Immigration Enforcement, the Supply of Home Care Workers, and Access to Long-Term Care: Evidence from Secure Communities*

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Abstract

Most Americans will need long-term care at some point in their lifetimes, with many relying on home care workers, like home health and personal care aides, to provide this care. Since nearly one-third of home care workers are immigrants, it is critical to understand how escalating US immigration enforcement impacts the supply of home care. Relying on economic theory, we first propose a conceptual model of the impact of immigration enforcement on the home care market. Then, we use data from the American Community Survey and the Health & Retirement Study to test the model's predictions. We exploit temporal and geographic variation in the rollout of a federal enforcement policy, Secure Communities, between 2008-2013, estimating difference-in-differences and event study models with time and location fixed effects to isolate the effect of the policy. We find that Secure Communities reduces the overall size of the home care workforce by 7.5%, with 70% of this effect driven by a reduction in the number of immigrant workers. Next, we test for negative externalities of this workforce reduction by examining receipt of home-based care among older adults with care needs. Overall, we find that older adults needing assistance are 2.9 percentage points less likely to receive any help at home, a 5% relative reduction. However, consistent with our model's predictions, these effects are concentrated among older adults with Medicaid coverage, who are 10.5% less likely to receive any help, and 23.2% less likely to receive formal (i.e., non-family) home care, following the introduction of Secure Communities.

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1 Introduction

Most Americans who turn 65 will develop substantial long-term care needs before they die, requiring assistance with essential tasks like dressing, eating, and bathing (R. W. Johnson 2019). While this assistance was historically provided in nursing homes, aging Americans are increasingly receiving care in home and community settings (i.e., home-based care or "home care"). States and the federal government play a critical role in ensuring access to care; more than half of all long-term care in the United States is financed by Medicaid, with more than 75% of this spending supporting home care (Chidambaram and Burns 2022). Maintaining a well-functioning home care market requires an adequate supply of workers; however, even while state Medicaid programs have dedicated considerable effort and resources to bolstering this workforce, recent worker shortages have raised questions about its sustainability (O'Malley Watts, Musumeci, and Ammula 2021).

Immigrants are critical to the functioning of the home care industry (Zallman et al. 2019); nearly one-third of home care workers in the United States are immigrants, compared with 17% of all workers. Yet, even while the nation contends with home care workforce shortages, it has dramatically expanded interior immigration enforcement efforts. The US today spends nearly $30 billion annually on such enforcement, which is roughly equal to $130 per working-age adult and reflects record-high investment in immigration enforcement globally (American Immigration Council 2024; Akkerman 2023).[1] Additionally, the new Presidential Administration has promised "mass deportation" and made immigration enforcement a key policy priority (American Immigration Council 2025). By curtailing immigration, state and federal policymakers could undermine a competing policy goal of ensuring an adequate supply of home-based long-term care. Indeed, both nursing homes and home care agencies have reported difficulty recruiting among immigrant communities in the context of expanded immigration enforcement (Spetz et al. 2019).

Policymakers commonly justify immigration enforcement policies on the basis of two goals: first, to prevent crime and safeguard national security, and second, to protect job opportunities

1. This figure comes from the federal budget for U.S. Immigration and Customs Enforcement (ICE) and U.S. Customs and Border Protection (CBP), and does not include state and local immigration enforcement expenditures, which can be substantial. For example, Texas alone spent nearly $3 billion on border security in FY 2022-2023 (Kriel, Trevizo, and Rodriguez Calderón 2022).

and wages for US-born workers. Yet, prior research has not found an observable effect of immigration enforcement on crime (Miles and Cox 2014). In addition, while there is a large literature devoted to understanding the impact of immigration on labor market outcomes for US-born workers, the theoretical predictions and empirical findings of this literature are mixed, depending on the model assumptions and empirical specification, and commonly suggest a small-to-null impact of immigration on US-born workers' wages and employment.[2] By contrast, through its impact on labor costs, immigration enforcement could reduce the supply of non-tradeable goods and services like home care (Cortes 2008), a consequence that is commonly overlooked. Given the increasing prevalence of enforcement policies at both local and federal levels, the emphasis on deportation among the incoming presidential administration, and critical shortages of workers in the home care industry, it is important to understand the effect of immigration enforcement on the supply of home care.

In this paper, we study how immigration enforcement impacts the supply of home care in the United States. We first rely on economic theory and develop a model for understanding this impact. In this model, consumers receive home care services from agencies,[3] which serve two distinct markets, a Medicaid market with a fixed price (determined by state governments) and a private-pay market with a downward-sloping demand curve.[4] First, our model predicts that immigration enforcement reduces the number of immigrants (i.e., people born outside the United States) working in home care. Prior literature suggests this could occur either directly, through deportations, or indirectly via "chilling effects" (Watson 2014), whereby undocumented immigrants and their families limit work outside the home due to fear of interacting with law enforcement. We model this reduction in supply of immigrant workers as an increase in home care agencies' labor costs, as immigrants have lower reservation wages than similarly-skilled US-born workers (Rivera-Batiz 1999; Kossoudji and Cobb-Clark 2002; Pan 2012; Albert 2021). Our model predicts that agencies respond to this increase in costs by reducing the total quantity of home care they pro-

2. See: G. E. Johnson (1980), Altonji and Card (1991), Borjas, Freeman, and Katz (1991), Borjas et al. (1997), Borjas (1999), Card (2001), Borjas (2003, 2006), Peri and Sparber (2007), Glitz (2012), Ottaviano and Peri (2012), Dustmann, Frattini, and Preston (2013), Chassamboulli and Peri (2015), Peri (2016), and Albert (2021).

3. In practice, while more than 80% of home care workers work for agencies (see Table 2), consumers may also hire home care workers directly.

4. This is a close approximation of the market for home care services, as most private health insurance does not cover long-term care, nor does Medicare. In addition, only about 13% of older adults carry private long-term care insurance (Friedberg et al. 2014).

vide. Medicaid enrollees, who generate lower revenue on the margin than private-pay patients, experience the brunt of this reduction.

To test the model's predictions and empirically investigate the impact of immigration enforcement on both the supply of home care workers and the quantity of home care that agencies provide, we leverage a natural experiment: the rollout of a federal enforcement policy, Secure Communities, between 2008-2013. Using data from the American Community Survey, we first examine the effect of the policy on the size of the home care workforce. We find that the policy leads to a 7.5% reduction in the number of home care workers per capita, on average, with about 70% of this effect driven by reductions in the supply of immigrant workers. Next, we use data from the Health & Retirement Study to examine how this reduction in labor supply impacts the quantity of home care provided to older adults. We find that older adults needing assistance at home are 2.9 percentage points less likely to receive any help following the policy's implementation, a 5% relative reduction. Consistent with our model's predictions, these effects are concentrated among older adults on Medicaid, who are 10.5% less likely to receive any help, and 23.2% less likely to receive formal (i.e., non-family) home care, after Secure Communities.

Our paper complements two existing streams of research. First, our paper relates closely to prior work examining the impact of US immigration enforcement on labor market outcomes. While a lengthy literature examines the impact of *immigration* on US labor markets, a smaller body of work addresses the impact of immigration *enforcement*. Amuedo-Dorantes and Bansak (2012) examine the effect of E-Verify legislation (i.e., legislation mandating verification of employment eligibility) on labor market outcomes, finding that this legislation reduces employment among likely authorized workers, but redistributes likely unauthorized workers across industries. East et al. (2022) examine the impact of Secure Communities on employment and wages, finding reductions in employment among both individuals who are likely undocumented immigrants and those who are US-born. East and Velásquez (2022) examine spillovers of Secure Communities to highly educated mothers with young children, finding that these mothers reduce their labor supply as a result of immigration enforcement. They show compelling evidence that this reduction is driven by an increased cost of childcare. Similarly, Cortés and Tessada (2011) and Farré, González, and Ortega (2011) find that immigration (by people who are low-skilled or female, respectively) increases the labor supply of highly skilled women.

Second, our paper adds to a growing literature studying the relationship between immigration, the supply of the long-term care workforce, and the care older adults receive. Most of this research uses shift-share instruments to examine the causal impact of immigration *inflows* on older adults needing long-term care. Furtado and Ortega (2023) and Grabowski, Gruber, and McGarry (2023) demonstrate that increased immigration improves nursing home staffing levels, which substantially improves both health outcomes and quality of care for nursing home residents. Additionally, Butcher, Moran, and Watson (2022) and Mockus (2021) find that increased immigration reduces the likelihood that older adults move to nursing homes in the first place.

Following the literature estimating the impact of immigration enforcement on labor market outcomes, we leverage the introduction of Secure Communities to study enforcement's effect on the supply of home care workers and the provision of care to older adults. It is the first paper we are aware of to examine the impact of immigration enforcement on labor supply in long-term care. More importantly, it is also the first paper to examine the causal impact of immigration (or immigration enforcement) on the provision of home-based long-term care to older adults. In this way, we contribute to a growing evidence base suggesting that policies to curtail immigration may produce negative spillovers to older adults and other people needing long-term care.

Our focus on the labor market for home care services is novel and highly policy-relevant. Having a well-functioning home care market is essential to policymakers interested in providing care to the nation's growing population of older adults and people with disabilities. Home care is of particular interest to policymakers, because it can be provided at a lower cost than institutional long-term care and is often more aligned with individual preferences. Additionally, a home care shortage may impose externalities on other types of workers. Specifically, family caregivers, predominantly daughters, fill in when formal care is unavailable or incomplete, with negative implications for their productivity and health.

The impact of immigration enforcement on home care markets may be especially pronounced for several reasons. First, nearly one-third of home care workers are immigrants. Second, home care workers commonly drive between multiple clients' homes, which increases their risk of interacting with law enforcement and could compound immigration enforcement's "chilling effects." Third, home care is primarily financed by Medicaid. Given that Medicaid sets fixed prices for long-term care and other health care services, which tend to be lower than prices paid by private health insurance, agencies are likely constrained in their ability to adjust prices in response to any enforcement-induced increases to labor costs. Effectively, Medicaid's price may act as a price ceiling for home care services, limiting agencies' ability to raise prices in response to shortages. Our findings raise important questions about the impact of immigration enforcement in markets where prices are constrained.

