



**The author(s) shown below used Federal funding provided by the U.S. Department of Justice to prepare the following resource:**

**Document Title: Do Local-Federal Immigration Enforcement Agreements Reduce Crime? A Nationwide Evaluation of the Crime Reduction Benefits of Section 287(g) of the United States Immigration and Nationality Act**

**Author(s): Joel A. Capellan, Evan T. Sorg**

**Document Number: 305488**

**Date Received: November 2022**

**Award Number: 2018-R2-CX-0020**

**This resource has not been published by the U.S. Department of Justice. This resource is being made publicly available through the Office of Justice Programs' National Criminal Justice Reference Service.**

**Opinions or points of view expressed are those of the author(s) and do not necessarily reflect the official position or policies of the U.S. Department of Justice.**

**Do local-federal immigration enforcement agreements reduce crime? A nationwide evaluation of the crime reduction benefits of section 287(g) of the United States Immigration and Nationality Act**

Authors

Joel A. Capellan and Evan T. Sorg  
Department of Law and Justice Studies  
Rowan University

**Correspondence**

Joel A. Capellan, Department of Law and Justice Studies  
Rowan University, 5<sup>th</sup> Floor Campbell Library  
201 Mullica Hill Road  
Glassboro, NJ 08028  
Email: [capellan@rowan.edu](mailto:capellan@rowan.edu)

This project was supported by Award No. 2018-R2-CX-0020, awarded by the National Institute of Justice, Office of Justice Programs, U.S. Department of Justice. The opinions, findings, and conclusions or recommendations expressed in this report are those of the authors and do not necessarily reflect those of the Department of Justice.

## TABLE OF CONTENTS

	<b>Pages</b>
Title Page	i
Table of contents	ii
Executive Summary	1
Introduction	2
Immigration and Nationality Act of 1952	3
287g Agreement Models	4
Literature Review and Relevant Theoretical Guidance	5
Immigration and Crime Literature	5
Theoretical Perspectives on the Potential Impacts of Increased Deportations	7
Evidence of Crime Reduction Benefits	8
Evidence of Racial/Ethnic Discrimination	10
The Current Study	8
Methods	11
Measurement	11
Analytic Strategy	12
Results	16
Descriptive Statistics	16
Cross-lagged Panel Models	24
Discussion	27
Conclusion	29
References	30
Appendix	32

## **Executive Summary**

*The Illegal Immigration Reform and Immigrant Responsibility Act of 1996 facilitated the arrest, detention, and deportation of illegal immigrants by local law enforcement officials by adding 287(g) to the Immigration and Nationality Act. This program allows the Department of Homeland Security to enter into agreements with state and local officials which authorizes them to perform the functions of a federal immigration officer. Under the program, law enforcement officers bestowed this authority have access to federal immigration databases and may detain, interrogate, and take into custody non-citizens who are believed to have violation federal immigration law. Notwithstanding concerns over racial profiling and the lack of local-level oversight of deputized officers, both federal and local law enforcement agencies tout 287(g) as an effective crime reduction program. Yet, there has been no nationwide examination of the crime reduction benefits of these agreements. Using crime, demographic, and detention data from the 167 counties that applied for 287(g) status from 2005-2010, we estimate three cross-lagged panel models to assess the impacts of detentions on total crime, violent crime, and property crime. We find no evidence that these 287(g) arrangements had meaningful crime reduction benefits. In light of the potential negative consequences of these agreements, we question the continued use of such agreements under 287(g).*

## **Keywords**

287(g), illegal immigration, Illegal Immigration Reform and Immigrant Responsibility Act of 1996, immigration enforcement, Immigration and Nationality Act

## 1 | INTRODUCTION

Coleman (2008, p. 5) has described immigration policing as, “playing out as an increasingly de-territorialized tangle of law enforcement practices.” That is, although immigration enforcement falls within the plenary powers of the federal government in the United States, local municipalities have begun to play a role in enforcing federal immigration laws. Consider the Illegal Immigration Reform and Immigrant Responsibility Act of 1996, which facilitated the arrest, detention, and deportation of non-citizens by local officials through the 287(g) program. Referring to section 287(g) of the Immigration and Nationality Act, this program allows the Department of Homeland Security to enter into written agreements with selected state and local officials and authorizes them to perform the functions of an immigration officer. Deputized officers who have been trained by Immigration and Customs Enforcement have access to federal immigration databases, and they may interrogate, apprehend, and issue detainers to hold non-citizens believed to have violated federal immigration law. These 287(g) agreements merge criminal with immigration law enforcement, and they create a situation where any law infraction may call into question a suspect’s immigration status (Golash-Boza & Hondagneu-Sotelo, 2013). Critics argue that this creates an environment rife for racial profiling (Coleman & Kocher, 2019).

As a result, 287(g) agreements have proven controversial and divisive. Some allege that 287(g) agreements are justified because undocumented immigrants are more likely to engage in violence (see Litwin, 2011, p. 405). The nexus between violent crime and immigrant populations, however, is oftentimes found to run counter to such assumptions (Sampson, 2008). Nevertheless, the expanded jurisdiction of immigration enforcement has contributed to an unprecedented surge in interior removals of non-citizens. Consider that between 1997 and 2012, the United States government executed twice as many deportations (n=4.2 million) than the total number of removals prior to 1997 (Golash-Boza & Hondagneu-Sotelo, 2013). Whether or not the desired violent crime reductions are being achieved via the 287(g) program remains a somewhat open question, but there is no doubt that the outputs (i.e. detentions and deportations) prescribed by 287(g) are being administered (Litwin, 2011).

Evaluations of the effects of 287(g) agreements on crime are scarce and those available consist of only local-level evaluations (Koper, Guterbock, Woods, & Taylor, 2013). This leaves open questions related to the efficacy of 287(g) agreements as a national strategy. For example, variation in on-the-ground implementation across jurisdictions (see Forrester & Nowrasteh, 2018) raises concerns related to external validity. There should also be unease over allegations of widespread racial profiling by local officials in jurisdictions where these agreements exist (American Immigration Policy Center, 2012). Given the gaps in this literature and the concerns raised, we engaged in the first nationwide evaluation of the crime reduction benefits of section 287(g) of the Immigration and Nationality Act.

Using a novel dataset including information on 167 counties that applied to the 287(g) program from 2005-2010, we employed cross-lagged panel analyses of the concurrent and lagged association between total, violent, and property crime and the number of illegal immigrants detained under a 287(g) agreement. Results suggest that no statistically significant impact of detentions executed under 287(g) on crime materialized from 2005-2010, regardless of whether we modeled the effects on total, violent, or property crime. Given these null findings and the concerns raised over the implementation of 287(g) agreements at the local level, we discuss the policy implications of a continued reliance on the law.

## **2 | IMMIGRATION AND NATIONALITY ACT OF 1952**

The Immigration and Nationality Act of 1952 (INA) was introduced by Senator Pat McCarran and Representative Francis Walter in 1951 and passed both chambers of Congress a year later. The law was vetoed by President Truman and only became law after a two-thirds majority of the House and Senate overrode the presidential veto. Within the Democratic Party, debate over the national origin quota system established by the Immigration Act of 1924 was at the heart of this controversy, not section 287. In this instance, a wing of the Democratic Party, including President Truman, were critical of the quota system that they considered discriminatory because it favored immigrants from European nations.

Section 287 of the 1952 bill gave *federal* immigration authorities the power to detain, interrogate, and arrest those believed to be present or entering the United States Illegally without a warrant and as directed by the Attorney General. Local authorities were not extended the authority to enforce the

provisions of INA. Even when the bill was revised in 1965 and signed by President Lyndon B. Johnson, federal immigration authorities retained their exclusive role in undertaking immigration enforcement. This changed when President Clinton signed the Illegal Immigration Reform and Immigrant Responsibility Act of 1996 (IIRIRA), which extended the ability to enforce federal immigration laws to local law enforcement officials.

### **3 | ILLEGAL IMMIGRATION REFORM AND IMMIGRANT RESPONSIBILITY ACT OF 1996**

Section 133 of IIRIRA dealt with the acceptance of state services to carry out immigration enforcement. It amended INA to include section 287(g), which permits the Attorney General to enter into written agreements with a state or political subdivision to allow qualified officials to investigate, apprehend, and detain those suspected of being in the United States illegally. Acting under the direction and supervision of the Attorney General, local officials are permitted to use federal property or facilities to carry out these functions, though the state or political subdivisions accepts the costs. Local officers are required to understand and adhere to the pertinent federal laws related to immigration enforcement, and they must undergo adequate training to ensure that they are well versed in federal immigration law.

#### **3.1 | 287(g) Agreement Models**

ICE employs two types of agreement models: A jail enforcement model and warrant service officer model. The jail enforcement model allows state and local enforcement officers to identify and process those assigned criminal charges for removal from the United States. Local officials are supervised by a local ICE Office of Enforcement and Removal Operations Field Office. As of January 2021, Immigration and Customs Enforcement (ICE) had entered into jail enforcement model agreements with 72 law enforcement agencies in 21 States. During fiscal year 2020, ICE reported that they trained 301 officers and that 4,318 removals were facilitated by jail enforcement model 287(g) agreements (ICE, 2021). The warrant service officer model trains and certifies officers to perform limited functions of an immigration officer within the agency's correctional facilities. As of January 2021, ICE has entered into warrant service officer agreements with 76 law enforcement agencies in 11 states. During fiscal year 2020, ICE credentialed 444 state and local warrant service officers, and over 500 arrests were made (ICE,

2021). Given the active and widespread use of 287(g) agreements, understanding their effect on crime is necessary so that policy-makers are equipped with pertinent knowledge so that they can pursue policies based on sound empirical evidence. As discussed below, however, politics continues to play a role in framing debate over immigration enforcement, and this can hamper the pursuit of evidence-based policy making.

## **4 | LITERATURE REVIEW AND RELEVANT THEORETICAL GUIDANCE**

Although the casual observer might conclude that debate over illegal immigration and immigration enforcement has been particularly vitriolic over the past several years, partisanship over this policy issue is not new. This partisanship oftentimes precludes the possibility of pursuing evidence-based policy.

Disagreement over the extent of involvement in criminal activity that illegal immigrants engage in also means that good-faith policy debate over how to respond begins at an impasse.

### **4.1 | Immigration and Crime Literature**

Despite dramatized claims of criminal involvement and the demeaning rhetoric that was a staple of the previous administration in the United States, research suggests that immigrant populations either commit less, or at least no more crime, than the native population (Sampson, 2008). One caveat to this interpretation is that a great deal of this empirical work utilizes data related to naturalized immigrant populations. As Sampson (2008) pointed out, however, there is little reason to believe that the relationship between crime and immigration would vary were richer data on undocumented individuals more readily available. Undocumented immigrants concentrate in geographic locations where legal immigrants reside, so this caveat should raise little concern, especially in community level analyses (ibid, 2008).

There is a great deal of research investigating the relationship between crime and the geographic concentration of immigrant populations, so it is most instructive to consult the most recent meta-analysis and systematic review in summarizing the current state of this literature. Ousey and Kubrin (2018) report that in the 51 studies that examined the relationship between immigrant concentrations and crime from 1994-2014, 64 percent report non-significant findings. Where an association between immigration and



crime reaches statistical significance, it is most often in the negative direction. In fact, a significant negative effect was 2.5 times more likely to result than a significant positive effect. Results from their meta-analysis reveal a statistically significant negative effect overall, which they describe as a, “detectable nonzero negative association between immigration and crime but with a magnitude that is so weak it is practically zero” (Ousey & Kubrin, 2018, p. 1.7). In other words, research overwhelmingly concludes that the presence of immigrant populations in communities either reduces crime or has no effect on crime at all.

