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Silence of the Innocents: Undocumented Immigrants' Underreporting of Crime and their Victimization*

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Abstract

Do undocumented migrants underreport crimes to the police in order to avoid deportations? And do criminals exploit such vulnerability? We use victimization surveys around the 1986 immigration amnesty to address two major identification issues: migrants' legal status is endogenous and unobserved.

Right after the amnesty, which according to administrative records disproportionately legalized individuals of Hispanic origin, crime victims of Hispanic origin in cities with a large proportion of Hispanic applicants show enormous improvements in reporting behavior. There is some evidence of a reduced victimization following the amnesty, which is coherent with a behavioral crime model that guides our empirical strategies.

Keywords: immigration, amnesty, crime reporting, victimization survey.
JEL classification codes: J15, K37, K42, R23.

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1 Introduction

In 2014 the estimated number of unauthorized immigrants living in the United States reached 11.3 million (representing 3.5 percent of the entire population), up from about 3.5 million in 1990.[1].

One of the most controversial issues is how to deal with this high number of undocumented immigrants, with the main policy option being an immigration amnesty. Yet, amnesties polarize the electorate.[2] Public opinion polls show that citizens tend to fear that undocumented immigration might not just bring lost jobs and rising welfare costs but also high rates of crime, even if there is no evidence that immigration overall increases crime or incarceration rates (Butcher and Piehl, 1998, Piehl, 2007) or that it severely worsens labor market outcomes of natives (Borjas, 1994, Card, 1990).

Because of such anti-immigration sentiments, a comprehensive immigration reform has eluded the US Congress, and in 2016 a perfectly divided US Supreme Court has blocked former President Obama's Immigration Plan that would have shielded up to half of the undocumented immigrant population from deportation, allowing them to work in the United States. European institutions, subject to similar political pressure, cannot agree on a common immigration policy. Anti-immigration sentiments have fueled the BREXIT vote in the UK referendum, and more anti-immigration acts may follow in other European countries.

Recently, President Trump's administration has made attempts to increase detection and deportation of undocumented immigrants (the so-called Secure Communities program), also involving local authorities in the enforcement of federal immigration

[1]See Krogstad and Passel (2014), Warren and Warren (2013)
[2]See for instance http://www.pollingreport.com/immigration.htm.

law (287(g) program).

In response to these Federal policies local authorities have set up "Sanctuary policies," which, in order to limit the fear of deportation and possible family break-up, attempt to limit the role of local officials in immigration enforcement.

A thorough evaluation of the various consequences of unauthorized migration represents the most likely solution to such gridlock. There is growing evidence on the positive consequences of immigration amnesties. Economists have shown that amnesties allow undocumented immigrants to access segments of the labor market granting enhanced employment protection, better working conditions, higher salaries, and the possibility to benefit from better health-care (Barcellos, 2010, Kossoudji and Cobb-Clark, 2002, Lozano and Sorensen, 2011). And, as pointed out by the Washington Post (Badger, November 26, 2014), acquiring legal status might influence many more outcomes. Immigrants who benefit from an amnesty might invest more in education, in community institutions, as well as in political participation. They may become more likely to learn English, and their children might become more likely to go to college, or to experience upward mobility.

A standard opportunity cost argument, supported by empirical evidence based on the 1986 US immigration amnesty (the Immigration Reform and Control Act, IRCA) (see Baker, 2015, Freedman et al., 2013), implies that documented immigrants should have a lower propensity to be involved in criminal activities than undocumented ones. As a result, immigration amnesties should reduce immigrants' participation in crime. This paper also exploits the IRCA, in particular its disproportionate impact on immigrants of Hispanic origin.[3]

[3]There is also evidence from other countries showing that granting legal status changes the criminal involvement of immigrants. Mastrobuoni and Pinotti (2015) exploit exogenous variation in legal status following the January 2007 European Union enlargement, while Pinotti (2017) employs

This study contributes to this debate providing evidence on an important negative consequence of illegally residing in the country which is directly borne by the undocumented immigrants: the inability to protect their property and their human right to security. We show that out of fear of deportation undocumented immigrants drastically lower their propensity to report a crime to the police, generating an essentially unenforced space of action for ruthless criminals.[5]

Amnesties might thus not only improve the labor market opportunities of immigrants, thus lowering their criminal propensity, they might also increase reporting rates and thus alter the expected cost of criminal behavior for immigrants and non-immigrants alike, increasing deterrence.

The evidence on the reporting behavior of undocumented immigrants is still scarce, as it either relies on correlational studies that do not measure legal status or on studies that do measure legal status but only for small convenience samples. In search for such evidence we use the National Crime Victimization Survey (NCVS) around the IRCA to deal with the endogeneity of legal status as well as with its measurement issue.

We show not only that undocumented immigrants are considerably less likely to report a crime to the police, but also that amnesties dramatically alter this situation. We develop a simple empirical strategy to circumvent the main issue when dealing with undocumented migrants: in most household surveys respondents are not asked about their legal status; this is also the case for the NCVS. Yet, if there is a good proxy

Italian data on legalization lotteries.[4] Both studies find similarly sized large negative legalization effects on the criminal behavior of immigrants. Several studies do not focus on amnesties but rather on the overall effect of immigration on crime. The results are rather mixed, although most recent studies find little evidence that immigration spurs crime (see, among others, Bianchi et al. (2012) and Bell et al. (2013).)

[5]Several newspapers have recently highlighted that immigrants face such a risk, even in Sanctuary Cities (see, among others, Brendal Cambell and Diestel, 2018, Queally, 2017, Robbins, 2018)

for the legal status, with known probabilities of misclassification, there are simple econometric techniques to adjust the biased estimates that rely on the proxy (see Aigner, 1973). We adapt this strategy to a difference-in-differences setup, around the IRCA, which granted legal status to about 2.7 million undocumented immigrants (out of 3 million who applied). Since most immigrants who applied for the amnesty were from Central American countries, mainly Mexico, we use Hispanic origin as a proxy for legal status. The 1980 and 1990 Census have information on Hispanic origin, and immigration year of respondents, which we use together with administrative records of IRCA applicants to derive the probabilities of misclassification.

Using this "adjusted proxy method" we show that amnesties change the immigrants' incentives to report a crime. Following the IRCA amnesty, as the risk of deportation ceased to exist for IRCA applicants, the reporting rates of IRCA applicants went from 17 percent to 37 percent, approaching the 39 percent reporting rates of non-Hispanics, who are almost exclusively legal citizens.

Since police investigations are unlikely to start without a formal report of the offence, amnesties are likely to increase conviction rate of criminals whose victim is a newly legalized individual, therefore changing the relative benefits of victimizing immigrants versus natives. Whenever ethnicity or other observable characteristics signal the legal status of immigrants, criminals may choose their targets based on such signals. We study an ethnicity-based targeting by criminals in a formal model developed In Section 2.[6] The comparative statics of this analysis highlight the identification strategy for this amnesty-induced displacement of victimization. Society is composed of two ethnic groups, a native ethnic group and an immigrant ethnic

[6]That higher reporting rates might reduce the incentives to commit a crime has been discussed in more general terms in a theoretical paper (Garoupa, 2003) and in two more empirical ones (Goldberg and Nold, 1980, Goudriaan et al., 2006).

group. Natives and immigrants (both the documented and the undocumented ones) choose whether or not to become criminals, and, in the latter case, against which ethnic group to commit crimes. Criminals trade-off the higher expected booty they can collect targeting more affluent native citizens with the lower probability of being convicted when targeting poorer immigrants. The model predicts amnesties to reduce the victimization of immigrants, and more so in places where a large fraction of them become legalized, delivering a clear difference-in-differences strategy.

We find evidence that following the 1986 IRCA amnesty Hispanics, living in metropolitan statistical areas with a large fraction of IRCA applicants, were less likely to become victims of crime compared to what happened in places with few Hispanic applicants. This implies not only that undocumented immigrants are unable to protect some of their fundamental human rights, but also that the absence of this fundamental human right makes them even more vulnerable. It also means that the deterrent effect of law enforcement might be severely damped by the mere existence of such victims.

Our findings are consistent with those found in a few convenience sample studies, which document the low propensity of undocumented immigrants to report crimes to the police. Based on interviews in Memphis, Tennessee, Bucher et al. (2010) find that these individuals experience a high rate of victimization and yet are reluctant to report crimes to the police, mainly because of the perceived risk of deportation.

That fear of deportation may induce underreporting amongst Latino immigrants' has also been mentioned in a study about immigrants in Phoenix, Arizona (Menjívar and Bejarano, 2004), and in one about immigrants in Reno, Nevada (Correia, 2010).[7]. The only study that also uses a large and representative sample (the NCVS), finds

[7]See also Barrick (2014)

that crime reporting rates are negatively correlated with the relative size of noncitizen and foreign-born individuals living in a metropolitan area (Gutierrez and Kirk, 2015), but does not exploit any exogenous variation in legal status.

In spirit this study is also closely related to recent research on the determinants of crime reporting of women and victimization against them. Miller and Segal (2014) use the NCVS to show that the integration of women in US police departments increased the reporting behavior of women who were victims of violent crimes, especially domestic violence. Consistent with our finding, they find that the increased reporting behavior leads to subsequent reductions in crime.

The paper is organized as follows. Section 2 sketches a simple model of crime and reporting behavior (all proofs are in the appendix). Results from the model guide the empirical strategy developed in Sections 3 and 4. Section 5 concludes.

2 The model

We consider a city composed of two ethnic groups − natives and immigrants −, each with mass 1.[8] Immigrants are either legal citizens (mass $1-\gamma$) or undocumented (mass $0<\gamma<1$). Individuals differ in terms of their wealth: all immigrants are poor, while natives can be rich (mass $1-\phi$) or poor (mass ϕ).[9]

Each individual chooses whether to be honest or to commit crimes. Criminals also choose which ethnic group they want to primarily target. Honest individuals who are

[8] We use the term immigrants loosely to indicate minorities that contain a group of undocumented individuals. Later on, in our empirical analysis, we focus on Hispanics, an ethnic group that includes legal citizens and a large fraction of undocumented individuals.

