic relationship between $\Pr(G \mid T, R)$ and $\Pr(T \mid V, R)$. As officers' perceived probability of a motorist's guilt increases, the motorist is more likely to be viewed as sufficiently likely to be stopped by a police officer who views him/her. Therefore, Equation 8 can be re-written:

$$\Pr(T \mid R) = \Pr(V \mid R) \times \Pr(G \mid T, R) \times \Phi$$

where Φ is a positive monotonic function. By Bayes rule:

$$\Pr(T \mid R) = [\Pr(R \mid T) \times \Pr(T)]/N_R$$

where N_R is the share of the population that is race R:

$$N_R = \text{(number of persons race R)} \,/\, \text{(total number of persons)}$$

Equivalently,

$$\begin{aligned}\Pr(R \mid T) &= \Pr(T \mid R) \times N_R / \Pr(T) \\ &= \Pr(V \mid R) \times \Pr(G \mid T, R) \times N_R \times \Phi'\end{aligned}$$

where $\Phi' = \Phi \times \Pr(T)$. Assuming that $\Delta\Phi = \Delta\Pr(T) = 0$, the implementation of secure communities yields

$$\Delta\Pr(R \mid T) = \Phi' \times \Delta[\Pr(V \mid R) \times \Pr(G \mid T, R) \times N_R]$$

Decomposing by race yields

$$\Delta\Pr(H \mid T) = \Phi' \times \Delta[\Pr(V \mid H) \times \Pr(G \mid T, H) \times N_H)]$$
$$\Delta\Pr(W \mid T) = \Phi' \times \Delta[\Pr(V \mid W) \times \Pr(G \mid T, W) \times N_W]$$

The difference-in-difference between Hispanics and whites is:

$$\begin{aligned}&\Delta\Pr(H \mid T) - \Delta\Pr(W \mid T) = \\ &\quad \Phi' \times [\Delta(\Pr(V \mid H) \times \Pr(G \mid T, H) \times N_H) - \\ &\quad\quad \Delta(\Pr(V \mid W) \times \Pr(G \mid T, W) \times N_W)]\end{aligned}$$

The probability of guilt decreases for Hispanics relatives to whites after the implementation of Secure Communities because of the deterrence of deportation, or that $\Delta\Pr(G \mid T, H) < \Delta\Pr(G \mid T, W)$. Furthermore, after implementation of Secure Communities, for the same deterrence reason, Hispanics would have more reason incentive than whites to decrease their exposure to police, or $\Delta\Pr(V \mid H) < \Delta\Pr(V \mid W)$.

Finally, it is unlikely the share of the population represented by whites and Hispanics will change dramatically due to outside factors immediately before and after the implementation of Secure Communities. As suggested by Massey (2012), the Great Recession may have decreased immigration or increased migration by illegal immigrants, but year fixed effects included in analysis will likely control for these changes. Quantifying migration flows is beyond the scope of this analysis, but the effect of local implementation of Secure Communities in early adopting counties, if anything, will be to provide illegal immigrants the incentive to leave the area to avoid the risk of deportation, which would result in the number of Hispanics in the area decreasing relative to whites. Assuming there are no other systematic changes occurring in migration flows, conservatively assume that $\Delta N_H = \Delta N_W$. Altogether, theory predicts that absent racial profiling, the implementation of Secure Communities should yield $\Delta \Pr(H \mid T) < \Delta \Pr(W \mid T)$; a finding of $\Delta \Pr(T \mid H) > \Delta \Pr(T \mid W)$ would provide evidence that police are racially profiling against Hispanics.

Method 4: Stop Outcome

The final method will employ a categorical outcome variable that denotes the outcome of a stop to determine whether the ratification of Secure Communities prompted a change in the distribution of stop outcomes for whites vs. Hispanics in a meaningful way. After a motorist has been stopped, police can take no action, issue a written warning, verbal warning or citation, or arrest the stopped motorist. In parallel with the model of taste based discrimination developed by Becker (1957), the utility function of a police officer is a function of the action they take against the stopped motorist, or decision d, and the race of the motorist, which for this purpose is either white or Hispanic, $R = \{W, H\}$. Next, assume police receive utility from doing their job well, $U_j(d)$, and from their treatment of people of their or the opposite race. The decision that maximizes the quality with which a police officer does his/her job is defined as d^*. Therefore, a police officer's full utility function is:

$$U(d|R, d^*) = \alpha \times [U_j(d) - U_j(d^*)] + U(d|H) \times \mathbb{1}(R = H)$$

With $\alpha > 0$ and

$$\mathbb{1}(R = H) = \begin{cases} 1 & \text{if R = H} \\ \\ 0 & \text{if R = W} \end{cases}$$

The outcome space for police officers can be reduced to three decisions for simplicity: arrest ($d = a$), citation ($d = c$), or no action ($d = n$), where n also includes both verbal and written warnings. Therefore a police officer chooses between three actions to maximize his/her utility:

$$U(a|R, d^*) = \alpha \times [U_j(a) - U_j(d^*)] + U(a|H) \times (1 \mid R = H)$$

$$U(c|R, d^*) = \alpha \times [U_j(c) - U_j(d^*)] + U(c|H) \times (1 \mid R = H)$$

$$U(n|R, d^*) = \alpha \times [U_j(n) - U_j(d^*)] + U(n|H) \times (1 \mid R = H)$$

Here, $U(d|H)$ represents the utility achieved by a police officer taking action d against a Hispanic motorist versus a white motorist. The ratification of Secure Communities has no effect on the utility police officers derive from doing their job well, or $\Delta U_j(d) = 0$. Furthermore, since Secure Communities only results in the identification of illegal immigrants when an arrest is made, its ratification would not affect the utility police receive from issuing warnings or citations to members of different races, or $\Delta U(c|R) = \Delta U(n|R) = 0$. Therefore, $\Delta U(c|R, d^*) = \Delta U(n|R, d^*) = 0$. Secure Communities would plausibly change $U(a|H)$, however, and therefore $\Delta U(a|R, d^*) \neq 0$. Assume that racially biased police who prefer to arrest members of other races over their own receive inherent pleasure from the action of arresting someone of another race, and also receive utility from knowledge of the long term ramifications of their arrest. The pleasure derived from the action of arresting an individual is independent of Secure Communities. Therefore, for racially biased police officers, $\Delta U(a|H)$

can be decomposed to reflect the change in perceived longer term outcome of a police officer's arrest, which can result in incarceration, i, deportation, dep, or the arrestee released free of charges, f:

$$\Delta U(a|H) = U_a(i) \times \Delta \Pr(i) + U_a(dep) \times \Delta \Pr(dep) + U_a(f) \times \Delta \Pr(f)$$

As shown in section 4.1, part B, the probability of deportation given arrest increases for Hispanics relative to whites, so that after the ratification of Secure Communities $\Delta \Pr(dep) > 0$. Therefore, assuming that a racist police officer would value deportation more than incarceration or the arrestee being let free, or that $U_a(dep) > max\{U_a(i), U_a(f)\}$, then the ratification of secure communities would result in $\Delta U(a|H) > 0$ and therefore $\Delta U(a|R, d^*) > 0$ for police officers who favor whites to Hispanics. Furthermore, $(U_j(a) - U_j(c))^2 < (U_j(a) - U_j(n))^2$, or for a given motorist, arrest is a closer substitute to citation than no action taken. Since arresting someone who would otherwise be cited incurs a lower cost to police officer's utility derived from doing his/her job well than arresting someone who would otherwise be given a warning, racially biased police are expected to decrease the share of Hispanics they cite relative to offer a warning. Together, racially biased police would be expected to arrest a larger share of Hispanics after the ratification of Secure Communities relative to the amount they cite, while the share of Hispanics against whom no action is taken should remain roughly constant. The absolute number of stops might decrease relative to whites if, as described in Section 4.2, Method 3, Hispanics are staying off of the roads for fear of deportation, but the ratio of changes in police actions will still indicate racial profiling.

