Preliminary Draft

Interior Immigration Enforcement and Childhood Poverty in the United States

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Abstract

Immigration enforcement has grown exponentially over the past two decades in the United States. In this paper, we use data from the American Community Survey to examine the negative impact that intensified immigration enforcement has had on the poverty exposure of households with U.S. citizen children and, at least, one likely unauthorized parent. We also show that the effect is driven, primarily, by police-based immigration enforcement measures adopted at the local level, such as 287(g) agreements between the local police and Immigration Customs Enforcement and participation in the Secure Communities program. The policy-making and societal implications of these findings are evident, especially at a time when President Obama's executive order to provide a reprieve from deportation and work permits to parents of these children has been placed on hold.

"Are we a nation that kicks out a striving, hopeful immigrant {…} or are we a nation that finds a way to welcome her in?"

President Barack Obama, November 2014

1. Introduction

In 2009, twenty-three percent of children under the age of 18 in the United States resided in an immigrant household, and 5.1 million of the 17.1 million children of immigrants had at least one unauthorized immigrant parent (Passel and Cohn 2011). Although nearly three-fourths of the children living with undocumented parents are citizens by birth, they often face significant social and economic disadvantages due to a parent's unauthorized status (Passel and Taylor 2010; Debry 2012). Many of these children reside in households that experience significant income shortfalls when their parents are apprehended, deported or unable to re-enter the United States –an increasingly common event with deportations reaching 1.8 million (Vaughan 2013). And, even when their parents are not detained, these children often endure worse living conditions as their families find it necessary to relocate or to start living in the shadows in order to evade apprehension (Chaudry *et al*. 2010; Lopez 2011). About 33 percent of children of unauthorized immigrants and approximately 20 percent of adult unauthorized immigrants live in poverty (Passel and Cohn 2009). The corresponding rates for children with U.S.-born parents and U.S.-born adults are 18 percent and 10 percent, respectively (Passel and Cohn 2009). Furthermore, undocumented immigrants and their U.S.-born children account for 11 percent of the people living in poverty –about twice their population share. Has intensified immigration enforcement made it worse for these American children? And, if so, of the plethora of policies set in place, which ones appear to have had a harsher impact on children?

In this paper, we aim to answer these questions by examining how intensified interior immigration enforcement is impacting the likelihood that households of U.S. citizen children with, at least, one likely unauthorized parent live in poverty. Intensified enforcement can increase the likelihood of life in poverty by negatively impacting the household heads' employment and earnings' capabilities. In some instances, this occurs through measures specifically aimed at restricting the employment opportunities of unauthorized immigrants, as in the case of employment verification (E-Verify) mandates. Other times, intensified enforcement in the form of 287g agreements between the local or state police with Immigration Customs Enforcement (ICE), participation in the Secure Communities program or the adoption of an omnibus immigration law by the state, can increase fear of apprehension and induce parents to live in the shadows to avoid apprehension and deportation. Such a decision can severely restrict their employment opportunities (Amuedo-Dorantes *et al*. 2013).[1]

To assess the role of intensified interior immigration enforcement on the likelihood of life in poverty for the children with a likely unauthorized parent, we combine data from the American Community Survey (ACS) and a population weighted index of the intensity of immigration enforcement for the 2005 through 2011 period. Because the ACS lacks information on the unauthorized immigration status of its respondents, we proxy for the latter using information on their Hispanic ethnicity and lack of citizenship. We then exploit the geographical and temporal variation in the intensification of interior immigration enforcement to identify the impact of tougher immigration enforcement on poverty, as opposed to that of other macro-economic factors that may have contributed to the generalized poverty increase during the decade 2000-2009 (Peri 2013). We find that a one standard

[1] Watson (2014) find support for this hypothesis, documenting how heightened federal immigration enforcement scared noncitizens to the point of leading to "chilling effects" in Medicaid participation, even when their children are themselves U.S. citizens.

deviation increase in interior immigration enforcement (roughly twice the average yearly increase in this type of enforcement during the time period under examination) raised the likelihood of living below the poverty line of families of U.S. citizen children with at least one likely unauthorized parent by as much as 18 percent. Our findings, which prove robust to a number of identification tests and robustness checks, suggest that the intensification of interior immigration enforcement is significantly curtailing the economic resources available to young generations of U.S. citizen children.

Our study contributes to a growing body of work examining the impact of tougher immigration policies on unauthorized immigrants and their families through changes in their residential choices, labor market outcomes and Medicaid participation (*e.g.* Amuedo-Dorantes *et al*. 2013, Kostandini *et al*. 2013, Watson 2013, Bohn *et al*. 2014, Watson 2014). Additionally, our findings add to the literature on the determinants of childhood exposure to poverty. Recent work by Bailey *et al*. (2014), Bitler *et al*. (2014) and Peri (2013) shows that child poverty drops with increased availability of family planning programs and higher unemployment rates, but it is independent of immigration. Our analysis contributes to this literature by assessing the role of, yet, another set of policies –namely intensified immigration enforcement. Given the importance of economic resources on children's health, education, and development outcomes later in life,[2] understanding how the piece-meal approach to immigration enforcement is impacting households' poverty exposure is crucial for a well-informed debate of comprehensive immigration reform and for the design of policies that safeguard children's well-being.

2. Institutional Framework and Motivation

More than 4.5 million undocumented immigrants have been removed since the U.S. Congress passed the Illegal Immigration Reform and Immigrant Responsibility Act of 1996

[2] See, for example, Case *et al*. 2002, Almond and Currie 2011, Bailey and Dynarski 2011 or Levine and Zimmerman 2010, among others.

(IIRIRA) (Bergeron and Hipsman 2014). Broadly, current interior enforcement initiatives under the act can be grouped into police-based measures, which involve either the local or state police (*i.e.* 287g agreements, Secure Communities and omnibus immigration laws), and employment-based measures, which require action on the part of employers (*i.e.*, employment verification mandates).[3] We refer to both of these categories in what follows.

A) Police-based Immigration Enforcement Measures

Among the police-based measures, 287(g) agreements between local/state police and Immigration Customs Enforcement (ICE) are the ones implemented earlier on, starting in 2002 with the state of Florida. The agreements provided authority to state and local officers to interrogate any immigrant, arrest without warrant, and begin the removal process (under a "task force" agreement). They also allowed local officers to question immigrants who had been arrested on state and local charges about their immigration status (under a "jail enforcement" agreement).

The Secure Communities program (2008-2014) was designed to prioritise immigration enforcement among non-citizens who had committed serious crimes. As such, it was effectively used as a substitute for 287(g) jail enforcement measures from 2012 onwards. By the end of 2013, all the nation's 3,181 jurisdictions were participating in Secure Communities (U.S. Immigration and Customs Enforcement 2013). The fingerprints of detainees were checked against the databases from the Federal Bureau of Investigation (FBI) and from the Department of Homeland Security (DHS) in order to get information on past criminal arrests, convictions, and immigration history. The Secure Communities program was replaced by the Priority Enforcement Program (PEP) in 2015. The PEP continues to rely on fingerprint-based biometric data submitted by state and local law enforcement agencies,

[3] See Appendix A2 for a detailed description of each of these measures.

and is mostly targeted to unauthorized immigrants convicted of specifically numbered crimes.[4]

In contrast to the 287(g) agreements and the Secure Community program, omnibus immigration laws (2010-present) were signed at the state level.[5] While the content of each omnibus immigration law differs, they typically include a "show me your papers' clause", which enables the police to request proper identification documentation during a lawful stop. In some cases, omnibus immigration laws required that schools verify students' legal status.[6] The first omnibus immigration law –the "Support Our Law Enforcement and Safe Neighbourhoods Act" (SB1070)– was signed by Arizona's governor in April 2010. Deemed to be one of the tougher immigration laws on its day, SB1070 considers a crime not registering with the U.S. authorities if an immigrant has been living in the United States for more than 30 days, or if they do not have their documents with them all the times. It also requires state and local enforcement officers to check an individual's immigration status during a "lawful stop, detention or arrest" if there is suspicion that the person is an undocumented immigrant. Within the same month of its enactment, HB2162 was passed, amending SB1070 to avoid racial and ethnic profiling. One day before these laws were to become effective, the U.S. Department of Justice argued that SB1070 was unconstitutional and filed a lawsuit asking for an injunction against it. The law's most questionable provisions were blocked.[7]

B) Employment-based Immigration Enforcement Measures

Employment-based immigration enforcement is exemplified by employment verification mandates (E-Verify). E-verify is an electronic program that allows employers to

[4] http://www.dhs.gov/sites/default/files/publications/14_1120_memo_secure_communities.pdf
[5] Arizona was the first state to sign an omnibus immigration law in 2010.
[6] See Alabama's HB56, National Conference of State Legislatures 2012, http://www.ncsl.org/research/immigration/omnibus-immigration-legislation.aspx#Fifty-Three_Omnibus_Bills
[7] See: http://www.ncsl.org/research/immigration/analysis-of-arizonas-immigration-law.aspx

screen newly hired workers for work eligibility. It is administered by the U.S. Department of Homeland Security in partnership with the Social Security Administration. With E-Verify, the employer introduces the biographic information (name, social security number, date of birth, citizenship and alien registration number) of the prospective employee into an online program. The software program then cross-checks the prospective employee's records between those in the Social Security Administration (SSA) database and the records from the Department of Homeland Security (DHS) to determine whether the worker is authorised to work in United States. In the case that work eligibility is not confirmed, the employer receives a "tentative no confirmation" that the worker has to resolve within eight business days.

While the use of E-Verify is obligatory in the hiring of federal employees, it has been optional at other levels. Some states have mandated its use, either by public agencies and contractors working for public agencies or, in more extreme cases, by all employers in the state. The first E-Verify mandate was implemented in 2006 in the state of Colorado. By 2014, the number of employers enrolled in E-Verify had risen to 482,692.[8]

The E-verify program is far from perfect when detecting identity fraud, and it still renders a large number of false positives and negatives despite recent improvements. While false positives are often related to document fraud, false negatives occur when the system fails to confirm the eligibility to work in the United States of someone authorized to do so, either due to errors in the way the employer entered the information, or to out-dated, missing and/or erroneous information in the federal database (see Meissner *et al*. 2013).

C) Poverty and the Intensification of Immigration Enforcement

One of the channels by which employment measures, like E-Verify, can result in higher poverty levels among American children with unauthorized parents is by restricting

[8] Please, visit: http://www.uscis.gov/e-verify/about-program/history-and-milestones

their parents' employment opportunities. This can occur if, for example, unauthorized migrants can no longer be hired by a promising employer who uses E-Verify and, as a result, they opt for a lower pay job. In this vein, Amuedo-Dorantes and Bansak (2012) find that E-Verify mandates reduced the employment of likely unauthorized immigrants, leading many of them to take jobs in industries benefiting from E-Verify exclusions, such as agriculture or food services. Likewise, Bohn and Lofstrom (2013) and Bohn *et al*. (2014), document that the 2007 Legal Arizona Workers Acts (LAWA) –which mandated, for the first time, all Arizona employers to use E-Verify– reduced the employment of likely unauthorized immigrants and raised self-employment among non-college Hispanic men.

