WHAT IS THE RELATIONSHIP BETWEEN DEPRIVATION AND CHILD SSI PARTICIPATION?

Michael Levere, David Wittenburg, and Jeffrey Hemmeter

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Center for Retirement Research at Boston College
Hovey House
140 Commonwealth Avenue
Chestnut Hill, MA 02467
Tel: 617-552-1762 Fax: 617-552-0191
https://crr.bc.edu

Michael Levere is a senior researcher at Mathematica Policy Research. David Wittenburg is senior director of disability business development at Mathematica Policy Research. Jeffrey Hemmeter is with the Office of Research, Demonstration, and Employment Support at the U.S. Social Security Administration (SSA). The research reported herein was pursuant to a grant from SSA funded as part of the Retirement and Disability Research Consortium.

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Affiliated Institutions:
The Brookings Institution
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Syracuse University
Urban Institute

Abstract

This paper examines how local deprivation relates to child Supplemental Security Income (SSI) participation. It uses Social Security Administration data on child SSI participation at the Census tract and county levels. It also uses American Community Survey data to construct a measure of economic deprivation that reflects a range of local socioeconomic factors including education, income, employment, and housing in local areas. In our analysis, we use this measure of deprivation and a predicted value of area child SSI participation based on this level of deprivation. We assess the extent of deviation between this predicted value of area child SSI participation and area child actual SSI participation.

The paper found that:

- Local areas with higher deprivation have higher levels of child SSI participation, explaining slightly more than 30 percent of the variation in SSI participation.
- Substantial geographic variation remains in child SSI participation rates, with some Census tracts showing higher predicted participation than actual participation, and others with lower predicted participation than actual participation.
- Factors correlated with the deviation between predicted and actual child SSI participation include a community's demographic composition, such as the share that is non-White or the share with a disability, and other factors such as social capital.
- Declines in SSI applications during the COVID-19 pandemic were largest in areas with higher deprivation.

The policy implications of the findings are:

- Local areas in which actual child SSI participation is substantially less than predicted might benefit from targeted outreach to better inform families about the SSI program.
- By measuring the deviation between predicted and actual SSI participation at the Census tract level, targeted outreach efforts can precisely pinpoint places in which they might plausibly have the greatest impact on local SSI participation.

Introduction

Recent reductions in the number of children receiving Supplemental Security Income (SSI) raise questions about whether the program currently reaches those who need it. The SSI program, administered by the Social Security Administration (SSA), provides cash payments to families that have children with significant disabilities and meet certain income and asset criteria. The number of children participating in SSI peaked in 2013, but has gradually declined since then, the reasons for which have not yet been fully understood. In addition, child applications for SSI dropped sharply during the COVID-19 pandemic, resulting in far fewer awards than SSA's projections (SSA 2021).

Because SSI participation varies by county and state, understanding the drivers of these regional differences could help identify children and families who might benefit from SSI but do not currently qualify. The factors driving the child SSI program's growth through 2013 are not well understood but likely include increases in the number of children living in low-income families, changes in state cash assistance programs, and increasing awareness of childhood disability (Wittenburg and Livermore 2021; Schmidt and Sevak 2017). Additionally, some factors directly relate to SSA administrative processes. For example, increases in continuing disability reviews likely play an important role in driving patterns of benefit receipt among SSI children (Hemmeter et al. 2021).

The decline in child SSI participation is directly relevant to SSA's ongoing programs required under the Social Security Act to support outreach to potentially eligible populations.[1] SSA has the flexibility to partner with federal, state, private, and nonprofit entities to support outreach efforts and received a funding increase for its outreach programs in response to the sharp declines during the pandemic to identify potential applicants (SSA 2021). In June 2021, SSA created the Vulnerable Population Liaison to work with over 1,100 external organizations helping take claims from targeted groups.[2]

Geographic variation, especially at the county level, represents an important consideration for outreach efforts and understanding SSI program dynamics more broadly. In 2013, rates of child SSI participation per capita were relatively higher in northeastern and

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[1] A description of the Social Security Act requirements is available at https://www.ssa.gov/OP_Home/ssact/title16b/1635.htm (accessed September 13, 2021).
[2] See the item from June 30, 2021 at https://www.ssa.gov/thirdparty/groups/whatsnew.html (accessed November 24, 2021).

southern states, though considerable variation existed even within these states at the county level (Schmidt and Sevak 2017). The large variation reflects how SSI operates alongside varying local and state systems that serve children with disabilities in different socioeconomic and political environments (Shogren and Wittenburg 2020). Initiatives that attempt to influence program participation, such as outreach, must therefore take these factors into account to use resources more efficiently. In addition, targeting efforts at more local levels can efficiently address the underlying geographic variations in SSI participation.

One likely driver of child SSI participation is the local area's deprivation, which reflects a variety of socioeconomic factors (e.g., income, education, employment, and housing quality). Our analysis uses a measure based on the Area Deprivation Index (ADI; University of Wisconsin School of Medicine and Public Health 2021), a measure that researchers and policymakers have used to inform health care delivery and policy. Our measure captures deprivation at the Census tract level, allowing an examination of variation in SSI participation within a highly localized geographic area. Because of SSI's stringent asset and income limits to qualify, families must have sufficiently low resources to participate. Almost half of child SSI recipients come from families with income below the poverty level, and median liquid assets in 2001 were less than $100 (Rupp et al. 2005/2006). The level of deprivation varies widely across the country (Kind et al. 2014), potentially explaining the variation in geographic patterns of participation.

This paper summarizes the role of deprivation in explaining geographic variation in SSI participation among children. We calculate local SSI participation rates at the county and Census tract levels. Census tract data allow us to better understand the variations that exist within counties. Our measure of deprivation allows for a ranking of socioeconomic factors across Census tracts (Kind et al. 2014) reflecting an area's general income, education, employment, and housing quality at a precise local level. Using a simple linear regression between child SSI participation per capita and deprivation, we developed a predicted measure of child SSI participation based on the local area deprivation. We define this measure as deviation, which captures the difference between predicted and actual SSI participation. We also analyzed the characteristics of communities that have lower-than-predicted SSI participation, which can help us understand the geographic variation in child SSI participation. Finally, we explore the extent to which areas with higher (or lower) deprivation experienced greater declines in applications during the pandemic.

These findings are important to understand broader trends in SSI participation, particularly in identifying areas most in need of SSI that might be best served by targeted outreach. We find that SSI participation often varies substantially within Census tracts, even after controlling for measures of deprivation. A caveat is that deviations represent only one measure of SSI participation and do not fully capture other issues, such as systemic issues, availability of related local programs, or the economic environment that might influence outcomes. Hence, a large deviation only reflects that the area's caseload is above or below the national average given its level of deprivation. Areas with actual participation greater than predicted participation might still have large populations of children who have not applied for SSI but are otherwise eligible. Nonetheless, the quantitative measures provide a way to initially categorize areas that potentially deviate from these averages, which can be especially useful in considering options for targeted outreach.

Background and Motivation

Overview of Child SSI and Outreach Efforts

The SSI eligibility requirements for children younger than age 18 include disability, income, and asset criteria. To meet the disability criteria, a child must have "a medically determinable physical or mental impairment, which results in *marked and severe functional limitations,* and which can be expected to result in death or which has lasted or can be expected to last for a continuous period of not less than 12 months" (42 U.S.C. § 1382c[C][i]; emphasis added). To meet the income and asset criteria, a child's own income and any parental income and resources deemed to the child must be sufficiently low.[3] SSA excludes certain resources, such as the primary residential home or one vehicle if it is used for transportation, in the calculation.[4] Local field offices handle the application process,[5] and access to field offices influences local SSI participation (Deshpande and Li 2019).

[3] A child's own countable resources must not exceed $2,000 to qualify. Additionally, parental resources can be deemed onto the child, so in a 2-parent household resources can be as high as $5,000 before the child is no longer eligible.

[4] For more details on resource limits, see https://www.ssa.gov/ssi/spotlights/spot-resources.htm (accessed September 13, 2021)

[5] For more details on the SSI application process for children which can also include phone and in-person applications, see https://www.ssa.gov/benefits/disability/apply-child.html (accessed September 13, 2021).

