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ABSTRACT

The Labor Market Effects of Immigration Enforcement*

This paper examines the effects of reducing the supply of low-skilled immigrant workers on the labor market outcomes of domestic workers. We use temporal and geographic variation in the introduction of Secure Communities (SC), a county-based immigration enforcement policy, combined with data over 2005-2014 from the American Community Survey to estimate a difference-in-difference model with geographic and time fixed effects. We find evidence that SC had a negative impact on the employment of low-skilled non-citizen workers, who are likely to be directly affected by the policy. Importantly, we also find that SC negatively impacted the employment of citizens working in middle to high-skill occupations. This is the first paper to provide quasi- experimental evidence on the labor market effects of immigration enforcement policies on citizens across the occupational skill distribution, which is of paramount importance given the current immigration policy debates.

JEL Classification: F22, J11, J23, K37
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1 Introduction

About 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). Policies aimed at reducing the number of undocumented immigrants through deportations were increasingly implemented in the past two decades, but it is unclear 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 native 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 and native 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 424,000, mostly male, individuals were removed under SC during 2010-2015.[3] As a result, SC led to a significant decrease in the availability of low-skill workers through its direct impact on deportations and potentially because the policy increased the fear of deportation among law-abiding undocumented immigrants. These "chilling effects" may have led to self-deportations, reduced the number of incoming undocumented immigrants, and impacted the willingness to work outside the home in order to limit interactions with

[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 and Stuhler (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 focused on the direct effects on the migrant population. See Phillips and Massey (1999), Bansak and Raphael (2001), Amuedo-Dorantes and Bansak (2014), Orrenius and Zavodny (2015), and Orrenius and Zavodny (2009).

[2] There are other immigration policies aimed at reducing the number of undocumented immigrants, such as 287(g) agreements and E-Verify. However, the implementation and nature of these policies differ compared to SC. For instance, 287(g) agreements are based on training local police to act as immigration agents (Pham and Van, 2010; Bohn and Santillano, 2017). And E-Verify is designed to curb access to employment, but not to deport undocumented immigrants (Karoly and Perez-Arce, 2016).

[3] Statistics on the number of individuals removed under SC from the Transactional Records Access Clearinghouse can be found at `http://trac.syr.edu/phptools/immigration/secure/`.

the local police (Kohli et al., 2011).[4]

The implementation of SC provides a unique natural experiment to measure the effects of immigration enforcement policies 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, 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 across early and late-adopters. 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 drawn from the 2005-2014 American Community Survey (ACS) and conduct the analysis at the Public-Use Microdata Area (PUMA) level - the smallest geographic area available in the public-use data. Empirically, we analyze the effects on citizen workers–which include all U.S. born individuals and naturalized foreign-born citizens–and non-citizen workers. For 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.[5] Given that most undocumented immigrants have low levels of education, we believe the latter group captures

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

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

a large portion of the undocumented population that will be directly affected by SC.

The results indicate that the introduction of SC is associated with about a 0.8% reduction in a PUMA's total employment, measured as a share of PUMA population. We further find that this reduction comes from a decrease in the employment of both citizen and non-citizen workers. Specifically, SC is associated with a reduction of 3.5% in the employment of non-citizens, and a reduction of 5% in the employment of low-skill non-citizens–the latter of whom are most likely to be directly affected by the policy. For citizens, the results indicate that SC is associated with a decline in employment of 0.5%.

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 and Stuhler, 2017; Lee et al., 2017). To better understand the impact of SC on the employment of citizens across the occupational skill distribution, we generate four skill groups containing occupations based on the share of workers with at least a college degree.[6] The results show that SC has a negative and statistically significant effect on the employment of citizen and non-citizen workers in the middle part of the skill distribution (middle two quartiles). Specifically, SC is associated with a reduction of 2.5% in the employment rates of citizen workers in the middle to high-skill group. In contrast, the effect on low-skill non-citizens in the low to middle-skill group is much larger–about a 13% reduction in employment. Thus, the results provide evidence that low-skill immigrant workers are complementary in production to high-skill domestic workers. These findings lend support to the job search model of Chassamboulli and Peri (2015) in which a policy aimed at reducing the number of undocumented immigrants may have a negative short-run effect on the employment of citizen workers.

More broadly, the paper contributes to existing literature in a number of important

[6] For expositional purposes, Appendix Table (A1) reports the 10 least and most skill intensive occupations measured by the share of workers with a college degree in each occupation.

ways. First, unlike most previous studies, we examine the impact of removing immigrants from the labor market on the outcomes of both immigrants and natives. The impact of an inflow or an outflow of low-skill immigrants might not be necessarily symmetric, because recent incoming immigrants are likely to differ in their skills compared to undocumented immigrants who have lived in the country for many years. Moreover, inflows and outflows of immigration can trigger adjustments in capital and technology that differ in their effect on the productivity of natives (Clemens et al., 2017).[7]

Second, the analysis relies on quasi-experimental variation to estimate the extent of substitution or complementarity between low-skill immigrant and native workers across the occupational skill distribution. 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).[8]

Finally, the 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 in 2015) and President Trump has recently proposed expanding other similar enforcement programs (Sakuma, 2017; Alvarez, 2017).

The paper proceeds as follows. Section 2 describes the Secure Communities 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 section 6.

[7] While the vast majority of the literature has examined the effect of immigration inflows on natives' labor outcomes, only a few papers have looked at the labor market effects of migratory outflows. Lee et al. (2017) and Clemens et al. (2017) measure the labor market effects on U.S. citizen workers of the repatriation of Mexican workers, during 1929-34, and during the implementation of the 1964 Bracero program, respectively.

[8] An exception is Lee et al. (2017), which provides empirical evidence on these complementarities exploiting the massive repatriation of Mexican workers during 1929-34. Similarly to our results, the authors found negative employment effects for high-skill natives, and no evidence of a substitution effect for low-skill natives.

2 Policy Background and Conceptual Framework

2.1 Policy Background

Secure Communities is one of the largest interior immigration enforcement policies over the last decade. The objective of SC is to facilitate information sharing between local law enforcement and federal immigration officials by requiring all individuals booked in state prisons or local jails to be screened regarding their immigration status. The federal government implemented SC and local agencies could not "opt in" or "opt out." 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. Once SC was enacted in a county, the fingerprints of all arrestees booked in jail were automatically sent to U.S. Immigration and Customs Enforcement (ICE), who subsequently ran the fingerprints against several federal databases to determine an individual's immigration status. Therefore, local agencies had much more limited discretion in the implementation and usage of the program, compared to other interior immigration enforcement polices (Miles and Cox, 2014). During 2010 to 2015, more than 424,000, mostly male, individuals were detained through SC.[9]

We gathered information on the rollout dates of SC from U.S. Immigration and Customs Enforcement (ICE). Under SC, "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, and did not have to be preceded by a conviction.[10] Because undocumented immigrants are disproportionately low-skill, we expect SC to have

[9]Statistics on the number of individuals removed under SC by county and gender from the Transactional Records Access Clearinghouse can be found at `http://trac.syr.edu/phptools/immigration/secure/`. We do not use information on the number of removals across counties and over time as this may be endogenous. Our model will only examine the effect of the implementation of SC.

[10]This policy language taken from the ICE website, is available here: `https://www.ice.gov/pep`. At the end of 2014, the Secure Communities program was replaced by the Priority Enforcement Program (PEP), so we end our sample period in 2014. Under PEP, the same screening process occurred as did under SC, but PEP would only issue a detainer for individuals "convicted of serious criminal offenses or who otherwise pose a threat to public safety".

affected the availability of low-skill labor through two main channels. First, SC reduced the number of low-skill workers by removing undocumented immigrants through detainers and eventual deportations. Second, fear from 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 to use minor violations to target the Hispanic population (Kohli et al., 2011).[11] Furthermore, SC had negative effects on the mental health of the migrant population (Wang and Kaushal, 2018). Thus, fear from detentions and eventual removal 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. Moreover, fear of driving a car or interacting with law enforcement, may have limited the participation of immigrants in the formal labor market, where they are required to submit a social security number or other forms of identification. Finally, SC may have also impacted the labor supply of documented immigrants because the documented and undocumented populations are heavily integrated. For example, 37% of individuals who were identified for deportation by ICE under SC had a citizen child, suggesting that there may be significant overlap across the undocumented and other populations.[12]

Our empirical strategy, described in more detail below, relies on the piecemeal implementation of SC across counties from 2008 to 2013. Therefore, it is important that the timing of the rollout across counties not be related to time-varying county characteristics. Evidence suggests the initial set of counties where SC was implemented were chosen by the federal government based on the size of their Hispanic population and proximity to the U.S.-Mexico border, but the timing of adoption in subsequent counties was more "random" because it

[11]Hispanic immigrants were disproportionately impacted by SC. 14% of people deported under SC had no criminal conviction, 5% had a traffic violation, and 8% had illegal entry or re-entry as their most serious conviction. Statistics on convictions from the Transactional Records Access Clearinghouse available here: `http://trac.syr.edu/phptools/immigration/secure/`.

