Racial Threat and the Emergence of Discriminatory Ordinances*

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Abstract

Where and why are discriminatory ordinances adopted? Theories of racial threat suppose that members of a racial majority group regard the presence of minorities as a threat to their socio-political status and implement policies to hurt that minority population. I use the racial threat hypothesis to examine the adoption of criminal activity nuisance ordinances (or crime-free housing laws). These ordinances allow officials to designate specific properties and residents as nuisances after repeated police interactions. After that designation, property owners are penalized with fines or the seizure of property if they do not respond by removing the residents. Using data from Ohio municipalities, I find that the racial composition of cities predicts the emergence of criminal activity nuisance ordinances. I attempt to rule out alternative hypotheses surrounding the proportion of renter-occupied housing, crime, and poverty. In further exploring the results, I use a machine learning technique called Random Forests to uncover the discontinuity or "tipping point" where the propensity for adopting such a policy sharply increases or decreases. This research speaks to the generalizability of the racial threat hypothesis, the importance of representation, and the nation's diversification.

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1 Introduction

Where and why are discriminatory ordinances adopted? In 2005, the City of Bedford, an inner-ring suburb of Cleveland, Ohio, adopted a discriminatory housing measure known as a criminal activity nuisance ordinance (CANO). This policy allows city officials to require landlords to "evict tenants who have had some degree of contact with the criminal legal system" (Archer, 2019, p. 175). Bedford's ordinance was one of the harshest in the nation. Enabled by the ordinance, city officials—specifically, the police—can designate a person or property a nuisance if there have been two or more real or perceived violations of the law or interactions with police.[1] Researchers have amassed a wealth of evidence that ordinances like those passed in Bedford have discriminatory impacts on people of color, people earning low incomes, and victims of violence (Desmond and Valdez, 2013; Kroeger and La Mattina, 2020). Yet, city officials justify the policy by citing either crime rates or the desire to keep people with "inner-city values" away from the city.

Theories of racial threat suggest that the ethnic majority group in a given area will regard the relative size of a minority group as a threat to its political, social, or economic well-being (Blalock, 1967; Key, 1949). Motivated by intergroup competition and its perception of the minority group as a threat, the majority will implement laws, policies, and norms that discriminate against the minority group. Scholars such as Bobo and Hutchings (1996) suggest a psychological mechanism to explain this phenomenon. Seeing individuals of a minority ethnicity or seeing the minority group's numbers increase triggers racial resentment.

Previous research finds evidence supporting this racial threat hypothesis in various national, sub-national, and local policies. I examine the incidence of a particular type of discriminatory housing ordinance—CANO—and the extent to which the racial threat hypothesis is consistent with its incidence. Using data from Ohio municipalities, I show that a robust cross-sectional relationship exists between the Black share of the population and the existence of a CANO that may be generalized across time periods. In particular, I find

[1] The ordinance specifically exempts traffic violations, i.e., speeding tickets.

that the relationship is non-linear and exhibits a concave form. While the inclusion of a quadratic term helps us understand the relationship, I go further to explore the levels at which the relationship shifts. Using a machine learning algorithm called Random Forests, I find three critical points or areas of interest. First, at low levels of the Black share of the population, CANOs are unlikely to emerge because the Black community is not perceived as a threat to the majority ethnic group. Next, at a 30% Black population share, CANOs begin to emerge. Lastly, the algorithm finds that the likelihood that CANOs will be adopted decreases once the Black population share surpasses 50%, which suggests that at that share, the Black population is able to elect or influence its city council to protect its interests. Furthermore, I disconfirm alternative hypotheses such as poverty, crime, and the proportion of renters by providing evidence that the Black percentage of the population is the primary driver of CANO adoption.

This research contributes to the vast literature on the racial threat hypothesis. Indeed, I find that the racial threat hypothesis generalizes to the case of CANOs. Moreover, the present study is timely and important as we seek to identify and understand racially discriminatory policies at all levels of government.

2 Racial Threat and Discriminatory Policies

Historically, the racial threat hypothesis arose out of general conflict theory, which defines the circumstances under which groups compete for status and power. It was later applied to racial groups to consider how the majority group uses social control against Blacks (Blalock, 1967; Key, 1949). The application of this inter-group conflict concept for studying race has been widely accepted and used since its formulation (Key, 1949; Blumer, 1958; Blalock, 1967; Bobo, 2004; Bobo and Hutchings, 1996). The racial threat hypothesis implies that a majority group (e.g., whites) "become more racially hostile as the size of the proximate subordinate group increase, which punitively threatens the former's economic and social privilege" (Eric Oliver and Wong, 2003, p. 568). Thus, the racial threat hypothesis links the size of the population to policies used to harm minorities. As Key (1949) insists, "the struggles of politics take place within an institutional framework fixed by considerations of race relations, a framework on the order of a mold which gives share and form to that which it contains" (Key, 1949, p. 665). In other words, racial threat is an inter-group competition over political power.[2]

The racial threat hypothesis is characterized by the *relative size* or the increase in the minority population and by the *actions* the majority ethnic group takes.[3] First, as Bobo and Hutchings (1996) argued, racial threat is essentially connected with the relative size of the minority group in the population. As the size of the minority population increases, the ethnic majority group will see this growth as a threat to its power. That is to say, the *visible presence* of minority group members prompts majority group members to use their power to maintain their dominant position. However, Blalock (1967) does not suggest a purely linear relationship. Instead, he suggests a j-curve, indicating that places with small minority populations are slightly tolerant of minority group members. Blalock's theory implies support for the contact thesis, i.e., contact with minority groups could lead to increased or non-negative interactions. However, as the minority population increases beyond a "tipping point," the majority will see minorities as competitors for power.

Furthermore, as the minority population increases beyond a certain point, its group members should be able to protect themselves from discriminatory policies via the political process (Carmichael and Kent, 2014; Chamlin, 2009). For example, Carmichael and Kent (2014) find that the Black share of the population has a nonlinear effect on the size of the police force. In addition, Stucky (2005) finds that with significant numbers, the Black population can stop the majority group's attempt to implement harmful policies towards them

[2]Both Key (1949) and Blalock (1967) focused their work on the racial politics of the American South. Key (1949), in particular, finds that white Americans in the Deep South were more likely to support candidates who favored harsher discriminatory policies against Blacks if they were in counties with higher Black populations.

[3]While the racial threat hypothesis is a theory about levels and change, in this project, I focus my attention on the levels or relative size.

within cities (See also Kent and Jacobs, 2005). This pattern even exists in the sentencing of juvenile offenders to terms in adult prisons (Carmichael, 2010; Carmichael and Burgos, 2012). Moreover, research into the racial threat hypothesis often shows that the negative majority behavior effect from the presence of minorities is ameliorated by minority representation (Griffin and Newman, 2007; Preuhs, 2006, 2007). In this vein, Preuhs (2007) finds that a strong Latino representation can counteract the negative effects of minority population growth on welfare restrictiveness. The literature provides ample evidence of these non-linear effects when testing the racial threat hypothesis.

Second, the racial threat hypothesis is about the majority group's actions. Blauner and Blauner (1972) argue that ethnic majority groups can maintain dominance by using law enforcement, the criminal justice system, and the legal process. Research on the application of the racial threat hypothesis has cited police expenditures (Huff and Stahura, 1980; Jackson and Carroll, 1981), arrests (Liska and Chamlin, 1984; Stolzenberg, D'Alessio and Eitle, 2004), and sentencing (Crawford, Chiricos and Kleck, 1998), to name a few. This is not to deny applications of the racial threat hypothesis outside the criminal justice system. Tolbert and Grummel (2003), for example, find that white Americans who lived in census tracts with more minority populations were more likely to support the objectives of affirmative action in California.[4] Similarly, Orey et al. (2011) find that white voters in areas with large Black populations display more 'anti-Black' voting behavior.[5]

In the larger literature, however, evidence for the racial threat hypothesis has been mixed (Acharya, Blackwell and Sen, 2016, 2018). Omitted variables may make the relationship between contemporary demographics and discriminatory attitudes and policies spurious. One example is the historical development of the institution of slavery and the concentration

[4]This study centered on the vote to end affirmative action (Proposition 209) in 1996 in the State of California. Importantly, it verified that racial threat operates not only with the African-American community but also in response to growing Latino and Asian-American communities. The authors state, "[O]ur results most clearly suggest the existence of a multi-racial racial threat effect, consistent with the cultural backlash process" (Tolbert and Grummel, 2003, p.197).

[5]Orey et al. (2011), in particular, examined voting patterns on referendum issues in Mississippi (where voters rejected a new flag that retained the confederate symbol) and Alabama (where voters preserved unconstitutional language about poll taxes and racially separate educational facilities).

of enslaved people in certain areas.[6] Furthermore, other factors may be at work for the racial threat in other local contexts. For example, Hopkins (2010) finds that intergroup competition is triggered only under certain local conditions. His study examines immigration and immigration attitudes under conditions of high unemployment.[7] Similarly, Oliver and Mendelberg (2000) find that the social environment, outside of race, impacts attitudes. Thus, the present study needs to examine the community's contemporary demographic makeup along with other characteristics to explain the probability of discriminatory policies.

In the following sections, I discuss crime-free housing ordinances, how the racial threat hypothesis applies to their emergence, and potential alternative explanations consistent with these ordinances.

3 The Case of CANOs

While one can trace the existence of CANOs, which are also known as "crime-free" housing ordinances[8] to before the 1980s, they are more widespread in the United States today.[9] CANOs are measures passed by city councils to enable officials to designate a property as a nuisance if there have been multiple interactions with or related calls to the police within a designated time frame. The typical parameters are three phone calls or interactions with the police within a twelve-month continuous time period. Once the property has been classified as a nuisance, usually by the police chief or deputy, the landlord must abate the nuisance. Research finds that "abatement" typically involves breaking leases and removing renters from the property (Desmond and Valdez, 2013; Lepley and Mangiarelli, 2018). Landlords who fail to abate the nuisance face fines, seizure of property, and in select

[6] I do not view the Acharya, Blackwell and Sen (2016) argument that slavery is an omitted variable as a threat to my inferences. The sample I use is derived from a non-slave state.

