Child Participation in Supplemental Security Income: Cross- and Within-State Determinants of Caseload Growth

Lucie Schmidt
Williams College

Purvi Sevak*
Mathematica Policy Research

February 2016

Abstract

Researchers have struggled to explain the substantial growth over recent years in Supplemental Security Income (SSI) receipt among children under the age of 18. While existing studies have examined caseloads at the state level, we explore the possibility that local conditions may play a more important role in driving caseload growth, and that different factors might matter in different parts of the country. In this paper, we examine the importance of a number of factors in explaining county-level child SSI caseloads over time. We find that nationally these factors explain between 30 and 40 percent of the 2003–2008 growth in SSI caseloads and about 25 percent of the trend from 2008–2012. We also find that the importance of these factors in explaining growth varies substantially regionally and across states, which suggests that national models may lead researchers to overlook important determinants of caseload growth by averaging variation across regions and states.

The research reported herein was pursuant to a grant from the U.S. Social Security Administration (SSA), funded as part of the Disability Research Consortium. The findings and conclusions expressed are solely those of the author(s) and do not represent the views of the SSA or any agency of the federal government. We are grateful to Priyanka Anand, David Stapleton, John Tambornino, and David Wittenburg for helpful comments.
* Corresponding author information: Purvi Sevak, Mathematica Policy Research, Post Office Box 2393, Princeton, NJ 08543; Telephone: (609) 945-6596; email: psevak@mathematica-mpr.com.

I. Introduction

The Supplemental Security Income (SSI) program provides means-tested income support to families of children with disabilities.[1] Participation in this program among children has increased substantially since the early 2000s—rising 55 percent between 2000 and 2012 (see Figure 1). This growth is striking, in part because it occurred in the absence of any major policy changes liberalizing eligibility.[2] Some have argued that SSI has become an alternate safety net after the 1996 welfare reform reduced the cash assistance available to low-income families with children (Berkowitz & DeWitt, 2013; Schmidt, 2013; Wittenburg et al., 2015). Wittenburg et al. (2015) note that 11 states currently have more SSI child recipients than child Temporary Assistance for Needy Families (TANF) recipients and that expenditures on the child SSI program currently exceed federal and state cash benefits provided by TANF.

Both levels and growth rates of child SSI vary substantially across states, and the factors driving recent growth are unclear. Researchers have examined variation across states but have not yet been able to explain much of the differential program growth with these analyses. Aizer, Gordon, and Kearney (2013) find that "no small set of factors can explain the differential growth across states" between 2002 and 2012. These differences across states are particularly puzzling given that SSI is a federal program, with federal eligibility standards. When the program was enacted in the 1970s, the intent of policy makers was to create a federal program that would standardize support across states for low-income people with disabilities and the elderly (Berkowitz & DeWitt, 2013).

One possible explanation for the lack of comprehensive findings at the state level is that state statistics obscure the important role of local conditions. Substantial heterogeneity in child SSI

[1] It also provides support to adults with disabilities and to the elderly.
[2] The growth of the program among children in the early 1990s and corresponding decrease after 1996 have been well documented in the literature and were largely due to changes in eligibility standards. See Duggan, Kearney, and Rennane (2015) for an overview.

receipt at the substate level suggests this may be the case. For example, Rhode Island has a relatively high state-level rate of child SSI participation (22 cases per 1,000 children). But within Rhode Island, participation rates range across counties from 6.3 to 28.8 cases per 1,000 children (in Bristol and Providence counties, respectively). Figure 2, replicated from Wittenburg et al. (2015), illustrates the variation in child SSI participation rates across counties at the national level for 2013.

This article examines variation in child SSI caseload growth at both the state and county levels. We first present a pooled time-series model on a panel of county-level data that analyzes the importance of a number of local factors, including disability and health conditions, economic conditions, and characteristics of special education programs. We then examine growth by region and within individual states to assess whether the effects of certain factors, such as poverty, are consistent between states and counties. Our analysis is the first to examine county-level variation over time in caseloads for insights on child SSI caseload growth.

Estimates from our pooled model using county-level data can explain about 30 to 40 percent of the upward trend in child SSI participation between 2003 and 2008 and about 25 percent of the growth between 2008 and 2011. However, even using county-level data, much of the growth in SSI participation over time is absorbed by year fixed effects, and much of the geographic variation is absorbed by county fixed effects. We also find that the determinants of within-county growth vary substantially regionally and across states. Some variables are positively associated with child SSI participation in certain states and negatively in others. This finding suggests that simple explanations of caseload growth may not apply in all states, and that constraining coefficients to be the same in a pooled model may lead researchers to overlook important determinants of caseload growth by averaging variation across states. This is not completely surprising given the dramatic variation across and within states in SSI growth over this time period, but it does suggest that state-by-state case studies of caseload growth with attention to local factors may be fruitful in providing additional explanations for growth in the child SSI program.

II. Background

The Supplemental Security Income program provides income support to low-income children and adults with disabilities (as well as the elderly) in the United States. The program was enacted in 1972 and began providing benefits in 1974. The program is fully federally funded, and benefits are set at the federal level, although 32 states provide additional supplemental benefits to child recipients (Social Security Administration, 2015). Eligibility is based on income and assets as well as medical criteria, and awards often follow a lengthy disability determination process (see Duggan, Kearney, & Rennane, 2015, for a detailed description of the disability determination process for children).

Before 1990, the child SSI program was quite small, serving only about 255,000 children in 1988. However, since then the program has evolved into an important part of the safety net, due in part to changes in eligibility criteria for benefits. Rapid growth in the program began in the early 1990s, when the Supreme Court decision *Sullivan v. Zebley* rejected what were in essence more restrictive SSI eligibility criteria for children relative to adults, and a number of mental conditions, such as severe Attention Deficit Hyperactivity Disorder (ADHD), were added to the list of qualifying conditions for children (Berkowitz & DeWitt, 2013). . Largely as a result of these changes, child SSI participation tripled between 1991 and 1996, rising from 300,000 to 900,000 cases in this five-year span. In response, the Personal Responsibility and Work Opportunity Reconciliation (PRWORA) bill of 1996 that enacted major welfare reform also included a number of provisions aimed at stemming the growth in the child SSI caseload (Schmidt, 2004). Figure 1 clearly illustrates the post-*Zebley* growth in child SSI cases, as well as the immediate decrease in child SSI participation following the enactment of PRWORA in 1996.[3]

However, child SSI participation begin to rise again in 2000, and the increase has continued nonstop despite the absence of major policy changes that would lead to this pattern. A General Accounting Office report from 2012 considered a number of potential explanations, including increases in the number of children in poverty, increases in awareness and improved diagnosis of various mental conditions, an increase in the share of children obtaining health insurance and therefore better access to physicians and diagnosis, increased identification of children with disabilities through public school special education services, and fewer child SSI exits due to lack of funding for Continuing Disability Reviews (General Accounting Office, 2012). A recent Institute of Medicine study commissioned by the Social Security Administration noted the possible role of increases in child poverty, but it also stressed the importance of differential state trends (National Academies, 2015).

As a result, researchers have turned to geographic variation in SSI participation rates to search for potential explanations for the growth of the program. Much of this analysis has been at the state level. Wittenburg et al. (2015) document that while some cross-state variation existed in child SSI participation in 1998, variability across states in child SSI population ratios had increased dramatically by 2013. Furthermore, Wittenburg et al. (2015) show that a significant share of the growth in the national SSI caseload has been driven by a small number of states. For example, Pennsylvania and Texas account for 30 percent of the national growth in the SSI child caseload between 1998 and 2013.