[12]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).

was based on resource constraints and waiting lists (Cox and Miles, 2013).[13] This pattern can be seen in Figure (1) which plots the rollout of SC across counties and over time. Given the potential selectivity of the early-adopters, in our main model we drop observations from counties that adopted SC before January 2009, but the main results are robust to including them.[14]

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 reduces the employment or wages of natives with comparable skills (Card, 1990; Altonji and Card, 1982; Hunt, 1992; Pischke and Velling, 1997; Friedberg, 2001; Cohen-Goldner and Paserman, 2006).[15] 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 numbers and skill composition of immigrants (Ottaviano and Peri, 2012).

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

[13]Importantly, Cox and Miles (2013) show that the implementation of SC was not related to the county's crime rates nor was it related to local attitudes about immigration enforcement. In contrast, they find strong evidence that a county's share of Hispanic population correlates strongly with SC implementation.

[14]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. Therefore, in our main model we do not include state by year fixed effects because this would absorb much of the variation of the rollout.

[15]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 and Stuhler, 2017).

workers 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 between 1990 and 2006 had a small positive effect on the average wages of native workers, and on the wages of workers with no high-school degree. Ottaviano and Peri (2012)'s analysis highlight the possibility that while immigrants can act as imperfect substitutes for some native workers, there could also be a degree of complementarity between immigrants and natives across different skill groups.

Although there is important 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-skill workers who are complementary in production. Undocumented immigrants are assumed to be low-skill and have the lowest reservation wages. Documented immigrants have higher reservation wages compared to undocumented immigrants, while natives have higher reservation wages than either group. As a result, an increase in the supply of low-skill undocumented immigrants reduces the labor cost for firms and induces them to create more jobs per unemployed worker. Consequently, deportation policies that reduce the availability of low-skill workers are expected to decrease the employment rates of low- and high-skill natives.

This is the first paper to analyze the labor market impacts of a nationwide immigration enforcement measure on both immigrants and native workers across the skill distribution.

There is limited prior research looking at the effects of SC by itself.[16] We are aware of only two published papers focusing on SC. The first examines the characteristics of adopting counties in relation to the date of SC implementation, which we rely on 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).

However, there is a larger literature examining the effects of other immigration policies on employment, which 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.[17] Like SC, 287(g) agreements provide a new mechanism through which the immigration status of individuals interacting with the criminal justice system is checked, and a new pathway for detainers to be issued and deportations undertaken. These papers find 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. But this effect is not disaggregated across immigrants and natives, or across low and high skill groups, 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).[18]

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

[17] There is a much larger literature examining the effect of state laws related to immigration on immigrant and natives' outcomes. However, these laws are typically not designed to deport immigrants, but rather reduce their access to employment, or change the public benefits they have access to. See Karoly and Perez-Arce (2016) for a summary of this literature.

[18] 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. But, these migratory effects are concentrated in Maricopa County, AZ and among the high-skill 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.

2.3 Predicted Effects of Secure Communities

Our results are broadly consistent with the model of Chassamboulli and Peri (2015). This model emphasizes that undocumented immigrants have the lowest reservation wage and therefore a reduction in the supply of undocumented immigrants–as we expect will be the result of SC due to deportations, voluntary return migration or individual decisions to drop out from the labor force–would increase the labor cost to firms. The main testable predictions of the model when SC is implemented on citizens are as follows. First, the model predicts an ambiguous effect on the employment of low-skill citizens.[19] The ambiguous effect of SC on low-skill citizens is driven by two opposite effects. On the one hand, the model predicts a positive effect of SC on the employment of low-skill citizens if they are substitutes of low-skill immigrants. On the other hand, if low-skill non-citizen workers are not identical to low-skill citizen workers, in particular because of their lower reservation wages, the model predicts a negative effect on the employment of low-skill citizens due to the higher costs associated with job creation.[20] Second, the effect on high-skill citizens will depend on the complementarity or substitution between high-skill and low-skill workers. If they are complementary in production, as is assumed in Chassamboulli and Peri (2015), then a decrease in the labor supply of low-skill undocumented workers would increase a firm's average labor costs and decrease labor demand for high-skill citizen workers. However, if low and high-skill workers are substitutes in production then, just as with the case of low-skill citizens, a decrease in the labor supply of undocumented workers would have an ambiguous effect on the employment rates of high-skill citizens.

[19]Theoretically, we would expect an ambiguous effect for low-skill documented immigrants as well. However, given the lack of data on the documentation status of immigrants we will not test empirically the effects on documented vs. undocumented immigrants.

[20]Importantly, this depends on whether or not firms can distinguish between undocumented immigrants and other low-skill workers. In the event that firms are unable to distinguish between low-skill citizens vs. non-citizens, they will be unable to substitute between these groups, and therefore the effect on low-skill citizen employment would be unambiguously negative. Conversely, if firms are perfectly able to observe status of workers, these two labor pools can be thought of as separate, and therefore, the effect on citizen employment will be unambiguously positive.

3 Data

In order to measure the labor market effects of SC we merge information on the SC rollout dates 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 ACS is a repeated cross-sectional dataset covering a 1% random sample of the U.S. 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. We begin our sample in 2005, as this is the first year we can identify Public-Use Microdata Area (PUMA) in the public-use data, and end in 2014 when SC was replaced by the Priority Enforcement Program. Some PUMAs are equivalent to counties, others include several counties, and some are smaller than individual counties. The SC data is at the county-level, so to merge this with the annual PUMA-level ACS data, 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).[21]

Our main outcome of interest is the employment to population ratio at the PUMA-year level. To construct this measure, we count the number of working-aged (20-64) individuals in each PUMA-year who report to be working at the time of the survey. We then divide the number of working individuals by the PUMA population, and multiply by 100,000 to ease the interpretation. We examine the employment rates of 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 education or less. We take this approach rather than separating our data into "undocumented" and "documented" because the ACS

[21]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.

does not include questions about immigration status.[22] While the foreign-born non-citizens with a high school education or less group is likely to be directly affected by the policy through deportations, the policy could also impact the labor market outcomes of documented immigrants and the native born or naturalized citizens.

To test the predictions about the differential effects of SC across the skill distribution, we examine the employment rates across the occupational skill distribution. Specifically, we tabulate the fraction of all workers that have at least a college degree in each occupation in 2005 (the first year of our sample). 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 rates as described above.

Finally, we stratify the sample by industry of employment. This allows us to examine the effects on employment within industries that, prior to SC, employed many low-skill non-citizens, compared to those that did not. Figure (4) shows the distribution of the share of low-skill non-citizen workers by industry in 2005. The median industry has about 4% low-skill non-citizen workers as a fraction of their total workforce (shown in the black line), but, it is clear from this figure that there are many industries that have almost no usage of low-skill non-citizens, and some industries that very heavily rely on low-skill non-citizen labor. In the main results we aggregate these finer industry categories into sector groups to ease interpretation and presentation. It is important to point out that even though we use a measure of low-skill non-citizens, rather than undocumented workers, we have compared the fraction of low-skill non-citizens across sectors with published statistics on the fraction of undocumented immigrants across sectors released by the PEW Center, and while the levels

[22] Measures of "likely undocumented" immigrants in the literature typically include individuals who are foreign-born non-citizens who are Hispanic, and have a high school diploma or less (Amuedo-Dorantes and Bansak, 2012, 2014; Orrenius and Zavodny, 2015).

are slightly different, the rank is the same (Passel and Cohn, 2016).

Since our sample period spans the Great Recession, we account for changes in economic conditions that may influence employment, by including several "Bartik-style" measures of labor demand (Bartik, 1992). We construct six Bartik-style measures of labor demand that correspond to the following six demographic groups: 1) all working-age adults, 2) foreign-born working-age adults, 3) working-age adults with more than a high-school diploma, 4) working-age adults with a high-school diploma or less, 5) working-age women with more than a high-school diploma, and 6) working-age men with more than a high-school diploma. 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 as in Watson (2013).

In addition to the Bartik controls we add controls for housing price values. 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 above for the SC variable. It is possible that SC changed the housing prices in a PUMA in which case we would be controlling for an endogenous variable. To address this concern, we check the robustness of our results to different measures of housing prices at the state-level and 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.[23] As described above, 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. There were three types of 287(g) agreements. First, the "Task Force" model, which permit-

[23]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. This information also allowed us to determine which type of agreement was in place.

ted trained law enforcement officials to screen individuals regarding their immigration status during policing operations, and arrest individuals due to suspected immigration violations. Second, the "Jail" model, which allowed screening of immigration status for individuals upon being booked in state prisons or local jails and was more similar to SC. And, third, a "Hybrid" model which includes both the Task Force and Jail models.[24] As plotted in Figure (5) there were changes in the number of 287(g)s during our sample period, so controlling for them may be important.