[9] This assumption is in line with what we observe in our data-set. Income differences between Hispanics and Non-Hispanics are shown to be large in the National Crime and Victimization Survey (see Appendix Figure A1). Household incomes are only available in broad intervals, but relative income differences between the two groups are at least equal to 1/4.

victimized decide whether to report the crime to the police. As we show below, the probability that victims report a crime, $\rho_{w,k}$, depends on their wealth $w \in \{r, p\}$, with $r > p$ (rich and poor), and on their legal status $k \in \{l, a\}$, legal citizen (l), or undocumented immigrant, for brevity, alien (a).

The utility of honest individuals increases with their wealth and their propensity to report crimes to the police; this latter assumption rests on the observation that a higher reporting rate increases the ability to protect one's property rights. Crime, instead, reduces the utility.

Summing up, the utility of an honest individual with wealth $w \in \{r, p\}$ and legal status $k \in \{l, a\}$ is:

$$u_{w,k}^{hon} = f(w, \rho_{w,k}) - \beta X,$$

where $f(\cdot)$ is an increasing function of the wealth and of the reporting rate of the individual. In turn, βX measures the disutility from crime, with $\beta > 0$ and X representing the overall number of criminals in the city.[10]

Individuals choose whether to be honest or criminals, and, in the latter case, which ethnic group to primarily target. Individuals differ in terms of their (potential) criminal ability. We let $\theta \in [0, 1]$ be a random variable measuring the individual's criminal ability, assumed to be uniformly distributed in the population. Criminals observe the ethnicity of potential victims, but not their wealth or their legal status.[11]

[10]Notice that the disutility from crime depends on the overall level of criminality and not just on the number of criminals targeting the ethnic group to which the individual belongs. This assumption greatly simplifies the computation of the equilibrium and it is in line with the fact that, despite targeting primarily one group, a criminal may end up committing offences to individuals belonging to the other group. Moreover, the disutility from crime incorporates all the direct and indirect welfare loss, as, for instance, the drop in real estate value (see Gibbons, 2004, Linden and Rockoff, 2008, Thaler, 1978), population, as well as economic activity (see Cullen and Levitt, 1999), when crime levels are high.

[11]This simplifies the notation, though it would be sufficient to assume that ethnicity is an informative signal for legal status and wealth.

By targeting immigrants, criminals know that, compared to natives, the average wealth is lower and, with probability γ, the victim is undocumented.[12]

Criminals choose which ethnic group to primarily target. When a criminal chooses to target primarily group j, then with probability ξ the crime is actually committed against an individual in group j, where $1/2 \leq \xi \leq 1$. With probability $1-\xi$, instead, the victim belongs to the other group; these "mistakes" – the criminal targets one group but ends up committing a crime against individuals belonging to the other group – may depend on victim's physical appearance, as well as on the level of segregation of ethnic groups. Taking the US case, not all Hispanic-looking individuals are necessarily of Hispanic origin, and viceversa. Though living in a severely segregated Hispanic neighborhood may lower $1-\xi$.

The expected utility of an individual with criminal ability θ who commits crimes targeting individuals belonging to the ethnic group $j \in \{n, i\}$ is:

$$u^{cr,j}(\theta) = \theta E(w|j) - C(\rho|j).$$

$E(w|j)$ is the expected wealth of the victim, conditional on the criminal targeting ethnic group j. The expectation operator accounts both for the fact that victims in the target group may have different levels of wealth (this is the case of natives) and for the fact that the victim belongs to the targeted group with probability $\xi \leq 1$. The term $C(\rho|j)$ is the expected cost of punishment, conditional on the criminal targeting individuals of group j. $C(\rho|j)$ is an increasing function of the average reporting rate of the ethnic groups weighted by ξ. Again, the expectation accounts for the fact that individuals in the target group may have different reporting rates and also for the

[12]The US are a clear example where ethnicity, particularly being of Hispanic origin, carries some signal for the migration status.

fact that the crime can end up being committed against an individual that does not belong to the target ethnicity.

The reporting decision

We assume that the monetary loss that a victim suffers is proportional to his level of wealth w, but in a stochastic way. The loss is $\alpha w \in [0, w]$, where α is the realization of a random variable distributed according to $F(\alpha)$, with support $[0, 1]$.

Victims report the crime to the police when the monetary loss is larger than the cost of reporting; formally, this occurs when:

$$\alpha w \geq T + g_k D \, , or \, \alpha \geq \frac{T + g_k D}{w} \equiv \bar{\alpha}_{w,k},$$

where T is a fixed cost of reporting crime, g_k is the risk of deportation for an individual with status k – which is zero for legal citizens and positive for undocumented immigrants (evidence is provided in the empirical section) – and D is the associated cost. Notice that the threshold $\bar{\alpha}_{w,k}$ decreases with wealth (w), and increases with the risk of deportation (g_k) and with the cost of deportation (D); hence, $\bar{\alpha}_{p,a} > \bar{\alpha}_{p,l} > \bar{\alpha}_{r,l}$. The probability that victims report a crime is simply $\rho_{w,k} \equiv 1 - F(\bar{\alpha}_{w,k})$, with $\rho_{r,l} > \rho_{p,l} > \rho_{p,a}$: the propensity to report crime to the police is largest for rich natives, lowest for undocumented immigrants, and intermediate for legal immigrants and poor natives. These inequalities imply that the average reporting rate is larger for natives compared to immigrants.

2.1 Equilibrium

Individuals observe their criminal ability θ and decide whether to be honest or to become criminals. Criminals also choose their target group, natives or immigrants.

Let us start with this latter decision. Criminals prefer to target primarily natives whenever:

$$\theta \geq \frac{C(\rho|n) - C(\rho|i)}{E(w|n) - E(w|i)} \equiv \bar{\theta}.$$

The relevant trade-off when deciding the target ethnic group is between a larger gain when targeting natives (among the natives there are also some rich individuals) with a smaller expected punishment when targeting immigrants (the average reporting rate is lower among immigrants). It follows that criminals with higher abilities ($\theta \geq \bar{\theta}$) prefer to target natives rather than immigrants.

Consider now the decision of whether to be honest or become criminal. We focus on the most interesting case in which the marginal criminal is indifferent between being honest and committing crimes targeting primarily immigrants.[13] Moreover, we assume that r is large enough so that all rich natives prefer to be honest. Poor natives and legal immigrants have the same wealth and reporting rate, therefore they behave in the same way. They prefer to commit crimes targeting immigrants rather than being honest when:

$$\theta \geq \frac{f(p, \rho_{p,l}) - \beta X + C(\rho|i)}{E(w|i)} \equiv \hat{\theta}_p(X).$$

The above condition says that these individuals prefer to be criminals rather than honest when their criminal ability is sufficiently large: $\theta \geq \hat{\theta}_p(X)$. Notice that the threshold $\hat{\theta}_p(X)$ depends on the level of criminality X

Similarly, for undocumented immigrants, committing crimes targeting group i is

[13]This is the interesting case since each group – natives and immigrants – is targeted by some criminals. By contrast, if the marginal criminal is indifferent between being honest and committing crimes targeting natives, then all criminals prefer to target the native group and no criminal targets the immigrant community. Formally, in the analysis, we focus on the case in which $\hat{\theta}_a(X) < \bar{\theta}$.

preferred to being honest when:

$$\theta \geq \frac{f(p, \rho_{p,a}) - \beta X + C(\rho|i)}{E(w|i)} \equiv \hat{\theta}_a(X).$$

Looking more closely to the thresholds $\hat{\theta}_p(X)$ and $\hat{\theta}_a(X)$, it follows that undocumented immigrants have a higher propensity to become criminals than poor natives/legal immigrants: $\hat{\theta}_a(X) < \hat{\theta}_p(X)$. This is due to their lower reporting rate ($\rho_{p,a} < \rho_{p,l}$) which implies a reduced ability to protect their property rights: $f(w_p, \rho_{p,a}) < f(w_p, \rho_{p,l})$.

In order to define the equilibrium, we need to determine the endogenous level of criminality, X. Since, $\theta \sim U(0,1)$, it follows that among the γ undocumented immigrants $\gamma(1 - \hat{\theta}_a(X))$ are criminals. The number of criminals in the pool of poor natives and legal immigrants, instead, amounts to $(1 - \gamma + \phi)(1 - \hat{\theta}_p(X))$. Therefore $X = \gamma(1 - \hat{\theta}_a(X)) + (1 - \gamma + \phi)(1 - \hat{\theta}_p(X))$ and the equilibrium is determined by the triple $\{\bar{\theta}, \hat{\theta}_p, \hat{\theta}_a\}$ satisfying:[14]

i) $\bar{\theta} = \frac{C(\rho|n) - C(\rho|i)}{E(w|n) - E(w|i)}$

ii) $\hat{\theta}_p$ and $\hat{\theta}_a$ that solve the system

$$\begin{aligned}
\hat{\theta}_p &= \frac{f(p, \rho_{p,l}) - \beta[\gamma(1 - \hat{\theta}_a) + (1 - \gamma + \phi)(1 - \hat{\theta}_p)] + C(\rho|i)}{E(w|i)} \\
\hat{\theta}_a &= \frac{f(p, \rho_{p,a}) - \beta[\gamma(1 - \hat{\theta}_a) + (1 - \gamma + \phi)(1 - \hat{\theta}_p)] + C(\rho|i)}{E(w|i)}
\end{aligned}$$

Figure 1 provides a graphical representation of the optimal choices of undocumented immigrants depending on θ: individuals with low criminal ability ($\theta < \hat{\theta}_a$)

[14] We implicitly assume $0 < \hat{\theta}_a < \hat{\theta}_p < \bar{\theta} < 1$.

are honest, those with intermediate ability ($\hat{\theta}_a \leq \theta < \bar{\theta}$) become criminals and target immigrants, while individuals with high criminal skills ($\theta \geq \bar{\theta}$) become criminals and target natives. For poor natives/legal immigrants the optimal choices and their graphical representation are similar, with threshold $\hat{\theta}_p$ in place of $\hat{\theta}_a$.