Several studies, including Aizer, Gordon, & Kearney (2013) and Schmidt (2013) have analyzed state and year variation in child SSI participation with the use of state and year fixed

[3] Graphs that denominate the SSI child caseload by the population count of children show similar trends.

effects to identify a number of potential explanatory factors for differences in child SSI participation across state and over time. At the national level, growth in diagnoses of mental impairments is correlated with SSI rates, but variation in in mental impairments across states is not significantly associated with variation in participation (Aizer, Gordon, & Kearney, 2013). The share of children in special education has been found to be positively and significantly associated with new child SSI mental allowances, but only if Texas is dropped from the analysis (Aizer, Gordon, & Kearney, 2013).[4] Schmidt (2013) finds that welfare reform significantly increased SSI participation for both adults and children, and that state policies that sanctioned welfare recipients for noncompliance had positive and significant effects on the SSI caseload. In addition, Schmidt (2013) finds that welfare reform appears to have changed the relationship between SSI participation and other variables. Notably, the SSI program has become more cyclical in response to business cycles in the years following welfare reform for women and children, but not for men. While these state-level analyses generally find that some factors are significant predictors, a large portion of the growth in child SSI caseloads remains unexplained.

There is also a great deal of variation in SSI participation across counties. As illustrated in Figure 2, Wittenburg et al. (2015) document substantial variation across counties in child SSI participation rates, even within the same state. This variation persists even after controlling for the number of children in poverty (Wittenburg et al., 2015). This suggests that economic conditions matter, but leave much of the variation in participation rates unexplained. There are counties with similar poverty rates that have very different child SSI participation rates. However, little work has been done to examine the effects of local factors on child SSI participation. One exception is a report by Cullen and Schmidt (2011) that shows a significant relationship between school district

[4] Texas saw one of the largest increases in the child SSI caseload over this time period but had declining participation in special education (Aizer, Gordon, & Kearney, 2013).

fiscal incentives for classifying children as special education and post-*Zebley* growth in child SSI caseloads at the county level in Texas.

This article adds to the existing literature by analyzing county-level variation in child SSI participation over time in two ways. First, we extend previous state modeling efforts of SSI caseloads by including county-level data, which is an important addition given the within-state variation in child SSI caseloads documented in Wittenburg et al. (2015). Second, we estimate separate models by region and for individual states to assess whether they yield coefficient estimates that differ from pooled national time-series models. The latter analysis allows us to test whether constraining the coefficients of model variables to be the same in each state and county is a valid assumption.

III. Data and Methodology

To examine county-level variation in SSI child caseloads, we construct a county-level panel using data from a number of different sources for 2003 through 2012. This is a period of high unexplained growth in caseloads, as described in the prior section, and the specific starting and ending years are driven by data availability. With these data, we begin with a pooled time-series model—a logical starting point for examining a federal program like SSI, which has the same eligibility standards in each state. These types of models have been used extensively to examine determinants of SSI participation, as well as welfare participation more generally.[5]

$$(SSIpartrate)_{ct} = E_{ct}\beta + H_{ct}\theta + F_{ct}\gamma + X_{ct}\lambda + T_t + \varepsilon_{ct}$$

[5] For SSI, examples include Garrett & Glied (2000); Schmidt & Sevak (2004); Aizer, Gordon, & Kearney (2013); and Schmidt (2013). For TANF, see Ziliak et al. (2000), Blank (2001), and Bitler & Hoynes (2016).

Our dependent variable is the child SSI participation rate used by Wittenburg et al. (2015), generated from SSA administrative data on the number of child SSI recipients by county (numerator) and U.S. Census child population counts (denominator).[6]

The vector *E* includes measures of county economic conditions. We examine county-level poverty rates from the U.S. Census Bureau, as these should be directly related to income eligibility for SSI. We also look at county-level unemployment rates from the Bureau of Labor Statistics Local Area Unemployment Statistics and the percentage of county jobs that are in manufacturing, as these factors reflect changing labor market opportunities for many low-income families. While state-level economic conditions do not appear to explain much of the growth in the child SSI caseload (Aizer, Gordon, & Kearney, 2013; Schmidt, 2013), within-state, county-level unemployment rates, which are spatially dispersed, particularly during recessions (Fogli, Hill, & Perri, 2012), could help explain within-state variation in caseload growth.

The vector *H* includes three proxies for disability and health conditions, which may affect the number of children determined eligible through the SSA Disability Determination Process. Two are measured at the county-year level, while one is only available at the state-year level. The state-level variable is the prevalence of ADHD diagnoses, collected from the Centers for Disease Control State Profiles. Much of the growth in child SSI participation has been for children with mental conditions, and ADHD is the most common condition for both allowances and recipients over our sample period (National Academies, 2015). At the county level, we include the number of low birth weight babies per 1,000 births, from the Area Health Resource File. Very low birth weight can itself qualify an infant for SSI (Guldi et al., 2016) and is also correlated with higher rates of childhood impairments.[7] We also include the percent of students classified as special education, calculated from school district data from the National Center for Educational Statistics and

[6] Results are robust when we use the log SSI recipiency rate as the dependent variable.
[7] Note that this is an incidence measure, not a prevalence measure – we do not have data on the share of children that were low birth weight by county and year.

aggregated up to the county level. We expect that special education enrollment will be positively correlated with county-level child disability rates (Aizer, Gordon, & Kearney, 2013).

The variable *F* is a measure of local fiscal incentives that could affect SSI participation among children. Research has documented that when local school districts receive additional funding as additional students are enrolled in special education, child disability rates and special education enrollment increase (Cullen, 2003). If enrollment in special education increases awareness about SSI, or helps to provide documentation that makes an award more likely, then these fiscal incentives might affect SSI participation rates.[8] To look at this empirically, *F* indicates whether the county is in a state with weighting formulas for providing funding for special education. In these states, the weights are a function of the number of classified children; therefore, there are higher fiscal incentives to classify the marginal child as special education. We compare states with weighting formulas to those that use payments that are not a function of the number of classified students.[9] We also allow the relationship between SSI rates and the percent of students classified as special education to vary by the state financing formula, through inclusion of an interaction term between the two variables.

Finally, we include controls for demographic characteristics at the county level, including the percentage of the population that is Hispanic and the percent that is black from the Census Bureau. We include the percentage of children in the school district that are English language learners, from the Common Core of Data from the National Center for Education Statistics, aggregated to the county level. Most students classified as English language learners likely come from immigrant families. A smaller share of immigrant families may apply for SSI, either because

[8] Aizer, Gordon, and Kearney (2013) find that the share of children in special education is predictive of allowances but not applications, which they interpret as indicative of special education increasing the probability of a successful disability application.
[9] We obtained codes for school financing formulas from Johnson (2015), who assembled these data from a survey from the Department of Education and the National Association of State Directors of Special Education Project Forum, following methods outlined in Parrish et al. (2003) and Ahearn (2010).

the child's undocumented status makes him or her ineligible or because undocumented family members may not want to draw attention from a federal agency.

All specifications include year fixed effects, *T*, to control for national trends in SSI participation over time. Our first specification includes no geographic fixed effects. These coefficients could overestimate or underestimate the effects of our potential explanatory factors on child SSI participation, because there are likely to be persistent differences across geographic regions that are correlated with both our explanatory variables and child SSI participation. For instance, the estimated coefficient on poverty rates in this regression is likely to be too large, because there are large time-invariant differences across states in both their poverty rates and disability program take-up that could be correlated with historical factors. Our second specification includes state fixed effects that control for time-invariant differences across states. These acknowledge that there are persistent state-level differences in SSI participation over time that are likely to be correlated with our explanatory variables. These could include state TANF features and state SSI supplementation, for example that do not change very much from year to year. Our most conservative specification includes county-level fixed effects, to control for time-invariant differences across counties. The coefficients of other variables in this specification are based solely on the relationship between changes in a variable and changes in child SSI participation within a county over time. The county fixed effects specifications are attractive because they are as close as we can get to causal estimates, but there is some concern that these models might understate the effects of interest because within-county variation might be reflecting primarily transitory changes that do not affect behavioral outcomes (McKinnish, 2008). This might be a particular issue when the geographical unit is as small as a county.

Finally, given regional variation in SSI rates and the varying growth rates across states (Wittenburg et al., 2015), it is possible that the dynamics behind the growth varies regionally or across states. To see if this is the case, we examine whether the relationship between these factors and the child SSI participation rate varies regionally and across states. We estimate separate regression equations for each of the four Census regions and each of 33 of the larger states.[10] We then compare the sign and the magnitude of the coefficient estimates by region and across states.