In 2021, the federal maximum payment from SSI was $794 per month, and 23 states provided an optional supplemental payment to children with disabilities.[6] On average, almost half the income for families who have children with disabilities comes from SSI (Davies et al. 2009). Children who qualify for SSI could qualify for services from other programs. Most children who receive SSI are automatically enrolled in Medicaid. Because of their limited income, many also qualify for other means-tested supports, such as the Supplemental Nutrition Assistance Program (Romig 2017).

SSA periodically reassesses the medical eligibility of recipients during medical Continuing Disability Reviews (CDR), which often result in benefit cessations. For a child whose impairment is expected to improve, SSA generally conducts CDRs within 6 to 18 months; for a child whose impairment is "probable", SSA is supposed to conduct CDRs every 3 years; for a child whose impairment is not expected to improve, SSA is supposed to conduct CDRs at least every 7 years. However, the numbers of CDRs SSA conducts varies over time depending on caseload size, administrative priorities, and budgets.[7] When recipients turn age 18, SSA also conducts a redetermination of eligibility, which entails a review of non-medical eligibility and new disability determination using the adult disability criteria.[8] In addition, at all ages, recipients must continue to not exceed the asset and income limits to remain eligible for benefits (including deemed income and assets from a parent for SSI recipients younger than age 18). The number of CDRs has increased substantially since 2015, which might be an important driver of the decrease in SSI participation during this time as frequent CDRs contribute to shorter duration of benefit receipt (Hemmeter et al. 2021).

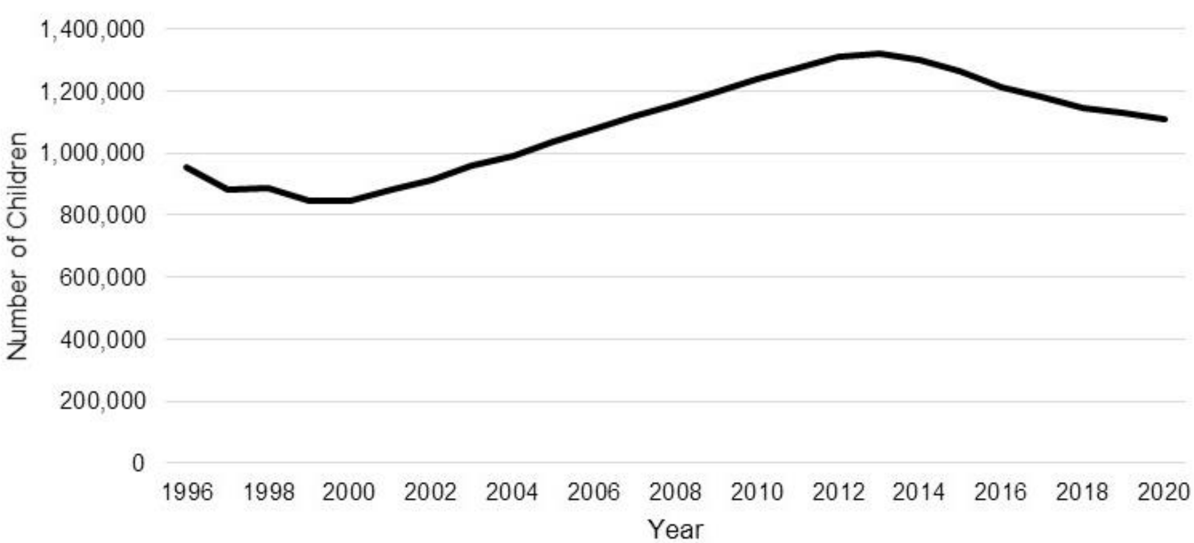
SSI Caseloads Trends

The number of children receiving SSI has fluctuated substantially since 1996 despite no

[6] The Policy Surveillance Program provides details on state supplemental payments for child and adult SSI recipients at http://lawatlas.org/datasets/supplemental-security-income-for-children-with-disabilities (accessed October 7, 2019).
[7] See 20 CFR 404.1590 for SSA's policies on how often it conducts CDRs. https://www.ssa.gov/OP_Home/cfr20/404/404-1590.htm (Last accessed July 10, 2020.)
[8] Unlike the child SSI eligibility criteria, the adult criteria rely on a disability definition that focuses on work (the inability to engage in substantial gainful activity, which in 2021 is defined as monthly earnings above $1,310 for the non-blind). The adult criteria also do not include any deeming of parental income. In making age-18 redeterminations, SSA uses the same medical, income, and asset criteria as it uses in adult application decisions. Most children receiving SSI have a redetermination at age 18 (82 percent), though some have redeterminations after 18 for various reasons (Hemmeter and Bailey 2015).

changes in the rules for eligibility (Figure 1). We chose 1996 as the starting point for the analysis of trends because the statutory definition of eligibility for children has not changed since that time. However, as noted above, there have been other changes in administrative processes that can influence who becomes and remains eligible for benefits, particularly the large increase in CDRs in recent years. From 1996 to 1998, caseloads dipped after the establishment of the current eligibility rules implemented as part of larger welfare reforms in 1996.[9] Caseloads increased from about 1998 to 2013, with much interest in the driving factors of this growth. The increase was the focal point of congressional debates (see Wittenburg 2011), particularly because of the contraction in other cash transfer programs, such as Temporary Assistance for Needy Families (Schmidt and Sevak 2004, 2017). Since 2013, caseloads declined from a high of 1.3 million; 1.1 million children received SSI as of December 2019. Caseloads declined further during the COVID-19 pandemic, with the closure of SSA field offices cited as an important driver (Emanuel 2021). Other factors, such as supplemental unemployment benefits, embargoes on evictions, and stimulus payments, that increased income and reduced poverty (Wheaton et al. 2021) might also have led to declines in participation.

Figure 1. *Trends in Child SSI Recipients, 1996 to 2020*



Source: SSA (2020).

[9] For a history of SSI program changes, including changes before 1996, see Wittenburg and Livermore (2021) and Berkowitz and DeWitt (2013).

Prior literature highlights substantial geographic variation in caseload growth through 2013. Wittenburg et al. (2015) showed that more than half the growth in caseloads from 1998 to 2013 took place in four states (California, Florida, Pennsylvania, and Texas). They also showed that, more generally, SSI participation rates per capita were higher in southern and northeastern states. Schmidt and Sevak (2017) showed that changes in the number of people living in poverty and the availability of special education, among other factors, were key contributors to SSI caseloads. Several other studies identified regional factors that could affect program caseloads, such as availability of advocacy networks, access to local field offices, information about SSI that is tied to other programs, and cultural issues (for example, views of disability that vary by region) (Deshpande and Li 2019; Hemmeter et al. 2017; Duggan et al. 2015; U.S. Government Accountability Office 2012).

Understanding recent geographic drivers of child SSI participation is important to ensure equitable access to the program. SSA has identified outreach to vulnerable populations, including children, as a key priority. It set aside $96 million in its 2021 budget to support outreach efforts. These efforts will be done in the context of recent program declines associated with the COVID-19 pandemic.

Our paper addresses three notable gaps in the literature to better inform outreach efforts and understand SSI program dynamics more generally. First, recent geographic variation in child SSI participation is not well understood. Most studies analyzed the period of large program growth through 2013, but recent declines in child SSI participation necessitate another look at whether geographic patterns might have changed. Second, most studies focused on larger geographic units, such as counties, whereas understanding even narrower geographic regions, such as Census tracts, might enable a deeper understanding of local patterns (for example, Chetty et al. 2016). Finally, limited quantitative information exists to create indicators for potential outreach areas or how those areas are correlated with other characteristics (for example, demographics of the population).