4.3 Specification 2: The lagged effect of Secure Communities

Police may engage in productive profiling, or searching people who have a higher probability of being guilty more often, in order to maximize their success rates of searches. Just as

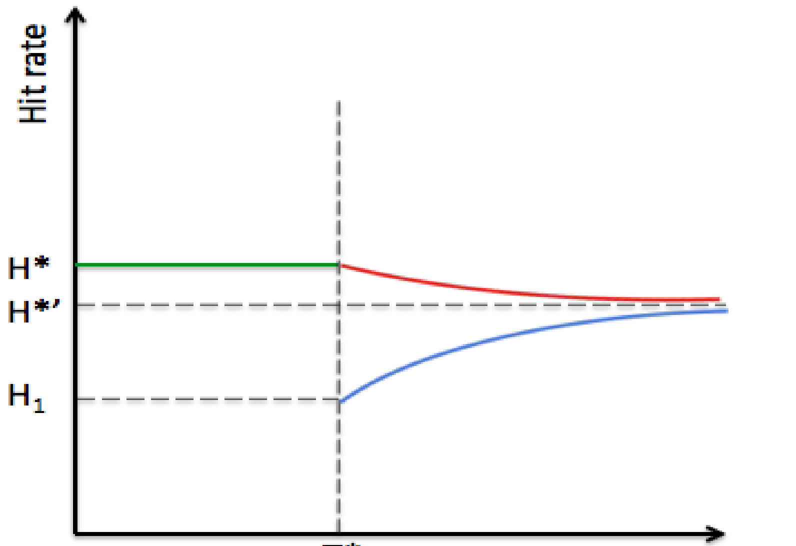

Figure 1: Change in hit rates absent racial profiling with ratification of Secure Communities. Blue = Hispanics' hit rates; red = whites'.

officers might search stopped motorists whose vehicles smell like alcohol or drugs more often than those that do not, they may justifiably search people based on, for example, their gender or race if doing so results in an improvement in their search success rates. Police determine the rate at which they will statistically discriminate through a learning process from working on the job; from realizing that their success rate in searching one race is higher than that of another, the hit rate maximizing officer would adjust his decision accordingly such that on the margin, each search would have an equal expected value. The statistical updating that prompts alteration of police search calculations takes time to be realized, even if only a very short amount of time. Assuming the ratification of Secure Communities results in Hispanics carrying contraband less frequently in order to avoid deportation, as described in section 4.2 part B, police should update their search decisions to reflect the change, but police behavior may not necessarily change immediately. Therefore, police might over-search Hispanics immediately after the ratification of Secure Communities if there is a lag between their perception of behavior changes and the time it takes for people to change behaviors. As a result, the Hispanic hit rate would decrease immediately after the ratification of Secure Communities, but ultimately reach a new equilibrium with whites after police officers have had the opportunity to update their statistical discrimination. This process is illustrated in Figure 1.[9]

To investigate the presence of potential statistical updating, the Secure Communities binary ratification variable was broken into a categorical variable that reflects how long prior to or after Secure Communities' ratification a police stop takes place. These timing variables are described in the data section. While average hit rates might decrease for Hispanics after the ratification of Secure Communities, this might not be an indication of racial bias if the decreased average is caused by an immediate decrease in hit rate that later returns to equilibrium, as illustrated in Figure 1. The timing variables will help identify how racial profiling reacts to the ratification of Secure Communities and how long, if not instantaneously, police take to complete the statistical updating necessary for continued hit rate maximization.

5 Data

The data used come from Stop, Search, and Contraband datasets collected by the North Carolina State Bureau of Investigation, and include all motor vehicle stops in the state of North Carolina between January 1, 2004 and December 31, 2012. I restricted the data to observations with either a coded race of $White$ or ethnicity of $Hispanic$. People who are listed as both white and Hispanic are considered $Hispanic$ in the analysis, so the only people

[9] The equilibrium hit rate is drawn lower after the ratification of Secure Communities than it was before because there will be fewer Hispanics carrying contraband, and therefore an equal number of total searches will yield fewer successes. In reality, general equilibrium suggests that with fewer Hispanics willing to carry contraband, the value of carrying contraband will increase and therefore others will take the place of the vacated Hispanics. Therefore, the change in equilibrium hit rate is theoretically ambiguous.

considered $White$ are those who are both white and non-Hispanic. All people who are neither white nor Hispanic are excluded from analysis.

The SC, or Secure Communities, variable indicates the timing of the stop relative to the local implementation of Secure Communities. In specification 1, the Secure Communities variable, SC, indicates whether a stop takes place in a jurisdiction that has previously ratified Secure Communities at the time of the stop:

$$SC = \begin{cases} 1 & \text{if stop occurs in county that has previously ratified Secure Communities} \\ 0 & \text{otherwise} \end{cases}$$

In specification 2, Secure Communities will be categorical rather than binary and will reflect the time that has passed since Secure Communities was ratified in the jurisdiction where the stop was made. For these specifications, $SecureCommunities = n > 1$ implies that the stop took place between $(6 \times (n-1))$ and $(6 \times n)$ months after the implementation of Secure Communities, and a value of $n = 0$ indicates the stop took place before Secure Communities. The final Secure Communities timing variable uses data confined to stops within a period of three months prior to Secure Communities and 6 months after its ratification, and indicates the month in which the stop occurred. Relatedly, the variable $287g$ will mark whether the jurisdiction in which a stop takes place has previously adopted 287g, a provision that, as described in the background information section, allows local police involvement in immigration enforcement.

The level of discretion that the police have in making a search is reflected in the data by the type for the search, with higher discretion searches denoted by the binary variable $HighDiscSearch$. Following Pickerill, Mosher, and Pratt (2009), searches are marked as high discretion if their search type is consent or protective frisk, and low discretion if the type is due to a search warrant, probable cause, or a search incident to arrest. The level of discretion for a stop is not reliably able to be inferred from its stated purpose.

The time of a stop is marked at night if it is between the hours of 20:00 and 5:00. Additionally, 99 binary variables will be created to add fixed effects for the 100 counties in which stops take place, and year fixed effects variables are also included. The data also contains information on the age and gender of the motorist. The data is confined to stops made by local police within a named county, because the ratification date of Secure Communities is unclear for highway stops not made within county lines. The purpose of a stop is also recorded and will be controlled for:

$$StopPurpose = \begin{cases} 1 & \text{If stop due to speed limit violation} \\ 2 & \text{If stop due to stop light/sign violation} \\ 3 & \text{If stop due to expected DWI} \\ 4 & \text{If stop due to sage movement violation} \\ 5 & \text{If stop due to vehicle equipment violation} \\ 6 & \text{If stop due to vehicle regulatory violation} \\ 7 & \text{If stop due to seat belt violation} \\ 8 & \text{If stop part of an investigation} \\ 9 & \text{If stop due to "other" motor vehicle violation} \\ 10 & \text{If stop occurs at checkpoint} \end{cases}$$

All other variables are will be used without manipulation. There are 3,837,247 motor vehicle stops and 268,372 motorist searches in the final dataset.

