What Is the Relationship Between Socioeconomic Deprivation and Child Supplemental Security Income Participation?

by Michael Levere, David C. Wittenburg, and Jeffrey Hemmeter*

This article examines how socioeconomic deprivation relates to child Supplemental Security Income (SSI) participation in local areas. We construct a deprivation index that reflects a range of socioeconomic factors. We find that local areas with higher deprivation generally have higher levels of child SSI participation, but we also see substantial geographic variation. To explore this variation, we assess the demographic and economic factors associated with the deviation between observed child SSI participation and a level of participation predicted by the deprivation index. Local areas in which child SSI participation is substantially lower than the deprivation index predicts might be promising targets for outreach to better inform families about the SSI program. By measuring the deviation between predicted and actual SSI participation at the census tract level, outreach efforts can pinpoint the precise locations where they might plausibly have the greatest effect.

Introduction

Recent reductions in the number of children receiving Supplemental Security Income (SSI) raise questions of how well the program currently reaches those who need it. Administered by the Social Security Administration (SSA), SSI 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, for reasons that are not yet fully understood. In addition, child applications for SSI have dropped sharply during the COVID-19 pandemic, resulting in far fewer awards than SSA had projected (SSA 2021b).

SSI participation varies by county and state. Understanding the drivers of these geographic differences could help identify local areas where children and families not currently receiving SSI are likely to benefit from SSI receipt. Factors that may have driven the growth in child SSI participation through 2013 include a tightening of eligibility requirements for other state programs as well as increases in the numbers of children living in low-income families, identification of mental disorders by special education services, frequency of childhood mental disorder diagnoses, and awareness of childhood disability prevalence (Government Accountability Office 2012; Schmidt and Sevak 2017). Additional factors may relate directly to administrative processes in SSA. For example, changes in the frequency of continuing disability reviews (CDRs)

Selected Abbreviations

ACS	American Community Survey
ADI	Area Deprivation Index
CDR	continuing disability review
MSA	metropolitan statistical area
SSA	Social Security Administration
SSI	Supplemental Security Income

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likely play an important role in driving patterns of payment receipt among SSI children (Hemmeter and others 2021).

The decline in child SSI participation since 2013 is directly relevant to SSA's responsibility under the Social Security Act to provide outreach to potentially eligible populations.[1] The act authorizes SSA to partner with federal, state, private, and nonprofit entities to support outreach efforts. The agency received increased funding beginning in fiscal year 2021 to identify and reach out to potential child SSI applicants in response to the sharp decline in applications during the pandemic (SSA 2021b). In June 2021, SSA designated certain claims officers as Vulnerable Population Liaisons to support and advise over 1,100 external organizations that take in and submit SSI applications on behalf of targeted groups.

Geographic variation, especially at local levels, represents an important consideration for outreach efforts and for understanding SSI program dynamics more broadly. In 2013, per capita child SSI participation was relatively higher in northeastern and southern states, although considerable variation existed within 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). Outreach and other initiatives that attempt to influence program participation must take these factors into account to make the most efficient use of available resources. In turn, by targeting outreach to highly localized areas, SSA and its partners can try to address the underlying geographic variations in SSI participation.

One likely driver of child SSI participation is the local area's socioeconomic deprivation, which reflects a variety of factors such as income, education, employment, and housing quality. Our analysis uses a measure that we developed by adapting the methodology used to create the Area Deprivation Index (ADI), a data set used by researchers and policymakers to study health care delivery and inform policy.[2] Our measure captures deprivation at the census tract level, allowing us to examine variation in SSI participation within highly localized areas. To qualify for payments under SSI's stringent asset and income limits, families must have sufficiently low resources. Almost half of child SSI recipients come from families with income below the poverty level, and median liquid family assets in 2001 were less than $100 (Rupp and others 2005/2006). Levels of deprivation vary widely across the United States (Kind and others 2014), which may explain the geographic variations in SSI participation.

This article examines the extent to which socioeconomic deprivation explains geographic variations in SSI participation among children. We calculate local SSI participation rates at the county and census tract levels. Census tract data can reveal the variations that exist within counties. Our measure of deprivation allows us to rank socioeconomic factors across census tracts. This measure is similar to the ADI measure used in Kind and others (2014), reflecting a given area's general income, education, employment, and housing quality at a precise local level. Using a simple linear regression, we develop a measure of predicted area child SSI participation based on local area deprivation, which we then compare against the area's actual participation. We define this measure as *deviation* to highlight the difference between predicted and actual SSI participation. We also analyze the characteristics of communities that have lower-than-predicted SSI participation, which might help us understand how various factors contribute to 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 after the onset of the COVID-19 pandemic.

These findings contribute to an understanding of broader trends in SSI participation, particularly in identifying the areas with the greatest unmet need for SSI, which 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. As a caveat, deviations represent only one measure of SSI participation and do not fully capture other factors that might influence outcomes, such as systemic disparities in access to resources and opportunities, the availability of related programs, or the economic environment in the local area. Hence, a large deviation only reflects that the area's caseload is above or below the national average for locations with a similar level of deprivation. Even in areas where actual participation exceeds predicted participation, large populations of eligible children might not currently receive SSI. Nonetheless, our quantitative measures provide a way to categorize areas that potentially deviate from these averages, which can be especially useful as an initial step in considering options for targeted outreach.

Background

SSI eligibility for applicants younger than age 18 is determined by 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 financial resources, as well as any parental resources "deemed" to the child, must be sufficiently low.[3] SSA excludes certain resources, such as the primary residential home or one vehicle (as long as it is used for transportation), in the calculation.[4] Local field offices handle the application process.[5] Recent research suggests that field office closures can affect local SSI participation by increasing the costs of application both for those who need to travel farther to access the office and for those affected by longer wait times (Deshpande and Li 2019).

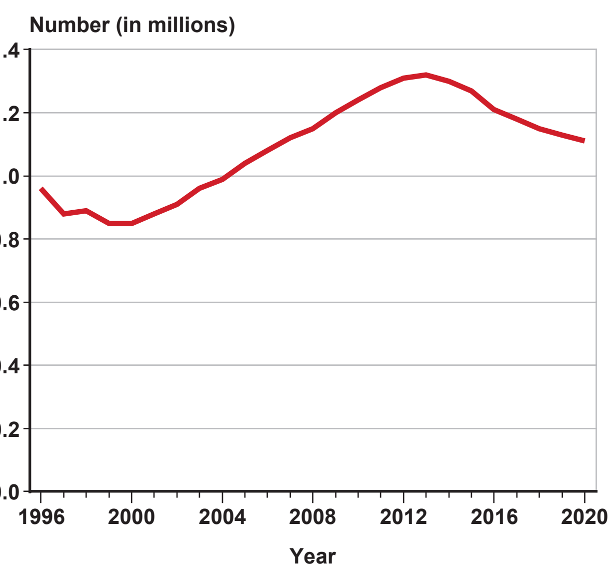
In 2021, the federal maximum SSI payment was $794 per month, and 23 states exercised their option to provide a supplementation payment to children with disabilities.[6] On average, among families that include a child SSI recipient, almost half of family income comes from SSI (Davies, Rupp, and Wittenburg 2009). Children who qualify for SSI may qualify for services from other programs as well. For example, 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 Supplemental Nutrition Assistance Program (food stamp) benefits (Romig 2017).

SSA periodically reassesses the medical eligibility of SSI recipients during medical CDRs, which often result in benefit cessations. For a child whose impairment is expected to improve, SSA generally conducts a CDR within 6 to 18 months of SSI award; for a child whose impairment is judged "probable" to improve, 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.[7] However, the numbers of CDRs SSA conducts varies over time depending on caseload size, administrative priorities, and budgets. SSA also conducts an eligibility redetermination when a recipient reaches age 18, which entails both a review of nonmedical eligibility and a new disability determination using the adult disability criteria.[8] At all ages, to remain eligible for payments, recipients must continue to not exceed the asset and income limits (including deemed income and assets from a parent for SSI recipients younger than 18). The number of CDRs SSA conducts 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 durations of payment receipt (Hemmeter and others 2021).

