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

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Do undocumented migrants underreport crimes to the police in order to avoid being deported? And do criminals exploit such vulnerability? We address these questions using victimization surveys and administrative data around the 1986 U.S. immigration amnesty. The amnesty allows us to solve two major identification issues that have plagued this literature: migrants' legal status is endogenous and unobserved. The results show that the reporting rate of undocumented immigrants is 17 percent, which limits the immigrants' ability to protect some of their fundamental human rights. However, right after the 1986 amnesty, which disproportionately legalized individuals of Hispanic origin, crime victims of Hispanic origin show enormous improvements in reporting behavior. The implied increase in the reporting rate by amnesty applicants is close to 20 percentage points. © 2020 The Authors. Journal of Policy Analysis and Management *published by Wiley Periodicals LLC on behalf of Association for Public Policy and Management*

INTRODUCTION

In recent years the estimated number of unauthorized immigrants living in the United States is estimated to have flattened at around 11 million (representing 3.5 percent of the entire population), up from about 3.5 million in 1990.[1] One of the most controversial issues in the United States and in several Western countries is how to deal with undocumented immigrants. The main policy options are usually amnesties, though these tend to polarize the electorate. Public opinion polls show that many citizens fear that undocumented immigration might not just bring job losses and rising welfare costs but also high rates of crime.[2]

Because of such anti-immigration sentiments, a comprehensive immigration reform has eluded the U.S. Congress, and in 2016 a perfectly divided U.S. Supreme Court 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

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[1] See Krogstad et al. (2019) and Warren and Warren (2013).
[2] See, for instance, http://www.pollingreport.com/immigration.htm.

sentiments have fueled the BREXIT vote in the UK referendum, and more anti-immigration acts may follow in other European countries.

A thorough evaluation of the various consequences of unauthorized migration represents the most likely solution to such gridlock. There is growing evidence of 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 of benefitting from better health-care (Barcellos, 2010; Kossoudji & Cobb-Clark, 2002; Lozano & 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 the host country language, and their children might become more likely to go to college. Alsan and Yang (2018) show that immigrants who fear deportation reduce the take-up of safety net programs, while Wang (2019) shows that with an increased risk of deportation immigrants become more likely to enter self-employment.

This study contributes to debate on illegal immigration and on amnesties providing evidence on an important negative consequence of illegally residing in the country: Undocumented immigrants are unable to protect their property and their human right to security. Arguably out of fear of deportation, undocumented immigrants who become crime victims are shown to under-report such crimes to the police, generating an essentially unenforced space for ruthless criminals. Amnesties might thus not only improve the labor market opportunities of immigrants, thus lowering their criminal propensity, they are shown to increase reporting rates and alter the expected cost of criminal behavior.

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 of such evidence, we use the National Crime Victimization Survey (NCVS) around the 1986 immigration amnesty (the Immigration Reform and Control Act [IRCA]) to deal with the endogeneity of legal status as well as with its measurement issue. 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 National Crime Victimization Survey (NCVS). But administrative records of IRCA applicants show that most of the undocumented immigrants were of Hispanic origin. This implies that we can use Hispanic ethnicity as a proxy for legal status. Since such proxy has known probabilities of misclassifying legal status, we can adapt Aigner's (1973) regression with a binary independent variable subject to errors of observation to our difference-in-differences setup, which is centered around the 1986 U.S. immigration amnesty. The amnesty granted legal status to about 2.7 million undocumented immigrants (out of three million who applied).

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 also likely to increase the 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 strategy by criminals in a formal model developed in Appendix A and briefly discussed in the next section.[3] The comparative statics of this analysis highlight the identification strategy for this amnesty-induced displacement of victimization. Specifically, 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. There is some evidence of these predictions in the data.

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 results on the underreporting of crime has implications for the current political debate. Recently, President Trump's administration has made attempts to increase detection and deportation of undocumented immigrants (the so-called Secure Communities program) by involving local authorities in the enforcement of federal immigration law (287(g) program). This is likely to lead to additional underreporting. One potential solution would be to limit the collaboration between local and federal authorities, when immigrants' human right to security is involved.

Some local authorities have indeed 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.

Our analysis has an additional implication that is worth mentioning. Investigating the consequences of amnesties by looking at reported crimes may be misleading, as an increase in reporting may be misinterpreted as an increase in crime. This happens for two reasons: i) legalized immigrants report more, and ii) criminals shift their targets from immigrants to natives, who are more likely to report.

RELATED LITERATURE

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. Our findings are consistent with those obtained in a few small-scale sample studies that 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 & Bejarano, 2004), and in one about immigrants in Reno, Nevada (Correia, 2010).[4] The only study that also uses a large and representative sample (the NCVS), finds that crime reporting rates are negatively correlated with the relative size of noncitizen and foreign-born individuals living in a metropolitan area (Gutierrez & Kirk, 2015), but does not exploit any exogenous variation in legal status.

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[3] 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 & Nold, 1980; Goudriaan et al., 2006).
[4] See also Barrick (2014).

In spirit, our study is also closely related to recent research on the determinants of crime reporting by women and victimization against them. Miller and Segal (2019) use the NCVS to show that the integration of women in U.S. 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.

Several contributions in the literature focus on the effect of immigration on crime.[5] The results are rather mixed, although most recent studies find little evidence that immigration spurs crime (see, among others, Bianchi et al., 2012; Bell et al., 2013).[6] A couple of recent articles focus on amnesties and employ IRCA data to study their effect on crime (see Baker, 2015; Freedman et al., 2013). The authors show that documented immigrants have a lower propensity to be involved in criminal activities than undocumented ones and interpret this finding using a standard opportunity cost argument. 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 Italian data on legalization lotteries. Pinotti (2015) also provides evidence that stricter enforcement of migration policy reduces the crime rate of undocumented immigrants.

A MODEL OF CRIME AND REPORTING: AN INFORMAL PRESENTATION

In this section, we offer an intuitive discussion of the theoretical model presented in the Appendix. In the model, we consider a city composed of two ethnic groups: natives and immigrants. Some immigrants are legal citizens while others are undocumented. Individuals differ also in terms of their wealth: All immigrants are poor, while natives can be rich or poor.[7]

We study the following decisions. Each citizen chooses whether to be honest or to commit crimes. Individuals who decide to become criminals observe the ethnicity—native or immigrant—of the potential victims and choose which ethnic group to target.[8] Honest individuals who are victimized decide whether to report the crime to the police. In our analysis, we first analyze the reporting decision of a victim. The propensity for victims to report a crime increases with the economic loss they suffer (which is proportional to their wealth) and it also depends on their legal status (legal or undocumented). Undocumented immigrants who are poor and who fear they could be deported if they contact the police have the smallest propensity to report crime. By contrast, rich natives have the largest propensity to contact the police and report crime. It follows that the average reporting rate is higher in the group of natives than in that of immigrants.