While the adverse employment effects stemming from employment-based measures are well-documented, the impact on wages is not. Still, a number of studies have pointed out their overall negative impact on immigrant wages. For example, Amuedo-Dorantes and Bansak (2012) find that the wages of likely unauthorized immigrants drop after the implementation of E-verify mandates, if not immediately after their enactment. Orrenius and Zavodny (2014) find evidence that E-Verify mandates reduce average hourly earnings among likely unauthorized male Mexican immigrants, resulting in higher earnings among competing low-skilled white men –a result underscored by Bohn and Lofstrom (2014) when analyzing the impact of LAWA.

In addition to the employment restrictions emanating from E-Verify, work constraints can also emerge when there is an enhanced fear of being stopped by the police, apprehended and deported, as has been the case with the implementation of police-based enforcement measures. By 2011, the number of fingerprints submitted through the 287(g) program had risen to 6.9 million from 828,119 in 2009 (Meissner *et al*. 2013). And, along with other police-based enforcement measures, the program had led to the identification of more than 373,800 potentially removable aliens between January 2006 and September 2014 (U.S.

Immigration and Customs Enforcement). Hence, it is not difficult to foresee how intensified enforcement might have steered some families to live in the shadows to minimize their exposure to the police. This decision might have, in turn, led them to accept worse jobs and living conditions.

Yet, unlike E-Verify, which is typically announced by a door sticker letting prospective employees know about the use of E-Verify in that establishment, migrants never know when the police might stop them and request proper identification. Furthermore, E-Verify is not directly linked to deportation, whereas police-based measures are. Therefore, the risk of deportation is constantly there and, as a result, is more likely to curtail undocumented migrants' behaviour and earnings to a greater extent. In that regard, Watson (2014) documents how unauthorized immigrant parents avoid applying for public assistance following the adoption of 287(g) agreements, despite their children's eligibility for such services. Similarly, Amuedo-Dorantes *et al*. (2013) use a unique survey of Mexican unauthorized immigrants interviewed upon their voluntary return or deportation to Mexico and document that almost a third reported experiencing difficulties in obtaining social or government services, finding legal assistance, or obtaining health care services. Fear of apprehension and deportation seems to have severely impacted the behaviour of undocumented immigrants. Supporting that claim, Kostandini *et al*. (2013) document a decline in labour expenses (owing to reduced hiring) in the farming sector (a sector that uses immigrant labour intensively) in U.S. counties where 287(g) agreements were signed.

In conclusion, both employment-based and police-based measures are deemed to have a negative impact on households' earnings capabilities. Nevertheless, the ultimate impact of intensified enforcement on poverty remains an empirical question that depends on household income dynamics. For example, is it the case that any lost income is made up by increases in other sources of household income, as when other household members increase their labor supply to offset any loss in household income? After all, prior studies have documented how immigrant women's employment increases in states that adopt E-Verify mandates –an effect believed to be the consequence of lower earnings among men inducing some women to enter the labor market (Orrenius and Zavodny 2014).

3. Data

Our main aim is to explore the impact that intensified interior immigration enforcement is having on the likelihood that American children with likely unauthorized parents live in poverty. To that end, we use household-level data from the U.S. Census Bureau's American Community Survey (ACS), along with local and state-level data on the implementation of the following immigration enforcement measures: E-Verify mandates, 287(g) agreements, omnibus immigration laws and the Securities Communities program.

3.1 The American Community Survey

The ACS data is a monthly national survey conducted by the U.S Census Bureau produced by the Integrated Public Use Microdata Series (Ruggles *et al*. 2010). Every year approximately 3.5 million randomly sampled households take part, of which around 24,000 are U.S. children with at least one unauthorized parent.

The ACS dataset is especially well-suited for the purpose of this paper. First, it contains detailed information on the outcome of interest to this study –namely household income and poverty exposure. Our main dependent variable, whether the child lives in poverty, takes the value of 1 if income in the household falls below the poverty line, and 0 otherwise (*e.g.* Bailey *et al*. 2014). This variable is created directly by ACS using detailed income and family structure information about each individual, and calculating the family income as a percentage of the appropriate official poverty threshold. The poverty threshold was established by the Social Security Administration in 1964 and subsequently revised in 1980. All persons related to the household head receive the same poverty value, while an unrelated person and her child would share their own value distinct from that of the primary family.[9] In 2010, the poverty threshold for a family of four (two adults plus two children) was $22,113.

There are a couple of important drawbacks to the official poverty measure (Bitler, Hoynes, and Kuka 2014). First, the threshold does not vary geographically, although the thresholds are updated for inflation using the Consumer Price Index (CPI). Second, the threshold only refers to money income before taxes. It does not include capital gains or noncash benefits, such as public housing, Medicaid, and food stamps. This last limitation should prove less relevant in the case of children with likely unauthorized parents, as many of them might not apply for them owing to their undocumented status. We consider alternative poverty measures, including a family's income 1.5 or 2 times above the poverty line. Because poverty is not only a function of earnings, but of household size and composition, we also experiment with directly assessing the impact of immigration enforcement on the logarithm of real household income.

Second, the ACS contains rich socio-demographic information that can play a decisive role in understanding children's poverty exposure, such as the number of years parents have lived in the United States. Third, the ACS consistently identifies very fine geographic units over time, allowing us to exploit the geographical and time variation of immigration policies. The area of analysis in the ACS is the Consistent Public Use Microdata Area (CONSPUMA), which contains several towns, cities and counties. In total, there are 543 geographic local areas (CONSPUMAs) covering the entire United States.

We limit our sample to families with at least one U.S.-citizen child ranging between 0 and 18 years of age living in the household during the 2005-2011 waves of the ACS for

[9] Throughout this paper we use family and household interchangeable. Technically speaking, ACS considers a "family" as a group of persons related by blood, adoption, or marriage. A household can be made up of one or more families living in the same house. An unrelated individual is considered a separate family. Thus, a household consisting of a widow and her servant contains two families; a household consisting of a large, multiple-generation extended family with no boarders, lodgers, or servants counts as a single family.

which the CONSPUMAs are identified (after 2012 the ACS stopped identifying the CONSPUMAs). We additionally restrict the sample to families where there is one or more unauthorized parent. Because the ACS, like all official representative datasets, does not contain information on the migrant's legal status, we rely on Hispanic ethnicity and lack of citizenship, shown to be good predictors of immigrants' unauthorized status (Passel and Cohn 2009, 2010), to proxy for the parents' likely unauthorized status.[10]

3.2 Enforcement Data

We gather data on the implementation of the following interior immigration enforcement initiatives: local and state-level 287(g) agreements with ICE, local participation in Secure Communities, state-level E-Verify mandates and omnibus immigration laws. Specifically, data on the 287(g) agreements signed at either the local or state level is gathered from ICE's 287(g) Fact Sheet website (U.S. Immigration and Customs Enforcement 2015) and from Amuedo-Dorantes and Puttitanun (2014), and Kostandini *et al*. (2013). Data on participation in Secure Communities program is gathered from the 2013 ICE's Activated Jurisdictions document, which contains detailed information on the rollout of the Secure Communities program across counties in the United States between 2008 and 2013 (U.S. Immigration and Customs Enforcement 2013). Information on the implementation dates of E-Verify mandates and omnibus immigration laws is gathered from the National Conference of State Legislatutres' website (Legislatures 2012).

Following Watson (2013) and Amuedo-Dorantes and Lopez (2015), we use an enforcement index for each CONSPUMA c in each year t ($Enforcement\ Index_{c,t}$), equal to the sum of five enforcement indices corresponding to each enforcement policy for each CONSPUMA and year as:

[10] In our robustness checks, we also experiment with alternative definitions of our sample to more accurately capture the population who is unauthorized.

(1) $E\_Index^{K}{}_{ct} = \frac{1}{N_{2000}} \sum_{\boldsymbol{a} \in \boldsymbol{A}}^{\boldsymbol{A}} \frac{1}{12} \sum_{\boldsymbol{m}=\boldsymbol{1}}^{\boldsymbol{12}} \mathbf{1}(Em, a) P_{a,2000}$

where E^K refers to the type K of immigration enforcement measure in question –that is, K stands for whether the measure is a local 287(g) agreement, participation in the Secure Communities program, a state-level 287(g) agreement, an omnibus immigration law or an E-Verify mandate; *a* refers to a given city (or town) in CONSPUMA *c*, and *m* stands for month of year *t*. Thus, $\mathbf{1}(Em, a)$ is an indicator function that takes the value of 1 if one of the immigration enforcement initiatives being looked at was in effect in city *a* and month *m*. It takes the value of 0 if the measure was not in place, the value of 1 if it was in place year round or, otherwise, a value equal to the a fraction equivalent to the number of months in that year when the measure was in place. For each type of immigration enforcement policy, the indicator: $\mathbf{1}(Em, a)$ is then weighted by the population $P_{a,t}$ in city *a* and year *t*, which is obtained from the 2000 Census. *N* stands for the population in each CONSPUMA *c*, calculated as the sum of the population in all cities and towns belonging to that CONSPUMA –that is: $N_{2000} = \sum_{\boldsymbol{a}=\boldsymbol{1}}^{\boldsymbol{A}} P_{a,2000}$, where A is the total number of cities (and towns) in the CONSPUMA.[11] Our final enforcement index is the sum of each of the indices constructed for each of the five policy measures by CONSPUMA and year.

Because, depending on their scope and design, one can foresee a differential impact of the interior immigration enforcement initiatives being examined, we experiment with grouping the indexes in various ways. Specifically, we distinguish between employment-based immigration enforcement initiatives (exemplified by employment verification mandates applied by employers), and what we refer to as police-based measures (as in the case of 287(g) programs, Secure Communities and state omnibus immigration laws that involve the participation of the local or state police). In other instances, the indexes are

[11] Local areas (CONSPUMAS) are combinations of Census public use micro data areas and may include several cities, towns, or counties. Local law enforcement agencies typically operate at the County, City or Town level and can only belong to a single CONSPUMA.

grouped so as to distinguish between local-level initiatives –as in the case of most 287(g) agreements and participation in the Secure Communities program, and state-level ones –as would be the case with state-level 287(g), E-Verify mandates and omnibus immigration laws.

