Racial Threat and the Emergence of Discriminatory Ordinances*

Bryant J. Moy†

September 7, 2022

Abstract

Where do discriminatory ordinances emerge? Theories of racial threat suppose that members of the racial majority group will see 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 via fines or the seizure of property if they do not abate the nuisance 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 policy adoption sharply increases and decreases. This research speaks to the generalizability of the racial threat hypothesis, the importance of representation, and the nation's diversification.

*I would like to thank the discussants and attendees at the Midwest Political Science Association conference 2022 for their helpful comments. **This is an early draft, please do not cite without permission.** Any and all questions/comments are welcome!

†Data Science Faculty Fellow in the Center for Data Science and Visiting Assistant Professor of Politics at New York University; bryant.moy@nyu.edu

1 Introduction

Where do discriminatory ordinances emerge? In 2005, the City of Bedford, an inner-right suburb of Cleveland, Ohio, adopted a discriminatory housing ordinance called a criminal activity nuisance ordinance. 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 – police – can designate a person or a property as a nuisance if there are 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 of low income, and victims of violence (Desmond and Valdez, 2013; Kroeger and La Mattina, 2020). Yet, city officials justify the policy either because of crime or to keep people with "inner-city values" away from the city.

Theories of racial threat suggest that the ethnic majority group in an area will see the relative size of the minority group as a threat to their political, social, or economic well-being (Blalock, 1967; Key, 1949). In so far as the minority is seen as a threat – due to intergroup competition – 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 an increase in minorities triggers racial resentment.

Previous research finds evidence of the racial threat hypothesis in various national, sub-national, and local policies. I seek to examine the emergence of a particular discriminatory housing ordinance – criminal activity nuisance ordinance – and the extent to which the racial threat hypothesis is consistent with their emergence. Using data from Ohio municipalities, I show that a robust cross-sectional relationship exists between Black share of the population and the existence of a CANO that generalizes across time periods. In particular, I find that the relationship is non-linear and takes a concave form. While the inclusion of the quadratic

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

term helps us understand the relationship, I go further to explore at what levels the relationship shifts. Thus I find three critical points/areas of interest using a machine learning algorithm called Random Forests. First, at low levels of the Black share of the population, CANOs are unlikely to emerge because they are not perceived as a threat to the majority ethnic group. Next, at 30% Black population share, CANOs start to emerge. Lastly, the algorithm finds that the likelihood of having a CANO decreases after 50%, suggesting that the Black population was able to elect or influence the council to protect their interests. Furthermore, I provide evidence that the Black share of the population is the primary driver of CANO adoption rather than alternative hypotheses such as poverty, crime, and rentership.

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, this present study is salient as we are pushing 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, where groups compete for status and power. It was later applied to racial groups and how the majority group uses social control against Blacks (Blalock, 1967; Key, 1949). The application of inter-group conflict to 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 is about the size of the population and the 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 the 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 their power. That is to say, the visible *presence* of minority groups prompts majority group members to use their power to maintain dominance in their position. However, Blalock (1967) does not suggest a purely linear relationship. Instead, he suggested a j-curve where places with small minority populations are slightly tolerant of minorities. His 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 increase beyond a "tipping point," the majority will see minorities as competitors for power.

Furthermore, as the minority population increases beyond a certain point, that group 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 police force size. In addition, Stucky (2005) finds that with sizable numbers, the Black population can stop the majority group's attempt to implement harmful policies towards them within cities (See also Kent and Jacobs, 2005). This pattern even exists in the sentencing of juvenile offenders in adult prisons (Carmichael, 2010; Carmichael and Burgos, 2012). Moreover, research into the racial threat hypothesis often shows that the negative effect of minority presence is ameliorated by minority representation (Griffin and Newman, 2007; Preuhs, 2006, 2007). In this vein,

[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 population.

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

Preuhs (2007) finds that 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 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 used 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. That is not to say that the application of the racial threat hypothesis has only used 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 end 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, the 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 of enslaved people in an area.[6] Furthermore, other factors may be at work when examining the racial threat and both discriminatory attitudes and policies like other local contexts. For example, Hopkins (2010) finds that intergroup competition only gets triggered under certain local contexts. His study examines immigration and immigration attitudes when

[4]This study centered on the vote to end affirmative action (Proposition 209) in 1996 in the State of California. Importantly, their study verified that racial threat operates not only with the African-American community, but also with the Latino and Asian-American community. The authors state, "our 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 keeping the confederate symbol) and Alabama (where voters kept unconstitutional language surrounding racially separate educational facilities and poll taxes).

[6]I do not see 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.

there is 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 that would explain emergence of discriminatory policies.

3 The Case of CANOs

While one can trace the existence of criminal activity nuisance ordinances – or "crime-free" housing ordinances[8] – to before the 1980s, they have become widespread throughout the United States today.[9] Criminal activity nuisance ordinances are ordinances passed by city councils to enable officials to designate a property as a nuisance if there are multiple interactions or calls to the police within a set timeframe. The typical parameters are three phone calls or interactions with the police within a twelve month continuous time period. After the property is classified as a nuisance, usually by the police chief or their designee, 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). If the landlord fails to abate the nuisance, the landlord faces fines, seizure of property, and, in select circumstances, jail time.

The detrimental impacts of criminal activity nuisance ordinances are known. Nuisance ordinances increase the eviction filings and court-ordered evictions in places that enact such policies (Kroeger and La Mattina, 2020). Using Ohio municipalities as the setting, they find that nuisance ordinances increase evictions by 14 percent. Moreover, the effects of the ordinances are concentrated among already vulnerable population groups: low-income

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

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

[9] To my knowledge, there does not existence a database or clearinghouse of all criminal activity nuisance ordinances. We know they have become widespread because of single state studies by legal researchers, lawsuits by organizations such as the ACLU, and other academic researcher's work who I build off of in this study.

women, minorities and domestic assault victims. Analogously, 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 domestic violence related (Desmond and Valdez, 2013).

Organizations from the left and right have challenged these policies. For example, the American Civil Liberties Union has challenged these policies across the country for being racially discriminatory and harmful to victims of crime 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 for violating landlords' right to decide who to provide housing to.[10]

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

- Increase power to the police department
- Serve as a formal response to resident complaints of unwelcome activities in their neighborhood
- Encode into law the regulation of resident behavior/activity according to unwritten community norms, values, or 'character'
- Enlist property owners in the policing of criminal activity and the regulation of resident behavior/activity

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 overlook that increasing power of the police to terminate leases, enlisting third-party enforcers (property owners), and the conformity to 'community norms' and 'neighborhood character' have racial implications. Evidence of racial motivations can be found throughout city council meeting minutes.