Table 1 presents summary statistics for our data and shows the variation in both county-level SSI participation rates and our explanatory variables across counties and over time.[11] For example, the mean percent of children with ADHD is 10 percent but ranges from a low of 5 percent to a high of 18.7 percent, and increased an average of 3.88 percentage points between 2003 and 2012. The low birth weight rate also increased over this period, by 4.7 per 1000 births. The unemployment rate averages 6.7 percent but ranges from about 1 to 29 percent. It is also higher at the end of our period of study than at the beginning, reflecting the slow labor market recovery from the Great Recession. The poverty rate also rose over the period, by almost 6 percentage points. The mean share of children receiving special education services is 14 percent, but the variable ranges from 0 to 57 percent and on average declined 0.9 percentage points from 2003 to 2012.

The mean child SSI participation rate is 1.67 percent, with a minimum of zero and a maximum of 10.28 percent, and rose 0.46 percentage points from 2003 to 2012. While these statistics provide a snapshot of the range of participation rates nationally, Figure 3 zooms in on three illustrative states—Michigan, Pennsylvania, and Texas—to look at this variation a little more closely. As noted above, Pennsylvania and Texas have seen the largest growth in child SSI participation over this period. In Michigan (with a state participation rate of 1.9 percent),

[10] We use the states with at least 30 valid county records per year from 2003 to 2012, which provides at least 300 observations for estimating the regressions. These states are Alabama, Arkansas, California, Colorado, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, New York, North Carolina, Ohio, Oklahoma, Oregon, Pennsylvania, South Carolina, South Dakota, Tennessee, Texas, Virginia, Washington, West Virginia, and Wisconsin.

[11] Our analysis sample includes 3,022 counties and excludes 118 counties with data limitations. States with at least one omitted county include Alaska, Colorado, Hawaii, Idaho, Kansas, Mississippi, Montana, Nebraska, Nevada, North Dakota, South Dakota, Texas, Utah, Virginia, and Wyoming.

participation is high in some obvious high poverty areas like Detroit and Flint in the southeast, and the area just outside of Gary, Indiana, in the southwest corner of the state. However, the rest of the state has substantial variation in participation without any obvious explanations. Pennsylvania, which has a relatively high child SSI participation rate of 2.8 percent, also has substantial county-level variation. Here, the counties with low rates stand out—they are in the affluent suburbs of Philadelphia (but not the affluent suburbs of Pittsburgh) and selected counties in the middle of the state. Rates are generally higher in the western part of the state. In Texas, with an overall child SSI participation rate of 2.1 percent, high county-level participation is clustered in the southern and eastern portions of the state, with rates significantly lower in the west and the north. Given that county-level variation in child SSI is so large even within states, this suggests a potential role for within-state differences in explanatory variables.

Figure 4 presents a scatterplot of the county child SSI rate in 2003 and 2012. This plot reveals a strong linear relationship between county rates in both years – most counties with relatively high participation rates in 2003 have relatively high participation rates in 2012, and vice versa. The points on the scatterplot are concentrated just below the 45 degree line, revealing that both high and low SSI counties in 2003 saw growth in participation. But, there are counties that had relatively low participation rates in 2003 that had moved to the higher end of the spectrum by 2012.

IV. National Regression Results

Results from the pooled time-series model can be found in Table 3. Column 1 presents results with no geographic fixed effects, column 2 adds state fixed effects, and column 3 replaces the state fixed effects with county fixed effects. The estimates in columns 1 and 2 reflect a combination of covariation between caseloads and our explanatory variables both across counties and over time. The estimates in column 3 are based solely on the the relationship between changes in the county variables and changes in child SSI participation within counties over time. For some variables, including the poverty rate and the share of students classified as English-language learners, the coefficients in the equation with no geographical fixed effects are the largest in magnitude, and they fall once state or county fixed effects are included. This suggests the presence of persistent geographical variation in these factors that is correlated with persistent geographical variation in child SSI participation.

The coefficients on the health variables are statistically significant and in the expected direction. The estimates without fixed effects predict that a county with rates of ADHD diagnosis 20 percent higher than the mean would have approximately 8 percent higher child SSI rates, but the estimates from the county fixed effects specification reduce the magnitude of this relationship significantly, suggesting that the same high-ADHD county would have approximately 2 percent higher child SSI rates.[12] Similarly, the number of low birth weight babies per 1,000 births is also positively and significantly associated with the child SSI participation rate. A county with 20 percent higher rates of low birth weight babies is predicted to have child SSI rates that are 4 percent higher than the mean in the specification, with or without controlling for state fixed effects, but when we include county fixed effects, the estimated magnitude falls. While statistically significant, these effects are quite small in magnitude and are therefore unlikely to explain a great deal of the growth in child SSI participation.

Similarly, poverty rates have a significant and persistent relationship with child SSI participation. Estimates from columns 1 and 2 imply that a county with a 20 percent higher poverty rate would have a 17 percent higher child SSI participation rate. The inclusion of county fixed effects, in column 3, generates coefficient estimates much lower in magnitude, implying that a poverty rate 20 percent higher than the mean would be associated with a child SSI participation rate

[12] The mean ADHD rate is 10.17 percent, so a 20 percent increase would translate into an increase of 2.034 percentage points. 2.034 * 0.015 = 0.0305, or 1.8 percent of the baseline SSI participation rate of 1.67 percent.

only 2 percent higher than the mean. The coefficients on the county-level unemployment rate are marginally or not significant in columns 1 and 2. However, once county fixed effects are included, the coefficient becomes statistically significant at the one-percent level, suggesting that higher unemployment rates are negatively and significantly associated with higher rates of child SSI participation.[13]

The percentage of students classified as special education is positively and significantly associated with child SSI participation in columns 1 and 2, but this relationship turns negative when we include county fixed effects. This suggests that it is positively correlated with variation across counties, but that is negatively correlated with changes in SSI rates within a county over time. As we discuss further in the next section, the direction of this relationship varies by region and is largely driven by Texas, a state that experienced large decreases in special education but rapid growth in child SSI participation. The coefficient on the special education weighted funding indicator is negative in column 3, but the coefficient on the interaction between the weighting indicator and the percent of students in special education is positive. This suggests that the effects of having a weighting formula versus a capitation formula vary dramatically depending on the share of students enrolled in special education services. At the average percent special education (14.39 percent), the positive effect of the interaction basically offsets the negative effect of the weighting formula, leading to no difference between weighting and capitation formulas. However, in counties with high shares of special education, the positive effect of the interaction dominates, and in these counties weighting formulas are positively associated with child SSI participation. This could be the case if a higher share of students in special education increases information among parents, or makes it more likely that school officials can recognize and exploit the opportunity to increase revenues via documentation of disabilities in an SSI application.

[13] This pattern, while somewhat counterintuitive, is consistent with other research using a specification with geographic and year fixed effects to look at the effects of unemployment on stocks of SSI participants, including Garrett & Glied (2000), Schmidt & Sevak (2004), Rutledge & Wu (2013), and Schmidt (2013).

The coefficients on the demographic variables are largely significant and in directions that would be expected given the prior literature. Counties with a higher share of Hispanics have lower child SSI participation, which is consistent with previous findings showing that Hispanics are underrepresented in disability populations (Ben-Shalom & Stapleton, 2014). Counties with a higher share of African Americans have higher rates of child SSI participation (Schmidt, 2013). The percentage of students at the school district level who are English-language learners is negatively and significantly associated with child SSI participation.

We then take our model estimates and ask how much of the recent growth in the child SSI program (between 2003 and 2011) can be explained by the variables in our model. To do this we compare the uncontrolled year-by-year differences in participation rates to the year fixed effects in the specification estimated with covariates and county fixed effects. If the covariates in the model can explain some of the growth, the year fixed effects should be smaller in the full model in Column 3. We find that the model does a better job explaining growth in the program in the earlier years of our sample period. Between 2003 and 2008, the model explains 30 to 40 percent of the trend. However, it explains less of the program growth during and since the Great Recession—only about 25 percent of the trend between 2008 and 2011.