In addition to these community level studies, individual-level research suggests that immigrants are less prone to offending relative to native born individuals. For example, Bersani (2014, p. 315) found that foreign-born individuals engage in a “remarkably low” level of offending over their life course, and that immigrants are no more involved in crime than their native born peers. Bersani, Loughran, and Piquero (2014) found that first generation immigrants are less likely to be involved in serious offending relative to their native born peers, and they also desist from offending at a faster rate. They also report that by the second generation, immigrants engage in crime in rates similar to their native-born peers; especially among second generation immigrants, the risk of offending was highest amongst those with high levels of assimilation who lived in disadvantaged communities. These more recent studies confirm research completed in the early 2000s that found low rates of violence among first generation immigrants, but that buffering effect declined quickly amongst second and third generation immigrants (Morenoff & Astor, 2006). For first generation immigrants, increases in time spent in the United States, and the more enmeshed in American society immigrants become, there is a higher the likelihood of engaging in violence.

Overall, the weight of the evidence suggests that immigrants, especially those who are foreign born and who immigrated to the United States, are much less crime prone relative to native populations. Although later generations of immigrants engaged in criminal behavior at a higher rate, they are no more involved in crime than native populations.

## 4.2 | Theoretical Perspectives on the Potential Impacts of Increased Deportations

A common argument in support of immigration enforcement generally, and immigration enforcement agreements more specifically, is that removing those in the United States illegally is justified because individuals violated the law upon entry. This may be true on its face, but at the heart of the justification for federal-local partnerships to increase interior removals is that it is a public safety issue. That is, federal and local funds should be spent because it will make our communities safer by removing these potential offenders (Golash-Boza & Hondagneu-Sotelo, 2013). Setting aside the evidence presented that contradicts the notion that immigrants engage in higher levels of offending relative to the native population, there remains a possibility that these agreements could backfire and drive up rates of crime.

The majority of undocumented immigrants living in the United States hail from Latin American countries (Coon, 2017). Latinos are more likely to be targeted under 287(g) agreements and they make up the overwhelming majority of recent deportations (Golash-Boza & Hondagneu-Sotelo, 2013). The Latino Paradox refers to the resiliency amongst Latino communities across numerous social indicators in the face of adverse social conditions (Martinez Jr, 2014), including their propensity to violence (Sampson, 2008). Despite historical socioeconomic disadvantage and inequality, which are conditions known to be criminogenic, Latino communities experience relatively low levels of violence when compared to similarly situated Whites and Blacks (Steffensmeier, Ulmer, Feldmeyer, & Harris, 2010). As has been argued elsewhere (Wright, Turanovic, & Rodriguez, 2016), this runs counter to the racial invariance thesis (Sampson & Bean, 2006), which would predict that structural conditions correlate to offending in similar ways across all races and ethnicities. This is important because whatever buffering effect toward propensity to violence (and a range of other social indicators, see Martinez Jr (2014)) that is present among Hispanic populations may be disrupted with increased deportations of the population. In turn, this may increase immigrant criminal involvement.

Social disorganization theory posits that criminal behavior is rooted in the social-economic structure of communities, rather than individual traits (Shaw & McKay, 1942). Specifically, poor economic conditions, high rates of residential instability, and racial heterogeneity in the community have

the potential to break down the cohesiveness of a collective and weaken its ability to instill and enforce consensus on its norms, values, and goals. In turn, this breakdown in social cohesion gives rise to crime and delinquency (Sampson and Groves, 1989; Sampson, Raudenbush, & Earls, 1997; Silver, 2000).

Research examining the social impacts of deportations suggest that they have been a disruptive agent to the economic, social, and residential stability of immigrant communities (Leyro, 2013; Roberson, 2011; and Rugh & Hall, 2016). It is therefore possible that this disruption may be eroding the social cohesion that may contribute to lower levels of criminal behavior.

On the other hand, these enforcement agreements, and the increased scrutiny by law enforcement officials that illegal immigrants might face if they are found to have violated the criminal code could exert a deterrent effect. The removal of immigrant offenders sends a powerful message of increased certainty and severity of punishment for violating the law, which in turn, may deter the remaining immigrant offenders from further criminal activity (Akers, 2013). While it is difficult to disentangle these causal mechanisms, research has consistently shown that increased policing, particularly policies that rely on emphasizing the certainty of detection, has significant marginal deterrent effects (Durlauf and Nagin, 2011). Although the marginal effects of incarceration, particularly criminal justice policies intended to expand the length of jail and prison sentences, have been found to be modest (Durlauf and Nagin, 2011), they have nevertheless been linked to reductions in crime in some studies under certain model specifications (Barbarino & Mastrobuoni, 2014; Drago, Galbiati, & Vertova, 2009, Levitt, 2004; Kessler, & Levitt, 1999). For instance, according to Levitt (2004), the deterrent and incapacitation effects of incarceration accounted for 12% of the biggest crime drop in American history. These findings suggest that interior removals under the 287(g) programs may lead to reductions in crime through the same causal mechanisms.

#### **4.3 | Evidence of Crime Reduction Benefits**

It is not our intention to test these competing theoretical perspectives here. Rather, our focus is to evaluate the crime reduction benefits of 287(g) agreements. 287(g) agreements are touted by ICE as being an effective “force multiplier” that enhances public safety by reducing the number of non-citizens suspected

of other criminal violations in the United States. Following this logic, it is supposed by ICE that these agreements reduce violent crime. Yet, robust evaluations of the crime reduction benefits of these agreements are few, and they are limited to the evaluations at the local, not federal level. We know of no other published research that has empirically examined this question. We do, however, have local-level evaluations to consult to get an idea of how these agreements perform.

Koper et al. (2013) evaluated the crime reduction benefits of 287(g) agreements in Prince William County, Virginia. Facing an increase in the foreign born population that doubled from 2000-2006, and complaints from residents regarding a deterioration of neighborhood conditions and overcrowding, the County Board of Supervisors passed a resolution in 2007 that required the Prince William County Police Department (PWCPD) to enter into a 287(g) agreement. From 2008-2010, the PWCPD had nearly 3,000 contacts with suspected illegal immigrants, and officers arrested 79 percent of those with whom they made contact. Within the local jail, 2,783 detainers for those suspected to be undocumented were issued, and 2,499 illegal immigrants were released to ICE. Koper et al. (2013) report a statistically significant reduction in violent offenses, but they do note that the violence reductions were experienced prior to the implementation of 287(g) policies. They conclude that it was simply the announcement of the 287(g) agreement that was responsible for the violence reductions, not necessarily the detention and deportation regime. Property crime, disorder, and drug offenses were not impacted by the policy.

An unpublished working paper by Forrester and Nowrasteh (2018) evaluates the effects of 287(g) in the state of North Carolina and finds not statistically significant impact on any crime measure. Using a panel of yearly, county-level crime and demographic data, participation in 287(g), and intensity of enforcement, they report no reductions in total crime or disaggregated violent and property crime that reached levels of statistical significance. Another study that did not directly test the effects of 287(g) was conducted by Miles and Cox (2014). In their evaluation of the Secure Communities program (a separate immigration enforcement program that allows federal authorities to check the immigration status of those arrested by local police), they enter 287(g) participation as a control variable in their models. They found

that having an active 287(g) agreement reduced index crimes by about 3 percent. Similarly, Hines and Peri (2019) included a 287(g) agreement control variable in their models estimating the effects of the Secure Communities program at the national level. They report that 287(g) agreements did not elicit statistically significant crime reductions. Overall, the findings regarding 287(g)'s effectiveness at reducing crime is mixed, and thus further investigation is warranted.

#### **4.4 | Evidence of Racial/Ethnic Discrimination**

In addition to having inconclusive evidence that 287(g) agreements reduce crime, entering into these agreements has coincided with increases in alleged racial profiling and civil rights violations. In 2009, the Government Accountability Office released a report that faulted DHS and ICE for a lack of program oversight. They also found that agencies with 287(g) agreements were using them to deport undocumented immigrants who had committed minor crimes such as traffic infractions (Lacayo, 2010). This is counter to the program's mission of removing undocumented individuals who commit serious violent crimes.

Federal investigations have confirmed allegations of racial profiling. For example, a federal investigation concluded that the Maricopa County (Arizona) Sheriff's Office, led by Joe Arpaio, routinely conducted sweeps in Latino neighborhoods. The investigation also found Latino drivers to be approximately nine times more likely to be stopped than their non-Latino counterparts (Department of Justice, 2011). Similar patterns of alleged constitutional violations have been found in other participating local law enforcement agencies (American Immigration Council, 2012). In September 2012, the Justice Department released a report that found that deputies in Alamance County, North Carolina, stopped Latinos four times more often than other ethnicities. It was also common practice to stop and arrest Latinos at checkpoints for minor traffic violations, while other ethnicities were issued warnings or traffic citations. In making an arrest in these instances, officers were able to process those arrested for these infractions in the local jail and thus check their immigration status (Golash-Boza & Hondagneu-Sotelo, 2013). This evidence of racial-profiling makes the study of 287(g), and its alleged crime reduction benefits, particularly timely.

## 4.5 | The Current Study

Despite being presented as a public safety measure, the 287(g) program has been subject to almost no empirical examination. The purpose of this study is to conduct the first nationwide evaluation of local 287(g) immigration enforcement agreements on general crime, violent and property crime indexes. To this end, this study employs a cross-lagged panel analyses to estimate the concurrent, lagged, and cross-lagged impact of entering in 287(g) agreement and intensity of implementation (number of illegal immigrants detained) on total, violent, and property crime.

## 5 | METHODS

### 5.1 | Measurement

#### Dependent Variables and Unit of Analysis

The outcomes of interest are *total*, *violent* and *property crime* per 100,000 residents across counties in mainland United States between 2005 to 2010. This study will focus on the seven Parts I Uniform Crime Report (URC) offenses that include measures of *violent crime* (criminal homicide, forcible rape, robbery, and aggravated assault) and measures of *property crime* (burglary, larceny-theft, and motor vehicle theft), and *total crime* consisting of all seven violent and property offenses listed above. Crime will be standardized by county as a yearly crime rate per 100,000 residents. United States counties are specified as the unit of analysis because the 287(g) agreements are made and enforced at the county level.

#### Independent Variable

The independent variable in the analysis is whether a county implemented a 287(g) agreement with the Department of Homeland Security. Data on historical and active agreements were obtained through Freedom of Information Act (FOIA) requests. These data are unique in that it contains information on 167 counties that applied for 287(g) the program between 2005 and 2010. Our files contain indicators for counties whose applications were accepted, and who subsequently implemented the agreements. Importantly, the files contain information on the number immigrant persons who were detained in each

participating county. This information is essential to evaluate the impact of the 287(g) program, as there is wide variability in the intensity of implementation (number of illegal immigrants detained). It could be argued that the potential deterrent or incapacitation effects, and therefore its effects on crime, would be maximized for counties that detained more illegal immigrants. The data files also contain information on counties that submitted an application to enter into 287(g) agreements but were rejected by the Department of Homeland Security.

### **Time-Varying Controls**

This study includes time-varying factors that may be associated with changes in crime rates. This study collected data on *population size* (total population), *percent White* (share of population who are White), *percent Hispanic* (share of population who are Hispanic), *percent foreign* (share of population who were born outside of the United States), *percent rural* (share of population who live in rural areas), *median income* (median household income), *percent bachelor* (share of population with a Bachelor's degree), *residential instability* (share of population who moved to county in the past two years), *unemployment* (share of population who are unemployed).

## **5.2 | Analytic Strategy**

A two-step analytical strategy was developed to evaluate the effects of 287(g) agreements on crime at the county level. First, the descriptive statistics for the analytical sample (N = 3,104) were produced. Second, the total number of crimes, the total number of violent crimes, and the total number of property crimes from 2005 to 2010 was regressed on the number of illegal immigrants detained under a 287(g) agreement from 2005 to 2010 using a cross-lagged panel design. Three separate cross-lagged panel models were estimated. Briefly, a cross-lagged panel model is a specialized path model that simultaneously estimates the concurrent and lagged association between two or more constructs while adjusting for previous observations and the residual error between equations (Kearney, 2017). While other techniques could achieve similar estimates (e.g., lagged fixed effects models; longitudinal propensity score matching; Singer and Willett, 2003; Silver et al., 2020), a cross-lagged panel analysis represents one of the most

robust statistical strategies for simultaneously estimating various associations within longitudinal panel data (Selig & Little, 2012; Shingles, 1976).

