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ABSTRACT

Immigration Enforcement and the Institutionalization of Elderly Americans*

This paper examines the relationship between immigration enforcement and institutionalization rates of the elderly. Exploiting the staggered implementation of the Secure Communities (SC) immigration enforcement program across U.S. counties from 2008 through 2014, we show that SC led to a 0.26 percentage points (6.8 percent) increase in the likelihood that Americans aged 65 and above live in an institution. Supportive of supply shocks in the household services market as a central mechanism, we find that the elderly who are most likely to purchase domestic worker services are also the most likely to move into nursing homes following the implementation of SC. Additionally, we find suggestive evidence of significant reductions in the work hours of housekeepers, personal care aids, and home health workers hinting at the critical role of negative supply shocks in occupations that facilitate aging in community.

JEL Classification: J14, J61, J68

Keywords: secure communities, elder care, immigration enforcement, aging, nursing homes

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1 Introduction

Over the past two decades, the United States has witnessed a spectacular increase in interior immigration enforcement. Since the inception of the U.S. Department of Homeland Security (DHS) after 9/11, the budget of Immigration Customs Enforcement (ICE)–the branch in charge of enforcing immigration law in the interior of the United States—has more than doubled. Its 2020 budget of $8.4 billion is almost equivalent to the $9.7 billion appropriated to the Federal Bureau of Investigation (FBI), far exceeding the $2.3 billion appropriated to the U.S. Drug Enforcement Administration (DEA) (Council, 2020). A broad literature has documented and examined the many ramifications of intensified immigration enforcement on undocumented immigrants, their families, and the communities in which they reside (e.g., Miles and Cox 2014; Alsan and Yang 2018; Hines and Peri 2019; Wang and Kaushal 2019; Amuedo-Dorantes et al. 2022; East and Velásquez 2022). In this paper, we focus on yet another consequence of intensified immigration enforcement on a growing population segment frequently relying on low-education domestic workers, many of whom are undocumented, for help with basic daily tasks –namely, American elderly. We examine how the implementation of Secure Communities –an interior immigration enforcement initiative responsible for the vast majority of the 200% increase in deportations from 2003 through the 2010s (East, 2020), led to increased institutionalization of older Americans through its impacts on the labor supply of workers in the household services market.

The importance of assessing the impact of immigration policy on the elderly cannot be overstated. The U.S. population is aging. Over the next 40 years, the U.S. population is expected to grow 25%. However, the number of people aged 65 and above is expected to grow by 92%, and the number of people aged 85 and above by an astonishing 198% (Vespa et al., 2018). The 2019 American Community Survey shows that within the elderly population, the likelihood of residing in an institutional setting quickly rises with age. While only 2.4% of individuals 65+ years old live in an institution, a total of 8.3% of 85+ years old do (ACS, 2019). In addition to the out-of-pocket costs paid by individuals and private long-term care insurance providers, Medicaid and Medicare spent roughly 93 billion dollars on institutional care in 2020 –a sum that is projected to reach 153 billion/year by 2030

(CMS, 2020). Yet, responses to surveys conducted before the COVID-19 pandemic suggest that the elderly overwhelmingly prefer to age in place –either in their own homes, or in the homes of loved ones (Binette and Vasold, 2018). These preferences are likely to have exacerbated following the pandemic given the overrepresentation of nursing home residents and staff among COVID-19 fatalities.

There is causal evidence that, in places with more immigrants, U.S.-born elderly are less likely to live in institutionalized settings (Butcher et al., 2021). This is presumably because immigrants are over-represented in household services sectors, such as housekeeping and home health aides, that the elderly needing assistance with independent living typically rely upon to age in place. We dig deeper into this finding to learn about the role of immigration policy in shaping the institutionalization rates of the elderly.

To that end, we focus on one critical policy, namely, the Secure Communities (SC) program. SC is an interior immigration enforcement initiative implemented in phases across U.S. counties between 2008 and 2014. Under SC, information gathered by local police after an arrest, including fingerprints, is entered into an electronic system connecting the Federal Bureau of Investigation (FBI) and Immigration Customs Enforcement (ICE) databases. Undocumented immigrants are flagged by the system, likely leading ICE to issue a detainer request asking the law enforcement agency to hold the individual for as much as 48 hours after his or her release date to provide ICE agents enough time to decide whether to take the individual into federal custody to initiate removal proceedings.

In theory, SC might not have had a discernible impact on the living arrangements of elderly Americans since most deported immigrants during that period were men (Carroll, 2014), whereas practically all domestic workers providing in-home support for the elderly are women. Nevertheless, SC may have impacted the market for household services –a market in which almost one in five workers are undocumented (Svajlenka, 2020). Specifically, SC could have reduced the number of individuals willing to work as housekeepers, home health workers and personal care aides due to deportation fears based on their own undocumented status or that of family members; East and Velásquez (2022) present evidence of SC-induced decreases in the number of hours worked by housekeepers and childcare workers. The lower labor supply in those occupations could stem from increased out-migration from, or decreased

in-migration to, counties with a tougher stance on immigration enforcement. Alternatively, decreased labor supply could arise from the decision of individuals that feel threatened by the policy, either directly or indirectly, to decrease their work hours in order to circumvent police encounters. In both instances, the adoption of SC would curtail the availability of housekeepers, home health aides, and personal care attendants. Elderly Americans who may have been able to age in place with such assistance may then find it increasingly necessary to rely on institutional long-term care.

Using data from the American Community Survey (ACS) from 2006 through 2012, we examine how a tougher stance on immigration may have impacted the institutionalization of elderly Americans by exploiting the temporal and geographic variation in the program's implementation. We find evidence of SC raising the institutionalization likelihood of elderly Americans by 0.26 percentage points (6.8 percent) –an impact that did not predate the policy's adoption and was evident during the first two years following its implementation.

Heterogeneity analyses reveal that the policy's impact was larger among Whites and college-educated elderly, who are more likely to afford domestic help. In addition, it is those with only moderate levels of disability that were most affected by the policy and, among those residing in a nursing home, policy adoption was not associated with higher disability levels. The results are not indicative of escalating care requirements of the elderly population, but they do align with an alternative scenario wherein elderly Americans with relatively minor disabilities gravitate towards institutionalized care if they have difficulties in securing domestic help. Finally, as we would expect given the demographic characteristics of the undocumented workers directly targeted by the policy, SC had a larger impact on the institutionalization of elderly Americans in localities with a greater share of less educated Hispanics in key health care and housekeeping occupations in the home health and private household services sectors.

To further understand the likely mechanisms at play, we examine the impact that SC had on the labor supply of housekeepers, home health workers, and personal care workers. We find evidence of reductions in the number of workers providing such services, although consistent with the findings by East and Velásquez (2022), it is hours of work that were more meaningfully reduced. Importantly, the labor supply decrease was mostly driven by

less-educated Hispanic workers from Mexico and Central America, who are also the ones most directly impacted by the SC policy.

The remainder of this paper is organized as follows. Section 2 provides background information on SC and discusses how the policy might have impacted the living arrangement choices of elderly Americans. The data and empirical modeling are discussed in section 3. Section 4 presents our main findings, along with a series of identification checks and heterogeneous analyses. Likely mechanisms are discussed in Section 5, and Section 6 concludes the study.

2 Background and Conceptual Framework

2.1 Immigration and Living Arrangements of the Elderly

Between 2000 and 2010, more than a quarter of elderly Americans ages 65 and above had difficulty performing daily activities (Hagen, 2013). While most elderly care is provided informally by friends and family members, approximately 37% of elderly Americans with a disability received formal care in their homes –an increasingly prevalent arrangement between 2004 and 2016 (Van Houtven et al., 2020). Nevertheless, despite substantial decreases in the nursing home residence over the last few decades (Hurd et al., 2014), long-term care provided in institutional settings will likely play an essential role in the foreseeable future.

Relative to care provided within homes, nursing homes and other institutions provide easier access to skilled medical care and specialized medical equipment. Despite constituting a significant expense (Chesak, 2021), nursing homes may be the most cost-effective way to provide adequate care for individuals with certain conditions, such as severe dementia. In-home care tends to be more labor intensive and especially intensive in labor lacking specialized medical training. Depending on the availability of family and friends, as well as the affordability of home care services, care provided within the community is often divided between unpaid family and friends and paid housekeepers and home health aides.

For individuals at either end of the care-needs distribution, the choice of whether to reside in an institutionalized setting is likely to be straightforward. For those with the

most intense care needs, nursing home residence may be the only cost-effective option. In contrast, for those who require only occasional assistance, paying for in-home services or receiving informal help will certainly make most sense. However, in the case of individuals with intermediate care needs, the decision to move into a nursing home for long-term care will depend on the willingness and ability of family members to provide care informally, as well as on the price and convenience of outsourcing home care to the market.[1]

There is a large and growing body of work showing that immigrant inflows to an area result in greater availability and less expensive caregiving and household services. In a seminal paper, Cortes (2008) shows that increases in the share of less educated immigrants in the workforce result in meaningful reductions in the cost of services, such as housekeeping and gardening. These immigrant-inflow effects are substantial enough to increase the labor supply of the high-wage native-born women who tend to use these services (Cortes and Tessada, 2011), reduce the provision of parent-provided childcare that can be easily outsourced (Amuedo-Dorantes and Sevilla, 2014), and raise fertility rates among high-education women in the United States (Furtado, 2015).[2]

In terms of studies focused on aging, Peri et al. (2015) use Italian data to show that in localities with larger immigrant inflows, older women retire later, presumably because they can better outsource care for their aging spouses while they are still working. Using Austrian data, Frimmel et al. (2020) find that the availability of low education immigrant labor softens the negative relationship between parental health shocks and their children's labor supply.