SSI Caseload Trends

The number of child SSI recipients has fluctuated substantially since 1996 despite no significant changes in the rules for eligibility (Chart 1). Although the statutory definition of eligibility for children has not changed in that time, administrative processes have changed in ways that can influence who becomes and remains eligible for SSI payments, with the most notable example being the large increase in CDRs in recent years. In the first years after the current SSI eligibility rules were implemented as part of larger welfare reforms in 1996, SSI caseloads dipped.[9] Caseloads then increased from 2000 through 2013. The possible causes for rising caseloads were discussed in congressional hearings (for example, Wittenburg 2011), which drew particular interest because the increase coincided with contractions in other cash transfer programs such as Temporary Assistance for Needy Families (Schmidt and Sevak 2004, 2017). Since their 2013 peak of 1.3 million, SSI child-recipient caseloads have declined; 1.1 million children received SSI as of December 2020. Caseloads have declined further during the COVID-19 pandemic, with the closure of SSA

Chart 1.
Number of child SSI recipients, 1996–2020



SOURCE: SSA (2021a, Table 7.A9).

field offices cited as an important driver (Emanuel 2021). Other factors, such as supplemental unemployment benefits, eviction embargoes, and stimulus payments—which increased income and reduced poverty (Wheaton and others 2021)—might also have contributed to declines in SSI participation.

Prior literature highlights substantial geographic variation in caseload growth through 2013. Wittenburg and others (2015) showed that more than half of the growth in caseloads from 1998 to 2013 took place in four states (California, Florida, Pennsylvania, and Texas). The authors also showed that, more generally, SSI participation rates per capita were higher in southern and northeastern states. Schmidt and Sevak (2017) showed that regional and state differences in the number of people living in poverty and the availability of special education services, among other factors, contributed to differential growth in child SSI caseloads. Several studies identified other factors that could affect local caseload trends, such as availability of advocacy networks, proximity and access to SSA 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; Duggan, Kearney, and Rennane 2016; Government Accountability Office 2012).

Understanding the drivers of recent geographic variation in child SSI participation is important to ensure equitable access to the program. SSA has prioritized outreach to vulnerable populations such as children. The agency set aside $96 million in its fiscal year 2022 budget to support outreach efforts designed to acknowledge and address recent program declines associated with the COVID-19 pandemic (SSA 2021b).

To better inform outreach efforts, and to understand SSI program dynamics more generally, this article addresses three notable gaps in the existing literature. First, recent geographic variation in child SSI participation is not well understood. Most studies analyze 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 focus on larger geographic units such as counties, whereas understanding even narrower geographic areas such as census tracts might enable a deeper understanding of local patterns.[10] Finally, quantitative information that could be used to identify promising targets for potential outreach (or to learn how child SSI participation in those areas is correlated with demographic and other characteristics) is not widely available.

Deprivation

We incorporate a measure of local area socioeconomic deprivation into our geographic analysis of child SSI participation rates. Our measure is based on the ADI, which was initially developed by the Health Resources and Services Administration. The ADI, and our deprivation measure, capture information about income, education, housing, and other local characteristics. 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 level of the census block group, a subunit of the census tract. Table 1 shows the correlations of child SSI participation with the full list of our deprivation input variables, which are based on data from the Census Bureau's American Community Survey (ACS).

Researchers and policymakers use measures of deprivation such as the ADI to examine health care delivery and inform policy. Not limited to measuring poverty or income alone, socioeconomic deprivation provides a more holistic view of the ways that a local area might be disadvantaged. We use this measure to rank neighborhoods by socioeconomic disadvantage relative to the national average. Research has linked areas with greater deprivation to worse health outcomes, such as higher rates of obesity and hospital readmission (Kind and others 2014; Hu, Kind, and Nerenz 2018). Areas with higher deprivation also have higher rates of infant mortality (Singh and Kogan 2007) and shorter life expectancies at birth (Singh and Siahpush 2006).

Socioeconomic deprivation is not the only way to measure local needs, which is a noteworthy consideration when interpreting findings. Kim and Loh (2020) identified eight measures developed by federal agencies or nonprofit research groups that capture different dimensions of local needs, including the ADI.[11] All eight measures included poverty rate as one of their input metrics, although some of the measures diverged notably from others in their regional results. The authors also showed that all high-need communities fare worse than other communities on a range of alternative measures, such as greater prevalence of employment in low-wage occupations. Although our ADI-based measure of deprivation captures an essential component of need, Kim and Loh showed that of the eight measures, ADI identified relatively few high-need areas in the West and Midwest. Hence, using this measure of deprivation might lead to characterizations of high-need local areas that differ from those of other measures, a notable caveat when targeting localized outreach efforts.

Table 1.
Correlation of deprivation input variables for the period 2015–2019 with child SSI participation in 2019 at the county and census tract levels

Variable	Coefficient		ACS question
	County	Census tract	
Educational attainment, adults aged 25 or older			
Less than 9 years	0.197	0.250	B15003
High school diploma/equivalent or more	-0.390	-0.409	B15003
Employment status, individuals aged 16 or older			
Employed in white-collar job [a]	-0.377	-0.491	C24010
Unemployed	0.456	0.419	B23025
Housing characteristics			
Homeowners	-0.326	-0.442	B25003
More than one person per room in household	0.019	0.135	B25014
Median monthly mortgage ($)	-0.376	-0.395	B25088
Median gross rent ($)	-0.403	-0.379	B25064
Median home value ($)	-0.376	-0.348	B25077
Income and poverty characteristics			
Median family income ($)	-0.624	-0.553	B19113
Disparity ratio [b]	0.658	0.355	B19001
Family poverty rate	0.721	0.600	B17010
Individuals with earnings under 150 percent of federal poverty limit	0.703	0.634	C17002
Households with—			
Single parent and child(ren) under age 18	0.713	0.569	B11003
No motor vehicle	0.377	0.450	B25044
No telephone	0.288	0.235	B25043
Occupied housing units without complete plumbing	0.318	0.277	B25047
Overall deprivation	**0.626**	**0.634**	. . .

SOURCE: Authors' calculations using SSA program records and ACS data.

NOTES: In a linear regression of child SSI participation, the coefficient is statistically significant at the 1-percent level for all input variables and both area types except "more than one person per room in household" at the county level.

. . . = not applicable.

a. Management, business, science, and arts occupations.

b. Ratio of individuals with income below $15,000 to individuals with income above $75,000.

Nevertheless, the families of children with disabilities in areas with high deprivation are likely to have greater need for services or income support such as SSI. Local areas with low child SSI participation relative to the level of participation one might expect based on a deprivation measure could therefore be suitable targets for outreach.

Data and Methods

We used administrative data from the Supplemental Security Record, SSA's main system of records for the SSI program, to measure the number of children receiving SSI payments at the census tract and county levels in 2019. We also measured the number of child SSI applicants at the county level for 2019 and 2020. The administrative data contain the recipient's address, including the county. To assign a census tract, we geocoded the addresses of all child SSI recipients.[12] We were able to assign a census tract with geocoding for 95 percent of the records. About 3.5 percent of the records had an unusable address, and 1.5 percent had an address that could not be geocoded for various reasons and thus could not be placed in a particular census tract. We dropped those 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 the population of individuals aged 0–17 from ACS 5-year estimates for the period 2015–2019. 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 distributions of child SSI recipients in each local area by sex, age (0–4, 5–13, 14–17), and primary diagnosis. For the latter, we used the standard list of primary diagnoses presented in the *SSI Annual Statistical Report* (SSA 2021c).