[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* landlord.

Take the City of Bedford, Ohio, for example. When a resident asked about the changing composition of the city, the Mayor explains his justification for passing the nuisance ordinance that night by stating, "One of the things that we take pride in is middle class values... We believe in neighbors not hoods." He goes on to state that this policy is necessary because of the type of people coming into the city. The mayor explains, "[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).

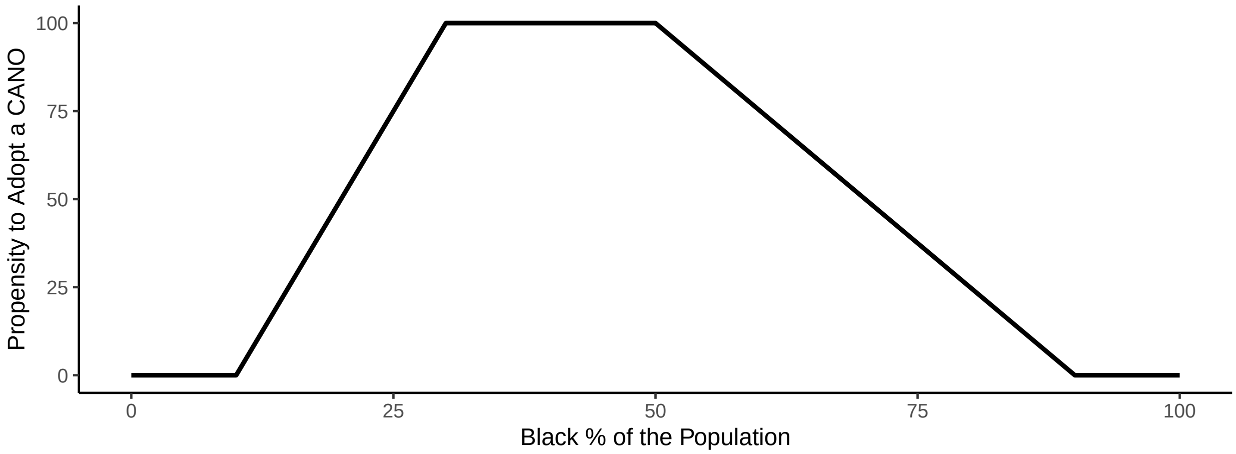
Given the potential racial motivations within city council meeting minutes that discussed the ordinance and the discriminatory impact of the ordinances, I assess whether the racial threat hypothesis can help us explain their emergence.

4 Applying Racial Threat to CANO Emergence

The research on criminal activity nuisance ordinances has largely focused on their impact. I seek to examine their determinants. I theorize that race is a driving factor that predicts the rise of discriminatory policies. Given the evidence from city council meeting minutes and the lawsuits challenging these discriminatory policies, I apply the racial threat hypothesis to the emergence of criminal activity nuisance ordinances. I argue that criminal activity nuisance ordinances arise when cities are perceived as being racially threatened.

A racially threatened city is one where the white majority are likely to adopt a discriminatory policy to hurt the Black minority group. Theories of racial threat suggest that as the relative population size of the minority group (i.e., Black residents) increase in 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 Blalock (1967) and others work to classify the relationship between Black share of the population and CANOs.

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



Notes: Depicts the theorized relationship between Black share of the population and the propensity to adopt a criminal activity nuisance ordinance.

There are three points of interest in how the racial threat hypothesis applies to discriminatory policies. In Figure 1, I summarize my expectations for the 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 below 17% Black share of the population I expect the probability of adopting a CANO to be arbitrarily low. The logic is that there are no or only a few minorities to target. At a certain point, where white residents view the Black population as sufficiently threatening (i.e., a proportion higher than 17% but lower than the majority), we should see the implementation of discriminatory policies. Thus the relationship should be positive (i.e., as the Black share of the population increases, the probability to implement CANO increase). Lastly, I expect the relationship between Black population and CANOs to be negative after the Black community is sufficiently large enough to be able to protect themselves from harmful policies through the electoral process (i.e., a population share near or after 50%). I summarize my expectations in Table 1.

In order to establish how much more likely racially threatened cities are to adopt CANOs, I first need to establish a positive relationship between Black share of the population and the adoption of CANOs. Second, as my theory suggests, I test whether non-linearities exist

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 Black share of the population and CANO adoption will decrease.
Critical Point (Lower)	A significant increase in 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 increase.
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.

between the Black share of the population and CANO relationship. That is to say, the positive relationship between Black share of the population and CANO adoption should invert after a certain level. Third, I will provide evidence of a critical point where the propensity to adopt CANOs increase and decrease. Lastly, I need to deal with alternative explanation, such as poverty, renter share of the population, and crime.