The relationship between the availability of less educated immigrant labor and the institutionalization rates of elderly Americans is, however, less clear. On one hand, nursing homes hire many foreign-born workers, and so an increase in immigrant labor supply may

[1]California's Paid Family Medical Leave Act (PFMLA) led to decreases in institutionalization rates of the elderly, presumably because the policy made it easier for family members to provide the necessary care within the community (Arora and Wolf, 2018). The policy allowed family caregivers to take work leaves of up to 6 weeks at 55% pay. Mommaerts and Truskinovsky (2020) show that in bad economic times, informal care provided by adult children tends to increase, most likely because the opportunity cost, in the form of lost wages, is lower when jobs are scarce.

[2]These general relationships are robust to examinations of different country settings and identification strategies (i.e., Cortes and Pan 2013; Farré et al. 2011; Barone and Mocetti 2011). For a review of this literature, see Furtado (2015).

reduce the price of nursing homes or improve their quality. Both could, in turn, lead to higher institutionalization rates. In that vein, Furtado and Ortega (2023) show that immigrant inflows to an area result in improvements in the quality of care provided by nursing homes in that locality.

On the other hand, if immigrant inflows make outsourcing home health care and private household services easier and more affordable, then more immigrant labor may make in-home caregiving more manageable for the family and friends of the most disabled elderly Americans. Access to services like housekeeping, cooking, and landscaping can enable the elderly with less severe disabilities to live independently, even without help from family and friends. In the end, whether immigrant labor has stronger impacts on the living arrangements of the elderly via changes in the nursing home sector or via changes in the home health and private household services sectors remains an empirical question.

In a paper closely related to our own, Butcher et al. (2021) show that localities with a higher share of less educated immigrants have lower institutionalization rates among the elderly, suggesting that immigrants play a stronger role in the market for home health care and private household services than in the nursing home market. We contribute to their analysis by assessing the role of immigration policy in shaping labor supply in home health care and private household services. To that end, we focus on a policy that symbolizes the rampant intensification of interior immigration enforcement throughout the entire United States from the mid-2000s onward –namely, the Secure Communities (SC) program. As we shall discuss, in addition to contributing to the largest number of deportations, SC was rolled out by the Department of Homeland Security (DHS), enabling us to estimate causal impacts of the policy.

2.2 Background on Secure Communities

Since 9/11, the United States has witnessed an unprecedented expansion of interior immigration enforcement. Between 2003 and 2013 alone, funding for the Immigration and Customs Enforcement (ICE) agency –the federal agency responsible for interior immigration enforcement– rose by 80 percent, apprehensions doubled, and removals increased by threefold (Council, 2020). The growth in interior immigration enforcement was possible thanks to

the cooperation of local and state enforcement agencies with ICE through various programs of which Secure Communities became the cornerstone.

Secure Communities (SC) was introduced in March 2008 (ICE, 2021), as controversy about the implementation costs of 287(g) agreements signed between ICE and local enforcement agencies and complaints about racial profiling grew.[3] SC is an information-sharing program aimed at facilitating the identification and removal of non-citizen criminals. Under SC, local police can submit information to an integrated database with ICE that allows for the identification of the immigration status and criminal activity of any individual. Specifically, when an individual is booked into a jail, fingerprints are shared with the Federal Bureau of Investigation (FBI), which in turn checks them against the U.S. Visitor and Immigrant Status Indicator Technology Program (US-VISIT) and the Automated Biometric Identification System (IDENT). If the arrested person is matched to an existing immigration violation, ICE and the local law-enforcement authorities are notified. ICE then evaluates each case and decides whether to take any action. If needed, ICE will issue a detainer against the arrested individual, requesting the arresting agency to hold the person for up to 48 hours after release, giving ICE time to decide whether to transfer the detainee to federal custody.

Unlike other immigration enforcement initiatives, such as the 287(g) agreements, SC does not require the deputization of local law enforcement, significantly lowering operationalization costs. As a result, the program, which started with a pilot implementation in March 2008, rolled out rapidly. At the beginning, ICE entered into Memoranda of Agreement (MOAs) with State Identification Bureaus responsible for data sharing between state and federal governments. As with 287(g) agreements, states believed they could opt not to enter or renew a MOA if they no longer wanted to participate in the program. Nevertheless,

[3] 287(g) agreements are formal written agreements or Memoranda of Agreements (MOAs) signed between the Department of Homeland Security (DHS) and state or local law enforcement agencies to deputize selected officers that, after undergoing some training, can perform some of the duties of federal immigration agents. These include interviewing individuals to ascertain their immigration status, issuing immigration detainers to hold individuals until ICE assumes custody and transferring non-citizens into ICE custody. When first created, there were three types of 287(g) agreements. One of them, the task force model, allowed deputized officers who encountered alleged noncitizens during their daily activities to question and arrest them if they believed they had violated federal immigration laws. This model quickly came under intense scrutiny after allegations that large shares of individuals detained through the program were individuals of color who posed no threat to public safety and had no criminal records. In some localities, such as Gaston, North Carolina, up to 57% of individuals detained through the 287(g) program were charged with traffic violations, such as speeding or driving without a license (Capps et al., 2011).

in August 2011, ICE rescinded all signed MOAs and announced the mandatory rollout of the program to all jurisdictions (Semple and Preston, 2011). By January 22, 2013, SC had reached nationwide coverage (see Figure 1).

As was the case with prior immigration enforcement initiatives, SC has been under great scrutiny. While ICE had argued that the program prioritized the removal of the most serious convicted criminals posing a threat to national security, that proved not to be the case. For instance, in Fiscal Year 2011, only 26% of SC deportations were immigrants with Level 1 convictions (the most serious offenses usually associated with felonies), followed by 19% with Level 2 convictions, 29% with Level 3 convictions for crimes with sentences of less than one year, and 26% with immigration violations or no criminal convictions (TRAC, 2020). As such, Kohli et al. (2011) show that more than 50% of deported individuals had no criminal conviction or were convicted of minor offenses, such as speeding or driving without a license. Moreover, around 40% of those arrested under SC reported having a U.S. citizen spouse or child, pointing to a potentially large emotional impact on a large segment of the U.S. citizen population (Kohli et al., 2011). Similarly, other authors maintain that, by aiding in the deportation of immigrants with no criminal records, SC created a strong fear of law enforcement officials among immigrants, pushing unauthorized migrants and their families into the shadows (e.g., Preston 2011; Aguilasocho et al. 2012; Nguyen and Gill 2016). In fact, there is evidence that the intensification of immigration enforcement largely brought about by SC was detrimental to community policing goals and public safety, with crime victims and witnesses hesitating to report to the police for fear of deportation (e.g., Hennessey 2011; Kirk et al. 2012; Amuedo-Dorantes et al. 2022). Lastly, there were concerns that local police would have an incentive to engage in racial profiling and pretextual arrests[4] –a worry further underscored by migrants' unfamiliarity with complaint procedures and the overall lack of oversight and transparency of the program (Waslin, 2011).

In response to these concerns, on November 20, 2014, the program was suspended and replaced by the Priority Enforcement Program (PEP) –intended to prioritize the arrest and deportation of serious criminals. Yet, on January 25, 2017, SC was reinstated by President

[4]Pretextual stops are those in which officers conducting a minor offense escalate it into an investigation of a more serious crime unrelated to the initial violation –a pattern that can explain increased reticence to cooperate with law enforcement, even on unrelated issues.

Donald Trump. While the re-activation of the program raised deportations, the increase in removals of serious criminals proved modest (TRAC, 2018). Nevertheless, restoring the program reignited deportation fears in immigrant communities (Hing, 2017). In 2021, President Joseph Biden suspended it.

2.3 Secure Communities and Institutionalization of the Elderly

The adoption of SC may have impacted the institutionalization of elderly Americans by curtailing the supply of home care and private household services upon which elderly Americans rely to age in place. In a paper examining the impact of SC on the labor supply of highly educated U.S.-born women, East and Velásquez (2022) discuss three ways in which the program might have altered the availability of household services. First, the policy could have lowered the number of workers able to provide such services through increased apprehensions and deportations of undocumented workers. After all, based on the 2006 ACS, approximately 13% of housekeepers, personal care aids, and home health providers in the United States are likely undocumented.[5] In practice, however, this is an unlikely channel given that 96% of apprehensions under the SC programs are male (East, 2020) and 89% of household service workers are female (authors' calculations).

A second channel for the impact of SC on the labor supply of household services by immigrant women is via migration (Borjas and Katz 2007; Cadena and Kovak 2016). Wives and daughters of deported males may have returned to their home countries to keep their families intact. Perhaps more significantly, concerns about increased apprehensions and deportations might have lowered the number of less skilled immigrant women residing in counties with more immigration enforcement–either by moving out of counties that had already adopted the program or by strategically locating in counties without the program. However, this channel might also be somewhat limited due to the quick rollout of the program throughout the entire country.

