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Secure communities as immigration enforcement: How secure is the child care market?

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ABSTRACT

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 advantaged children and in jurisdictions with a greater fraction of undocumented individuals. We also find that SC reduced the equilibrium supply and wages of immigrant *and* native workers in the center-based sector as well as the number of center-based facilities. There is no compensating increase in the home-based or private household sectors. Our findings suggest that immigrants and natives are likely to be complements in child care service production.

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).[2] 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; 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

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2 In this context, an immigrant is defined as someone who is born abroad, and is either a non-citizen or a naturalized citizen.

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deportation-driven reductions in immigrant labor supply. Instead, such effects are expected to operate through two alternative channels, one affecting the supply of child care workers and the other affecting the demand for child care services. First, SC created a climate of fear and confusion within immigrant communities around the possibility of being deported, leading to a generalized "chilling effect" in which (documented and undocumented) 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 not just immigrants' employment in the child care industry but also 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. They are also likely to interact with government officials who regularly inspect child care centers, often unannounced. 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 parental employment. Previous work finds that SC reduced the employment and wages of immigrant *and* native workers, most likely because of a decrease in overall job creation (due to higher labor costs since immigrants are less willing to work) and to a decline in local consumption (East et al., 2023). In addition, 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 and availability of household and work-enabling services (other than child care) in ways that reduce the amount of maternal time allocated to employment. Indeed, a recent paper by East and Velasquez (2024) 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 females. 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). Together, this research suggests that any SC-induced reductions in 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 by studying the impact of SC on child care participation among preschool-age children of citizen mothers. Relying on data from the American Community Survey (ACS) over the years 2005 to 2014, we estimate difference-in-differences (DD) models that exploit the staggered introduction of SC across counties. The outcome is defined as a binary indicator equal to one if a given child attends a child care program. Given that the ACS inquires about school (including child care) attendance for individuals ages three and over, we restrict the analytic sample to children ages three and four.[3] Informed by the research discussed above showing that low-skilled immigration (and related policy reforms) may have different effects on low- and high-skilled natives, an important feature of our analysis is to examine the impact of SC separately for subsets of disadvantaged and advantaged families, as defined by mothers' marital status and education as well as family income.

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 0.6 percentage points. Given that the pre-reform participation rate is 48%, this result implies that utilization fell by 1.3%. Consistent with (East and Velasquez, 2024) and East et al. (2023), we find substantial heterogeneity across families, with children of advantaged mothers experiencing much larger participation drops than their disadvantaged counterparts. Furthermore, the estimated reductions are larger in areas with greater populations of Hispanic and undocumented individuals, as one would expect under the assumption that such areas might be more affected by a policy of immigration enforcement. Our results are robust to a variety of specification changes, such as the exclusion of early-adopting and border jurisdictions. Finally, the event study analyses using the standard two-way fixed effects (TWFE) design as well as the Borusyak et al. (2024) and Callaway and Sant'Anna (2021) estimators show that the drop in child care participation occurs after the enactment of SC, providing further evidence in support of our DD model.

We then turn our attention to measures of the provider-side of market by analyzing the equilibrium quantity supplied and compensation of child care labor. We first use data from the Quarterly Census Of Employment and Wages (QCEW) between 2005 and 2014 to estimate the impact of SC on the number of child care industry establishments and workers. Our DD estimates show that the introduction of SC reduced the number of child care establishments by 1.6% and the number of child care industry employees by 1.5%. To explore heterogeneity in these employment changes by education and immigrant status, we draw once again on the ACS, selecting a sample of prime working-age (immigrant and native) female respondents. Our key outcomes include a proxy for child care supply, defined as a binary indicator for whether a given respondent 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., 2023).

Consistent with a "chilling effects" story, the DD results show 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. 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. Our results are robust to a range of specification tests, and the event-study analyses show no evidence of pre-trends.

In a final set of analyses, we study the implications of SC adoption for child care quality, as proxied by the density of providers accredited by the National Association for the Education of Young Children (NAEYC). Despite the overall decrease in child care supply,

[3] Since five-year-olds are largely enrolled in kindergarten – recent estimates show that 72% of such children are in kindergarten (Snyder et al., 2019) – we exclude these (and older) children from the main analysis.

our analysis of quality shows no change in the number of high-quality, NAEYC-accredited programs.

The findings in this paper have a number of important policy implications. First, by reducing the supply of child care, SC further destabilized an already insecure industry. Indeed, recent work shows that the child care industry is characterized by comparatively high rates of staff turnover (Bassok et al., 2013; Brown and Herbst, 2022), is among the most sensitive sectors to macro-economic shocks (Brown and Herbst, 2022), and was severely affected by the recent COVID-19 pandemic (Ali et al., 2021). Our results suggest that immigration enforcement policies may be a further destabilizing force. The reduction in high-skilled teachers may be particularly concerning insofar as it is indicative of a decrease in the availability of high-quality services, which are shown to be beneficial to child development (Auger et al., 2014; Hamre et al., 2014; Markowitz, 2019). Second, the loss of immigrant child care workers raises concerns about the availability of caregivers who can meet the cultural, linguistic, and developmental needs of immigrant children. One in four preschool-age children live with at least one immigrant parent (Migration Policy Institute, 2021). Of these, 52% regularly attend a child care arrangement (authors' calculations). 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). In the early childhood space, a study of Head Start programs finds that teacher–child matches based on race/ethnicity improves parental engagement and reduces child absences (Markowitz et al., 2020). 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.

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 impact of SC on the overall low-skilled labor market (East et al., 2023) and on maternal employment (East and Velasquez, 2024). Neither study, however, focuses specifically on spillovers to the child care industry.[4] Our paper also contributes to a larger literature using the traditional shift-share methodology to study how immigrant in-flows affect immigrant and native labor market outcomes (Cortes, 2008; Cortes and Tessada, 2011) as well as maternal time investments in children (Amuedo-Dorantes and Sevilla, 2014). Again, none of these papers examine child care-related outcomes.

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 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 by exploiting a plausibly exogenous policy shock that led to widespread reductions in immigrant labor supply. Second, 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 before being revoked again by President Biden. Given the longstanding uncertainty about the most appropriate level of interior enforcement, it is important to understand how such programs affect labor markets that rely heavily on immigrant workers.

Finally, our paper may shed 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. This logic would seem to imply that a decrease in the labor supply of low-skilled female immigrants would increase the wages of native child care workers. However, we find the opposite effect, which seems to run contrary to the view that an increase in the supply of immigrant labor places downward pressure on natives' wages. In addition, 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) implies that both sets of workers possess non-substitutable skills to the production of child care. Therefore, immigrants and natives may not compete for the same child care jobs.

The remainder of the paper proceeds as follows. Section 2 provides a descriptive portrait of the immigrant child care workforce, discusses the roll-out of the SC program, and provides a theoretical framework for understanding the potential impact of SC. 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 ACS surveys 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 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 as for- or non-profit centers, community-based organizations, or places of worship, in which classrooms are led by head and (sometimes) assistant

[4] It is important to note that East and Velasquez (2024) conduct an auxiliary analysis on the combined child care and household services sector, showing that SC reduced employment but increased wages in the sector. Our paper is distinct from this work in at least two ways. First, our paper focuses specifically and exclusively on the child care market. Furthermore, the authors do not conduct separate analyses on the private household, home-based, and center-based child care sectors (or on separate education and racial/ethnic groups), which, when performed, lead to different conclusions about the impact of SC.

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

teachers. Immigrants make up a smaller share of the workforce in the center-based sector, comprising only 15% of its employees.

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 native counterparts. Although immigrants and natives have similar (child care) work experience profiles, 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 qualifications like the Child Development Associate (CDA) credential and state teaching certifications, and they are more likely than natives to invest 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 on some 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. 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, while native lead teachers are more likely to work in classrooms with non-minority 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. Together, such patterns suggest that immigrants and natives may not compete for the same child care jobs. Instead, they likely possess complementary or at least imperfectly-substitutable skills, an issue we return to in Section 7 when discussing the results.

2.2. The secure communities program

Enacted in the fall of 2008 by the U.S. Immigration and Customs Enforcement Agency (ICE), the 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, 2008b). A collaboration between 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, may be deportable. The program prioritized the apprehension and removal of non-citizens with serious ("Level 1") prior convictions, including homicide, assault, and kidnapping.

