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IZA DP No. 15821

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ABSTRACT

Secure Communities as Immigration Enforcement: How Secure Is the Child Care Market?*

Immigrants comprise nearly 20% of the child care workforce in the U.S. This paper studies the impact of a major immigration enforcement policy, Secure Communities (SC), on the structure and functioning of the child care market. Relying on the staggered introduction of SC across counties between 2008 and 2014, we find that the program reduced children's participation in center-based child care programs. The estimated reductions are substantially larger among disadvantaged children, raising questions about the possibility of health and developmental spillovers. We also find that SC reduced the supply and wages of immigrant and native child care workers in the center-based sector. We provide descriptive evidence that immigrants and natives may not compete for the same jobs: immigrant child care teachers are more highly skilled, and the children assigned to their classrooms differ on some observable characteristics. Therefore, immigrants and natives are likely to be complements to child care service production.

JEL Classification: J13, J15, J21, K39

Keywords: child care, maternal employment, immigration, Secure Communities

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* These views are our own and do not reflect those of any affiliated institutions.

1 Introduction

Immigrants are essential to the functioning of the U.S. child care market. Nationally, about one out of every five child care workers is an immigrant, which makes child care one of the most immigrant-dense sectors in the low-wage labor market (Table A1 and Figure A1). Furthermore, urban areas often contain a significantly larger share of foreign-born caregivers. For example, they make up nearly half of the child care workforce in cities like New York, Los Angeles, and San Jose. The evidence also suggests that immigrant child care workers are relatively high-skilled: they are more likely than their native counterparts to have a college degree, and they earn higher wages on average (Table A2). These stylized facts are important, given that millions of parents rely on child care to support their employment and that early care participation can have powerful consequences for child development (Baker et al., 2019; Bernal and Keane, 2011; Herbst, 2013, 2022; Havnes and Mogstad, 2011). As a result, it is critical to understand whether shocks to immigrant labor supply—for example, through changes in geographic settlement patterns, economic conditions, or policy—alter the structure and functioning of the child care market.

In this paper, we study the impact of a federal immigration enforcement policy, Secure Communities (SC), on families' use of child care, the labor market outcomes of immigrant and native child care workers, and the quality of child care services. Enacted in 2008, the SC program allowed the U.S. Immigration and Customs Enforcement Agency (ICE) to check the immigration status of all individuals arrested by local police. Under SC's rules, after an arrestee's fingerprints were sent to the Federal Bureau of Investigation (FBI) to check the individual's criminal history, they were automatically forwarded to ICE to determine whether the person was also in violation of any immigration laws. If such violations were identified, the individual could then be transferred to the custody of ICE agents for the initiation of deportation proceedings. The program was introduced on a county-by-county basis until 2013, but its operation was halted (albeit temporarily) in late 2014. Over the course of its enactment, SC led to 46 million fingerprint submissions to ICE, 2.3 million arrests and/or convictions, and 440,000 deportations (U.S. Immigration and Customs Enforcement, 2014; TRAC Immigration, 2022).

Given that nearly all individuals deported under SC were male but that most child care workers are female, we hypothesize that any changes to the child care market are not likely to be explained by deportation-driven reductions in immigrant labor supply. Instead, such effects are expected to operate through two alternative channels. First, SC may have created a climate of fear and confusion within immigrant communities around the possibility of being deported, leading to a generalized "chilling effect" in which (legal and illegal) immigrants ceased many normal activities, including employment, in order to remain hidden from local police. As discussed in Section 2, there is substantial anecdotal and empirical evidence that SC and other interior immigration enforcement policies generate large chilling effects. Therefore, the fear created by SC may have decreased immigrants' employment in the child care industry, the supply of child care, and as a result families' use of such services. We further posit that the largest chilling effects occurred among those employed in the formal child care market—particularly in the center-based sector—where the opportunity to interface with government agencies is greater. For example, center-based workers are more likely than those employed directly by households (e.g., nannies and au pairs) to have their earnings reported for tax purposes and to submit personal information to state and local governments to comply with licensing and accreditation standards. The possibility of such interactions may increase immigrants' sense of vulnerability, leading to further reductions in labor supply.

A second and related mechanism operates through a decrease in maternal employment. Given that high-income families in particular are likely to outsource many aspects of household production, a decrease in immigrant labor supply may alter the price of household and work-enabling services in ways that reduce the amount of maternal time allocated to employment. Indeed, a recent paper by East and Velasquez (2022) finds that SC reduced the employment of high-skilled mothers, especially those with very young children. This is consistent with the results in Cortes and Tessada (2011), who find that increases in the local supply of low-skilled immigrants increase the employment of high-earning women. Furthermore, Amuedo-Dorantes and Sevilla (2014) show that low-skilled immigration reduces the amount of time that high-skilled mothers engage in housework and basic child care duties (e.g., bathing and feeding), and it has been shown to increase native fertility (Furtado, 2016). Together, this research suggests that any SC-induced reductions in mothers' employment may spillover to the child care market, decreasing the demand for child care services and, in turn, the supply and wages of child care labor.

We begin the analysis on the demand-side, studying the impact of SC on the use of child care among preschool-age children. Relying on data from the American Community Survey (ACS) over the years 2005 to 2014, our identification strategy exploits the staggered introduction of SC across counties along with the fact that children, who, by virtue of their age, are differentially exposed to any SC-driven changes in the immigrant labor market.

The ACS inquires about the child care or school attendance of all individuals ages three and over, and we assign three- and four-year-olds to the treatment group, while children aged five are included in the comparison group. Those in the treatment group are substantially more likely to be exposed to an immigrant teacher because of their participation in child care (as opposed to kindergarten), where the density of immigrant labor is relatively high. Conversely, five-year-olds are a plausible comparison group because their enrollment in kindergarten means that they are significantly less likely to be exposed to an immigrant teacher. Indeed, the immigrant share of the child care workforce is about 20%, as already discussed, compared to 10% among kindergarten teachers (Furuya et al., 2019).[1] Therefore, our triple differences model estimates the change in child care participation for three- and four-year-olds before versus after a county enacted SC, relative to the change in kindergarten participation that occurred among five-year-olds. We estimate this model first on a sample of three- to five-year-olds with citizen mothers, and in later analyses on a sample of children with non-citizen mothers.

In a model that controls for geography and time fixed effects as well as time-varying geographic characteristics, we find that the enactment of SC reduced the child care participation rate of three- and four-year-olds (with citizen mothers) by 1.8 percentage points. Given that the treated pre-reform child care participation rate is 49.4%, this result implies that utilization fell by nearly 4%. Although children in all demographic groups experienced a drop in child care use, we find significantly larger effects among Hispanic children as well as those from economically-disadvantaged families. We also find that participation in child care declined by 1.5 percentage points among all children of non-citizen mothers, with even larger reductions among disadvantaged families. Our results are robust to a variety of specification and sample changes, including the use of alternative comparison groups (i.e., six- and seven-year-olds), the use of an alternative dataset that records children's ages at the start of each school year (i.e., the October Current Population Survey), the inclusion of state-by-year fixed effects, and the exclusion of early-adopting jurisdictions. In addition, we conduct a falsification test in which three-year-olds are assigned to the treatment group, and four-year-olds are assigned to the comparison group. The triple differences estimate in this model is statistically insignificant, as one would expect under the assumption that both sets of children are equally exposed to any SC-induced changes in immigrant labor supply.

We then turn our attention to the supply-side of market by analyzing the supply and compensation of child

[1]In further support of our identification strategy is the fact that kindergarten is an entitlement in most jurisdictions, so that any local teacher supply shocks should not affect children's enrollment in these programs.

care labor. The analysis sample again draws on the 2005 to 2014 waves of the ACS and includes prime working-age (immigrant and native) women. Our key outcomes include a proxy for child care supply, defined as a binary indicator for whether a given woman is employed in the child care industry, as well as hourly wages. We report separate results for sub-sets of low- and high-education immigrants and natives across three sectors of the child care market: private household caregivers and home- and center-based providers. Indeed, we are interested not only in whether immigration enforcement policies like SC influence the labor market outcomes of immigrant child care workers, but also whether such policies are beneficial or harmful to native workers—a topic of intense debate in the immigration literature (Borjas, 2003; Card, 1990, 2005; Chassamboulli and Peri, 2015; Cortes, 2008; East et al., 2022). For these analyses, we rely on a difference-in-differences (DD) strategy that takes advantages of the differential timing in SC's roll-out across counties, controlling for geographic and time fixed effects.

Consistent with a "chilling effects" story, we find that SC reduced low-education immigrants' employment in the child care industry, a result that is concentrated among Hispanic immigrants. Given that about 3% of low-education immigrants were employed as child care workers in the pre-SC period, our result implies a 9% reduction in the share of such individuals choosing child care employment. The implied reduction among Hispanics is approximately 16%. We find no evidence that SC reduced the number of high-education immigrant workers. Turning to natives, we uncover striking evidence that SC reduced the employment of low- and high-education workers in the child care sector by 4% and 7%, respectively. These overall reductions were driven by white and black workers. We also find that the decrease in employment occurred primarily in the center-based sector, with the private household and home-based sectors experiencing little change in the number of workers. Consistent with these results, we find that SC reduced the number of child care establishments by 1.6% and the number of child care industry employees by 1.5%, using administrative data from the Quarterly Census of Employment and Wages (QCEW). Despite these overall decreases in supply, our analysis of child care quality shows no change in the number of high-quality, NAEYC-accredited programs.[2] Finally, our results suggest that hourly wages in the child care industry fell approximately 3% following the enactment of SC, with reductions of about 5% among immigrants and 2% among natives. Once again, these reductions were concentrated in the center-based sector. As with the triple differences model, our labor supply results are robust to a range of specification tests.

[2]NAEYC: National Association for the Education of Young Children

The findings in this paper have a number of important policy implications. First, there has been phenomenal growth in the number of preschool-age children of immigrants residing in the U.S. Currently, 5.3 million children ages 0 to 5—equivalent to 25% of the preschool population—live with at least one immigrant parent (Migration Policy Institute, 2021), and 52% of children of immigrants regularly attend a child care arrangement (Authors' calculations). Therefore, the loss of immigrant child care workers from policies like SC raises concerns about the ability of caregivers to meet the cultural, linguistic, and developmental needs of immigrant children. Although we are not aware of any studies on caregiver-child matching (based on culture or language) in the early years, the evidence from K-12 schools suggests that race-matching teachers and students generates positive effects on test scores, classroom behavior, and educational attainment (Dee, 2005; Gershenson et al., 2022; Wright et al., 2017).[3] Thus, there are reasons to be concerned about the loss of immigrant child care providers at a time when the preschool population is becoming increasingly diverse.

A second policy implication is that, by reducing the supply of child care, SC potentially created further instability in an industry that already has comparatively high rates of staff turnover. Indeed, recent studies find turnover rates of 12% per quarter (Brown and Herbst, 2022) or 25% per year—four times higher than that within elementary schools (Bassok et al., 2013). Furthermore, our results show that high-skilled native teachers were disproportionately affected by SC, raising concerns that immigration enforcement policies may aggravate staff turnover in ways that reduce the availability of high-quality services and, in turn, have negative consequences for child development. Indeed, there is substantial evidence showing the importance of high-quality early care services for child development (Auger et al., 2014), and it seems particularly important when that care includes stable, warm, and stimulating interactions between children and teachers (Hamre et al., 2014; Markowitz, 2019).

Finally, our results suggest that disadvantaged children experienced the largest reductions in child care participation from SC. This finding applies to children of both citizen and non-citizen parents. It is important to recall that our analysis focuses on participation in formal child care settings, including center-based programs. Although we cannot directly address this question, it is reasonable to assume that these reductions were offset by an increase in the amount of time spent in informal, non-parental arrangements (e.g., relative care) and maternal care. These dynamics raise additional concerns about child development. Recent work by Flood et al. (2021) shows

[3]The most relevant research to the child care market comes from a study of Head Start programs, which finds that teacher-child matches based on race/ethnicity improves parental engagement and reduces child absences (Markowitz et al., 2020)

that the average quality of non-parental care used by disadvantaged children is 0.6 standard deviations (SD) lower than that for advantaged children. Much of this quality gap is explained by low-income children's heavy reliance on relative caregivers, whose quality is rated to be significantly lower than center-based settings. Furthermore, the authors find a similarly large difference in the quality of children's home environments, with disadvantaged children experiencing a home-quality deficit of 0.85 SDs compared to their advantaged counterparts. Together, this discussion suggests that SC likely shifted disadvantaged children from higher-quality, center-based arrangements to lower-quality settings like informal child care providers and parental caregivers.

This paper makes several contributions to the immigration and child care literature. Ours is the first paper to document the impact of immigration enforcement policy on the child care market. In doing so, it contributes to a small set of studies evaluating the broad labor market effects of the SC program. For example, a recent paper by East et al. (2022) finds that SC reduced the employment and wages of low-education immigrants and natives, while East and Velasquez (2022) show that SC reduced employment but increased wages in the private household services industry. Given that child care workers comprise only 25% of those in household services (Authors' calculations), the findings in their paper may not be applicable to child care employment per se.[4] Furthermore, East and Velasquez (2022) do not examine employment in other child care sectors, including the home- and center-based sectors, where most caregivers are working (National Survey of Early Care and Education Project Team, 2014, 2016).

Our paper also contributes to a larger literature using the traditional shift-share methodology to study the labor market effects of immigrant in-flows. Particularly relevant are the papers by Cortes and Tessada (2011) and Cortes (2008), who use this methodology to study prices and wages in immigrant-intensive sectors as well as household expenditures on housekeeping services. In addition, Amuedo-Dorantes and Sevilla (2014) examine maternal time investments in children. Again, however, none of these papers examine the child care industry specifically. To our knowledge, one previous paper uses the shift-share approach to study the impact of immigrant in-flows on child care supply and wages, finding a positive effect on the former and a negative effect on the latter (Furtado and Hock, 2008). The current paper adds to this work in two distinct ways. First, the shift-share instrument has recently been criticized for confounding the short- and long-run effects of immigrant settlement patterns, raising questions about the credibility of the research design (Jaeger et al., 2018). Our paper, in contrast, studies the impact of immigration

[4]The private household services industry includes workers across a large number of occupations, ranging from housekeepers and chefs to file clerks and clergy members.

by exploiting a plausibly exogenous policy shock that led to widespread reductions in immigrant labor supply. A second and related contribution is that we shed light on how immigration enforcement policy—of which there have been several recently, including S.B. 1070 in Arizona and the federal 287(g) agreements—influences the labor market. Although the SC program is no longer in effect, it was reinstated during the Trump presidency and was ultimately replaced by another policy (the Priority Enforcement Program or PEP) that continues to deport large numbers of immigrants (TRAC Immigration, 2022). As a result, such policy-relevant evidence remains important today.