2 Background

2.1 Long-Term Care and the Home Care Workforce

More than nine million adults in the United States require assistance with activities of daily living, like dressing, eating, and bathing (Kreider and Werner 2023). While people with long-term care needs historically relied on institutional care in nursing homes, today the majority receive services in home and community-based settings (Chidambaram and Burns 2022). This shift in location of care has been driven by people's wishes to age in place along with states' obligations following the Supreme Court's *Olmstead* decision, requiring that care be provided in the least restrictive setting possible. As a result, the provision of long-term care has shifted shift from institutional settings, like nursing homes and skilled nursing facilities, to the home (Musumeci and Claypool 2014; Scales 2020). Demand for home-based long-term care is expected to grow over time as the population ages; however, there is concern about shortages of workers to provide this care (Galewitz 2021; Laughlin 2022; Gifford et al. 2018; Espinoza 2019; Deppen and Rihl 2021), and the pandemic has amplified these concerns (Laughlin 2022; Deppen and Rihl 2021).

Formal home-based care is provided by home care workers, including home health aides and personal care aides, who are typically employed agencies. Home care workers are disproportionately women of color who do not have education beyond high school, and immigrants make up a sizable and important part of this workforce. While about 17% of the US labor force are immigrants, some industries experience higher rates of labor force participation by immigrant workers. Immigrant workers are disproportionately employed in low-skilled jobs that are unattractive to US workers because of wages or working conditions, including service occupations, construction, agriculture, and health care. Particularly since the COVID-19 pandemic, the health care system has relied on immigrant workers to fill frontline, low-wage jobs. In home care, immigrants account for about 31% of the home care workforce nationally (PHI 2020), and over half of the workforce in some states, like New York, New Jersey, and Florida (Batalova 2020). Prior research has found that approximately one-fifth of these workers enter the US as undocumented immigrants (Chen et al. 2013).

Importantly, long-term care in the United States, including home-based care, is primarily financed by Medicaid, a fact we return to in Section 3. Medicare and private insurance generally do not cover long-term care, and most Americans do not have private long-term care insurance. Therefore, if a person in the United States requires long-term care, they must either pay for it out of pocket or obtain it through their state's Medicaid program, which generally requires meeting stringent income (and, in some cases, asset) criteria. Even for Medicaid-insured people, home care provision is limited and often incomplete, and for the non-Medicaid-insured, the out-of-pocket costs of home care can be prohibitively expensive. Therefore, most people who need help at home supplement paid home care with unpaid caregiving, typically provided by family members.

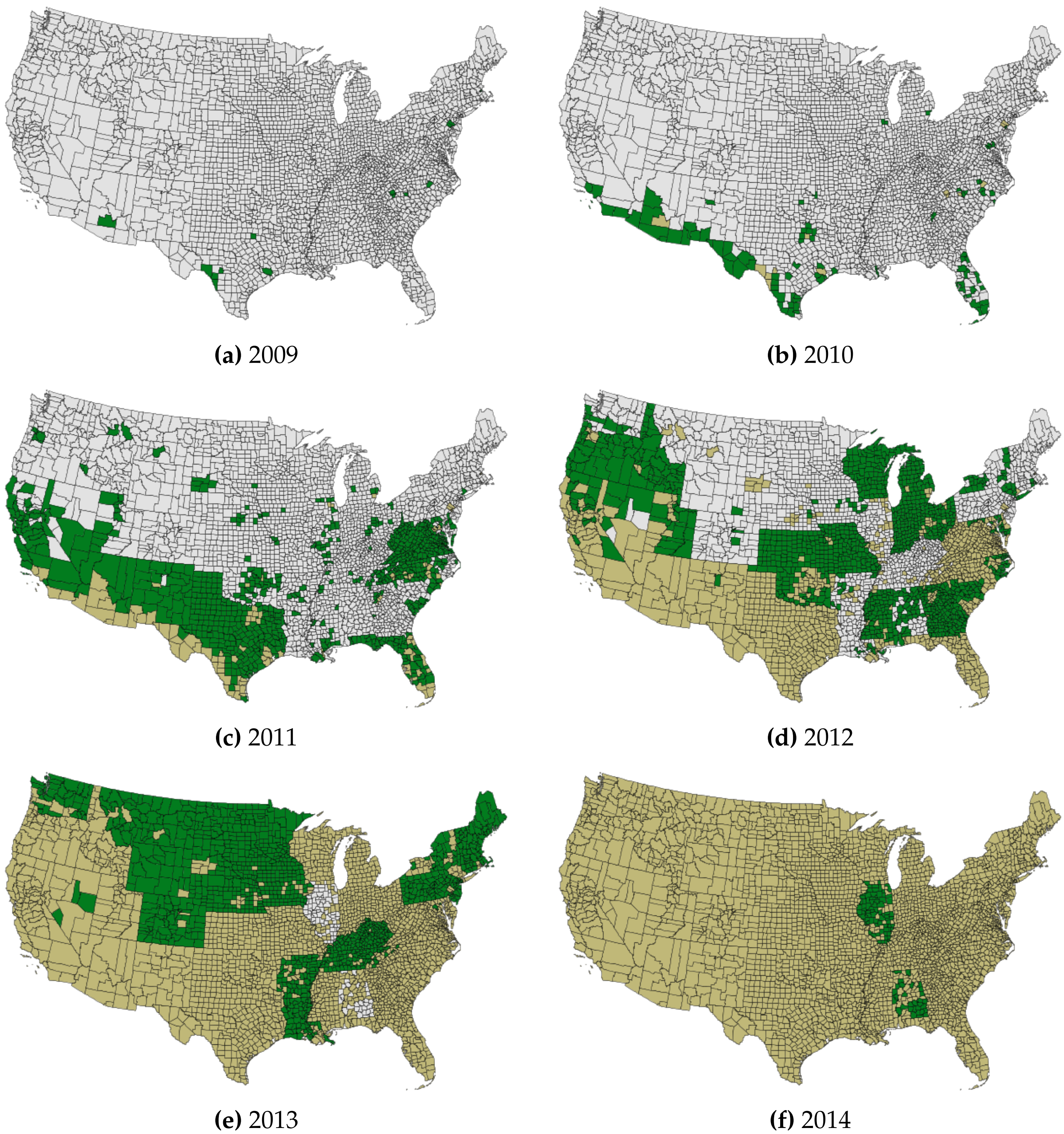
2.2 Immigration Enforcement

A functioning home care market requires a sufficient supply of workers. However, recent reports have suggested that the supply of home care workers is not keeping pace with demand. In addition, the demographics of the home care workforce, with nearly one-third of workers born outside the US, may make this labor market particularly sensitive to immigration enforcement.

To examine the impact of immigration enforcement on the home care workforce, we focus on a specific law enforcement-based immigration enforcement policy called Secure Communities, which was administered by U.S. Immigration and Customs Enforcement (ICE). It was first piloted in 2008, then rolled out on a quasi-random basis at the county level between 2008-2013. The timing of the rollout was determined federally, and counties did not have the ability to opt out. By 2014, all counties in the United States were participating in the program. Secure Communities was temporarily suspended in 2014 amid concerns regarding its constitutionality, and it was replaced with the Priority Enforcement Program (C.K. 2018); however, Secure Communities was reinstated in 2017 under the first Trump Administration (C.K. 2018). While the Biden administration modified how aggressively Secure Communities was implemented in 2021, the program effectively remains in place to this day.

Secure Communities dramatically expanded the reach of immigration enforcement in the United States by allowing ICE to check the immigration status of anyone arrested by state or local law enforcement across the country, regardless of the nature or seriousness of their arrest. Typically, when a person is arrested, their fingerprints are sent to the FBI for a federal background check; however, under Secure Communities, ICE had access to all fingerprints sent to the FBI and could place a detainer on anyone found to be in the country illegally. This meant that local law enforcement was required to hold the person until they could be picked up by ICE and processed for deportation. As a result of Secure Communities, more than 454,000 people were deported from the United States between 2008-2014 alone (East et al. 2022). Secure Communities had profound effects on immigrant communities in the United States, with effects spilling over to documented immigrants residing legally in the United States (Alsan and Yang 2022a).

To estimate the effect of immigration enforcement on home care labor supply, our identification strategy relies on the quasi-random rollout of Secure Communities across counties. Figure 3 depicts the rollout of the policy. While Secure Communities was initially rolled out to counties with close proximity to the U.S.-Mexico border, as well as counties with large Hispanic populations, prior work has established that Secure Communities' activation was unrelated to time-varying county-level demographic and economic characteristics, including labor market outcomes. (Cox and Miles 2013; East et al. 2022).



(a) 2009 (b) 2010 (c) 2011 (d) 2012 (e) 2013 (f) 2014

Figure 1: Rollout of Secure Communities by County

Note: Shaded areas indicate the counties that activated Secure Communities prior to January 1st of the listed year. Areas shaded in green represent newly activated counties; areas shaded in yellow represent counties that were activated in previous years.
Source: Authors' analysis of data from Alsan and Yang (2022b), U.S. Immigration and Customs Enforcement (2013), and U.S. Immigration and Customs Enforcement (2014).