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, 2008b). 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).[8]

Under SC, however, fingerprints sent to the FBI were automatically routed to DHS/ICE for analysis in its Automated Biometric Identification System (IDENT), a database of every fingerprinted non-citizen in the U.S.[9] ICE agents then reviewed the arrested person's immigration status – assuming a fingerprint match occurred – to determine whether he/she was in violation of immigration law. If such a determination was made, ICE agents could request that local law enforcement hold the individual for up to 48 h (known as a "detainer") so that ICE could transfer him/her to federal custody for the initiation of removal proceedings (U.S. Immigration and Customs Enforcement, 2008b). 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. Figs. 1 and 2 provide additional information on the temporal and geographic roll-out of SC. Panel A of Fig. 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 starting in 2010. 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 Fig. 1 and in Fig. 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, 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 (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 male (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.

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

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

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

[8] 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).

[9] 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.

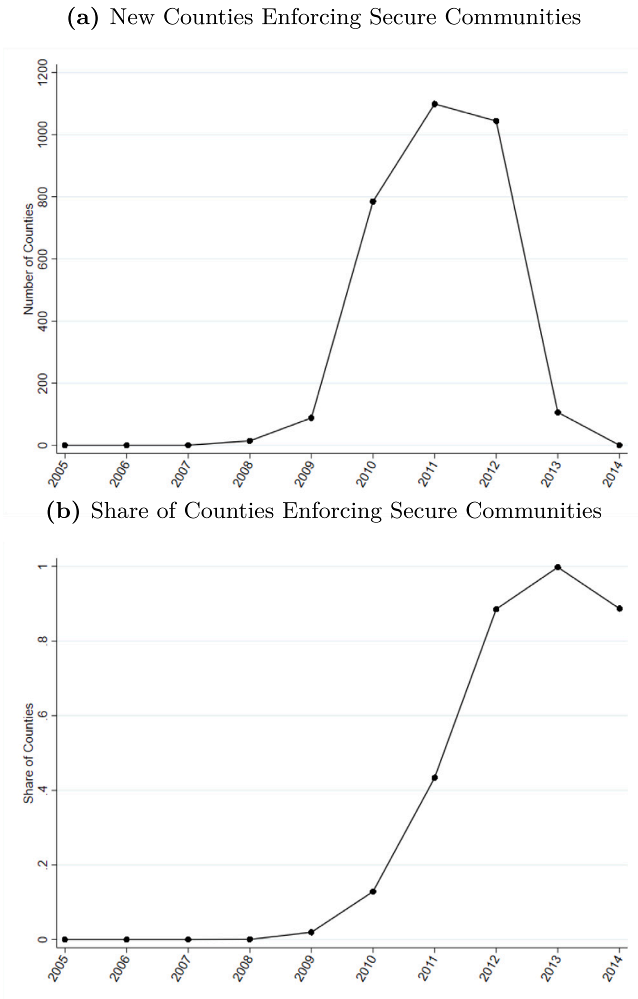

Fig. 1. Adoption of Secure Communities, 2005–2014.
Notes: Panel (a) shows the number of new counties enforcing the Secure Communities program in each year between 2005 and 2014. Panel (b) shows the cumulative share of counties enforcing the Secure Communities program in each year between 2005 and 2014.
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014).

2008a).[10] 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 advantage is that DHS was fairly clear about the other criteria that would drive early-adoption decisions. 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, 2008a). 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. The final advantage is that participation in SC by local communities was mandatory and virtually impossible to opt out of, although initially there was substantial confusion over the program's compulsory nature (Cox and Miles, 2013; U.S. Department of Homeland Security, 2012). Indeed, 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. These institutional features make pre-reform adjustments and endogenous participation by communities less likely.

2.3. Theoretical considerations

There are several channels through which SC can affect the child care market. Generally speaking, changes in child care participation and employment could be due to factors affecting child care providers on the supply side or due to changes in parental employment or preferences on the demand side. Regarding the supply side, SC might reduce the willingness of female immigrants to work in child care – perhaps because of a "chilling effect" – thereby affecting the available labor pool for child care providers. On the demand side, there are several possible channels, including a decrease in native and immigrant parental employment as well as a chilling effect that reduces the willingness of immigrants to bring their children to child care centers. Each of these potential mechanisms and their observable effects is explained in more detail below.

To understand how these channels may affect the child care market, it is useful to describe a simple model of child care production, which can be expressed as: $f(l_{il}, l_{ih}, l_{nl}, l_{nh}, k)$. Child care slots are produced using inputs of capital (k) and labor, of which we consider four types: low-education immigrants (l_{il}), high-education immigrants (l_{ih}), low-education natives (l_{nl}), and high-education natives (l_{nh}). For context, 13% of female child care workers are low-education immigrants, 3% are high-education immigrants, 66% are low-education natives, and 18% are high-education natives, as shown in Table A4.[11] These labor types may be complements or substitutes in production, with different implications for the predicted effect of SC. It is important to consider low- and high-education workers as separate inputs in this context since many classrooms consist of a high-education lead teacher paired with an assistant teacher who may have less formal education. In addition, separating immigrants and natives is important because they may have different skills, and parents exhibit a preference for homophilous caregivers (Boyd-Swan and Herbst, 2019). Furthermore, we assume that the child care options in different sectors (i.e., center-based, home-based, and private households) act as substitutes.

The first channel through which SC might affect the child care market is a reduction in the willingness of female immigrants to work – particularly in sectors with more contact with government authorities – by way of a "chilling effect".[12] 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 who feared deportation (Lind, 2014).[13] Such fears led immigrants to report fewer crimes and limit their assistance with crime scene investigations (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 (Fernelius and Garcia,

[10] In addition, not all local police forces had live fingerprint scanning capability at the start of SC's activation period.

[11] Interestingly, as shown in Table A5, immigrants and natives of the same education level choose child care employment at similar rates, with about 3% of immigrants and natives without a bachelor's degree employed in child care and 2% of immigrants with a bachelor's degree employed in child care.

[12] Table A5 shows that female immigrants are less likely to be in the labor force than female natives, but even still, 75% of female immigrants without a bachelor's degree are in the labor force, along with 85% of female immigrants with a bachelor's degree.

[13] For example, Boston's then-mayor argued that residents believed police officers were working with ICE agents to deport immigrants, and that such beliefs would erode the relationship between police and residents (Preston, 2011).

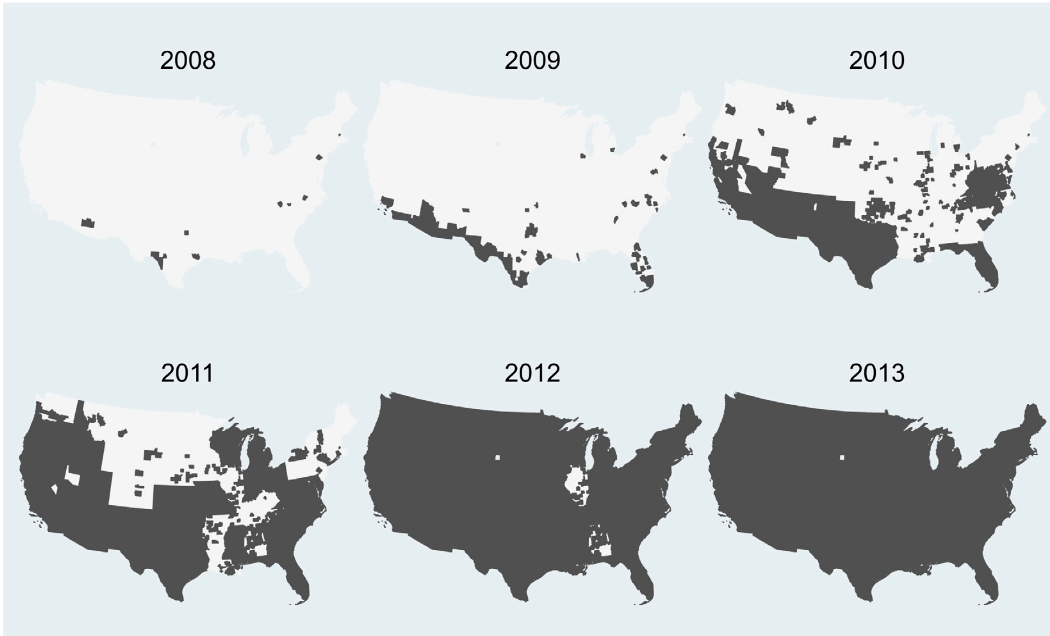

Fig. 2. County-level adoption of secure communities, 2008–2013.
Notes: The maps show the county-level adoption of Secure Communities in various years. Shaded counties are those that had Secure Communities active for at least 50% of days in the respective calendar year. There are no data for Shannon County, South Dakota, since the county does not have an administrative office. Neighboring Fall River County serves as its administrative center.
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014).

2018).[14] Finally, worries over deportation 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).