For the current study, the cross-lagged panel models were specified where the number of crimes (total, violent, or property) in 2005 predicted the number of crimes in 2006 and the number of illegal immigrants detained under a 287(g) agreement in 2006. Moreover, the number of illegal immigrants detained under a 287(g) agreement in 2005 was specified to predict the number of crimes in 2006 and the number of illegal immigrants detained under a 287(g) agreement in 2006. These paths provide the lagged effects for the relationship between number of crimes (total, violent, and property) and the number of illegal immigrants detained under a 287(g) agreement while adjusting for the previous number of crimes and illegal immigrants detained under a 287(g) agreement. In addition to the specified paths, the effects of the number of illegal immigrants detained under a 287(g) agreement on the number of crimes at the same time period was evaluated by specifying a residual covariance between the terms for the equations associated with 2006 to 2010. The model did not estimate the covariance between the number of illegal immigrants detained under a 287(g) agreement on the number of crimes in 2005.<sup>1</sup> Similar to Fixed Effects model, cross-lagged panel models require sufficient within variability of time variant variables to successfully estimate their effects. Limited variability in *percent White*, *percent Hispanic*, *percent rural*, *median income*, *percent bachelor*, and *residential instability* between 2005 and 2010 rendered them practically time-invariant, and therefore their effects could not be specified in the model. All of the paths controlled for the percentage of the population that was Hispanic and unemployed, while all of the paths and covariances adjusted for the correlated error between equations with the same dependent variable at different time periods.

After specifying the paths and covariances, the cross-lagged panel models were estimated using version 0.6-7 of Lavaan in version 4.0.3 of R (Rosseel, 2012). Specifically, the models were estimated using maximum likelihood estimator with robust standard errors and a Satorra-Bentler test statistic

---

<sup>1</sup> The model covariance matrix could not be inverted when the specification included a covariance between the number of illegal immigrants detained under a 287(g) agreement on the number of crimes in 2005.



(MLM) from Lavaan (Rosseel, 2012). During this estimation procedure, it was recognized that the variance covariance matrix was ill-scaled and did not permit the specified model to converge upon a single solution. Following the guidance of Kline (2016 [pg. 81-82]), the variances of all of the measures in the models were rescaled by multiplying the item by a constant that were zeros but end in 1 (e.g., .1, .01, .001, .0001) to maintain the interpretability of the remaining measures (Bowen and Guo, 2011). After rescaling the variances – balancing the variance covariance matrix – the specified model converged upon a single solution (Kline, 2016). Table 1 presents the descriptive statistics of the analytical sample.

Table 1. Descriptive Statistics for the Analytical Sample

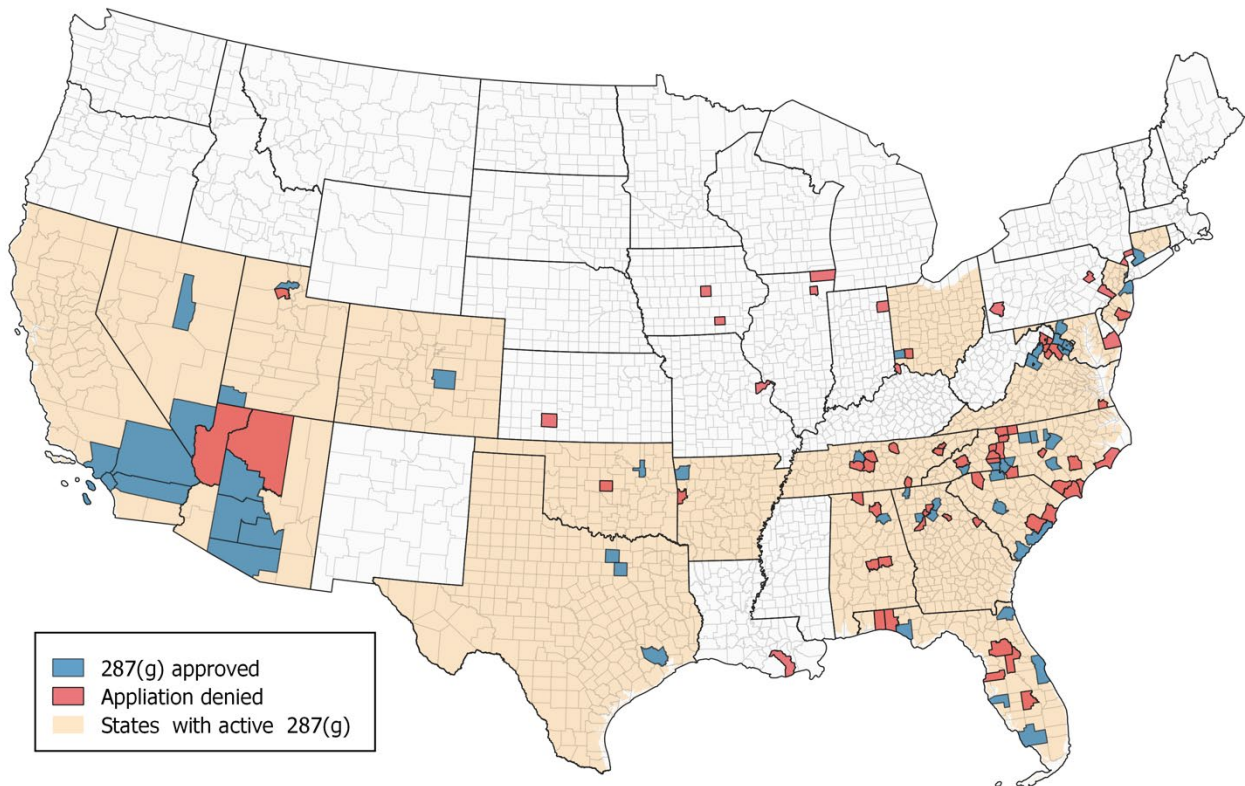
	Mean	SD	Range
<i>Dependent Variables</i>			
Total Crime Count (2005)	3599.23	2330.95	29733.19
Total Crime Count (2006)	3643.03	2349.25	47157.89
Total Crime Count (2007)	3697.38	2610.24	55667.51
Total Crime Count (2008)	3671.71	2514.03	50761.42
Total Crime Count (2009)	3554.85	2399.06	48271.28
Total Crime Count (2010)	3463.48	2299.09	48223.35
Violent Crime Count (2005)	272.87	251.55	2925.53
Violent Crime Count (2006)	302.79	308.02	5255.08
Violent Crime Count (2007)	311.01	334.23	8564.23
Violent Crime Count (2008)	304.89	313.85	7868.02
Violent Crime Count (2009)	295.30	302.63	8111.70
Violent Crime Count (2010)	281.63	282.42	7487.31
Property Crime Count (2005)	2455.89	1588.59	17819.15
Property Crime Count (2006)	2486.04	1552.11	29263.16
Property Crime Count (2007)	2498.03	1775.98	39168.77
Property Crime Count (2008)	2483.52	1686.79	35279.19
Property Crime Count (2009)	2363.18	1612.23	32446.81
Property Crime Count (2010)	2299.31	1520.73	31979.70
<i>Independent Variable</i>			
Number of Illegal Immigrants Detained (2005)	1.17	65.44	3646.00
Number of Illegal Immigrants Detained (2006)	1.95	70.38	3646.00
Number of Illegal Immigrants Detained (2007)	6.99	150.64	4586.00
Number of Illegal Immigrants Detained (2008)	15.42	320.01	15504.00
Number of Illegal Immigrants Detained (2009)	19.47	349.78	14769.00
Number of Illegal Immigrants Detained (2010)	15.57	253.56	10241.00
<i>Control Variables</i>			
Percentage of Population Hispanic (2005)	7.10	12.61	98.29
Percentage of Population Hispanic (2006)	7.27	12.69	98.49
Percentage of Population Hispanic (2007)	7.40	12.76	98.68
Percentage of Population Hispanic (2008)	7.61	12.87	98.88
Percentage of Population Hispanic (2009)	7.83	13.00	99.10
Percentage of Population Hispanic (2010)	8.30	13.23	95.70
Percentage of Population Unemployed (2005)	6.51	2.72	26.56
Percentage of Population Unemployed (2006)	6.49	2.79	25.82
Percentage of Population Unemployed (2007)	6.62	2.87	26.87
Percentage of Population Unemployed (2008)	6.53	2.94	28.22
Percentage of Population Unemployed (2009)	7.22	3.20	29.57
Percentage of Population Unemployed (2010)	7.46	3.28	30.93
N		3,104	

## 6 | RESULTS

### Descriptive Statistics

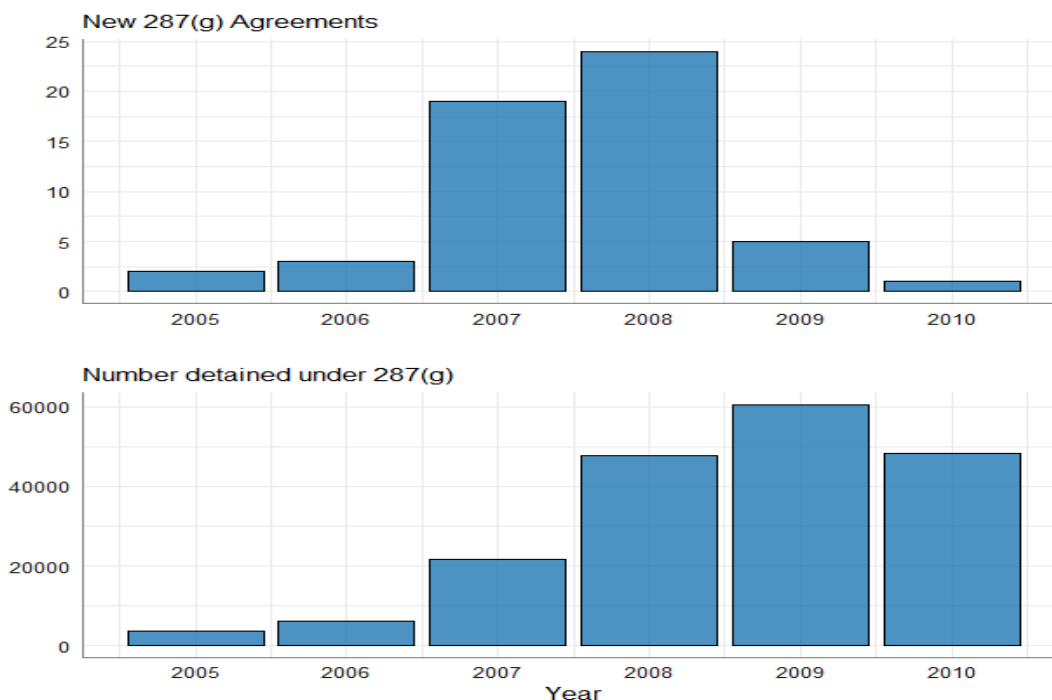
Between 2005 and 2010, 167 counties that applied for the 287(g) program. Of those who applied only 54 (32%) law enforcement agencies across 19 states the United States were selected. Figure 1 presents the spatial distribution of counties that entered into 287(g) agreements, and those who applied and were denied. The map shows strong spatial clustering. With some exceptions, counties that entered into 287(g) agreement with the Federal government, and those who applied and were denied are located in the South of the United States.