6 Empirical Methodology

As outlined in the theory section, four methods will be used to jointly determine whether the implementation of Secure Communities increased racial bias by police. Each method will use an extended difference-in-difference approach to isolate the effect of Secure Communities on the policing of whites vs. Hispanics. The methods will be distinguished by the unique outcome variable that each employs, and they will largely share covariates and controls in the difference-in-differences; each model will include available covariates to prevent confoundedness to the extent possible. There will likely still exist signals observable to the police but not the data analyst, like the smell of the car or the shiftiness of its driver's eyes, but assuming these signals are not correlated with both the outcome variable and the race/ethnicity of the driver, these omitted variables will not bias the results. Covariates used include the age, gender, and ethnicity of the driver; the county, time of day, and year of the stop; whether the stop was made in a jurisdiction that previously ratified 287g; whether the stop was before or after the implementation of Secure Communities (and in Specification 2 how long before or after the ratification of Secure Communities it was made); and the level of discretion associated with the search. The potential existence of omitted signals that correlate with both the outcome variable and race is a natural limitation of this analysis.

Method 1: Hit rates

The first model will measure hit rates, which is the proportion of motor vehicle searches that yield contraband findings. To do so, it will employ a binary dependent variable of search outcome that indicates whether the search successfully uncovered contraband that the motorist was transporting:

$$Contraband = \begin{cases} 1 & \text{if contraband is found in a motor vehicle search} \\ 0 & \text{if no contraband is found} \end{cases}$$

Since the outcome variable is whether or not police find contraband in a search, the data used to fit this model will be confined to the subset of stopped motorists who are searched.

The model will be fitted using a difference-in-difference-in-difference-in-difference (DDDD) methodology to attempt to isolate the effect of Secure Communities on the hit rates of whites vs. Hispanics. The first difference is whether the search occurs before vs. after the implementation of Secure Communities. By differencing before and after Secure Communities, pre-existing, baseline variation in the propensity of whites vs. Hispanics to carry contraband can be controlled for to isolate the effect of the implementation. The next difference will be Hispanics vs. whites. This difference prevents the influence of exogenous changes that affect the entire population over time (e.g., police budget cuts), and allows determination of how police behavior changed toward Hispanics relative to whites.

The third difference is whether the search occurred in jurisdictions that had previously ratified 287g vs. those that had not, henceforth referred to treatment jurisdictions. Prior to the implementation of Secure Communities, 287g jurisdictions already provided local police the ability to aid in immigration enforcement and initiate the deportation process for illegal immigrants, so the ratification of Secure Communities in those jurisdictions did not change police incentives as much as in treatment jurisdictions. Therefore, treatment jurisdictions in which police incentives changed more dramatically are expected to experience greater effects of racial bias stemming from Secure Communities. The adoption of 287g requires an agreement between ICE and a local police jurisdiction, and is therefore self-selected by police jurisdictions, making it prone to confounding. However, it is likely that the jurisdictions who enacted 287g were more predisposed to racial profiling against Hispanics, and therefore using them as a control group would, if anything, understate the effect that Secure Communities would have had on increasing racial bias in police absent the existence of 287g.

The final difference used will be the discretion level of a search, as employed in Pickerill, Mosher, & Pratt (2009):

$$HighDiscSearch = \begin{cases} 1 & \text{if Search Type is consensual or initiated by protective} \\ & \text{frisk by a police officer} \\ 0 & \text{if Search Type is due to a search warrant, probable} \\ & \text{cause, or a search incident to arrest} \end{cases}$$

Police will be more able to exhibit racial bias in searches associated with higher discretion levels, so the effect of Secure Communities on racial bias should be more apparent for high relative to low discretion searches. The results of high and low discretion searches will be differenced to determine if this holds empirically.

Racial bias will be determined by the subset of variables that contain the interaction $Hispanic{:}SC$, which is the effect of Secure Communities on search success rates of Hispanics relative to whites, controlling for the presence of 287g, search discretion, and available covariates.

Method 2: Search rates

The second model will measure the rate at which motorists of different ethnicities are searched conditional on their being stopped. To do so, it will use a binary outcome variable of whether someone is searched:

$$Search = \begin{cases} 1 & \text{if a stopped motorist is searched} \\ 0 & \text{if a stopped motorist is not searched} \end{cases}$$

Since the outcome variable is whether or not police search a vehicle conditional on stop, the data used to fit this model will be include all stopped motorists. The DDD methodology used in Method 2 is similar to that described in Method 1, but search discretion cannot be used since the outcome variable predicts search, and only searched motorists have a value of search discretion. Stop purpose will be controlled for but different purposes are not reliably correlated with police discretion.

Again, racial bias will be determined by the subset of variables that contain the interaction $Hispanic{:}SC$, which is the effect of Secure Communities on police propensity to search Hispanics relative to whites, controlling for the presence of 287g and available covariates.

Method 3: Stop rates

The third model will measure the rate at which motorists of different ethnicities are stopped. To do so, it will employ the binary outcome variable Hispanic

$$Hispanic = \begin{cases} 1 & \text{if a stopped motorist is Hispanic} \\ 0 & \text{if a stopped motorist is white and not Hispanic} \end{cases}$$

Since data is not present on motorists who are not stopped, or equivalently every motorist in the dataset has been stopped, an outcome variable for the stop itself cannot be created. Therefore, Hispanic enters the model as an outcome variable instead of an independent variable as in methods 1 and 2. This model will again employ a DDDD methodology to determine the rate at which Hispanics are stopped vs. whites controlling for, similar to Models 1 and 2, the implementation of Secure Communities and the presence of 287g. The final difference used in this model is the ease with which police can determine the race of the driver, or whether the stop takes place at night. As suggested by Grogger & Ridgeway

(2006), police will more easily be able to identify motorists' races during daylight hours than when the sun is down, or the motorist is "behind a veil of darkness." Therefore, racial bias should be more prevalent during the day than at night; this added control will make up the final difference used in the DDDD model.

Here, racial bias will be determined by the subset of variables that contain SC, which is the effect of Secure Communities on police propensity to stop Hispanics relative to whites, controlling for the presence of 287g, whether the stop occurred at night or during the day, and available covariates.

Method 4: Stop outcome

The fourth model will measure the change in probability of different stop outcomes for whites vs. Hispanics after the ratification of Secure Communities. It will employ a categorical outcome variables:

$$\textit{Stop Action} = \begin{cases} 1 & \text{if stopped motorist is given a verbal warning} \\ 2 & \text{if stopped motorist is given a written warning} \\ 3 & \text{if stopped motorist is given a citation} \\ 4 & \text{if stopped motorist is arrested} \\ 5 & \text{if no action is taken against stopped motorist} \end{cases}$$

This model will again employ a DDD methodology to determine the rate at which Hispanics experience different motor vehicle stop outcomes vs. whites controlling for, similar to Models 1 - 3, the implementation of Secure Communities and the presence of 287g. Here, racial bias will be inferred from the effect of the subset of variables that contain interactions of $Hispanic{:}SC$ on the propensity of police to perform different stop actions, which is the effect of Secure Communities on police propensity to stop Hispanics relative to whites, controlling for the presence of 287g, whether the stop occurred at night or during the day, and available covariates.

