The Labor Market Effects of Immigration Enforcement*

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Abstract

We examine the labor market effects of Secure Communities (SC)–an immigration enforcement policy which led to over 450,000 deportations. Using a difference-in-difference model that takes advantage of the staggered rollout of SC we find that SC significantly decreased male employment. Importantly, the negative effects are concentrated among low-educated non-citizens in low-skilled occupations and citizens in high-skilled occupations–reducing employment of citizens by approximate 300,000 nationally. These findings are consistent with low-skilled immigrants and higher-skilled citizens being complements in production. This is the first quasi-experimental evidence on the labor market effects of immigration enforcement policies on citizens.

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1 Introduction

Approximately 8 million undocumented immigrants participated in the U.S. labor market in 2015, constituting about five percent of the total U.S. labor force (Passel and Cohn, 2016). An increasing number of policies aimed at reducing the number of undocumented immigrants through deportations have been implemented in the past two decades, but it is still largely unknown how such policies have impacted the U.S. labor market and to what extent they have been costly or beneficial to U.S. firms and citizen workers across the skill distribution (Chassamboulli and Peri, 2015).[1]

This is the first paper to examine the impacts of a nationwide immigration enforcement policy on the labor market outcomes of likely undocumented immigrants as well as citizen workers. Specifically, we analyze the labor market effects of one of the largest immigration enforcement policies in the U.S.: Secure Communities (SC).[2] SC was designed to increase information sharing between local police agencies and the federal government in an attempt to detect and remove undocumented immigrants. The policy was ultimately adopted by all U.S. counties, and more than 454,000 individuals, 96% of whom were male, were removed under SC during 2008-2015.[3] As a result, SC led to a significant decrease in the availability of low-skilled men through its direct impact on deportations, and potentially because of "chilling effects" due to the increased risk of deportation among immigrants. These chilling effects of SC may have led to self-deportations, reduced the number of incoming undocu-

[1]A large body of literature has focused on analyzing the effect of migration inflows on native wages and employment. See for example, Card (2001), Borjas (2003), Boustan et al. (2010), and Dustmann et al. (2017). For excellent reviews of the literature see Friedberg and Hunt (1995), Longhi et al. (2005), and Longhi et al. (2006). Previous studies on the labor market impacts of recent immigration enforcement policies in the U.S. have mostly focused on the direct effects on the migrant population. See Phillips and Massey (1999), Bansak and Raphael (2001), Orrenius and Zavodny (2009), Amuedo-Dorantes and Bansak (2014), and Orrenius and Zavodny (2015).

[2]Other immigration enforcement policies, such as 287(g) agreements and E-Verify, differ from SC in their implementation and design. For instance, 287(g) agreements train local police to act as immigration agents (Pham and Van, 2010; Bohn and Santillano, 2017). E-Verify is designed to curb access to employment, but not to deport undocumented immigrants (Karoly and Perez-Arce, 2016). See Karoly and Perez-Arce (2016) for a summary of the literature on state immigration policies.

[3]Statistics on removals under SC come from the Transactional Records Access Clearinghouse (TRAC).

mented immigrants, and impacted the willingness of immigrants to work outside the home in order to limit interactions with the local police (Kohli et al., 2011).[4]

The implementation of SC provides an ideal natural experiment to measure the effects of a decrease in the supply of low-skilled immigrants on labor market outcomes. First, because the Department of Homeland Security (DHS) was unable to simultaneously implement SC nationwide, the program was rolled out on a county-by-county basis over 4 years. Cox and Miles (2013) provide evidence that, after controlling for geographic and year fixed effects, the rollout of SC was largely exogenous to county characteristics such as crime or unemployment rates. We provide additional evidence on the exogeneity of the rollout of SC through an event-study analysis that shows no significant differences in trends in labor market outcomes before implementation. Thus, the timing of SC implementation can be thought of as plausibly exogenous and labor market impacts are identified off of the differential timing of SC implementation across counties. Second, the relative speed of the rollout, and the fact that all U.S. counties eventually adopted SC, limits the scope of cross-county mobility by immigrants and natives alike, and thus concerns about spatial arbitrage of employment should be minimal (Borjas, 2003; Borjas and Katz, 2007; Cadena and Kovak, 2016).

We use data from the 2005-2014 American Community Survey (ACS) and conduct the analysis at the Public-Use Microdata Area (PUMA) level - the smallest, comprehensive geographic area available in the public-use data. We analyze the effects of SC on non-citizen workers, as well as citizen workers–which include all U.S.-born individuals and naturalized foreign-born citizens. Within the non-citizen group, we cannot precisely distinguish between documented and undocumented immigrants because documentation status is not available in the data. Instead, we consider two groups of immigrant workers: the first includes all non-citizens, and the second includes all non-citizens with a high-school degree or less: we

[4]Wang and Kaushal (2018) found that the implementation of 287(g) agreements and Secure Communities increased the share of Latino immigrants with mental distress.

call this group "low-educated non-citizens".[5] Given that most undocumented immigrants have low levels of education, we believe the latter group captures a large portion of the undocumented population that will be directly affected by SC.[6]

The results indicate that the introduction of SC is associated with a roughly 0.75% reduction in a PUMA's total male employment, measured as a share of the PUMA's working age population. We further find that this reduction comes from a decrease in the employment of both male citizen and male non-citizen workers. Specifically, SC is associated with a reduction of 3.4% in the employment of male *non-citizens*, and a reduction of 5% in the employment of *low-educated male non-citizens*–the latter of whom are most likely to be directly affected by the policy as undocumented immigrants have low levels of education on average. For male *citizens*, the results indicate that SC is associated with a decline in employment of 0.5%. Interestingly, we find little evidence of analogous effects for female employment regardless of citizenship status.[7]

Recent research indicates that the degree to which the arrival (or the removal) of immigrants impacts the labor market outcomes of natives crucially depends on the skill composition of immigrants, and their degree of substitutability with native workers across the skill distribution (Borjas, 2003; Ottaviano and Peri, 2012; Dustmann et al., 2017; Lee et al., 2017). To better understand the impact of SC on employment across the *occupational* skill distribution, we generate four skill groups containing occupations based on the share of workers with at least a college degree.[8] The results show that SC has a negative and

[5]Non-citizens refer to foreign-born individuals who report not holding U.S. citizenship.

[6]The results are robust to using more restrictive measures to define the population of "likely undocumented". We discuss these results in section 5.2.

[7]The lack of effects for women, both for citizens and non-citizens, suggest that on average they are less affected by SC. However, the effects for women might be more concentrated in particular occupations, since they have a large representation in the household services' industry. East and Velasquez (2018) find a positive effect of enforcement policies on the wages of female household workers, which has a spillover effect on the labor outcomes of high-skilled women with children, who are the most likely to outsource household services.

[8]For expositional purposes, Appendix Table (A1) reports 10 occupations near the 25th percentile of the occupational skill distribution and 10 occupations near the 75th percentile of the occupational skill distribution, measured by the share of workers with a college degree in each occupation.

statistically significant effect on the employment of male citizen and non-citizen workers in the middle part of the occupational skill distribution (middle two quartiles). Specifically, SC is associated with a reduction of 2.6% in the employment of male citizen workers in middle- to high-skill occupations. In contrast, the effect on low-educated non-citizen males is concentrated in the low- to middle-skill occupations and is much larger–about a 13.5% reduction in employment.

To shed light on the mechanism through which immigration enforcement policies impact the employment of citizens in high-skilled occupations, we rely on the predictions of a job search model by Chassamboulli and Peri (2015). In their model, a policy aimed at reducing the number of undocumented immigrants has a negative effect on the employment of high-skilled citizen workers if the two groups of workers are complements in production. To provide further support that complementarities in production are the main mechanism, we show that the effect on citizen men in high-skilled occupations is larger in sectors which relied more heavily on low-educated non-citizen labor prior to SC, and these are also the sectors that see the largest declines in male non-citizen employment. Moreover, we show graphically that there is a positive relationship between the size of the effect on male non-citizen and male citizen employment across sectors.[9]

More broadly, this paper contributes to the existing literature in a number of important ways. Unlike most previous studies which examine the labor market effects of immigration inflows, we examine the impact of reducing the supply of male undocumented immigrants on labor market outcomes. This is an important distinction because reducing the supply of a more assimilated group of immigrants is likely to generate different short-run adjustments compared to adjustments in response to an inflow of newly arrived immigrants (Acemoglu, 2010).

A recent paper by Clemens et al. (2018) provide historical evidence that reducing

[9]Beerli and Peri (2015) and Lee et al. (2017) also find evidence for complementarities between low-skilled immigrants and high-skilled natives.

the supply of Mexican Bracero farm workers at the end of 1964 had little effect on the labor market outcomes of domestic farm workers, suggesting that firms did not substitute Bracero workers with domestic ones. In comparison, this paper estimates the labor market effects of a contemporary deportation policy which affected a wide range of industries, and provides evidence for complementarities between low-skilled non-citizens and high-skilled citizen workers. Previous papers have pointed to the importance of complementarities in production between immigrants and natives but most have not used an experimental setting to test them (Ottaviano and Peri, 2012; Chassamboulli and Peri, 2015).[10]

Finally, our paper contributes to an important policy debate on the effects of deporting undocumented immigrants on the labor market. This is particularly relevant since SC was reactivated in January of 2017 (SC was replaced by the Priority Enforcement Program at the end of 2014) and President Trump has recently proposed expanding other similar enforcement programs (Alvarez, 2017; Sakuma, 2017).

The paper proceeds as follows. Section 2 describes the SC program, discusses the conceptual framework, and the predicted effects of SC on different groups of workers. Section 3 describes our data sources and the construction of the analysis sample. Section 4 outlines the empirical strategy, and we discuss the results in section 5. We conclude in section 6.

2 Policy Background and Conceptual Framework

2.1 Policy Background

Secure Communities (SC) is one of the largest interior immigration enforcement programs and is administered by the U.S. Immigration and Customs Enforcement (ICE).[11] SC's main

[10] An exception is Lee et al. (2017), which provides empirical evidence on these complementarities exploiting the repatriation of Mexican workers. Similar to our results, the authors find negative employment effects for high-skilled natives, and no evidence of substitution with low-skilled natives.

[11] For excellent reviews of the Secure Communities program's implementation see Cox and Miles (2013), Miles and Cox (2014), and Alsan and Yang (2018). The information in this section comes primarily from

objectives were to identify undocumented immigrants arrested by local law enforcement agencies, and to prioritize their deportation. In practice, the enforcement program relied on facilitating information sharing between local and state law enforcement agencies, the Federal Bureau of Investigation (FBI), and the Department of Homeland Security (DHS). Usually, local law enforcement agencies conduct a criminal background investigation after a person is arrested by sending their fingerprints to the FBI. Prior to SC, fingerprints received by the FBI were not used to check the legal status of a person or their eligibility for removal.[12] Under SC, the fingerprints received by the FBI were automatically sent to the DHS, who subsequently ran the fingerprints against their biometric database, known as the Automated Biometric Identification System (IDENT) to determine an individual's immigration status.[13]

At this point, "detainers could be issued when an immigration officer had reason to believe the individual was removable," which could be for criminal reasons or for immigration-crime-related reasons. A detainer did not have to be preceded by a conviction.[14] The detainer required state or local law enforcement agencies to hold an arrested individual for up to 48 hours until ICE could obtain custody and start the deportation process. Thus, a detainer prevented the release of individuals whose cases were dismissed and, for those who were charged with a crime, did not provide them the opportunity for a pre-trial release through bail. As a result, conditional on being arrested, the administration of SC substantially increased the probability of apprehension and deportation of non-citizens by ICE.

Unlike previous voluntary information sharing programs, SC is a federal program, and local and state law agencies could not "opt in" or "opt out" of SC. For empirical purposes,

these reviews.

[12]Instead, violators of immigration law were identified via interviews conducted by federal agents under a program called the Criminal Alien Program (CAP), or by local agents authorized to act as immigration agents under written voluntary agreements with the DHS: 287(g) agreements.

[13]IDENT includes biometric and biographical information on non-U.S. citizens who have violated immigration law, or are lawfully present in the U.S., but have been convicted of a crime and are therefore subject to removal, as well as naturalized citizens whose fingerprints were previously included in the database. In addition, the IDENT system includes biometric information on all travelers who enter or leave the U.S. through an official port, and when applying for visas at U.S. consulates.

[14]This policy language taken from the ICE website, is available here: https://www.ice.gov/pep.

this is important for two reasons. First, local agencies have much more limited discretion in the usage of the program, compared to other interior immigration enforcement polices (Miles and Cox, 2014).[15] Second, despite being a federal program, SC was rolled out on a county-by-county basis between 2008 and 2013, until the entire country was covered. We gathered information on the rollout dates of SC from the U.S. Immigration and Customs Enforcement (ICE). Our empirical strategy, described in more detail below, relies on the piecemeal implementation of SC across counties. Therefore, it is important that the timing of the rollout across counties not be related to time-varying county characteristics. Cox and Miles (2013) show that the earliest activations were related to the fraction of the county's Hispanic population, distance from the U.S.-Mexico border, and presence of local 287(g) agreements. Importantly for the purpose of our study, their results also show that early adopters were not selected in terms of the county's economic performance, crime rates and potential political support for SC. In addition, the timing of adoption in subsequent counties was more "random" because the government shifted to mass activations, and this was based on resource constraints and waiting lists (Cox and Miles, 2013). This pattern can be seen in Figure (1) which plots the rollout of SC across counties and over time.[16] Given the potential selectivity of the early-adopters, in our main model we drop observations from counties that adopted SC before January 2010, but the main results are robust to including them.[17]

Because undocumented immigrants have disproportionately low levels of education, we expect SC to have affected the availability of low-skilled labor through two main channels. First, SC reduced the number of low-skilled workers by removing undocumented immigrants

[15]After the activation of SC, some jurisdictions known as "sanctuary cities" started refusing to cooperate with ICE detainer requests by claiming that the policy was unconstitutional under the Fourth Amendment. We discuss heterogeneous effects of SC by "sanctuary city" status in Appendix B.

[16]Alsan and Yang (2018) provide additional evidence on the selectivity of earlier adopters, by testing whether differences in demographic characteristics between Hispanics and other ethnic groups before the activation of SC, were significantly different in early versus later adopters. Relevant for their study, they find the differences in food stamp take-up between different ethnic groups are not related with the SC activation timing.

[17]Some states, especially towards the end of the implementation period, adopted SC across all counties at once. Figure (2) plots the share of counties within each state that had SC over time.

through detainers and eventual deportations. From 2008 to 2014, more than 454,000 individuals, nearly all male, were detained through SC.[18] As shown in Appendix Table (A2), 17% of deported individuals were not convicted of a crime, and among those that were convicted, it was often not a serious crime; of all of those deported, 6% had a traffic violation, 12% had a DUI, 5% had a crime related to marijuana, and 8% had illegal entry or re-entry as their most serious criminal conviction. Thus, a broad swath of the undocumented population may have been affected, and not just the most serious criminals (Amuedo-Dorantes et al., forthcoming). Second, fear of detentions and deportations may have limited the labor supply of undocumented immigrants and impacted their job search efforts. Anecdotal evidence suggests that immigrant communities believed that SC allowed police officers to act as ICE agents, and advocacy groups suggested that SC provided a way for law enforcement to use minor violations to target the Hispanic population (Kohli et al., 2011). Consequently, fear of driving a car, interacting with law enforcement, or having to present forms of identification may have limited the participation of immigrants in the formal labor market.[19] Moreover, increased immigration enforcement could have changed the number of undocumented immigrants by increasing voluntary out-migration from the U.S., or by reducing in-migration to the U.S. Finally, SC may have also impacted the labor supply of documented immigrants because the documented and undocumented populations are heavily integrated (Alsan and Yang, 2018).[20]

[18]At the end of 2014, the SC program was replaced by the Priority Enforcement Program (PEP). Under PEP, the same screening process occurred as did under SC, but PEP would only issue a detainer for individuals convicted of serious crimes or those who were deemed to pose a threat to public safety. We use restricted-access data on deportations and detentions under SC from the Transactional Records Access Clearinghouse (TRAC) at Syracuse University, to provide context for understanding the potential effects of SC. Details about this data can be found in Appendix A.

[19]SC could have also directly increased the uncertainty of hiring an undocumented immigrant and hence increased their labor costs.

[20]The screening process by ICE is subject to error, and roughly 2% of individuals who were identified for deportation by ICE under SC turned out to be citizens, thus SC may result in fear of being held in custody or detained among documented individuals (Kohli et al., 2011).

2.2 Conceptual Framework

A large body of literature using both experimental and non-experimental methods finds little empirical evidence that an increase in the fraction of immigrants in the population substantially reduces the employment or wages of natives with comparable skills (Altonji and Card, 1982; Card, 1990; Hunt, 1992; Pischke and Velling, 1997; Friedberg, 2001; Cohen-Goldner and Paserman, 2006).[21] These studies do not differentiate the impact of immigrants by their legal status, and have focused on both the short- and long-run impact of immigration inflows on the outcomes of native workers. Their empirical approaches have typically relied on cross-market variation in the number of immigrants and, in the absence of a natural experiment, have used shift-share instruments to address the possible endogeneity of the location choices of immigrants as well as the number and skill composition of immigrants (Ottaviano and Peri, 2012).[22]

Borjas (2003) and Borjas and Katz (2007) argue that cross-market studies cannot adequately account for the equalizing pressure arising from the spatial arbitrage of mobile workers and capital, and instead conduct their analysis at the national level. Under the assumption that workers with similar education and experience are perfectly substitutable, Borjas (2003) and Borjas and Katz (2007) find that immigration has a sizable effect on the wages of natives. However, using a similar national level approach, Ottaviano and Peri (2012) do not assume ex-ante that immigrants and natives with similar education and experience are perfectly substitutable and find that the increase in immigration in 1990-2006 had a small positive effect on the average wages of native workers and on the wages of workers without a high school degree. Ottaviano and Peri's analysis highlights the possibility that while immigrants can act as imperfect substitutes for some native workers, there could

[21] See also Altonji and Card (1982), Grossman (1982), and Card (2001). A handful of papers suggest that immigrants negatively affect the wages and employment of natives, see, e.g., (Mansour, 2010; Glitz, 2012; Dustmann et al., 2017).