To provide a sense of the evolution of interior immigration enforcement during the time period under consideration, Figure 1 shows the increase in the number of CONSPUMAS toughening immigration enforcement for the first time. In 2002, only 20 CONSPUMAS (out of 543 CONSPUMAS in the United States) had at least one active enforcement policy. This number stayed relatively constant until 2006. After 2006, the number of CONSPUMAS with active policies gradually increased and, by 2010 (the last year in our sample), the number of CONSPUMAS with at least one active policy had gone up to 276 –a 431 percent increase. Despite its rapid intensification, there is a great deal of temporal variation in the adoption of tougher enforcement measures. A significant level of geographic variation accompanied the temporal variation in the adoption of tougher immigration enforcement measures. Figure 2 shows the geographic roll out of tougher immigration enforcement measures between 2002 and 2010. Lighter colours correspond to an earlier exposure to the introduction of interior immigration laws (with the exception of light blue, which stands for "no immigration law").

Similarly, Table 2 shows the average $Enforcement\ Index_{c,t}$ at the state level and how it changed between 2004 and 2010. A higher value of the index indicates higher levels of enforcement. Enforcement levels in the United States increased ten-fold during this period. The states experiencing the largest increase in interior immigration enforcement during this period were Virginia, North Carolina, California and Utah. However, some states did not experience an increase in enforcement regulation over this period, and their enforcement levels were still fairly low in 2010. There was only one state (Florida) whose immigration regulation eased up during this time, although it started off with a relatively high regulatory environment.

4. Methodology

We are interested in examining the impact of intensified interior enforcement on the probability that household income falls below the poverty line for households with at least one U.S.-citizen child and one likely unauthorized parent. To achieve this aim, we exploit the geographical and temporal variation in interior enforcement measures. Our benchmark model is given by:

(2) $$y_{h,c,t} = \alpha + \beta_1 \, Enforcement\ Index_{c,t} + X'_{h,c,t} \, \alpha + Z'_{c,t}\mu + \gamma_c + \theta_t + \gamma_c t + \varepsilon_{h,c,t}$$

where $y_{h,c,t}$ is either a dummy variable indicative of whether household income for household *h*, in CONSPUMA *c* in year *t* is under the poverty line. As mentioned in Section 3, we experiment with alternative definitions of the poverty threshold, as well as with household income in our robustness checks in Table 8.

The *Enforcement Index*$_{c,t}$ is our key regressor. As we described in Section 3, it captures the intensity of local and state-level immigration enforcement in CONSPUMA *c* at time *t*. Additionally, equation (2) includes the vector $X_{h,c,t}$, which accounts for a range of household characteristics known to be potentially correlated with household income and poverty exposure. The latter include dummy variables for whether the household is a single headed household, as well as indicators for the age, English proficiency, educational attainment, employment and years of U.S. residency of the household head, and information on the number of children residing in the household. Equation (2) also incorporates a number of CONSPUMA-specific and time-varying characteristics potentially influencing household income and its exposure to poverty, as could be the case with unemployment rates. In order to address any concerns regarding the possibility that the coefficient on the enforcement index might be capturing the role played by other local area characteristics, such as the presence of large population of likely unauthorized migrants or the political inclination of the electorate, we also include the vector $Z_{c,t}$. This vector contains data on the share of likely unauthorized migrants residing in the CONSPUMA at a specific point in time, as well as data on the share of the electorate voting Republican in the last congressional elections.[12]

To conclude, we also incorporate in equation (2) a range of geographic and temporal fixed-effects, as well as region-specific time trends. The geographic fixed-effects(γ_c) address unobserved and time-invariant local area characteristics potentially correlated with household income and the household's exposure to poverty, as could be the case if the household resides in an economically depressed area. The temporal fixed-effects, captured by θ_t, account for aggregate level shocks potentially impacting poverty, as could have been the case with the 2008-2009 downturn. Finally, we include area-specific time trends ($\gamma_c t$) to capture a variety of unobserved time-varying characteristics at the CONSPUMA level not addressed by the controls in $Z_{c,t}$. In all regressions, the standard errors are clustered at the CONSPUMA level. Table 1 present summary statistics of the dependent variable and regressors.

Our coefficient of interest is β_1, which captures the relationship between the intensity of immigration enforcement and the household's income and poverty exposure. A negative coefficient would be consistent with the hypothesis that tougher enforcement increases the economic difficulties experienced by the families of U.S. citizen children with likely unauthorized parents.

4.1. Econometric Challenges

We face a number of econometric challenges when trying to assess the impact of intensified immigration enforcement on the household incomes and poverty exposure of U.S. citizen children with, at least, one likely unauthorized parent. A first challenge is the self-selection of migrants and CONSPUMAS into different levels of enforcement. One could imagine that households with, at least, one likely unauthorized parent would be sensitive to immigration enforcement due to fear of deportation. Because migrants, especially

[12] See Table A.1 in the appendix for greater detail on the variables being used.

unauthorized ones, are a relatively mobile population, they are likely to move in response to the adopted enforcement measures. As such, exposure to tougher immigration enforcement is likely to be endogenous and our ordinary least squares (OLS) estimates downward biased. In other words, because likely unauthorized migrants might respond by moving to areas without immigration enforcement, we may find that tougher immigration enforcement does not significantly impact the household incomes or likelihood of life in poverty of families of U.S. citizen children with likely unauthorized parents.

To address this limitation, we instrument the location of migrants using information on the historical location of similar likely unauthorized immigrants. Even though the earliest immigration enforcement initiative examined herein –namely the 287(g) agreements– was not signed until 2002 by the state of Florida, 287(g) were regulated in the Illegal Immigration Reform and Immigrant Responsibility Act of 1996. Therefore, we look at where similar likely unauthorized parents chose to reside at a much earlier date, such as in 1980. Looking at the location of alike migrants in excess of 20 years ahead of the time when the first measures are implemented (*i.e.* 2002) also allows us to address any concerns regarding the role that economic conditions not captured by the CONSPUMA unemployment rates, fixed-effects or specific time trends could be playing in the location of the household and in how well the household does economically. The location of immigrants is instrumented with the term: $Share\ of\ Undocumented\ Immigrant_{c,o,1980}$, which represents the share of likely unauthorized migrants from country of origin *o* residing in CONSPUMA *c* in the 1980 Census computed as:

(3) $$Share\ of\ Undocumented\ Immigrant_{c,o,1980} = \frac{undocumented\ immigrants_{c,o,1980}}{immigrants_{o,1980}}$$

In that manner, we proxy for the likely residential choices of likely unauthorized immigrants if immigration enforcement had never been intensified in order to get around the non-random location of immigrants once enforcement escalated. We then interact the above term with the immigration enforcement index for a given CONSPUMA in a particular year in order to capture the likely exposure to the strengthened enforcement.[13] As such, in a first-stage regression, individuals' likely exposure to immigration enforcement is instrumented with the following term:

(4) $IV_{c,o,t} = Share\ of\ Undocumented\ Immigrant_{c,o,1980} * Enforcement\ Index_{c,t}$

where the subindex *c* stands for CONSPUMA and *o* for the migrant's country of origin in the 1980 Census.

For the above instrument to be valid, it needs to be highly correlated to the likelihood of being exposed to treatment. In our case, that is the case given the entrenched tendency for immigrants to locate in areas with established networks of their countrymen (Bartel 1989; Massey *et al*. 1993; Munshi 2003; Card 2001; Cortés and Tessada 2010, among many others). Yet, it should also be independent of the likelihood of poverty exposure during the 2000s after we account for a range of household, CONSPUMA and temporal characteristics discussed earlier. In other words, even if immigration enforcement is not random, it needs to be the case that CONSPUMAS are not self-selecting into tougher immigration enforcement measures based on the incidence of poverty. To assess whether that is a valid assumption, we follow La Ferrara *et al*. (2012) and aggregate the data at the CONSPUMA level and estimate the following model:

(5) $Enforcement\ Index\ Year_c = \alpha + X'^{2000}_c \alpha + Z'^{2000}_c \mu + \lambda W^{2000}_c + \varepsilon_c$

where $Enforcement\ Index\ Year_c$ is the first year when the enforcement index turned positive in CONSPUMA *c*, and X^{2000}_c are the same vectors of family characteristics as in Equation (1) aggregated at the CONSPUMA level, reflecting average CONSPUMA characteristics before any measure came into effect, *i.e.* the year 2000. In some specifications

[13] In other words, the enforcement index in the first-stage regression is now given by: $IV_{c,o,t} = Share\ of\ Undocumented\ Immigrant_{c,o,1980} * Enforcement\ Index_{c,t}$, where the sub index *c* stands for CONSPUMA and *o* for the migrant's country of origin in the 1980 Census.

we also control for and Z_c^{2000}, which contains the unemployment rate and the proportion of likely unauthorized immigrants in CONSPUMA *c*, as well as the share voting Republican in the state to which CONSPUMA *c* belongs. Most importantly, the vector W_c^{2000} is the share of Hispanic families living in poverty in CONSPUMA *c* in 2000. We estimate equation (5) with and without MSA fixed-effects. The errors are being clustered at the MSA level. In the absence of selection effects, we should find that the coefficient λ is not statistically different from zero. In that case, our instrument for the location of immigrants should prove valid.

A second challenge is the assumption of parallel poverty trends between households of U.S. citizen children with likely unauthorized parents (treated households) and households of U.S. citizen children with naturalized parents (control households). To test that assumption, we pool treated and control households and estimate Equation (6) with a full set of dummies going from seven years before to four years after the enforcement index turns positive. The dummies are, in turn, interacted with a dichotomous variable indicative of whether the household is one with likely unauthorized parents (LU_h) follows:

(6) $$y_{h,c,t} = \alpha + \beta_{-7}D_{-7} * LU_h + \cdots + \beta_4 D_4 * LU_h + \delta_0 D_0 + \cdots + \delta_4 D_4 + \varphi LU_h + X'_{h,c,t} + Z'_{c,t}\mu + +\gamma_c + \theta_t + \gamma_c t + \varepsilon_{h,c,t}$$

where D_0 is a dummy for the year in which the enforcement index first turns positive. In the absence of any pre-existing differential poverty trends between treated and control households, the estimated coefficients on the interaction terms corresponding to the years *prior* to the activation of tougher enforcement should be non-statistically different from zero.

To conclude, we perform a number of falsification and robustness checks to assess the non-spurious nature of our results, as well as to test the sensitivity of our findings to alternative definitions of poverty and to the focus on alternative demographic groups likely to better capture the likely unauthorized population, despite their smaller sample size.