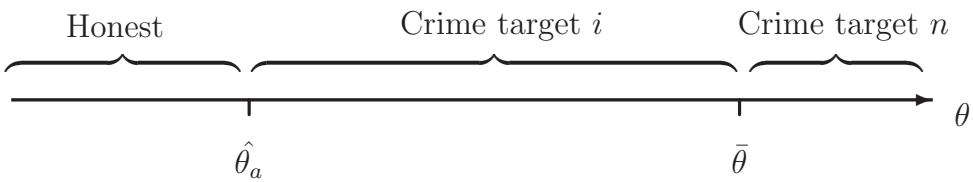

Figure 1: Optimal choice of undocumented immigrants

2.2 The effect of an amnesty

Consider now the effects of an amnesty that legalizes a fraction $\delta \in (0, \gamma]$ of undocumented immigrants. The amnesty eliminates the risk of deportation, thus increasing the reporting rate of legalized immigrants from $\rho_{p,a}$ to $\rho_{p,l}$. This fact has two direct consequences. First, legalized immigrants are better able protect their property rights, and therefore their utility when honest increases. Second, the average reporting rate of immigrants increases, and such an increase is stronger the larger δ, i.e. the larger the number of legalized immigrants. The effects that these changes have on crime are described in the following proposition.

Proposition 1. *An amnesty reduces the overall number of crimes. It also reduces the number of crimes committed against immigrants while, depending on the parameter ξ, it can either increase or decrease those committed against natives. The reduction in the overall number of crimes and in the number of crimes committed against immigrants is larger the greater the mass of legalized immigrants (the larger δ)*

The increased opportunity cost of becoming criminal for legalized immigrants and the deterrent effect on crime of the higher average reporting rate of the immigrant group reduce the number of individuals who choose to become criminals ($\hat{\theta}_p$ and $\hat{\theta}_a$ increase) and, therefore, reduce crime. In addition to that, the higher reporting rate of immigrants also changes the distribution of crime, inducing some criminals to shift from the immigrant to the native target ($\bar{\theta}$ decreases). These two effects, overall reduction in criminality and shift in targeting, are stronger the larger the share of legalized immigrants (the larger δ), and both reduce the number of crimes committed against the immigrants. By contrast, the effect of an amnesty on the number of crimes committed against natives is, in general, ambiguous. On one side, some criminals shift from targeting immigrants to targeting natives; on the other side, natives benefit from the spillovers related to the overall reduction in criminality. As the marginal criminal targets immigrants, such spillovers are proportional to $1-\xi$ (the probability that the marginal criminal targets immigrants but actually commits crimes against natives). The larger $1-\xi$ the larger the spillovers and the larger the crime reduction for natives.

2.3 Discussion

Our model is based on some important assumptions which are worth discussing before moving to the empirical analysis. We assume that the only effect of an amnesty is to reduce the risk of deportation, thus increasing the reporting rate of legalized immigrants. In principle, however, an amnesty may also augment their actual or prospective wealth, for instance by increasing the chances of employment. This fact may affect both the incentives of legalized immigrants to become criminals and their appeal as victims of crime. Nevertheless, two considerations are in order. First, a larger wealth (both actual or prospective) would further increase the opportunity cost

of becoming criminal, thus reinforcing our findings in terms of larger incentives to be honest for legalized individuals. Second, as long as the effect of the greater propensity to report is stronger than the effect related to the increase in actual wealth, we would still have that an amnesty reduces the incentives to commit crimes against immigrants. Given this, we do not expect an increase in the actual level of wealth, which is likely to take some time, to play a major role in our empirical analysis which focusses on the short-run effect of legalization.

Another important assumption of the model is that undocumented immigrants can obtain the amnesty irrespective of their criminal ability. Governments, however, may choose to grant legalization only to individuals without a criminal history. This would potentially introduce a negative correlation between legalization and criminal activity. If this were the case, then the effect of amnesties on crime would be dampened by the fact mainly honest immigrants would benefit from the amnesty. However, the deterrence effect of an increasing reporting rate would still generate a crime reduction.

Finally, it is worth noticing that the findings shown in Proposition 1 are consistent with an alternative way of modeling criminals' behavior. Evidence suggests that offenders often target individuals that belong to their own ethnicity or race (see for instance Morgan, 2017). If this is the case, then an amnesty would mostly affect immigrants' victimization. Sill the effect on natives would be ambiguous because of spillover effects. Only in the limiting case of perfectly separated ethnicities – criminals of group j never commit crimes against group $-j$ – an amnesty would entail no effect on the number of crimes committed against natives.

3 The IRCA, Data and Measurement Strategies

This section describes the IRCA and main data sources used in the empirical section.

3.1 The IRCA

The US Senate introduces the IRCA bill in May 1985 and President Ronald Reagan signs the bill in June 1986.[15]

In order to be eligible unauthorized immigrants had to be in continuous residence since January 1, 1982 (for a total of 5 years.) Temporary residency lasted 18 months, after which the legalized immigrants became eligible for permanent residency (i.e., green cards). Approximately 1.75 million people applied for legalization through the program and about 94% of applications were approved for temporary residency.[16]

3.2 Reporting and Victimization data

The analysis of crime reporting behavior and victimization relies on victimization surveys. We use the National Crime Victimization Survey (NCVS), conducted by the Bureau of Justice Statistics (BJS) since 1973. Like most surveys there is no information on the legal status of immigrants, in fact there is not even information on migration or on the country of birth.[17]

But the NCVS-MSA version of the survey contains information on the 40 largest Metropolitan Statistical Areas (MSAs) and can be merged with geographic informa-

[15] See Appendix Figure A2 for a full timing of all the amnesty proposals.

[16] Alternatively, in more rural places the Special Agricultural Worker (SAW) program provided permanent residency to aliens who could demonstrate they had 60 days of seasonal agricultural work experience in qualifying crops from May 1985 to May 1986. Nearly 1.3 million people applied for the SAW program.

[17] Without this information it is impossible to use a residual approach to predict whether a respondent is an undocumented immigrant (see Borjas, 2017).

tion about IRCA applicants. The survey asks a nationally representative sample of individuals about crime incidents, and whether these have been reported or not to police. Crimes include rapes, assaults, including sexual ones, robberies, purse snatching, burglaries, motor vehicle thefts, and other thefts.

We focus on a symmetric time window–from 1981 to 1994–around 1987 and 88, when the IRCA applications were filed (see the left panel of Fig. 2). Post 1994 years are excluded because of the 1994 Immigration and Nationality Act (which went into effect at the end of 1994) which introduced a temporary amnesty for about half a million undocumented immigrants. We exclude from the NCVS data American Indians (less 1 percent of the sample), Asians (about 4 percent) and individuals for whom no race is specified (about 7 percent).[18]

The right panel of Figure 2 shows, based on Immigration and Naturalization Service data, that the number of yearly deportations fell immediately after the IRCA, and started growing again in 1990, which is something we are going to come back shortly.

The NCVS contains information about the age range of respondents in 5 or 10-year intervals, starting with age 12.[19] We focus our analysis on respondents between the age of 18 and 39, whose chance of applying for the amnesty is more than twice as large as for younger and older respondents. The 18 to 39-year-old respondents represent about 50 percent of the population but more than 70 percent of the victims. The Summary Statistics Table 1 shows that we have an overall sample of about half a million respondents, about 15 percent of which are victims of a crime.[20] Of these

[18] Adding these small groups does not alter the results.

[19] Appendix Figure A3 plots the probability of IRCA application by Hispanic origin and age. In the next two sections we explain how we compute the probability.

[20] For respondents who report being victimized several times there is one observation for each incident. This allows us to properly characterize the incident and to properly account for multiple

only 39 percent report the crime to the police. The list of MSAs included in the sample is reported in Table 2.

The victimization survey contains information on whether the victim reported the crime to the police but does not contain information about the immigration status of respondents. To reconstruct such a measure we exploit two additional datasets.

3.3 IRCA's Legalization Summary Public Use Tape

In order to measure the fraction of Hispanic and Non-Hispanic population that applied for the amnesty in each MSA we merge the NCVS-MSAs with administrative records of IRCA applicants and the 1980 and 1990 US CENSUS. The IRCA records give us the exact number of applicants. Next, to measure the fraction of applicants by Hispanic origin we need the corresponding population, which we get from the 1980 and 1990 Census.

3.4 CENSUS data

The 1980 and 1990 decennial Censuses from the IPUMS allow us to estimate the population of Hispanic and non-Hispanic individuals by MSA. While the IRCA years do not coincide with a Census year, we interpolate the 1980 and 1990 Census population to get an estimate of 1987 one (the starting year of the amnesty).

3.5 Measurement Strategies

We exploit two features about the 1986 IRCA amnesty to circumvent the issue that immigration status and legal status are both unobserved in the victimization surveys.

victimizations.

The first is that Hispanics represent the grand majority of applicants and can thus be used as their proxy. The left panel of Figure 2 shows that between 1987 and 1988 about 1.6 million Hispanics apply for legal status in the MSAs covered by the NCVS. The number of non-Hispanic applicants is almost an order of magnitude smaller. Given that Hispanics made up only about 10 percent of the total population, the likelihood that someone of Hispanic origin was an IRCA applicant is about two orders of magnitude larger than for non-Hispanics.

The MSA-NCVS version of the US victimization survey can be linked with the US Census, which has information about Hispanic origin, allowing us to compute the corresponding overall population.