To limit their interactions with government authorities, female immigrants may be less likely to seek child care employment, particularly in the formal sector where their employment and earnings are reported to the government, and the workplace is subject to (often unannounced) government inspections. A reduction in the willingness to work in the formal sector would have the largest impact on center-based providers and can be represented by an upward shift of the labor supply curve for immigrants, which in the absence of changes in the demand for immigrants would reduce their equilibrium quantity and increase their equilibrium wage. Any labor types that are substitutes for immigrant labor would expect to see an increase in wages and employment, while any labor types that are complements would expect to see a decrease in wages and employment. In summary, a chilling effect would lead to a decrease in immigrant employment in the center-based sector with possible smaller declines in the home-based and private household sectors. Such declines would be larger among Hispanic and low-education immigrants, who are more likely to be undocumented (East et al., 2023). Furthermore, the wages of immigrants might increase due to the decrease in labor supply, although East et al. (2023) finds no change in immigrant wages despite the decrease in labor supply. The wages and employment of native workers will increase if they are substitutes for immigrants and decrease if they are complements.

Second, SC may influence the demand for child care services and therefore employment and wages in the sector. For immigrants, any chilling effect that reduces labor force participation could decrease the demand for child care for their child(ren). Indeed, East et al. (2023) find that SC decreased employment among low-education immigrants, particularly males. In addition, a chilling effect could reduce the willingness of immigrant parents to bring their child(ren) to a child care provider. Under both scenarios, we would expect to see a decrease in child care participation among children of immigrants, leading to a decrease in employment and wages in the center-based sector. The reduction in child care employment is expected to be larger among immigrants, since they work in classrooms with a higher share of Hispanic children, on average (Table A3). An increase in parent-only care would additionally lead to a decline in the demand for child care services, while a decrease in the willingness of parents to bring children to center-based settings could increase the demand for more informal services. Therefore, the impact of SC's chilling effect on the home-based and private household sectors is ambiguous.

Finally, SC can influence the demand for child care among native parents by reducing their employment and wages. Indeed, East et al. (2023) provide evidence that SC decreased parental labor supply due to an increase in labor costs from the decline in immigrant labor supply (which in turn reduces overall job creation) and a reduction in local consumption. Another mechanism operates through a change in the price or availability of goods and services complementary to employment (other than child care). East and Velasquez (2024) find that SC decreased the supply of household workers (e.g., cleaners) and increased their wages. If native parents increase non-work, the demand for child care should fall accordingly. In isolation, this shift is expected to decrease the equilibrium number of child care workers and their wages across all sectors, although lower wages could induce a shift from more expensive center-based care to less formal home-based care. Reductions in child care employment due to changes in the demand for child care among native households would likely affect native and immigrant child care workers. In fact, native workers are likely to be more affected than immigrants from a reduction in child care demand

[14] 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).

because they serve a higher fraction of white children.[15] Previous work also suggests that immigrant teachers' employment is not very sensitive to changes in child care demand: when child care employment falls during economic downturns, the employment of workers who are not fluent in English remains steady (Brown and Herbst, 2022).

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 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 available in the ACS.[16] 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 and four whose mothers are citizens ages 20 to 64. These restrictions provide a sample of 578,722 children. Citizens are defined as U.S.-born individuals or those who are foreign-born but report being naturalized citizens. Our key outcome variable is a measure of children's child care participation. Specifically, it is a binary indicator equal to one if a given child attends child care or preschool 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.[17] Importantly, the questionnaire prompts individuals to include child care services (e.g., nursery school and preschool) in each household member's school attendance response. Approximately 49% of three- and four-year-olds (of citizen mothers) attended child care over the study period. The participation rate among four-year-olds (62%) is substantially higher than that among three-year-olds (36%).

A key caveat regarding the ACS's school attendance question is that it 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 enforcement policy influences participation in the informal sector.

3.2. Child care labor market

The analysis of the child care labor market draws on two data sources. First, we use the Quarterly Census of Employment and Wages (QCEW), which is an establishment-level database of employment information for individuals covered by state unemployment insurance (UI) laws. These data are advantageous because they represent a virtual census of firms from all NAICS industries.[18] Specifically, the public release version of the data includes the quarterly number of employees and establishments disaggregated by industry (up to the six-digit NAICS industry code), ownership status, and county. Our analysis relies 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 important to note that the data include workers performing a variety of pedagogical (e.g., teachers and teacher assistants) and non-pedagogical (e.g., CEOs and managers of national chains, program administrators, food preparation workers, and bus drivers) tasks. The data on employment contain 65,854 county × quarter combinations, while the data on establishments contain 112,061 county × quarter combinations.

We then return to the ACS to examine heterogeneity and a different measure of employment as well as wages in the child care industry. The sample includes females (immigrants and natives) ages 20 to 55, regardless of whether they are employed. Males are not included in the sample, given that they comprise only 5% of the child care workforce (authors' calculation). We further limit the sample to those not residing in group quarters and those not in the Armed Services.[19] 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 of employment in the child care industry. Specifically, the outcome is expressed as a binary indicator equal to one if a given respondent 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 those 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 and working in the "child daycare services" industry with an occupation of child care worker or education administrator. Finally, center-based workers include the non-self-employed working 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 individuals 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.

[15] Table A3 shows that native child care teachers' classrooms are on average 60% white, while immigrant teachers' classrooms are only 38% white.

[16] 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.

[17] 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.

[18] There are at least two additional advantages of the QCEW compared to the ACS. It provides child care industry data at the county-level, which corresponds with the data on SC's roll-out. Furthermore, it provides higher-frequency observations (i.e., four per year), allowing for a tighter temporal match between the implementation dates of SC and the reporting of child care data.

[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 h per week.

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 Fig. 2 shows this information at the county-level.

4. Empirical implementation

To study the impact of SC on child care participation, we exploit the staggered introduction of the program across counties between 2008 and 2013, as highlighted in Figs. 1 and 2. Using the ACS sample of three- and four-year-old children of citizen mothers, our DD model is specified in the following manner:

$$Y_{ipt} = \alpha + \beta_1 SC_{pt} + \theta X'_{ipt} + \eta Y'_{pt} + \zeta_p + \xi_t + \varepsilon_{ipt}, \tag{1}$$

where Y_{ipt} denotes a binary indicator that equals one if child i in PUMA p and year t is enrolled in child care and zero otherwise, while the variable SC_{pt} is the population-weighted average fraction of the year in which SC was active in PUMA p and year t. The variable takes a value of zero in PUMA-years in which the program was never in effect, and it takes a value of one when the program was in effect for the full year. The coefficient of interest is β_1, providing the DD estimate of the impact of SC on child care participation.

The matrix X'_{ipt} represents a set of observable child and maternal characteristics, including the child's age, gender, and citizenship status as well as binary indicators for the mother's age, race, marital status, education level, and number of own children. The matrix Y'_{pt} includes a set of time-varying PUMA controls. We account for the share of 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. 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 introduction. 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.[22] The model is weighted by the ACS person weight, and the standard errors are adjusted for clustering at the PUMA level.

In light of previous work finding that immigration and related policy reforms may have different effects on the labor supply of low- and high-skilled natives, we investigate whether SC had differential effects on child care participation across a wide range of proxies for economic advantage (Cortes and Tessada, 2011; East and Velasquez, 2024; East et al., 2023). We define disadvantaged families as those whose mothers who are younger (i.e., ages 20 to 35), non-white, never married, with less than a high school degree, and from families at or below the sample median income (i.e., $55,000). Advantaged families are defined as those whose mothers are older (i.e., ages 36 to 64), white non-Hispanic, ever married, with at least a high school degree, and from families above the sample median income.

The key identifying assumption in our DD model is that there are no unobserved, county-specific shocks that occurred contemporaneously with the enactment of SC that caused child care participation to trend differently across counties. In particular, we assume that in the absence of SC the trend in child care participation among three- and four-year-olds would have evolved smoothly in the period following SC's activation. We probe this assumption in a variety of ways. First, some states may have undertaken their own immigration enforcement activities that had similar chilling effects, while jurisdictions in other states may have self-designated as "sanctuary cities", whose laws protect undocumented immigrants from deportation. Furthermore, states on the border with Mexico as well as early-adopting jurisdictions may have deployed enforcement technologies or specialist labor even in the absence of SC. Thus, we conduct sensitivity tests in which select states that fit any of these criteria are removed from the analysis. Second, we estimate TWFE event-study models that include a set of time-to-enactment indicator variables. Formally, the model is specified as follows:

$$Y_{ipt} = \alpha + \sum_{j=-5, j\neq -1, j\neq -3}^{4} \beta_1^j d_{pt}^{0+j} + \theta X'_{ipt} + \eta Y'_{pt} + \zeta_p + \xi_t + \varepsilon_{ipt}, \tag{2}$$

where d_{pt}^{0+j} denotes a set of three pre-SC indicator variables and a set of five post-SC indicators centered around the year in which each county activated SC, t_0.[23] To avoid multicollinearity, we omit from the model the variables denoting the year prior and three years prior to SC's enactment. Thus, the coefficients β_1^j estimate the difference in child care participation in each year before and after SC's enactment relative to the year prior and three years prior to enactment. Support for the identifying assumption would emerge if the pre-reform indicator variables are not statistically significant, suggesting that any post-reform trend changes are due to SC.[24] In other words, there should be no evidence of a differential pre-reform trend evident in Eq. (2).