Deprivation

We incorporate a measure of local area deprivation into our geographic analysis of child SSI participation rates. Our measure is based on the Area Deprivation Index (ADI) initially developed by a team of researchers from the Health Resources and Service Administration

(University of Wisconsin School of Medicine and Public Health 2021). A research team from the University of Wisconsin updates and maintains a data set on the ADI, which offers a relative ranking of socioeconomic disadvantage at the Census block group level, a subunit of the Census tract. Deprivation captures information about income, education, housing, and other local characteristics. The full list of input variables (listed in Appendix Exhibit 1) come from American Community Survey (ACS) data.[10]

Researchers and policymakers have used the ADI to inform health care delivery and policy. By capturing more than just a measure of poverty or income, the ADI takes a more holistic view of the ways that a local area might be disadvantaged, understanding that income often does not fully capture a family's needs. We use the index to rank neighborhoods by socioeconomic disadvantage relative to the nation as a whole. Research has linked areas with greater deprivation to worse health outcomes, such as higher rates of obesity and readmission to hospitals (Kind et al. 2014; Hu et al. 2018). Areas with higher deprivation also have higher rates of infant mortality and shorter life expectancies at birth (Singh and Kogan 2007; Singh and Siahpush 2006). Economic deprivation is one of several measures that examine local needs, which is notable in interpreting findings. Kim and Hadden Loh (2021) identified eight measures that captured different dimensions of localized need, including the ADI.[11] All eight measures identified the highest levels of need in the Southern US. In part, this consistency reflects that all eight measures included some measure of poverty. They also showed that all high-need communities fare worse than other communities on a range of alternative measures, such as greater prevalence working in low-wage occupations. Hence, our measure of economic deprivation (based on ADI) captures an essential component of need. However, Kim and Hadden Loh also showed ADI in particular identified relatively few high-need areas in the West and Midwest. Hence, using economic deprivation might lead to different characterizations of high-need local areas as compared to other measures, which is notable in considering more localized outreach efforts.

[10] Appendix Exhibit 1 also shows the correlation between each of these input measures and youth SSI participation.
[11] In addition to ADI, the seven other measures included: (1) federal statute's for Low-Income Communities; (2) the Treasury and Internal Revenue Service designation of Qualified Opportunities Zones; (3) the Centers for Disease Control and Preventions Social Vulnerability Index; (4) Diversity Data Kids' Child Opportunity Index; (5) the Robert Graham Center's Social Deprivation Index; (6) the Economic Innovation Group's Distressed Communities Index; and (7) an author adaption of the US Department of Agriculture Economic Research Service's classification of persistent poverty counties.

The families of children in areas with high deprivation are therefore more likely to have a greater need for services, particularly those services offered to families of children with disabilities through SSI. Low child SSI participation in an area relative to that expected based on its deprivation measure could indicate a need for outreach.

Data and Methods

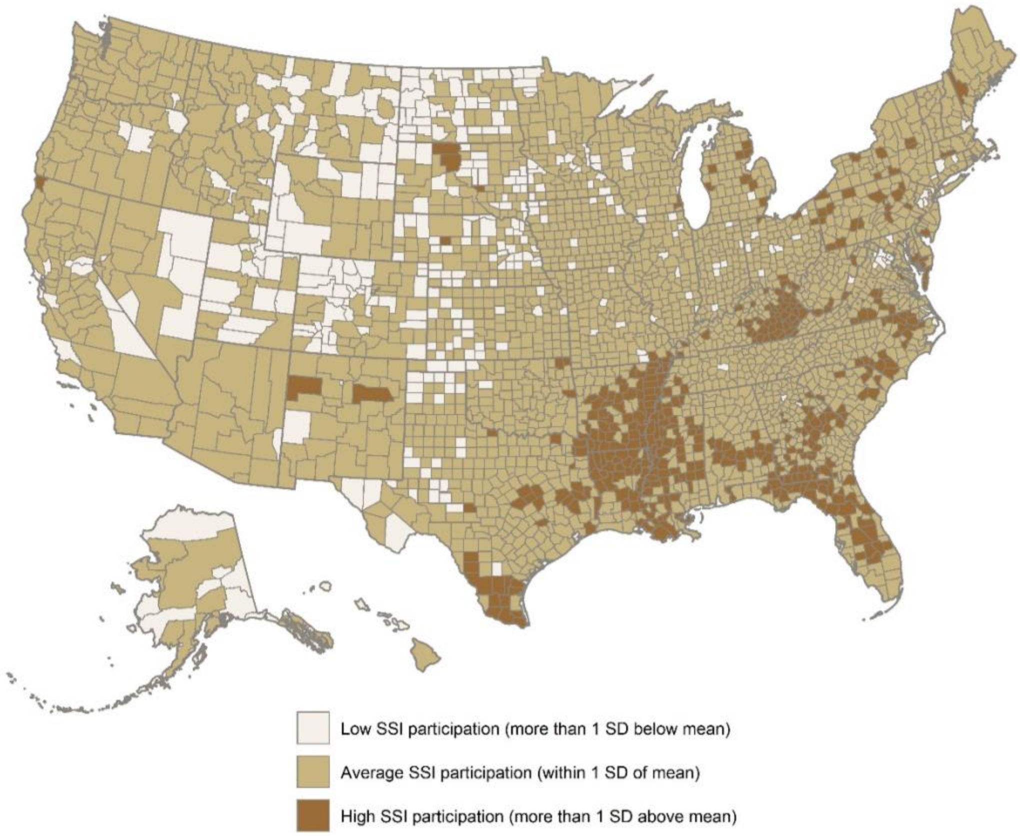
We used administrative data from the Supplemental Security Record, the main SSA system of records for the SSI program, to measure the number of children receiving SSI at the Census tract and county levels in 2019. The United States is composed of about 74,000 Census tracts, which are designed to have about 4,000 people each, though can range from 2,500 to 8,000 people. The administrative data contain information on the address of the recipient, including county. To assign a Census tract, we geocoded the addresses of all child SSI recipients. We were able to successfully geocode 95 percent of the records. Of the remaining 5 percent, about 3.5 percent had an unusable address, and 1.5 percent had an address that could not be geocoded and thus could not be placed in a particular Census tract. We dropped these records from the analysis.

Our primary outcome measure is the number of child SSI recipients per 1,000 children in the geographic unit. We gathered data on population for children (that is, those younger than age 18) from ACS 5-year statistics from 2015 to 2019. These data were available at the Census tract and county levels.

We also explored the characteristics of child SSI recipients in each local area. Specifically, we measured the percentage of child SSI recipients in each local area who were (1) male or female; (2) younger than age 5, ages 5 to 13, or older than age 13; and (3) had a variety of primary diagnoses. We used the standard list of primary diagnoses presented in the SSI statistical report (SSA 2020).

Figure 2 shows the geographic variation in child SSI participation in 2019 at the county level. As in previous studies, we continue to show heavier concentrations of children receiving SSI in the Southeast and Northern regions.

Figure 2. *Child SSI Participation Rates in 2019, County Level*



Notes: Child SSI participation rates are calculated by dividing the number of child SSI recipients in each county (from SSA program records) by the child population in the county (from ACS data). Darker colors indicate higher levels of child SSI participation.
Source: Authors' calculations using SSA program records and ACS data.