[22] Dustmann et al. (2016) argue that empirical approaches estimating the effect of immigration on relative wages are not comparable to empirical approaches estimating the effect of immigration on total wages.

also be a degree of complementarity between immigrants and natives across different skill groups.

This is the first paper to analyze the labor market impacts of a modern nationwide immigration enforcement policy on both immigrants and citizen workers across the skill distribution. We are aware of only three papers focusing on other impacts of SC. The first examines the characteristics of counties in relation to their date of SC implementation; we rely on this analysis for some of the information provided above (Cox and Miles, 2013). The second paper examines the effect of SC on local crime and finds little evidence that SC leads to a decline in the crime rate (Miles and Cox, 2014). The third paper by Alsan and Yang (2018) finds that SC reduced sign-ups for the Affordable Care Act (ACA) and participation in the Supplemental Nutrition Assistance Program (SNAP) for Hispanic citizens, suggesting important spillover effects on the documented immigrant population.[23]

A larger literature has examined the effects of other immigration policies on employment, and these analyses are informative for thinking about the potential effects of SC. A number of studies have examined the effects of the 287(g) agreements, which deputize local law enforcement agencies to enforce immigration law. Like SC, 287(g) agreements act as a mechanism to check the immigration status of individuals interacting with the criminal justice system and as a pathway for initiating deportations. These papers find that the presence of a 287(g) agreement in a local area reduces total employment in that area, with mixed effects in industries in which undocumented immigrants are overrepresented. However, this effect is not disaggregated across immigrants and natives, or across low- and high-skill occupations, so it is unclear what is the direct effect of enforcement on immigrants' employment and what may be spillover effects due to substitution or complementarities in production (Pham and Van, 2010; Bohn and Santillano, 2017).[24]

[23]Several papers include SC as part of a summary index of interior immigration enforcement; see for example Amuedo-Dorantes and Lopez (2017).

[24]Watson (2013) examines the effect of 287(g)s on migration and finds they do not cause immigrants to leave the United States, but they do increase migration to a new region within the United States. These

2.3 Predicted Effects of Secure Communities

Although there is ample evidence on the labor market effects of immigration inflows on native workers, relatively little theoretical or empirical attention has been devoted to studying the labor market effects of immigration enforcement measures on both immigrant and native workers across the skill distribution. Chassamboulli and Peri (2015) build on a job search model developed by Liu (2010), and extended by Chassamboulli and Palivos (2014), to examine the labor market impacts of different enforcement policies. The model includes two separate labor markets for low- and high-skilled workers who are complementary in production. Undocumented immigrants are assumed to be low-skilled and have the lowest reservation wages. Documented immigrants have higher reservation wages compared to undocumented immigrants, while natives have higher reservation wages compared to either group. Because we cannot identify undocumented immigrants in our data, and there may be spillover effects on documented immigrants, we simplify this model to think about two groups: 1) citizens, and 2) non-citizens, where the latter includes both documented and undocumented immigrants.

The model of Chassamboulli and Peri (2015) identifies two main channels through which the supply of non-citizens impacts the employment and wages of low-skilled citizens. SC will result in a reduction in the supply of non-citizens (assumed to be all low-skilled) through the mechanisms described above, which increases the marginal productivity of low-skilled citizens, who are substitutes for low-skilled non-citizens. Thus, we would expect a positive effect on the demand for low-skilled citizens, which would increase their employment and wages. However, due to the reduced supply of non-citizens, the expected labor cost of hiring low-skilled workers increases, resulting in firms posting fewer vacancies, placing downward pressure on employment and wages of low-skilled citizens. Therefore, the net

migratory effects are concentrated in Maricopa County, AZ and among the college-educated foreign-born, who are unlikely to be undocumented. Moreover, the effect of 287(g)s on migration is likely different than the effect of SC, since 287(g)s were optional and not all locations had an agreement.

effect on the employment and wages of low-skilled citizens is theoretically ambiguous. The effect on high-skilled citizens depends on the degree of complementarity between high- and low-skilled workers. If low- and high-skilled workers are complementary in production (as is assumed in the theoretical model), then a decrease in the labor supply of low-skilled workers would have a negative effect on the demand for, and thus the employment and wages of, high-skilled citizens. To examine the effects on low- and high-skilled workers empirically, we examine effects across the *occupational* skill distribution, described in more detail in section 3.[25]

Additionally, the effect of immigration on the local labor market could also be driven by changes in demand for local goods. Enforcement policies could also have a negative effect on the demand for citizen labor due to a decline in migrant's' consumption of local goods. Only a few papers have empirically examined the relationship between immigrant consumption and natives' labor outcomes when examining the impact of migration. Hercowitz and Yashiv (2002) and Bodvarsson et al. (2008) study the effect of mass migration to Israel in the 1990s, and the Mariel boatlift, respectively, and find that the increase in the demand for local goods by the immigrant population explained the lack of decline in native employment. In our context, however, if non-citizen consumption was the main mechanism, we would not expect to find differential effects of enforcement policies across the occupational skill distribution.

3 Data

To measure the labor market effects of SC, we merge information on the rollout dates of SC with data on local-level employment drawn from the 2005-2014 American Community Survey (ACS) Integrated Public Use Microdata Series (IPUMS) (Ruggles et al., 2017). The

[25]Note that this is different than our focus on "low-educated non-citizens", who are non-citizens with a high school degree or less– this group is only intended to better capture those directly impacted by the policy.

ACS is a repeated cross-sectional dataset covering a 1% random sample of the U.S. We begin our sample in 2005, as this is the first year we can identify the Public-Use Microdata Area (PUMA) geographic level in the public-use data, and end in 2014 when SC was replaced by the Priority Enforcement Program. Although we observe the month in which SC was implemented in a given county, the ACS data only includes the year in which the survey was conducted. As a result, we create a variable that indicates the fraction of the survey year SC was in place in each county. Some PUMAs are equivalent to counties, others include several counties, and some are smaller than individual counties. Because data on the SC rollout dates are at the county-level, we calculate the population-weighted average of the county values of the SC variable within each PUMA, similar to the approach taken by Watson (2013).[26]

Our main outcome of interest is the employment-to-population ratio at the PUMA-year level for various demographic groups. To construct these measures, we count the number of working-aged (20-64) individuals in each demographic group in each PUMA-year who report working at the time of the survey, and divide this by the *total* working-age population in the PUMA-year. We use the same denominator for all demographic groups because we are interested in capturing the total effects of SC through all potential mechanisms described above. Specifically, this outcome variable will allow us to capture both changes in population, as well as changes in labor market participation, among individuals that remain after SC. To calculate both the numerator and the denominator we use the ACS-provided person-level weights. We multiply these employment-to-population ratios by 100,000 to ease the presentation. We examine this measure separately for males and females for three demographic groups: 1) individuals who are U.S.-born or naturalized citizens, 2) foreign-born non-citizens, and 3) foreign-born non-citizens with a high school degree or less. There are three reasons

[26] If a PUMA is equivalent to a county, or smaller than a county, the PUMA will get the value of the SC variable for that county. If multiple counties are contained within a PUMA, we weight the value of the SC variable for each county by the fraction of the total PUMA population that each county represents. Additionally, the PUMA codes were revised after the 2011 ACS survey, so we use the time-consistent version of the PUMA codes provided by the IPUMS website.

we look at non-citizens, regardless of their immigration status. First, firms might not be able to perfectly distinguish between documented and undocumented immigrants, making the local environment less hospitable towards foreign-born people in general. Second, undocumented and documented immigrants may live in the same household, and enforcement policies could affect the labor decisions of documented workers through their impact on their undocumented relatives or friends. Finally, it is not possible to perfectly identify undocumented status in the data.[27] In what follows we use "employment-to-population ratio" and "employment" interchangeably to describe our outcome variables.

To test whether the implementation of SC impacted the labor market outcomes of workers across the occupational skill distribution, we examine the employment-to-population ratios across 3-digit SOC occupations classified based on the fraction of workers in each occupation in 2005 (the first year of our sample) that have at least a college degree. Figure (3) shows the distribution of this measure across occupations. The median occupation has roughly 13% of workers with a college degree, and the cutoffs for the 25th and 75th percentiles are 5% and 42%, respectively. We generate four skill groups of occupations, based on the four quartiles of the distribution, and calculate the employment-to-population ratio for each group as described above.

Splitting our sample by occupations, rather than simply by education, enables us to identify whether changes in the labor demand for citizens and non-citizens is occurring within versus across occupations, providing a better understanding of the interaction between these two types of labor in production.[28] Moreover, the literature investigating polarization (Autor and Dorn, 2013) shows that labor demand shifters, including those in response to im-

[27] We test the robustness of the results using more restrictive definitions of "likely undocumented" immigrants, such as foreign-born non-citizens with a high school education or less who were born in Mexico or Central America and entered the U.S. after 1986, and Hispanic foreign-born non-citizens with a high school education or less who entered the U.S. after 1986 (Amuedo-Dorantes and Bansak, 2012, 2014; Orrenius and Zavodny, 2015). We also examine effects of SC by race/ethnicity for both citizens and non-citizens. We discuss these results in Section 5.

[28] To preview our results, we find compelling evidence that the complementarities between citizens and non-citizens is across rather than within occupation.

migration, have non-monotonic effects on employment across occupations (Tuzemen and Willis, 2013; Zlate and Mandelman, 2016). Therefore, splitting our sample only by a binary measure of individual skill based on education would obfuscate any underlying non-monotonicity.

Since our sample period spans the Great Recession, we account for changes in economic conditions that may influence employment by including "Bartik-style" measures of labor demand (Bartik, 1992), as well as controls for housing price values. It is possible that SC had a direct effect on housing prices, so to ensure controlling for this does not bias our results, we alternatively include housing prices at the state-level, both including and excluding housing prices in the affected PUMA. We also control for the presence of 287(g) agreements across PUMAs in our sample period. These controls are described in detail in Appendix A. We show summary statistics for all main variables in Table (1).

4 Empirical Strategy

Our empirical strategy uses both the geographic and temporal variation in the implementation of the SC program to identify its effect on PUMA-level employment. In order to estimate the causal effect of adopting SC on local employment we estimate the following model separately by gender:

$$emp_{pt} = \alpha + \beta SC_{pt} + X'_{pt}\gamma + \nu_p + \lambda_t + t\delta_p + \epsilon_{pt} \tag{1}$$

where emp_{pt} is the number of males or females employed, divided by the total working age population per 100,000 people in PUMA p at time t: $\frac{Emp_{pt}}{Pop_{pt}/100{,}000}$.[29] The model includes year fixed effects, λ_t, to account for national economic shocks, and fixed effects at the PUMA

[29]SC's impact on the employment-to-population ratio as defined above can be the result of changes in the number of employed individuals or by changes in a PUMA's population at time t. We provide evidence in section 5 that SC primarily impacted the number of employed individuals by using employment-to-population ratios based on pre-SC population counts, and by examining whether SC impacted migration across PUMAs.

level, ν_p, to control for time-invariant unobserved heterogeneity, such as the pre-SC share of Hispanics and proximity to the border. Our main specification also includes PUMA-by-year linear trends, $t\delta_p$ to account for differential trends in employment within PUMAs over time.[30] X_{pt} is a vector of PUMA-by-year controls which includes 287(g) programs, measures of local labor demand, and local house prices.[31] We also estimate equation (1) separately for citizens, non-citizens, and low-educated non-citizens, and by occupational skill group. The analysis by citizenship status and across the skill distribution allows us to test the direct effects of SC on the population of likely undocumented immigrants and the spillover effects of SC on the labor market outcomes of citizens.

As described in the data section, SC_{pt} is a continuous variable indicating exposure to SC and ranges between zero and one. Once SC has been implemented by January 1st of year t in all counties in a PUMA p, the variable SC_{pt} takes a value of one for the remainder of the sample. Therefore, β measures the effect of 100% of the PUMA population being covered by SC for the entire survey year. The baseline model is weighted by the PUMA population in 2000.[32]

The underlying identification assumption is that there were no time-varying PUMA-specific factors which are correlated with the timing of the adoption of SC. To provide support for this assumption, we test for parallel trends by estimating the effect of SC on employment for four years before and after the implementation of SC through an "event

[30]Our results are similar if we instead only model pre-trends and use this to predict post-treatment trends, which is preferred if there are dynamic treatment effects (Wolfers, 2006; Lee and Solon, 2011; Goodman-Bacon, 2016; Borusyak and Jaravel, 2017).

[31]As we discuss in section 5, the baseline results are also similar if we include more flexible housing price controls including quadratic and cubic terms, as well as the size of the boom in housing prices prior to SC interacted with a linear trend.

[32]Following the suggestion of Solon et al. (2015) we test the robustness of our main results to a model without weights. The results are very similar as shown in Appendix Table (A3). We do not include state by year fixed effects because 10 states and the District of Columbia implemented SC on a state-wide basis. These states are Alaska, Delaware, DC, Main Minnesota, New Hampshire, New Jersey, North Dakota, Rhode Island, Vermont, West Virginia, Wyoming. However, results are very similar when we include Census region by year fixed effects (results available upon request).

study" model as follows:

$$emp_{pt} = \alpha + \sum_{\substack{k=-4 \\ k \neq -1}}^{4} \beta_k 1_{pk} + X'_{pt}\gamma + \nu_p + \lambda_t + t\delta_p + \epsilon_{pt} \tag{2}$$

where 1_{pk} is an indicator variable equal to one k years before or after SC is first implemented in any county in PUMA p. β_k therefore identifies the effect of SC on employment in PUMA p and year k. The year prior to SC adoption, $k = -1$, is the excluded group; therefore, all marginal effects should be interpreted as relative to the year before adoption. In order for our identification strategy to be valid, there should be no discernible differential trends present before SC's implementation. We report the results of this specification in Figure (4) on the full sample of men, where the blue dots show the effect of SC, and dashed lines represent 95% confidence intervals. The results provide no evidence that employment was following a differential trend across locations prior to the adoption of SC, and there is suggestive evidence that following SC implementation total employment was negatively affected, although the point estimates are not statistically different from zero.

5 Results

5.1 Employment

We begin by presenting estimates of the effects of SC on the employment of men as specified in equation (1). Panel A of Table (2) shows the results for all men, Panel B shows the effect on citizens (natives and naturalized citizens), Panel C shows the effect on all non-citizens, and Panel D shows the effect on low-educated non-citizens, who are the most likely to be undocumented and to be directly affected by SC. The first column shows the effect on total employment for each group, and across columns 2-5, we show the impact of SC by quartiles of the occupational skill distribution for these same groups. Note that across all panels and columns the denominator is the same–total PUMA working age population in time t divided by 100,000–however, the numerator changes across panels and columns depending on the demographic and occupational skill group of interest. The results in column 1 of Panel A indicate that SC reduces the employment-to-population ratio of 20-64 year old men by 281 workers per 100,000 people, significant at the 1% level. The mean male employment-to-population ratio per 100,000 people is 37,423 (implying that, on average, roughly 37% of the total working age PUMA population is employed men) and relative to this average, the point estimate indicates about a 0.75% reduction in a PUMA's total male employment (281/37,422). Interestingly, as seen in columns 2-5 of Panel A, the effects of SC are concentrated in the middle of the occupational skill distribution. Specifically, SC is associated with a reduction of 1.8% in a PUMA's male employment in the second quartile of the occupational skill group ($p<0.05$) and a reduction of about 2.5% in the employment of men working in occupations in the third quartile of the distribution ($p<0.01$).

The negative effects on the total employment-to-population ratio found in Panel A may be driven by a number of mechanisms, so in Panels B-D, we estimate the effects of SC separately by citizenship status. We first focus on the overall effects shown in the first column. The results indicate that SC has a significant negative effect on the employment of low-educated non-citizen workers, as well as a significant *negative* spillover effect on the employment of citizens. Specifically, the implementation of SC reduces the employment-to-population ratio of non-citizen workers by 113 per 100,000 people, significant at the 10% level (Panel C, column 1), which, relative to the mean employment-to-population ratio, is a 3.4% percent reduction in the employment of non-citizens. In Panel D we further restrict our sample to include only low-educated non-citizens and the effect of SC is a reduction of the employment-to-population ratio by 5% (108/2171). Turning to the effects on citizens, the results in Panel B indicate that, on average, SC reduces the employment of citizen workers by 168 workers per 100,000 individuals, or by about 0.5%, significant at the 10% level. Thus, approximately 60% of the reduction in total employment is due to depressed citizen employment. This is novel evidence that a decrease in the supply of low-skilled immigrant workers leads to a decline in the employment of citizen workers.[33]

To better understand the size of the point estimate on non-citizens, we conduct a back-of-the-envelope calculation. We calculate the number of deportations of employed males per 100,000 people and then compare this to our point estimate of the reduction in non-citizens per 100,000 people, which occurs through all potential mechanisms, not just deportations. Based on this calculation, SC would have resulted in a reduction of 104 employed male non-citizens per 100,000 people just through deportations.[34] We also directly examine changes in population and changes in labor force participation in Appendix Table (A5). The results indicate that both mechanisms may be playing a role, although neither effect is precisely estimated.

