Immigrants' Deportations, Local Crime and Police Effectiveness *

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Abstract

This paper analyzes the impact of immigrant deportations on local crime and police efficiency. Our identification relies on increases in the deportation rate driven by the introduction of the Secure Communities (SC) program, an immigration enforcement program based on local-federal cooperation which was rolled out across counties between 2008 and 2013. We instrument for the deportation rate by interacting the introduction of SC with the local presence of likely undocumented in 2005, prior to the introduction of SC. We document a surge in local deportation rates under SC, and we show that deportations increased the most in counties with a large undocumented population. We find that SC-driven increases in deportation rates did not reduce crime rates for violent offenses or property offenses. Our estimates are small and precise, so we can rule out meaningful effects. We do not find evidence that SC increased either police effectiveness in solving crimes or local police resources. Finally, we do not find effects of deportations on the local employment of unskilled citizens or on local firm creation.

JEL codes: K24, K37

Key Words: Immigrants, Deportation, Crime, Police Effectiveness, Secure Communities

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1 Introduction

Despite popular belief, academic studies find little correlation between immigration and crime rates in the US. Most find that immigrants are less likely to commit crimes and less likely to be incarcerated than similar natives (Butcher and Piehl, 2008), while undocumented immigrants have lower conviction and arrest rates (Nowrasteh, 2018). There is evidence that immigration decreases local crime rates (Chalfin, 2015), but no evidence that the presence of undocumented immigrants is associated with more crime (Light and Miller, 2018). More recent research examines the impact of increased enforcement on local crime. For example, Chalfin and Deza (2018) find that the E-Verify program, allowing employers to check the work eligibility status of their employees, reduced the population of young males in Arizona thus reduced the occurrence of property crime by changing Arizona's demographic composition. Overall, the literature finds a negative or null association between immigrants and crime.

Immigrant deportations that explicitly prioritize removing people convicted of a crime, some advocates claim, is a more direct enforcement policy to meet the goal of reducing crime. The Trump administration has claimed that undocumented immigrants pose a security risk to justify increased deportations. [1]. This recent surge in deportations under President Trump is not the first time the US federal government has taken a harder line on immigration enforcement. As early as 1929-1934, the US carried out a forced repatriation of about 500,000 Mexicans and Mexican Americans, claiming, incorrectly, that this measure would have improved the working opportunities for natives (Lee, Peri and Yasenov, 2017). More recently, in the period 2008-2012, the US deported substantially more undocumented immigrants than it had in past decades.[2] The stated intent was to remove serious criminals and to reduce local crime. However, few studies have attempted to test these claims. Were enforcement policies effective at reducing crime rates or increasing police effectiveness? This paper seeks to answer this question empirically by identifying the impact of deportations on local crime rates and on police effectiveness in solving and preventing crime.

Deportations should reduce crime if the deported people are serious criminals or more likely to commit crimes in the future. If people who commit immigration violations are also more likely to commit other offenses, as some politicians claim, enforcement programs

[1]For example, see Politifact, Friday, February 24th, 2017, "Trump moves on Immigration. Deportations in First month"

[2]While all non-citizens are eligible for deportation, most increases in deportation efforts focus on undocumented immigrants. Other non-citizens may be deported if, for example, they commit an aggravated felony.

that provide immigration information to the police may help local law enforcement prevent crimes. In 2008, the Department of Homeland Security (DHS) launched Secure Communities (SC) as a tool to engage the resources of local police in federal immigration enforcement efforts by screening anyone booked into jail, no matter the reason, for immigration violations. Immigration and Customs Enforcement (ICE), the federal immigration enforcement agency, could then take custody of any person found to have violated immigration law. Between its introduction in 2008 and temporary suspension in 2014, SC led to over 450,000 deportations.

This paper considers whether more intense immigration enforcement, as measured by deportations per population, decreased crime rates for violent offenses or property offenses. First, we document that the staggered introduction of SC significantly increased the risk of deportation for undocumented immigrants once introduced. Then, we estimate the effect the deportation rate, measured as the number of deportations divided by the adult population, on changes in crime rates. Of course, deportations may be endogenous: unobserved factors such as local attitudes towards undocumented immigrants, or changes in police behavior, may impact both the local intensity of immigration enforcement and crime rates. Therefore, to identify a causal effect of deportations on crime, we instrument for the deportation rate with the interaction of the adoption of SC and the local presence of likely undocumented immigrants in 2005. To capture potential local economic effects of the Great Recession, we control for industry-specific employment shares in construction and manufacturing. In addition, we check the correlation of the timing of the rollout of SC with pre-2008 trends in crime, economic characteristics, and demographics.

Our main findings show that increased deportations did not reduce local crime rates. The estimated effect on violent crime is small and not statistically significant. The effect on property crime, while positive and usually significant, is also small. In most cases, the number of people removed by deportation did not have a large impact on the undocumented population at the local level. On average, one percent of the likely undocumented population was deported, although the share was as high as ten percent in some counties. This is likely too small a share to see a significant effect on crime from compositional changes. Deportations may also affect the undocumented population if immigrants move in response to more intense enforcement in an area. However, we do not find a significant correlation between deportation rates and changes in the likely undocumented population, suggesting that SC did not reduce the undocumented population in net. Of course, heightened enforcement may still have deterred crime if it reduced the propensity of the targeted population to commit crimes, but this seems unlikely considering that we do not find an impact on crime rates or demographic composition.

Beyond removing criminals, SC may have impacted police efficiency and resources indirectly by altering how local law enforcement allocated limited resources and changing the demands on those resources. To measure changes in police efficiency, we examine the local clearance rate, or the number of crimes cleared by arrest, relative to all crimes reported in a year. To check whether SC impacted police resources, as SC put higher demands on the local law enforcement by requiring jails to detain potential violators of immigration law, we examine the number of law enforcement personnel per capita. We do not find any evidence that increases in the deportation rate affected police efficiency or altered the level of police resources. Finally, SC could have affected crime indirectly by changing local employment opportunities or firm creation. However, we do not find evidence of unintended economic consequences through firm creation or the employment of less educated workers.

The paper is organized as follows. Section 2 reviews the literature on immigration and crime. Section 3 describes the features of the Secure Communities program, its timing and intensity and the consequences in terms of deportations. Section 4 describes the data we use and it shows the summary statistics and trends of the main crime, enforcement and deportation variables. Section 5 presents the empirical specification and discusses identification. Section 6 shows the main results on crime rates and section 7 presents results on police effectiveness and shows robustness checks. Section 8 explores local economic effects of enforcement, Section 9 discusses our results in relation to other policies aimed at reducing crime, and Section 10 concludes the paper.

2 Literature Review

While there is a series of studies by economists, sociologists and demographers on the correlation between immigration and crime, much less is known about the effectiveness of immigration enforcement in reducing crime. The second is a more specific question, but it is of great policy importance. First, policy evaluation is of direct interest to governments. Second, advocates of aggressive immigration enforcement policies often appeal to the need for public safety, hence implying that enforcement reduce crime. Evaluating the evidence of such claims is immediately relevant to forming effective public policy.

Butcher and Piehl were the first to show that immigrants are less likely to commit criminal offenses than natives (Butcher and Piehl, 1998a) and that, conditional on demographic characteristics, immigrants are less likely to be incarcerated (Bucther and Piehl

2007). Analyzing a panel of metropolitan areas, they show that there is no correlation between immigrant population share and crime, controlling for city demographic characteristics (Butcher and Piehl, 1998b). More recently Martinez, Stonewell and Lee (2010) find a negative correlation between homicides and immigration across census tracts in the San Diego metropolitan area, while Chalfin (2014) instruments for migration using rainfall shocks in Mexico and finds no correlation between immigration from Mexican and crime in the US. Likewise, Spenkuch (2014) does not find evidence of a correlation between immigration and violent crime in US states over three decades, but he does find a positive, though statistically insignificant, association with property crime. On the other hand Chalfin (2015) find that an increase in Mexican immigration, instrumented by the size of Mexican birth cohort, is associated with lower property crime and higher aggravated assaults.

Overall, this literature establishes that it is hard to find evidence of a positive relationship between immigration and crime in panel data. Several studies find that immigrants are less likely to commit crimes than similar natives, and this is now a well-established result. This paper asks a narrower and less understood question. Does immigration enforcement, in the form of deportations, reduce local crime? If immigrants targeted for deportation are more likely to be criminals then deporting them should reduce crime. And does it help local police to solve outstanding crimes and secure to justice its perpetrators?

The existing literature is sparse on both questions. Mastrobuoni and Pinotti (2015) and Baker (2014) analyze the effect of granting amnesty to undocumented immigrants on crime. These papers find that providing legal status reduces crime rates among immigrants. Ciancio (2017) uses variation from the drop in federal immigration enforcement that began in 2011 to examine crime rates and police efficiency. He finds that reductions in enforcement did not increase crime and may have increased police efficiency. Efficiency, measured as clearance rates could have increased with enforcement reductions because non-citizens were more willing to cooperate with the police, or because police could focus their efforts on more serious crimes rather than spending resources on immigration violations. Freedman, Owens and Bohn (2018) find that the 1986 Immigration, Reform, and Control Act increased crime among the recent immigrants most likely to be negatively impacted by IRCA employment regulations, suggesting that a lack of legal job opportunities drives crime; however, Freedman, Owens and Bohn (2015) suggest that IRCA changed police behavior, which may confound estimates of its effect on crime rates. We consider potential impacts of SC on police behavior by examining the local clearance rate, a measure of police efficiency, as well as considering potential employment effects of SC that might drive crime changes.