Because our identification strategy relies on a staggered roll-out design with variation in treatment timing, the TWFE estimates could be biased (Borusyak et al., 2024). In particular, bias can occur if there are heterogeneous or dynamic treatment effects, and already-treated units are used as the comparison group for newly-treated units.[25] Therefore,

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

[22] 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.

[23] 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.

[24] Recall that in Eq. (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 any part of 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.

[25] Such issues would occur in our setting if the child care market adjusted over several years to SC, and since all counties are eventually treated, some of the "bad" comparisons between newly-treated and already-treated units are made.

Table 1
Estimates from the DD model of child care participation, full sample.
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014.

	Dep Var:= 1 if Child is Enrolled in Child Care			
	(1)	(2)	(3)	(4)
Secure Communities	−0.0084**	−0.0064	0.0079**	−0.0008
	(0.0034)	(0.0045)	(0.0039)	(0.0049)
Secure Communities × Undocumented			−0.4525***	−0.1476***
			(0.1069)	(0.0543)
Sample	Full	Full	Full	Full
Observations	578,722	578,722	578,722	578,722
Dep Var Mean	0.481	0.481	0.481	0.481
Demographic Controls	No	Yes	No	Yes
Time-Varying PUMA Controls	No	Yes	No	Yes
PUMA Fixed Effects	No	Yes	No	Yes
Year Fixed Effects	No	Yes	No	Yes

Notes: The analysis sample includes children ages three and four of citizen mothers ages 20 to 64. The dependent variable is an indicator that equals one if a child is enrolled in child care and equals zero otherwise. Columns (1) and (3) include no controls. Columns (2) and (4) add the child and mother demographic characteristics, PUMA characteristics, PUMA fixed effects, and year fixed effects. Columns (3) and (4) include an interaction between the Secure Communities variable and a proxy for the 2005 PUMA share of the population that is undocumented. Undocumented is defined as the share of low-education Hispanic immigrants arriving in the U.S. after 1980. The model is weighted by the ACS person weight, and the standard errors are corrected for clustering at the PUMA level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

we examine whether the standard TWFE results are consistent with two alternative estimators, as described in Borusyak et al. (2024) and Callaway and Sant'Anna (2021), which are robust to heterogeneous treatment effects in a staggered roll-out setting. Broadly, Borusyak et al. (2024) is an imputation estimator that uses predicted values of the outcome variable based on a regression of the outcome on not-yet-treated observations to estimate the DD effect, while Callaway and Sant'Anna (2021) uses the last period before treatment as the counterfactual. For Borusyak et al. (2024), the pre-period estimates are computed by using observations from all periods before the first estimated event-time coefficient (e.g., if the pre-period goes back to four years before treatment, then the imputed counterfactual values are based on observations five or more years before treatment), while in Callaway and Sant'Anna (2021) the pre-period coefficients are estimated using the immediately-prior period as the counterfactual.

Following the analysis of child care participation, we turn to the provider-side of the market, analyzing the impact of SC on the quantity of child care services supplied and the compensation of child care workers. These analyses are similarly based on a DD framework in which we rely on the geographic and temporal roll-out of the program. First, we use data from the QCEW to estimate the impact of SC on child care industry employment and establishments. Our model is specified as follows:

$$Y_{ct} = \alpha + \beta_1 SC_{ct} + \eta log(pop_{ct}) + \zeta_c + \xi_t + \varepsilon_{ct}, \tag{3}$$

where Y_{ct} is either the log of average monthly employment or establishments in county c and quarter t, SC_{ct} is population-weighted average fraction of the year in which SC was active in county c and quarter t, and $log(pop_{ct})$ is the log of total county level population for quarter t. Population is measured annually, so this measure is the same for all quarters within a given year. The ζ_c and ξ_t denote county and quarter-year fixed effects, respectively. The regression is weighted by county population, and the standard errors are adjusted for clustering at the county level. The coefficient of interest is β_1, which indicates that the enactment of SC is associated with a β_1*100% change in the number of child care employees or establishments. The identifying assumption for this model is that, in the absence of SC adoption, the outcomes would have trended similarly in earlier-treated and later-treated counties. To test for pre-trends, we implement an event-study specification analogous to that found in Eq. (2). We also present event-study estimates using the alternative estimators from Borusyak et al. (2024) and Callaway and Sant'Anna (2021).

Next, we study heterogeneity in the changes in employment and wages in the child care industry using ACS data between 2008 and 2014. Our DD model is specified as follows:

$$Y_{ipt} = \alpha + \beta_1 SC_{pt} + \theta X'_{ipt} + \eta Y'_{pt} + \zeta_p + \xi_t + \varepsilon_{ipt}, \tag{4}$$

where Y_{ipt} is either a binary indicator for employment in the child care industry or the log of hourly wages of female 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 whether female respondents work in the child care industry. The main variable of interest is SC_{pt}, which is defined in the same manner as Eq. (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 and ethnicity, educational attainment, current school enrollment, marital status, and the number of own children. It also include a set of PUMA-level time varying characteristics, including the share foreign born, population density, and a binary indicator equal to one if a 287(g) agreement is in effect. All other controls are the same as those in Eq. (1). Recall that this model is estimated on subsets of low- and high-education immigrants and natives, and for three sectors of the child care market (i.e, private household, home-based, and center-based). The model is weighted by the ACS person weight, and the standard errors are adjusted for clustering at the PUMA level.

The key identifying assumption in Eq. (4)'s DD model is that there are no unobserved, geography-specific (i.e., county or PUMA) shocks that caused the child care labor market outcomes to trend differently across geographies. To test for the presence of pre-trends, we present results from the standard TWFE event-study analysis analogous to Eq. (2) as well as estimates using the alternative estimators outlined in Borusyak et al. (2024) and Callaway and Sant'Anna (2021).

5. Results

The discussion of results proceeds in two steps. We begin by presenting results from the DD model of child care participation (i.e., Eqs. (1) and (2)). We then turn our attention to the analysis of child care labor supply (i.e., Eqs. (3) and (4)). All of the robustness checks are presented alongside the main results for each outcome.

5.1. Child care participation

Columns (1) and (2) of Table 1 present the baseline results from the DD model of child care participation. Column (1) includes no controls, while column (2) adds the child and mother characteristics, PUMA characteristics, PUMA fixed effects, and year fixed effects. The estimates suggest that the enactment of SC reduced the likelihood that children participate in child care by 0.6 to 0.8 percentage points. The coefficient magnitudes are indicative of fairly small effects. Indeed,

Table 2
Estimates from the DD model of child care participation, by demographic sub-group.
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014.

	Dep Var:= 1 if Child is Enrolled in Child Care				
	(1)	(2)	(3)	(4)	(5)
Panel A: Disadvantaged Families					
Secure Communities	−0.0007	0.0025	0.0131	0.0145	−0.0030
	(0.0053)	(0.0076)	(0.0104)	(0.0147)	(0.0064)
Sample	Younger	Non-Wh	Single	Low-Ed	Low-Inc
Observations	388,699	171,867	96,818	39,568	262,812
Dep Var Mean	0.441	0.469	0.427	0.314	0.402
Panel B: Advantaged Families					
Secure Communities	−0.0192**	−0.0095*	−0.0117**	−0.0079*	−0.0094*
	(0.0078)	(0.0056)	(0.0050)	(0.0047)	(0.0056)
Sample	Older	White	Married	High-Ed	High-Inc
Observations	190,023	406,855	481,902	539,125	315,909
Dep Var Mean	0.569	0.487	0.493	0.497	0.561

Notes: The analysis sample includes children ages three and four of citizen mothers ages 20 to 64. In the top panel, the analysis is further restricted to mothers who are ages 20 to 35, non-white, never married, with less than a high school degree, and with family income less than/equal to \$55,000 in columns (1) through (5), respectively. In the bottom panel, the analysis is further restricted to mothers who are ages 36 to 64, white non-Hispanic, ever married, with at least a high school degree, and with family income greater than \$55,000 in columns (1) through (5), respectively. The dependent variable is an indicator that equals one if a child is enrolled in child care and equals zero otherwise. The dependent variable is an indicator that equals one if a child is enrolled in child care and equals zero otherwise. All models include controls for the baseline child and mother characteristics, 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
Estimates from the DD model of child care participation, exploiting geographic variation in the size of the undocumented population.
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014.

