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The Unintended Consequence of Stringent Immigration Enforcement on Staffing in Nursing Homes: Evidence from Secure Communities

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Abstract

The provision of healthcare in the United States is increasingly more reliant on immigrant workers. In this paper, I examine the impact of Secure Communities, a major immigration enforcement program that was designed to check the immigration status of all individuals arrested by local police, on staffing in nursing homes. Using difference-in-differences strategy that exploits staggered activation of Secure Communities across U.S. counties, I found that the program reduced direct-care staff hours per resident day by 0.082, an approximately 2.2% decline relative to the mean of treatment counties in the baseline period. This finding suggests that stringent immigration enforcement may exacerbate the healthcare worker shortage in the United States.

JEL Classification: K37, J61, I11, J2, J15

Keywords: Staffing, Nursing Homes, Secure Communities, Immigration

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1 Introduction

The United States is facing a severe healthcare worker shortage. Roughly 84% of nursing homes are experiencing moderate to high levels of staffing shortages and 96% are struggling to hire new staff ([American Health Care Association, 2023](#)). At the same time, healthcare provision in the U.S. is increasingly more reliant on immigrant workers. About one in four direct-care workers in long-term care facilities are immigrants ([Lee et al., 2020](#)). These workers are more likely to work non-traditional shifts that are hard to fill and help to alleviate shortages in under-resourced facilities ([Zallman et al., 2019](#); [Lee et al., 2020](#)).

In this paper, I examine the impact of a major immigration enforcement program, Secure Communities, on staffing in nursing homes. Rolled out on a county-by-county basis from 2008 to 2013, Secure Communities enabled the federal government to check the immigration status of all individuals arrested by local police. Its activation led to more than 454,000 individuals removed, mostly for non-violent crimes, in 2008-2014 period ([East et al., 2018](#)).¹ While Secure Communities can affect staffing in nursing homes directly through removals of immigrant workers, there are other, more indirect, ways. Previous work has documented the chilling effect of Secure Communities on the take up of public welfare programs among Hispanic citizens, who are not themselves eligible for removal, because of deportation fear ([Alsan and Yang, 2022](#)). This chilling effect has further been shown to reduce the labor supplied by less-skilled immigrant workers ([East et al., 2018](#); [East and Velásquez, 2022](#)), since staying at home and not working is a strategy to avoid contact with law enforcement.² There is also evidence that Secure Communities raised mental health distress among Hispanic immigrants ([Wang and Kaushal, 2019](#)); mental health problems have been linked to absenteeism

¹Only 18.54% of individuals were removed due to violent crimes, while the others were removed without being convicted of a crime (20.63%) or due to non-violent crimes (60.83%) such as driving under influence (10.94%) and other traffic conviction (7.01%) ([East et al., 2018](#)).

²Consistent with the chilling effect explanation, recent work by ([Grittner and Johnson, 2022](#)) found that Secure Communities reduced worker complaints to the Occupational Safety and Health Administration (OSHA) and increased injuries at workplaces with a high share of Hispanic workers. The authors argue that the rise in injuries was due to employers reducing safety inputs in response to workers' reluctance to complain to the government safety regulator.

and reduced work hours as well as a decline in the probability of being in the labor force ([Bartel and Taubman, 1979](#); [Ettner et al., 1997](#); [French and Zarkin, 1998](#); [Banerjee et al., 2017](#); [Chatterji et al., 2011](#); [Bryan et al., 2021](#)). Therefore, Secure Communities can directly reduce staffing in nursing homes through removals or indirectly by adversely impacting the labor supplied by immigrants.