[7] His findings suggest that negative views are triggered only when there is high unemployment and *changes* in immigration into the community.

[8] The terms "criminal activity nuisance ordinances" ("CANOs") and "crime-free' housing ordinances" are interchangeable. I use CANOs throughout this paper, following Kroeger and La Mattina (2020).

[9] To my knowledge, there is no database or clearinghouse of all CANOs. They have become widespread, as has been shown by single-state studies by legal researchers, lawsuits filed by organizations such as the ACLU, and other academic research, which I build on in this study.

circumstances, jail time.

The detrimental impacts of CANOs are known. Nuisance ordinances increase eviction filings and court-ordered evictions in places that enact them (Kroeger and La Mattina, 2020). Taking Ohio municipalities as an example, nuisance ordinances increase evictions by 14 percent. Moreover, the effects of the ordinances are concentrated among already vulnerable population groups: low-income women, minorities, and domestic assault victims. Similarly, Desmond and Valdez (2013) find that Black neighborhoods receive a disproportionate number of citations. Furthermore, these nuisance designations also tend to fall on victims of crime. One-third of all citations in their sample were related to domestic violence (Desmond and Valdez, 2013).

Organizations from the left and right have challenged these policies. For example, the American Civil Liberties Union has fought such measures as racially discriminatory and harmful to crime victims in localities in New York, Illinois, Ohio, and Missouri. The Institute for Justice, a right-leaning legal advocacy group, has also challenged these policies in Illinois because they can punish a resident for a crime someone else committed and violate a landlord's right to choose tenants.[10]

While the impacts of CANOs are known, the motivations for adopting such policies are less clear. In their report exploring city council minutes and other public records surrounding CANOs, Mead et al. (2017) find four common motivations:

- Increase the power of the police department
- Serve as a formal response to resident complaints about unwelcome activities in their neighborhood
- Codify the previously unwritten community values and norms for resident behavior and activities
- Enlist property owners in the policing of criminal activity and the regulation

[10] In *Barron et al. vs. The City of Granite City, Illinois*, lawyers from the Institute for Justice challenged the constitutional validity of the ordinances, representing both the renter *and* the landlord.

of resident behavior and activities.

While Mead et al. (2017) state that residents "complain about annoying or rude behavior and their wish for a certain community character," we should not forget that increasing police power to terminate leases and enlist third-party enforcers (property owners) to enforce conformity to "community norms" and "neighborhood character" have racial implications. Indeed, Archer (2019) argues that these ordinances not only reinforce racial housing segregation because of their targeted use but also emerge in response to increasing diversity. Evidence of racial motivations could be found throughout city council meeting minutes.

The City of Bedford, Ohio provides an example. When a resident asked about the changing composition of the city, the Mayor explained his justification for passing the nuisance ordinance as follows: "One of the things that we take pride in is middle class values... We believe in neighbors not hoods." He went on to state that this policy was necessary because of the types of people coming into the city. The mayor explained: "[I] made mention of the students walking down the streets and those are *predominately African American* kids who *bring in that mentality from the inner city* where that was a gang related thing by staking their turf. We are trying to stop that" (emphasis added).

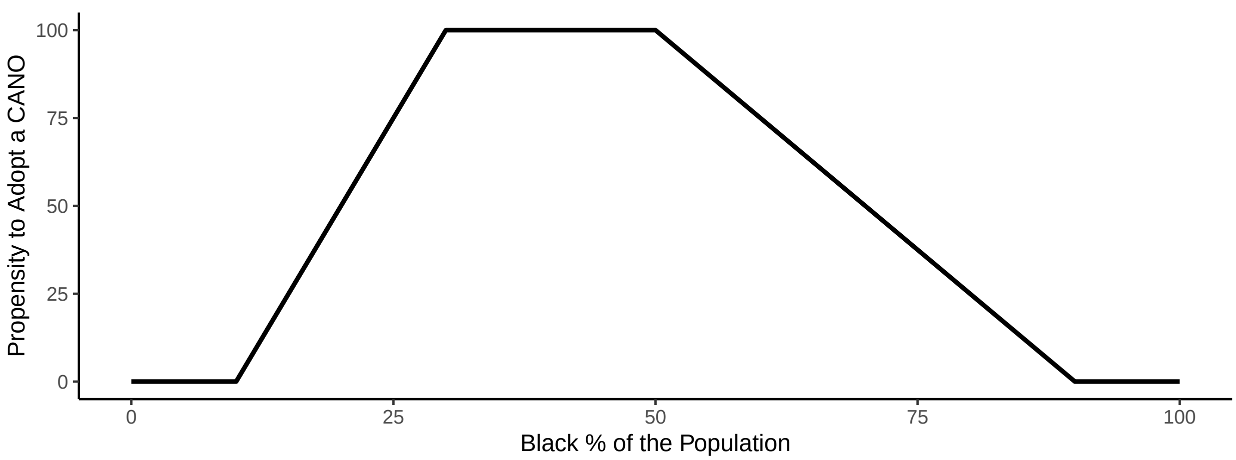
Given the potential racial motivations seen in the minutes of the city council meeting where the ordinance was discussed as well as the ordinance's discriminatory impact, I investigate whether the racial threat hypothesis can help us explain the increasing incidence of such ordinances.

4 Applying the Racial Threat Hypothesis to the Incidence of CANOs

The research on CANOs has largely focused on their impact; I seek to examine their determinants. I theorize that race is a factor that drives the rise of discriminatory policies. Given the evidence from the minutes of the city council's meeting and the lawsuits challenging these discriminatory policies, I apply the racial threat hypothesis to the emergence of CANOs. I argue that CANOs arise when ethnic majority group members perceive racial threats.

A racially threatened city is one in which the white majority is likely to adopt a discriminatory policy to hurt a Black or other minority group. Theories of racial threat suggest that as the relative population size of the minority group (i.e., Black residents) increases within a jurisdiction, members of the majority group will see the growing minority population as a threat to their socio-economic position and create policies to counter-act the perceived threat (Blalock, 1967). I build on research by Blalock (1967) and others to classify the relationship between the Black share of a city's population and the likelihood that the city will adopt a CANO.

Figure 1: Stylized Relationship Between the Black Share of a Population and CANOs



Notes: Depicts the stylized relationship between the Black share of a population and the propensity to adopt a CANO.

There are three points of interest on how the racial threat hypothesis applies to discriminatory policies. In Figure 1, I summarize my expectations for a community's propensity to adopt a CANO. First, in places with a very low Black population, discriminatory policies are unlikely to exist. As shown in the figure, in localities where the Black share of the population falls below 17%, I expect a community's probability of adopting a CANO to be predictably low. The logic is that there are no or only a few minorities to target. At a certain point, when white residents regard the Black population as sufficiently threatening (i.e., at a proportion higher than 17% but lower than the majority), we may expect the implementation of discriminatory policies. Thus, the relationship between the two factors should be positive (i.e., as the Black share of the population increases, the probability that a CANO will be adopted increases). Lastly, I expect the relationship between the Black population share and CANOs to be negative after the Black community is sufficiently large (i.e., a population share near or over 50%) to be able to use the electoral process to protect itself from harmful policies. I summarize my expectations in Table 1.

To establish how much more likely racially threatened cities are to adopt CANOs, I first need to establish a positive relationship between the Black share of the population and the adoption of CANOs. Second, as my theory suggests, I must test whether non-linearities exist between the Black share of the population and the CANO relationship. That is to say, the positive relationship between the Black share of the population and CANO adoption should be inverted after a certain level. Third, I must provide evidence of critical points where the propensity to adopt CANOs increases and decreases. Lastly, I need to address alternative explanations, such as poverty, the renters' share of the population, and crime.

Table 1: Summary of Expectations

Expectations	Explanation
Positive Linear Relationship	As the size of the Black population increases, the likelihood of cities adopting CANOs will increase.
Concave Relationship	As the size of the Black population increases, the likelihood of cities adopting CANOs will increase. At a certain level, the relationship between the Black share of the population and CANO adoption will decrease.
Critical Point (Lower)	A significant increase in the propensity to adopt a CANO will occur between 17-20% Black population share.
Critical Point (Upper)	A significant decrease in the propensity to adopt a CANO will occur after 50%.
Alternative Explanation: Crime	As crime increases, the likelihood of cities adopting CANOs increases.
Alternative Explanation: Renter	As renters' share of the population increases, the likelihood of cities adopting CANOs increase.
Alternative Explanation: Poverty	As poverty increases, the likelihood of cities adopting CANOs increase.

5 Data and Methods

The target population of this analysis comprises all of the charter and statutory cities in the State of Ohio. Only charter and statutory cities have the ability to pass independent criminal activity nuisance ordinances.[11] There are 246 charter and statutory cities with home rule in Ohio. The data primarily exploit Kroeger and La Mattina's replication file.[12] I verify their data and add additional cities and covariates using data from the U.S. Census Bureau. The time frame of the study covers 2004 to 2016.

The dependent variable for this study is the existence of CANOs. I follow the Kroeger and La Mattina (2020) coding method of ordinances. In my sample, 43 cities have CANOs. Beginningin 2004, at least one additional city adopted a CANO each year until 2016. The largest increase in this activity was in 2006 when the number of cities with CANOs increased from five to 12 localities.