	Dep Var:= 1 if Child is Enrolled in Child Care				
	(1)	(2)	(3)	(4)	(5)
Panel A: Disadvantaged Families					
Secure Communities	0.0056	0.0072	0.0187*	0.0130	0.0004
	(0.0058)	(0.0083)	(0.0109)	(0.0161)	(0.0069)
Secure Communities × Undocumented	−0.1636**	−0.0982	−0.1502*	0.0303	−0.0856
	(0.0667)	(0.0650)	(0.0882)	(0.1238)	(0.0614)
Sample	Younger	Non-Wh	Single	Low-Ed	Low-Inc
Observations	388,699	171,867	96,818	39,568	262,812
Dep Var Mean	0.441	0.469	0.427	0.314	0.402
Panel B: Advantaged Families					
Secure Communities	−0.0164**	−0.0054	−0.0067	−0.0017	−0.0027
	(0.0082)	(0.0060)	(0.0056)	(0.0051)	(0.0063)
Secure Communities × Undocumented	−0.0786	−0.1373*	−0.1313**	−0.1665***	−0.1863***
	(0.0735)	(0.0724)	(0.0616)	(0.0540)	(0.0711)
Sample	Older	White	Married	High-Ed	High-Inc
Observations	190,023	406,855	481,902	539,125	315,909
Dep Var Mean	0.569	0.487	0.493	0.497	0.561

Notes: The analysis sample includes children ages three and four of citizen mothers ages 20 to 64. In the top panel, the analysis is further restricted to mothers who are ages 20 to 35, non-white, never married, with less than a high school degree, and with family income less than/equal to \$55,000 in columns (1) through (5), respectively. In the bottom panel, the analysis is further restricted to mothers who are ages 36 to 64, white non-Hispanic, ever married, with at least a high school degree, and with family income greater than \$55,000 in columns (1) through (5), respectively. The dependent variable is an indicator that equals one if a child is enrolled in child care and equals zero otherwise. All models include an interaction between the Secure Communities variable and a proxy for the 2005 PUMA share of the population that is undocumented. Undocumented is defined as the share of low-education Hispanic immigrants arriving in the U.S. after 1980. In addition, all models include controls for the baseline child and mother characteristics, 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

given that the pre-SC child care participation rate is 48.1%, the estimate in column (2) implies that participation fell by 1.3%.[26]

The estimates presented in columns (3) and (4) of Table 1 explore heterogeneity and begin to probe the robustness of the baseline results. We would expect the effect of SC to be larger in areas that are more exposed to the reform, specifically in areas with a larger population of immigrants. We test this by exploiting geographic variation in the pre-SC share of the PUMA working-age population that is undocumented. Our proxy for the undocumented population is defined as low-education Hispanic immigrants arriving in the U.S. on or after

[26] In a series of robustness checks, we estimate the specification in column (2) to produce an average of the post-period coefficients from an event study specification as well as estimates from Borusyak et al. (2024). These methods yield coefficients (and standard errors) of −0.009 (0.005) and −0.015 (0.002), respectively, which are similar to the estimate from the standard TWFE model. Given these similarities coupled with the fact that the standard TWFE specification can better accommodate our heterogeneity analysis, we continue to report results from the TWFE model in the main paper, but whenever relevant we discuss results from these alternative models in the footnotes.

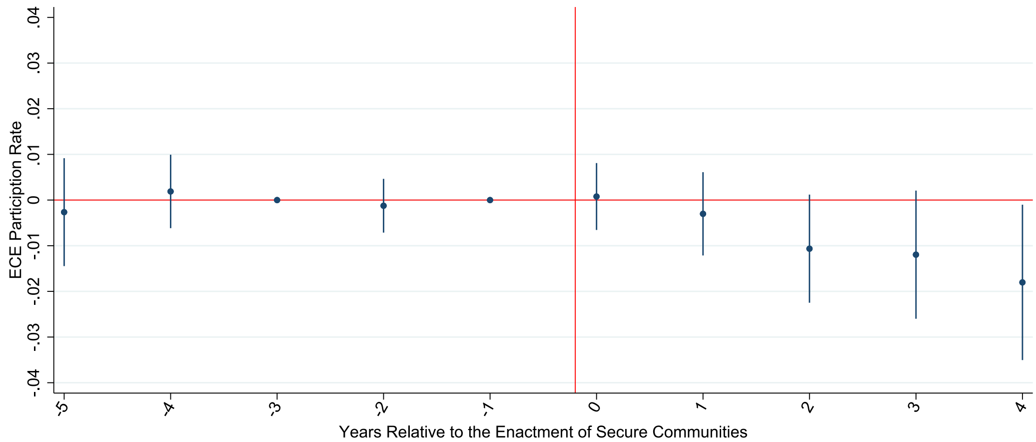

Fig. 3. Event-study estimates of the impact of secure communities on child care participation.
Notes: The dependent variable is an indicator that equals one if a child is enrolled in child care and equals zero otherwise. The figure plots event-time coefficients of year relative to the enactment of Secure Communities, with error bars representing 95% confidence intervals. The model includes controls for child and mother characteristics, 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.
Source: ICE IDENT/IAFIS interoperability statistics (through December 2014) and ACS from 2005 to 2014.

1980. We measure this variable at the PUMA level in 2005, and it is interacted with SC_{pt}. Both the interaction and SC_{pt} are included in the model. The results show that, as expected, the impact of SC is stronger in communities with a larger number of undocumented individuals. Looking at column (4) – the full specification – the coefficient on the interaction term implies that the child care participation rate fell by nearly 15 percentage points as the PUMA undocumented share increased from zero to 100%. It is noteworthy that the main effect associated with the coefficient on SC_{pt} is comparatively small in magnitude – and is positively signed in one of the models – indicating that the program had virtually no impact on child care participation in communities with few undocumented individuals. Such results provide support for our hypothesis that SC is responsible for the decrease in child care participation.

To more fully understand this reduction, we estimate the DD model on subsets of economically disadvantaged and advantaged families. As shown in Table 2, the top panel presents estimates based on various definitions of disadvantaged families, while the bottom panel provides the analogous results for advantaged families.[27] Results in the top panel show that disadvantaged children's participation in child care did not respond to the enactment of SC. Indeed, the coefficients are generally small in magnitude, inconsistently signed, and never precisely estimated.[28] Conversely, the bottom panel reveals that the enactment of SC reduced the child care participation rate of advantaged children, irrespective of how "advantaged" is defined. The point estimates consistently show that the share of three- and four-year-olds from advantaged families attending child care fell between one and two percentage points after the enactment of SC. Again, however, the coefficients indicate small effect sizes. For example, among children of older mothers (i.e., those ages 36 to 64), the pre-SC child care participation rate is 56.9%, meaning that the coefficient on SC implies that the program reduced participation by 3.3%. For children of more highly educated mothers, their pre-SC participation rate is 49.7%, indicating that participation fell by 1.6%.[29]

The results presented in Table 3 show how these sub-group estimates vary over the distribution of the undocumented population, by adding interactions of the SC_{pt} variable with the PUMA undocumented share. Our results provide consistent evidence – among disadvantaged and advantaged families – that the impact of SC is stronger in communities with a larger share of undocumented individuals. Indeed, looking at disadvantaged families, the coefficient on four of the five interactions is negative and two are statistically significant. Nevertheless, the results continue to show larger reductions in child care participation among their advantaged counterparts. All five interactions are negatively signed, and all but one are statistically significant. Given that the effect on child care participation is larger in areas that were more affected by SC, the results again provide support for the hypothesis that the changes in child care participation are due to SC. The point estimates range from an eight to a 20 percentage point drop in child care participation as the PUMA undocumented share increases from zero to 100%. It is noteworthy that the main effect associated with the coefficient on SC_{pt} is comparatively small in magnitude, indicating that the program had virtually no impact on child care participation in communities with few undocumented individuals.

Fig. 3 displays the TWFE event-study estimates of the impact of SC on child care participation. In the years prior to SC's implementation, the event-time point estimates are very close to zero and are statistically insignificant, suggesting that the results are not driven by pre-trends. Such results provide support for the identifying assumption that the later-treated counties provide a good counterfactual for earlier-treated counties. The decline in child care participation occurs only after the enactment of SC. The effect becomes larger over time, consistent with the employment and establishment results presented in the next section. Specifically, our results indicate that two to four years after SC was enacted, the child care participation rate of three- and four-year-olds declined one to two percentage points.