Miles and Cox (2014), the closest work to our research, also consider the effect of the rollout of SC on local crime immigration enforcement under SC on crime; however, there are several contributions from our approach. First, we establish the role of SC in increasing deportation intensity and exploit variation across counties. This approach draws on the fact that communities with more undocumented immigrants are more affected by this policy. If SC impacts crime, we should see a larger effect in those places. Second, we provide additional validity checks by showing low correlation between the rollout of SC and pre-SC changes in crime rates, income, and the non-citizen population share. Third, we expand the analysis to look at potential effects of enforcement on local population, employment and firm creation, as well as discussing the potential channels through which changes in these variables can affect local crime. Finally, we analyze the effect of deportations on local police effectiveness and police resources, considering whether a larger or more effective police force accompanies higher enforcement. Overall, our analysis confirms some findings of Miles and Cox (2014), in that we also find small and generally not significant effects of deportation on crime. We also produce a more complete picture of the local effects of enforcement and deportations. We do not find any significant effect of deportations on crime reduction or police effectiveness, local population, firm creation, or low-skill employment.[3]

More papers have used variation in enforcement and deportation intensity from SC to examine other outcomes. East et al. (2018) find that SC adoption reduced the employment of low-skilled non-citizen workers and middle-skilled native workers. Wang and Kaushal (2018) find an increase in the share of Latino immigrants reporting mental health issues after SC, and Alsan and Yang (2018) find that SC decreased SNAP take-up and ACA sign-ups for Hispanic citizens, suggesting the presence of spillover effects from enforcement. Overall, the existing literature shows that increased enforcement, and specifically SC, has had unintended negative consequences on both US citizens and immigrants. This paper re-assesses the role of SC in increasing deportations and the impact of enforcement, as measured by deportations, on local crime, police effectiveness, and economic and demographic outcomes.

3 Deportations and Secure Communities

The Department of Homeland Security (DHS) introduced Secure Communities beginning in 2008 and expanding to the entire US by January 2013. The program flagged immigrants in violation of immigration laws when local authorities arrested them for any reason, vastly increasing the number of people deported from the US. Between SC's inception in October

[3]East et al. (2018) find negative effect on the employment of low-skilled non-citizen men and middle to high-skill citizen men, defining skill according to occupational skill rather than education.

2008 and its temporary suspension in October 2014[4], Immigration and Customs Enforcement (ICE) deported over 450,000 people under its jurisdiction.

Prior to SC, ICE and local law enforcement would have to collaborate on a case-by-case basis to check the immigration status of arrested persons. Therefore, police only checked the immigration records of a small fraction of people booked into jail. Under SC, police had to check the fingerprints and bio-metric information of any arrested person against the DHS immigration database, IDENT, in addition to the standard procedure of checking fingerprints against the FBI criminal database. Because federal authorities mandated the implementation of SC, local authorities could not opt out of the program[5]. DHS staggered the implementation of SC due to resource constraints, beginning in counties near the Mexican border in 2008 and expanding to the entire US by January 2013. In this paper, we take advantage of the variation in timing across counties from this staggered roll-out to identify the effects of deportation.

Any arrested person found in violation of immigration laws could be subject to deportation. Following a fingerprint match in IDENT, ICE could issue a detainer request to the local jail, telling local authorities to hold the individual for an additional 48 hours. During that period, ICE would take custody and potentially begin deportation proceedings. Non-citizens can be deported for a variety of reasons. For a person legally present in the country, felony convictions can result in deportation. For undocumented immigrants, even minor offenses can trigger deportations, as can an arrest resulting in no charges or no criminal conviction at all. Table 2 shows that nearly half of deportees under SC had only minor offenses as their most serious criminal conviction (MSCC) or no offense at all. Specifically, 5% had been convicted of a traffic violation, 8% had immigration violations, 11% had a DUI and 5% were convicted of marijuana possession. 16% of deportees had no conviction at all. In total, 45% of deportees had only minor convictions or no conviction, suggesting that the increase in deportations under SC was not necessarily concentrated on serious criminals.

Beyond whether SC benefited local communities by preventing crime, or increased crime due to a less efficient allocation of police resources, we may also be interested in the relative costs to evaluate the net contribution of the program. The costs of setting up SC are not entirely clear, but Congress appropriated funding to implement the program in 2008 and 2009[6]. However, local and state authorities undertook the cost of detaining

[4]The Trump administration reinstated the program as of January 2017.

[5]While there was some uncertainty as the program was implemented on whether counties could opt out, all counties eventually enrolled

[6]According to Alsan and Yang (2018), Congress appropriated $150 million in additional funding to ICE in FY 2009 for SC, as well as directing ICE to allocate an extra $850 million to the program. In FY 2010,

people prior to ICE taking custody [7]. These non-reimbursed costs could have led local authorities to redistribute their resources. If SC effectively targeted criminals or increased police effectiveness, this redistribution of resources may have helped reduce crime. However, if most people detained under SC were not serious criminals, and the program did not deter future crimes, then SC would be an ineffective and costly measure that may have further diverted resources in a way that reduced local capacity to fight crime. Despite the potential for resource displacement, we did not find evidence of any change in local resources.

4 Data and Trends

We merge data on deportations, immigration enforcement policies, crime, police performance, population, and economic outcomes from 2005 to 2015. Data on deportations under Secure Communities come from individual-level ICE records, which we obtained from the Transactional Records Access Clearinghouse (TRAC) at Syracuse University. These data contain each deportation record, including the location, the date of apprehension, the gender and the major criminal conviction of the deportee. The dates of SC implementation by county come from ICE publications[8]. Although these data only cover deportations under SC, so we cannot see prior patterns in deportations at the county level, Figure 1 shows the evolution of interior (non-border) ICE apprehensions in the US, which increased substantially after SC began in 2008. We also use information on the presence of county and state-level 287(g) agreements in each year. These voluntary agreements between ICE and local authorities deputized local police to enforce federal immigration law, including detaining people for suspected immigration violations[9]. These agreements were voluntary and their adoption signaled a more aggressive stance towards enforcement. We control for 287(g) agreements in some specifications, but do not include them in our instrument because the adoption was not random; rather, it was a decision by counties or states and likely to be strongly correlated with local attitudes towards immigration. In the case that these underlying attitudes are similarly correlated with crime, this would lead to biased estimates.

Congress increased the amount it directed ICE to allocate to SC to $1.5 billion. This suggests annual cost of SC in the first two years was over $1 billion.

[7]Some counties, such as Cook County, Illinois, passed local ordinances stating that they would not comply with ICE detainer request and citing the expenses that the county incurred from holding detained aliens for the additional 48 hours. For a list of county detainer policies, see ILRC (2015). For more background on the legal issues surrounding ICE detainer requests, see Manuel (2015).

[8]We thank Laura Bellows for sharing both the original ICE publications and her digitization of the roll-out-dates dates.

[9]We are grateful to Chloe East for sharing data on the presence of 287(g) agreements

We measure the presence of SC as the fraction of the year SC was in place in counties[10] As we discuss below, SC led to a large increase in deportations and its start date was staggered across counties, providing the first component of our identifying variation. One might be concerned that SC began earlier in counties with high crime rates, selected economic or demographic characteristics, or other unobservable features correlated with crime. While timing of the roll-out is correlated with some characteristics of counties such as the Hispanic share of the population and the distance from the border, we will show that there is no evidence of correlation with pre-2005 trends in economic and crime variables.[11]. The second source of identifying variation is the county population share of likely undocumented immigrants. Specifically, counties with a larger population of likely undocumented immigrants experienced larger increase in deportations per capita following the introduction of SC. While any non-citizen can be deported, undocumented immigrants are the most likely to be deported. As described below, our instrument proxies for the policy-driven increase in deportations by interacting the SC indicator with the population share of likely undocumented immigrants.

We obtain data on the likely undocumented immigrant population from the American Community Survey (ACS). Due to privacy concerns, the ACS does not provide county-level detail, so we aggregate the data by Public Use Microdata Area (PUMA) as our geographic unit of analysis.[12] We follow the literature in defining likely undocumented immigrants as low-education Mexican and Central American non-citizens who arrived in the U.S. after 1986.[13] We also use the ACS to measure population and employment across localities. We limit our sample to people between the ages of 16 and 64 when measuring population and employment rates in the ACS, and we exclude those living in group quarters. We define population in hundreds, so that variables defined relative to population can be interpreted as percents.[14] We fix the population values in the denominator to the 2005 level, so that our measures are not affected by potential endogenous changes of population after 2005.

[10]This definition follows East et al. (2018). We aggregate county data to the PUMA level and weight all variables by the PUMA population share attributed to each county in a given PUMA.

[11]Cox and Miles (2013) document the correlates with time of SC activation

[12]PUMAs can represent either aggregations of smaller counties or part of a larger county. They do not cross state boundaries

[13]We exclude non-citizens who entered the US prior to 1986 because the Immigration Reform and Control Act, passed in 1986, granted amnesty to many immigrants already in the US. Low-skill refers to people with a high-school degree or less. We grant that this is not a perfect proxy, but is the standard method in these data and allows a sub-state level of geography. See Warren (2014), Passel and Cohn (2016), and Capps et al. (2018) for a discussion of methods on estimating the US undocumented population.

[14]These variables include the population share of police and employment-to-population ratio. In calculating crime rates, we follow the FBI UCR in defining crime rates per 100,000 population.

Figure 2 shows the PUMA-level evolution of deportations relative to 2005 population (top panels) and SC activation (bottom panels) from 2008 through 2012. While all counties eventually adopt SC, deportation intensity does not increase uniformly across the US. Instead, deportation rates remain low in some places and increase substantially in others. A large part of this variation is due to geographic differences in undocumented immigrants, the population with the highest risk of deportation. Figure 2 also shows that counties at the U.S.-Mexico border adopted SC first; these counties also have a larger share of undocumented immigrants and may have different economic and demographic composition, or vary in unobservable dimensions correlated with crime rates. Therefore, our preferred specification excludes border counties.[15]

Table 1 describes the undocumented population share, the deportation rate, and deportations per undocumented across PUMAs.[16] The median deportation rate across PUMAs, relative to the total working-age population, is zero. As less than 1.6% of the the median PUMA population is likely undocumented, the share of people deported is relatively low even after the introduction of SC. However, the undocumented population constitutes over 15% of the population in places with the highest undocumented share. In places with the highest deportation intensity, ICE deported over 10% of undocumented in a given year, and 0.2% of the total population.