We next explore heterogeneous effects across the occupational skill distribution for citizens and non-citizens. The results in Panel B for citizens suggest that the decline in their employment is entirely driven by a decline of about 2.6% in the employment-to-population ratio in the third quartile of the occupational skill distribution. The effect on citizens in the lowest quartile of the occupational skill distribution is positive but is small in magnitude and imprecisely estimated. In contrast, the effect on non-citizen men (Panel C) and low-educated non-citizen men (Panel D) is concentrated among workers in the second quartile of the occupational skill distribution. The results in column 3 of Panel D suggest that SC

[33]We interpret this as evidence of complementarities between citizen and non-citizen labor. To provide more context for the relative magnitudes, consider that citizens make up the vast majority of the labor force– for every one low-educated non-citizen worker there are approximately 24 citizen workers. This implies that if citizens and low-educated non-citizens were perfect complements (i.e. the aggregate production function was Leontief), we would expect the marginal effect on citizen employment to be 12 times larger than we estimate. Therefore, our estimates allow us to reject the hypothesis that citizens and non-citizens are perfect complements.

[34]This calculation is done as follows. First, we know that 454,413 people were deported under SC, 436,236 of whom were male. This implies there were about 134 deported males per 100,000 people in total in the U.S. (when scaled by the U.S. population of 326 million). We calculate from the ACS an average male non-citizen employment rate of 78%, and assume the same employment rate among those deported to estimate the number of deported employed individuals. Another important assumption underlying this calculation is that we assume deportations are evenly spread across PUMAs. We do not use the deportation data by PUMA for this exercise because this data only contains deportations flagged as being conducted under SC, so that we observe no pre-SC deportations in the data. This may cause us to misspecify the effect of SC on deportations since we cannot take account of underlying trends.

reduces the employment of non-citizen men with a high school degree or less by 13.5%, significant at the 1% level.[35]

The estimates in Table (2) provide little evidence of *substitution on net* between citizen and non-citizen workers across the occupational skill distribution.[36] In fact, we find evidence suggesting *complementarities* between non-citizens in lower-skilled occupations and citizens in higher-skilled occupations, and no evidence of spillover effects on net (either positive or negative) onto citizens in lower-skilled occupations. Both findings are consistent with the job search model developed by Chassamboulli and Palivos (2014) and Chassamboulli and Peri (2015), discussed above, which predicts an ambiguous effect on low-skilled citizens and a negative effect on high-skilled citizens (if they are complements in production).[37]

The results are not sensitive to the choice of cutoffs in the skill distribution. Figure (5) plots the estimated coefficients from our main specification for different groups of workers and by gradually shifting the occupational skill group to include occupations with a higher share of college educated workers (a "moving window" approach). Panel A suggests that the introduction of SC had negative employment effects on workers in the middle of the skill distribution. The effect on citizens, depicted in Panel B, show that the introduction of SC negatively impacted citizen workers in the middle to high occupational skill groups. In contrast, Panels C and D show that the negative employment effects on non-citizens and low-educated non-citizens are concentrated among workers in the low to middle part of the occupational skill distribution. This supports our main findings that SC had a direct negative employment effect on the likely undocumented population and had a negative spillover effect

[35]As shown in Appendix Table (A1) the majority of workers just above the 25th percentile of the occupational skill distribution have some college education, while only 5-6% are college graduates. In the group of workers in occupations just below the 75th percentile of the skill distribution, slightly over half have some college education, while 40-45% have a college degree.

[36]The coefficient on citizens in the low to medium occupational skill group is negative, and we can rule out effect sizes bigger than 0.008% or smaller than -2.3%.

[37]Our citizen group includes both U.S.-born and foreign-born citizens. We break these two groups out to further understand the effect, and because there may be measurement error in the citizenship question(Brown et al., 2018). Appendix Table (A6) indicates the effect on citizens is primarily driven by the effect on U.S.-born.

on the employment of citizen workers. The pattern of results provides further evidence that low-educated non-citizens working in low-skilled occupations are complementary in production to citizens working in high-skilled occupations.

5.1.1 Heterogeneity

The effect of SC on the average cost of labor is expected to be larger in sectors which have traditionally relied on unskilled immigrant labor, and if the effect on citizens is operating through complementarities in production, we would expect the employment effect on citizens to be larger in these unskilled-immigrant-reliant sectors. Figure (6) shows the distribution of the share of low-educated non-citizen workers by industry in 2005. The median industry has about 4% low-educated non-citizen workers as a fraction of its total workforce (shown in the black line), but it is clear from this figure that there are many industries that do not employ low-educated non-citizens, and some industries that very heavily rely on low-educated non-citizen labor. We estimate equation (1) by aggregating these finer industry categories into two groups: the first includes industries where the share of non-citizen workers in 2005 is above 4%, and the second includes industries where the share of non-citizen workers in 2005 is below 4%.[38] Table (3) shows the results across the two groups of sectors for citizens (Panels A and B) and for low-educated non-citizens (Panels C and D). Panel A shows that the effect of SC on the employment of citizen men is concentrated among workers in high-skilled occupations in sectors that have above median share of low-educated non-citizen workers. Specifically, the results in column 4 of Panel A suggest that SC reduces the employment of citizens in the third quartile of the occupational skill distribution by about 2.5% (23/928). In contrast, the effect of SC among workers in the third quartile of the occupational skill distribution in sectors employing less than the median share of low-

[38] We have compared the fraction of low-educated non-citizens across sectors with published statistics on the fraction of undocumented immigrants across sectors released by the PEW Center, and while the levels are slightly different, the rank is similar (Passel and Cohn, 2016).

educated non-citizen workers is smaller in magnitude and statistically insignificant (Panel B). Moreover, the decline in the employment of low-educated non-citizens is concentrated in sectors that rely more on them (column 3 of Panel C).

As an additional test, Figure (7) plots the effect of SC on sector-specific low-educated non-citizens' employment in the second occupational skill quartile (horizontal axis) against the effect on sector-specific citizens' employment in the third occupational skill quartile (vertical axis). To more easily compare the magnitude of the effect across sectors, we scale each β by the sector and demographic group specific mean employment, so the graph plots the percentage effects. This figure indicates a strong relationship between these two groups: in sectors where non-citizens are more affected by SC, citizens also experience larger reductions in employment. Moreover, sectors with very small impacts on low-educated non-citizens–Finance, Insurance and Real Estate; Mining; Agriculture; and Personal and Entertainment Services–show similarly small effects on citizens. All of this provides further evidence that the effect on citizens is operating through complementarities in production.[39]

We also explore the extent to which the effects of SC vary across areas based on the PUMA's pre-policy share of the likely undocumented population. This could be important if it is a proxy for the intensity of SC implementation across areas. We report in Table (4) results from estimating equation (1), interacting the SC variable with quartiles of the likely undocumented population distribution. The distribution of the likely undocumented population is calculated by dividing the low-educated non-citizen population in 2005 by the total population in 2005. For convenience, we only present results for citizens (Panel A) and low-educated non-citizens (Panel B). Focusing on the effects in the middle two-quartiles of the occupational skill distribution (columns 3 and 4), the results suggest that the effects of SC on low-educated non-citizens (Panel B) do not vary much based on intensity, although the

[39]The regression results that correspond to Figure (7) for citizens and low-educated non-citizens are significant only in a handful of industries. This is likely due to sample size limitations. These results are reported in Table Appendix (A7) and (A8).

effects are somewhat larger in areas with the highest share of likely undocumented workers. The effects on citizens (Panel A) follow a similar pattern with little evidence of heterogeneity, except for possibly larger effects in the highest quartile.

The lack of heterogeneity in the effects of SC by the initial share of the likely undocumented population suggests that SC was possibly not implemented uniformly across areas, and thus SC intensity may vary based on other dimensions. In fact, we provide evidence in Appendix B that "deportation risk", measured as total deportations between 2008-2014 divided by the population of low-educated non-citizens in 2005, is negatively related to the share of low-educated non-citizens in 2005.[40]

5.1.2 Effects on Women

We present a similar set of results for women in Appendix Table (A9). The results show little evidence that SC impacted the overall employment of either non-citizen or citizen women. None of the point estimates are significant, and most of them are smaller in magnitude than the comparable results for men. For example, the point estimate on citizen women in the middle to high occupation skill group is 1.3 and insignificant, compared to the negative and significant coefficient of 216 for men in this group. This may be because the vast majority of targeted immigrants under SC (roughly 96% of those deported) were men, and because women are less likely to work in sectors that intensively employ undocumented workers. We further investigate whether, for citizen women in the 50-75th percentile of the occupation skill distribution (where we found large, consistent declines in employment for men), there are negative effects in sectors that experienced large declines in male low-educated non-citizen employment. Appendix Figure (A2) plots the effect of SC on sector-specific *male* low-

[40]We report in Appendix Table (B1) results from estimating equation (1) by interacting the SC variable with quartiles of the deportation risk distribution. The results provide evidence that the effects of SC on low-educated non-citizen employment were larger in areas with higher deportation risk, but these results should be interpreted with caution since deportation risk is likely endogenous. More discussion on this analysis can be found in Appendix B.

educated non-citizens' employment in the second occupational skill quartile (horizontal axis) against the effect on sector-specific *female* citizens' employment in the third occupational skill quartile (vertical axis). The figure provides suggestive evidence that women may have been affected in sectors with large effects on the likely undocumented group, however, none of these point estimates for female citizens are statistically significant (results available upon request).[41] We conclude that SC primarily impacted male workers, but the results indicate that there may be some subgroups of citizen women that were also negatively affected.[42]

5.2 Robustness Checks

We conduct a number of robustness checks. First, while the relative speed of the rollout, and the fact that all U.S. counties eventually adopted SC, limits the possibility of internal migration as a result of SC; non-random migration as a response to SC could mask the true effects of the policy on employment outcomes. Table (5) shows the results of a model that estimates the effects of SC on the migration rates of citizens, non-citizens, and low-educated non-citizens. This migration outcome comes from information provided by the ACS about place of residence last year.[43] We use two different dependent variables: the migration rate for the entire population (Panel A), defined as $\frac{Migrants_{pt}}{Pop_{p2005}/100{,}000}$, and the male migration rate (Panel B), defined as $\frac{MaleMigrants_{pt}}{MalePop_{p2005}/100{,}000}$.

The results in Panel A show that SC did not have a significant effect on overall migration rates. This suggests that the main effects on the employment to population ratios are not driven by changes in the population, but instead they are driven by changes in employment. Similarly, we find no effects of SC on the migration rates of citizens, but there is

[41]We drop from this figure Health and Education Services because we find a very large and imprecisely estimated positive effect on citizen women in this sector, which makes the figure difficult to read when included.

[42]East and Velasquez (2018) document that high-educated citizen women with children were negatively affected by SC, likely due to changes in the cost of outsourcing household production due to a reduction in the supply of low-educated non-citizens.

[43]ACS provides information on place of residence at the MIGPUMA level (slightly larger than the PUMA level in our main analysis), which identifies the place of residence the year prior to the interview. We generate migration rates at the consistent MIGPUMA level using this information.

evidence of a decrease in migration rates of low-educated non-citizens.[44]

To further address this, we report estimates in Table (6) where the dependent variable has the population denominator fixed as the total PUMA population in 2000, prior to the implementation of SC. (The numerator across panels and columns are the same as before.) For convenience, we report the estimates on overall employment and on the employment of the two middle occupational skill quartiles, for specifications using contemporaneous (columns 1, 3 and 5) and fixed populations (columns 2, 4 and 6). Although the magnitude of the estimates using population in 2000 are smaller, the effect of SC relative to the mean employment-to-population ratio is remarkably similar whether we use contemporaneous population or population in the year 2000. This provides further evidence that changes in population are not driving the effects of SC on employment rates.

Second, since the effect of SC on employment might not be linear, Table (7) reports estimates from a specification where the dependent variable is the log of total employment, controlling for the log of population.[45] Again, the results are consistent with the main conclusion that SC negatively impacts the employment of workers in the middle two occupation groups. Moreover, for citizens in the middle to high occupational-skill group, and low-educated non-citizens in the low to middle occupational skill group, the magnitude of the effects are very similar to our baseline model (a 2.8% and 9.1% decline in employment, respectively, compared to our baseline estimates of 2.5% and 13.5%), although for non-citizens the estimates are no longer statistically significant.

Third, we test the robustness of the results to including additional, and more flexible, housing price controls. Panel A of Appendix Table (A10) reports our baseline results where we only control for the PUMA-level housing prices. In Panel B we add quadratic and cubic

[44]Note that this is a slightly different exercise than in Appendix Table (A5) which looks at the effect on population shares of non-citizens. Here, the analysis is on a sample of citizens and non-citizens that are surveyed by the ACS and move *within* the US.

[45]The ACS sample includes some PUMAs in which there are no employed non-citizens age 20-64, so the sample sizes are slightly smaller than the baseline models in Panels C and D. Estimating models with an inverse hyperbolic sine transformation yields very similar results to those in logs shown here.

housing price controls which control for the impact of the recession more flexibly. The inclusion of these controls has little effect on the coefficients for workers in the middle of the occupational skill distribution. This suggests that our estimates are not driven by the impact of the Great Recession on employment.[46]

Fourth, we test the robustness of the results using more restrictive definitions of "likely undocumented" than non-citizens with a high school degree or less. Panel B of Appendix Table (A12) proxies for the population of the likely undocumented immigrants by limiting the sample to non-citizens with a high school degree or less, who were born in Mexico or Central America and entered the U.S. after 1980. The results suggest that SC reduced their employment by about 7.5%. Using an alternative sample of non-citizens of Hispanic origin with a high school degree or less, who entered the U.S. after 1980 in Panel C, the results suggest that SC reduced the employment of this population by about 6.3%. Finally, Panel D approximates a method of identifying likely undocumented immigrants used by Borjas (2017).[47] Across the different samples, the negative impacts on employment are concentrated among workers in the second quartile of the occupational skill distribution, as in our main results.[48]

Some undocumented immigrants might choose not to participate in surveys conducted by the U.S. government (Passel and Cohn, 2011; Hoefer et al., 2012; Warren and Warren, 2013; Van Hook et al., 2014; Genoni et al., 2017; Brown et al., 2018). For instance, Genoni

[46]It is possible that the implementation of SC could have impacted housing prices directly, making them endogenous to the policy. We check the robustness of the results to alternative measures of housing prices in Appendix Table (A11). The first column of each panel repeats our main specification using housing prices at the PUMA-year level. The second column replaces the PUMA-level housing index with changes in housing prices at the state level over the same period, which is arguably more exogenous to the policy which is implemented at the PUMA-level. Finally, we use state housing prices excluding housing prices from the individual PUMA. The results across all these different specifications are very similar and strongly suggest that housing prices do not suffer from being a "bad control" (Angrist and Pischke, 2008).

[47]Details regarding the difference between our preferred measure and the Borjas measure can be found in Appendix A.3.

[48]We also estimated the effects of SC by citizenship status and across different racial and ethnic groups. Results in Appendix Table (A13) indicate that SC reduced the employment of Hispanic non-citizens but had little impact on non-citizens who are white. SC also impacted the employment of black non-Hispanic non-citizens, especially in the second quartile of the occupational skill distribution. There is little evidence of heterogeneity by race or ethnicity for citizens.

et al. (2017) provides evidence that between 2000 and 2005 U.S. surveys (such as the ACS) were more likely to undercount young, single, male, and less educated migrants. It is important to note, however, that such an undercount does not affect our estimates for citizen workers. Furthermore, although undercounting likely undocumented immigrants might lead to underestimating the effect of SC in levels, it should not affect the magnitude of effects relative to population means.[49]

5.3 Hours of Work and Wages

If, as expected, SC increased the labor costs of low-skilled non-citizen workers, we would expect the introduction of SC to have also impacted working hours and hourly wages. To examine this possibility, we look at several alternative outcome variables: 1) the log of usual hours of work per week, and 2) the log of hourly wages (calculated by dividing labor income in the past year by total hours worked in the past year and adjusting to constant 2014 dollars).

The results thus far provide strong evidence that the implementation of SC led to a decrease in the demand for citizens working in higher-skilled occupations. It is also possible that firms adjust to an increase in the labor cost of low-skilled labor by changing the number of hours their employees work. We test this hypothesis by replacing the dependent variable in equation (1) with the average log of usual hours of work per week calculated at the PUMA-industry-year level. Note this is collapsed at a different level than our main estimates and thus sample sizes differ compared to previous tables.[50] The results in Panel A of Table (8) indicate that SC is associated with a decline of about 0.7% in usual hours of work per week.

[49] The internal validity of our estimates for low-educated non-citizen workers would be affected if the number or type of undocumented immigrants that respond to the ACS survey is related to the implementation of SC. While previous studies estimate an overall 7.5% undercount of undocumented immigrants (Warren, 2014), we are unable to assess how the undercount varies in response to SC.

[50] The average log of usual hours of work at the PUMA-year level depends on the industrial composition in a given PUMA. Because SC likely changes the industry composition of employment, we calculate the average log of usual hours worked at the PUMA-industry-year level and we weight the regressions by the PUMA-industry employment for men in 2005.