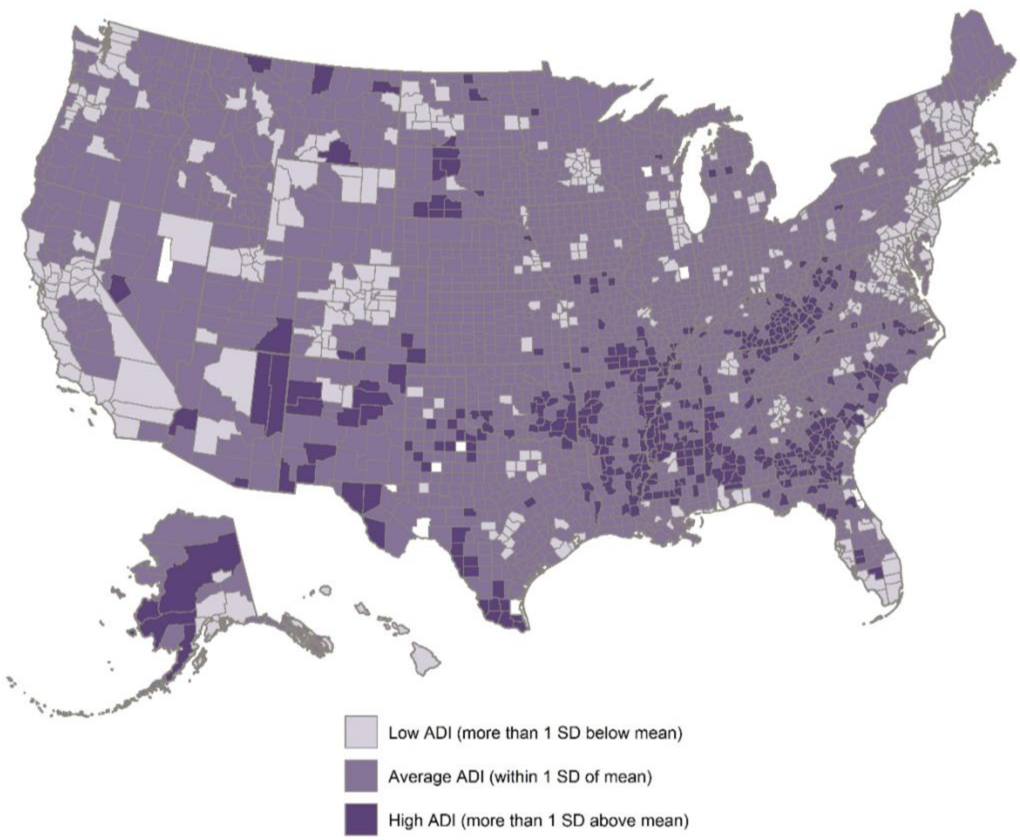
We measured deprivation at the Census tract and county levels using data from the 2015–2019 ACS 5-year statistics. Because the ADI available from the University of Wisconsin is only available at the Census block group level and captures a relative ranking, we followed an identical procedure to the process described in Singh (2003) to create a measure of deprivation at a different geographic level.[12] Specifically, we gathered data on the components of the ADI.[13] We conducted a factor analysis to create weights assigned to each of the components, and then

[12] Because the ADI is a relative ranking, we cannot simply average across geographies to aggregate up to a higher geographic level (for example, averaging across all Census block groups within a tract or all block groups within a county). Rather, we need an underlying raw score, which we can then use to construct a relative percentile at the geographic variable of interest. However, there is a strong positive correlation (greater than 0.80) between averaging the percentile across the subunits and the final percentile calculated from the raw data.
[13] At the Census tract level, input variables are missing for as many as 5.9 percent of Census tracts. In these instances, we impute the tract level value using the county level value when it is available, following the same procedure used to create ADI.

we created a raw index measure using the weights. Finally, we converted the index to a percentile so that the final index indicates the relative level of deprivation in the local geography compared with the rest of the country.

Figure 3 shows the geographic variation in deprivation across the United States at the county level. Deprivation is relatively high in the Southeast, such as states like Arkansas, Kentucky, and Louisiana, that had high levels of SSI participation as well (shown in Figure 2). However, there are numerous areas with relatively higher areas of deprivation that also had lower levels of SSI participation, like in North Dakota and South Dakota, as well as areas with lower deprivation and higher SSI participation.

Figure 3. *Deprivation in 2015-2019, County Level*



Notes: We calculated deprivation following the method summarized in University of Wisconsin School of Medicine and Public Health (2021) using the 2015–2019 ACS 5-year statistics. Deprivation is expressed as a percentile, and thus indicates deprivation relative to the rest of the country. Darker colors indicate a higher value of deprivation. *Source:* Authors' calculations using ACS data.

To better understand the relationship between deprivation and SSI, we developed a regression framework to examine correlations between the two measures. We first estimated a simple linear regression of child SSI participation on deprivation as shown in equation (1). We weighted this regression by the child population in the geographic unit. Using the coefficient β from the regression, we created a predicted value of child SSI participation based on the local level of deprivation. As discussed above, we conducted this analysis for geographies g at the Census tract and county levels separately.

(1) $SSI_g = \alpha + \beta Deprivation_g + \varepsilon_g$

Our primary analysis stems from measuring the deviation between actual SSI participation and the predicted SSI participation after adjusting for deprivation (equation (1)). The deviation is the residual from the regression (). It represents the difference between the predicted value of child SSI participation based on the local level of deprivation and the observed child SSI participation.

Deviation can be negative or positive. A negative deviation indicates that actual child SSI participation was lower than predicted participation. Conversely, a positive deviation indicates that actual SSI participation was higher than predicted participation. In the maps that follow, we consider a geographic unit to have less-than-predicted participation if deviation in that unit is lower than the 25th percentile of the deviation distribution. Similarly, we consider a geographic unit to have greater-than-predicted participation if deviation in that unit is greater than the 75th percentile of the deviation distribution.[14] All metrics, even when presented for specific local areas, are based on the national distribution of deviation.

We then explore characteristics of local areas associated with larger or smaller deviation to better understand the places that likely would most benefit from outreach (Table 1). These measures capture a range of local regional characteristics in publicly available data. Our analysis includes information about demographic, disability, or other features of the local areas (population density, social capital and opportunity zones) that might be correlated with deviations. We regress deviation (from equation (1)) on the list of measures from Table 1, signified as $\mathbf{X_g}$ in equation (2).[15] We estimated multivariate regressions, including all control

[14] The choice of 25^{th} and 75^{th} percentile is somewhat arbitrary, but the interquartile range provides a reasonable definition of low and high deviation. Alternatives, such as the standard deviation, could also be used.

[15] Many of these measures are correlated with both deprivation and SSI participation. However, this regression seeks

variables and weighted the regression by population. Because deviation does not have a readily intuitive cardinal interpretation, we only present standardized coefficients and p-values. This enables us to identify measures that have relatively higher and lower correlations with deviation. Because this estimation relies on a two-step process, we bootstrap the entire process to calculate standard errors.

(2) $Deviation_g = \gamma + \delta \boldsymbol{X_g} + \omega_g$

Table 1. *Measures Potentially Correlated with Deviation Between Actual and Predicted Child SSI Participation*

Characteristic	Source and description
Geographic region	Defined by the Census classification of states into Northeast, South, Midwest, and West
Urbanicity	From USDA Rural-Urban Continuum Codes. Areas are classified into metropolitan (indicating the county is part of a metropolitan area), suburban (the remainder) or rural (completely rural areas).
Percentage of population that is non-white	From ACS 2015–2019 5-year estimates
Percentage of population that has a disability	From ACS 2015–2019 5-year estimates
Population density (county-level only)	Total population from ACS 2015–2019 5-year estimates divided by land area from U.S. Gazetteer Files
Social capital (county-level only)	Measures participation in civic, religious, and sports organizations as defined by Rupasingha et al. (2006)
Opportunity zone (tract-level only)	Distressed Census tracts, from the U.S. Department of Treasury's Community Development Financial Institutions Fund