5. Results

5.1 Main Findings

The results from estimating equation (2) using OLS on the sample of households with U.S.-citizen children and, at least, one undocumented parent are displayed in the first four columns of Table 3A. We estimate a number of specifications that progressively add controls. According to the OLS estimates in the fourth and most complete model specification in Table 3A, a one standard deviation increase in the immigration enforcement index raises the likelihood that a household of U.S. citizen children with, at least, one likely unauthorized parent lives in poverty by 1.3 percentage points or 4 percent.[14]

However, if likely unauthorized immigrants choose their residential location based, at least in part, on the degree of immigration enforcement to which they will be exposed to, the OLS estimates are likely to be downward biased. Hence, in the next four columns of Table 3A, we use an IV approach to instrument for the location of likely unauthorized immigrants using information on the location of other countrymen throughout the United States prior to the implementation of any of the immigration enforcement measures being examined. Exposure to immigration enforcement is, then, dependent on what the location of likely unauthorized immigrants would have been had these enforcement initiatives never been in place. The bottom rows display the results from the first-stage estimation. The coefficient on the IV is positive and statistically different from zero at the 1 percent level. The last row confirms that the IV is a good instrument. The F-stat is equal to 38.46, thus larger than the recommended size of 10 (Stock and Yogo 2005). Most importantly, the IV estimates from the most complete specification in Table 3A reveal that the same one standard deviation increase in immigration enforcement raises the likelihood of poverty exposure of households

[14] According to the descriptive statistics in Table 1, the standard deviation of the enforcement index is 0.64. The average share of children living below the poverty line is 0.32 or 32 percent.

of U.S. citizen children with, at least, one likely unauthorized by approximately 6 percentage points or 18 percent. Thus, as predicted, the OLS estimates are downward biased.

The remaining coefficient estimates in Table 3A look as expected. For example, residing in a single headed household raises the likelihood of living in poverty by as much as 25 percentage points. The number of children in the household also matters, with each additional child raising the likelihood of life in poverty by close to 7 percentage points. In contrast, having a household head who is older, more educated, employed or a long-time resident of the United States significantly lowers the poverty risk.

However, were these impacts unique among households of American children with likely unauthorized parents? To answer that question, we re-estimate equation (2) using a control sample of households with U.S. citizen children whose parents are naturalized and, therefore, should not be negatively impacted by the intensification of immigration enforcement. The results from this exercise are displayed in Table 3B. Regardless of the specification and estimation methodology being used, there is no evidence of a significant impact of immigration enforcement on the poverty exposure of these families. Yet, the remaining determinants of childhood poverty across Tables 3A and 3B are rather similar with regards to both statistical significance and magnitude.

5.2 Channels for the Observed Policy Impacts

The estimates in Table 3A inform about the role that intensified immigration enforcement might be having on the exposure to poverty of households of U.S. citizen children with, at least, one likely unauthorized parent. The enforcement index, however, encompasses a number of local and state-level enforcement measures. Similarly, it groups what we refer to as police-based measures –as would be the case with 287g agreements, Secure Communities and Omnibus Immigration Laws that involve either the local or state police, versus employment-based measures like employment verification mandates that involucrate employers.

To learn more about the sources of the found impacts of intensified enforcement, we distinguish according to the geographic scope of the enforcement measure, as well as by whether or not the measure involves the police or, rather, employers. Results from this exercise are displayed in Tables 4 and 5. As in Tables 3A and 3B, we estimate a number of model specifications that progressively add controls, both using OLS as well as an IV approach. In the latter case, we construct two instruments for the two types of immigration enforcement being examined in the spirit of the instrument constructed in equation (4). That is, when instrumenting for police-based immigration enforcement, our IV is given by:

(7) $$IV_{c,o,t} = Share\ of\ Undocumented\ Immigrant_{c,o,1980} * Police\ Based\ Enforcement\ Index_{c,t}$$

Similarly, we construct an instrument for the employment based immigration enforcement exemplified by the E-Verify mandates, as well as instruments for the local and state-level immigration enforcement measures.

According to the most complete IV specification in Table 4, both local and state level policies significantly impacted households' poverty exposure. A one standard deviation increase in local-level enforcement (approximately 0.27) raises the likelihood of life in poverty by approximately 3 percentage points or 9 percent. In the case of state-level enforcement, a one standard deviation increase (approximately equal to 0.52) yields a similar increase in the probability of poverty exposure of roughly 3.7 percentage points or 11.5 percent.

Similarly, the figures in Table 5 inform about the differential role of police-based versus employment-based enforcement measures on the incidence of poverty among families with U.S.-citizen children with, at least, one likely unauthorized parent. Not surprisingly, the observed impact of intensified enforcement primarily stemming from measures involving the local and state police more likely to result in apprehension and deportation. Indeed, a one standard deviation increase in those measures (approximately equal to 0.45) results in a 4 percentage points or 13 percent higher likelihood of living below the poverty line. Employment-based measures, captured by the employment verification mandates, only have a marginally statistically significant impact on poverty. A one standard deviation increase in the immigration enforcement exemplified by E-Verify mandates would increase the poverty exposure of the families under study by 2 percentage points or 7 percent.

The above findings are not surprinsing. The vast majority of unauthorized immigrants are employed in the underground or informal economy, where the use of E-Verify is null –as would be the case with women working as nannies and housekeepers, or with men having their own repair or construction business. In other instances, unauthorized migrants work in sectors that are exempted from the use of E-Verify –as would be the case with firms in the private sector in the most common instance of the mandate referring to public sector employers or contractors. And, even in the more unique case of having a universal E-Verify mandate, a number of employees are excluded from the use of E-Verify if they have short-term contracts (as in agriculture and construction) or work in small businesses with fewer than 10 employees (as it is often the case in retail or food & drink entrepreneurship).

In sum, the estimates in Tables 4 and 5 suggest that police-based measures, whether at the local or state level, are the ones driving the observed negative impacts of intensified immigration enforcement on the poverty exposure of households of U.S. citizen children with, at least, one likely unauthorized parent. This finding is consistent with the idea that, unlike E-Verify mandates, police-based enforcement is directly linked to apprehension and deportation. Furthermore, unlike employment-based enforcement, police-based enforcement cannot be easily evaded by seeking a job in the private sector (if the mandate only refers to public employers) or in the informal sector (if the mandate refers to all employers, public and private). As such, it is more likely to induce families to live in the shadows, trying to minimize their exposure to the police, taking worse jobs if needed and, overall, accepting worse living conditions.

5.3 Identification Tests

As discussed earlier in the methodology section, the credibility of the IV approach relies on the assumption that the instrument, which involves current immigration enforcement levels, is uncorrelated with the error term in the main equation. For that to be the case, the intensified enforcement levels must have been exogenous to the incidence of poverty in the area. To assess whether that is the case, we estimate equation (5). Results from that exercise are displayed in Table 6. In all specifications, we fail to see any statistically significant relationship between past poverty levels in the CONSPUMA prior to the implementation of tougher immigration enforcement levels and the timing of tougher immigration enforcement.

In addition to the exogeneity of immigration enforcement with respect to poverty, a key identification assumption in our approach is that households of U.S. citizen children with likely unauthorized parents and similar households with naturalized parents were exhibiting parallel poverty trends prior to the intensification of immigration enforcement. Otherwise, we cannot conclusively attribute the poverty impacts to the escalation of immigration enforcement at the local and state levels. To assess whether that was the case, we estimate equation (6) using the same model specifications as in Table 3A. None of the coefficients on the interaction terms for the years preceding the implementation of tougher immigration enforcement are statistically different from zero. The positive impact of intensified enforcement on the poverty exposure of families with children and, at least, on likely unauthorized parent, does not emerge until it is implemented in $t>0$. As such, there is no evidence of a differential pre-trend in the incidence of poverty across households with U.S. citizen children that have likely unauthorized parents and those that with naturalized parents.

To conclude, we perform a falsification test to confirm the non-spurious nature of our results. With that aim, we randomly generate an enactment year for each enforcement measure being considered in the construction of the enforcement index, making sure it is a year different from the actual year in which each immigration measure was enacted (see La Ferrara *et al.* 2012). We then re-construct the enforcement index and re-estimate equation (2) using the false immigration enforcement index. We repeat the exercise 500 times and plot the cumulative distribution function and density of the estimated coefficients. As shown in Figure 3, the distribution of the estimated coefficients on the placebo enforcement index is centered around zero, and our benchmark estimate from column 4 of Table 3.A, (indicated by a vertical line in correspondence of the value 0.031) clearly lies outside the range of coefficients estimated in our simulation exercise. Altogether, the results suggest our results are genuine.

5.4 Robustness Checks

In addition to the identification checks from the previous section, we perform a number of robustness checks testing the sensitivity of our findings to the use of alternative definitions of poverty exposure and different samples of families –some of which might be considered a better match to a likely unauthorized household. Tables 8A and 8B display our findings for the sample of likely unauthorized households and for similar households with naturalized parents, respectively, using alternative measures of poverty exposure. As noted earlier on, a common criticism is that the official poverty level is too low and that, on average, families need an income of about twice the federal poverty level just to afford basic expenses (Bitler *et al.* 2014). Therefore, in Tables 8A and 8B, we experiment with using two additional dummy variables as dependent variables: one that equals 1 if the household had an income up to 1.5 times the poverty threshold (Panels A), and another one that equals 1 if the household's income was twice the poverty threshold (Panels B). Additionally, in a third panel (Panels C), we use as our dependent variable the logarithm of real household income. OLS and IV estimates continue to be rather consistent. Focusing on the most complete IV specification, we can conclude that a one standard deviation increase in immigration enforcement leads to increases in the likelihood that household income is either 1.5 times or 2 times above the poverty line in the order of 5 percentage points and 3.4 percentage points, respectively. These effects are equivalent to 10 percent and 5 percent increases in such likelihoods. Similarly, focusing on household income, we find that the same increase in the immigration enforcement would yield the equivalent to a 10 percent drop in household income. In contrast, none of these impacts are observed when we look, instead, at similar families where the parents are naturalized.

Finally, we experiment with performing the analysis using alternative samples of likely unauthorized households in Table 9. In Panel A of Table 9, we focus on families of U.S. citizen children with, at least, one likely unauthorized parent with more than 5 years residing in the United States. In this manner, we address any concerns regarding the possibility that our sample of likely unauthorized households –defined as Hispanic non-citizens– might be including many individuals with non-immigrant visas –typically shorter than 5 years in duration. In Panel B of Table 9, we then consider households with, at least, one likely unauthorized parent who, in addition, does not have a high school diploma. Finally, in Panel C, we restrict our initial sample of households to those outside Maricopa County in Arizona –well-known for its tough approach to immigration enforcement under Sheriff Arpaio. In all instances, we continue to find similar results. Namely, the one standard deviation increase in immigration enforcement raises the likelihood of life in poverty for these sets of households by approximately 3.7 percentage points (12 percent), 5.6 percentage points (18.6 percent), and 2.9 percentage points (9.3 percent), respectively.