To examine the impact of Secure Communities, I used county-level nursing home data from LTCFocus ([LTCFocus, 2022](#)) and utilized difference-in-differences (DID) strategy that exploits the staggered activation of Secure Communities across U.S. counties. Since recent advances in DID methodology have shown that two-way fixed effects DID estimates that rely on the variation in the treatment timing are biased in the presence of heterogeneous treatment effects ([Goodman-Bacon, 2021](#); [Callaway and Sant'Anna, 2021](#); [Sun and Abraham, 2021](#)), I also employed Callaway and Sant'anna estimator that is robust to this concern ([Callaway and Sant'Anna, 2021](#)). The preferred estimate indicates that Secure Communities reduced the direct-care staff hours per resident days in nursing homes by 0.082, an approximately 2.2% decline relative to the mean of treatment counties in the baseline period. Exploring the heterogeneity in the effects, I found that the decline in direct-care staff hours is mainly driven by the reduction in hours among staff employed as Certified Nursing Assistant, which typically has lower educational and training requirements compared to Licensed Practical Nurse or Registered Nurse.

This paper contributes to recent studies that examine the impacts of the Secure Communities program. While introduced as a crime control measure, there is a lack of evidence that it had a meaningful impact on crime rates ([Miles and Cox, 2014](#); [Hines and Peri, 2019](#)).³ At the same time, the negative spillover effects to U.S.-born population have been documented. [East and Velásquez \(2022\)](#) found that Secure Communities reduced the labor supply of highly educated U.S-born mothers with young children due to the increased cost of outsourcing household production led by a reduction in immigrants' labor supply. Secure Communities also increased the cost of in-home help, leading to more elderly individuals living at nursing homes ([Mockus and Jung, 2022](#)).

³Consistent with the finding that the program did not make communities safer, [Gunadi \(2019\)](#) did not find evidence that the subjective well-being (i.e., life satisfaction) of white or black non-Hispanic individuals was improved due to Secure Communities.

My work contributes to these studies by showing evidence that Secure Communities had a negative consequence on care in nursing homes.

More generally, my paper is also related to the literature that examines the determinants of the healthcare worker shortage in the United States. An aging population and growing disease burden contribute to the rising demand for health care services ([Angus et al., 2000](#); [Wroe et al., 2012](#); [Dall et al., 2013](#)). On the supply side, studies have documented that poor quality of direct care jobs characterized by heavy workloads, inadequate supervision, and lack of upward mobility play a part in job dissatisfaction and intent to leave the job ([Brannon et al., 2007](#); [Kemper et al., 2008](#); [Franzosa et al., 2019](#); [Scales, 2021](#)). My work expands this literature by showing evidence that a stringent immigration enforcement program, such as Secure Communities, may have the unintended consequence of worsening the healthcare worker shortage in the United States.

The rest of this paper is constructed as follows. Section 2 describes the background of Secure Communities program. Section 3 describes the LTCFocus data and methodology to examine the impact of Secure Communities. Section 4 documents the results. Section 5 concludes.

2 Background

First activated in Harris County, Texas, on October 27th, 2008, Secure Communities was a major immigration enforcement program administered by U.S. Immigration and Customs Enforcement (ICE). It advanced information sharing between local law enforcement agencies, the Federal Bureau of Investigation (FBI), and the Department of Homeland Security (DHS). The goal was to check the immigration status of all individuals arrested by local law enforcement agencies anywhere in the country ([Cox and Miles, 2013](#)).

Typically, when a person is arrested by a state or local law enforcement agency, his/her fingerprints are sent electronically to the Federal Bureau of Investigation (FBI) for a criminal background check. With Secure Communities, however, the fingerprints

are sent not only to the FBI but also rerouted to DHS, where they are checked against its database, known as Automated Biometric Identification System (IDENT). IDENT is a database that stores biometric and other personal information on individuals encountered by the agency during the course of its immigration-related activities, including those of non-citizens who are living in the U.S. in violation of immigration law (e.g., visa overstay), non-citizens who are legally living in the U.S. but who might become deportable if they were convicted of the crime for which they have been arrested, and citizens who naturalized after their fingerprints were added to the database (Miles and Cox, 2014).

If the fingerprints match a set in IDENT, a DHS official assesses the case and decides whether to place a “detainer” on the person. When a detainer is placed, ICE requests the local authority to hold the arrestee for 48 hours beyond the scheduled release date in order to take custody of the arrestee and start deportation proceedings.