Finally, the number of less educated immigrant women residing and even working in SC counties may have remained the same; however, these women may have chosen to work

[5]Authors calculations assuming foreign-born Hispanics with high school degree or less working in these occupations to be likely undocumented.

fewer hours to limit their exposure, as well as that of their families, to intensified immigration enforcement. Given that home care and housekeeping workers often have multiple clients in the same day, the fear of being stopped by the police while driving between different clients may have induced undocumented workers to drop or not replace some of their clients.[6]

Using a similar identification strategy as ours, East and Velásquez (2022) show that SC significantly reduced the hours worked by less educated Hispanic immigrant women employed as housekeepers and childcare workers. We find similar evidence when focusing on sectors most relevant to elderly care, such as home health care and private household services. This response, which is accompanied by increases in their hourly wages in some cases, is suggestive of the relevant role of immigration policy in shaping labor supply in services critical in allowing American elderly to age in place and, in turn, explains how immigration policy may have contributed to their institutionalization rate.

3 Data and Methodology

3.1 Data

Data on the implementation of SC at the county level are obtained from the replication files of East and Velásquez (2022). The files specify the program's activation date in each Public Use Microdata Areas (PUMA), which occurred between 2008 and 2014. Data on the institutionalization of the elderly, as well as data on employment and wages in housekeeping, personal care, home health aides, and related occupations originate from the American Community Survey (ACS), covering the 2006 through 2012 period. The ACS provides information on the living arrangements of a representative large sample of individuals, along with geographical identifiers down to the Public Use Microdata Areas (PUMA) level.

[6]Consistent with a role played by fear of deportation in determining time use decisions of undocumented families, Arenas-Arroyo and Schmidpeter (2022) show a SC-induced reduction in pre-school enrollment among children of undocumented parents and a reduction in time spent socializing among these parents. Alsan and Yang (2018) show that the SC policy resulted in significant declines in SNAP and SSI enrollment among Hispanic citizens despite the fact that they were not themselves eligible for deportation, a result they attribute to network effects spreading fear through Hispanic communities. In a paper related to ours, East and Velásquez (2022) present evidence suggesting that the decrease in hours worked by housekeepers and childcare workers following SC implementation was sufficiently large to induce highly educated native-born women to decrease their own labor supply.

Our main sample when assessing the impact of SC on the institutionalization of the elderly is composed of U.S. citizens 65 years of age and older surveyed between 2006 and 2012. We start in 2006 since that is the first year that the ACS records whether the individual is institutionalized. We do not use data beyond 2012 in order to use PUMAs that implemented SC in 2013 and 2014 as a never treated group in the two-stage approach proposed by Gardner (2022).

Table 1 provides summary statistics for the sample of interest. On average, individuals in our sample are 75 years old. Women account for 57% of the sample, and approximately half of respondents are married. Eighty-two of the sample is White, eight percent is Black, and 6% is Hispanic. About 40% of respondents have a disability, 43% have a high school degree, 16% have some college, and 21% have a college degree or more. Four percent reside in an institutionalized setting and, altogether, close to 21% of the sample was exposed to SC at some point over the period covered by our analysis.

3.2 Empirical Specification

To estimate the impact of Secure Communities on the institutionalization of the elderly, we use a difference in differences identification strategy that exploits the staggered rollout of the SC program, as illustrated by equation (1):

$$INST_{ipt} = \alpha + \beta SC_{pt} + X'_{ipt}\delta + Z'_{pt}\gamma + \mu_p + \phi_t + \epsilon_{ipt} \tag{1}$$

where $INST_{ipt}$ equals one if individual i in PUMA p at time t resides in an institution (most likely a nursing home) and zero otherwise.[7] The vector SC_{pt} is a continuous measure for the degree of exposure of the PUMA to SC in year t.[8] The vector X'_{ipt} includes information

[7] We are not able to identify the type of institution in which an individual resides. Nevertheless, as noted by Butcher et al. (2021), the vast majority of those in prison (more than 85%) are men under the age of 40. Therefore, institutionalized status among those age 65 and older can be considered a reasonable proxy for living in a caregiving facility for the elderly. Nevertheless, as we show after presenting our main findings, we obtain comparable results when using the number of nursing home residents as the dependent variable.

[8] We follow East and Velásquez (2022) and consider a county to be treated if SC was implemented in that county by January of the survey year. However, in robustness checks, we experiment with alternative measures of the SC program implementation. To map county-level variation in sanctuary policies to the PUMA level, the level of geography available in the ACS data, we use an approach similar to East and Velásquez (2022), Alsan and Yang (2018), and Watson (2013). If an individual resides in a PUMA that is

on individual-level controls including age, age squared, race, marital status, and education of the respondent. The vector Z'_{pt} includes PUMA-year level controls, such as a Bartik-style measure of labor demand and information on the existence of a 287(g) agreement,[9] E-Verify mandate, or a sanctuary policy.[10] The vectors μ_p and ϕ_t denote PUMA and year fixed effects that account for time-invariant and unobservable macro-level traits or year-specific shocks, respectively.

To address concerns regarding potential biases in the two-way fixed-effects (TWFE) estimates in the presence of heterogeneous treatment effects, as was the case with the staggered adoption of the SC program, we conduct a diagnostic check using the Goodman-Bacon (2021) decomposition. Even though the check suggests the bias is small, we estimate equation (1) using the Gardner (2022) methodology that yields robust estimates of heterogenous treatment effects.[11]

Identification in the difference-in-differences setting described above relies on the assumption that, in the absence of SC, the institutionalization rates of elderly Americans in PUMAs that adopt SC at an earlier time would have resembled rates in later-adopting PUMAs. While this assumption is ultimately untestable, we conduct an event study that enables us to examine if institutionalization among the elderly already trended differently in PUMAs that adopted SC early (versus late) prior to the policy adoption, conditional on our control variables, as well as local area and year fixed effects.

In addition, we address other identification concerns stemming from the potential policy

equivalent in size or smaller than the county, the SC variable for that individual takes on the value of one if the person's county has implemented SC and zero otherwise. However, if the person resides in a PUMA that contains multiple counties, we assign a population-weighted policy value to the PUMA based on whether the person's potential counties of residence had implemented SC.

[9] As discussed previously, Section 287(g) agreements are written agreements between the Immigration and Customs Enforcement and local law enforcement agencies that deputize local officers to act as immigration officials and enforce immigration laws. It thus differs from SC, which does not deputize local law enforcement. Rather, SC is an information-sharing program between the Department of Homeland Security (DHS) and the Federal Bureau of Investigation (FBI).

[10] We consider a county to be treated by a sanctuary policy if such a policy had been implemented in that county by January of the survey year. To assign sanctuary policies (varying at the county level) to PUMAs, we follow the same technique used to assign SC policies to PUMAs described in footnote 8.

[11] The procedure proposed by Gardner (2022) consists of two steps. In the first step, institutionalization rates are estimated using PUMAS with counties that implemented SC after our sample period -that is, in 2013 and 2014. This is done to predict the counterfactual outcome in all periods and residualize institutionalization rates. Then, in a second step, the residualized institutionalization rates are regressed on the treatment variable (SC) to derive the treatment effect. Standard errors are constructed using GMM.

endogeneity, as would be the case if the timing of SC implementation was associated with changes in PUMA characteristics that predated the policy adoption. To that end, we *first* experiment with including as controls PUMA traits interacted with a time trend in equation (1). *Subsequently,* we model the adoption timing of SC as a function of changes in PUMA characteristics predating the policy implementation. Not surprisingly, given the mandatory nature of SC, we find that the timing of the policy implementation was not meaningfully correlated to changes in PUMA characteristics predating the program.

Finally, we conduct a series of robustness checks, which involve: (1) gauging the sensitivity of the estimates to different measurements of the SC adoption timing; (2) excluding early adoption years from our sample; and (3) conducting a placebo exercise in which we randomly assign SC activation dates to gauge if the policy estimates are spurious.

4 Did Secure Communities Impact the Institutionalization of the Elderly?

4.1 Main Findings

Table 2 reports the results from estimating equation (1) using the two-stage approach proposed by Gardner (2022), which yields robust estimates in the presence of heterogeneous treatment effects.[12] We consider multiple specifications that progressively add more controls. In column (1), we report the baseline impact of SC after including, exclusively, PUMA and year fixed effects. SC increased institutionalization among the elderly by 0.21 percentage points –a 5.6% reduction relative to the sample mean. Based on the results in column (2), this effect persists after accounting for individual level traits, such as age, marital status, education level, and a set of dummy variables indicative of whether the individual identifies as Black, Hispanic or has any disability. Next, in column (3), we further account for

[12]As noted in the methodology section, to assess the extent to which TWFE estimates could be biased due to the staggered adoption of the SC program, we conduct the Goodman-Bacon decomposition as a diagnostic check. The results are displayed in Appendix Table B1. Up to 67% of our estimate is driven by good comparisons of early treated PUMAs, which constitute our treated group, to later treated PUMAs, which compose our control group. Nevertheless, to ensure the estimates are not biased, we compute heterogeneous treatment robust estimates.

other immigration enforcement laws potentially impacting our outcomes, including the existence of a 287(g) agreement between local law enforcement agencies and ICE, E-Verify mandates, or the presence of a sanctuary policy. The estimated impact of SC remains practically unchanged. Finally, in column (4), we account for overlapping changes in economic conditions, as would have been the case during and after the 2008 recession. To that end, we include Bartik-style measures of labor demand that allows us to account for potentially confounding variations in economic conditions.[13] The estimated impact from this preferred model specification remains practically unaffected. The adoption of SC was accompanied by a 0.26 percentage point or 6.8% increase in the institutionalization propensity of elderly Americans.[14]

Our estimate is consistent with findings from Butcher et al. (2021), who report that a 10-percentage point increase in the share of less-educated immigrant workers was associated with a 1.5 percentage point (5.2%) reduction in the likelihood of living in an institutionalized setting for individuals ages 65 and up. In a similar vein, we find that a county's adoption of SC raised the reliance of American elderly on institutionalized care.