3 Conceptual Framework

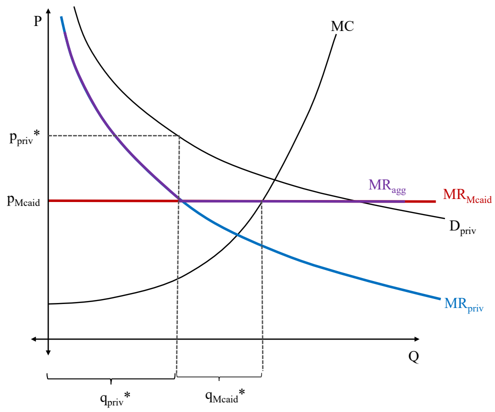
In this section, we propose a conceptual framework for predicting the impact of Secure Communities on the market for long-term, home-based care ("home care"). Specifically, we rely on economic theory to model the policy's impact on: (1) the employment of home care workers born outside the US, (2) the employment of US-born home care workers, and (3) the overall supply of home care. As a starting point, we adopt a two-market, or "mixed-economy" model, which was originally developed by Sloan, Mitchell, and Cromwell (1978) to model physicians' decisions to participate in state Medicaid programs.[5]

3.1 Market for Home Care

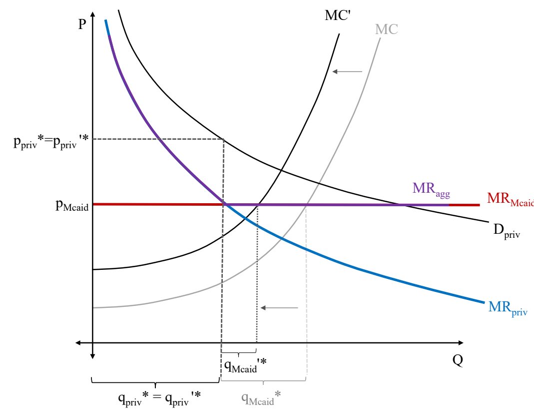
Figure 2a presents a graphical depiction of the market for home care. The vertical axis represents costs (or prices) of home care services, and the horizontal axis represents the quantity of home care services supplied (or demanded). In the model, home care is provided by home care agencies, which have the option of serving patients in two markets: a private-pay market, with downward-sloping demand D_{priv}, and a Medicaid market, with prices p_{Mcaid} that are set administratively by state governments. MR_{priv} represents agencies' marginal revenues from serving private-pay patients, and MR_{Mcaid} represents their marginal revenues from serving Medicaid patients (i.e., the fixed reimbursement rate for Medicaid-financed home care). MR_{agg} represents aggregate marginal revenues, that is, the maximum marginal revenue that an agency obtains by serving an additional patient (private-pay or Medicaid-enrolled) in the market.

The upward-sloping black line labeled MC represents agencies' marginal costs. Home care is a highly labor-intensive service, with low fixed costs due to the fact that service provision takes place in clients' homes (Jung and Polsky 2014); therefore, we assume that agencies' only costs are labor costs (i.e., wages). Additionally, we assume that agencies are wage-takers, i.e., they are sufficiently small purchasers such that they cannot unilaterally impact workers' wages (Hay and Mandes 1984). Intuitively, to serve a single patient, agencies will hire the worker in the local market with the lowest reservation wage. To serve additional patients, agencies must employ

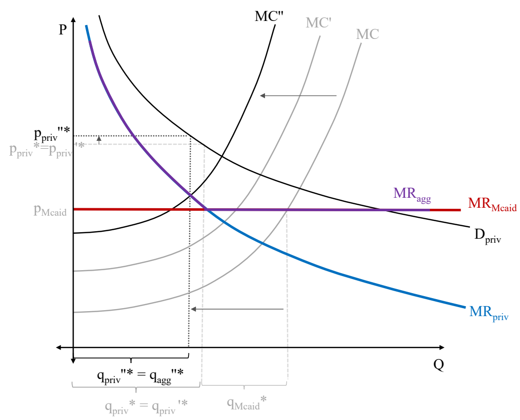
5. This model has since been extended by other work in health economics to model the impact of health insurance expansions on the already-insured (Garthwaite 2012; Carey, Miller, and Wherry 2020).



(a) Pre-Secure Communities



(b) Post-Secure Communities



(c) Post-Secure Communities (Extreme Case)

Figure 2: Conceptual Framework

Note: Figure 2 represents the market for home care services. Home care agencies serve patients in two markets: a private-pay market, with downward-sloping demand D_{priv}, and a Medicaid market with fixed/administered prices p_{Mcaid}. Agencies' marginal costs (i.e., wages) are represented as MC. MR_{priv} represents marginal revenues from serving private-pay patients, and MR_{Mcaid} represents marginal revenues from serving Medicaid patients (i.e., the reimbursement rate for Medicaid-covered personal care services). Agencies choose $q*$ such that $MR_{total} = MC$. They will serve private-pay patients as long as $MR_{priv} \geq MR_{Mcaid}$. Then, they will serve Medicaid patients as long as $MR_{Mcaid} \geq MC$.

additional workers, and we assume that each agency's marginal costs are strictly increasing in the total number of patients served (or workers employed). That is, each time an agency wishes to expand quantity supplied, it must raise wages to attract additional workers.[6]

In our model, immigrant and US-born workers are perfect substitutes in production, but consistent with the literature, undocumented immigrants have the lowest reservation wages, fol-

6. It is plausible, but not necessary, to assume that there is no wage discrimination, i.e., agencies must pay the same wage to all workers.

lowed by documented immigrants, and US-born workers have the highest reservation wages (Rivera-Batiz 1999; Kossoudji and Cobb-Clark 2002; Pan 2012; Albert 2021). This heterogeneity in the reservation wage across worker types reflects differences in bargaining power, deportation risk, and unemployment insurance (Albert 2021). Under these assumptions, and assuming no legal constraints on hiring undocumented workers, each agency will minimize costs by hiring undocumented workers first. To expand quantity supplied, the agency will eventually need to hire documented immigrant workers, and finally US-born workers. Thus, it may be helpful to visualize the MC curve as an ordering of workers in the local labor market, from those with the lowest reservation wages (on the left) to those with the highest reservation wages (on the right).

The total quantity of private-pay patients $q_{priv}*$ and Medicaid patients $q_{Medicaid}*$ that an agency ultimately serves is the result of the agency's profit maximization problem. To maximize profits, agencies choose $q*$ such that the aggregate marginal revenue equals marginal cost, $MR_{agg} = MC$. Agencies serve private-pay patients as long as the marginal revenue from these patients MR_{priv} exceeds the fixed Medicaid reimbursement rate $p_{Medicaid}$. Then, they serve Medicaid patients up until the point where the marginal revenue from these patients $MR_{Medicaid}$ equals marginal costs MC.

3.2 Impact of Immigration Enforcement

Figure 2b presents a graphical depiction of the effect of immigration enforcement on the market for home care. Following prior literature, immigration enforcement leads some immigrant workers to exit the labor force. Since immigrant workers have lower reservation wages than other workers, this reduction in labor supply shifts agencies' marginal cost curve to the left ($MC \rightarrow MC'$). Agencies respond to the resulting increase in average labor costs by reducing quantity supplied. As long as marginal revenues obtained from Medicaid patients MR_{Mcaid} are less than the marginal revenues obtained from private-pay patients MR_{priv}, agencies will reduce quantity provided to Medicaid patients ($q_{Mcaid}*$) but continue to serve the same number of patients in the private-pay market ($q_{priv}*$).

In the extreme case (Figure 2c), immigration enforcement shifts the marginal cost curve so far to the left that agencies stop serving Medicaid patients altogether. Once agencies have stopped serving Medicaid patients, a shift in MC to the left ($MC' \to MC''$) will lead agencies to serve fewer private-pay patients, and prices will increase in the private-pay market ($p'_{priv}* \to p''_{priv}*$). These predictions are consistent with evidence from Ruffini (2022) in the nursing home setting, which found that nursing homes responded to an increase in labor costs by serving fewer Medicaid patients and charging private-pay patients higher prices.

3.3 Model Predictions

Taken together, we hypothesize that immigration enforcement directly impacts the market for home care by reducing the number of immigrants working in the market, with enforcement having the strongest impact on undocumented workers. This reduction could occur because of deportations, chilling effects, or both. Additionally, enforcement could lower labor force participation on both the extensive and intensive margins; even if immigrant workers don't exit the labor force in response to immigration enforcement, they may reduce their hours worked due to fear of interacting with law enforcement.

While we expect immigration enforcement to inhibit labor force participation among immigrant workers, its impact on the overall supply of home care is less clear. As previously pointed out by Chassamboulli and Peri (2015), Albert (2021), and East et al. (2022), immigration enforcement has a theoretically ambiguous impact on the number of US-born home care workers, as this depends in part on the relative substitutability between US- and non-US-born workers. On the one hand, if home care agencies can respond to a reduction in immigrant workers by hiring more US-born workers, then enforcement's impact on the overall supply of home care will be less severe. However, the home care industry has been heavily reliant on low-wage, low-skill immigrant workers, who often fill jobs that US-born workers do not want. Turning to US-born workers to maintain an adequate workforce is likely to increase agencies' average costs, given higher reservation wages among the US-born. Thus, enforcement may result in lower job creation and hiring in the home care sector as average costs increase. This could result in a significant shortage of home care workers, which would have serious implications for older adults and people with disabilities who rely on paid home care.

By reducing the supply of home care workers, we hypothesize that immigration enforcement reduces the amount of formal (i.e., non-family) care that older adults receive. We expect these reductions to be borne primarily by Medicaid-enrolled patients. Agencies will only supply care to people insured by Medicaid as long as the marginal revenues from Medicaid-insured people (i.e., the local Medicaid reimbursement rate) remain above marginal costs. With immigration enforcement and a reduced labor supply of lower-wage immigrant workers, agencies' marginal costs increase, resulting in a reduction in quantity supplied to lower-revenue Medicaid-insured patients. If immigration enforcement results in a sufficiently large increase in marginal costs (Figure 2c), immigration enforcement will reduce the supply of formal home care to non-Medicaid-insured people and increase prices in the non-Medicaid (i.e., private-pay) market.

Finally, we hypothesize that immigration enforcement increases the provision of family caregiving. The provision of formal care from home care workers does not completely cover the long-term care needs of those requiring assistance with their daily activities. These gaps in coverage are typically filled by family caregivers. If formal home care and family caregiving are substitutes, then immigration enforcement may also increase the provision of family caregiving.

4 Data

Our analysis relies on several data sources. The first dataset includes the date when Secure Communities was activated in each of 3,143 US counties between 2008-2013. To analyze the impact of immigration enforcement on the size of the home care workforce, we merge this dataset with data on the home care workforce from the American Community Survey (ACS). Then, to examine the policy's effects on receipt of home care, including the direct impact on the receipt of formal (i.e., non-family) care and the indirect impact on receipt of family care, we use data from the Health and Retirement Study (HRS). Each of these data sources is described in more detail in the following sections.