4 Empirical Strategy

Our empirical strategy exploits both the geographic and temporal variation in the implementation of the SC program to identify its effect on total employment, as well as the employment of citizen and non-citizens across the distribution of occupational skill intensity. In order to estimate the causal effect of adopting SC on local employment we estimate the following model:

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

where emp_{pt} is the level of employment in PUMA p at time t, per 100,000 people in PUMA p at time t ($\frac{Emp_{pt}}{Pop_{pt}/100{,}000}$). The model includes year fixed effects, λ_t, to account for national economic shocks, and fixed effects at the PUMA level, ν_p, to control for time-invariant unobserved heterogeneity. Our preferred specification also includes PUMA-by-year linear trends, $t\delta_p$ to account for differential trends in employment within PUMAs over time. X_{pt} is a vector of PUMA-by-year controls which includes the presence of the 287(g) program, measures of local labor demand, and local house price values. In addition to looking at the effect of SC on total employment, we also estimate equation (1) separately for citizens,

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

non-citizens, and low-skilled non-citizens, and by occupational skill group. The analysis by citizenship status and across the skill distribution allows us to provide an empirical test to the theoretical predictions explained in the previous section. We expect a negative $\hat{\beta}_{non-citizen}$ due to the nature of SC. The predicted effects for citizens on the other hand are ambiguous in sign.

As described in the data section, SC_{pt} is a continuous variable indicating the length of exposure to SC. It is constructed as the product of the share of counties within PUMA p that have adopted SC in year t, and the share of year t for which SC was in effect. Thus, SC_{pt} ranges between zero and 1 during the year SC was implemented. 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 being covered by SC for the entire survey year. The baseline model is weighted by the PUMA population in 2000.[25]

We limit our sample to those counties that adopted SC after 2009 because, as we have discussed above, the first adopters appear to have been highly selected. For all counties adopting SC after 2009 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 in those PUMAs. 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 study" model as follows:

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

[25]The results are robust to the inclusion of state-by-year fixed effects; however, this is not our preferred specification 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. Similarly, we do not control for E-verify and state-level 287(g) agreements since these policies only vary at the state by year level. However, including these policies does not substantially impact our results.

where 1_k 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 t. 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 (6) where the blue line shows the effect of SC, and 95% confidence intervals are represented by the dashed lines. The results provide no evidence that employment was following a differential trend across locations prior to the adoption of SC, and following SC implementation there is evidence that total employment was negatively affected. Having provided evidence to support the validity of our empirical strategy we now describe our main empirical results.

5 Effect of SC on Employment

5.1 Main Results

We begin by estimating equation (1) to measure the effect of SC on men's total employment as a share of a PUMA's population. Our main specifications focus on men, since 96% of the removals under SC were males.[26] The baseline model in Panel A of Table (1) includes PUMA and year fixed effects, PUMA specific linear time trends, and indicators for the presence of 287(g) agreements. The first column shows the effect for total employment rate, and moving across the columns, we show the impact of SC across the occupational skill distribution. The samples in columns 2 to 5 are defined according to our measure of skill intensity based on the share of college educated workers in each occupation, described in section 3.

The results in column 1 of Panel A indicate that SC reduces employment by 457 workers per 100,000 people, significant at the 10% level, which relative to the mean employment

[26] Information available at `http://trac.syr.edu/phptools/immigration/secure/`.

rate is about a 1.2% reduction in the total employment rate of men (457/37,709). In the remaining columns of Panel A, we estimate the same specification by quartiles of the skill distribution. Interestingly, the effects of SC are concentrated in the middle of the skill distribution. Specifically, SC is associated with a reduction of 2% in the employment rate of men in the low to middle occupational skill group and a reduction of about 2.9% in the employment rate of men working in occupations in the third quartile of the distribution, both effects are significant at the 1% level.

We sequentially include two different types of economic controls in Panels B and C to address the possibility that the estimated effect of SC is partially driven by local economic conditions. Adding controls for labor demand factors in Panel B of Table (1) does not affect either the significance or magnitude of the estimated coefficients. The specification in Panel C adds controls for housing prices at the PUMA-year level. The addition of controls for housing prices reduces the magnitude of the effect of SC by about a third, such that the implementation of SC is associated with about a 0.8% reduction in the employment rate. The effects among workers in the middle of the skill distribution, however, are only slightly reduced in size and remain statistically significant. Since the timing of SC implementation could potentially be correlated with local impacts of the Great Recession, our preferred specification controls both for PUMA-level labor demand conditions and housing prices. Because changes in labor demand conditions or housing prices may be endogenous to the implementation of SC, we examine the sensitivity of the results to an alternative set of controls in section 5.3.[27]

The negative effects on total employment found in Table (1) may be driven by a number of mechanisms. To begin, we expect there to be a negative direct effect of SC on the

[27]A similar set of results for women are presented in Appendix Tables (A2) and (A3). The results show little evidence that SC impacted the employment of either immigrant or citizen women. This is not surprising since the vast majority of targeted immigrants under SC were men. Appendix Tables (A4) and (A5) report estimates where we include the very early adopters of SC. The results are virtually unchanged when including these counties.

available labor pool of low-skill non-citizens, who are the most likely to be directly impacted by these enforcement policies. As previously discussed, we expect this direct effect to be the result of removing individuals in this group from the local labor force through detention and deportation, as well as the fear of deportation causing increased out-migration from the U.S., reduced in-migration to the U.S., or reduced labor market participation. The predicted effects on citizen employment, however, are less clear since the effect of SC depends on the level of substitution or complementarity in production between citizen and non-citizen workers and between workers with different skills. Thus, in Table (2) we estimate the effects of SC separately by citizenship status and by occupational skill group.

Panel A of Table (2) repeats the results from the fully specified model in Panel C of Table (1). Panel B shows the effect of SC for citizen employment (natives and naturalized citizens), Panel C shows the results for all non-citizens, and Panel D for low-skill non-citizens, who are the most likely to be undocumented and to be directly affected by SC. There are three main reasons to look at the sample of non-citizens, regardless of their likely 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.[28] Second, it is possible that undocumented and documented immigrants 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, although SC is expected to directly affect undocumented immigrants, it is not possible to perfectly identify who is an undocumented immigrant in the data.

The results in Table (2) indicate that SC had a significant negative direct effect on the employment of low-skill non-citizen workers, as well as a significant *negative* spillover effect on the employment of citizens. Specifically, the implementation of SC reduces the employment of non-citizen workers by 118.9 per 100,000 people, significant at the 10% level

[28]Watson (2013), for example, finds that 287(g)s increased migration within the United States among high-skill immigrants, who are unlikely to be undocumented.

(Panel C, column 1), which relative to the mean employment rate is a 3.5% percent reduction in employment of non-citizens. In Panel D we further restrict our sample to include only low-skill non-citizens. We find that SC reduces the employment rate of low-skill non-citizen workers by 5.2%. Importantly, the results in Panel B indicate that, on average, SC reduces the employment of citizen workers by 178 workers per 100,000 individuals, or by about 0.5%, marginally 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-skill immigrant workers leads to a decline in the employment of citizen workers.

The impact of SC on overall employment could mask important heterogeneous effects across the skill distribution. For example, although citizens working in occupations in the lowest quartile of the skill distribution could substitute for immigrant workers, citizens in higher-skill occupations could act as complements. The results in Panel B for citizens suggest that the decline in their employment rate is entirely driven by a decline of about 2.5% in the employment rate of men in the middle to high part of the skill distribution. The effect on citizens in the lowest quartile of the skill distribution is positive but is small in magnitude and imprecisely estimated. In contrast, the effect on non-citizen men (panel C) and low-skill non-citizen men (panel D) is concentrated among workers in the second quartile of the skill distribution. The results in column 3 of Panel D suggest that SC reduces the employment of low-educated immigrant men by a staggering 13%, significant at the 1%. These results provide evidence that citizens in middle skill occupations are complements to low-skill non-citizens working in low skill occupations. We find little evidence of substitution between citizen and non-citizen workers across the occupational skill distribution. This is consistent with the job search model developed by Chassamboulli and Palivos (2014) and Chassamboulli and Peri (2015), discussed above. In these models, a reduction in the labor supply of non-citizens increases the average cost of matching with low-skill workers because non-citizens have lower reservation wages than citizens. Additionally, if low and high-skill workers are complements in production, the increased cost of hiring low-skill workers would also reduce the demand for high-skill workers.

These results are not sensitive to the choice of cutoffs in the skill distribution. Figure (7) plots the estimated coefficients from our main specification by gradually shifting the skill group to include occupations with a higher share of college educated workers. This is done with a "moving window" approach. Panel A suggests that the total effect on employment is driven by workers in the middle of the skill distribution. Panel B clearly shows that the effects on citizens are driven by workers in the middle to high skill groups, while Panels C and D show that the effects on non-citizens are driven by workers in the low to middle part of the skill distribution. This is strong evidence that non-citizen workers in low to middle-skill occupations are complementary in production to citizen workers in middle to high-skill occupations.

5.2 Heterogeneous Effects Across Industries

Table (3) shows the results by the share of low-skill non-citizens in different sectors, for citizens (Panels A and B) and for low-skill non-citizens (Panels C and D). This analysis is informative since we would expect the effects of SC on the average cost of labor to be larger in sectors that rely more heavily on the employment of low-skill immigrant workers.