The decision of whether to be honest or criminal is based on a comparison of the utility enjoyed in the two cases. The utility of honest individuals increases

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[5] The consequences of immigration for labor market outcomes is also a topic that is intensively investigated in the literature. See Borjas (1994) and Card (1990) among others.
[6] Also, Butcher and Piehl (1998) and Piehl (2007) find no evidence that immigration overall increases crime or incarceration rates.
[7] This assumption is in line with what we observe in our dataset. Income differences between Hispanics and non-Hispanics are shown to be large in the National Crime and Victimization Survey (see Appendix Figure A2). Household incomes are only available in broad intervals, but in relative terms non-Hispanics versus Hispanic income differences are at least equal to 25 percent.
[8] We assume that criminals cannot observe the wealth or the legal status of potential victims; but they do observe an informative signal, their ethnic group—ethnicity may be an observable characteristic due to different physical appearance or urban segregation by ethnicity. The U.S. is a clear example of where ethnicity, particularly being of Hispanic origin, carries some signal for the migration status.

with their wealth and their propensity to report crimes to the police. This latter assumption rests on the observation that the probability that a victim of a crime receives a monetary compensation, for instance by means of the (partial) return of the stolen goods or an insurance compensation, increases with the reporting rate: A higher reporting rate increases the capacity to protect one's property rights.

The utility of criminals depends on their ability to commit crimes. From this assumption, it follows that only those who are skilled enough to commit offences actually choose to become criminals. The decision of which ethnic group to target depends on a trade-off between a larger gain when targeting natives—natives are richer on average—with a smaller expected punishment when targeting immigrants—the average reporting rate is lower among immigrants. It follows that criminals with higher criminal abilities prefer to target natives while those with a lower criminal ability commit offences primarily against immigrants.

In the Appendix, we characterize the equilibrium choices of individuals. We then study how these decisions change in the case of an amnesty that legalizes a fraction of undocumented immigrants. The direct consequence of an amnesty is that legalized individuals do not fear the risk of deportation anymore and, therefore, increase their reporting rate. This fact has two effects. First, legalized immigrants are better able to protect their property rights, and therefore the utility of honesty increases for them—their opportunity cost of becoming criminals gets larger. Second, the average reporting rate of the immigrant group increases, and such an increase is stronger the larger the number of legalized immigrants. The predictions of the model regarding the consequences of amnesties are the following:

Predictions of the Model

1. Amnesties increase the reporting rate of undocumented migrants, while they do not change those of legal immigrants and natives.
2. Amnesties reduce the overall number of crimes.
3. Amnesties reduce the number of crimes committed against immigrants while they can either increase or decrease those committed against natives.
4. The reduction in the overall number of crimes and in the number of crimes committed against immigrants is larger the larger the fraction of legalized immigrants.

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. This fact implies that crime reduces. 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. These two effects, overall reduction in criminality and shift in targeting, are stronger the larger the share of legalized immigrants and they 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.

Discussion of the Modeling Assumptions

Our model is based on some important assumptions that 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. In principle, however, amnesties may also increase immigrants' labor market prospects. This may lower the incentives to become criminals and increase the likelihood to become victims of crime. Nevertheless, two considerations are in order. The first effect would increase the opportunity cost of crime, thus reinforcing our findings. As for the second effect, 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 see that an amnesty reduces the incentives to commit crimes against immigrants. Moreover, the increase in wealth would not be immediate, while our empirical analysis is going to focus on the short-run effect of legalization.

Another important assumption of the model is that undocumented immigrants can benefit from an amnesty irrespective of their skill at criminal activity. 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 that only 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 noting that some of the predictions of the model are consistent with an alternative way of modeling criminals' behavior. Evidence suggests that offenders often target individuals who 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. But because of spillover effects, the effect on natives would still be ambiguous. Only in the limiting case of perfectly separated ethnicities would an amnesty entail no effect on the number of crimes committed against natives.

THE IRCA, DATA, AND MEASUREMENT STRATEGIES

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

The IRCA

The U.S. Senate introduced the IRCA bill in May 1985 and President Ronald Reagan signed the bill in June 1986.[9] In order to be eligible, unauthorized immigrants had to be in continuous residence since January 1, 1982 (for a total of five 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 percent of applications were approved for temporary residency (on average in about seven months). Alternatively, in more rural places, the Special Agricultural Worker (SAW) program provided permanent residency to undocumented immigrants 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. We are going to use both types of applicants: in our sample applicants are split approximately 50/50 across the two programs. About 2.7 million applicants, or about 90 percent, were ultimately approved for permanent residence (Rytina, 2002).

The administrative records of the 1986 amnesty, called IRCA's Legalization Summary Public Use Tape, contains information about all applicants. County of residence is supplied only when the county had at least 100,000 residents in the 1990

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[9] See Appendix Figure A3 for a full timing of all the amnesty proposals.

Census, and at least 25 legalization applicants. Since we focus on large Metropolitan Statistical Areas (MSAs) that are part of the NCVS-MSA victimization survey, this is not a constraint. The other information we use is age and race of the applicants (there are five categories: Asian; Black, non-Hispanic; Hispanic; White, non-Hispanic; Unknown).[10]

The IRCA records give us the exact number of applicants for Hispanic and non-Hispanic adults. Next, to measure the fraction of applicants by Hispanic origin, we need the corresponding population, which we get from the 1980 and 1990 Census.

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 (the starting year of the amnesty). The fraction of Hispanic and non-Hispanic applicants in each NCVS-MSA is shown in Table 1.

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.[11]

But the NCVS-MSA version of the survey contains information on the 40 largest MSAs and can be merged with geographic information 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 1988, when the IRCA applications were granted (see the left panel of Figure 1). 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 than one percent of the sample), Asians (about 4 percent), and individuals for whom no race is specified (about 7 percent).[12] The right panel of Figure 1 shows, based on Immigration and Naturalization Service (now called U.S. Citizenship and Immigration Services [USCIS]) 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 to shortly.

The NCVS contains information about Hispanic origin and about the age range of respondents in five- or 10-year intervals, starting with age 12.[13] We focus our

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[10] The administrative records also contain information about the country of origin, gender, wages, occupation, marital status, date of entry in the U.S., date of application, and whether the application was approved.

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

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

[13] Appendix Figure A4 plots the probability of IRCA application by Hispanic origin and age. In the next two sections, we explain how we compute the probability.

