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Evidence from the 287(g) Program in North Carolina

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Abstract

The 287(g) program enables local law enforcement agencies to enforce federal immigration laws. We examine 287(g)'s implementation across multiple counties in North Carolina and identify its impact on local crime rates and police clearance rates by exploiting time variation in regional immigration enforcement trends. We find no causal relationship between apprehensions through the 287(g) program and measures of crime rates or police clearances. However, we do find a significant relationship between the activation of 287(g) agreements and assaults against police officers. The 287(g) program did not affect the crime rate in North Carolina or police clearance rates but it did boost the number of assaults against police officers.

Keywords: 287(g) Program, Interior Immigration Enforcement
JEL Codes: K14, K37, K42, J18

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1 Introduction

There is a common public perception that immigrants commit more crimes than native-born Americans despite vast empirical evidence to the contrary (Adelman, Reid, Markle, Weiss, and Jaret 2017; Green 2016; Lee and Martinez 2009; Mears 2001; Ousey and Kubrin 2018). Congress has responded to public opinion by creating federal immigration enforcement programs to assist local and state police in the identification and removal of illegal immigrants in the hope of also reducing crime rates (Kandel 2016). There is little research investigating whether federal immigration enforcement programs affect violent and property crime rates, research that is essential to judge whether they are a worthwhile expenditure of scarce law enforcement resources (Miles and Cox 2014).

We investigate how the federal immigration program 287(g) affected violent and property crimes rates in the state of North Carolina. The 287(g) program is named after §287(g) of the Immigration and Nationality Act (INA). 287(g) permits state and local law enforcement agencies (LEAs) to investigate, apprehend, and detain illegal immigrants after receiving training by the Department of Homeland Security (DHS) (Kandel 2016). Local police officers with 287(g) training have access to federal immigration databases, can hold illegal immigrants for deportation, and produce court appearance documents for deportation proceedings (Kandel 2016). By September 2012, 71 jurisdictions participated in 287(g) task force agreements that allowed police to arrest people solely on suspicion that they violated federal immigration law (Outten-Mills 2012). President Barack Obama canceled many 287(g) agreements that empowered local police at the end of 2012 (Rosenberg and Levinson 2017). Recently, President Trump reactivated the program in January 2017 and requested DHS to participate in more 287(g) agreements (Rhodan 2017). As of April 2018, 76 jurisdictions participated in the reinstated 287(g) program.[1]

In order to participate in 287(g) programs, local jurisdictions must sign a memorandum of agreement (MOA) with DHS that sets the parameters of cooperation (U.S. Immigration and Customs Enforcement n.d.-a). There are three different types of 287(g) MOAs. The first are 287(g) jail enforcement agreements that allow local police to enforce federal immigration laws in jails and prisons by screening and identifying inmates who can be deported. The second are 287(g) task force agreements that deputize police officers to arrest illegal immigrants upon contact (Kandel 2016). The third are hybrid 287(g) MOAs that combine both jail and task force agreements. In all three agreements, the LEA bears virtually all of the costs of enforcing 287(g) MOAs. President Obama canceled the task force agreements at the end of 2012.

This paper focuses on measuring how 287(g) agreements affected crime rates in participating counties relative to other North Carolina counties that did not participate in the program. The effect of 287(g) task force agreements on crime rates is difficult to discover because police departments must voluntarily join the program, introducing significant endogeneity. To address this concern, we adopt an instrumental variables strategy in line with the work of Bove and Gavrilova (2017), who construct an instrument to exploit time variation in aggregate military spending to explain variability in federal military equipment aid to local LEAs. Accordingly, we identify variation in crime rates attributable to the 287(g) program by interacting exogenous time variation in Immigration and Customs Enforcement (ICE) deportation operations within the Atlanta Area of Responsibility (AOR) with an indicator for an active 287(g) MOA as a proxy for the likelihood of 287(g) program participation. This specification allows us to compare counties within regions

[1] See `https://www.ice.gov/287g`.

of high immigration–related enforcement activity. To test a proposed linkage between the 287(g) program and crime rates, we use a panel of yearly observations for the state of North Carolina, including index crime rates, demographic characteristics, and economic indicators. We provide further insight into how interior immigration enforcement and changes in incentives affect police production functions that, in turn, affect clearance rates.

2 Background and Literature Survey

Congress created the 287(g) program, which is named after §287(g) of the Immigration and Nationality Act, in 1996 as part of the Illegal Immigration Reform and Immigrant Responsibility Act. 287(g) permits local and state LEAs to sign a memorandum of agreement (MOA) with DHS to enforce federal immigration law. LEAs that sign the MOA then receive federal training in the investigation, apprehension, and detention of illegal immigrants. The federal government also monitors how LEAs enforce immigration laws to guarantee that they comply with the terms of the MOA.

There are three types of 287(g) MOAs: jail enforcement agreements, task force agreements, and hybrid agreements that include both jail enforcement and task force agreements. The most common 287(g) MOAs are jail enforcement agreements whereby specially trained officers within state and local correctional facilities identify criminal aliens in their custody through interviews and biometric information checks against DHS databases. The local correctional officers then identify illegal immigrants and detain them for deportation (Kandel 2016). As of January 2012, the government maintained 287(g) jail enforcement MOAs with 60 law enforcement agencies in 18 different states (U.S. Immigration and Customs Enforcement n.d.-a). Although 287(g) corrections operations are restricted to jails on paper, counties were able to subvert these restrictions. A specific example of this took place in Alamance County, North Carolina, in which state troopers requested assistance from the Alamance County Sheriff's 287(g) deputies who were trained in corrections operations after pulling over a bus destined for Mexico (United States. Cong. House. Committee on Homeland Security 2009). Despite being deputized officially under a corrections MOA, 287(g) sheriff's deputies conducted immigration-related enforcement activities and summoned ICE agents to arrest five of the passengers (United States. Cong. House. Committee on Homeland Security 2009).

The second type of 287(g) MOA is a task force agreement that allows deputized local law enforcement officers to question and arrest illegal immigrants because of a suspected violation of federal immigration law (Kandel 2016). In late 2012, President Barack Obama ordered all 287(g) task force agreements to expire at the end of that year while the jail enforcement agreements would continue (Kandel 2016). State governments can also sign MOAs for state-wide police to participate in 287(g) but they are not very active compared to local LEAs. Local LEAs that participate in 287(g) are responsible for more than 15 times as many arrests of illegal immigrants that lead to deportation than state agencies that also participate in the program. A full 93.9 percent of those deported under 287(g) task force agreements were arrested by local LEAs while state-wide police agencies are responsible for a mere 6.1 percent of all illegal immigrants removed under this program (U.S. Immigration and Customs Enforcement 2010).

The Secure Communities program overlapped with 287(g) agreements in North Carolina. Secure Communities is a universal and automated screening system that uses existing criminal background checks to immediately run an arrested individual's identity against federal government databases to identify illegal immigrants. If the arrested individual's fingerprints are flagged by DHS as likely belonging to an illegal immigrant, then the federal government issues a detainer that requests the local LEA to hold him for 48 hours beyond their scheduled release so that ICE can take custody for deportation. This also includes arrested illegal immigrants who were not charged with or convicted of crimes.

The federal government intended to roll out Secure Communities on a county-by-county basis beginning in October-2008 (U.S. Immigration and Customs Enforcement n.d.-c). About 97 percent of counties participated in Secure Communities by the Fall 2012 (Rosenblum and Kandel 2012). Once enrolled, counties could not back out of the program or otherwise diminish their participation except by refusing to fingerprint arrestees, an option that no police departments exercised (Cox and Posner 2012). President Barack Obama suspended Secure Communities in November 2014 (U.S. Immigration and Customs Enforcement n.d.-b).