A noteworthy feature of Secure Communities program is that participation was mandatory. Although some jurisdictions did not wish to participate, there was practically no way to opt-out since it is not possible to prevent the FBI from sharing the fingerprints with DHS (Cox and Miles, 2013). At the same time, simultaneous implementation of Secure Communities nationwide was not an option due to resource bottlenecks and various technological challenges (Cox and Miles, 2013). Consequently, the federal government rolled out the program county by county from 2008 to 2013 (Figure 1).

While ICE stated that Secure Communities prioritized the removals of criminal “aliens” (i.e., non-citizens) who posed a threat to public safety as well as the most dangerous and violent offenders, it was not focused exclusively on these individuals (Waslin, 2011). ICE classifies aliens charged with or convicted of a crime into the following levels: 1) Aliens convicted of aggravated felonies or two or more crimes each punishable by more than one year such as murder, rape, and robbery (Level 1); 2) Aliens convicted of any felony or three or more crimes each punishable by less than one year such as burglary, larceny, and fraud (Level 2); 3) Aliens convicted of crimes punishable

less than one year (Level 3).⁴ In Fiscal Year 2011, only 26% of Secure Communities deportations were individuals with Level 1 convictions, while others were individuals with Level 2 convictions (19%), Level 3 convictions (29%), and immigration violations but no criminal convictions (26%) (Waslin, 2011). Similarly, over the 2008-2014 period, East et al. (2018) showed that only 18.54% of Secure Communication deportations were due to violent crimes, while the majority was due to non-violent crimes (60.83%) such as driving under influence (10.94%) and other traffic convictions (7.01%).

Secure Communities program was discontinued in late 2014 over the concern of racial profiling (DHS, 2014). It was reactivated again by President Trump in January 2017 under Executive Order 13768 before President Biden revoked it in January 2021.

3 Data and Methodology

This study used county-level nursing home data from LTCFocus (2022). Sponsored by the National Institute on Aging (1P01AG027296) through a cooperative agreement with the Brown University School of Public Health, LTCFocus provide information on facility staffing aggregated at the county level annually from 2000, allowing me to examine the impact of Secure Communities on nursing home staffing. The main outcome variable is direct-care staff hours per resident day. However, I also examine the heterogeneity in the effects by analyzing the different types of staff separately (Certified Nursing Assistant, Licensed Practical Nurse, and Registered Nurse). Since variables from 2011 onward are not comparable to prior years (Furtado and Ortega, 2022), the period of the analysis is 2000-2010. LTCFocus (2022) has data on roughly 2,900 U.S. counties every year, and I included all counties with full information (no missing values) on all variables used in the analysis throughout the 2000-2010 period, yielding 2,868 counties in the sample. The summary statistics are reported in Table 1.

Secure Communities activation date by counties were obtained from ICE (2014). To analyze the impacts of Secure Communities, I utilized difference-in-differences (DID) strategy, exploiting the staggered activation of Secure Communities program across

⁴The description of the levels were obtained from <https://www.dhs.gov/xlibrary/assets/privacy/pia-ice-acrime-eid-update-20100929.pdf>.

U.S. counties. Specifically, I employed the following empirical specifications:

$$y_{ct} = \delta_c + \delta_t + \gamma \text{SecureCommunities}_{ct} + \alpha \text{Unemployment}_{ct} + \varepsilon_{ct} \quad (1)$$

where y_{ct} is the outcome for county c at year t . δ_c and δ_t are county and year fixed effects, respectively. Since staffing in nursing homes has been shown to be countercyclical (Stevens et al., 2015), I added county-level unemployment rate (Unemployment_{ct}) from Bureau of Labor Statistics Local Area Unemployment Statistics in the model. The main variable of interest is $\text{SecureCommunities}_{ct}$, which is an indicator variable that takes a value of one for all years after Secure Communities is activated (including the activation year) and zero otherwise. The main coefficient of interest is γ , which is the estimated effect of Secure Communities. The model is weighted by the county population, and the standard errors are clustered by county.⁵