Table 1. 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). δ represents the fraction of Hispanics in the MSA.
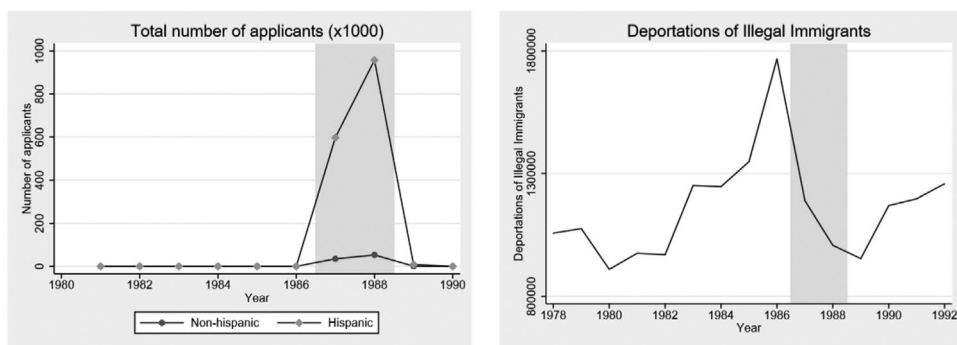
Notes: The number of NCVS-MSA IRCA applicants is based on authors' calculation by matching the Legalization Summary Public Use Tape with the NCVS survey. The number of deportations refers to the entire U.S. and is based on the U.S. Citizenship and Immigration Services data.

Figure 1. IRCA Applicants and Deportations of Unauthorized Immigrants.

Table 2. Summary statistics.

	Victims		All			
	Mean	Std. Dev.	Mean	Std. Dev.	Min	Max
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
Observations		73,248		518,596		

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

analysis on respondents between the ages of 18 and 39, whose chance of applying for the amnesty is more than twice as much 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. Given the MSA-level stratified cluster sample design of the NCVS data, we cluster the standard errors at the MSA level.[14]

Table 2 (Summary Statistics) shows that we have an overall sample of about half a million respondents, about 15 percent of whom are victims of a crime.[15]

Of these, only 39 percent report the crime to the police. In Appendix Table A1, we divide the summary statistic by whether in an MSA more or less than 10 percent

[14] While we do not use sampling weights, this makes almost no difference.
[15] 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 victimizations.

of the Hispanic population were amnesty applicants (see Table 1). Not surprisingly, the main difference is in the fraction of Hispanic individuals and Hispanic victims. The likelihood of victimization is also larger in MSAs when a larger fraction of Hispanics applied for IRCA. All other variables appear to be well-balanced.

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. The first is that Hispanics represent the grand majority of applicants and can thus be used as their proxy. The left panel of Figure 1 shows that between 1987 and 1988 about 1.6 million Hispanics applied 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 U.S. victimization survey can be linked with the U.S. 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 1 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 later on. The second feature that we exploit is that the distribution of applicants across U.S. cities was quite uneven.

Table 1 ranks cities based on the fraction of Hispanics who applied for the IRCA. The MSAs where more than 10 percent of the Hispanic population were amnesty applicants 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.

REPORTING BEHAVIOR, VICTIMIZATION, AND LEGAL STATUS

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, and we allow these behaviors to change with the IRCA.

Right before the IRCA, we know that at least three million undocumented immigrants, mostly of Hispanic origin, resided in the United States (the applicants) out of about 18.5 million Hispanics, while after the IRCA an estimated flow of 800,000 undocumented immigrants would enter the country every year (Warren & Warren, 2013). We also know that by 1990, the estimated stock of undocumented immigrants had already reached 3.5 million (Warren & Warren, 2013). This implies that the IRCA effect should be short-lived, as the stock of eligible migrants would quickly mix with the new flow of ineligible migrants (Orrenius & Zavodny, 2003).[16] This is consistent with the observed resurgence of deportations following the end of the amnesty (right panel of Figure 1).

The main identification assumption is that treated and control individuals would have followed parallel trends in the absence of the amnesty.

Reporting Behavior

Our theoretical model predicts that undocumented immigrants should increase their reporting following the IRCA, while natives should not (Prediction 1). 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 to 1986) and after (1989 to 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. This empirical strategy is supposed to isolate the changes in reporting that are driven by the amnesty (underreporting may be driven by many other factors, but as long as these factors are not changing over time they are going to be differenced out). 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 a 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-Hispanics 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 a resident for less than five years at the time of the IRCA), as well as from those who were already U.S. citizens 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:

$$E(R|H = 1, t) = \alpha + \delta E_t(R|A = 1, t) + (1 - \delta)E(R|A = 0, t)$$

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[16] These numbers imply that in 1986, the fraction of undocumented Hispanics was at least 3/18.5=16.2 percent. In 1990, the same fraction was 3.5/21=16.6 percent.

$$E(R|H = 0, t) = q E(R|A = 0, t) + (1 - q)E(R|A = 1, t).$$

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:

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

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 1, 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. Focusing on MSAs with a very small fraction of Hispanic applicants is also going to provide an interesting placebo group. With respect to the parallel trends assumption, it is important to add that differences in policing would be differenced out across individuals residing in the same MSA, unless the police responded to the amnesty by changing their focus based on ethnicity (with victims noticing such changes).

Victimization Behavior

According to our model, Hispanics are estimated to be victimized at lower rates following the IRCA (Prediction 3), and the changes are predicted to be increasing in the share δ of eligible immigrants in the MSA (Prediction 4).[17] Victimization rates against non-Hispanics might increase or decrease depending on the degree of spillover in victimization across ethnicity. 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 ($V = 0,1$) that is run separately for Hispanics and non-Hispanics is:

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

The indicator variable $TOP(\delta)_i$ indicates whether the individual resides in an MSA where the number of Hispanic amnesty applicants was more than 10 percent of 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. Regarding the parallel trends assumption, changes in policing would not be differenced out as we are taking changes across different MSAs. For this reason, we allow for differential trends, but cannot rule out that changes in policing may alter the results.