At its peak in 2012, the 287(g) program had 71 signed MOAs in over 25 states. However, not every 287(g) program was implemented in the same way. A 2009 study by the Government Accountability Office (GAO) found significant disparities in program implementation across 29 surveyed agencies due to limited guidance and oversight from ICE (Government Accountability Office [GAO] 2009). To isolate how the 287(g) program affected crime and clearance rates, we focus on its implementation in the state of North Carolina.[2] Focusing on North Carolina provides numerous advantages over looking at other states or the nation as a whole along two dimensions: empirical concerns of simultaneity between other programs in other states and the nature of 287(g) program implementation among North Carolina counties.

North Carolina law and its geographic location allow us to avoid numerous potential avenues of cross-correlation between other federal and state immigration enforcement programs. North Carolina's geographic position as a non-border state vastly reduces contamination by removing most federal law enforcement agency operations by the Customs and Border Patrol (CBP) in border states. Border states are more likely to face negative crime outcomes from transnational criminal organizations that are distinct but empirically impossible to disentangle from illegal immigrants. Similarly, North Carolina is free of additional, overarching state-level immigration enforcement laws that may be correlated with, and thus impede, our identification of any effects of the 287(g) program.[3] Accordingly, North Carolina allows us to evaluate 287(g) solely as an interior enforcement program without issues of simultaneity arising from other contemporaneous enforcement activity through state-level legislation or federal enforcement operations along the border.

According to ICE, the 287(g) program's intent was "to increase the safety and security of our communities by apprehending and removing undocumented criminal aliens who are involved in violent and serious crimes" (United States. Cong. House. Committee on Homeland Security 2009). This objective of crime reduction is echoed by Mecklenburg County, North Carolina sheriff Jim Pendergraph, who describes his office's participation in 287(g) as a response to "the lack of [Congressional] action on the illegal immigration issue for decades, leaving those of us responsible for local law enforcement to deal with not only the fall-out of the criminal element, but the ire of the public for their perception of our inaction on a Federal issue" (United States. Cong. House. Committee on Government Reform, Subcommittee on Criminal Justice, Drug Policy, and Human Resources 2006). Similarly, Gaston County sheriff Alan Cloninger notes the aim of his office's enrollment in 287(g) was "for the protection of the citizens of Gaston County" (United States. Cong. House. Committee on Government Reform, Subcommittee on Criminal Justice, Drug Policy, and Human

[2] See Nguyen and Gill (2010) and Nguyen and Gill (2016).

[3] Of states with local 287(g) agreements, states with overarching state-level policies include: Alabama (HB 56), Arizona (SB 1070), Georgia (HB 87), South Carolina (SB 20), and Utah (HB 497).

Resources 2006).

The actual implementation of 287(g) in North Carolina bore little resemblance to the anti-crime objectives of its proponents. A study by the North Carolina ACLU in 2009 examined arrest data in Alamance and Mecklenburg Counties and found that local enforcement disproportionately targeted individuals for traffic violations based on race and nationality. Further investigation into the 287(g) program by Nguyen and Gill (2010) found that other LEAs with 287(g) agreements in North Carolina showed a similar pattern and found no association between 287(g) enforcement and crime rates.

Considering all of these factors, North Carolina presents an excellent target to empirically evaluate the 287(g)'s effect on crime and clearance rates without cross-contamination from other coexisting state and federal immigration enforcement programs.

Social scientists have studied immigrant impacts on criminality for more than a century and have generally found that immigration is negatively associated with crime (Mears 2001; Reid, Markle, Weiss, and Jaret 2017; Green 2016; Lee and Martinez 2009; Ousey and Kubrin 2018). This general finding holds whether it comes from measuring how local crime rates change as a result of immigrants moving to an area (Spenkuch 2012) or their rate of incarceration (Ewing, Martinez, and Rumbaut 2015). A minor strand of the empirical literature seeks to explain how immigration enforcement programs, especially those intended to remove criminal immigrants, affect crime. Immigration enforcement programs like 287(g) could affect crime rates by removing criminal immigrants, altering police allocation of anti-crime resources, reducing immigrant cooperation with law enforcement, or through myriad other dynamic effects that are poorly understood.

There are few articles that estimate how immigration enforcement schemes affect crime rates although several document the proliferation of such policies over the last few decades (Sklansky 2012). The earliest article to estimate the effect of immigration enforcement programs on crime rates found no relationship between violent crime rates and deportations in metropolitan areas (Stowell, Messner, Barton, and Raffalovich 2013).

Two other articles used the rollout of the Secure Communities program, an immigration enforcement scheme whereby local police use federal databases to identify and turn over arrested illegal immigrants to federal immigration enforcement officers, and found that local involvement had no effect on monthly-interpolated county level crime rates (Cox and Miles 2013; Miles and Cox 2014). The rollout of Secure Communities appears to be a quasi-natural experiment because the federal government activated it on a county-by-county basis beginning in October 2008 (U.S. Immigration and Customs Enforcement 2009) and every month after then until about 97 percent were expelled by Fall 2012 (Rosenblum and Kandel 2012, 18). According to Cox and Miles (2013) and Miles and Cox (2014), the federal government chose which counties would participate and, once enrolled, they could not back out of the program or otherwise diminish their participation except by refusing to fingerprint arrestees, an option that no police departments exercised (Cox and Posner 2012). However, the federal government first rolled out Secure Communities in counties bordering Mexico and others with high immigrant populations, which calls into question the claim that it was a true quasi-natural experiment (U.S. Immigration and Customs Enforcement 2009, 10). There are no journal articles that estimate how the 287(g) program affected crime rates.

3 Methodology

We use a panel of annual county-level crime and demographic data for the state of North Carolina from 2003–2013. Each county-year cell contains various demographic, economic, and crime-related data for each of North Carolina's 100 counties throughout the sample, comprising a panel of 1,100 observations. Population and demographic characteristics are sourced from intercensal population estimates from SEER (Surveillance, Epidemiology, and End Results Program).[4] To supplement demographic data, we use yearly economic data on poverty rates from the Census Bureau's Small Area Income and Poverty Estimates (SAIPE) program and unemployment rates and median household income from the Bureau of Labor Statistics Local Area Unemployment Statistics (LAUS) files.

Data on county crimes, arrests, and police agency characteristics come from the FBI Uniform Crime Reports (UCR) county-level files and Law Enforcement Officers Killed and Assaulted (LEOKA) agency-level files.[5] The county-level crime data files are published by the Inter-university Consortium for Political and Social Research (ICPSR) and cleaned by the National Archive of Criminal Justice Data (NACJD), accounting for jurisdictional overlap, missing values, and other irregularities present in the agency level crime files. The UCR files break down the major crime indexes into the individual violent crimes (murder, rape, assault, and robbery) and property crimes (larceny, burglary, and motor vehicle theft).[6] From the LEOKA files, we obtain data on the number of sworn officers and civilian employees, the number of assaults on police officers under multiple circumstances (including assaults during traffic stops, disturbance calls, and ambushes), and the number of officers killed.

As an indicator of 287(g) program participation and activity, we acquire data on the number of deportations pursuant to 287(g) in North Carolina from ICE FOIA requests over the span of 2003-2013.[7] These data indicate the number of individuals identified and removed pursuant to 287(g) for each 287(g) county in each year. Additionally, we identify the dates of 287(g) MOA activation and program type from the original MOA documents available on the ICE website. Since counties that enroll in the 287(g) program must first receive training for deputized officers, we consider the actual start date for each program as the year in which the program makes arrests. These data and dates of activation are presented in Appendix Table A1.

Summary statistics for the above variables are listed in Table 1. Within our sample, the average county in North Carolina contains approximately 92,066 individuals, of which 21 percent are African American, 5.9 percent are Hispanic, and 6.7 percent are young males between the ages 15-25. In addition, the average county has a median household income of \$39,313, an unemployment rate of 8.1 percent, and a poverty rate of nearly 17.6 percent. With respect to criminal activity, North Carolina experienced downward trending crime rates over our sample period, aligning with similar national trends, as shown for corrections, task force, and other non-287(g) counties in Figure 2. Throughout our sample period, the average county in

[4]These data are available on the NBER website and are published by the National Cancer Institute and the National Institutes of Health.