IV. Regional- and State-Level Regression Results

Given the regional variation in SSI rates illustrated in the map in Figure 2 and differential growth rates across the states, it is possible that the determinants of SSI caseload growth vary regionally or by state. If so, a national model that averaged variation across states would produce estimates that would dampen the significance of factors that are important in some states but not in others. To examine this possibility, we separately estimate regressions of caseloads by year by region and state.

Table 4 shows that the estimated relationship between specific variables and SSI rates varies substantially across Census regions. In general, there are more significant coefficients in the model estimated on Southern states. The positive relationship with ADHD and low birth weight observed in the national model is present only among counties in the South. However, we cannot reject the hypothesis that the coefficients on these health variables are significantly different across regions. In contrast, poverty is a significant predictor in all four regions. Unemployment is positively associated with caseloads in the Midwest but negatively associated with caseloads in the South, and the coefficient on the unemployment rate is statistically different across the four census regions. The relationship between special education variables and SSI rates is not significant in the Midwest and West and is of opposite signs in the Northeast and the South. In the South, an increase in the percent of students receiving special education services is associated with decreases in child SSI participation, while in the Northeast both rates move in the same direction. In addition, traditional weighting formulas for financing special education are positively and significantly associated with SSI rates in the Northeast and negatively in the South. These regional differences are also statistically significant.

We next look more closely at four southern states to see if there is subregional variation in determinants of SSI growth, as well. Table 5 presents separate estimates for Alabama, Arkansas, Mississippi, and Texas. Because these are estimated from state-specific models, we cannot get estimates for the ADHD and school finance variables that vary only at the state-year level. We find that even within the South, there are statistically significant differences across states in the estimated relationship between particular variables and SSI rates. In Alabama, poverty does not have a significant relationship with SSI rates, but we find a large positive estimate for the unemployment rate. In Texas, but not the other states, an increase in manufacturing jobs is associated with lower rates of SSI receipt. The hypothesized positive relationship between special education and SSI is observed only in Arkansas. Lastly, the coefficients on the race and ethnicity variables are widely and statistically different and across the four states.

Table 6 presents results from four additional states—California, Ohio, Pennsylvania, and Texas. We showcase these states because they are large states, with many county observations, and they have substantial geographic and caseload diversity.[14] From 1998 to 2013, Ohio had a relatively low growth rate of 21 percent (compared with the national growth rate of 45 percent), while caseloads grew by 52 percent in California, 105 percent in Pennsylvania, and 140 percent in Texas (Wittenburg et al., 2015).

Results from these state-specific regressions also suggest that our model variables have different explanatory power across states. In Ohio, the share of low birth weight births is positively and significantly associated with the child SSI caseload, while the estimated coefficients on this variable are essentially zero for the three other states, and the estimated coefficients are statistically different across the four states. The poverty rate is positively and significantly associated with child SSI participation in all four states, but the magnitude of the coefficient in Pennsylvania is twice that of the other states. Unemployment rates are not significantly associated with child SSI participation in California. Ohio, or Pennsylvania. However, in Texas the coefficient on the unemployment rate is positively associated with child SSI and significant at the 10 percent level.

Finally, we find that the model explains a higher percentage of the time trend in Ohio, which had the lowest growth rate of these four states, than California, but it does a poor job of explaining the time trends in Pennsylvania and Texas, the states with the highest growth rates. These state-specific results suggest that further state-level case studies might help explain some of the puzzling growth differentials in the child SSI program.

[14] Results for other states are available upon request.

VI. Conclusion

Previous research examining state-level determinants of child SSI caseloads found few statistically significant predictors. In this paper, we account for the fact that there is a great deal of regional and cross-state heterogeneity—both in child SSI participation and in factors that might affect child SSI participation. Our results suggest that a number of variables at the county level can help explain the geographic variation in child SSI participation, as well as some of the growth in child SSI rates. Poverty rates, health conditions, and special education are important predictors of child SSI participation. These factors can explain 30 to 40 percent of the growth in child SSI participation between 2003 and 2008, prior to the Great Recession, and about 25 percent of the growth since 2008.

We also find statistically significant differences in the variables correlated with caseload growth across regions and across states. These variables explain more of the growth in states that had relatively low caseload growth and less of the growth in states that had high caseload growth including Texas. These state differences are particularly interesting, given that one of the goals of the SSI program from its inception in the 1970s was to standardize support across states for low-income individuals with disabilities. Understanding this heterogeneity has important implications for program costs and for equity.

While our research provides new evidence on some of the factors associated with child SSI caseload growth, a great deal of the growth, especially in the more recent period, remains unexplained, warranting additional research. Additional factors that affect eligibility including child health conditions and local labor market conditions may be contributing to differential growth over this period, but difficulty measuring these factors for all counties and years limits the ability to test this. An additional avenue for future research is to focus on growth in SSI child applications or new awards, rather than total caseloads as contemporaneous health, economic, and fiscal conditions may have larger behavioral effects on applications. Existing research on adult SSI applicants finds the determinants of new applications can differ from determinants of caseloads (Nichols et al., 2015). Finally, the variation we find across states in the relationship between SSI participation and economic and health conditions suggests that state-specific specific case studies of caseload growth that pay careful attention to local factors may be fruitful in providing additional understanding of the child SSI caseload.

References

Ahearn, E. (2010). Financing special education: State funding formulas. Alexandria, VA: Project Forum, National Association of State Directors of Special Education.

Aizer, A., Gordon, N., & Kearney, M. (2013). Exploring the growth of the child SSI caseload in the context of the broader policy and demographic landscape (NBER Disability Research Consortium working paper NB13–02). Cambridge, MA: National Bureau of Economic Research.

Berkowitz, E. D., & DeWitt, L. (2013). The other welfare. Ithaca, NY: Cornell University Press.

Ben-Shalom, Y., & Stapleton, D. (2014). National and state program participation ratios for working-age people with disabilities (Mathematica Policy Research final report). Princeton, NJ: Mathematica Policy Research.

Bitler, M., & Hoynes, H. (2016). The more things change, the more they stay the same? The safety net and poverty in the Great Recession. Journal of Labor Economics, 34 (S1, part 2), S404–444.

Blank, R. (2001). What causes public assistance caseloads to grow? Journal of Human Resources, 36, 85–118.

Cullen, J. B. (2003). The impact of fiscal incentives on student disability rates. Journal of Public Economics, 87, 1557–1589.

Cullen, J. B., & Schmidt, L. (2011). Growth in the Supplemental Security Income program for children: The role of local jurisdictions and fiscal incentives. Unpublished manuscript.

Duggan, M., Kearney, M. S., & Rennane, S. (2015). The Supplemental Security Income (SSI) program (NBER working paper no. 21209). Cambridge, MA: National Bureau of Economic Research.

Fogli, A., Hill, E., & Perri, F. (2012). The geography of the Great Recession (NBER working paper no. 18447). Cambridge, MA: National Bureau of Economic Research.

Garrett, B., & Glied, S. (2000). Does state AFDC generosity affect child SSI participation? Journal of Policy Analysis and Management, 19, 275–295.

General Accountability Office. (2012). Supplemental Security Income: Better management oversight needed for children's benefits (GAO–14–497). Washington, DC: Government Accounting Office.

Guldi, M., Hawkins, A., Hemmeter, J., & Schmidt, L. (2016). Supplemental Security Income, Medicaid, and child outcomes: Evidence from birth weight eligibility cut-offs. Unpublished mimeo.

Johnson, R. (2015). Details on financing coding. Princeton University unpublished mimeo.

McKinnish, T. G. (2008). Panel data models and transitory fluctuations in the explanatory variable. Advances in Econometrics, 21, 335-358.

National Academies of Sciences, Engineering, and Medicine. (2015). Mental disorders and disabilities among low-income children. Washington, DC: The National Academies Press.

Nichols, A., Schmidt, L., & Sevak, P. (2015) Economic Conditions and Supplemental Security Income Applications. Unpublished mimeo.

Parrish, T., Harr, J., Anthony, J., Merickel, A., & Esra, P. (2003). State special education finance systems, 1999–2000. Washington, DC: Center for Special Education Finance, American Institutes for Research.