We find evidence in support of this hypothesis in Table (3). Panel A shows that the effects of SC on the employment of citizen men are concentrated among the middle to high-skill workers in sectors that have above median share of low-skill non-citizen workers (about 4%). Specifically, column 4 in Panel A of Table (3) suggests that SC reduces the employment of citizen men by about 3% (28/855), on average. In contrast, no such effects are found in sectors employing less than the median share of low-skill non-citizen workers (Panel B). Similarly, the declines in the employment of low-skill non-citizens are concentrated among low to middle-skill men in sectors that rely more on them (see column 3 of Panel C).[29] In summary, when looking at the effects across columns in Table (3), we find reinforcing evidence that low-skill immigrants working in low-skill occupations are complements to citizen men working in higher skill occupations.[30]

5.3 Robustness Checks

We conduct a number of robustness checks. First, we test whether SC had an effect on the total population of immigrants in a PUMA. Internal migration of immigrants because of SC could mask the true effects of the policy on employment outcomes. The results in Table (4) do not show any evidence that SC lead to significant changes in a PUMA's total population, the population of non-citizens, or the population of low-skill non-citizens, who are most likely to be targeted by SC. This suggests that the main effects on the employment rates are not driven by changes in the population but by changes in employment. To further address this concern, we report estimates in Table (5) where the dependent variable is measured as the ratio of employment to population, where population is fixed and measured in 2000 prior to the implementation of SC. For convenience, we report the estimates on overall employment and on the employment rates of the two middle skill groups, for specifications using contemporaneous (columns 1, 3 and 5) and fixed populations (columns 2, 4 and 6). The magnitude of the results using contemporaneous or fixed populations are very similar across specifications, suggesting that changes in population are not driving the effects of SC on employment rates.

Second, since the effect of SC on employment rates might not be linear, in Table (6)

[29]We also estimated the results by detailed industries for citizens and low-skill non-citizens. Although the results are negative for many of them, declines in the employment of citizen men are significant only in a handful of industries. This is not surprising given sample size limitations. The results are reported in Table Appendix (A6) and (A7).

[30]As expected, the negative effects on the overall population of non-citizens are also driven by sectors with a larger share of undocumented immigrants

we report estimates where we apply the inverse hyperbolic sine to our dependent variable.[31] Again, the results are consistent with the main conclusion that SC negatively impacts the employment of citizen workers in the middle to high-skill occupations, and to a much larger extent, the employment of non-citizen workers in the lower to middle skill occupations.

Finally, we check the robustness of the results to alternative measures of changes in housing prices. This is important since the implementation of SC could have impacted housing prices directly, making them endogenous to the policy. For ease of exposition, we report in Table (7) the estimates for overall employment and for workers in the middle of the occupational skill distribution. 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. Since the variation in SC is at the PUMA level, controlling for housing prices at the state level should be more exogenous to the implementation of the policy. Finally, in the third column of each panel, we use state housing prices excluding housing prices from the own 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).

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 other enforcement measures, such as the 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

[31] We use the hyperbolic sine instead of the log transformation, since in our ACS sample there are PUMAs in which there are no employed low-skill non-citizens age 20-64. However, estimating models with logged employment rates yields similar results.

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 1-2%, which is similar to our estimated effects of SC on the overall employment rate. This 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 attempted to estimate 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, it also allows us to estimate the relationship between immigrant and native employment, under the assumption that SC only impacts citizen employment through it's 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 removing one non-citizen reduces the employment of native workers by 1.5 (178/118).[32]

We expect the effect of SC on the employment of natives to be different compared to existing estimates on the relationship between immigrants and native employment. First, our variation utilizes a decrease in the supply of low skill 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

[32]This estimate should be interpreted with caution especially if SC changed the number or type of undocumented immigrants that respond to the ACS survey after the implementation of SC. Although Van Hook et al. (2014) found a decline in the coverage error of the Mexican-born population when using the 2001-2010 ACS data, an underestimate of the first stage would lead to an upwardly biased estimate of the relationship between the employment of citizens and non-citizens.

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 (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-skill 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 share of the foreign-born. 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 and Stuhler (2017) found that a 1 percentage point increase in the share of Czeck 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 workers, we use our variation to estimate the relationship between immigrants and natives working in different parts of the skill distribution. Consistent with our evidence on complementarity between low-skill immigrants and higher skill natives, Beerli and Peri (2015) found that the inflow of EU immigrants to Switzerland complemented the employment of highly educated native workers, negatively impacted the employment of middle educated natives and had no impact on the employment of low-skill natives.

Our results are more easily compared with two recent papers that estimate the effect of 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, their findings suggest that repatriations had no positive effect on the employment of natives, and in some specifications even depressed their employment and wages. Importantly, the authors provide evidence of complementarities between low-skill repatriated Mexicans and high-skill natives. Clemens et al. (2017) analyze the impact of excluding almost half a million Mexican bracero agricultural workers from the U.S. on native employment and wages. They found little effects of the bracero program on the labor market outcomes for domestic farm workers. The lack of substitution between Mexican and native workers was mitigated by employers adopting new technologies and changing their crops. This suggests that firms do not simply substitute immigrant and domestic labor and might adjust to a reduction in the supply of immigrants by endogenously changing their technology or the type of product they produce.

6 Conclusion

Secure Communities, one of the largest interior federal immigration enforcement policies over the last decade, resulted in the deportation of more than 424,000 individuals during 2010-2015. 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-skill non-citizens, who are more likely to be undocumented. Applying our local-level estimates to the national population of low-skill non-citizens, we estimate that SC reduced the employment of low-skill non-citizens by approximately 400,000.

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 natives across the occupational skill distribution. Our findings indicate that SC not only had a negative effect on employment for male non-citizens, but it also negatively impacts the employment of citizen men. Applying our local-level estimates to the national population of citizens, we estimate that SC reduced the employment of male citizens by approximately 600,000. Thus, the results suggest important complementarities between likely undocumented workers in low-skill occupations and citizens in higher-skill occupations.

These findings are consistent with a model of labor markets exhibiting search frictions as in Chassamboulli and Peri (2015). In the model, low and high-skill workers are complementary in production and low-skill undocumented immigrants have the lowest reservation wages. As a result, a policy aimed at 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-skill workers. Our findings suggest that immigration policies aimed at reducing the number of undocumented immigrants should take into account the potential for harming the labor market outcomes for medium to high-skill citizens.

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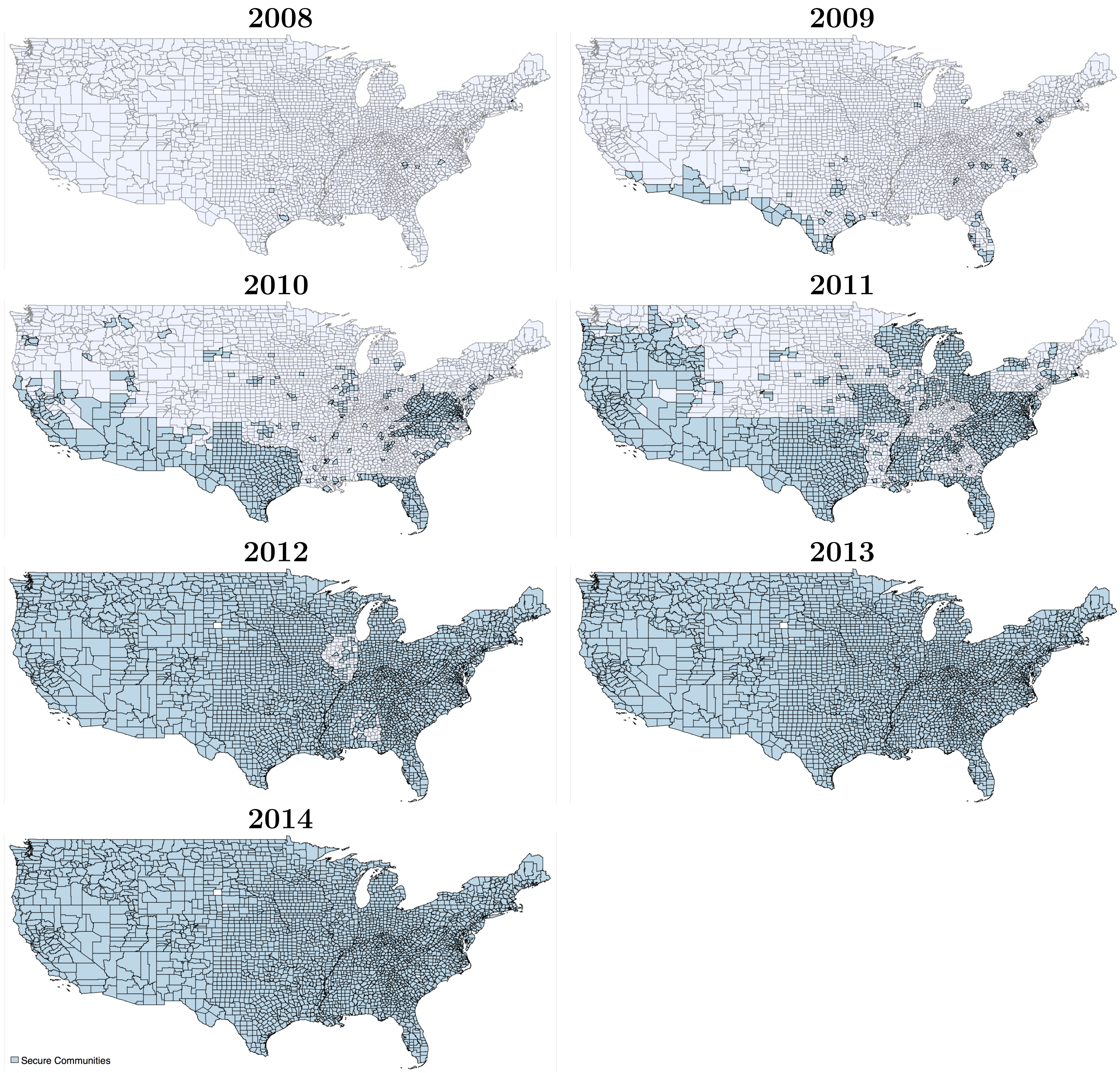
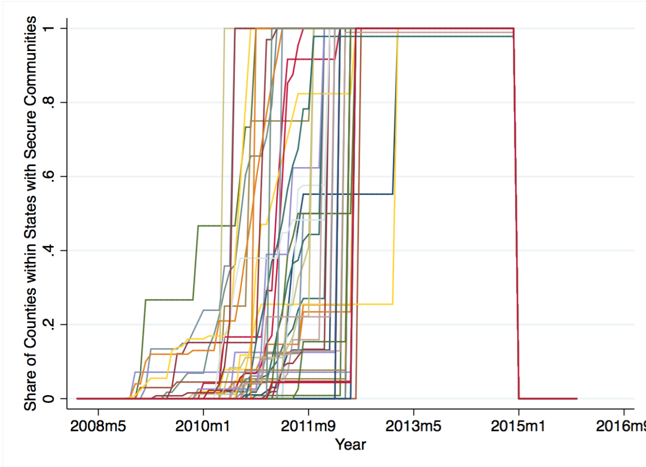
7 Figures