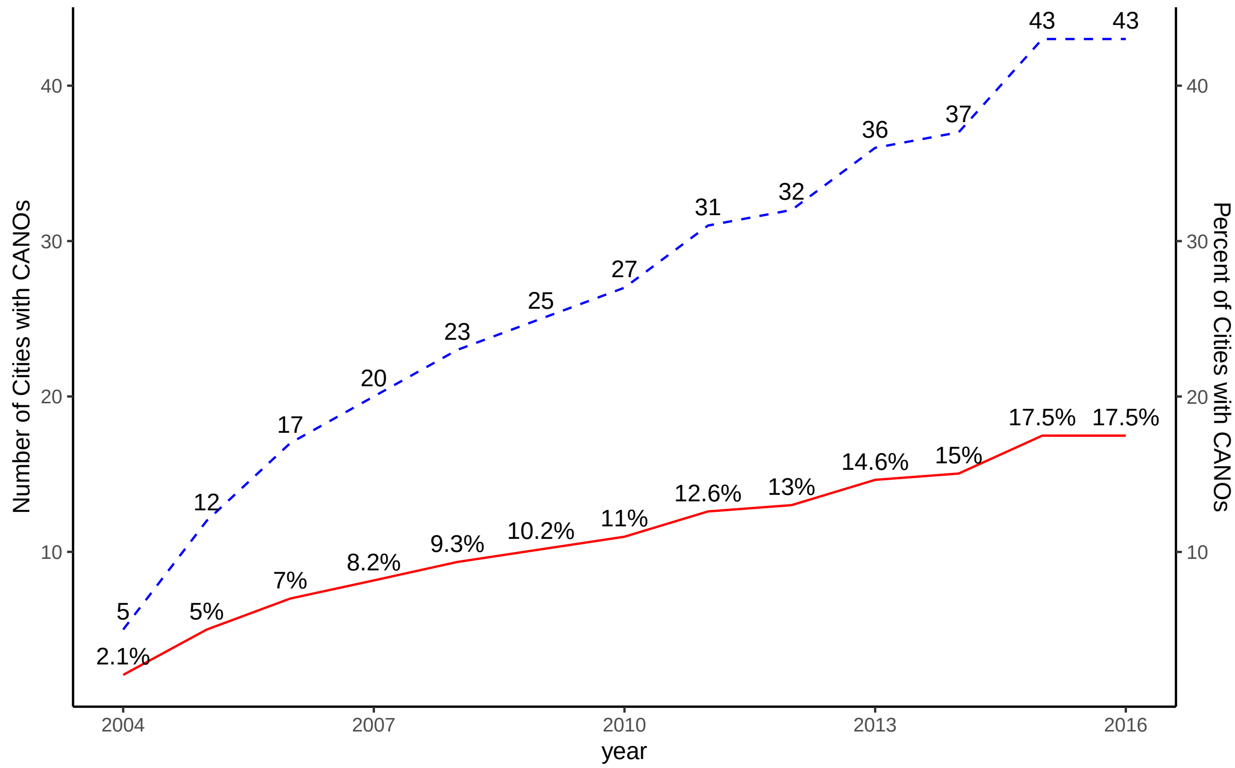
5 Data and Methods

The target population of this analysis is all 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.

[11] That is to say, only charter and statutory cities in Ohio have 'home rule' or the ability to decide what ordinances to pass as long as the law is not preempted by the state or federal government.

The data primarily exploits Kroeger and La Mattina's replication file. I verify their data and add additional cities and covariates using the U.S. Census Bureau data. The timeframe of the study is from 2004 to 2016.

Figure 2: CANOs Over Time



Notes: Depicts the growth of criminal activity nuisance ordinances over time. The x-axis is represents years. The left y-axis represents the number of cities with CANOs. The blue dashed line corresponds with the left y-axis. The right y-axis represents the share of cities with CANOs. The red solid line corresponds with the right y-axis. In 2004, there were only 5 charter or statutory cities in Ohio which had a CANO or 2.1% of cities. In 2016, the number of cities with a CANO increased to 43 (or 17.5% of cities).

The dependent variable for this study is the existence of criminal activity nuisance ordinances. I follow Kroeger and La Mattina (2020) coding of ordinances. In my sample, forty-three cities have criminal activity nuisance ordinances. Starting in 2004, at least one additional city adopted a criminal activity nuisance ordinance each year until 2016. The largest increase was in 2006, where the number of cities with CANOs increased from five to twelve 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. The next racial or ethnic group are those who identify with two or more races and then Asians (2.88% and 2.22%, respectively). The large majority of cities are predominantly white. Given the sample demographics, I believe the Black vs. non-Black dichotomy is a superior modeling approach for its simplicity and the lack of reasonable threats to inferences making such a simplification.[12]

In addition to the Black share of the population, I collect data to test alternative explanations and to adjust for other between unit differences: crime per 100k, percent renter-occupied housing, poverty rate, population, eviction rate, eviction filings, and median household income. I collect crime data from the Ohio Office of Criminal Justice Services.[13] Unless otherwise noted, all other variables come from the U.S. Census Bureau.

[12]This is not to say that Black share of the population is the only way operationalize inter-group conflict. While much the literature uses Black share of the population, others expand the operationalization away from Black-White conflict 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 in localities in the Western half of the United States or communities on the U.S. - Mexico border to have different racial cleavages.

[13]It is important to note that crime data in the United States is 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 access 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 emergence of criminal activity nuisance ordinances follows the racial threat hypothesis. While there are a few ways to answer this question, I choose to focus on the between-unit variation that explains CANO emergence. In other words, I am comparing 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.[14] In all models, I cluster standard errors by city. This analysis will provide evidence as to 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 am modeling y_{it} or the existence of a criminal activity nuisance ordinance 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 – a positive linear relationship exists – I simply include 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 will examine the following set of coefficients in λ^T: crime per 100K, renter share of the population, and poverty. Outside of the alternative expectations, I include variables associated with the emergence of CANO,

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

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 outperforms 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 share for U.S. President.

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). And in this study, I want to be able to identify these non-linear functional forms.

Previous work 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 change given 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 less than that point is put into 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 squared errors between prediction and observed values of the dependent variable. This "best" variable is now considered a node or split. This is done for each group. Then within each node-split, the process starts again. A point in a feature is chosen, sub-groups of the data are made, you find the best variable that minimizes the sum of squared errors between predicted and observed values, and then a node/split is created. The process continues until some determined stopping rule (e.g., only a set number of observations are left in each branch).

Three processes make Random Forests different from decision trees. First, Random Forests – as the "forest" in the name suggests – contains 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.[15] This bootstrapping procedure creates uncorrelated models, which is called bootstrap aggregation.[16]

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, like in decision trees, Random Forests randomly selects 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, Random Forests aggregate or average the predictions across the multiple trees to make a final prediction.[17]

Usually, one can look at the tree graph and determine where the splits were made to infer

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

[16]This is also known as 'bagging.'

[17]For further discussion of Random Forests please see the discussion in Siroky (2009).

their importance. However, this approach is difficult to present and harder to interpret. For purposes of this project, I rely on figures to tell the story. In particular, I use partial dependence plots to map the relationship of Black share and 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 interpret 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.[18]

Outside of finding non-linear effects, Random Forests provide a mechanism for testing competing hypotheses based on prediction. 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 of assess competing theories is by using variable importance.

Variable importance assesses the predictive accuracy of each variable by using random permutations of each variable. For example, if one randomly permutes a single variable and re-runs the model, variable importance indicates how much the prediction error increases.[19] If the increase is large, we expect that variable to contribute a lot to the model's predictive accuracy. If the predictive error is small or unchanging, we expect the variable to contribute less to the accuracy of the model.

[18] See Greenwell (2017) for a further discussion of partial dependence plots.