Rutledge, M. S., & Wu, A. Y. (2013). Why do SSI and SNAP enrollments rise in good economic times and in bad? (working paper). Boston, MA: Center for Retirement Research at Boston College.

Schmidt, L. (2004). Effects of welfare reform on the Supplemental Security Income (SSI) program. (National Poverty Center policy brief no. 4). Ann Arbor, MI: National Poverty Center.

Schmidt, L. (2013). The new safety net? Supplemental Security Income after welfare reform (Williams College working paper 2013–07). Williamstown, MA: Williams College.

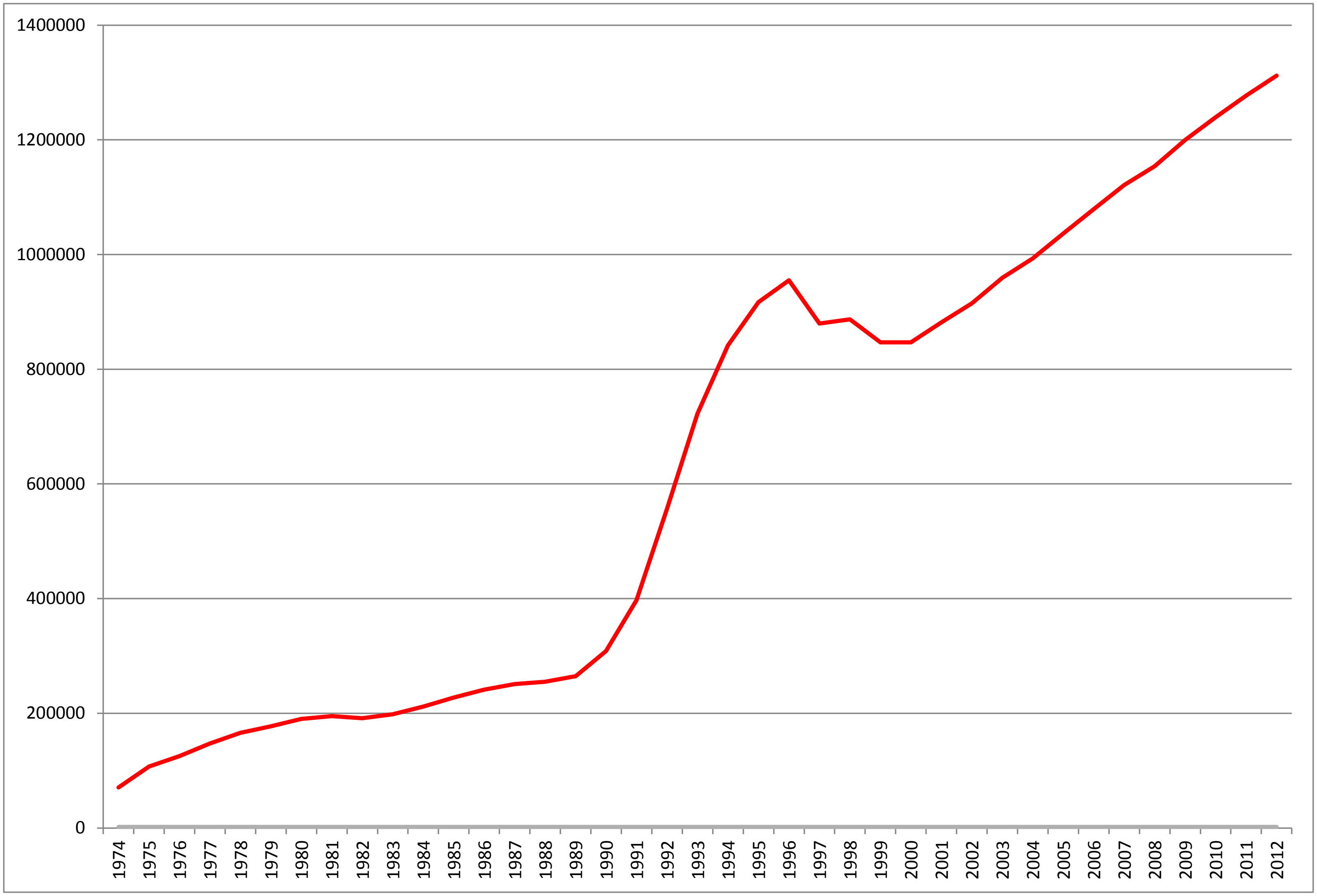
Schmidt, L., & Sevak, P. (2004). AFDC, SSI, and welfare reform aggressiveness: Caseload reductions vs. caseload shifting. Journal of Human Resources, 39, 792–812.

Social Security Administration. (2015). Understanding Supplemental Security Income SSI for children—2015 Edition. https://www.socialsecurity.gov/ssi/text-child-ussi.htm.

Wittenburg, D., Tambornino, J., Brown, E., Rowe, G., DeCamillis, M., & Crouse, G. (2015). The changing role of the child SSI program in the safety net. Washington, DC: Office of the Assistant Secretary for Planning and Evaluation, U.S. Department of Health and Human Services.

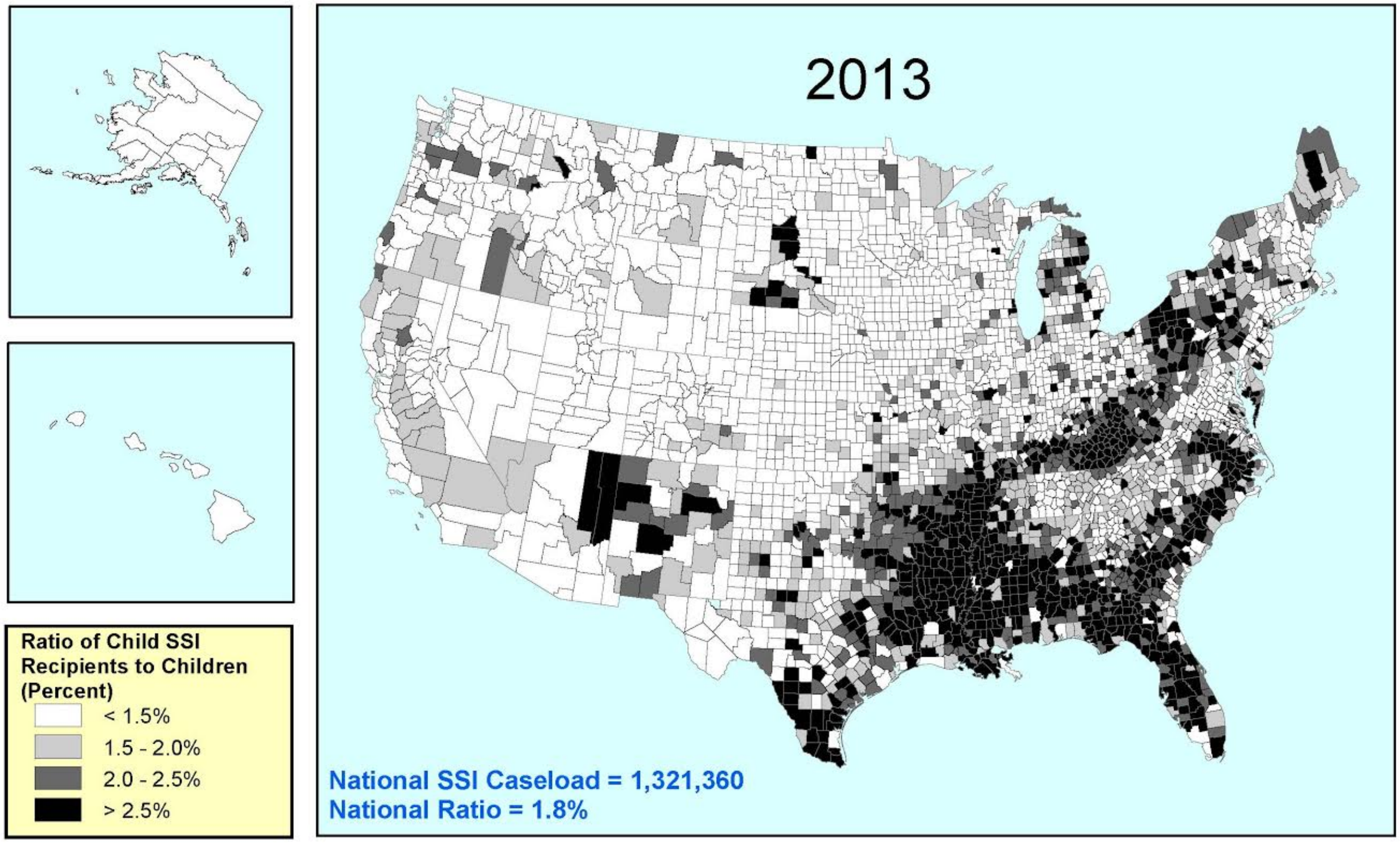
Ziliak, J., Figlio, D., Davis, E., & Connelly, L. (2000). Accounting for the decline in AFDC caseloads: Welfare reform and the economy. Journal of Human Resources, 35, 570–586.