For citizens we see this decline across all skill quartiles, although it is the largest in the first quartile. Interestingly, SC seems to have also negatively impacted the log hours of work of non-citizens and low-educated non-citizens in the lowest occupational skill quartile (Panels C and D, column 2).

Finally, in Table (9) we examine the impact of SC on average log hourly wages at the PUMA-industry-year level. If SC leads to a decrease in the demand for citizens working in higher-skilled occupations, we would expect SC to have a negative effect on their wages. The results in Panels A and B provide suggestive evidence that SC is associated with a decrease in average hourly wages, but the effects are not statistically significant.[51] The effect of SC on the hourly wages of workers in lower-skilled occupations is theoretically ambiguous because a decrease in the supply of low-skilled undocumented immigrants raises their marginal productivity leading to an increase in their wage, but the increase in the expected labor cost of firms puts a downward pressure on wages. We see a negative coefficient in the second quartile of occupational skill (Panel A), although this effect again is not statistically significant.

5.4 Discussion

Although this is the first paper to estimate the labor market effects of SC, it is informative to compare our findings to the labor market effects of another enforcement policy: 287(g) agreements. Using a contiguous counties approach, Bohn and Santillano (2017) found that the introduction of 287(g) agreements did not have a significant effect on overall employment, but there was a reduction in some industries that employ many immigrants of similar magnitude to our estimated effects. For instance, they found that 287(g) reduced the employment in administrative services by about 7%. Taking a more traditional difference-in-difference approach, Pham and Van (2010) found that 287(g)s reduced overall employment by about

[51]Note that detecting effects on wages for citizens in higher-skilled occupations is complicated by the fact that SC is associated with a decrease in their average hours of work which is likely to push their hourly wages up.

1-2%, which is similar to our estimated effects of SC on the overall employment rate. Ours is the first study to estimate the labor market impacts of an immigration enforcement policy by citizenship status and across the occupational skill distribution. As a result, we cannot compare our estimates on these groups with the potential effects of 287(g) on these populations.

A large literature on immigration has estimated the effect of immigration inflows on natives' labor market outcomes. Our empirical strategy not only enables us to identify the reduced form effect of SC on the employment of citizen and non-citizen workers, but it also allows us, under some assumptions, to estimate the relationship between non-citizen and citizen employment. The assumption needed for such analysis is that SC only impacts citizen employment through its effect on non-citizen employment. This is analogous to assuming that SC is a valid instrument for estimating the effect of non-citizen workers on citizen employment. Under this assumption, we can calculate the relationship between non-citizen and citizen employment as the ratio of the coefficient in Panel B of Table (2) (the reduced form effect) and the coefficient in Panel C (the first stage). This exercise suggests that for a 10% reduction in employment of non-citizens due to SC, citizen employment is reduced by 1.5%.[52]

There are several reasons why one might expect that the effect of SC on the employment of natives may differ from existing estimates of the relationship between immigrants and native employment. First, our variation utilizes a decrease in the supply of low-skilled immigrants instead of an increase in their supply. This is important because firms may adjust differently in the short-run to removing part of their labor pool, compared to adjusting to an inflow of new untrained immigrants. In fact, previous findings in the literature based on quasi-experimental variation in the inflow of immigrants indicate that there is only a small

[52]This estimate should be interpreted with caution since the first stage has relatively low power, with an F-stat of 4.477. Moreover, if SC changed the number or type of undocumented immigrants that respond to the ACS, an underestimate of the first stage would lead to an upwardly biased estimate of the relationship between the employment of citizens and non-citizens.

(if any) relationship between the employment of immigrants and natives. For example, using linked employee-employer data Foged and Peri (2016) found little evidence that the inflow of immigrants negatively affects the employment outcomes of low-skilled natives. Likewise, Friedberg (2001) found no significant effects on the employment or wages of native workers in Israel after a massive immigration wave from the former Soviet Union, and Pischke and Velling (1997) found no effects on the employment of native German workers in response to an increase in the foreign-born share.

Second, SC targeted the undocumented population who, because of their legal status, are likely to have lower reservation wages compared to similarly skilled native men and are thus not perfect substitutes to native employment. Although Dustmann et al. (2017) found that a 1 percentage point increase in the share of Czech migrants commuting to work in neighboring German cities is associated with a 0.9% decrease in local native employment, they show that the effect is driven by previously non-employed workers and not by substituting currently employed Germans.

Third, while previous papers have focused on the substitution between immigrants and similarly skilled domestic workers, we use our variation to estimate the relationship between non-citizens and citizens working in different parts of the skill distribution. Consistent with our evidence of complementarity between low-skill non-citizens and high-skilled citizens, Beerli and Peri (2015) found that the inflow of EU immigrants to Switzerland: 1) complemented the employment of highly educated native workers, 2) negatively impacted the employment of middle educated natives, and 3) had no impact on the employment of low-skilled natives.

Our results are more easily compared with two recent papers that estimate the effect of *historical* migration outflows on labor market outcomes of natives. Lee et al. (2017) study the effect of the repatriation of Mexican-born migrants living in the U.S. between 1930 and 1940. Consistent with our results, repatriations had no positive effect on the employment of natives, and may have depressed their employment and wages. Importantly, the authors provide evidence of complementarities between low-skilled repatriated Mexicans and high-skill natives. Clemens et al. (2018) analyze the impact of excluding almost half a million Mexican Bracero agricultural workers from the U.S. on native employment and wages. They find little effects on the labor market outcomes of domestic farm workers and provide evidence that this lack of substitution was due to employers adopting new technologies and changing their crops, suggesting that firms do not simply substitute immigrant and domestic labor and might adjust to a reduction in the supply of immigrants by endogenously changing technology or products.[53]

6 Conclusion

Secure Communities, one of the largest interior federal immigration enforcement policies over the last decade, resulted in the deportation of almost half a million individuals during 2008-2015. This is the first paper to estimate the effects of the SC program on the labor market outcomes of both citizen and non-citizen workers. We find that SC caused a significant reduction in the employment of non-citizens and that this effect was highly concentrated among low-educated male non-citizens, who are more likely to be undocumented.

In addition to estimating the direct effect of SC on non-citizen employment, we also use the rollout of the SC program as quasi-experimental variation to estimate the effect of an exogenous change in non-citizen employment on the employment of citizens across the occupational skill distribution. Our findings indicate that SC not only had a negative effect on employment for male non-citizens, but also it negatively impacted the employment of *citizen* men. We hypothesize that this spillover effect onto citizens is due to complementarities in production and provide suggestive evidence to support this mechanism. Applying

[53] Ager and Hansen (2018) found that the introduction of nationality-specific immigration quotas in the 1920s, which reduced immigration flows, had a negative effect on the earnings of white natives, and benefited the earnings of black workers in the most affected areas.

our local-level estimates to the national population of male citizens, we estimate that SC reduced the employment of male citizens by approximately 300,000.

These findings are consistent with a model of labor markets exhibiting search frictions, as in Chassamboulli and Peri (2015): reducing the number of undocumented immigrants is expected to increase the average labor costs of firms and lead firms to reduce demand for both low- and high-skilled workers. Our findings suggest that immigration policies aimed at reducing the number of undocumented immigrants should take into account the potential negative spillover effects on the labor market outcomes for citizens in high-skilled occupations.

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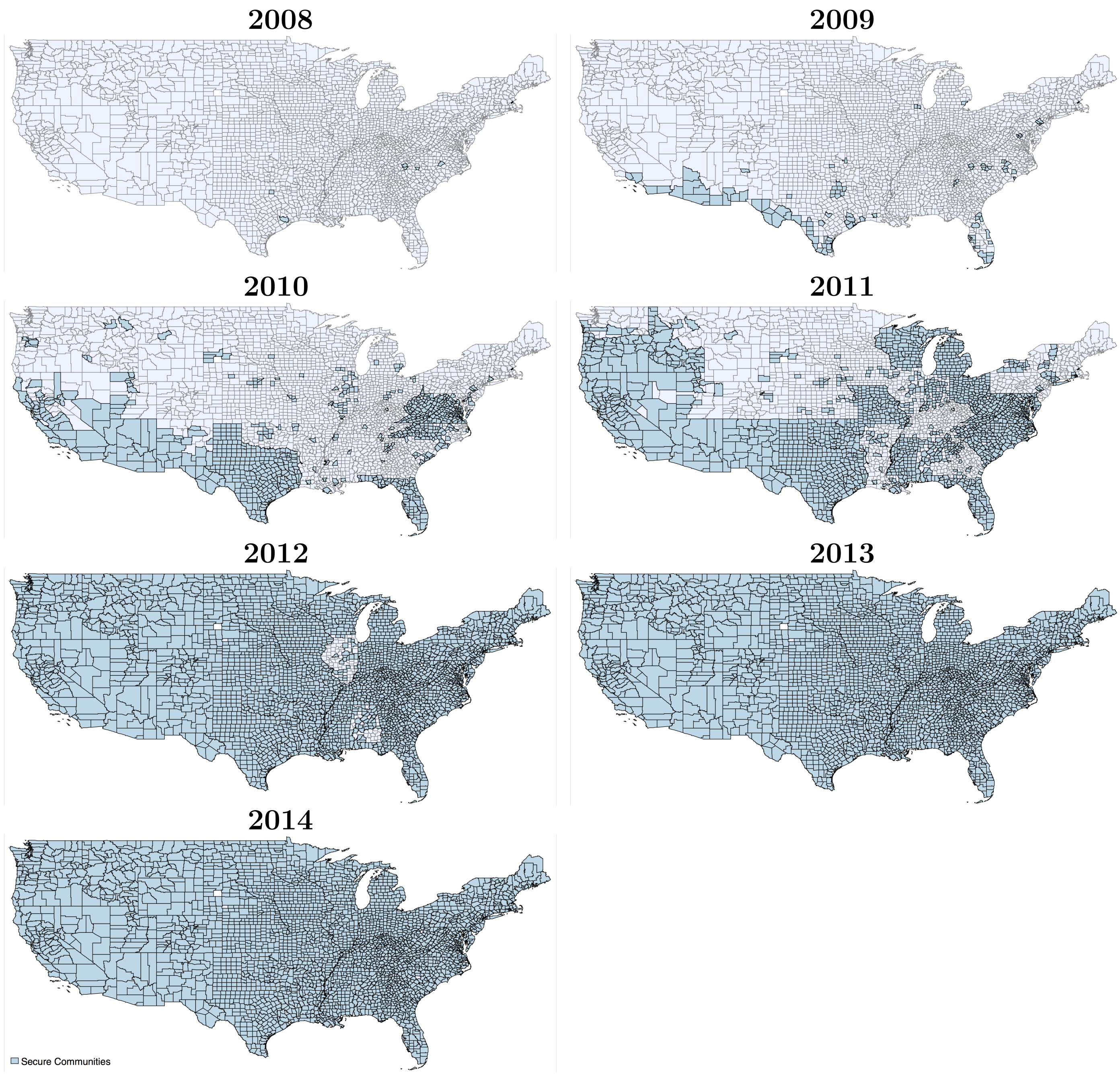
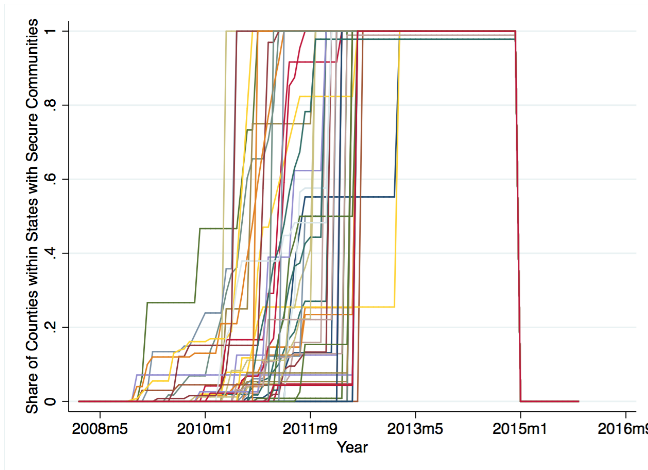
7 Figures

Figure 1: Rollout of Secure Communities by Year



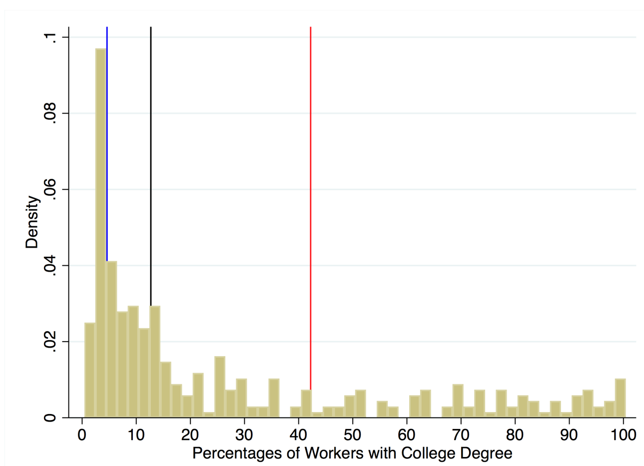
Notes: Counties that had adopted the Secure Communities based on December of each year are shaded. See text for sources.

Figure 2: Rollout of Secure Communities across Counties within States



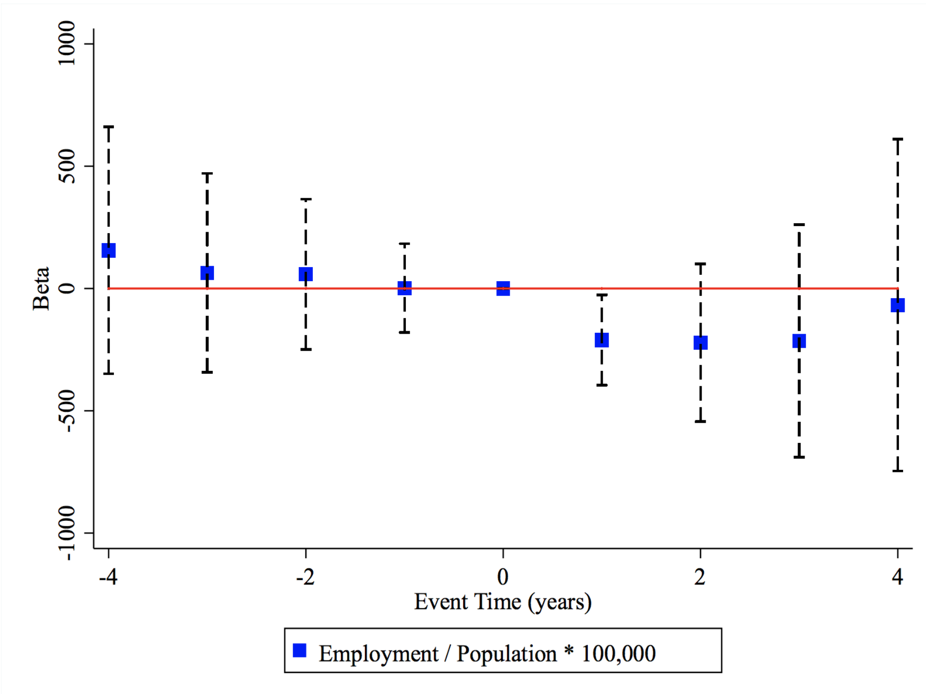
Notes: The above figure plots the phase in of Secure Communities within States. In January of 2015 SC was replaced by the Priority Enforcement Program, by the Obama administration.

Figure 3: Distribution of Skill Intensity Across Occupations



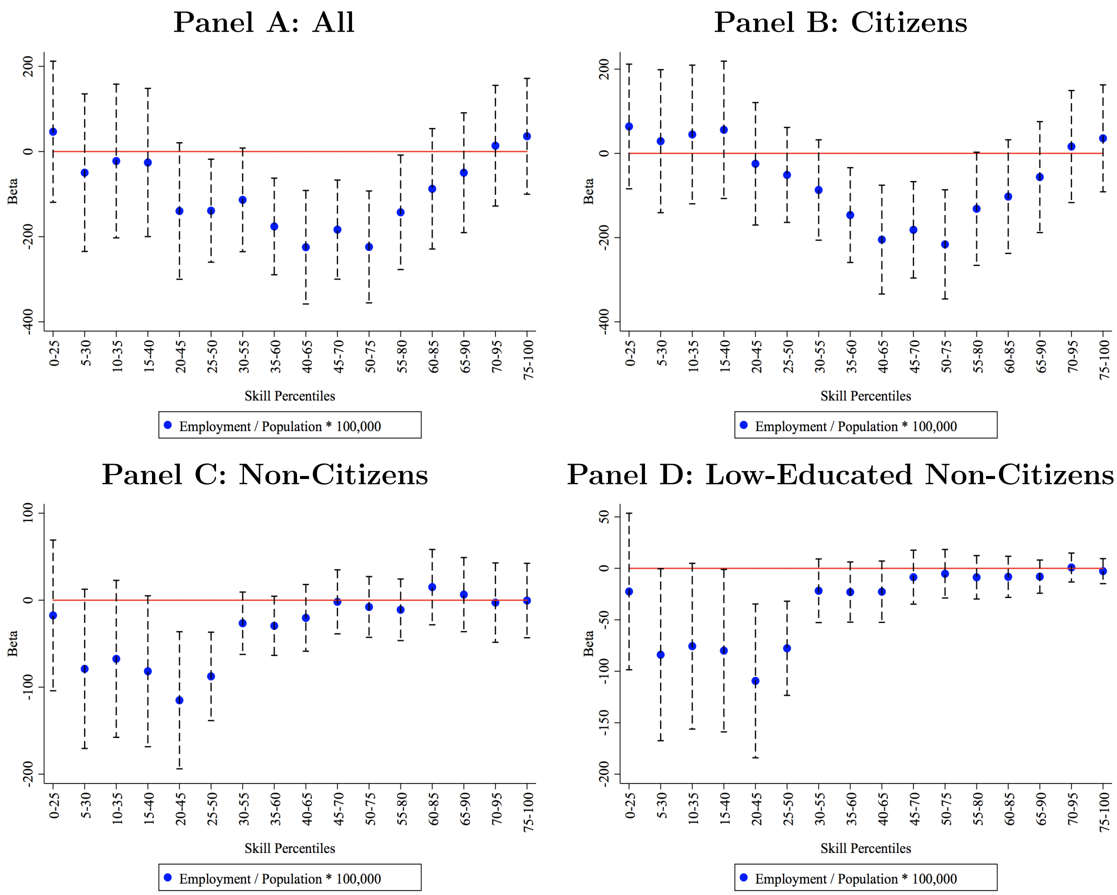
Notes: The above figure plots density of skill intensity across occupations as measured by the share of workers within an occupation with a college degree. This is estimated using the 2005 American Community Survey (ACS). The black bar indicates the occupation with the median skill (12.7) the blue and red bars depict the 25th and 75th percentile skill occupations respectively (4.6 and 42.2).