4.2 Identification Checks

Our identification strategy relies on the assumption that the implementation of SC was uncorrelated with any PUMA-specific traits or underlying trends impacting elderly institutionalization rates. To assess if this is a reasonable assumption, we conduct a few checks. *First,* in Appendix Table B3, we include interactions between changes in the PUMA characteristics from 2000 through 2005 and a linear trend.[15] The inclusion of these additional controls en-

[13]These measures are constructed by first calculating the share of each PUMA's employment that was in each industry in 2005 (before our sample period) by demographic group. These shares are then multiplied by yearly changes in demographic-group specific national employment in each industry. Finally, to construct Bartik measures of local labor demand in each year, the weighted industry shares are summed together in each PUMA in each year. Following East and Velásquez (2022), we control for separate Bartik measures for the following demographic groups: 1) all working-age adults, 2) working-age females with a college degree or more, 3) working-age males with a college degree or more, and 4) foreign-born working-age adults.

[14]We arrive to a similar conclusion if, instead of the ACS, we use data from the LTCFocus database on the number of nursing home residents per county and year. As shown in Appendix Table B2, column (2), the number of nursing home residents rose by approximately 3% following the implementation of SC.

[15]In particular, we consider the five-year change in the labor force participation rate, the unemployment rate, a housing price index, the share of the PUMA population that are citizens, the share Black, the share that work more than 50 hours a week, the share that have a college degree, the share that have a master's

ables us to account for the influence of any pre-trends in the economic conditions that could correlate with the implementation of SC in each county. The estimated impact from this preferred model specification remains practically unchanged, with the institutionalization propensity of American elderly rising by 0.24 percentage points or 6.3% with the adoption of SC.

Next, we examine if the adoption timing of SC was correlated with PUMA-specific pre-SC demographic and economic trends, including their respective institutionalization rates. To that end, we estimate equation (2):

$$Year_p = \alpha + \theta \Delta W'_p + \epsilon_p \tag{2}$$

where $Year_p$ stands for the year when SC was first implemented in PUMA p and the vector $\Delta W'_p$ includes changes in PUMA-level demographics and economic conditions between 2000 and 2005. Appendix Table B4 displays the results from this exercise. Only two PUMA traits appear to be significantly correlated with adoption timing of SC, *i.e.,* the change in the non-citizen population and changes in housing prices.[16] The former is likely related to the earlier adoption of SC by counties along the U.S.-Mexico border. Yet, the estimated coefficients are rather small, with a one standard deviation increase in each regressor accelerating the adoption of SC by 0.1 and 0.2 or the equivalent of 1 and 2.5 months, respectively. More generally, PUMA-specific pre-trends in demographic and economics traits do not seem to perform well in predicting the adoption timing of SC, as revealed by the low R-squared in the model.

Finally, we assess if institutionalization rates were already trending differently prior to the adoption of SC. To that end, we estimate the event study described by equation (3):

$$Y_{ipt} = \alpha + \sum_{j=-6}^{3} \beta_j 1(SC^j_{pt} = 1) + X'_{ipt}\delta + Z'_{pt}\gamma + \mu_p + \phi_t + \epsilon_{ipt} \tag{3}$$

where $1(SC^j_{pt} = 1)$ is an indicator variable equal to 1 if year t is the year SC is implemented in PUMA p and zero otherwise. As in the primary model, X'_{ipt} includes individual level

degree, and the share that have a doctoral degree, and the share of females that have each of these degrees, and the institutionalization rate of the elderly.

[16] We use the same variables listed in footnote 15.

controls and Z'_{pt} incorporates PUMA-year level controls, such as Bartik-style measures of labor demand and 287(g) agreements. The vectors μ_p and ϕ_t represent the PUMA and year fixed effects, respectively. We estimate the event study following Gardner (2022), clustering standard errors at the PUMA level. Figure 2 displays the coefficients and 95% confidence intervals from estimating equation (3). There is no evidence of differential pre-trends in institutionalization rates prior to the implementation of SC. However, there is a clear break in the trend following the program's implementation, with institutionalization rates rising. Overall, the event study supports the interpretation of the estimates in Table 2 as causal.

4.3 Robustness Checks

We conduct three additional checks aimed at assessing the robustness of our results. *First,* we experiment with alternative measures of the SC policy implementation. In Appendix Table B5, after displaying in column (1) the main results from Table 2,[17] we experiment with transforming the SC measure in column (1) into a binary variable equal to one if any county within the PUMA had enacted SC by January of the survey year (see column (2)). Next, in column (3), we code SC as the fraction of the year *before* the survey when SC was active. Finally, in column (4), we experiment with using county-level data on SC deportations to address concerns related to the distinct implementation of the program and/or that of other immigration policy measures across U.S. counties. In all instances, we obtain alike estimates to those in Table 2.

Second, we experiment with dropping PUMAs with early adopting counties. By the end of 2009, only 105 counties representing approximately 3% of the counties in the United States had activated the program. However, by the end of 2010 and 2011, the activation rate reached around 28% and 64%, respectively. Appendix Table B6 displays the results from eliminating early adopters. The estimated impact remains the same when we eliminate PUMAs with counties adopting SC during the first year of the program (see column (2)) –when counties believed they would be able to opt-in and out of the program. If we further restrict the sample by dropping PUMAs that adopted the program in 2009 (see column (3)),

[17] In Table 2, SC is a continuous value ranging between 0 and 1 based on the population-weighted share of counties in each PUMA where SC was activated by January of the survey year.

our sample is cut down by close to 600,000 observations and we lose some precision in our estimate. However, it remains largely of the same in magnitude, suggesting early adopters do not solely drive the results.

Finally, we assess the possible spurious nature of our findings through a placebo test in which we randomly assign SC PUMA-level implementation dates 1,000 times. Then, we estimate the model in equation (1) on data collapsed at the PUMA level. Appendix Figure B1 displays the results from this exercise. Only 0.3% of the estimates fall to the right of the actual estimate depicted by the vertical line, suggesting the estimated policy impact is not a spurious result.

4.4 Heterogeneous Impacts

An abundance of research has documented how the likelihood of residing in an institutionalized setting, versus aging in place, varies largely with demographic, family, and socioeconomic traits (e.g., Kobrin 1981; Wolf 1984; Wolf and Soldo 1988). For instance, financial constraints, the presence of other family members able to provide care, and the individual's ability to care for her/himself might prove critical in determining living arrangements. Elderly people with more severe health problems and mobility challenges might have care needs that cannot be met at home, regardless of the affordability of home care services. Hence, we would expect the impact of SC on institutionalization rates of the elderly to vary with their likely financial constraints, family situation, and health limitations. We examine whether that is the case in Tables 3 through 6.

To begin with, Table 3 displays the estimated impact of SC on the institutionalization of the elderly based on their race, ethnicity, educational attainment, and gender. Most of the SC-induced increase in institutionalization among the elderly stems from the rise among White and college-educated respondents. The adoption of SC is associated with a 7.5% increase in the institutionalization of non-Hispanic Whites, but it has no statistically significant impact on Black or Hispanic individuals. Black and Hispanic individuals may be less likely to use outsourced home care due to its high cost, making them less sensitive to changes in the availability of home care services. Also pointing to the fact that these services are a caregiving option for those who can afford them, SC has a stronger impact

on the institutionalization rates of the elderly with at least some college (9.8%) than on those with no college (4.2%). The last two columns of Table 3 present results for women and men. While the point estimate is greater for women (0.0031 vs. 0.0016), the percent increase is similar across gender (6.7% for women vs. 6.3% for men) due to the higher rates of institutionalization among women.

Next, in Table 4, we explore the impact of SC on the institutionalization of the elderly based on their age and disabilities. As can be seen in columns (1) and (2), SC is associated with a larger estimated impact on those ages 80 and above than on those 65 years of age and older, likely reflecting the greater help that older individuals might need with everyday tasks. Nevertheless, relative to their mean rates of institutionalization, the SC-induced increases in institutionalization rates appear rather similar across age groups.

In columns (3) and (4), we consider heterogeneity by level of disability. We classify those with light forms of disability, i.e., having difficulties in hearing or moving around, as having a moderate disability, whereas those having difficulties living independently are classified as having a severe form of disability. We estimate a 4.6% (0.77 percentage point) increase in the institutionalization rate of elderly with severe disabilities compared to, an albeit imprecisely estimated, 11.7% (0.11 percentage point) increase for elderly with a moderate disability. The higher impact among those with a moderate disability aligns with the hypothesis that, in the absence of SC, these individuals might have been able to age in place with the help of housekeepers and home health aides. On the other hand, those with a severe disability will likely require more sophisticated care that can be provided more efficiently in an institutional setting, regardless of the price or availability of homecare services. Column (5), which considers the impact of SC on the level of disability among those residing in nursing homes, supports that hypothesis. While imprecisely estimated, the estimate suggests that SC lowered the average disability level observed among the elderly residing in institutionalized settings, supporting the notion that SC made it difficult for those with moderate care needs to get the help needed to age in place. Overall, the results in Table 4 are not suggestive of increased institutionalization rates being driven by a larger number of people with disabilities or by the severity of their disabilities.