[5]The UCR files are widely used in both economic and criminology research; see Bove and Gavrilova (2017), Harris, Park, Bruce, and Murray (2017), Chalfin and McCrary (2013), and Miles and Cox (2014) among others.

[6]Throughout this paper, crime rates are reported as the rate of crime per 100,000 residents and clearance rates are reported as the ratio of arrests per 100 crimes.

[7]ICE publishes 287(g) removals data up to 2011. To extend our sample to 2013 we use additional FOIA data acquired from `https://www.muckrock.com/foi/united-states-of-america-10/ice-deportation-statistics-through-287g-for-fy2014-fy2015-and-fy2016-34719/`.

North Carolina experiences 3,290 crimes per 100,000 residents, of which 302 are violent crimes and 2,988 are property crimes. Of these crimes, the most frequent crime is larceny theft, constituting an average of 1,830 larcenies per 100,000 residents. Finally, the average North Carolina police force contains 2,837 sworn officers and 1,259 civilian employees.

For our empirical analyses, we consider the following fixed effects specification,

$$Y_{it} = \alpha_i + \phi_t + \delta R_{it} + \mathbf{X}'_{it}\beta + \varepsilon_{it} \tag{1}$$

where Y_{it} is the natural log of the index crime rate and R_{it} is the natural log of the number of 287(g) removals in county i in year t.[8] $\mathbf{X}_{it}$ is a vector of controls listed in Table 1 and were chosen to align with prior studies. α_i represents a set of county fixed effects to control for county-specific factors affecting index crime rates, i.e. a county's geographic positioning, and ϕ_t is a set of year fixed effects to absorb yearly trends in crime rates and variation from the incremental adoption of Secure Communities. We are interested in the coefficient estimate δ, which indicates the elasticity between the removal of illegal immigrants and the index crime rate.

Since counties must apply to join the 287(g) program, our coefficient of interest δ is likely to be biased as a result of endogenous selection into the program. To combat endogeneity concerns, we adopt an identification strategy similar to Nunn and Qian (2014) and Bove and Gavrilova (2017), in which we examine exogenous variation in regional ICE removal operations. Since ICE regional removal operations only vary by time and therefore collinear with the time fixed effects, we interact ICE removals with a county's participation in the 287(g) program. This implies the first stage regression,

$$R_{it} = \alpha_i^2 + \phi_t^2 + \gamma\left(Removals_t \otimes \frac{1}{11}\sum_{t=2003}^{2013}\left[R_{it}^T \; R_{it}^J\right]'\right) + \mathbf{X}'_{it}\beta + \eta_{it} \tag{2}$$

where $Removals_t$ is the number of ICE arrests in the Atlanta AOR and R_{it}^T and R_{it}^J are the number of removals pursuant to 287(g) for task force and corrections model counties, respectively. This procedure creates two sources of identifying variation, particularly variation in whether 287(g) counties with outstanding MOAs actually participate in the removal process and the overall extent of regional ICE operations in a given year. First, this strategy captures variation with respect to the probability of county participation in immigration enforcement. Nunn and Qian (2014) and Bove and Gavrilova (2017) note that this methodology generates a positive covariance between the instrument and dependent variable in the first stage; however, including county-level fixed effects absorb this probability factor. Accordingly, we are left with variation in regional ICE removal operation trends to explain the differential adoption and participation in 287(g) agreements in North Carolina. We are thus able to compare counties that actively participate in immigration law enforcement relative to others.[9] This strategy is based on the assumption that, conditional on other factors, the instrument relates to crime rates only through 287(g) program enforcement – trends in regional ICE removals relate to North Carolina crime rates only through their relation to the 287(g) programs. This condition would be violated if North Carolina counties contributed significantly to total regional trends

[8]Similar to Miles and Cox (2014), when crime rates or removals are equal to 0, we add one to the crime rate to avoid taking the natural logarithm of zero.

[9]This method allows us to assign greater weight to counties that began 287(g) operations earlier and therefore contribute more to removal operations.

within the Atlanta AOR.[10] Figure 1 indicates that removals under 287(g) in North Carolina represent a very small fraction of the overall yearly removal operations by ICE's Atlanta AOR. Finally, we compute clustered standard errors in each specification to ensure proper statistical inference in the presence of serially correlated county crime rates.

4 Results

In this section, we present empirical results describing the relation of 287(g) removals, local crime rates, and police outcome metrics. Each specification for crime and clearance rates estimates the elasticity between immigrant deportations under 287(g) programs and crime rates per $100,000$ residents or clearance rates per 100 crimes. Using these results, we asses whether local immigration enforcement operations translate into lower overall crime rates or higher rates of clearances by arrest. Further, we examine individual police outcome metrics, including the number of police officers and employees in a county and the circumstances under which officers were assaulted. On a visual basis, Figure 3 shows the relation between crime rate and 287(g) deportations among counties with 287(g) MOAs, indicating no clear relationship between crime rates and immigrant removals. Considering these factors on an empirical basis, we determine whether the removal of illegal immigrants through the 287(g) program translated into public safety benefits.

4.1 Did 287(g) Agreements Help Fight Crime?

Tables 2 and 3 present estimates for the effect of 287(g) program participation on North Carolina counties. For each specification we report the Kleibergen-Paap F-statistic for weak instruments, which is adjusted for clustering in standard errors. We find F-statistics of 78.83 for reported crime and clearance rates and of 20.25 for policing outcomes, both exceeding levels indicative of weak instruments. With two instruments we have one overidentifying restriction to test, for which we compute Hansen's J-test and report its p-value for each specification. Large p-values in each test fail to reject the joint null hypothesis that our instruments are valid – i.e. the overidentifying restrictions are valid.

Column 1 of Table 2 presents OLS estimates for the relative change in the total county crime rate during the 287(g) program, indicating no significant relationship between 287(g) removals and the total crime rate. Since this estimate is likely to suffer from endogeneity, we implement an instrumental variables approach in Columns 2 through 4. Similarly, we find no statistically significant impact of 287(g) program participation on either violent or property crime rates. In particular, Column 4 indicates no significant effect of a percentage increase in 287(g) removals on violent crime rates – a stated goal of 287(g) agreement participation by both federal, state, and local LEA officials.[11]

Although these estimates suggest that 287(g) removals do not impact aggregate index crime rates, we further examine crime rates for individual crimes. The results, presented in Table 3, indicate no significant elasticity between the 287(g) deportations and individual index crime rates. In sum, these results suggest that immigration enforcement under 287(g) is statistically unrelated to changes in crime rates – removals under

[10] We examine whether overarching ICE immigration law enforcement activity is correlated with local crime rates in the Appendix. We regress crime rates on Atlanta AOR removals and our control set. Results for these regressions are presented in Appendix Table A2 and indicate no correlation between Atlanta AOR removals and crime rates.

[11] See and United States. Cong. House. Committee on Government Reform, Subcommittee on Criminal Justice, Drug Policy, and Human Resources (2006) United States. Cong. House. Committee on Homeland Security (2009).

287(g) did not translate into lower crime rates for North Carolina counties. Given the prior justifications for 287(g) programs as a means to assist law enforcement to reduce violent crime, no statistical change in violent crime rates associated with 287(g) removals suggests that this goal was not achieved.

4.2 How Did 287(g) Agreements Impact Policing Activity?

To obtain a clear view of the 287(g) program and crime, we shift our attention to various policing outcome metrics. First, we consider the rate at which local law enforcement is able to clear reported crimes by arrest. Clearance rates are a common way to measure police efficiency, as an increase in the number of arrests per crime indicate more successful policing efforts. Thus, examining clearance rates allow us to gauge whether police agencies within a 287(g) county were more efficient at performing law enforcement activity.