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[17] The amnesty should also reduce overall crime, though such a prediction is more difficult to test given that several factors may influence overall crime.
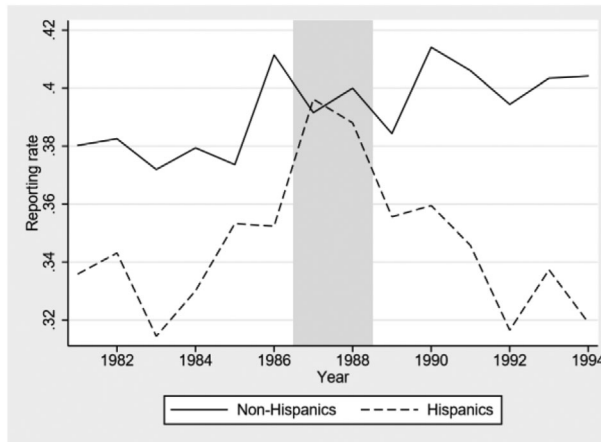
Figure 2. Unconditional Reporting Rates for Hispanics and Non-Hispanics.
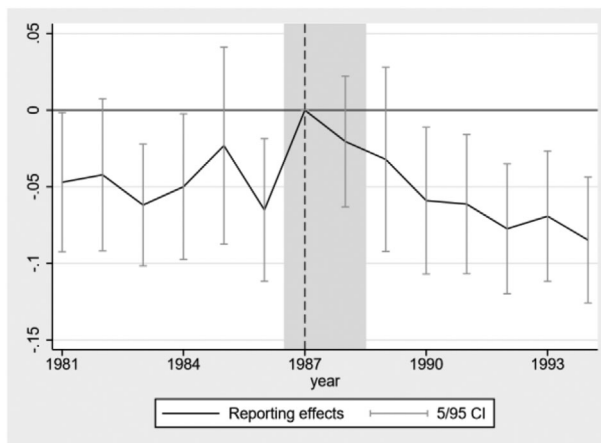
Figure 3. Difference-in-Differences in Reporting Rates Between Hispanics and Non-Hispanics in all MSAs with Base Year 1987.

RESULTS

Reporting Rates

The evolution of the difference-in-differences in reporting rates between Hispanics and non-Hispanics using 1987 as a base year is shown in Figure 3 (the raw series is shown in Figure 2).[18] 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 five 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

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[18] The regression controls for year and MSA fixed effects.
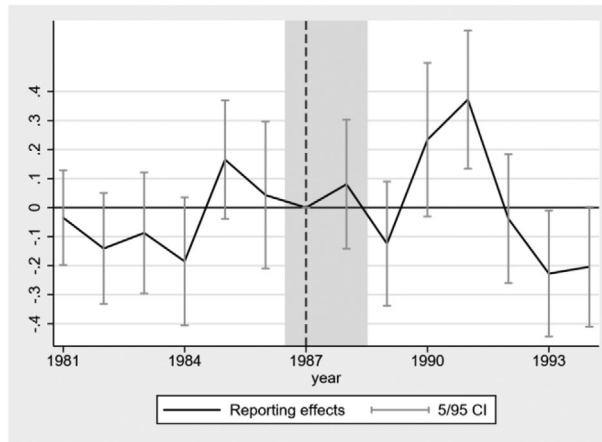
Notes: The sample is made of MSAs where less than 3 percent of Hispanics applied for the IRCA. The base year is 1987.

Figure 4. Placebo Difference-in-Differences in Reporting Rates Between Hispanics and Non-Hispanics.

Table 3. Reporting regressions.

	All MSAs			
	(1)	(2)	(3)	(4)
Amnesty years × Hispanic	0.051***	0.046***	0.036**	0.036**
	(0.018)	(0.017)	(0.014)	(0.014)
Hispanic	−0.055***	−0.038***	−0.048***	−0.047***
	(0.013)	(0.00)	(0.008)	(0.008)
Year fixed effects	✓	✓	✓	✓
MSA fixed effects		✓	✓	✓
Socioeconomic characteristics		✓	✓	✓
Crime-type fixed effects			✓	✓
MSA-specific time trends				✓
Observations	73,248	73,248	73,248	73,248
R-squared	0.002	0.009	0.108	0.109
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) are in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.1$.

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 4 focuses on communities where the fraction of IRCA applicants is less than 3 percent. The estimates are necessarily noisier, 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

Table 4. Placebo regressions: Reporting in MSAs in which less than 3 percent of the Hispanic population were amnesty applicants.

	(1)	(2)	(3)	(4)
	MSAs with less than 3% of Hispanic Applicants.			
Amnesty years × Hispanic	0.050	0.048	0.026	0.021
	(0.048)	(0.054)	(0.046)	(0.045)
Hispanic	−0.041	−0.034	−0.042	−0.038
	(0.026)	(0.021)	(0.025)	(0.024)
Year fixed effects	✓	✓	✓	✓
MSA fixed effects		✓	✓	✓
Socioeconomic characteristics		✓	✓	✓
Crime-type fixed effects			✓	✓✓✓
MSA-specific time trends				✓
Observations	14,213	14,213	14,213	14,213
R-squared	0.004	0.012	0.107	0.109
Mean dep. var	0.395	0.395	0.395	0.395

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

Table 5. Reporting regressions by crime types.

| Crime type	(1) Violent	(2) Economic	(3) Robbery	(4) Burglary	(5) Theft	(6) Assault
Amnesty years × Hispanic	0.027	0.042**	−0.005	0.031	0.043**	0.038
	(0.050)	(0.016)	(0.086)	(0.048)	(0.020)	(0.065)
Hispanic	−0.011	−0.039***	−0.112***	−0.028	−0.044***	0.027
	(0.019)	(0.008)	(0.036)	(0.023)	(0.008)	(0.020)
Observations	12,844	61,352	2,765	10,896	47,691	9,723
R-squared	0.026	0.011	0.076	0.038	0.011	0.026
Mean dep. var	0.521	0.365	0.557	0.523	0.318	0.512

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) are in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.1$.

non-Hispanics alike. Hispanic reporting rates are estimated to go up by 5.1 percentage points in the two years of the amnesty. Adding MSA fixed effects and controlling for socioeconomic characteristics lowers the effect only slightly.

In column 3, we add 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-differences estimate is equal to 3.6 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 individuals in MSAs in which the number of Hispanic amnesty applicants was less than 3 percent of the Hispanic population, 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 have to be inflated by a factor of 5.5, meaning that based on the last column of Table 3, applicants' chance of reporting
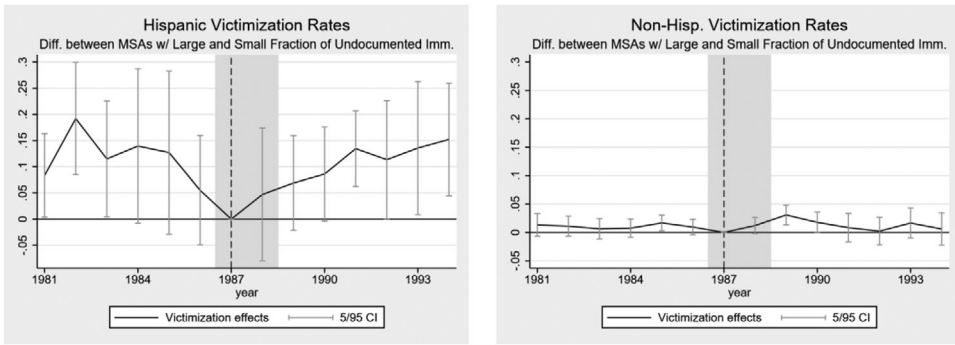
Notes: In top MSAs at least 10 percent of Hispanics applied for the IRCA, in bottom ones less than 3 percent did. The base year is 1987.