Figure 1: Rollout of Secure Communities by Year



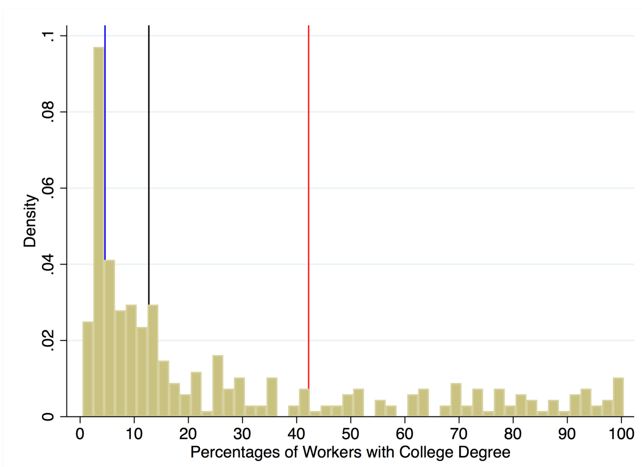
Notes: Counties that had adopted the Secure Communities based on December of each year are shaded. See text for sources.

Figure 2: Phase of Secure Communities within States



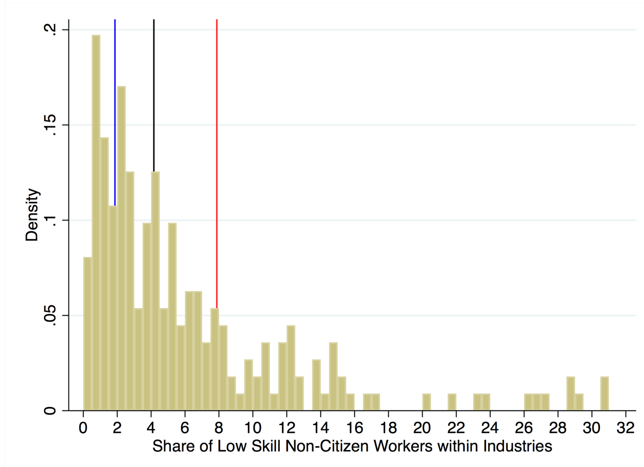
Notes: The above figure plots the phase in of Secure Communities within States. In January of 2015 SC was replaced by the Priority Enforcement Program, by the Obama administration. For this reason we restrict our sample to the period 2005-2014 to identify changes in labor demand that are the result of the staggered phase in only.

Figure 3: Distribution of Skill Intensity Across Occupations



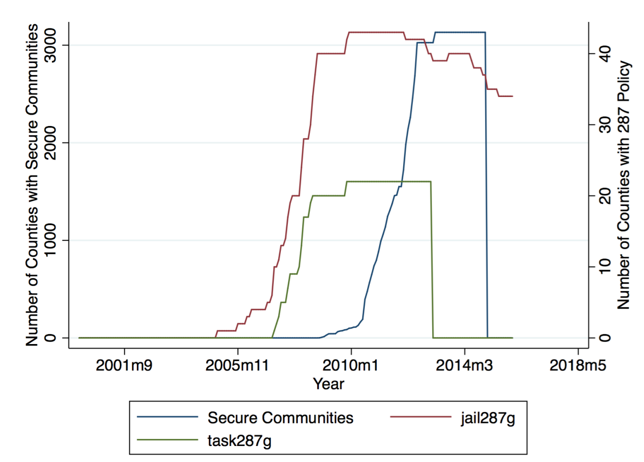
Notes: The above figure plots density of skill intensity across occupations as measured by the share of workers within an occupation with a college degree as estimated by the American Community Survey (ACS). We estimate skill intensity using the 2005 ACS. The black bar indicates the occupation with the 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: Distribution of Non-Citizen Low Skill Labor Across Industries



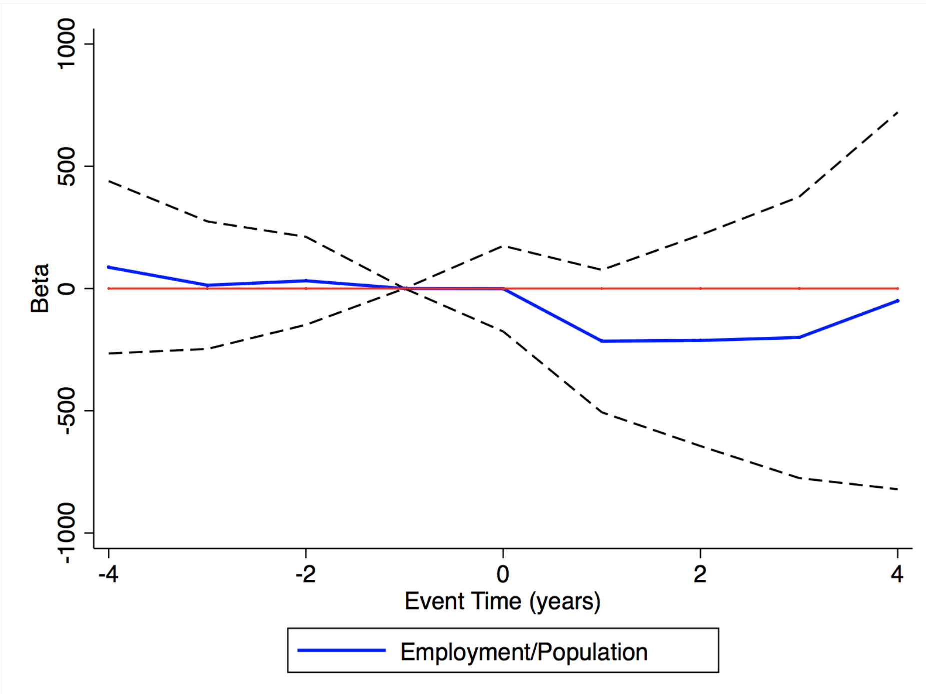
Notes: The above figure plots density of low skill non-citizen labor intensity across industries as measured by the American Community Survey (ACS), estimated using the 2005 ACS. The black bar indicates the industry with the median low skill non-citizen labor intensity (4.16) the blue and red bars depict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