For the fraction of Hispanic ($H=1$) and Non-Hispanic ($H=0$) individuals who applied for the IRCA in a given MSA we simply take the ratio between the total number of IRCA applicants and the corresponding total population from the CENSUS:

$$\delta_{MSA,H} = \frac{\text{IRCA Applicants}_{MSA,H}}{\text{CENSUS Population}_{MSA,H}} \tag{1}$$

Table 2 lists the fraction of applicants by Hispanic origin. In almost all MSAs Non-Hispanics have less than a one percent chance of applying for the amnesty. Their overall chance of applying is 0.25 percent, while it is 18 percent for Hispanics.

These numbers imply that using Hispanic origin as proxy for IRCA applicants is subject to misclassification, an issue we are going to tackle further down. The second feature that we exploit is that the distribution of applicants across US cities was quite uneven.

Table 2 ranks cities based on the fraction of Hispanics who applied for the IRCA. The MSA's with 10 percent or more Hispanic applicants over the total population of

Hispanics are, starting from the top, Atlanta, GA, Anaheim-Santa Ana, Riverside-San Bernardino, Portland-Vancouver, San Diego, Los Angeles-Long Beach, Houston, Dallas, West Palm Beach-Boca Raton, Phoenix-Mesa, Chicago, Washington (DC), San Jose, Tampa-St. Petersburg-Clearwater, Charlotte-Gastonia-Rock Hill, Fort Worth-Arlington, Fort Lauderdale, and Orlando. For these cities the average probability is almost one-third.

For the bottom nine MSAs, all with Hispanic fractions that are less than 3 percent,–Columbus, Detroit, Cleveland, Lorain, Elyria (OH), Cincinnati, Pittsburgh, and Norfolk-Virginia Beach-Newport News–the overall number is just 1.55 percent.

The next section describes how we plan to exploit these differences for identification.

4 Reporting Behavior, Victimization, and Legal Status

4.1 Identification Strategy

We model two different behaviors, the victims' reporting behavior as a function of whether they are legal immigrants or not, and the criminals' "ethnic targeting" behavior as a function of whether there is a large or small fraction of IRCA applicants in the city (large or small δ), and we allow these behaviors to change with the IRCA.

Right before the IRCA we know that at least 3 million undocumented immigrants resided in the United States (the applicants), while after the IRCA an estimated flow of 800 thousand undocumented immigrants would enter the country every year (Warren and Warren, 2013). We also know that by the 1990 the estimated stock

of undocumented immigrants had already reached 3.5 million (Warren and Warren (2013)). This implies that the IRCA effect should be a short-lived, as the stock of eligible migrants would quickly mix with the new flows of ineligible migrants (Orrenius and Zavodny, 2003). This is coherent with the observed resurgence of deportations following the end of the amnesty (right panel of Fig. 2).

Given that 1989 is harder to categorize in most regressions we simply exclude that year (though we do show the entire evolution of reporting and victimization rates including 1989, and including that year does not significantly alter any of the results).

4.1.1 Reporting Behavior

Our theoretical model predicts that undocumented immigrants should increase their reporting following the IRCA, while natives should not. This leads to an empirical strategy where we compare the indicator variable for reporting a crime to the police ($R = 0, 1$) depending on Hispanic ($H = 1$) and the non-Hispanic ($H = 0$) origin of the victim in the two IRCA amnesty years 1987 and 1988 ($AY = 1$), with those before ($1981 - 1986$) and after ($1990 - 1994$) the amnesty ($AY = 0$):

$$R_i = \beta_1 H_i + \beta_2 H_i \times AY_i + \beta_3' X_i + \epsilon_i. \tag{2}$$

The coefficient β_2 measures the difference in reporting rates between Hispanics and Non-Hispanics in 1987 and 1988 compared to the years before and after the amnesty. The vector of regressors X_i contains year and MSA fixed effects, and in some specifications crime-type fixed effects, as well as MSA-specific time trends. Errors can be correlated across individuals living in the same MSA in a given year.

Given that from the victims' perspective the aim is to estimate these difference-in-differences conditional on being an IRCA applicant A as opposed to just an Hispanic individual H, the estimates are subject to misclassification bias. On one side, not all Hispanics were eligible and applied for the amnesty, $P(A = 1|H = 1) = \delta < 1$, on the other side, some non-Hispanic might also have applied, or $P(A = 0|H = 0) = q < 1$. Since most eligible applicants are believed to have applied (which is unsurprising given the incentives of becoming legalized), these errors stem from Hispanics who entered the country after January 1, 1982 (they had been resident for less than 5 years at the time of the IRCA), as well as from those who were already US citizen by the time of the IRCA.

The misclassification probabilities $1 - \delta$ and $1 - q$ are known to bias the results (Aigner, 1973). Assuming that conditional on the application status Hispanic origin has an additive effect α on reporting, we have that the application rates for Hispanics and Non-Hispanics are

$$\begin{aligned} E\left(R|H = 1, t\right) &= \alpha + \delta E_t\left(R|A = 1, t\right) + (1 - \delta)\, E\left(R|A = 0, t\right) \\ E\left(R|H = 0, t\right) &= qE\left(R|A = 0, t\right) + (1 - q)\, E\left(R|A = 1, t\right), \end{aligned}$$

Taking first a difference between the two equations and, after rearranging, taking a second difference across time (Δ_t) we get rid of α and obtain our difference-in-difference:

$$\Delta_t[E\left(R|A = 1\right) - E\left(R|A = 0\right)] = \frac{\Delta_t[E\left(R|H = 1\right) - E\left(R|H = 0\right)]}{\delta + q - 1}, \tag{3}$$

which is biased by the factor $\delta+q-1$. Similarly to Card and Krueger (1992), we are

going to first estimate the differences across Hispanic and Non-Hispanic respondents and later adjust the estimates based on MSA-level numbers for q and p.

In Table 2 the fraction of applicants for non-Hispanics is an estimate of $1 - q$, while for Hispanics it is an estimate of δ. Across all MSAs, the estimated q is larger than 99.75 percent, while the estimated overall δ is 18 percent. Since the differences-in-differences are downward biased by a factor equal to $\delta + q - 1$, they have to be inflated by a factor of 5.6. Focussing on MSAs with a very small fraction of Hispanic applicants is also going to provide an interesting placebo group.

4.1.2 Victimization Behavior

According to our model Hispanics are estimated to be victimized at lower rates following the IRCA, and the changes are predicted to be increasing in the share δ of eligible immigrants in the MSA. Victimization rates against non-Hispanics might increase or decrease depending on the degree of spillovers in victimization across ethnicity (depending on ξ). For this reason the ideal difference-in-differences strategy compares victimization rates of individuals of Hispanic origin in places with large and small δs. We compare victimization rates in the top and bottom MSAs based on δ, providing a full spectrum of robustness checks about how we define such groups.

Unlike what happens for reporting, predictions are about differences based on ethnicity rather than IRCA applicants, which implies that the estimates do not need to be adjusted for misclassification. The difference-in-differences model in victimization ($V = 0, 1$) which is run separately for Hispanics and non-Hispanics is:

$$V_i = \delta_1 TOP(\delta)_i \times AY_i + \delta_2' X_i + \varepsilon_i. \tag{4}$$

The indicator variable $TOP(\gamma)_i$ indicates whether the individual resides in a MSA with more than 10 percent of applicants among the Hispanic population. The regressors X_i contain year and MSA fixed effects, and in some specifications MSA-specific time trends. We allow errors to be correlated across individuals living in the same MSA in a given year.

4.2 Results

4.2.1 Reporting Rates

The evolution of the differences in reporting rates between Hispanics and non-Hispanics are shown in Figure 4, while the raw series are shown in Figure 3. Reporting rates are usually lower for Hispanics than for non-Hispanics, but not in the years of the amnesty.

Unconditional reporting rates for Hispanics and non-Hispanics differ by about 5 percentage points. The only years where the reporting rates are quite close to each other are 1987 and 1988. Then they start diverging again, in line with growing numbers of undocumented Hispanics who keep on entering the country. It is comforting to notice that the figure shows no pre-trends in the difference between Hispanics and Non-Hispanics, which is a necessary condition for the appropriateness of the difference-in-differences strategy.

As a placebo exercise, Figure 5 focuses on communities where the fraction of IRCA applicants is less than 3 percent. The estimates are necessarily more noisy, given the small sample of Hispanics, but no differences emerge during the Amnesty years.

Whether all these differences are statistically significant and robust when controlling for potential confounders is evidenced in Table 3. We estimate Equation 2 using

a linear probability model. The first column controls only for year fixed effects, capturing changes in reporting behavior that are shared by Hispanics and non-Hispanics alike. Hispanic reporting rates are estimated to go up by 5.3 percentage points in the two years of the amnesty. Adding MSA fixed effects lowers the effect only slightly.

In column 3 we add socioeconomic variables and crime-type fixed effects that might be correlated with the legal status of the respondents (as well as with the reporting behavior). When doing so the difference-in-difference estimate is equal 3.7 percentage points, and is still significant at the one percent level. To make sure that the results are not driven by pre-existing differential trends in the last column we add MSA-specific time trends and the results are basically unchanged. Replicating the previous analysis for the sample of MSAs with less than 3 percent of Hispanic applicants shows that the estimated difference-in-differences end up being very close to zero (see Table 4).

Table 5 shows that the results are more precisely estimated for economic crimes, especially thefts. Most differences by types of crime are positive, though statistical power is an issue, particularly for the less prevalent violent crimes.

Given the misclassification the effects has to be inflated by a factor of 5.5, meaning that based on the last column of Table 3 applicants' chance of reporting goes up by 0.037×5.5, or more than 20 percentage points. What does this imply for the level of underreporting of undocumented immigrants?