4.1 Secure Communities

We obtain county-level data on the timing of the rollout of Secure Communities from Alsan and Yang (2022a, 2022b), which we cross-reference with publicly available reports from U.S. Immigration and Customs Enforcement (ICE) (U.S. Immigration and Customs Enforcement 2013, 2014).[7] These data include the exact date of Secure Communities' activation in each county in the United States between 2008-2013. In some cases, county names and boundaries changed over time; where necessary, we referenced Dorn (2021) to map these changes to counties and their relevant Federal Information Processing Standards (FIPS) codes.

4.2 American Community Surveys

To measure the size of the home care workforce in each geographic area (i.e., the total number of home care workers), along with sociodemographic characteristics of that workforce, we use data from the ACS Integrated Public Use Microdata Series (IPUMS) from 2005-2014 (Ruggles et al. 2022). The ACS is a nationally representative survey of 3.5 million households conducted annually by the Census Bureau and is designed to capture demographic, socioeconomic, and housing characteristics of the US population (United States Census Bureau 2017). The IPUMS data include geographic information on respondents' residency at the level of the public-use microdata area (PUMA). PUMAs are non-overlapping geographic areas that subdivide states into regions, cover the entirety of the United States, and contain populations of at least 100,000 people each (Missouri Census Data Center 2022; United States Census Bureau, n.d.). While large, urban counties may be split into separate PUMAs, PUMAs typically represent combinations of multiple counties (Missouri Census Data Center 2022). Since PUMAs are redefined every ten years (Missouri Census Data Center 2022), and the PUMA boundaries changed during our sample period, we conduct our analyses at the level of the "consistent PUMA (CPUMA)."[8] We begin the ACS sample in 2005, because the CPUMA variable became available that year, and we end the sample in 2014 because Secure Communities was discontinued that year.

We use the ACS data to measure the number of home care workers in each CPUMA. To identify home care workers in the ACS, we use respondents' reported industry and occupation. Following

7. Specifically, we use the ICE reports to verify the activation dates for a subset of counties in Alaska, all of which were activated on April 10, 2012. The activation dates for each county are available on the ICE website and the Internet Archive (U.S. Immigration and Customs Enforcement 2013, 2014).

8. IPUMS constructs CPUMAs to "support spatio-temporal analysis of PUMS data." Each CPUMA used in our analysis is an "aggregation of one or more 2010 PUMAs (Public Use Microdata Areas) that, in combination, align closely (within a 1% population error tolerance) with a corresponding set of 2000 PUMAs" (Minnesota Population Center, University of Minnesota 2023).

previous research, we define home care workers as nursing, psychiatric, and home health aides (occupation code 3600) and personal and home care aides (occupation code 4610) who reported working in the following industries: home health care services (industry code 8170), individual and family services (industry code 8370), and private households (industry code 9290). We restrict to respondents who report being employed at the time of the survey. We also use the ACS to categorize workers as agency/government workers or as household employees/independent contractors, following the classification methodology used by (Kim 2022). More information on this classification is included in an Appendix.

We also use the ACS data to measure demographic and socioeconomic characteristics of CPUMAs that might be correlated with the size of the home care workforce. These characteristics include the mean age of CPUMA residents, percentage of the population over age 65, percent female, racial composition, educational composition, percent receiving SSI payments, and Bartik-style measures of local labor demand. We construct the Bartik measures, which capture differential impacts of national economic trends (such as the Great Recession) on CPUMAs according to the industrial composition of CPUMAs, following methods from East and Velásquez (2022). We describe the process of calculating the Bartik measures in an Appendix.

Finally, we use the ACS to construct a measure of the percentage of a CPUMA's population who are "likely undocumented," i.e., immigrants living in the United States without legal status. Following prior literature, we define "likely undocumented" people as Hispanic respondents born outside the US who have less than a high school education (East and Velásquez 2022).

4.3 Health and Retirement Study

To examine the effect of Secure Communities on the supply of home care to older adults, we use data from the 2000-2014 waves of the Health and Retirement Study (HRS), a longitudinal panel study designed to be nationally representative of the US population over age 50 (National Institute on Aging 2025). We start the sample in 2000 because the questions about caregiving changed in that year, and we end the sample in 2014 since Secure Communities was discontinued that year. The HRS introduces new birth cohorts every 6 years, and participants and their spouses are surveyed every two years from study entry until death or loss to follow-up. In addition to socioeconomic characteristics, the survey includes rich detail on respondents' care needs (i.e., their difficulty with activities of daily living (ADLs) and instrumental activities of daily living (IADLs)), receipt of help at home, and the people who provide that help.[9] Specifically, participants who indicate that they need help with ADLs or IADLs are asked about each of their helpers in the last month, including their relationship with each helper, the number of hours of care each helper provided, and the amount each helper was paid (if applicable). For all analyses, we restrict to adults over age 65 who report difficulty with at least one ADL or IADL.

To measure receipt of "any home care," we identify HRS respondents who report having had at least 1 helper in the prior month who helped with ADLs or IADLs. We exclude helpers whose relationship to the respondent is reported as "self," as well as those who were reported as providing zero days of help in the prior month. We define formal caregiving as caregiving where (1) the helper was reported to be an organization, employee of an institution, paid helper, professional, agency, or "other individual" (i.e., not a relative), or (2) the helper's relationship to the respondent was unknown, but the helper was paid. We define family caregiving as caregiving for which the helper was reported to be a relative,[10] regardless of whether or not the helper received payment.[11]

5 Empirical Strategy

Our empirical strategy leverages geographic and temporal variation in Secure Communities' activation across counties to estimate the causal effect of immigration enforcement on the outcomes of interest, which include the size of the home care workforce (i.e., the total number of home care workers) and older adults' receipt of home care.

5.1 Effect on the Number of Home Care Workers

To quantify Secure Communities' effect on the total number of home care workers in a local area, we use data from the American Community Survey (ACS) and estimate the following two-way

9. ADLs reported in the HRS include: dressing, walking across a room, bathing, eating, getting into or out of bed, and using the toilet. IADLs include: preparing a hot meal, shopping for groceries, making phone calls, taking medications, and managing money.

10. In the HRS, relatives include: spouse, child, grandchild, child-in-law, sibling, stepchild, parent, sibling-in-law, parent-in-law, or "other relative."

11. In practice, family caregivers sometimes receive payment from state Medicaid programs (Burns et al. 2025). We consider this type of care distinct from hiring a formal (i.e., non family) caregiver.

fixed-effects (TWFE) equation:

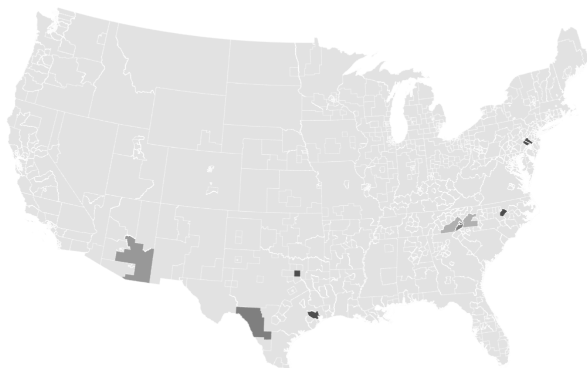
$$Y_{ct} = \beta \cdot SC_{ct} + \vec{X}_{ct} \times \gamma + \alpha_c + \delta_t + \epsilon_{ct} \tag{1}$$

The analysis is at the level of the CPUMA-year, which is the level at which we observe the number of home care workers.[12] The dependent variable Y_{ct} is the number of home care workers per capita in CPUMA c and year t. SC_{ct} is a continuous variable ranging from 0 to 1 (inclusive), representing the percentage of the population of CPUMA c that was covered by Secure Communities before January 1 of year t. $\vec{X}_{ct}$ is a vector of time-variant characteristics of CPUMAs that correlate with the size of the workforce (described below). α_c represents CPUMA fixed effects, allowing us to control for both observable and unobservable time-invariant CPUMA characteristics, and δ_t represents year fixed effects. We cluster standard errors at the level of the CPUMA.

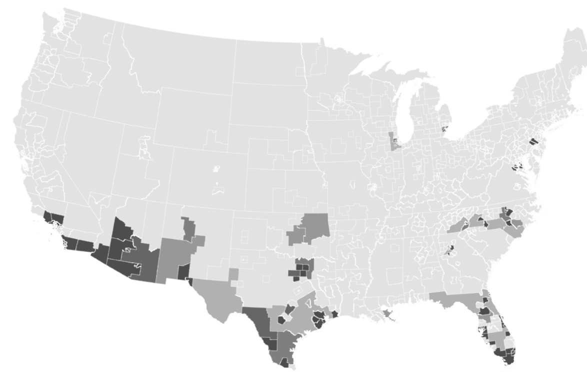
We control for time-variant characteristics of CPUMAs $\vec{X}_{ct}$. These include demographic characteristics, including mean age of CPUMA residents, the share of residents over age 65, the share female, and the racial and educational compositions of the CPUMA. We also control for the share of the CPUMA receiving supplemental security income (SSI) and for ACA Medicaid expansion. Finally, since the Great Recession occurred during the sample period, and following East and Velásquez (2022), we control for time-varying economic conditions at the level of the CPUMA, including a housing price index and Bartik measures of labor demand (Bartik 1991; Blanchard and Katz 1992). We include these labor demand measures for four groups of workers: all workers, immigrant workers, workers with a high school education or less, and female workers. We describe these measures in more detail in an Appendix.

The coefficient of interest in Equation 1 is β. Under some assumptions, β identifies the average treatment effect on the treated (ATT) of the introduction of Secure Communities on the size of the home care workforce. The first assumption is that, in the absence of Secure Communities, the number of home care workers in different CPUMAS would have evolved in parallel (i.e., the parallel trends assumption). To visually test for parallel trends, we estimate a fully dynamic event study version of Equation 1. The second assumption is that the average treatment effect of Secure Communities is constant across CPUMAs and over time (i.e., treatment effects are homogeneous)

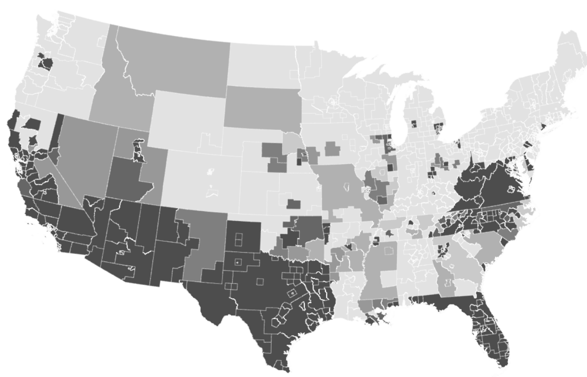
12. While Secure Communities was implemented at the county level, the most granular level of geographic data in the ACS is the CPUMA.