Using the sample instrumental variables strategy, Table 4 presents estimates of 287(g) participation on crime clearance rates as an indicator of policing activity and effectiveness. With respect to aggregated crime clearance indexes, presented in Columns 1 through 3 of Table 4, we find a similar non-result: 287(g) programs had no statistically significant impact on total clearance rates. Shifting our attention to individual clearance rates, as shown in Columns 4 through 9 of Table 4, we similarly estimate no significant elasticity between crime rates and immigrant removals through the 287(g) program. Overall, no significant changes in clearance rates associated with 287(g) removals indicate no relationship between the removal of immigrants and police efficacy.

Second, we consider whether 287(g) program participation had any effect on the size of police departments and assaults committed against officers. Table 5 assesses the degree to which 287(g) programs impacted law enforcement agencies themselves. Columns 1 through 3 present estimates for changes in police department employment as a result of 287(g) participation. Of these estimates, Columns 1 and 2 indicate no statistically significant changes in average police department size within 287(g) counties – either in terms of the number of sworn officers and civilians employed by law enforcement.

In addition to county police composition, we also consider whether the 287(g) program had an impact on hostility to police, as proxied by assaults on police officers. Nguyen and Gill (2010) note that surveyed immigrant communities in North Carolina developed distrust of local law enforcement, leading to their under-reporting of crime among immigrant communities and a decrease in cooperation with authorities after they implemented 287(g) programs. Accordingly, we examine whether this sense of distrust translated into aggression against police and the contexts in which aggression may occur.

First, we find a significant uptick in the average number of assaults against officers with nearly 5 additional assaults in 287(g) counties, as shown in Column 5 of Table 5. This estimated increase in police assaults associated with 287(g) removals suggests that noncooperation and distrust increased between the public and police agencies. Further, we examine the individual contexts of assaults against police officers. We estimate an increase of one assault during disturbance calls being associated with a percentage point increase in the number of 287(g) deportations.

Our estimates further suggest that local immigration enforcement operations have no impact on either violent or property crime rates, which means that the 287(g) program did not fulfill its original intent to assist local law enforcement to fight crime.

5 Robustness Tests

In this section we perform multiple robustness tests to further validate our results. We first consider an alternate specification of our instrument. Second, we consider the potential for geographic spillovers in crime rates. Third, we examine dynamic panel specifications for crime and clearance rates. Fourth, we assess the sensitivity of our results to our set of chosen controls using the LASSO model selection framework. Finally, we use alternative model specifications.

5.1 Alternate Instrument Specifications

To examine the sensitivity of our estimates to the specification of our instrument, we consider two additional methods to construct an instrument for 287(g) removals. First, we consider the simple case of an indicator variable equal to one in counties with an active 287(g) MOA. Under this specification, each county with a 287(g) agreement is weighted equally relative to other 287(g) counties.

Additionally, we consider the number of individuals deported from each county . We obtain data for the recorded number of immigration court cases by county from the Transactional Records Access Clearinghouse (TRAC) at Syracuse University, which indicates the number of individuals deported by federal immigration courts by county. These data are based on the count of individuals tried for immigration law violations in federal immigration court, in which an individual was sentenced to deportation. Since orders of deportation do not necessarily imply deportation, this measure effectively serves as an upper bound for the number of potential immigrant deportations through immigration enforcement programs in North Carolina.

Using these two instrument specifications, we construct two comparable instruments for 287(g) removal operations. These procedures consider different aspects of immigration law enforcement that are still related to removal operations through the 287(g) program. First, we consider a scheme that weights each 287(g) county equally – regardless of the extent of its participation in 287(g) removal operations. Second, we consider another estimate for the number of immigrants deported in North Carolina, similar to a split-sample instrumental variable strategy that considers two uncorrelated measures of an outcome.[12] Using these two additional measures of immigration enforcement, consider the modified first stage,

$$R_{it} = \alpha_i^2 + \phi_t^2 + \gamma\bigg(Removals_t \otimes \frac{1}{11}\sum_{t=2003}^{2013}\left[I_{it}^T\ I_{it}^J\right]'\bigg) + \mathbf{X}_{it}'\beta + \eta_{it} \tag{3}$$

where I_{it}^T and I_{it}^J are indicators of immigration enforcement activity. In the case of 287(g) MOA activation, these variables become indicators equal to one if county i posesses an active 287(g) agreement in year t. In the latter case of court-ordered deportations, this variable reflects the total count of immigrants withdeportation ordered issued in county i in year t. These new indicator of 278(g) participation act as catch-all indicators, making no distinction of the scale of 287(g) removal operations, only the presence of immigration enforcement activity. Using these alternate first stage, we estimate Model 1 and present results in Panels A and B of Table 6. For each specification, we report the Kleibergen-Paap F-statistic for weak instruments, whose value of 69.84 exceeds thresholds that indicate weak instruments. Similarly, large p-values for Hansen's

[12]This methodology assumes two separate measures of immigrant enforcement operations that are assumed to be independently measured. Since the TRAC data series on immigration-court-related deportation orders is collected independently through FOIA request, we have reason to believe that ICE deportation counts pursuant to 287(g) and the number of court-ordered deportations are measured independently.

J-test fail to reject the joint null of valid instruments.

Under these new instrument specifications we similarly find no significant relationship between the number of 287(g) program deportations and the major index crime rates. Furthermore, each point estimate for the elasticity between crime rates and illegal immigrant removals is comparable to IV estimates presented in Tables 2 and 3. This robustness check indicates no statistically significant change in crime rates associated with the removal of illegal immigrants after allowing for each 287(g) county to be considered equally, regardless of their scale of participation in the 287(g) program.

5.2 Examining Spatial Dependency in Crime Rates

Immigrant mobility is one concern from any analysis of the 287(g) program's impact on crime. In Gary Becker's (1968) model, potential criminal offenders weigh the utility of committing an offense relative to the disutility of punishment (Becker 1968). Accordingly, we can expect a similar decision-making process for potential criminal offenders who are immigrants, in which disutility associated with punishment is augmented by local immigration law enforcement. Facing deportation in addition to any criminal sentence could induce an illegal immigrant to commit crimes in counties without 287(g) programs. Nguyen and Gill (2010) describe the degree to which immigrant communities—both legal and illegal—were aware of the 287(g) program and its potential consequences. We therefore examine the possibility for spatial relationships in crime rates to assess the possibility of spillover effects in crime rates. To conduct this test, we consider the spatial regression specification,

$$Y_{it} = \rho \mathbf{W} Y_{it} + \alpha_i + \phi_t + \delta R_{it} + \mathbf{X}'_{it}\beta + \varepsilon_{it} \tag{4}$$

where $\mathbf{W}$ is a row standardized spatial weighting matrix. Each $w_{ij} \in \mathbf{W}$ represents the degree of connectivity between counties i and j for all $i \neq j$. We define this matrix to represent direct contiguity between counties, with w_{ij} entries equal to one if county i shares a border with county j and zero otherwise.[13] Each row of this spatial weighting matrix is then standardized to sum to one, implying that the spatially-lagged crime rate for county i is a weighted average of crime rates in neighboring counties. We then estimate equation 4 with our instruments for 287(g) removals and include instruments for spatially lagged independent variables using generalized method of moments (GMM).

We present results for these spatial regressions in Panel B of Table 6. Once again, we find no significant relationship between 287(g) enforcement and crime indexes. Furthermore, numerous specifications produce low Kleibergen-Paap F-statistics that are indicative of weak instruments. In particular, only specifications for the violent crime index, aggravated assaults, and vehicle thefts yield F-statistics that surpass thresholds for weak instruments. Combined with statistically insignificant estimates for ρ in each specification, we find no evidence for spatial dependency for crime rates, conditional on other factors. This result therefore suggests that a spillover effect for crime rates due to the 287(g) program is unlikely, given no evidence for spatial dependency in crime rates.

[13] We defined county contiguity based on the county adjacency file from the U.S. Census Bureau, available at `https://www.census.gov/geo/reference/county-adjacency.html`.