Finally, our paper sheds light on a longstanding question in the child care literature as to why the wages of child care workers have grown very little over time, despite the large and persistent increase in the demand for these services (Blau, 1992; Herbst, 2018). One possibility, advanced by Blau and Currie (2004), is that the supply of child care has been buoyed by the influx of low-skilled, female immigrants, for whom such employment is attractive and accessible. To be consistent with this explanation, the SC program would have to increase the wages of native child care workers. However, we find the opposite effect, which suggests that the increase in immigration over the past few decades is not responsible for the tepid wage growth in the child care industry. This view is further bolstered by our finding that immigrant child care workers may be more highly skilled than natives (Table A2) and are employed at programs in different markets (Table A3), implying that both sets of workers possess non-substitutable skills to the production of child care.

The remainder of the paper proceeds as follows. Section 2 provides a descriptive portrait of the immigrant child care workforce and discusses the roll-out of the SC program. Section 3 introduces the data sources, while Section 4 describes the identification strategy. Our results are presented in Sections 5 and 6, and we end the paper with a discussion of policy implications in Section 7.

2 Background

2.1 Immigrants and the Child Care Workforce

Immigrants constitute an important part of the U.S. child care workforce. Approximately 19% of (female) child care workers are immigrants, compared to about 17% of workers in all other industries (Table A1). Their presence in urban areas is particularly important, where, for example, they comprise 44% of child care workers in New York City, 47% of workers in Los Angeles, and 25% of workers in Chicago. In fact, in seven of the 10 largest urban areas in the U.S., the immigrant share of the child care workforce exceeds that in all other industries (Table A1). Figure A1 provides additional evidence on the relative importance of immigrants to the child care industry. Specifically, we use the 2017 through 2019 waves of the ACS to calculate immigrant workforce shares in the 53 sectors that make up the retail and (professional) services industries.[5] Among these sectors, child care has the sixth highest concentration of immigrant labor.

Child care workers are generally employed in one of three primary settings, and there is considerable heterogeneity in the number of immigrants employed in these contexts. Immigrants comprise about 30% of caregivers in *private household* settings, which refers to unregulated child care usually provided in the home of the child, such as that provided by nannies, au pairs, and babysitters. These workers can be unpaid or paid; if they are paid, it is typically at a rate negotiated with the family, and sometimes the payment is off the record. Second, immigrants make up about 28% of individuals employed in the *home-based* sector, which consists of lightly regulated providers—usually functioning as small, independent businesses—caring for small groups of children in the home of the provider. Finally, there are *center-based* workers, who are employed by licensed and regulated entities, usually operating in a stand-alone building or one that is shared with another organization. Such settings can be for- or non-profit centers, community-based organizations, or places of worship, in which children are organized into age-specific classrooms led by head and (sometimes) assistant teachers. Immigrants are the least likely to work in the center-based sector, comprising only 15% of its workforce.

The data presented in Table A2 provide a descriptive portrait of the immigrant child care workforce, drawing on the 2019 wave of the National Survey of Early Care and Education (NSECE).[6] Immigrant workers are more likely to be Hispanic and to speak a non-English language than their natives counterparts, and they are more likely to be married. Interestingly, immigrants and natives have similar (child care) work experience profiles, but immigrants have higher levels of education, on average. For example, nearly 64% of immigrant child care workers have a college degree (i.e., an AA or BA), compared to 53% among natives. Furthermore, while natives are more likely to have field-relevant academic degrees (e.g., a college major in education), immigrants are more likely to obtain professional

[5] We analyze these sectors because they employ a comparatively high proportion of women, and they contain large a number of low-wage jobs.

[6] These data describe lead teachers in center-based settings.

qualifications like the Child Development Associate (CDA) credential and state teaching certifications, and they are more likely than natives to invest time every month in professional development activities. Immigrants also score slightly higher on the Hamre's scale, which tests teacher knowledge about age-appropriate strategies for interacting with children. Given that immigrant teachers appear to be more highly skilled, at least on these observable dimensions, it is not surprising that their wages are higher than their native counterparts ($16.01 compared to $14.82).

Table A3 provides information on the classroom and program environments in which immigrant child care teachers are employed, also using the 2019 NSECE. Immigrant-led classrooms are comparable in terms of the number of children being cared for (i.e., its classroom group size) and the number of other teachers in the classroom. However, classrooms in which immigrant lead teachers are working are more likely to include a minority teacher—primarily Hispanic or Asian teachers—while native lead teachers are more likely to work in classrooms with non-minority (i.e., white) teachers.[7] In addition, immigrant teachers are substantially more likely to work in classrooms with a larger share of Hispanic children as well as those who speak a non-English language at home. Finally, programs that employ immigrant teachers are more likely to be located in high-poverty, urban neighborhoods.

2.2 The Secure Communities Program

Enacted in the fall of 2008 by the U.S. Immigration and Customs Enforcement Agency (ICE), the Secure Communities (SC) program sought to increase public safety by implementing a system to efficiently identify and remove non-citizen individuals who were in violation of federal immigration law (U.S. Immigration and Customs Enforcement, 2008a). A collaboration between the local law enforcement agencies, the Federal Bureau of Investigation (FBI), and the U.S. Department of Homeland Security (DHS)/ICE, SC used biometric technology—via fingerprinting—to identify individuals who were already in the custody of local police and who, because of a potential immigration violation (e.g., overstaying a visa or failing to appear in court), may be deportable. The program prioritized the apprehension and removal of non-citizens with serious ("Level 1") prior convictions, including homicide, assault, and kidnapping.[8]

[7] Note that these figures include the (lead) teacher being interviewed as well as assistant teachers or other staff within the classroom.

[8] Indeed, in its strategic plan submitted to Congress, ICE stipulated that SC would focus on the relatively narrow goal of removing "high-risk" criminal aliens, defined as those convicted of major drug and violent offenses, as well as those who posed a risk to national security (U.S. Department of Homeland Security, 2012).

Prior to the enactment of SC, any individual arrested and booked by local police would have his/her fingerprints taken and, along with the person's biographic information, submitted to the FBI for a determination of criminal history, using the Bureau's Integrated Automated Fingerprint Identification System (IAFIS) (U.S. Immigration and Customs Enforcement, 2008a). The identification of criminal non-citizens by local authorities required a separate, manual process that included the submission of information to ICE agents, who would check the person's immigration status using their own databases and/or authorize an in-person interview at the local jail to verify his/her status (Venturella, 2010).[9] Under SC, however, fingerprints sent to the FBI were automatically routed to the Department of Homeland Security/ICE for analysis in its Automated Biometric Identification System (IDENT), a database of every fingerprinted non-citizen in the U.S.[10] ICE agents then reviewed the arrested person's immigration status—assuming a fingerprint match occurred—to determine whether he/she was in violation of any immigration laws. If such a determination was made, ICE agents could place a detainer on the individual, requesting that local law enforcement hold that person for up to 48 hours so that ICE could transfer him/her to federal custody for the initiation of removal proceedings (U.S. Immigration and Customs Enforcement, 2008a). The SC program was far more ambitious than the system it replaced: it ensured that every individual arrested by local police would undergo a screening for immigration violations (Cox and Miles, 2013).

The activation of SC occurred on a county-by-county basis. The first county to do so was Harris County (Texas) in October 2008, while the remaining counties enacted the program by January 2013. Figures 1 and 2 provide additional information on the temporal and geographic roll-out of SC. Panel A of Figure 1 shows that while new activations were fairly slow in 2008 and 2009—with 14 and 88 counties enacting the program in these years, respectively—the speed of adoption grew rapidly during the years 2010 to 2012. The peak year was 2011, when nearly 1,100 counties adopted the program. By the end of 2013, all counties had SC in place, as shown in Panel B of Figure 1 and in Figure 2. Adoption rates began to fall in 2014, after the program was suspended in November of that year and replaced by the Priority Enforcement Program (PEP), which instructed ICE to detain only those individuals convicted of high priority offenses or who were involved in a gang (Alsan and Yang, 2018). However,

[9]These interviews were performed by either local police under a written, cooperative law enforcement agreement called the 287(g), which allowed local officers to provide immigration screening, or by federal agents through the Criminal Alien Program (CAP), which allowed such individuals to conduct interviews in federal, state, and local jails and prisons for the purpose of identifying potentially deportable non-citizens (Cox and Miles, 2013).

[10]It is important to note that IDENT is not exclusively a database of suspected and convicted criminals. It includes non-citizens lawfully in the U.S., but who may be deported if convicted of the crime for which they were arrested by local law enforcement, as well as non-citizens who violated immigration law, perhaps because they overstayed a visa or were previously deported.

SC was initiated once again in January 2017.

Between 2008 and 2014—the period covered in this analysis—the enactment of SC produced 440,000 deportations, a number that grew to 686,000 as of 2018 (TRAC Immigration, 2022). Fully 62% of all individuals removed from the U.S. were apprehended in Texas (200,884), California (167,906), and Arizona (54,131), and the vast majority of those removed were men (96%). In addition, most individuals held citizenship in Mexico (75%), followed by Guatemala (7%), Honduras (7%), and El Salvador (5%). The most common reasons for removal include individuals who did not undergo a formal, legal admittance process into the country as well as those who were previously deported and attempted to reenter. Finally, approximately one-third of all individuals removed had a prior Level 1 conviction or were charged with such an offense by local authorities.

Given that nearly all deported individuals under SC were male but that most child care workers are female, any changes in the child care labor market are unlikely to be driven by an increase in forcible removals by ICE. Instead, we hypothesize that SC may drive changes in labor supply through a "chilling effect." There is ample anecdotal and systematic evidence that interior immigration enforcement policies, including SC, have large chilling effects. The program created its first outspoken critics—leading to the first "sanctuary jurisdictions"—over concerns that it would make policing harder by alienating those in immigrant communities (Lind, 2014). For example, Boston's then-mayor argued that residents had come to believe that police officers were working with ICE agents to deport immigrants, and that such beliefs would erode the relationship between police and residents (Preston, 2011). The growing fear of deportation led immigrants to report fewer crimes, limit their assistance with crime scene investigations, and reduce their participation in court proceedings (American Civil Liberties Union, 2018; Dhingra et al., 2022; Jácome, 2022; Wong et al., 2021). In addition, immigrants were reportedly afraid to drive to work or school (to pick up their children), and they avoided crowded areas and busy streets (Fernelius and Garcia, 2018).[11] Finally, such fear altered an array of other behaviors, reducing the take-up of social safety net benefits (Alsan and Yang, 2018; Watson, 2014), complaints to government regulators about unsafe working conditions (Grittner and Johnson, 2022), and self-petitions under the Violence Against Women Act (Amuedo-Dorantes and Arenas-Arroyo, 2021).

Several factors make SC particularly attractive for studying the impact of immigration enforcement policy. First,

[11] In one extraordinary account from North Carolina, residents communicated with one another over WhatsApp whenever they spotted a black SUV on the road, which they suspected was an ICE vehicle. Volunteers were then sent out to follow the vehicle to track its activities (Fernelius and Garcia, 2018).

the pattern of SC's staggered geographic and temporal roll-out was not decided at the state or local level, but rather at the federal government level. The decision to stagger SC's introduction was driven in part by the realization that local ICE facilities required substantial resources—specifically, labor, beds, and transportation—to carry out the program (U.S. Immigration and Customs Enforcement, 2008b). In addition, not all local police forces had live fingerprint scanning capability at the start of SC's activation period. Therefore, one criterion used by DHS to select the group of early adopters was whether a community had the labor and technological infrastructure in place to implement SC. A second and related advantage is that DHS was fairly clear about the other criteria that would drive early-adoption decisions. For example, the stated goal of SC was to "identify, detain, and return removable criminal aliens," suggesting that the program would target counties with high crime rates, those with large shares of non-citizens or Hispanics, or those on the Mexico border (U.S. Immigration and Customs Enforcement, 2008b). Indeed, a detailed analysis by Cox and Miles (2013) finds that three of these factors—pre-existing technological capacity, the Hispanic share of the population, and proximity to the border—are the most powerful predictors of early-SC adoption. Therefore, we control for these characteristics in the empirical models.[12] The final advantage is that participation in SC by local communities was mandatory and that it was virtually impossible to opt out of participation, although initially there was substantial confusion over the program's compulsory nature (Cox and Miles, 2013; U.S. Department of Homeland Security, 2012)[13] These institutional features make pre-reform adjustments and endogenous participation by communities less likely.

3 Data Description

3.1 Child Care Participation

To study the impact of SC on child care participation, we use data from the American Community Survey (ACS) over the period 2005 to 2014 (Ruggles et al., 2022). The ACS provides detailed demographic and employment

[12]A small number of counties were selected for a pilot program: Boston, MA; Dallas County, TX; Harris County, TX; Wake County, NC; Henderson County, NC; Buncombe County, NC; and Gaston County, NC (U.S. Immigration and Customs Enforcement, 2008b). In addition to controlling for the factors correlated with the timing of SC's implementation, we check the sensitivity of our results to excluding all early-adopters from the analysis.

[13]Indeed, DHS Inspector General report concluded that "ICE failed to clearly communicate the intent and expectation of participation. As required by Congress, ICE's strategic plan included goals, but did not specify whether participation would be mandatory and did not communicate statutory or other legal support for nationwide implementation" (U.S. Department of Homeland Security, 2012). In addition, there was no way for local authorities to control whether fingerprints sent to the FBI would also be forwarded to DHS/ICE. This occurred automatically.

information on a 1% random sample of the population each year. We begin the analysis in 2005 because it is the first year in which the 1-in-100 sampling strategy is utilized and Public Use Microdata Area (PUMA) geographic identifiers are publicly available in the ACS.[14] The analysis ends in 2014 because, as previously noted, SC was suspended at the end of 2014 and replaced by the Priority Enforcement Program.

The main analysis sample is limited to children ages three through five whose mothers are citizens ages 20 to 64. These restrictions provide a sample of 877,256 children. Citizens are defined as U.S.-born individuals or those who are foreign-born but report being naturalized citizens. For reasons described below, the main analysis assigns three- and four-year-olds to the treatment group, and five-year-olds are assigned to the comparison group. We also conduct a series of robustness checks that expand the sample to include six- and seven-year-olds as alternative comparison groups. In addition, we conduct auxiliary analyzes of the impact of SC for a sample of children whose mothers are non-citizens.