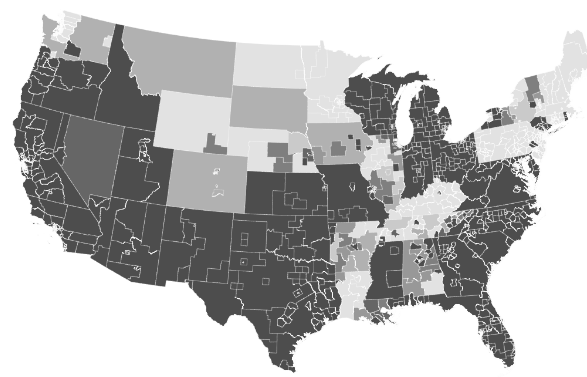
(a) 2009



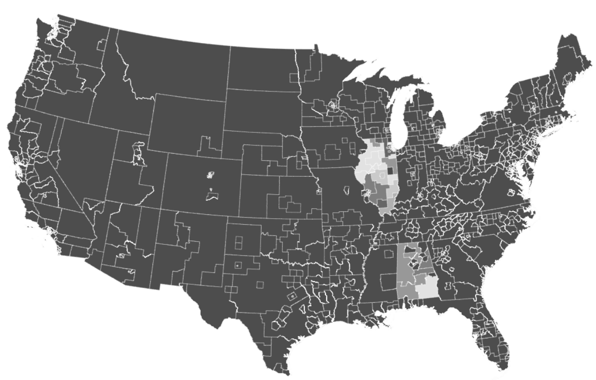
(b) 2010



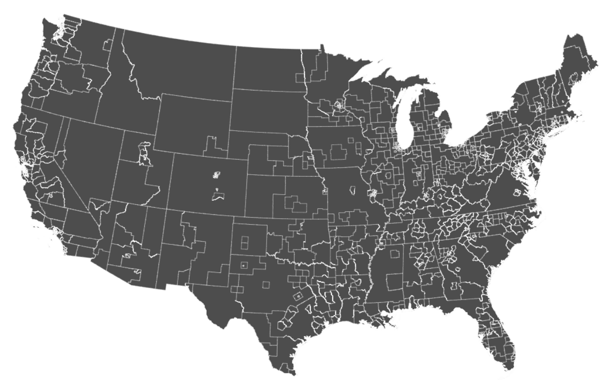
(c) 2011



(d) 2012



(e) 2013



(f) 2014

Figure 3: Rollout of Secure Communities by Consistent Public-Use Microdata Area (CPUMA), Continental United States, 2009-2014

Note: This figure demonstrates the variation in the rollout of Secure Communities upon which we rely to identify its impact on the size of the home care workforce in Equation 1. The shading represents the percentage of the population of each Consistent Public Use Microdata Area (CPUMA) that was covered by Secure Communities before January 1st of the year.

(Callaway and Sant'Anna 2021; Sun and Abraham 2021; Goodman-Bacon 2021; de Chaisemartin and D'Haultfœuille 2020). To assuage concerns about heterogeneous treatment effects, we employ the robust estimator introduced in Callaway and Sant'Anna (2021).

5.2 Effects on the Provision of Care

$$Y_{ict} = \beta \cdot SC_{ct} + \vec{X}_{it} \times \gamma + \vec{Z}_{ct} \times \eta + \alpha_c + \delta_t + \epsilon_{ict} \tag{2}$$

To analyze the effect of Secure Communities on the provision of home care - both formal and family care, we employ a similar methodology to Equation 1, this time using data from the Health and Retirement Study (HRS). The first difference between the two analyses is that the HRS analysis is conducted at the individual level. Second, the restricted-use HRS files include data on respondents' county of residence as well as the exact date of the survey, which allows us to precisely align the timing of individual survey responses with the implementation of Secure Communities. Finally, this specification does not rely on the same baseline CPUMA- (or county-) level parallel trends assumption. Rather, this specification compares individuals surveyed in the same wave and county who had been exposed to Secure Communities for different lengths of time, depending on the date of their HRS survey.

In the HRS analyses, the dependent variable Y_{ict} is a binary variable representing the outcome of interest for individual i in county c at time t. We estimate the effect of Secure Communities on the following outcomes: (1) receipt of any home-based care in the prior month, (2) receipt of formal (i.e., non-family) care in the prior month, and (3) receipt of family care in the prior month. In addition, we estimate the effects on (4) whether the respondent's primary caregiver was a family caregiver, conditional on receipt of any home-based care, and (5) whether the respondent was coresiding with their child(ren), conditional on having at least one living child. In this specification, SC_{ct} is an indicator for whether Secure Communities was implemented in county c at least one month prior to individual i's survey date. β is the coefficient of interest, representing the average treatment effect on the treated of Secure Communities on receipt of care. $\vec{X}_{it}$ is a vector of individual characteristics, including age, sex, race, marital status (alone and interacted with sex), income, education, family structure (i.e., the presence and number of living siblings, the presence and number of living children, and whether the respondent had a daughter), counts of ADL and

IADL limitations, and whether the respondent was ever enrolled in Medicaid or SSI during their HRS panel. $\vec{Z}_{ct}$ is a vector of time-variant characteristics of counties. α_c represents county fixed effects and δ_t represents survey month fixed effects. The HRS analyses are clustered at the level of the county.

6 Results

6.1 Summary Statistics

We first compare baseline sociodemographic characteristics of geographic areas (i.e., CPUMAS), as calculated from the ACS data, stratifying by when Secure Communities was implemented in each. Table 1 presents characteristics of CPUMAs in the pre-period (2005), disaggregated by timing of Secure Communities activation. CPUMAs are defined as early, mid-period, or late adopters according to the year when the *first county within the CPUMA* implemented Secure Communities. If the first county implemented Secure Communities between 2008-2009, the CPUMA is considered an early adopter. If the first county implemented Secure Communities between 2010-2011, the CPUMA is considered a mid-period adopter. If the first county implemented Secure Communities between 2012-2013, the CPUMA is considered a late adopter.

There are a few key differences at baseline between early, mid-period, and late adopters. The first is population size; early-adopter CPUMAs had much larger population sizes, on average (428,000) than mid-period and late adopters (261,000 and 202,000, respectively). Second, there were more home care workers per capita at baseline in late-adopter CPUMAS (337 workers per 100,000 people) relative to mid-period adopters (234 per 100,000) and early adopters (265 per 100,000). Third, people in early-adopter CPUMAs were less likely to be white (50.0%) and more likely to be Black (15.9%) or Hispanic (26.3%) than people in mid- or late-adopter CPUMAs. Finally, the percentage of the population that was born outside the US was higher in the early adopter CPUMAs (21.2%) relative to mid-period (10.2%) and late adopters (15.8%).

Table 2 presents demographic and socioeconomic characteristics of home care workers for years 2005-2014. For comparison purposes, we also present characteristics of fast food workers, an occupation requiring a lower skill level than home care,[13] but which home care agencies anec-

13. Fast food workers have a Specific Vocational Preparation (SVP) of < 4.0, while home care workers have an SVP

Table 1: Summary Statistics by CPUMA, 2005

	All CPUMAs	Early Adopters	Mid-Period Adopters	Late Adopters
	(1)	(2)	(3)	(4)
N	1,078	162	580	336
Percent	100.00	15.03	53.80	31.17
Population (mean)	267,512	427,808	260,981	201,500
Workers per 100,000 population (mean)				
Home Care Workers	271	265	234	337
Personal Care Aides	126	130	123	128
Home Health Aides	145	135	112	208
Age (mean)	36.8	35.7	36.9	37.2
Percent over 65 (mean)	12.5	11.7	12.7	12.6
Percent female (mean)	51.1	50.9	51.0	51.4
Race/ethnicity (%)				
White	68.5	50.0	72.8	70.1
Black	11.6	15.9	10.5	11.7
Hispanic	12.8	26.3	9.9	11.3
Asian/PI	4.7	5.6	4.3	5.0
AIAN	0.7	0.6	0.8	0.5
Multiracial	1.4	1.3	1.6	1.2
Other Race	0.3	0.4	0.2	0.4
Percent born outside US (mean)	13.6	21.2	10.2	15.8
Education (mean %)				
Less than HS	34.7	37.8	34.4	33.6
High School	30.1	27.5	30.7	30.2
Some College	16.2	15.8	16.8	15.4
Bachelor's Degree	12.2	12.2	11.7	13.0
5+ Years College	6.9	6.7	6.5	7.8
Percent SSI (mean)	1.8	1.8	1.7	2.1

Note: CPUMAs are defined as early, mid-period, or late adopters using the year the first county within the CPUMA implemented Secure Communities. If the first county implemented Secure Communities between 2008-2009, the CPUMA is considered an early adopter. If the first county in a CPUMA implemented Secure Communities between 2010-2011, the CPUMA is considered a mid-period adopter. If the first county in a CPUMA implemented Secure Communities between 2012-2013, the CPUMA is considered to be a late adopter. Source: Authors' analysis of data from the American Community Survey.

of 4.0 to < 6.0. SVPs are defined by the U.S. Department of Labor and take into account "the amount of lapsed time required by a typical worker to learn the techniques, acquire the information, and develop the facility needed for dotally report losing workers to (Abelson and Rios 2023), and of all US workers. Approximately 0.78% of US workers, or 1.07 million people, are home care workers. Relative to all US workers, home care workers are slightly older, on average (45.1 vs. 41.2); much more likely to be female (89.3% vs. 47.7%); more likely to be Black (26.5% vs. 10.9%), Hispanic (19.8% vs. 14.9%), Asian or Pacific Islander (Asian/PI, 6.2% vs. 5.0%), and American Indian or Alaska Native (AIAN, 1.1% vs. 0.5%); and much more likely to be born outside the United States (29.9% vs. 17.6%). They are also more likely to have children (50.4% vs. 43.9%), and their educational status is lower, with 9.3% having at least a bachelor's degree, relative to 30.8% of all US workers. Notably, home care workers earn very low incomes and wages ($\approx$ \$17,900 per year, or \$13.70 per hour), relative to all US workers ($\approx$ \$46,300 per year, or \$24.70 per hour).[14]

Comparing home care workers to fast food workers, we find that fast food workers earn lower wages (\$9.88 per hour) and incomes (\$10,640) than home care workers (\$13.72; \$17,860). However, after restricting to workers who work full-time and adjusting for age and level of education, we find that fast food workers make about 6.5% higher wages and income than home care workers.[15] While full-time fast food workers with the same education and age as home care workers make an estimated \$27,550 per year and \$12.81 per hour, full-time home care workers make only \$25,860 per year and \$11.59 per hour. Finally, the prevalence of poverty among home care workers and fast food workers is similar (19.2% and 21.1%, respectively), and these workers also have a similar likelihood of being on food stamps (26.8%, 23.5%), Medicaid (20.9%, 21.0%), or public assistance (3.0%, 2.3%). By contrast, 6.2% of all US workers are in poverty, 7.9% are on food stamps, 5.4% report being on Medicaid, and 0.7% receive public assistance.

average performance in a specific job-worker situation" (U.S. Department of Labor 1991).