Chart 2 shows the prevalence of child SSI participation in 2019 by county. As previous studies have shown, we find heavier concentrations of children receiving SSI in the southern and northeastern states.

We measured deprivation using ACS 5-year estimates for the period 2015–2019. We calculated deprivation at the county and census tract levels by following the process described in Singh (2003).[13] Specifically, we gathered data on the components of the ADI.[14] We conducted a factor analysis to assign weights to each of the components, then created a raw index measure using those weights. We express the resulting value as a percentile so that the final index indicates the level of deprivation in the local area relative to the rest of the country.

Chart 3 shows the geographic variation in relative deprivation across the United States at the county level. Deprivation is relatively high in southern states such as Arkansas, Kentucky, and Louisiana, many of which also have high levels of SSI participation (shown in Chart 2). However, many counties with relatively high deprivation also have lower levels of SSI participation, for example in North Dakota and South Dakota, and some counties combine lower deprivation with higher SSI participation.

To better understand the relationship between deprivation and child SSI participation, 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:

$$\text{SSI}_g = \alpha + \beta \text{Deprivation}_g + \varepsilon_g . \qquad (1)$$

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 separate analyses for census tracts and counties (both designated with the geographic variable g).

Based on this regression, we then calculated deviation, which captures the gap between actual SSI participation and a prediction based on deprivation. In short, the deviation is the residual from the regression (ε_g).

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.[15] All metrics, even those presented for specific local areas, are based on the national distribution of deviation.

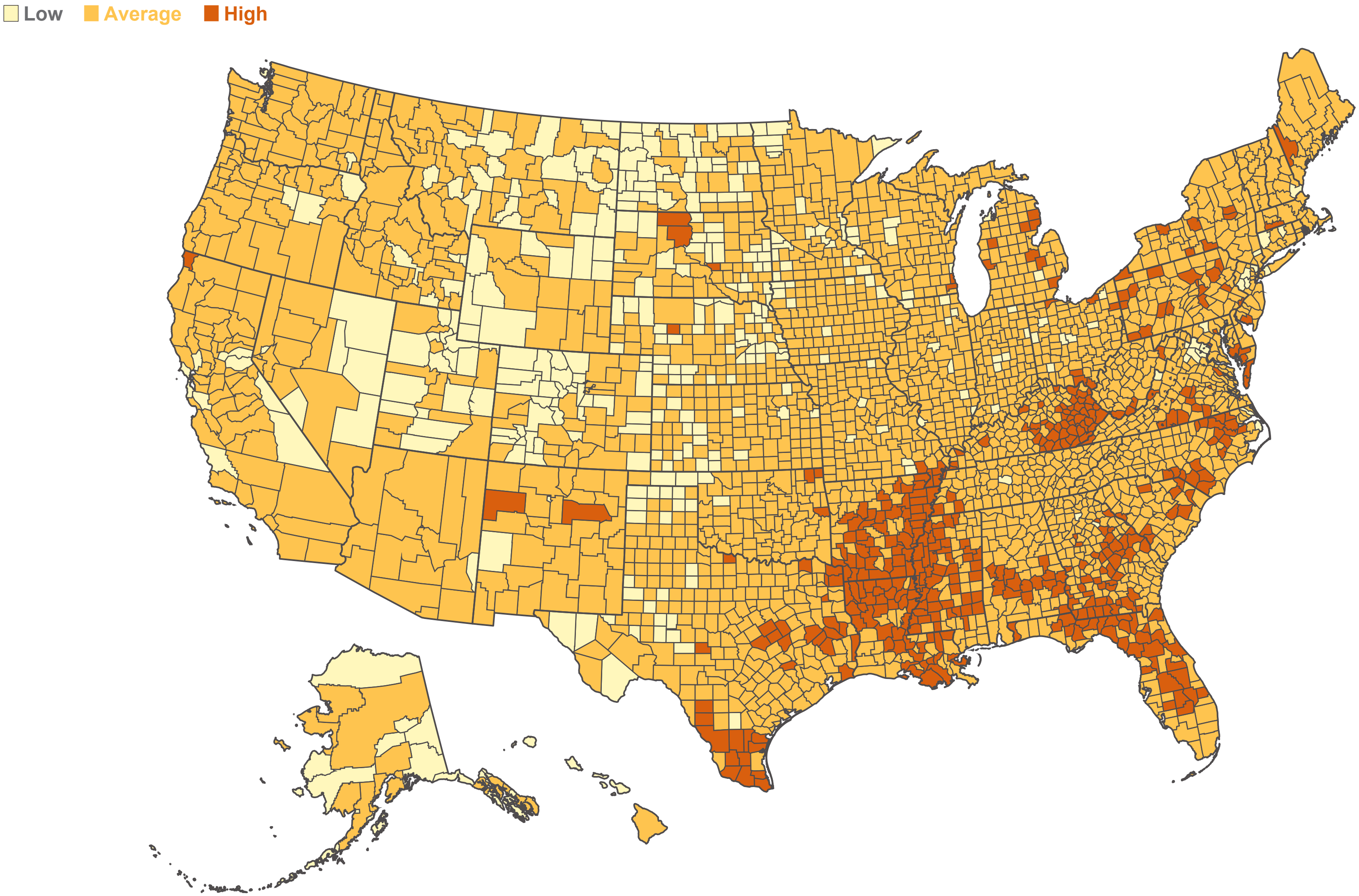
We next explore how characteristics of local areas, listed in Box 1, are associated with larger or smaller deviations to help identify the types of places that would most likely benefit from outreach. These measures capture a range of local and regional characteristics in publicly available data. Our analysis includes information on demographic characteristics, disability prevalence, and other features of the local areas (such as population density, availability of social capital, and presence of Opportunity Zones) that might be correlated with deviations. We regress deviation (ε_g in equation 1) on the list of measures from Box 1, signified as X_g in equation 2:[16]

$$\text{Deviation}_g = \gamma + \delta X_g + \omega_g . \qquad (2)$$

We estimated multivariate regressions, including all control variables, and weighted the regressions by population size. Because deviation does not have a readily intuitive cardinal interpretation, we present only standardized coefficients and p-values. This enables us to identify measures that have relatively higher and lower correlations with deviation. Because this estimation requires two steps, we bootstrap the entire process to calculate standard errors.

Finally, we explore how the COVID-19 pandemic has affected the underlying relationship between deprivation and child SSI participation. Specifically, we assess whether the change in SSI applications from 2019 to 2020 was associated with deprivation and deviation. SSI applications for children declined by 17 percent in 2020 (SSA 2021c, Table 57), with substantial geographic variation in the decline. Because census tract–level data were not available, we focused on counties for this aspect of the analysis.