Figure 1. SSI Child Disabled Cases, 1974–2012



Source: Social Security Administration, *Annual Statistical Supplement*, various years.

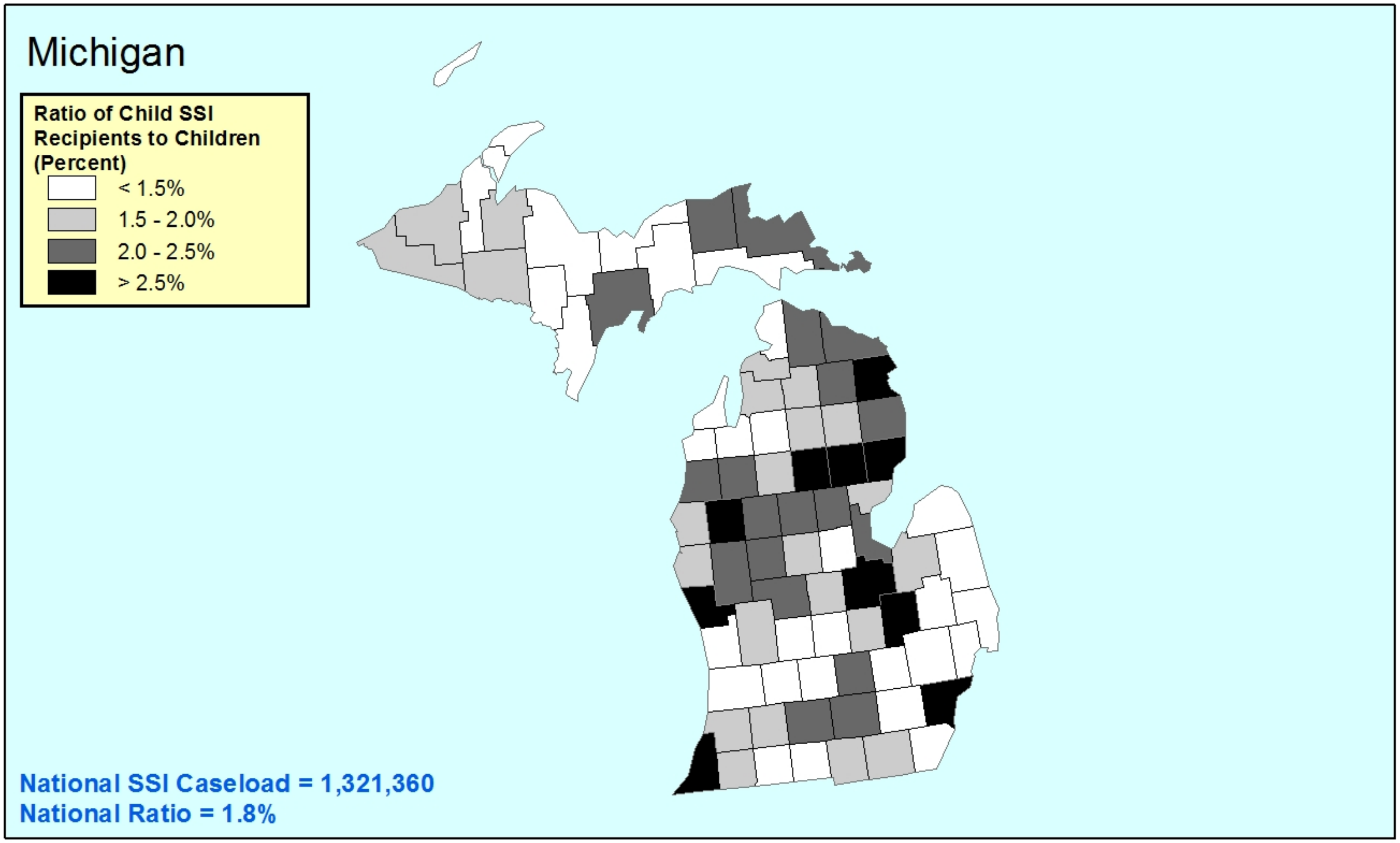
Figure 2. County-Level Variation in Child SSI Population Ratios, 2013



Source: Wittenburg et al. (2015).

Note: SSI child population ratio is calculated by dividing the number of child SSI recipients (Social Security Administration, 2014) by the number of children in the United States (U.S. Census Bureau, 2013).

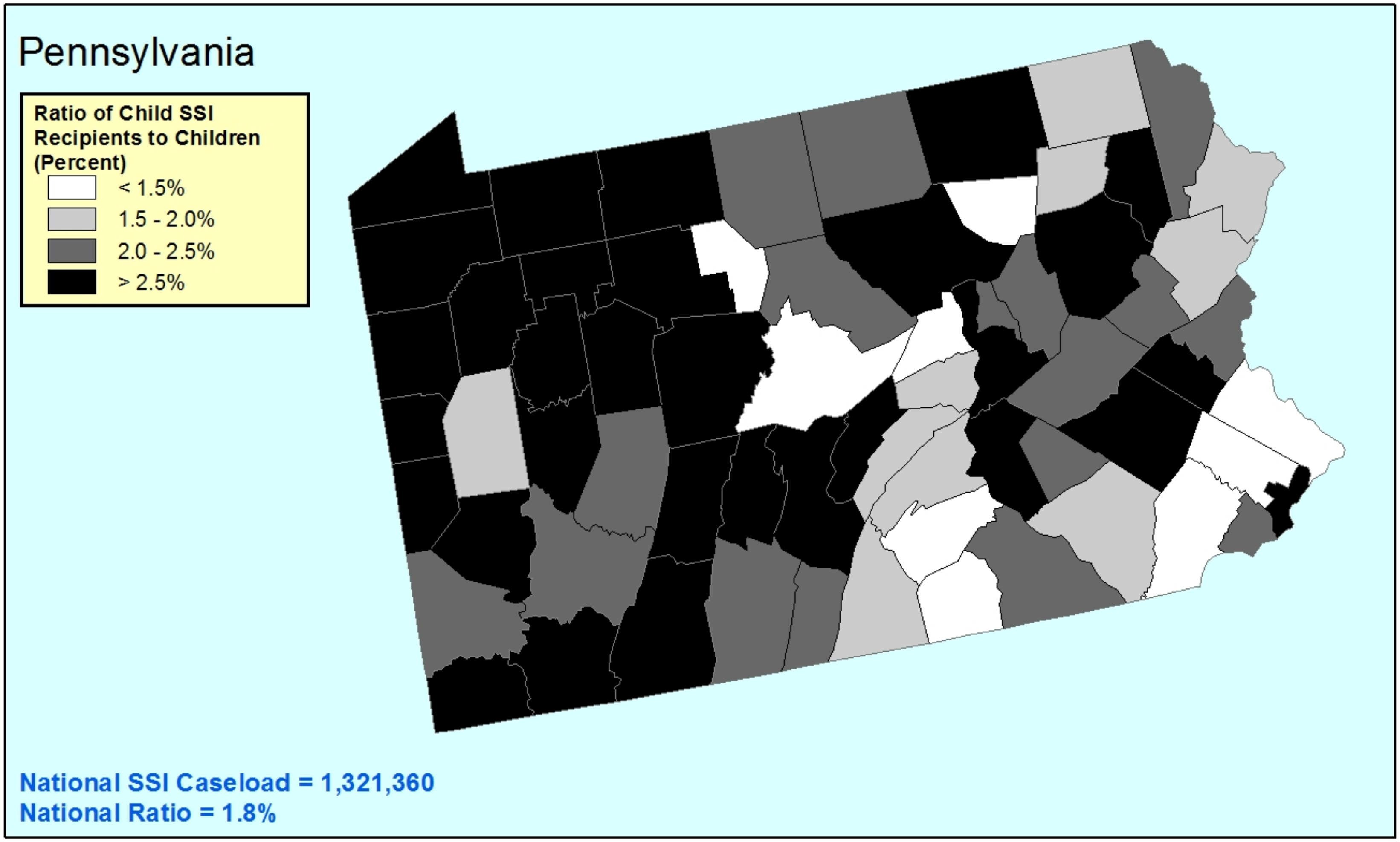
Figure 3a. County-Level Variation in Child SSI Population Ratios, Michigan 2013