Figure 5: Phase in/out of Secure Communities and 287g



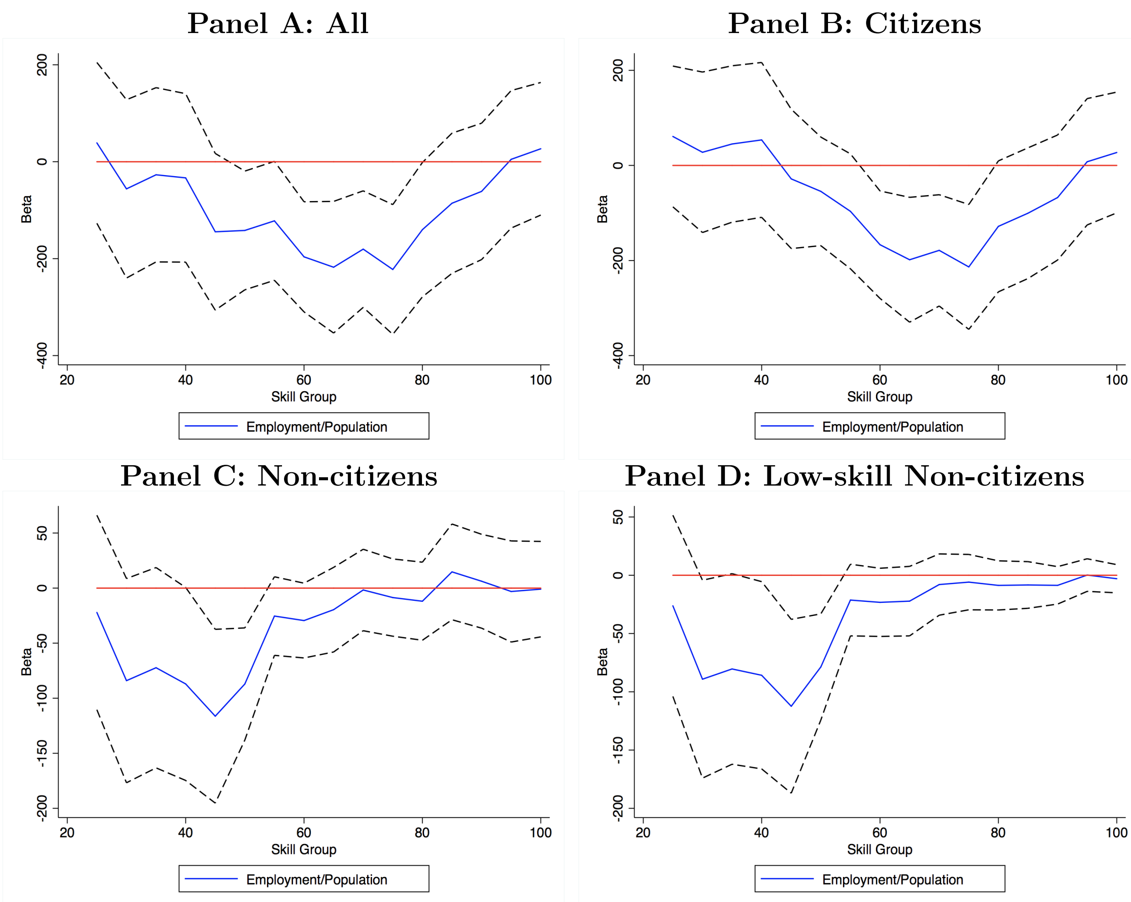
Notes: The above figure plots the phase in of Secure Communities and the phase in and out of the 287g program. In January of 2015 SC was replace by the Priority Enforcement Program, by the Obama administration. For this reason we restrict our sample to the period 2005-2014 to identify changes in labor demand that are the result of the staggered phase in only.

Figure 6: Effect of SC on Total Employment



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

Figure 7: 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-ages (20-64) males. All specifications include year and PUMA fixed effects, as well as PUMA-year linear time trends. The blue line shows 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, 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.

8 Tables

Table 1: Effect of Immigration Laws on Employment, Men

	Dep. Var: Employment/Population				
	All	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
A: Baseline					
β^1: SC	-456.898***	1.735	-163.713***	-258.799***	-36.121
	(98.842)	(84.843)	(62.066)	(66.035)	(73.033)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Y mean	37709.43	11460.23	7889.75	8826.42	9533.04
Observations	9170	9170	9170	9170	9170
	Dep. Var: Employment/Population				
	All	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
B: Add Labor Demand Controls					
β^1: SC	-439.695***	-2.511	-163.210***	-253.531***	-20.443
	(98.810)	(82.868)	(61.759)	(66.213)	(68.380)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Y mean	37709.43	11460.23	7889.75	8826.42	9533.04
Observations	9170	9170	9170	9170	9170
	Dep. Var: Employment/Population				
	All	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
C: Add Housing Price Controls					
β^1: SC	-296.502***	40.196	-140.685**	-223.658***	27.645
	(95.634)	(84.673)	(62.395)	(68.295)	(69.769)
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	37709.43	11460.23	7889.75	8826.42	9533.04
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-ages (20-64) males. The dependent variable in column 1 is total employment by PUMA and year, 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. 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 2: Effect of Immigration Laws on Employment by Citizenship Status, Men

	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: Total					
β^1: SC	-296.502***	40.196	-140.685**	-223.658***	27.645
	(95.634)	(84.673)	(62.395)	(68.295)	(69.769)
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	37709.43	11460.23	7889.75	8826.42	9533.04
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
B: Citizen					
β^1: SC	-177.870*	62.931	-53.823	-214.934***	27.956
	(96.265)	(75.547)	(58.116)	(66.997)	(64.796)
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	34345.44	9858.32	7132.76	8423.86	8930.50
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^1: SC	-118.880*	-22.844	-86.707***	-8.527	-0.802
	(62.196)	(45.024)	(25.954)	(17.893)	(22.098)
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	3363.60	1601.88	756.87	402.51	602.34
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
D: Low Skill Non-Citizen					
β^1: SC	-113.764**	-26.592	-78.351***	-5.901	-2.920
	(52.298)	(39.627)	(23.221)	(12.119)	(6.164)
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	2190.28	1382.55	578.97	185.16	43.61
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-ages (20-64) males. The dependent variable in column 1 is total employment by PUMA and year, 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. Panel A includes the full sample, and Panels B-D restrict the sample to citizens, non-citizens, and low-skill non-citizens, respectively. All specifications include year and PUMA fixed effects. 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 by Sector, Men

	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: Citizen, Sector w/ LSNCshr >4%					
β: SC	-11.926	4.810	-4.361	-27.631***	15.257**
	(15.755)	(10.901)	(7.759)	(8.437)	(6.184)
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	3423.05	1271.01	795.53	855.30	501.21
Observations	54791	54791	54791	54791	54791
	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
B: Citizen, Sector w/ LSNCshr <4%					
β: SC	-14.573	11.612	-13.378	0.544	-13.352
	(22.409)	(10.106)	(9.756)	(10.426)	(15.327)
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	3080.97	563.93	518.57	591.35	1407.12
Observations	32985	32985	32985	32985	32985
	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
C: Low Skill Non-Citizen, Sector w/ LSNCshr >4%					
β: SC	-20.157**	-5.494	-12.801***	-1.083	-0.778
	(7.982)	(6.096)	(3.561)	(1.760)	(0.643)
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	323.69	210.35	86.38	23.02	3.94
Observations	54791	54791	54791	54791	54791
	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
D: Low Skill Non-Citizen, Sector w/ LSNCshr <4%					
β: SC	5.060	3.373	0.146	0.769	0.773
	(3.849)	(2.760)	(1.866)	(1.564)	(1.062)
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	64.74	32.35	15.68	11.68	5.03
Observations	32985	32985	32985	32985	32985

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-ages (20-64) males. The dependent variable in column 1 is total employment by PUMA and year, 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. Panel A-B restrict the sample to citizens and Panels C-D restrict the sample to low-skill non-citizens. All specifications include year and PUMA fixed effects. 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 Immigration Laws on PUMA Population by Citizenship

	All
A: Total	
β^1: SC	2652.751
	(1612.325)
PUMA-Year Trends	X
287g	X
Labor Demand	X
PUMA Housing Prices	X
Y mean	421091
Observations	9160.00
	All
B: Non-Citizen	
β^1: SC	187.742
	(662.952)
PUMA-Year Trends	X
287g	X
Labor Demand	X
PUMA Housing Prices	X
Y mean	31041
Observations	9160.00
	All
C: Low Skill Non-Citizen	
β^1: SC	-253.480
	(655.220)
PUMA-Year Trends	X
287g	X
Labor Demand	X
PUMA Housing Prices	X
Y mean	19652
Observations	9160.00

Notes: Data are from the 2005-2014 American Community Survey. The dependent variable is the population in PUMA p in year t. Panel A includes the full sample, and Panels B-D restrict the sample to citizens, non-citizens, and low-skill non-citizens, respectively. All specifications include year and PUMA fixed effects. 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 5: Effect of Immigration Laws on Employment Robustness to Fixed Population, Men

	All		$25 < skill < 50$		$50 < skill < 75$	
A: Total						
β^1: SC	-296.502***	-126.713*	-140.685**	-81.557*	-223.658***	-122.442***
	(95.634)	(75.027)	(62.395)	(41.715)	(68.295)	(45.087)
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	37709	24379	7890	5087	8826	5733
Observations	9160	9160	9160	9160	9160	9160
	All		$25 < skill < 50$		$50 < skill < 75$	
B: Citizen						
β^1: SC	-177.870*	-70.617	-53.823	-26.341	-214.934***	-118.144***
	(96.265)	(69.596)	(58.116)	(38.340)	(66.997)	(44.158)
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	34345	22169	7133	4589	8424	5468
Observations	9160	9160	9160	9160	9160	9160
	All		$25 < skill < 50$		$50 < skill < 75$	
C: Non-Citizen						
β^1: SC	-118.880*	-56.207	-86.707***	-55.107***	-8.527	-4.135
	(62.196)	(43.183)	(25.954)	(17.669)	(17.893)	(12.208)
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	3364	2210	757	497	403	265
Observations	9160	9160	9160	9160	9160	9160
	All		$25 < skill < 50$		$50 < skill < 75$	
D: Low Skill Non-Citizen						
β^1: SC	-113.764**	-56.562	-78.351***	-49.509***	-5.901	-2.212
	(52.298)	(35.866)	(23.221)	(15.553)	(12.119)	(8.092)
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	2190	1435	579	381	185	121
Observations	9160	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-ages (20-64) males. The dependent variable in columns 1-2 is total employment by PUMA year and industry, in columns 2-6 the dependent variable is employment by occupational skill intensity for the two middle quartiles. In all specifications employment is divided by PUMA population and multiplied by 100,000. Panel A includes the full sample, and Panels B-D restrict the sample to citizens, non-citizens, and low-skill non-citizens, respectively. All specifications include year and PUMA fixed effects.. 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 Immigration Laws on Employment, Inverse Hyperbolic Sine