14. Income and wages are inflation-adjusted and reported in 2014 dollars.

15. Here, "full-time" is defined as 35 hours or more per week for at least 48 weeks out of the year. We adjust wage and income estimates for home care workers, fast food workers, and all US workers to reflect estimated wages and incomes if these workers had the same education level and age as the average full-time US home care worker. To do this, we run OLS regressions separately for each group (i.e., full-time home care workers, full-time fast food workers, and all full-time workers) with income (wages) as the dependent variable and age and education as independent variables. Then, we use the estimated coefficients from each regression to estimate predicted income (wages) for the home care workers in the ACS sample.

Table 2: Summary Statistics, American Community Survey Respondents, 2005-2014 (Weighted)

	Home Care Workers	Fast Food Workers	All US Workers
	(1)	(2)	(3)
N (mean per year)	1,065,849	1,027,152	136,620,602
Percentage of US workers	0.78	0.75	100.00
Age (mean)	45.1	26.1	41.2
Female (%)	89.3	72.7	47.7
Has Children (%)	50.4	25.5	43.9
Num. Children	0.9	0.5	0.8
Race/ethnicity (%)			
White	44.4	48.1	67.1
Black	26.5	19.5	10.9
Hispanic	19.8	23.1	14.9
Asian/PI	6.2	6.2	5.0
AIAN	1.1	0.6	0.5
Multiracial	1.6	2.3	1.3
Other Race	0.3	0.3	0.2
Born Outside US (%)	29.9	18.8	17.6
Education (%)			
Less than HS	18.0	34.2	9.3
High School	47.2	42.5	34.5
Some College	25.4	19.6	25.4
Bachelor's Degree	7.4	3.2	19.8
5+ Years College	1.9	0.5	11.0
Income ($2014)	17,860	10,640	46,340
Adj. Income, FT ($2014)	25,860	27,550	47,310
Hourly Wage ($2014)	13.72	9.88	24.69
Adj. Wage, FT ($2014)	11.59	12.81	21.28
Works $>=$ Full Time (%)	52.9	32.8	79.1
On Food Stamps	26.8	23.5	7.9
On Medicaid	20.9	21.0	5.4
On Public Assistance	3.0	2.3	0.7
In Poverty (<=100% FPL)	19.2	21.1	6.2

Note: The sample includes ACS respondents between 2005-2014 who were employed and reported any earned income in the prior year. Excluded from the sample are incorporated business owners and unpaid family workers, as well as institutional residents and residents of group quarters. Estimates are weighted to be representative of the noninstitutionalized US population. See section 4.2 for a definition of home care workers. Source: Authors' estimates using data from the American Community Survey.

6.2 Results: Workforce Size (ACS Analysis)

Next, we turn to the effect of Secure Communities on the total number of home care workers. Table 3 presents results of the primary two-way fixed effects (TWFE) analysis specified in Equation 1. Column 1 presents the results of the analysis without controls, and column 2 presents the results with the full set of controls (the preferred specification). Focusing on the results of the fully-specified model in column 2, we find that Secure Communities reduces the size of the home care workforce by 29.7 workers per 100,000 residents, relative to a baseline of 396.8 workers per 100,000 residents. This represents a 7.5% reduction in the overall size of the workforce.

Table 3: Effect of Secure Communities on the Total Number of Home Care Workers per 100,000 Residents

	No Controls	Full Set of Controls	Below-Median Undocumented	Above-Median Undocumented
	(1)	(2)	(3)	(4)
Secure Communities	-27.956**	-29.727**	-16.968	-42.557**
	(10.771)	(10.644)	(14.615)	(16.356)
Controls	No	Yes	Yes	Yes
CPUMA FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	10,780	10,780	5,390	5,390
Adj. R^2	0.719	0.723	0.456	0.776
Margins Pre-SC	396.2	396.8	307.9	486.4
Margins Post-SC	368.3	367.1	290.9	443.9

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

We expect the effect of the policy to be heterogeneous by the size of CPUMAs' undocumented populations, with larger expected effects in CPUMAs with more undocumented residents. To test for this heterogeneity, we stratify the analysis by the percentage of the CPUMA's population who are likely undocumented at baseline (i.e., above and below the median).[16] Results are presented in Table 3, columns 3 and 4. Column 3 displays results for CPUMAs with low (i.e., below-median)

16. Due to concern regarding misreporting of citizenship status in US surveys, we use a proxy measure for undocumented status. Following East and Velásquez (2022), we classify non-US-born Hispanic residents with less than a high school education as "likely undocumented."

numbers of likely undocumented residents, and column 4 presents results for CPUMAs with high (i.e., above-median) numbers of likely undocumented residents. From these results, it is clear that the effect of Secure Communities observed in column 2 is driven by geographic areas with large numbers of likely undocumented residents. In these areas, Secure Communities reduces the size of the home care workforce by 42.6 per 100,000 residents, an 8.7% reduction relative to a baseline of 486.4 workers. By contrast, there is no statistically significant change in the number of home care workers per capita in areas with low numbers of undocumented residents (column 3).

To further provide support for the hypothesis that Secure Communities caused the observed effect on workforce size, we examine whether the effect was concentrated among workers born outside the United States. Specifically, we stratify the analysis by US-born vs. non-US-born home care workers, expecting larger effects among non-US-born workers. Table 4 presents results for workers born outside the US, and Table 5 presents results for US-born workers. We find that Secure Communities reduces the number of immigrant home care workers per capita; specifically, the policy reduces the number of home care workers who were born outside the US by 20.7 workers per 100,000 residents (Table 4, column 2). This represents a 14.6% reduction from a baseline of 142.1 non-US-born home care workers. Conversely, we do not find a statistically significant effect on the number of US-born home care workers per capita. Directionally, Secure Communities reduces the number of US-born home care workers by about 9 workers per 100,000 residents, or 3.5% (Table 5, column 2); however, this result is not statistically significant. The only exception is in geographic areas with large undocumented populations (Table 5, column 4). In these areas, the number of US-born home care workers declines by 17.8 workers per 100,000 residents (7.2%) following the policy's activation, a result that is marginally significant at the 10% level.

6.2.1 Event Study Analysis

In addition to the static analyses described above, we estimate the effect of Secure Communities on the home care workforce using a fully dynamic event study analysis. This allows us to visually inspect for parallel trends in the size of the home care workforce prior to the implementation of Secure Communities. It also allows us to examine dynamic treatment effects over time by producing annual estimates of how Secure Communities impacts the workforce size in the years

Table 4: Effect of Secure Communities on the Number of Non-US-Born Home Care Workers per Capita (per 100,000 Residents)

	No Controls	Full Set of Controls	Below-Median Undocumented	Above-Median Undocumented
	(1)	(2)	(3)	(4)
Secure Communities	-19.363**	-20.687**	-14.781*	-24.743+
	(7.294)	(6.992)	(5.845)	(12.937)
Controls	No	Yes	Yes	Yes
PUMA FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	10,780	10,780	5,390	5,390
Adj. R^2	0.832	0.836	0.692	0.838
Pre	141.7	142.1	44.0	239.9
Post	122.3	121.4	29.2	215.1

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 5: Effect of Secure Communities on the Number of US-Born Home Care Workers per Capita (per 100,000 Residents)

	No Controls	Full Set of Controls	Below-Median Undocumented	Above-Median Undocumented
	(1)	(2)	(3)	(4)
Secure Communities	-8.594	-9.039	-2.187	-17.813+
	(7.660)	(7.835)	(13.061)	(9.822)
Controls	No	Yes	Yes	Yes
PUMA FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	10,780	10,780	5,390	5,390
r2_a	0.454	0.458	0.413	0.500
Pre	254.5	254.7	263.9	246.6
Post	245.9	245.6	261.7	228.7

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

following the policy's activation. We estimate the following two-way fixed effects (TWFE) event study regression:

$$Y_{ct} = \beta_k \times \sum_{k=-4, k\neq 0}^{4} 1(SC_k = 1)_{ct} + \vec{X}_{ct} \times \gamma + \alpha_c + \delta_t + \epsilon_{ct} \tag{3}$$

This regression is nearly identical to the one specified in Equation 1, but instead of the continuous treatment variable SC_{ct}, here the treatment variables $1(SC_k = 1)_{ct}$ are binary and indicate the time elapsed, as of time t, since the first year when *any* county in CPUMA c implemented Secure Communities. Y_{ct} represents the number of home care workers in CPUMA c and year t, α_c are CPUMA fixed effects, and δ_t are year fixed effects. We again control for a vector of time-variant demographic and economic characteristics of CPUMAS, $\vec{X}_{ct}$, which was elaborated in Section 5.1. Figure 4 presents the results.

