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Immigration enforcement and the institutionalization of elderly Americans

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ABSTRACT

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 aides, and home health workers hinting at the critical role of negative supply shocks in occupations that facilitate aging in community.

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

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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 (Ruggles et al., 2023). 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 per 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 long as 48 h after a 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.

In a study showing that SC led to increases in labor supply of college-educated U.S. born mothers, 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, their reduced labor supply could arise from the decision of individuals that feel threatened by the policy, either directly or indirectly, to decrease their work hours 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.

Focusing on data from the American Community Survey (ACS) from 2006 through 2012, we examine how a tougher stance on immigration affected institutionalization rates of elderly Americans by exploiting the temporal and geographic variation in the implementation of SC. 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 immediately evident during the first two years following its implementation.[1]

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. Among those residing in a nursing home, the policy adoption was associated with lower disability levels –a finding suggestive of elderly Americans with relatively minor disabilities gravitating towards institutionalized care as domestic help became harder to find. 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 of SC 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 curtailed. Importantly, the labor supply reduction was mostly driven by less-educated Hispanic workers from Mexico and Central America, who are also the ones most directly impacted by SC.

The remainder of this paper is organized as follows. Section 2 provides background information on Secure Communities and discusses how the policy may 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.

[1] As a reference, East and Velásquez (2022) estimate a 0.99% reduction in the likelihood of mothers with young children working and a 1.5% reduction in hours worked in response to SC. We find evidence of much larger impacts on the living arrangements of the elderly, a population for whom the move to a nursing home is likely to be a monumental life change. This was made especially evident during the pandemic; the staggering number of Covid-19 deaths among nursing home residents suggests that even postponing a move to a nursing home could protect a person from many contagious diseases.

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 serious 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.

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, the out-of-pocket costs associated with nursing home care, and importantly for our purposes, the price and convenience of outsourcing home care to the market.[2]

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, 2016).[3]

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. (2023) 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 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 a specific 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. A priori, it is unclear how Secure Communities would impact the labor supply in elderly-related household service occupations and, in turn, the institutionalization rate of elderly Americans. For instance, undocumented women may have increased their labor supply informally in response to fears of working in the formal sector or because of SC-induced drops in household income. Alternatively, they may have reduced their labor supply due to increased fear of apprehension.

In addition, our identification approach relies on a staggered difference-in-differences analysis that circumvents the concerns regarding the shift-share instruments employed in Butcher et al. (2021) (e.g., Goldsmith-Pinkham, Sorkin, and Swift 2020). Furthermore, our event study enables us to gauge the presence of parallel pre-trends, followed by an immediate response to SC, as we would expect if the elderly were quite quickly unable to find the help needed to age in place. Because of its reliance on cross-decade

[2] 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 (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.

[3] 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).

differences in the foreign-born population in different MSAs, the analysis in Butcher et al. (2021) is not able to document such an immediate response.

Finally, Butcher et al. (2021) use data from 1980 through 2000. Our focus is on a more recent period during which both the size of migration inflows and their characteristics have changed. For instance, migration flows grew significantly through the 1990s, reaching a peak around the year 2000, but they declined by approximately 25 % in the 5-year period that followed –a reduction driven by legal inflows while undocumented flows rose through 2004 (Passel and Suro, 2005). In addition to their size, inflows changed in composition around the turn of the century –the share of Mexicans dropped, while that of Central and South American countries rose. These newer migrant inflows also differed in their characteristics, with higher levels of human capital as captured by their educational attainment and English proficiency (Haner and Hugo Lopez, 2023).

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 three-fold (American Immigration Council, 2021). 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.[4] 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 has 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 an additional 48 h, 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, 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 Fig. 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[5] –a worry further underscored by

[4] 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 empowering selected officers, trained for specific tasks, to undertake certain responsibilities 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, permitted deputized officers to question and arrest alleged noncitizens they encountered in their routine duties if they suspected a violation of federal immigration laws. This model quickly came under intense scrutiny after allegations that large shares of those 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).

[5] 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.