	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: Total					
β^1: SC	-0.004	0.009	-0.015*	-0.023***	0.009
	(0.003)	(0.009)	(0.009)	(0.008)	(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	12.04	10.80	10.46	10.57	10.58
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
B: Citizen					
β^1: SC	-0.001	0.011	-0.006	-0.024***	0.010
	(0.004)	(0.010)	(0.009)	(0.008)	(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	11.94	10.62	10.35	10.52	10.52
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^1: SC	-0.041	0.035	-0.111	-0.138	0.012
	(0.037)	(0.062)	(0.104)	(0.109)	(0.090)
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	9.06	7.99	6.87	6.23	6.83
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
D: Low Skill Non-Citizen					
β^1: SC	-0.042	0.052	-0.186*	0.093	-0.289
	(0.061)	(0.081)	(0.111)	(0.168)	(0.222)
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	8.35	7.71	6.31	4.74	2.77
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-ages (20-64) males. The dependent variable in column 1 is total employment by PUMA year and industry, in columns 2-5 the dependent variable is employment by occupational skill intensity. In all specifications employment is divided by PUMA population and multiplied by 100,000. Panel A includes the full sample, and Panels B-D restrict the sample to citizens, non-citizens, and low-skill non-citizens, respectively. All specifications include year and PUMA fixed effects. 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 7: Effect of Immigration Laws on Employment Robustness to Alternative Housing Controls, Men

	All			$25 < skill < 50$			$50 < skill < 75$		
A: Total									
β^1: SC	-296.502***	-271.116***	-267.717***	-140.685**	-124.631**	-120.862*	-223.658***	-221.285***	-218.708***
	(95.634)	(96.355)	(96.344)	(62.395)	(62.564)	(62.662)	(68.295)	(68.450)	(68.493)
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	37709	37709	37709	7890	7890	7890	8826	8826	8826
Observations	9160	9170	9140	9160	9170	9140	9160	9170	9140
	All			$25 < skill < 50$			$50 < skill < 75$		
B: Citizen									
β^1: SC	-177.870*	-149.801	-146.902	-53.823	-39.185	-35.424	-214.934***	-207.448***	-204.864***
	(96.265)	(96.081)	(96.189)	(58.116)	(58.105)	(58.092)	(66.997)	(67.062)	(67.111)
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	34345	34345	34345	7133	7133	7133	8424	8424	8424
Observations	9160	9170	9140	9160	9170	9140	9160	9170	9140
	All			$25 < skill < 50$			$50 < skill < 75$		
C: Non-Citizen									
β^1: SC	-118.880*	-121.549**	-121.072**	-86.707***	-85.249***	-85.268***	-8.527	-13.646	-13.650
	(62.196)	(61.486)	(61.461)	(25.954)	(25.756)	(25.795)	(17.893)	(18.223)	(18.278)
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	3364	3364	3364	757	757	757	403	403	403
Observations	9160	9170	9140	9160	9170	9140	9160	9170	9140
	All			$25 < skill < 50$			$50 < skill < 75$		
D: Low Skill Non-Citizen									
β^1: SC	-113.764**	-109.716**	-109.612**	-78.351***	-73.113***	-72.932***	-5.901	-8.098	-8.151
	(52.298)	(50.915)	(50.927)	(23.221)	(22.920)	(22.941)	(12.119)	(12.152)	(12.173)
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	2190	2190	2190	579	579	579	185	185	185
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-ages (20-64) males. The dependent variable in columns 1-2 is total employment by PUMA year and industry, in columns 2-6 the dependent variable is employment by occupational skill intensity for the two middle quartiles. In all specifications employment is divided by PUMA population and multiplied by 100,000. Panel A includes the full sample, and Panels B-D restrict the sample to citizens, non-citizens, and low-skill non-citizens, respectively. All specifications include year and PUMA fixed effects. 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

A Appendix

Table A1: Occupations with Highest and Lowest Shares of College Graduates

Lowest Skill Occupations			
Occupation	**Less Than HS**	**Some College**	**College Graduates**
Materials movers	.3257	.9956	.0043
Apparel operatives	.4088	.9893	.0106
Concrete and cement workers	.4501	.9828	.0171
Paving, surfacing equipment operators	.395	.9821	.0178
Rollers, roll hands, and finishers of metal	.2819	.9816	.0183
Welders and metal cutters	.2590	.980	.0193
Forge and hammer operators	.2544	.9805	.0194
Drywall installers	.4612	.9790	.0209
Crane, derrick, winch, and hoist operators	.2237	.9782	.0217
Vehicle washers and equipment cleaners	.4194	.9779	.0220
Highest Skill Occupations			
Occupation	**Less Than HS**	**Some College**	**College Graduates**
Physical scientists, n.e.c.	.0018	.0296	.9703
Speech therapists	.0030	.0259	.9740
Medical scientists	.0019	.0205	.9794
Psychologists	.0021	.0116	.9883
Lawyers	.0015	.0113	.9886
Optometrists	.0014	.0106	.9893
Veterinarians	.0016	.0093	.9906
Physicians	.0024	.0083	.9917
Podiatrists	.0009	.0072	.9927
Dentists	.0015	.0070	.9929

Notes: This table reports the 10 least and most skill intensive occupations as measure by the share of workers in each occupation with a college degree. Estimates are based off of the 2005 American Community Survey. Or sample contains 339 occupations based off of the 1990 Census occupational codes. The 25th percentile of occupational skill intensity is 4.59 percent college graduates. Occupations on either side of this cutoff are barbers (4.53) and Industrial machinery repairers (4.67). The median occupational skill intensity is 12.70 percent college graduates. Occupations on either side of this cutoff are correspondence clerks (12.67) and photographic process worker (12.72). The 75th percentile of occupational skill intensity is 42.12 percent college graduates. Occupations on either side of this cutoff are real estate sales occupations (41.13) and Insurance sales occupations (42.29).

Table A2: Effect of Immigration Laws on Employment, Women

	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: Baseline					
β^1: SC	24.536	115.456**	-95.399	-42.754	47.233
	(85.880)	(52.033)	(64.753)	(70.786)	(69.991)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Y mean	33884.01	4751.26	8115.49	10600.23	10417.02
Observations	9170	9170	9170	9170	9170
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
B: Add Labor Demand Controls					
β^1: SC	32.008	111.122**	-94.621	-34.580	50.087
	(85.923)	(51.531)	(65.255)	(71.414)	(69.995)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Y mean	33884.01	4751.26	8115.49	10600.23	10417.02
Observations	9170	9170	9170	9170	9170
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
C: Add Housing Price Controls					
β^1: SC	97.502	81.912	-79.797	4.697	90.690
	(85.918)	(53.213)	(67.611)	(73.156)	(70.939)
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	33884.01	4751.26	8115.49	10600.23	10417.02
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-ages (20-64) females. The dependent variable in column 1 is total employment by PUMA and year, in columns 2-5 the dependent variable is employment by occupational skill intensity for each skill quartile. All specifications include year and PUMA fixed effects. 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 A3: Effect of Immigration Laws on Employment by Citizenship Status, Women

	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: Total					
β^1: SC	97.502	81.912	-79.797	4.697	90.690
	(85.918)	(53.213)	(67.611)	(73.156)	(70.939)
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	33884.01	4751.26	8115.49	10600.23	10417.02
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
B: Citizen					
β^1: SC	53.035	45.497	-76.379	4.963	78.954
	(85.651)	(46.965)	(66.096)	(71.441)	(69.533)
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	31900.66	3993.36	7611.48	10263.90	10031.92
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^1: SC	46.066	36.140	-2.790	1.595	11.121
	(39.094)	(26.362)	(21.942)	(17.503)	(16.033)
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	1983.00	757.92	504.04	336.04	384.99
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
D: Low Skill Non-Citizen					
β^1: SC	23.255	24.165	1.311	-1.891	-0.329
	(31.186)	(24.153)	(17.040)	(11.815)	(4.202)
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	1126.11	639.06	321.04	136.57	29.45
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-ages (20-64) females. The dependent variable in column 1 is total employment by PUMA and year, in columns 2-5 the dependent variable is employment by occupational skill intensity for each skill quartile. Panel A includes the full sample, and Panels B-D restrict the sample to citizens, non-citizens, and low-skill non-citizens, respectively. All specifications include year and PUMA fixed effects. 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 A4: Effect of Immigration Laws on Employment, Men & ALL PUMAs