In sum, the robustness checks in Tables 8A, 8B and 9 reveal that our results are qualitatively and quantitatively the same, regardless of the poverty measure being used or sample restrictions being imposed.

6. Summary and Conclusions

The past two decades have witnessed an escalation of interior immigration enforcement at both the local and state levels. Using data from the American Community Survey (ACS) and an enforcement index created using data on a number of state-level and local immigration enforcement initiatives for the period 2005-2011, we explore the impact that intensified enforcement has had on the poverty risk of families of U.S. citizen children with likely unauthorized parents. We find that tougher enforcement is associated with lower family income and a higher probability of life in poverty, with most of the impact originating from local police-based measures, such as 287(g) agreements and the Secure Communities program. Our results are robust to a number of identification and robustness checks.

Given the strong relationship between the household income of children and children's future adult outcomes, the fact that U.S. citizen children with likely unauthorized parents account for roughly 8 percent of all American children, and the still pending comprehensive immigration reform, public awareness of the unintended consequences of intensified enforcement on these households' incomes and poverty exposure is imperative. With this study, we hope to shed some light into this crucial relationship.

Figure 1: Enforcement Law Expansion 2004-2010

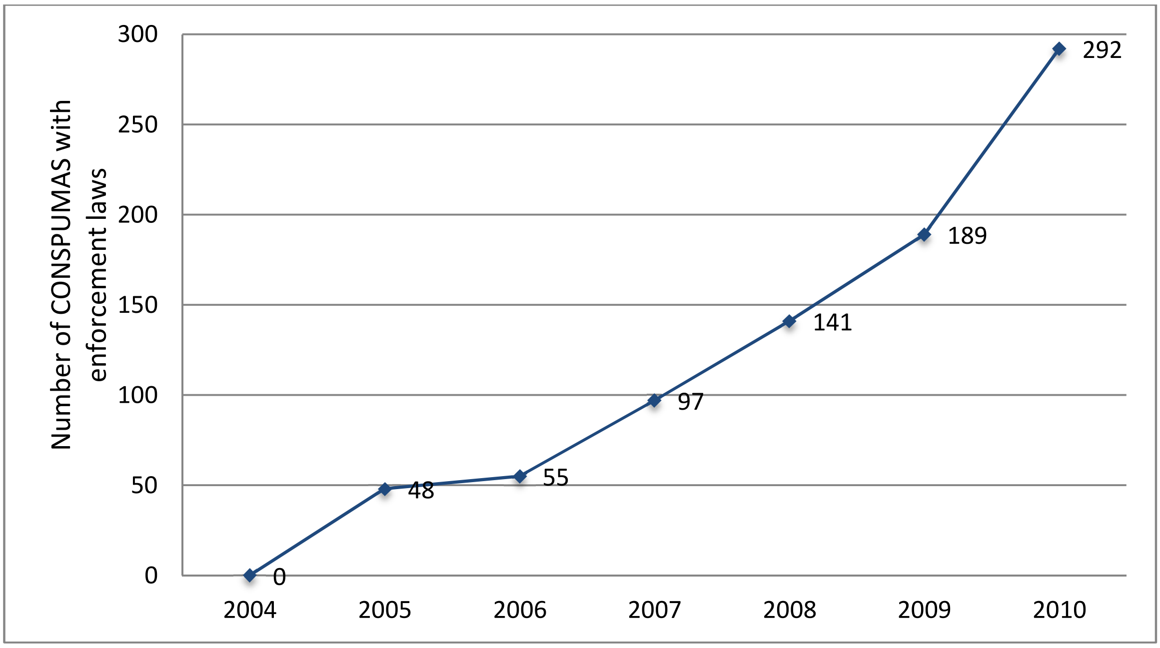


Figure 2: Geographic Enforcement Laws Expansion 2004-2010

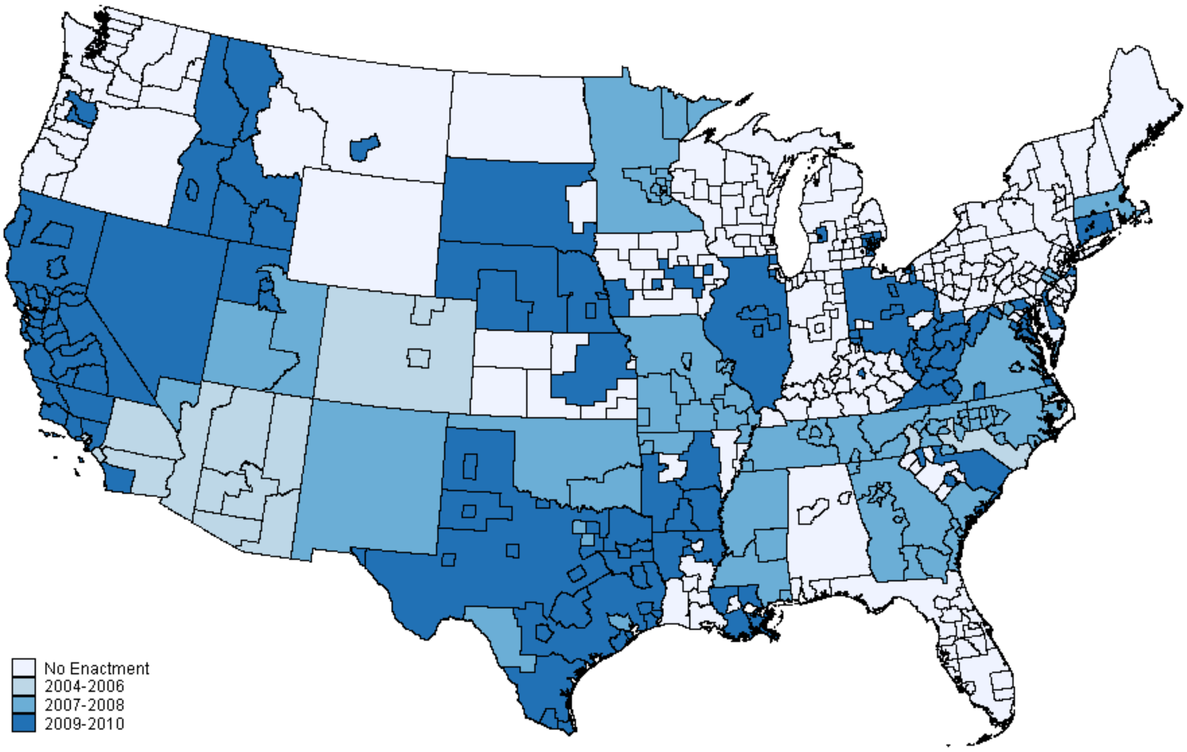


Table 1: Summary Statistics

Descriptive Statistic	Mean	S.D.	Min	Max	Observations
Panel A:Enforcement Index					
Enforcement Index	0.37	0.64	0.00	4.18	150,141
Local-level Enforcement	0.19	0.27	0.00	1.48	150,141
State-level Enforcement	0.19	0.52	0.00	3.00	150,141
Police-based Enforcement	0.28	0.45	0.00	3.18	150,141
Employment-based Enforcement	0.09	0.27	0.00	1.00	150,141
IV for the Following Enforcement Indexes					
Enforcement Index	0.05	0.13	0.00	2.09	150,141
Local-level Enforcement	0.04	0.07	0.00	0.34	150,141
State-level Enforcement	0.02	0.10	0.00	1.75	150,141
Police-based Enforcement	0.05	0.10	0.00	1.51	150,141
Employment-based Enforcement	0.01	0.04	0.00	0.58	150,141
Panel B: Poverty measure					
Poverty 100	0.32	0.47	0.00	1.00	150,141
Poverty 150	0.54	0.50	0.00	1.00	150,141
Poverty 200	0.70	0.46	0.00	1.00	150,141
Log Family income	10.09	0.84	-0.30	13.78	147,049
Panel C: Other controls					
Single Headed HH	0.24	0.43	0.00	1.00	150,141
HH Head w/HS+	0.17	0.37	0.00	1.00	150,141
HH Head Does not Speak English	0.47	0.50	0.00	1.00	150,141
Years in the U.S. for the HH Head	13.37	9.57	-2.00	65.00	150,141
Employed HH Head	0.76	0.42	0.00	1.00	150,141
Age of the HH Head	34.93	8.43	13.00	92.00	150,141
No. of Kids in the HH	2.42	1.15	1.00	14.00	150,141
Unemployment Rate in CONSPUMA	0.08	0.03	0.01	0.35	150,141
Share of Likely Unauthorized in CONSPUMA	0.09	0.05	0.00	0.26	150,141
Share Voting Republican in State	0.46	0.10	0.00	0.69	150,141

Notes: Sample: families with at least one U.S.-citizen child ranging between 0 and 18 years old with at least one undocumented parent. Data from ACS 2005-2011.