Chart 2.
Child SSI participation rate relative to the national mean, by county, 2019

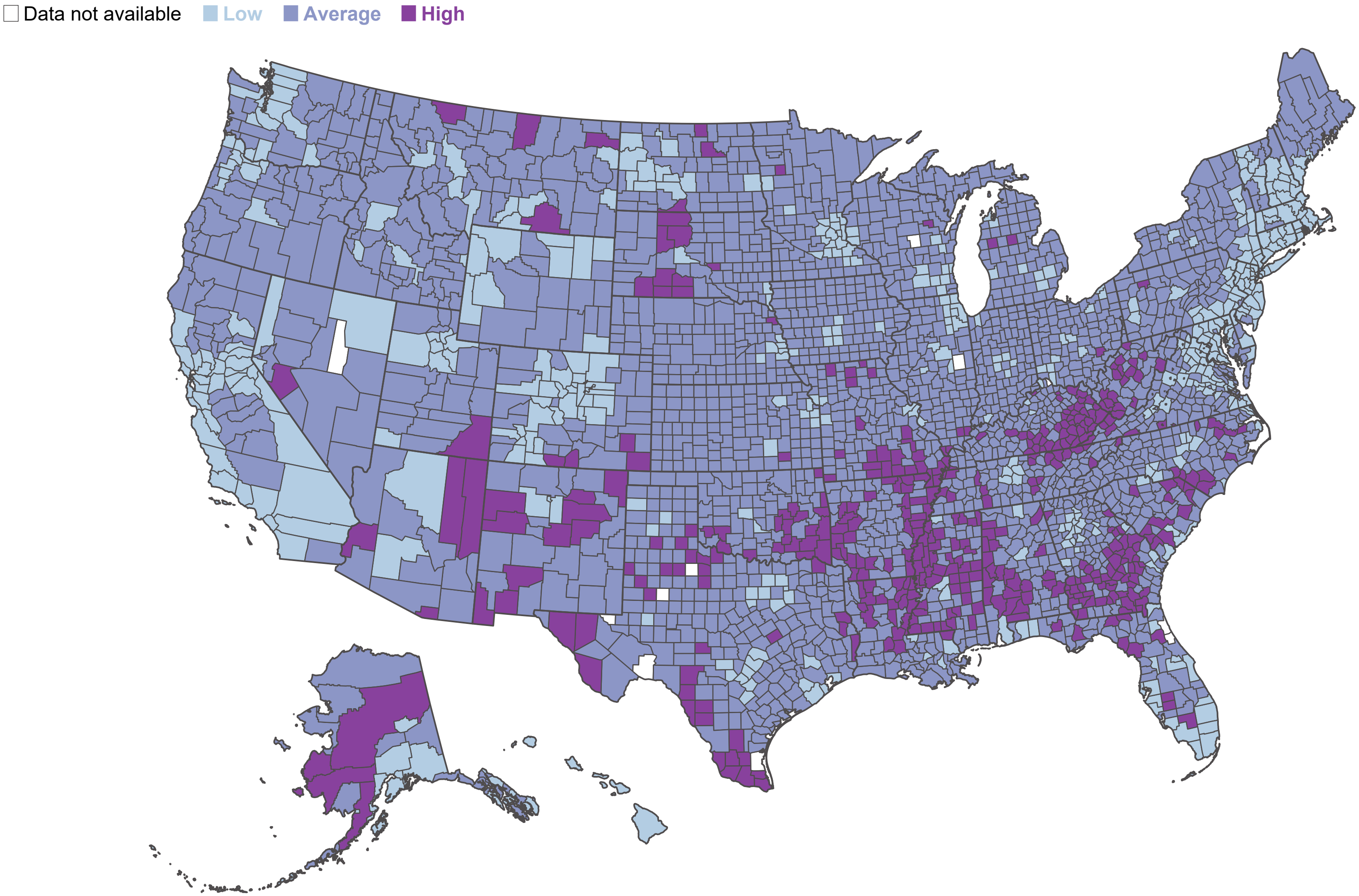


SOURCE: Authors' calculations using SSA program records and ACS data.

NOTES: Participation rate is calculated relative to child population size.

"Average" participation is within one standard deviation of the national mean. Respectively, "low" and "high" participation are more than one standard deviation below and above the national mean.

Chart 3.
Socioeconomic deprivation relative to the national mean in the period 2015–2019, by county



SOURCE: Authors' calculations using ACS data.

NOTE: "Average" deprivation is within one standard deviation of the national mean. Respectively, "low" and "high" deprivation are more than one standard deviation below and above the national mean.

Box 1.
Selected sociodemographic characteristics of local areas with which deviations between predicted and observed child SSI participation can be associated

Characteristic	Description and/or data source
Percentage of population that is non-White	Based on ACS 2015–2019 5-year estimates.
Percentage of population that has a disability	Based on ACS 2015–2019 5-year estimates.
Region	Northeast, South, Midwest, and West, defined at Census Bureau (2021a).
Urbanicity	Metropolitan, suburban, and rural, based on categories adapted from Economic Research Service (2020).
Population density (counties only)	Population from ACS 2015–2019 5-year estimates; land area from Census Bureau (2021b).
Social capital (counties only)	Measures of participation in civic, religious, and sports organizations, defined in Rupasingha, Goetz, and Freshwater (2006).
Opportunity Zone (census tracts only)	Economically distressed areas nominated by governors and certified by the Secretary of the Treasury. Opportunity Zones are listed at https://www.irs.gov/pub/irs-drop/n-18-48.pdf.

SOURCES: Cited above.

Results

There is a strong positive relationship between deprivation and child SSI participation (Chart 4), which is expected because SSI serves low-income populations. For each successive decile of deprivation (for example, the 20th percentile relative to the 10th), child SSI participation increases by 3.5 per 1,000, on average. Relative to the 17.3 child recipients per 1,000 child residents in the average census tract, this represents an increase of nearly 20 percent. Table 2 presents the results of this regression at both the county and census tract levels, weighted and not weighted for the area's child population size. Results are statistically significant at both geographic levels, although the magnitude of the relationship is substantially stronger in the census tract analysis.[17] The R^2 from the simple linear regression in equation 1 (weighted for child population) is 0.392 at the county level and 0.402 at the census tract level. This indicates that although there is a strong correlation between deprivation and SSI receipt, much variation remains in predicting local area SSI participation.

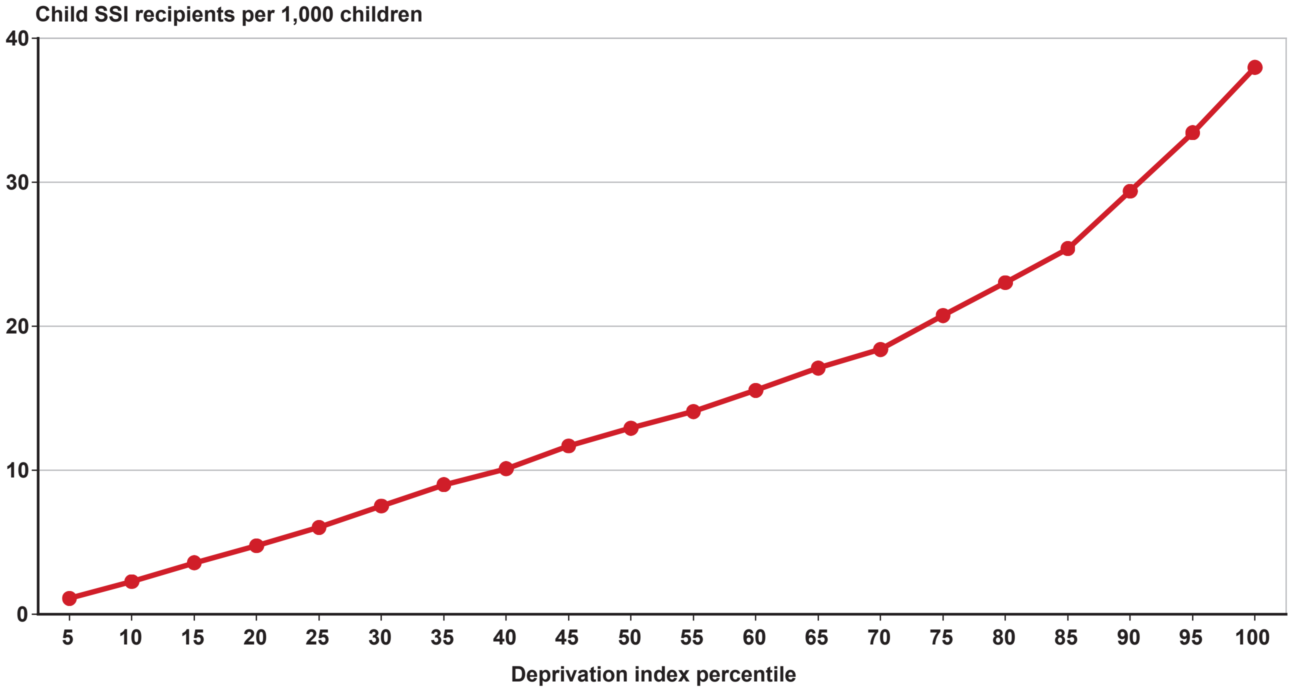
The distribution of child SSI recipients by primary diagnosis[18] varies depending on the level of deprivation (Chart 5), while distributions by sex and age do not (Table 3). Using descriptive data on the average characteristics of child SSI recipients in each census tract, we find that communities with higher levels of deprivation have a lower percentage of child SSI recipients with autistic disorders as their primary diagnosis.[19] This is consistent with evidence that autism diagnosis rates are higher in places with higher socioeconomic status (Thomas and others 2012). By contrast, children in communities with higher deprivation have greater incidence of developmental disorders or other childhood and adolescent disorders as their primary diagnosis.[20] The age and sex distributions of child SSI recipients are mostly constant across communities regardless of the level of deprivation.