We use the ACS data to construct our key outcome, which is a measure of children's child care (or school) participation. Specifically, it is a binary indicator equal to one if a given child attends child care or kindergarten and zero otherwise. For all individuals in the household ages three and over, the survey asks whether they attended school or college at some point in the last three months, and, if so, at what grade-level.[15] Importantly, the questionnaire prompts individuals to include child care services (e.g., nursery school and preschool) in each household member's school attendance response. Our methodology assigns three- and four-year-olds to the treatment group because, by virtue of their age, they are assumed to be exposed primarily to child care services (rather than kindergarten). Five-year-olds, on the other hand, are assigned to the comparison group because they are assumed to be exposed to kindergarten (rather than child care). These assumptions seem appropriate in light of the data on age-specific enrollment rates. Indeed, 48% of three- and four-year-olds participate in (center-based) child care, while only 4% are enrolled in kindergarten (Snyder et al., 2019). Among five-year-olds, 16% and 72% are in child care and kindergarten, respectively.[16] Thus, it is reasonable to assume that the ACS's school attendance question reflects child care use among three- and four-year-olds and kindergarten enrollment among five-year-olds.

There are, however, two disadvantages associated with the ACS's survey design and school attendance question.

[14]The PUMA is the smallest geographic unit of analysis available in the IPUMS version of the ACS. Although county identifiers are also provided, they are not available for counties outside of urban or metropolitan areas.

[15]Unfortunately, the follow-up question about grade-level—which includes discrete categories for nursery school and preschool, kindergarten, and various grades in elementary school—is not included in the public release of the ACS.

[16]Another way to confirm this is by looking at the age distribution of children enrolled in kindergarten. Of those attending kindergarten (for the first time), only 6% are under age five, while 85% are five years old (Snyder and Dillow, 2013).

First, the survey is fielded throughout the year, asking about school attendance over the last three months. This rolling design can cause some children to be assigned to the incorrect care-type (i.e., child care or kindergarten). For example, consider a five-year-old child whose birthday is in February and whose family was interviewed for the ACS in March. Our methodology would assign this child to the comparison group because, given his/her observed age on the day of the interview, we would assume the child is exposed to kindergarten. However, this child should be assigned to the treatment group because he/she is not age-eligible to attend kindergarten in the current school year.[17] As a result, we present a series of robustness checks using the Education Supplement to the Current Population Survey (CPS), which inquires about school attendance every October. This fixed point-in-time (and start-of-school-year) design is advantageous, because children's ages in October are more indicative of their grade-level (Cascio, 2021).[18]

The other drawback is that the ACS's school attendance question likely elicits responses about center-based child care participation, thereby excluding many forms of informal care (e.g., relative and neighbor caregivers and au pairs) as well as other formal providers (e.g., home-based care). Although center-based care is the predominant non-parental arrangement for preschool-age children, particularly for three- and four-year-olds, our empirical estimates should be interpreted as the center-based participation response to the enactment of SC (Herbst, 2022). In other words, this paper is unlikely to shed light on how immigration reform influenced participation in the informal sector.

3.2 Child Care Labor Market

The analysis of the child care labor market draws on two key data sources. First, we once again use the ACS between 2005 and 2014 to examine employment and wages in the child care industry. The sample includes women (immigrants and natives) ages 20 to 55, regardless of whether they are employed. Men are not included in the sample, given that they comprise only 5% of the child care workforce (authors' calculation). We further limit the

[17] Most state (and local) governments stipulate that children must reach age five by September of a given calendar year to be eligible for kindergarten in that school year.

[18] This improvement particularly relates to children whose ACS interview occurs after September of a given school year, as explained in the text. Of course, the mismeasurement of care-type may still occur for children interviewed in the October CPS and whose birthday occurs early in the school year. For example, children aged four in September may turn five in October and therefore might not be eligible to attend kindergarten.

sample to those not residing in group quarters and those not in the Armed Services.[19] Immigrants are those who report being a non-citizen or a naturalized citizen. We report separate results for sub-sets of low- and high-education immigrants and natives. Low-education individuals have less than a four-year college degree, while high-education individuals have at least a four-year degree.

The ACS analyses use the survey's industry and occupation codes to first study the impact of SC on the likelihood that a woman is employed in the child care industry. Specifically, the outcome is expressed as a binary indicator equal to one if a given woman is employed in the child care industry and zero otherwise. This dichotomous measure of child care employment is used as a proxy for supply. Our second outcome is a measure of hourly wages, defined as annual earnings divided by annual hours of work.[20] We also examine employment choices and wages within three sectors of the child care industry: private household settings, home-based providers, and center-based providers (Brown and Herbst, 2022; Herbst, 2018). Private household caregivers are defined as women employed in the "private household services" industry and whose primary occupation is a child care worker. Those in the home-based sector are self-employed women working in the "child daycare services" industry and whose occupation is a child care worker or an education administrator. Finally, center-based workers include non-self-employed women who work in the child daycare services industry or the elementary/secondary school industry. If employed in the former industry, the occupation must be a child care worker, preschool or kindergarten teacher, education administrator, special education teacher, or assistant teacher. If employed in the latter industry, the occupation must be a child care worker or preschool or kindergarten teacher. The remaining women in the sample are coded as non-child care workers or non-workers. Our analysis sample includes 7,065,928 observations, of which 173,036 are child care workers, 5,964,967 are all other workers, and 927,926 are non-workers.

Our second data source, the Quarterly Census of Employment and Wages (QCEW), allows us to examine some alternative measures of child care supply. The QCEW is an establishment-level database of employment information for individuals covered by state unemployment insurance (UI) laws. Specifically, the public release version of the data includes the monthly number of employees and the quarterly number of establishments disaggregated by industry (up to the six-digit NAICS industry code), ownership status, and geographic area. Our analysis relies

[19]Finally, we drop a small number of observations with positive work hours but zero reported earnings, and those with non-zero earnings but zero hours of work.

[20]A measure of annual hours of work is not provided in the ACS. Therefore, we multiply (usual) weekly hours of work by the number of weeks of work. In addition, we constrain the wage analysis to full-time workers, defined as those employed at least 25 hours per week.

on county × quarter data between 2005 and 2014 to examine the impact of SC on the number of establishments and workers in the "child daycare services" industry (NAICS code 624410). Included in the child daycare services industry are individuals working in the public (e.g., Head Start) or private (e.g., for-profit centers and non-profit churches) sector as well as some UI-eligible workers in home-based settings. It is also important to note that it includes workers performing a variety of pedagogical (e.g., teachers and teacher assistants) and non-pedagogical (e.g., CEOs and managers of national chains, programs administrators, food preparation workers, and bus drivers) tasks.

3.3 Secure Communities

Data on the adoption of SC comes from U.S. Immigration and Customs Enforcement (2014). In particular, this publication provides the activation date of the SC program in each county, along with the number of fingerprint submissions, IDENT matches and convictions, and removals. We construct a variable representing the proportion of the year SC was activated in each county × year combination. If the policy was never in effect in a given year, the variable takes a value of zero; if the policy was enacted for the entire year, the variable takes a value of one. As noted earlier, the PUMA is the smallest (and most consistent) geographic identifier available in the ACS. Therefore, we crosswalk the county-level activation dates to each PUMA.[21] We then assign each county to a PUMA. In some instances, the PUMA is either the same size as or smaller than the county, in which case the value of the county-level SC variable is applied to the relevant PUMA(s). In other cases, the PUMA is larger than a given county (i.e., there are multiple counties within the PUMA). Here, we express the variable as the population-weighted average of the county-specific SC values within the PUMA, weighting by the total population in each county. Thus, our key policy variable measures the weighted average proportion of the year in which SC was activated in each PUMA × year combination. For the analyses using the QCEW, the SC activation variable is merged to the data on establishments and employees in county × year × quarter cells. Figure A2 displays the roll-out of SC at the PUMA-level, while Figure 2 shows this information at the county-level.

[21]The crosswalk data can be obtained here: https://mcdc.missouri.edu/applications/geocorr2014.html.

4 Empirical Implementation

To study the impact of SC on child care participation, we exploit the staggered introduction of the program across counties as well as the differential exposure to SC of children of different ages. Specifically, our triple differences model estimates the change in child care participation for three- and four-year-olds before versus after a county enacted SC, relative to the change in kindergarten participation that occurred among five-year-olds. As previously mentioned, three- and four-year-olds are considered treated in this analysis, while five-year-olds are in the comparison group. The key insight justifying the use of five-year-olds as the comparison group is that they are substantially more likely to attend kindergarten (as opposed to child care), and as a result, they are less likely to be exposed to an immigrant teacher, whose labor supply might be affected by SC. Recall that 72% of five-year-olds are enrolled in kindergarten, while 16% participate in child care (Snyder et al., 2019). Furthermore, the immigrant share of the kindergarten teacher workforce is only 10% (Furuya et al., 2019), compared to 20% within the child care workforce (Table A1). These stylized facts suggest that children of different ages are differentially exposed to immigrant teachers, and therefore to any SC-driven changes in the immigrant labor market.[22]

Using the sample of three- to five-year-old children of citizen mothers from the ACS between 2008 and 2014, our triple differences model is specified in the following manner:

$$Y_{ipt} = \alpha + \beta_1 a_{ipt} + \beta_2 SC_{pt} + \beta_3 (T_{it} \times SC_{pt}) + \theta X_{ipt}^{'} + \eta Y_{pt}^{'} + \zeta_p + \xi_t + \varepsilon_{ipt}, \quad (1)$$

where Y_{ipt} denotes a binary indicator that equals one if child i in PUMA p and year t is enrolled in child care or kindergarten and zero otherwise. The a_{ipt} is a set of child-age fixed effects, while SC_{pt} is the population-weighted average fraction of the year in which SC was active in PUMA p and year t. The key variable of interest is the interaction $T_{it} \times SC_{pt}$, where T_{it} is a treatment indicator equal to one for three- and four-year-olds and equal to zero for five-year-olds. Therefore, the coefficient β_3 is the triple differences estimate of the impact of SC on the child care participation of three- and four-year-olds. In a set of robustness checks, we use six- and seven-year-olds as alternative comparison groups, given that these children are even less likely to be in kindergarten and exposed

[22] In addition, as previously noted, kindergarten is an entitlement in most jurisdictions. Therefore, any local teacher supply shocks should not affect children's enrollment in these programs.

to immigrant teachers.[23]

The matrix X'_{ipt} represents a set of observable child and maternal characteristics, including the child's citizenship status as well as the mother's age (and age squared), marital status, Hispanic ethnicity, education level, and number of own children. The matrix Y'_{pt} includes the following time-varying PUMA controls: the share Hispanic, share foreign born, population density, and a binary indicator equal to one if a 287(g) agreement is in effect. Recall that the analysis by Cox and Miles (2013) found these factors to be among the strongest correlates of the timing of counties' SC activation. In robustness checks, we enrich the set of PUMA controls by adding variables for median family income, poverty rate, share married, share with less than a college degree, and the labor force participation rate. The model also includes a set of PUMA fixed effects, ζ_p, to account for any time-invariant differences across PUMAs that may be correlated with SC's roll-out. For example, they control for the distance of areas from the Mexico border as well as any permanent differences in attitudes toward immigrants. Finally, we include year fixed effects, ξ_t, to account for any time-varying national economic or policy shocks that may be correlated with the activation of SC, such as other immigration reforms.[24]

The key identifying assumption in our triple differences model is that there are no unobserved, county-specific shocks that occurred contemporaneously with the enactment of SC that differentially affected three-/four-year-olds and five-year-olds. In particular, we assume that in the absence of SC the trend in child care/school participation rates for three-/four-year-olds and five-year-olds would have remained constant in the period following SC's activation. We probe this assumption in a variety of ways. First, we estimate a model that includes state-by-year fixed effects, which accounts for time-varying, state-specific shocks that may be correlated with SC's roll-out. For example, some states may have undertaken their own immigration enforcement activities (e.g., Arizona's SB 1070) that had a similar chilling effect on immigrant communities. We also estimate models that remove states on the border with Mexico, given that they may have deployed enforcement technologies or specialist labor even in the absence of SC. Finally, we estimate an event-study model that interacts the treatment status variable, T_{it}, with a set of time-to-event fixed effects, omitting the year prior to SC's enactment. Formally, the model is specified as follows:

[23] Generally speaking, children age six are in first grade, while those age seven are in second grade. Just 7% of elementary and middle school teachers are foreign born (Furuya et al., 2019).

[24] One such immigration "policy" absorbed by the year fixed effects is the Morton memo, issued in 2011, which explained, in an effort to clear up any confusion, that county participation in SC was compulsory.

$$Y_{ipt} = \alpha + \beta_1 a_{ipt} + \sum_{j=-5}^{4} \beta_2^j (T_{it} \times d_{pt}^{0+j}) + \sum_{j=-5}^{4} \beta_3^j T_{it} + \theta X_{ipt}^{'} + \eta Y_{pt}^{'} + \zeta_p + \xi_t + \varepsilon_{ipt}, \tag{2}$$

where d_{pt}^{0+j} denotes a set of four pre-SC indicator variables and a set of five post-SC indicators centered around the year in which each county activated SC, t_0.[25] The set of coefficients β_2^j estimate the difference in child care/school enrollment rates between three-/four-year-olds and five-year-olds in each year before and after SC's enactment. The main triple differences estimates in Equation 1 could be considered causal only if a change in the differential enrollment rates across the treatment and comparison groups emerged post-activation.[26] In other words, there should be no evidence of a differential pre-reform trend evident in Equation 2.

Following the analysis of child care participation, we turn our attention to the supply-side of the market, analyzing the impact of SC on the supply and compensation of child care workers. These analyses are based on a difference-in-differences (DD) framework in which we rely on the geographic and temporal roll-out of the program, again using ACS data between 2008 and 2014. Our two-way fixed effects (TWFE) DD model is specified as follows:

$$Y_{ipt} = \alpha + \beta_1 SC_{pt} + \theta X_{ipt}^{'} + \eta Y_{pt}^{'} + \zeta_p + \xi_t + \varepsilon_{ipt}, \tag{3}$$

where Y_{ipt} is either a binary indicator for employment in the child care industry or the hourly wages of woman i in PUMA p and year t. Recall that we use the dichotomous child care employment choice as a proxy for supply, and examine whether the enactment of SC alters the decision to work in the child care industry. The main variable of interest is SC_{pt}, which is defined in the same manner as Equation 1. Therefore, β_1 provides the DD estimate of the impact of SC on the child care labor market outcomes. The model includes in $X_{ipt}^{'}$ a set of individual-level controls, such as age (and age-squared), race/ethnicity, educational attainment, current school enrollment, marital status, and the number of own children. All other controls are the same as those in Equation 1. Recall that this model is estimated on subsets of low- and high-education immigrants and natives, and on employment choices in three sectors of the child care market (i.e, private household, home-based, and center-based).