5.3 Log-Log Model Specification

In addition to IV regressions, we also consider a basic log-log specification to estimate the elasticity of illegal immigrant removals on local crime rates. This basic specification is equivalent to estimating equation 1 using OLS. Results for these log-log models are presented in Panel C of Table 6. Comparing these results to those presented in Tables 2 and 3, we find a similar pattern with respect to both the magnitude of our elasticity estimates and their statistical insignificance. These results further indicate no relationship between illegal immigrant removals and improvements in public safety.

5.4 Sensitivity to Covariates

We also consider the sensitivity of our results to changes in our control set. For these purposes, we utilize the LASSO model selection framework of Tibshirani (1996) according to the double selection framework of Belloni, Chernozhukov, and Hansen (2014). This procedure allows us to narrow down our control set by eliminating potentially redundant regressors from our model specifications. Results for these LASSO specifications are listed in Table 7 and tell a story similar to Tables 2 and 3 with results similar in both statistical insignificance and magnitude.

This procedure involves three steps: first, we run a LASSO regression for each dependent variable with the entire control set included; second, we run a LASSO regression of our covariate set on 287(g) removals to capture correlation between our control variables and our variable of interest. We then drop variables with zero coefficients in either stage from the control set and use them as regressors in a third step IV regression. The λ for each first step LASSO regression is presented in the third row of Panels A and B underneath the results for IV regressions carried out in step two. Panel A reports IV estimates for the elasticity of crime rates to 287(g) removals using covariates selected by LASSO, in which only covariates are penalized. Panel B reports similar elasticity estimates; however, we allow time fixed effects to be penalized. In each case, results are very similar to those presented in Tables 2 and 3.

5.5 Alternate Model Specifications

In addition, we consider two different model specifications to examine the relationship between 287(g) removals and crime rates. First, we consider the time series persistence of crime rates using dynamic panel models of Arellano and Bover (1995) and Blundell and Bond (1998), in which we include temporally lagged crime rates as covariates. We then estimate the elasticity of 287(g) deportations to crime rates while controlling for lagged crime rates using the ArellanoBover/BlundellBond estimator to avoid bias in our estimates resulting from the inclusion of a lagged dependent variable. Results for these estimates are presented in Table 8 for crime and clearance rates and indicate a similar pattern of insignificance compared to their IV regression counterparts in Tables 2, 3, and 4.

6 Conclusion

President Trump's reactivation of 287(g) task force agreements has prompted us to evaluate how this program has affected crime rates and police clearance rates in the past. We find that the 287(g) program had no causal effect on total crime rates, conditional on numerous factors related to the incidence of crime.

We find no statistically significant elasticity between immigrants deported through the 287(g) program and the index crime rates under multiple specifications. Similarly, we find no significant elasticity between crime clearance rates and 287(g) deportations. Combined, these results demonstrate that the 287(g) program did not reduce crime in North Carolina.

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Figures

Figure 1: ICE Deportations, Atlanta AOR and NC 287(g)

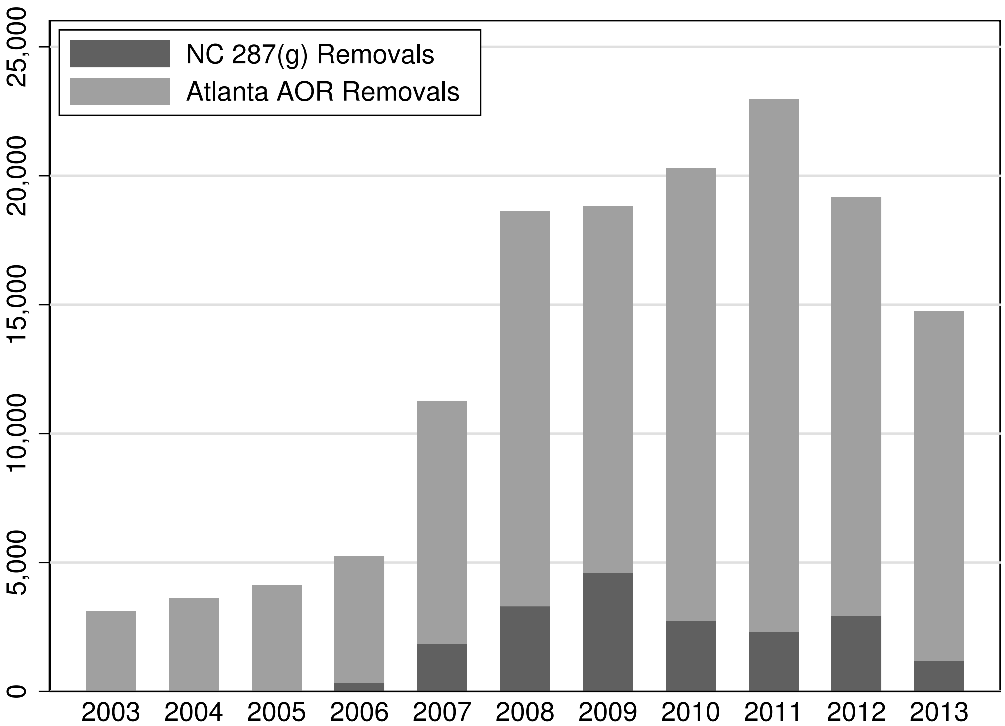


Figure 2: Average Crime Rates in North Carolina

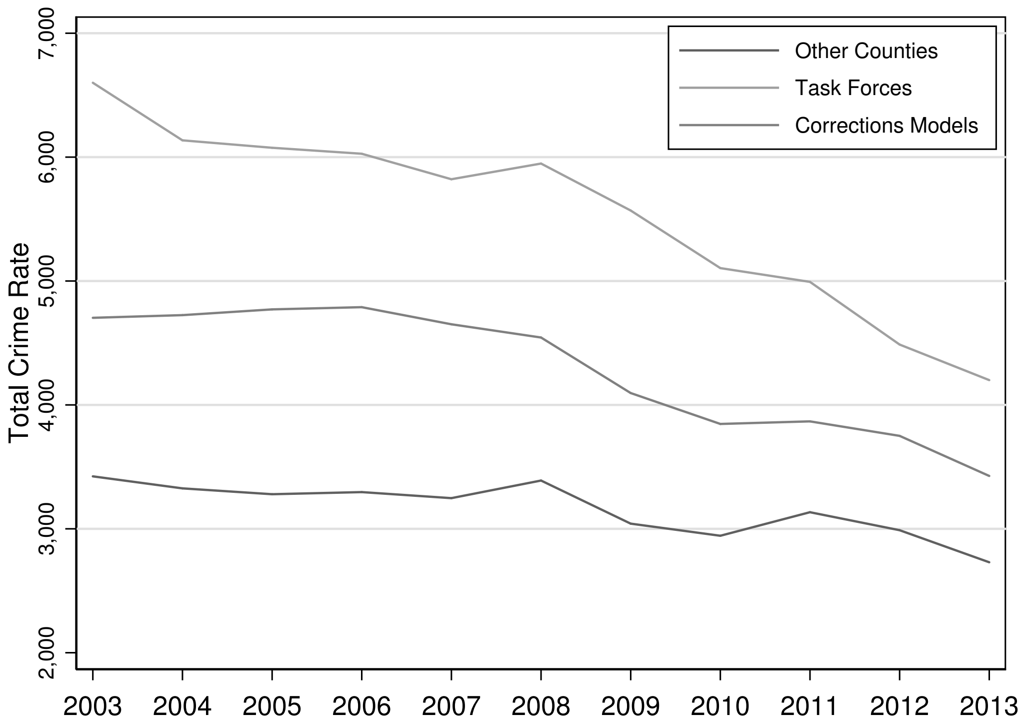
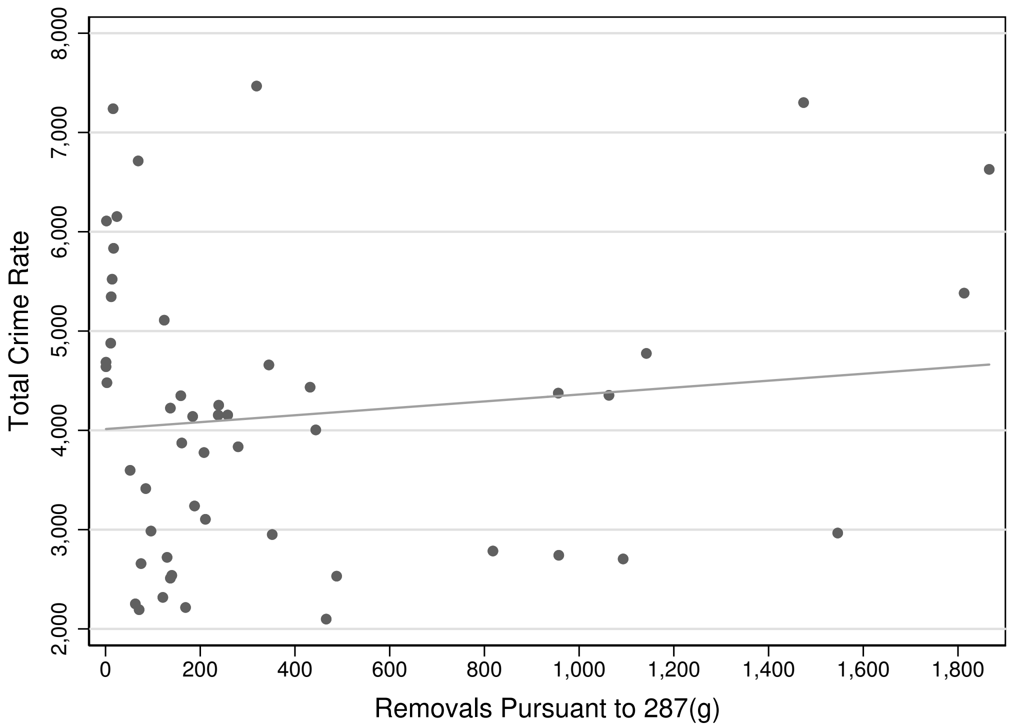