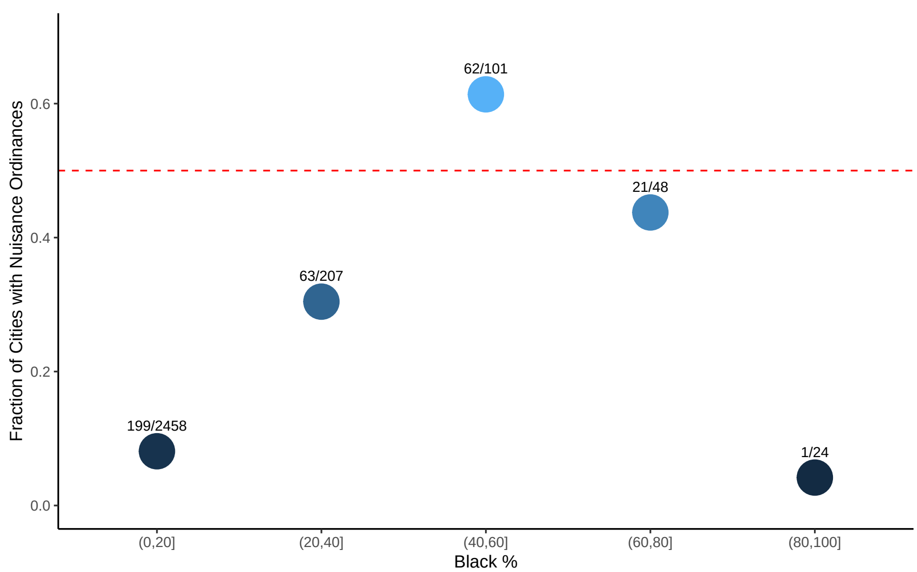
[19] The algorithm randomly shuffles the variables and runs the regression tree comparing the unshuffled model with the shuffled model.

7 Results

7.1 Preliminary Evidence

The raw data, plotted in Figure 3, illustrates a clear pattern. As the Black share of the population increases from low to half of the population, the proportion of cities with a CANO increases. Indeed, of the around 2,500 cities with Black population shares between 0% and 20%, only 8% have a CANO. For cities that have between 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 CANO reduces below 50%. The story in the raw data is consistent with the broader racial threat hypothesis.

Figure 3: Binned Raw Data Point

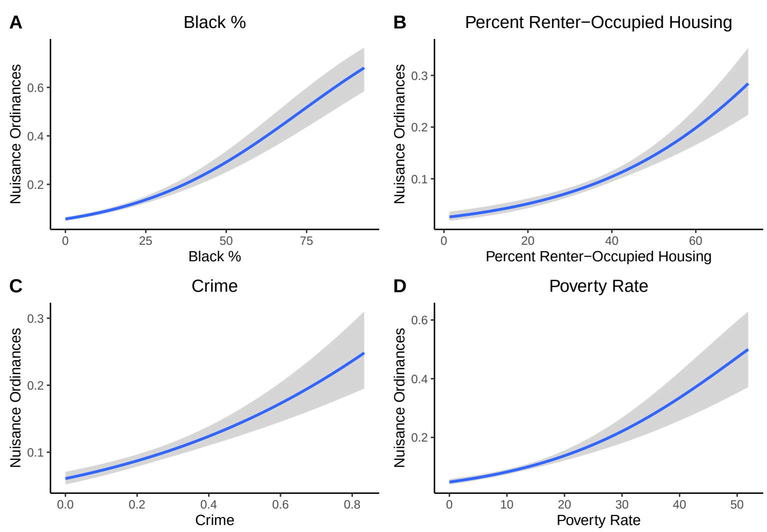


Notes: Depicts the relationship between CANO adoptions and the Black share of the population. The Black share of the population is on the x-axis. The observations are binned at every twenty percentage points. The y-axis is the share of cities that have a criminal activity nuisance ordinance.

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 %, (B) share of renter occupied housing units, (C) crime per 100k, 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, I show the same four variables with a LOESS curve, allowing the slope to change directions with the data. In Panel A (Black %), one can clearly see evidence of concavity. That is to say, at a certain point, the probability of adopting a CANO increases than decreases.

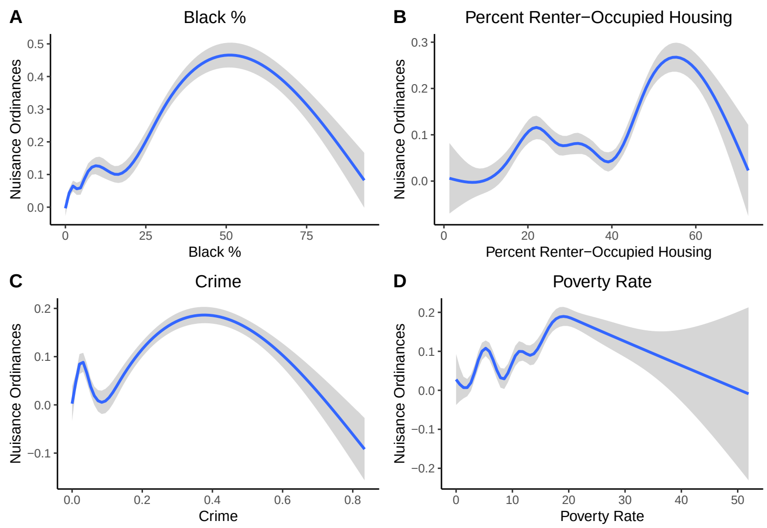
In sum, the preliminary evidence points to a few features of the data. First, we should care how we model the data in terms of monotonicity. As Figure 4 shows, there is a positive relationship between the Black share of the population and the emergence of CANOs. But this strictly linear and monotone relationship fails to capture the raw data as shown in the raw data (See Figure 3). Second, by allowing for the slope to change directions, like shown in Figure 5, we can better fit 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 is 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 100k is on the x-axis. Lastly, in Panel D, the poverty rate is on the x-axis. All four city characteristics of cities 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 is 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 100k is on the x-axis. Lastly, 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 CANO. 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 rate – and additional covariates (See Table 2 model 2). I find evidence supporting a linear positive relationship between the Black share and CANOs. Turning my attention to the alternative explanations, crime is a significant predictor of CANO emergence. I fail to find evidence that poverty rates and share of renters influence the adoption of CANOs.

Moreover, in Column 3, I include a squared term on Black share 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 Black share and CANO takes on a concave form.[20]

Table 2: Racial Composition and Adoption of CANO

	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 %)ˆ2			−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 criminal activity nuisance ordinance is the dependent variable. Standard errors (clustered by unit/municipality) in parentheses. Column 1 is a bivariate analysis reporting the associations between the Black share of the population and CANO. Column 2 includes covariates and alternative hypotheses. Column 3 is a bivariate analysis reporting the associations between Black share squared and CANO. 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.