Specification 2: The lagged effect of Secure Communities

All empirical models will be fit for specification 1, which treats Secure Communities as a binary variable, and models 1-3 will also be fit for Specification 2, which employs information about the timing of the stop relative to the ratification of Secure Communities.

7 Results

The regressions modeled above as specification 1, methods 1-3, were run using the full dataset, the results of which are in Table 1. Analysis was done in R using the *bigglm* function from the *biglm* package. Due to memory constraints, a subset of 100,000 randomly sampled observations from the full dataset was used to fit the models corresponding to method 4 and methods 1-3, specification 2. These statistical analyses were also done in R. For all regressions, year and county fixed effects were included but are not reported. Gender, age, and stop purpose are also controlled for but not reported.

Method 1, which quantifies the effect of the ratification of Secure Communities on police search hit rates of white vs. Hispanic motorists, indicates no effect of Secure Communities on racial bias (Table 1, Column 3). The variable of interest, $Hispanic{:}SC$, is not significant at conventional levels. Classification as a high discretion search, which should be less successful than searches that are low discretion and prompted by events more indicative of the presence of contraband, is correctly associated with significantly lower hit rates than low discretion searches. Furthermore, Hispanics are searched with higher probability in high discretion searches vs. low discretion searches after the ratification of Secure Communities, further rejecting increased racial bias due to Secure Communities. Similarly, 287g was found to be associated with higher hit rates for Hispanics vs. whites, indicating that it also did not prompt increased racial bias by police. There was no significant difference in the effect of Secure Communities in areas that had and had not previously adopted 287g.

Method 2, which quantifies the effect of ratification of Secure Communities on the rate at which Hispanics vs. whites are searched conditional on being stopped, also provides no evidence that Secure Communities affected racial bias by police (Table 1, Column 2). The variable of interest, $Hispanic{:}SC$, is significantly negative, indicating that fewer fewer Hispanics were searched conditional on being stopped after the ratification of Secure Communities. Therefore, while Hispanics may be searched significantly more in general, this disparity is not exacerbated by Secure Communities. The decrease in search rate that occurs after ratification of Secure Communities is partially reversed for stops made in areas that had previously adopted 287g, but the net effect of Secure Communities still does not suggest an increase in racial bias.

Method 3, which quantifies the effect of the ratification of Secure Communities on police stop rates of white vs. Hispanic motorists, also does not strongly indicate that Secure Communities increased racial bias by police (Table 1, Column 1). After the ratification of Secure Communities, police were significantly more likely to stop Hispanic motorists, as demonstrated by the variable of interest SC. Furthermore, they were significantly less likely to stop Hispanic motorists at night and in areas where 287g had previously been adopted. Both of these results are indicative of racial bias: racially biased police would exhibit less bias both at night when motorist race is harder to perceive before a stop, and in jurisdictions that had previously adopted 287g because the ease with which they could identify illegal immigrants after an arrest increased less than in jurisdictions that had not previously enacted 287g. While these observations provide suggestive evidence of racial bias by police, when considered holistically, the numbers become less compelling. The magnitude of increase in stops due to Secure Communities is considerably less than that of the decrease in areas in which 287g had been ratified, so taken together Secure Communities appears to have had a minimal effect on the composition of stops in North Carolina. Given the lack of information on population changes for whites vs. Hispanics, and in context with the results from methods 1 and 2, there is not compelling evidence of racial bias.

Method 4, which assess the propensity of police to take different actions against stopped motorists, also suggests no evidence of racial bias by police, the results of which are presented in Table 2. There is no significant effect of Secure Communities on the rate at which Hispanics vs. whites are arrested relative to given warnings or cited. Hispanics are arrested relatively more after the ratification of Secure Communities in places that had previously adopted 287g, but less at night, the aggregation of which yield no evidence that Secure Communities caused an increase in racial bias by police.

The regressions fit to model Methods 1-3 were re-run with Secure Communities timing indicator variables to assess the existence of a lagged effect of Secure Communities, the results of which are included in tables 3-4. The month indicators do not help to tell a story that indicates racial bias or updating of statistical discrimination as outlined in section 4.3. There are no consistent trends of the measured effect of the ratification of Secure Communities on racial bias of police against Hispanics vs. whites. This result provides compelling evidence against the theory that Secure Communities led to increased racial bias by police. The results also suggest that either there was no change in the behavior of whites vs. Hispanics after the implementation of Secure Communities, or that police behavior adjusted instantaneously in response to any changes in the behavior of Hispanics vs. whites.

Table 1: Regression Results, Specification 1, Methods 1-3

	Dependent variable:		
	Hispanic (Method 3)	Search (Method 2)	Contraband (Method 1)
SC	0.060***	−0.137***	0.186***
	(0.007)	(0.011)	(0.025)
Night	−0.497***	0.319***	0.060**
	(0.009)	(0.013)	(0.027)
287g	0.0371***	0.010	0.191***
	(0.006)	(0.010)	(0.020)
SC:287g	−0.178***	−0.141***	−0.176***
	(0.008)	(0.013)	(0.026)
Night:SC	−0.023***	−0.064***	0.014
	(0.007)	(0.011)	(0.022)
Hispanic		0.091***	−0.834***
		(0.026)	(0.060)
Hispanic:SC		−0.353***	−0.048
		(0.021)	(0.059)
Hispanic:287g		−0.014	0.121***
		(0.358)	(0.033)
Hispanic:Night		−0.364***	0.343***
		(0.012)	(0.027)
Hispanic:SC:287g		0.152***	−0.108*
		(0.027)	(0.059)
Hispanic:Night:SC		−0.013	0.184***
		(0.025)	(0.057)
HighDiscSearch			−0.502***
			(0.011)
SC:HighDiscSearch			−0.142***
			(0.022)
Hispanic:HighDiscSearch			−0.119***
			(0.027)
Hispanic:SC:HighDiscSearch			0.159***
			(0.056)
Observations	3,837,247	3,837,247	268,372
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 2: Regression Results, Specification 1, Method 4. Baseline is Verbal Warning ($N_{\text{Verbal Warning}} = 24,124; N_{\text{All}} = 100,000$)