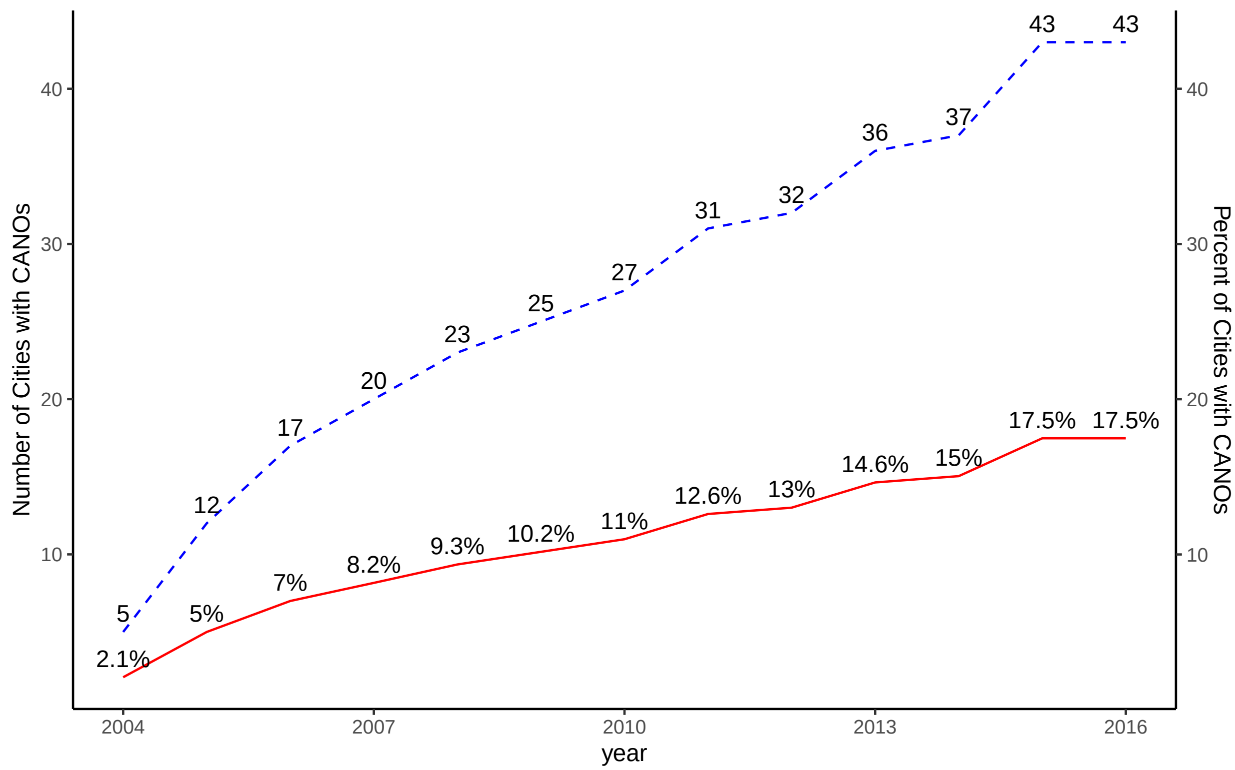
The main explanatory variable is the share of Black residents in a locality. I chose this measure because of its theoretical backing in the literature (Bobo and Hutchings, 1996; Eric Oliver and Wong, 2003) and its ease of interpretation. Moreover, the Black and non-Black dichotomy is parsimonious and fits with the history of my sample. According to the American Community Survey, the State of Ohio is 81% white and 12.41% Black, followed by those who identify as two or more races (2.88%) and Asians (2.22%). The majority of cities are predominantly white. Given these sample demographics, I believe the Black vs. non-Black dichotomy is a superior modeling approach due to its simplicity and the lack of reasonable threats to inferences making such a simplification.[13]

[11] That is to say, only charter and statutory cities in Ohio have "home rule" or the ability to decide which ordinances to pass (so long as they are not preempted by the state or federal government).

[12] The study of the effect of CANOs conducted by Kroeger and La Mattina included years when CANOs did not exist in Ohio. Thus, I use a subset of their replication data.

[13] This is not to say that Black share of the population is the only way to operationalize inter-group conflict. While much of the literature uses the Black share of the population, others expand the operationalization away from Black-White conflicts to include other races and ethnicities such as Hispanics and the Asian/Pacific Islander communities. I welcome future research conceptualizing racial threat and criminal activity nuisance ordinances differently. I can imagine that localities in the Western half of the United States or communities on the U.S.–Mexico border have different racial cleavages.

Figure 2: CANOs Over Time



Notes: Depicts the growth of CANOs over time. The x-axis represents years. The left y-axis represents the number of cities with CANOs. The blue dashed line corresponds to the left y-axis. The right y-axis represents the share of cities with CANOs. The red solid line corresponds to the right y-axis. In 2004, there were only five charter or statutory cities in Ohio that had a CANO (2.1% of cities). By 2016, the number of cities with a CANO had increased to 43 (17.5% of cities).

In addition to data about the Black share of the population, I collect data to test alternative explanations and to adjust for other between-unit differences: crime per 100,000 people, the percentage of renter-occupied housing, the poverty rate, population, the eviction rate, eviction filings, and median household income. I collect crime data from the Ohio Office of Criminal Justice Services.[14] Unless otherwise noted, the U.S. Census Bureau is the source of all other variables.

[14]It is important to note that crime data in the United States are not fully available. Local law enforcement agencies voluntarily report their crime statistics to the Uniform Crime Reporting program run by the FBI. I use summary crime statistics from the Ohio Office of Criminal Justice Services. Data can be accessed using the following website: `https://www.ocjs.ohio.gov/crime_stats_reports.stm`.

6 Methods

6.1 Time-Fixed Effects in Time-Series Cross-Sectional Data: Cross-Sections That Generalize Across Time

The main question this study seeks to answer is whether the incidence of CANOs is explained by the racial threat hypothesis. While there are several ways to answer this question, I chose to focus on the between-unit variation that explains CANO probabilities. In other words, I compare cities with and without a CANO at a particular time. Thus, I use a regression that models the cross-sectional (between-unit) variation and aggregate between the years.[15]

In all models, I cluster standard errors by city. This analysis will provide evidence about whether the cross-sectional relationship between the Black share of the population and CANO adoption generalizes across time. The model is the following:

$$y_{it} = \alpha + \beta_1 black_{it} + \beta_2 black_{it}^2 + \lambda^T \mathbf{Z}_{it} + \gamma^T \mathbf{X}_{it} + \phi_t + \epsilon_{it}, \tag{1}$$

where i represents cities and t represents time (year). I model y_{it} or the existence of a CANO as a function of the Black share of the population, a set of alternative explanations ($\lambda^T \mathbf{Z}_{it}$), a set of covariates ($\gamma^T \mathbf{X}_{it}$), and time-fixed effects (ϕ_t).

To test my first expectation, namely, that a positive linear relationship exists, I simply include the Black share of the population (β_1). For my second expectation—whether a non-linear, inverted-"U" relationship exists—I include a quadratic term (Black share squared) to the above equation (β_2). For a concave relationship, the Black share of the population (β_1) should be positive and significant while the squared term (β_2) should be negative and significant.

To provide evidence for alternative expectations, I examine the following set of coefficients

[15] For further discussion of the different ways of modeling the data and answering the underlying question, see Appendix B.

in λ^T: crime per 100,000 people, the renters' share of the population, and the extent of poverty. Outside of the alternative expectations, I include variables associated with the incidence of CANOs, such as logged population, eviction rate, eviction filings, and median household income (γ^T).

6.2 Supervised Machine Learning: Tree-Based Models

In addition to the main results, I use a tree-based machine learning approach to assess the existence of discontinuities and nonlinear effects in the data. Moreover, I use a variable influence algorithm to measure the relative importance of each competing hypothesis in predicting the adoption of CANOs.

Political scientists are increasingly using tree-based models to answer substantively important questions and improve predictions (Hill and Jones, 2014; Kaufman, Kraft and Sen, 2019; Montgomery and Olivella, 2018; Stewart and Zhukov, 2009). For example, Muchlinski et al. (2016) find that Random Forests outperform logistic regressions in the predictions of civil war in out-of-sample data. Similarly, Kaufman, Kraft and Sen (2019) find that boosted decision trees outperform existing predictive models in predicting county-level vote shares for U.S. presidential elections.

Tree-based models are ideal in the present study because of their ability to capture non-linear function forms. Indeed, tree-based models "are designed to incorporate flexible functional forms, avoid parametric assumptions, perform vigorous variable selection, and prevent overfitting" (Kaufman, Kraft and Sen, 2019, p. 382). In this study, I aim to identify these non-linear functional forms.

Previous studies in political science have used tree-based models to assess variable importance and non-linear relationships (Funk, Paul and Philips, 2021; Montgomery et al., 2015; Muchlinski et al., 2016; Bonica, 2018). Funk, Paul and Philips (2021), for example, use a Random Forest algorithm to identify a "critical mass" or proportion of women elected to a legislature and governmental expenditures. The tree-based machine-learning approach was able to recover a point or critical mass interval where spending in certain areas changed the percentage of women's representation.

To explain the operation of Random Forests, take a decision tree as an example. First, one variable and one point within that variable is selected. All data valued at less than that point are confined to one group, while everything greater than that point is put into a separate group. Next, for each group, the algorithm makes predictions and chooses the best variables from the subset of all variables that minimize the sum of the squared errors between the prediction and the observed values of the dependent variable. This "best" variable is now considered a node, or split. This is done for each group. Then, the process starts again within each node-split. A point in a feature is chosen, sub-groups of the data are made, the program finds the best variable to minimize the sum of squared errors between predicted and observed values, and then a node/split is created. The process continues until it reaches a determined stopping rule (e.g., only a set number of observations are left in each branch).