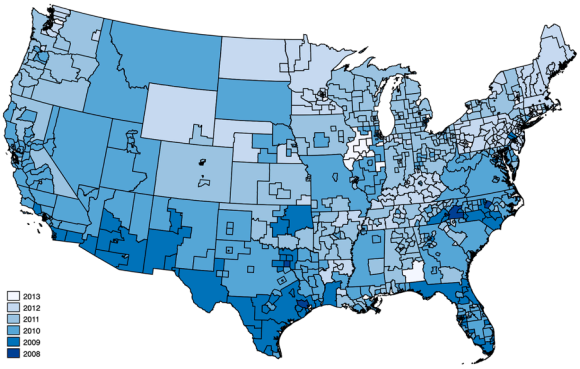

Fig. 1. The Rollout Date of SC Across the U.S. PUMAs.
Notes: Data are from the U.S. Immigration and Customs Enforcement Secure Communities Activation Report. The figure depicts the year SC was first activated in any of the counties within each PUMA.

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), which prioritized the arrest and deportation of serious criminals. Yet, on January 25, 2017, SC was reinstated by President 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) and, 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 due to the growing number of deportations of undocumented workers. Based on the 2006 ACS, approximately 13 % of housekeepers, personal care aids, and home health providers in the United States are likely undocumented.[6] However, in practice, this is an unlikely channel given that 96 % of apprehended migrants under SC are men (East, 2020) and 89 % of household service workers are women (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 to counties with less enforcement or by initially settling in counties without the program. Yet, this channel too may have been limited given the quick and nationwide rollout of the program.

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 worked fewer hours to limit their exposure, as well as that of their families, to intensified enforcement. Given that home care and housekeeping workers often assist multiple clients in the same day, the fear of being stopped by the police while driving from one client to the next may have induced undocumented workers to reduce or contain the size of their clientele.[7]

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 we focus on sectors most relevant to elderly care, such as home health care and private household services. This response, which is accompanied by higher hourly wages in some cases, is suggestive of the relevant role of immigration policy in shaping the labor supply in services

[6] This figure is based on authors' calculations assuming foreign-born Hispanics with high school degree or less working in these occupations to be likely undocumented.

[7] 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 (2022) 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 closely 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.

critical for elderly Americans 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

Information on the date of SC activation in each county, between 2008 and 2013, comes from the U.S. Immigration and Customs Enforcement Secure Communities Activation Report. However, for our analysis, we use data on SC exposure at the PUMA-year level from 2006 to 2014 obtained from the replication files of East and Velásquez (2022). Data on institutionalization of the elderly, as well as data on employment in housekeeping, personal care, home health aides, and related occupations originate from the american community survey (ACS). 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.

Our main sample of interest 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 end in 2012 to ensure our sample includes some never-treated PUMAs –a necessary condition when implementing the approach proposed by Gardner (2022) to address biases in staggered difference-in-differences analyses. We also use ACS data from 2013 to 2014 to construct predictions in the two-stage Gardner (2022) technique.

Table 1 provides summary statistics for the sample of interest. On average, individuals in our elderly American 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, and 37 % have at least some college. Four percent reside in an institutionalized setting and, altogether, close to 21 % of the individuals in our sample are living in a PUMA with SC at the time of the survey.

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):

$$INST_{ipt} = \alpha + \beta SC_{pt} + X_{ipt}^{'}\delta + Z_{pt}^{'}\gamma + \mu_p + \phi_t + \varepsilon_{ipt} \quad (1)$$

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.[8]

Our right-hand-side variable of interest, SC_{pt}, is a continuous measure for the degree of exposure of the PUMA to SC in year t. 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 SC program implementation. To map county-level variation in immigration enforcement 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 falls entirely within a larger 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 spans multiple counties, we assign a population-weighted policy value to the PUMA based on the respondent's county of residence and whether it had implemented SC.[9]

The vector $X_{ipt}^{'}$ includes information on individual-level characteristics including age, age squared, race, marital status, and education of the respondent. The vector $Z_{pt}^{'}$ includes PUMA-year level controls. These include a Bartik-style measure of labor demand that allows us to account for potentially confounding variations in economic conditions stemming from the 2008 Great Recession, as well as information on the contemporaneous implementation of other immigration enforcement measures, such as 287(g) agreements, E-Verify mandates, or sanctuary policies.[10] The vectors μ_p and ϕ_t denote PUMA and year fixed effects that account for time-invariant PUMA characteristics and unobservable macro-level traits or year-specific shocks, respectively.