The key identifying assumption in Equation 3's DD model is that there are no unobserved, county-specific shocks

[25] A point of clarification: the five post-SC indicator variables include one indicator denoting the year of enactment and four indicators for the first four years after enactment.

[26] Recall that in Equation 1 the measure of SC ranges between zero and one. However, for the event-study analysis, the time-to-event variable must take a value of zero or one. Therefore, we classify SC activation as equal to one if the program was running for at least half the year in a given county, and zero if it was running for less than half the year. We experimented with some alternative measures, and the results are robust to these changes.

that caused the child care labor market outcomes to trend differently across counties. To test for the presence of pre-trends, we conduct the standard TWFE event-study analysis, whose model takes the form:

$$Y_{ipt} = \alpha + \sum_{j=-5}^{4} \beta_1^j d_{pt}^{0+j} + \theta X_{ipt}^{'} + \eta Y_{pt}^{'} + \zeta_p + \xi_t + \varepsilon_{ipt}, \tag{4}$$

where d_{pt}^{0+j} denotes a set of four pre-SC indicator variables and a set of five post-SC indicators centered around the year in which each county activated SC, t_0. The coefficients represented by β_1^j estimate period-specific changes in the labor market outcomes before and after SC's activation relative to the year prior to enactment. Support for the identifying assumption would emerge if the pre-reform indicator variables are not statistically significantly different zero, suggesting that any trend changes post-reform are due to SC.

5 Results

The discussion of results proceeds in two steps. We begin by presenting results from the triple differences model of child care participation (i.e., Equations 1 and 2). We then turn our attention to the analysis of child care labor supply (i.e., Equations 3 and 4). All of the robustness checks are presented alongside the main results for each outcome. All models are weighted by the ACS person weight, and the standard errors are adjusted for clustering at the PUMA level.

5.1 Child Care Participation

Table 1 presents the main results from the triple differences model of child care participation. The model in column (1) includes the PUMA and year fixed effects, while those in columns (2) and (3) add the individual-level and PUMA-level controls, respectively. It is clear that child care/school participation increases with age, with three-year-olds the least likely to be enrolled in a non-parental care setting. The coefficient on the interaction term $T_{it} \times SC_{pt}$ indicates that the enactment of SC reduced the child care participation rate of three- and four-year-olds (of citizen mothers) by 1.8 percentage points, a result that is robust to the inclusion of additional controls. Given that the treated pre-SC child care participation rate is 49.4%, the coefficient implies a 3.6% reduction in utilization. This result is broadly consistent with previous work by Amuedo-Dorantes and Sevilla (2014) and Cortes and Tessada (2011), who find that increases in low-skilled immigration reduces high-skilled women's time allocated to child care and increases the amount of time in market work. More directly, our results are consistent with East and Velasquez (2022)'s paper showing that SC activation reduced the labor supply of high-skilled women. However, given that the current analysis focuses on the children of all citizen women—whereas these papers focus on high-skilled citizen women—it seems likely that changes in immigration enforcement have significantly broader effects on labor supply than documented in previous work.

Figure 3 displays the event-study estimates of the impact of SC on child care/school participation. In the years prior to SC's implementation, the coefficients on the interaction of treatment status (i.e., child-age) and event-time are statistically indistinguishable from zero, suggesting that any differences in the participation rate between three-/four-year-olds and five-year-olds are small and relatively constant in the pre-reform period. In contrast, the interactions become negative and statistically significant in the years following SC's enactment, revealing that three-/four-year-olds experienced a differential decline in participation in the post-reform period. In particular, the estimates indicate that child care participation decreased between one and three percentage points after SC's introduction. Together, this evidence provides support for our identifying assumption of no discernible pre-reform trend in the child care/school participation rate across the treatment and comparison groups.

The models presented in Appendix Tables A4 and A5 begin to probe the robustness of the main results. In particular, Appendix Table A4 tests alternative comparison groups, as defined by children's ages. Column (1) presents the main estimates from the Table 1. The model in column (2) is estimated on the subset of three- and four-year-olds, coding the former as the treatment group and the latter as the comparison group and then interacting the new treatment status indicator with SC_{pt} in the triple differences model. This analysis serves as a useful falsification test, given that both sets of children participate in child care (rather than kindergarten) and therefore are equally exposed to any SC-driven changes in the immigrant labor market. Thus, the coefficient on the interaction term $T_{it} \times SC_{pt}$ should be small and statistically indistinguishable from zero. As shown in column (2), this is the case, thereby lending some initial support for the identification strategy. The remaining columns use six- and seven-year-olds, respectively, as the comparison group, under the assumption that such children are even less likely to participate in child care. Results from these models are quite close to the baseline model using five-year-olds as the comparison group.

Appendix Table A5 presents results based on the October CPS. Recall that this survey may be advantageous because it asks about school attendance and children's ages in October, which coincides with the start of each school year. This allows for a more accurate coding of children to child care versus school attendance, given that a child's reported age in October is better aligned with their actual grade-level (Cascio, 2021). However, a drawback of the October CPS, in addition to having a smaller sample, is that the state (rather than PUMA) is the smallest identifiable geographic unit. Therefore, the variable SC_{pt} represents the population-weighted average share of counties within a state that enacted SC, making the treatment variable less precise. Despite this difference, the results in columns (1) through (3), which use five-year-olds as the comparison group, are similar to the equivalent (baseline) ACS estimates. In particular, the triple differences estimate in column (3) implies a 2.4 percentage point reduction in child care participation among three-/four-year-olds. Columns (4) and (5) use six- and seven-year-olds as the comparison groups, with the estimates again showing similarly-sized reductions in child care participation.

We present a number of additional robustness checks in Appendix Table A6. All models use five-year-olds as the comparison group. Column (1) includes state-by-year fixed effects; column (2) controls for several additional PUMA-level characteristics; column (3) interacts the treatment status indicator with the PUMA-level controls; column (4) uses the child's citizenship status rather than the mother's status to define the analysis sample; column (5) excludes Arizona; and column (6) excludes the border states of Arizona, California, New Mexico, and Texas.We exclude Arizona in column (5) given that the state enacted its own anti-illegal immigration policy, SB 1070, contemporaneously with the operation of SC, in July 2010. Recall that the state-by-year fixed effects control for time-varying state unobservables that may be correlated with introduction of SC at the local level. The treatment-PUMA interactions allow for the possibility that the effect of PUMA characteristics vary with the child's age. In addition, using the child's citizenship status to define the sample may be important if parents make child care and schooling decisions based on the child's status. It is also possible that the child's status is used to determine eligibility for various education programs. Finally, estimating a model that excludes the border states is important for two reasons: many of their counties were among the earliest-adopting jurisdictions of SC, and a few of these states have attempted to enact their own immigration enforcement policies—both of which may confound the impact of SC. Our results are robust to all of these changes in the specification and sample construction.

Having established the robustness of our results, we now explore whether SC had heterogeneous effects on child care participation across various demographic groups. As shown in Table 2, we begin by looking at a comparison of Hispanic and non-Hispanic families [columns (1) and (2)]. SC generated a three percentage point decline in child care use among Hispanic children, but only a one percentage point decline among non-Hispanics. The larger effect among Hispanics may be indicative of a "dual chilling effect," in which SC reduced the supply of immigrant teachers while making it more costly for some (citizen) families with children to use child care services. The remaining columns in Table 2 examine separate effects by parents' marital status and education level as well as family income. These analyses suggest that SC had broad participation effects, but it is also clear that the program had larger effects on disadvantaged families. For example, child care use fell by 3.3 percentage points among children of low-education parents, compared to a 1.6 percentage point decline among children of high-education parents.[27] Such results may have implications for children's health and development, particularly disadvantaged children, who benefit substantially more from attending center-based child care programs (Chaparro et al., 2020; Kline and Walters, 2016; Herbst, 2017), perhaps because they are higher-quality than most alternative care settings (Bassok et al., 2016; Flood et al., 2021). We return to this point in the final section of the paper.

Up to this point, the analysis has focused on the children of citizen mothers. It is possible, however, that SC also influenced the child care use of children of non-citizen mothers. Indeed, a large number of such children enroll in center-based programs: during the study period, about 40.8% of three- and four-year-old children of non-citizen mothers were enrolled, compared to 49.1% among the children of citizen mothers (authors' calculation of the ACS). Therefore, we end the discussion of child care participation by examining this group of non-citizens. Column (1) of Table 3 shows that, overall, SC reduced their participation rate by 1.5 percentage points, a result that is driven by Hispanic non-citizens [column (2) versus column (3)]. The remaining columns show once again that disadvantaged children were considerably more likely to be affected by SC than their advantaged counterparts. Therefore, like their citizen counterparts, the enactment of SC had broad (negative) effects on non-citizens' child care participation, but those effects were disproportionately experienced by disadvantaged children.

[27] We define low-education as mothers with no more than a high school degree, while high-education consists of those with more than a high school degree.

5.2 Child Care Labor Supply

We now turn our attention to the analysis of the child care labor market, beginning with women's child care occupational choices, which we view as a proxy for child care teacher labor supply. Recall that this analysis is conducted on a sample of all women ages 20 to 55 using a DD model. Our first set of results, shown in Table 4, examines whether a given woman is employed at all as a child care worker, and we stratify the estimation by education level and immigrant status as well as by race and ethnicity. Looking first at Panel A, we find that low-education immigrants were less likely to be employed in the child care industry after the enactment of SC. Specifically, the coefficient in column (1) implies a 0.25 percentage point decline in the likelihood of being a child care worker. Given that 2.9% of low-education immigrants were employed as child care workers in the pre-SC period, this coefficient implies an 8.6% reduction in the share of such individuals choosing child care employment. The remaining columns in Panel A reveal that this effect is driven by Hispanic immigrants, particularly Mexicans, who became 15.8% less likely to work in the child care industry. Such results are consistent with the view that SC disproportionately targeted the Hispanic community.[28] Turning to Panel B, we find little evidence that SC influenced the occupational choices of high-education immigrants.[29]

Panels C and D of Table 4 conduct the comparable analyses on natives. We uncover evidence that SC similarly reduced supply of low- *and* high-education *natives* in the child care industry. Given the pre-SC employment means of 2.8% and 2.0%, respectively, the coefficients imply small reductions in native child care employment, of 4% and 7%, respectively. The remaining columns in Panels C and D suggest that these overall effects were driven by reductions in employment among whites and particularly blacks. Our finding that immigration enforcement via SC did not benefit native workers—and indeed reduced their employment in the child care industry—is consistent with previous work by East et al. (2022), who find that SC had broad-based negative effects on native employment, and by East and Velasquez (2022), who find that the program reduced employment in the household services sector. It is also consistent with the more general finding in the literature that an increase in immigration does not reduce labor market opportunities for low-skilled natives (Card, 2005).

[28] For example, of the 687,000 deportations under the SC program, 516,000 were individuals from Mexico (TRAC Immigration, 2022).

[29] However, it should be noted that child care employment among high-education Mexican immigrants was reduced by 0.75 percentage points, a result that is not statistically significant given the limited sample size. Nevertheless, it is consistent with the overall pattern that SC disproportionately affected Mexican immigrants.

Figure 4 presents the key event-study results, for low-education black and white natives (Panel A), high-education black and white natives (Panel B), and low-education immigrants (Panel C).[30] All three analyses show no evidence of differential outcome trends between treated and comparison areas in the period before SC's roll-out, as depicted by the flat and statistically insignificant pre-reform coefficients. However, the coefficients reveal a distinct shift following SC's introduction, consistent with a reduction in child care employment for all three groups.

Appendix Table A7 presents a variety of robustness checks on our main employment results. We limit the discussion of robustness to low- and high-education immigrants, as shown in Panels A and B, respectively.[31] Column (1) provides the baseline estimates shown in Table 4; column (2) restricts the analysis to immigrants who entered the U.S. after 1980; column (3) adds a control for the (self-reported) English speaking ability of individuals; column (4) includes the additional PUMA-level controls; column (5) omits the most heavily-populated PUMAs; column (6) excludes early-adopting PUMAs; and column (7) excludes all PUMAs in Arizona. The restriction to those entering after 1980 has been used in prior work to focus the analysis on potential illegal immigrants (East et al., 2022). Excluding large and early-adopting PUMAs (as well as Arizona) tests for the possibility that such areas may be confounded with SC's activation or may be driving the overall results. Our main results are robust to all of these changes in the specification and sample.

We now separately examine the impact of SC on occupational choices by child care sector. Specifically, the outcomes consistent of separate binary indicators that equal one if a given woman is employed in the private household child care sector, the home-based sector, and the center-based sector. As shown in Table 5, we present estimates for each sector, again disaggregated by education level and immigrant status. Two noteworthy results emerge from this analysis. First, consistent with the results in the previous analysis, the reduction in labor supply occurred among low-education immigrants and (low- and high-education) natives. Second, the reduction occurred primarily in the center-based sector. In other words, SC led to broad-based declines in the supply of child care workers—that is, among immigrants *and* natives alike—within the sector of the market providing the most formal care services. Our results differ slightly from those in East and Velasquez (2022), who find that SC lowered the overall supply of private household service workers. In contrast, our results indicate that the number of private

[30] Although we present only these results in the paper—both for the sake of brevity and because these groups were the only ones influenced by SC—we perform the equivalent analysis on the samples defined in column (1) of Table 4. The results are consistent with those presented here, and are available upon request.

[31] We restrict the robustness analysis to immigrants because at least one of the specifications can be implemented on immigrants only, and a few others are predicted to disproportionately affect immigrants.

household *child care workers* did not change, suggesting that the decline documented by East and Velasquez (2022) is driven by other types of workers.