Table 2: Immigration Enforcement Index by State and Year

State	2004	2005	2006	2007	2008	2009	2010	Growth
Virginia	0	0	0	0.004	0.009	0.046	0.48	119.000
North Carolina	0	0	0.013	1.042	1.107	1.317	1.448	110.385
California	0	0.012	0.04	0.054	0.052	0.054	0.315	25.250
Utah	0	0	0	0	0.036	0.607	0.903	24.083
Tennessee	0	0	0	0.044	0.631	1.012	1.1	24.000
Texas	0	0	0	0	0.017	0.146	0.374	21.000
South Carolina	0	0	0	0.015	0.069	0.081	0.216	13.400
Illinois	0	0	0	0	0	0.007	0.087	11.429
Louisiana	0	0	0	0	0	0.004	0.045	10.250
Arizona	0	0.333	0.999	0.333	2.232	2.51	3.469	9.417
Pennsylvania	0	0	0	0	0.002	0.02	0.02	9.000
U.S.	***0.046***	***0.032***	***0.027***	***0.087***	***0.188***	***0.299***	***0.421***	***8.152***
Nevada	0	0	0	0	0.044	0.132	0.323	6.341
Michigan	0	0	0	0	0	0.015	0.103	5.867
Delaware	0	0	0	0	0	0.25	1.596	5.384
Oklahoma	0	0	0	0.18	1.037	1.025	1.114	5.189
Colorado	0	0	0.416	1.919	2.122	2.129	2.127	4.113
New Jersey	0	0	0	0	0.004	0.012	0.02	4.000
Arkansas	0	0	0	0.043	0.128	0.128	0.19	3.419
Connecticut	0	0	0	0	0	0.25	1.063	3.252
Nebraska	0	0	0	0	0	0.248	1.041	3.198
Missouri	0	0	0	0	0.559	1.906	1.931	2.454
Georgia	0	0	0	0.515	1.018	2.036	1.694	2.289
Maryland	0	0	0	0	0.051	0.056	0.147	1.882
New Mexico	0	0	0	0.333	1	1.063	0.883	1.652
Idaho	0	0	0	0	0	0.483	1.06	1.195
Minnesota	0	0	0	0	1.322	1.997	1.994	0.508
Massachusetts	0	0	0	0.833	1.006	1.037	1.037	0.245
Mississippi	0	0	0	0	1	1	1.048	0.048
Alabama	0.999	0.999	0.998	0.996	0.999	1.002	1.001	0.002
Iowa	0	0	0	0	0	0	0.016	0.000
Kansas	0	0	0	0	0	0	0.001	0.000
Oregon	0	0	0	0	0	0	0.067	0.000
Kentucky	0	0	0	0	0	0	0.005	0.000
West Virginia	0	0	0	0	0	0	0.199	0.000
Ohio	0	0	0	0	0	0	0.067	0.000
Montana	0	0	0	0	0	0	0.091	0.000
South Dakota	0	0	0	0	0	0	0.038	0.000
North Dakota	0	0	0	0	0	0	0	0.000
Maine	0	0	0	0	0	0	0	0.000
Indiana	0	0	0	0	0	0	0	0.000
New Hampshire	0	0	0	0	0	0	0	0.000
Alaska	0	0	0	0	0	0	0	0.000
Wisconsin	0	0	0	0	0	0	0	0.000
Wyoming	0	0	0	0	0	0	0	0.000
Rhode Island	0	0	0	0	0	0	0	0.000
Vermont	0	0	0	0	0	0	0	0.000
D.C.	0	0	0	0	0	0	0	0.000
Washington	0	0	0	0	0	0	0	0.000
Hawaii	0	0	0	0	0	0	0	0.000
New York	0	0	0	0	0	0	0	0.000
Florida	1	0.5	0	0.001	0.011	0.14	0.503	-0.497

Notes: Average of the enforcement index by state and year. Growth is calculated as $[(X_{2010} - X_t)/X_t,]*100$ where X_t is the first year where the index was different from zero.

Table 3A: Probability of Living below the Poverty Line

Model Specification	OLS				IV			
	1	2	3	4	1	2	3	4
Enforcement Index	0.045***	0.018***	0.019***	0.020**	0.050***	0.023**	0.023**	0.090***
	(0.008)	(0.007)	(0.005)	(0.010)	(0.012)	(0.011)	(0.011)	(0.021)
Single Headed HH	0.251***	0.246***	0.246***	0.246***	0.251***	0.246***	0.246***	0.246***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
HH Head w/HS+	-0.083***	-0.084***	-0.084***	-0.084***	-0.083***	-0.084***	-0.084***	-0.084***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
HH Head Does Not Speak English	0.115***	0.111***	0.111***	0.111***	0.116***	0.111***	0.111***	0.111***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Years in the U.S. for the HH Head	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Employed HH Head	-0.219***	-0.210***	-0.210***	-0.210***	-0.219***	-0.210***	-0.210***	-0.210***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age of the HH Head	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. of Kids in the HH	0.070***	0.069***	0.069***	0.069***	0.070***	0.069***	0.069***	0.069***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Unemployment Rate in CONSPUMA			0.764***	0.053			0.769***	0.048
			(0.187)	(0.209)			(0.186)	(0.219)
Share of Likely Unauthorized in CONSPUMA			0.162	-0.205			0.203	-0.217
			(0.255)	(0.297)			(0.256)	(0.282)
Share Voting Republican in State			-0.110	-0.062			-0.112	-0.095
			(0.085)	(0.120)			(0.085)	(0.128)
First-stage Results								
IV					3.399***	2.675***	2.624***	1.556***
					(0.816)	(0.659)	(0.597)	(0.268)
Observations	150,141	150,141	150,141	150,141	150,141	150,141	150,141	150,141
R-squared	0.186	0.209	0.209	0.214	0.186	0.203	0.205	0.208
F-statistics					5.069	29.29	24.37	38.46
CONSPUMA FE		Yes	Yes	Yes		Yes	Yes	Yes
Year FE		Yes	Yes	Yes		Yes	Yes	Yes
CONSPUMA-specific Time Trend				Yes				Yes

Notes: Sample: families with at least one U.S.-citizen child ranging between 0 and 18 years old with at least one undocumented parent. Specification 1 includes only family characteristics. Specification 2 includes area and time fixed effects. Specification 3 adds aggregate CONSPUMA-time controls and Specification 4 coincides with Equation 1 in the text. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Standards errors are clustered by CONSPUMA.

Table 3B: Probability of Living below the Poverty Line – Families with Naturalized Parents

Model Specification	OLS				IV			
	1	2	3	4	1	2	3	4
Enforcement Index	0.010*	-0.000	0.000	-0.014	0.007	-0.011	-0.011	0.002
	(0.006)	(0.007)	(0.007)	(0.013)	(0.007)	(0.010)	(0.010)	(0.020)
Single Headed HH	0.183***	0.173***	0.173***	0.173***	0.183***	0.173***	0.173***	0.173***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
HH Head w/HS+	-0.061***	-0.065***	-0.065***	-0.064***	-0.061***	-0.065***	-0.065***	-0.064***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)
HH Head Does Not Speak English	0.085***	0.079***	0.079***	0.078***	0.085***	0.079***	0.079***	0.078***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
Years in the U.S. for the HH Head	-0.002***	-0.001***	-0.001***	-0.001***	-0.002***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Employed HH Head	-0.231***	-0.226***	-0.225***	-0.225***	-0.231***	-0.226***	-0.225***	-0.224***
	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)
Age of the HH Head	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. of Kids in the HH	0.036***	0.037***	0.037***	0.037***	0.036***	0.037***	0.037***	0.036***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Unemployment Rate in CONSPUMA			0.414**	0.459			0.393*	0.510**
			(0.208)	(0.312)			(0.208)	(0.256)
Share of Likely Unauthorized in CONSPUMA			-0.013	0.167			-0.118	-0.198
			(0.340)	(0.419)			(0.335)	(0.380)
Share Voting Republican in State			0.002	0.117			0.013	0.068
			(0.114)	(0.156)			(0.112)	(0.140)
First-stage Results								
IV					3.245***	2.624***	2.589***	1.479***
					(0.636)	(0.456)	(0.422)	(0.192)
Observations	48,238	48,238	48,238	48,238	48,238	48,238	48,238	48,238
R-squared	0.171	0.200	0.200	0.215	0.171	0.200	0.200	0.213
F- statistics					5.309	32.61	27.76	38.59
CONSPUMA FE		Yes	Yes	Yes		Yes	Yes	Yes
Year FE		Yes	Yes	Yes		Yes	Yes	Yes
CONSPUMA -specific Time Trend				Yes				Yes

Notes: Sample: families with naturalized parents and children between 0 and 18 years old. Specification 1 includes only family characteristics. Specification 2 includes area and time fixed effects. Specification 3 adds aggregate CONSPUMA-time controls and Specification 4 coincides with Equation 1 in the text. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Standards errors are clustered by CONSPUMA.

Table 4: Probability of Living below the Poverty Line – By Geographic Scope of the Enforcement Measure

Model Specification	OLS				IV			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Local-level Enforcement	0.081***	0.020	0.019*	0.025*	0.107***	0.026	0.030*	0.109***
	(0.016)	(0.014)	(0.011)	(0.015)	(0.023)	(0.018)	(0.018)	(0.035)
State-level Enforcement	0.033***	0.017**	0.019***	0.018	0.021*	0.022*	0.019*	0.071**
	(0.010)	(0.008)	(0.006)	(0.011)	(0.012)	(0.012)	(0.011)	(0.028)
First-stage Results								
IV1					3.086***	2.215***	2.171***	1.538***
					(0.188)	(0.224)	(0.212)	(0.281)
IV2					3.620***	3.129***	3.146***	1.547***
					(1.071)	(0.897)	(0.882)	(0.398)
Observations	150,141	150,141	150,141	150,141	150,141	150,141	150,141	150,141
R-squared	0.187	0.209	0.209	0.214	0.186	0.209	0.209	0.214
F-statistics-1					54.63	54.94	62.13	281.02
F-statistics-2					7.177	6.137	5.921	21.89
CONSPUMA FE		Yes	Yes	Yes		Yes	Yes	Yes
Year FE		Yes	Yes	Yes		Yes	Yes	Yes
CONSPUMA-specific Time Trend				Yes				Yes

Notes: Sample: families with at least one U.S.-citizen child ranging between 0 and 18 years old with at least one undocumented parent. Specification 1 includes only family characteristics. Specification 2 includes area and time fixed effects. Specification 3 adds aggregate CONSPUMA-time controls and Specification 4 coincides with Equation 1 in the text. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Standards errors are clustered by CONSPUMA.

Table 5: Probability of Living below the Poverty Line – By Type of Enforcement Measure

Model Specification	OLS				IV			
	1	2	3	4	1	2	3	4
Police-based Enforcement	0.045***	0.013	0.017**	0.021**	0.079***	0.020	0.024*	0.092***
	(0.014)	(0.008)	(0.007)	(0.009)	(0.019)	(0.014)	(0.014)	(0.026)
Employment-based Enforcement	0.045***	0.026**	0.022**	0.019	-0.027	0.031	0.020	0.086*
	(0.013)	(0.012)	(0.011)	(0.024)	(0.028)	(0.026)	(0.026)	(0.044)
First-stage Results								
IV1					2.988***	2.280***	2.226***	2.988***
					(0.335)	(0.268)	(0.254)	(0.335)
IV2					4.373***	3.683***	3.695***	2.478***
					(1.194)	(0.986)	(0.981)	(0.669)
Observations	150,141	150,141	150,141	150,141	150,141	150,141	150,141	150,141
R-squared	0.186	0.209	0.209	0.214	0.185	0.209	0.209	0.214
F-statistics-1					29.51	41.31	39.68	69.56
F-statistics-2					5.217	3.772	3.484	57.97
CONSPUMA FE		Yes	Yes	Yes		Yes	Yes	Yes
Year FE		Yes	Yes	Yes		Yes	Yes	Yes
CONSPUMA-specific Time Trend				Yes				Yes

Notes: Sample: families with at least one U.S.-citizen child ranging between 0 and 18 years old with at least one undocumented parent. Specification 1 includes only family characteristics. Specification 2 includes area and time fixed effects. Specification 3 adds aggregate CONSPUMA-time controls and Specification 4 coincides with Equation 1 in the text. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Standards errors are clustered by CONSPUMA.