Given these dynamic treatment effects, it is important to verify that our estimates are not biased by comparisons using already-treated counties as a comparison group for later-treated counties. Doing so is particularly important given that there are virtually no never-treated counties (Fig. 2). Therefore, we consider the two alternative estimators, from Borusyak et al. (2024) and Callaway and Sant'Anna (2021). The results, which are presented in Figure A3, are consistent with the standard TWFE estimates. Although the Borusyak et al. (2024) estimator exhibits an upward trend pre-SC, the trend immediately turns downward post-SC. To estimate the Callaway and Sant'Anna (2021) model, the individual-level data are aggregated to create a panel of

[27] Note that if the decline in child care participation is driven by a reduction in parental employment, we might expect to see declines in participation across both sets of families. However, because participation is higher among advantaged families, effects will be easier to detect in that group.

[28] Given that several of the point estimates are positive, a lack of precision due to lower average participation does not seem to be the cause of the null results.

[29] In results not reported here, we estimate the effect of SC on child care participation of immigrant children and find no discernible effects.

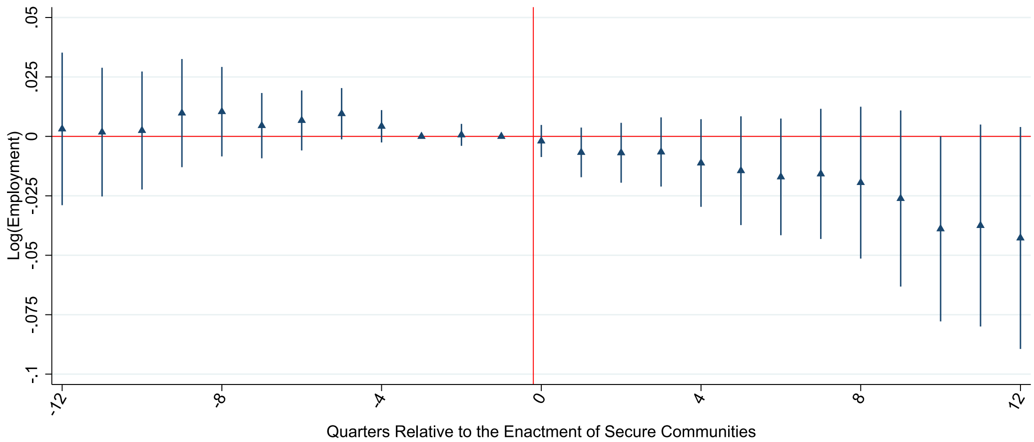

Fig. 4. Event-study estimates of the impact of secure communities on child care employment (QCEW).
Notes: The data include employment in the "Child Day Care Services" industry at the county × quarter level. The figure plots event-time coefficients of quarter relative to the enactment of Secure Communities, with error bars representing 95% confidence intervals. The figure restricts event time from 12 quarters before through 12 quarters after Secure Communities is enacted in order to retain a more balanced panel. The model includes county and quarter-year fixed effects. The model is weighted by county population, and the standard errors are corrected for clustering at the county level.
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and QCEW from 2005Q1 to 2014Q3.

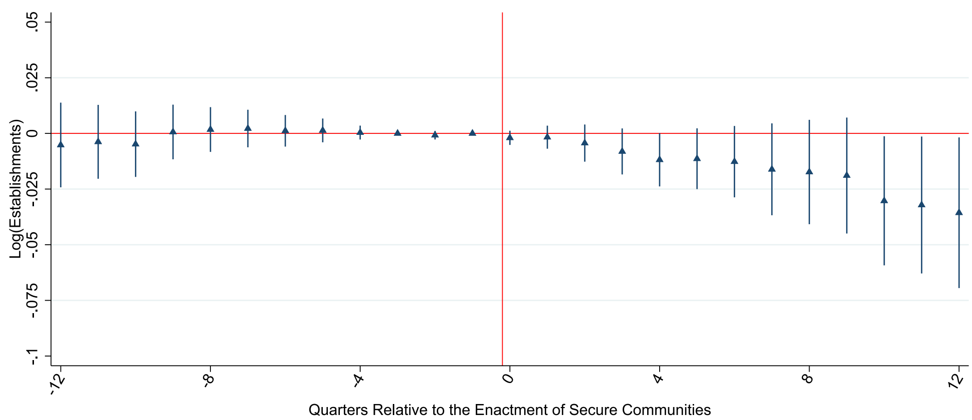

Fig. 5. Event-study estimates of the impact of secure communities on child care establishments (QCEW).
Notes: The data include the number of establishments in the "Child Day Care Services" industry at the county × quarter level. The figure plots event-time coefficients of quarter relative to the enactment of Secure Communities, with error bars representing 95% confidence intervals. The figure restricts event time from 12 quarters before through 12 quarters after Secure Communities is enacted in order to retain a more balanced panel. The model includes county and quarter-year fixed effects. The model is weighted by county population, and the standard errors are corrected for clustering at the county level.
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and QCEW from 2005Q1 to 2014Q3.

PUMAs. This appears to introduce significant noise into the estimates, leading to large standard errors. Thus, although the point estimates do not demonstrate a clear pattern, the confidence intervals overlap our main estimates.

We present a number of additional robustness checks in Table 4. Panel A uses the child's citizenship status rather than the mother's status to define the analysis sample; Panel B excludes early-adopting jurisdictions; and Panel C excludes California. Note that these analyses are restricted to the subsets of advantaged families. 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. Removing the early-adopting jurisdictions – defined as those introducing SC in 2008 – is important for two reasons: first, many of the these communities are located in border states that may have either had the technology or expertise in place to implement SC more vigorously or attempted to enact their own immigration enforcement policies—both of which may confound the impact of SC. Finally, we exclude all PUMAs in California because it is a border state containing a large number of "sanctuary cities". Our results are robust to all of these changes in the specification and sample construction.

5.2. *Child care labor supply*

We now turn to the analysis of measures of the child care labor market. First, drawing on the QCEW, we estimate the effect of SC on the equilibrium number of employees in the Child Day Care Services industry. As shown in Table 5, we find that SC enactment is associated with a 1.5% decline in employment (column (1)) or a decline of about 30 child care employees per one million population (column (2)). The reduction in employment could be due to a decrease in the number of staff per child care center, a decrease in the number of child care centers, or both. This distinction is important because the latter likely has a larger impact on access to child care. In addition, a reduction in the number of facilities is more difficult to recover from, since recovery requires opening or reopening a center as opposed to restaffing an existing center. We estimate that SC led to a 1.6% reduction in the number of child care establishments (column (3)), or about three facilities per one million population (column (4)).[30] The decline in

[30] Results from the alternative estimators are similar. For $log(employment)$, the average of the event study post-period coefficients is −0.016 with a

Table 4
Estimates from the DD model of child care participation, robustness checks on the subset of advantaged families.
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014.

	Dep Var:= 1 if Child is Enrolled in Child Care				
	(1)	(2)	(3)	(4)	(5)
Panel A: Sample is Restricted to Child Citizens					
Secure Communities	−0.0160**	−0.0097*	−0.0101**	−0.0067	−0.0081
	(0.0073)	(0.0054)	(0.0048)	(0.0045)	(0.0054)
Sample	Older	White	Married	High-Ed	High-Inc
Observations	215,820	416,370	546,814	588,761	341,665
Dep Var Mean	0.566	0.500	0.491	0.501	0.561
Panel B: Drop Early Adopters					
Secure Communities	−0.0193**	−0.0095*	−0.0116**	−0.0078*	−0.0092
	(0.0078)	(0.0056)	(0.0050)	(0.0047)	(0.0056)
Sample	Older	White	Married	High-Ed	High-Inc
Observations	189,364	405,822	480,318	537,395	314,804
Dep Var Mean	0.584	0.498	0.505	0.506	0.567
Panel C: Drop California					
Secure Communities	−0.0197**	−0.0092	−0.0142***	−0.0083*	−0.0121**
	(0.0086)	(0.0059)	(0.0053)	(0.0050)	(0.0061)
Sample	Older	White	Married	High-Ed	High-Inc
Observations	167,025	381,118	432,580	484,494	279,379
Dep Var Mean	0.579	0.493	0.501	0.502	0.564

Notes: Unless otherwise specified, the analysis sample includes children ages three and four of citizen mothers ages 20 to 64. All analyses are further restricted to mothers who are ages 36 to 64, white non-Hispanic, ever married, with at least a high school degree, and with family income greater than $55,000 in columns (1) through (5), respectively. The dependent variable is an indicator that equals one if a child is enrolled in child care and equals zero otherwise. In Panels A and B, the analysis is conducted on children age six (instead of those ages three and four); in Panel C, the sample is restricted to child citizens (instead of mother citizens); Panel D drop early adopters, defined as counties that enacted Secure Communities in 2008; and Panel E drops PUMAs located in California. Panel B includes an interaction between the Secure Communities variable and a proxy for the 2005 PUMA share of the population that is undocumented. Undocumented is defined as the share of low-education Hispanic immigrants arriving in the U.S. after 1980. In addition, all models include controls for the baseline child and mother characteristics, 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
Estimates from the DD model of child care industry employment and establishments (QCEW).
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and QCEW from 2005Q1 to 2014Q3.