Figure 3 displays the total number of SC deportations and those associated with only minor and non-criminal offenses.[17] There is clearly a sharp increase in deportations as more counties implemented SC between 2008 and 2012. However, despite the jails being the initial contact between immigrants and potential deportation proceedings under SC, not all deportations removed serious criminals. As shown in 2 over 15% of deportations are for individuals without any criminal conviction, while minor offenses such as immigration violations and traffic offenses make up another 30% of deportations.

Data on crime rates by county and on reported offenses cleared by arrest comes from the FBI Uniform Crime Reporting, which we obtained through ICPSR. Our main dependent variable is the local crime rate, defined as the number of crimes reported per 100,000 population.[18] We separate crimes into violent crimes and property crimes, as the two types of

[15] We follow East et al. (2018) and Alsan and Yang (2018) in excluding border counties.

[16] These variables average the entire 2005-2015 period. Due to the nature of our data, which only measures deportations under SC, we do not observe deportations in the period prior to the SC rollout.

[17] Minor offense deportations refer to individuals whose most serious criminal conviction is an immigration violation, a traffic offense, or the possession of marijuana. Non-criminal deportations refer to individuals who have not been convicted of a crime.

[18] Our measure of county population is from the ACS.

crime often have different motives and consequences, and thus immigration enforcement may not impact them in the same way. On average there were 3033 property crimes per 100,000 people per year in this period and 427 violent crimes per 100,000 people per year.

Besides the impact on crime we are also interested in the impact of deportations, as a tool of law enforcement, on outcomes relative to police efficiency and police resources. We use police per capita and crime clearance rate as outcomes in our regressions. If the police resources did not increase with SC or with the increase in deportation, this may imply that Police had to divert some resources to implement this program. If a goal of SC was to give local police more tools to combat crime, especially crime committed by immigrants, one outcome could be higher ability to solve crimes and clear them with an arrest. Hence we use clearance rates as outcomes. We also examine the change in police per capita using the ACS data to measure employees in police occupations relative to local population.[19]

As a measure of police efficiency, we examine the clearance rate, or the share of reported offenses cleared by arrest. Specifically, the clearance rate is the total number of clearances divided by the difference of total offenses and unfounded offenses.[20] Because the UCR records clearance rate data by agency rather than county, and agencies may span multiple counties (or vice-versa), we aggregate to the county level. Our procedure allocates the total number of offenses and clearances for each category across the three largest counties covered by the agency in proportion to the population of the county within the borders of each jurisdiction.[21] We then calculate clearance rates at the county level for property offenses and violent offenses, and finally aggregate to the PUMA level as in the previous analyses. We express clearance rates in percents, or clearances per 100 offenses, and we exclude observations outside a range of two standard deviations from the mean clearance rate. Our sample excludes PUMAs with missing clearance rates and those with fewer than five years of data on clearance rates[22]. Table 1 describes the distribution of crime rates and clearance rates. The average clearance rate for violent crimes is over 52%, while the average clearance rate for property crimes is less than 18%.

Finally, we analyze whether deportation intensity had unintended effects on firm creation and employment. Data on firms by sector comes from the County Business Patterns.

[19]Specifically, we consider people employed as police, detectives, and private investigators, as well as other law enforcement officers: sheriffs, bailiffs, and correctional institution officers.

[20]Unfounded offenses are reported offenses that the police determine did not occur.

[21]Some agencies may map to only one county; others may cover multiple counties. Our data report only the three largest counties. Also note that a single county may include multiple agencies (for example, the state police and a local police agency).

[22]Excluding PUMAs with fewer than five years of data drops 1.5% of the sample. Results including these PUMAs are similar in both magnitude and precision.

We consider three types of sectors that employ a large share of undocumented immigrants. First, we examine firms in the agricultural industry, which we define according to the broader two-digit NAICS code and the narrower three-digit NAICS code. We also consider the construction industry and the service industry. We focus on the food service industry, building services, and landscape work as they employ the largest share of likely undocumented workers[23]. The dependent variable of interest in these specifications is the change in firms per 1,000 population. To examine employment shares of low-skill workers, we measure employed workers using the ACS and define skill according to education as before, where low-skill workers refers to individuals with a high school degree or less.

5 Empirical Model, identification and Discussion of Causality

Our main specification analyzes whether deportations affect local crime rates. We define deportations under SC relative to the working-age population to capture local enforcement intensity.

$$\Delta y_{c,t} = \alpha + \beta \frac{D_{c,t}}{Pop_{c,2005}} + \gamma X_{c,t} + \phi_c + \tau_t + \varepsilon_{c,t}$$

The dependent variable $\Delta y_{c,t}$ measures change in reported crimes per 100,000 residents in location c (PUMA) between year t and year $t-1$. Our analysis considers both property crimes and violent crimes. $\frac{D_{c,t}}{Pop_{c,2005}}$ is the number of deported people from location c in year t as a percent of 2005 working-age population. If SC effectively targets criminals, then deportations under this program should reduce the crime rate. $X_{c,t}$ includes controls for the manufacturing share and the construction share of employment in location c in year t, relative to total employment in 2005. The term τt represents year fixed effects, and ϕ_c represents PUMA-level fixed effects. Because the dependent variable is expressed in annual changes, ϕ_c captures a location-specific trend in the the level of the crime rate.

The goal of the analysis is to understand whether higher deportation rates, induced by tougher enforcement, reduce crime. Deportations could affect crime through multiple channels, primarily through the deportation of potential criminals, but also through changes in resource allocation and police efficiency or impacts on local labor markets and demographic

[23] We tabulate industries by share of likely undocumented workers using the ACS

composition. If deportations remove individuals who are more likely to commit crimes, then changes in the deportation rate should lead to a proportional reduction in the crime rate. However, OLS estimates of equation 5 are likely to be biased due to unobservable changes in local economic, political, and demographic conditions which may affect both deportations and crime rates. We address this problem by taking advantage of the staggered roll-out of SC across counties as quasi-experimental variation in the intensity of enforcement. Specifically, we instrument for the deportation rate, $\frac{D_{c,t}}{Pop_{c,2005}}$, with the interaction of an indicator for SC activation and the share of likely undocumented immigrants in 2005, or $SC_{c,t} * \frac{Undoc_{c,2005}}{Pop_{c,2005}}$.

As described above, proximity to the border was the main factor correlated with the timing of SC roll-out across countries. Table 3 shows a regression of time of SC activation on county characteristics. Time to activation is measured in months from January 2008. Again, we drop border counties from our sample, as they were the earliest to activate SC and may differ in other dimensions correlated with crime that would confound our estimates, and Table 3 examines correlates of SC activation among the remaining sample to ameliorate further concerns. Densely populated counties and counties with a larger Hispanic population share activated SC earlier (this is consistent with Miles and Cox (2014)). However, the time to activation is correlated with neither the trend in the average pre-activation (2005-2008) crime rate nor changes in construction and manufacturing employment that are indicative of the intensity of the Great Recession in the location.

As another source of variation comes from differential deportation intensity induced by differences in the initial population share of undocumented immigrants, Figure 4 shows an event study of deportations stratified by the 2005 undocumented share. The PUMAs with a high share of undocumented are those in the top quartile, and those with a low share undocumented are in the bottom quartile. As expected, most deportations occur in the counties with the largest share of people eligible to be deported. Table 4 shows the power of the instrument more formally. Column (1) shows the first stage regression of our main specification, which interacts SC with the population share of all likely undocumented immigrants as the group at risk of deportation. This regression suggests that SC activation increases the deportation rate by 0.007 percentage points for every percent of the population that is undocumented, or 33%relative to the mean deportation rate of 0.021. At the mean undocumented share of 3.3%, SC activation led to a 0.023 percentage point increase in the deportation rate. This coefficient is statistically significant and the F-statistic indicates it is a strong instrument. In column (2) we interact SC with the share of undocumented men in constructing the IV, as men are at much higher risk of deportation[24] This regression suggests a 0.013% increase in deportations per year for every population percent undocumented when the SC program is activated.

6 Effects on Crime Rates

Table 5 shows the main 2SLS estimates from equation (5) when the dependent variable is the change in violent crime (Panel A) or property crime (Panel B)[25].

All regressions follow the specification in equation 5, with slight modifications. Column (1) is our preferred specification, which drops PUMAs bordering Mexico and includes controls for construction and manufacturing employment in addition to PUMA and year fixed effects. Column (2) drops controls for the manufacturing construction employment shares, while column (3) adds border PUMAs, which adopted SC earlier and where the rollout may be correlated with other factors related to crime.

Looking at the estimated coefficients, two results stand out. First, deportations have a small and non-significant impact on violent crime. To put the estimates in perspective, consider the relatively large increase in deportation rates between the median PUMA, with no deportations, and the 99th percentile PUMA, which deports 0.2% of its working age population per year. Our estimates suggest that a 0.2% increase in the deportation rate increases the violent crime rate by only 4.8 offenses per 100,000 persons per year, relative to the average violent crime rate of 654 offenses per 100,000. Not only is this positive coefficient inconsistent with deportations removing criminals and thus reducing crime, it is not statistically distinguishable from zero. Therefore, we do not find evidence that even a large increase in the local deportation rate was associated with any significant change in crime, particularly not a decrease in crime. Second, the impact of deportations on property crimes is also very small and positive, although it is statistically significant. In this case, a 0.2% increase in the deportation rate would increase property crimes by 205 per 100,000, relative to an average of 4534 property crimes per 100,000 people per year. Again, while statistically significant, this value is still quite small, and a positive effect is inconsistent with claims of deportations reducing crime.

[24] Approximately 96% of deportees are male in our data.

[25] Violent crimes include murder, manslaughter, rape, robbery, and aggravated assault. Property crimes include burglary, larceny theft, and motor vehicle theft. Crime variables are expressed as rates per 100,000 population.