The main identification assumption of the DID strategy above is the parallel trend assumption. That is, there are no unobserved time-varying county-specific factors that were correlated with the timing of the activation of Secure Communities. To give support that this assumption holds, I estimated the following event study model:

$$y_{ct} = \delta_c + \delta_t + \sum_{\tau=2}^4 \beta_{-\tau} \text{SecureCommunities}_{c,t-\tau} + \sum_{\tau=0}^1 \beta_{+\tau} \text{SecureCommunities}_{c,t+\tau} + \alpha \text{Unemployment}_{ct} + \varepsilon_{ct} \quad (2)$$

The variables are defined in the same way as before. $\text{SecureCommunities}_{c,t-1}$ is omitted from the model, so the estimated effects (β) should be interpreted as relative to time $t - 1$. For $\text{SecureCommunities}_{c,t-4}$, the variable is equal to one for $t - 4$ and each year prior to $t - 4$. Similarly, $\text{SecureCommunities}_{c,t+1}$ is equal to one for $t + 1$ and each year after $t + 1$. For the validity of difference-in-differences strategy, there should be no discernible difference in the trends prior to the activation of Secure Communities.

Recent work in DID methodology has shown that two-way fixed effects DID estimates that rely on the variation in the treatment timing are biased in the presence of

⁵County-level population data were obtained from U.S. Census Bureau, Population Division.

heterogeneous treatment effects ([Goodman-Bacon, 2021](#); [Callaway and Sant'Anna, 2021](#); [Sun and Abraham, 2021](#)). Therefore, I also employed Callaway and Sant'anna estimator that is robust to this concern ([Callaway and Sant'Anna, 2021](#)). The key innovation of Callaway and Sant'anna approach is the estimation of cohort-time average treatment effects (i.e., the average treatment effect for a cohort at a specific time); in this case, cohort is defined by the time when units are first treated. The appealing feature of these cohort-time average treatment effect parameters is that they do not directly restrict heterogeneity with regard to covariates, the time in which units are first treated, or the changes in treatment effects over time ([Callaway and Sant'Anna, 2021](#)). After cohort-time average treatment effects are estimated, they can be used to construct other more aggregated causal parameters.⁶

4 Results

4.1 Nursing Home Staffing

The main results are reported in Table 2. The OLS estimate shows that Secure Communities reduced direct-care staff hours per resident day in nursing homes by 0.132 (Panel A Column 1). Evaluate at the mean of treatment counties in the pre-2008 period prior to the activation of Secure Communities (baseline period), this result implies an approximately 3.6% decrease in direct-care staff hours per resident day. Adding unemployment rate as control in the model slightly increase the magnitude of the effect (Column 2).

The preferred estimates obtained using [Callaway and Sant'Anna \(2021\)](#) estimator are reported in Panel B of Table 2. The result indicates that Secure Communities decreased direct-care staff hours per resident day by 0.082 (Column 1).⁷ Evaluated at the mean

⁶To employ [Callaway and Sant'Anna \(2021\)](#) estimator, I used CSDID package developed by [Rios-Avila et al. \(2022\)](#).

⁷Simply averaging all of the identified cohort-time average treatment effects together has a drawback of allocating more weight on cohorts that participate in the treatment longer ([Callaway and Sant'Anna, 2021](#)). Therefore, following the suggestion by [Callaway and Sant'Anna \(2021\)](#), the overall treatment effect estimates reported in Table 2 are obtained by first calculating the average effect for each cohort across all periods and then averaging these effects together across cohorts.

of treatment counties in the baseline period, this estimate represents a 2.2% decline. Including unemployment rate as control does not change the point estimate (Column 2).

The event study results are illustrated in Figure 2. The direct-care staff hours per resident day abruptly declined in the year of Secure Communities activation, and the magnitude of the effect became larger in the following year. There is a lack of evidence that the estimates reported in Table 2 are driven by differences in trends prior to the activation of Secure Communities across U.S. counties.

Overall, there is strong evidence that Secure Communities had a negative consequence on staffing in nursing homes. The effect is observed right after Secure Communities was activated, and the magnitude of the effect appeared to become larger over time. The preferred estimate suggests a 2.2% decline in direct-care staff hours per resident day due to Secure Communities.