Geographic Heterogeneity and Deviation Between Predicted and Actual Child SSI Participation

We next examine the geographic dispersion of deviation (Chart 6). We show that most census tracts have deviation values close to zero, although some can be very high (or low). Note that Chart 6 top-codes values at 65, representing the 99th percentile of deviation, to simplify the presentation.

Chart 7 shows that child SSI participation in many areas is notably higher—or lower—than predicted. Recall that we define an area to have higher-than-predicted participation if the deviation measure is greater than the 75th percentile, and lower-than-predicted participation if the measure is below the 25th percentile, of the deviation distribution.[21]

Chart 4.
Relationship between census tract socioeconomic deprivation in the period 2015–2019 and child SSI participation rate in 2019



SOURCE: Authors' calculations using SSA program records and ACS data.

NOTE: Plotted points represent the average participation rate in all census tracts within a given ventile (5th-percentile interval). For example, the point plotted for the 5th percentile represents the average participation rate among all census tracts in the 1st through 5th percentiles of socioeconomic deprivation.

Table 2.
Results of separate linear regressions on the relationship between child SSI participation and each of two measures of local area socioeconomic conditions in 2019 (weighted and not weighted for child population)

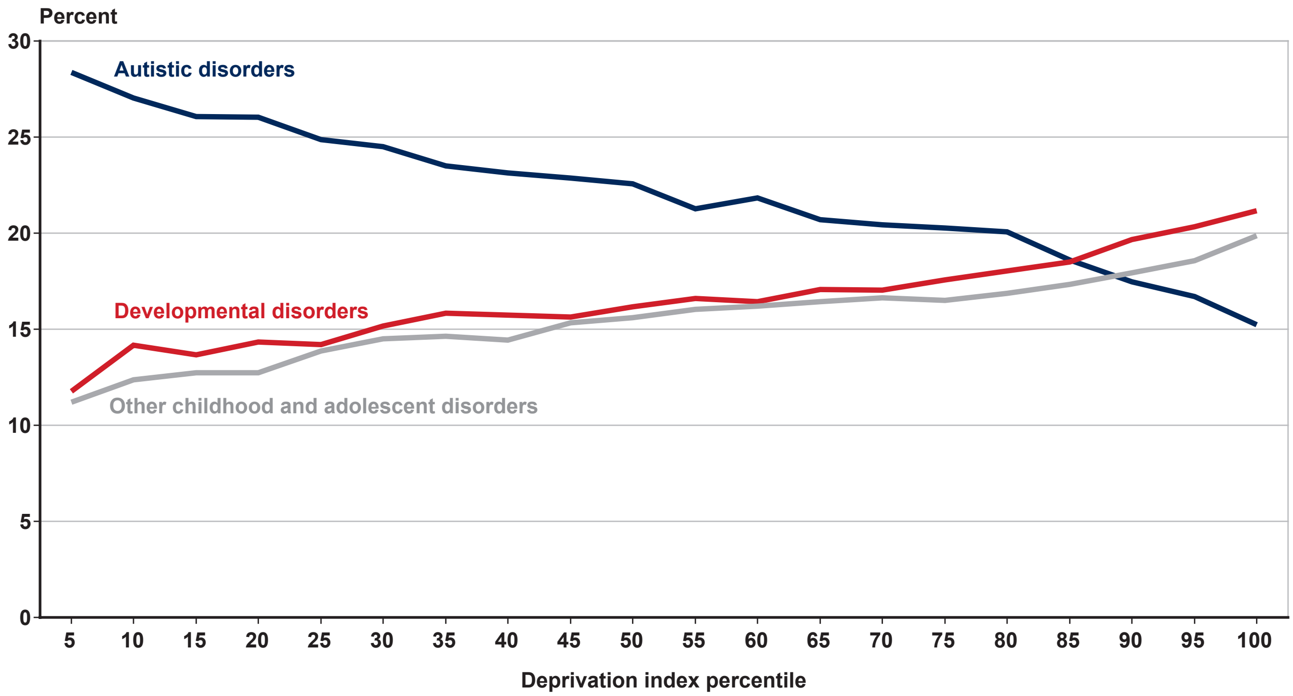
Measure	County level		Census tract level	
	Weighted	Not weighted	Weighted	Not weighted
Number of observations	3,130	3,130	71,976	71,976
Regression 1: Deprivation [a]				
Coefficient	0.209	0.197	0.349	0.407
Standard error	0.014	0.006	0.002	0.004
R^2	0.392	0.331	0.402	0.089
Regression 2: Poverty rate [b]				
Coefficient	0.229	0.206	0.335	0.392
Standard error	0.013	0.005	0.002	0.007
R^2	0.487	0.378	0.375	0.084

SOURCE: Authors' calculations using SSA program records and ACS data.

a. Local area percentile on a deprivation index. The deprivation measure is based on data for the period 2015–2019.

b. Percentage of population with family income below 150 percent of the federal poverty level. The percentage is converted to a percentile for consistency with the deprivation measure.

Chart 5.
Percentage of child SSI recipients with selected primary diagnoses in 2019, by census tract deprivation index for the period 2015–2019



SOURCE: Authors' calculations using SSA program records and ACS data.

NOTES: For each primary diagnosis, the plotted points represent the average percentage of child SSI recipients with that diagnosis in all census tracts within a given deprivation ventile (5th-percentile interval). For example, the point plotted for the 5th percentile represents the average percentage among all census tracts in the 1st through 5th percentiles of socioeconomic deprivation.

Percentages for other primary diagnoses are available on request from the authors.

Areas with lower-than-predicted participation are disproportionately located in the Midwest, where about 32 percent of census tracts fall into this category, versus 23 percent in the rest of the country. Outreach might benefit areas with relatively limited SSI participation such as these. Areas with higher-than-predicted participation 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. The areas with higher-than-predicted participation drove much of the growth in child SSI caseloads from 1996 to 2015 (Wittenburg and others 2015).