	Dependent variable:			
	Written Warn	Citation	Arrest	No Action
SC	0.071	-0.132^{***}	0.035	0.886^{***}
	(0.055)	(0.042)	(0.124)	(0.136)
Hispanic	0.063	0.366^{***}	1.119^{***}	0.700^{***}
	(0.109)	(0.073)	(0.144)	(0.168)
287g	-0.066	0.035	-0.136^{*}	-0.218^{**}
	(0.055)	(0.037)	(0.082)	(0.090)
Night	-0.263^{***}	-0.436^{***}	0.008	-0.114
	(0.068)	(0.050)	(0.117)	(0.121)
Hispanic:SC	-0.011	0.075	-0.249	0.294
	(0.194)	(0.132)	(0.270)	(0.237)
SC:287g	-0.309^{***}	-0.345^{***}	-0.323^{***}	0.084
	(0.067)	(0.047)	(0.114)	(0.110)
Night:SC	-0.038	-0.039	-0.066	-0.173^{*}
	(0.056)	(0.040)	(0.102)	(0.094)
Hispanic:Night	0.199^{**}	0.277^{***}	0.240^{**}	0.041
	(0.099)	(0.065)	(0.118)	(0.153)
Hispanic:287g	-0.085	0.005	-0.098	0.113
	(0.132)	(0.079)	(0.141)	(0.172)
Hispanic:SC:287g	-0.262	-0.051	0.543^{**}	-0.109
	(0.200)	(0.116)	(0.240)	(0.239)
Hispanic:Night:SC	-0.163	-0.263^{**}	-0.660^{***}	0.039
	(0.178)	(0.107)	(0.224)	(0.223)
Observations	12,384	57,187	3,462	2,843

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3: Regression Results, Specification 2a, Methods 1-3 (baseline is prior to ratification of Secure Communities)

	Dependent variable:		
	Hispanic (Method 3)	Search (Method 2)	Contraband (Method 1)
SC(0-6mo)	−0.050	−0.112	0.260***
	(0.092)	(0.183)	(0.072)
SC(6-12mo)	−0.001	−0.074	0.393***
	(0.092)	(0.199)	(0.073)
SC(>12mo)	0.034	−0.160	0.227***
	(0.059)	(0.128)	(0.047)
SC(0-6mo):287g	−0.116	0.137	−0.198***
	(0.083)	(0.142)	(0.073)
SC(6-12mo):287g	−0.152*	−0.059	−0.253***
	(0.082)	(0.145)	(0.078)
SC(>12mo):287g	−0.207***	−0.058	−0.113**
	(0.056)	(0.099)	(0.051)
Night:SC(0-6mo)	−0.021	−0.169	0.013
	(0.084)	(0.136)	(0.070)
Night:SC(6-12mo)	0.064	0.012	−0.052
	(0.083)	(0.140)	(0.071)
Night:SC(>12mo)	0.057	−0.093	−0.0004
	(0.051)	(0.090)	(0.045)
Hispanic:SC(0-6mo)		−0.387	0.216
		(0.427)	(0.182)
Hispanic:SC(6-12mo)		0.152	0.121
		(0.406)	(0.189)
Hispanic:SC(>12mo)		−0.162	−0.105
		(0.277)	(0.126)
Hispanic:SC(0-6mo):287g		0.425	−0.017
		(0.320)	(0.173)
Hispanic:SC(6-12mo):287g		0.503*	−0.053
		(0.301)	(0.185)
Hispanic:SC(>12mo):287g		0.228	−0.179
		(0.210)	(0.123)
Hispanic:Night:SC(0-6mo)		−0.110	−0.068
		(0.316)	(0.171)
Hispanic:Night:SC(6-12mo)		−0.128	0.097
		(0.302)	(0.185)
Hispanic:Night:SC(>12mo)		−0.184	0.252**
		(0.204)	(0.121)
Hispanic:SC(0-6mo):HighDiscSearch			0.143
			(0.170)
Hispanic:SC(6-12mo):HighDiscSearch			0.039
			(0.181)
Hispanic:SC(>12mo):HighDiscSearch			0.139
			(0.119)
Observations	100,000	100,000	100,000
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4: Regression Results, Specification 2b, Methods 1-3 (baseline is 2-3 months prior to ratification of Secure Communities)

	Dependent variable:		
	Hispanic (Method 3)	Search (Method 2)	Contraband (Method 1)
SC(1-2mo prior)	−0.159	0.122	0.091
	(0.099)	(0.219)	(0.158)
SC(0-1mo prior)	0.033	0.414**	−0.011
	(0.097)	(0.204)	(0.154)
SC(0-1mo after)	0.027	0.283	0.068
	(0.098)	(0.206)	(0.151)
SC(1-2mo after)	−0.037	0.294	0.114
	(0.097)	(0.202)	(0.151)
SC(2-3mo after)	−0.086	0.110	0.222
	(0.097)	(0.208)	(0.148)
SC(3-4mo after)	−0.066	−0.003	−0.278*
	(0.096)	(0.212)	(0.154)
SC(4-5mo after)	−0.075	0.228	−0.638***
	(0.096)	(0.206)	(0.153)
SC(5-6mo after)	0.053	0.205	0.111
	(0.094)	(0.208)	(0.152)
Hispanic:SC(1-2mo prior)		−1.283**	−0.309
		(0.499)	(0.391)
Hispanic:SC(0-1mo prior)		−0.578	−0.393
		(0.400)	(0.414)
Hispanic:SC(0-1mo after)		−0.969**	−0.402
		(0.452)	(0.395)
Hispanic:SC(1-2mo after)		−0.937**	0.021
		(0.445)	(0.368)
Hispanic:SC(2-3mo after)		−0.610	−0.623
		(0.432)	(0.387)
Hispanic:SC(3-4mo after)		−0.302	−0.102
		(0.423)	(0.389)
Hispanic:SC(4-5mo after)		−1.314***	−0.348
		(0.469)	(0.417)
Hispanic:SC(5-6mo after)		−0.642	−0.614
		(0.424)	(0.403)
Observations	100,000	100,000	21,731
Note:			*p<0.1; **p<0.05; ***p<0.01

8 Potential Limitation: the value of a successful search

A potential limitation in this analysis is the possibility that the change from before to after Secure Communities in the expected value of a search conditional on finding contraband is not the same for whites and Hispanics. Extending the notation defined in the section 4, define {Punishment $= P$, illegal immigrant $= I$, deportation $= D$, race $= R$, white $= W$, and Hispanic $= H$, contraband $= C$, search $= S$, outcome of judicial system (e.g., jail, probation, case dismissed) $= J$}. The expected value of finding contraband on the marginal motorist is the weighted average of the values of their punishment conditional on deportation and on the case entering the judicial system, weighted by the probability of deportation. The expected value of punishment conditional on finding contraband is modeled as follows:

$$\begin{aligned}
\mathrm{E}[P \mid C, R] = & \Pr(I \mid R) \times \Pr(D \mid I) \times \mathrm{E}[D \mid R] + \\
& \Pr(I \mid R) \times (1 - \Pr(D \mid I)) \times \mathrm{E}[J \mid R] + \\
& (1 - \Pr(I \mid R)) \times \mathrm{E}[J \mid R] \\
= & \Pr(I \mid R) \times \Pr(D \mid I) \times \mathrm{E}[D \mid R] + \cancel{\Pr(I \mid R) \times \mathrm{E}[J \mid R]} - \\
& \Pr(I \mid R) \times \Pr(D \mid I) \times \mathrm{E}[J \mid R] + \mathrm{E}[J \mid R] - \\
& \cancel{\Pr(I \mid R) \times \mathrm{E}[J \mid R]} \\
= & \Pr(I \mid R) \times \Pr(D \mid I) \times (\mathrm{E}[D \mid R] - \mathrm{E}[J \mid R]) + \mathrm{E}[J \mid R]
\end{aligned}$$