Three processes differentiate Random Forests from decision trees. First, just as the term "forest" suggests, Random Forests contain many decision trees. Yet, each decision tree uses a different bootstrap of the main data. In other words, each tree takes a random subset of the data (with replacement) to run the tree.[16] This bootstrapping procedure creates uncorrelated models, which is called bootstrap aggregation.[17]

Second, Random Forests limit the number of variables the model splits on. This feature-randomness means that instead of splitting the data on a node and finding the best variable from the larger subset of features, as in decision trees, Random Forests randomly select a set of variables to include in the model. The purpose of this process is to increase the variability across each tree.

In the end, Random Forests use bagging (bootstrap aggregation) such that each tree sees different data and uses a different subset of variables to create predictions. Lastly,

[16]Thus, one can have the same dataset and run two trees, but the trees may have different predictions because the data for each tree were randomly sampled with replacement from the larger data.

[17]This is also known as "bagging."

Random Forests aggregate or average the predictions across the multiple trees to make a final prediction.[18]

Usually, one can look at a tree graph and determine where the splits were made to infer their importance. For the purposes of this project, I rely on figures to tell the story. Specifically, I use partial dependence plots to map the relationship between the Black share of a city population and the city's propensity to adopt CANOs non-linearly. According to Friedman et al. (2001), partial dependence plots are a graphical representation of the predicted values of the outcome as a function of specified features. In other words, partial dependence plots "can be interpreted as the effect of one or more variables on the response (in their original scale), averaging over the effects of other variables used to grow the forest" (Cafri and Bailey, 2016). One can easily interpret nonlinear effects by examining where the predicted outcomes change as a function of a specified variable.[19]

Outside of finding non-linear effects, Random Forests provide a mechanism for testing competing hypotheses based on predictions. While it is important to acknowledge that prediction is *not* inference, prediction is a useful and under-utilized way to assess competing theories (Cranmer and Desmarais, 2017).

One way to assess competing theories is by using variable importance. Variable importance judges the predictive accuracy of the variables by using random permutations of each. For example, if one randomly permutes a single variable and re-runs the model, variable importance indicates how much the prediction error increases.[20] If the increase is large, one would expect that variable to contribute substantially to the model's predictive accuracy. If the predictive error is small or unchanged, one would expect the variable to contribute less to the accuracy of the model.

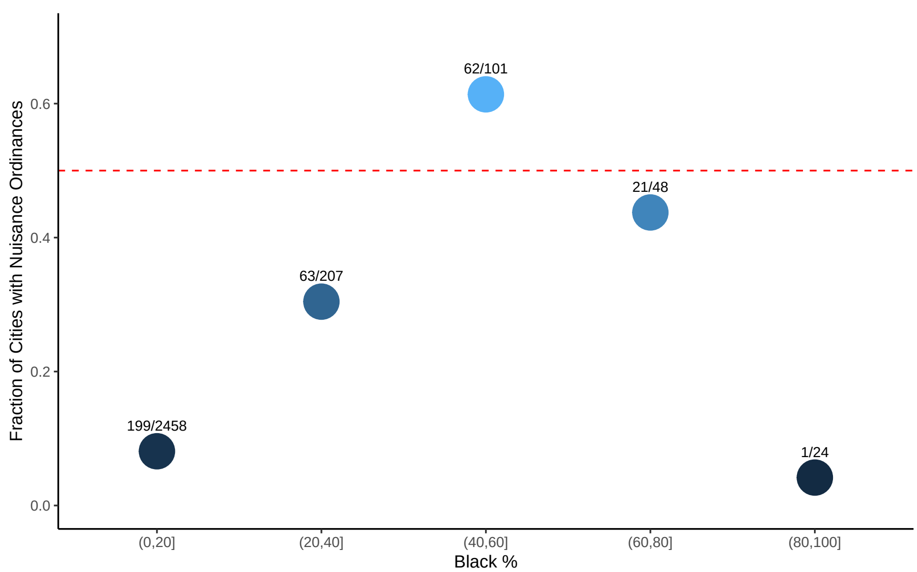
[18]For further discussion of Random Forests, please see the discussion in Siroky (2009).
[19]See Greenwell (2017) for a further discussion of partial dependence plots.
[20]The algorithm randomly shuffles the variables and runs the regression tree comparing the unshuffled model with the shuffled model.

7 Results

7.1 Preliminary Evidence

The raw data, plotted in Figure 3, illustrate a clear pattern. As the Black share of the population increases from a low proportion to half, the proportion of cities with a CANO increases. Indeed, of the approximately 2,500 cities with Black population shares between 0% and 20%, only 8% have a CANO. For cities that have between a 40% and 60% Black population share, over half of those cities have a CANO. For cities with Black populations between 60-80% and 80-100%, the proportion of cities with a CANO falls to below 50%. The story in the raw data is consistent with the broader racial threat hypothesis.

Figure 3: Binned Raw Data Points

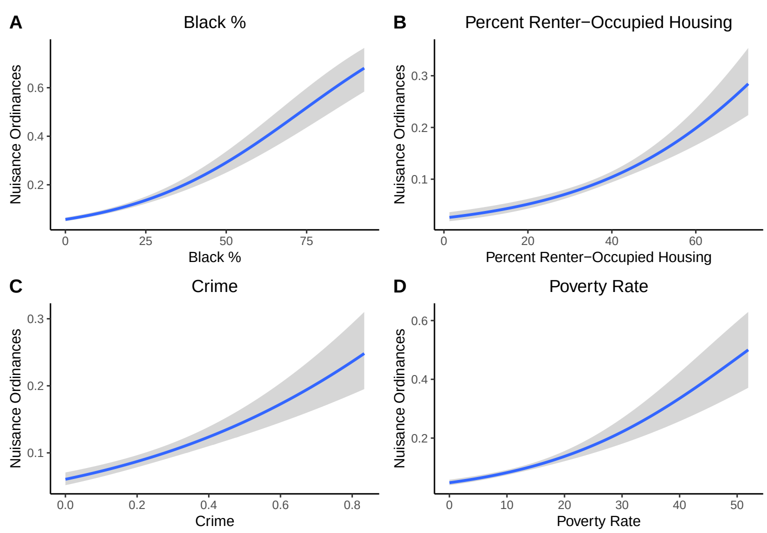


Notes: Depicts the relationship between CANO adoptions and the Black share of the population. The Black share of the population is on the x-axis. The observations are binned at every twenty percentage points. The y-axis is the share of cities that have a CANO.

Further, in Figures 4 and 5, I show how different functional form assumptions shape the story. First, in Figure 4, I show the association of CANOs and four potential explanations: (A) Black population percentage, (B) share of renter-occupied housing units, (C) crime per 100,000, and (D) poverty rate. The binomial curve shows a positive slope in the data pooled across time. Among the four variables in the figure, the Black share has the largest slope. All variables show a positive relation. However, in Figure 5, we see the same four variables with a LOESS curve, allowing the slope to change directions with the data. In Panel A (Black %), we see evidence of concavity. Thus, at a certain point, the probability of adopting a CANO increases rather than decreases.

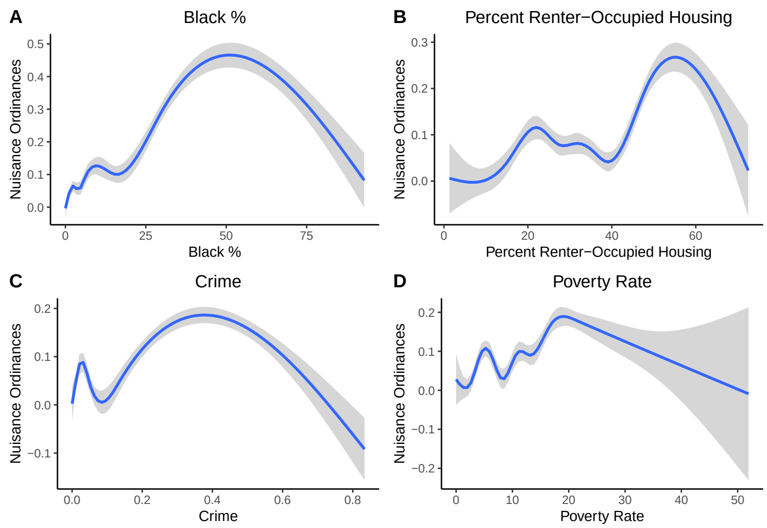
In sum, the preliminary evidence points to a few features of the data. How the data are modeled is significant in terms of monotonicity. As Figure 4 shows, there is a positive relationship between the Black share of the population and the incidence of CANOs. However, this strictly linear and monotone relationship fails to capture the raw data as shown in Figure 3. Second, by allowing the slope to change directions, as shown in Figure 5, we achieve a better fit for the pattern seen in the raw data.

Figure 4: Correlates of CANO Adoption: Binomial



Notes: Depicts the relationship between CANO adoptions and city characteristics. The data are pooled across city and time. The curve is generated from the logistic/binomial distribution. In Panel A, the Black share of the population is on the x-axis. In Panel B, the share of renter-occupied housing is on the x-axis. In Panel C, crime per 100,000 is on the x-axis. Lastly, in Panel D, the poverty rate is shown on the x-axis. All four city characteristics are positively related to CANOs.

Figure 5: Correlates of CANO Adoption: LOESS Smooth



Notes: Depicts the relationship between CANO adoptions and city characteristics. The data are pooled across city and time. The curve is generated from the logistic/binomial distribution. In Panel A, the Black share of population is on the x-axis. In Panel B, the share of renter-occupied housing is on the x-axis. In Panel C, crime per 100,000 people is on the x-axis. Finally, in Panel D, the poverty rate is on the x-axis. A distinct curvilinear relationship is shown with the Black share of the population.