While the roll-out of SC provides a more credible identification strategy, due to the quasi-experimental nature of its activation timing, we already mentioned an even more aggressive program during the same period, 287(g) agreements. These agreements between ICE and local law enforcement agencies gave police the authority to enforce immigration law more directly. Under the task-force model, the most forceful version of 287(g), local police had similar authority to ICE agents in arresting and detaining people for immigration violations. Only a select group of counties enacted such controversial policies, and entering 287(g) agreements likely corresponded to local preferences for an aggressive stand on immigration enforcement. To check whether the effect of deportations varied in places with 287(g) agreements, Table 6 includes an indicator for the PUMAs and years in which a 287(g) agreement was in place. The results for the change in violent crime rates (Panel A) and property crime rates (Panel B) are estimated using 2SLS and follow our preferred specification including controls for industry shares, PUMA and year fixed effects, and dropping border counties. Controlling 287(g) agreements does not change the estimated effect of deportations significantly. Considering the 287(g) indicator itself, we do not find a statistically significant association between 287(g) agreements and crime.

Next, we consider whether deportations had a measurable effect on the size of the low-skilled population, and specifically the low-skilled non-citizen or likely undocumented population. While low-skilled individuals, defined as those with a high school degree or less, are more likely to commit a crime[26], the average number of deportees per year was only 0.02% of the working-age population and likely too small to produce a measurable effect on crime. In principle, however, aggressive enforcement and deportations may induce other immigrants to leave, therefore magnifying any effects on local demographic composition. Table 7 examines the effect of deportations on changes in the low-skilled working-age population, the low-skilled non-citizen population, and the likely undocumented population. None of the estimated coefficients are statistically significant, and most estimates are positive[27]. This suggests that deportations did not have a significant effect on the size of the low-skilled population or the likely undocumented population in a PUMA and indicates that deportations did not affect crime through compositional change.

[26] Lochner and Moretti (2004), for instance, show that high school graduation and additional education are related to a significant decline in the probability of committing crimes, especially violent crimes.

[27] Bohn, Lofstrom and Raphael (2013) find that harsher sanctions of employers who hire undocumented immigrants, brought by the Legal Arizona Workers Act, reduced the state's likely undocumented population

7 Effects on Police Effectiveness and Police Resources

7.1 Clearance Rates

There is another potential role of the SC program and in general of providing more aggressive enforcement tools to local police. If immigrants, and especially undocumented immigrants, are involved in a large fraction of crimes, then the ability to detain them may be a tool for the police to pressure them and to solve crimes, ensuring more arrests of criminals. Alternatively, however, if few undocumented immigrants are criminals, then the procedures and costs involved in detaining them may divert resources from where they can be more productive in fighting crime. In this section we analyze the correlation between enforcement driven deportations and two measures related to the effectiveness of local police. One captures police efficiency in solving crimes, the other measures local police resources.

We measure police efficiency using clearance rates for violent and property crimes. The clearance rate is the number of crimes cleared by arrest[28], relative to all the reported (and confirmed) crimes (see Federal Bureau of Investigation (2017)). The clearance rate is significantly higher for violent crimes, averaging 52% from 2005-2015, than for property crimes, where the average clearance rate was only 18% from 2005-2015), and is a proxy for the investigative effectiveness of the police. Table 8 shows the impact of deportations on the annual change in PUMA-level clearance rates. The estimates are small, and only the estimate for the property crime clearance rate is statistically significant. These results imply that a large increase in the deportation rate of 0.2 percentage points will increase the clearance rate by about 0.23 percentage points for violent crimes (on an average of 53%) and by 0.04 percentage points for property crimes (relative to an average of 18%). These are negligible effects, supporting the hypothesis that increased enforcement did not result in efficiency gains for local law enforcement.

7.2 Police Resources

The mandate of SC to local police requires jails to keep people suspected of immigration violations in custody for up to 48 hours past the normal detention period, and this comes with a cost to local law enforcement. Jails must have space available to hold suspects, as well as agents to assist in the detention and transfer process. The federal government did not

[28]For a crime to be cleared, the police must arrest the perpetrator, who is then charged with the crime, and the government must begin prosecution.

directly appropriate funds to local agencies when implementing SC, so we must ask whether SC put a strain on local police resources.

First, we analyze whether counties with larger increases in the deportation rate also increased the number of law enforcement officers to manage any additional costs of the program. Specifically, we regress the change in number of police officers per 100 population the deportation rate at the PUMA-year level. Column (1) of Table 9 shows the reduced form and column (2) shows the estimates using 2SLS. These results show that deportation rates were not associated with changes police resources in this period. Therefore, counties with more deportations may have had to devote a larger fraction of prior local resources to enforcement, or divert them from other uses. This may be consistent with an actual increase in property crime rates due to more thinly spread resources for crime prevention[29].

7.3 Crime Reporting Rates

Official crime reports (such as the FBI Unified Crime Report) are based on reported offenses, so a concern related to any analysis relying on these data is that reporting rates, rather than in crime rates themselves, may have changed in response to a policy change. In our case, deportations may cause a change in crime reporting, perhaps due to fear of interacting with local law enforcement. If reporting changes are in the opposite (same) direction of crime changes, our analysis may underestimate (overestimate) the impact of enforcement on crime. Absent county-level data on crime reporting across the US, we cannot decompose the impact of deportations on reporting versus actual crime changes. However, we look at information on reporting rates by type of crime from the National Crime Victimization Survey across forty Metropolitan Statistical Areas (MSAs) in 1990 amd 2000. We match each MSA to its central county (or, in some cases, multiple counties), and obtain county-level data on reporting rates of violent and property crimes. Then, we analyze the correlation between the change in crime reporting rates and the change in the population share of foreign-born between 1990 and 2000.[30]

Figure 5 plots the correlation between the change in violent crime reporting (panel A) and property crime reporting (panel B) and the change in the foreign-born population. Both

[29] We do not find evidence, however, that controlling for changes in police resources attenuates the small positive effect of immigration enforcement on local property crime.

[30] In addition to standard categories of violent offenses and property offenses, the NCVS also includes reports of the verbal threat of assault. There are not many reports in this category, and we include it with violent crimes. We obtain data on the county-level population share of foreign-born from the NHGIS, which we to the MSAs in the NCVS

property crime and violent crime reporting rates are have a negative association with the change in foreign-born, although the correlation is only statistically significant for violent crime reporting. It is possible that deportations could decrease crime reporting, either through demographic changes or by changing the willingness of the immigrant community to report crimes to the police, we do not find any evidence of population changing as a result of SC. The small positive effect of SC on property crime could be biased down by a decrease in reporting, but violent crime, composed of more serious offenses, is less likely to be subject to under-reporting.

8 Local Economic Effects

While we do not find evidence for a significant impact of deportations on crime rates, the main motivation for more aggressive immigration enforcement, such policies may have unintended consequences on local economies. The removal of undocumented workers, or fear generated by deportations in immigrant communities, may disrupt sectors such as agriculture, construction, and service industries that employ a relatively large share of undocumented workers, reduce the employment rate of immigrant workers if undocumented employees are afraid to go to work, and potentially have spillover effects that reduce the employment of native workers. On the other hand, if deportations remove criminals, then more aggressive enforcement could attract more firms and increase employment.

Existing studies find negative employment effects of enforcement (East et al., 2018), and we supplement our analysis of crime by considering whether deportations affect local firm creation and employment using a different identification strategy. Table 10 considers the impact of deportations on the change in the number of firms relative to initial population in different sectors. We focus on industries that employ a larger share of low-skilled immigrants; specifically, we examine agriculture (Panel A), construction and food services (Panel B), and building and landscape services (Panel C). Column (1) of Panel A shows a possible negative effect of deportation on firm creation in agriculture, but the coefficient becomes positive, smaller, and only marginally significant when we define agriculture according to a stricter definition that excludes fishing and hunting. The estimates for other industries are not statistically significant and do not show convincing evidence of either a positive or negative effect of deportations on firm creation.

Table 11 analyzes the effect of deportations on the employment-to-population ratio for low-skilled workers and for low-skilled non-citizen workers. These estimates do not show any statistically significant effect of deportations on employment. While our analysis focuses on crime rather than the potential economic effects of enforcement, these estimates do not show any support for claims that deporting undocumented immigrants will improve economic conditions or provide work opportunities for natives. Ifft and Jodlowski (2016) find evidence of a negative impact of 287(g) agreements on agricultural productivity and firms. While we find suggestive evidence to confirm this negative effect on firm creation in the broadly-defined agricultural sector, we do not find this effect using a narrower definition, nor do we find significant effects in other sectors. We also do not find any significant effects on low-skilled employment.

9 Comparison with other Crime-reducing Policies

A large literature in criminology has evaluated the effectiveness of different policing methods in reducing crime, especially violent crime and murder. In this section, we review some typical (or meta-) estimates of the effect of some these policies on crime and compare them to our estimates of the average change in violent crime due to ICE deportations of immigrants. As a case study, we consider the intensive immigration enforcement that occurred in Maricopa County, Arizona, where average deportation rate from 2008-2012 was 0.17% of the 2005 working-age population. We compare the estimated effect on crime in this county to estimates of crime reductions from well-known law-enforcement interventions designed to reduce crime rates. This allows us to consider whether small effects on violent crime are a constant feature of programs directed at fighting crime, or whether deportations have effectively no impact in comparison to more successful crime-reducing policies.

Maricopa County had the second largest number of total deportations from 2008-2012, with 20,603 immigrants deported under SC, and the third largest average deportation rate, as shown in Table 12[31]. Maricopa County is well-known for the extreme stance on immigration enforcement of local Sherrif Joe Arpaio, who held the office from 1993-2017 and was accused of police misconduct and racial profiling [32]. Our estimates, though not statistically significant, would predict that deporting such a large number of immigrants (0.173 percent of the working-age population, on average, in Maricopa County), increases the violent crime rate by 4.2 offenses per 100,000 working-age adults, relative to an average violent crime rate of 654 per 100,000. This impact is only 0.6% of the average violent crime

[31]This county, however, was not among those with highest total crime rate or the highest violent crime rate. Table 13 lists the areas with the highest crime rates over this period.