Figure 1. Map of Participating 287(g) Counties



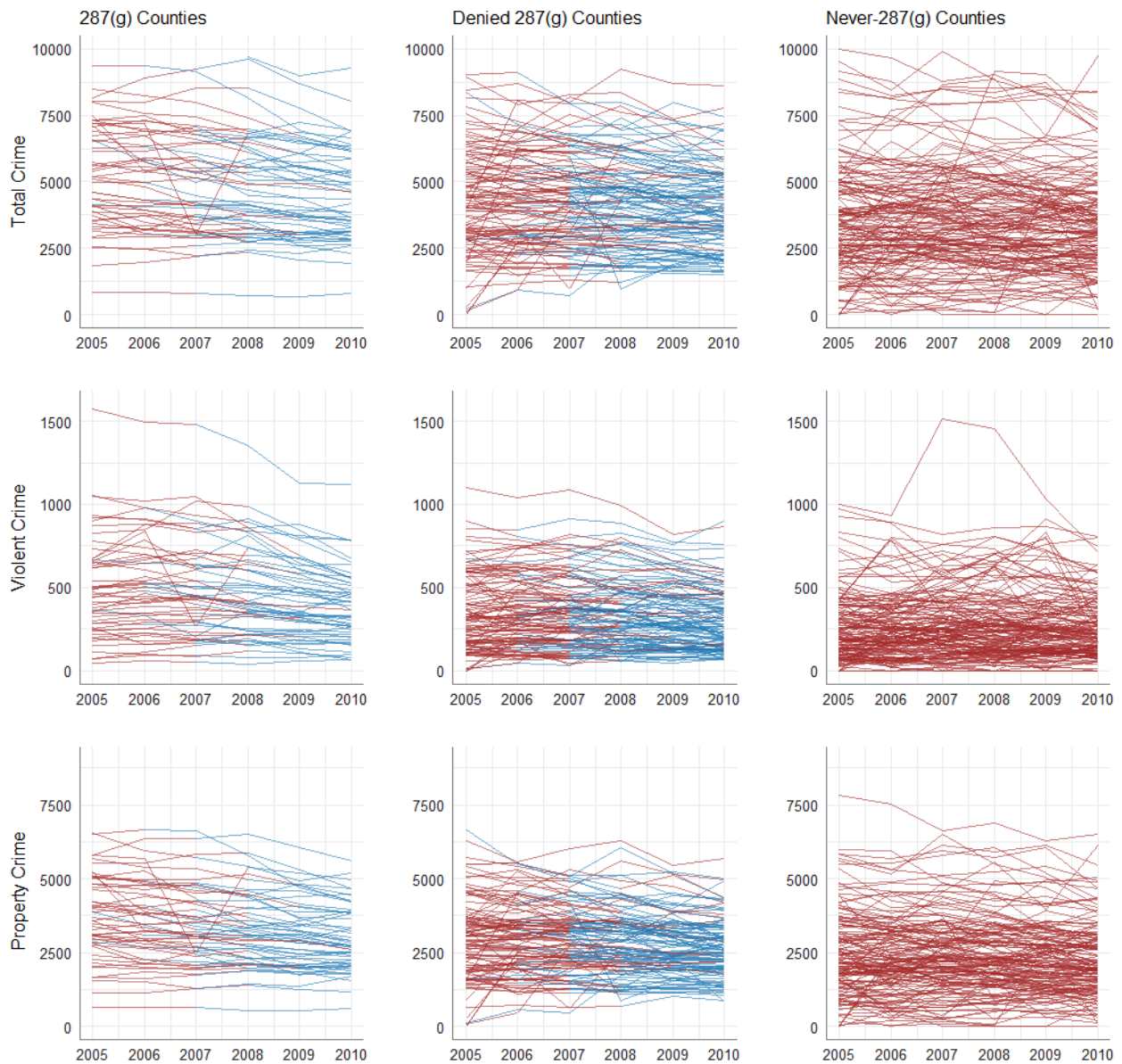
The spatial patterns tell only half of the story. There is wide variation in the timing of activation of 287(g) agreements and intensity of implementation. Figure 2 presents the number of new 287(g) agreements, and number of illegal immigrants detained under 287(g) per year. Prior to 2005, only two 287(g) programs were implemented: one in Alabama (2003), and the other in Florida (2002). Formally, the 287(g) agreements started their rollout in 2005 with two new agreements. The rate of adoption surged in 2007 with 19 new agreements, reaching its peak in 2008 with 23 agreements. The number of new agreements declined precipitously in 2009 as former President Obama’s administration prioritized removals through the Secure Communities program, reaching its lowest adoption rate (n=1) at the end of our time series. While the adoption of 287(g) agreements during the analysis time is relatively low given the total number of counties in the United States, the volume of detentions is significant. The data indicate that approximately 188,038 immigrants were detained and identified for removal by participating 287(g) counties during the years available. The temporal variation in 287(g) adoption and the large volume of detentions over time provide us an excellent opportunity to examine the effects of program implementation on crime rates.

Figure 2. New 287(g) Agreements and Number of Illegal Immigrants detained, 2005 - 2010



Despite being presented as a public safety program, little is known about the effect of 287(g) agreement implementation on violent and property crime. Figure 3 presents the total, violent, and property crime trends for three types of counties: *287(g) counties* (counties that entered into 287(g) agreements), *denied 287(g) agreements* (counties that applied for 287(g) program but were denied by the Federal Government), and *never 287(g) counties* (rest of counties in the United States).

Figure 3. 287(g) Implementation and Crime trends



For *287(g) counties*, the crime trends are color-coded, where brown represents crime pre and blue post-287(g) agreement activation. Both total, violent, and property seem to decline in magnitude and variance post-287(g) implementation. Looking at crime trends of pre-post 287(g) agreements alone, might lead us to conclude that 287(g) agreement, as advertised, reduces crime. However, examining the crime trends for *denied 287(g) counties* reveal a familiar downward trend. Similar for the *287(g) counties*, *denied 287(g)* are color coded brown, and blue to represent pre-post 287(g) program application denials. Despite never being denied for the program, these counties saw similar drops in total, violent and property crime. The last column presents crime trends for the rest of the counties (*never-287(g) counties*)<sup>2</sup>. These counties also experienced a decline in total, violent and property crime during the analysis period, though not as apparent or sharp a drop.

Table 2 presents the median crime rates for *287(g) counties*, and *denied 287(g) counties* pre-post 287(g) program implementation and application rejection respectively. Additionally, we have the yearly median crime rate for the rest counties in the United States. These summary statistics confirm the visualization above, but also gives us additional information. The data shows that counties with prior to 287(g) implementation, *287(g) counties* had much higher crime rates than *denied 287(g) counties*. Importantly, both *287(g) counties* and *denied 287(g) counties* had much higher crime rates than the rest of the country. This suggests that counties were motivated, at least in part, by lack of public safety to enter into 287(g) agreements with the federal government. Whether a significant share of those crimes was committed by illegal immigrants in those counties in reality or perception is a separate issue. Furthermore, this higher-than-average crime rates among *287(g)* and *denied 287(g)* counties at the start of time series may be partly be responsible for the steep decline in crime. It is possible that *287(g)* counties and *denied 287(g)* counties were regressing towards the mean.

---

<sup>2</sup> A random sample of 200 *Never-287(g) counties* are presented here. The random selection was done exclusively for visualization purposes.

Table 2. Median crime rates by 287(g) agreement county

<b>287(g) Counties</b>						
	Pre-287(g) <sup>1</sup>			Post -287(g)		
Violent crime	442 (295)			411 (252)		
Property crime	3,401 (1,347)			3,036 (1,231)		
Total crime	5,166 (2,021)			4,740 (1,863)		
<b>Denied 287(g) Counties</b>						
	Pre-287(g) Application			Post -287(g) Application		
Violent crime	325 (234)			282 (190)		
Property crime	3,025 (1,372)			2,646 (1,103)		
Total crime	4,321 (2,009)			3,979 (1,649)		
<b>Never-287(g) Counties</b>						
	2005	2006	2007	2008	2009	2010
Violent crime	208 (249)	226 (307)	235 (336)	229 (315)	224 (303)	215 (283)
Property crime	2,217 (1,583)	2,243 (1,550)	2,221 (1,787)	2,230 (1,695)	2,111 (1,617)	2,067 (1,523)
Total crime	3,245 (2,323)	3,232 (2,346)	3,224 (2,626)	3,243 (2,524)	3,161 (2,405)	3,098 (2,302)

1. Median (standard deviation)

If entering into 287(g) agreements had any effect on crime at all it likely comes from the intensity of implementation. Presumably, the higher number of illegal immigrants detained under those agreements, the higher the deterrent and incapacitation effect, and consequently, the higher the crime reductions. There is wide variation in the number of detained illegal immigrants under the 287(g) program among 287(g) counties. Figure 4a presents a density plot of the variation in number of illegal immigrants detained under 287(g) program between 2005 and 2010. This figure shows a wide variation, with most 287(g) counties apprehending zero suspects after entering into the agreements. On average, 287(g) counties apprehended 271 illegal immigrants as marked by the red line. Whether over the entire observation period (a), or by year (b), the distribution of number detained is severely skewed to the right. Figure 4c presents the top-ten implementers conceptualized as the share of the total number of illegal immigrants detained in the country (n = 188,038). Maricopa County, Arizona detained 25% of all illegal immigrants detained under 287(g) program. These top-ten implementers are responsible for approximately 75% (n = 141,028) of all illegal immigrants detained under the agreements. The temporal variation in volume of detentions over time provide an excellent opportunity to examine the impact of program implementation on crime rates.



