5. CASE STUDIES USING ACS DATA

Case Study #1: Mobility and Economic Opportunity in New York City Neighborhoods

Skill Level: Intermediate/Advanced

Subject: Commuting/transportation challenges

Type of Analysis: Analysis of job opportunities, household income, and population size across New York City neighborhoods

Tools Used: Application Programming Interface (API), spreadsheet

Author: Sarah Kaufman, Assistant Director for Technology Programming at the New York University (NYU) Rudin Center for Transportation

The ability of a public transportation network to physically link residents to jobs has become a central point of concern for urban policy in an era of uneven unemployment and rapidly changing job markets. The economy of New York City is unique in North America due to the high proportion of residents using public transportation. In 2016, more than half of the population in New York City (56.6 percent) used some kind of public transportation to get to work, and an individual's ability to access a job is largely a function of how well their neighborhood is served by the public transportation system.

In a recent report, the Rudin Center for Transportation Policy and Management at NYU's Robert F. Wagner School of Public Service explored some of the key transportation challenges facing New York City residents, based on data from the American Community Survey (ACS) and other sources.⁴⁷ An accompanying interactive map enables users to explore the data for their neighborhoods.⁴⁸

Results showed disparities in transportation access. Furthermore, low levels of transit access were associated with lower income and employment among residents, while high levels of transit access were associated with higher income and employment.

Methods

Rudin Center staff analyzed and ranked 177 New York City neighborhoods based on access to job opportunities, household income, and population size. The rankings reflect the number of jobs that can be reached within 1 hour by public transportation. (A commute time of 1 hour or less was selected based on prior research showing that commuters prefer to travel less than 1 hour.)

Demographic data are from the U.S. Census Bureau's ACS 5-year estimates for ZIP Code Tabulation Areas (ZCTAs). ZCTAs are aggregations of census blocks that form "generalized areal representations of United States Postal Service (USPS) ZIP code service areas."⁴⁹

New York City fully contains 186 ZCTAs as defined in the 2010 Census. In this work, ZCTAs are only included as a unit of observation if they contain populations of at least 2,500 according to the 2008-2012 ACS. It should be noted that the estimates included in the report and interactive maps do not account for margins of error. However, the population threshold helps to ensure accurate demographic data exist within the ZIP code (unlike park areas), and to avoid small areas that would not be representative of a larger neighborhood. Of the 186 ZIP codes, 177 have a population of at least 2,500.⁵⁰

ACS estimates for ZCTAs were accessed through the Census Data API.⁵¹

To access 2008–2012 ACS 5-year employment and unemployment data from the Census Data API, enter the following query in your Web browser: https://api.census.gov/data/2012/acs/acs5?get=group(B23025)&for=ZIP %20code%20tabulation%20area:*> as described in the steps below (see Figure 5.1).

1. Start your query with the host name: "https://api.census.gov/data."

⁴⁷ The Rudin Center for Transportation Policy and Management, Mobility, Economic Opportunity and New York City Neighborhoods, November 2015, https://wagner.nyu.edu/impact/research/publications/mobility-economic-opportunity-and-new-york-city-neighborhoods>.

⁴⁸ Datapolitan, NYC Neighborhoods: Mobility & Economic Opportunity, <www.datapolitan.com/job_access/>.

⁴⁹ U.S. Census Bureau, ZIP Code Tabulation Areas (ZCTAs), <www.census.gov/programs-surveys/geography/guidance/geo-areas/zctas.html>. ⁵⁰ In cases where ZCTA-level data were unavailable, census tract estimates were "cross-walked" to conform to ZCTA boundaries using an allocation algorithm provided by the Missouri Census Data Center.

⁵¹ U.S. Census Bureau, Census Data API User Guide, <www.census.gov/data/developers/guidance/api-user-guide.html>.

- 2. Add the data year (2012) to the URL: "https://api.census.gov/data/2012."
- 3. Add the data set name acronym for the ACS 5-Year Detailed Tables, and follow this base URL with a question mark: "https://api.census.gov/data/2012/acs/acs5?."
- 4. Add variables starting with a get clause, "get=": "https://api.census.gov/data/2012/acs/acs5?get=."
- 5. Use the group feature to return all data items for Table B23025 (which contains labor force, employment, and unemployment details): "https://api.census.gov/data/2012/acs/acs5?get=group(B23025)."
- Add geography using a predicate clause starting with an ampersand (&) to separate it from your "get" clause and then a "for=" to identify geographic areas of interest: "https://api.census.gov/data/2012/acs/acs5?get=group(B23025)&for=."
- Identify the geographic area(s) that you need (ZCTAs) by reviewing the list of geographies available for the 2008–2012 ACS 5-year Detailed Tables.⁵²
- Because you need data for many ZIP codes, add a wildcard (*) to get all ZCTA values: "https://api.census.gov/data/2012/acs/acs5?get=group(B23025)&for=ZIP%20code%20tabulation%20area:*."