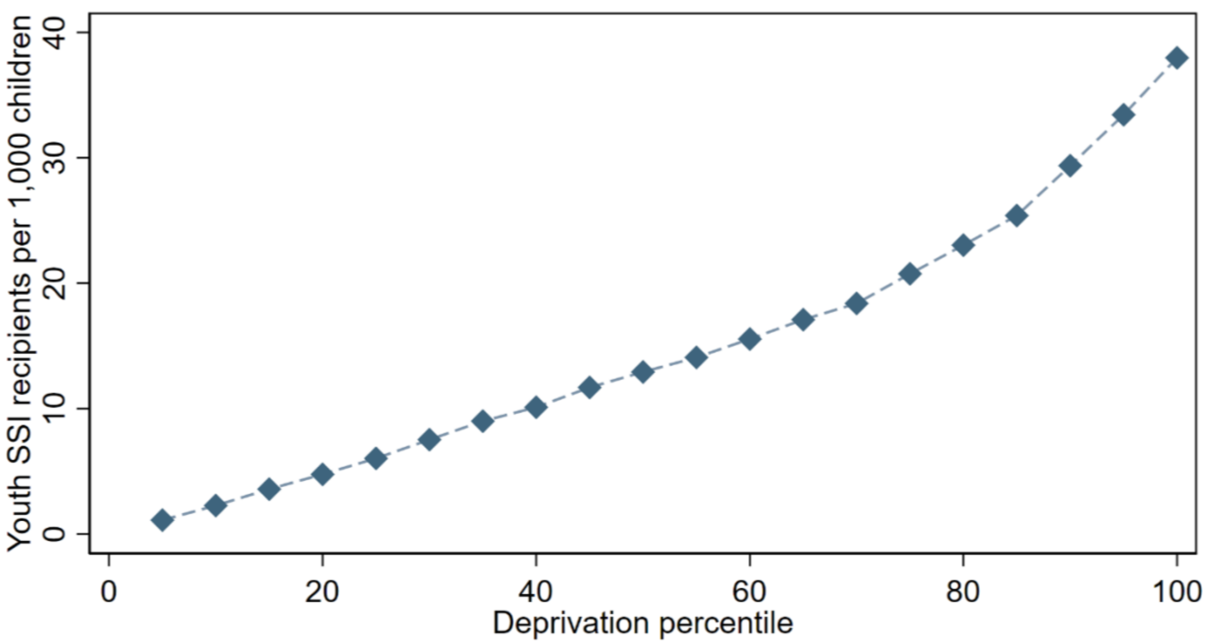
Finally, we also explored how the COVID-19 pandemic affected the underlying relationship between deprivation and child SSI participation. Specifically, we assessed whether the change in SSI applications from 2019 to 2020 was associated with deprivation and deviation. SSI applications declined by 17 percent in 2020, with substantial geographic variation in the decline. For this analysis, we focused only on the county level because of data availability.

to correlate each measure with *deviation*, not directly with either deprivation or actual SSI participation. Put differently, just because a measure is correlated with both deprivation and SSI participation does not mean it will also inherently be correlated with the *gap* between actual SSI participation and a predicted measure of SSI participation that is based on deprivation.

Results

There is a strong positive relationship between deprivation and area child SSI participation, which is expected because SSI serves low-income populations (Figure 4). For each additional decile higher deprivation score (for example, the 20th percentile rather than the 10th percentile), child SSI participation on average increases by 3.3 per 1,000.[16] Relative to the mean of 17.3 per 1,000 in the average Census tract, this represents an increase of nearly 20 percent. Results are statistically significant at the Census tract and county levels, though the magnitude of the relationship is substantially stronger in the Census tract analysis (Appendix Exhibit 2).[17] The R^2 from the simple linear regression in equation (1) is 0.40 at the Census tract level and 0.39 at the county level. This indicates that though there is a strong correlation between deprivation and SSI, much variation remains in predicting local area SSI participation.

Figure 4. *Relationship Between ADI and Child SSI Participation*



Notes: This figure characterizes census tracts by their level of deprivation and the number of child SSI recipients per 1,000 people younger than age 18 in that tract. Each point shows the average for all tracts within each ventile (splitting the distribution of deprivation into 20 groups of based on five-percentile buckets).
Source: Authors' calculations using SSA program records and ACS data.

[16] Appendix Exhibit 2 presents the results of this regression, including for whether we weight by the population of the local area.
[17] We also include in Appendix Exhibit 2 an alternative specification that replaces deprivation with a percentile score for the percentage of the population earning less than 150 percent of the federal poverty limit, which yields remarkably similar results.

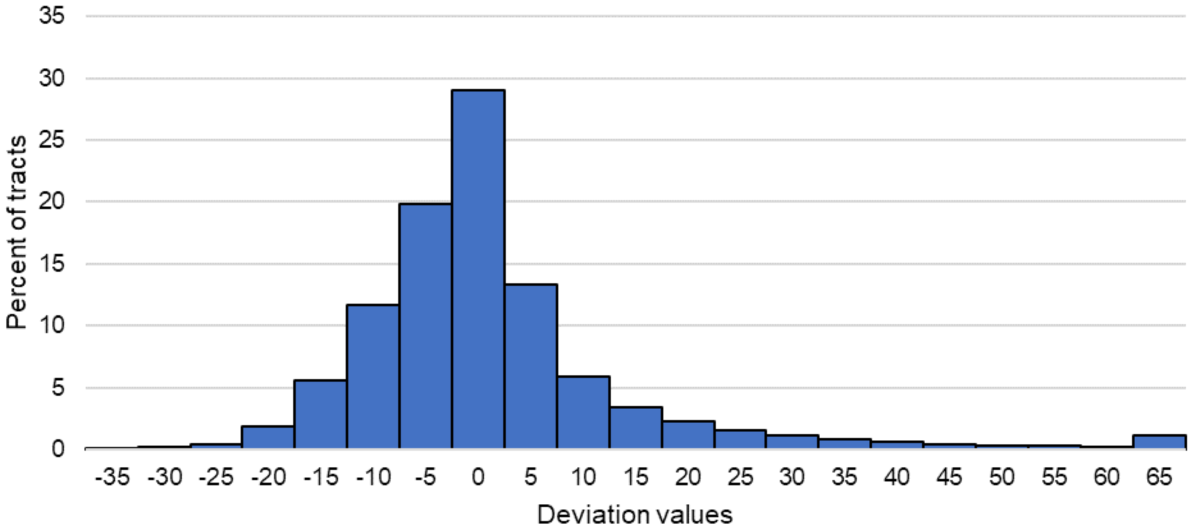
The primary diagnoses[18] of child SSI recipients varied depending on the level of deprivation, while sex and age of recipients did not vary. Using descriptive data on the average characteristics of child SSI recipients in each Census tract, we find that communities with higher levels of deprivation have a smaller percentage of child SSI recipients with autistic disorders as their primary diagnosis (Appendix Exhibit 3).[19] This is consistent with evidence that rates of autism diagnosis are higher in places with higher socioeconomic status (Thomas et al. 2012). In contrast, communities with higher levels of deprivation have greater incidence of developmental disorders and other childhood and adolescent disorders as their primary diagnosis.[20] Shares of child SSI recipients who were male and who were various ages were mostly constant across communities regardless of the level of deprivation (Appendix Exhibit 4).

Geographic Heterogeneity and Deviation Between Predicted and Actual Child SSI Participation

We next examine the geographic dispersion of deviation. Figure 5 shows that most Census tracts have deviations around zero, though they can be very high or low (note that the figure top-codes values above 64, representing the 99th percentile of deviation, to make it more readable).

[18] Children may have more than one diagnosis; however, not all are recorded in SSA's administrative records. The primary diagnosis may or may not reflect the condition causing the most significant functional barriers to the child. Additionally, it may reflect underlying differences in access to medical care or SSA's disability determination process itself.
[19] On average, nearly one in five youth SSI recipients had autistic disorders. For those in the highest deprivation areas, fewer than 15 percent had autistic disorders, while in the lowest deprivation areas, nearly 30 percent did.
[20] On average, about 30 percent of youth SSI recipients had either developmental disorders or other childhood and adolescent disorders. For those in the highest deprivation areas, more than 40 percent had one of these two diagnoses, while in the lowest deprivation areas, only about 23 percent did.