Figure 3: §287(g) Deportations and Crime Rates



Tables

Table 1: Summary Statistics for Counties

Variable	Mean	Std. Dev.	Min.	Max.	N
County Characteristics					
Population	92,066	134,702	4,101	991,322	1,100
Fraction black, %	21.14	16.626	0.226	62.875	1,100
Fraction Hispanic, %	5.923	3.642	0.955	20.96	1,100
Unemployment rate, %	8.101	3.061	2.9	18.1	1,100
All Ages in Poverty, %	17.623	4.856	7.8	34.7	1,100
Median Household Income ($)	39,312.60	7,158.28	25,843	65,487	1,100
Fraction Ages 15-19, %	6.286	2.666	3.708	22.672	1100
Fraction Ages 20-24, %	5.716	1.108	3.568	11.452	1100
Fraction Ages 25-29, %	6.066	0.977	3.828	9.504	1100
Fraction Ages 30-34, %	6.5	0.903	4.273	9.079	1100
Reported Crime Rates per 100,000 Pop.					
All Crimes	3,290.147	1,550.29	0	8,457.870	1,100
Violent Crimes	302.25	187.702	0	1,036.433	1,100
Property Crimes	2,987.897	1,392.18	0	7,767.431	1,100
Murders	5.266	5.463	0	46.631	1,100
Rapes	20.008	12.701	0	98.81	1,100
Robberies	69.934	67.763	0	471.766	1,100
Aggr. Assaults	207.042	128.907	0	875.787	1,100
Burglaries	988.215	489.257	0	2,837.006	1,100
Larcenies	1,830.692	889.562	0	5,005.678	1,100
Vehicle Thefts	168.99	110.062	0	933.14	1100
Clearance Rates per 100 Crimes					
All Crimes	34.751	49.553	0	814.286	1,100
Violent Crimes	113.206	189.497	0	2,600	1,100
Property Crimes	28.227	42.067	0	760	1,100
Murders	123.722	178.678	0	2,900	1,100
Rapes	45.545	54.387	0	900	1,100
Robberies	69.559	85.574	0	900	1,100
Aggr. Assaults	124.852	208.206	0	2,800	1,100
Burglaries	34.491	108.044	0	2,000	1,100
Larcenies	29.518	37.001	0	750	1,100
Vehicle Thefts	17.311	25.453	0	500	1,100
Police Agency Characteristics					
Sworn Officers	2,837.335	5,810.838	84	50,148	1,100
Civilian Employees	1,259.422	3,074.077	0	25,200	1,100
Officer to Civilian Ratio	3.244	2.933	0	30	1,100
Total Killed	0.026	0.205	0	3	1,100
Total Assaults	171.824	80.554	58	638	1,100

Notes: Table presents summary statistics for North Carolina counties from 2003-2013. Demographic and economic characteristics data are sourced from SEER, BLS, and SAIPE. Crime and police force data are sourced from the FBI.

Table 2: Impact of 287(g) Programs, Total Crime Rates

	OLS	*IV*		
	Crime	Crime	Property	Violent
Log(287g Removals)	-0.042	-0.034	-0.033	-0.029
	(0.033)	(0.032)	(0.032)	(0.025)
Observations	1,100	1,100	1,100	1,100
Kleibergen-Paap F-statistic	.	78.830	78.830	78.830
Hansen J-test P-value	.	0.406	0.423	0.324

Notes: The dependent variable is the log index crime rate per $100,000$ residents listed in each column header. Each specification includes controls for population; the fraction of African Americans, Hispanics, ages 15-19, 20-24, 25-29, and 30-34; unemployment and poverty rates; median household income; and the number of sworn police officers. Median household income, population, and officer counts are expressed as natural logs. Specifications also include county and year fixed effects. Standard errors are clustered by county and presented in parentheses. Significance codes are: * $p < 0.05$, ** $p < 0.01$.

Table 3: Impact of 287(g) Programs on Crime, Individual Crime Rates

	Violent Crime				*Property Crime*		
	Murder	Rape	Aggr. Assault	Robbery	Larceny	Burglary	Vehicle Theft
Log(287g Removals)	-0.029	-0.027	-0.027	-0.010	-0.021	-0.038	-0.012
	(0.021)	(0.025)	(0.022)	(0.023)	(0.030)	(0.028)	(0.026)
Observations	1,100	1,100	1,100	1,100	1,100	1,100	1,100
Kleibergen-Paap F-statistic	78.830	78.830	78.830	78.830	78.830	78.830	78.830
Hansen J-test P-value	0.328	0.837	0.292	0.311	0.528	0.315	0.578

Notes: The dependent variable is the log index crime rate per $100,000$ residents listed in each column header. Each specification includes controls for population; the fraction of African Americans, Hispanics, ages 15-19, 20-24, 25-29, and 30-34; unemployment and poverty rates; median household income; and the number of sworn police officers. Median household income, population, and officer counts are expressed as natural logs. Specifications also include county and year fixed effects. Standard errors are clustered by county and presented in parentheses.
Significance codes are: * $p < 0.05$, ** $p < 0.01$.