Figure 4: Effect of SC on Total Male Employment



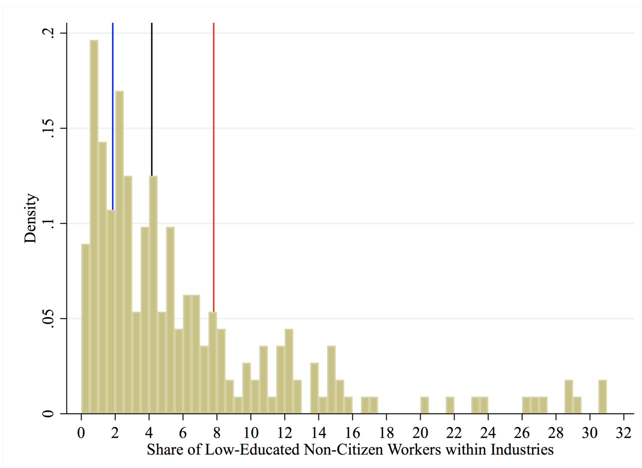
Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. The figure plots the marginal effect of SC on total employment. Total employment is divided by PUMA population and multiplied by 100,000. Event time is measured in years and all coefficients are relative to the year prior to SC adoption in each county. The blue dots show the marginal effects in event time and the dashed black lines show the 95% confidence intervals. We include our full set of controls, including year and PUMA fixed effects, PUMA-year linear trends, policy controls related to 287(g) programs, labor demand controls, and housing price controls. We weight the results by the PUMA population in 2000 and cluster the standard errors at the PUMA level.

Figure 5: Effect of SC on Men's Employment Across the Skill Distribution



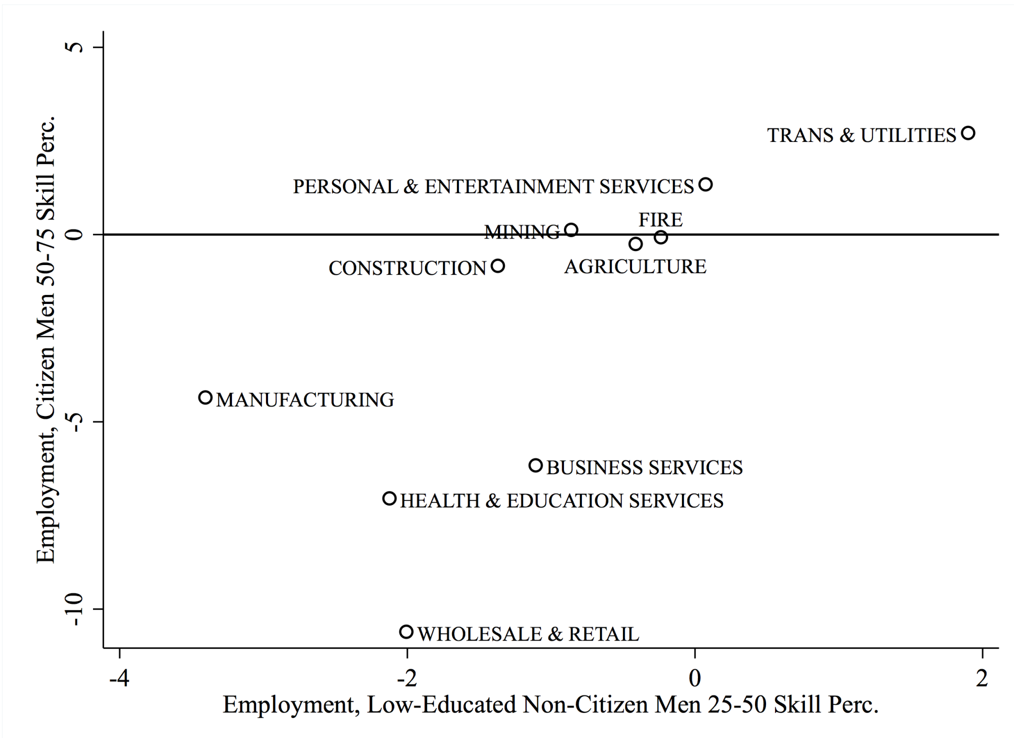
Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. We include our full set of preferred controls, including year and PUMA fixed effects, PUMA-year linear trends, policy controls related to 287(g) programs, labor demand controls, and housing price controls. The blue dots show the marginal effects and the dashed black lines show the 95% confidence intervals. The marginal effects are from "moving window" style regressions with bin sizes of 25 percentage points. The estimate on the far left is for occupations below the 25th percentile in skill, the next estimate to the right is for occupations from the 5th to 30th percentile in skill, and so on, up until the far right estimate for the 75th to 100th percentile in skill. We weight the results by the PUMA population in 2000 and standard errors are clustered at the PUMA level.

Figure 6: Distribution of Low-Educated Non-Citizen Across Industries



Notes: The above figure plots density of low-educated non-citizen labor intensity across industries as measured by the 2005 American Community Survey (ACS). The black bar indicates the industry with the median low-educated non-citizen labor intensity (4.16) the blue and red bars depict the 25th and 75th percentile industries, respectively (1.86 and 7.87).

Figure 7: Effect of SC on Men's Employment Across Sectors



Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. The horizontal axis plots the percent effect for each sector on the sample of low-educated non-citizen men in the 25-50th occupational skill percentiles. The vertical axis plots the percent effect for each sector on the sample of citizen men in the 50-75th occupational skill percentiles. The percent effect is calculated by taking the β from equation (1) for each demographic and sector group, and then dividing this β by the sample mean employment to population ratio for each demographic and sector. We include our full set of preferred controls, including year and PUMA fixed effects, PUMA-year linear trends, policy controls related to 287(g) programs, labor demand controls, and housing price controls. The sector "FIRE" stands for "Finance, Insurance and Real Estate". We weight the results by the PUMA population in 2000 and standard errors are clustered at the PUMA level.

8 Tables

Table 1: Summary Statistics

Employment / Population * 100,000 by Demographic Group	
All Men	37422.36
Male Citizens	34088.03
Male Non-Citizens	3333.93
Male Low-Educated Non-Citizens	2171.49
All Women	33697.10
Female Citizens	31725.82
Female Non-Citizens	1970.97
Female Low-Educated Non-Citizens	1122.27
PUMA-Year Variables	
SC	0.35
Jail 287(g)	0.04
Task 287(g)	0.01
Housing Prices	139.85
Shift-share- all working-age adults	10200000
Shift-share- foreign-born working-age adults	10400000
Shift-share- working-age adults with more than a high-school diploma	10500000
Shift-share- working-age adults with a high-school diploma or less	9957070

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) individuals. We weight the results by the PUMA population in 2000.

Table 2: Effect of SC on Employment by Citizenship Status, Men

	Dep. Var: Employment/Population				
	All	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
A: Total					
β: SC	-280.806***	46.472	-138.978**	-224.073***	35.773
	(97.158)	(84.567)	(61.709)	(67.041)	(69.392)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	37423.09	11381.03	7838.75	8719.45	9483.87
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
B: Citizen					
β: SC	-167.768*	63.841	-51.213	-216.101***	35.705
	(98.875)	(75.489)	(57.518)	(66.092)	(64.762)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	34091.44	9795.92	7085.67	8321.58	8888.28
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
C: Non-Citizen					
β: SC	-113.230*	-17.472	-87.589***	-7.776	-0.392
	(61.308)	(44.187)	(25.916)	(17.827)	(21.817)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	3331.25	1585.08	752.95	397.82	595.40
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
D: Low-Educated Non-Citizen					
β: SC	-108.143**	-22.500	-77.684***	-5.250	-2.709
	(51.492)	(38.809)	(23.337)	(12.036)	(6.194)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	2170.94	1367.84	576.90	183.29	42.91
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. The dependent variable in column 1 is total employment by PUMA and year, and in columns 2-5 the dependent variable is employment by occupational skill intensity for each skill quartile. In all specifications employment is divided by PUMA population and multiplied by 100,000. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Panel A includes the full sample, and Panels B-D restrict the sample to citizens, non-citizens, and low-skill non-citizens, respectively. All regressions are weighted by the PUMA population in 2000. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table 3: Effect of Immigration Laws on Employment by Sector, Men

	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
A: Citizen, Sector w/ LENCshr >4%					
β: SC	-8.558	10.402	-3.018	-23.252**	7.311
	(19.503)	(12.478)	(9.134)	(9.655)	(6.671)
Y mean	3605.13	1365.57	859.96	928.31	451.29
Observations	45615	45615	45615	45615	45615
	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
B: Citizen, Sector w/ LENCshr <4%					
β: SC	-13.071	1.593	-2.982	-11.698	0.016
	(14.841)	(6.530)	(6.461)	(7.646)	(9.588)
Y mean	2503.30	468.21	435.58	563.50	1036.01
Observations	55457	55457	55457	55457	55457
	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
C: Low-Educated Non-Citizen, Sector w/ LENCshr >4%					
β: SC	-23.556***	-8.668	-13.600***	-0.793	-0.494
	(9.089)	(6.870)	(4.137)	(1.965)	(0.660)
Y mean	353.49	225.80	98.26	25.70	3.73
Observations	45615	45615	45615	45615	45615
	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
D: Low-Educated Non-Citizen, Sector w/ LENCshr <4%					
β: SC	3.713	4.692**	-1.029	0.079	-0.030
	(3.037)	(2.318)	(1.407)	(1.044)	(0.745)
Y mean	64.02	37.98	13.63	8.60	3.81
Observations	55457	55457	55457	55457	55457

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. Individuals who report no industry are dropped from the sample. The dependent variable in column 1 is total employment by PUMA and year, and in columns 2-5 the dependent variable is employment by occupational skill intensity for each skill quartile. In all specifications employment is divided by PUMA population and multiplied by 100,000. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Panel A-B restrict the sample to citizens, and Panels C-D restrict the sample to low-educated non-citizens. All regressions are weighted by the PUMA population in 2000. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table 4: Effect of SC on Employment by Low-Educated Non-Citizen Population Intensity, Men

	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: Citizen					
SC * Below 25th Perc (.01) Low-Educated Non-Citizen	-256.039	93.379	-55.467	-183.690*	-110.262
	(173.314)	(151.400)	(106.797)	(103.692)	(106.332)
SC * 25th-50th Perc (.01-.02) Low-Educated Non-Citizen	-79.583	86.620	-33.291	-238.453**	105.541
	(140.464)	(109.267)	(87.536)	(94.751)	(94.529)
SC * 50th-75th Perc (.02-.04) Low-Educated Non-Citizen	-78.395	138.517	-75.375	-103.448	-38.089
	(143.470)	(109.186)	(89.391)	(99.621)	(94.264)
SC * Above 75th Perc (.04) Low-Educated Non-Citizen	-258.893*	-36.889	-41.911	-315.674***	135.581
	(148.167)	(106.302)	(81.732)	(99.898)	(91.829)
Y mean Below P 25	35382.77	35382.77	35382.77	35382.77	35382.77
Y mean P 25 - P 50	35078.25	35078.25	35078.25	35078.25	35078.25
Y mean P 50 - P 75	33604.34	33604.34	33604.34	33604.34	33604.34
Y mean Above P 75	29467.66	29467.66	29467.66	29467.66	29467.66
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
B: Low-Educated Non-Citizen					
SC * Below 25th Perc (.01) Low-Educated Non-Citizen	-70.526	-3.171	-55.626**	-6.404	-5.325
	(46.779)	(38.179)	(23.995)	(12.432)	(5.641)
SC * 25th-50th Perc (.01-.02) Low-Educated Non-Citizen	-92.299*	-32.789	-51.020*	-5.930	-2.560
	(53.431)	(42.119)	(28.033)	(13.947)	(7.045)
SC * 50th-75th Perc (.02-.04) Low-Educated Non-Citizen	-20.645	4.235	-17.242	-8.547	0.908
	(65.222)	(53.158)	(32.364)	(15.679)	(7.525)
SC * Above 75th Perc (.04) Low-Educated Non-Citizen	-219.492**	-49.494	-164.548***	-1.153	-4.297
	(104.158)	(82.239)	(48.108)	(27.408)	(12.655)
Y mean Below P 25	371.45	371.45	371.45	371.45	371.45
Y mean P 25 - P 50	873.10	873.10	873.10	873.10	873.10
Y mean P 50 - P 75	1962.19	1962.19	1962.19	1962.19	1962.19
Y mean Above P 75	5539.56	5539.56	5539.56	5539.56	5539.56
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. The dependent variable in column 1 is total employment by PUMA and year, and in columns 2-5 the dependent variable is employment by occupational skill intensity for each skill quartile. In all specifications employment is divided by PUMA population and multiplied by 100,000. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Panel A restricts the sample to citizens, and Panel B restricts the sample to low-skill non-citizens. Models are weighted by the PUMA population in 2000. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table 5: Effect of SC on PUMA Migration Rates

	All	Citizens	Non-Citizens	Low-Educated Non-Citizens
A: All				
SC	-14.528	13.805	-28.146	-28.439**
	(97.832)	(90.134)	(20.744)	(13.724)
PUMA-Year Trends	X	X	X	X
287g	X	X	X	X
Labor Demand	X	X	X	X
Housing Prices	X	X	X	X
Y mean	5380.76	4976.40	404.41	184.23
Observations	7336	7336	7336	7336
B: Males				
SC	-129.919	-94.065	-36.161	-43.395**
	(114.834)	(105.904)	(28.003)	(19.276)
PUMA-Year Trends	X	X	X	X
287g	X	X	X	X
Labor Demand	X	X	X	X
Housing Prices	X	X	X	X
Y mean	5521.82	5070.79	450.97	214.82
Observations	7336	7336	7336	7336

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) individuals. The dependent variable in column 1 is total migration rate at the PUMA and year level, in columns 2-4 the dependent variable measures migration rates for citizens, non-citizens and low-educated non-citizens, respectively. Panel A shows total migration rates and Panel B restrict the sample to males. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. All regressions are weighted by the PUMA population in 2000. Standard errors are clustered by PUMA and are reported in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 6: Effect of SC on Employment, Robustness to Fixed Population, Men

	All		$25 < skill < 50$		$50 < skill < 75$	
A: Total						
β: SC	-280.806***	-115.995	-138.978**	-80.681*	-224.073***	-122.500***
	(97.158)	(75.774)	(61.709)	(41.224)	(67.041)	(44.173)
PUMA-Year Trends	X	X	X	X	X	X
287g	X	X	X	X	X	X
Labor Demand	X	X	X	X	X	X
PUMA Housing Prices	X	X	X	X	X	X
Time-Varying Pop	X		X		X	
Fixed Pop		X		X		X
Y mean	37423	24192	7839	5054	8719	5663
Observations	9160	9160	9160	9160	9160	9160
	All		$25 < skill < 50$		$50 < skill < 75$	
B: Citizen						
β: SC	-167.768*	-63.188	-51.213	-24.937	-216.101***	-118.580***
	(98.875)	(71.192)	(57.518)	(37.940)	(66.092)	(43.498)
PUMA-Year Trends	X	X	X	X	X	X
287g	X	X	X	X	X	X
Labor Demand	X	X	X	X	X	X
PUMA Housing Prices	X	X	X	X	X	X
Time-Varying Pop	X		X		X	
Fixed Pop		X		X		X
Y mean	34091	22003	7086	4559	8322	5401
Observations	9160	9160	9160	9160	9160	9160
	All		$25 < skill < 50$		$50 < skill < 75$	
C: Non-Citizen						
β: SC	-113.230*	-52.879	-87.589***	-55.621***	-7.776	-3.758
	(61.308)	(42.594)	(25.916)	(17.667)	(17.827)	(12.157)
PUMA-Year Trends	X	X	X	X	X	X
287g	X	X	X	X	X	X
Labor Demand	X	X	X	X	X	X
PUMA Housing Prices	X	X	X	X	X	X
Time-Varying Pop	X		X		X	
Fixed Pop		X		X		X
Y mean	3331	2189	753	495	398	262
Observations	9160	9160	9160	9160	9160	9160
	All		$25 < skill < 50$		$50 < skill < 75$	
D: Low-Educated Non-Citizen						
β: SC	-108.143**	-53.090	-77.684***	-49.024***	-5.250	-1.860
	(51.492)	(35.345)	(23.337)	(15.634)	(12.036)	(8.033)
PUMA-Year Trends	X	X	X	X	X	X
287g	X	X	X	X	X	X
Labor Demand	X	X	X	X	X	X
PUMA Housing Prices	X	X	X	X	X	X
Time-Varying Pop	X		X		X	
Fixed Pop		X		X		X
Y mean	2171	1422	577	379	183	120
Observations	9160	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. The dependent variable in columns 1-2 is total employment by PUMA and year, and in columns 3-6 the dependent variable is employment by occupational skill intensity for the middle two occupational skill quartiles. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Panel A includes the full sample, and Panels B-D restrict the sample to citizens, non-citizens, and low-skill non-citizens, respectively. Specifications in the odd columns (1, 3, 5) divide employment by time-varying working-age PUMA population and multiply by 100,000. Specifications in the even columns (2, 4, 6) divide employment by total PUMA population as of 2000 and multiply by 100,000. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table 7: Effect of SC on Log of Employment Counts, Men