Figure 4. Summary statistics for number of illegal immigrants detained

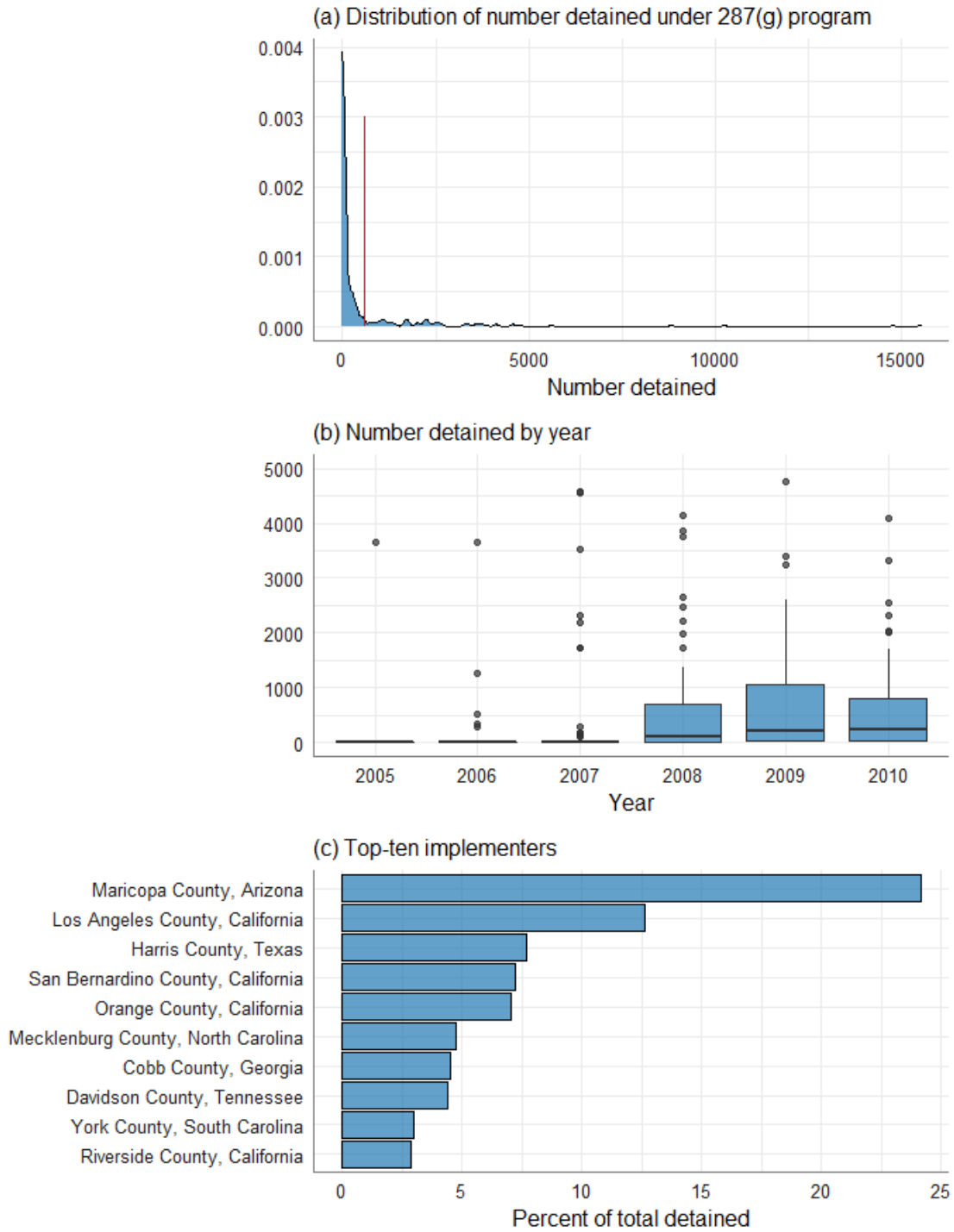
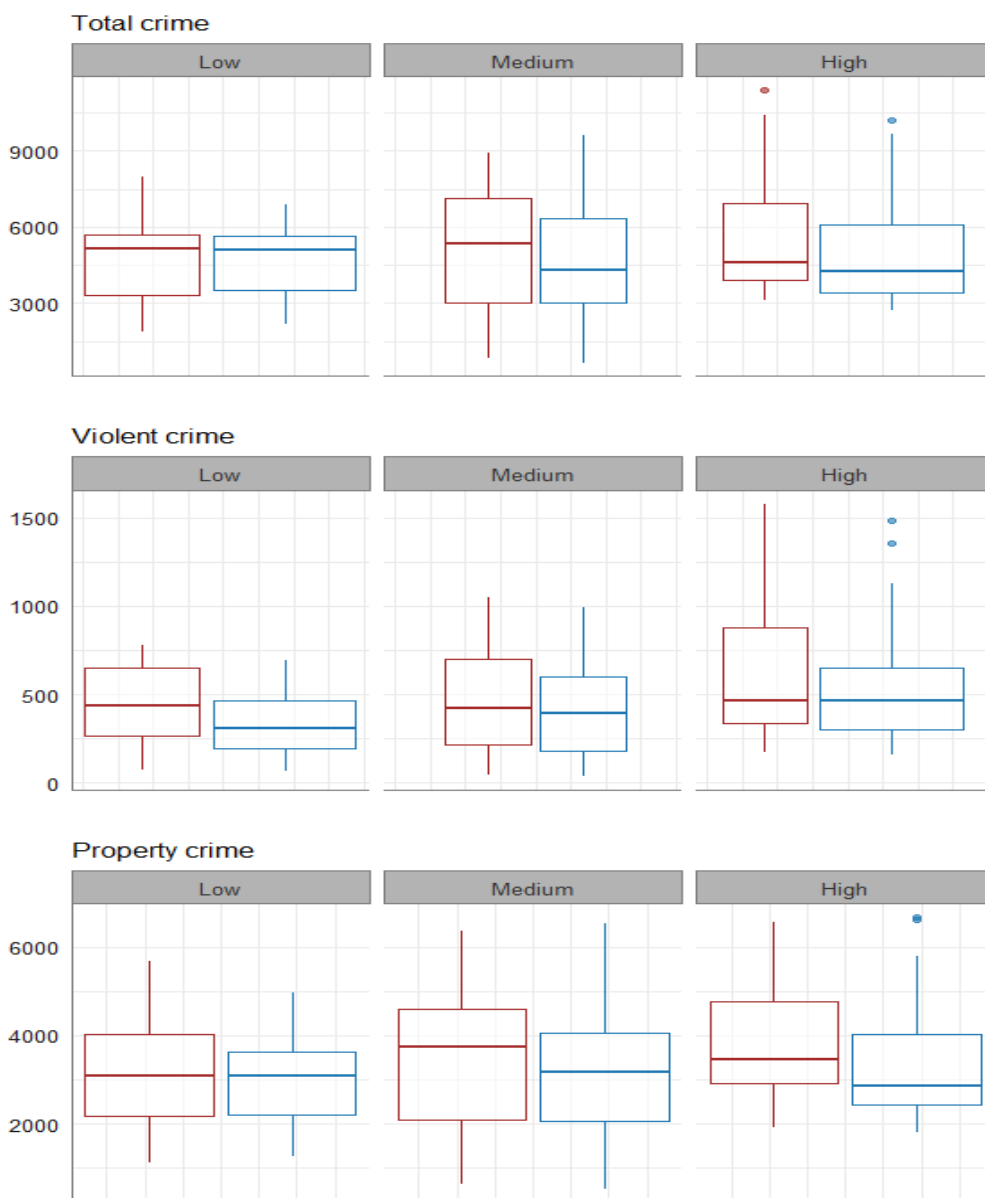


Figure 5 presents the total, violent and property crime before (brown) and after entering into 287(g) agreements across three types of implementation intensity: *high intensity* (counties that detained over 1,000 persons), *medium intensity* (between 100 and 999) and *low intensity* (less than 100). The figure indicate that total and property crime went down for all three types of implementers, but slightly steeper decline for *medium* and *high* implementers. There is a similar pattern for violent crime, but there is a slightly steeper decline for *low* implementers.

Figure 5. Changes in crime among 287(g) counties by level of implementation

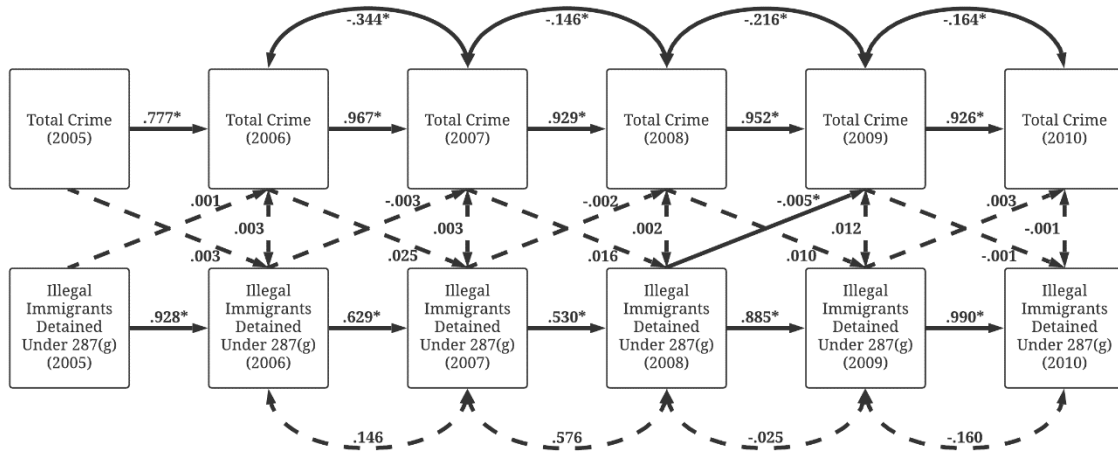


The descriptive analysis provides two key insights. First, crime rates for all counties were trending downward during the analysis time, but the decline was a slightly steeper for counties with active 287(g) agreements. The steeper decline cannot be attributed to 287(g) implementation alone as counties who applied but were denied from the 287(g)-program experienced similar declines. Their higher-than-average crime rates in 2005 creates the possibility that 287(g) counties, and denied 287(g) counties may have been, in part, regressing towards the mean. Second, there are slightly different rates of decline in total and property crime across 287(g) counties that has low, medium, and high levels of implementation. Counties with medium and high levels of implementation experienced slightly steeper decline in total and property crime relative to low implementers. However, the opposite pattern exists for violent crime, with low implementers experiencing a steeper decline compared to medium and high counterparts.

### **Cross-Lagged Panel Model**

Figure 6 provides the results of the cross-lagged panel analysis of total crime. The model generates separate path models to assess whether detainment of illegal immigrants lead to crime reduction or backfire effects, before, during, and after each of implementation. The cross lagged panel analysis appeared to fit the data well and within the standards described by Hu and Bentler (1999;  $\chi^2 = 1752.186$ ,  $p < .001$ ; Model  $\chi^2 = 151.908$ ,  $p = .007$ ; CFI = .993; TLI = .990; RMSEA = .033; RMSEA 90%CI = .018, .046.  $N = 3,104$ ,  $p < 0.05$ ). The autoregressive part of the model indicates that counties with high levels of crime, also tend to have high levels of crime in the subsequent years; similarly, counties that detained high numbers of immigrants, also tend to detain high number of immigrants in subsequent year. The concurrent model part of the model suggests that there is no association of program implementation (detaining illegal immigrants) and crime during the same time period. In other words, there is no evidence of immediate effect of 287(g) implementation on crime. The cross-lagged part of the model suggests that 287(g) implementation has no impact on crime rates in the subsequent year, as four of five paths were not statistically significant. While there is a significant negative association between 287(g) implementation in 2008 and total crime in 2009, the magnitude of the effect suggests this may be a statistical artifact.

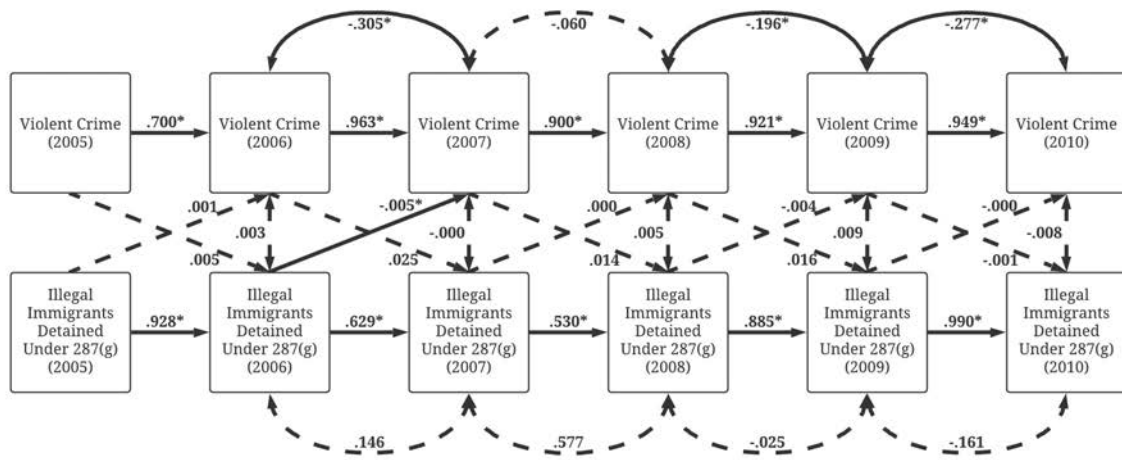
Figure 6. Cross-lagged panel analysis of the association between total crime and the number of illegal immigrants detained under a 287(g) agreement



Notes: The current model was estimated using maximum likelihood estimator with robust standard errors and a Satorra-Bentler test statistic (MLM) from Lavaan (Rosseel, 2012). The standardized path coefficients are provided on the single headed arrows, while the doubled headed arrows provide the standardized residual covariances between the specified items. The solid lines and \* indicate the associations statistically significant beyond the  $p < .05$  level. All of the paths within the figure are adjusted for the percentage of the population that was of Hispanic heritage and the percentage of the population that was unemployed in the county. The specified model appeared to fit the data beyond the gold standard set by Hu and Bentler (1999). Baseline  $\chi^2 = 1752.186$ ,  $p < .001$ ; Model  $\chi^2 = 151.908$ ,  $p = .007$ ; CFI = .993; TLI = .990; RMSEA = .033; RMSEA 90%CI = .018, .046. N = 3,104.  
\*  $p < .05$

Figure 7 and 8 presents the results of the cross-lagged panel analysis of violent and property crimes. Both models fit the data well (violent crime:  $\chi^2 = 1574.871$ ,  $p < .001$ ; Model  $\chi^2 = 162.399$ ,  $p = .001$ ; CFI = .992; TLI = .988; RMSEA = .036; RMSEA 90%CI = .023, .048. N = 3,104,  $p < 0.05$ ; property crime:  $\chi^2 = 1693.211$ ,  $p < .001$ ; Model  $\chi^2 = 150.368$ ,  $p = .009$ ; CFI = .993; TLI = .990; RMSEA = .034; RMSEA 90%CI = .018, .048. N = 3,104,  $p < .05$ . Similar to the total crimes, the results suggest that 287(g) implementation had no immediate impact on violent and crime rates. Importantly, four of five cross-lagged paths show that the number of illegal immigrants detained under 287(g) has no significant bearing on property and violent crime in the following year. The one significant cross-lagged path in both models suggest significant reduction in the subsequent year, however, the magnitude of the association suggest these are statistical artifacts.