Finally, in Table 5, we explore the heterogeneous impact of SC on the institutionaliza-

tion rates of the elderly based on their marital status. It appears that the increase in the institutionalization rate of the elderly following the adoption of SC stems from the higher likelihood to live in an institution among elderly without a spouse. This finding is congruent with spouses performing some of the in-home caregiving and housekeeping duties that would otherwise be outsourced. However, because institutionalization rates are generally much higher among those without a spouse, the point estimates suggest that SC induced similar percent increases in institutionalization rates among those with and without a spouse present, i.e., around 6%.

To conclude, we explore whether the program's impact was greater in PUMAs with a greater concentration of individuals likely targeted or impacted by SC –a heterogeneous analysis that also serves as a robustness check. To that end, we interact the SC variable with information on the share of the 2005 PUMA population born in Mexico or Central America (row (2) of Table 6) and the share of the 2005 PUMA population that have less than a high school degree and born in Mexico or Central America (row (3) of Table 6). The point estimates suggest that the impact of SC on the institutionalization rate of the elderly rises with the share of individuals likely targeted or affected by the program. In the last two rows of Table 6, we zoom in further on PUMAs that had a large share of Mexicans and Central Americans working in key occupations and industries in 2005 before the implementation of SC. Specifically, we first focus on individuals who report being employed in home health, personal care, or housekeeping occupations. According to the estimate in row (4), a one standard deviation increase in the 2005 PUMA share of Hispanic workers from Mexico or Central America employed in the occupations and sectors of interest contributed to raising the institutionalization of elderly Americans following the implementation of SC by 3%. This pattern persists when we zoom in further on the subset of these workers in the home health or private households industries, as reflected by the estimates in row (5). In what follows, we discuss likely mechanisms at play.

5 Changes in the Home Health Care and Private Household Services as Mechanisms

Thus far, we have documented how the adoption of SC led to an increased likelihood of institutionalization among the elderly –an impact that we hypothesize has been driven by a diminished availability of migrant labor in household services. To assess the validity of this hypothesis, we conduct several additional analyses. To start, we examine how SC might have impacted the labor supply in housekeeping, personal care, and home health care occupations. We focus on individuals between 20 and 63 years of age who report their current or most recent occupation to fall within housekeeping, personal or home health care. We look at the total number of workers, and the total work hours supplied. Both are scaled by the population of the PUMA in each given year and multiplied by 100 to facilitate the interpretation of the estimates. In so doing, we achieve several aims. *First,* we can differentiate between the impact of SC on the number of workers in the market (extensive margin) as opposed to their hours of work (intensive margin). *Second,* by aggregating these variables at the PUMA level, we focus on market impacts.

Table 7 displays the results from that exercise using a model specification containing PUMA and temporal fixed effects, as well as the PUMA-specific time-varying controls in the most complete model specification of Table 2. We focus on respondents whose current or last occupation was in housekeeping, personal care and home health care, but to further ensure we are capturing workers likely to facilitate aging in place, we consider heterogeneity by industry as classified by *the North American Industry Classification System* (NAICS). The estimate in column (1) of Panel A might not be suggestive of an overall decrease in the number of housekeepers, personal care attendants, and home health workers in response to the implementation of SC. However, when we further restrict our attention to individuals employed by private households or in home health in column (2), the estimate becomes negative and statistically significant, albeit marginally at the 10 percent level. In particular, the SC program appears to have resulted in a 4.2% drop in the number of individuals working as housekeepers, personal care aides, and home health workers in the home health and private

households' sectors. Meanwhile, the estimates in columns (3) through (5), which focus on the impacts of SC on labor in the nursing home (column (3)), health sector (column (4)), and other sectors (column (5)), are not statistically significant. These results make sense, as undocumented workers are more likely to work informally for private households than formally in nursing homes and other segments of the health sector.

In Panel B, we consider impacts on the total hours of work by workers in these home care occupations. Again, the estimate is only statistically different from zero when we focus on the private households and home health sectors. In those sectors, the SC program lowered total hours of work among individuals offering services in the home health and private household sectors by 6%. Importantly, the impact of SC at the intensive margin is larger and statistically significant at conventional levels, unlike its impact at the extensive margin in Panel A. These findings are suggestive of SC primarily influencing hours of work, as opposed to mobility, the decision to participate in the labor market, or occupational choices. In addition, our findings are similar to those reported by East and Velásquez (2022), who find evidence of a 7.1% reduction in work hours when focusing, exclusively, on likely undocumented women in childcare and household services.

The analysis in Table 7 is certainly informative about the impacts of SC on the labor supply in occupations and sectors of interest. However, for further evidence that these changes are causal impacts of SC implementation, we look more closely at changes in the labor supply of less educated Hispanic immigrants who are more likely to be directly impacted by SC.[18] In Table 8, we explore the impacts of the SC program on workers in housekeeping, personal care and home health occupations employed in the home health and private household sectors separately by ethnicity and education. As in Table 7, in Panel A of Table 8, we continue to observe reductions in both the number of workers and their supplied hours of work. The reductions in the number of workers remain only marginally different from zero, even though they are non-negligible for less educated workers (8%) and less educated

[18]Because of its size and representativeness, the ACS is frequently used to gauge the impact of immigration policies on the labor supply patterns of immigrants, including those likely undocumented, e.g., Borjas (2017), Borjas and Cassidy (2019), Amuedo-Dorantes et al. (2020), East (2020), and East and Velásquez (2022), among many other ones. As in many of these studies, we consider less educated Hispanic immigrants as a group more likely to include undocumented immigrants. We note, however, that any errors in our measurement of this population should not affect the estimated impact of SC on the institutionalization of the elderly.

immigrants from Mexico and Central America (11%). What becomes more apparent from Panel B in Table 8 is the significant reduction in hours worked by Mexican and Central American immigrants (17%), less educated workers (15%), and less educated Mexican and Central American immigrants (23%) –incidentally, those most likely to be directly impacted by the SC program.

Finally, one might be interested in deciphering whether the observed labor reductions were primarily demand or supply led. To that end, we examine the responsiveness of log hourly wages to the program's implementation. Specifically, in Table 9, we estimate the impact of SC on log hourly wages in home health, personal care, and housekeeping occupations. The results in column (1) do not point to strong statistically significant wage impacts for the general population –a result that may be explained by sticky wages for many home care workers. However, when focusing on individuals with less than high school – potentially more likely to be among those impacted by SC, we find evidence of SC leading to 5% higher hourly wages –a wage impact in line with the 6.5% increase documented by East and Velásquez (2022) for low-educated female workers in household services. The overall evidence supports the notion of labor supply, rather than demand, reductions in home care occupations and sectors.

Summarizing, the results in Tables 7, 8 and 9 are suggestive of significant reductions in the supply of home health, personal care, and housekeeping services, especially by less educated Hispanic immigrants more likely to be directly impacted by SC. These reductions, which did not occur in other segments of the health sector, might have made it harder for elderly Americans to age in place, ultimately leading to increased likelihoods of institutionalization.

6 Summary and Conclusions

The stated intent of the Secure Communities policy was to provide protection from dangerous criminals living in the United States illegally. While there is little evidence that the policy significantly curtailed crime (Miles and Cox 2014; Hines and Peri 2019), a growing literature is identifying unintended consequences of the policy on legal immigrants and, more broadly, Americans. This paper contributes to this literature by showing that the policy led

to increased institutionalization rates among elderly Americans. This is not only a more expensive long-term care option for those paying for it out-of-pocket, but also appears to be a least favored option by most Americans. Based on survey data, Americans have a strong preference to age in place (Binette and Vasold, 2018), a preference that would seem substantiated by the little to non-existence evidence on the health benefits of aging at a nursing home (Werner et al. 2019; Bakx et al. 2020). In fact, high rates of COVID-19 mortality rates at nursing homes would support postponing nursing home stays for those able to age in place.

Moreover, since Medicare and Medicaid are the primary payers for the care of close to 60% of nursing home residents, this policy is costly for all U.S. taxpayers, not just the individuals who reside in nursing homes. In 2020, a total of 93 billion dollars were paid by Medicare and Medicaid to finance nursing care facilities and continuing care retirement communities (CMS, 2020), even though only 2.4% of Americans 65 years of age and older resided in an institutionalized setting in the 2019 ACS. Based on our estimates, the adoption of SC alone would have risen the share of institutionalized elderly by 6.8%, further accentuating the rising cost of caring for a rapidly aging American population. Post-pandemic staffing-shortages, specifically in healthcare and caregiving sectors, have made it very difficult to provide high quality care to those needing assistance. In the long run, if nothing is done, concerns about the quality and expense of elderly care are likely to intensify as the U.S. population ages and fertility rates decline. In this vein, Bahar and Wright (2023) place home health and personal care aids at the top of their list of fast-growing, immigrant-intensive occupations. While there is some evidence that new technologies may ease the burden on caregivers (Eggleston et al., 2021), this type of care is likely to remain labor intensive.