Table 6: First Year the Enforcement Immigration Index Turns Positive

Model Specification	**1**	**2**	**3**	**4**
Share of HHs living below the poverty line	68.816	61.275	-26.722	-18.215
	(56.010)	(47.802)	(64.452)	(57.025)
Share of single-headed HHs		7.787	-28.660	-28.470
		(46.315)	(37.536)	(33.253)
Share of HH heads with a HS education or more		91.410	70.078	61.114
		(77.142)	(69.247)	(62.260)
Share of HH heads without a HS diploma		49.234	47.195	42.506
		(41.065)	(46.480)	(50.936)
Share of non-English proficient HH heads		14.537	-1.357	-3.355
		(57.573)	(36.797)	(28.607)
Average number of years in the U.S.		-2.931	-0.805	-1.174
		(2.564)	(3.137)	(3.128)
Share of working HH heads		-26.691	24.489	-1.931
		(58.498)	(41.367)	(26.230)
Average age of HH head		1.557	-2.322	-0.551
		(3.012)	(4.275)	(2.959)
Average number of kids per HH		3.449	-5.653	-8.733
		(21.629)	(25.970)	(22.787)
Average unemployment rate in CONSPUMA				-1,014.315
				(1,298.036)
Share of likely unauthorized in CONSPUMA				3.656
				(998.799)
Share voting Republican in State				45.351
				(176.358)
Constant	1,945.144***	1,896.877***	2,024.108***	2,031.832***
	(30.860)	(90.854)	(111.957)	(128.612)
Observations	478	478	478	478
R-squared	0.002	0.006	0.500	0.504
MSA FE	No	No	Yes	Yes

Notes: Standards errors are clustered by METAREA.

Table 7: Event Study – Probability of Living Below the Poverty Line

Model Specification	1	2	3	4
Elapsed time* LU parents				
-7*LU	-0.006	-0.012	-0.013	-0.011
	-0.028	-0.026	-0.026	-0.027
-6*LU	0.017	0.006	0.004	0.007
	-0.024	-0.021	-0.021	-0.021
-5*LU	0.011	0.002	0.000	0.000
	-0.023	-0.02	-0.020	-0.020
-4*LU	0.032	0.023	0.02	0.02
	-0.024	-0.021	-0.021	-0.021
-3*LU	0.037*	0.029	0.027	0.028
	-0.022	-0.019	-0.019	-0.019
-2*LU	0.036	0.028	0.026	0.027
	-0.022	-0.019	-0.019	-0.02
-1*LU	0.035	0.028	0.026	0.026
	-0.023	-0.02	-0.02	-0.02
0*LU	0.053**	0.044**	0.043**	0.044**
	-0.022	-0.019	-0.019	-0.02
1*LU	0.060***	0.049**	0.048**	0.048**
	-0.023	-0.02	-0.02	-0.021
2*LU	0.065***	0.048**	0.047**	0.049**
	-0.023	-0.021	-0.021	-0.021
3*LU	0.065***	0.047**	0.045**	0.044**
	-0.023	-0.022	-0.021	-0.022
4*LU	0.071***	0.058**	0.057**	0.056**
	-0.027	-0.026	-0.026	-0.026
Elapsed time				
-7	0.023	-0.015	-0.016	-0.009
	-0.015	-0.019	-0.019	-0.026
-6	0.012	-0.019	-0.015	-0.009
	-0.012	-0.021	-0.02	-0.04
-5	0.023*	-0.016	-0.013	-0.004
	-0.012	-0.023	-0.023	-0.053
-4	0.011	-0.034	-0.031	-0.015
	-0.01	-0.021	-0.021	-0.062
-3	0.011	-0.042*	-0.040*	-0.019
	-0.011	-0.024	-0.023	-0.07
-2	0.017	-0.047*	-0.044*	-0.019
	-0.01	-0.025	-0.023	-0.076
-1	0.028**	-0.042	-0.038	-0.011
	-0.011	-0.026	-0.025	-0.081
0	0.018*	-0.062**	-0.059**	-0.029
	-0.01	-0.027	-0.026	-0.081
1	0.027**	-0.057**	-0.055**	-0.021
	-0.011	-0.029	-0.028	-0.081
2	0.025**	-0.053*	-0.053*	-0.024
	-0.011	-0.031	-0.029	-0.076
3	0.028***	-0.055	-0.059*	-0.025
	-0.011	-0.035	-0.033	-0.071
4	0.019**	-0.058	-0.067*	-0.025
	-0.008	-0.037	-0.035	-0.062
LU Parents	0.032	0.038**	0.039**	0.039**
	-0.021	-0.018	-0.018	-0.019
Observations	198577	198577	198379	198379
R-squared	0.202	0.221	0.221	0.225

Notes: Sample: families with undocumented parents and naturalized parents. Specification 1 includes only family characteristics. Specification 2 includes area and time fixed effects. Specification 3 adds aggregate CONSPUMA-time controls and Specification 4 coincides with Equation 1 in the text. All regressions include a constant term. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Standards errors are clustered by CONSPUMA.

Table 8A: Using Alternative Dependent Variables

Model Specification	OLS				IV			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Panel A: HH Income is 1.5 Times the Poverty Line								
Enforcement Index	0.048***	0.011	0.011**	0.018**	0.051***	0.018*	0.016	0.082***
	(0.010)	(0.007)	(0.005)	(0.009)	(0.012)	(0.010)	(0.010)	(0.023)
Observations	150,141	150,141	150,141	150,141	150,141	150,141	150,141	150,141
R-squared	0.180	0.205	0.206	0.210	0.180	0.205	0.206	0.210
Panel B: HH Income is 2 Times the Poverty Line								
Enforcement Index	0.042***	-0.000	-0.000	0.012	0.044***	0.002	-0.001	0.053***
	(0.009)	(0.005)	(0.004)	(0.009)	(0.010)	(0.011)	(0.009)	(0.020)
Observations	150,141	150,141	150,141	150,141	150,141	150,141	150,141	150,141
R-squared	0.163	0.187	0.187	0.192	0.163	0.187	0.187	0.192
Panel C: Log (Real HH Income)								
Enforcement Index	-0.084***	-0.028**	-0.029***	-0.028**	-0.094***	-0.038**	-0.033*	-0.132***
	(0.017)	(0.011)	(0.007)	(0.012)	(0.022)	(0.019)	(0.018)	(0.037)
Observations	147,049	147,049	147,049	147,049	147,049	147,049	147,049	147,049
R-squared	0.241	0.272	0.272	0.277	0.241	0.272	0.272	0.277
IV					3.399***	2.675***	2.624***	1.556***
					(0.816)	(0.659)	(0.597)	(0.268)
F-statistics					5.069	29.29	24.37	38.46
CONSPUMA FE		Yes	Yes	Yes		Yes	Yes	Yes
Year FE		Yes	Yes	Yes		Yes	Yes	Yes
CONSPUMA-specific Time Trend				Yes				Yes

Notes: Sample: families with at least one U.S.-citizen child ranging between 0 and 18 years old with at least one undocumented parent. Specification 1 includes only family characteristics. Specification 2 includes area and time fixed effects. Specification 3 adds aggregate CONSPUMA-time controls and Specification 4 coincides with Equation 1 in the text. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Standards errors are clustered by CONSPUMA.

Table 8b: Using Alternative Dependent Variables – Families with Naturalized Parents

Model Specification	OLS				IV			
	1	2	3	4	1	2	3	4
Panel A: HH Income is 1.5 Times the Poverty Line								
Enforcement Index	0.017***	-0.007	-0.004	-0.017	0.021***	-0.001	-0.001	0.008
	(0.006)	(0.006)	(0.006)	(0.012)	(0.008)	(0.013)	(0.013)	(0.039)
Observations	48,238	48,238	48,238	48,238	48,238	48,238	48,238	48,238
R-squared	0.211	0.241	0.241	0.251	0.211	0.241	0.241	0.251
Panel B: HH Income is 2 Times the Poverty Line								
Enforcement Index	0.029***	0.004	0.005	0.006	0.042***	0.007	0.004	0.024
	(0.007)	(0.006)	(0.006)	(0.011)	(0.012)	(0.015)	(0.014)	(0.049)
Observations	48,238	48,238	48,238	48,238	48,238	48,238	48,238	48,238
R-squared	0.224	0.252	0.253	0.261	0.224	0.252	0.253	0.261
Panel C: Log (Real HH Income)								
Enforcement Index	-0.041***	0.008	0.007	0.019	-0.048***	0.010	0.017	-0.025
	(0.013)	(0.013)	(0.011)	(0.022)	(0.018)	(0.029)	(0.026)	(0.082)
Observations	47,836	47,836	47,836	47,836	47,836	47,836	47,836	47,836
R-squared	0.324	0.359	0.360	0.370	0.324	0.359	0.360	0.370
First-stage Results								
IV					3.245***	2.624***	2.589***	1.479***
					(0.636)	(0.456)	(0.422)	(0.192)
F-statistics					5.309	32.61	27.76	38.59
CONSPUMA FE		Yes	Yes	Yes		Yes	Yes	Yes
Year FE		Yes	Yes	Yes		Yes	Yes	Yes
CONSPUMA-specific Time Trend				Yes				Yes