In the non-amnesty years and in the amnesty years the reporting rate of Hispanics

is a weighted average of documented (R^D) and undocumented Hispanics(R^U).

$$\begin{aligned} R_0^H &= \gamma R^U + (1-\gamma)\, R^D \\ R_1^H &= (\gamma-\delta)R^U + (1-(\gamma-\delta))R^D \end{aligned}$$

Taking the difference and solving for the unobserved R^U

$$R^U = R^D - \frac{R_1^H - R_0^H}{\delta},$$

which, importantly, does not depend on the fraction of undocumented Hispanics γ (as it is unobserved). But it does depend on the reporting rate of documented Hispanics. Taking the reporting rate in MSA with almost no Hispanics as a benchmark for R^D, we get that $R^U = 0.37 - 0.20 = 0.17$.

There is clear evidence that Hispanic victims are less likely to report crimes to the police and that these effects narrow when amnesties are passed. Undocumented victims' reporting rate is less than half the size of documented ones. Whether these differences trigger a criminal response is going to be our next research question.

4.2.2 Victimization Rates

The left panel of Figure 6 shows the difference in Hispanic victimization rates between the top and the bottom MSAs in terms of δs. The effect is large, but is mainly driven by an increase in victimization in the "control MSAs," those with few Hispanic applicants. This implies that the results are correct as long as that pattern would

have been the counterfactual victimization in the MSAs with many applicants in the absence of the IRCA.

In most years victimization rates of Hispanics are significantly larger in MSAs with more Hispanic applicants. The two years where victimization rates are aligned are 1987 and 1988. There is evidence that the decrease in victimization might start a year earlier, which would be consistent with some anticipation effect. There are no apparent changes in victimization for non-Hispanics, and there is also no evidence of pre-trends. The absence of crime displacement against non-Hispanics is in line with the model's predictions with intermediate ξ (probability of targeting the wrong ethnic group).

Estimating Equation 4 using a linear probability model of victimization, we find similar effects to the ones shown in the figures (see Table 6). Comparing victimization probabilities of Hispanics, depending on whether they live in MSAs with a small or a large fraction of Hispanic IRCA applicants, both before, during, and after the IRCA, we find evidence that during the IRCA years victimization rates drop by about 10 percentage points (-75 percent). The first three columns show that the results are robust to various controls (age, gender, number of household members, and income). Adding MSA level time trends in Column 3 makes little difference. The last three columns show that there is no change with respect to non-Hispanic victims.

Since the treatment and control separation around the top and bottom half of the MSAs is arbitrary, one thing we can do in Appendix Figure A5 is to test whether the effects are robust to a different choice of treatment MSAs. Each dot corresponds to a separate difference-in-differences in victimization rates among Hispanics (vertical caps shows the 95 percent confidence intervals). There are a total of 40 MSAs and we always use the bottom 9 as our control MSAs. Moving to the right we add more

and more MSAs to the treatment group. The difference-in-differences is decreasing as one adds MSAs with a lower fraction of Hispanic applicants, but the effects are significant all the way to the 29th MSA.

Alternatively we can change the composition of the control MSAs. This turns out to generate much larger changes in the effects. Starting with the two MSAs with the lowest fraction Hispanics that applied for the IRCA, Cincinnati MSA, and Norfolk-Virginia Beach-Newport News MSA, the effects are close to -20 percent. Adding more and more MSA with larger fractions lowers the effects substantially. The one MSA that really lowers the effects dramatically is NYC (the 11th added control MSA). Since it is not unimaginable that NYC represents an outlier, in the right panel we exclude NYC from the sample. When we do this the effects converge to about -5 percentage points.

The results are robust to the exclusion of the first two years before the IRCA, 1984 and 1985 (see Column 1 of Table 7) and to the exclusion of New York City (Columns 3 and 4)and Los Angeles. The last 4 columns show that the changes in victimization appear to be concentrated among economic crimes (which is consistent with the results in reporting behavior). These crimes could arguably be the ones where criminals act in a more rational way.

5 Conclusions

We provide evidence that out of fear of deportation undocumented immigrants are considerably less likely to report crimes to the police compared to natives (17 percent against almost 40 percent).

The 1986 US amnesty that provided legal status to 2.7 million immigrants, mainly

of Hispanic origin, allows for a difference-in-differences strategy that deals with the issue that in victimization surveys information about legal status is unavailable. It also deals with the issue that legal status is typically endogenous. Right after the amnesty, Hispanic immigrants become considerably more likely to report a crime to the police. Taking into account that not all Hispanic immigrants are undocumented, the changes in reporting rates are close to 20 percentage points.

This implies that the estimated 11.3 million undocumented immigrants are vulnerable when trying to safeguard their fundamental right to protect their property and their human right to security. Taking into account that every year about 15 percent of them are victimized, an additional 400,000 crimes would have been reported to the police if the undocumented immigrants were not fearing deportation.

In line with the predictions of a simple model of crime, with their lower reporting rates, there is some evidence that undocumented immigrants may be preferred victims of crime. In recent years US lawmakers have partially addressed the issue. In order to favor the reporting of undocumented immigrants, in 2008 the US congress approved a special Visa program ("U nonimmigrant status"). According to this program, every year victims of serious offences that are willing to work with local enforcement authorities are given temporary legal status and work eligibility in the United States. The U Visa is unlikely to be sufficient to protect immigrants' right to property and security. On one side only violent crimes are considered. On the other side, the U Visa is only temporary, up to 4 years, which might not be enough to incentivize immigrants to report the crime to the police. And, finally, the number of U visas is capped at 10,000.

An open question is whether our results are generalizable to other countries. This should depend on whether, like in the US, immigrants are at risk of deportation when

reporting a crime. It also depends on whether criminals can somehow predict the legal status of their victims. For example, in many European countries African and Asian immigrants have a higher likelihood of being undocumented immigrants.

Our analysis has additional implications that are worth mentioning. It points out that investigating the consequences of amnesties by looking at reported crimes may have some important undesirable pitfalls. The increase in reporting might turn out to be a rise in crime rates even if the true crime rates decreased. These effects should be carefully taken into account in the empirical investigation of amnesties, especially when the size of the undocumented immigration is large.

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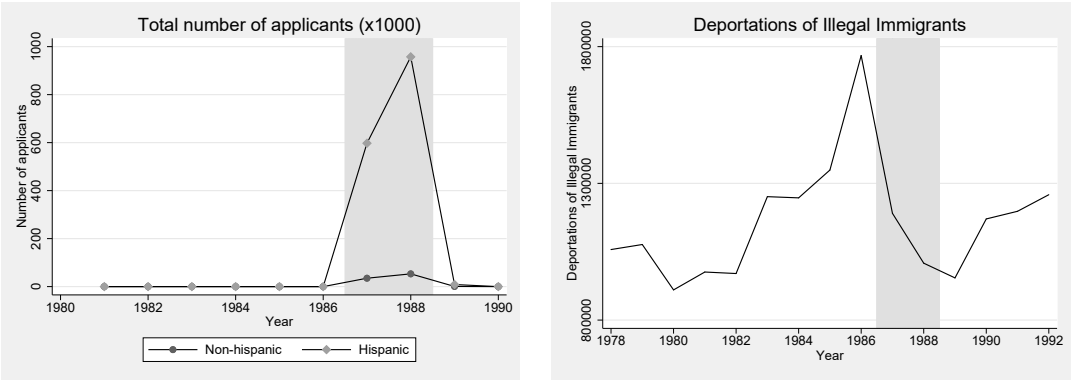

Figure 2: IRCA Applicants and Deportations of Unauthorized Immigrants

Notes: The number of NCVS-MSA IRCA applicants are based on authors' calculation by matching the Legalization Summary Public Use Tape with the NCVS survey. The number of deportations refer to the entire US, and are based on the Immigration and Naturalization Service data.

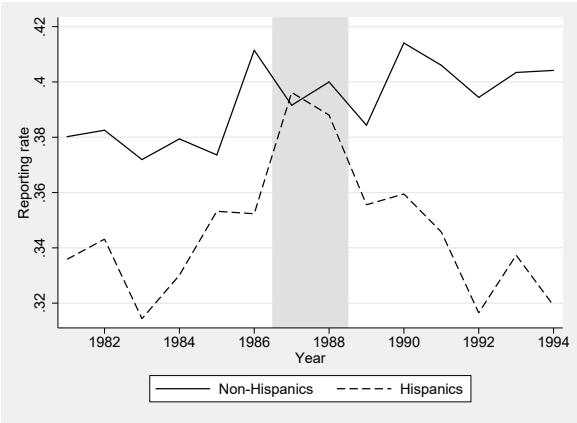

Figure 3: Unconditional reporting rates for Hispanics and Non-Hispanics.

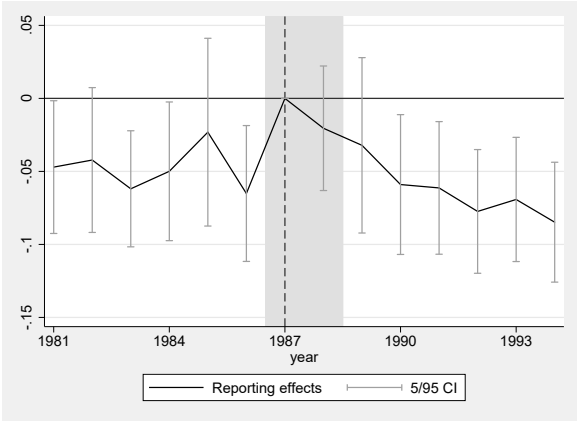

Figure 4: Difference-in-differences in reporting rates between Hispanics and Non-Hispanics in all MSAs with base year 1987.