To address concerns regarding potential biases in two-way fixed-effects (TWFE) estimates in the presence of heterogeneous

[8] 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 ages 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, retrieved from a nursing home-focused data set, as the dependent variable.

[9] There are 3,244 counties and county equivalents in the U.S. and 1,078 consistent PUMAs. Around 64% of PUMAs lie exactly within one county, but because the elderly are underrepresented in those PUMAs, only 44% of them live in PUMAs with a unique county assigned to them. However, in most of the cases in which a PUMA spans multiple counties, all the counties in the PUMA adopted SC within the same year. As shown in Appendix Table B1, when we restrict the sample to individuals in PUMAs where everyone was first exposed to SC in the same year, our estimate of interest remains practically the same (Column 2). The estimate is statistically insignificant, but of broadly similar magnitude, when we restrict the sample to observations for which the PUMA includes only one county, as the sample is cut by more than half in this case (Column 3).

[10] We consider a county to be treated by these policies if they had been implemented by January of the survey year. To assign these policies (varying at the county level) to PUMAs, we follow the same technique used to assign SC policies to PUMAs.

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 U.S. 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 has a vision, hearing, cognitive, ambulatory, independent living, or self-care difficulty and zero otherwise.

treatment effects, as is likely in the case of the staggered adoption of the SC program, we conduct a diagnostic check using the Goodman-Bacon (2021) decomposition using data from 2006 to 2014. Even though the check suggests that the bias is small, we estimate equation (1) using the Gardner (2022) methodology that yields robust estimates of heterogeneous treatment effects.[11]

The procedure proposed by Gardner (2022) consists of two steps. In the first step, institutionalization rates are estimated using only PUMAs with counties that implemented SC after our sample period (i.e., 2013 and 2014). Approximately 24 % of the individuals in our 2006–2012 sample reside in PUMAs that were eventually treated in 2013–2014. This was done to predict the counterfactual outcome in all periods and to 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 and clustered at the PUMA level.[12]

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 potential policy endogeneity, as would be the case if the timing of SC implementation was associated with changes in PUMA characteristics that predated 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 individuals in PUMAs with 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 addresses problems caused by staggered treatment adoption. We consider multiple specifications that progressively add more controls. In column (1), we report the baseline impact of SC when 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

[11] Because we conduct the Goodman-Bacon decomposition using data from 2006 through 2014, all PUMAs are eventually treated in that sample. The results from this decomposition are displayed in Appendix Table B2. Up to 67% of our estimate is driven by good comparisons of early treated PUMAs, our treated group, to later treated PUMAs, our control group. It should not be surprising then that, when we use data from 2006 to 2014 (including the late adopters, to derive a TWFE estimate), the estimate is very similar to the Gardner estimate we use as our baseline (Appendix B). Moreover, Appendix Table B3 shows that our results are robust to using the Sun and Abraham (2021) technique for addressing problems from staggered difference in differences analyses.

[12] We made use of the *did2s* Stata package for constructing Gardner estimates throughout our analysis.

indicative of whether the individual identifies as Black, Hispanic or has any disability. Next, in column (3), we further account for 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 Great Recession. To that end, we include Bartik-style measures of labor demand that allow us to account for potentially confounding variations in economic conditions.[13] The estimated impact from this preferred model specification remains practically unaffected, suggesting that PUMA-level industry exposure to the Great Recession is not driving our results.[14] Our preferred specification implies that the adoption of SC led to a 0.26 percentage point or 6.8 % increase in the institutionalization propensity of elderly Americans.[15]

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 un- correlated 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 B6, we include interactions between changes in the PUMA characteristics from 2000 through 2005 and a linear trend.[16] The inclusion of these additional controls enables us to account for the influence of any pre-trends in economic conditions potentially correlated 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 % following 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):

$$Year_p = \alpha + \theta \Delta W_p^{'} + \varepsilon_p \tag{2}$$

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 B7 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 share non-citizen and the change in the housing price index.[17] The former is likely related to the earlier adoption of SC by counties along the U.S.-Mexico border. Nevertheless, 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, the low R-squared in the model reveals that PUMA-specific pre-trends in demographic and economics traits do not perform well in predicting the adoption timing of SC.