Figure 5. Difference-in-Differences in Victimization Rates of Hispanics (left) and Non-Hispanics (right) in Top and Bottom MSAs.

goes up by 0.036 × 5.5, or 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).

$$R_0^H = \gamma R^U + (1 - \gamma)R^D$$
$$R_1^H = (\gamma - \delta)R^U + (1 - (\gamma - \delta))R^D$$

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 MSAs with almost no Hispanics as a benchmark for R^D, we get that $R^U = 0.36 - 0.20 = 0.16$.

Could these results be compounded by changes in police behavior? Reporting depends on victims' cost/benefit calculations. For the observed changes in reporting to be driven by police behavior, the victims would have to quickly realize that an increased police effort is aimed at helping Hispanic victims. While police officers may devote more effort to protecting legal citizens, it would probably be hard for victims to observe such changes.

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.

Victimization Rates

The left panel of Figure 5 shows the difference in Hispanic victimization rates between the top and the bottom MSAs in terms of δs. The effect is large, but Appendix Figure A5 shows that this result is driven by an increase in victimization in the control MSAs, those with few Hispanic applicants, around the years of the

Table 6. Victimization regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
	Has been victimized (0/1)					
Amnesty years ×	−0.095[*]	−0.096[*]	−0.096[*]	−0.006	−0.005	−0.005
Large fraction of Hisp. applicants	(0.055)	(0.054)	(0.053)	(0.007)	(0.007)	(0.007)
MSA fixed effects	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓
Socioeconomic characteristics		✓	✓		✓	✓
MSA specific time trends			✓			✓
Observations	42,406	42,406	42,406	309,974	309,974	309,974
R-squared	0.005	0.009	0.011	0.008	0.023	0.024
Mean dep. var	0.134	0.134	0.134	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) are in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.1$.

amnesty. 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. Later we are going to see that the results are driven by the bottom 10 MSAs in terms of share of applicants among the Hispanic population, and that the effects are increasing as we reduce the number of control MSAs.

An additional issue is that the decrease in victimization appears to start in 1986, one year ahead of the amnesty. This would be consistent with some anticipation effect, as criminals may fear a delayed reporting once it is known that an immigration amnesty is going to take place.

There are no apparent changes in victimization for non-Hispanics. The absence of crime displacement against non-Hispanics is in line with the model's predictions with intermediate probability of targeting the wrong ethnic group (see the Appendix).[19]

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 the 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 the victimization rates drop by about 9.5 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 A6 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 is a total of 40 MSAs and we

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[19] In our theoretical model, crime is assumed to be linked to the likelihood of reporting. In order to make this relationship explicit, we would have to regress victimization on reporting, instrumenting the likelihood of reporting to get rid of the endogeneity. In order to do this, we would face three major issues: i) we would have to define the likelihood of reporting; ii) we would have to assume that the amnesty only has an impact through reporting; and iii) we would have to deal with the fact that the reporting regression model and the victimization regression model use different treatment and control groups: Hispanics vs. non-Hispanics and MSAs with a small vs. large fraction of Hispanic applicants.

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	
Amnesty years × Large fraction of Hisp. applicants (IRCA)	−0.102[*]	−0.102[*]	−0.095[*]	−0.096[*]	−0.080	−0.080	−0.083	−0.084	−0.030	−0.031
	(0.053)	(0.050)	(0.055)	(0.053)	(0.056)	(0.053)	(0.055)	(0.053)	(0.020)	(0.020)
Observations	37,351	37,351	42,406	42,406	25,738	25,738	41,634	41,634	37,655	37,655
R-squared	0.006	0.011	0.005	0.011	0.008	0.016	0.005	0.010	0.002	0.007
Mean dep. var	0.136	0.136	0.134	0.134	0.134	0.134	0.117	0.117	0.0242	0.0242

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

always use the bottom nine 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 of 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 MSAs 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.

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 vs. almost 40 percent). The 1986 U.S. 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 endogenous. We develop an empirical model that uses Hispanic origin around amnesties as a proxy (with known probabilities of mis-classification) for changes in legal status. The strategy could be used to analyze other outcomes—for example, employment (Barcellos, 2010).

We show that right after the amnesty, Hispanic immigrants became 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.

Undocumented immigrants who are currently living in the U.S. and in other Western countries are at least as likely as undocumented immigrants living in the U.S. around the 1986 IRCA to be deported. This implies that an estimated 11 million undocumented immigrants are vulnerable when trying to safeguard their fundamental right to protect their property and their human right to security.

Given that about 15 percent of them are victimized, a 20 percentage point gap in reporting implies that because of their legal status immigrants have been unwilling to report 330,000 crimes to the police. Moreover, by increasing the risk of deportation and its salience, the current U.S. federal policy has probably pushed undocumented immigrants to further underreport crime incidents. Several newspapers have covered stories of immigrant victims who stay away from the police, even in Sanctuary Cities (see, among others, Campbell, Mendoza, Diestel, 2018; Queally, 2017; Robbins, 2018).

The most recent announcements of immigration crackdowns by U.S. immigration officials may also influence reporting rates, but not necessarily in the expected direction. In our model, victims report crimes when the benefits are larger than the cost of reporting and the expected cost of deportation. If the risk of deportation

increases across the board, even without reporting, undocumented immigrants may actually become more likely to report a crime, as the relative cost of doing so is decreasing.

In line with the predictions of this model of crime, there is also some evidence that undocumented immigrants may be preferred victims of crime, though this evidence is certainly weaker and requires additional research. In recent years, U.S. lawmakers have partially addressed the issue. In order to favor the reporting of undocumented immigrants, in 2008 the U.S. Congress approved a special Visa program (U nonimmigrant status). According to this program, every year victims of serious offences who are willing to work with local law 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, lasting up to four 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, as in the U.S., 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 immigrant population is large.

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APPENDIX

The Model

We consider a city composed of two ethnic groups—natives and immigrants—each with mass 1.[20] Immigrants are either legal citizens (mass $1 - \gamma$) or undocumented (mass $0 < \gamma < 1$). Individuals differ in terms of their wealth:

Table A1. Summary statistics.