Our findings suggest that stricter immigration enforcement policies make aging at home more difficult by decreasing the supply of housekeepers, home health aides, and personal care workers that elderly Americans rely upon. Given demographic trends, labor shortages in these occupations and sectors may prove a persistent problem. Immigration policy could partially help address this challenge by facilitating immigrant employment in those jobs and, in doing so, improve the standard of living for vulnerable Americans requiring care.

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7 Tables

Table 1: Summary Statistics

	Mean	SD	Min	Max	Observations
Age	75.15	7.70	65	95	3,312,484
Female	0.57	0.49	0	1	3,312,484
Married	0.54	0.50	0	1	3,312,484
White	0.82	0.39	0	1	3,312,484
Black	0.08	0.28	0	1	3,312,484
Hispanic	0.06	0.23	0	1	3,312,484
Disabled	0.40	0.49	0	1	3,312,484
High School	0.43	0.50	0	1	3,312,484
Some College	0.16	0.37	0	1	3,312,484
College or More	0.21	0.41	0	1	3,312,484
Institutionalized	0.04	0.19	0	1	3,312,484
Secure Communities	0.21	0.40	0	1	3,312,484

Notes: Data are from the 2006-2012 American Community Survey. The sample includes US citizens 65 years of age and older. Data on Secure Communities are from the replication files of East and Velásquez (2022). The table presents the means, standard deviations, minimum, maximum, and sample size for the sample of interest. The variable "Disabled" takes the value one if the person have vision, hearing, cognitive, ambulatory, independent living, or self-care difficulties and zero otherwise.

Table 2: Effect of SC on the Institutionalization of the Elderly

	(1)	(2)	(3)	(4)
SC	0.00212**	0.00232**	0.00241**	0.00257***
	(0.00094)	(0.00091)	(0.00095)	(0.00096)
Mean Y	0.04	0.04	0.04	0.04
P-Value	0.02	0.01	0.01	0.01
% Effect	5.61	6.14	6.40	6.81
Observations	3,312,484	3,312,484	3,312,484	3,312,484
PUMA Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Individual Characteristics	No	Yes	Yes	Yes
Other Immig. Polices	No	No	Yes	Yes
PUMA-Year Controls	No	No	No	Yes

Notes: Data are from the 2006-2012 American Community Survey. The sample includes US citizens 65 years of age and older. All models include PUMA fixed effects and year fixed effects. Column (2) adds individual characteristics (i.e., age, age squared, gender, marital status, whether identified as Black, Hispanic, whether has a high school degree, some college, college or more and whether have any disability). Column (3) also adds other immigration policy controls, in particular 287(g) agreements, E-Verify mandates, and sanctuary policies. Finally, column (4) adds Bartik-style measures of labor demand for the following groups: all individuals, immigrants, high education women, and high education men. Standard errors are clustered at the PUMA level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 3: Heterogeneous Effects of SC on the Institutionalization of the Elderly by Demographic Group

	(1) All	(2) White	(3) Black	(4) Hispanic	(5) No College	(6) Some College	(7) Female	(8) Male
SC	0.00257***	0.00286***	-0.00070	0.00072	0.00196	0.00221**	0.00308**	0.00164*
	(0.00096)	(0.00104)	(0.00283)	(0.00220)	(0.00124)	(0.00093)	(0.00125)	(0.00090)
Mean Y	0.04	0.04	0.05	0.03	0.05	0.02	0.05	0.03
P-Value	0.01	0.01	0.81	0.75	0.11	0.02	0.01	0.07
% Effect	6.81	7.51	-1.39	2.79	4.20	9.78	6.65	6.25
Observations	3,312,484	2,770,675	255,317	161,257	2,101,517	1,210,967	1,878,583	1,433,901
PUMA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Immig. Polices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PUMA-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Data are from the 2006-2012 American Community Survey. The sample includes US citizens 65 years of age and older. All models include PUMA fixed effects and year fixed effects along with the set of controls in column (4) of Table 2. Standard errors are clustered at the PUMA level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 4: Heterogeneous Effects of SC on the Institutionalization of the Elderly by Age and Disability Status

	(1)	(2)	(3)	(4)	(5)
	Institutionalization				Disability
	All	Age: 80+	Moderate Disability	High Disability	Index
SC	0.00257***	0.00637**	0.00112	0.00766*	-0.02378*
	(0.00096)	(0.00253)	(0.00083)	(0.00399)	(0.01413)
Mean Y	0.04	0.09	0.01	0.17	0.02
P-Value	0.01	0.01	0.18	0.05	0.09
% Effect	6.81	6.97	11.68	4.57	
Observations	3,312,484	934,070	653,296	661,247	143,320
PUMA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Individual Characteristics	Yes	Yes	Yes	Yes	Yes
Other Immig. Polices	Yes	Yes	Yes	Yes	Yes
PUMA-Year Controls	Yes	Yes	Yes	Yes	Yes

Notes: Data are from the 2006-2012 American Community Survey. The sample includes US citizens 65 years of age and older. Column (1) reproduces the estimate using the full sample, while column (2) limits the sample to those age 80 and above. Column (3) only includes those with moderate levels of disability, i.e., having difficulties in hearing or moving around, while column (4) only includes those with any physical or mental health condition that lasted at least 6 months, making it difficult for them to take care of their own personal needs, such as bathing, dressing, and getting around the home. Finally, the sample in column (5) includes only individuals residing in an institution and the dependent variable is a disability index. The index is constructed by taking the average of standardized dummy variables that indicate the presence of vision, hearing, cognitive, ambulatory, independent living, or self-care difficulties. All models include PUMA fixed effects and year fixed effects, along with the set of controls in column (4) of Table 2. Standard errors are clustered at the PUMA level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 5: Heterogeneous Effects of SC on the Institutionalization of the Elderly by Marital Status

	(1) All	(2) Have Spouse	(3) No Spouse
SC	0.00257***	0.00078	0.00433***
	(0.00096)	(0.00057)	(0.00166)
Mean Y	0.04	0.01	0.07
P-Value	0.01	0.17	0.01
% Effect	6.81	5.92	6.49
Observations	3,312,484	1,866,156	1,446,328
PUMA Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Individual Characteristics	Yes	Yes	Yes
Other Immig. Polices	Yes	Yes	Yes
PUMA-Year Controls	Yes	Yes	Yes

Notes: Data are from the 2006-2012 American Community Survey. The sample includes US citizens 65 years of age and older. Column (1) reproduces the estimate using the full sample, while column (2) limits the sample to those reporting having a spouse, either present or absent. Finally, column (3) includes individuals that are separated, divorced, widowed, or never married. All models include PUMA fixed effects and year fixed effects, along with the set of controls in column (4) of Table 2. Standard errors are clustered at the PUMA level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 6: Heterogeneous Effects of SC on the Institutionalization of the Elderly by Intensity of Treatment

	(1)	(2)	(3)	(4)
SC	0.00097	0.00101	0.00117	0.00123
	(0.00103)	(0.00102)	(0.00101)	(0.00098)
SC * Share Born in Mex/CA	0.02689***			
	(0.00932)			
SC * Share LE Born in Mex/CA		0.04483***		
		(0.01496)		
SC * Share of Related Workers Born in Mex/CA			0.00885***	
			(0.00286)	
SC * Share of Workers of Interest Born in Mex/CA				0.00784***
				(0.00227)
Mean Y	0.04	0.04	0.04	0.04
Mean Intensity	0.01	0.01	0.03	0.04
SD Intensity	0.04	0.02	0.11	0.13
β–Mean Int	0.0013	0.0013	0.0015	0.0015
β–1 SD Higher Int	0.0023	0.0024	0.0024	0.0025
P-Value SC	0.34	0.32	0.25	0.21
P-Value SC & Interaction	0.00	0.00	0.00	0.00
Observations	3,312,484	3,312,484	3,312,484	3,312,484
PUMA Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Individual Characteristics	Yes	Yes	Yes	Yes
Other Immig. Polices	Yes	Yes	Yes	Yes
PUMA-Year Controls	Yes	Yes	Yes	Yes

Notes: Data are from the 2006-2012 American Community Survey. The sample includes US citizens 65 years of age and older. Shares are calculated using the 2005 ACS. "Related workers" are those whom reported occupation is in home heath, personal care, and Housekeeping occupations, while "workers of interest" is a group further limited to those whose reported sector is either Home health care or private households sectors. All models include PUMA fixed effects and year fixed effects, along with the set of controls in column (4) of Table 2. Standard errors are clustered at the PUMA level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 7: Effects of SC on the Labor Supply in Home Heath, Personal Care, and Housekeeping Occupations by Sector

	All Sectors	Home Health & Private HH Sectors	Nursing Homes Sector	Health Sector	Other Sectors
A: Number of Workers					
SC	0.00826	-0.02922*	0.01546	0.02023	0.00180
	(0.03222)	(0.01691)	(0.01558)	(0.01547)	(0.01911)
Mean Y	2.63	0.69	0.63	0.57	0.74
P-Value SC	0.80	0.08	0.32	0.19	0.93
% Effect	0.31	-4.23	2.47	3.57	0.24
Observations	7,518	7,518	7,518	7,518	7,518
B: Number of Hours Worked					
SC	-0.04567	-1.29715**	0.79826	0.88845	-0.43524
	(1.21655)	(0.61382)	(0.58319)	(0.59057)	(0.69704)
Mean Y	90.58	21.82	23.15	20.85	24.76
P-Value SC	0.97	0.03	0.17	0.13	0.53
% Effect	-0.05	-5.95	3.45	4.26	-1.76
Observations	7,518	7,518	7,518	7,518	7,518