Figure 5. *Distribution of Deviation*



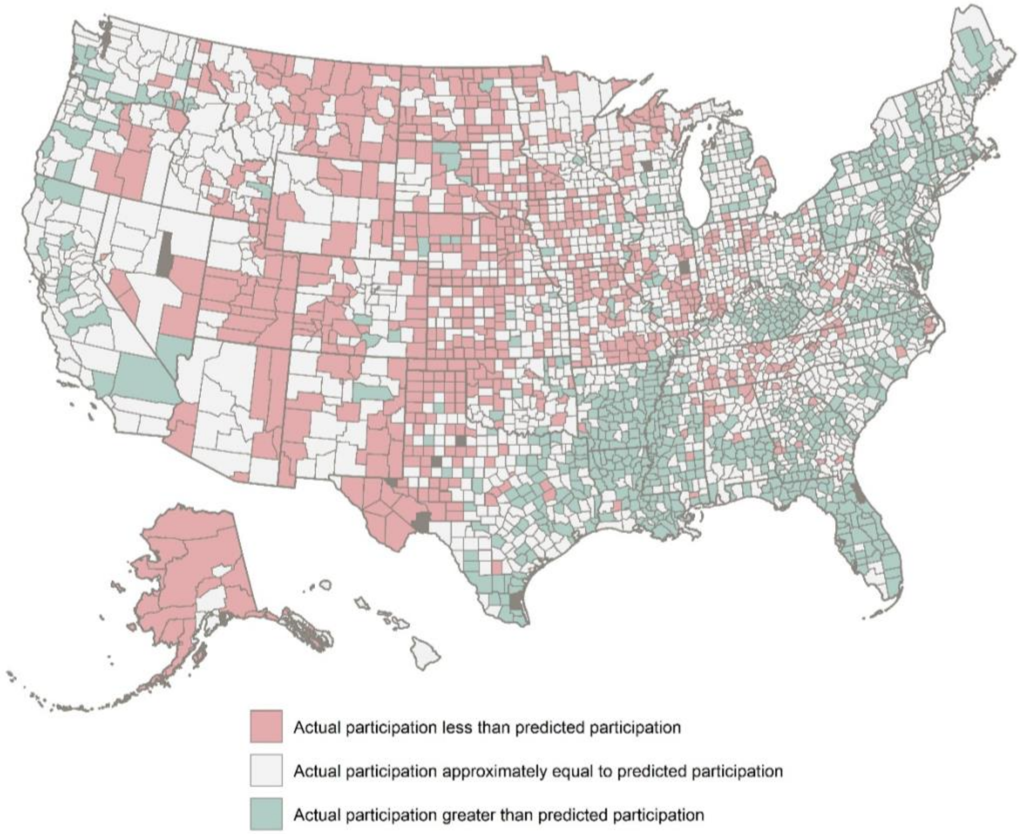
Notes: Each bar shows the percent of tracts that have deviations in a bucket centered at the number shown. For example, the bucket around 0 shows tracts with deviations between -2.5 and 2.5. Deviations above 64, representing the 99th percentile of the deviation distribution, are top coded to 64 for ease of presentation. Our primary analyses do not use this top coding, though doing so would not affect the actual regression analyses.
Source: Authors' calculations using SSA program records and ACS data.

Many regions have higher or lower actual SSI participation than predicted (Figure 6). As we noted, we define an area to have higher (lower) actual participation than predicted if the deviation measure is greater than the 75th percentile (lower than the 25th percentile) of the deviation distribution.[21]

The areas with lower actual participation than predicted are disproportionately located in the Midwest: about 32 percent of Census tracts in the Midwest fall in this category versus 23 percent in the rest of the country. These areas might benefit from outreach because of their relatively limited SSI participation. The areas with higher actual participation than predicted are disproportionately located in the Northeast and the South; about 35 percent of Census tracts in the Northeast and 32 percent in the South fall into this category versus 16 percent in the rest of the country. These areas drove much of the growth in SSI from 1996 to 2015 (Wittenburg et al. 2015).

[21] Motivated by the findings in Appendix Exhibit 2 indicating a similar relationship between the percentage of people earning less than 150 percent of the federal poverty limit and youth SSI participation, we constructed an alternative measure of deviation based on this regression. This alternative deviation (based on a regression of the percentage earning less than 150 percent of the federal poverty level) is highly correlated with our standard deviation (based on a regression of deprivation). The correlation is about 0.95 at the county level and 0.99 at the Census tract level. Using a simpler measure would yield nearly identical findings throughout, but not explicitly account for other socioeconomic factors.

Figure 6. *Deviation Between Actual and Predicted Child SSI Participation in 2019, County Level*



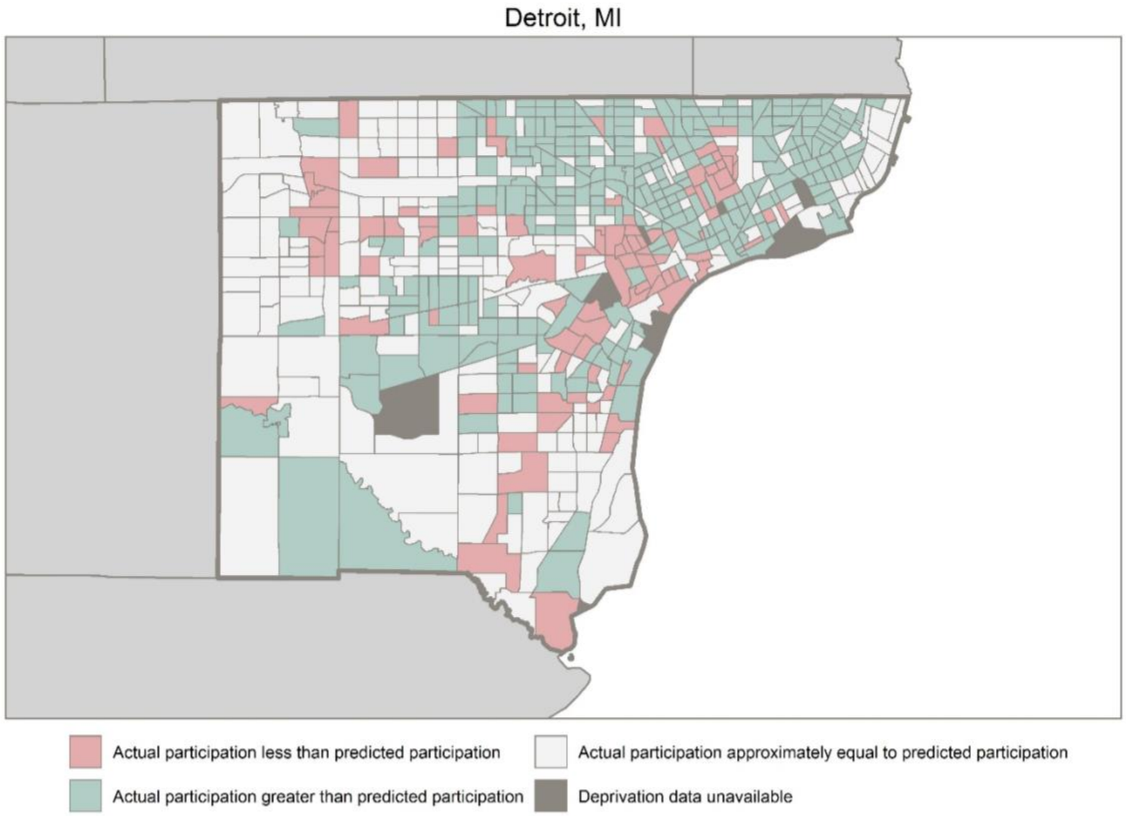
Note: Counties are characterized as having actual participation greater (less) than predicted participation if deviation is greater than the 75th percentile (less than the 25th percentile).
Source: Authors' calculations using SSA program records and ACS data.

Within counties, individual Census tracts often vary in whether actual participation is higher or lower than predicted. For example, Figure 7 shows the Census tracts that make up the metropolitan statistical area for Detroit, Michigan. Detroit has about 4.4 million people, making it the 14th largest metropolitan area in the country. It ranks 92 out of 384 metropolitan statistical areas in per capita personal income.[22] The city contains a mix of areas in which actual participation is greater than predicted (positive deviation in green) and in which actual participation is less than predicted (negative deviation in red). This prompts a question (what factors are associated with local areas having higher or lower deviation) that we address below. Narrowing in on these highly localized regions can help SSA precisely pinpoint where to target resources, for example, by helping identify local partners in specific neighborhoods. More

[22] See the Bureau of Economic Analysis personal income statistics found at https://www.bea.gov/data/income-saving/personal-income-county-metro-and-other-areas.

broadly, it can help researchers and policymakers better understand the heterogeneity of SSI participation at local levels, including factors such as networking effects (learning about the program through local relationships) that might influence program dynamics and interactions with other programs.

Figure 7. *Deviation Between Actual and Predicted Child SSI Participation, Census Tract Example*



Note: Tracts are characterized as having actual participation greater (less) than predicted participation if deviation is greater than the 75th percentile (less than the 25th percentile). All percentiles are based on the national distribution.
Source: Authors' calculations using SSA program records and ACS data.