	Victims				All			
Sample:	Large fraction of Hispanic applicants		Small fraction of Hispanic applicants		Large fraction of Hispanic applicants		Small fraction of Hispanic applicants	
MSAs with:	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Reported the crime	0.38	0.49	0.39	0.49				
Crime victim	1.00	0.00	1.00	0.00	0.15	0.36	0.13	0.34
Hispanic	0.15	0.35	0.09	0.29	0.17	0.37	0.09	0.29
White	0.85	0.36	0.84	0.36	0.85	0.35	0.85	0.36
Female	0.51	0.50	0.52	0.50	0.51	0.50	0.53	0.50
Age 25–29	0.26	0.44	0.26	0.44	0.25	0.43	0.24	0.43
Age 30–34	0.23	0.42	0.22	0.42	0.25	0.43	0.24	0.43
Age 35–39	0.19	0.39	0.19	0.39	0.21	0.41	0.22	0.42
Income $7,500-$14,999	0.17	0.37	0.16	0.36	0.14	0.34	0.13	0.33
Income $15,000-$24,999	0.20	0.40	0.19	0.40	0.19	0.39	0.19	0.39
Income $25,000-$29,999	0.08	0.27	0.09	0.28	0.09	0.28	0.09	0.28
Income $30,000-$49,999	0.19	0.39	0.19	0.39	0.22	0.41	0.22	0.41
Income $50,000 and over	0.12	0.32	0.11	0.32	0.15	0.35	0.13	0.34
Income missing	0.12	0.33	0.12	0.32	0.13	0.34	0.14	0.35
Observations	37,254		35,994		246,972		271,624	

Notes: Based on NCVS data matched with the 1980 Census. Large and small are defined based on whether in an MSA more or less than 10 percent of the Hispanic population were amnesty applicants.

[20] 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.
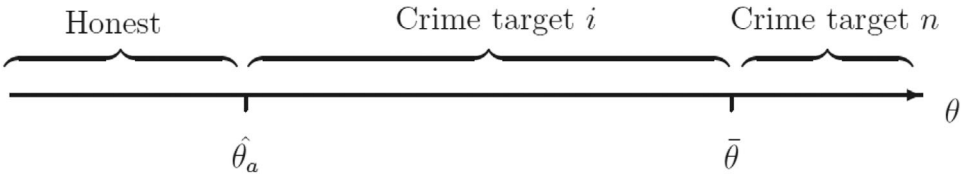
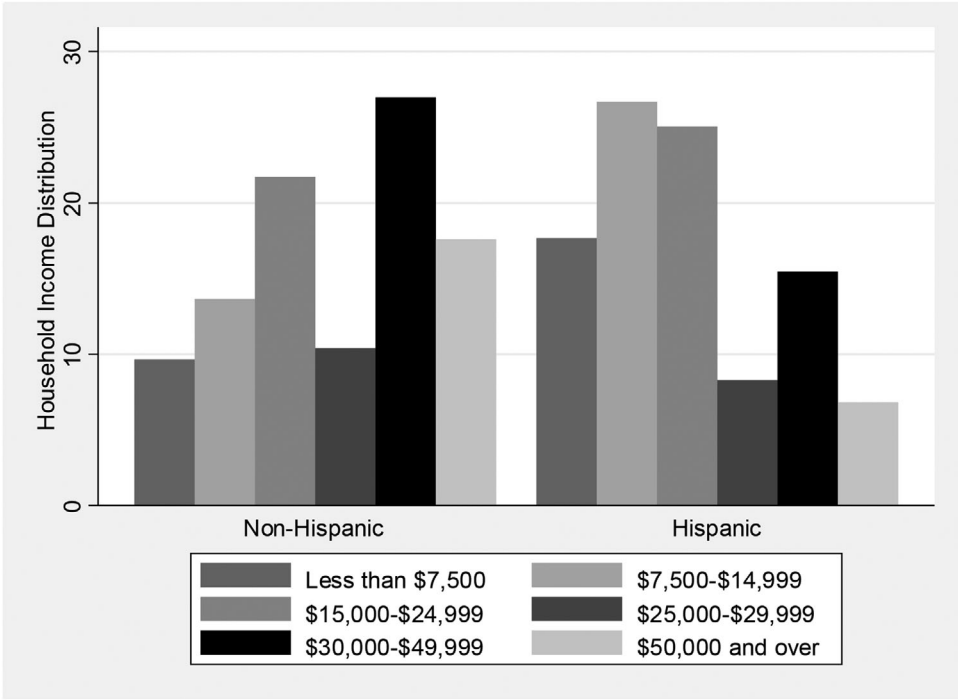**Figure A1.** Optimal Choice of Undocumented Immigrants.

Figure A2. Distribution of Household Income by Hispanic Origin (in percentage).

all immigrants are poor, while natives can be rich (mass $1 - \varphi$) or poor (mass φ).[21]

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 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, undocumented (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 the probability that a victim of a crime receives a monetary compensation—for instance,

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[21] This assumption is in line with what we observe in our dataset. Income differences between Hispanics and Non-Hispanics are shown to be large in the National Crime and Victimization Survey (see Appendix Figure A2). Household incomes are only available in broad intervals, but relative income differences between the two groups are at least equal to 1/4.
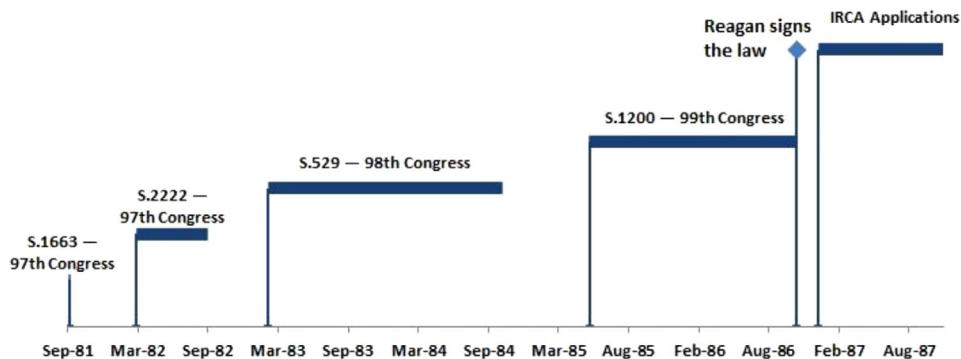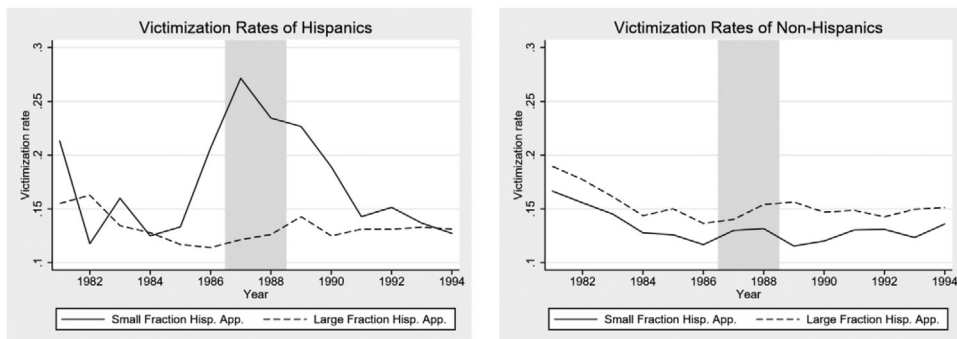
**Figure A3.** Time and Duration of Immigration Amnesty Proposals.
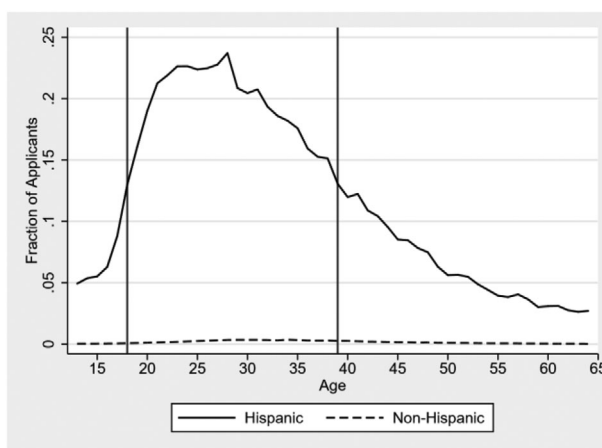
Notes: The fraction of IRCA applicants by age and Hispanic origin is based on authors' calculation matching the Legalization Summary Public Use Tape with the Census.