	Dep. Var: Employment/Population				
	All	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
A: Total					
β: SC	-0.008***	0.004	-0.020**	-0.027***	0.006
	(0.003)	(0.009)	(0.008)	(0.008)	(0.008)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	11.34	10.10	9.76	9.86	9.88
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
B: Citizen					
β: SC	-0.005	0.006	-0.010	-0.028***	0.007
	(0.003)	(0.009)	(0.009)	(0.009)	(0.008)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	11.24	9.93	9.65	9.81	9.82
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
C: Non-Citizen					
β: SC	-0.009	0.040	-0.044	-0.066	0.039
	(0.026)	(0.043)	(0.052)	(0.059)	(0.049)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	8.43	7.69	7.05	6.53	6.82
Observations	9008	8347	7480	7039	7702
	Dep. Var: Employment/Population				
	All	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
D: Low-Educated Non-Citizen					
β: SC	-0.003	0.030	-0.091	-0.167*	0.047
	(0.038)	(0.044)	(0.060)	(0.089)	(0.186)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	7.94	7.56	6.87	6.07	5.41
Observations	8579	8070	6805	5155	2615

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. The dependent variable in columns 1-2 is total employment by PUMA and year, and in columns 3-6 the dependent variable is employment by occupational skill intensity for the middle two skill quartiles. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Panel A includes the full sample, and Panels B-D restrict the sample to citizens, non-citizens, and low-skill non-citizens, respectively. All regressions are weighted by the PUMA population in 2000. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table 8: Effect of SC on Log of Usual Hours Worked, Men

	Dep. Var: Log Usual Hours Worked				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
A: Total					
β^1: SC	-0.007***	-0.014***	-0.004	-0.005	-0.004
	(0.002)	(0.004)	(0.005)	(0.004)	(0.003)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	3.66	3.61	3.61	3.69	3.74
Observations	99945	76655	84618	89053	78478
	Dep. Var: Log Usual Hours Worked				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
B: Citizen					
β^1: SC	-0.007***	-0.015***	-0.009	-0.005	-0.003
	(0.002)	(0.005)	(0.006)	(0.004)	(0.003)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	3.66	3.60	3.60	3.70	3.74
Observations	99750	75737	83967	88713	78159
	Dep. Var: Log Usual Hours Worked				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
C: Non-Citizen					
β^1: SC	-0.011	-0.021**	-0.002	-0.033	-0.001
	(0.008)	(0.011)	(0.017)	(0.022)	(0.013)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	3.67	3.65	3.64	3.69	3.72
Observations	57312	34335	27778	22121	23987
	Dep. Var: Log Usual Hours Worked				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
D: Low-Educated Non-Citizen					
β^1: SC	0.001	-0.017	0.018	-0.045	0.169
	(0.013)	(0.012)	(0.015)	(0.028)	(0.119)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	3.65	3.66	3.65	3.69	3.63
Observations	43114	31117	22034	11738	4215

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. The dependent variable in column 1 is PUMA by year by sector average of the log of usual hours worked for the full sample, in columns 2-5 the dependent variable is PUMA by year by sector average of the log of usual hours worked by occupational skill intensity for each skill quartile. These averages are computed by collapsed the individual level ACS data to the PUMA-year-sector averages using the individual survey weights. All specifications include year, PUMA, and sector fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Panel A includes the full sample, and Panels B-D restrict the sample to citizens, non-citizens, and low-skill non-citizens, respectively. Regressions are weighted by the PUMA-year-sector employment for men (and by skill quartile for columns 2-5) in 2005. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table 9: Effect of SC on Log of Hourly Wages, Men

	Dep. Var: Log Wages				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
A: Total					
β^1: SC	0.002	0.006	-0.004	-0.004	-0.008
	(0.006)	(0.008)	(0.009)	(0.009)	(0.009)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	3.29	2.90	3.01	3.28	3.74
Observations	98975	75425	82678	85164	75587
	Dep. Var: Log Wages				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
B: Citizen					
β^1: SC	0.002	0.011	-0.007	-0.004	-0.005
	(0.006)	(0.009)	(0.009)	(0.009)	(0.010)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	3.31	2.92	3.03	3.29	3.75
Observations	98620	74291	81573	84661	75218
	Dep. Var: Log Wages				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
C: Non-Citizen					
β^1: SC	0.019	0.013	0.006	0.029	0.018
	(0.017)	(0.022)	(0.024)	(0.041)	(0.029)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	3.04	2.63	2.71	3.05	3.68
Observations	53296	32236	24646	17375	21317
	Dep. Var: Log Wages				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
D: Low-Educated Non-Citizen					
β^1: SC	0.018	-0.011	0.006	-0.032	0.064
	(0.022)	(0.022)	(0.032)	(0.070)	(0.193)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	2.70	2.61	2.65	2.80	3.17
Observations	40211	29602	20134	9006	3041

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. The dependent variable in column 1 is PUMA by year by sector average of the log of hourly wages for the full sample, in columns 2-5 the dependent variable is PUMA by year by sector average of the log of hourly wages by occupational skill intensity for each skill quartile. These averages are computed by collapsed the individual level ACS data to the PUMA-year-sector averages using the individual survey weights. All specifications include year, PUMA, and sector fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Panel A includes the full sample, and Panels B-D restrict the sample to citizens, non-citizens, and low-skill non-citizens, respectively. Regressions are weighted by the PUMA-year-sector employment for men (and by skill quartile for columns 2-5) in 2005. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Appendix For Online Publication

A Data Description and Additional Results

A.1 PUMA-Year Control Variables

In the regressions, we include controls for labor demand as well as housing prices. We construct four Bartik-style measures of labor demand that correspond to the following four demographic groups: 1) all working-age adults, 2) foreign-born working-age adults, 3) working-age adults with more than a high-school diploma, and 4) working-age adults with a high-school diploma or less. For each group, we calculate the PUMA-level employment by industry, as a fraction of total PUMA employment in 2005. We then apply to these industry shares the changes in national employment for the full national sample of working age adults for each industry over time, to obtain a measure of predicted changes in local labor demand. The housing prices information comes from the Federal Housing Finance Agency and is available at the county by year level, which we aggregate up to the PUMA level using a similar weighting process as described in the main text for the SC variable.

We also include controls for the presence of 287(g) Agreements. As described in the main text, 287(g) agreements were similar to SC, but 287(g)s were optional agreements law enforcement agencies could choose to enter into with the federal government. Start and end dates for all 287(g) agreements came from reports published by ICE, the Department of Homeland Security, the Migration Policy Institute, as well as Kostandini et al. (2013), and various news articles. There were three types of 287(g) agreements and this information also allowed us to determine which type of agreement was in place. The "Task Force" model permitted trained law enforcement officials to screen individuals regarding their immigration status during policing operations, and arrest individuals due to suspected immigration violations. The "Jail" model allowed screening of immigration status for individuals upon being booked in state prisons or local jails and was more similar to SC. A third "Hybrid" model includes both the Task Force and Jail models.[54] Because the number of 287(g)s changed during our sample period, as shown in Figure (A1), controlling for these policies is potentially important.

A.2 TRAC Data Description

Data on deportations under SC comes from the Transactional Records Access Clearinghouse at Syracuse University. TRAC obtained these data from ICE through a series of Freedom of Information Act requests. The data contain individual-level records of each deportation under SC, beginning in November 2008 and continuing through the end of SC in 2014. They also include information on deportations under the temporary Priority Enforcement Program through January 2017. The county given in this file is the county of apprehension, the date is the date of removal. Because deportations do not happen immediately upon apprehension, there is a lag between the initial apprehension and the date recorded in our data. For each individual, we have information on the deportation proceedings as well as various demographics, including age, gender, and country of citizenship. The data also contain information on the criminal background of the deportee, including their most serious criminal conviction (MSCC).

TRAC provides a similar file of records for ICE detainers under all programs, but we cannot separately identify which were done under SC. ICE issues detainers when there is a fingerprint match between an arrestee and the IDENT biometric database maintained by DHS and ICE believes the person has committed an immigration violation. While these data contain the date the detainer was prepared by ICE, which is close to the date of apprehension, we choose to focus on deportations because these records are restricted to the Secure Communities program. Furthermore, the preparation of a detainer does not guarantee that ICE eventually took custody.

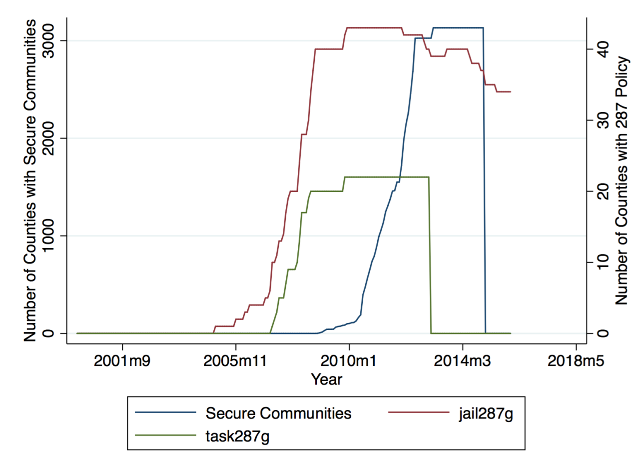
[54] Background information on 287(g)s is obtained from Capps et al. (2011).

A.3 Measuring the Non-Citizen Population

Our preferred measure of the population most directly affected by SC is foreign-born non-citizens with a high school degree or less. We view this as a proxy for those most likely to be undocumented, which we cannot directly observe in the ACS, as it does not include questions about immigration status.

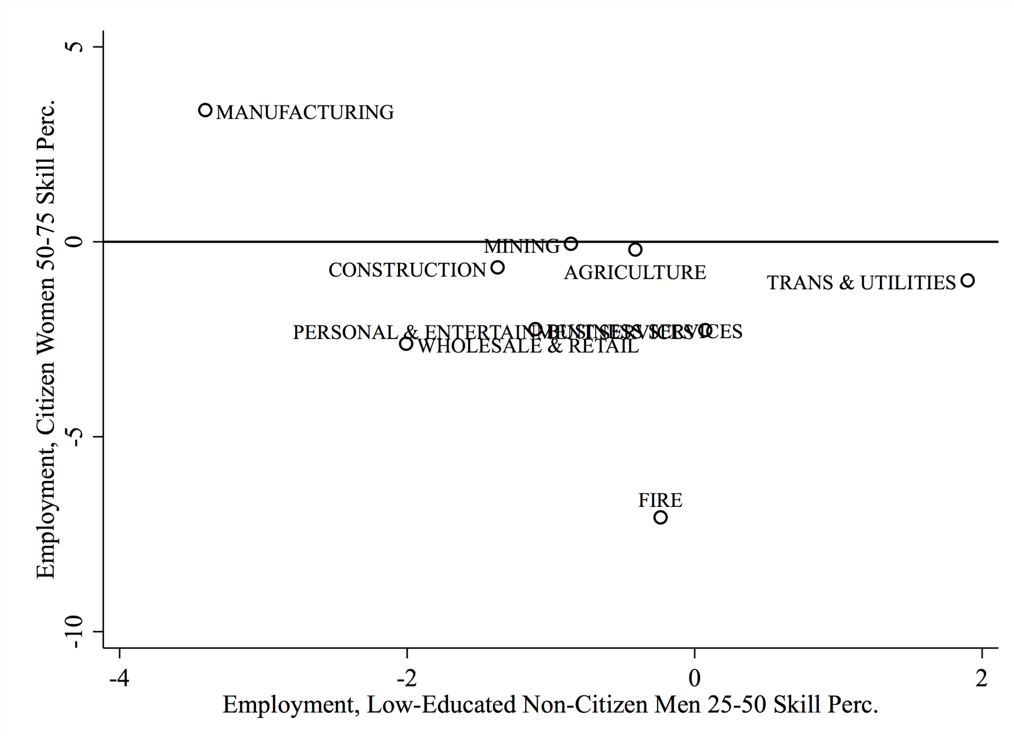
An alternative measure proposed by Borjas (2017) cannot be directly applied to our sample due to data limitations. Borjas (2017) describes an algorithm to define legal immigrants in the CPS, and then considers all others as likely undocumented. While he also applies his algorithm to later years of the ACS, our use of pre-2008 samples of the ACS limits our ability to fully replicate this method. We approximate this method by defining likely undocumented immigrants as non-citizens who meet the following requirements: a. Arrive after 1980; b. Do not receive Social Security or SSI income; c. Not a veteran; d. Does not work in public administration, or occupations that require licensing (lawyer, registered nurses, physicians); e. Not from Cuba. Finally, we consider all remaining non-citizens with a legal immigrant or citizen spouse, according to the above restrictions, to be a legal immigrant. Compared to the algorithm of Borjas (2017), we cannot base our definition on the receipt of Medicaid or Medicare benefits (these variables are not available in the ACS prior to 2008), or the receipt of public housing or rental subsidies. In addition, we do not use a complete list of occupations that require licenses (e.g., air traffic controllers, noted by Borjas, is not included in the ACS). This definition results in a larger and more educated sample of likely undocumented than our preferred measure of low-educated non-citizens. Results using our preferred measure, as well as the Borjas measure can be found in Appendix Table (A12).

Figure A1: Phase in/out of Secure Communities and 287(g) Agreements



Notes: The above figure plots the phase in of Secure Communities and the phase in and out of the 287(g) program. In January of 2015 SC was replace by the Priority Enforcement Program, by the Obama administration.

Figure A2: Effect of SC on Citizen Women's Employment Across Sectors



Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) individuals. The horizontal axis plots the percent effect for each sector on the sample of low-educated non-citizen *men* in the 25-50th occupational skill percentiles. The vertical axis plots the percent effect for each sector on the sample of citizen *women* in the 50-75th occupational skill percentiles. The percent effect is calculated by taking the β from equation (1) for each demographic and sector group, and then dividing this β by the sample mean employment to population ratio for each demographic and sector. We include our full set of preferred controls, including year and PUMA fixed effects, PUMA-year linear trends, policy controls related to 287(g) programs, labor demand controls, and housing price controls. The sector "FIRE" stands for "Finance, Insurance and Real Estate". "Health and Education Services" dropped from the figure. We weight the results by the PUMA population in 2000 and standard errors are clustered at the PUMA level.

Table A1: Occupations by Share of College Graduates

Occupation	Less Than HS	HS or Some College	College Graduates
Lower skill occupations: 25th percentile of occupational skill intensity			
Host and Hostesses, Restaurant, Lounge, and Coffee Shop	.3991	.5476	.0533
Parts Salespersons	.119	.8269	.0542
Grounds Maintenance Workers	.4268	.5190	.0542
Heat Treating Equipment Setters, Operators, and Tenders	.1975	.7462	.0563
Food Servers, Non-restaurant	.2980	.6437	.0583
Bakers	.3317	.6095	.0587
Bookbinders, Printing Machine Operators, and Job Printers	.1672	.7739	.0588
Maintenance and Repair Workers	.1724	.7686	.0590
Carpenters	.2795	.6605	.0600
Computer Control Programmers and Operators	.1166	.8225	.0609
Higher skill occupations: 75th percentile of occupational skill intensity			
Occupation	**Less Than HS**	**HS or Some College**	**College Graduates**
Designers	.0461	.4994	.4545
Claims Adjusters, Appraisers, Examiners, and Investigators	.0157	.5337	.4506
Credit Counselors and Loan Officers	.0169	.5330	.4501
Media and Communication Workers, n.e.c.	.0273	.5273	.4454
Sales Representatives, Wholesale and Manufacturing	.0477	.5210	.4313
Insurance Sales Agents	.0183	.5522	.4295
Logisticians	.0154	.5557	.4289
Other Business Operations and Management Specialists	.0337	.5479	.4185
Paralegals and Legal Assistants	.0107	.5754	.4139
Real Estate Brokers and Sales Agents	.0232	.5631	.4137

Notes: This table reports the first 10 occupations above the 25th percentile of occupational skill intensity and the 10 occupations just below the 75th percentile of occupational skill intensity. We measure occupational skill intensity by the share of workers in each occupation with a college degree. Estimates are based off of the 2005 American Community Survey. Our sample contains 452 occupations based off of the 2010 Census occupational codes. The 25th percentile of occupational skill intensity is 5.31 percent college graduates. Occupations on either side of this cutoff are crossing guards (5.29) and host and hostesses (5.32). The median occupational skill intensity is 14.64 percent college graduates. Occupations on either side of this cutoff are transportation inspectors (14.63) and word processors and typists (14.64). The 75th percentile of occupational skill intensity is 45.51 percent college graduates. Occupations on either side of this cutoff are designers (45.45) and sales and related workers (45.57).