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):

$$Y_{ipt} = \alpha + \sum_{j=-6}^{3} \beta_j SC_{pt}^{j} + X_{ipt}^{'} \delta + Z_{pt}^{'} \gamma + \mu_p + \phi_t + \varepsilon_{ipt} \tag{3}$$

[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 also experimented with dropping the recession years from our sample. Results, shown in Appendix Table B4, show that our baseline findings prove robust to dropping 2008 (column 2) as well as 2008 and 2009 (column 3). Moreover, neither estimate is statistically different from our baseline estimate (reproduced in column 1 for convenience).

[15] We arrive at 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. LTCFocus (2021) is sponsored by the National Institute on Aging (1P01AG027296) through a cooperative agreement with the Brown University School of Public Health. As shown in Appendix Table B5, column (2), the number of nursing home residents rose by approximately 3% following the implementation of SC.

[16] 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 has a college degree, the share that has a master's degree, and the share that has a doctoral degree, along with the share of females that has each of these degrees, and the institutionalization rate of the elderly.

[17] We use the same variables listed in the previous footnote.

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	3312,484	3312,484	3312,484	3312,484
PUMA Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Individual Characteristics	No	Yes	Yes	Yes
Other Immigration Policies	No	No	Yes	Yes
PUMA-Year Controls	No	No	No	Yes

Notes: Data are from the 2006–2012 American Community Survey. The sample includes U.S. 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, particularly 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.

where SC_{pt}^{j} is a dichotomous variable that equals 1 for each of the j periods preceding or following the first year in which SC was implemented in any county within the PUMA; otherwise, it equals zero. As in the primary model, $X_{ipt}^{'}$ includes individual level 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. Fig. 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 adoption of SC. Recall that 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. In Appendix Table B8, after displaying in column (1) the main results from Table 2, 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 estimates similar 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 had reached around 28 % and 64 %, respectively. Appendix Table B9 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)) –that is, 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)), our sample is cut down by close to 600,000 observations. While we lose some precision in our estimate, it remains largely of the same in magnitude, suggesting our results are not solely driven by early adopters.

Finally, we assess the possible spurious nature of our findings through a placebo test in which we randomly assign SC PUMA-level implementation dates 1000 times. Then, we estimate the model in equation (1) on data aggregated at the PUMA level. Appendix Fig. 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,

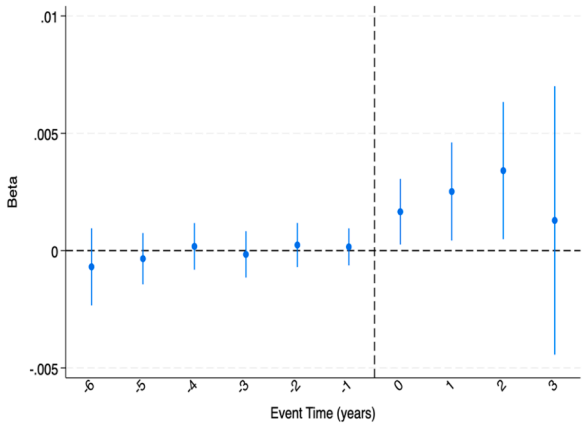

Fig. 2. Effect of SC on the Institutionalization of the Elderly.
Notes: Data are from the 2006–2012 American community survey. The sample includes all U.S. citizens 65 years of age and older. The model includes PUMA fixed effects and year fixed effects, along with the set of controls in column (4) of 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.

varies largely with demographic, family, and socio-economic 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.[18] We examine whether that is the case in Tables 3-6.

To begin with, Table 3 displays the estimated impact of SC on the institutionalization of the elderly based on their race, ethnicity, educational attainment, whether they reside in their state of birth, 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 outsource home care due to its high cost, making them less sensitive to changes in the availability of such services. Also pointing to the fact that these services are only 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 next columns of Table 3 show the results according to whether individuals are still living in the state in which they were born. Impacts are stronger for individuals living outside of their state of birth. This may be because those living outside of their state of birth have fewer family and friends whom they can rely on for care. However, the elderly living outside of their states of birth might also have larger incomes and assets. This might increase the affordability of at-home market-provided care services, making them more sensitive to SC-induced changes in the price or quality of such services. Finally, 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, 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, at least in percentage terms, 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 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 only statistically significant at the 10 percent level, the estimate suggests that SC lowered the average disability level among the elderly residing in institutionalized settings. Again,

[18] Out-of-pocket costs of nursing home stays are also likely to moderate the impacts of SC. These vary substantially even among residents within the same nursing home depending on whether residents qualify for Medicaid or have long-term care insurance. This type of information is not available in our data.