Correlations with Deviation

To understand the factors associated with higher and lower levels of deviation, we next estimate regressions using equation (2). We use measures of deviation as an outcome variable with the control variables that are listed in Table 1. We weight the regression by child population. These regressions explore the extent to which certain community characteristics predict positive or negative deviation. By identifying patterns common to local areas with a mismatch between deprivation and SSI participation, policymakers can potentially better target resources to address the community characteristics frequently associated with high measures of deviation.

Areas that have a larger share of non-White population have greater positive deviation (Table 2). Put differently, the larger the share of White residents in a local area, the lower actual SSI participation is relative to predicted participation based on deprivation (that is, the smaller positive or larger negative [in magnitude] the measure of deviation). This finding is consistent with evidence showing that Black individuals are about twice as likely to receive SSI benefits as White individuals (Musumeci and Orgera 2021). The standardized coefficients for the non-White population has a large magnitude for both geographies, indicating that, among the chosen predictors, this has a strong relationship with deviation.

A variety of the other factors prior research has found to be associated with SSI participation are also associated with deviation (Table 2). Deviation increases with the share of the population that has a disability, consistent with the disability criteria for children to receive SSI. There are notable differences in deviation by region, with areas in the Northeast and the South having higher deviation than those in the Midwest and the West. Areas with higher social capital have greater deviation, indicating that places with lower participation in civic, religious, and sports organizations do not participate in SSI to the extent that would otherwise be expected based on the level of deprivation. Metropolitan areas have substantially higher deviation, while rural areas tend to have lower deviation.

Table 2. *Characteristic Correlations with Deviation*

	Census tract level		County level	
Characteristic	Standardized coefficient	*p*-value	Standardized coefficient	*p*-value
Percentage of population that:				
Is non-white	0.105	0.000	0.337	0.000
Has a disability	0.146	0.000	0.276	0.000
Population density	n.a.	n.a.	0.178	0.049
Social capital	n.a.	n.a.	0.246	0.000
Urbanicity (omitted: suburban)				
Rural	-0.028	0.000	-0.071	0.000
Metropolitan area	0.135	0.000	0.326	0.000
Region (omitted: Midwest)				
Northeast	0.159	0.000	0.255	0.000
South	0.069	0.000	0.112	0.004
West	-0.140	0.000	-0.195	0.000
Opportunity zone	0.037	0.000	n.a.	n.a.

Notes: n.a. = not available. A positive coefficient indicates that the characteristic is positively associated with deviation so that higher values are associated with larger actual participation than predicted participation.
Sources: Authors' calculations using SSA program records, ACS data, U.S. Census state classifications, USDA Rural-Urban Continuum Codes, U.S. Gazetteer Files, Rupasingha et al. (2006), and U.S. Department of Treasury's Community Development Financial Institutions Fund.

We also consider an alternative specification in which the outcome is an indicator of negative deviation (that is, actual participation is less than predicted participation) rather than the continuous value of deviation (Appendix Exhibit 5). The geographic pattern of results is similar, with tracts or counties in the Northeast and South less likely than those in the Midwest and West to have actual participation less than predicted participation. However, some of the other characteristics exhibit different patterns. For example, tracts with a higher percentage of the population that is non-White are more likely to have actual participation less than predicted participation, while the percentage that is non-White is not a significant predictor at the county level. Other characteristics, such as population density, are no longer significant predictors either.

SSI Applications during the COVID-19 Pandemic

Total child SSI applications during 2020 fell to 310,688, a decline of 17.5 percent from the 376,557 child SSI applications during 2019. Counties with higher deprivation had slightly larger declines in child SSI applications in 2020 (Table 3). For each additional decile higher deprivation score, SSI applications declined by an additional 0.5 percentage points. Relative to the total decline in child SSI applications over this period of 17.5 percent, this represents only a 3 percent change. In addition, areas with greater deviation saw larger declines in child SSI applications. Areas that had smaller deviation (or larger negative deviation) likely already had low levels of applications because actual participation was already less than predicted participation, making them unlikely to decline further.

Table 3. *Correlations with Decline in SSI Applications from 2019 to 2020*

Characteristic	Deprivation	Deviation
Coefficient	-0.053	-0.799
Standard error	[0.024]	[0.073]
Number of observations	3,130	3,130

Notes: This table estimates a regression of the percentage change in SSI applications from 2019 to 2020 on either deprivation (column 1) or deviation (column 2). All regressions are weighted by population.
Source: Authors' calculations using SSA program records and ACS data.

Conclusion

We find substantive differences in child SSI participation across geographic areas even after controlling for deprivation. These differences existed before the drop in applications associated with COVID-19, yet high-deprivation areas saw somewhat larger drops in applications during the pandemic. As a result of this drop in SSI applications, SSA increased its efforts to reach out to at-risk communities and populations facing barriers to participation.[23] It established new liaisons and partnerships to facilitate applications and conducted public service campaigns focusing on children with disabilities.

One way this research can support SSA's outreach is by suggesting a metric to use for targeting areas. Deprivation succinctly identifies areas with multiple characteristics likely associated with barriers to participating in social programs, such as SSI. As such, it could be a more useful metric to tailor SSA's outreach efforts than single-measure identifiers (for example, the poverty rate alone). By pinpointing specific geographic areas with notably lower SSI participation than expected, SSA can further narrow its outreach efforts.

While deprivation is one potential metric, our work highlights several other factors

[23] For more information, see SSA (2021).

correlated with areas that still have gaps between predicted and actual SSI participation, such as race, disability prevalence, geography, and social capital. Other important factors that we do not explicitly consider in this paper could also include the local program environment such as the availability of services and supports, which vary substantially by region and within county (NASEM 2018), SSA field office proximity (Deshpande and Li 2019), and recent trends in CDRs.

While a useful starting point for understanding geographic variation in program dynamics, deviation has limitations. The deviation measure, which represents deviations from average national caseloads, can only capture whether SSI participation is low relative to other areas, not whether all who are eligible are participating. Any systemic barriers that influence outcomes are also reflected in the measure. For example, larger systemic structures such as residential segregation from residential redlining (e.g., Aaronson, Hartley, and Mazumder 2021) might lead the underlying input measures of deprivation (which include housing and other measures) to capture the local area's need for SSI differently. If the measure of deprivation underestimates or overestimates the need for SSI in communities with a larger non-White population, then deviation might capture something different depending on the share of the population that is non-White, threatening our ability to draw conclusions from the model.[24] Despite these limitations, using deviation provides SSA a useful starting point for identifying potentially underserved populations.

Though we focus on areas with high deprivation and low SSI participation among children, it is also important to understand more about areas in which actual participation exceeds predicted participation. Perhaps through stronger community ties (such as social capital) and greater understanding of available programs, people in such areas can take advantage of services and supports available to them. Yet many people do not take up benefits for which they are eligible (Currie 2006). Though these areas have greater actual participation than predicted, this is relative to a national average; such areas might still have many children who are eligible but do not participate in SSI and thus might also benefit from outreach efforts.

[24] As another example, in health care, health outcomes are worse among Black patients relative to White patients among groups with the same levels of spending, perhaps because of differential access to care (Obermeyer et al. 2019). This leads to bias in comparing measures of spending across racial groups. If the same type of issues affect the input measures to deprivation—and SSI participation—we would face similar challenges.