	(1) Log(Employment)	(2) Employment per 1 million population	(3) Log(Establishments)	(4) Establishments per 1 million population
Secure Communities	−0.0153***	−29.75*	−0.0158**	−2.982**
	(0.0059)	(15.61)	(0.0068)	(1.360)
Dep Var Mean	2758	2758	218	225
Observations	65,854	65,854	111,337	112,061

Notes: The data include quarterly establishments and average quarterly employment levels in the “Child Day Care Services” industry (NAICS code 6244) in county × quarter cells. In columns (2) and (4), employment and establishments are measured per one million population at the county level. All regressions include county and quarter-year fixed effects as well as a control for the log of county population. Regressions are weighted by county population, and the standard errors are corrected for clustering at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

establishments suggests that families may have less convenient child care options, which likely contributed to the decline in child care participation among advantaged children.

The corresponding TWFE event-study results are displayed in Figs. 4 (employment) and 5 (establishments). 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-SC coefficients. However, the coefficients reveal a distinct shift following SC’s introduction, consistent with a reduction in the number of child care employees and establishments as a result of the policy. Again, it is important to verify that our TWFE estimates are not biased. Figures A4 and A5 present estimates using Borusyak et al. (2024) and Callaway and Sant’Anna (2021) for employment and establishments, respectively, and their results confirm the TWFE estimates. In particular, the confidence intervals from both alternative estimators overlap with the TWFE estimates, and the point estimates show the same pattern of results. If anything, the alternative estimators reveal a larger decline in establishments than the TWFE design.

Next, we turn to the ACS to explore heterogeneity in the labor supply response to SC by education level and immigrant status. These analyses may shed light on the mechanisms underlying the change in child care participation and employment discussed in Section 2.3. Our first set of results, shown in Table 6, examines whether a given female respondent is employed at all as a child care worker. Looking 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 2.8% of low-education female immigrants were employed as child care workers in the pre-SC period, this coefficient implies a 9% reduction in child care employment within this group. The remaining columns in Panel A reveal that this effect is driven by Hispanic immigrants, particularly Mexicans, who became 16% less likely to work in the child care industry. Turning to Panel B, we find little evidence that SC influenced the occupational choices of high-education immigrants, although

standard error of 0.009, while the Borusyak et al. (2024) estimate is −0.037 with a standard error of 0.021. For $log(establishments)$, the corresponding estimates (and standard errors) are −0.019 (0.013) and −0.025 (0.015).

Table 6
Estimates from the DD model of occupational choices.
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014.

	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
Dep Var Mean	0.028	0.030	0.024	0.028	0.040
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
Dep Var Mean	0.018	0.033	0.031	0.019	0.014
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
Dep Var Mean	0.028	0.029	0.029	0.027	0.033
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
Dep Var Mean 0.020	0.019	0.021	0.021	0.019	0.019

Notes: The analysis sample includes female respondents (immigrants and natives) ages 20 to 55. The sample "Low-Education" consists of respondents with less than a four-year college degree, while the sample "High-Education" consists of respondents 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the sample sizes are much smaller.[31] Such results are consistent with a chilling effect among immigrants, particularly since low-education Hispanic immigrants are more likely to be undocumented than other immigrant subgroups.

Panels C and D of Table 6 conduct the comparable analyses on natives. We uncover evidence that SC similarly reduced the supply of low- *and* high-education *natives* in the child care industry. Given the pre-SC employment means of 2.8% and 1.9%, respectively, the coefficients imply moderate reductions in native child care employment, of 4% and 7%, respectively.[32] The remaining columns in Panels C and D suggest that these overall effects were driven by reductions in employment among whites and particularly blacks.[33] The relatively small decrease in natives' child care employment suggests that such individuals are complements in production with low-education immigrant workers, whose own employment declines are most likely due to the chilling effects of SC. As discussed in Section 2.3, demand-driven responses would most likely affect native employment in child care more than immigrant employment.

Fig. 6 presents the key event-study results, for all female respondents (Panel A), low-education immigrants (Panel B), low-education black and white natives (Panel C), and high-education black and white natives (Panel D).[34] All four analyses show no evidence of differential outcome trends between treated and not-yet-treated areas in the period before SC's roll-out, as depicted by the flat and statistically insignificant pre-SC coefficients. However, the coefficients reveal a distinct shift following SC's introduction, consistent with a reduction in child care employment for all four groups, particularly among low-education immigrants. The corresponding figures based on the Borusyak et al. (2024) and Callaway and Sant'Anna (2021) estimators are presented in Figure A6 and are consistent with the standard TWFE results.

Table 7 presents a variety of additional 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.[35] Column (1) provides the baseline estimates shown in

[31] Results from the event study average of the post-period coefficients and from the Borusyak et al. (2024) estimator are very similar. For low-education immigrants, the coefficients (and standard errors) are −0.004 (0.002) and −0.003 (0.002) for the two models, respectively. For high-education immigrants, the coefficients (and standard errors) are 0.001 (0.002) and −0.002 (0.003).

[32] The average of the post-period coefficients from the event study model yields point estimates (and standard errors) of −0.002 (0.001) for both high-education and low-education natives, while those from the Borusyak et al. (2024) estimator are −0.003 (0.001) for low-education natives and −0.002 (0.001) for high-education natives.

[33] We also estimate the models in Table 6 using as outcomes binary indicators for whether a given female respondent is employed in an industry other than child care or is not employed. We find suggestive evidence that low-education immigrants – particularly Mexican immigrants – were more likely to be both employed elsewhere and unemployed. This suggests that the child care industry lost low-education immigrants to less exposed industries and to a chilling effect that drove such individuals out of the workforce. In terms of low- and high-education natives, we find we clear evidence of a reduction in non-child care employment along with an increase in non-work. Results from these analyses are available upon request.

[34] Although we present only these results in the paper – both for the sake of brevity and because these groups are the only ones influenced by SC – we perform the equivalent analysis on the samples defined in column (1) of Table 6. The results are consistent with those presented here, and are available upon request.

[35] 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.

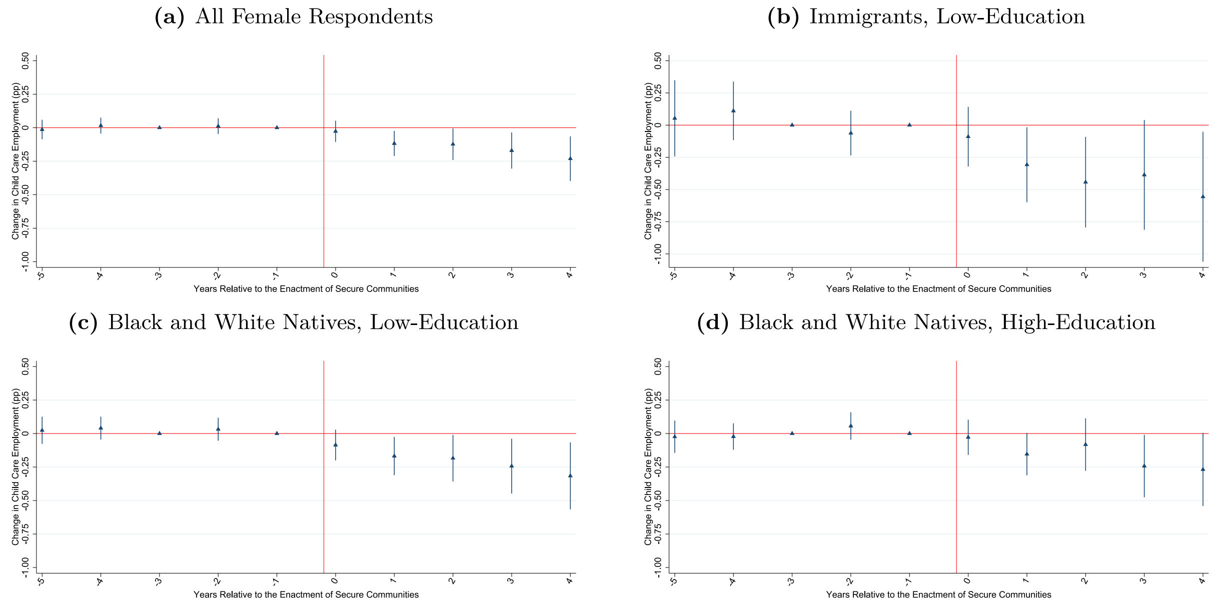

Fig. 6. Event-study estimates of the impact of secure communities on child care occupational choices.
Notes: The dependent variable in all plots is an indicator that equals one if the woman is employed in the child care sector and equals zero otherwise. The figure plots event-time coefficients of year relative to the enactment of Secure Communities, with error bars representing 95% confidence intervals. The sample for each sub-figure is restricted to the group indicated in each plot. The models include PUMA and year fixed effects as well as controls for demographic characteristics and time-varying PUMA characteristics. The model is weighted by the ACS person weight, and the standard errors are corrected for clustering at the PUMA level.
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014.