Table 4: Impact of 287(g) Programs on Crime, Index Clearance Rates per 100 Crimes

	Total Crime			*Violent Crime*				*Property Crime*		
	Crime	Property	Violent	Murder	Rape	Aggr. Assault	Robbery	Larceny	Burglary	Vehicle Theft
Log(287g Removals)	-0.000	0.001	0.019	0.044	0.034	0.012	-0.037	-0.004	0.013	-0.011
	(0.024)	(0.024)	(0.028)	(0.057)	(0.038)	(0.025)	(0.033)	(0.024)	(0.030)	(0.035)
Observations	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100
Kleibergen-Paap F-statistic	78.830	78.830	78.830	78.830	78.830	78.830	78.830	78.830	78.830	78.830
Hansen J-test P-value	0.854	0.784	0.681	0.841	0.336	0.449	0.885	0.783	0.684	0.256

Notes: The dependent variable is the log index clearance rate per 100 crimes listed in each column header. Each specification includes controls for population; the fraction of African Americans, Hispanics, ages 15-19, 20-24, 25-29, and 30-34; unemployment and poverty rates; median household income; and the number of sworn police officers. Median household income, population, and officer counts are expressed as natural logs. Specifications also include county and year fixed effects. Standard errors are clustered by county and presented in parentheses.
Significance codes are: * $p < 0.05$, ** $p < 0.01$.

Table 5: Impact of 287(g) Programs on Crime, Police Outcomes

	Police Forces			*Assaults on Police*				
	Officers	Civilian Employees	Officers to Civilians	Killed	Assaulted	Ambushes	Traffic Pursuits	Disturbance Calls
Log(287g Removals)	1.006	12.844	0.034	0.104	5.343**	-0.044	0.344*	1.439**
	(3.357)	(8.853)	(0.038)	(0.073)	(1.180)	(0.079)	(0.148)	(0.333)
Observations	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100
Kleibergen-Paap F-statistic	20.250	20.250	20.250	20.250	20.250	20.250	20.250	20.250
Hansen J-test P-value	0.596	0.395	0.311	0.526	0.282	0.401	0.702	0.258

Notes: The dependent variable is the police outcome metric listed in each column header. Each specification includes controls for population; the fraction of African Americans, Hispanics, ages 15-19, 20-24, 25-29, and 30-34; unemployment and poverty rates; median household income; and the number of sworn police officers. Median household income, population, and officer counts are expressed as natural logs. Specifications also include county and year fixed effects. Standard errors are clustered by county and presented in parentheses.
Significance codes are: * $p < 0.05$, ** $p < 0.01$.

Table 6: Impact of 287(g) Programs on Crime, Robustness Checks

	Total Crime			*Violent Crime*				*Property Crime*		
	Crime	Property	Violent	Murder	Rape	Aggr. Assault	Robbery	Larceny	Burglary	Vehicle Theft
					Panel A. Alternate IV Specification					
Log(287g Removals)	-0.044	-0.043	-0.045	-0.025	-0.021	-0.040	-0.034	-0.033	-0.053	-0.021
	(0.029)	(0.029)	(0.027)	(0.019)	(0.024)	(0.025)	(0.027)	(0.027)	(0.029)	(0.028)
Observations	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100
Kleibergen-Paap F-statistic	69.880	69.880	69.880	69.880	69.880	69.880	69.880	69.880	69.880	69.880
Hansen J-test P-value	0.625	0.596	0.872	0.331	0.419	0.416	0.970	0.473	0.960	0.979
					Panel B. Immigration Court Case IV Specification					
Log(287g Removals)	-0.052	-0.050	-0.053	-0.015	-0.018	-0.052	-0.029	-0.040	-0.057	-0.020
	(0.036)	(0.036)	(0.031)	(0.025)	(0.028)	(0.029)	(0.030)	(0.033)	(0.034)	(0.032)
Observations	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100
Kleibergen-Paap F-statistic	43.350	43.350	43.350	43.350	43.350	43.350	43.350	43.350	43.350	43.350
Hansen J-test P-value	0.496	0.479	0.795	0.879	0.304	0.644	0.757	0.405	0.779	0.566
					Panel C. Neighboring County Placebo					
Spatial Lag: $\mathbf{W}y_{it}$	0.025	0.027	0.017	-0.069	0.131	0.002	-0.009	0.006	0.028	0.006
	(0.025)	(0.025)	(0.028)	(0.094)	(0.069)	(0.026)	(0.032)	(0.021)	(0.027)	(0.027)
Log(287g Removals)	-0.024	-0.023	-0.025	-0.022	-0.012	-0.020	-0.015	-0.022	-0.013	-0.003
	(0.016)	(0.016)	(0.014)	(0.018)	(0.014)	(0.016)	(0.011)	(0.015)	(0.015)	(0.020)
Observations	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100
Kleibergen-Paap F-statistic	11.900	11.890	49.110	18.080	11.410	88.600	11.700	12.160	12.570	76.030
Hansen J-test P-value	0.781	0.707	0.974	0.137	0.164	0.503	0.902	0.437	0.883	0.938
					Panel D. Log-Log Specification					
Log(287g Removals)	-0.042	-0.041	-0.033	-0.007	-0.021	-0.023	-0.029	-0.042	-0.035	-0.014
	(0.033)	(0.033)	(0.025)	(0.019)	(0.024)	(0.026)	(0.023)	(0.030)	(0.031)	(0.026)
Observations	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100
Within R-Sq.	0.043	0.043	0.038	0.018	0.012	0.039	0.017	0.058	0.042	0.032

Notes: The dependent variable is the log index crime rate per $100,000$ residents listed in each column header. Each specification includes controls for population; the fraction of African Americans, Hispanics, ages 15-19, 20-24, 25-29, and 30-34; unemployment and poverty rates; median household income; and the number of sworn police officers. Median household income, population, and officer counts are expressed as natural logs. Specifications also include county and year fixed effects. Standard errors are clustered by county and presented in parentheses.
Significance codes are: * $p < 0.05$, ** $p < 0.01$.

Table 7: Impact of 287(g) Programs on Crime, LASSO Selected Covariates

Panel A. Penalize Covariates

	Total Crime			*Violent Crime*				*Property Crime*		
	Crime	Property	Violent	Murder	Rape	Aggr. Assault	Robbery	Larceny	Burglary	Vehicle Theft
Log(287g Removals)	-0.034	-0.032	-0.032	-0.028	-0.027	-0.037	-0.033	-0.051	-0.014	-0.014
	(0.032)	(0.031)	(0.025)	(0.021)	(0.025)	(0.023)	(0.024)	(0.034)	(0.027)	(0.021)
Observations	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100
Kleibergen-Paap F-statistic	83.400	116.850	155.390	105.060	90.840	222.760	172.190	116.700	87.870	162.390
Hansen J-test P-value	0.400	0.616	0.323	0.340	0.803	0.436	0.305	0.454	0.423	0.712
Lambda	0.0042	0.0147	0.0087	0.0203	0.0078	0.0088	0.0092	0.0099	0.0039	0.0082

Panel B. Penalize Covariates and Year FE

	Total Crime			*Violent Crime*				*Property Crime*		
	Crime	Property	Violent	Murder	Rape	Aggr. Assault	Robbery	Larceny	Burglary	Vehicle Theft
Log(287g Removals)	-0.043	-0.055	-0.034	-0.027	-0.026	-0.008	-0.037	-0.057	-0.033	-0.020
	(0.034)	(0.041)	(0.025)	(0.020)	(0.024)	(0.024)	(0.027)	(0.037)	(0.037)	(0.022)
Observations	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100
Kleibergen-Paap F-statistic	338.140	167.680	248.450	100.200	151.530	86.780	165.950	166.800	167.660	93.010
Hansen J-test P-value	0.425	0.644	0.377	0.356	0.939	0.305	0.305	0.375	0.730	0.822
Lambda	0.017	0.0119	0.0066	0.002	0.0051	0.0033	0.0075	0.0131	0.017	0.0044

Notes: The dependent variable is the log index crime rate per $100,000$ residents listed in each column header. Each specification includes controls selected by LASSO. The pool of candidate variables includes population; the fraction of African Americans, Hispanics, ages 15-19, 20-24, 25-29, and 30-34; unemployment and poverty rates; median household income; and the number of sworn police officers. Median household income, population, and officer counts are expressed as natural logs. Specifications also include county and year fixed effects. Standard errors are clustered by county and presented in parentheses. Significance codes are: * $p < 0.05$, ** $p < 0.01$.