After downloading the comma-separated file, we opened it in a spreadsheet to analyze the data.

Figure 5.1. ZIP Code Tabulation Area Query for Employment and Unemployment Data From Table B23025: 2008–2012
← → C 🏠 🕯 api.census.gov/data/2012/acs/acs5?get=group(B23025)&for=ZIP%20code%20tabulation%20area:* 🖈
<pre>[["GEO_ID","B23025_001E","B23025_001M","B23025_002E","B23025_002H","B23025_003E","B23025_003M","B23025_004E",</pre>
Note: Data are shown for the first five rows. Source: U.S. Census Bureau, <https: 2012="" acs="" acs5?get="group(B23025)&for<br" api.census.gov="" data="">=ZIP%20code%20tabulation%20area:*>.</https:>

To calculate the unemployment rate, we divided a ZCTA's unemployed population (B23025_005E) by its civilian labor force (B23025_003E). Using the example of Chelsea (North), ZCTA 10001, we calculated an unemployment rate of 9 percent (see Figure 5.2).

⁵² U.S. Census Bureau, <https://api.census.gov/data/2012/acs/acs5/geography.html>.

We repeated a similar process for all other ACS variables of interest. ACS data were then combined with information from the Google Maps Routing API and the Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) data set.

Fi	gure 5.2. U	nemplo	byment	Rate fo	r Chelse	ea (Nor	th) ZCT	a 1000 [.]	1: 2008-	-2012	
J5	•	× ✓	<i>f</i> _x =J2/	F2							
4	A	В	с	D	E	F	G	н	1	J	
1	geo_id	B23025_001E	B23025_001	M B23025_002E	B23025_002M	B23025_003E	B23025_003M	B23025_004E	B23025_004M	B23025_005E	B
2	8600000US10001	19026	9:	13734	856	13734	856	12538	816	1196	;
3		population ages 16 and older		labor force		civilian Iabor force		employed		unemployed	
4											
5					L	unemployme	nt rate = unem	ployed / civili	ian labor force	9%	1
6											Γ.
So	ource: Autho	or's analys	is of data	a from the	U.S. Censi	us Bureau	ı, America	n Commu	inity Surve	ey.	

The Google Maps Routing API was used to estimate travel times between origins and destinations. The API can be queried with origin and destination pairs to output the estimated travel time according to Google's algorithm. This project used this service to generate a data set containing all ZIP code-level travel times in the region, which originated in New York City and terminated anywhere in the New York, New Jersey, or Connecticut region.

The LEHD data set provides employment counts by subcategories at the census block level. LODES provides a level of detail regarding employment that is not available from the ACS. LODES data were cross-walked from census blocks to ZIP codes using a Missouri Census Data Center tool.⁵³ Because census blocks are even smaller than the census tracts used for demographic data, there is essentially no loss of precision due to cross-walking to the much larger ZIP-code level. This report uses the LODES data for 2013, which were the most current at the time of publication.

Data points from the three aforementioned sources were merged together to create a single observation for each ZIP code in New York City. LODES data were downloaded for all of New York State, New Jersey, and Connecticut; this allowed job counts to be assigned to ZIP codes for the entire region. Google routing data were collected for journeys originating within a ZIP code in New York City, but ending in any ZIP code within the larger region. ACS data were collected for New York City only.

More detailed information about these methods is available in the report.

Results

The data show that mass transit access is associated with job opportunities and household income levels in most New York City neighborhoods.

The rankings, along with the summary chart below, show the swoosh-shaped relationship between transit and income in New York City: Neighborhoods with some, but insufficient transit access—those ranked in the middle third—faced higher rates of unemployment than those in the top or bottom third (see Figure 5.3).

Our partners at Datapolitan then turned the resulting data, for all ZIP codes, into an online, interactive application (see Figures 5.4 and 5.5).