Table A2: Deportees by Most Serious Criminal Conviction, 2008-2014

MSCC	Share of Deportees (percent)
None	17.45
Traffic	5.57
Immigration	7.67
DUI	11.50
Marijuana	4.63
Other	53.18

Notes: Data on deportees comes from individual listings of all deportations under SC from TRAC records. This table summarizes the share of deportees by most serious criminal conviction. These categories include no criminal conviction, convictions for traffic offenses, convictions for immigration-related offenses, driving under the influence, and marijuana-related convictions. Note that the most serious criminal conviction may be, but is not necessarily, the crime for which the deportee was initially apprehended.

Table A3: Effect of SC on Employment by Citizenship Status, Men, Unweighted

	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: Total					
β: SC	-154.547	55.274	-151.450*	-122.895	64.524
	(119.484)	(100.831)	(83.719)	(84.964)	(80.022)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	37417.54	11314.95	7846.34	8681.25	9575.00
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
B: Citizen					
β: SC	-82.783	51.642	-51.898	-138.581*	56.054
	(120.047)	(89.198)	(77.121)	(82.124)	(77.551)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	33927.77	9675.13	7051.25	8248.97	8952.42
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
C: Non-Citizen					
β: SC	-72.766	3.203	-99.747***	15.706	8.072
	(65.620)	(50.980)	(33.233)	(24.601)	(23.902)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	3489.18	1639.72	794.93	432.16	622.38
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
D: Low-Educated Non-Citizen					
β: SC	-94.004*	-20.253	-81.341***	11.084	-3.494
	(56.835)	(45.865)	(29.624)	(16.980)	(6.505)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	2255.24	1408.36	602.37	199.14	45.36
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. The dependent variable in column 1 is total employment by PUMA and year, and in columns 2-5 the dependent variable is employment by occupational skill intensity for each skill quartile. In all specifications employment is divided by PUMA population and multiplied by 100,000. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Panel A includes the full sample, and Panels B-D restrict the sample to citizens, non-citizens, and low-skill non-citizens, respectively. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A4: Effect of SC on Employment by Citizenship Status including all PUMAs, Men

	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: Total					
β: SC	-205.070**	94.418	-79.033	-226.523***	6.068
	(85.000)	(66.774)	(48.741)	(47.313)	(53.500)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	37535.12	11218.97	7923.70	8827.10	9565.35
Observations	10710	10710	10710	10710	10710
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
B: Citizen					
β: SC	-88.249	120.641**	-17.460	-212.648***	21.217
	(83.716)	(59.608)	(43.559)	(46.403)	(49.091)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	33461.86	9260.06	6947.08	8339.89	8914.82
Observations	10710	10710	10710	10710	10710
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
C: Non-Citizen					
β: SC	-117.686**	-26.533	-61.428***	-13.970	-15.754
	(47.954)	(37.056)	(23.256)	(14.876)	(16.430)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	4072.78	1958.86	976.46	487.13	650.33
Observations	10710	10710	10710	10710	10710
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
D: Low-Educated Non-Citizen					
β: SC	-123.698***	-44.879	-56.474***	-16.119	-6.226
	(44.095)	(34.872)	(21.516)	(10.587)	(5.378)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	2754.17	1703.03	764.44	230.96	55.75
Observations	10710	10710	10710	10710	10710

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males and here includes all PUMAs and not just the ones who adopted SC after 2009. The dependent variable in column 1 is total employment by PUMA and year, and in columns 2-5 the dependent variable is employment by occupational skill intensity for each skill quartile. In all specifications employment is divided by PUMA population and multiplied by 100,000. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Panel A includes the full sample, and Panels B-D restrict the sample to citizens, non-citizens, and low-skill non-citizens, respectively. All regressions are weighted by the PUMA population in 2000. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A5: Effect of SC on Migration and Labor Force Participation

	Population Share	Labor Force Part Rate
A: Non-Citizen		
β: SC	-39.980	-0.001
	(65.290)	(0.006)
PUMA-Year Trends	X	X
287g	X	X
Labor Demand	X	X
Housing Prices	X	X
Y mean	4136.08	0.44
Observations	9160	9146
	Population Share	Labor Force Part Rate
B: Low-Educated Non-Citizen		
β: SC	-77.798	-0.003
	(54.850)	(0.009)
PUMA-Year Trends	X	X
287g	X	X
Labor Demand	X	X
Housing Prices	X	X
Y mean	2698.27	0.45
Observations	9160	9062

Notes: Data are from the 2005-2014 American Community Survey. The dependent variables in column 1 are the number of working-age (20-64) non-citizen males (Panel A), and the number of low-educated working-age non-citizen males (Panel B), both divided by the PUMA-year population, multiplied by 100,000. The dependent variables in column 2 are the labor force participation rate of working-age non-citizen males (Panel A), and the labor force participation rate of working-age low-educated non-citizen males (Panel B). All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Models are weighted by the PUMA population in 2000. Standard errors are clustered by PUMA and are reported in parenthesis. * p¡0.10, ** p¡0.05, *** p¡0.01

Table A6: Effect of SC on Citizen Employment, U.S. vs. Foreign Born, Men

	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: Citizen					
β: SC	-167.768*	63.841	-51.213	-216.101***	35.705
	(98.875)	(75.489)	(57.518)	(66.092)	(64.762)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	34091.44	9795.92	7085.67	8321.58	8888.28
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
B: US Born Citizen					
β: SC	-187.795*	58.703	-22.966	-215.011***	-8.520
	(99.168)	(71.989)	(54.631)	(61.467)	(59.286)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	31423.54	9079.55	6547.40	7701.60	8094.99
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
D: Foreign Born Citizen					
β: SC	20.027	5.138	-28.247	-1.089	44.225*
	(44.118)	(24.263)	(22.468)	(22.433)	(23.513)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	2667.91	716.36	538.27	619.98	793.29
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. The dependent variable in column 1 is total employment by PUMA and year, and in columns 2-5 the dependent variable is employment by occupational skill intensity for each skill quartile. In all specifications employment is divided by PUMA population and multiplied by 100,000. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Panel A includes the all citizens, Panel B includes only US-born citizens, and Panel C includes only foreign-born citizens. All regressions are weighted by the PUMA population in 2000. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A7: Effect of SC by Detailed Sector, Citizen Men

	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
A: AGRICULTURE (23.02)					
β: SC	-35.288	-12.653	-14.211	-5.763	-2.662
	(23.613)	(10.288)	(14.901)	(14.759)	(5.655)
Y mean	978.45	211.19	311.22	392.05	64.00
Observations	8976	8976	8976	8976	8976
	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
B: CONSTRUCTION (15.38)					
β: SC	-14.454	6.869	5.894	-12.822	-14.395
	(50.354)	(31.901)	(29.436)	(15.329)	(12.666)
Y mean	3830.39	1711.71	1405.26	472.43	240.99
Observations	9159	9159	9159	9159	9159
	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
C: PERSONAL & ENTERTAINMENT SERVICES (10.87)					
β: SC	-5.184	-5.808	-17.524	14.583	3.566
	(27.000)	(12.925)	(16.874)	(14.906)	(9.636)
Y mean	1061.74	244.22	347.28	316.60	153.64
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
D: WHOLESALE & RETAIL (7.57)					
β: SC	-61.212	4.104	-5.463	-80.227**	20.374
	(63.131)	(37.087)	(26.584)	(40.827)	(17.282)
Y mean	6367.02	2085.05	1095.27	2687.89	498.81
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
E: MANUFACTURING (7.4)					
β: SC	76.141	60.372	16.120	-32.195	31.843
	(58.553)	(40.022)	(23.375)	(21.192)	(25.027)
Y mean	5750.44	2558.85	1132.35	764.94	1294.30
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
F: BUSINESS SERVICES (7.350000000000001)					
β: SC	-15.886	-20.354	-8.969	-45.308**	58.745***
	(41.148)	(22.397)	(17.498)	(19.754)	(21.365)
Y mean	2454.13	767.00	458.51	480.94	747.67
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
G: TRANS & UTILITIES (3.61)					
β: SC	-17.697	18.277	-30.469	9.798	-15.303
	(44.774)	(30.740)	(23.876)	(19.078)	(18.202)
Y mean	3378.70	1319.26	909.71	578.83	570.91
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
H: MINING (2.76)					
β: SC	14.260	3.799	3.928	0.347	6.186
	(19.844)	(14.045)	(11.050)	(4.861)	(7.228)
Y mean	434.74	259.16	83.95	32.43	59.20
Observations	5388	5388	5388	5388	5388
	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
I: FIRE (1.78)					
β: SC	-23.385	3.654	-20.103*	-0.126	-6.810
	(33.774)	(7.690)	(10.369)	(20.871)	(23.469)
Y mean	1887.25	90.51	162.73	767.99	866.03
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
J: HEALTH & EDUCATION SERVICES (1.7)					
β: SC	-36.591	5.572	-4.371	-12.003	-25.788
	(61.043)	(17.270)	(24.204)	(24.538)	(48.447)
Y mean	5821.14	484.72	785.11	809.22	3742.09
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) citizen males. Public administration, active military, and no reported industry are not shown. The dependent variable in column 1 is total employment by PUMA and year, and in columns 2-5 the dependent variable is employment by occupational skill intensity for each skill quartile. The sector "FIRE" stands for "Finance, Insurance and Real Estate". In all specifications employment is divided by PUMA population and multiplied by 100,000. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Models are weighted by the PUMA population in 2000. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A8: Effect of SC by Detailed Sector, Low-Educated Non-Citizen Men

	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: AGRICULTURE (23.02)					
β: SC	2.723	9.197	-9.494	1.732	1.287
	(16.576)	(10.669)	(12.585)	(3.405)	(1.029)
Y mean	310.58	156.62	136.66	16.36	0.94
Observations	8976	8976	8976	8976	8976
	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
B: CONSTRUCTION (15.38)					
β: SC	-89.319***	-63.963***	-21.082	-2.318	-1.955
	(25.519)	(19.393)	(13.215)	(3.389)	(1.856)
Y mean	535.04	336.68	183.05	11.44	3.88
Observations	9159	9159	9159	9159	9159
	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
C: PERSONAL & ENTERTAINMENT SERVICES (10.87)					
β: SC	14.291	13.006*	0.802	0.220	0.264
	(9.343)	(6.975)	(5.830)	(2.695)	(0.850)
Y mean	88.04	41.72	36.36	8.46	1.50
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
D: WHOLESALE & RETAIL (7.57)					
β: SC	-7.205	11.458	-15.182	-6.265	2.784*
	(28.182)	(24.291)	(10.690)	(8.117)	(1.609)
Y mean	525.75	360.03	81.87	79.05	4.80
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
E: MANUFACTURING (7.4)					
β: SC	-49.713**	-21.326	-25.200***	1.692	-4.879*
	(20.510)	(16.424)	(8.288)	(3.105)	(2.640)
Y mean	308.10	233.53	53.91	13.16	7.50
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
F: BUSINESS SERVICES (7.350000000000001)					
β: SC	2.325	14.218	-8.143	-1.504	-2.246
	(12.461)	(11.400)	(5.264)	(3.110)	(2.055)
Y mean	158.96	119.29	25.75	9.02	4.89
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
G: TRANS & UTILITIES (3.61)					
β: SC	23.042**	13.795	6.856	2.272	0.118
	(11.529)	(9.019)	(4.357)	(4.676)	(1.609)
Y mean	127.93	75.79	23.23	25.49	3.42
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
H: MINING (2.76)					
β: SC	3.579	6.383	-2.376*	-0.870	0.442
	(4.406)	(4.121)	(1.265)	(0.688)	(0.482)
Y mean	12.56	10.78	1.32	0.24	0.22
Observations	5388	5388	5388	5388	5388
	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
I: FIRE (1.78)					
β: SC	-2.149	-4.976*	-0.422	0.199	3.050***
	(5.009)	(2.839)	(3.078)	(2.561)	(1.126)
Y mean	31.35	11.03	9.45	7.81	3.06
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
J: HEALTH & EDUCATION SERVICES (1.7)					
β: SC	-1.286	0.933	-3.620	1.198	0.203
	(8.263)	(5.088)	(4.637)	(2.860)	(3.333)
Y mean	71.16	25.57	24.41	9.66	11.52
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) low-educated non-citizen males. Public administration, active military, and no reported industry are not shown. The dependent variable in column 1 is total employment by PUMA and year, and in columns 2-5 the dependent variable is employment by occupational skill intensity for each skill quartile. The sector “FIRE” stands for “Finance, Insurance and Real Estate”. In all specifications employment is divided by PUMA population and multiplied by 100,000. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Models are weighted by the PUMA population in 2000. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A9: Effect of SC on Employment by Citizenship Status, Women

	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: Total					
β: SC	90.092	84.797	-78.800	2.480	81.616
	(87.280)	(52.911)	(67.697)	(72.974)	(70.772)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	33695.09	4714.59	8073.10	10531.58	10375.83
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
B: Citizen					
β: SC	43.926	49.550	-76.959	1.322	70.013
	(86.657)	(46.547)	(66.052)	(71.348)	(69.404)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	31726.38	3959.56	7572.18	10199.27	9995.37
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
C: Non-Citizen					
β: SC	47.681	34.971	-1.196	2.962	10.944
	(38.869)	(26.379)	(22.083)	(17.371)	(15.864)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	1968.39	755.05	500.96	332.02	380.36
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
D: Low-Educated Non-Citizen					
β: SC	23.413	24.514	2.052	-2.495	-0.659
	(30.848)	(23.990)	(17.108)	(11.677)	(4.197)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	1121.81	637.25	319.93	135.61	29.02
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) females. The dependent variable in column 1 is total employment by PUMA and year, and in columns 2-5 the dependent variable is employment by occupational skill intensity for each skill quartile. In all specifications employment is divided by PUMA population and multiplied by 100,000. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Panel A includes the full sample, and Panels B-D restrict the sample to citizens, non-citizens, and low-skill non-citizens, respectively. All regressions are weighted by the PUMA population in 2000. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A10: Effect of SC on Employment including Additional Housing Price Controls, Men

	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: Baseline					
β: SC	-280.806***	46.472	-138.978**	-224.073***	35.773
	(97.158)	(84.567)	(61.709)	(67.041)	(69.392)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	37423.09	11381.03	7838.75	8719.45	9483.87
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
B: Housing Prices Additional Functional Form					
β: SC	-239.867**	53.977	-123.555**	-213.033***	42.745
	(96.322)	(84.940)	(61.995)	(66.898)	(70.966)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	37423.09	11381.03	7838.75	8719.45	9483.87
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. Panel A reproduces panel C from Table 1. Panel B includes additional quadratic and cubic housing price controls and Panel C adds a control for the change in housing prices between 2000-2007 and 2007-2009 interacted with a PUMA-specific linear trend. The dependent variable in column 1 is total employment by PUMA and year, and in columns 2-5 the dependent variable is employment by occupational skill intensity for each skill quartile. In all specifications employment is divided by PUMA population and multiplied by 100,000. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Models are weighted by the PUMA population in 2000. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A11: Effect of SC on Employment Robustness to Alternative Housing Controls, Men

	All			25 < *skill* < 50			50 < *skill* < 75		
A: Total									
β: SC	-280.806***	-255.093***	-252.651***	-138.978**	-124.197**	-120.927*	-224.073***	-219.082***	-216.307***
	(97.158)	(97.817)	(97.757)	(61.709)	(61.893)	(61.985)	(67.041)	(67.393)	(67.435)
PUMA-Year Trends	X	X	X	X	X	X	X	X	X
287g	X	X	X	X	X	X	X	X	X
Labor Demand	X	X	X	X	X	X	X	X	X
PUMA Housing Prices	X			X			X		
State Housing Prices		X			X			X	
State Housing Prices Leave out PUMA			X			X			X
Y mean	37423.09	37422.36	37392.25	7838.75	7836.06	7834.99	8719.45	8719.19	8698.51
Observations	9160	9170	9140	9160	9170	9140	9160	9170	9140
	All			25 < *skill* < 50			50 < *skill* < 75		
B: Citizen									
β: SC	-167.768*	-139.221	-137.424	-51.213	-37.820	-34.525	-216.101***	-205.777***	-203.026***
	(98.875)	(98.726)	(98.751)	(57.518)	(57.573)	(57.560)	(66.092)	(66.365)	(66.419)
PUMA-Year Trends	X	X	X	X	X	X	X	X	X
287g	X	X	X	X	X	X	X	X	X
Labor Demand	X	X	X	X	X	X	X	X	X
PUMA Housing Prices	X			X			X		
State Housing Prices		X			X			X	
State Housing Prices Leave out PUMA			X			X			X
Y mean	34091.44	34088.03	34030.51	7085.67	7082.84	7074.42	8321.58	8320.86	8296.30
Observations	9160	9170	9140	9160	9170	9140	9160	9170	9140
	All			25 < *skill* < 50			50 < *skill* < 75		
C: Non-Citizen									
β: SC	-113.230*	-116.051*	-115.432*	-87.589***	-86.163***	-86.213***	-7.776	-13.114	-13.088
	(61.308)	(60.686)	(60.662)	(25.916)	(25.711)	(25.742)	(17.827)	(18.185)	(18.245)
PUMA-Year Trends	X	X	X	X	X	X	X	X	X
287g	X	X	X	X	X	X	X	X	X
Labor Demand	X	X	X	X	X	X	X	X	X
PUMA Housing Prices	X			X			X		
State Housing Prices		X			X			X	
State Housing Prices Leave out PUMA			X			X			X
Y mean	3331.25	3333.93	3361.35	752.95	753.09	760.45	397.82	398.28	402.17
Observations	9160	9170	9140	9160	9170	9140	9160	9170	9140
	All			25 < *skill* < 50			50 < *skill* < 75		
D: Low-Educated Non-Citizen									
β: SC	-108.143**	-103.651**	-103.446**	-77.684***	-72.392***	-72.270***	-5.250	-7.552	-7.610
	(51.492)	(50.174)	(50.187)	(23.337)	(23.027)	(23.036)	(12.036)	(12.075)	(12.098)
PUMA-Year Trends	X	X	X	X	X	X	X	X	X
287g	X	X	X	X	X	X	X	X	X
Labor Demand	X	X	X	X	X	X	X	X	X
PUMA Housing Prices	X			X			X		
State Housing Prices		X			X			X	
State Housing Prices Leave out PUMA			X			X			X
Y mean	2170.94	2171.49	2188.05	576.90	576.99	582.55	183.29	183.45	185.09
Observations	9160	9170	9140	9160	9170	9140	9160	9170	9140