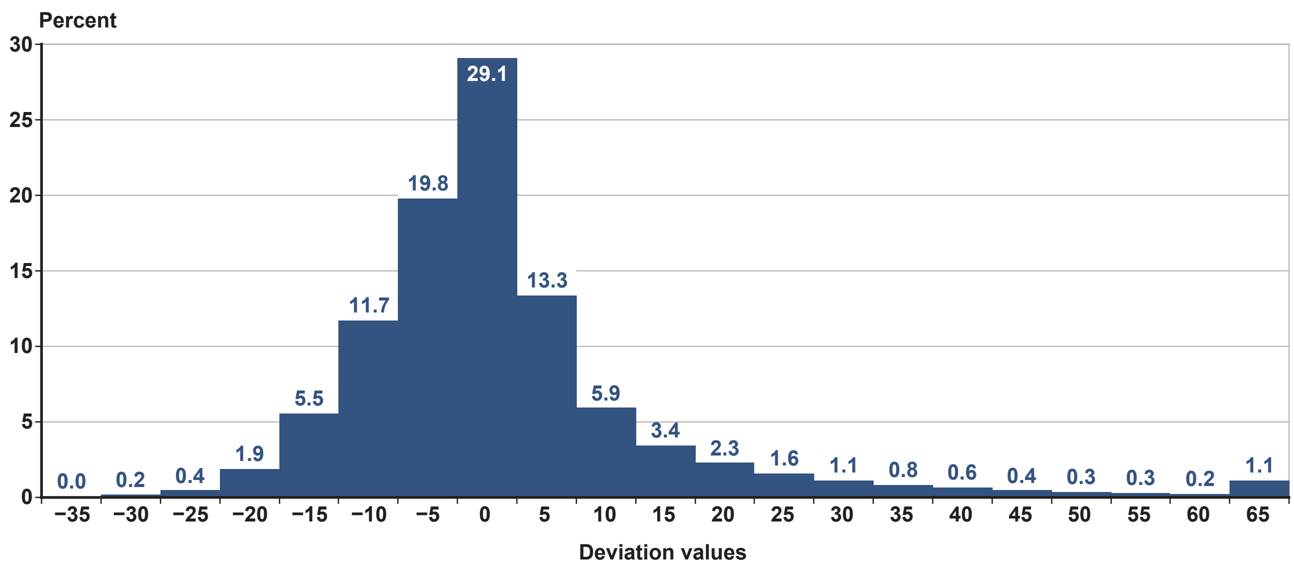
Within counties, individual census tracts often vary in whether actual participation is higher or lower than predicted. For example, Chart 8 shows the census tracts that make up the metropolitan statistical area (MSA) for Detroit, Michigan. Metro Detroit has about 4.4 million people, making it the 14th largest MSA in the country. In 2019, it ranked 91st of 384 MSAs in per capita personal income (Bureau of Economic Analysis 2020). The Detroit MSA contains a mix of areas in which actual participation is greater than predicted (positive deviation, shown in green) and in which actual participation is less than predicted (negative deviation, in brown). This result prompts a question, which we address below: What factors are associated with local areas having higher or lower deviations? Narrowing in on these highly localized areas can help SSA precisely pinpoint where to target resources; for example, by helping identify specific neighborhoods in which to recruit local partners. More broadly, it can help researchers and policymakers better understand the heterogeneity of SSI participation at local levels, including factors such as the relative prevalence of networking (that is, learning about the program through local relationships) that might influence SSI dynamics and interactions with other programs.

Table 3.
Percentage distributions of child SSI recipients in 2019 by age and sex, by local area deprivation index percentile for the period 2015–2019

Deprivation index percentile	Age			Sex	
	0–4	5–12	13–17	Female	Male
5	15.76	50.17	34.08	31.90	68.10
10	15.22	48.50	36.29	32.55	67.45
15	14.98	48.76	36.27	34.27	65.73
20	15.04	49.98	34.98	33.59	66.41
25	14.80	50.05	35.15	32.81	67.19
30	14.38	50.94	34.69	32.83	67.17
35	14.63	50.14	35.23	32.93	67.07
40	14.45	50.61	34.94	32.73	67.27
45	14.20	50.45	35.35	32.96	67.04
50	14.09	50.55	35.36	32.49	67.51
55	13.95	50.62	35.43	32.28	67.72
60	13.74	50.63	35.63	32.44	67.56
65	13.38	50.71	35.91	32.52	67.48
70	13.76	51.05	35.19	32.40	67.60
75	13.66	50.73	35.61	32.57	67.43
80	13.67	50.98	35.35	32.26	67.74
85	13.30	51.15	35.55	32.41	67.59
90	13.79	51.17	35.04	32.76	67.24
95	13.05	51.30	35.65	32.33	67.67
100	13.11	51.82	35.07	32.44	67.56

SOURCE: Authors' calculations using SSA program records and ACS data.

Chart 6.
Percentage distribution of census tracts by deviation between actual child SSI participation and the level of participation predicted by deprivation index in 2019

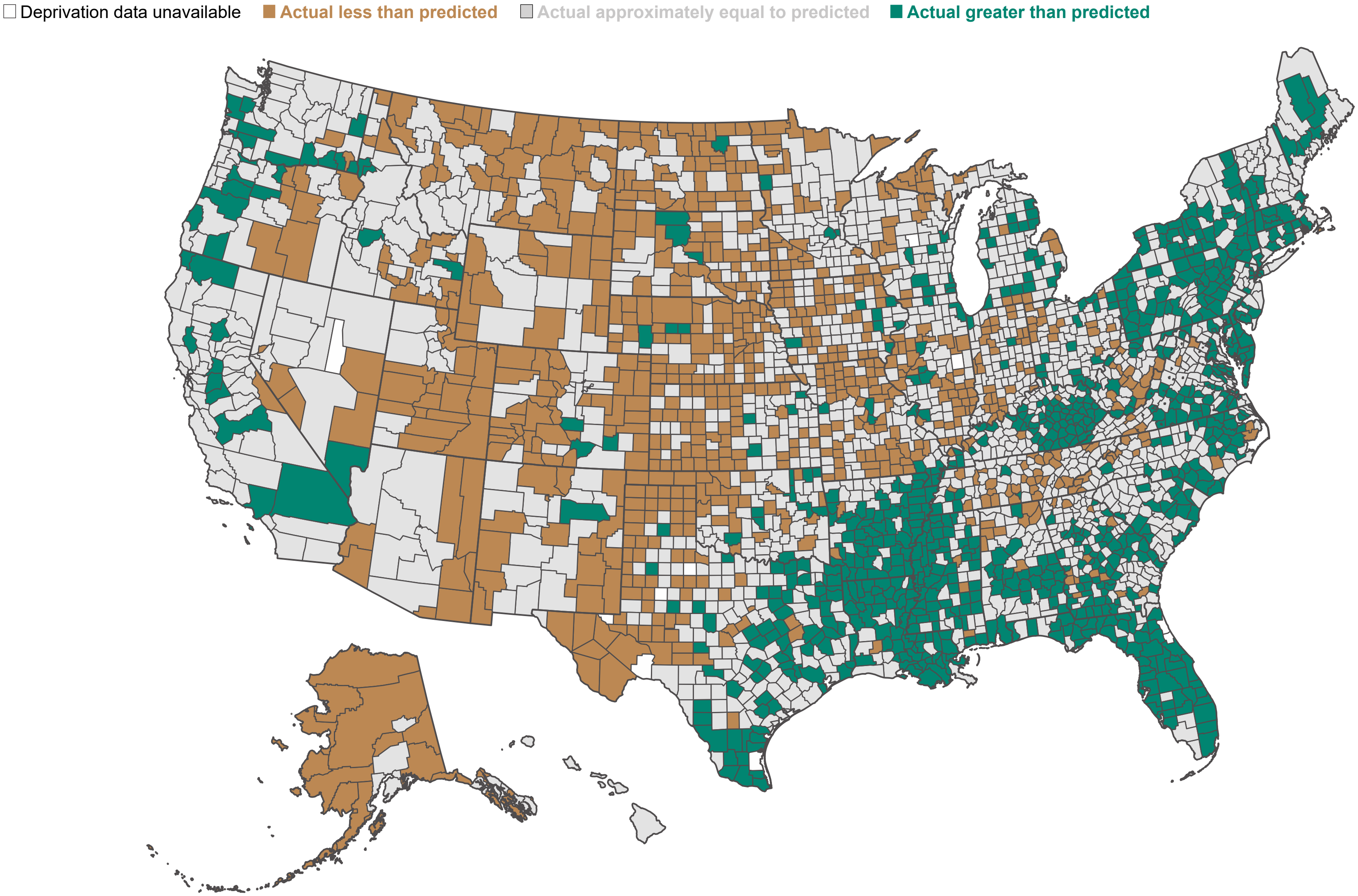


SOURCE: Authors' calculations using SSA program records and ACS data.