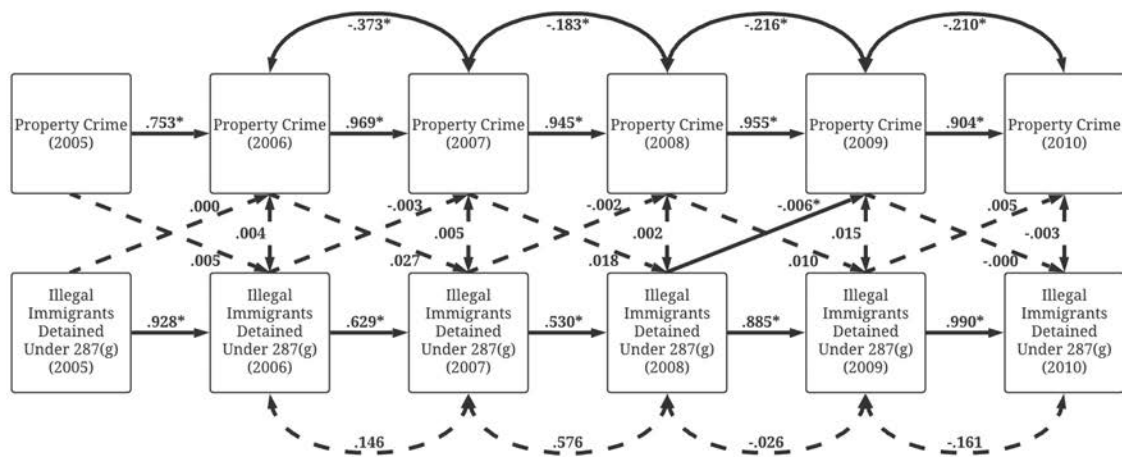
Figure 7: Cross-lagged panel analysis of the association between violent crime and the number of illegal immigrants detained under a 287(g) agreement.



Notes: The current model was estimated using maximum likelihood estimator with robust standard errors and a Satorra-Bentler test statistic (MLM) from Lavaan (Rosseel, 2012). The standardized path coefficients are provided on the single headed arrows, while the doubled headed arrows provide the standardized residual covariances between the specified items. The solid lines and \* indicate the associations statistically significant beyond the  $p < .05$  level. All of the paths within the figure are adjusted for the percentage of the population that was of Hispanic heritage and the percentage of the population that was unemployed in the county. The specified model appeared to fit the data beyond the gold standard set by Hu and Bentler (1999). Baseline  $\chi^2 = 1574.871, p < .001$ ; Model  $\chi^2 = 162.399, p = .001$ ; CFI = .992; TLI = .988; RMSEA = .036; RMSEA 90%CI = .023, .048. N = 3,104.

\*  $p < .05$

Figure 8: Cross-lagged panel analysis of the association between total crime and the number of illegal immigrants detained under a 287(g) agreement.



Notes: The current model was estimated using maximum likelihood estimator with robust standard errors and a Satorra-Bentler test statistic (MLM) from Lavaan (Rosseel, 2012). The standardized path coefficients are provided on the single headed arrows, while the doubled headed arrows provide the standardized residual covariances between the specified items. The solid lines and \* indicate the associations statistically significant beyond the  $p < .05$  level. All of the paths within the figure are adjusted for the percentage of the population that was of Hispanic heritage and the percentage of the population that was unemployed in the county. The specified model appeared to fit the data beyond the gold standard set by Hu and Bentler (1999). Baseline  $\chi^2 = 1693.211, p < .001$ ; Model  $\chi^2 = 150.368, p = .009$ ; CFI = .993; TLI = .990; RMSEA = .034; RMSEA 90%CI = .018, .048. N = 3,104.

\*  $p < .05$

## 7 | DISCUSSION

Given the accumulation of crime policies over the last three decades, Mears (2007, p. 668; emphasis added) noted that, “The question of whether various crime polices are *needed, effective, or efficient*...has assumed particular importance.” The *need* for immigration enforcement programs and partnerships such as 287(g) can be assessed by examining the extent to which immigrant populations engage in criminal behavior and whether their offending surpasses that of the native born population. Policy-makers supporting programs like 287(g) appear to make the a priori assumption that immigrant populations engage in a high volume of crime. There is no empirical basis to make that assumption. Immigrants residing in the United States do not commit more crime than the native-born population. Although researchers are hampered by the difficulties inherent in reaching illegal immigrant populations, there is little reason to believe that their offending patterns are different from those who have immigrated to the United States legally (Sampson, 2008). Programs such as 287(g), therefore, appear to be a solution in search of a problem. This makes our findings regarding the *effectiveness* of 287(g) somewhat unsurprising.

In what we believe is the first nationwide examination of the impact of 287(g) agreements on crime, we find little evidence that they are effective in achieving their goal of violent crime reduction at a national level. According to ICE, 287(g) agreements enhance public safety by removing non-citizens suspected of criminal violations—immigrants removed from the country cannot commit future offences. By exploiting local law enforcement officers as force multipliers, it is assumed that a greater dosage of interior removals will reduce crime. Given that there appears to be no link between immigrant populations and increased offending, it follows that attempts to broadly remove those residing in the United States

illegally in greater numbers will not influence crime. Our non-significant findings do not support 287(g) as a crime-prevention tool. It appears that the deterrent effect that some posit will result from increasing detentions and deportations has not materialized when we examined the nationwide effectiveness of 287(g).

We also find no evidence to support that 287(g) agreements, and the increased detentions and removals that they elicit, are *efficient*. In four of our five models, we found no relationship between the number of detentions in a jurisdiction and subsequent levels of crime. Although one path in our model significantly predicted lower violent crime a year later, the small magnitude of the effect demonstrates that increasing detentions is quite inefficient in terms of crime prevention potential. It is also likely that this relationship is simply a statistical artifact. Criminal justice spending is expansive, but it is not unlimited. In the context of criminal justice spending, most efficiently reducing crime requires a reliance on evidence-based crime policies. Policies that are deemed either ineffective or inefficient should be abandoned and replaced with policies that find strong support through rigorous empirical evaluation. In the case of 287(g), we urge local law enforcement agencies to consider whether pursuing these agreements are worth the cost, as local level funds are used to implement 287(g) agreements. It is also important to consider the potential disruption to immigrant communities that deportations may have and their negative consequences. In addition to the potential for increasing social disorganization, there are a range of other negative social, economic, political, and mental health outcomes of these policies.

It is unsurprising that programs such as 287(g) have proliferated over the last few decades despite much empirical support, and we do not expect our findings will disrupt this trend. It appears that lawmakers are either poorly versed in research evidence examining the immigrant-crime relationship or the partisan politics of immigration leaves them willfully ignorant. Although appearing to be tough on immigration might be politically expedient for some, the potential for harm (i.e. racial profiling) that programs like 287(g) have caused, combined with a lack empirical support, leads us to question the continued reliance on these agreement both federally and locally.

## 8 | CONCLUSION

In what we believe is the first nationwide examination of 287(g) agreements and their impact on crime, we find no support that they are an effective or efficient crime prevention tool. Given the research evidence that consistently reports that foreign born individuals commit no more crime than American nationals, we cannot advocate for 287(g) as a tool to reduce violent or property crime. At the national level, all but one of our models were non-significant, and the one significant path suggests a trivial crime reduction benefit. Lawmakers should reconsider the allocation of funds used to implement the 287(g) program.



## REFERENCES

- Bersani, B. E. (2014). An examination of first and second generation immigrant offending trajectories. *Justice quarterly*, 31(2), 315-343.
- Bersani, B. E., Loughran, T. A., & Piquero, A. R. (2014). Comparing patterns and predictors of immigrant offending among a sample of adjudicated youth. *Journal of youth and adolescence*, 43(11), 1914-1933.
- Center, A. I. P. (2012). *The 287(g) Program: A flawed and obsolete method of immigration enforcement*. Washington, D.C. Retrieved from [https://www.americanimmigrationcouncil.org/sites/default/files/research/the\\_287g\\_program\\_an\\_overview\\_0.pdf](https://www.americanimmigrationcouncil.org/sites/default/files/research/the_287g_program_an_overview_0.pdf)
- Coleman, M. (2008). Between public policy and foreign policy: US immigration law reform and the undocumented migrant. *Urban Geography*, 29(1), 4-28.
- Coleman, M., & Kocher, A. (2019). Rethinking the “Gold Standard” of Racial Profiling: § 287 (g), Secure Communities and Racially Discrepant Police Power. *American Behavioral Scientist*, 63(9), 1185-1220.
- Coon, M. (2017). Local immigration enforcement and arrests of the Hispanic population. *Journal on Migration and Human Security*, 5(3), 645-666.
- Forrester, A., & Nowrasteh, A. (2018). Do immigration enforcement programs reduce crime. *Evidence from the 287 (g) Program in North Carolina*.
- Golash-Boza, T., & Hondagneu-Sotelo, P. (2013). Latino immigrant men and the deportation crisis: A gendered racial removal program. *Latino Studies*, 11(3), 271-292.
- Kearney, M. W. (2017). Cross lagged panel analysis. In Allen, M. (Ed.) *The SAGE encyclopedia of communication research methods* (pg. 313-319). Thousand Oaks, CA: Sage Publishers.
- Kline, R. B. (2016). *Principles and practice of structural equation modeling*. New York, NY: Guilford Publications.
- Hines, A. L., & Peri, G. (2019). Immigrants' deportations, local crime and police effectiveness.
- Koper, C. S., Guterbock, T. M., Woods, D. J., & Taylor, B. (2013). The effects of local immigration enforcement on crime and disorder: A case study of Prince William County, Virginia. *Criminology & Pub. Pol'y*, 12, 239.
- Lacayo, A. E. (2010). The impact of Section 287 (g) of the Immigration and Nationality Act on the Latino community.
- Litwin, M. B. (2011). The Decentralization of Immigration Law: The Mischief of 287 (g). *Seton Hall L. Rev.*, 41, 399.
- Little, T. D. (2013). *Longitudinal structural equation modeling*. New York, NY: Guilford press.
- Martinez Jr, R. (2014). *Latino homicide: Immigration, violence, and community*: Routledge.
- Miles, T. J., & Cox, A. B. (2014). Does immigration enforcement reduce crime? evidence from secure communities. *The Journal of Law and Economics*, 57(4), 937-973.
- Morenoff, J. D., & Astor, A. (2006). Immigrant assimilation and crime. *Immigration and crime: Race, ethnicity, and violence*, 36-63.
- Ousey, G., & Kubrin, C. (2018). Immigration and Crime: Assessing a Contentious Issues. *Annu. Rev. Criminol*, 1, 1.1-1.22.
- Rosseel, Y. (2012). Lavaan: An R package for structural equation modeling and more. Version 0.5–12 (BETA). *Journal of Statistical Software*, 48, 1-36.
- Sampson, R. J. (2008). Rethinking crime and immigration. *Contexts*, 7(1), 28-33.