[20]In the appendix, I compare the fit of both models (Table 2 Columns 2 and 4). Using an 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

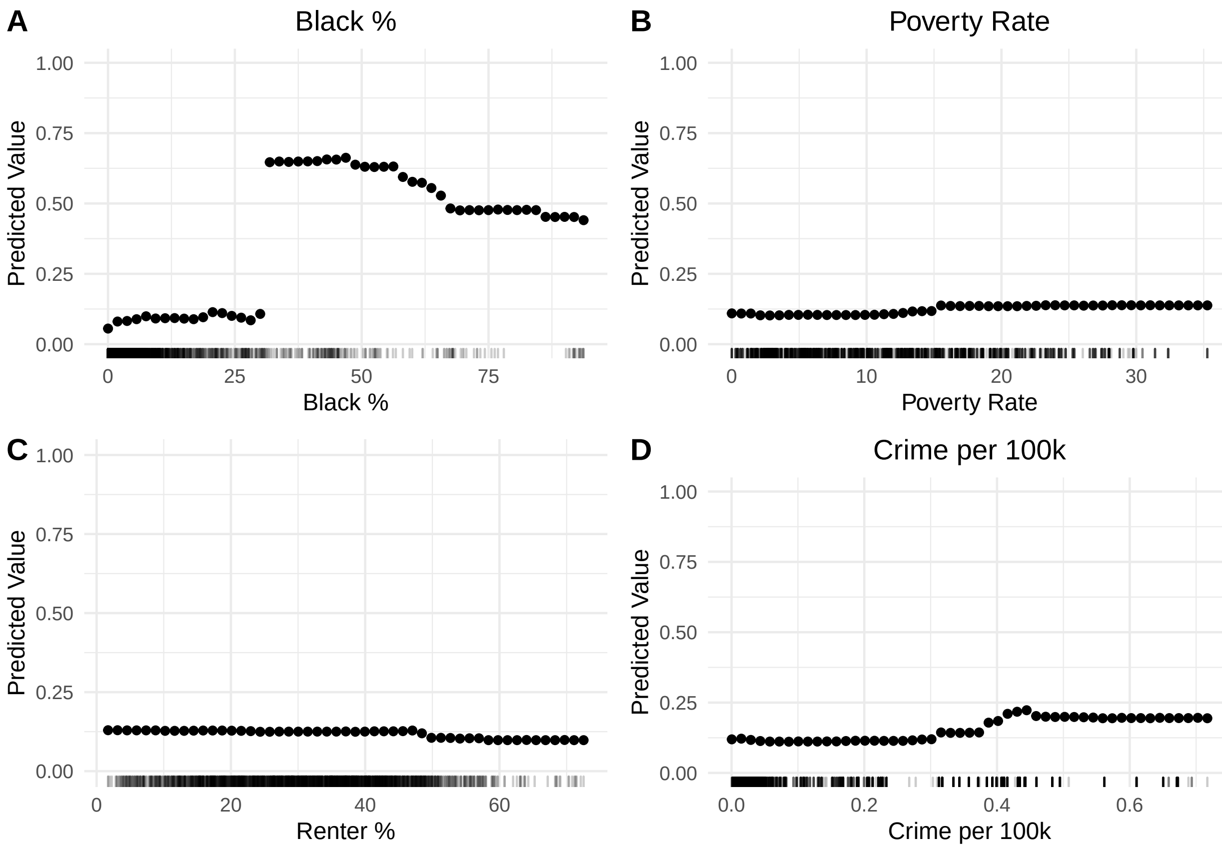
I use Random Forests as a non-parametric approach to detect non-linear and discontinuous effects of between Black share and CANO adoption. This approach is ideal because the literature on racial threat hypothesis posits this non-linearity (Blalock, 1967; Carmichael and Kent, 2014; Chamlin, 2009).

Figure 6 depicts the partial dependence plot the expected effect that the Black share of the population, poverty rate, renter share, and crime per 100k has on CANO emergence. Consistent with general expectations, when the Black share is below 30%, the predicted CANO adoption is relatively low (See Panel A).[21] When the Black share of the population reaches 30%, a clear discontinuity occurs and the predicted values increases to 62%. The average above 30% Black share of the population is around 55%. After 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 Panel B - D (Figure 6), I show predicted values of the alternative explanations. The propensity to adopt a CANO are relatively flat and none of the propensity 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 renter 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 share is contributing most of the predictive power. To verify this finding, I assess each variable's importance.

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

Figure 6: Partial Dependence Plot



Notes: PDPs of Black share of the population (Panel A), poverty rate (Panel B), % renter (Panel C), and Crime (Panel D). The plot shows a clear discontinuity around 30% Black share of the population where predicted values increase from 12% to over 50%. Once the share of Black population reached 50%, the predicted value decreases. All other predicted values for alternative explanation are below 25%.

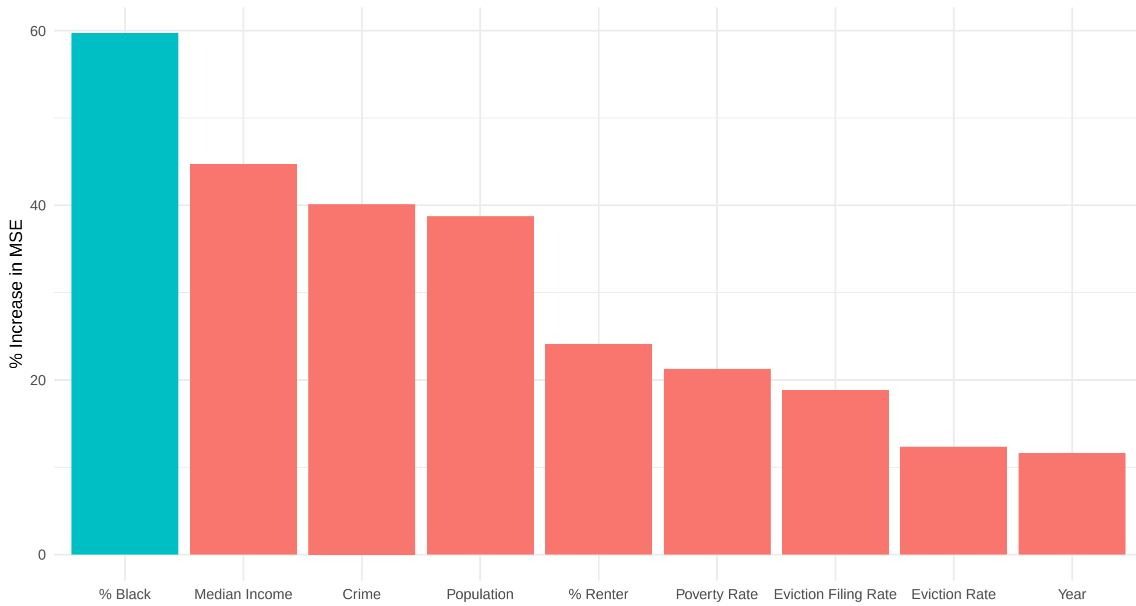
7.3.2 Variable Importance

I use out-of-bag variable importance to determine the relative predictive accuracy of competing hypothesis: Black share, renter share, crime, and poverty rate.[22] The algorithm uses the rates of how well the model predict 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 the variable for prediction purposes. As