4.2 Heterogeneity Analysis

To explore the heterogeneity in the impacts of Secure Communities, Table 3 reports the results separately by the types of staff employed in nursing homes. Columns 1 and 2 report the results for Certified Nursing Assistant (CNA). Columns 3 and 4 report the results for Licensed Practical Nurse (LPN). Columns 5 and 6 report the results for Registered Nurse (RN).

Focusing on the estimates when county-level unemployment rate is added as a control variable, the result indicates that Secure Communities reduced the CNA hours per resident day by 0.052. Using Callaway and Sant'anna estimator, I obtained a similar but slightly larger decline in hours per resident day (-0.057). Evaluated at the mean of treatment counties in the baseline period, this estimate implies a 2.3% decrease in CNA hours per resident day. Secure Communities also appeared to decrease LPN hours per resident day. However, the effects are imprecisely estimated. For Registered Nurse, the two-way fixed effects OLS estimate shows that Secure Communities reduced RN hours per resident day by 0.029, but this relationship does not hold when Callaway and

Sant’anna estimator is used.

All in all, the results of heterogeneity analysis indicate that the decrease in the overall direct-care staff hours per resident day due to Secure Communities was mainly driven by the decline in hours among staff employed as Certified Nursing Assistant, which usually has lower educational and training requirement compared to Licensed Practical Nurse or Registered Nurse.