The final set of ACS analyses in this section examines the impact of SC on the hourly wages of immigrant and native child care workers. We begin with Table 6, which presents the wage results for the full sample of child care workers (Panel A), the subset of immigrant workers (Panel B), and the subset of native workers (Panel C). We further disaggregate the results by education level. Generally speaking, the results suggest that SC reduced the wages of child care workers. For example, column (1) of Panel A shows that SC activation generated a 2.8% decline in hourly wages. Although the wage declines occurred for low- and high-education workers, as shown in columns (2) and (3), it is noteworthy that the effects are twice as large for high-education workers. Panel B reveals that immigrant child care workers overall experienced a 5.4% reduction in wages [column (1)], and that this effect is driven by the comparatively large reduction among high-education immigrants [column (3)]. Finally, we provide evidence that the wages of native child care workers also fell, by 2.1%, following the enactment of SC, as shown in column (1) of Panel C. A negative effect persists across both education levels, although neither estimate is statistically significant. It is also noteworthy that the wage response among immigrants is twice as large as it is among natives.

Table 7 further dissects the wage results by private household child care workers (Panel A), home-based workers (Panel B), and center-based workers (Panel C). Although most of the coefficients on SC_{pt} are negatively signed—and some imply economically meaningful effects—the statistically-significant coefficients are mostly clustered in the center-based sector. This is likely explained by the relatively large sample of workers employed in the the center-based sector. The estimate in column (1) of Panel C indicates that SC led to a 2.2% reduction in center wages overall, along with a 6.3% reduction among immigrants employed in the sector. Again, the results suggest that the wages of high-education center workers were disproportionately affected, but neither of the education-specific coefficients are statistically significant.

Our last set of analyses uses a different data source, the QCEW, to examine alternative measures of child care supply. Specifically, while the ACS provides individual-level data on child care employment, the QCEW data are drawn from a virtual census of firms representing all NAICS industries. Therefore, the QCEW provides data on the number of firms and workers in the child care industry (NAICS code 6244). The DD results using the QCEW are presented in Table 9, and the corresponding event-study estimates are shown in Figures 5 and 6. It is clear that the results overall are consistent with those from the ACS, showing a reduction in child care supply. Specifically, the estimate in column (1) implies that SC reduced the number of establishments by 1.6% (or approximately three establishments per one million in the population, as shown in column(2)), while column (3) shows that it reduced the number of employees by 1.5% (or approximately 28 employees per one million in the population, as shown in column(4)). The corresponding event-study results are displayed in Figures 5 (establishments) and 6 (employment). Both analyses show no evidence of differential outcome trends in the period before SC's introduction, as shown by the flat and statistically insignificant pre-reform coefficients. However, the coefficients reveal a distinct shift following SC's introduction, consistent with a reduction in the number of child care establishments and employees.

6 Child Care Quality

The preceding discussion notes that SC reduced employment in the child sector as well as the supply of child care services, particularly in the center-based sector. A key question is whether the reduction in overall supply had consequences for the number of high-quality providers. Although the current paper is not able to examine the direct relationship between immigration (and related policies like SC) on child development, understanding whether such policies influence quality—a key determinant of child development—is an important first step. Indeed, a number of recent studies provide credible evidence that increases in early care service quality have moderate-sized, positive impacts on children's school readiness outcomes (Auger et al., 2014).

To assess the impact of SC on child care quality, we obtained from the market research company AggData a listing of all center-based providers that are accredited by the National Association for the Education of Young Children (NAEYC) between 2011 and 2014. The NAEYC's accreditation, called the Early Learning Program (ELP), is widely considered one of the most rigorous quality accreditations available in the child care market. Providers undergo a prolonged, four-step evaluation process that requires considerable effort and resources.[32] Xiao (2010) estimates that the cost of completing the initial accreditation process is approximately $4,000, while the

[32] Providers must submit an application for NAEYC accreditation, pay a fee, and complete a self-study, which is aimed at helping staff understand NAEYC's quality standards. Providers must then apply for a site visit and submit documentation in support of meeting the quality standards. In the third step, the site visit is conducted, while the final step involves maintaining accreditation. To highlight one example of the kinds of standards in the ELP: providers must demonstrate that every classroom has a teacher with at least an associate's degree in ECE (or a related field) or has a non-ECE bachelor's degree and either 36 credit hours of ECE coursework (or a related field) or a state teaching certificate.

cost of subsequent maintenance (e.g., completing annual follow-up paperwork and maintaining staff quality and training) is approximately $2,000 per year. Our data suggest that at most 17% of center-based providers achieved the ELP accreditation during the study period.[33]

Using AggData's child care listing, which includes the name and physical address of each provider along with its county and state of operation, we assigned to each firm the relevant state and county FIPS identifiers. We then constructed a dataset of the number of NAEYC-accredited providers, the number of accredited providers per 1 million in the population, the presence of any accredited provider, and the share of accredited providers in county $\times$ year $\times$ quarter cells between 2011 and 2014. These data were then merged with the information on SC's roll-out over the same period, which allowed us to estimate DD regressions that include county and quarter-year fixed effects as well as a control for the log of county population. It is important to note that, unlike the results for all of the above-discussed outcomes—whose observation period begins in 2005—the limited availability of NAEYC data prevents us from starting this analysis as early as the preceding analyses.

Results from the DD models are presented in Table 9. The estimates suggest that SC enactment did not influence the number of high-quality, NAEYC-accredited providers. Looking across all four columns, which vary the way the outcome variable is measured, it is clear that the coefficients on SC are inconsistently signed, and they are never statistically significant. Thus, while the supply of child care overall may have contracted because of SC, the availability of high-quality programs appears to have remained unchanged. It is important to note that these results shed light on whether SC affected the stock—or density—of accredited providers within counties. These results do not necessarily permit conclusions about changes in quality within child care providers. Therefore, it is possible that SC altered the mix of services and staffing related to quality production within individual child care programs.

7 Conclusion

This paper combines multiple data sources to provide a comprehensive analysis of the impact of SC on the U.S. child care market. Given the importance of immigrants to the provision of child care, it is critical to understand

[33]Note that the numerator for this figure comes from the AggData listing of NAEYC-accredited providers, while the denominator comes from the QCEW's data on the number of child care industry establishments. We say "at most" because the numerator likely covers more providers than the denominator.

how such policies affect the structure and functioning of the market. Furthermore, although the SC program was discontinued in 2014 (for the first time), well over 200,000 individuals continue to be deported each year (TRAC Immigration, 2022). As a result, any labor shortages and the consequent chilling effects of a deportation-centric policy remains a key concern for industries that rely on immigrant labor.

We find that the enactment of SC reduced preschool-aged children's participation in formal child care. This result persists across a broad swath of children: it applies to children of citizen and non-citizen parents, and it applies to multiple demographic groups. Nevertheless, we find substantially larger participation effects for disadvantaged children, including Hispanics as well as those from low-education and -income families. Recall that East and Velasquez (2022) find that SC reduced the employment of highly-educated native mothers. Insofar as the reduction in mothers' employment is linked to the decrease in child care demand, our results suggest that the employment effects of SC are likely to apply to more demographic groups than just high-skilled mothers. As for the supply-side of the market, we find that SC reduced the supply and compensation of child care workers. These reductions are concentrated on low-education immigrants as well as (low- and high-education) natives employed primarily in the center-based sector. Consistent with this, we find that SC's enactment led to fewer child care establishments. Unlike East and Velasquez (2022), we find no evidence that SC influenced those working in child care in the private household sector. That SC affected only employees in the formal care market is plausible, given that such workers are more likely to interface with multiple government entities.

Our results appear to be consistent with those in Furtado and Hock (2008) who, using the shift-share methodology, find that the in-migration of low-skilled immigrants increases the supply of child care. In other words, assuming that an increase in immigrant in-flows affects the child care market through the same mechanisms as SC's reduction in immigrant labor, it is perhaps not surprising that SC led to decreases in the supply of child care labor, in light of Furtado and Hock (2008)'s results. In addition, our results are consistent with those in East et al. (2022), who find that SC reduced the labor supply and wages of low-education foreign-born as well as U.S.-born workers. Together, these results call into question the possibility that low-skilled immigration is responsible for the stagnation in wages in the child care market despite the fact that the demand for such services has increased over the past few decades.

Insights from a simple trade model, such as that developed in Cortes (2008), may shed light on why SC reduced the supply and wages of both immigrant and native child care workers. In particular, such a model allows for the possibility that immigrants and natives do not compete for the same jobs at child care firms. Instead, they possess complementary—or at least imperfectly substitutable—skills, such that changes in the demand for immigrant workers generate similar changes in the demand for native workers. Indeed, we provide descriptive evidence that along some dimensions of observable skill—for example, education and other human capital investments—immigrant child care workers are actually more skilled than their native counterparts. Therefore, insofar as natives act as complementary inputs to child care production with their immigrant counterparts, one would expect immigration enforcement policies like SC to have negative effects on natives' labor market outcomes.

We also note the descriptive evidence showing that immigrants and natives are likely to be employed at programs in different markets, and that the children assigned to their classrooms differ on some observable characteristics. In particular, immigrants are more likely to work in classrooms with a greater share of Hispanic and non-English language children and for programs in high-poverty, urban neighborhoods. These data suggest that immigrant and native child care workers are bifurcated (within and between programs) in ways that may further mitigate their competition in the labor market. On the one hand, this implies that SC would have neutral or positive effects on native child care workers. Once again, however, our results are more aligned with the possibility that both group are complements. For example, the assignment of immigrants and natives to different classrooms could be made purposefully to achieve a good fit between the characteristics of the children and those of the teachers.

Another possibility, which draws on job search models from Albert (2021), for example, posits that a decrease in job competition faced by natives from policies like SC (which would tend to improve natives' labor market outcomes) may be offset by a simultaneous reduction in job creation (which would tend to worsen natives' labor market outcomes). A decline in job creation would occur if reservation wages among natives are higher, on average, than those for immigrants. As a result, child care providers, who face higher labor costs after the enactment of SC, might respond by lowering their demand for native workers. This dynamic could be exacerbated in a market like child care, whose consumers are shown in some studies to be very sensitive to the cost of such services (Connelly and Kimmel, 2003).

A major open question is whether immigration enforcement policies like SC have implications for child development. Although it is unclear a priori whether such policies have positive or negative effects on children, our results, along with those in East and Velasquez (2022), indicate that one potentially important mechanism may operate through reductions in maternal employment and participation in formal child care. That we find comparatively large decreases in formal care use among disadvantaged children raises concerns that these children are being cared for in less optimal environments, including lower-quality informal arrangements or at home by a resource-constrained parent (Flood et al., 2021). Understanding how policies like SC shift children's care environments and, in turn, their developmental outcomes is therefore a key task for future research.

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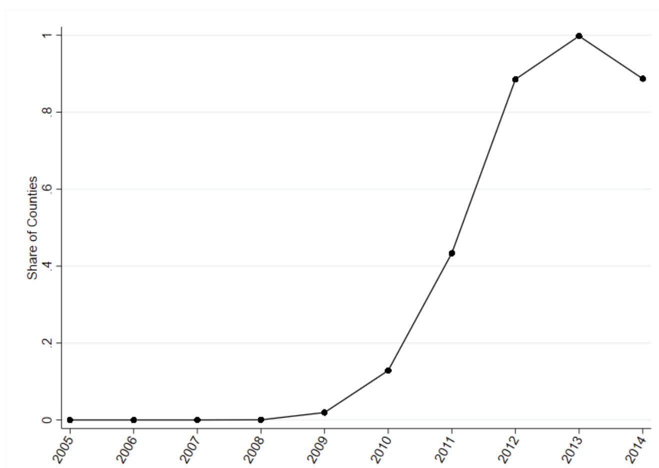
Figures and Tables

Figure 1: Adoption of Secure Communities, 2005-2014

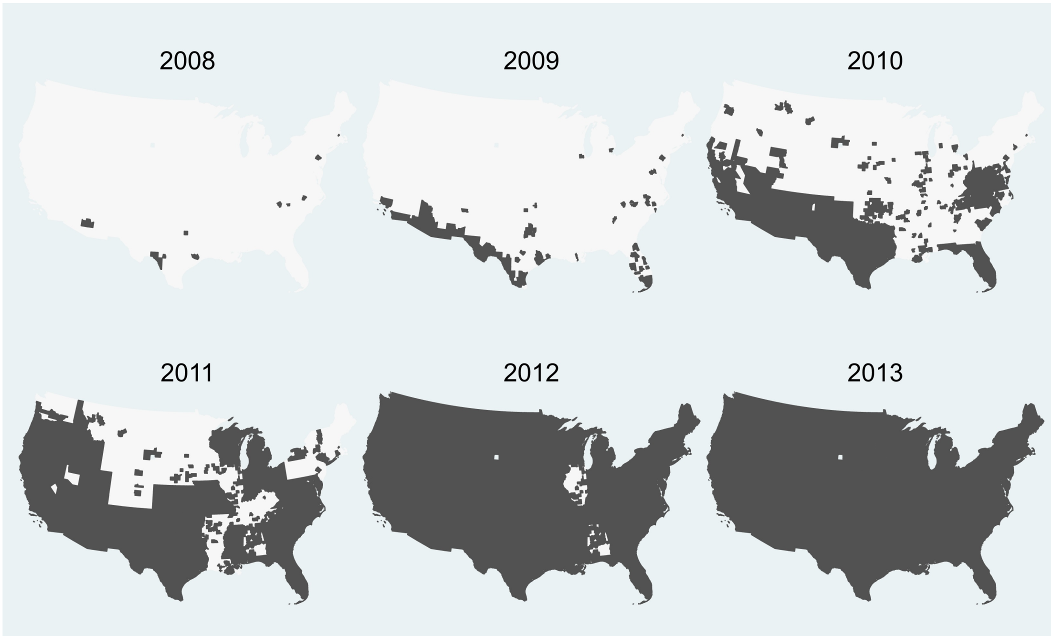
(a) Panel A: New Counties Enforcing Secure Communities

(b) Panel B: Share of Counties Enforcing Secure Communities



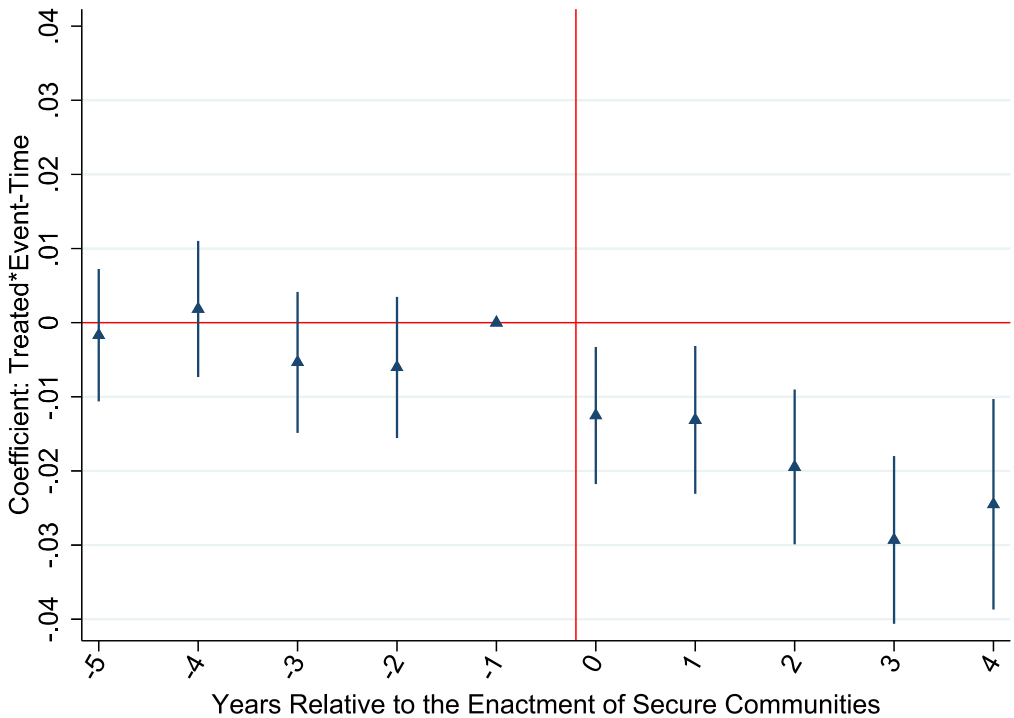
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014)
Notes: Panel (a) shows the number of new counties enforcing the Secure Communities program in each year between 2005 and 2014. Panel (b) shows the cumulative share of counties enforcing the Secure Communities program in each year between 2005 and 2014.