Sources: Social Security Administration (2014); U.S. Census Bureau (2013).

Note: SSI child population ratio is calculated by dividing the number of child SSI recipients by the number of children in the state.

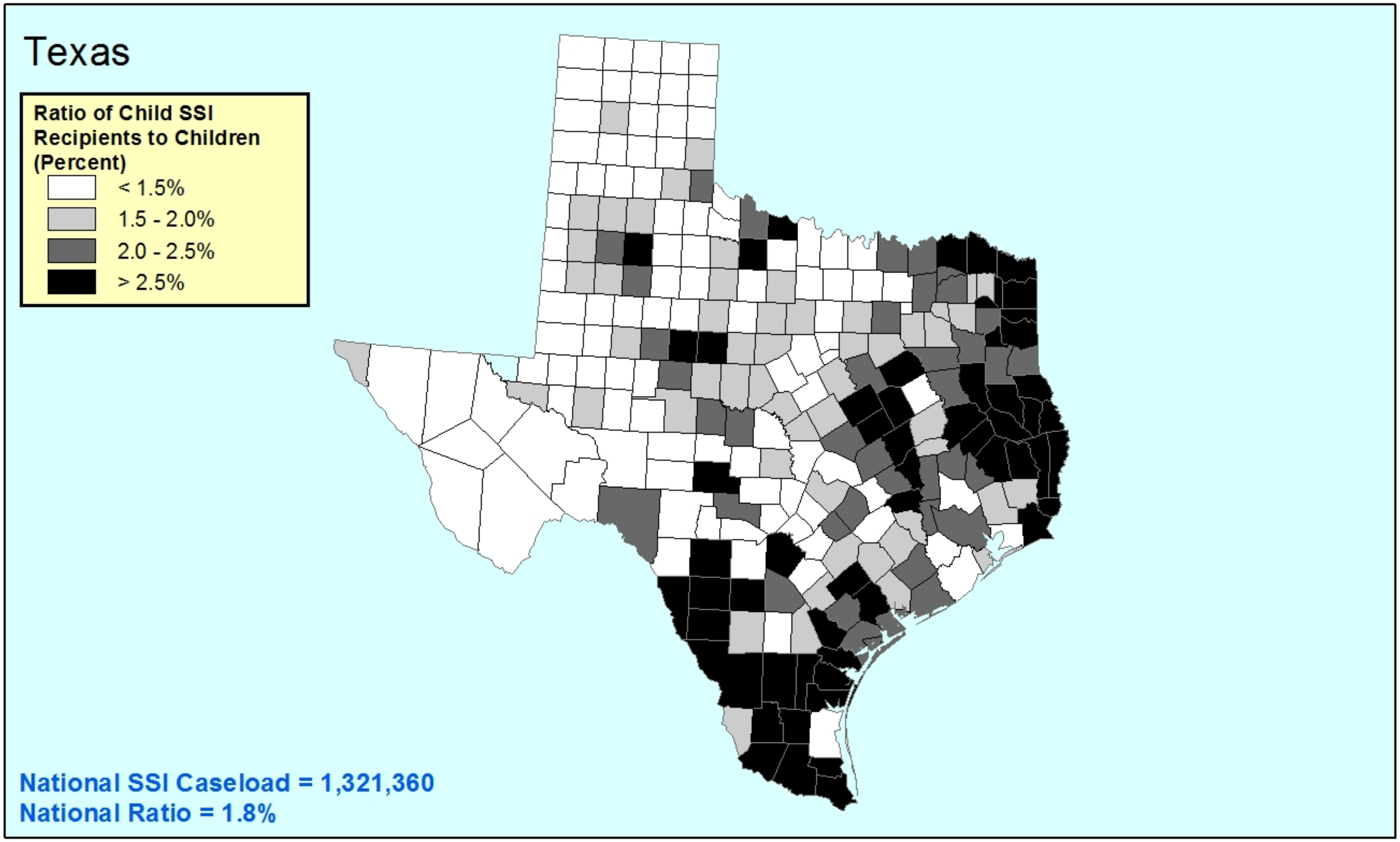
Figure 3b. County-Level Variation in Child SSI Population Ratios, Pennsylvania 2013



Sources: Social Security Administration (2014); U.S. Census Bureau (2013).

Note: SSI child population ratio is calculated by dividing the number of child SSI recipients by the number of children in the state.

Figure 3c. County-Level Variation in Child SSI Participation Ratios, Texas, 2013



Sources: Social Security Administration (2014); U.S. Census Bureau (2013).

Note: SSI child population ratio is calculated by dividing the number of child SSI recipients by the number of children in the state.