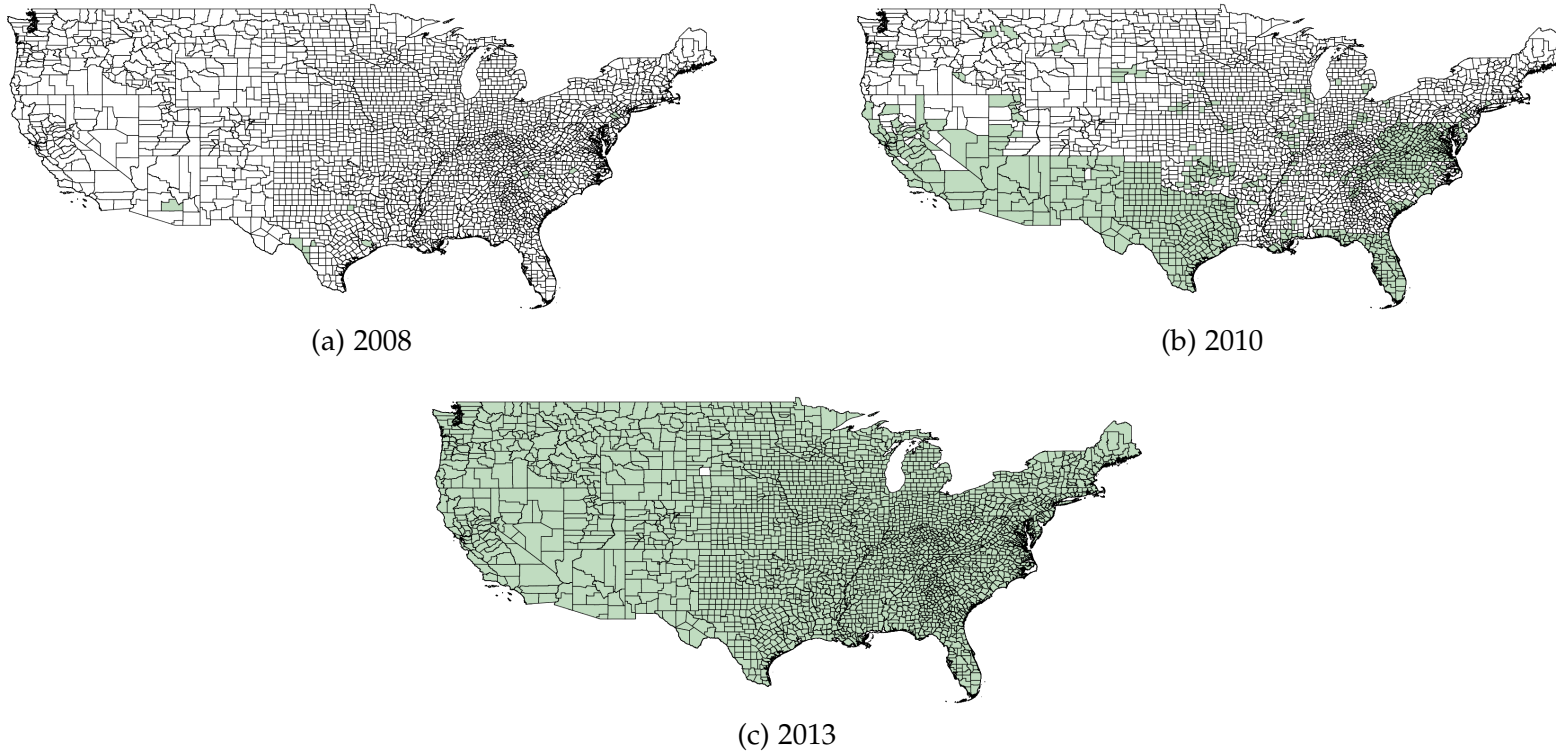
5 Conclusion

Currently, there is a severe healthcare worker shortage in the United States. At the same time, healthcare provision in the U.S. is increasingly more reliant on immigrant workers. About one in four direct-care workers in long-term care facilities are immigrants ([Lee et al., 2020](#)). Consequently, immigration policies have the potential to alleviate or exacerbate the shortage of healthcare workers.

In this paper, I examine the impact of a major immigration enforcement program, Secure Communities, on staffing in nursing homes. Under Secure Communities, the federal government was able to check the immigration status of all individuals arrested by local police. Using difference-in-differences strategy that exploits the staggered activation of Secure Communities across U.S. counties, I found strong evidence that Secure Communities reduced staffing in nursing homes. The decline is observed shortly after Secure Communities was activated, and its effect appeared to become larger in magnitude over time. The preferred estimate indicates that Secure Communities reduced direct-care staff hours per resident day by 0.082, a 2.2% decline relative to the mean of treatment counties at the baseline period. Further analysis shows that this decline is mainly driven by the reduction in hours among staff employed as Certified Nursing Assistant, which typically has lower educational and training requirements compared to Licensed Practical Nurse or Registered Nurse. These findings suggest that a stringent immigration enforcement program, such as Secure Communities, may have the unintended consequence of exacerbating the healthcare worker shortage in the United States.