Figure 2: County-Level Adoption of Secure Communities, 2008-2013



Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014).
Notes: The maps show the county-level adoption of Secure Communities in various years. Shaded counties are those that had Secure Communities active for at least 50% of days in the respective calendar year. There is no data for Shannon County, South Dakota, since the county does not have an administrative office. Neighboring Fall River County serves as its administrative center.

Figure 3: Event-Study Estimates of the Impact of Secure Communities on Child Care Participation



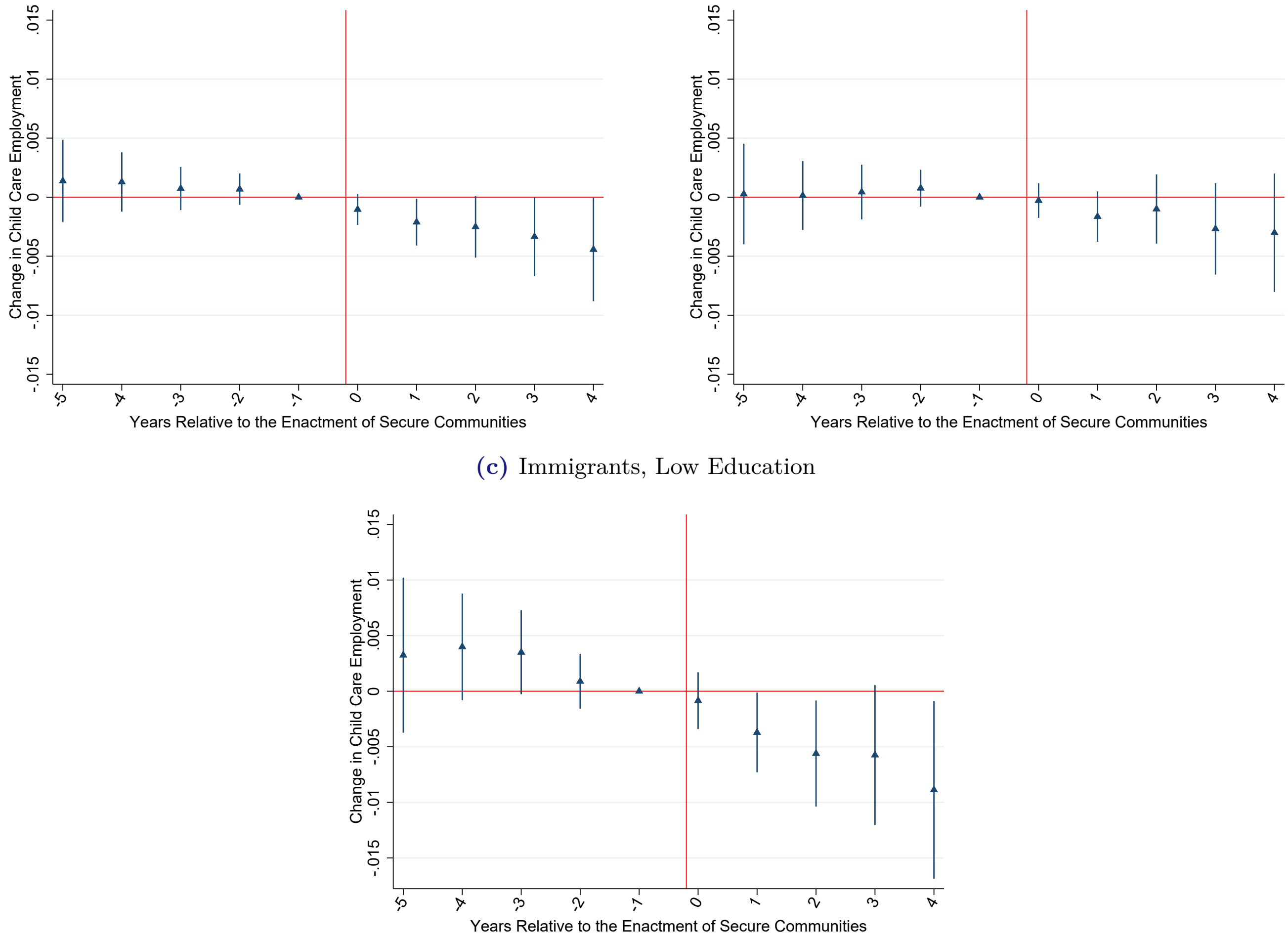
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014.
Notes: The figure shows the estimated difference in the likelihood of child care/schooling participation between three-/four-year-olds and five-year-olds in various years before and after the enactment of Secure Communities (compared to the year prior to its enactment). The horizontal axis denotes "event time" in which the omitted year is the year before Secure Communities was enacted in a given PUMA. The analysis sample includes children ages three to five of citizen mothers ages 20 to 64. The model includes four lagged and five lead indicator variables as well as controls for child-age fixed effects, baseline child and mother characteristics, baseline PUMA characteristics, main effect event-time indicators, PUMA fixed effects, and year fixed effects. The model is weighted by the ACS person weight, and the standard errors are corrected for clustering at the PUMA level.

Figure 4: Event-Study Estimates of the Impact of Secure Communities on Child Care Occupational Choices

(a) Black and White Natives, Low Education

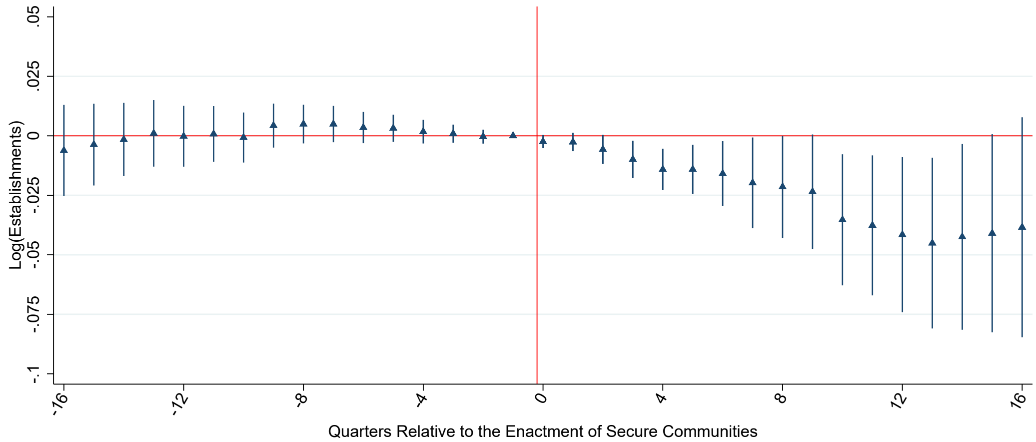
(b) Black and White Natives, High Education

(c) Immigrants, Low Education



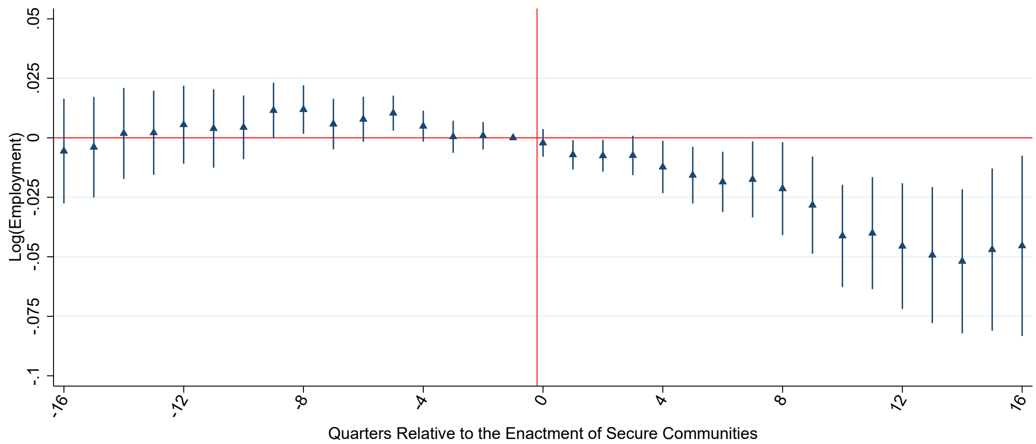
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014
The dependent variable in all plots is an indicator that equals one if the woman is employed in the child care sector and equals zero otherwise. The figure plots event-time coefficients of year relative to exposure to Secure Communities with error bars representing 95% confidence intervals. The data for each subfigure is restricted to the group indicated for each plot. The models include PUMA and year fixed effects as well as demographic and time-varying PUMA-level controls, and the standard errors are clustered at the PUMA level.

Figure 5: Event-Study Estimates of the Impact of Secure Communities on Child Care Establishments



Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and QCEW from 2005 to 2014
The data include the number of establishments in the "Child Day Care Services" industry at the county-by-quarter level. The figure plots event-time coefficients of quarter relative to exposure to Secure Communities with error bars representing 95% confidence intervals. The figure restricts to event time from 16 quarters before through 16 quarters after Secure Communities in order to retain a more balanced panel. The models include county and year-quarter fixed effects, and the standard errors are clustered at the county level.

Figure 6: Event-Study Estimates of the Impact of Secure Communities on Child Care Employment (QCEW)



Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and QCEW from 2005 to 2014
The data include employment in the "Child Day Care Services" industry at the county-by-quarter level. The figure plots event-time coefficients of quarter relative to exposure to Secure Communities with error bars representing 95% confidence intervals. The figure restricts to event time from 16 quarters before through 16 quarters after Secure Communities in order to retain a more balanced panel. The models include county and year-quarter fixed effects, and the standard errors are clustered at the county level.

Table 1: Main Estimates from the Triple Differences Model of Child Care Participation

	Dep Var: Child Care Participation		
	(1)	(2)	(3)
Age 4	0.2593***	0.2564***	0.2564***
	(0.0025)	(0.0025)	(0.0025)
Age 5	0.4930***	0.4867***	0.4867***
	(0.0039)	(0.0040)	(0.0040)
Secure Communities	0.0094**	0.0098**	0.0106***
	(0.0043)	(0.0043)	(0.0043)
Treated × Secure Communities	-0.0182***	-0.0182***	-0.0182***
	(0.0032)	(0.0032)	(0.0032)
Observations	877,256	877,256	877,256
PUMA Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Demographic Controls	No	Yes	Yes
Time-varying PUMA Controls	No	No	Yes

Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014
Notes: The analysis sample includes children ages three to five of citizen mothers ages 20 to 64. The model includes a binary indicator denoting the enactment of Secure Communities and a variable denoting the interaction of Secure Communities enactment with the age of the child ("Treated"). Child-age is expressed as a binary indicator equal to one for children ages three and four and zero for children age five. The model includes controls for child-age fixed effects, baseline child and mother characteristics, baseline PUMA characteristics, PUMA fixed effects, and year fixed effects. The model is weighted by the ACS person weight, and the standard errors are corrected for clustering at the PUMA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Sub-Group Estimates from the Triple Differences Model of Child Care Participation

	Dep Var: Child Care Participation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Secure Communities	0.0250**	0.0043	0.0153**	0.0065	0.0249***	0.0053	0.0211***	0.0048
	(0.0112)	(0.0043)	(0.0075)	(0.0046)	(0.0072)	(0.0050)	(0.0079)	(0.0065)
Treated × Secure Communities	-0.0290***	-0.0102***	-0.0225***	-0.0133***	-0.0331***	-0.0157***	-0.0235***	-0.0129***
	(0.0069)	(0.0032)	(0.0050)	(0.0035)	(0.0048)	(0.0035)	(0.0051)	(0.0047)
Comparison Group	5-year-olds	5-year-olds	5-year-olds	5-year-olds	5-year-olds	5-year-olds	5-year-olds	5-year-olds
Sample	Hispanic	Non-Hispanic	Single	Married	Low-Ed	High-Ed	Low-Income	High-Income
Observations	107,870	769,374	228,249	649,007	325,340	551,916	228,027	214,884
PUMA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying PUMA Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014

Notes: The analysis sample includes children ages three to five of citizen mothers ages 20 to 64. The sample "Low-Ed" consists of mothers with no more than a high school degree, while sample "High-Ed" consists of mothers with more than a high school degree. The sample "Low-Income" consists of families at or below the bottom quintile of family income, while the sample "High-Income" consists of families at or above the top quintile of family income. The model includes a binary indicator denoting the enactment of Secure Communities and a variable denoting the interaction of Secure Communities enactment with the age of the child ("Treated"). Child-age is expressed as a binary indicator equal to one for children ages three and four and zero for children age five. The model includes controls for child-age fixed effects, baseline child and mother characteristics, baseline PUMA characteristics, PUMA fixed effects, and year fixed effects. The model is weighted by the ACS person weight, and the standard errors are corrected for clustering at the PUMA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Non-Citizen Sub-Group Estimates from the Triple Differences Model of Child Care Participation