Notes: Data are from the 2006-2012 American Community Survey. The sample includes those aged 20-63 who report their current or most recent occupation in Home Health, Personal Care, or Housekeeping occupations. Sectors are defined using the NAICS codes (see Appendix A). In Panels A and B, we group the number of total workers (hours worked), divide that number by the PUMA population, and multiply that by 100. All specifications control for PUMA and year fixed effects, as well as for other immigration policies, such as 287(g) agreements, E-Verify mandates, and sanctuary policies. In addition, we include Bartik-style measures of labor demand. Standard errors are clustered at the PUMA level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 8: Effects of SC on the Labor Supply in Home Heath, Personal Care, and Housekeeping Occupations within Home Health Care and Private Households Sectors

	All	Mex/CA	Others	All LE	Mex/CA LE	Other LE
A: Number of Workers						
SC	-0.02922*	-0.01084	-0.01839	-0.01390*	-0.00869*	-0.00521
	(0.01691)	(0.00712)	(0.01496)	(0.00794)	(0.00486)	(0.00566)
Mean Y	0.69	0.13	0.56	0.17	0.08	0.10
P-Value SC	0.08	0.13	0.22	0.08	0.07	0.36
% Effect	-4.23	-8.23	-3.28	-7.99	-11.36	-5.35
Observations	7,518	7,518	7,518	7,518	7,518	7,518
B: Number of Hours Worked						
SC	-1.29715**	-0.66923***	-0.62792	-0.76954***	-0.50633***	-0.26321
	(0.61382)	(0.23922)	(0.55153)	(0.27108)	(0.16683)	(0.20504)
Mean Y	21.82	3.85	17.97	5.22	2.18	3.04
P-Value SC	0.03	0.01	0.25	0.00	0.00	0.20
% Effect	-5.95	-17.38	-3.49	-14.74	-23.22	-8.66
Observations	7,518	7,518	7,518	7,518	7,518	7,518

Notes: Data are from the 2006-2012 American Community Survey. The sample includes those aged 20-63 who report their current or most recent occupation in Home Health, Personal Care, or Housekeeping occupations and are employed in Home Health Care or Private Households sectors based on the reported NAICS codes. Columns (2) and (5) include those who report being born in Mexico or Central America, while columns (3) - (6) include those with low education levels (less than high school). In Panels A and B, we group the number of total workers (hours worked), divide that number by the PUMA population, and multiply it by 100. All specifications control for the set of fixed effects and controls in Table 7. Standard errors are clustered at the PUMA level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

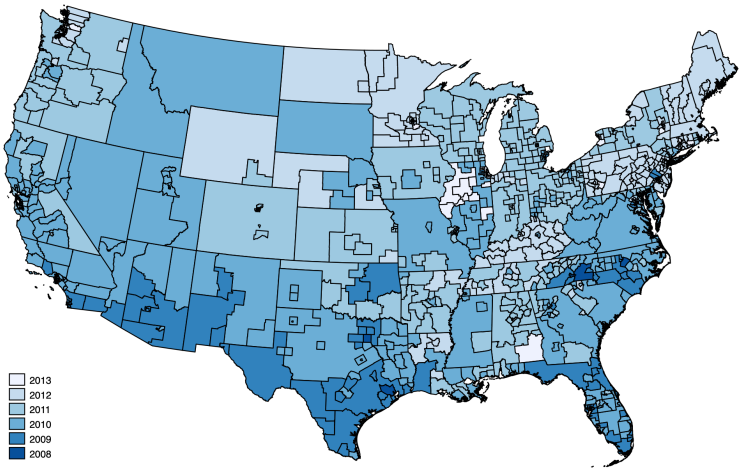
Table 9: Effects of SC on Wages in Home Heath, Personal Care, and Housekeeping Occupations

	All	LE
SC	0.00944	0.04803**
	(0.00822)	(0.02078)
Mean Y	2.45	2.31
P-Value SC	0.25	0.02
Observations	258,445	46,146
PUMA Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Individual Characteristics	Yes	Yes
Other Immig. Polices	Yes	Yes
PUMA-Year Controls	Yes	Yes

Notes: Data are from the 2006-2012 American Community Survey. The sample includes those aged 20-63 who report their current or most recent occupation in Home Health, Personal Care, or Housekeeping occupations. Column (1) reports the estimated impact on hourly wages for the full sample, while column (2) includes those with low education levels (less than high school). All specifications control for the set of fixed effects and controls in Table 7. All specifications also controls for individual characteristics including age, age squares, gender, marital status, number of children, whether identified as Black or Hispanic, and whether has a high school degree, some college, and college or more. Standard errors are clustered at the PUMA level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

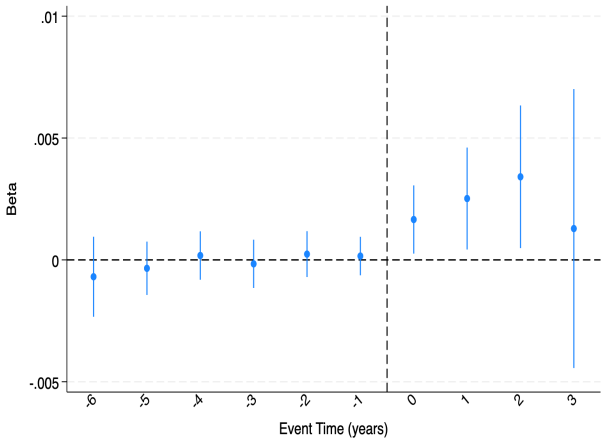
8 Figures

Figure 1: The Rollout Date of SC Across the US PUMAs



Data are from the U.S. Immigration and Customs Enforcement Secure Communities Activation Report. Figure depicts the year SC was first activated in any of the counties within each PUMA.

Figure 2: Effect of SC on the Institutionalization of the Elderly



Data are from the 2006-2012 American Community Survey. The sample includes all US citizens 65 years of age and older. The model includes PUMA fixed effects and year fixed effects, along with the set of controls in column (4) of Table 2. The figure depicts an event study constructed following Gardner (2022). The vertical line signifies the adoption of SC. Since all PUMAs were eventually treated, PUMAs treated in 2013 and 2014 are used as the comparison group, and the sample ends in 2012. Standard errors are clustered at the PUMA level.

9 Appendix A

9.1 Matching SC, Deportations, and Other Immigration Policies to the PUMA level:

Data on the activation of Secure Communities along with other immigration policies are obtained from the replication files of East and Velásquez (2022). In order to link the county-level data to the PUMA level, the SC variable for PUMAs that are equivalent to or smaller than a county receive the value of the SC variable for the corresponding county. For PUMAs that contain several counties, the value of the SC variable in each county is weighted by the fraction of the total PUMA population residing in the county. The data is then collapsed to the PUMA level. We use the Geographic Correspondence Engine (Geocorr 2014) at the Missouri Census Data Center to obtain data on the proportion of the PUMA population that lives in each underlying county. We follow a similar procedure to construct the sanctuary policy measure used as a control.

9.2 Bartik Labor Demand Measures:

We obtained the Bartik Measures of labor demand from East et al. (2023). The authors calculated these measures as follows:

$$Bartik_{pt} = \sum_{i=1}^{20} \frac{emp_{ip2005}}{emp_{p2005}} * emp_{it} \tag{4}$$

where $Bartik_{pt}$ is the group specific[19] Bartik measure of labor demand in PUMA p at year t, emp_{ip2005} is the number of workers in industry i in PUMA p in year 2005, emp_{p2005} is the number of workers in PUMA p in year 2005, and emp_{it} is the nation-wide number of workers in industry i in year t.

9.3 LTCFocus Data

We use data on the number of nursing home residents within the county from LTCFocus. Since the number of residents is not available in the LTCFocus dataset, we derive it as follows: occupancy rate multiplied by number of beds. The occupancy rate is the average number of occupied beds among all facilities divided by the total number of beds. Both numbers are obtain by LTCFocus from the Online Survey Certification and Reporting (OSCAR) system. Both occupancy rate and number of beds are obtained by surveying nursing homes. If a nursing home was not surveyed during a certain year, LTCFocus imputes the values with the closest values either from previous or next year. Finally, they aggregate the values to the county and state level.

[19]The groups we use in our preferred specification are: all working-age adults, foreign-born working-age adults, college-educated working-age females, and college-educated working-age males.

9.4 Occupations and Sectors:

We use the variables occ2010 "Occupation, 2010 basis" and INDNAICS "Industry, NAICS classification" in the American Community Surveys to identify workers likely to be connected to the provision of services that facilitate aging in community among the elderly. The selected occupations and sectors are presented below.