- Sampson, R. J., & Bean, L. (2006). Cultural mechanisms and killing fields: A revised theory of community-level racial inequality. *The many colors of crime: Inequalities of race, ethnicity, and crime in America*, 8-36.
- Selig, J. P., & Little, T. D. (2012). Autoregressive and cross-lagged panel analysis for longitudinal data. In B. Laursen, T. D. Little, & N. A. Card (Eds.), *Handbook of developmental research methods* (pp. 265-278). New York, NY: Guilford Press.
- Shingles, R. D. (1976). Causal inference in cross-lagged panel analysis. *Political Methodology*, 3, 95-133.
- Singer, J. D. and Willett, J. B. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence*. Oxford University Press.
- Silver, I. A., Wooldredge, J., Sullivan, C. J., & Nedelec, J. L. (2020). Longitudinal Propensity Score Matching: A Demonstration of Counterfactual Conditions Adjusted for Longitudinal Clustering. *Journal of Quantitative Criminology*, 1-35.
- Steffensmeier, D., Ulmer, J. T., Feldmeyer, B., & Harris, C. T. (2010). Scope and conceptual issues in testing the race–crime invariance thesis: Black, White, and Hispanic comparisons. *Criminology*, 48(4), 1133-1169.
- Wright, K. A., Turanovic, J. J., & Rodriguez, N. (2016). Racial inequality, ethnic inequality, and the system involvement of at-risk youth: Implications for the racial invariance and Latino paradox theses. *Justice quarterly*, 33(5), 863-889.

## APPENDIX

Table 1: Full results of the cross-lagged panel model estimating the effects of individuals detained under a 287g and total crime count

	Regression Coefficients					
	<i>b</i>	SE	<i>p</i>	L95%CI	U95%CI	B
<i>Total Crime Count (2006)</i>	~					
Total Crime Count (2005)	0.784	0.029	0.000	0.727	0.840	0.777
Number of Illegal Immigrants Detained (2005)	0.000	0.000	0.101	0.000	0.001	0.001
Percentage of Population Hispanic (2005)	-0.023	0.015	0.131	-0.053	0.007	-0.012
Percentage of Population Unemployed (2005)	0.289	0.149	0.053	-0.003	0.581	0.033
<i>Number of Illegal Immigrants Detained (2006)</i>	~					
Number of Illegal Immigrants Detained (2005)	0.998	0.001	0.000	0.996	1.001	0.928
Total Crime Count (2005)	0.010	0.009	0.264	-0.007	0.026	0.003
Percentage of Population Hispanic (2005)	0.135	0.101	0.181	-0.063	0.332	0.024
Percentage of Population Unemployed (2005)	-0.003	0.051	0.950	-0.103	0.096	0.000
<i>Total Crime Count (2007)</i>	~					
Total Crime Count (2006)	1.074	0.056	0.000	0.965	1.183	0.967
Number of Illegal Immigrants Detained (2006)	-0.001	0.001	0.069	-0.002	0.000	-0.003
Percentage of Population Hispanic (2006)	0.028	0.027	0.313	-0.026	0.082	0.013
Percentage of Population Unemployed (2006)	0.007	0.173	0.967	-0.331	0.345	0.001
<i>Number of Illegal Immigrants Detained (2007)</i>	~					
Number of Illegal Immigrants Detained (2006)	1.346	0.085	0.000	1.179	1.513	0.629
Total Crime Count (2006)	0.159	0.114	0.164	-0.065	0.383	0.025
Percentage of Population Hispanic (2006)	0.463	0.257	0.072	-0.041	0.968	0.039
Percentage of Population Unemployed (2006)	-0.779	0.515	0.131	-1.789	0.232	-0.014
<i>Total Crime Count (2008)</i>	~					
Total Crime Count (2007)	0.895	0.028	0.000	0.839	0.950	0.929
Number of Illegal Immigrants Detained (2007)	0.000	0.000	0.147	-0.001	0.000	-0.002
Percentage of Population Hispanic (2007)	-0.009	0.013	0.488	-0.035	0.017	-0.005
Percentage of Population Unemployed (2007)	0.472	0.189	0.013	0.101	0.843	0.054
<i>Number of Illegal Immigrants Detained (2008)</i>	~					
Number of Illegal Immigrants Detained (2007)	1.126	0.207	0.000	0.721	1.530	0.530
Total Crime Count (2007)	0.200	0.106	0.058	-0.007	0.407	0.016
Percentage of Population Hispanic (2007)	0.452	0.246	0.066	-0.030	0.934	0.018
Percentage of Population Unemployed (2007)	-1.643	0.777	0.035	-3.167	-0.119	-0.015
<i>Total Crime Count (2009)</i>	~					
Total Crime Count (2008)	0.908	0.038	0.000	0.834	0.983	0.952
Number of Illegal Immigrants Detained (2008)	0.000	0.000	0.004	-0.001	0.000	-0.005
Percentage of Population Hispanic (2008)	0.012	0.017	0.459	-0.020	0.045	0.007
Percentage of Population Unemployed (2008)	0.175	0.111	0.117	-0.044	0.393	0.021
<i>Number of Illegal Immigrants Detained (2009)</i>	~					
Number of Illegal Immigrants Detained (2008)	0.967	0.033	0.000	0.903	1.032	0.885
Total Crime Count (2008)	0.143	0.128	0.266	-0.109	0.394	0.010
Percentage of Population Hispanic (2008)	0.664	0.511	0.194	-0.338	1.666	0.024
Percentage of Population Unemployed (2008)	-0.394	0.326	0.226	-1.033	0.245	-0.003
<i>Total Crime Count (2010)</i>	~					
Total Crime Count (2009)	0.887	0.038	0.000	0.812	0.963	0.926
Number of Illegal Immigrants Detained (2009)	0.000	0.000	0.085	0.000	0.000	0.003
Percentage of Population Hispanic (2009)	-0.016	0.011	0.150	-0.039	0.006	-0.009
Percentage of Population Unemployed (2009)	0.315	0.132	0.017	0.057	0.573	0.044
<i>Number of Illegal Immigrants Detained (2010)</i>	~					
Number of Illegal Immigrants Detained (2009)	0.718	0.023	0.000	0.673	0.763	0.990
Total Crime Count (2009)	-0.010	0.021	0.630	-0.052	0.032	-0.001
Percentage of Population Hispanic (2009)	0.154	0.120	0.198	-0.081	0.389	0.008

Percentage of Population Unemployed (2009)	0.276	0.232	0.234	-0.179	0.731	0.003
Residual Covariances						
	Cov.	SE	<i>p</i>	L95%CI	U95%CI	SD.Cov
Total Crime Count (2006)	~~					
Total Crime Count (2007)	-0.007	0.002	0.004	-0.012	-0.002	-0.344
Total Crime Count (2007)	~~					
Total Crime Count (2008)	-0.002	0.001	0.019	-0.004	0.000	-0.146
Total Crime Count (2008)	~~					
Total Crime Count (2009)	-0.002	0.001	0.000	-0.003	-0.001	-0.216
Total Crime Count (2009)	~~					
Total Crime Count (2010)	-0.001	0.000	0.000	-0.002	-0.001	-0.164
Number of Illegal Immigrants Detained (2006)	~~					
Number of Illegal Immigrants Detained (2007)	0.042	0.032	0.190	-0.021	0.105	0.146
Number of Illegal Immigrants Detained (2007)	~~					
Number of Illegal Immigrants Detained (2008)	1.336	1.051	0.204	-0.724	3.397	0.576
Number of Illegal Immigrants Detained (2008)	~~					
Number of Illegal Immigrants Detained (2009)	-0.088	0.228	0.700	-0.535	0.359	-0.025
Number of Illegal Immigrants Detained (2009)	~~					
Number of Illegal Immigrants Detained (2010)	-0.155	0.215	0.472	-0.577	0.267	-0.160
Total Crime Count (2006)	~~					
Number of Illegal Immigrants Detained (2006)	0.000	0.000	0.294	0.000	0.000	0.003
Total Crime Count (2007)	~~					
Number of Illegal Immigrants Detained (2007)	0.001	0.001	0.540	-0.001	0.002	0.003
Total Crime Count (2008)	~~					
Number of Illegal Immigrants Detained (2008)	0.000	0.001	0.598	-0.001	0.002	0.002
Total Crime Count (2009)	~~					
Number of Illegal Immigrants Detained (2009)	0.002	0.002	0.409	-0.003	0.006	0.012
Total Crime Count (2010)	~~					
Number of Illegal Immigrants Detained (2010)	0.000	0.000	0.715	0.000	0.000	-0.001
Baseline X2				1725.186	( <i>p</i> < .001)	
Model X2				151.908	( <i>p</i> = .007)	
CFI (TLI)				.993	(.990)	
RMSEA (90%CI)				.033	(.018, .046)	
N				3,104		

Notes: Cov = covariance; SE = Standard error; L95%CI = Lower interval of the 95% confidence interval; U95%CI = Upper interval of the 95% confidence interval; SD.Cov = Standardized covariance; The model was estimated using the MLM specification in Lavaan (version: 06-8), which estimates robust standard errors and a Satorra-Bentler scaled test statistic.

Table 2: Full results of the cross-lagged panel model estimating the effects of individuals detained under a 287g and violent crime count

	Regression Coefficients					
	<i>b</i>	SE	<i>p</i>	L95%CI	U95%CI	B
<i>Violent Crime Count (2006)</i>						
Violent Crime Count (2005)	0.857	0.028	0.000	0.802	0.912	0.700
Number of Illegal Immigrants Detained (2005)	0.000	0.000	0.311	0.000	0.001	0.001
Percentage of Population Hispanic (2005)	0.004	0.026	0.879	-0.048	0.056	0.002
Percentage of Population Unemployed (2005)	0.754	0.329	0.022	0.110	1.398	0.067
<i>Number of Illegal Immigrants Detained (2006)</i>						
Number of Illegal Immigrants Detained (2005)	0.998	0.001	0.000	0.996	1.001	0.928
Violent Crime Count (2005)	0.013	0.011	0.230	-0.008	0.035	0.005
Percentage of Population Hispanic (2005)	0.133	0.099	0.176	-0.060	0.327	0.024
Percentage of Population Unemployed (2005)	-0.015	0.042	0.717	-0.097	0.067	-0.001
<i>Violent Crime Count (2007)</i>						
Violent Crime Count (2006)	1.045	0.039	0.000	0.968	1.122	0.963
Number of Illegal Immigrants Detained (2006)	-0.003	0.001	0.024	-0.005	0.000	-0.005
Percentage of Population Hispanic (2006)	0.070	0.043	0.106	-0.015	0.155	0.027
Percentage of Population Unemployed (2006)	-0.190	0.202	0.347	-0.586	0.206	-0.016
<i>Number of Illegal Immigrants Detained (2007)</i>						
Number of Illegal Immigrants Detained (2006)	1.346	0.085	0.000	1.179	1.513	0.629
Violent Crime Count (2006)	0.124	0.090	0.169	-0.053	0.300	0.025
Percentage of Population Hispanic (2006)	0.459	0.258	0.075	-0.047	0.966	0.039
Percentage of Population Unemployed (2006)	-0.834	0.527	0.114	-1.868	0.199	-0.015
<i>Violent Crime Count (2008)</i>						
Violent Crime Count (2007)	0.845	0.036	0.000	0.774	0.916	0.900
Number of Illegal Immigrants Detained (2007)	0.000	0.000	0.975	-0.001	0.001	0.000
Percentage of Population Hispanic (2007)	0.051	0.024	0.030	0.005	0.098	0.021
Percentage of Population Unemployed (2007)	0.766	0.194	0.000	0.387	1.146	0.070
<i>Number of Illegal Immigrants Detained (2008)</i>						
Number of Illegal Immigrants Detained (2007)	1.125	0.206	0.000	0.721	1.530	0.530
Violent Crime Count (2007)	0.132	0.069	0.055	-0.003	0.267	0.014
Percentage of Population Hispanic (2007)	0.451	0.255	0.077	-0.049	0.950	0.018
Percentage of Population Unemployed (2007)	-1.621	0.715	0.023	-3.022	-0.219	-0.015
<i>Violent Crime Count (2009)</i>						
Violent Crime Count (2008)	0.888	0.042	0.000	0.806	0.971	0.921
Number of Illegal Immigrants Detained (2008)	0.000	0.000	0.090	-0.001	0.000	-0.004
Percentage of Population Hispanic (2008)	0.014	0.023	0.544	-0.031	0.060	0.006
Percentage of Population Unemployed (2008)	0.182	0.214	0.394	-0.237	0.602	0.018
<i>Number of Illegal Immigrants Detained (2009)</i>						
Number of Illegal Immigrants Detained (2008)	0.967	0.033	0.000	0.902	1.032	0.885
Violent Crime Count (2008)	0.173	0.148	0.245	-0.118	0.464	0.016
Percentage of Population Hispanic (2008)	0.632	0.486	0.194	-0.321	1.584	0.023
Percentage of Population Unemployed (2008)	-0.585	0.463	0.207	-1.493	0.323	-0.005
<i>Violent Crime Count (2010)</i>						
Violent Crime Count (2009)	0.886	0.018	0.000	0.850	0.922	0.949
Number of Illegal Immigrants Detained (2009)	0.000	0.000	0.996	0.000	0.000	0.000
Percentage of Population Hispanic (2009)	-0.012	0.020	0.549	-0.051	0.027	-0.005
Percentage of Population Unemployed (2009)	0.252	0.137	0.065	-0.016	0.520	0.029
<i>Number of Illegal Immigrants Detained (2010)</i>						
Number of Illegal Immigrants Detained (2009)	0.718	0.023	0.000	0.673	0.763	0.990
Violent Crime Count (2009)	-0.005	0.018	0.778	-0.041	0.030	-0.001
Percentage of Population Hispanic (2009)	0.154	0.119	0.195	-0.079	0.387	0.008
Percentage of Population Unemployed (2009)	0.270	0.227	0.233	-0.174	0.714	0.003
Residual Covariances						
	Cov.	SE	<i>p</i>	L95%CI	U95%CI	Sd.Cov