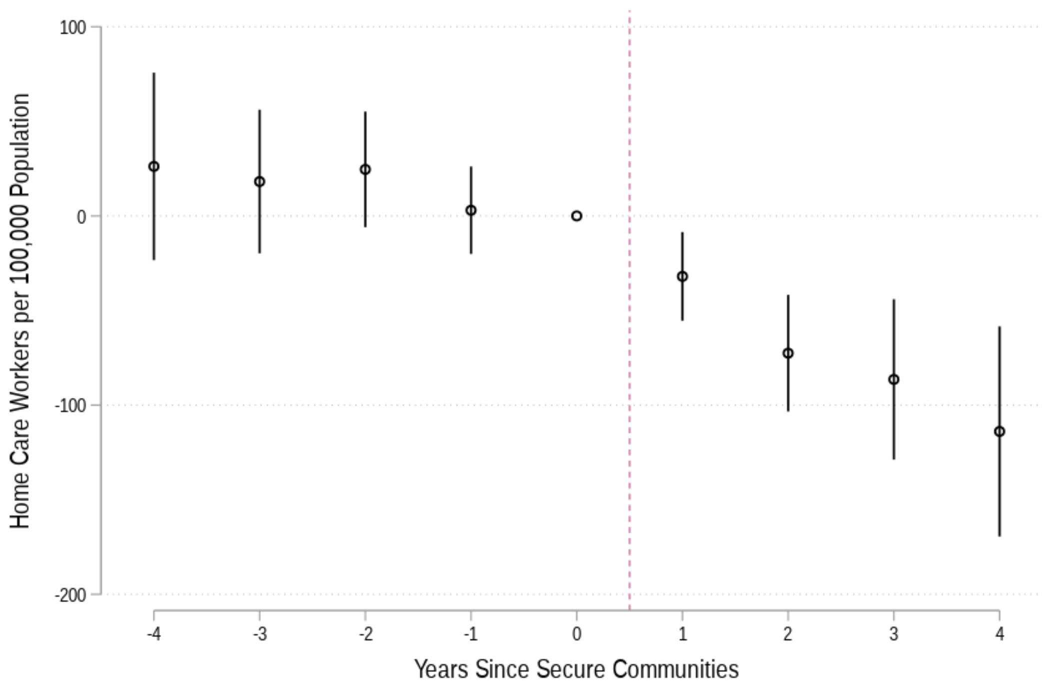


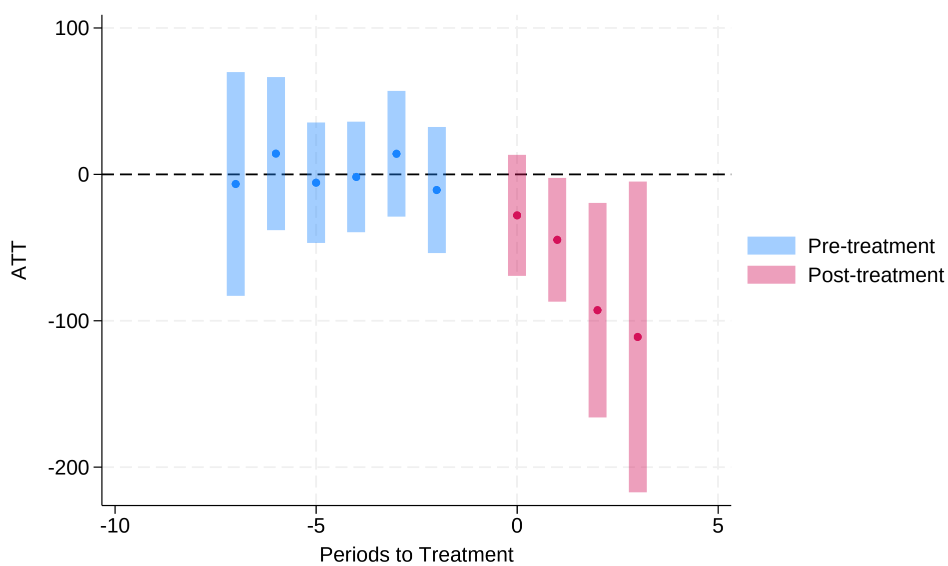
Figure 4: Event Study: Effect of Secure Communities on the Number of Home Care Workers per 100,000 Residents

Prior to Secure Communities' implementation, the coefficients are not significantly different from zero and do not exhibit a pre-trend. However, once Secure Communities is activated, the home care workforce begins to decline in size, and this decline continues for several years following Secure Communities' activation. This gradual reduction in the size of the workforce is consistent with the fact that generally only a fraction of a CPUMA's population (i.e., a subset of counties within the CPUMA) is affected by Secure Communities in the first year of implementation This percentage grows over time as more counties in the CPUMA are exposed to the policy.

Finally, to allow for heterogeneity in treatment effects over time and across geographic areas, we employ the estimator proposed by Callaway and Sant'Anna (2021), which is robust to treatment effect heterogeneity.[17] We find that our results are robust to this alternative specification.[18] Figure 5a presents results for all home care workers, Figure 5b presents results for workers born outside the US, and Figure 5c presents results for US-born workers. In all three figures, coefficients are close to zero in years prior to the introduction of Secure Communities, with no discernable pretrends. However, beginning in the year following Secure Communities' introduction, we observe a decline in the number of workers, which grows over time and significantly deviates from zero.

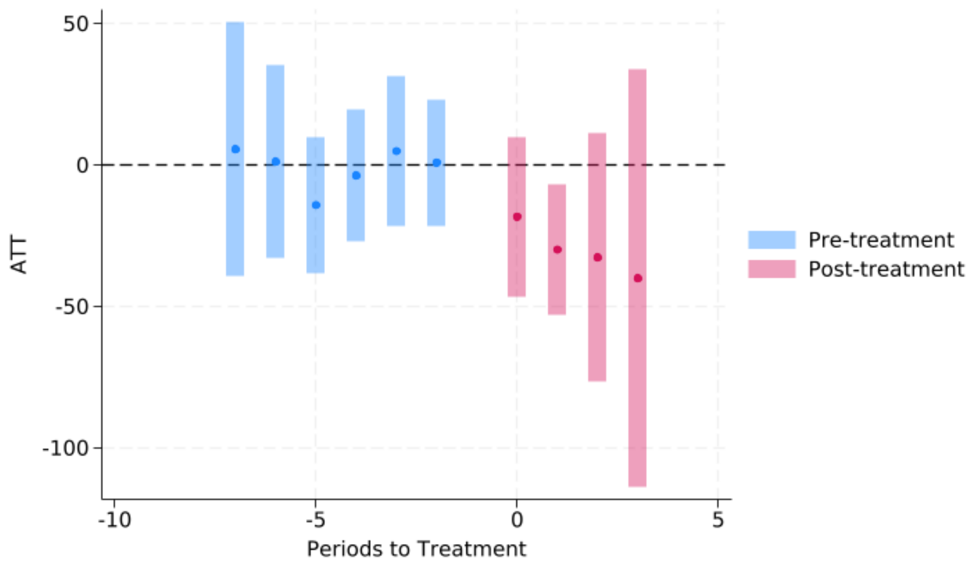
Figure 5: Effect of Secure Communities on the Total Number of Home Care Workers per 100,000 Residents (Callaway Sant'Anna Estimator)

(a) All Home Care Workers

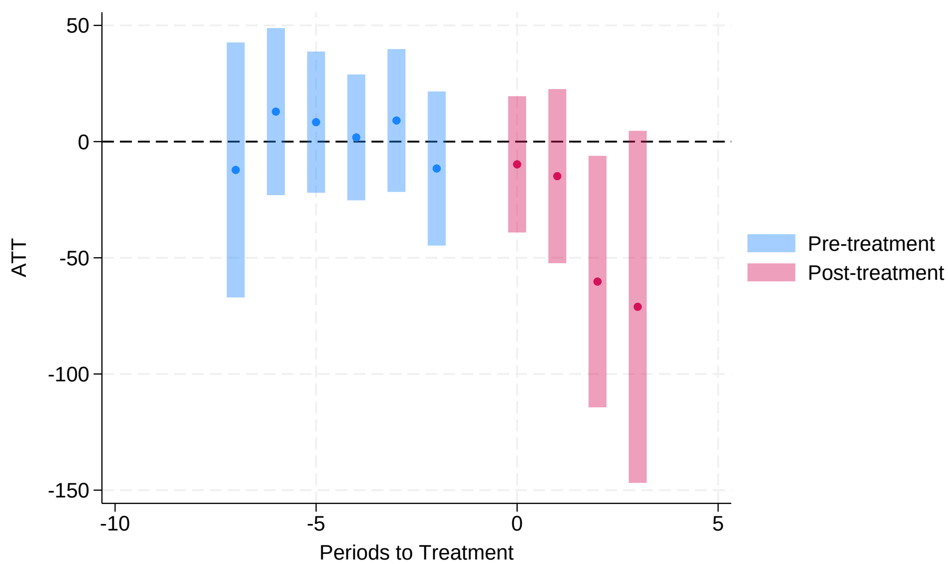


17. Specifically, we use Fernando Rios-Avila's "csdid2" package in Stata (Rios-Avila 2024).
18. Note that we censor these results, dropping from the figures periods more than 7 years prior to Secure Communities' activation and more than 3 years after, because the sample becomes much smaller moving further away from t=0, and the confidence intervals become quite large. We present the full results in an Appendix.

(b) Non-US-Born Home Care Workers



(c) US-Born Home Care Workers



To aid in interpreting these results, we present aggregated coefficients in Table 6, again using the Callaway Sant'Anna estimator (csdid2). We aggregate the coefficients over the first three years following Secure Communities' introduction to isolate the proximal effect of the policy. We find that the total number of home care workers declines by 47.39 per 100,000 workers, on average, following Secure Communities' activation. Relative to a baseline of 438.47 workers, this represents a 10.8% decline, which is similar to the results of our primary specification. This result is primarily driven by a reduction in non-US-born workers. Specifically, the number of non-US-born workers declines by 25.08 per 100,000 workers following the introduction of Secure Communities, a 16.1% reduction from baseline. Directionally, the number of US-born home care workers also declines, in this case by 22.30 per 100,000 workers. This represents a 7.9% reduction from baseline; however, this result is not statistically significant.