7.2 Main Results

Table 2 reports the time-series cross-sectional estimates with year-fixed effects. In Model 1, I report the bivariate association between the Black share of the population and CANOs. I show a positive relationship between the Black share of the population and CANO adoption. This result is robust to the inclusion of alternative theories—such as renter share of population, crime, and poverty rates—and additional covariates (see Table 2 Model 2). I find evidence supporting a linear positive relationship between the Black population share and CANOs. Turning my attention to the alternative explanations, crime is also a significant predictor of CANO incidence. I fail to find evidence that poverty rates and the share of renters influence the adoption of CANOs.

Moreover, in Column 3, I include a squared term on the Black share of population and find substantive results consistent with the racial threat hypothesis. The main effect is significantly positive, while the quadratic term is small but significantly negative. This is evidence that the relationship between the Black share of a population and CANOs takes on a concave form.[21]

Table 2: Racial Composition and Adoption of CANOs

	Dependent variable:			
	CANO			
	(1)	(2)	(3)	(4)
Black %	0.007***	0.006**	0.017***	0.014***
	(0.002)	(0.003)	(0.004)	(0.005)
(Black %)^2			−0.0001***	−0.0001**
			(0.0001)	(0.0001)
Crime per 100K		0.290*		0.252
		(0.156)		(0.158)
% Renter		−0.003		−0.003
		(0.003)		(0.003)
Poverty Rate		0.001		0.0002
		(0.004)		(0.004)
Median HHI		−0.028**		−0.028**
		(0.012)		(0.012)
Eviction Filing Rate		−0.001		0.0001
		(0.007)		(0.007)
Eviction Rate		−0.007		−0.007
		(0.015)		(0.015)
Log(Population)		0.044		0.022
		(0.033)		(0.034)
Constant	−0.141	−0.480	−0.277**	−0.330
	(0.133)	(0.361)	(0.122)	(0.375)
Year FE	Yes	Yes	Yes	Yes
Observations	2,048	2,038	2,048	2,038

Notes: Adoption of a CANO is the dependent variable. Standard errors (clustered by unit/municipality) are in parentheses. Column 1 is a bivariate analysis reporting the associations between the Black share of the population and CANOs. Column 2 includes covariates and alternative hypotheses. Column 3 is a bivariate analysis reporting the associations between the Black share of the population squared and CANOs. Column 2 includes Black share squared, covariates, and alternative hypotheses. Year-fixed effects are not reported. *p<0.1; **p<0.05; ***p<0.01.

[21]In the appendix, I compare the fit of both models (Table 2 Columns 2 and 4). Using an analysis of variance (ANOVA) test, I find evidence that the inclusion of the polynomial terms on Black share of the population fits the data better (see Table 4 in Appendix C, F= 52.62, Pr(>F)=5.734e-13).

7.3 Machine Learning Approach

7.3.1 Evidence of Tipping Point: Partial Dependence Plots

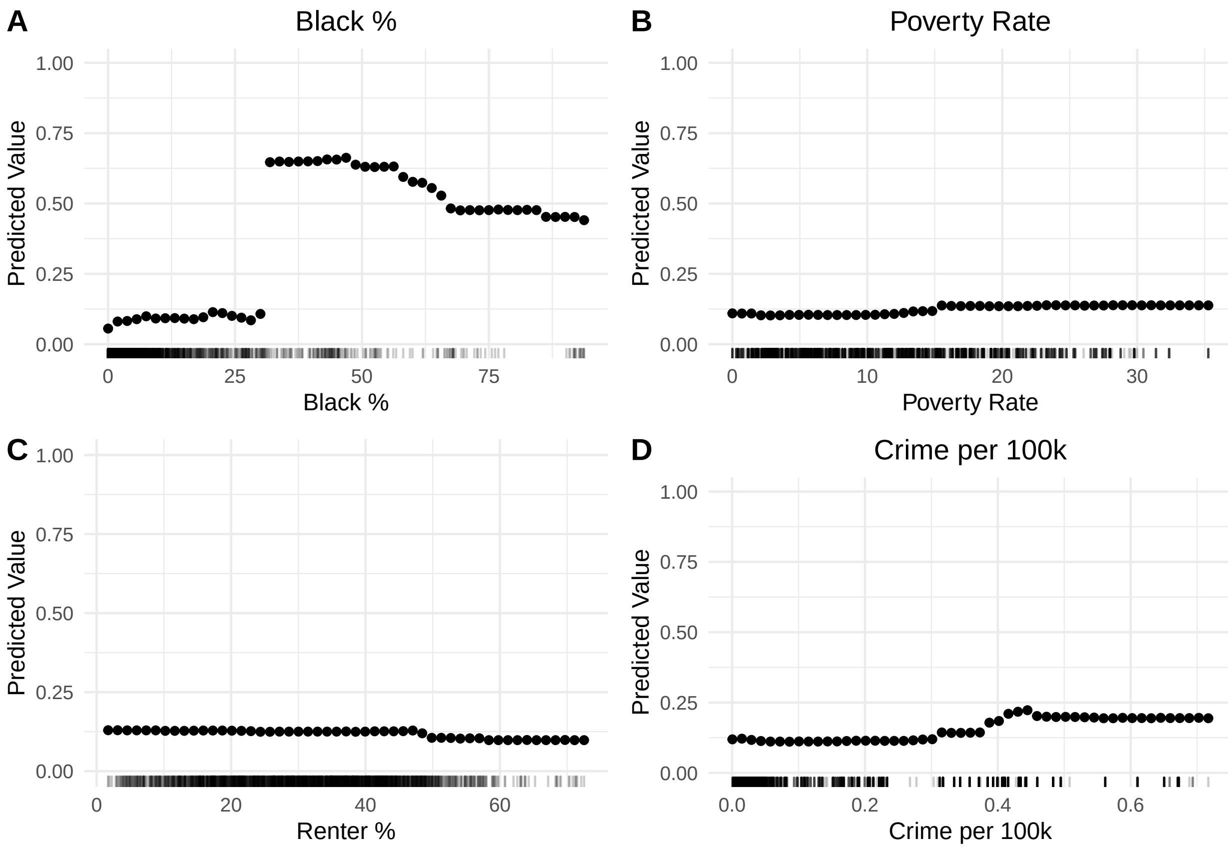
I use Random Forests as a non-parametric approach to detect non-linear and discontinuous effects between the Black share of a population and CANO adoption. This approach is ideal because the literature on the racial threat hypothesis posits this non-linearity (Blalock, 1967; Carmichael and Kent, 2014; Chamlin, 2009).

Figure 6 depicts the partial dependence plot of the expected effect that the Black share of the population, poverty rate, renter share, and crime per 100,000 people have on CANO incidence. Consistent with general expectations, when the Black share is below 30%, the predicted CANO adoption is relatively low (see Panel A).[22] When the Black share of the population reaches 30%, a clear discontinuity occurs and the predicted values increase to 62%. The average above 30% of the Black share of the population is approximately 55%. After a 50% Black share of the population, the propensity to adopt a CANO decreases. In all, the sharp increase (or discontinuity) at 30% is consistent with the racial threat hypothesis, though the tipping point is higher than the 17-20% implied by Blalock.

In Panels B through D (Figure 6), I show predicted values of the alternative explanations. The propensity to adopt a CANO is relatively flat; and none of them are over 25%. At a 17% poverty rate, the model expects the chances of adopting a CANO to be under 14%. Similarly, the highest predicted value for the renters' share of the housing population is 13%. For crime, the predicted values range from 7.5% to 15%. It is clear from the partial dependence plots that the Black residential share is contributing most of the predictive power. To verify this finding, I assess each variable's importance.

[22]When the Black share of the population is low, the average propensity to adopt a CANO is approximately 10%.

Figure 6: Partial Dependence Plot



Notes: PDPs of the Black share of the population (Panel A), poverty rate (Panel B), percentage of renters (Panel C), and crime (Panel D). The plot shows a clear discontinuity at approximately a 30% Black share of the population, where predicted values increase from 12% to over 50%. Once the share of Black population reaches 50%, the predicted value decreases. All other predicted values for alternative explanations are below 25%.

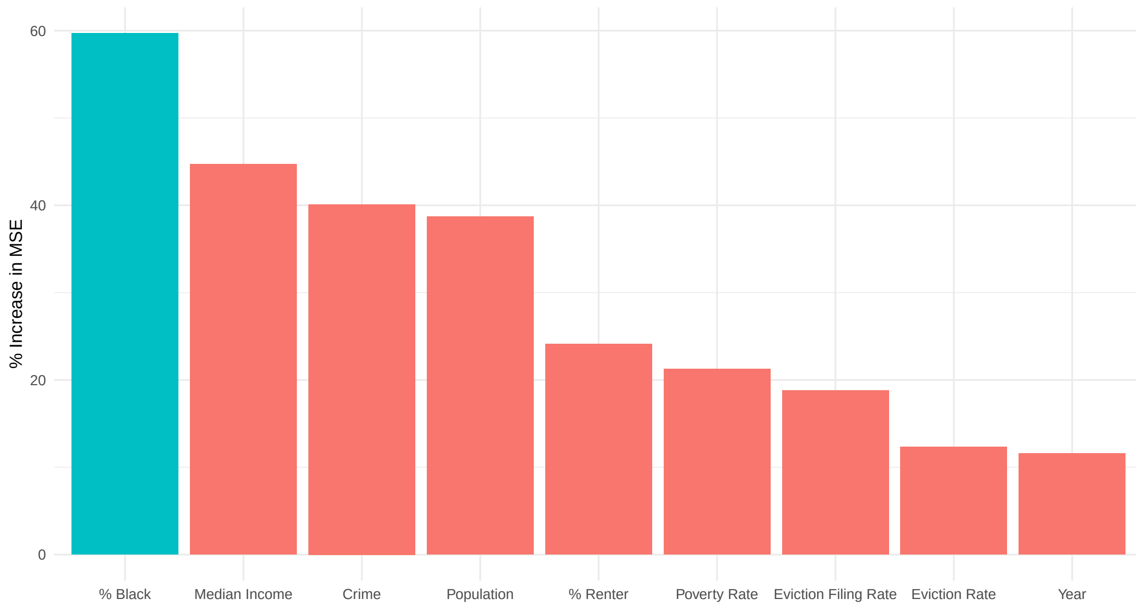
7.3.2 Variable Importance

I use out-of-bag variable importance to determine the relative predictive accuracy of competing hypotheses: Black share, renter share, crime, and poverty rate.[23] The algorithm uses the rates of how well the model predicts data not randomly sampled for inclusion in the model when one variable is permuted or shuffled.