NOTES: Deviations are top-coded at 65.

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.

Chart 7.
Deviation between actual child SSI participation and the level of participation predicted by deprivation index, by county, 2019

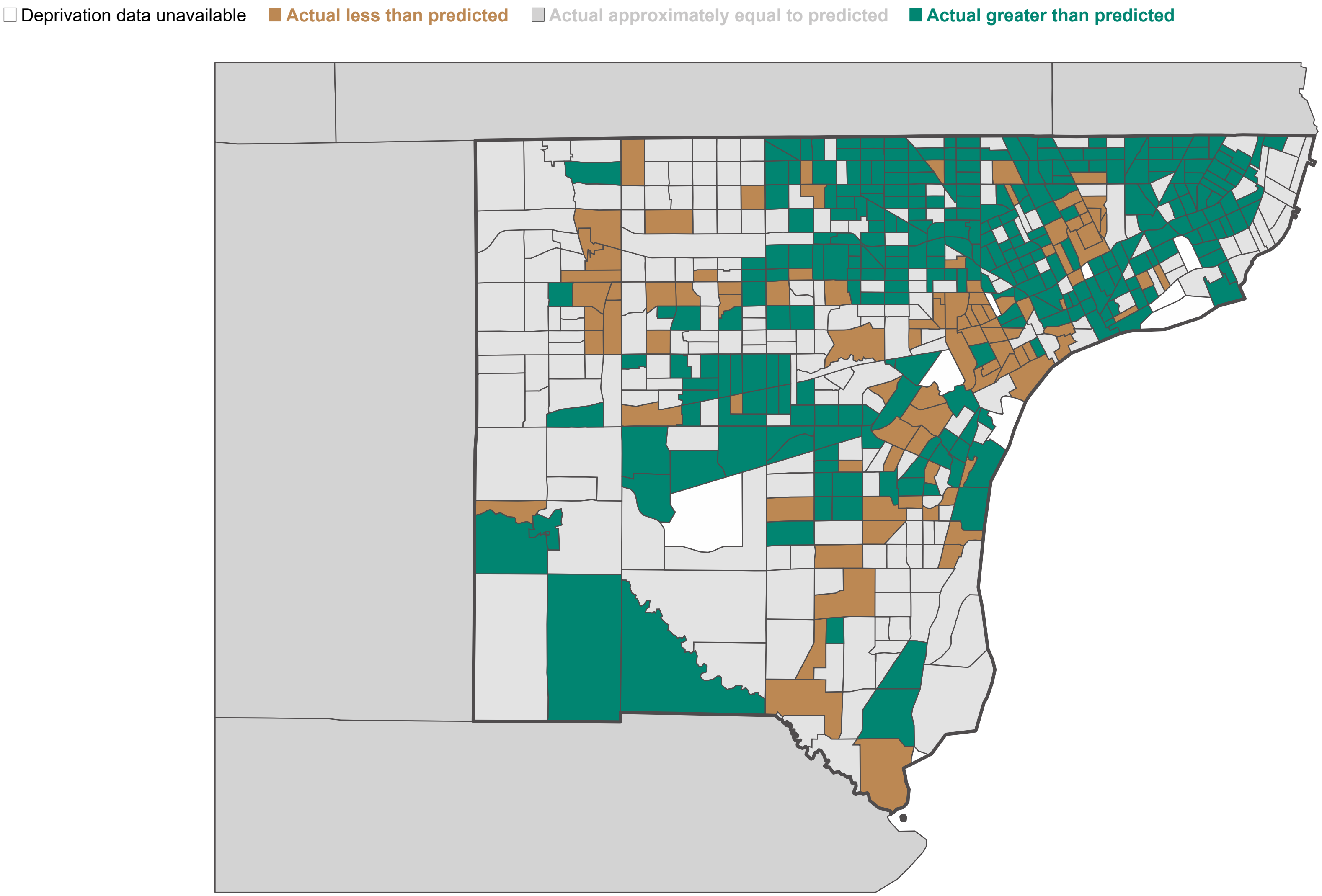


SOURCE: Authors' calculations using SSA program records and ACS data.

NOTE: Counties are characterized as having actual participation greater (or less) than predicted participation if deviation is greater than the 75th percentile (or less than the 25th percentile).

Chart 8.

Deviation between actual child SSI participation and the level of participation predicted by deprivation index for the Detroit MSA, by census tract, 2019



SOURCE: Authors' calculations using SSA program records and ACS data.

NOTE: Census tracts are characterized as having actual participation greater (or less) than predicted participation if deviation is greater than the 75th percentile (or less than the 25th percentile).

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 Box 1. We weight the regression by child population in the local area. 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 could target resources to communities with the characteristics frequently associated with high measures of deviation.

Areas that have a larger share of non-White residents have greater positive deviation (Table 4). Conversely, the larger the share of White residents in a local area, the lower the actual child SSI participation relative to predicted participation based on deprivation. In other words, a smaller positive or larger negative magnitude in the measure of deviation is associated with a larger White share of the population. This finding is consistent with evidence showing that Black individuals are about twice as likely to receive SSI payments as White individuals (Musumeci and Orgera 2021). The standardized coefficient for the non-White population variable has a large magnitude for counties and census tracts alike, indicating that among the chosen predictors, this one has a strong relationship with deviation.

Other factors that prior research has associated with SSI participation are also associated with deviation. For example, 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. Counties 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.

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 (Table 5). The geographic pattern of results

Table 4.
Correlations of selected local area characteristics with deviation in 2019

Characteristic	County level: Standardized coefficient	County level: *p*-value	Census tract level: Standardized coefficient	Census tract level: *p*-value
Percentage of population that—				
Is non-White	0.337	0.000	0.105	0.000
Has a disability	0.276	0.000	0.146	0.000
Region				
Northeast	0.255	0.000	0.159	0.000
South	0.112	0.004	0.069	0.000
Midwest (reference variable omitted)	. . .	. . .	. . .	. . .
West	-0.195	0.000	-0.140	0.000
Urbanicity				
Metropolitan	0.326	0.000	0.135	0.000
Suburban (reference variable omitted)	. . .	. . .	. . .	. . .
Rural	-0.071	0.000	-0.028	0.000
Population density	0.176	0.049	. . .	. . .
Social capital	0.246	0.000	. . .	. . .
Opportunity Zone	. . .	. . .	0.037	0.000

SOURCE: Authors' calculations using SSA program records, ACS data, and the sources cited in Box 1.

NOTES: A positive coefficient indicates that the characteristic is positively associated with deviation.

Results are weighted by local area child population.

. . . = not applicable.

Table 5.
Correlations of selected local area characteristics with lower-than-predicted child SSI participation in 2019

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

SOURCE: Authors' calculations using SSA program records, ACS data, and the sources cited in Box 1.

NOTES: Results are weighted by local area child population.

. . . = not applicable.

is similar, with counties or census tracts in the Northeast and South less likely than those in the Midwest and West to have lower-than-predicted participation. However, some of the other characteristics exhibit different patterns. For example, census tracts with a higher percentage of the population that is non-White are more likely to have lower-than-predicted participation, while the non-White share of the population is not a significant predictor at the county level. Other characteristics, such as population density, also are no longer significant predictors.

SSI Applications During the COVID-19 Pandemic

We estimate that the number of child SSI applications filed during 2020 fell to 310,688, a decline of 17.5 percent from the 376,557 child SSI applications filed during 2019.[22] Counties with higher deprivation had slightly larger declines in child SSI applications in 2020 (Table 6). For each successively higher decile of deprivation, SSI applications declined by an additional 0.5 percentage points, indicating that these changes contributed a very small fraction to the total decline in child SSI applications during 2020. In addition, counties with greater deviation saw larger declines in child SSI applications. Counties that had smaller positive deviation (or larger negative deviation) likely began 2019 with low application levels because actual participation was already less than predicted participation, making application numbers in those areas unlikely to decline.