	Dep Var: Child Care Participation								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Secure Communities	0.0145*	0.0116	-0.0007	0.0404**	0.0077	0.0282***	-0.0100	0.0146	0.0096
	(0.0084)	(0.0099)	(0.0161)	(0.0169)	(0.0092)	(0.0109)	(0.0151)	(0.0114)	(0.0115)
Treated × Secure Communities	-0.0152**	-0.0151*	0.0107	-0.0320**	-0.0106	-0.0225***	-0.0027	-0.0158*	-0.0089
	(0.0074)	(0.0081)	(0.0107)	(0.0130)	(0.0080)	(0.0087)	(0.0094)	(0.0093)	(0.0091)
Comparison Group	5-year-olds	5-year-olds	5-year-olds	5-year-olds	5-year-olds	5-year-olds	5-year-olds	5-year-olds	5-year-olds
Sample	All Non-Citizens	Hispanic	Non-Hispanic	Single	Married	Low-Ed	High-Ed	Low-Income	High-Income
Observations	135,879	82,864	52,957	30,051	105,744	86,703	49,140	62,016	73,823
PUMA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying PUMA Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014

Notes: The analysis sample includes children ages three to five of non-citizen mothers ages 20 to 64. The sample "Low-Ed" consists of mothers with no more than a high school degree, while the sample "High-Ed" consists of mothers with more than a high school degree. The sample "Low-Income" consists of families at or below the median of family income, while the sample "High-Income" consists of families above the median of family income. The model includes a binary indicator denoting the enactment of Secure Communities and a variable denoting the interaction of Secure Communities enactment with the age of the child ("Treated"). Child-age is expressed as a binary indicator equal to one for children ages three and four and zero for children age five. The model includes controls for child-age fixed effects, baseline child and mother characteristics, baseline PUMA characteristics, PUMA fixed effects, and year fixed effects. The model is weighted by the ACS person weight, and the standard errors are corrected for clustering at the PUMA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Estimates from the DD Model of Occupational Choices

	Dep Var:=1 if Occupation is Child Care				
	(1)	(2)	(3)	(4)	(5)
Panel A: Low-Education Immigrants					
Secure Communities	-0.0025**	-0.0031*	-0.0038**	-0.0018	-0.0013
	(0.0012)	(0.0017)	(0.0019)	(0.0035)	(0.0045)
Sample	Overall	Hispanic	Mexican	White	Black
Observations	746,713	427,114	284,890	102,179	56,633
PUMA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Time-Varying PUMA Controls	Yes	Yes	Yes	Yes	Yes
Panel B: High-Education Immigrants					
Secure Communities	0.0012	0.0020	-0.0075	0.0020	-0.0059
	(0.0017)	(0.0058)	(0.0096)	(0.0031)	(0.0054)
Sample	Overall	Hispanic	Mexican	White	Black
Observations	339,683	59,589	20,172	85,498	21,792
PUMA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Time-Varying PUMA Controls	Yes	Yes	Yes	Yes	Yes
Panel C: Low-Education Natives					
Secure Communities	-0.0011*	0.0018	-0.0017	-0.0012*	-0.0042**
	(0.0006)	(0.0017)	(0.0023)	(0.0007)	(0.0017)
Sample	Overall	Hispanic	Mexican	White	Black
Observations	4,062,328	385,246	248,441	2,983,364	534,483
PUMA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Time-Varying PUMA Controls	Yes	Yes	Yes	Yes	Yes
Panel D: High-Education Natives					
Secure Communities	-0.0014**	-0.0007	-0.0015	-0.0012*	-0.0072***
	(0.0006)	(0.0034)	(0.0050)	(0.0007)	(0.0025)
Sample	Overall	Hispanic	Mexican	White	Black
Observations	1,917,204	97,764	51,148	1,600,958	138,816
PUMA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Time-Varying PUMA Controls	Yes	Yes	Yes	Yes	Yes

Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014
Notes: The analysis sample includes women (immigrants and natives) ages 20 to 55. The sample "Low-Education" consists of women with less than a four-year college degree, while the sample "High-Education" consists of women with a four-year degree or more. The model includes a binary indicator denoting the enactment of Secure Communities, as well as controls for individual and PUMA characteristics, PUMA fixed effects, and year fixed effects. The model is weighted by the ACS person weight, and the standard errors are corrected for clustering at the PUMA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: DD Model of Sector-Specific Child Care Occupational Choices

	Dep Var:=1 if CC Worker in Sector		
	(1)	(2)	(3)
	Pr HH	Home	Center
Panel A: Low-Education Immigrants			
Secure Communities	-0.0002	-0.0007	-0.0015*
	(0.0005)	(0.0008)	(0.0008)
Observations	746,713	746,713	746,713
PUMA Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Time-Varying PUMA Controls	Yes	Yes	Yes
Panel B: High-Education Immigrants			
Secure Communities	0.0006	0.0001	0.0006
	(0.0007)	(0.0007)	(0.0012)
Observations	339,683	339,683	339,683
PUMA Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Time-Varying PUMA Controls	Yes	Yes	Yes
Panel C: Low-Education Natives			
Secure Communities	0.0001	-0.0002	-0.0010*
	(0.0002)	(0.0002)	(0.0005)
Observations	4,062,328	4,062,328	4,062,328
PUMA Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Time-Varying PUMA Controls	Yes	Yes	Yes
Panel D: High-Education Natives			
Secure Communities	-0.0001	-0.0003	-0.0010*
	(0.0002)	(0.0002)	(0.0006)
Observations	1,917,204	1,917,204	1,917,204
PUMA Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Time-Varying PUMA Controls	Yes	Yes	Yes

Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014
Notes: The analysis sample includes immigrant and native women ages 20 to 55. The sample "Low-Education" consists of women with less than a four-year college degree, while the sample "High-Education" consists of women with a four-year degree or more. The text "Pr HH" refers to the sample of private household child care workers, "Home" refers to home-based child care workers, and "Center" refers to center-based child care workers. The models include a binary indicator denoting the enactment of Secure Communities, as well as controls for individual and PUMA characteristics, PUMA fixed effects, and year fixed effects. The model is weighted by the ACS person weight, and the standard errors are corrected for clustering at the PUMA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: DD Model of Child Care Workers' Hourly Wages

	Dep Var: ln(hourly wages)		
	(1)	(2)	(3)
Panel A: Full Sample			
Secure Communities	-0.0278***	-0.0235*	-0.0504**
	(0.0103)	(0.0123)	(0.0211)
Sample	Full	Low-Ed	High-Ed
Observations	115,359	86,069	29,288
PUMA Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Time-Varying PUMA Controls	Yes	Yes	Yes
Panel B: Immigrants			
Secure Communities	-0.0544**	-0.0438	-0.1213**
	(0.0273)	(0.0306)	(0.0591)
Sample	Full	Low-Ed	High-Ed
Observations	17,851	13,722	3,876
PUMA Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Time-Varying PUMA Controls	Yes	Yes	Yes
Panel C: Natives			
Secure Communities	-0.0210*	-0.0204	-0.0301
	(0.0121)	(0.0143)	(0.0228)
Sample	Full	Low-Ed	High-Ed
Observations	97,387	72,195	25,184
PUMA Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Time-Varying PUMA Controls	Yes	Yes	Yes

Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014
Notes: The analysis sample includes immigrant and native women ages 20 to 55 employed as a full-time child care worker. Full-time is defined as more than 25 hours of work per week. The sample "Low-Ed" consists of women with less than a four-year college degree, while the sample "High-Ed" consists of women with a four-year degree or more. The models include a binary indicator denoting the enactment of Secure Communities, as well as controls for individual and PUMA characteristics, PUMA fixed effects, and year fixed effects. The model is weighted by the ACS person weight, and the standard errors are corrected for clustering at the PUMA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: DD Model of Sector-Specific Hourly Wages

	Dep Var: ln(hourly wages)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Private Household Workers					
Secure Communities	-0.0025	0.0534	-0.0514	-0.0114	-0.1010
	(0.0390)	(0.0585)	(0.0511)	(0.0442)	(0.0801)
Sample	Full	Immigrants	Natives	Low-Ed	High-Ed
Observations	9,499	2,950	6,309	7,488	1,739
PUMA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Time-Varying PUMA Controls	Yes	Yes	Yes	Yes	Yes
Panel B: Home-Based Workers					
Secure Communities	-0.0243	-0.0444	-0.0227	-0.0061	-0.1570**
	(0.0281)	(0.0573)	(0.0353)	(0.0303)	(0.0782)
Sample	Full	Immigrants	Natives	Low-Ed	High-Ed
Observations	27,062	4,715	22,108	23,341	3,448
PUMA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Time-Varying PUMA Controls	Yes	Yes	Yes	Yes	Yes
Panel C: Center-Based Workers					
Secure Communities	-0.0218*	-0.0627*	-0.0123	-0.0176	-0.0318
	(0.0120)	(0.0330)	(0.0132)	(0.0141)	(0.0231)
Sample	Full	Immigrants	Natives	Low-Ed	High-Ed
Observations	78,681	9,736	68,780	55,071	23,603
PUMA Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Time-Varying PUMA Controls	Yes	Yes	Yes	Yes	Yes

Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014
Notes: The analysis sample includes immigrant and native women ages 20 to 55 employed as a full-time child care worker. Full-time is defined as more than 25 hours of work per week. The sample "Low-Ed" consists of women with less than a four-year college degree, while the sample "High-Ed" consists of women with a four-year degree or more. The models include a binary indicator denoting the enactment of Secure Communities, as well as controls for individual and PUMA characteristics, PUMA fixed effects, and year fixed effects. The model is weighted by the ACS person weight, and the standard errors are corrected for clustering at the PUMA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: DD Model of Child Care Establishments and Employment

	(1) ln(estabs)	(2) Estabs per 1 million	(3) ln(emp)	(4) Emp per 1 million
Secure Communities	-0.0158**	-2.982**	-0.0153***	-28.00*
	(0.0068)	(1.360)	(0.0059)	(15.36)
Mean Level	218	225	2,758	2,572
N	111,337	112,061	65,854	112,061

Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and QCEW from 2005 to 2014
Notes: The data include quarterly establishments and average employment levels in the "Child Day Care Services" industry (NAICS code 6244) at the county level. Regressions are weighted by county population. All regressions include county and quarter-year fixed effects as well as a control for the log of county population. In columns (2) and (4), establishments and employment are measured per 1 million population at the county level. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

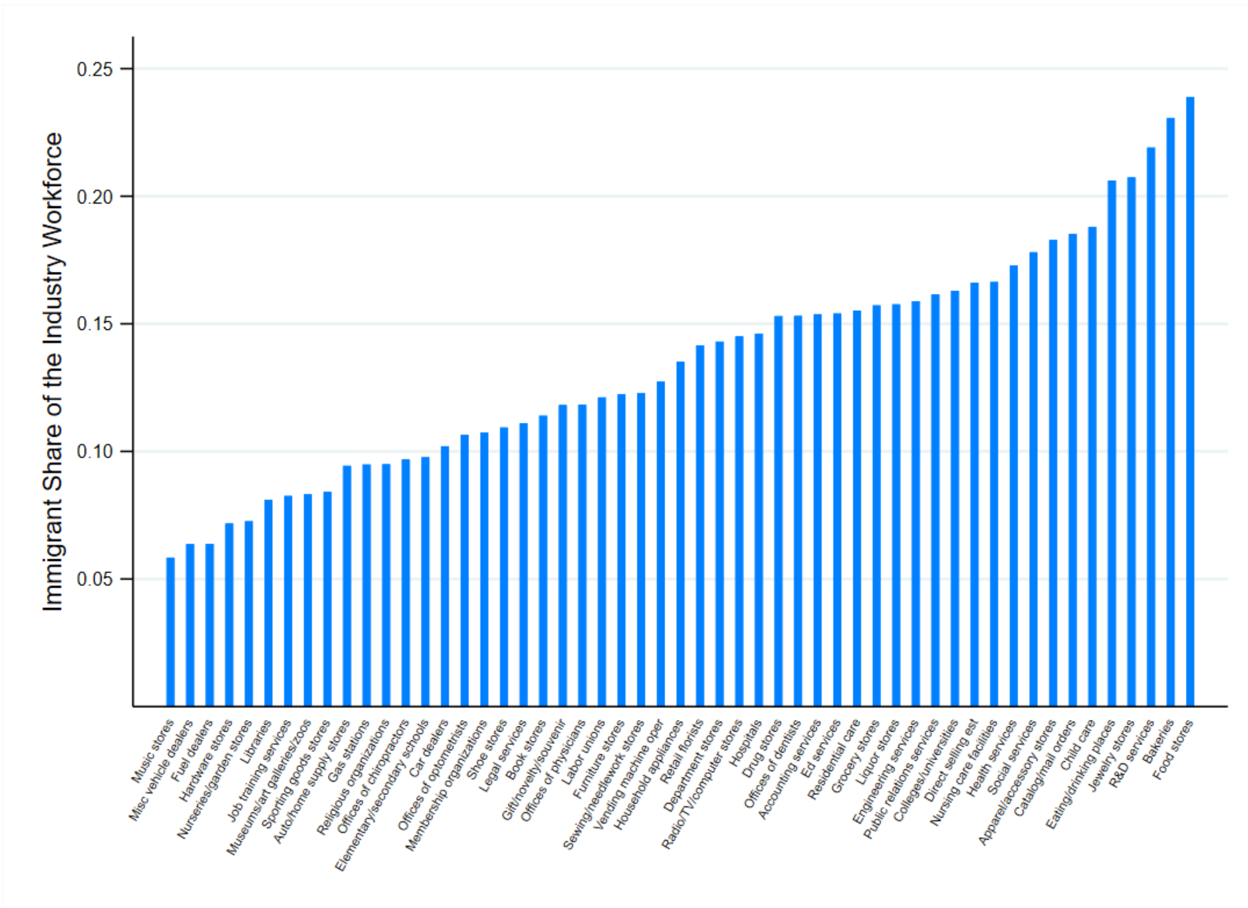
Table 9: DD Model of NAEYC-Accredited Providers

	(1) Num. NAEYC	(2) NAEYC per 1 million	(3) Any NAEYC	(4) Fraction NAEYC
Secure Communities	-0.942	0.653	-0.007	0.001
	(1.370)	(0.751)	(0.014)	(0.004)
Dep. Var. Mean	36.68	40.72	0.954	0.172
N	5,418	5,418	5,418	5,333

Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and AggData from 2011 to 2014
Notes: The data include the number of NAEYC-accredited facilities in a county. Only counties that did not have SC as of May 2011, the first observation in the data, are included. Regressions are weighted by county population. All regressions include county and quarter-year fixed effects as well as a control for the log of county population. Regressions include observations for all available quarters (i.e., approximately two per year). In columnn (1), the outcome of interest is the number of NAEYC-accredited facilities in that county; in column (2), it is the number of NAEYC-accredited providers per 1 million in the population; in column (3), it is a dummy variable that equals one if there are any NAEYC-accredited providers in that county and equals zero otherwise; in column (4), it is the number of NAEYC-accredited providers divided by the number of child care establishments from the QCEW. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

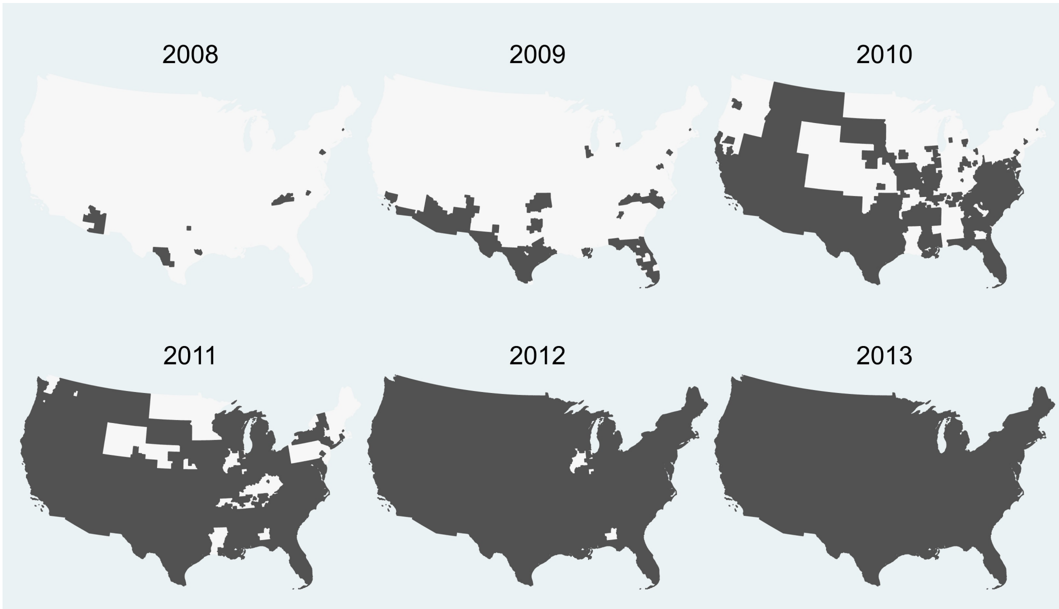
8 Appendix Figures and Tables

Figure A1: Immigrant Share of the Female Labor Force, by Industry



Source: ACS from 2017 to 2019.
Notes: The sectors included here are drawn from the retail trade and professional services industries. All figures are weighted by the ACS person weight.

Figure A2: PUMA-Level Adoption of Secure Communities, 2008-2013



Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014).
Notes: The maps show the PUMA-level adoption of Secure Communities in various years. Shaded PUMAs are those that had Secure Communities active for at least 50% of days in the respective calendar year.

Table A1: Immigrant Share of the Female Labor Force, Child Care and All Other Industries

	Child Care	All Other
U.S.	0.188	0.165
	(0.391)	(0.371)
New York	0.440	0.351
	(0.496)	(0.477)
Los Angeles	0.471	0.382
	(0.499)	(0.486)
Chicago	0.247	0.206
	(0.431)	(0.404)
Houston	0.315	0.275
	(0.465)	(0.447)
Phoenix	0.196	0.174
	(0.398)	(0.379)
Philadelphia	0.132	0.135
	(0.338)	(0.342)
San Antonio	0.113	0.136
	(0.317)	(0.342)
San Diego	0.305	0.285
	(0.461)	(0.451)
Dallas	0.220	0.222
	(0.414)	(0.416)
San Jose	0.518	0.495
	(0.500)	(0.500)

Source: ACS from 2017 to 2019

Notes: All figures are weighted using the ACS person weight. Standard deviations are in parentheses.

Table A2: Native and Immigrant Center-Based Child Care Teachers

	Native	Immigrant
Female	0.976	0.993*
	(0.154)	(0.082)
White	0.638	0.133*
	(0.481)	(0.340)
Black	0.193	0.125*
	(0.395)	(0.331)
Hispanic	0.119	0.529*
	(0.323)	(0.500)
Other race/ethnicity	0.050	0.213*
	(0.218)	(0.410)
Married	0.543	0.689*
	(0.498)	(0.463)
Speaks a non-English language	0.191	0.840*
	(0.393)	(0.367)
Child care experience: 0-5 years	0.272	0.264
	(0.445)	(0.441)
Child care experience: 6-10 years	0.230	0.219
	(0.421)	(0.414)
Child care experience: 11-15 years	0.174	0.246*
	(0.379)	(0.431)
Child care experience: 16-20 years	0.137	0.102*
	(0.344)	(0.303)
Child care experience: 21+ years	0.187	0.170
	(0.390)	(0.376)
Time at current program: 0-11 months	0.178	0.168
	(0.382)	(0.374)
Time at current program: 1-3 years	0.346	0.309
	(0.476)	(0.463)
Time at current program: 4-6 years	0.168	0.148
	(0.374)	(0.356)
Time at current program: 7-9 years	0.079	0.133*
	(0.271)	(0.340)
Time at current program: 10+ years	0.229	0.241
	(0.420)	(0.428)
High school degree or less	0.189	0.190
	(0.392)	(0.392)
Some college	0.283	0.172*
	(0.451)	(0.378)
AA degree	0.195	0.234
	(0.396)	(0.424)
BA+ degree	0.333	0.405*
	(0.471)	(0.491)
ECE major	0.555	0.567
	(0.497)	(0.496)
ECE- or education-related major	0.199	0.157
	(0.399)	(0.364)
Child Development Associate (CDA) credential	0.255	0.472*
	(0.436)	(0.500)
State teaching certification	0.425	0.531*
	(0.494)	(0.500)
Spends 1+ day(s)/month on prof dev	0.396	0.462*
	(0.489)	(0.499)
All Hamre scale items answered correctly	0.547	0.575
	(0.498)	(0.495)
Hourly wage	14.82	16.01*
	(10.17)	(8.01)

Source: 2019 National Survey of Early Care and Education (NSECE)
Notes: All calculations are based on a sample of lead teachers in center-based child care programs. All figures are weighted using the 2019 NSECE sampling weight. Standard deviations are in parentheses. * indicates that the difference between natives and immigrants is significantly different at the 0.10 level.

Table A3: Classroom and Program Characteristics for Native and Immigrant Center-Based Child Care Teachers

	Native	Immigrant
Number of children in classroom	14.28	14.92
	(7.17)	(7.91)
Number of teachers in classroom	2.71	2.31*
	(2.00)	(1.37)
Any black teachers in classroom	0.451	0.421
	(0.498)	(0.494)
Any Hispanic teachers in classroom	0.350	0.711*
	(0.477)	(0.454)
Any white teachers in classroom	0.827	0.576*
	(0.379)	(0.495)
Any Asian teachers in classroom	0.086	0.368*
	(0.281)	(0.483)
Share of white children in classroom	60.20	37.65*
	(33.57)	(33.05)
Share of Hispanic children in classroom	13.96	35.30*
	(22.44)	(37.25)
Share of black children in classroom	22.95	22.79
	(29.93)	(28.94)
Share of children speaking non-English language	13.38	42.99*
	(21.49)	(35.86)
Provider located in high-poverty neighborhood	0.261	0.311*
	(0.439)	(0.463)
Provider located in urban neighborhood	0.656	0.948*
	(0.475)	(0.221)

Source: 2019 National Survey of Early Care and Education (NSECE)
Notes: All calculations are based on a sample of lead teachers in center-based child care programs. All figures are weighted using the 2019 NSECE sampling weight. Standard deviations are in parentheses. * indicates that the difference between natives and immigrants is significantly different at the 0.10 level.

Table A4: Robustness Estimates from the Triple Differences Model of Child Care Participation

	Dep Var: Child Care Participation			
	(1)	(2)	(3)	(4)
Secure Communities	0.0106**	-0.0056	0.0069*	0.0039
	(0.0043)	(0.0050)	(0.0038)	(0.0038)
Treated × Secure Communities	-0.0182***	0.0013	-0.0152***	-0.0118***
	(0.0032)	(0.0035)	(0.0034)	(0.0035)
Comparison Group	5-year-olds	4-year-olds	6-year-olds	7-year-olds
Observations	877,256	578,722	879,522	883,397
PUMA Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Time-varying PUMA Controls	Yes	Yes	Yes	Yes

Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014
Notes: The analysis sample includes children ages three to seven of citizen mothers ages 20 to 64. The model includes a binary indicator denoting the enactment of Secure Communities and a variable denoting the interaction of Secure Communities enactment with the age of the child ("Treated"). Child-age is expressed as a binary indicator equal to one for children ages three and four and zero for children age five (model (1)), age six (model (2)), and seven (model (3)). The model includes controls for child-age fixed effects, baseline child and mother characteristics, baseline PUMA characteristics, PUMA fixed effects, and year fixed effects. The model is weighted by the ACS person weight, and the standard errors are corrected for clustering at the PUMA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Robustness Estimates from the Triple Differences Model of Child Care Participation: October CPS

	Dep Var: Child Care Participation				
	(1)	(2)	(3)	(4)	(5)
Secure Communities	0.0059	0.0086	0.0129	0.0204	0.0203
	(0.0184)	(0.0196)	(0.0201)	(0.0164)	(0.0151)
Treated × Secure Communities	-0.0210	-0.0242*	-0.0240*	-0.0440***	-0.0373***
	(0.0134)	(0.0143)	(0.0141)	(0.0147)	(0.0123)
Comparison Group	5-year-olds	5-year-olds	5-year-olds	6-year-olds	7-year-olds
Observations	32,706	32,706	32,706	32,941	32,869
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Demographic Controls	No	Yes	Yes	Yes	Yes
Time-varying State Controls	No	No	Yes	Yes	Yes

Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and October CPS from 2005 to 2014
Notes: The analysis sample includes children ages three to seven of citizen mothers ages 20 to 64. The model includes a binary indicator denoting the enactment of Secure Communities and a variable denoting the interaction of Secure Communities enactment with the age of the child ("Treated"). Child-age is expressed as a binary indicator equal to one for children ages three and four and zero for children age five (models (1)-(3)), age six (model (4)), and seven (model (5)). The model includes controls for child-age fixed effects, baseline child and mother characteristics, baseline PUMA characteristics, state fixed effects, and year fixed effects. The model is weighted by the CPS person weight, and the standard errors are corrected for clustering at the PUMA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Additional Robustness Estimates from the Triple Differences Model of Child Care Participation

	Dep Var: Child Care Participation					
	(1)	(2)	(3)	(4)	(5)	(6)
Secure Communities	0.0287***	0.0116***	0.0073*	0.0121***	0.0113**	0.0109**
	(0.0073)	(0.0043)	(0.0041)	(0.0040)	(0.0044)	(0.0052)
Treated × Secure Communities	-0.0177***	-0.0182***	-0.0136***	-0.0208***	-0.0175***	-0.0142***
	(0.0032)	(0.0032)	(0.0028)	(0.0033)	(0.0032)	(0.0034)
Comparison Group	5-year-olds	5-year-olds	5-year-olds	5-year-olds	5-year-olds	5-year-olds
Observations	877,256	877,256	877,256	992,774	859,133	692,374
State × Year Fixed Effects	Yes	No	No	No	No	No
Add'l PUMA Controls	No	Yes	No	No	No	No
Treated × PUMA Controls	No	No	Yes	No	No	No
Child's Citizenship Status	No	No	No	Yes	No	No
Exclude AZ	No	No	No	No	Yes	Yes
Exclude AZ, CA, NM, TX	No	No	No	No	No	Yes

Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014

Notes: The analysis sample includes children ages three to five of citizen mothers ages 20 to 64. The model includes a binary indicator denoting the enactment of Secure Communities and a variable denoting the interaction of Secure Communities enactment with the age of the child ("Treated"). Child-age is expressed as a binary indicator equal to one for children ages three and four and zero for children age five. The model (unless specified otherwise in the table) includes controls for child-age fixed effects, baseline child and mother characteristics, baseline PUMA characteristics, PUMA fixed effects, and year fixed effects. The model is weighted by the ACS person weight, and the standard errors are corrected for clustering at the PUMA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Estimates from the DD Model of Occupational Choices: Robustness

	Dep Var:=1 if Occupation is Child Care						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Low-Education Immigrants							
Secure Communities	-0.0025**	-0.0024*	-0.0025**	-0.0024**	-0.0025*	-0.0022*	-0.0025**
	(0.0012)	(0.0013)	(0.0012)	(0.0012)	(0.0014)	(0.0012)	(0.0012)
Sample	Full	Entry>1980	Full	Full	Excl. Big PUMAs	Excl. Early Adpt	Excl. AZ
Observations	746,713	630,178	746,713	746,713	569,319	703,834	726,815
PUMA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	No	No	No	No	No	No	No
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-Varying PUMA Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	No	English lang.	Addtl. PUMA	No	No	No
Panel B: High-Education Immigrants							
Secure Communities	0.0012	0.0017	0.0011	0.0011	-0.0005	0.0018	0.0013
	(0.0017)	(0.0020)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Sample	Full	Entry>1980	Full	Full	Excl. Big PUMA's	Excl. Early Adpt	Excl. AZ
Observations	339,683	288,860	339,683	339,683	278,617	325,122	334,356
PUMA Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region x Year FE	No	No	No	No	No	No	No
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-Varying PUMA Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	No	English lang.	Addtl. PUMA	No	No	No

Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014
Notes: The analysis sample includes immigrant women ages 20 to 55. The sample "Low-Education" consists of women with less than a four-year college degree, while the sample "High-Education" consists of women with a four-year degree or more. The model includes a binary indicator denoting the enactment of Secure Communities, as well as controls for individual and PUMA characteristics, PUMA fixed effects, and year fixed effects. The model is weighted by the ACS person weight, and the standard errors are corrected for clustering at the PUMA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.