Figure A4. Fraction of IRCA Applicants by Hispanic Origin and Age.

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

Figure A5. Victimization Rates for Hispanics and Non-Hispanics by MSA type.
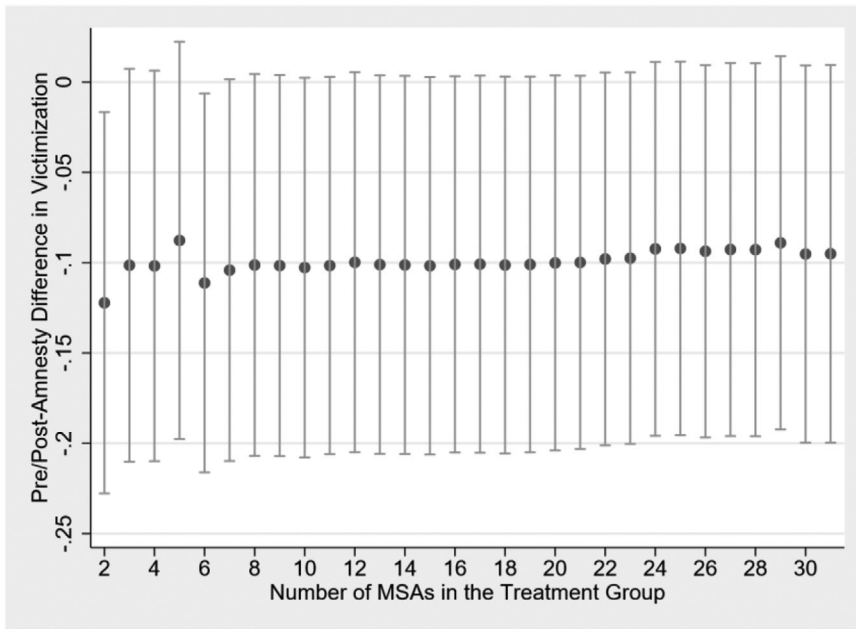
Notes: Each dot corresponds to a separate difference-in-differences in victimization rates among Hispanics. Vertical caps represent the corresponding 95 percent confidence intervals. There are a total of 40 MSAs. The control cities are always the bottom 9 based on δ. MSAs are added to the treatment group starting from top.

Figure A6. Difference-in-Differences in Victimization When Changing the Treated MSAs.

by means of the (partial) return of the stolen goods or an insurance compensation—is increasing in the reporting rate: A higher reporting rate increases the capacity 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:

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

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.[22]

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.

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[22] 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 & Rocko, 2008; Thaler, 1978), population, as well as economic activity (see Cullen & Levitt, 1999), when crime levels are high.
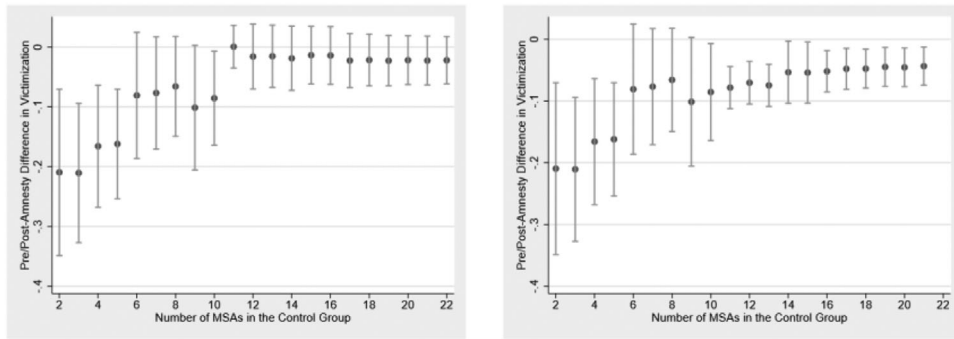
Notes: Each dot corresponds to a separate difference-in-differences in victimization rates among Hispanics. Vertical caps represent the corresponding 95 percent confidence intervals. There are a total of 40 MSAs. The treated cities are always the top 18 based on δ. MSAs are added to the control group starting from the bottom based on δ. The right panel excludes the 11th control MSA, NYC, a clear outlier.

Figure A7. Difference-in-Differences in Victimization Rates When Changing the Control MSAs.

By targeting immigrants, criminals know that, compared to natives, the average wealth is lower, and, with probability γ, the victim is undocumented.[23]

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 the victim's physical appearance, as well as on the level of segregation of ethnic groups. Taking the case of the U.S., not all Hispanic-looking individuals are necessarily of Hispanic origin, and vice versa, although 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 fact that the crime can end up being committed against an individual who does not belong to the target ethnicity.

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[23] The U.S. is a clear example of where ethnicity, particularly being of Hispanic origin, carries some signal for the migration status.

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:

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

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.

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 a criminal. We focus on the most interesting case in which the marginal criminal is indifferent between being honest and committing crimes targeting primarily immigrants.[24] Moreover, we assume that r (the wealth of the rich) 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:

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

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[24] This is an interesting case since each group of 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 $\hat{\theta}_a(X) < \bar{\theta}$.