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

Figure 7: Variable Importance



Notes: Variable importance plot. Each variable is ordered by percent increase in mean squared error. The share of Blacks in a locality is the most important variable in predicting criminal activity nuisance ordinances.

shown in Figure 7, permuting the Black share of the population variable in the model increases mean squared error by around 60%. Thus, the predictions become almost 60% worse without this variable. Permuting crime increases mean squared error by 38%. Similarly, renter share of population and poverty increases 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 emergence of criminal activity nuisance ordinance. In this section, I briefly examine the extent that the emergence of

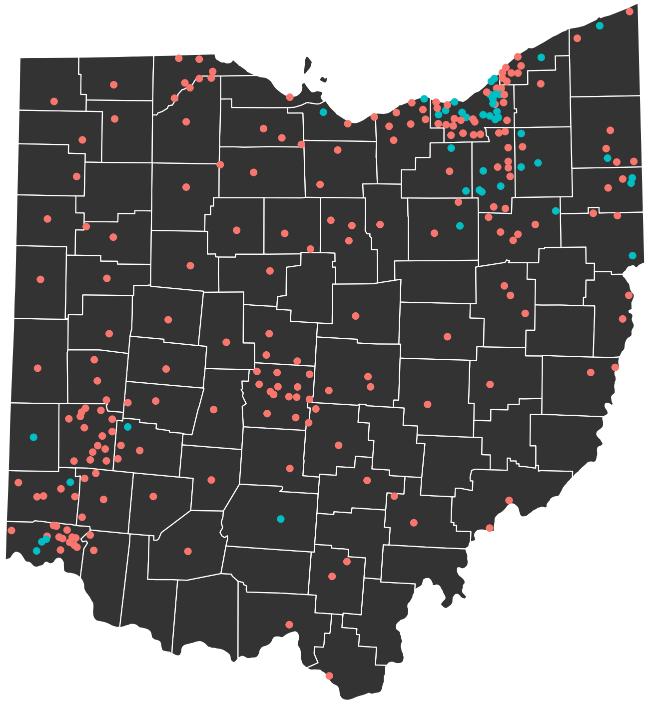
CANOs is associated with their nearest neighbor adoption pattern. In Figure 8, I show all of the municipalities in the sample and indicate whether a CANO exist in them signified by a blue dot in the last year of the time frame. The figure shows clear evidence of clustering.[23] That is to say, most of the CANOs emerge together either around Cuyahoga County (the upper right around 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 *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 substantive 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, rentership, and poverty continue to have no estimable association.

[23]See Appendix D for a discussion about spatial autocorrelation. In sum, 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 Ohio and CANOs



Notes: Depicts a map of Ohio municipalities. Each dot corresponds to a municipality in the sample. A blue dot indicates a CANO exists in that municipality. A red dot indicates a CANO does not exist in the municipality. 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: Adoption of criminal activity nuisance ordinance is the dependent variable. Standard errors (clustered by unit/municipality) in parentheses. Column 1 is a bivariate analysis reporting the associations between Black share of 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 shown up across the United States. Criminal activity nuisance ordinances – one of many discriminatory policies – have previously been shown to disproportionately harm people of color, victims of violence, and people of low income. 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 substantively high to be seen by the majority as threatening. This occurs between 30% and 50%. Consistent with expectation, I also find that the relationship decreases after 50%. Future research should establish why this pattern occurs. One potential reason is that the minority community is able to stop discriminatory policies through representation (i.e., 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 criminal activity nuisance ordinances in Ohio municipalities. Second, I add nuance to the theory insofar as we now have a guide about where and when discriminatory policies should emerge. Future research can use this guide to search for additional discriminatory policies as we start to build large dataset on the local level. Examining policies of cities that are "racially threatened" – or between 30-50% Black – may be a starting point.

While I argue, in this study, that the racial threat hypothesis explains the emergence of a particular discriminatory housing policies, future research should assess the extent to which this pattern of CANOs generalizes beyond Ohio municipalities. Data has limited the exploration of CANOs nationwide, but compiling a nation-wide dataset of this matter will be fruitful for academic research and have policy implications for legal practitioners. Furthermore, researcher should turn our attention towards how local governments and their ordinances may lead to entrenchment of racial and economic inequality. While much of the research has focused on land use and zoning, 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 struggling to manage a multiracial democracy.

References

Acharya, Avidit, Matthew Blackwell and Maya Sen. 2016. "The political legacy of American slavery." *The Journal of Politics* 78(3):621–641.

Acharya, Avidit, Matthew Blackwell and Maya Sen. 2018. Deep roots. In *Deep Roots*. Princeton University Press.

Archer, Deborah N. 2019. "The housing segregation: the jim crow effects of crime-free housing ordinances." *Mich. L. Rev.* 118:173.

Blalock, Hubert M. 1967. *Toward a theory of minority-group relations*. Vol. 325 New York: Wiley.

Blauner, Bob and Robert Blauner. 1972. *Racial oppression in America*. HarperCollins College Division.

Blumer, Herbert. 1958. "Race prejudice as a sense of group position." *Pacific sociological review* 1(1):3–7.

Bobo, Lawrence. 2004. Group conflict, prejudice and the paradox of contemporary racial attitudes. In *Political psychology*. Psychology Press pp. 333–357.

Bobo, Lawrence and Vincent L Hutchings. 1996. "Perceptions of racial group competition: Extending Blumer's theory of group position to a multiracial social context." *American sociological review* pp. 951–972.

Bonica, Adam. 2018. "Inferring roll-call scores from campaign contributions using supervised machine learning." *American Journal of Political Science* 62(4):830–848.

Cafri, Guy and Barbara A Bailey. 2016. "Understanding variable effects from black box prediction: Quantifying effects in tree ensembles using partial dependence." *Journal of*

Data Science 14(1):67–95.

Carmichael, Jason T. 2010. "Sentencing disparities for juvenile offenders sentenced to adult prisons: An individual and contextual analysis." *Journal of Criminal Justice* 38(4):747–757.

Carmichael, Jason T and Giovani Burgos. 2012. "Sentencing juvenile offenders to life in prison: The political sociology of juvenile punishment." *American Journal of Criminal Justice* 37(4):602–629.

Carmichael, Jason T and Stephanie L Kent. 2014. "The persistent significance of racial and economic inequality on the size of municipal police forces in the United States, 1980–2010." *Social Problems* 61(2):259–282.

Chamlin, Mitchell B. 2009. "Threat to whom? Conflict, consensus, and social control." *Deviant behavior* 30(6):539–559.

Cranmer, Skyler J and Bruce A Desmarais. 2017. "What can we learn from predictive modeling?" *Political Analysis* 25(2):145–166.