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
SC	0.00257***	0.00286***	−0.00070	0.00072	0.00196
	(0.00096)	(0.00104)	(0.00283)	(0.00220)	(0.00124)
Mean Y	0.04	0.04	0.05	0.03	0.05
P-Value	0.01	0.01	0.81	0.75	0.11
% Effect	6.81	7.51	−1.39	2.79	4.20
Observations	3312,484	2770,675	255,317	161,257	2101,517
	(6) Some College	(7) In State of Birth	(8) Out State of Birth	(9) Female	(10) Male
SC	0.00221**	0.00171	0.00225**	0.00308**	0.00164*
	(0.00093)	(0.00136)	(0.00104)	(0.00125)	(0.00090)
Mean Y	0.02	0.05	0.03	0.05	0.03
P-Value	0.02	0.21	0.03	0.01	0.07
% Effect	9.78	3.67	7.84	6.65	6.25
Observations	1210,967	1730,563	1581,921	1878,583	1433,901

Notes: Data are from the 2006–2012 American Community Survey. The sample includes U.S. 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) Institutionalization	(2)	(3)	(4)	(5) 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	3312,484	934,070	653,296	661,247	143,320

Notes: Data are from the 2006–2012 American Community Survey. The sample includes U.S. 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.

this supports the notion that SC made it difficult for those with moderate care needs to get the help needed to age in place.

In Table 5, we explore the heterogeneous impact of SC on the institutionalization 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 likelihoods of

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	3312,484	1866,156	1446,328

Notes: Data are from the 2006–2012 American Community Survey. The sample includes U.S. 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.

living in an institution among elderly without a spouse. This finding is consistent 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 %.

In Table 6, we explore the impact of Secure Communities on other living arrangements. SC very clearly increases the likelihood of living in an institution (replicated in column 1) and decreases the likelihood of living with a spouse (column 2). The estimates for living with a child (column 3) and alone (column 4) are both negative, but not statistically significant, which could be partially attributed to the lower prevalence of such living arrangements.

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 evidence that our main results can be interpreted in a causal way. 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 7) and the share of the 2005 PUMA population that has less than a high school degree and born in Mexico or Central America (row (3) of Table 7). 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 7, we zoom in further on PUMAs that had a large share of Mexicans and Central Americans working in key occupations and industries. 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 these occupations contributed to raising the institutionalization of elderly Americans following the implementation of SC by 3 %. The estimates in row (5) show that this pattern persists when we further focus on a subset of these workers in the home health or private households industries as classified by the *North American Industry Classification System* (NAICS). 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 care, or home health care. We look at the total number of workers, and the total work hours supplied within each PUMA-year. 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-year level, we focus on market impacts.

Table 8 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 also consider heterogeneity by industry. 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 sector (column (3)), the health sector (column (4)), and all 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 column 6, we consider construction occupations since adding handrails to stairwells and bathrooms may allow the elderly to remain in their own homes or their children's homes more

Table 6
Effects of SC on living arrangements.

	(1) Institution	(2) With Spouse	(3) With a Child	(4) Alone
SC	0.00257*** (0.00096)	−0.00113** (0.00055)	−0.00209 (0.00148)	−0.00135 (0.00141)
Mean Y	0.04	0.52	0.16	0.32
P-Value	0.01	0.04	0.16	0.34
% Effect	6.81	−0.22	−1.28	−0.42
Observations	3312,484	3312,484	3312,484	3312,484

Notes: Data are from the 2006–2012 American Community Survey. The sample includes U.S. 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 in the manuscript. Standard errors are clustered at the PUMA level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 7
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 Workers Born in Mex/CA in Relevant Occupations			0.00885***	
			(0.00286)	
SC * Share of Workers Born in Mex/CA in Relevant Occupations within Relevant Industries				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
B-Mean Int	0.0013	0.0013	0.0015	0.0015
B-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	3312,484	3312,484	3312,484	3312,484

Notes: Data are from the 2006–2012 American Community Survey. The sample includes U.S. citizens 65 years of age and older. Shares are calculated using the 2005 ACS. Relevant occupations are home health, personal care, and housekeeping occupations, while relevant industries are home health care and private households. 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 8
Effects of SC on the labor supply in home health, personal care, and housekeeping occupations by sector.