Figure 7 depicts variable importance plots for CANOs. A larger increase in mean squared errors can be interpreted as the relative importance of the variable for prediction purposes.

[23]I show all variables in the model for consistency.

Figure 7: Variable Importance



Notes: Each variable is ordered by the percent increase in the mean squared error. The share of Blacks in a locality is the most important variable in predicting CANOs.

As shown in Figure 7, permuting the Black share of the population variable in the model increases the mean squared error by approximately 60%. Thus, the predictions become nearly 60% worse without this variable. Permuting crime increases the mean squared error by 38%. Similarly, the renter share of population and poverty increases the mean squared error by 36 and 28 percent, respectively.

In sum, the Black share of the population is the most important variable for explaining and predicting the existence of CANOs relative to alternatives. These findings are consistent with the partial dependence plots shown in Figure 6.

8 Learning from Your Neighbors: Diffusion

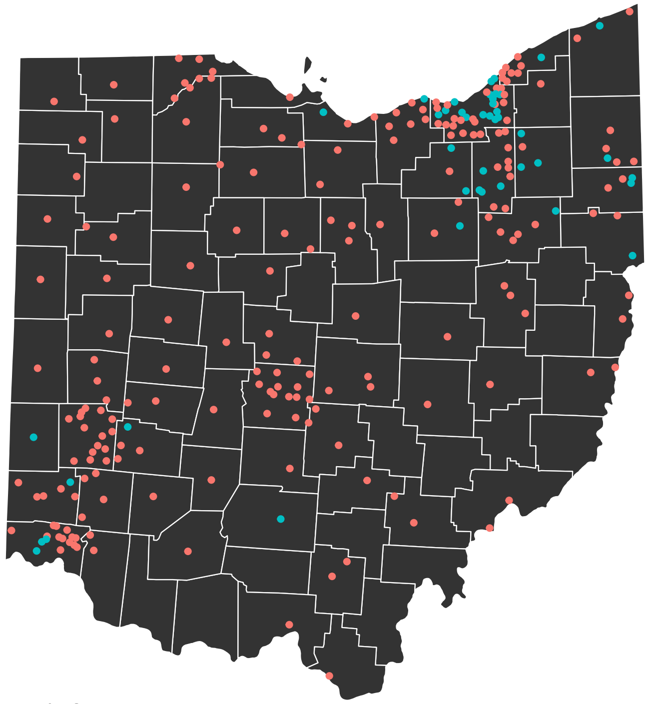
Neighbor-to-neighbor diffusion is another way of viewing the incidence of CANOs. In this section, I briefly examine the extent to which the incidence of CANOs is associated with their nearest-neighbor adoption pattern. In Figure 8, I show all of the municipalities in the sample and indicate whether a CANO exists in them as signified by a blue dot in the last year of the time frame. The figure shows clear evidence of clustering.[24] That is to say, most of the CANOs emerge together either around Cuyahoga County (in the upper right area of Ohio) or around Hamilton County (in the lower left quadrant of the state). For reference, Cleveland—in Cuyahoga County—is the second largest city in Ohio, while Cincinnati—in Hamilton County—is the third largest city.

For the analysis of neighbor-to-neighbor diffusion, I created a *nearest-neighbor* variable by first geo-locating all cities in the sample and computing pairwise distances. The *nearest-neighbor* variable takes on the value of 1 if the city's nearest-neighboring city in the sample has a CANO and 0 otherwise. I include this variable in the analysis and replicate Table 2 from the main text.

I find results consistent with the nearest-neighbor diffusion story (see Table 3). In both models, the coefficient on the *nearest neighbor* is positive and statistically significant. In other words, having a neighboring city implement a CANO increases the likelihood of that city also adopting one. Including the spatial dynamic does not substantively change the results from the main text. Indeed, the coefficient on *Black %* continues to be positive and significant, while the coefficient on *Black %ˆ2* is significant and slightly negative. Moreover, the alternative hypotheses of crime, proportion of renters, and poverty continue to have no estimable associations.

[24]See Appendix D for a discussion about spatial autocorrelation. In short, I find that spatial autocorrelation exists. I adjust for the existence of spatial autocorrelation in two ways: (1) by including the latitude and longitude as covariates, and (2) by jointly estimating a spline of space (latitude and longitude). Adjusting for spatial autocorrelation does not change the main results of the paper.

Figure 8: Map of CANOs in Ohio



Notes: Depicts a map of Ohio municipalities. Each dot corresponds to a municipality in the sample. A blue dot indicates that a CANO exists in that municipality while a red dot indicates that no CANO exists there. The figure shows clear evidence of clustering.

Table 3: Adoption of CANOs and Nearest Neighbor

	CANO	
	(1)	(2)
Black %	0.014***	0.012**
	(0.004)	(0.005)
(Black %)ˆ2	−0.0001***	−0.0001**
	(0.00005)	(0.0001)
Nearest Neighbor	0.331***	0.328***
	(0.079)	(0.077)
Crime per 100K		0.091
		(0.142)
% Renter		−0.002
		(0.003)
Poverty Rate		0.001
		(0.004)
Median HHI		−0.00000
		(0.00000)
Eviction Filings		−0.003
		(0.006)
Eviction Rates		−0.003
		(0.013)
Log(Population)		0.034
		(0.031)
Constant	0.034	−0.225
	(0.137)	(0.276)
Year FE	Yes	Yes
Observations	2,048	2,038

Notes: The adoption of a CANO is the dependent variable. Standard errors (clustered by unit/municipality) are in parentheses. Column 1 is a bivariate analysis reporting the associations between the Black share of a population and CANO. Column 2 includes covariates and alternative hypotheses. Year-fixed effects are not reported.
*p<0.1; **p<0.05; ***p<0.01.

9 Discussion and Conclusion

Discriminatory policies have been adopted across the United States. CANOs are one among many types of discriminatory policies and have previously been shown to disproportionately harm people of color, victims of violence, and low-income individuals. In the present study, I examine the extent to which the racial composition of the locality predicts the adoption of such policies consistent with the racial threat hypothesis. I find a robust pattern in the data. CANOs emerge where the Black population is high enough to be considered threatening by the majority. This occurs at levels between 30% and 50%. Consistent with expectations, I also find that the relationship decreases after the population level exceeds 50%. Future research should establish why this pattern occurs. One potential reason is that the minority community is able to stop discriminatory policies through political representation (specifically, voting or political organizing). A way of testing this mechanism is by examining the selection of city councilors.

This research makes two contributions. First, I show that the racial threat hypothesis generalizes to the emergence of CANOs in Ohio municipalities. Second, I add nuance to the theory insofar as we now have a guide to the locations and conditions under which discriminatory policies are likely to be adopted. Future research can use this guide to search for additional discriminatory policies as we begin to build large datasets on the local level. Examining policies of cities that are "racially threatened"—or 30–50% Black—may be a starting point.

While I argue in this study that the racial threat hypothesis explains the probability of a particular discriminatory housing policy, future research should assess the extent to which this pattern generalizes beyond Ohio municipalities. Data have limited the exploration of CANOs nationwide, but compiling a national dataset regarding this matter will be fruitful for academic research and provide policy implications for legal practitioners. Furthermore, researchers should turn their attention toward how local governments and their ordinances may entrench racial and economic inequality. While much of the research has focused on land use and zoning, and other discriminatory ordinances have been left unexamined. Race is a defining social cleavage in the United States. The importance of this issue will only grow as the nation diversifies and as we continue to see signs that we are struggling to manage a multiracial democracy.

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Appendix A. Model Comparison

Table 4: Analysis of Variance: Comparing Model with % Black and % Black Squared

Model	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	2029	220.12				
2	2028	214.56	1	5.5671	52.62	5.734e-13***

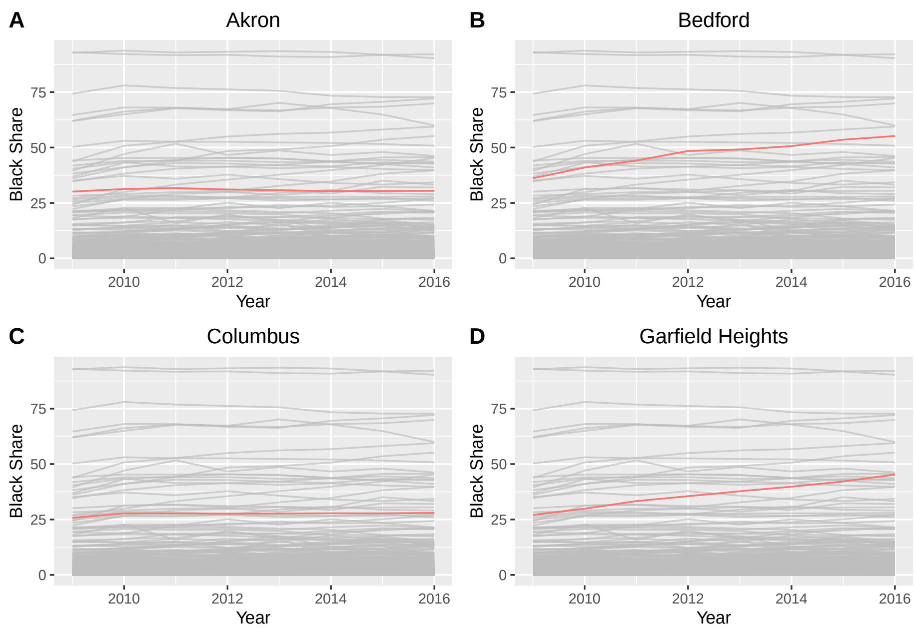
Notes: Report results from an analysis of variance. Model 1 corresponds to Table 2, Column 2: Criminal activity nuisance ordinances as a function of black share of the population, % renters, poverty rates, median household incomes, eviction filing rates, eviction rates, and logged populations. Model 2 corresponds to Table 2, Column 4: Criminal activity nuisance ordinances as a function of Black share of the population, Black share of the population squared, % renters, poverty rates, median household incomes, eviction filing rates, eviction rates, and logged populations. The tables show the model with the polynomial terms on Black percentage of the population provides a better parsimonious fit of the data.
*p<0.1; **p<0.05; ***p<0.01.