Table 6.
Correlations of the county-level decline in child SSI applications from 2019 to 2020 with deprivation and with the deviation between actual and predicted child SSI participation

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

SOURCE: Authors' calculations using SSA program records and ACS data.

NOTES: Correlation coefficients reflect the regression of the percentage change in SSI applications.

Regressions are weighted by county child population.

Conclusion

We find substantial differences in child SSI participation across geographic areas even after controlling for deprivation. These differences existed before the drop in applications associated with the COVID-19 pandemic, yet high-deprivation areas saw somewhat larger declines in application volume during the first year of the pandemic. In response to that drop, SSA increased outreach efforts in at-risk communities and for populations facing barriers to participation (SSA 2021b). The agency established new liaisons and partnerships to facilitate application and released public service announcements focusing on children with disabilities.

Our research can support SSA by suggesting a metric with which to target areas for more effective outreach. A deprivation metric succinctly identifies areas with multiple characteristics that are likely to be associated with barriers to participating in SSI (and other programs). As such, deprivation could be more useful than single-measure identifiers such as poverty rate. By identifying specific geographic areas with notably lower-than-expected SSI participation, SSA can effectively pinpoint its outreach efforts.

Although the deprivation index is one potential metric, our work highlights several additional local-area factors, such as race, disability prevalence, and social capital, that are correlated with gaps between predicted and actual SSI participation. Other factors beyond the scope of this article that could also inform targeted outreach include aspects of the local program environment such as the availability of services and supports, which vary substantially by region and within counties (National Academies of Sciences, Engineering, and Medicine 2018); SSA field office proximity (Deshpande and Li 2019); and CDR frequencies.

Although our deviation metric is a useful starting point for understanding geographic variation in program dynamics, it has limitations. Deviation is measured relative to the average national caseload, so it can only capture whether SSI participation is low relative to all other areas, not whether all who are eligible are participating. Further, deviation may not reveal some of the systemic barriers that can influence outcomes. For example, residential segregation resulting from redlining and other discriminatory practices (Aaronson, Hartley, and Mazumder 2021) might unevenly affect the underlying input measures, which include housing variables, as the extent of such practices varies from location to location. If the measure of deprivation underestimates or overestimates the need for SSI in communities with a larger non-White population because it cannot distinguish the relative effects of such systemic factors, our ability to draw conclusions from the model may be limited.[23] Despite these limitations, using the deviation measure provides SSA a useful starting point for identifying potentially underserved populations.

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

Notes

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[1] For the Social Security Act section requiring SSA outreach to children who are potentially eligible for SSI payments, see https://www.ssa.gov/OP_Home/ssact/title16b/1635.htm.

[2] Singh (2003) developed the ADI methodology. The University of Wisconsin maintains and updates the ADI data set.

[3] A child can qualify for SSI if her or his own countable resources do not exceed $2,000. Parental resources deemed to the child affect the eligibility threshold; in a 2-parent household, for example, 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.

[5] Applicants can be assisted in person or by phone. For more details on the child SSI application process, see https://www.ssa.gov/benefits/disability/apply-child.html.

[6] The Policy Surveillance Program provides details on state supplementation payments for child SSI recipients at http://lawatlas.org/datasets/supplemental-security-income-for-children-with-disabilities.

[7] For SSA's policies on the frequency of CDRs, see https://www.ssa.gov/OP_Home/cfr20/404/404-1590.htm.

[8] Unlike those for children, the adult criteria rely on a disability definition that focuses on work (the inability to engage in substantial gainful activity, which in 2021 was defined as monthly earnings above $1,310 for a nonblind individual). In making age-18 redeterminations, SSA uses the same medical, income, and asset criteria it uses in adult application decisions. Among children receiving SSI payments on reaching age 18, 82 percent have a redetermination at that time; the others do not have redeterminations until after age 18, for various reasons (Hemmeter and Bailey 2015).

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

[10] One example of a study using census tract–level analysis is Chetty, Hendren, and Katz (2016).

[11] The other seven measures are (1) the federal statutory definition of Low-Income Community; (2) the Internal Revenue Service designation as a Qualified Opportunity Zone; (3) the Centers for Disease Control and Prevention's Social Vulnerability Index; (4) diversitydatakids.org's Child Opportunity Index; (5) the Robert Graham Center's Social Deprivation Index; (6) the Economic Innovation Group's Distressed Communities Index; and (7) Kim and Loh's adaptation of the "persistent poverty counties" classification used by the Department of Agriculture's Economic Research Service.

[12] The United States is composed of about 74,000 census tracts, which are designed to have about 4,000 people each, although their populations range roughly from 2,500 to 8,000.

[13] The ADI provided by the University of Wisconsin is only available at the census block group level and captures a relative ranking. Because the ADI is a relative ranking, we could not convert the census block group values to census tract or county values simply by aggregating the narrower units into the broader ones and then computing an average. Rather, we needed the underlying raw score, which we could use to construct a relative percentile at the geographic variable of interest. Even so, there is a strong positive correlation (greater than 0.80) between the percentile computed by averaging the values for an area's component subunits and the percentile calculated from the raw data.

[14] Input variables are missing for as many as 5.9 percent of census tracts. In these instances, we imputed the tract-level value using the county-level value (when available), following the same procedure used to create the ADI.

[15] The choice of 25th and 75th percentiles is somewhat arbitrary, but the interquartile range provides a reasonable definition of low and high deviation. Alternative thresholds, such as those based on the standard deviation, could also be used.

[16] Many of these measures are correlated with both deprivation and SSI participation. However, this regression seeks to correlate each measure with *deviation,* not directly with either deprivation or actual SSI participation. In other words, a measure that is correlated with both deprivation and SSI participation is not necessarily correlated with the *gap* between actual SSI participation and a level of SSI participation that is predicted based on deprivation.

[17] Table 2 also includes an alternative specification that replaces deprivation with a measure of poverty rate—specifically, the percentage of the local population earning less than 150 percent of the federal poverty limit, converted to a percentile score—which yields remarkably similar results.

[18] Children may have more than one diagnosis; however, not all are recorded in SSA's administrative records. Additionally, the primary diagnosis may or may not reflect the condition causing the most significant functional barriers to the child. Whether a given condition is identified as the primary diagnosis may reflect underlying differences in access to medical care or SSA's disability determination process itself.

[19] On average, nearly one child SSI recipient in five had a primary diagnosis of autistic disorders. In the highest deprivation areas, fewer than 15 percent had that primary diagnosis, while in the lowest deprivation areas, nearly 30 percent did.

[20] On average, about 30 percent of child SSI recipients had a primary diagnosis of either developmental disorders or other childhood and adolescent disorders. In the highest deprivation areas, more than 40 percent had one of these two conditions as a primary diagnosis, while in the lowest deprivation areas, only about 23 percent did.

[21] Because Table 2 indicates a similar relationship between our poverty measure and child SSI participation, we constructed an alternative measure of deviation based on the regression on poverty. This alternative deviation is highly correlated with deviation based on the regression on 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 but would not explicitly account for other socioeconomic factors.

[22] Our estimates may not match official SSA statistics because of differing estimation methodologies for cases involving individuals with more than one application or applications that are not recorded timely.

[23] As another example, health care outcomes are worse for Black patients than for White patients with the same levels of spending, suggesting differential access to care (Obermeyer and others 2019). This leads to bias in comparing measures of spending across racial groups. If similar issues affect the deprivation inputs—and thus SSI participation—our findings may be compromised.

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