	(1) All Sectors	(2) Home Health & Private HH	(3) Nursing Homes	(4) Health Sector	(5) Other Sectors	(6) Construction (All Occupations)
A: Number of Workers						
SC	0.00826	−0.02922*	0.01546	0.02023	0.00180	−0.35987***
	(0.03222)	(0.01691)	(0.01558)	(0.01547)	(0.01911)	(0.07074)
Mean Y	2.63	0.69	0.63	0.57	0.74	5.99
P-Value	0.80	0.08	0.32	0.19	0.93	0.00
% Effect	0.31	−4.23	2.47	3.57	0.24	−6.01
Observations	7518	7518	7518	7518	7518	7518
B: Number of Hours Worked						
SC	−0.04567	−1.29715**	0.79826	0.88845	−0.43524	−15.79640***
	(1.21655)	(0.61382)	(0.58319)	(0.59057)	(0.69704)	(2.90852)
Mean Y	90.58	21.82	23.15	20.85	24.76	245.90
P-Value	0.97	0.03	0.17	0.13	0.53	0.00
% Effect	−0.05	−5.95	3.45	4.26	−1.76	−6.42
Observations	7518	7518	7518	7518	7518	7518

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). Column (6) reports the results for the construction sector and includes all occupations in that sector. 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.

safely. We find evidence of SC impacting the labor supply of construction workers –a finding that captures the fact that most deportees through the SC program were men, as it is also the case with most construction workers. Because construction workers are likely to be less directly involved with home care services, we do not focus on this occupation.

In Panel B, we consider impacts on the total hours of work by workers in home care occupations. Again, the estimate is only statistically different from zero when we focus on workers within the private households and home health sectors (column 2). 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, shown in Panel B, 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. These 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 8 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.[19] In Table 9, 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. To be as conservative as possible, we do not include construction workers in this table. As in Table 8, in Panel A of Table 9, 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 immigrants from Mexico and Central America (11 %). What becomes more apparent from Panel B in Table 9 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 10, 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 a high school degree –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 8, 9 and 10 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, raising their institutionalization likelihood.

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 the least preferred option for most Americans. Based on survey data, Americans have a strong preference to age in place (Binette and Vasold, 2018) –a pattern potentially substantiated by the little to non-existing evidence on the health benefits of aging at a nursing home (Bakx et al., 2020; Werner et al., 2019). 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 Right (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.

[19] 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, Arenas-Arroyo, and Sevilla (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.

Table 9
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	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	7518	7518	7518	7518	7518	7518
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	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	7518	7518	7518	7518	7518	7518

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 10
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	0.25	0.02
Observations	258,445	46,146

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 control 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.

CRediT authorship contribution statement

Abdulmohsen Almuhaisen: Conceptualization, Methodology, Software, Writing – original draft. **Catalina Amuedo-Dorantes:** Conceptualization, Methodology, Writing – review & editing. **Delia Furtado:** Conceptualization, Methodology, Writing – review & editing.

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Appendix A

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 aggregated to the PUMA level. We use the geographic correspondence engine (Missouri Census Data Center, 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.

Bartik labor demand measures

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

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

where $Bartik_{pt}$ is the group specific[20] 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.

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 obtained 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.

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 8:
  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
     62,131: Office of chiropractors
     62,132: 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

[20] 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.

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

Appendix B

Table B1
Effect of SC on the institutionalization of the elderly (Robustness to PUMAs in exactly one county/ PUMAs where everyone first exposed to SC in the same year).

	(1)	(2)	(3)
SC	0.00257***	0.00275***	0.00168
	(0.00096)	(0.00099)	(0.00123)
Mean Y	0.04	0.04	0.04
P-Value	0.01	0.01	0.17
% Effect	6.81	7.41	4.80
Observations	3312,484	2550,553	1466,610
Individual Characteristics	Yes	Yes	Yes
Other Immigration 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 in the manuscript. Column (1) reproduce the main result while column (2) limits the sample to PUMAs in counties enacting SC within the same year. Finally, column (3) limits the sample to PUMAs lying in exactly one county. Standard errors are clustered at the PUMA level. ***, **, and * denote significance at the 1, 5, and 1 percent levels, respectively.