Table 8: Impact of 287(g) Programs on Crime, Dynamic Panel Estimates

Panel A. Reported Crime Rates per 100,000

	Total Crime			*Violent Crime*				*Property Crime*		
	Crime	Property	Violent	Murder	Rape	Aggr. Assault	Robbery	Larceny	Burglary	Vehicle Theft
Log(287g Removals)	-0.111	-0.102	-0.060	0.000	-0.050	-0.075	-0.042	-0.029	-0.213	-0.094
	(0.077)	(0.077)	(0.063)	(0.075)	(0.059)	(0.082)	(0.080)	(0.072)	(0.125)	(0.092)
Observations	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000

Panel B. Clearance Rates per 100 Crimes

	Total Crime			*Violent Crime*				*Property Crime*		
	Crime	Property	Violent	Murder	Rape	Aggr. Assault	Robbery	Larceny	Burglary	Vehicle Theft
Log(287g Removals)	-0.036	0.014	-0.027	0.138	-0.202	0.196	-0.125	-0.025	0.035	0.000
	(0.075)	(0.072)	(0.113)	(0.154)	(0.141)	(0.150)	(0.132)	(0.083)	(0.093)	(0.120)
Observations	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000

Notes: The dependent variable is the log index crime rate per 100,000 residents listed in each column header. Each specification includes controls for lagged crime rates, population; the fraction of African Americans, Hispanics, ages 15-19, 20-24, 25-29, and 30-34; unemployment and poverty rates; median household income; and the number of sworn police officers. Median household income, population, and officer counts are expressed as natural logs. Specifications also include county and year fixed effects. Robust Standard errors are presented in parentheses.
Significance codes are: * $p < 0.05$, ** $p < 0.01$.

Appendix

A Additional Tables

In this Appendix section we present removals data through the 287(g) program in North Carolina. Raw data for the number of removals – itemized by county, year, and type of MOA – are presented in A1. The distribution of 287(g) deportations is shown in A1 and show that a majority of 287(g) deportations took place in Mecklenburg and Wake Counties – both of which are corrections enforcement models. Additionally, the two task forces – within the city of Durham and Guilford county – apprehended and removed the fewest immigrants through the 287(g) program.

These data were disseminated by ICE for other individuals' FOIA requests and obtained from two sources:

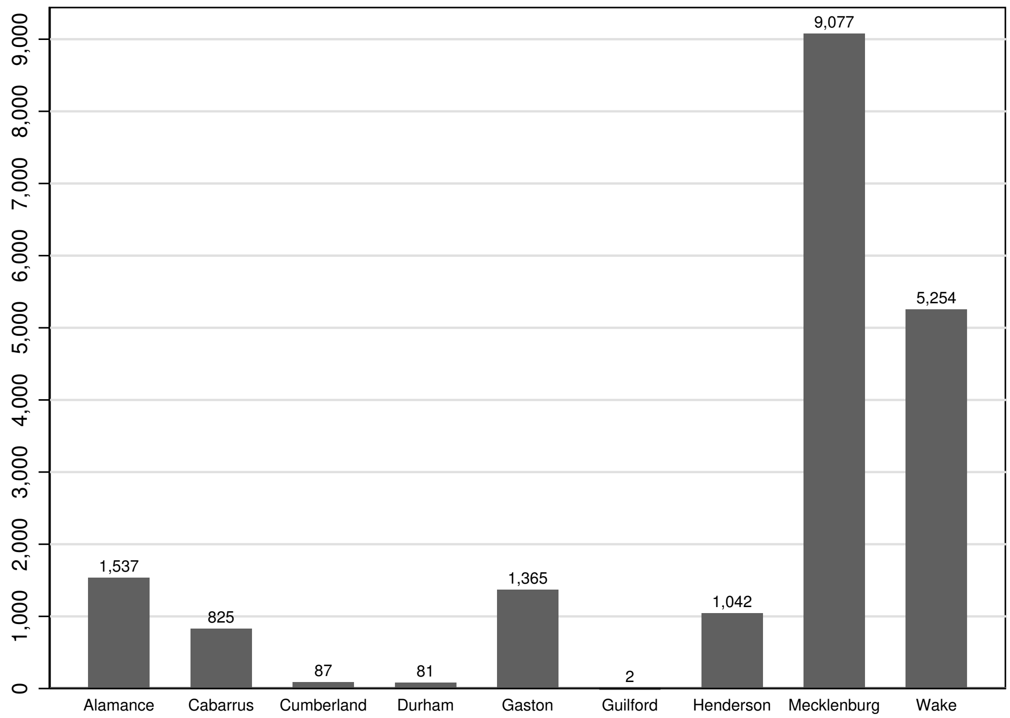
- https://www.ice.gov/foia/library
- https://www.muckrock.com/foi/united-states-of-america-10/ice-deportation-statistics-through-287g-for-fy2014-fy2015-and-fy2016-34719/

Table A1: Removals Pursuant to §287(g) by County

	Corrections Models							*Task Forces*		
Year	Alamance	Cabarrus	Cumberland	Gaston	Henderson	Mecklenburg	Wake	Durham	Guilford	Total
2003	0	0	0	0	0	0	0	0	0	0
2004	0	0	0	0	0	0	0	0	0	0
2005	0	0	0	0	0	0	0	0	0	0
2006	0	0	0	0	0	319	0	0	0	319
2007	238	0	0	124	0	1,474	0	0	0	1,836
2008	432	188	16	345	75	1,866	352	24	0	3,298
2009	239	211	69	258	466	1,813	1,546	17	0	4,619
2010	137	130	2	184	169	1,142	957	14	1	2,736
2011	159	96	0	161	121	956	818	12	1	2,324
2012	280	137	0	208	140	1,063	1,093	11	0	2,932
2013	52	63	0	85	71	444	488	3	0	1,206
Total	1,537	825	87	1,365	1,042	9,077	5,254	81	2	19,270
MOA Signed	1/10/2007	8/2/2007	6/25/2008	2/22/2007	6/25/2008	2/27/2006	6/25/2008	2/1/2008	10/15/2009	

Notes: Table presents the number of ICE removals pursuant to §287(g) by county and year and the date of MOA adoption. Source: ICE

Figure A1: Removals Pursuant to 287(g), by County



B ICE AOR Removals and Crime Rates

Finally, we examine whether ICE AOR removals are correlated with crime rates themselves as an additional examination of the exclusion restriction. We regress each index crime rate on the number of total ICE removals in the Atlanta AOR.[14] To avoid perfect collinearity, we consider only county fixed effects and our chosen set of controls. Results for this specification are presented in Appendix Table A2. We find no statistical significant coefficient estimates associated with ICE AOR removals, indicating no correlation between regional ICE removal trends and local crime rates.

Table A2: Impact of ICE Regional Activity on Crime Rates per 100,000

	Total Crime			*Violent Crime*				*Property Crime*		
	Crime	Property	Violent	Murder	Rape	Aggr. Assault	Robbery	Larceny	Burglary	Vehicle Theft
Removals (in 1,000)	-0.000	0.000	-0.002	0.007	-0.004	-0.003	0.009	0.001	0.001	0.006
	(0.007)	(0.007)	(0.006)	(0.008)	(0.009)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
(0.007)	(0.007)									
Observations	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100	1,100
WithinR-Sq.	0.053	0.052	0.067	0.035	0.034	0.041	0.064	0.051	0.057	0.167

Notes: The dependent variable is the log index crime rate per $100,000$ residents listed in each column header. Each specification includes controls for population; the fraction of African Americans, Hispanics, ages 15-19, 20-24, 25-29, and 30-34; unemployment and poverty rates; median household income; and the number of sworn police officers. Median household income, population, and officer counts are expressed as natural logs. Specifications also include county fixed effects. Standard errors are clustered by county and presented in parentheses.
Significance codes are: * $p < 0.05$, ** $p < 0.01$.

[14] For viewing clarity, we divide these counts by 1,000.