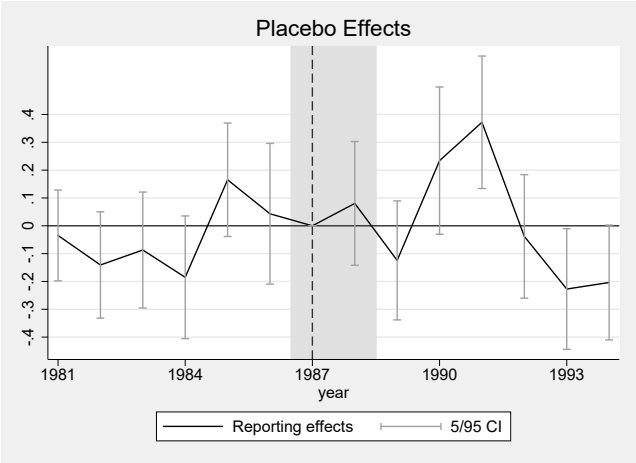

Figure 5: Placebo difference-in-differences in reporting rates between Hispanics and Non-Hispanics. These are MSAs where less than 3 percent of Hispanics applied for the IRCA.

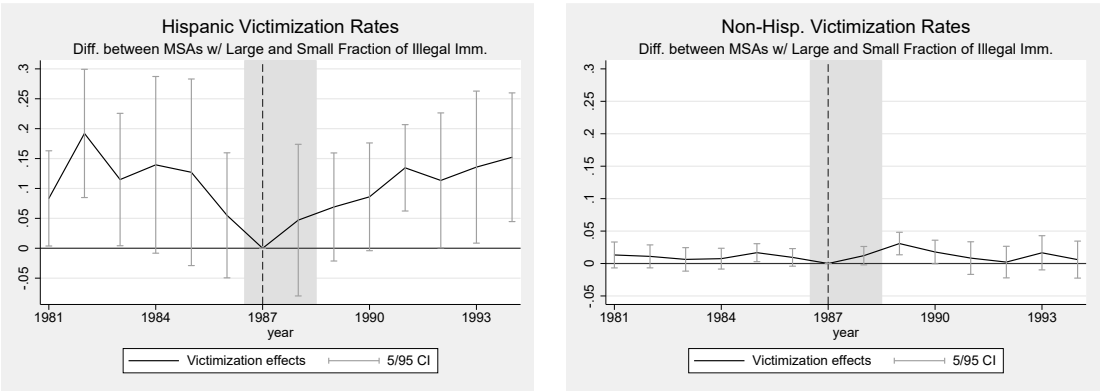

Figure 6: Difference-in-differences in victimization rates of Hispanics (left) and Non-Hispanics (right) in top and bottom MSAs.

Notes: In top MSAs at least 10 percent of Hispanics applied for the IRCA, in bottom ones less than 3 percent did.

Table 1: Summary Statistics

	Victims		All		Min	Max
	Mean	Std. Dev.	Mean	Std. Dev.		
Reported the crime	0.39	0.49	–	–	0	1
Crime victim	1.00	0.00	0.14	0.35	0	1
Hispanic	0.12	0.32	0.13	0.33	0	1
White	0.84	0.36	0.85	0.36	0	1
Female	0.52	0.50	0.52	0.50	0	1
Age 25-29	0.26	0.44	0.25	0.43	0	1
Age 29-34	0.23	0.42	0.24	0.43	0	1
Age 35-39	0.19	0.39	0.22	0.41	0	1
Income $7,500-$14,999	0.16	0.37	0.13	0.34	0	1
Income $15,000-$24,999	0.20	0.40	0.19	0.39	0	1
Income $25,000-$29,999	0.08	0.28	0.09	0.28	0	1
Income $30,000-$49,999	0.19	0.39	0.22	0.41	0	1
Income $50,000 and over	0.11	0.32	0.14	0.35	0	1
Income missing	0.12	0.33	0.14	0.34	0	1
Year	1987	4	1987	4	1981	1994
N. obs.	73,248		518,596			

Notes: Based on NCVS data matched with the 1980 Census.

Table 2: Fraction of Hispanic Population by MSA (Undocumented and Total)

	Fraction of applicants in the IRCA amnesty	
MSA	Non-Hispanics	Hispanics
Atlanta, GA	0.17%	**45.07%**
Anaheim-Santa Ana, CA	0.23%	**42.92%**
Riverside-San Bernardino, CA	0.22%	**41.68%**
Portland-Vancouver, OR-WA	0.03%	**40.38%**
San Diego, CA	0.13%	**33.32%**
Los Angeles-Long Beach, CA	0.46%	**33.19%**
Houston, TX	0.23%	**25.05%**
Dallas, TX	0.12%	**24.72%**
West Palm Beach-Boca Raton, FL	2.17%	**24.38%**
Phoenix-Mesa, AZ	0.16%	**24.05%**
Chicago, IL	0.16%	**19.82%**
Washington, DC-MD-VA-WV	0.31%	**16.37%**
San Jose, CA	0.16%	**16.05%**
Tampa-St. Petersburg-Clearwater, FL	0.10%	**12.81%**
Charlotte-Gastonia-Rock Hill, NC-SC	0.04%	**12.16%**
Fort Worth-Arlington, TX	0.10%	**12.14%**
Fort Lauderdale, FL	1.52%	**12.00%**
Orlando, FL	0.32%	**11.94%**
Average for MSAs with $\delta > 10\%$	0.27%	**28.80%**
Sacramento, CA	0.06%	*8.71%*
Seattle-Bellevue-Everett, WA	0.04%	*8.07%*
Nassau-Suffolk, NY	0.16%	*8.04%*
Oakland, CA	0.10%	*7.81%*
San Francisco, CA	0.07%	*7.15%*
Miami, FL	3.78%	*6.10%*
Kansas City, MO-KS	0.02%	*5.96%*
Denver, CO	0.03%	*5.66%*
Boston, MA-NH	0.16%	*4.77%*
Newark, NJ	0.39%	*4.58%*
San Antonio, TX	0.09%	*3.91%*
New York, NY	0.70%	*3.52%*
Philadelphia, PA-NJ	0.04%	*3.40%*
Minneapolis-St. Paul, MN-WI	0.03%	**2.88%**
Baltimore, MD	0.03%	**1.95%**
St. Louis, MO-IL	0.01%	**1.81%**
Detroit, MI	0.02%	**1.77%**
Columbus, OH	0.07%	**1.46%**
Cleveland, Lorain, Elyria, OH	0.02%	**1.22%**
Pittsburgh, PA	0.00%	**0.49%**
Cincinnati, OH-KY-IN	0.01%	**0.47%**
Norfolk-Virginia Beach-Newport News, VA	0.01%	**0.28%**
Average for MSAs with $\delta < 3\%$	0.02%	**1.55%**
Overall Average	0.25%	18.07%

Notes: The fraction of applicants is the ratio between IRCA's total number of applicants and the corresponding population based on the 1980 and 1990 CENSUS, linearly interpolated to get the figure for 1987 (the onset of the amnesty).

Table 3: Reporting Regressions

	(1)	(2)	(3)	(4)
	All MSAs			
Amnesty years × Hispanic	0.053***	0.048***	0.037***	0.037***
	(0.018)	(0.016)	(0.014)	(0.014)
Hispanic	-0.057***	-0.040***	-0.049***	-0.048***
	(0.012)	(0.008)	(0.008)	(0.008)
Year fixed effects	√	√	√	√
MSA fixed effects		√	√	√
Socioeconomic characteristics			√	√
Crime-type fixed effects			√	√
MSA specific time trends				√
Observations	68,480	68,480	68,480	68,480
R-squared	0.002	0.010	0.110	0.111
Mean dep. var	0.385	0.385	0.385	0.385

Notes: The socioeconomic variables include age group dummies, gender, number of household members, and dummies for household income categories. Clustered standard errors (by MSA) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Placebo Regressions: Reporting in MSAs with less than 3% of Undocumented Hispanics

	(1)	(2)	(3)	(4)
	MSAs with less than 2% of Undoc. Hisp.			
Amnesty years × Hispanic	0.038	0.038	0.019	0.014
	(0.055)	(0.062)	(0.060)	(0.059)
Hispanic	-0.029	-0.022	-0.033	-0.029
	(0.029)	(0.028)	(0.035)	(0.034)
Year fixed effects	√	√	√	√
MSA fixed effects		√	√	√
Socioeconomic characteristics			√	√
Crime-type fixed effects			√	√
MSA specific time trends				√
Observations	13,400	13,400	13,400	13,400
R-squared	0.004	0.012	0.110	0.111
Mean dep. var	0.396	0.396	0.396	0.396

Notes: This Table mimics Table 3. Clustered standard errors (by MSA) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Reporting Regressions by Crime Types

	(1)	(2)	(3)	(4)	(5)	(6)
Crime type	Violent	Economic	Robbery	Burglary	Theft	Assault
Amesty years × Hispanic	0.026	0.046***	-0.000	0.040	0.045**	0.033
	(0.049)	(0.016)	(0.087)	(0.048)	(0.019)	(0.064)
Hispanic	-0.010	-0.041***	-0.120***	-0.035	-0.044***	0.030
	(0.018)	(0.008)	(0.041)	(0.025)	(0.007)	(0.020)
Observations	12,099	57,242	2,603	10,212	44,427	9,161
R-squared	0.027	0.012	0.076	0.039	0.011	0.028
Mean dep. var	0.522	0.365	0.558	0.524	0.317	0.514

Notes: All regressions are restricted to MSAs with many undocumented immigrants of Hispanic origin. All regressions include MSA and year fixed effects, as well as age group dummies, gender, number of household members, and dummies for household income categories. Clustered standard errors (by MSA) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Victimization Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	Has been victimized (0/1)					
	Hispanics			Non-Hispanics		
Amnesty years ×	-0.100*	-0.101*	-0.101*	-0.004	-0.003	-0.003
Large fraction of Hisp. applicants	(0.056)	(0.054)	(0.053)	(0.008)	(0.007)	(0.008)
MSA fixed effects	√	√	√	√	√	√
Year fixed effects	√	√	√	√	√	√
Socioeconomic characteristics		√	√		√	√
MSA specific time trends			√			√
Observations	39,377	39,377	39,377	288,441	288,441	288,441
R-squared	0.005	0.009	0.011	0.008	0.023	0.024
Mean dep. var	0.133	0.133	0.133	0.148	0.148	0.148