Appendix B. Comments on Fixed Effects

I model the data in this project using a one-way fixed effect on year instead of the more often used unit-fixed effect or the two-way fixed effects. In this section, I detail my reasoning.

First, there is little variation in the Black Share of the population at the longitudinal level. As shown in Figure 9, I plot each city's Black share of the population over time. Each city is identified with a grey line. The general pattern is relatively constant. In Panel A - D, I highlight four cities: Akron, Bedford, Columbus, and Garfield Heights. Akron and Columbus tended to have little variation over time, like the vast majority of the cities. Bedford and Garfield Heights showed a modest increase in the Black share of the population. I highlight these two cities because they had the largest changes over my sample.

Figure 9: Little to No Variation at the Longitudinal Level



Notes: Depicts how the Black share of the population varies over time. Each line represents a different city. The x-axis shows years, while the y-axis shows the Black share of the population. Each line represents a different city. I highlight four cities (Akron, Bedford, Columbus, and Garfield Heights) in red. Little variation exists in the main explanatory variable over time.

In Table 5, I model the data with unit-fixed effects. In Table 6, I model the data using a two-way fixed effect on unit and time. To examine within unit variation and over time variation, one requires a sufficient amount of change over time in both the dependent and independent variables. Unfortunately, my sample does not contain enough over-time variation for this analysis to be useful. Thus, in both models, the Black share of the population is insignificant. Given the lack of variation, I interpret these null findings as a lack of variation and not as a zero association.

Table 5: Unit FE: Racial Composition on Adoption of CANO

	Dependent variable:	
	CANO	
	(1)	(2)
Black Share	0.006	0.001
	(0.006)	(0.007)
I(Black Share^2)	0.00001	0.00001
	(0.0001)	(0.0001)
Crime per 100K		−0.216
		(0.136)
% Renter		0.009***
		(0.003)
Poverty Rate		0.001
		(0.003)
Median HHI		0.017
		(0.011)
Eviction Filing Rate		−0.001
		(0.001)
Eviction Rate		0.003
		(0.005)
Log(Population)		−0.223
		(0.150)
Constant	0.804***	3.238*
	(0.195)	(1.823)
Year FE	No	No
City FE	Yes	Yes
Observations	2,048	2,038
R^2	0.871	0.875
Adjusted R^2	0.853	0.857
Residual Std. Error	0.134 (df = 1800)	0.133 (df = 1784)
F Statistic	49.250*** (df = 247; 1800)	49.307*** (df = 253; 1784)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6: TWFE: Racial Composition on Adoption of CANO

	Dependent variable:	
	CANO	
	(1)	(2)
Black Share	−0.002	−0.001
	(0.007)	(0.007)
I(Black Shareˆ2)	0.0001	0.00005
	(0.0001)	(0.0001)
Crime per 100K		0.230
		(0.144)
% Renter		0.006*
		(0.003)
Poverty Rate		−0.001
		(0.003)
Median HHI		−0.004
		(0.012)
Eviction Filing Rate		−0.0001
		(0.002)
Eviction Rate		0.003
		(0.005)
Log(Population)		−0.160
		(0.145)
Constant	0.755***	2.447
	(0.247)	(1.799)
Year FE	Yes	Yes
City FE	Yes	Yes
Observations	2,048	2,038
R^2	0.878	0.879
Adjusted R^2	0.861	0.862
Residual Std. Error	0.131 (df = 1789)	0.131 (df = 1773)
F Statistic	50.135*** (df = 258; 1789)	49.012*** (df = 264; 1773)
Note:		*p<0.1; **p<0.05; ***p<0.01

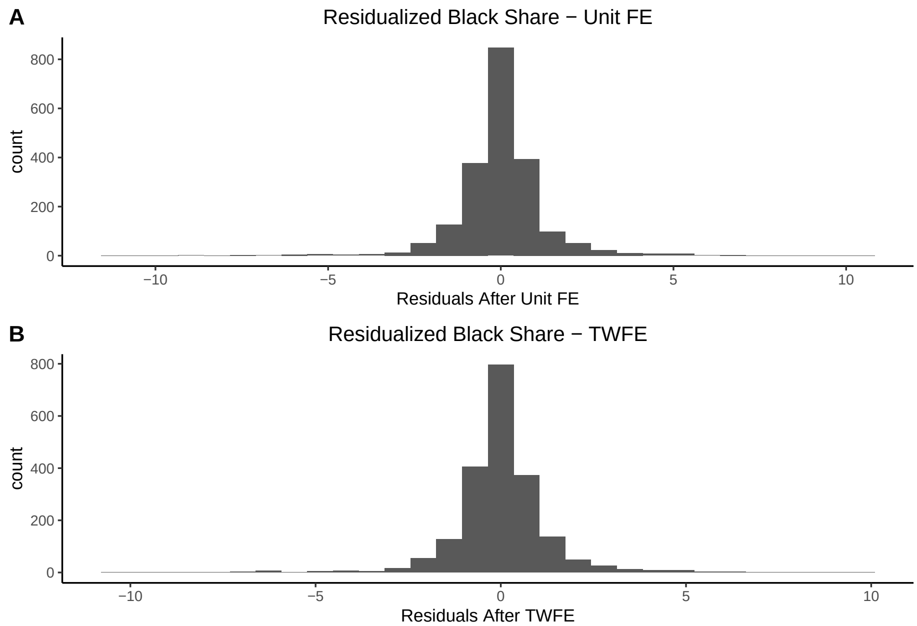
Another way to understand the variation in the data is to examine how much of the variation in the independent variable is left to be explained after fixed effects. In Table 7, I fit the Black share of the population as a function of two-way fixed effects, unit-fixed effects, and year-fixed effects. Using both two-way fixed effects and unit-fixed effects explains virtually all of the variation in the Black share of the population. In other words, after two-way fixed effects and unit-fixed effects, there is no more variation left to explain. The R^2 in both Models 1 and 2 are .99, while the R^2 in Model 3 is .074. This is similar to Figure 9.

Lastly, an alternative way of viewing issues about variation is by examining the residuals of each model in Table 7. The typical shift in the Black share for the two-way fixed effect model is 1.28, for unit-fixed effects it is 1.35, and for the time-fixed effect models it is 15.32.

Table 7: Variation in Black Share

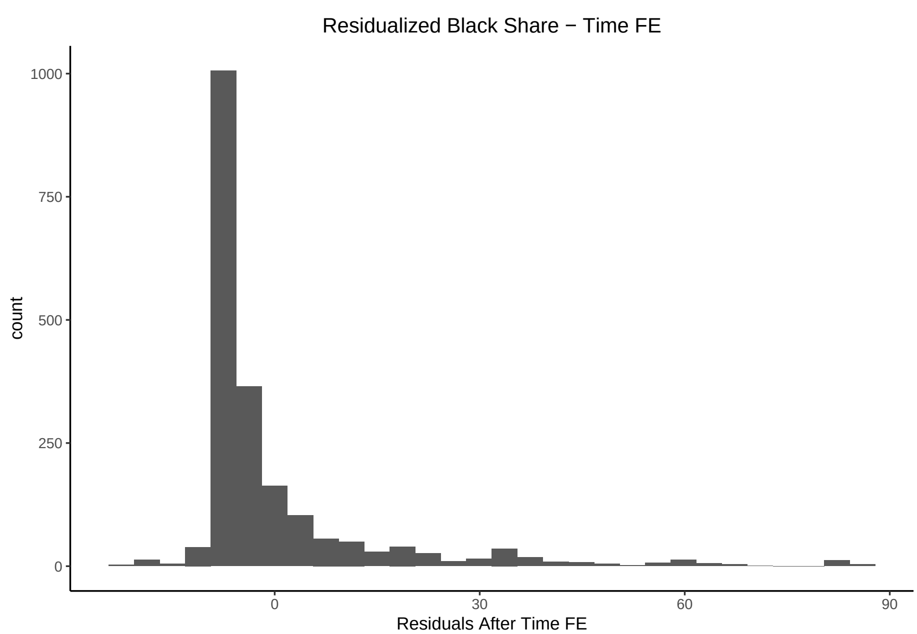
	Dependent variable:		
	black share		
	(1)	(2)	(3)
Constant	31.873***	30.737***	35.338***
	(0.591)	(0.416)	(5.119)
Year FE	Yes	No	Yes
Unit FE	Yes	Yes	No
Observations	2,048	2,048	2,048
R^2	0.993	0.993	0.074
Adjusted R^2	0.993	0.992	0.069
Note:			*p<0.1; **p<0.05; ***p<0.01

Figure 10: TWFE and Unit Residual



Notes: Depicts a histogram of the residualized Black share of the population after unit-fixed effects (Panel A) and two-way fixed effects (Panel B). The typical shift in variation of Black shares is 1.35 and 1.28 for unit- and two-way fixed effects, respectively.