[32]See, for instance, the Wikipedia entry on Joe Arpaio, https://en.wikipedia.org/wiki/JoeArpaio

rate, and, though not statistically significant, the magnitude is positive, rather than the expected negative estimate if SC had successfully reduced crime.

Existing studies on crime reduction have several limitations. First, they often rely on correlation evidence in panel regression, rather than a well identified strategy to isolate a causal effect. Second, they often use a treatment and control framework to evaluate broad policies that act on many different dimensions at the same time. This makes it difficult to estimate a clear effect of a specific measure on crime rates. With these caveats in mind, we focus on three types of policies which share some underlying premises with immigration enforcement policies that are used to justify deportations as a crime-deterrent or crime-incapacitating policy.

The first type of policy is "broken window policies" that increases the probability of arrest and punishment for small crimes. The underlying assumption is that people who commit a misdemeanor would eventually be more likely to commit violent crimes. Therefore, being arrested earlier for a smaller crime prevents them, either through deterrence or incapacitation, from committing a more serious crime later. This premise has been criticized by several criminologists, but early studies of the connection between arrests for misdemeanors and crime found significant effects. Kelling and Sousa (2001) used precinct-level data from New York City to examine whether higher rates of misdemeanor arrest were associated with lower levels of crime, after taking account of other characteristics of the precincts. They concluded that aggressive misdemeanor arrests produced a statistically significant 5% reduction in violent crime. This would imply, in our sample, a reduction by 21 violent crimes per 100,000 individuals from an average of 416 crimes per 100,000. However, a more recent study by Rosenfeld, Fornango and Rengifo (2007) found smaller effects of increased misdemeanor arrests on crime incidence, and studies by Fagan and Davies (2003) and Harcourt and Ludwig (2006) found no evidence of a statistically significant effect at all. All of these studies are based on panel correlations and do not have an experimental or quasi-experimental design. A recent meta-analysis (Braga, Welsh and Schnell, 2015) of the relationship between misdemeanor arrests and crime, which includes experimental and quasi-experimental evidence, does not find significant evidence of misdemeanor arrests in reducing serious crime.

A second type of policy used to reduce crime is "Stop, question and frisk policies". Under such policies, police officers patrol areas by foot, and they actively stop pedestrians, question them, and often search them. This type of intervention is usually implemented in high-crime areas. While the correlational evidence on the the effectiveness of these methods is inconclusive, two randomized experiments in Philadelphia (the Foot Patrol Experiment, (Ratcliffe et al., 2011) and the Philadelphia Policing Tactics Experiment (Groff et al., 2015)), allowed researchers to evaluate the impact of this type of method on randomly selected crime hot-spots. These studies find a 23% decrease in violent crime three months after the experiment. This effect corresponds to 96 fewer violent crimes per 100,000 citizens for the average PUMA in our sample. This would be a substantial decrease and much larger than the magnitudes of the effects we estimate in this paper.

Finally, a third type of intervention believed to be effective at reducing crime is the category of person-focused strategies and deterrence. These are strategies implemented to halt ongoing violence by gangs and other criminally active groups and to disrupt disorderly and violent drug markets. The idea is that by targeting groups likely to commit crimes and participating in crime-related activities, these policies will reduce violent crime. One important example of such a policy is Operation Ceasefire in Boston. The local police identified gangs and dangerous individuals, gave them warnings to deter crime, and used all available legal means to disrupt drug activity by enlisting informants, seizing drugs and proceeds, and maintaining strict enforcement of probation and parole. Several studies evaluated the effect of this policy on reducing youth homicide in Boston. They compare Boston with similar cities using a treatment-control analysis. Braga et al. (2001) find a 66% reduction of youth homicide and a 25% reduction in gun violence, which are remarkable results. Such results correspond to a decline of between 104 and 276 violent crimes per 100,000 people in the average PUMA in our sample. Again, this is a substantially larger impact than the deportation policy that we analyze in this paper.

While the policies considered above often involve a combination of actions, their estimated impact on violent crime rates give us an idea of the magnitude of effects one can expect form effective crime reducing policies[33]. In general, policies targeted to individuals more likely to be involved in violent crime (such as gangs and serious drug traffickers) are the most effective at reducing violent crime and can have strong impacts. Policies that target high crime areas and use foot patrols to stop, question and frisk may also be quite effective. There is much less evidence on the effectiveness of arresting people for committing minor crime (misdemeanors) as a way to prevent more serious crime. Our findings are consistent with these results: targeting a population that has a low probability of committing crimes, such as the undocumented immigrants, with deportations does not affect crime rates through deterrence or through incapacitation. Using deportation as a way to reduce crime can be seen as a more extreme extension of a policy that targets people for very minor violations under the assumption that they may commit more serious crimes in the future; however,

[33]For a more systematic summary and evaluation of the recent literature on policies reducing crime rates see National Academies of Sciences (2018).

empirical evidence does not support this argument.

10 Conclusions

Using county-level variation in deportation increases due to SC, we analyze the potential effects of deportation on local crime rates and police efficiency. We instrument for deportations using the staggered roll-out of SC interacted with the initial presence of likely undocumented immigrants in a county. If SC was effective at targeting serious criminals and removing them from the US, these deportations should decrease crime. However, we find that higher deportation rates are not associated with lower crime rates. In fact, accounting for the potential endogeneity of deportations, we find a very small and positive, though usually non-significant, effect of deportations on crime. In considering the potential mechanisms for a possible effect, or lack of effect, of SC on crime, we document that more enforcement-driven deportations do not increase police efficiency in solving criminal cases, nor they bring more police resources to the local community. Similarly, higher deportation rates do not attract businesses or increase job opportunities for low-skilled workers.

Of course, there are still caveats to our analysis. For example, if there are differential deviations from average changes in crime rates across counties with large and small shares of undocumented immigrants that are correlated with confounding factors, such as changes in local attitudes towards immigration, our location and time fixed effects will not account for such remaining confounding variation. However, we show that pre-existing trends in crime and economic characteristics are not correlated with the timing of SC activation, addressing concerns about endogenous program implementation, and we include controls for manufacturing and construction employment shares in an attempt to account for potential effects of the Great Recession that vary across places. Overall, our analysis suggests that there is not empirical support for the claims of the Trump Administration and other public figures that immigrant deportations reduce crime and make communities safer.

References

Baker, Scott R. 2014. "Effects of Immigrant Legalization on Crime: The 1986 Immigration Reform and Control Act." SIEPR https://siepr.stanford.edu/research/publications/effects-immigrant-legalization-crime-1986-immigration-reform-control-act 12-012, Stanford, CA.

Bohn, Sarah, Magnus Lofstrom, and Steven Raphael. 2013. "Did the 2007 Legal Arizona Workers Act Reduce the State's Unauthorized Immigrant Population?" *The Review of Economics and Statistics*, 96(2): 258–269.

Braga, Anthony A., Brandon C. Welsh, and Cory Schnell. 2015. "Can Policing Disorder Reduce Crime? A Systematic Review and Meta-analysis." *Journal of Research in Crime and Delinquency*, 52(4): 567–588.

Braga, Anthony A., David M. Kennedy, Elin J. Waring, and Anne Morrison Piehl. 2001. "Problem-oriented policing, deterrence, and youth violence: An evaluation of Boston's Operation Ceasefire." *Journal of Research in Crime and Delinquency*, 38(3): 195–225.

Butcher, Kristin F., and Anne Morrison Piehl. 2008. "Crime, Corrections, and California: What Does Immigration Have to Do with It?"

Chalfin, Aaron. 2014. "What is the Contribution of Mexican Immigration to U.S. Crime Rates? Evidence from Rainfall Shocks in Mexico." *American Law and Economics Review*, 16(1): 220–268.

Chalfin, Aaron. 2015. "The Long-Run Effect of Mexican Immigration on Crime in US Cities: Evidence from Variation in Mexican Fertility Rates." *American Economic Review*, 105(5): 220–225.

Chalfin, Aaron, and Monica Deza. 2018. "New Evidence on Mexican Immigration and Crime in the United States: Evidence from a Natural Experiment in Immigration Enforcement."

Ciancio, Alberto. 2017. "The Impact of Immigration Policies on Local Enforcement, Crime, and Policing Efficiency."

Cox, Adam B, and Thomas J Miles. 2013. "Policing immigration." *The University of Chicago Law Review*, 80(1): 87–136.

East, Chloe N, Philip Luck, Hani Mansour, and Andrea Velasquez. 2018. "The Labor Market Effects of Immigration Enforcement." *IZA*, DP No. 11486.

Fagan, J, and G Davies. 2003. "Policing guns: order maintenance and crime control in New York." In *Guns, Crime, and Pun ishment in America.* , ed. B Harcourt, 191–221. New York:New York Universtiy Press.

Freedman, Matthew, Emily Owens, and Sarah Bohn. 2015. "The Criminal Justice Response to Policy Interventions: Evidence from Immigration Reform." *American Economic Review*, 105(5): 214–219.

Freedman, Matthew, Emily Owens, and Sarah Bohn. 2018. "Immigration, Employment Opportunities, and Criminal Behavior." *American Economic Journal: Economic Policy*, 10(2): 117–151.

Harcourt, Bernard, and Jens Ludwig. 2006. "Broken Windows: New Evidence from New York City and a Five-City Social Experiment." *University of Chicago Law Review*, 73(1).

Ifft, Jennifer, and Margaret Jodlowski. 2016. "Is ICE Freezing US Agriculture? Impacts of Local Immigration Enforcement on US Farm Profitability and Structure."