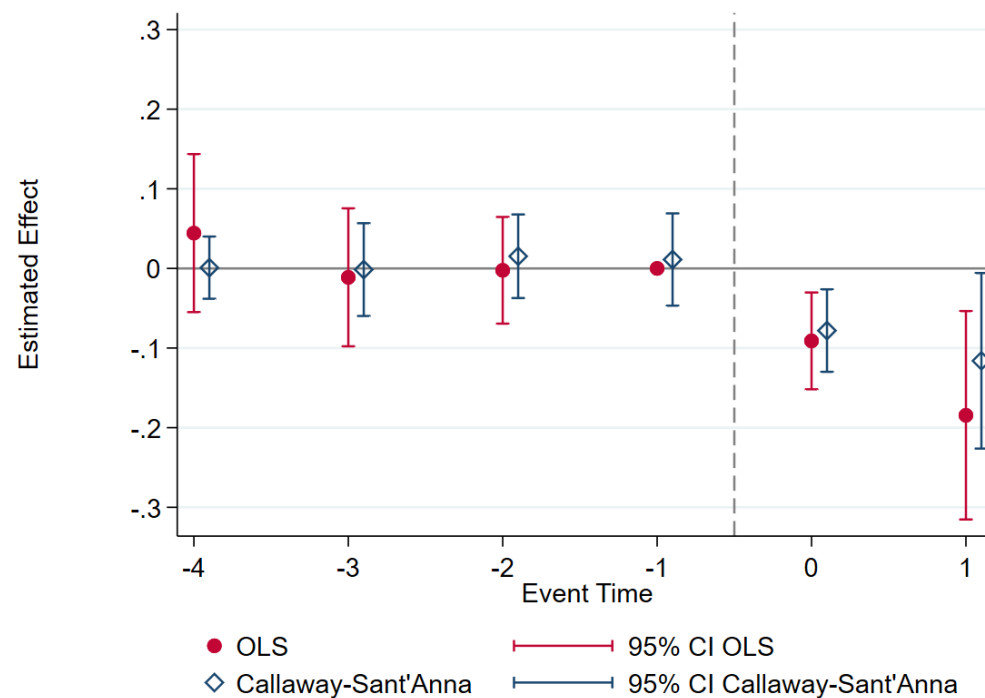
6 Figures and Tables

Figure 1: Secure Communities Activation by County 2008-2013



Note: Secure Communities activation dates by county were obtained from [ICE \(2014\)](#).

Figure 2: The Effect of Secure Communities on Direct-Care Staff Hours per Resident Day



Notes: Data are from [LTCFocus \(2022\)](#). The red dot shows the point estimates based on OLS. Each dot displays the estimated effect of Secure Communities on direct-care staff hours per resident day relative to the year prior to the activation (the omitted year). The OLS regression model includes state and year fixed effects as well as control for county-level unemployment rate. The blue diamond hollow shows the point estimates using Callaway and Sant'Anna estimator. Control includes county-level unemployment rate. The results are weighted using the county population. 95% confidence intervals constructed with standard errors clustered by county are provided in the figure.

Table 1: County Summary Statistics in the Baseline Period (2000-2007)

	All Counties	Non-Treatment Counties	Treatment Counties
Direct-Care Staff Hours per Resident Day	3.559	3.394	3.715
Certified Nursing Assistant (CNA) Hours per Resident Day	2.341	2.222	2.453
Licensed Practical Nurse Hours (LPN) per Resident Day	0.864	0.769	0.954
Registered Nurse Hours (RN) per Resident Day	0.500	0.483	0.516
Unemployment Rate	5.120	5.173	5.071

Notes: Data are from [LTCFocus \(2022\)](#) and U.S. Bureau of Labor Statistics Local Area Unemployment Statistics. The summary statistics are weighted by the county population.

Table 2: Effect of Secure Communities on
Direct-Care Staff Hours per Resident Day

	(1)	(2)
<i>Panel A: OLS</i>		
Secure Communities	-0.132*** (0.050)	-0.135*** (0.051)
<i>Panel B: Callaway and Sant'Anna (2021) Estimator</i>		
Secure Communities	-0.082*** (0.028)	-0.082*** (0.027)
Outcome Mean for Treatment Counties in Baseline Period	3.715	3.715
Controls: Unemployment Rate	No	Yes
Observations	31548	31548

Notes: Data are from [LTCFocus \(2022\)](#). The estimates show the effects of Secure Communities on direct-care staff hours per resident day. The OLS model includes state and year fixed effects. The results are weighted using the county population. Standard errors clustered by county are reported in parentheses. The baseline period is defined as pre-2008, prior to the activation of Secure Communities. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 3: Effect Heterogeneity (Hours per Resident Day)

	Certified Nursing Assistant		Licensed Practical Nurse		Registered Nurse	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A: OLS</i>						
Secure Communities	-0.053** (0.023)	-0.052** (0.023)	-0.024 (0.019)	-0.028 (0.019)	-0.030** (0.014)	-0.029** (0.014)
<i>Panel B: Callaway and Sant'Anna (2021) Estimator</i>						
Secure Communities	-0.056** (0.024)	-0.057** (0.024)	-0.025 (0.020)	-0.022 (0.020)	0.012 (0.015)	0.014 (0.014)
Outcome Mean for Treatment Counties in Baseline Period	2.45	2.45	0.95	0.95	0.52	0.52
Controls:						
Unemployment Rate	No	Yes	No	Yes	No	Yes
Observations	31548	31548	31548	31548	31548	31548

Notes: Data are from [LTCFocus \(2022\)](#). The estimates show the effects of Secure Communities on staff hours per resident day. The OLS model includes state and year fixed effects. The results are weighted using the county population. Standard errors clustered by county are reported in parentheses. The baseline period is defined as pre-2008, prior to the activation of Secure Communities. * $p < .1$, ** $p < .05$, *** $p < .01$

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