Notes: The socioeconomic variables include age group dummies, gender, number of household members, and dummies for household income categories. Clustered standard errors (by MSA) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Robust Victimization Regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable: Has the Respondent been victimized (0/1)									
Sample:	No 85, 86		No NYC		No LA		Economic Crimes		Violent Crimes	
Amesty years ×	-0.109*	-0.109**	-0.100*	-0.101*	-0.086	-0.086	-0.087	-0.088	-0.031	-0.033
Large fraction of Hisp. applicants (IRCA)	(0.054)	(0.051)	(0.056)	(0.053)	(0.056)	(0.053)	(0.056)	(0.055)	(0.020)	(0.019)
Observations	34,322	34,322	39,377	39,377	23,982	23,982	38,654	38,654	35,010	35,010
R-squared	0.006	0.011	0.005	0.011	0.008	0.015	0.005	0.010	0.002	0.008
Mean dep. var	0.135	0.135	0.133	0.133	0.134	0.134	0.116	0.116	0.0245	0.0245

Notes: The socioeconomic variables include age group dummies, gender, number of household members, and dummies for household income categories. Clustered standard errors (by MSA) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

A Mathematical Appendix

Proof of Proposition 1

Let $\overline{\rho}_i(\delta)$ and $\overline{\rho}_n$ be the average reporting rate of immigrants and natives respectively. From our assumptions about the masses of the different groups of individuals, it follows that:

$$\begin{aligned}\overline{\rho}_i(\delta) &= (1-\gamma+\delta)\rho_{p,l} + (\gamma-\delta)\rho_{p,a}, \\ \overline{\rho}_n &= \phi\rho_{p,l} + (1-\phi)\rho_{r,l}.\end{aligned}$$

Notice that the average reporting rate of immigrants depends on δ, the mass of legalized individuals. Specifically, since $\rho_{p,l} > \rho_{p,a}$, $\overline{\rho}_i(\delta)$ increases with δ and takes the lowest value when $\delta = 0$, i.e. before the amnesty.

The expected cost of punishment when targeting primarily immigrants and natives is:

$$\begin{aligned}C(\rho|i,\delta) &= C\left(\xi\overline{\rho}_i(\delta) + (1-\xi)\overline{\rho}_n\right), \\ C(\rho|n,\delta) &= C\left(\xi\overline{\rho}_n + (1-\xi)\overline{\rho}_i(\delta)\right),\end{aligned}$$

respectively. Notice that since we assume that $C(\cdot)$ is increasing in the average reporting rate, then it follows that both $C(\rho|i)$ and $C(\rho|n)$ are increasing in δ.

The expected wealth of the victim when targeting primarily immigrants and natives is:

$$\begin{aligned}E[w|i] &= \xi p + (1-\xi)\left(\phi p + (1-\phi)r\right), \\ E[w|n] &= \xi\left(\phi p + (1-\phi)r\right) + (1-\xi)p.\end{aligned}$$

respectively; notice that these expressions do not depend on δ.

Before demonstrating the statement of Proposition 1, we determine the equilibrium of the model. Following the discussion in the text, the equilibrium is defined by the triple:[21]

i) $\bar{\theta}(\delta) = \frac{C(\rho|n,\delta)-C(\rho|i,\delta)}{E(w|n)-E(w|i)}$

ii) $\hat{\theta}_p(\delta)$ and $\hat{\theta}_a(\delta)$ that solve the system:

$$\begin{aligned}
\hat{\theta}_p(\delta) &= \frac{f(p,\rho_{p,l}) - \beta[(\gamma-\delta)(1-\hat{\theta}_a(\delta)) + (1-\gamma+\delta+\phi)(1-\hat{\theta}_p(\delta))] + C(\rho|i,\delta)}{E(w|i)}, \\
\hat{\theta}_a(\delta) &= \frac{f(p,\rho_{p,a}) - \beta[(\gamma-\delta)(1-\hat{\theta}_a(\delta)) + (1-\gamma+\phi)(1-\hat{\theta}_p(\delta))] + C(\rho|i,\delta)}{E(w|i)}.
\end{aligned}$$

Simple algebra leads to the following expressions:

$$\begin{aligned}
\hat{\theta}_p(\delta) &= \frac{E(w|i)(\beta(1+\phi) - f(p,\rho_{p,l}) - C(\rho|i,\delta)) + \beta(\gamma-\delta)(f(p,\rho_{p,l}) - f(p,\rho_{p,a}))}{E(w|i)\,(\beta(1+\phi) - E(w|i))}, \\
\hat{\theta}_a(\delta) &= \frac{E(w|i)(\beta(1+\phi) - f(p,\rho_{p,a})) - C(\rho|i,\delta)) - \beta(1-\gamma+\delta+\phi)(f(p,\rho_{p,l}) - f(p,\rho_{p,a}))}{E(w|i)\,(\beta(1+\phi) - E(w|i))}.
\end{aligned}$$

We first characterize the effect of the amnesty on the thresholds $\hat{\theta}_p(\delta)$, $\hat{\theta}_a(\delta)$ and $\bar{\theta}(\delta)$. This is shown in Claim 1 below.

For the sake of simplicity, we let $\hat{\theta}_p^0$, $\hat{\theta}_a^0$ and $\bar{\theta}^0$ denote the thresholds before the amnesty is in place (when $\delta = 0$). Similarly, we let $C^0(\rho|i)$ and $C^0(\rho|n)$ the expected costs of punishment before the amnesty. Finally, notice that neither $E[w|i]$ nor $E[w|n]$ change because of the amnesty.

[21] We implicitly assume $0 < \hat{\theta}_a < \hat{\theta}_p < \bar{\theta} < 1$.

Claim 1. An amnesty which legalized $\delta \in (0, \gamma]$ undocumented immigrants increases $\hat{\theta}_p(\delta)$ and $\hat{\theta}_a(\delta)$ while reducing $\bar{\theta}(\delta)$. These changes are larger the greater δ.

Proof of Claim 1. Consider the effect of the amnesty on $\hat{\theta}_p(\delta)$. The change in the threshold equals

$$\hat{\theta}_p(\delta = 0) - \hat{\theta}_p(\delta > 0) = \frac{E(w|i)[C(\rho|i, \delta > 0) - C(\rho|i, \delta = 0)] + \beta\delta(f(p, \rho_{p,l}) - f(p, \rho_{p,a}))}{E(w|i)\left(\beta(1+\phi) - E(w|i)\right)}. \tag{5}$$

Expression (5) is positive since $C(\rho|i, \delta > 0) > C(\rho|i, \delta = 0)$, $f(p, \rho_{p,l}) > f(p, \rho_{p,a})$, and the denominator is positive since $0 < \hat{\theta}_p(\delta) < 1$. These conditions and the fact that $C(\rho|i, \delta)$ increases with δ ensures that expression (5) is larger the greater δ. Similar arguments apply for the other two thresholds, $\hat{\theta}_a(\delta)$ and $\bar{\theta}(\delta)$. ■

Claim 1 and condition $\hat{\theta}_a(\delta) < \hat{\theta}_p(\delta)$ ensure that the level of criminality – i.e. $(\gamma - \delta)(1 - \hat{\theta}_a(\delta)) + (1 - \gamma + \phi)(1 - \hat{\theta}_p(\delta))$ – reduces after the amnesty and that the reduction is stronger the larger δ.

Consider now the number of criminals targeting the two ethnic groups and the number of crimes committed against immigrants and natives. Criminals primarily targeting immigrants and natives is

$$I(\delta) = (\gamma - \delta)(\bar{\theta}(\delta) - \hat{\theta}_a(\delta)) + (1 - \gamma + \delta + \phi)(\bar{\theta}(\delta) - \hat{\theta}_p(\delta)),$$

$$N(\delta) = (\gamma - \delta)(1 - \bar{\theta}(\delta)) + (1 - \gamma + \delta + \phi)(1 - \bar{\theta}(\delta)) = (1 + \phi)(1 - \bar{\theta}(\delta)),$$

respectively. Since criminals targeting group $j \in \{n, i\}$ commit crimes against members of the other group with probability $(1 - \xi)$, the number of criminals actually committing crimes against immigrants is $X^i(\delta) = \xi I(\delta) + (1 - \xi)N(\delta)$ while that of

criminals actually committing crimes agains natives is $X^n = \xi N(\delta) + (1-\xi)I(\delta)$. Simple algebra leads to the following expressions:

$$\begin{aligned} X^i(\delta) &= (1+\phi)\bar{\theta}(\delta)(2\xi-1) + (1-\xi)(1+\phi) - \xi\left((\gamma-\delta)\hat{\theta}_a(\delta) + (1-\gamma+\delta+\phi)\hat{\theta}_p(\delta)\right), \\ X^n(\delta) &= (1+\phi)\bar{\theta}(\delta)(1-2\xi) + \xi(1+\phi) - (1-\xi)\left((\gamma-\delta)\hat{\theta}_a(\delta) + (1-\gamma+\delta+\phi)\hat{\theta}_p(\delta)\right) \end{aligned}$$