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 that target group i is preferred to being honest when:

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

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 $(1 - \gamma + \varphi)(1 - \hat{\theta}_p(X))$. Therefore, $X = \gamma(1 - \hat{\theta}_a(X)) + (1 - \gamma + \varphi)(1 - \hat{\theta}_p(X))$ and the equilibrium is determined by the triple $\{\bar{\theta}, \hat{\theta}_p, \hat{\theta_a}\}$ satisfying:[25]

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

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

$$\hat{\theta}_p = \frac{f\left(p, \rho_{p,l}\right) - \beta\left[\gamma\left(1 - \hat{\theta}_a\right) + (1 - \gamma + \varphi)\left(1 - \hat{\theta}_p\right)\right] + C(\rho|i)}{E(w|i)}$$

$$\hat{\theta}_a \frac{f\left(p, \rho_{p,a}\right) - \beta\left[\gamma\left(1 - \hat{\theta}_a\right) + (1 - \gamma + \varphi)\left(1 - \hat{\theta}_p\right)\right] + C(\rho|i)}{E(w|i)}.$$

Figure A1 provides a graphical representation of the optimal choices of undocumented immigrants depending on θ: Individuals with low criminal ability $(\theta < \hat{\theta}_a)$ 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 $\hat{\theta}_a$.

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 to protect their property rights, and therefore their utility when honesty 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.

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[25] We implicitly assume $0 < \hat{\theta_a} < \hat{\theta_p} < \bar{\theta} < 1$.

Proposition A1

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).

Proof of Proposition A1

Let $\bar{\rho}_i(\delta)$ and $\bar{\rho}_n(\delta)$ 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:

$$\bar{\rho}_i(\delta) = (1 - \gamma + \delta)\rho_{p,l} + (\gamma - \delta)\rho_{p,a},$$
$$\bar{\rho}_n = \varphi\rho_{p,l} + (1 - \varphi)\rho_{r,l}$$

Notice that the average reporting rate of immigrants depends on δ, the mass of legalized individuals. Specifically, since $\rho_{p,l} > \rho_{p,a}$, $\bar{\rho}_i(\delta)$ 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:

$$C(\rho|i, \delta) = C\left(\xi\bar{\rho}_i(\delta) + (1 - \xi)\bar{\rho}_n\right),$$
$$C(\rho|n, \delta) = C\left(\xi\bar{\rho}_n + (1 - \xi)\bar{\rho}_i(\delta)\right),$$

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:

$$E[w|i] = \xi p + (1 - \xi)(\varphi p + (1 - \varphi)r),$$
$$E[w|n] = \xi(\varphi p + (1 - \varphi)r) + (1 - \xi)p,$$

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

Before demonstrating the statement of Proposition A1, we determine the equilibrium of the model. Following the discussion in the text, the equilibrium is defined by the triple:[26]

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:

$$\hat{\theta}_P(\delta) = \frac{f(p, \rho_{p,l}) - \beta[(\gamma - \delta)(1 - \hat{\theta}_a(\delta)) + (1 - \gamma + \delta + \varphi)(1 - \hat{\theta}_p(\delta))] + C(\rho|i, \delta)}{E(w|i)},$$

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

---

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

Simple algebra leads to the following expressions:

$$\hat{\theta}_p(\delta) = \frac{E(w|i)(\beta(1+\varphi) - f(p, \rho_{p,l}) - C(\rho|i, \delta)) + \beta(\gamma - \delta)(f(p, \rho_{p,l}) - f(p, \rho_{p,a}))}{E(w|i)(\beta(1+\varphi) - E(w|i))},$$

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

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 A1 below. For the sake of simplicity, we let $\hat{\theta}_p(\delta = 0)$, $\hat{\theta}_a(\delta = 0)$, and $\bar{\theta}(\delta = 0)$ denote the thresholds before the amnesty is in place (when $\delta = 0$). Similarly, we let $C^0(\rho|i)$ and $C^0(\rho|n)$ be the expected costs of punishment before the amnesty. Finally, notice that neither $E[w|i]$ nor $E[w|n]$ change because of amnesty.

Claim A1

An amnesty that 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 A1

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

$$\hat{\theta}_p(\delta = 0) - \hat{\theta}_p(\delta > 0)$$

$$= \frac{E(w|i)[C(\rho|i, \delta)0) - C(\rho|i, \delta = 0)] + \beta\delta(f(p, \rho_{p,l}) - f(p, \rho_{p,a}))}{E(w|i)(\beta(1+\varphi) - E(w|i))}. \quad \text{(A.1)}$$

This expression is positive since $C(\rho \mid i, \delta > 0) > C(\rho \mid i, \delta = 0)$, $f(p, \rho_{p,l}) > f(p, \rho_{p,a})$, 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 the above expression is larger the greater δ. Similar arguments apply for the other two thresholds, $\hat{\theta}_a(\delta)$ and $\bar{\theta}(\delta)$.

Claim A1 and condition $\hat{\theta}_a(\delta) < \hat{\theta}_p(\delta)$ ensure that the level of criminality—i.e., $(\gamma - \delta)(1 - \hat{\theta}_a(\delta)) + (1 - \gamma + \varphi)(1 - \hat{\theta}_p(\delta))$—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 who are primarily targeting immigrants and natives are

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

$$N(\delta) = (\gamma - \delta)(1-) + (1 - \gamma + \delta + \varphi)(1-) = (1 + \varphi)(1-)),$$

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

$$X^i(\delta) = (1 + \varphi)\bar{\theta}(\delta)(2\xi - 1) + (1 - \xi)(1 + \varphi) - \xi((\gamma - \delta)\hat{\theta}_a(\delta) + (1 - \gamma + \delta + \varphi)\hat{\theta}_p(\delta)),$$

$$X^n(\delta) = (1 + \varphi)\bar{\theta}(\delta)(1 - 2\xi) + \xi(1 + \varphi) - (1 - \xi)((\gamma - \delta)\hat{\theta}_a(\delta) + (1 - \gamma + \delta + \phi)\hat{\theta}_p(\delta)).$$

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 lessens 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 $-(1 + \varphi)\bar{\theta} + (1 + \varphi)$, which increases with δ (since $\bar{\theta}(\delta)$ decreases with δ). By contrast, for $\xi = 1/2$, $X^n(\delta)$ becomes

$$\frac{1}{2}(1 + \varphi) - \frac{1}{2}((\gamma - \delta)\hat{\theta}_a(\delta) + (1 - \gamma + \delta + \varphi)\hat{\theta}_p(\delta)),$$

which reduces with δ since: $\hat{\theta}_a(\delta)$ and $\hat{\theta}_p(\delta)$ increase with δ, and $\hat{\theta}_p(\delta) < \hat{\theta}_p(\delta)$. 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).