Crawford, Charles, Ted Chiricos and Gary Kleck. 1998. "Race, racial threat, and sentencing of habitual offenders." *Criminology* 36(3):481–512.

Desmond, Matthew and Nicol Valdez. 2013. "Unpolicing the urban poor: Consequences of third-party policing for inner-city women." *American sociological review* 78(1):117–141.

Eric Oliver, J and Janelle Wong. 2003. "Intergroup prejudice in multiethnic settings." *American journal of political science* 47(4):567–582.

Friedman, Jerome, Trevor Hastie, Robert Tibshirani et al. 2001. *The elements of statistical learning*. Vol. 1 Springer series in statistics New York.

Funk, Kendall D, Hannah L Paul and Andrew Q Philips. 2021. "Point break: using machine learning to uncover a critical mass in women's representation." *Political Science Research and Methods* pp. 1–19.

Greenwell, Brandon M. 2017. "pdp: An R package for constructing partial dependence plots." *R J.* 9(1):421.

Griffin, John D and Brian Newman. 2007. "The unequal representation of Latinos and whites." *The Journal of Politics* 69(4):1032–1046.

Hill, Daniel W and Zachary M Jones. 2014. "An empirical evaluation of explanations for state repression." *American Political Science Review* 108(3):661–687.

Hopkins, Daniel J. 2010. "Politicized places: Explaining where and when immigrants provoke local opposition." *American political science review* 104(1):40–60.

Huff, C Ronald and John M Stahura. 1980. "Police employment and suburban crime." *Criminology* 17(4):461–470.

Jackson, Pamela Irving and Leo Carroll. 1981. "Race and the war on crime: The sociopolitical determinants of municipal police expenditures in 90 non-southern US cities." *American Sociological Review* pp. 290–305.

Kaufman, Aaron Russell, Peter Kraft and Maya Sen. 2019. "Improving supreme court forecasting using boosted decision trees." *Political Analysis* 27(3):381–387.

Kent, Stephanie L and David Jacobs. 2005. "Minority threat and police strength from 1980 to 2000: A fixed-effects analysis of nonlinear and interactive effects in large US cities." *Criminology* 43(3):731–760.

Key, Valdimer O. 1949. *Southern politics*.

Kroeger, Sarah and Giulia La Mattina. 2020. Do Nuisance Ordinances Increase Eviction Risk? In *AEA Papers and Proceedings*. Vol. 110 pp. 452–56.

Lepley, Michael and Lenore Mangiarelli. 2018. "The State of Fair Housing in Northeast Ohio.".

Liska, Allen E and Mitchell B Chamlin. 1984. "Social structure and crime control among macrosocial units." *American journal of sociology* 90(2):383–395.

Mead, Joseph, Megan Hatch, J Rosie Tighe, Marissa Pappas, Kristi Andrasik and Elizabeth Bonham. 2017. "Who is a nuisance? Criminal activity nuisance ordinances in Ohio." *Urban Publications* .

Montgomery, Jacob M and Santiago Olivella. 2018. "Tree-Based Models for Political Science

Data." *American Journal of Political Science* 62(3):729–744.

Montgomery, Jacob M, Santiago Olivella, Joshua D Potter and Brian F Crisp. 2015. "An informed forensics approach to detecting vote irregularities." *Political Analysis* 23(4):488–505.

Muchlinski, David, David Siroky, Jingrui He and Matthew Kocher. 2016. "Comparing random forest with logistic regression for predicting class-imbalanced civil war onset data." *Political Analysis* 24(1):87–103.

Oliver, J Eric and Tali Mendelberg. 2000. "Reconsidering the environmental determinants of white racial attitudes." *American journal of political science* pp. 574–589.

Orey, Byron D'Andra, L Marvin Overby, Peter K Hatemi and Baodong Liu. 2011. "White support for racial referenda in the Deep South." *Politics & Policy* 39(4):539–558.

Preuhs, Robert R. 2006. "The conditional effects of minority descriptive representation: Black legislators and policy influence in the American states." *The Journal of Politics* 68(3):585–599.

Preuhs, Robert R. 2007. "Descriptive representation as a mechanism to mitigate policy backlash: Latino incorporation and welfare policy in the American states." *Political Research Quarterly* 60(2):277–292.

Siroky, David S. 2009. "Navigating random forests and related advances in algorithmic modeling." *Statistics Surveys* 3:147–163.

Stewart, Brandon M and Yuri M Zhukov. 2009. "Use of force and civil–military relations in Russia: An automated content analysis." *Small Wars & Insurgencies* 20(2):319–343.

Stolzenberg, Lisa, Stewart J D'Alessio and David Eitle. 2004. "A multilevel test of racial threat theory." *Criminology* 42(3):673–698.

Stucky, Thomas D. 2005. "Local politics and police strength." *Justice quarterly* 22(2):139–169.

Tolbert, Caroline J and John A Grummel. 2003. "Revisiting the racial threat hypothesis: White voter support for California's Proposition 209." *State Politics & Policy Quarterly* pp. 183–202.

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, % renter, poverty rate, median household income, eviction filing rate, eviction rate, and logged population. 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, % renter, poverty rate, median household income, eviction filing rate, eviction rate, and logged population. The tables show the model with the polynomial terms on Black percent of the population provides a better parsimonious fit of the data.

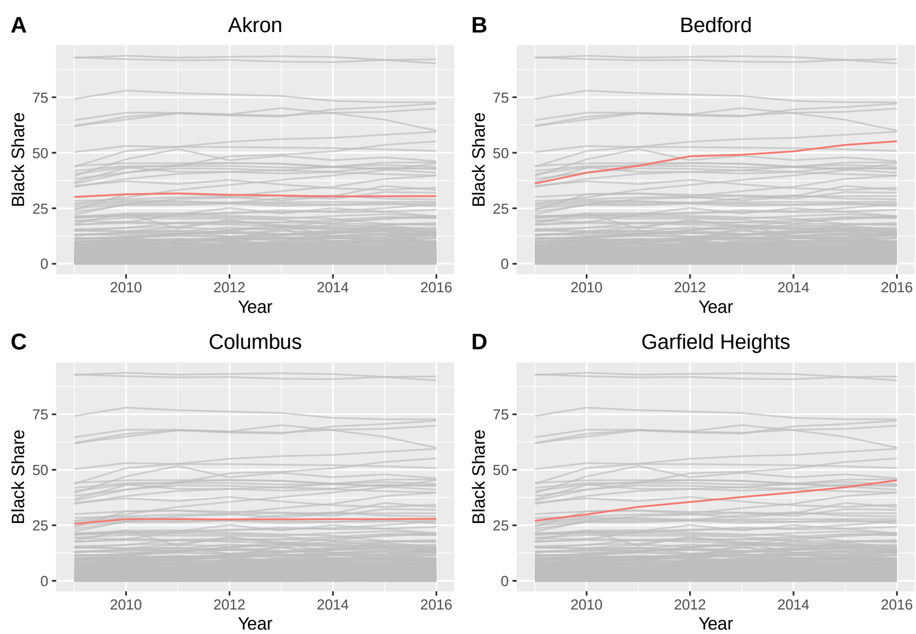
*p<0.1; **p<0.05; ***p<0.01.