Notice that $X^i(\delta)$ decreases with δ since: $\xi \geq 1/2$, $\bar{\theta}(\delta)$ decreases with δ, $\hat{\theta}_a(\delta)$ and $\hat{\theta}_p(\delta)$ increase with δ, and $\hat{\theta}_a(\delta) < \hat{\theta}_p(\delta)$. Moreover the higher δ the stronger the reduction in $X^i(\delta)$. Therefore, the number of crimes committed against immigrants reduces after the amnesty and the reduction is stronger the larger the number of legalized individuals (the larger δ). Consider now the crimes that are committed against natives. For $\xi = 1$, $X^n(\delta)$ becomes $-(1+\phi)\bar{\theta}(\delta) + (1+\phi)$ which increases with δ (since $\bar{\theta}(\delta)$ decreases with δ). By contrast, for $\xi = 1/2$, $X^n(\delta)$ becomes $\frac{1}{2}(1+\phi) - \frac{1}{2}\left((\gamma-\delta)\hat{\theta}_a(\delta) + (1-\gamma+\delta+\phi)\hat{\theta}_p(\delta)\right)$ which reduces with δ since: $\hat{\theta}_a(\delta)$ and $\hat{\theta}_p(\delta)$ increase with δ, and $\hat{\theta}_a(\delta) < \hat{\theta}_p(\delta)$. Therefore, after the amnesty, the number of crimes committed against natives can increase (when ξ is close to 1) or decrease (when ξ is close to 1/2). ■

B Figures

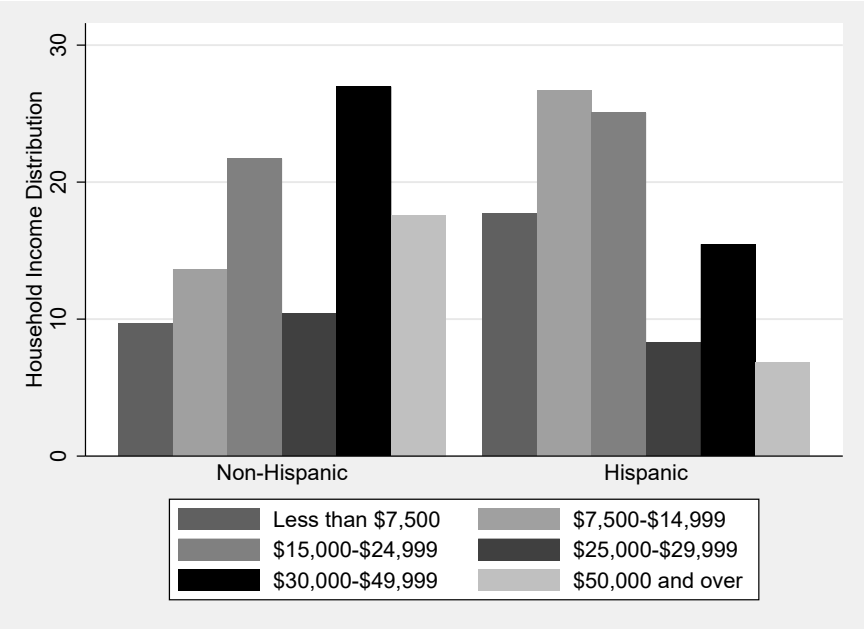

Figure A1: Distribution of Household Income by Hispanic Origin (in %)

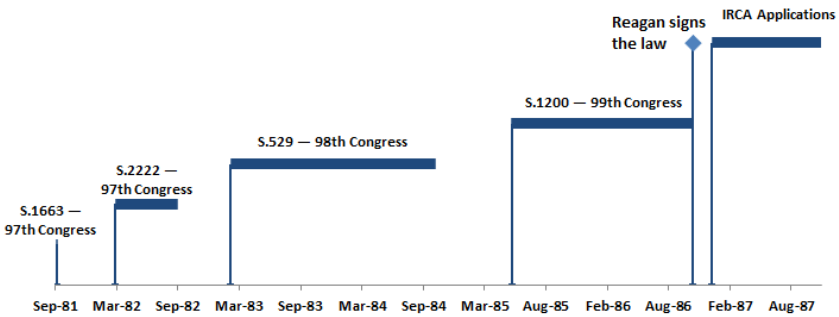

Figure A2: Time and Duration of Immigration Amnesty Proposals

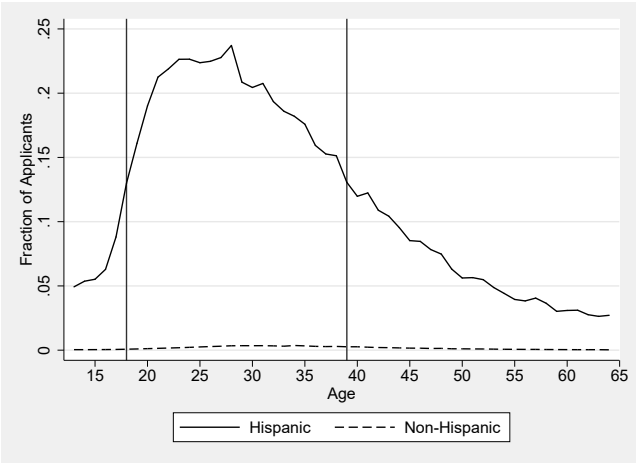

Figure A3: Fraction of IRCA Applicants by Hispanic Origin and Age

Notes: The fraction of IRCA applicants by age and Hispanic origin are based on authors' calculation matching the Legalization Summary Public Use Tape with the CENSUS.

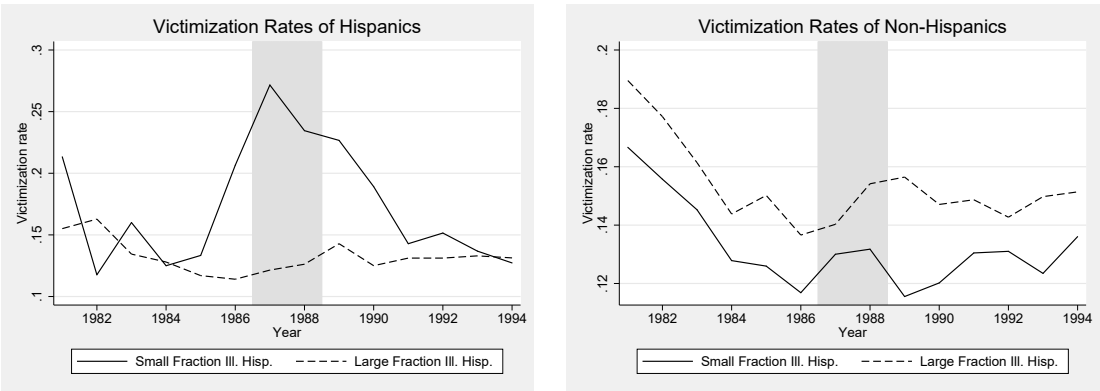

Figure A4: Reporting rates in MSAs with top tercile (top) and bottom two terciles (bottom) by size of the documented or undocumented Hispanic population.

Notes: Based on NCVS data matched with IRCA Administrative data and the 1980/1990 Census.

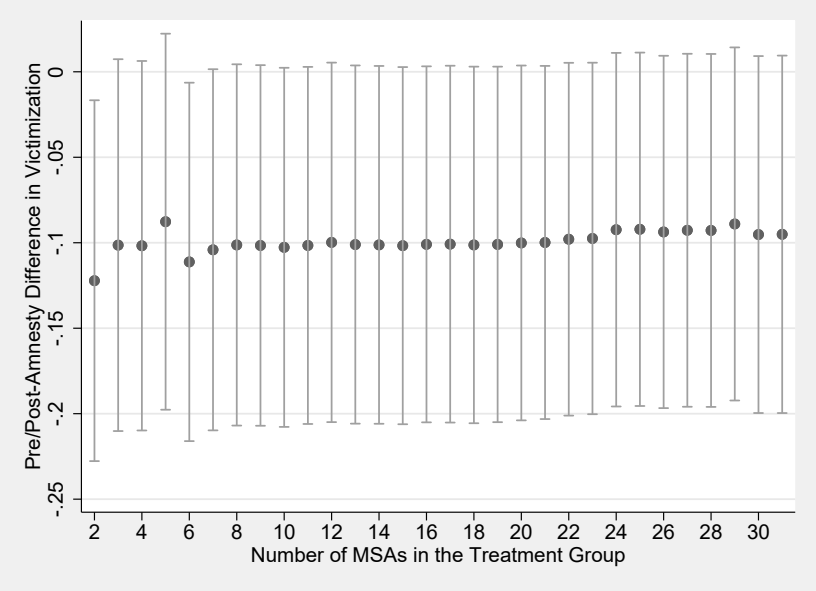

Figure A5: Difference-in-differences in Victimization When Changing the Treated MSAs

Notes: Each dot corresponds to a separate difference-in-differences in victimization rates among Hispanics. Vertical caps represent the corresponding 95 percent confidence intervals. There are a total of 40 MSAs. The control cities are always the bottom 9 based on δ. MSAs are added to the treatment group starting from top.

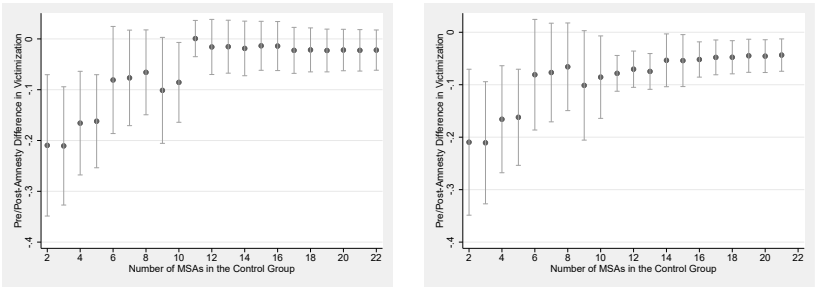

Figure A6: Difference-in-differences in Victimization Rates When Changing the Control MSAs

Notes: Each dot corresponds to a separate difference-in-differences in victimization rates among Hispanics. Vertical caps represent the corresponding 95 percent confidence intervals. There are a total of 40 MSAs. The treated cities are always the top 18 based on δ. MSAs are added to the control group starting from bottom based on δ. The right panel excludes the 11th control MSA, NYC, a clear outlier.