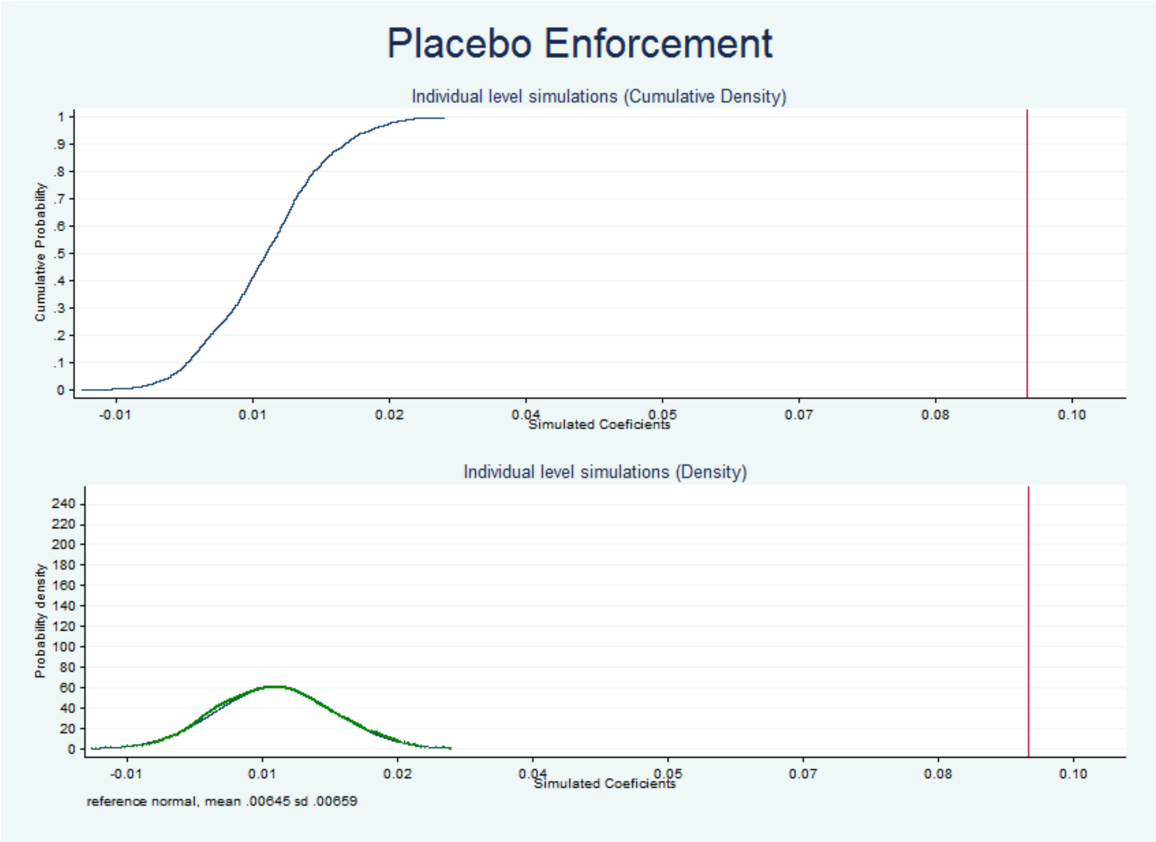
Notes: Sample: families with naturalized parents and children between 0 and 18 years old. Specification 1 includes only family characteristics. Specification 2 includes area and time fixed effects. Specification 3 adds aggregate CONSPUMA-time controls and Specification 4 coincides with Equation 1 in the text. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Standards errors are clustered by CONSPUMA.

Table 9: Probability of Living below the Poverty Line – Alternative Samples

Model Specification	OLS				IV			
	1	2	3	4	1	2	3	4
Panel A: Likely Unauthorized Parents with More than 5 Years of U.S. Residency								
Enforcement Index	0.050***	0.021***	0.022***	0.027**	0.054***	0.021**	0.019**	0.058***
	(0.009)	(0.006)	(0.005)	(0.012)	(0.013)	(0.010)	(0.009)	(0.019)
IV					3.424***	2.872***	2.831***	2.033***
					(0.832)	(0.693)	(0.637)	(0.305)
Observations	118,529	118,529	118,529	118,529	118,529	118,529	118,529	118,529
R-squared	0.182	0.206	0.206	0.212	0.182	0.206	0.206	0.212
F-statistics					5.606	28.50	24.05	37.15
Panel B Without Maricopa County								
Enforcement Index	0.055***	0.010	0.013**	0.010	0.066***	0.011	0.013	0.087***
	(0.008)	(0.006)	(0.006)	(0.009)	(0.015)	(0.012)	(0.013)	(0.028)
IV					2.653***	2.151***	2.160***	1.960***
					(0.509)	(0.347)	(0.349)	(0.310)
Observations	145,924	145,924	145,924	145,924	145,924	145,924	145,924	145,924
R-squared	0.186	0.209	0.210	0.215	0.186	0.209	0.210	0.214
F-statistics					7.460	31.53	26.84	38.41
Panel C: Only US-born children with LU parents								
Enforcement Index	0.045***	0.018***	0.019***	0.019**	0.051***	0.026**	0.025**	0.045***
	(0.008)	(0.007)	(0.005)	(0.007)	(0.012)	(0.010)	(0.010)	(0.008)
IV					3.404***	2.676***	2.694***	1.963***
					(0.813)	(0.593)	(0.596)	(0.289)
Observations	148,812	148,812	148,812	148,812	148,812	148,812	148,812	148,812
R-squared	0.186	0.209	0.210	0.213	0.186	0.209	0.209	0.186
F-statistics					5.017	32.29	27.63	37.52
CONSPUMA FE		Yes	Yes	Yes		Yes	Yes	Yes
Year FE		Yes	Yes	Yes		Yes	Yes	Yes
CONSPUMA-specific Time Trend				Yes				Yes

Notes: Sample Panel A and B: families with at least one U.S.-citizen child ranging between 0 and 18 years old with at least one undocumented parent. Sample Panel C: families with only U.S. born children and with at least one unauthorized parent. Specification 1 includes only family characteristics. Specification 2 includes area and time fixed effects. Specification 3 adds aggregate CONSPUMA-time controls and Specification 4 coincides with Equation 1 in the text. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Standards errors are clustered by CONSPUMA.

Figure 3: Placebo Enforcement Simulations



APPENDIX

Table A1: Construction of main Variables

Poverty 100	Dummy variable 1-the family is below the poverty line 0-Otherwise Poverty line: Established by the Social Security Administration in 1964, and subsequently modified by Federal interagency committees in 1969 and 1980
Poverty 150	Dummy variable 1-the family below 1.5 times below the poverty line 0-Otherwise
Poverty 200	Dummy variable 1-the family below 2 times below the poverty line 0-Otherwise
Log real family income	Family income is defined as the total pre-tax money income earned by all members in the family from all sources for the previous year.
Single headed family	Dummy variable 1-Dingle headed family 0-Two-parent family
HH head w/HS +	Educational attainment of the head of the family 1-Head of the household with more than HS diploma 0-Otherwise
HH Head Does not Speak English	English proficiency of the household head 1-Household head does not speak English/speak but not well 0-Otherwise
Years in the U.S. for the HH Head	Number of Years in the US for the household head
Age of the HH Head	Age of household head
No. of Kids in the HH	Number of children in the family between 0 and 18 years old
Unemployment Rate in CONSPUMA	Unemployment rate by CONSPUMA and year
Share of Likely Unauthorized in CONSPUMA	Percentage of Hispanic no-citizen population by CONSPUMA and year
Share Voting Republican	Percentage of people voting Republican party by state and year

Note: All the variables are constructed using ACS data from 2005 to 2011.

A.2. Interior Immigration Enforcement

This appendix provides a brief history of interior enforcement immigration legislation, and Table A.2 describes the main features of each piece of legislation.

Police-Based Enforcement: The 287(g) agreements were enacted as a section of the Illegal Immigration Reform and Immigrant Responsibility Act of 1996 (IIRIRA), and was the only program which permitted state and local law enforcement officials to enforce federal immigration law directly. State and local (at the country, town, or city level) agencies were able to enforce civil immigration law by signing an agreement (so-called Memorandum of Agreement or MOA) with the U.S. Immigration and Customs Enforcement (ICE). The first 287(g) program was signed by the Department of Law Enforcement in the state of Florida and ICE in 2002, and the number of 287(g) agreements grew quickly after that.

In 2012, the Department of Homeland Security (DHS) ended the signing of 287(g) agreements due to the increased number of complaints about racial profiling, their high implementation cost, and accusations that the agreements were used as a political tool that interfered with protecting and serving communities (see Amuedo-Dorantes and Puttitanun, 2014). In place of the 287(g) agreements, DHS promoted participation in its Secure Communities program. The funding for the Secure Communities program grew considerably over the period 2008 to 2011, which allowed for the speedy implementation of the program and for the massive increase in the numbers of individuals screened by ICE. In 2014, DHS ended the Secure Communities program.

Omnibus immigration laws were enacted and passed by a number of states, starting with Arizona in 2010. While the content of each omnibus immigration law differs, they typically include the well-known "show me your papers' clause", which enables the police to request proper identification documentation during a lawful stop. Governor Jan Brewer signed the "Support Our Law Enforcement and Safe Neighbourhoods Act" (SB 1070) into law on April 23, 2010. Once of the tougher immigration laws, SB 1070 considers a misdemeanour crime if aliens over 14 years of age residing in the United States for longer than 30 days are not properly registered or do not have their documentation with them at all times. Additionally, it makes state and local enforcement officers responsible for determining an individual's immigration status during a "lawful stop, detention or arrest" if there is a suspicion that the person might be an undocumented immigrant. The Act bans state or local officials, as well as agencies, from restricting the enforcement of federal immigration laws, establishes penalties on those harbouring, hiring and transporting undocumented immigrants, and allows legal residents to sue state or localities that limit the implementation of immigration enforcement. One day before these laws were to become effective on July, 2010, the U.S. Department of Justice argued that SB 1070 was unconstitutional and filed a lawsuit asking for an injunction against it. The law's most questionable provisions were blocked. By the end of the same month when it was signed into law, HB 2162 was approved to rectify SB 2010 and make sure that law enforcement cannot consider race, color or national origin when implementing the provisions of the original law, except as permitted by the U.S. or Arizona Constitution.

Employment-based Enforcement: E-verify is a voluntary program that allows employers to screen newly hired workers for work eligibility. Enrolment in E-Verify grew fairly quickly from 1,064 in 2001 to 482,692 in 2014 (Department of Homeland, 2014).

Table A2.1: Description of Enforcement Laws

Nature of the Laws	Law	Years	Area of application	Objective	Who is applying it?	Geographic Coverage	Signed by	Types
Police-Base Measures	**287g**	2002-	Street/Jail	Make communities safer by the identification and removal of serious criminals	State and local law enforcement entities	State and Local	State and local enforcement entities signed a contract (Memorandum of Agreement -MOA) with the U.S. Immigration and Customs Enforcement (ICE)	**Task Force**: allows local and state officers interrogate and arrest noncitizens during their regular duties on law enforcement operations. **Jail enforcement** permits local officers to question immigrant who have been arrested on state and local charges about their immigration status. **Hybrid model:** which allow participate in both types of programs.
	SC	2009-2014	Nation's jail and prisons	Identify noncitizens who have committed serious crime using biometric information	Police	Local	Jurisdictions	
	OIL-SB1070	2010	Street/Jail	Identification noncitizen	State and local law enforcement entities	State	State governor	
Employment-Base Measures	**E-Verify**	2006-	Firms	Deter the hiring of unauthorized immigrants.	Employer	State	State governor	

Note: Sources: National Conference of State Legislatures (NCSL) and U.S. Immigration and Customs Enforcement (ICE): http://www.ice.gov/factsheets/287g, https://www.ice.gov/secure-communities, http://www.ncsl.org/research/immigration/omnibus-immigration-legislation.aspx, http://www.ncsl.org/research/immigration/everify-faq.aspx

Table A.3.: Descriptive Statistics for Living in Poverty for Alternatives Samples

Samples:	Mean	S.D.	Min	Max	Observations
More than 5 year of U.S. Residency	0.30	0.46	0.00	1.00	118,529
Without Maricopa County	0.30	0.46	0.00	1.00	145,924
Families with only U.S.-citizen children	0.31	0.46	0.00	1.00	148,812

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