Kelling, G.L., and W.H. Sousa. 2001. "Do Police Matter? An Analysis of the Impact of New York Citys Police Reforms." Manhattan Institute for Policy Research Civic Report 22, New York.

Lee, Jongkwan, Giovanni Peri, and Vasil Yasenov. 2017. "The Employment Effects of Mexican Repatriations: Evidence from the 1930's." National Bureau of Economic Research Working Paper 23885.

Light, Michael T., and Ty Miller. 2018. "Does Undocumented Immigration Increase Violent Crime?*." *Criminology*, 56(2): 370–401.

Lochner, Lance, and Enrico Moretti. 2004. "The Effect of Education on Crime: Evidence from Prison Inmates, Arrests, and Self-Reports." *American Economic Review*, 94(1): 155–189.

Mastrobuoni, Giovanni, and Paolo Pinotti. 2015. "Legal Status and the Criminal Activity of Immigrants." *American Economic Journal: Applied Economics*, 7(2): 175–206.

Miles, Thomas J, and Adam B Cox. 2014. "Does immigration enforcement reduce crime? evidence from secure communities." *The Journal of Law and Economics*, 57(4): 937–973.

National Academies of Sciences, Engineering. 2018. *Proactive Policing: Effects on Crime and Communities.* The National Academies Press.

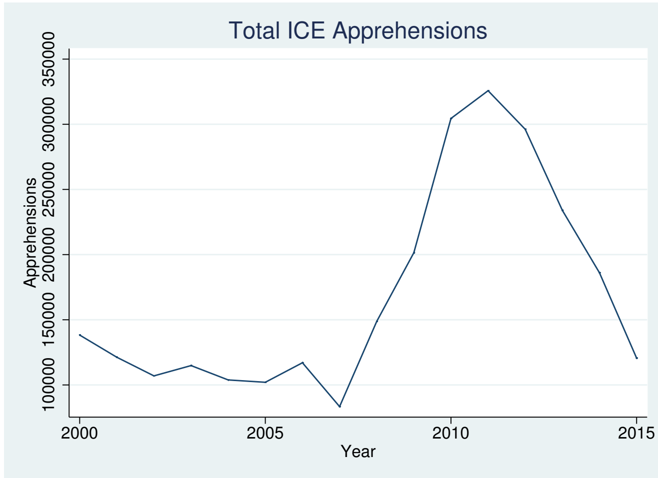
Nowrasteh, Alex. 2018. "Criminal Immigrants in Texas: Illegal Immigrant Conviction and Arrest Rates for Homicide, Sex Crimes, Larceny, and Other Crimes." Cato Institute.

Rosenfeld, Richard, Robert Fornango, and Andres F. Rengifo. 2007. "The Impact of Order-Maintenance Policing on New York City Homicide and Robbery Rates: 1988-2001*." *Criminology*, 45(2): 355–384.

Spenkuch, Jrg L. 2014. "Understanding the Impact of Immigration on Crime." *American Law and Economics Review*, 16(1): 177–219.

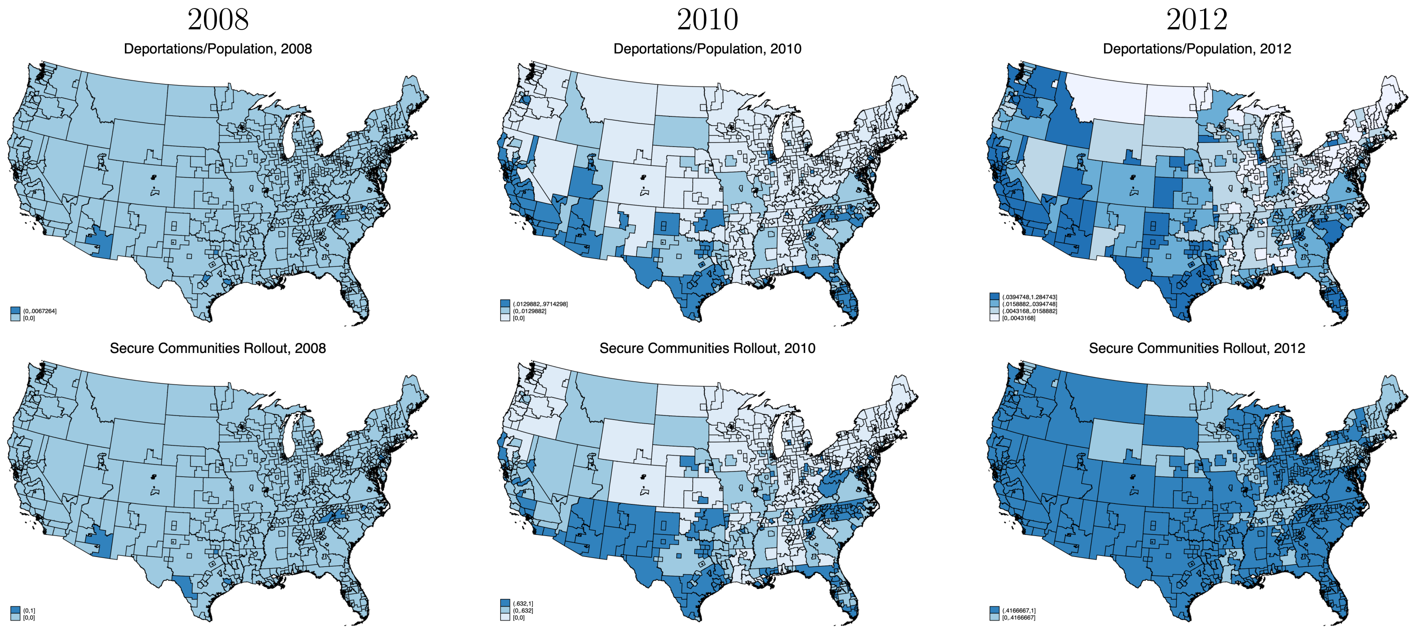
Wang, Julia Shu-Huah, and Neeraj Kaushal. 2018. "Health and Mental Health Effects of Local Immigration Enforcement." National Bureau of Economic Research Working Paper 24487.

Figure 1: Total Interior Apprehensions: 2000-2015



Notes: Figure displays total yearly apprehensions by ICE Investigative Districts and ICE ERO. Data source: Department of Homeland Security Yearbook of Immigration Statistics.

Figure 2: Deportation Rate and SC Rollout by PUMA



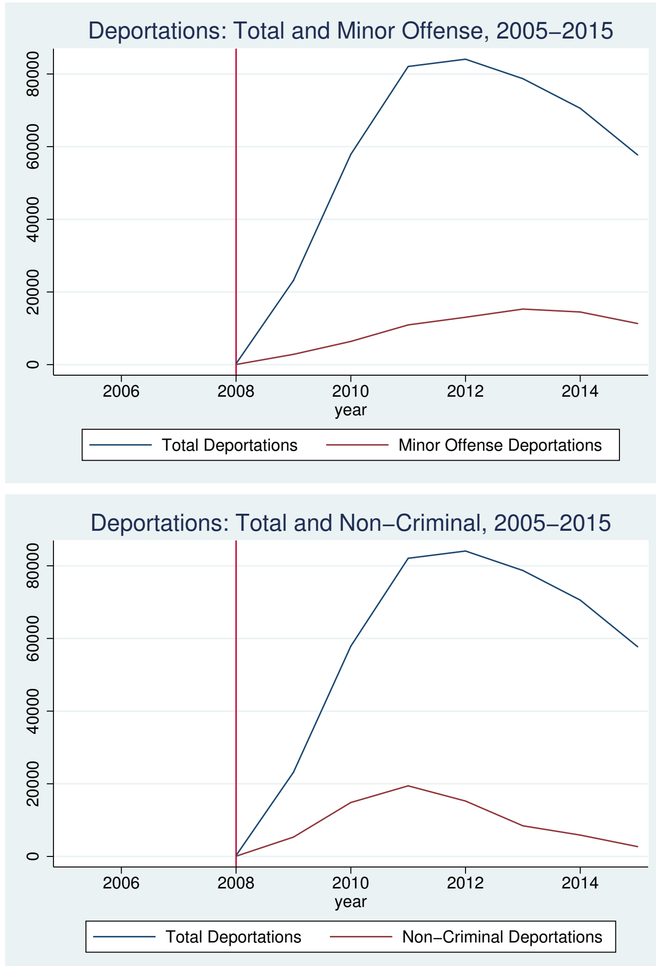
Notes: Map displays PUMA-level deportations per 100 working-age population in 2005. Population data are from the American Community Survey. Population measures total working age (16-64) population at the PUMA-level. Rollout of SC at the PUMA level is the average of counties in each PUMA, weighted by population. The variable is also weighted to account for the fraction of the calendar year during which SC was active.

Table 1: Deportations and Undocumented Share

	Mean	SD	Median	99th percentile
Undoc/Pop (pct), 2005	3.306	4.201	1.633	16.607
Deportations/Pop. (pct)	0.021	0.068	0.000	0.221
Deportations/Undocumented	0.998	3.195	0.000	11.236
Property crimes per 100,000 pop.	4783.894	1922.003	4444.875	10099.227
Violent crimes per 100,000 pop.	671.965	411.514	612.149	2137.917
Clearance rate - property (pct)	17.730	7.264	17.212	36.169
Clearance rate - violent (pct)	52.165	18.145	53.639	87.780

Notes: Population data are from the 2005-2014 American Community Survey. Undocumented/Pop is the undocumented share of the population (undocumented per 100 total working-age population). The deportation rate is the number of deportations in a given year divided by 100 working age population. Deportations/Undocumented is the number of deportations divided by 100 undocumented population. Deportation rates are for the entire period, coding pre-SC deportations to zero. All denominators for population are fixed to 2005 values. Undocumented immigrants are defined as non-citizens with a high school degree or less, arrived in the US after 1986, and are from Mexico or Central America (excluding Cuba). Low-skilled individuals are those with a high school degree or less. All variables are collapsed at the PUMA-Year level and weighted by the 2005 PUMA population.