Table 7
Estimates from the DD model of occupational choices, robustness.
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014.

	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
Additional Controls	No	No	English lang.	Addtl. PUMA	No	No	No
Observations	746,713	630,178	746,713	746,713	569,319	703,834	726,815
Dep Var Mean	0.028	0.028	0.028	0.028	0.028	0.028	0.028
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
Additional Controls	No	No	English lang.	Addtl. PUMA	No	No	No
Observations	339,683	288,860	339,683	339,683	278,617	325,122	334,356
Dep Var Mean	0.018	0.019	0.018	0.018	0.018	0.017	0.018

Notes: The analysis sample includes female immigrants ages 20 to 55. The sample “Low-Education” consists of respondents with less than a four-year college degree, while the sample “High-Education” consists of respondents 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 6; 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 potentially undocumented immigrants (East et al., 2023). 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 examine the impact of SC on occupational choices by child care sector. Specifically, the outcomes consist of separate binary indicators that equal one if a given female is employed in the private household child care sector, the home-based sector, and the center-based sector. As shown in Table 8, 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

Table 8
DD model of sector-specific child care occupational choices.
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014.

	Dep Var:= 1 if CC Worker in Sector		
	(1) Pr HH	(2) Home	(3) 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
Dep Var Mean	0.005	0.009	0.014
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
Dep Var Mean	0.002	0.003	0.012
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
Dep Var Mean	0.002	0.006	0.019
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
Dep Var Mean	0.001	0.002	0.016

Notes: The analysis sample includes female immigrants and natives ages 20 to 55. The sample "Low-Education" consists of respondents with less than a four-year college degree, while the sample "High-Education" consists of respondents 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 9
DD model of child care workers' hourly wages.
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014.

	Dep Var: Log(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
Mean Hourly Wages	13.55	11.76	20.10
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	3876
Mean Hourly Wages	12.70	11.70	16.65
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
Mean Hourly Wages	13.71	11.77	20.73

Notes: The analysis sample includes female immigrants and natives ages 20 to 55 employed as a full-time child care worker. Full-time is defined as more than 25 h of work per week. The sample "Low-Ed" consists of respondents with less than a four-year college degree, while the sample "High-Ed" consists of respondents 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

care services.[36] Such patterns are important from a child development perspective, given that center-based care is rated to be the highest-quality non-parental care type, on average (Bassok et al., 2016). In addition, these findings provide further evidence that the reduction in low-education immigrant child care labor is driven by an SC-induced chilling effect, given their concentration in the sector with the most exposure to government authorities.

The final set of ACS analyses examines the impact of SC on the hourly wages of immigrant and native child care workers. We begin with Table 9, 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)].[37] 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 10 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 there. The estimate in column (1) of Panel C indicates that SC led to a 2.2% reduction in center-based 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.

6. Child care quality

The preceding discussion notes that SC reduced the supply of child care services, particularly in the center-based sector. A key question

[36] Our results differ slightly from those in East and Velasquez (2024), who find that SC lowered the overall supply of private household service workers. In contrast, our results indicate that the number of private household *child care workers* did not change, suggesting that the decline documented by East and Velasquez (2024) is driven by other types of workers.

[37] If the reduction in child care employment among low-education immigrants is driven by undocumented immigrants, then the estimated effect of SC on the wages of this group could partially be driven by selection. Given that undocumented immigrants face a wage penalty (Borjas and Cassidy, 2019), if we were able to control for legal status, we would expect the coefficient to indicate a larger decline in wages for low-education immigrants. Given that there was no change in child care employment among high-education immigrants, the estimated wage changes for that group are unlikely to be driven by selection.

Table 10
DD model of sector-specific hourly wages.
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and ACS from 2005 to 2014.

	Dep Var: Log(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	9499	2950	6309	7488	1739
Mean Hourly Wages	11.86	12.01	11.79	11.42	14.14
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	4715	22,108	23,341	3448
Mean Hourly Wages	10.23	9.78	10.34	9.85	13.22
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	9736	68,780	55,071	23,603
Mean Hourly Wages	14.99	14.58	15.05	12.66	21.69

Notes: The analysis sample includes female immigrants and natives ages 20 to 55 employed as a full-time child care worker. Full-time is defined as more than 25 h of work per week. The sample "Low-Ed" consists of respondents with less than a four-year college degree, while the sample "High-Ed" consists of respondents 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 11
DD model of NAEYC-accredited providers.
Source: ICE IDENT/IAFIS Interoperability Statistics (through December 2014) and AggData from 2011 to 2014.

	(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
Observations	5418	5418	5418	5333

Notes: The data include the number of NAEYC-accredited center-based providers in a county. Only counties that did not have SC in effect as of May 2011 – the first observation in the data – are included. The regressions include observations for all available quarters (i.e., approximately two per year). All regressions include county and quarter-year fixed effects as well as a control for the log of county population. In column (1), the outcome is the number of NAEYC-accredited providers in a given county; in column (2), it is the number of NAEYC-accredited providers per one million in the population; in column (3), it is a dummy variable that equals one if there are any NAEYC-accredited providers in a 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. Regressions are weighted by county population, and the standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 SC and child development, understanding its influence on 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 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 four-step evaluation process that requires considerable effort and resources.[38] (Xiao, 2010) estimates that the cost of completing the initial accreditation process is approximately $4,000, while the 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.[39]

Using AggData's child care listing, we constructed a dataset of the number of NAEYC-accredited providers, the number of accredited

[38] 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 then apply for and undergo a site visit, and finally take steps to maintain accreditation. To highlight one example of the 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.

[39] 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 since it includes school-based programs that would fall under the education sector in the QCEW.

providers per one million in the population, the presence of any accredited provider, and the share of accredited providers in county × year × 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. Nevertheless, given the importance of child care quality for child development, we think this is an important margin to explore even if the results are only suggestive.

Results from the DD models are presented in Table 11. 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 decreased because of SC, the availability of high-quality programs appears to have remained stable. While these results shed light on whether SC affected the stock – or density – of accredited providers within counties, they 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 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 (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, particularly among those from economically-advantaged families and those residing in areas with large numbers of undocumented individuals. These patterns are consistent with the main findings in East and Velasquez (2024) and East et al. (2023), who find that SC had disproportionate labor supply impacts on high-skilled natives. As for the provider-side of the market, we find that SC reduced the number of child care establishments as well as the supply and compensation of child care industry workers. These reductions are concentrated among low-education immigrants as well as (low- and high-education) natives employed primarily in the center-based 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 child care participation results are broadly consistent with previous work by Amuedo-Dorantes and Sevilla (2014) and Cortes and Tessada (2011), who find that high-skilled females reduce the amount of time allocated to child care and increase time spent in market work in response to increases in low-skilled immigration. More directly, our results are consistent with (East et al., 2023)'s paper showing that the reduction in natives' employment following the introduction of SC was concentrated among those with more education. Furthermore, East and Velasquez (2024)'s study of high-skilled females shows that SC activation reduced their labor supply. Our finding that SC decreased the number of child care establishments – thereby making accessible services more difficult to find – may provide one explanation for the decline in mothers' labor supply.

Regarding the provider-side analyses, our results are consistent with those in Furtado and Hock (2008) who finds that the in-migration of low-skilled immigrants increases the supply of child care. 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. Furthermore, our finding that immigration enforcement via SC did not benefit native workers – and indeed reduced their employment – is consistent with previous work by East et al. (2023), who find that SC had broad-based negative effects on native employment, and by East and Velasquez (2024), 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).

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 teachers.

Another possibility, which draws on job search models from Albert (2021), 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 (2024), indicate that one potentially important mechanism may operate through reductions in maternal employment and participation in formal child care. That we find decreases in the use of formal care raises concerns that some children are being cared for in less optimal environments, including lower-quality informal arrangements or at home by a resource-constrained parent (Bassok et al., 2016). Understanding how policies like SC shift children's care environments and, in turn, their developmental outcomes is therefore a key task for future research.

Declaration of competing interest

There are no conflicts of interest to report.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jpubeco.2024.105101.

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