	Dep. Var: Employment/Population				
	All	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
A: Baseline					
β^1: SC	-368.545***	43.222	-107.633**	-259.023***	-45.111
	(86.798)	(66.804)	(48.772)	(46.880)	(54.567)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Y mean	37815.78	11293.95	7974.70	8935.62	9611.51
Observations	10720	10720	10720	10720	10720
	Dep. Var: Employment/Population				
	All	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
B: Add Labor Demand Controls					
β^1: SC	-360.074***	38.922	-103.131**	-256.786***	-39.079
	(88.560)	(66.211)	(48.839)	(47.165)	(52.983)
PUMA-Year Trends	X	X	X	X	X
287g	X	X	X	X	X
Labor Demand	X	X	X	X	X
Y mean	37815.78	11293.95	7974.70	8935.62	9611.51
Observations	10720	10720	10720	10720	10720
	Dep. Var: Employment/Population				
	All	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
C: Add Housing Price Controls					
β^1: SC	-215.073**	87.223	-74.629	-230.879***	3.212
	(84.757)	(67.421)	(48.715)	(48.316)	(53.509)
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	37815.78	11293.95	7974.70	8935.62	9611.51
Observations	10710	10710	10710	10710	10710

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-ages (20-64) males. The dependent variable in column 1 is total employment by PUMA and year, 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. 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 Immigration Laws on Employment by Citizenship Status, Men & ALL PUMAs

	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: Total					
β^1: SC	-215.073**	87.223	-74.629	-230.879***	3.212
	(84.757)	(67.421)	(48.715)	(48.316)	(53.509)
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	37815.78	11293.95	7974.70	8935.62	9611.51
Observations	10710	10710	10710	10710	10710
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
B: Citizen					
β^1: SC	-90.099	122.121**	-14.375	-216.199***	18.354
	(82.444)	(59.995)	(43.504)	(47.235)	(49.115)
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	33712.85	9320.35	6994.23	8443.85	8954.42
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^1: SC	-125.801***	-35.214	-60.116**	-14.721	-15.750
	(48.426)	(37.227)	(23.509)	(15.174)	(16.490)
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	4102.44	1973.55	980.32	491.68	656.89
Observations	10710	10710	10710	10710	10710
	Dep. Var: Employment/Population				
	All	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
D: Low Skill Non-Citizen					
β^1: SC	-131.721***	-52.393	-55.786***	-16.991	-6.552
	(44.276)	(35.004)	(21.616)	(10.720)	(5.398)
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	2771.53	1715.83	766.48	232.77	56.44
Observations	10710	10710	10710	10710	10710

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-ages (20-64) males. The dependent variable in column 1 is total employment by PUMA and year, 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. Panel A includes the full sample, and Panels B-D restrict the sample to citizens, non-citizens, and low-skill non-citizens, respectively. All specifications include year and PUMA fixed effects. 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 A6: Effect of Immigration Laws on Employment by Detailed Sector, Citizen Men

	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
A: AGRICULTURE (23.04)					
β: SC	-35.048	-10.733	-15.014	-6.674	-2.627
	(23.442)	(11.173)	(14.909)	(14.760)	(5.654)
Y mean	982.71	213.60	312.62	392.48	64.01
Observations	8991	8991	8991	8991	8991
	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
B: CONSTRUCTION (15.38)					
β: SC	-15.413	5.500	6.100	-12.898	-14.115
	(50.579)	(32.046)	(29.416)	(15.240)	(12.676)
Y mean	3835.98	1714.94	1407.09	472.77	241.18
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
C: PERSONAL & ENTERTAINMENT SERVICES (10.87)					
β: SC	-3.984	-5.414	-14.580	13.333	2.677
	(26.944)	(12.798)	(16.978)	(14.887)	(9.647)
Y mean	1070.32	246.38	351.02	318.66	154.26
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	-71.310	0.301	-9.688	-81.616**	19.693
	(63.677)	(37.205)	(26.545)	(40.892)	(17.378)
Y mean	6398.64	2101.53	1102.95	2694.88	499.27
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	75.313	60.227	15.539	-31.965	31.511
	(58.516)	(39.931)	(23.420)	(21.178)	(24.999)
Y mean	5761.67	2566.34	1134.12	765.93	1295.28
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
F: BUSINESS SERVICES (7.35)					
β: SC	-18.391	-19.662	-8.963	-46.322**	56.556***
	(41.339)	(22.407)	(17.480)	(19.771)	(21.623)
Y mean	2462.96	771.95	460.25	482.17	748.59
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	-21.001	19.165	-32.474	8.366	-16.059
	(44.836)	(31.031)	(23.822)	(18.968)	(18.200)
Y mean	3383.23	1321.63	910.65	579.68	571.28
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	10.679	2.515	0.917	0.889	6.358
	(20.227)	(14.018)	(11.569)	(5.011)	(7.197)
Y mean	434.11	258.61	84.00	32.47	59.03
Observations	5430	5430	5430	5430	5430
	Dep. Var: Employment/Population				
	Total	$skill < 25$	$25 < skill < 50$	$50 < skill < 75$	$75 < skill$
I: FIRE (1.78)					
β: SC	-22.027	4.124	-20.772**	2.055	-7.434
	(33.854)	(7.712)	(10.314)	(20.878)	(23.690)
Y mean	1889.91	90.81	163.34	769.03	866.74
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 (1.27)					
β: SC	-29.771	12.329	-2.559	-13.141	-26.400
	(62.389)	(17.882)	(24.389)	(24.542)	(48.949)
Y mean	5903.18	502.37	799.16	833.59	3768.07
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-ages (20-64) male citizens. The dependent variable in column 1 is total employment by PUMA, year and industry, in columns 2-5 the dependent variable is employment by industry and occupational skill intensity. In all specifications employment is divided by PUMA population and multiplied by 100,000. Industries are presented in descending order of intensity of low skill non-citizen labor, which is reported in parenthesis for each industry for 2005. All specifications include year and PUMA fixed effects, PUMA-year linear trends and our full set of 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 A7: Effect of Immigration Laws on Employment by Detailed Sector, LS Non-Citizen Men

	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
A: AGRICULTURE (23.04)					
β: SC	-3.011	5.315	-10.879	1.381	1.172
	(17.955)	(12.276)	(12.501)	(3.393)	(1.035)
Y mean	322.18	167.51	137.21	16.49	0.98
Observations	8991	8991	8991	8991	8991
	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
B: CONSTRUCTION (15.38)					
β: SC	-90.423***	-64.551***	-21.549	-2.401	-1.922
	(25.444)	(19.377)	(13.183)	(3.388)	(1.859)
Y mean	535.78	337.26	183.16	11.47	3.88
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
C: PERSONAL & ENTERTAINMENT SERVICES (10.87)					
β: SC	13.884	12.410*	1.417	-0.222	0.278
	(9.300)	(6.999)	(5.820)	(2.729)	(0.851)
Y mean	88.62	41.99	36.54	8.59	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	-6.921	11.344	-14.783	-6.316	2.834*
	(28.223)	(24.358)	(10.652)	(8.127)	(1.616)
Y mean	527.08	360.96	82.08	79.23	4.81
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	-47.460**	-19.537	-24.872***	1.760	-4.810*
	(20.507)	(16.445)	(8.282)	(3.093)	(2.645)
Y mean	309.23	234.49	54.00	13.22	7.52
Observations	9160	9160	9160	9160	9160
	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
F: BUSINESS SERVICES (7.35)					
β: SC	2.270	14.225	-8.205	-1.493	-2.257
	(12.480)	(11.376)	(5.262)	(3.111)	(2.055)
Y mean	159.25	119.44	25.84	9.07	4.90
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	22.201*	13.327	6.735	2.118	0.022
	(11.513)	(8.980)	(4.343)	(4.675)	(1.617)
Y mean	128.21	75.97	23.28	25.51	3.45
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	3.501	6.331	-2.378*	-0.858	0.406
	(4.377)	(4.094)	(1.257)	(0.685)	(0.481)
Y mean	12.51	10.73	1.32	0.24	0.22
Observations	5430	5430	5430	5430	5430
	Dep. Var: Employment/Population				
	Total	*skill* < 25	25 < *skill* < 50	50 < *skill* < 75	75 < *skill*
I: FIRE (1.78)					
β: SC	-2.110	-4.926*	-0.485	0.212	3.089***
	(5.003)	(2.838)	(3.085)	(2.561)	(1.125)
Y mean	31.43	11.06	9.45	7.82	3.09
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 (1.27)					
β: SC	-1.482	1.019	-3.535	1.090	-0.056
	(8.219)	(5.090)	(4.638)	(2.877)	(3.311)
Y mean	72.72	25.81	24.79	10.07	12.05
Observations	9160	9160	9160	9160	9160

Notes: Data are from the 2005-2014 American Community Survey. The sample is based on all working-ages (20-64) male non-citizens with a high school degree or less. The dependent variable in column 1 is total employment by PUMA year and industry, in columns 2-5 the dependent variable is employment by industry and occupational skill intensity. In all specifications employment is divided by PUMA population and multiplied by 100,000. Industries are presented in descending order of intensity of low skill non-citizen labor, which is reported in parenthesis for each industry for 2005. All specifications include year and PUMA fixed effects, PUMA-year linear trends and our full set of 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