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Appendix Exhibit 1. *Input Measures to Deprivation*

Measure	**ACS data question**	**Correlation with child SSI participation**	
		Tract	**County**
Population aged 25 and older with less than 9 years of education	B15003	0.250	0.197
Population aged 25 and older who completed at least a high school education	B15003	-0.409	-0.390
Employed persons aged 16 and older in white collar occupations (management, business, science and arts occupations)	C24010	-0.491	-0.377
Population aged 16 and older who are unemployed	B23025	0.419	0.456
Owner-occupied housing units (home ownership rate)	B25003	-0.442	-0.326
Households with more than one person per room	B25014	0.135	0.019
Median monthly mortgage ($)	B25088	-0.395	-0.376
Median gross rent ($)	B25064	-0.379	-0.403
Median home value ($)	B25077	-0.348	-0.376
Median family income ($)	B19113	-0.553	-0.624
Income disparity (ratio of people with income under $15,000 to people with income over $75,000)	B19001	0.355	0.658
Families below poverty level	B17010	0.600	0.721
Population earning less than 150 percent of the federal poverty limit	C17002	0.634	0.703
Single parent households with children under 18 years old	B11003	0.569	0.713
Households without a motor vehicle	B25044	0.450	0.377
Households without a telephone	B25043	0.235	0.288
Occupied housing units without complete plumbing	B25047	0.277	0.318

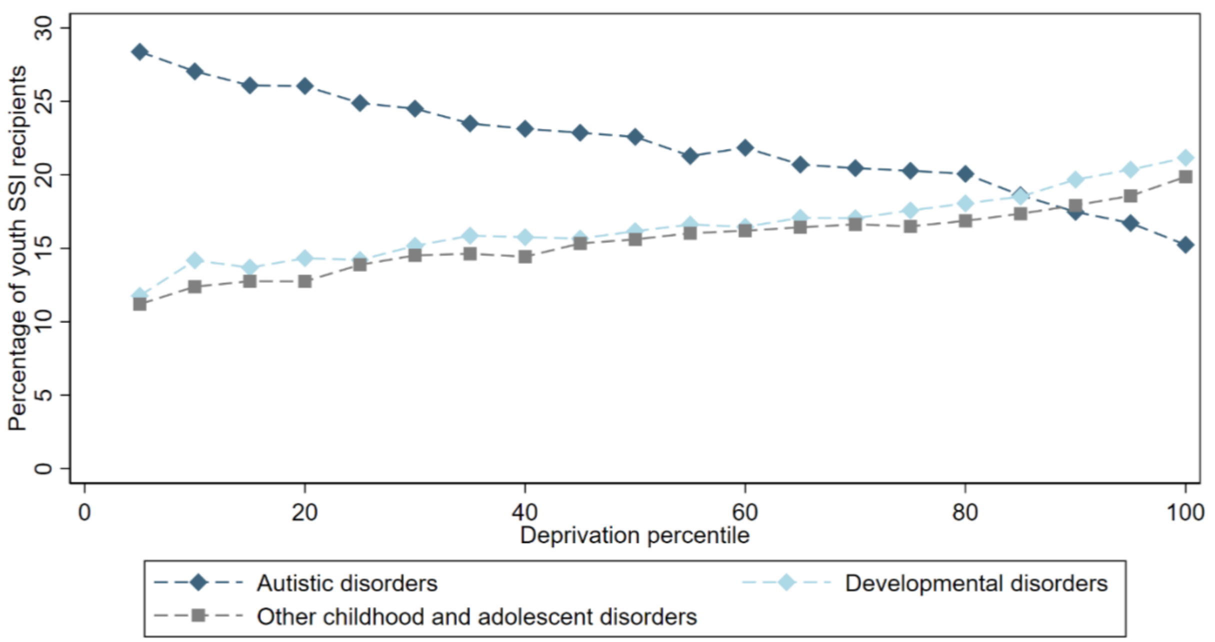
Notes: All values indicate correlation coefficients. In a linear regression of the child SSI participation rate on each individual variable, each of the coefficients would be significant at the 1 percent level with the exception of households with more than one person per room at the county level. For reference, the correlation between deprivation and child SSI participation is 0.634 at the Census tract level and 0.626 at the county level.
Source: Authors' calculations using SSA program records and ACS data.

Appendix Exhibit 2. *Linear Regression Results on the Relationship Between Deprivation and Child SSI Participation*

Measure	**(1)**	**(2)**	**(3)**	**(4)**
Panel A				
Deprivation	0.349	0.407	0.209	0.197
	[0.002]	[0.004]	[0.014]	[0.006]
R^2	0.402	0.089	0.392	0.331
Panel B				
Poverty (below 150 percent)	0.335	0.392	0.229	0.206
	[0.002]	[0.007]	[0.013]	[0.005]
R^2	0.375	0.084	0.487	0.378
Geographic	Tract	Tract	County	County
Weighted by population	Yes	No	Yes	No
Number of observations	71,976	71,976	3,130	3,130

Notes: This exhibit shows the coefficient on deprivation from an estimate of equation (1) using a measure of deprivation (Panel A) or a measure of the percentage of the population earning less than 150 percent of the federal poverty limit (Panel B). To facilitate a consistent comparison across the two panels, we converted the percentage of population below 150 percent of the poverty level to a percentile. Each panel is a separate regression.
Source: Authors' calculations using SSA program records and ACS data.

Appendix Exhibit 3. *Primary Diagnosis of Child SSI Recipients, by Deprivation Percentile*



Notes: This exhibit reports the average value of the percentage of child SSI recipients with each primary diagnosis across all Census tracts in that percentile. Each point shows the average for all tracts within each ventile (splitting the distribution of deprivation into 20 groups of based on five-percentile buckets). The relationship between deprivation and primary diagnosis of child SSI recipients for other diagnoses is not shown but is available on request.
Source: Authors' calculations using SSA program records and ACS data.

Appendix Exhibit 4. *Age and sex of child SSI recipients, by deprivation percentile.*

	Percentage of child SSI recipients that are			
Deprivation percentile	**Ages 0 to 4**	**Ages 5 to 12**	**Ages 13 to 17**	**Female**
5th percentile	15.76	50.17	34.08	31.90
10th percentile	15.22	48.50	36.29	32.55
15th percentile	14.98	48.76	36.27	34.27
20th percentile	15.04	49.98	34.98	33.59
25th percentile	14.80	50.05	35.15	32.81
30th percentile	14.38	50.94	34.69	32.83
35th percentile	14.63	50.14	35.23	32.93
40th percentile	14.45	50.61	34.94	32.73
45th percentile	14.20	50.45	35.35	32.96
50th percentile	14.09	50.55	35.36	32.49
55th percentile	13.95	50.62	35.43	32.28
60th percentile	13.74	50.63	35.63	32.44
65th percentile	13.38	50.71	35.91	32.52
70th percentile	13.76	51.05	35.19	32.40
75th percentile	13.66	50.73	35.61	32.57
80th percentile	13.67	50.98	35.35	32.26
85th percentile	13.30	51.15	35.55	32.41
90th percentile	13.79	51.17	35.04	32.76
95th percentile	13.05	51.30	35.65	32.33
100th percentile	13.11	51.82	35.07	32.44

Notes: This exhibit reports the average value of the percentage of child SSI recipients with the characteristic across all Census tracts in that percentile. Each entry is the average for all tracts within each ventile (splitting the distribution of deprivation into 20 groups of based on five-percentile buckets) so that the percentile lists the top value of the range.
Source: Authors' calculations using SSA program records and ACS data.

Appendix Exhibit 5. *Characteristic Correlations with Having Actual Participation Less Than Predicted Participation*

	Census tract level		County level	
Characteristic	Standardized coefficient	*p*-value	Standardized coefficient	*p*-value
Percentage of population that:				
Is non-White	0.135	0.000	0.044	0.335
Has a disability	0.047	0.000	0.100	0.012
Population density	n.a.	n.a.	-0.017	0.712
Social capital	n.a.	n.a.	-0.078	0.009
Urbanicity (omitted: suburban)				
Rural	0.037	0.000	0.111	0.000
Metropolitan area	-0.205	0.000	-0.323	0.000
Region (omitted: Midwest)				
Northeast	-0.152	0.000	-0.095	0.000
South	-0.132	0.000	-0.092	0.002
West	0.028	0.000	0.003	0.946
Opportunity zone	0.030	0.000	n.a.	n.a.

Notes: n.a. = not available. A positive coefficient indicates that the characteristic is positively associated with deviation so that higher values are associated with larger actual participation than predicted participation.
Sources: Authors' calculations using SSA program records, ACS data, U.S. Census state classifications, USDA Rural-Urban Continuum Codes, U.S. Gazetteer Files, Rupasingha et al. (2006), and U.S. Department of Treasury's Community Development Financial Institutions Fund.

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