Violent Crime Count (2006)	~~					
Violent Crime Count (2007)	-0.012	0.004	0.003	-0.020	-0.004	-0.305
Violent Crime Count (2007)	~~					
Violent Crime Count (2008)	-0.001	0.002	0.538	-0.006	0.003	-0.060
Violent Crime Count (2008)	~~					
Violent Crime Count (2009)	-0.004	0.001	0.000	-0.005	-0.002	-0.196
Violent Crime Count (2009)	~~					
Violent Crime Count (2010)	-0.005	0.002	0.044	-0.009	0.000	-0.277
Number of Illegal Immigrants Detained (2006)	~~					
Number of Illegal Immigrants Detained (2007)	0.042	0.032	0.191	-0.021	0.105	0.146
Number of Illegal Immigrants Detained (2007)	~~					
Number of Illegal Immigrants Detained (2008)	1.337	1.053	0.204	-0.726	3.401	0.577
Number of Illegal Immigrants Detained (2008)	~~					
Number of Illegal Immigrants Detained (2009)	-0.087	0.228	0.703	-0.533	0.360	-0.025
Number of Illegal Immigrants Detained (2009)	~~					
Number of Illegal Immigrants Detained (2010)	-0.155	0.215	0.472	-0.577	0.267	-0.161
Violent Crime Count (2006)	~~					
Number of Illegal Immigrants Detained (2006)	0.000	0.000	0.406	0.000	0.001	0.003
Violent Crime Count (2007)	~~					
Number of Illegal Immigrants Detained (2007)	0.000	0.001	0.961	-0.003	0.003	0.000
Violent Crime Count (2008)	~~					
Number of Illegal Immigrants Detained (2008)	0.001	0.001	0.172	-0.001	0.003	0.005
Violent Crime Count (2009)	~~					
Number of Illegal Immigrants Detained (2009)	0.002	0.003	0.497	-0.004	0.008	0.009
Violent Crime Count (2010)	~~					
Number of Illegal Immigrants Detained (2010)	-0.001	0.000	0.069	-0.001	0.000	-0.008
Baseline X2			1574.871	$(p < .001)$		
Model X2			162.399	$(p = .001)$		
CFI (TLI)			.992	$(.988)$		
RMSEA (90%CI)			.036	$(.023, .048)$		
N			3,104			

Notes: Cov = covariance; SE = Standard error; L95%CI = Lower interval of the 95% confidence interval; U95%CI = Upper interval of the 95% confidence interval; SD.Cov = Standardized covariance; The model was estimated using the MLM specification in Lavaan (version: 06-8), which estimates robust standard errors and a Satorra-Bentler scaled test statistic.

Table 3: Full results of the cross-lagged panel model estimating the effects of individuals detained under a 287g and property crime count

	Regression Coefficients					
	<i>b</i>	SE	<i>p</i>	L95%CI	U95%CI	B
<i>Property Crime Count (2006)</i>						
Property Crime Count (2005)	0.736	0.030	0.000	0.678	0.794	0.753
Number of Illegal Immigrants Detained (2005)	0.001	0.002	0.616	-0.002	0.004	0.000
Percentage of Population Hispanic (2005)	-0.164	0.112	0.143	-0.383	0.056	-0.013
Percentage of Population Unemployed (2005)	1.814	0.942	0.054	-0.032	3.660	0.032
<i>Number of Illegal Immigrants Detained (2006)</i>						
Number of Illegal Immigrants Detained (2005)	0.998	0.001	0.000	0.996	1.001	0.928
Property Crime Count (2005)	0.002	0.002	0.113	-0.001	0.005	0.005
Percentage of Population Hispanic (2005)	0.133	0.100	0.183	-0.063	0.329	0.024
Percentage of Population Unemployed (2005)	-0.011	0.048	0.826	-0.105	0.084	0.000
<i>Property Crime Count (2007)</i>						
Property Crime Count (2006)	1.109	0.082	0.000	0.948	1.269	0.969
Number of Illegal Immigrants Detained (2006)	-0.008	0.005	0.130	-0.017	0.002	-0.003
Percentage of Population Hispanic (2006)	0.178	0.175	0.312	-0.166	0.521	0.013
Percentage of Population Unemployed (2006)	-0.151	1.386	0.913	-2.867	2.565	-0.002
<i>Number of Illegal Immigrants Detained (2007)</i>						
Number of Illegal Immigrants Detained (2006)	1.346	0.085	0.000	1.179	1.513	0.629
Property Crime Count (2006)	0.026	0.018	0.138	-0.009	0.062	0.027
Percentage of Population Hispanic (2006)	0.460	0.255	0.071	-0.039	0.959	0.039
Percentage of Population Unemployed (2006)	-0.753	0.515	0.144	-1.763	0.256	-0.014
<i>Property Crime Count (2008)</i>						
Property Crime Count (2007)	0.898	0.026	0.000	0.847	0.948	0.945
Number of Illegal Immigrants Detained (2007)	-0.002	0.002	0.252	-0.006	0.002	-0.002
Percentage of Population Hispanic (2007)	-0.214	0.092	0.020	-0.394	-0.033	-0.016
Percentage of Population Unemployed (2007)	2.831	1.127	0.012	0.622	5.039	0.048
<i>Number of Illegal Immigrants Detained (2008)</i>						
Number of Illegal Immigrants Detained (2007)	1.126	0.207	0.000	0.721	1.530	0.530
Property Crime Count (2007)	0.032	0.020	0.105	-0.007	0.070	0.018
Percentage of Population Hispanic (2007)	0.448	0.239	0.061	-0.020	0.916	0.018
Percentage of Population Unemployed (2007)	-1.603	0.795	0.044	-3.160	-0.045	-0.014
<i>Property Crime Count (2009)</i>						
Property Crime Count (2008)	0.913	0.036	0.000	0.843	0.983	0.955
Number of Illegal Immigrants Detained (2008)	-0.003	0.001	0.001	-0.005	-0.001	-0.006
Percentage of Population Hispanic (2008)	0.177	0.110	0.108	-0.039	0.392	0.014
Percentage of Population Unemployed (2008)	0.255	0.611	0.677	-0.943	1.452	0.005
<i>Number of Illegal Immigrants Detained (2009)</i>						
Number of Illegal Immigrants Detained (2008)	0.967	0.033	0.000	0.902	1.032	0.885
Property Crime Count (2008)	0.020	0.017	0.251	-0.014	0.054	0.010
Percentage of Population Hispanic (2008)	0.669	0.516	0.195	-0.343	1.680	0.025
Percentage of Population Unemployed (2008)	-0.340	0.282	0.228	-0.893	0.213	-0.003
<i>Property Crime Count (2010)</i>						
Property Crime Count (2009)	0.853	0.071	0.000	0.713	0.992	0.904
Number of Illegal Immigrants Detained (2009)	0.002	0.001	0.131	-0.001	0.005	0.005
Percentage of Population Hispanic (2009)	-0.112	0.085	0.187	-0.279	0.054	-0.010
Percentage of Population Unemployed (2009)	2.693	1.207	0.026	0.328	5.059	0.057
<i>Number of Illegal Immigrants Detained (2010)</i>						
Number of Illegal Immigrants Detained (2009)	0.718	0.023	0.000	0.673	0.763	0.990
Property Crime Count (2009)	0.000	0.003	0.983	-0.006	0.006	0.000
Percentage of Population Hispanic (2009)	0.152	0.119	0.199	-0.080	0.385	0.008
Percentage of Population Unemployed (2009)	0.260	0.220	0.237	-0.171	0.690	0.003
Residual Covariances						
	Cov.	SE	<i>p</i>	L95%CI	U95%CI	Sd.Cov

Property Crime Count (2006)	~~					
Property Crime Count (2007)	-0.385	0.150	0.010	-0.678	-0.092	-0.373
Property Crime Count (2007)	~~					
Property Crime Count (2008)	-0.133	0.051	0.009	-0.233	-0.034	-0.183
Property Crime Count (2008)	~~					
Property Crime Count (2009)	-0.097	0.029	0.001	-0.154	-0.040	-0.216
Property Crime Count (2009)	~~					
Property Crime Count (2010)	-0.097	0.030	0.001	-0.157	-0.038	-0.210
Number of Illegal Immigrants Detained (2006)	~~					
Number of Illegal Immigrants Detained (2007)	0.042	0.032	0.190	-0.021	0.105	0.146
Number of Illegal Immigrants Detained (2007)	~~					
Number of Illegal Immigrants Detained (2008)	1.336	1.051	0.204	-0.723	3.395	0.576
Number of Illegal Immigrants Detained (2008)	~~					
Number of Illegal Immigrants Detained (2009)	-0.088	0.228	0.699	-0.536	0.359	-0.026
Number of Illegal Immigrants Detained (2009)	~~					
Number of Illegal Immigrants Detained (2010)	-0.155	0.215	0.472	-0.577	0.267	-0.161
Property Crime Count (2006)	~~					
Number of Illegal Immigrants Detained (2006)	0.001	0.001	0.261	-0.001	0.003	0.004
Property Crime Count (2007)	~~					
Number of Illegal Immigrants Detained (2007)	0.005	0.007	0.444	-0.008	0.019	0.005
Property Crime Count (2008)	~~					
Number of Illegal Immigrants Detained (2008)	0.003	0.006	0.684	-0.010	0.015	0.002
Property Crime Count (2009)	~~					
Number of Illegal Immigrants Detained (2009)	0.016	0.018	0.382	-0.020	0.052	0.015
Property Crime Count (2010)	~~					
Number of Illegal Immigrants Detained (2010)	-0.001	0.001	0.241	-0.003	0.001	-0.003
	Baseline X2			1693.211	( <i>p</i> < .001)	
	Model X2			150.368	( <i>p</i> = .009)	
	CFI (TLI)			.993	(.990)	
	RMSEA (90%CI)			.034	(.018, .048)	
	N			3,104		

Notes: Cov = covariance; SE = Standard error; L95%CI = Lower interval of the 95% confidence interval; U95%CI = Upper interval of the 95% confidence interval; SD.Cov = Standardized covariance; The model was estimated using the MLM specification in Lavaan (version: 06-8), which estimates robust standard errors and a Satorra-Bentler scaled test statistic.