With the change in secure communities, the change in expected value of punishment conditional on finding contraband is:

$$\begin{aligned}
\Delta\mathrm{E}[P \mid C, R] = & \Delta\left(\Pr(I \mid R) \times \Pr(D \mid I) \times (\mathrm{E}[D \mid R] - \mathrm{E}[J \mid R])\right) + \\
& \Delta\mathrm{E}[J \mid R]
\end{aligned}$$

First, assume that there Secure Communities prompts no change in the expected value of jail time or deportation, that $\Delta \mathrm{E}[J \mid R] = \Delta \mathrm{E}[D \mid R] = 0$. Decomposing by race yields:

$$\Delta \mathrm{E}[P \mid C, H] = (\mathrm{E}[D \mid H] - \mathrm{E}[J \mid H]) \times \Delta \left(\Pr\left(I \mid H\right) \times \Pr\left(D \mid I\right)\right)$$
$$\Delta \mathrm{E}[P \mid C, W] = (\mathrm{E}[D \mid W] - \mathrm{E}[J \mid W]) \times \Delta \left(\Pr\left(I \mid W\right) \times \Pr\left(D \mid I\right)\right)$$

Absent racial profiling, assuming that whites and Hispanics carry, on average, the same quantity of contraband, $\mathrm{E}[J \mid H] = \mathrm{E}[J \mid W] = \mathrm{E}[J \mid R]$ and $\mathrm{E}[D \mid H] = \mathrm{E}[D \mid W] = \mathrm{E}[D \mid R]$, but it is not necessarily true that $\mathrm{E}[D \mid R] = \mathrm{E}[J \mid R]$. Secure Communities results in improved identification of illegal immigrants, or an increase in the probability of deportation conditional on an illegal immigrant being found with contraband, which implies $\Delta \Pr\left(D \mid I\right) > 0$. Also, there is a larger share of the Hispanic population who are illegal immigrants than the white population, which implies that $\Pr\left(I \mid H\right) > \Pr\left(I \mid W\right)$. The difference in the change in expected value for Hispanics versus whites is equal to:

$$\begin{aligned}
\Delta \mathrm{E}[P \mid C, H] - \Delta \mathrm{E}[P \mid C, W] = \\
& (\mathrm{E}[D \mid H] - \mathrm{E}[J \mid H]) \times \Delta \left(\Pr\left(I \mid H\right) \times \Pr\left(D \mid I\right)\right) - \\
& (\mathrm{E}[D \mid W] - \mathrm{E}[J \mid W]) \times \Delta \left(\Pr\left(I \mid W\right) \times \Pr\left(D \mid I\right)\right) \\
&= (\mathrm{E}[D \mid R] - \mathrm{E}[J \mid R]) \times \Delta \Pr\left(D \mid I\right) \times \left(\Pr\left(I \mid H\right) - \Pr\left(I \mid W\right)\right) \\
&= (\mathrm{E}[D \mid R] - \mathrm{E}[J \mid R]) \times \phi
\end{aligned}$$

where $\phi > 0$ is a positive constant such that

$$\phi = \Delta \Pr\left(D \mid I\right) \times \left(\Pr\left(I \mid H\right) - \Pr\left(I \mid W\right)\right)$$

Therefore, if $\mathrm{E}[D \mid R] > \mathrm{E}[J \mid R]$, then $\Delta \mathrm{E}[P \mid C, H] - \Delta \mathrm{E}[P \mid C, W] > 0$, so the value of arresting Hispanics increases relative to whites at a given probability. The reality of whether or not deportation is better for society than putting someone through the judicial system is unknown, and police perception that deportation is more valuable could be an accurate and welfare enhancing belief or a source of racial bias, depending on its merit. According to Cox & Miles (2014), deporting illegal immigrants does not reduce crime and detaining illegal immigrants pending deportation can be costly. Conversely, while many individuals who are deported would not face jail time, since deportation is paid for by the federal government, it may be a cheaper alternative to incarceration for local police jurisdictions. A full evaluation on the comparative value of deportation vs. incarceration is beyond the scope of this analysis and a potential limitation of the study that requires further research.

Second, it is possible that the quantity of contraband that whites vs. Hispanics carry conditional on carrying contraband is not independent of Secure Communities, which would imply $\Delta \mathrm{E}[P \mid C, W] \neq \Delta \mathrm{E}[P \mid C, H]$. This might be true if, for example, illegal immigrants believe they will be deported instead of incarcerated if they are found with contraband. Since unlike jail sentences, which vary by severity, all deportation is equally bad for the person being deported, illegal immigrants might believe their punishment is the same regardless of the magnitude of their crime. As a result, they might decide that in order to justify their carrying of contraband, they need a higher expected payoff, which can be achieved by carrying more contraband. The end result would be that illegal immigrants carry more contraband when they carry contraband, so that the expected value of their being caught with contraband is higher than that of U.S. citizens. Since a larger share of the Hispanic population are illegal immigrants than the white population, this would imply that Secure Communities yields $\Delta \mathrm{E}[P \mid C, W] < \Delta \mathrm{E}[P \mid C, H]$ which, borrowing from the theory developed in section 4.2, would justify that on the margin $\Pr(C \mid S, W) > \Pr(C \mid S, H)$. This simple example is illustrative and likely misses the full effect of secure communities on $\Delta \mathrm{E}[P \mid C, W]$ and $\Delta \mathrm{E}[P \mid C, H]$. Regardless, violation of the assumption that $\Delta \mathrm{E}[P \mid C, W] = \Delta \mathrm{E}[P \mid C, H]$ is a potential limitation that requires further research.

9 Conclusions

Four methodologies were developed using different outcome variables to identify if the ratification of Secure Communities, a federal program that allows police officers to more easily identify illegal immigrants, affected racial bias by police against Hispanics vs. whites. Given the assumptions behind the models, analysis of motor vehicle stop and search data from the North Carolina State Bureau of Investigation from 2004 to 2012 indicates no strong evidence of an increase in racial profiling by police officers due to Secure Communities. The lack of evidence to support the claim that Secure Communities has prompted racial profiling by police against Hispanics is at odds with the numerous anecdotes of seemingly clear examples of racial profiling and the descriptive statistics that some have used to infer widespread racial bias by police; if racial bias does exist among police officers, it must have existed before the ratification of Secure Communities and was not exacerbated by its implementation. Furthermore, the prospect of policy founded on conclusions from anecdotes and other circumstantial evidence threatens societal well-being. One illustrative example can be found in a closer examination of the scandal that surrounded the adoption and existence of 287g in Alamance County, NC.