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 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 tend to have little variation over time, like the vast majority of the cities. The city of Bedford and Garfield Heights show a modest increase in the Black share of the population. I highlight these two cities because they have the largest changes over my sample.

Figure 9: Little to No Variation at the Longitudinal Level



Notes: Depicts how Black Share of the population varies over time. Each line represents a different city. The x-axis shows years, while the y-axis shows 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 a 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, Black share of the population is insignificant. Given the lack of variation, I interpret these null findings as a lack of variation, and not 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	
	(1)	(2)
black share	−0.002	−0.001
	(0.007)	(0.007)
I(black share^2)	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 of understanding variation in the data is by examining the how much of the variation in the independent variable is left to be explained after fixed effects. In Table 7, I fit 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 others 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.

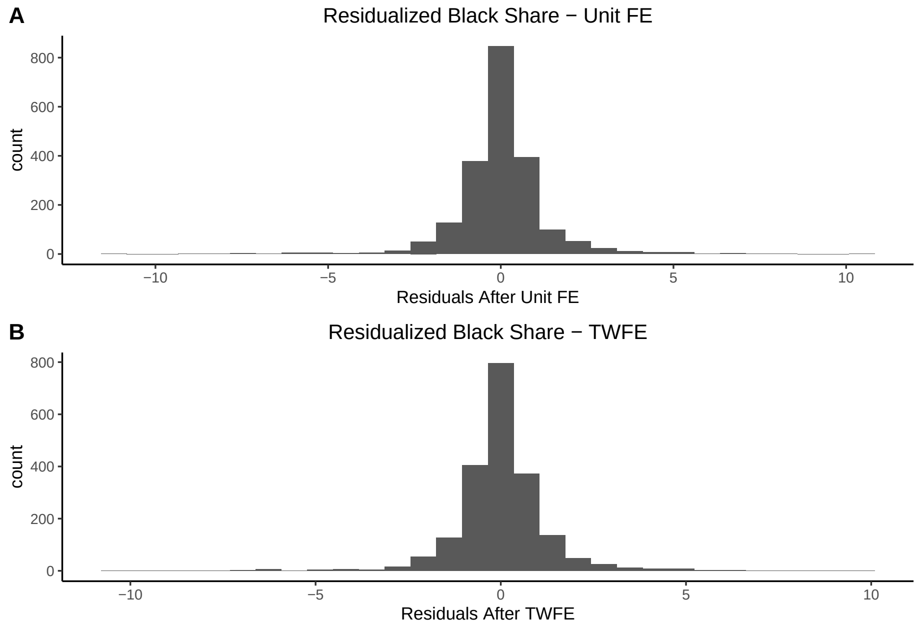
Lastly, an alternative way of viewing issues about variation is by examining the residuals of each model in Table 7. The typical shift in Black share for the two-way fixed effect model is 1.28, for unit fixed effects it is 1.35, and for the time fixed effect models it is 15.32.

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

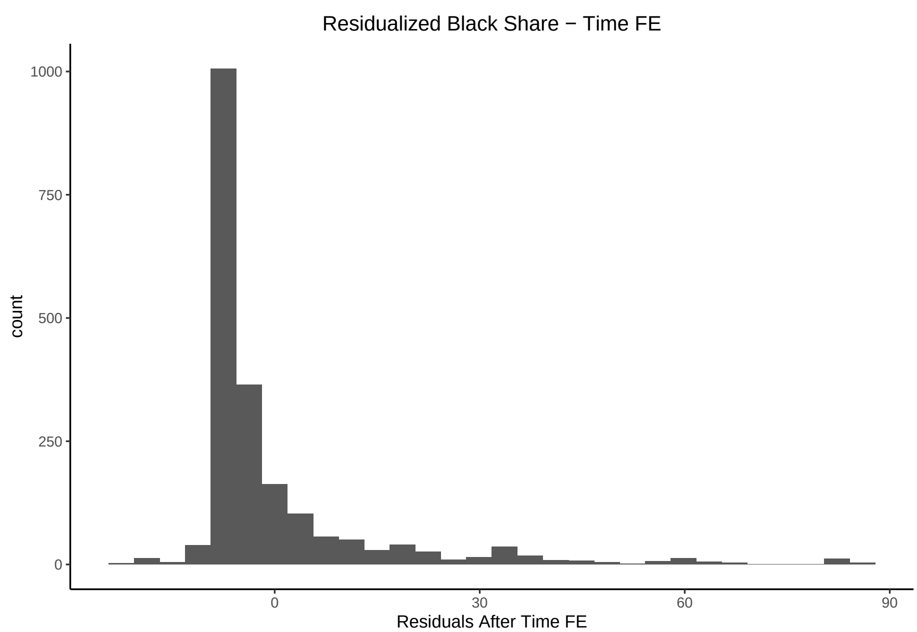
Note: *p<0.1; **p<0.05; ***p<0.01

Figure 10: TWFE and Unit Residual



Notes: Depicts a histogram of 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 share is 1.35 and 1.28 for unit and two-way fixed effect, respectively.

Figure 11: Time Residual



Notes: Depicts a histogram of residualized Black share of the population after time fixed effects. The typical shift in between unit variation 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 effect are used to adjust for between-county difference. 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 analysis not shown, I estimated the 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 clustering geographically as a smooth function. The racial threat hypothesis still holds (See Table 10).

Table 9: Racial Composition on Adoption of CANO, 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 Adoption of CANO, 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 School District Report Cards.[24] Each school district is given a letter grade (A-F).[25] I use this letter grade in two ways: ordered and as a factor.

In Table 11, I include the letter grade as an ordered features such that higher scores are between and lower scores are worse. In 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. In Columns 3 and 4, I include the rest of the covariates. Across all models the racial threat hypothesis remains in the expected pattern and statistically significant.

[24] `https://reportcard.education.ohio.gov/`

[25] For further detail, please refer to the 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 CANO, with school quality

	Dependent variable:			
	CANO_1			
	(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)	
gradeD		0.426***		0.385***
		(0.127)		(0.117)
gradeC		0.436***		0.370***
		(0.132)		(0.129)
gradeB		0.382***		0.292*
		(0.134)		(0.155)
gradeA		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