⁵³ Missouri Census Data Center, Geocorr 2014: Geographic Correspondence Engine, <http://mcdc.missouri.edu/applications/geocorr2014.html>.

igure 5.3. New York Ranked Neighborhoods: Income, Unemployment, and Commuting: 2008–2012										
Ranked Neighborhoods	Median Household Income	Unemployment Rate	Commute by Transit or Walking (avg)	Commute by Car (avg)						
1-59	\$81,286	8.1%	79.1%	10.8%						
60-119	\$46,937	12.6%	67.1%	27.6%						
120-177	\$59,949	10.4%	44.2%	52.1%						

Source: Author's analysis of data from the U.S. Census Bureau, American Community Survey.



Source: Datapolitan, NYC Neighborhoods: Mobility & Economic Opportunity, <www.datapolitan .com/job_access/>.



Case Study #2: State Level Trends in Children's Health Insurance Coverage

Skill Level: Intermediate/Advanced

Subject: State-level trends in children's health insurance coverage

Type of Analysis: Analysis of changes in children's health insurance coverage over time

Tools Used: American Community Survey Public Use Microdata Sample (PUMS) files, statistical software, spread-sheet

Author: Brett Fried, Senior Research Fellow, State Health Access Data Assistance Center (SHADAC)

The State Health Access Data Assistance Center (SHADAC) is a multidisciplinary health policy research center affiliated with the University of Minnesota that focuses on state health policy. "State-Level Trends in Children's Health Insurance Coverage" (the "Kids' Report") is one of many reports that SHADAC produces at the state level to show trends over time in insurance coverage, access, cost, utilization, and outcomes, as well as in equity and economic measures.⁵⁴

Approach

To generate reports from the American Community Survey (ACS) PUMS files, SHADAC started by creating an analytical data set using SAS. The microdata allowed us to create custom variables such as a health insurance unit (HIU) in this data set. The HIU defines "family" based on who is likely considered part of a "family unit" in determining eligibility for either private or public coverage. HIU is a narrower definition of family, compared with the Census Bureau's general definition of family that groups all related members of a household into a family.⁵⁵ We also created Affordable Care Act (ACA)-relevant poverty-level categories—0 to 138 percent of the Federal Poverty Guideline (FPG); 139 to 400 percent FPG; and 401 percent FPG or more. To measure family poverty, income is totaled for all individuals in the health insurance unit. The income is divided by the FPG produced by the U.S. Department of Health and Human Services to calculate the income as a percentage of FPG. (In 2016, the federal poverty guideline for a family of four was \$24,300.) We used SAS to create the analytic data set that included the custom HIU and poverty-level categories and then transferred the data set using StatTransfer software into a STATA data set to produce relevant estimates.

After transferring the data set into STATA, we created variables for other subjects of interest such as race/ethnicity and educational attainment. Then we produced estimates for all the custom HIU and income categories, broken down by coverage type, using STATA code. For example, we produced estimates of children by private coverage, public coverage, and uninsurance by three income categories from 2011 to 2016. If someone had more than one source of coverage, we considered private coverage as primary over public sources.

Next, we tested for statistically significant percentage-point differences in the estimates between 2013 (generally, pre-ACA implementation) and 2016 (post-ACA implementation). Percentage-point differences between years are reported in the tables. We produced three products from these estimates. The first product is a summary report where we use maps, tables, and figures to highlight the main findings. Estimates with coefficients of variation (standard error/estimate) greater than 30 percent are not included in the report (see Figure 5.6).

⁵⁴ SHADAC, "State-Level Trends in Children's Health Insurance Coverage," 2013-2016, <www.shadac.org/KidsReport2016>.

⁵⁵ SHADAC has a more detailed description of how we create the HIU in SHADAC I (Defining Family for Studies of Health Insurance Coverage), <www.shadac.org/publications/defining-family-studies-health-insurance-coverage>.



The second product is a set of 50-state tables. These detailed tables allow for cross-year comparisons between states from 2013 to 2016. Statistically significant differences between years at a 95 percent confidence level are indicated with an asterisk (see Figure 5.7).