Figure 4. Scatterplot of 2003 and 2012 County Child SSI Rate

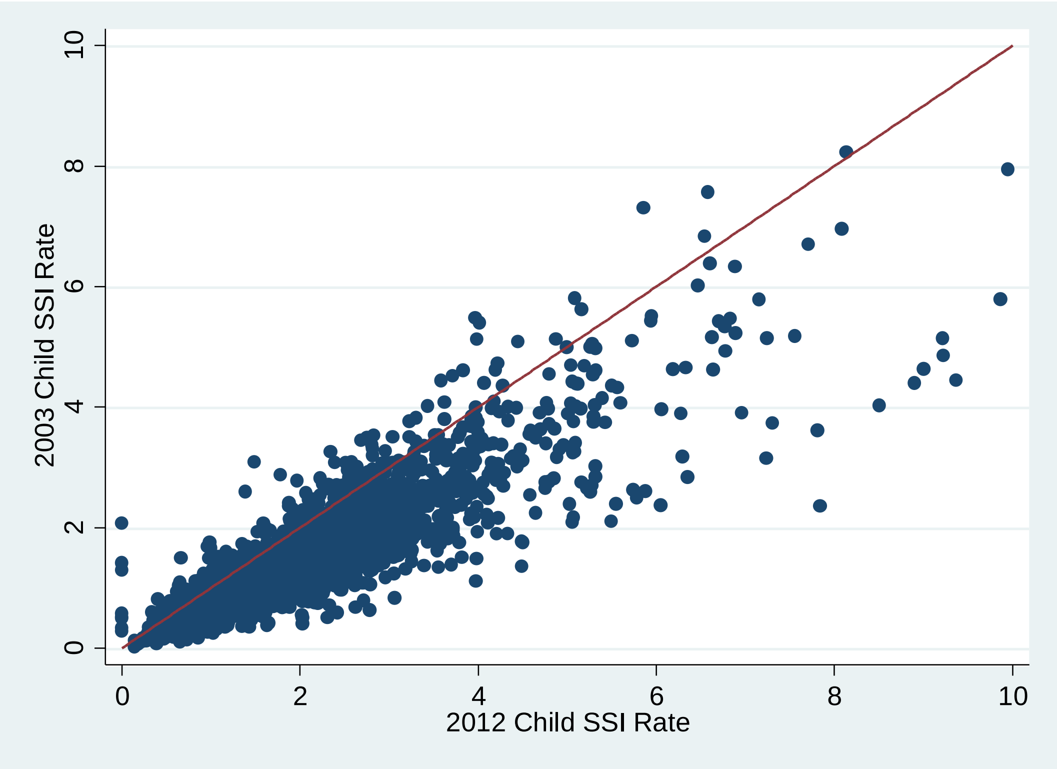


Table 1. Summary statistics

	Mean (SD)	Minimum	Maximum	Mean Change 2003-2011
Percentage of children receiving SSI	1.67	0.00	10.28	0.46
	(1.12)			
ADHD rate (%)	10.17	5.00	18.70	3.88
	(2.51)			
Low birth weight (per 1,000)	82.60	0.00	203.35	4.70
	(22.01)			
Poverty rate (%)	21.71	2.10	70.10	5.86
	(8.84)			
Unemployment rate (%)	6.68	1.10	29.00	2.86
	(2.79)			
Manufacturing jobs (%)	4.98	0.00	45.04	-1.37
	(4.32)			
Hispanic (%)	7.68	0.10	97.30	1.81
	(12.82)			
Black (%)	10.20	0.00	86.30	0.20
	(14.98)			
English-language learners (%)	3.70	0.00	59.94	0.67
	(6.17)			
Weighted school finance formula	0.81	0.00	1.00	-0.02
	(0.39)			
Special education (%)	14.39	0.00	56.64	-0.92
	(3.42)			
Number of county-year records	23,456			
Number of counties	3,022			

Table 3. Regression estimates for county child SSI rate

	No Fixed Effects	State Fixed Effects	County Fixed Effects
ADHD (% of children)	0.059	0.009	0.015
	(10.68)***	(1.46)	(3.04)***
Low birth weight (per 1,000)	0.004	0.005	0.001
	(7.21)***	(8.97)***	(3.45)***
Poverty rate	0.069	0.067	0.008
	(33.65)***	(34.51)***	(6.16)***
Unemployment rate	-0.004	-0.009	-0.019
	(0.89)	(1.82)*	(5.65)***
Manufacturing jobs (%)	0.006	0.008	-0.003
	(2.84)***	(3.57)***	(0.98)
Hispanic (%)	-0.002	-0.004	-0.012
	(1.24)	(2.36)**	(2.59)***
Black (%)	0.022	0.031	0.022
	(15.27)***	(21.76)***	(3.37)***
English-language learners (%)	-0.014	-0.010	-0.007
	(6.50)***	(4.98)***	(3.18)***
Weighting school finance formula	-0.388	0.052	-0.251
	(3.08)***	(0.46)	(3.73)***
Weighting formula*(%) special education	0.003	-0.006	0.015
	(0.37)	(0.79)	(3.22)***
Special education (%)	0.032	0.021	-0.012
	(3.77)***	(2.75)***	(2.37)**
Constant	-1.136	-0.694	1.266
	(8.72)***	(4.21)***	(10.58)***
R^2	0.71	0.80	0.34
N	23,453	23,453	23,453

* p<0.1; ** p<0.05; *** p<0.01. Unit of observation is the county. All specifications include year fixed effects.

Table 4. Regression estimates for county child SSI rate, by region

	Northeast	Midwest	South	West
ADHD (% of children)	0.011	-0.004	0.015	0.005
	(1.04)	(1.16)	(1.96)*	(0.29)
Low birth weight (per 1,000)	-0.000	0.000	0.001	0.001
	(0.40)	(0.57)	(2.68)***	(1.22)
Poverty rate	0.013	0.011	0.008	0.008
	(4.01)***	(5.44)***	(4.11)***	(3.16)***
Unemployment rate	0.006	0.009	-0.041	-0.006
	(0.55)	(2.93)***	(7.11)***	(1.38)
Manufacturing jobs (%)	0.003	-0.004	-0.001	0.003
	(0.26)	(1.45)	(0.19)	(0.41)
Hispanic (%)	0.029	-0.026	-0.015	-0.014
	(1.33)	(3.69)***	(2.04)**	(1.87)*
Black (%)	-0.018	0.011	0.027	-0.013
	(0.69)	(1.09)	(3.77)***	(0.75)
English-language learners (%)	-0.010	0.003	-0.017	0.001
	(1.05)	(0.56)	(4.02)***	(0.23)
Weighting school finance formula	1.000	-0.020	-0.691	-0.037
	(6.37)***	(0.20)	(3.34)***	(0.76)
Weighting formula*(%)special education	-0.052	-0.001	0.051	-0.007
	(6.20)***	(0.14)	(4.22)***	(1.31)
Special education (%)	0.048	0.001	-0.034	0.005
	(6.13)***	(0.10)	(2.85)***	(1.25)
Constant	0.160	0.876	1.818	0.928
	(0.74)	(7.63)***	(6.99)***	(3.64)***
R^2	0.67	0.40	0.36	0.26
N	1,904	7,279	11,498	2,772

* $p<0.1$; ** $p<0.05$; *** $p<0.01$. Unit of observation is the county. All specifications include year fixed effects.

Table 5. Regression estimates for county child SSI rate, among selected southern states

	Alabama	Arkansas	Mississippi	Texas
Low birth weight (per 1,000)	-0.003	0.005	-0.001	0.001
	(1.21)	(2.30)**	(0.47)	(1.66)*
Poverty rate	0.008	0.027	0.015	0.012
	(1.21)	(2.16)**	(2.67)***	(3.35)***
Unemployment rate	0.079	-0.031	0.004	0.025
	(3.05)***	(0.46)	(0.25)	(1.88)*
Manufacturing jobs (%)	0.022	-0.008	-0.007	-0.019
	(1.34)	(0.39)	(0.48)	(2.37)**
Hispanic (%)	-0.039	-0.124	0.037	-0.060
	(1.27)	(2.47)**	(1.05)	(4.73)***
Black (%)	0.022	0.243	0.052	-0.055
	(0.56)	(3.07)***	(2.29)**	(2.31)**
English-language learners (%)	0.004	-0.050	-0.010	-0.009
	(0.17)	(2.01)**	(0.50)	(1.16)
Special education (%)	0.006	-0.011	0.078	0.015
	(0.44)	(0.30)	(2.81)***	(1.62)
Constant	1.595	-1.822	-0.495	2.675
	(1.26)	(1.22)	(0.41)	(5.31)***
R^2	0.31	0.73	0.38	0.67
N	535	625	722	1,807

* $p<0.1$; ** $p<0.05$; *** $p<0.01$. Unit of observation is the county. All specifications include year fixed effects.

Table 6. Regression estimates for county child SSI rate, for selected states

	California	Ohio	Pennsylvania	Texas
Low birth weight (per 1,000)	0.001	0.004	-0.001	0.001
	(0.38)	(4.26)***	(0.71)	(1.66)*
Poverty rate	0.009	0.013	0.024	0.012
	(2.32)**	(3.81)***	(3.48)***	(3.35)***
Unemployment rate	-0.001	-0.002	0.025	0.025
	(0.07)	(0.18)	(1.35)	(1.88)*
Manufacturing jobs (%)	-0.018	-0.021	0.035	-0.019
	(0.90)	(1.56)	(2.42)**	(2.37)**
Hispanic (%)	0.010	0.015	0.025	-0.060
	(0.93)	(0.31)	(0.86)	(4.73)***
Black (%)	-0.074	0.008	-0.057	-0.055
	(2.15)**	(0.32)	(3.00)***	(2.31)**
English-language learners (%)	0.001	0.012	-0.020	-0.009
	(0.34)	(0.75)	(0.61)	(1.16)
Special education (%)	0.006	0.035	-0.009	0.015
	(0.90)	(3.99)***	(0.81)	(1.62)
Constant	0.741	0.308	1.332	2.675
	(2.53)**	(1.15)	(4.57)***	(5.31)***
R^2	0.41	0.64	0.78	0.67
N	485	791	586	1,807

* $p<0.1$; ** $p<0.05$; *** $p<0.01$. Unit of observation is the county. All specifications include year fixed effects.