In 2012, 5 years after Alamance County adopted 287g in 2007, the Alamance County Sheriff's Office was taken to court and found guilty on the grounds that the program promoted racial profiling by police, which precipitated the repeal of 287g in Alamance County.[10] The case largely rested on the analysis of "experts," who used statistics to demonstrate the existence of racial bias by police that was due to the 287g program.[11,12] Contrary to their findings, running the models developed above with the dataset confined to observations from exclusively Alamance County from January 1, 2004, to December 31, 2012, yields no com-

[10]Perez, *Re: United States' Investigation of the Alamance County Sherriff 's Office.*
[11]MacDonald, *Expert Report on the Alamance County Sheriff 's Office.*
[12]Lamberth, *Expert Report on the Alamance County Sheriff 's Office.*

pelling statistical evidence of a change in racial profiling, as evidenced by tables 5-6. In Table 5, results from method 3 indicate that the ratification of 287g actually decreased the propensity of police to stop Hispanic vs. white motorists. This could be consistent with racial bias and due to a departure of Hispanics from Alamance county after its adoption; method 2, however, rejects this possibility. Results from method 2 indicate that there is no change in the rate at which stopped motorists are searched for Hispanics vs. whites coinciding with the adoption and repeal of 287g. Furthermore, hit rates did not significantly change with the adoption of 287g, as evidenced by the results from method 1. Finally, results from method 4 suggest that the adoption of 287g is associated with an increase in the rate at which Hispanics are arrested relative to given verbal warnings, which provides suggestive evidence of racial bias by police. In context with the unaffected hit rates, however, it seems that the increase in arrests has not been detrimental to police ability to do their jobs as well as possible, and therefore not indicative of negative racial bias.

Taken together, there is little evidence that the adoption of 287g had any incremental effect on racial bias by police against Hispanics in Alamance County. These results should alert people to the risks of taking circumstantial statistics at face value. It is possible that police in Alamance County may disadvantage Hispanics relative to whites, but the level of bias appears unaffected by 287g; since the statistics used by the experts did not control for the ratification of 287g, their analysis could have confused racial bias that has always existed in the Alamance police force with an effect of the 287g program. For example, results from method 2 reveal that Hispanics in Alamance County are significantly more likely to be searched conditional on stop relative to whites, and results from method 4 indicate that police are significantly more likely to arrest or give a citation to a stopped Hispanic motorist than a white motorist. If this illustrative example is true, citizens may be appeased by the repeal of 287g, but it would not actually solve the problem of racial bias in Alamance County. A better policy would allow 287g to continue but attempt to decrease racial bias

Table 5: Regression Results for Alamance, Methods 1-3, Spec. 1

	Dependent variable:		
	Hispanic (Method 3)	Search (Method 2)	Contraband (Method 1)
SC	-0.267^{***}	0.082	0.088
	(0.053)	(0.108)	(0.178)
287g	-0.171^{***}	-0.164^{**}	0.648^{***}
	(0.034)	(0.071)	(0.173)
Night	-0.434^{***}	0.410^{***}	0.318
	(0.060)	(0.101)	(0.220)
Night:SC	-0.147^{***}	0.429^{***}	0.154
	(0.055)	(0.099)	(0.194)
Night:287g	-0.094^{*}	-0.211^{**}	-0.364^{*}
	(0.051)	(0.094)	(0.189)
Hispanic		1.026^{***}	-0.201
		(0.160)	(0.337)
Hispanic:SC		0.032	0.674^{**}
		(0.203)	(0.343)
Hispanic:g		0.014	-0.414
		(0.115)	(0.302)
Hispanic:Night		-0.334^{***}	-0.314
		(0.098)	(0.211)
Hispanic:Night:SC		-0.036	-0.534
		(0.177)	(0.399)
Hispanic:Night:287g		-0.116	0.223
		(0.158)	(0.361)
HighDiscSearch			-0.545^{***}
			(0.118)
SC:HighDiscSearch			-0.462^{**}
			(0.187)
287g:HighDiscSearch			-0.285
			(0.185)
Hispanic:HighDiscSearch			-0.137
			(0.213)
Hispanic:SC:HighDiscSearch			0.434
			(0.437)
Hispanic:287g:HighDiscSearch			-0.310
			(0.406)
Observations	61,066	61,066	6,021

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: Regression Results in Alamance, Specification 1, Method 4. Baseline is Verbal Warning ($N_{\text{Verbal Warning}} = 22,207; N_{\text{All}} = 61,066$)

	Dependent variable:			
	Written Warn	Citation	Arrest	No Action
287g	-0.313^{***}	-0.325^{***}	-0.506^{***}	-0.217^{**}
	(0.068)	(0.035)	(0.106)	(0.093)
SC	-0.122^{**}	0.037^{*}	0.034	-0.076
	(0.049)	(0.023)	(0.080)	(0.104)
Hispanic	0.010	0.447^{***}	1.511^{***}	0.675^{***}
	(0.147)	(0.070)	(0.140)	(0.196)
Night	-0.326^{***}	-0.606^{***}	0.123	-0.342^{**}
	(0.122)	(0.063)	(0.143)	(0.151)
SC:287g	-0.122^{**}	0.037^{*}	0.034	-0.076
	(0.049)	(0.023)	(0.080)	(0.104)
Hispanic:287g	-0.039	0.103	0.534^{***}	0.074
	(0.172)	(0.081)	(0.170)	(0.201)
Hispanic:SC	-0.014	-0.108^{*}	-0.190	-0.343^{**}
	(0.156)	(0.065)	(0.146)	(0.168)
Night:SC	0.386^{***}	-0.226^{***}	-0.105	-0.115
	(0.119)	(0.058)	(0.141)	(0.130)
Night:287g	-0.134	0.011	0.250^{*}	0.184
	(0.110)	(0.057)	(0.133)	(0.133)
Hispanic:Night	-0.103	-0.117	-0.281^{*}	0.283
	(0.156)	(0.080)	(0.145)	(0.189)
Hispanic:SC:287g	-0.014	-0.108^{*}	-0.190	-0.343^{**}
	(0.156)	(0.065)	(0.146)	(0.168)
Hispanic:Night:SC	-0.978^{***}	-0.124	-0.045	0.369
	(0.320)	(0.126)	(0.241)	(0.288)
Hispanic:Night:287g	-0.084	0.287^{**}	-0.203	-0.522^{*}
	(0.269)	(0.121)	(0.219)	(0.279)
Observations	3,023	30,197	3,380	2,259
Note:				*p<0.1; **p<0.05; ***p<0.01

in the Alamance County Police by putting officers through training programs, hiring a more diverse police force, or relieving the officers with the most severe record of bias of their duties.

References

Albert, Jared I. "How Secure is Secure Communities? The Future of One of ICE's most Controversial Programs". In: *Georgetown Immigration Law Journal* (2011).

Antonovics, Kate and Brian G. Knight. "A New Look at Racial Profiling: Evidence from the Boston Police Department". In: *Review of Economics and Statistics* 91.1 (2009), pp. 163–177.

Anwar, Shamena and Hanming Fang. "An Alternative Test of Racial Prejudice in Motor Vehicle Searches: Theory and Evidence". In: *American Economic Review* 96 (2006), pp. 127–151.

Becker, Gary S. *The Economics of Discrimination*. Chicago: Univ. Chicago Press, 1957.

Bjerk, David. "Racial Profiling, Statistical Discrimination, and the Effect of a Colorblind Policy on the Crime Rate". In: *Journal of Public Economic Theory* 9.3 (2007), pp. 521–545.

Brock, William A. et al. "On the observational implications of taste-based discrimination in racial profiling". In: *Journal of Econometrics* 166.1 (2012), pp. 66–78.

Bunzel, Helle and Philippe Marcoul. "Can racially unbiased police perpetuate long-run discrimination?" In: *Journal of Economic Behavior & Organization* 68.1 (2008), pp. 36–47.