			TREND IN C	OVERAGE	FOR CH	ILDREN			
39	PRIV	ATE COVE	RAGE	PUBLIC COVERAGE			UNINSURED		
State	2013 %	2016 %	Percent Point Change	2013 %	2016 %	Percent Point Change	2013 %	2016 %	Percent Poin Change
Alabama	55.80%	55.4%	-0.4%	39.2%	41.9%	2.7% *	5.0%	2.6%	-2.3% *
Alaska	62.6%	58.6%	-4.0%	25.2%	30.6%	5.4%	12.2%	10.8%	-1.4%
Arizona	53.9%	55.6%	1.8%	33.4%	36.6%	3.2%*	12.7%	7.8%	-5.0% *
Arkansas	46.8%	48.1%	1.3%	46.7%	47.8%	1.1%	6.5%	4.1%	-2.4% *
California	54.7%	55.5%	0.8%	37.4%	41.3%	3.9%*	7.9%	3.2%	-4.6% *
Colorado	64.5%	63.6%	-0.9%	26.5%	31.9%	5.4% *	9.0%	4.4%	-4.5% *
Connecticut	66 506	67 194	0.6%	20 296	30.4%	1 106	4 306	7 696	1 704 *

Source: Author's analysis of data from the U.S. Census Bureau, American Community Survey Public Use Microdata Samples, 2013 and 2016.

The third product is a set of individual state profiles. These two-page profiles provide "at-a-glance" graphic summaries of 5-year trends in children's health insurance coverage for each state and the United States, including statistical comparisons (see Figure 5.8).



Findings

In the Kids' Report released in June 2018, we found that since the coverage provisions of the ACA took effect, children in the United States have seen significant declines in uninsurance, with the number of uninsured children dropping by 2.2 million, or 2.9 percentage points, between 2013 and 2016. These coverage gains were sustained despite an uncertain policy climate around the ACA. Drops in uninsurance were seen across demographic categories, and some of the largest coverage gains were made by groups of children who historically have had the highest rates of uninsurance: low-income, Hispanic, and non-White children, and children in households with low educational attainment. Despite coverage gains, coverage rates for these groups are still significantly below those of high-income children and White children, and coverage varies across states.

Lessons Learned

One of the lessons learned from this and other similar projects that include data for all states is that category definitions matter. For example, if the categories are too narrow, then estimates in many states will be suppressed (for example, if "American Indian and Alaska Native" is one of categories that is cross tabulated with children's coverage, then most state estimates will be suppressed due to small sample size and large margins of error around the estimates).

Impact

The SHADAC Kids' Report is updated annually as new data become available. The report is used as a resource by state and federal analysts, academic researchers, the media, nonprofits, advocacy groups, foundations, and the public, as well as by internal SHADAC coworkers. In the first 3 weeks after its release, the report was viewed nearly 250 times.

Case Study #3: Children Living in Areas of Concentrated Poverty

Skill Level: Advanced

Subject: Neighborhood poverty

Type of Analysis: Estimating the percentage of children who live in neighborhoods of concentrated poverty **Tools Used**: American Community Survey (ACS) Summary File, statistical software (SAS), spreadsheet **Author**: Jean D'Amico, Senior Research Associate, Population Reference Bureau (PRB)

Researchers largely agree that the residential clustering of poverty adversely affects the life chances of residents living in those high-poverty areas. There is also general consensus in the literature that the deleterious effects of residential concentrated poverty can occur once poverty rates reach a level of 20 to 40 percent. For this case study, we analyzed the percentage of children under the age of 18 living in areas of concentrated poverty—defined as census tracts with overall poverty rates of 30 percent or more.

Because we wanted to work with census-tract level data, we needed to use ACS 5-year data. We used the ACS Summary File because we needed data for a large number of geographic areas (every census tract in the nation).

Step 1. Extract the Data

There are several ways to access census tract data from the U.S. Census Bureau's Web site, including data.census.gov. However, for this example, we use a SAS macro program to extract data from the ACS Summary File. This program is intended for advanced users who need to extract data for many geographies at once.

Our first step is to download the SAS program that we need to merge the ACS estimate and margin of error files with the geography files.⁵⁶ The "5-Year Macros" program is designed to read in the ACS 5-year Summary File. The program includes detailed comments that guide users through each procedure and macro (see Figure 5.9).

SAS Programs Contains SAS programs for each sequence per state, which can be used to convert each estimate and margin error into SAS Datasets with table stubs 1-year SAS programs [41.0 5-year SAS programs [31.0 MB] 5-year SAS programs [31.0 MB] Example of Creating a Table Using SAS [<1.0 MB] Detailed example SAS program containing SAS macros which access the geography, estimate and margin of error data. It creates one table for all geographies from the AC Summary File. Segments of the SAS codes can be used to	-documentation
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Summary File. Segments of the SAS codes can be used to	ie ACS
convert geography files into SAS datasets	ed to
1-Year Macros [<1.0MB] 5-Year Macros [<1.0 MB]	MB]

⁵⁶ SAS programs for 2016 data can be found at <www.census.gov/programs-surveys/acs/technical-documentation/summary-file -documentation.2016.html> under the heading "SAS Programs."