Figure 3: Total Deportations vs. Minor Offenses

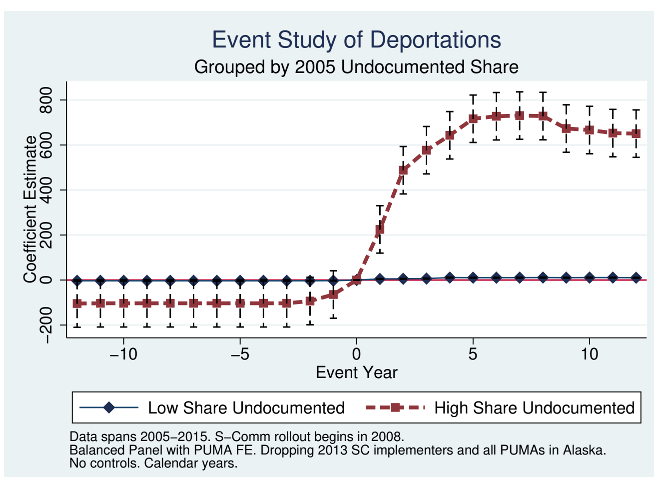


Notes: Minor crimes are disorderly conduct, marijuana possession, traffic offenses (excluding DUIs), and immigration offenses (Illegal Entry, Illegal Re-Entry, and Possession of fraudulent immigration documents). Data obtained from ICE records via the Transactional Records Access Clearinghouse. We categorize crimes according to the most serious criminal conviction of the deportee (note that this is not necessarily the crime for which the person was apprehended prior to removal). Data not available prior to 2008.

Table 2: Share of Deportations by Most Serious Criminal Conviction

Traffic MSCC (%)	5.18
Immigration MSCC (%)	8.39
DUI MSCC (%)	11.34
Marijuana MSCC (%)	5.16
No MSCC (%)	15.83
Other MSCC (%)	54.11

Figure 4: Event Study of Deportations by 2005 Undocumented Share



Notes: Figure displays an event study of deportations relative to SC activation across PUMAS. Deportation data comes from TRAC, and covers the 2008-2015 time period. In years and locations prior to the data coverage, deportations under SC take a value of zero.

Table 3: Regression of Time to SC Activation on 2008 county characteristics (cross-section)

	Dep. Var: Quarters to Activation	
	(1)	(2)
Avg. crime rate change 2005-2008	0.000	0.000
	(0.000)	(0.000)
Non-Citizen/Pop. (percent)	0.000	0.000
	(0.000)	(0.000)
Hispanic/Pop. (percent)	-0.001***	-0.001***
	(0.000)	(0.000)
ln(Population)	-1.316***	-1.312***
	(0.116)	(0.117)
Average total income (1000s)	0.015	0.015
	(0.012)	(0.012)
Avg. manuf. change 2005-2008		4.849
		(19.354)
Avg. constr. change 2005-2008		-14.087
		(20.725)
Border PUMAs	No	No
Y Mean	11.7095	11.7095
Observations	1044	1044
R2	0.2002	0.2006

Notes: Population data are from the 2005-2014 American Community Survey. Secure Communities Activation defined by quarter, relative to the first quarter of 2008. Controls include total crimes per 100,000 population, an indicator for PUMAs on the US-Mexico border, the non-citizen% of the population (non-citizens per 100 total population), the Hispanic% of the population (Hispanic per 100 total population), the log of the total working-age population, and average total income per person, in 2008 dollars in 1000s. All regressions are weighted by the 2005 PUMA population. Standard errors are clustered by PUMA and are reported in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 4: Dependent variable: Interaction between 2005 undocumented share and SC

	(1) Deport/Pop	(2) Deport/Pop
(Undoc/Pop)_05 *SC	0.007***	
	(0.001)	
(MaleUndoc/Pop)_05 *SC		0.013***
		(0.001)
Border PUMAs	No	No
Industry Shares	X	X
PUMA FE	X	X
Year FE	X	X
Y Mean	0.0203	0.0203
Observations	9396	9396
R2	0.6376	0.6345
F	48.34	47.75

Notes: Population data are from the 2005-2014 American Community Survey. Deportations and detainers are collapsed at the PUMA-year level. The dependent variable is the deportation or detainer rate in each PUMA-year, calculated as the number of deportations divided by 100 working age population in 2005 (ages 16-64) . Undocumented immigrants are defined as non-citizens with a high school degree or less, arrived in the US after 1986, and are from Mexico or Central America (excluding Cuba). The regressor of interest is the interaction between the undocumented percent of the population in 2005 (undocumented/100 population) and the presence of Secure Communities (SC). The low-skilled population is defined as working-age (16-64) individuals with a high school degree or less. SC is a weighted average of all counties in a PUMA and weighted by the month of implementation in the implementation year. All regressions are weighted by the 2005 PUMA population. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table 5: IV: Crime Rate

	Dep. Var:		
	(1)Δ Violent/Pop	(2)Δ Violent/Pop	(3)Δ Violent/Pop
A: Violent Crimes			
Deport/Pop	24.296	24.275	24.572
	(40.324)	(40.221)	(33.094)
Border PUMAs	No	No	Yes
Industry Shares	X		X
PUMA FE	X	X	X
Year FE	X	X	X
Avg. Rate	654.631	654.631	654.631
Observations	9396	9396	9594
R2	0.1445	0.1440	0.1430
	Dep. Var:		
	(1)Δ Property/Pop	(2)Δ Property/Pop	(3)Δ Property/Pop
B: Property Crimes			
Deport/Pop	1028.672**	1027.653**	760.910**
	(422.543)	(424.510)	(355.386)
Border PUMAs	No	No	Yes
Industry Shares	X		X
PUMA FE	X	X	X
Year FE	X	X	X
Avg. Rate	4534.522	4534.522	4534.522
Observations	9396	9396	9594
R2	0.1446	0.1444	0.1319

Notes: Population data are from the 2005-2014 American Community Survey. The total crime rate is the sum of violent crimes and property crimes. Crime rates are crimes divided by 100,000 working0-age population in 2005. Deportations and detainers are collapsed at the PUMA-year level. The low-skilled population is defined as working-age (16-64) individuals with a high school degree or less. SC is a weighted average of all counties in a PUMA and weighted by the month of implementation in the implementation year. All regressions are weighted by the 2005 PUMA population and include PUMA and year fixed effects. Standard errors are clustered by PUMA and are reported in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 6: Change in Crime Rates, 287g controls

	Dep. Var:	
	(1)Δ Violent/Pop	(2)Δ Violent/Pop
A: Violent Crime		
Deport/Pop	24.296	20.404
	(40.324)	(39.421)
Any 287(g)		5.016
		(6.382)
Border PUMAs	No	No
Industry Shares	X	X
PUMA FE	X	X
Year FE	X	X
Avg. Rate	654.631	654.631
Observations	9396	9396
R2	0.1445	0.1448
	Dep. Var:	
	(1)Δ Property/Pop	(2)Δ Property/Pop
B: Property Crime		
Deport/Pop	1028.672**	988.829**
	(422.543)	(448.390)
Any 287(g)		51.349
		(32.659)
Border PUMAs	No	No
Industry Shares	X	X
PUMA FE	X	X
Year FE	X	X
Avg. Rate	4534.522	4534.522
Observations	9396	9396
R2	0.1446	0.1457

Notes: Population data are from the 2005-2014 American Community Survey. Deportations and detainers are collapsed at the PUMA-year level. The low-skilled population is defined as working-age (16-64) individuals with a high school degree or less. SC is a weighted average of all counties in a PUMA and weighted by the month of implementation in the implementation year. All regressions are weighted by the 2005 PUMA population and include PUMA and year fixed effects. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table 7: IV: Population Shares

	Dep. Var:		
	(1)Δ LS/Pop	(2)Δ LS/Pop	(3)Δ LS/Pop
A: LS Pop			
Deport/Pop	0.759	0.710	1.618
	(2.486)	(2.210)	(1.796)
Border PUMAs	No	No	Yes
Industry Shares		X	
PUMA FE	X	X	X
Year FE	X	X	X
Avg. Rate	51.079	51.079	51.079
Observations	10520	10520	10740
R2	0.0634	0.1167	0.1167
	Dep. Var:		
	(1)Δ LSNC/Pop	(2)Δ LSNC/Pop	(3)Δ LSNC/Pop
B: LSNC Pop.			
Deport/Pop	0.917	0.884	0.638
	(1.405)	(1.332)	(1.072)
Border PUMAs	No	No	Yes
Industry Shares		X	
PUMA FE	X	X	X
Year FE	X	X	X
Avg. Rate	6.12	6.12	6.12
Observations	10520	10520	10740
R2	0.0280	0.0535	0.0539
	Dep. Var:		
	(1)Δ Undoc./Pop	(2)Δ Undoc./Pop	(3)Δ Undoc./Pop
C: Undoc. Pop.			
Deport/Pop	-0.152	-0.175	0.019
	(0.959)	(0.947)	(0.772)
Border PUMAs	No	No	Yes
Industry Shares		X	
PUMA FE	X	X	X
Year FE	X	X	X
Avg. Rate	3.105	3.105	3.105
Observations	10520	10520	10740
R2	0.0218	0.0414	0.0419

Notes: Population data are from the 2005-2014 American Community Survey. Deportations and detainers are collapsed at the PUMA-year level. The low-skilled population is defined as working-age (16-64) individuals with a high school degree or less. SC is a weighted average of all counties in a PUMA and weighted by the month of implementation in the implementation year. All regressions are weighted by the 2005 PUMA population and include PUMA and year fixed effects. Standard errors are clustered by PUMA and are reported in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 8: IV Change in Clearance Rate by type

	Dep. Var:	
	(1)Δ Violent Clr Rate	(2)Δ Property Clr Rate
Deport/Pop	6.331	-3.721**
	(5.424)	(1.566)
Border PUMAs	No	No
Industry Shares	X	X
PUMA FE	X	X
Year FE	X	X
Avg. Rate	52.897	18.483
Observations	7911	7911
R2	0.0484	0.0679