Figure 11: Time Residual



Notes: Depicts a histogram of the residualized Black share of the population after time-fixed effects. The typical shift in between unit variations of Black share is 15.

Appendix C. County-Fixed Effects

In Table 8, I re-run the main specification with the inclusion of county-fixed effects. County-fixed effects are used to adjust for between-county differences. The results are robust and consistent with the racial threat hypothesis.

Table 8: County FE: Racial Composition on Adoption of CANO

	Dependent variable:	
	CANO	
	(1)	(2)
Black Share	0.018***	0.013***
	(0.004)	(0.005)
I(Black Shareˆ2)	−0.0002***	−0.0002**
	(0.00005)	(0.0001)
Crime per 100K		0.301*
		(0.174)
% Renter		−0.00002
		(0.003)
Poverty Rate		0.006
		(0.005)
Median HHI		−0.017
		(0.013)
Eviction Filing Rate		−0.008
		(0.006)
Eviction Rate		0.013
		(0.013)
Log(Population)		−0.003
		(0.035)
Constant	−0.447***	−0.447
	(0.167)	(0.406)
Year FE	Yes	Yes
County FE	Yes	Yes
Observations	2,048	2,038
R^2	0.348	0.370
Adjusted R^2	0.320	0.340
Residual Std. Error	0.289 (df = 1962)	0.285 (df = 1946)
F Statistic	12.315*** (df = 85; 1962)	12.545*** (df = 91; 1946)
Note:		*p<0.1; **p<0.05; ***p<0.01

Appendix D. Spatial Autocorrelation

In this section, I address spatial autocorrelation or clustering in the data. In an analysis not shown, I estimate Moran's I—the amount of auto-correlation within the data—for each year in my sample. In all years, there exists evidence of spatial auto-correlation. In order to adjust for this clustering, I first add latitude and longitude to the main model specification. As shown in Table 9, the pattern of racial threat is robust to spatial auto-correlation.

The inclusion of latitude and longitude in the model as linear terms is not the only way of adjusting for the clustering found in the data. Indeed, I also run a generalized additive model (GAM) and include longitude and latitude as a joint spline, such that I estimate geographic clustering as a smooth function. The racial threat hypothesis still holds (see Table 10).

Table 9: Racial Composition on the Adoption of CANOs, with Lat., Long.

	Dependent variable:	
	CANO	
	(1)	(2)
Black%	0.017***	0.014***
	(0.004)	(0.005)
I(Black%ˆ2)	−0.0002***	−0.0001**
	(0.0001)	(0.0001)
Crime per 100K		0.281*
		(0.155)
% Renter		0.0004
		(0.003)
Poverty Rate		0.001
		(0.004)
Median_HHI_000		−0.015
		(0.013)
Eviction Filing Rate		0.0004
		(0.006)
Eviction Rate		−0.002
		(0.014)
Log(Population)		0.010
		(0.034)
Lat	0.053**	0.059**
	(0.021)	(0.023)
Long	0.043***	0.041***
	(0.015)	(0.016)
Constant	1.141	0.646
	(1.712)	(1.816)
Year FE	Yes	Yes
Observations	2,048	2,038
R^2	0.202	0.217
Adjusted R^2	0.196	0.209
Residual Std. Error	0.314 (df = 2032)	0.313 (df = 2015)
F Statistic	34.290*** (df = 15; 2032)	25.433*** (df = 22; 2015)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 10: Racial Composition on the Adoption of CANOs, GAM with splines

	Dependent variable:	
	CANO	
	(1)	(2)
Black%	0.017***	0.012***
	(0.001)	(0.001)
I(Black%^2)	−0.0002***	−0.0001***
	(0.00002)	(0.00002)
Crime per 100K		0.027
		(0.065)
% Renter		0.001
		(0.001)
Poverty Rate		0.005**
		(0.002)
Median HHI		−0.010*
		(0.005)
Eviction Filing Rate		−0.009**
		(0.004)
Eviction Rate		0.011*
		(0.007)
Log(Population)		0.004
		(0.011)
Constant	−0.242**	−0.288*
	(0.103)	(0.156)
Approx. sign. of spline	p-value	p-value
s(lat,long)	$< 2e-16$***	$< 2e-16$***
Year FE	Yes	Yes
Observations	2,048	2,038
Adjusted R^2	0.269	0.284
Log Likelihood	−460.019	−443.778
UBRE	0.092	0.090
Note:	*p<0.1; **p<0.05; ***p<0.01	

Appendix E. School Quality

In this section, I address the extent to which school quality could explain the relationships we observe in Table 2 in the main text. I collect data on school district quality from the Ohio Department of Education's School District Report Cards.[25] Each school district is given a letter grade (A-F).[26] I use this letter grade in two ways: ordered and as a factor.

In Table 11, I include the letter grade as an ordered feature such that higher scores are between and lower scores are worse. Column 1 replicates the bivariate analysis in the main text with the inclusion of the ordered letter grade. Column 2 includes the letter grade as a factor in the otherwise bivariate analysis. Columns 3 and 4 include the rest of the covariates. Across all models, the racial threat hypothesis remains in the expected pattern and is statistically significant.

[25] https://reportcard.education.ohio.gov/

[26] For further detail, please refer to the state's School District Report Card technical documentation: https://education.ohio.gov/Topics/Data/Report-Card-Resources/Resources-and-Technical-Document

Table 11: Racial Composition on Adoption of CANOs with School Quality

	Dependent variable:			
	CANO			
	(1)	(2)	(3)	(4)
Black%	0.022***	0.020***	0.022***	0.020***
	(0.005)	(0.005)	(0.006)	(0.006)
I(Black%ˆ2)	−0.0002***	−0.0002**	−0.0002***	−0.0001**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Grade (ordered)	0.0001		−0.018	
	(0.029)		(0.046)	
Grade D		0.426***		0.385***
		(0.127)		(0.117)
Grade C		0.436***		0.370***
		(0.132)		(0.129)
Grade B		0.382***		0.292*
		(0.134)		(0.155)
Grade A		0.424***		0.324*
		(0.153)		(0.192)
Crime 100K			0.274	0.281
			(0.272)	(0.273)
% Renter			−0.007	−0.007
			(0.004)	(0.004)
Poverty Rate			−0.006	−0.005
			(0.005)	(0.005)
Median HHI			−0.063*	−0.053*
			(0.032)	(0.031)
Eviction Filing Rate			−0.001	−0.007
			(0.017)	(0.017)
Eviction Rate			−0.015	−0.011
			(0.026)	(0.025)
Log(Population)			0.022	0.026
			(0.044)	(0.043)
Constant	−0.354**	−0.776***	0.043	−0.458
	(0.173)	(0.203)	(0.494)	(0.528)
Year FE	Yes	Yes	Yes	Yes
Observations	1,412	1,412	1,402	1,402
R^2	0.172	0.187	0.206	0.219
Adjusted R^2	0.164	0.177	0.194	0.205
Residual Std. Error	0.364 (df = 1397)	0.361 (df = 1394)	0.358 (df = 1380)	0.356 (df = 1377)
Note:				*p<0.1; **p<0.05; ***p<0.01

Appendix F. Majority Black vs. Non-Majority Black

In Table 12, I show two models in which the data are split between Black majority cities (greater than 50%) and Black minority cities (less than 50%). In this analysis, I expect a positive slope for cities with a low Black population and a negative slope for cities with a high Black population. The model matches these expectations. Indeed, for non-majority Black cities, an increase in the Black share translates to an increase in CANO probability. After a city contains a Black majority, the relationship between the Black share of the population and CANO probability decreases.

Table 12: Racial Composition on Adoption of CANO (Low vs. High Black Share)

	Dependent variable:	
	CANO	
	(Less than 50% Black)	(Greater than 50% Black)
Black Share	0.009**	−0.029***
	(0.004)	(0.004)
Crime 100K	0.221	2.857***
	(0.157)	(0.253)
% Renter	−0.002	−0.027***
	(0.003)	(0.004)
Poverty Rate	0.001	−0.050***
	(0.004)	(0.017)
Median HHI	−0.023**	−0.850***
	(0.011)	(0.146)
Eviction Filing Rate	0.002	0.026***
	(0.007)	(0.007)
Eviction Rate	−0.013	−0.015
	(0.015)	(0.013)
Log(Population)	0.018	−0.031
	(0.033)	(0.052)
Constant	−0.273	5.016***
	(0.344)	(0.803)
Year FE	Yes	Yes
Observations	1,961	77
R^2	0.116	0.889
Adjusted R^2	0.107	0.852
Residual Std. Error	0.317 (df = 1941)	0.193 (df = 57)
F Statistic	13.389*** (df = 19; 1941)	24.023*** (df = 19; 57)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 13: Racial Composition on the Adoption of CANOs + Change in Black Share

	Dependent variable:	
	CANO_1	
	(1)	(2)
Black Share	0.017***	0.014***
	(0.004)	(0.005)
I(Black Shareˆ2)	−0.0001***	−0.0001**
	(0.0001)	(0.0001)
Δ Black	−0.001	−0.002
	(0.010)	(0.009)
Crime 100K		0.253
		(0.165)
% Renter		−0.003
		(0.003)
Poverty Rate		0.001
		(0.004)
Median HHI		−0.028**
		(0.013)
Eviction Filing Rate		0.001
		(0.007)
Eviction Rate		−0.010
		(0.015)
log(Population)		0.024
		(0.035)
Constant	−0.050	−0.124
	(0.119)	(0.321)
Year FE	Yes	Yes
Observations	1,801	1,792
R^2	0.136	0.155
Adjusted R^2	0.129	0.145
Residual Std. Error	0.334 (df = 1787)	0.331 (df = 1771)
F Statistic	21.585*** (df = 13; 1787)	16.209*** (df = 20; 1771)
Note:		*p<0.1; **p<0.05; ***p<0.01