Table B2
Bacon decomposition of the baseline estimates.

	(1)
SC	0.0022***
	(0.0007)
Good Comparison (early treatment vs. late control):	
Weight	0.6738
Effect	0.0019
Bad Comparison (late treatment vs. 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 includes 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 B3
Effect of SC on the institutionalization of the elderly (Robustness to Sun and Abraham, 2021).

	(1)	(2)
SC	0.00257***	0.00237**
	(0.00096)	(0.00083)
Mean Y	0.04	0.04
P-Value	0.01	0.02
% Effect	6.81	6.28
Observations	3312,484	3312,484
Individual Characteristics	Yes	Yes
Other Immigration Polices	Yes	Yes
PUMA-Year Controls	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 in the manuscript. Column (1) reproduce the main result while column (2) uses the methodology proposed by Sun and Abraham (2021). Standard errors are clustered at the PUMA level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table B4
Effect of SC on the Institutionalization of the Elderly (Robustness to Dropping Recession Years).

	(1)	(2)	(3)
SC	0.00257***	0.00189**	0.00190*
	(0.00096)	(0.00091)	(0.00107)
Mean Y	0.04	0.04	0.04
P-Value	0.01	0.04	0.08
% Effect	6.81	5.11	5.24
Observations	3312,484	2855,992	2387,626
Individual Characteristics	Yes	Yes	Yes
Other Immigration 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 in the manuscript. Column (1) reproduce the main result while column (2) drops observations from year 2008. Finally, column (3) drops observations from year 2008 and 2009. Standard errors are clustered at the PUMA level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table B5
Effect of SC on the Institutionalization of the Elderly (Robustness to Alternative Measure).

	(1) Baseline Results	(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	3312,484	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 B6
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	3312,484	3312,484
PUMA Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Individual Characteristics	Yes	Yes
Other Immigration Policies	Yes	Yes
PUMA-Year Controls	Yes	Yes
PUMA Characteristics 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 h, have a college degree, master's 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 B7
Correlation between 2000 and 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 Participation	0.588	2.543	0.001	(0.015)
Change Non-Citizen	0.009	0.024	−5.477**	(2.025)
Change% Work > 50 H	−1.023	2.111	0.041	(0.023)
Change% Work > 60 H	−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	
Observations			1078	

Notes: Data are from the 2005 American Community Survey and the 2000 Census. We estimate the following regression: $Year_p = \alpha + \theta \Delta W_p^{'} + \varepsilon_p$, 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 B8
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	3312,484	3312,484	3312,484	3312,484
PUMA Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Individual Characteristics	Yes	Yes	Yes	Yes
Other Immigration Policies	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 B9
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**

(*continued on next page*)

Table B9 (*continued*)

	(1) Full sample	(2) Excluding 2008	(3) Excluding 2008, 2009
	(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	3312,484	3255,900	2708,846
PUMA Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Individual Characteristics	Yes	Yes	Yes
Other Immigration Policies	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.

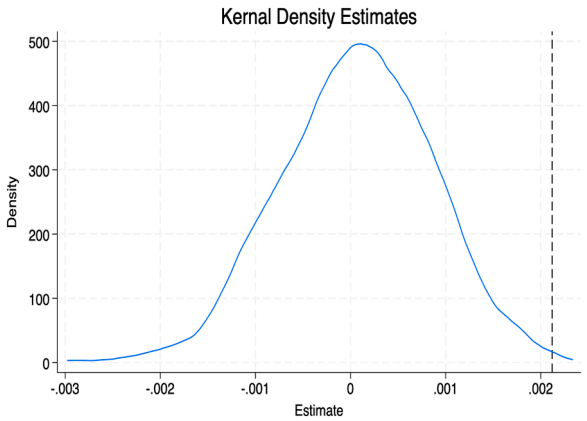

Fig. B1. Effect of SC on the Institutionalization of the Elderly (Placebo Test)
Notes: Data are from the 2006–2012 American Community Survey. The sample includes all US citizens 65 years of age and older. and above. We randomly assign the distribution of SC activation dates to the actual data, collapsed 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.

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