Charles, Kerwin Kofi and Jonathan Guryan. "Studying Discrimination: Fundamental Challenges and Recent Progress". In: *Annual Review of Economics* 3 (2011), pp. 479–511.

Coleman, Mathew. "The Local Migration State: The Site-Specific Devolution of Immigration Enforcement in the U.S. South". In: *Law & Policy* 34.2 (2012), pp. 159–190.

Cox, Adam B. and Thomas J. Miles. "Does Immigration Enforcement Reduce Crime? Evidence from Secure Communities". In: *(Forthcoming) The Journal of Law and Economics* (2014).

— "Policing Immigration". In: *The University of Chicago Law Review* Vol. 80 (2012).

Dhammika, Dharmapala and L. Ross Stephen. "Racial Bias in Motor Vehicle Searches: Additional Theory and Evidence". In: *The B.E.Journal of Economic Analysis & Policy* 3.1 (2004), pp. 1–23.

Dominitz, Jeff and John Knowles. "Crime minimisation and racial bias: what can we learn from police search data?" In: *The Economic Journal* 116.515 (2006), pp. 368–384.

Donohue III, John J. and Steven D. Levitt. "The Impact of Race on Policing and Arrests". English. In: *Journal of Law and Economics* 44.2 (2001), pp. 367–394.

Durlauf, Steven N. “Assessing Racial Profiling”. English. In: *The Economic Journal* 116.515 (2006), pp. 402–426.

Gill, Lindsey J. “Secure Communities: Burdening Local Law Enforcement and Undermining the U Visa”. In: *William & Mary Law Review* (2013).

Glaser, Jack. “The Efficacy and Effect of Racial Profiling: A Mathematical Simulation Approach”. English. In: *Journal of Policy Analysis and Management* 25.2 (2006), pp. 395–416.

Grogger, Jeffrey and Greg Ridgeway. “Testing for Racial Profiling in Traffic Stops From Behind a Veil of Darkness”. In: *Journal of the American Statistical Association* 101 (2006), pp. 878–887.

Hanson, Gordon H. “Illegal Migration from Mexico to the United States”. English. In: *Journal of Economic Literature* 44.4 (2006), pp. 869–924.

Heaton, Paul. “Understanding the Effects of Antiprofiling Policies”. English. In: *Journal of Law and Economics* 53.1 (Feb. 2010), pp. 29–64.

Hernandez-Murillo, Rubin and John Knowles. “Racial Profiling Or Racist Policing? Bounds Tests in Aggregate Data”. In: *International Economic Review* 45.3 (2004), pp. 959–989.

Hlavac, Marek. “stargazer: LaTeX/HTML code and ASCII text for well-formatted regression and summary statistics tables. R package version 5.1.” In: (2014). URL: `http://CRAN.R-project.org/package=stargazer`.

Immigration and Customs Enforcement. “Delegation of Immigration Authority Section 287(g) Immigration and Nationality Act”. In: *U.S. Department of Homeland Security* (2014). URL: `http://www.ice.gov/factsheets/287g`.

— “Secure Communities”. In: *U.S. Department of Homeland Security* (2014). URL: `http://www.ice.gov/secure-communities`.

— “Secure Communities Monthly Statistics through May 31, 2013”. In: *U.S. Department of Homeland Security* (2013). URL: `http://www.ice.gov/doclib/foia/sc-stats/nationwide_interop_stats-fy2013-to-date.pdf`.

Kang, Stephanie. “A Rose by Any Other Name: The Chilling Effect of ICE’s "Secure" Communities Program”. In: *Hastings Race & Poverty Law Journal* (2012).

Knowles, John, Nicola Persico, and Petra Todd. “Racial Bias in Motor Vehicle Searches: Theory and Evidence”. In: *National Bureau of Economic Research Working Paper Series* No. 7449 (1999).

Kohli, Aarti, Peter L. Markowitz, and Lisa Chavez. *Secure Communities by the Numbers: An Analysis of Demographics and Due Process*. Tech. rep. The Chief Justice Earl Warren Institute on Law and Social Policy, 2011.

Lamberth, John. *Expert Report on the Alamance County Sheriff’s Office*. Tech. rep. Lamberth Consulting, 2013.

MacDonald, John M. *Expert Report on the Alamance County Sheriff’s Office*. Tech. rep. University of Pennsylvania, 2013.

Massey, Douglas S. *Immigration and the Great Recession*. Tech. rep. Stanford Center on Poverty and Inequality, 2012.

Passel, Jeffrey S. *The Size and Characteristics of the Unauthorized Migrant Population in the U.S.* Tech. rep. Pew Hispanic Center, 2006.

Perez, Thomas E. *Re: United States' Investigation of the Alamance County Sherriff's Office*. Tech. rep. US Department of Justice, 2012.

Persico, Nicola. "Racial Profiling? Detecting Bias Using Statistical Evidence". In: *Annual Review of Economics* 1.1 (2009), pp. 229–254.

Persico, Nicola and Petra Todd. "Generalising the Hit Rates Test for Racial Bias in Law Enforcement, With an Application to Vehicle Searches in Wichita". In: *The Economic Journal* 116.515 (2006), pp. 351–367.

Petrocelli, Matthew, Alex R. Piquero, and Michael R. Smith. "Conflict theory and racial profiling: An empirical analysis of police traffic stop data". In: *Journal of Criminal Justice* 31.1 (2003), pp. 1–11.

Pickerill, J. Mitchell, Clayton Mosher, and Travis Pratt. "Search and Seizure, Racial Profiling, and Traffic Stops: A Disparate Impact Framework". In: *Law & Policy* 31.1 (2009), pp. 1–30.

Ridgeway, Greg. *Analysis of Racial Disparities in the New York Police Department's Stop, Question, and Frisk Practices*. Santa Monica, CA: RAND Corporation, 2007.

Ridgeway, Greg and John M. MacDonald. "Doubly Robust Internal Benchmarking and False Discovery Rates for Detecting Racial Bias in Police Stops". In: *Journal of the American Statistical Association* 104.486 (2009). doi: 10.1198/jasa.2009.0034; 03, pp. 661–668.

Sanga, Sarath. "Reconsidering Racial Bias in Motor Vehicle Searches: Theory and Evidence". English. In: *Journal of Political Economy* 117.6 (2009), pp. 1155–1159.

Schroeder, Thomas D. *Memorandum Opinion and Order: USA v. Terry S. Johnson, in his official capacity as Alamance County Sherriff*. Tech. rep. US District Court for the Middle District of North Carolina, 2014.

Smith, Michael R. and Matthew Petrocelli. "Racial Profiling? A Multivariate Analysis of Police Traffic Stop Data". In: *Police Quarterly* 4.1 (2001), pp. 4–27.

Tomic, Aleksandar and Jahn K. Hakes. "Case Dismissed: Police Discretion and Racial Differences in Dismissals of Felony Charges". In: *American Law and Economics Review* 10.1 (2008), pp. 110–141.

Warren, Patricia Y. and Donald Tomaskovic-Devey. "Racial profiling and searches: Did the politics of racial profiling change police behavior?" In: *Criminology & Public Policy* 8.2 (2009), pp. 343–369.

Weinstein, Hannah. "S-Comm: Shattering Communities". In: *Cardozo Public Law, Policy & Ethics Journal* (2012).