Table 6: Effect of Secure Communities on the Number of Home Care Workers per 100,000 Residents (Callaway Sant'Anna Estimator)

	All Home Care Workers	Non-US-Born Workers	US-Born Workers
	1	2	3
Secure Communities	-47.39	-25.08	-22.30
SE	(19.47)	(12.69)	(15.17)
P-value	0.015	0.048	0.141
CI	[-85.55, -9.23]	[-49.96, -0.21]	[-52.03, 7.42]
Dependent Variable Mean (t-1)	438.47	156.14	282.32
Δ from Baseline (%)	10.80	16.06	7.90

6.3 Results: Home Care Supply (HRS Analysis)

Finally, we turn to our analysis of older adults' receipt of formal and family care, using data from the Health & Retirement Study (HRS) for years 2002-2014 (seven total survey waves). Table 7 presents descriptive statistics for all HRS respondents (column 1) and for the analysis sample (column 2). We restrict the sample to respondents ages 65+ who reside in the community and report difficulty with at least one activity of daily living (ADL) or instrumental activity of daily living (IADL). Columns 3 and 4 split the analysis sample by whether the respondent ever reported having Medicaid coverage (column 3) or did not report Medicaid coverage (column 4).

The analysis sample comprises 19,461 respondent-years. The mean age of sample respondents is 78.1, which is slightly older than the mean age of all HRS respondents (67.4) due to our sample restrictions. 61.5% of sample respondents are female, 48.0% are married, and 11.5% are born outside the United States. The mean income of the sample is 335.5% of the federal poverty level (FPL), representing about $39,150 for an individual in 2014. The majority of the sample has at least one living child (91.7%) and at least one living sibling (76.8%). On average, sample respondents have difficulty with 1.7 ADLs and 1.4 IADLs. 13.7% ever report having SSI income, and 30.2% ever report having Medicaid coverage. The racial/ethnic makeup of the analysis sample if similar to that of the full HRS sample: 69.8% of respondents are white, 17.4% are Black, 10.8% are Hispanic, and 2.0% report having other race/ethnicity. The majority of sample respondents (70.6%) have a high school education or less.

Turning to the outcomes of interest, 57.3% of respondents in the analysis sample report having received help in the prior month. Sample respondents with Medicaid coverage are more likely to report receiving help than respondents without Medicaid (64.4% vs. 54.3%), which is attributable, in part, to much higher rates of formal (i.e., non-family) care receipt among Medicaid respondents (18.3%) than among non-Medicaid respondents (9.8%). Finally, 24.5% of sample respondents co-reside with their children (32.9% in the Medicaid subsample; 20.8% in the non-Medicaid subsample).

Table 7: Summary Statistics, HRS Sample

	All HRS Respondents	Analysis Sample	Medicaid Sub-Sample	Sub-Sample without Medicaid
	1	2	3	4
N	134,419	19,461	5,814	13,552
Percent	100.0	14.5	4.3	10.1
Age (mean)	67.4	78.1	77.0	78.6
Female (%)	58.7	61.5	68.7	58.3
Married (%)	64.4	48.0	33.9	54.1
Born Outside US (%)	12.0	11.5	21.0	7.4
Percent FPL (mean)	496.8	335.5	193.7	396.6
Has Children (%)	90.1	91.7	90.9	92.1
Num. Children (mean)	2.7	3.2	3.8	2.9
Has Sibling (%)	85.6	76.8	79.2	75.8
Num. Siblings (mean)	2.8	2.3	2.7	2.1
Has ADL Difficulty (%)	19.2	75.9	78.8	74.7
ADLs (mean)	0.5	1.7	2.0	1.5
Has IADL Difficulty (%)	16.7	65.2	71.4	62.6
IADLs (mean)	0.4	1.4	1.6	1.3
Mobility Index (mean)	1.2	2.8	3.0	2.7
Ever SSI (%)	7.7	13.7	38.8	2.8
Ever Medicaid (%)	18.4	30.2	100.0	0.0
Race/ethnicity (%)				
White	69.8	69.8	42.6	81.5
Black	16.2	17.4	30.8	11.7
Hispanic	11.2	10.8	23.2	5.5
Other Race	2.8	2.0	3.3	1.4
Education (%)				
Less than HS	21.5	36.6	60.5	26.4
High School	34.7	34.0	25.8	37.4
Some College	22.8	16.8	9.7	19.8
College Deg.	21.0	12.6	4.0	16.4
Outcomes (%)				
Any Help	13.0	57.3	64.4	54.3
Has Family Helper	11.7	51.2	55.8	49.2
Has Formal Helper	2.3	12.4	18.3	9.8
Coresides with Kid(s)	26.1	24.5	32.9	20.8

6.3.1 HRS Analysis Results

We examine the effect of Secure Communities on older adults' receipt of home care. By reducing workforce size (i.e., the total supply of home care workers), we expect Secure Communities to pose negative externalities on older adults who need help at home. We first examine the effect on caregiving for our full HRS sample by estimating the regression specified in Equation 2. Then, we present results stratified by whether the HRS respondent was ever enrolled in Medicaid coverage. This is because our conceptual model predicts stronger effects for older adults enrolled in Medicaid relative to other older adults (see Section 3.)

Table 8 presents results for the full HRS sample. First, column 1 presents the effect of Secure Communities on the likelihood of receiving any help at home. We find that overall, older adults needing assistance are 2.9 percentage points less likely to receive any help at home. This is relative to a baseline mean of 58.3%, representing a 5.0% relative reduction in home care receipt. Columns 2-6 of Table 8 show the effect of Secure Communities on other outcomes of interest, indicating whether the HRS respondent: (2) received help from a family caregiver at home; (3) received help from a formal caregiver at home; (4) reported that their primary caregiver was family (conditional on receiving any help); (5) reported that their primary caregiver was formal (conditional on receiving any help); and (6) co-resided with at least one of their children, conditional on having any living children. In the full sample, we do not find significant effects of Secure Communities on these outcomes.

Next, we present results stratified by Medicaid enrollment. Results for older adults with Medicaid coverage are presented in Table 9, and results for older adults without Medicaid coverage are presented in Table 10. Consistent with our model's predictions, the effects of Secure Communities are concentrated among older adults with Medicaid coverage. Specifically, we find that Medicaid-enrolled older adults with care needs are 7 percentage points less likely to receive help at home following the introduction of Secure Communities, a 10.5% reduction from a baseline of 66.7%. Second, we find that this reduction is driven primarily by a reduciton in the likelihood of having a formal helper. Older adults with Medicaid coverage are 4.6 percentage points (23.2%) less likely to receive formal home care following the implementation of Secure Communities. By contrast, we do not find a significant effect on having a family helper; however, the likelihood that the

Table 8: HRS Results: Full Sample

	(1) Any Home- Based Care	(2) Has Family Caregiver	(3) Has Formal Caregiver	(4) Primary Family	(5) Primary Formal	(6) Cores- idence
Secure Communities	-0.029*	-0.015	-0.013	0.015	-0.017	-0.002
	(0.014)	(0.015)	(0.012)	(0.019)	(0.017)	(0.017)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	19,461	19,461	19,461	11,068	11,068	17,729
Adj. R^2	0.419	0.364	0.230	0.209	0.181	0.197
Pre	0.583	0.517	0.128	0.807	0.161	0.263
Post	0.554	0.501	0.115	0.822	0.144	0.261

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

primary helper was a family member increases by 7.5 percentage points (10.3%), consistent with substitution toward family care post-Secure Communities. Finally, we do not find a significant effect on the likelihood of co-residing with one's children, nor do we find any significant effect on caregiving for older adults not enrolled in Medicaid.

Table 9: HRS Results: Medicaid Sample

	(1) Any Home- Based Care	(2) Has Family Caregiver	(3) Has Formal Caregiver	(4) Primary Family	(5) Primary Formal	(6) Cores- idence
Secure Communities	-0.070**	-0.020	-0.046*	0.075*	-0.053^{+}	0.033
	(0.022)	(0.026)	(0.021)	(0.035)	(0.031)	(0.030)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	5,814	5,814	5,814	3,703	3,703	5,237
Adj. R^2	0.452	0.390	0.248	0.218	0.188	0.252
Pre	0.667	0.564	0.198	0.730	0.228	0.345
Post	0.597	0.544	0.152	0.805	0.175	0.378

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 10: HRS Results: Non-Medicaid Sample

	(1) Any Home- Based Care	(2) Has Family Caregiver	(3) Has Formal Caregiver	(4) Primary Family	(5) Primary Formal	(6) Cores- idence
Secure Communities	-0.010	-0.015	0.006	-0.028	0.011	-0.010
	(0.018)	(0.018)	(0.013)	(0.020)	(0.018)	(0.020)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	13,552	13,552	13,552	7,281	7,281	12,403
Adj. R^2	0.407	0.361	0.232	0.231	0.200	0.186
Pre	0.546	0.497	0.096	0.850	0.123	0.226
Post	0.536	0.482	0.102	0.823	0.134	0.216

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

7 Conclusion

Persistent shortages of home care workers, coupled with the prevalence of immigrant workers in home care, have raised questions about the impact of stepped-up immigration enforcement on the home care industry and older adults' ability to obtain care at home. Our analyses reveal significant and consequential effects of enforcement on both the size of the workforce and receipt of formal home care.

Specifically, our empirical findings demonstrate that immigration enforcement led to a substantial reduction in the size of the home care workforce (7.5-10.8%), which was driven by a reduction in workers born outside the United States (14.6-16.1%) and by geographic regions with large numbers of undocumented people. Second, turning to receipt of care, we find that older adults are less likely to receive help at home following the introduction of Secure Communities. This reduction is concentrated among older adults with Medicaid coverage, who are 10.5% less likely to receive help at home, and 23.2% less likely to receive formal (i.e., non-family) care. By contrast, older adults on Medicaid are 10.3% more likely to use a family caregiver as their primary helper following Secure Communities' activation. This suggests that older adults respond to reductions in non-family care by substituting toward family care.

Policymakers must carefully consider the unintended consequences of immigration enforcement strategies, particularly in sectors like health care that rely heavily on immigrant labor. Our research suggests that enforcement can create substantial disruptions in caregiving to older adults, an impact that will grow ever more important as the US population ages.

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