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. The dependent variable in columns 1-3 is total employment by PUMA and year, and in columns 4-9 the dependent variable is employment by occupational skill intensity for the middle two skill quartiles. In all specifications employment is divided by PUMA population and multiplied by 100,000. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, and labor demand controls. Panel A includes the full sample, and Panels B-D restrict the sample to citizens, non-citizens, and low-skill non-citizens, respectively. Specifications in the columns 1, 4, and 7 include controls for PUMA by year housing prices. Specifications in the columns 2, 5, and 8 include controls for state by year housing prices. Specifications in the columns 3, 6, and 9 include controls for state by year housing prices leaving out the individual PUMA for each observation. All regressions are weighted by the PUMA population in 2000. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A12: Effect of SC on Employment with Alternative Measures of Non-Citizen Men

	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: Low-Educated Non-Citizens					
β^1: SC	-108.143**	-22.500	-77.684***	-5.250	-2.709
	(51.492)	(38.809)	(23.337)	(12.036)	(6.194)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	2170.94	1367.84	576.90	183.29	42.91
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
B: Low-Educated Non-Citizens, enter US after 1980, born in Mexico/Central America					
β^1: SC	-103.469**	-31.915	-60.408***	-2.421	-8.725**
	(40.844)	(32.844)	(18.776)	(7.625)	(3.441)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	1375.81	930.02	365.39	67.43	12.97
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
C: Low-Educated Non-Citizens, enter US after 1980, Hispanic					
β^1: SC	-97.026**	-30.210	-60.128***	1.291	-7.978**
	(43.208)	(34.375)	(19.577)	(8.028)	(3.839)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	1522.68	1017.53	404.29	85.12	15.73
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
D: Borjas approximation					
β^1: SC	-58.151	1.669	-63.844***	-12.502	16.526
	(48.914)	(33.838)	(21.476)	(14.453)	(15.615)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	1785.46	868.97	424.31	226.81	265.36
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. The dependent variable in column 1 is total employment by PUMA and year, and in columns 2-5 the dependent variable is employment by occupational skill intensity for each skill quartile. In all specifications employment is divided by PUMA population and multiplied by 100,000. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Panel A includes only low-educated non-citizens, as in the main tables. Panel B restricts the sample to low-educated non-citizens who entered the U.S. after 1980 and were born in Mexico or Central America. Panel C restricts the sample to low-educated non-citizens who entered the U.S. after 1980 and are Hispanic. Panel D restricts the sample to non-citizens who meet the following requirements: a. Arrive after 1980; b. Does not receive Social Security or SSI income; c. Not a veteran; d. Does not work in public administration, or occupations that require licensing (lawyer, registered nurses, physicians); e. Not from Cuba. Additionally, this specification considers all remaining non-citizens with a legal immigrant or citizen spouse, according to the above restrictions, to be a legal immigrant. All regressions are weighted by the PUMA population in 2000. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A13: Effect of SC on Employment by Race/Ethnicity, Men

	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: White Citizens					
β: SC	-64.985	76.697	-25.159	-130.921**	14.398
	(84.495)	(64.146)	(46.743)	(55.081)	(53.239)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	26665.77	7246.80	5337.02	6702.22	7379.73
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
B: Black Citizens					
β: SC	-69.375	-32.614	-21.577	-14.650	-0.534
	(51.701)	(31.568)	(21.715)	(22.417)	(24.015)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	3144.18	1197.32	786.62	637.23	523.01
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
C: Hispanic Citizens					
β: SC	19.334	21.381	-1.285	-15.420	14.658
	(49.571)	(29.915)	(25.400)	(22.447)	(18.035)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	2532.24	955.11	623.98	557.50	395.65
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
D: White Non-Citizens					
β: SC	16.903	14.476	1.586	-6.345	7.186
	(19.959)	(13.716)	(9.574)	(8.303)	(10.050)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	492.32	128.87	86.72	96.10	180.62
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
E: Black Non-Citizens					
β: SC	-21.511	-1.923	-19.018***	-3.374	2.804
	(13.786)	(8.024)	(7.348)	(6.271)	(5.685)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	211.69	70.40	62.12	42.24	36.93
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
F: Hispanic Non-Citizens					
β: SC	-110.887**	-44.854	-65.087***	-0.033	-0.915
	(48.042)	(38.738)	(21.739)	(10.567)	(7.917)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Housing Prices	X	X	X	X	X
Y mean	1984.78	1238.43	519.67	155.66	71.03
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. The dependent variable in column 1 is total employment by PUMA and year, and in columns 2-5 the dependent variable is employment by occupational skill intensity for each skill quartile. In all specifications employment is divided by PUMA population and multiplied by 100,000. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Panels A-C restrict the sample to citizens, and Panels D-F restrict the sample to low-educated non-citizens. Models are weighted by the PUMA population in 2000. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

B Local Exposure to Secure Communities

In the main text, we find little evidence of heterogeneous effects of SC depending on the PUMA-level intensity of the low-educated non-citizen population (defined as the low-educated non-citizen population in 2005, divided by the total population in 2005). To shed light on this finding, we consider here the intensity of local exposure to SC more broadly.

First, we investigate the correlation between the 2005 low-educated non-citizen population in a given PUMA and the number of deportations between 2008-2014 in that PUMA in Appendix Figure (B1). The two variables are positively correlated, with a statistically significant slope coefficient of 0.036, suggesting that low-educated non-citizens are at least a rough proxy for the population "at risk" of being deported under SC. However, there appears to be significant variation in deportations across PUMAs that is not explained by the size of the low-educated non-citizen population; the R-squared on this regression is 0.505. Looking at the figure, this may be driven by PUMAs with many low-educated non-citizens but relatively few deportations, and vice versa. This remaining variation in deportations–not explained by low-educated non-citizens–is likely due to differences in the intensity of enforcement of SC, which itself may have a substantial effect on labor force participation of low-skill non-citizens.[55]

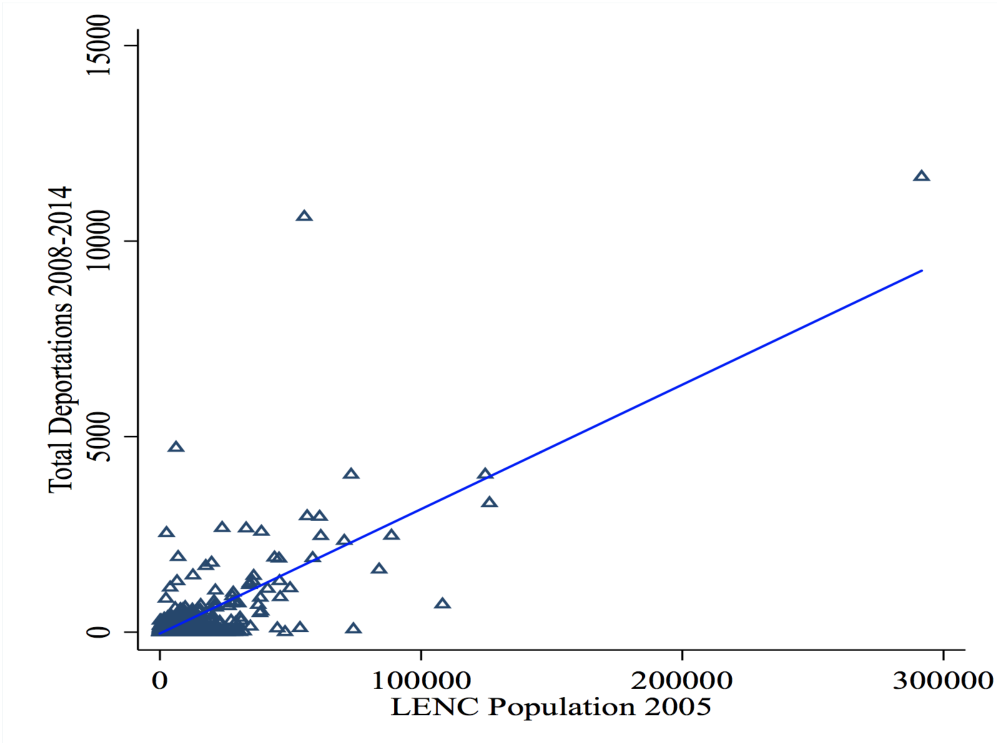
Therefore, we also explore heterogeneity across "deportation risk", conditional on the size of the PUMA's low-educated non-citizen population. We measure this "deportation risk" as total deportations in 2008-2014 divided by the low-educated non-citizen population in 2005. Before turning to those results, we show in Appendix Figure (B2) that the deportation risk of SC is higher in PUMAs with a *low* initial share of low-educated non-citizens. Using this alternative measure of intensity of SC, we find suggestive evidence of a larger impact of SC in the highest quartile of deportation risk for total low-educated non-citizens employment,

[55]Two other potential sources of variation that may also explain this are: 1) variation in the quality of the proxy of low-educated non-citizens for undocumented immigrants across PUMAs, and 2) variation in the likelihood of undocumented immigrants to commit a crime across PUMAs.

relative to the bottom three quartiles, shown in Appendix Table (B1). This suggests that the additional component of variation in deportations may be also relevant as a measure of intensity, perhaps because it is related to the fear effects and voluntary out-migration effects of SC. This may also explain why we find little heterogeneity by low-educated non-citizen intensity share in the main text: because PUMAs with many low-educated non-citizens have low deportation risk (and vice versa). Indeed, there are almost twice as many low-educated non-citizens in the lowest quartile of deportation risk compared to the higher three quartiles (4442 per 100,000 compared to 1242-2481 per 100,000). However, the confidence intervals for all quartiles of deportation risk are overlapping, so these patterns are only suggestive.

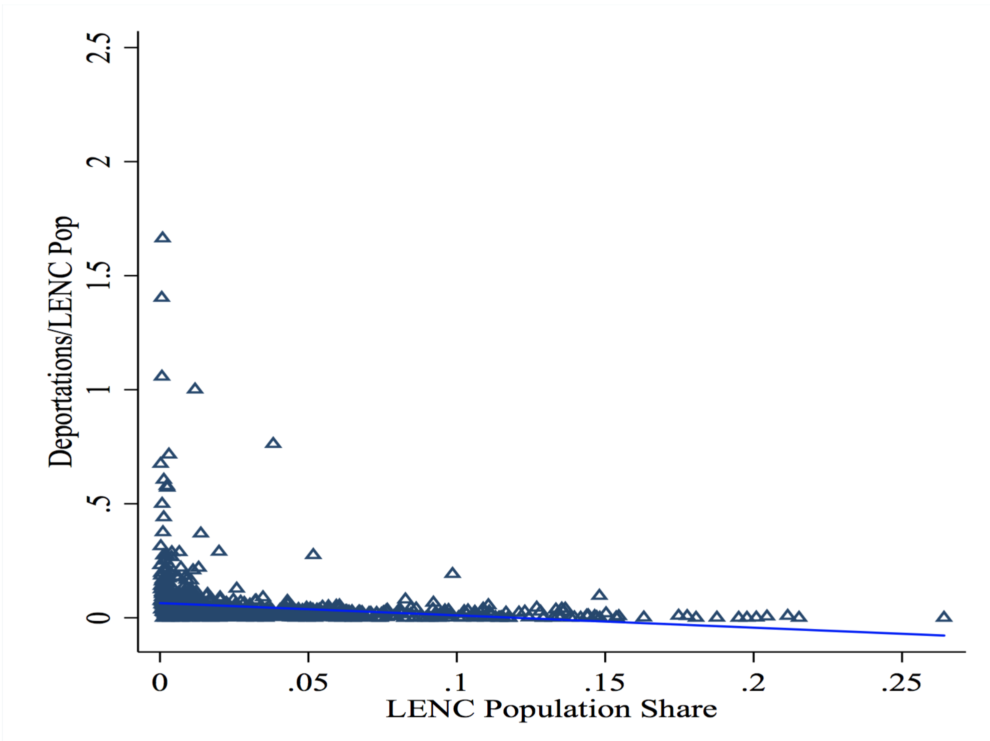
We also check for heterogeneity across "sanctuary cities." While there are a variety of methods to classify sanctuary cities, we follow Steil and Vasi (2014) and consider jurisdictions that adopted local pro-immigrant ordinances between 1976 and 2014. This classification allows for a more comprehensive measure of locations that likely had less cooperation with ICE, and it varies over time, accounting for the fact that some jurisdictions adopted sanctuary legislation after the implementation of SC. However, we do not find consistent heterogeneity for any of our main outcomes by sanctuary city status, so these results are not reported here.

Figure B1: Correlation of Deportations and Low-Educated Non-Citizen Population



Notes: The figure plots the correlation between the number of low-educated non-citizens within a PUMA in 2005 and the total number of deportations in the PUMA between 2008 and 2014. The R^2 of this correlation is 0.505 and the marginal effect is 0.036 with a standard error of 0.005. The blue line is the marginal effect.

Figure B2: Correlation of Deportation Intensity and Low-Educated Non-Citizen Population Intensity



Notes: The figure plots the correlation between the low-educated non-citizen population share within a PUMA in 2005 and the total number of deportations between 2008 and 2014 divided by the PUMA-level low-educated non-citizen population in 2005. The blue line is the marginal effect, which has a magnitude of -1.023 and a standard error of 0.0362.

Table B1: Effect of Immigration Laws by SC Deportation Intensity, Men

	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: Citizens					
SC * Below 25th Perc (.02) Total Deportations / Total LENC Pop in 2005	-303.193*	-111.857	-120.817	-144.754	74.234
	(172.272)	(145.122)	(104.040)	(125.644)	(106.377)
SC * 25th-50th Perc (.02-.06) Total Deportations / Total LENC Pop in 2005	-159.424	13.763	-6.740	-250.735**	84.288
	(151.313)	(119.898)	(88.451)	(101.750)	(95.172)
SC * 50th-75th Perc (.06-.15) Total Deportations / Total LENC Pop in 2005	-265.808*	67.771	-8.040	-283.604***	-41.935
	(144.274)	(98.155)	(85.484)	(92.962)	(86.947)
SC * Above 75th Perc (.15) Total Deportations / Total LENC Pop in 2005	48.702	231.041*	-98.023	-148.112	63.797
	(145.373)	(119.584)	(86.942)	(92.267)	(100.257)
Y mean Below P 25	30560.55	8047.34	6641.01	7506.17	8366.03
Y mean P 25 - P 50	34480.86	9410.29	7128.54	8453.54	9488.49
Y mean P 50 - P 75	34020.55	9932.86	7059.71	8279.58	8748.39
Y mean Above P 75	35461.04	10534.83	7221.73	8516.61	9187.87
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
D: Low-Educated Non-Citizens					
SC * Below 25th Perc (.02) Total Deportations / Total LENC Pop in 2005	-90.210	-42.731	-57.056	-5.445	15.022
	(102.022)	(81.085)	(53.306)	(29.933)	(13.912)
SC * 25th-50th Perc (.02-.06) Total Deportations / Total LENC Pop in 2005	-72.144	7.601	-68.628*	-6.612	-4.506
	(75.670)	(62.013)	(39.818)	(16.576)	(7.561)
SC * 50th-75th Perc (.06-.15) Total Deportations / Total LENC Pop in 2005	-130.411*	-17.638	-94.447***	-9.222	-9.104
	(74.961)	(55.915)	(32.294)	(17.180)	(8.527)
SC * Above 75th Perc (.15) Total Deportations / Total LENC Pop in 2005	-125.334**	-41.963	-79.140***	1.284	-5.514
	(57.825)	(44.092)	(28.112)	(14.729)	(7.019)
Y mean Below P 25	3992.93	2381.65	1072.30	456.17	82.80
Y mean P 25 - P 50	2311.65	1412.49	668.33	185.25	45.58
Y mean P 50 - P 75	2335.96	1520.25	600.39	172.59	42.73
Y mean Above P 75	1064.33	684.43	270.96	83.64	25.31
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-aged (20-64) males. The dependent variable in column 1 is total employment by PUMA and year, and in columns 2-5 the dependent variable is employment by occupational skill intensity for each skill quartile. In all specifications employment is divided by PUMA population and multiplied by 100,000. All specifications include year and PUMA fixed effects, PUMA linear trends, controls for 287(g) programs, labor demand controls, and housing price controls. Panel A restricts the sample to citizens and Panel B restricts the sample to low-educated non-citizens. Data on deportation intensity from TRAC. All regressions are weighted by the PUMA population in 2000. Standard errors are clustered by PUMA and are reported in parenthesis. * p<0.10, ** p<0.05, *** p<0.01