Notes: Data on clearance rates come from the FBI UCR, available through ICPSR. Clearance rates are the percent of reported offenses cleared in a given year. The denominator is the difference between total reported offenses and unfounded offenses. The sample is restricted to PUMAs with defined clearance rates and drops those with fewer than five years of data. Deportations and detainers are collapsed at the PUMA-year level. The low-skilled population is defined as working-age (16-64) individuals with a high school degree or less. SC is a weighted average of all counties in a PUMA and weighted by the month of implementation in the implementation year. All regressions are weighted by the 2005 PUMA population and include PUMA and year fixed effects. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table 9: Change in Police/Population

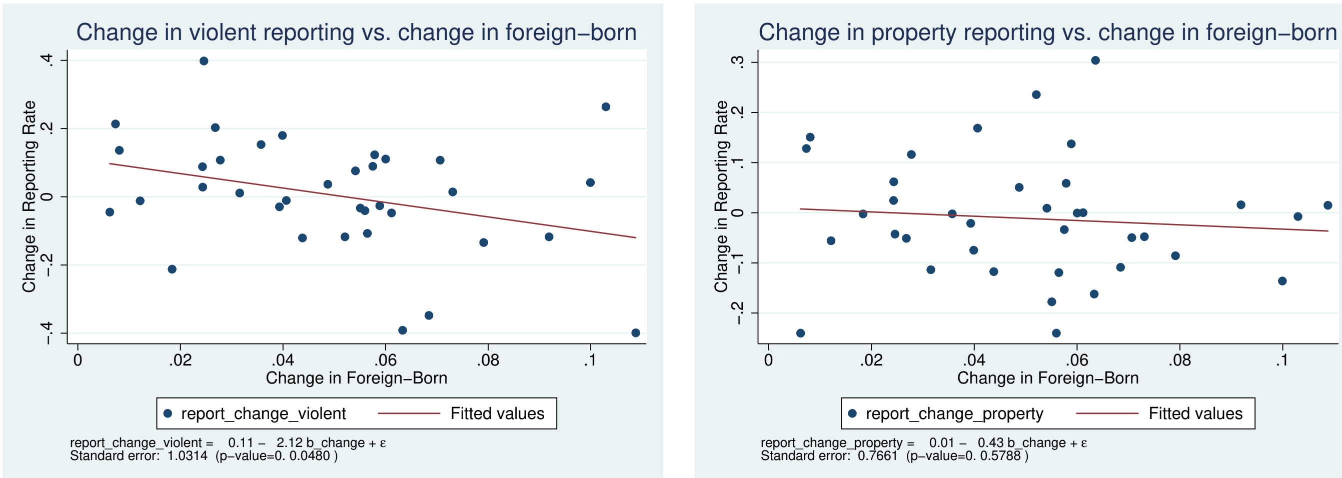
	Dep. Var:	
	(1) RF: Δ Police/Pop	(2) IV: Δ Police/Pop
(Undoc/Pop)_05 *SC	-0.000	
	(0.001)	
Deport/Pop		-0.034
		(0.150)
Border PUMAs	No	No
Industry Shares	X	X
PUMA FE	X	X
Year FE	X	X
Avg. Rate	.855	.855
Observations	9396	9396
R2	0.0180	0.0180

Notes: The dependent variable is the annual change in police per capita, where police per capita is defined as the number of police per 100 population in 2005, calculated using the ACS.Deportations and detainers are collapsed at the PUMA-year level. The low-skilled population is defined as working-age (16-64) individuals with a high school degree or less. SC is a weighted average of all counties in a PUMA and weighted by the month of implementation in the implementation year. All regressions are weighted by the 2005 PUMA population and include PUMA and year fixed effects. Standard errors are clustered by PUMA and are reported in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Figure 5: Change in crime reporting vs. change in foreign-born population

a. Change in violent crime reporting rate

b. Change in property crime reporting rate



Notes: Crime reporting data come from the National Crime Victimization Survey (NCVS). County-level data on the population share of foreign-born comes from the NHGIS. Change refers to the change in the share of crimes reported or the change in the foreign-born share of total population between 1990 and 2010. The sample covers 37 MSAs in the US.

Table 10: IV: Change in Firms (per population)

	Dep. Var:	
	(1)Δ Firms (Agr.)/Pop	(3)Δ Firms (Agr2)/Pop
A: Firms: Total and Agr		
Deport/Pop	-1.579**	0.897*
	(0.769)	(0.490)
Border PUMAs	No	No
Industry Shares	X	X
PUMA FE	X	X
Year FE	X	X
Avg. Rate	11.68	5.61
Observations	9396	9396
R2	0.1668	0.0834
	Dep. Var:	
	(1)Δ Constr.	(2)Δ FoodSvc
B: Firms: ACS Ind		
Deport/Pop	13.049	5.977
	(19.436)	(5.304)
Border PUMAs	No	No
Industry Shares	X	X
PUMA FE	X	X
Year FE	X	X
Avg. Rate	382.51	312.29
Observations	9396	9396
R2	0.5327	0.3240
	Dep. Var:	
	(1)Δ BldgSvc	(2)Δ Landscape
C: Firms: Svc Ind, detail		
Deport/Pop	0.912	0.701
	(1.736)	(1.210)
Border PUMAs	No	No
Industry Shares	X	X
PUMA FE	X	X
Year FE	X	X
Avg. Rate	94.7	49.81
Observations	9396	9396
R2	0.2140	0.1829

Notes: Firm data come from the County Business Patterns survey, with firms defined as the number of establishments in a given PUMA, by industry. The dependent variable is the change in firms per 100,000 population, with population fixed to its 2005 level. Panel A shows results for all industries, agricultural industries according to the two-digit NAICS code, and agriculture more narrowly defined according to the three-digit NAICS code. Panel B shows results for construction, food, services, and other support services, according to the two-digit NAICS codes. These are the dominant industries employing low-skilled non-citizens and likely undocumented workers in the ACS. Panel C shows results for all support services, as well as separating building services and landscape work by the three digit NAICS codes. Deportations and detainers are collapsed at the PUMA-year level. The low-skilled population is defined as working-age (16-64) individuals with a high school degree or less. SC is a weighted average of all counties in a PUMA and weighted by the month of implementation in the implementation year. All regressions are weighted by the 2005 PUMA population and include PUMA and year fixed effects. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table 11: IV: Employment Shares

	Dep. Var:		
	(1)Δ LS Emp./Pop	(2)Δ LS Emp./Pop	(3)Δ LS Emp./Pop
A: LS Employment			
Deport/Pop	2.603	2.570	2.104
	(1.956)	(1.692)	(1.401)
Border PUMAs	No	No	Yes
Industry Shares		X	
PUMA FE	X	X	X
Year FE	X	X	X
Avg. Rate	30.854	30.854	30.854
Observations	10520	10520	10740
R2	0.1130	0.1630	0.1621
	Dep. Var:		
	(1)Δ LSNC Emp./Pop	(2)Δ LSNC Emp./Pop	(3)Δ LSNC Emp./Pop
B. LSNC Employment			
Deport/Pop	0.812	0.785	0.374
	(1.190)	(1.113)	(0.893)
Border PUMAs	No	No	Yes
Industry Shares		X	
PUMA FE	X	X	X
Year FE	X	X	X
Avg. Rate	4.001	4.001	4.001
Observations	10520	10520	10740
R2	0.0258	0.0525	0.0538

Notes: Population data are from the 2005-2014 American Community Survey. Deportations and detainers are collapsed at the PUMA-year level. The low-skilled population is defined as working-age (16-64) individuals with a high school degree or less. SC is a weighted average of all counties in a PUMA and weighted by the month of implementation in the implementation year. All regressions are weighted by the 2005 PUMA population and include PUMA and year fixed effects. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table 12: Locations with the highest deportation intensity

Rank	PUMA	Avg. Deportation/Pop (2008-2012)
1	Walker County, TX	0.751
2	Collier County, FL	0.192
3.	Maricopa County, AZ	0.173
4.	Santa Barbara County, CA	0.155
5.	Harris County, TX	0.150
Rank	PUMA	Total Deportations, 2008-2012
1.	Houston, TX	27197
2.	Maricopa County, AZ	20643
3.	Orange County, CA	12914
4.	Dallas, TX	11600
5.	Central Texas, TX	8173

Notes: The deportation rate is the number of deportations in a given year divided by 100 working age population, based on data on deportations under SC from TRAC. The population denominator is fixed to 2005 levels using data from the ACS. Deportations prior to SC implementation are coded to zero. The table ranks PUMAs by total deportations and the average deportation rate, and it lists the main county or metropolitan area in that PUMA as the location. In the case that multiple PUMAs in the top 5 ranking are in the same county or city, the deportation number is an average of those PUMAs.

Table 13: Locations with the highest crime rates

Highest Crime	PUMA	Total Crime Rate (per 100,000)
1	St. Louis, MO	16631.26
2	Pulaski County, AR	13113.20
3.	Richmond County, GA	11961.59
4.	Marion County, IN	11795.02
5.	Bibb County, GA	11788.56
Highest Crime	PUMA	Violent Crime Rate (per 100,000)
1.	St. Louis City, MO	3142.09
2.	Baltimore City, MD	2506.96
3.	Philadelphia, PA	2462.53
4.	District of Columbia	2456.91
5.	Memphis, TN	2145.50

Notes: Crime rates defined as total offenses or violent offenses per 100,000 working-age population. The population denominator is fixed to 2005 levels using data from the ACS. Data on crimes reported comes from the FBI UCR. The table ranks the highest crime PUMAs and lists the main county or metropolitan area in that PUMA as the location. In the case that multiple PUMAs in the top 5 ranking are in the same county or city, the ranked crime rate reflects the average crime rate for those PUMAs.