- Related Occupations (occ2010):
    1. 3600: Nursing, Psychiatric, and Home Health Aides
    2. 4230: Maids and Housekeeping Cleaners
    3. 4610: Personal Care Aides
- Classification of NAICS (indnaics) in Table 7:
    1. Home health & Private HH:
        - 6216: Home health care services
        - 814: Private households
    2. Nursing Homes:
        - 6231: Nursing care facilities
        - 623M: Residential care facilities, without nursing
    3. Health Sector:
        - 6211: Offices of physicians
        - 6212: Offices of dentists
        - 62131: Office of chiropractors
        - 62132: Offices of optometrists
        - 6213ZM: Offices of other health practitioners
        - 6214: Outpatient care centers
        - 621M: Other health care services
        - 622: Hospitals
    4. Other Sectors (top 10 sectors):
        - 531: Real Estate
        - 5613: Employment Services
        - 5617Z: Services to Buildings and Dwellings
        - 6111: Elementary and Secondary Schools
        - 611M1: Colleges and Universities
        - 6241: Individual and Family Services
        - 6243: Vocational Rehabilitation Services
        - 713Z: Amusement, Gambling, and Recreation Industries
        - 7211: Traveler Accommodation
        - 923: Administration of Human Resource Programs

10 Appendix B

10.1 Tables

Table B1: Bacon Decomposition of the Baseline Estimates

	(1)
SC	0.0022***
	(0.0007)
Good Comparison (early treatment v.s. late control):	
Weight	0.6738
Effect	0.0019
Bad Comparison (late treatment v.s. early control):	
Weight	0.3262
Effect	0.0003

Notes: Data are from the 2006-2014 American Community Survey. The sample includes US citizens 65 years of age and older. The model include PUMA and year fixed effects. Standard errors are clustered at the PUMA level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table B2: Effect of SC on the Institutionalization of the Elderly (Robustness to Alternative Measure)

	(1) Baseline Result	(2) LTCFocus log(# of residents)
SC	0.00212**	0.02714***
	(0.00094)	(0.00508)
Mean Y	0.04	7.32
P-Value	0.02	0.00
% Effect	5.61	-
Observations	3,312,484	20,428
Area Fixed Effects	PUMA	County
Year Fixed Effects	Yes	Yes

Notes: Data are from the 2006-2012 American Community Survey and the 2006-2012 LTCFocus database. The sample in column (1) includes US citizens 65 years of age and older, while the sample in column (2) includes all nursing home residents (see Appendix A). Column (1) reproduces the baseline result. In column (2), we use the number of nursing homes residents at the county level to estimate the impact of SC on the number of all nursing homes residents. Column (1) includes PUMA and year fixed effects, while column (2) includes county and year fixed effects. Standard errors are clustered at the PUMA level in column (1) and the county level in column (2). ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table B3: Effect of SC on the Institutionalization of the Elderly (Robustness to adding PUMA Characteristics × Time Trend)

	(1)	(2)
SC	0.00257***	0.00236**
	(0.00096)	(0.00099)
Mean Y	0.04	0.04
P-Value	0.01	0.02
% Effect	6.81	6.26
Observations	3,312,484	3,312,484
PUMA Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Individual Characteristics	Yes	Yes
Other Immig. Polices	Yes	Yes
PUMA-Year Controls	Yes	Yes
PUMA Characteristic Trends	No	Yes

Notes: Data are from the 2006-2012 American Community Survey. The sample includes US citizens 65 years of age and older. All models include PUMA fixed effects and year fixed effects, along with the set of controls in column (4) of Table 2. Column (2) also includes PUMA characteristic trends (1- interactions of a time trend with the change in the following PUMA characteristics between 2000 and 2005: labor force participation rate, unemployment rate, housing price index, the share of the PUMA that are citizens, black, non-citizens, work more than 50 and 60 hours, have a college degree, masters degree, or a Ph.D., as well as the same education categories just for females. 2- interaction of a time trend with the change in the share of institutionalized elderly between 2000 and 2006 at the PUMA level). Standard errors are clustered at the PUMA level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table B4: Correlation between 2000-2005 Changes in PUMA Characteristics and SC Adoption Year

	Mean	SD	Estimate	SE
Change Citizen	0.005	0.023	-1.543	(2.197)
Change % Black	0.001	0.025	-1.648	(1.414)
Change % Labor Force Part	0.588	2.543	0.001	(0.015)
Change Non-Citizen	0.009	0.024	-5.477**	(2.025)
Change % Work > 50 Hours if Work	-1.023	2.111	0.041	(0.023)
Change % Work > 60 Hours if Work	-0.432	1.243	-0.034	(0.037)
Change % with College	0.017	0.021	2.325	(2.746)
Change % with Masters	0.010	0.013	7.003	(4.624)
Change % with Ph.D.	0.001	0.008	7.918	(6.376)
Change % Women with College	0.010	0.014	-1.348	(4.082)
Change % Women with Masters	0.007	0.008	4.735	(6.985)
Change % Women with Ph.D.	0.001	0.005	-13.205	(10.611)
Change Unemployment Rate	0.010	0.015	-4.915	(2.539)
Change Housing Prices	48.370	31.391	-0.007***	(0.001)
Change Institutionalization	-0.003	0.025	0.739	(1.347)
Mean Y			2011.72	
R-Squared			0.07	
N	1078		1078	

Notes: Data are from the 2005 American Community Survey and the 2000 Census. We estimate the following regression: $Year_p = \alpha + \theta \Delta W_p' + \epsilon_p$, where $Year_p$ is the first year SC was implemented in the PUMA and $\Delta W_p'$ denote changes in PUMA-level demographics and economic conditions between 2000 and 2005 (2006 for change institutionalization).

Table B5: Effect of SC on the Institutionalization of the Elderly (Robustness to Different Coding Methods for SC Variable)

	(1) Main Result	(2) Binary Treatment	(3) Fraction Last Year	(4) Based on SC Deportations
SC	0.00257***	0.00221**	0.00270**	0.00291***
	(0.00096)	(0.00090)	(0.00107)	(0.00097)
Mean Y	0.04	0.04	0.04	0.04
P-Value	0.01	0.01	0.01	0.00
% Effect	6.81	5.85	7.15	7.70
Observations	3,312,484	3,312,484	3,312,484	3,312,484
PUMA Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Individual Characteristics	Yes	Yes	Yes	Yes
Other Immig. Polices	Yes	Yes	Yes	Yes
PUMA-Year Controls	Yes	Yes	Yes	Yes

Notes: Data are from the 2006-2012 American Community Survey. The sample includes US citizens 65 years of age and older. All models include PUMA fixed effects and year fixed effects, along with the set of controls in column (4) of Table 2. Column (1) reproduces the main result, while in column (2) SC values above zero are transformed to one. In column (3), SC is coded based on the fraction of the previous year that SC was active in the PUMA. Finally, in column (4), we use deportations under SC to identify the activation of SC, instead of the program activation dates (i.e., PUMAs are assumed untreated until a deportation is observed). We obtain data on deportations under SC from TRAC: https://trac.syr.edu/phptools/immigration/secure/. Standard errors are clustered at the PUMA level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

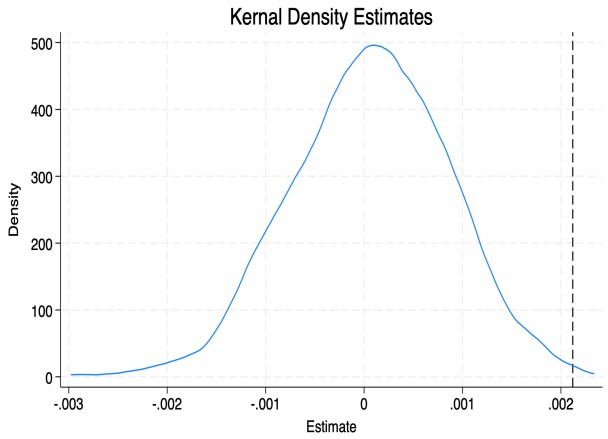
Table B6: Effect of SC on the Institutionalization of the Elderly (Robustness to Dropping Early Adopters)

	(1) Full Sample	(2) Excluding 2008	(3) Excluding 2008, 2009
SC	0.00257***	0.00235**	0.00197**
	(0.00096)	(0.00096)	(0.00100)
Mean Y	0.04	0.04	0.04
P-Value	0.01	0.01	0.05
% Effect	6.81	6.22	4.99
Observations	3,312,484	3,255,900	2,708,846
PUMA Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Individual Characteristics	Yes	Yes	Yes
Other Immig. Polices	Yes	Yes	Yes
PUMA-Year Controls	Yes	Yes	Yes

Notes: Data are from the 2006-2012 American Community Survey. The sample includes US citizens 65 years of age and older. All models include PUMA fixed effects and year fixed effects, along with the set of controls in column (4) of Table 2. Column (1) reproduces the main result, while column (2) excludes data from PUMAs in which SC was activated in any of their underlying counties in 2008. Finally, column (3) excludes data from PUMAs in which SC was activated in any of their underlying counties in 2008 or 2009. Standard errors are clustered at the PUMA level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

11 Figures

Figure B1: Effect of SC on the Institutionalization of the Elderly (Placebo Test)



Data are from the 2006-2012 American Community Survey. The sample includes all US citizens 65 years of age and older. and above. We randomly assign the distribution of SC activation dates to the actual data, collapsed to the PUMA level. Then, we estimate the impact of these random activations and repeat the process 1000 times. Only 0.3% of the estimates fall to the right of the baseline estimate.