Step 2. Identify the Tables of Interest

Using the Sequence Number/Table Number Lookup file, we identify the tables needed to calculate our measure and note three key pieces of information for each: the table number, the sequence number, and the line numbers.⁵⁷

To determine the poverty rate of each tract, we need:

- 1. The table number (B17001).
- 2. The sequence number (48).
- 3. The line numbers needed for calculations (2 and 31) (see Figure 5.10).

			ie Pas		iontins	by Ser	by Age	
		Sequence	Line	Start	Total Cells	Total Cells		Subject
File ID Tab	ble ID I	Number	Number	Position	in Table	in Sequence	Table Title	Area
ACSSF B1	7001	48	_	7	59 CELLS		POVERTY STATUS IN THE PAST 12 MONTHS BY SEX BY AGE	Povert
ACSSF B1	7001	(48					Universe: Population For Whom Poverty Status Is Determined	
ACSSF B1	7001	48	1				Total:	
ACSSF B1	7001	48	(2				Income in the past 12 months below poverty level:	
ACSSF B1	7001	48	3	-			Male:	
ACSSF B1	7001	48	4				Under 5 years	
B17001 Cd	ontinue	≥d						
ACSSF B1	7001	48	29				65 to 74 years	
ACSSF B1	7001	48	30				75 years and over	
ACSSF B1	7001	48	31)			Income in the past 12 months at or above poverty level:	
ACSSF B1	7001	48	32				Male:	
ACSSF B1	7001	48	33				Under 5 years	
ACSSE B1	7001	48	34				5 years	

To determine the total population of children living in each tract, we need:

- 1. The table number (B09001).
- 2. The sequence number (34).
- 3. The line number needed for calculations (1) (see Figure 5.11).



⁵⁷ U.S. Census Bureau, American Community Survey (ACS), Summary File Documentation, <www.census.gov/programs-surveys/acs /technical-documentation/summary-file-documentation.html>.

Step 3. Download the Data

Now that we know which files we need, we can download them from the Census Bureau's File Transfer Protocol server.⁵⁸

Since we are interested in collecting tract-level data for the entire United States, and we are using SAS statistical software, we access the complete set of ACS 5-year Summary Files from the "5_year_entire_sf/" directory, which includes data for all census tracts in all states (see Figure 5.12).⁵⁹

Name	Last modified	Size Description
Parent Directory		-
1_year_by_state/	29-Aug-2017 17:01	-
1_year_entire_sf/	29-Aug-2017 17:30	-
1_year_seq_by_state/	29-Aug-2017 17:36	-
5_year_by_state/	22-Nov-2017 09:54	-
5_year_entire_sf/	12-Dec-2017 10:32	-
5_year_seq_by_state/	22-Nov-2017 15:47	1
2016_1yr_Summary_FileTemplates.zip	29-Aug-2017 16:55	2.3M
2016_5yr_Summary_FileTemplates.zip	22-Nov-2017 12:50	1.7M

Within the "5_year_entire_sf" directory, there are several files. We need to download files with 2016 tract-level ACS estimates and their associated margins of error. We also need the 2016 ACS geography files. We download and unzip the geography files (2016_ACS_Geography_Files.zip) and the estimate and margin of error files (Tracts_Block_Groups_Only.tar.gz) (see Figure 5.13).

Figure 5.13. Summary File Download: 2016		
Name	Last modified	Size Description
Parent Directory		-
2016_ACS_Geography_Files.zip	28-Dec-2017 11:4:	5 34M
All_Geographies_Not_Tracts_Block_Groups.tar.g	z 22-Nov-2017 10:4	6 6.3G
Tracts_Block_Groups_Only.tar.gz	22-Nov-2017 11:0	8 3.5G
Source: U.S. Census Bureau, <https: 5_year_entire_sf="" data="" p="" www2.census.gov=""></https:> .	programs-surveys/acs	/summary_file/2016

⁵⁸ U.S. Census Bureau, American Community Survey (ACS), Data via FTP, <www.census.gov/programs-surveys/acs/data/data-via-ftp.html>. ⁵⁹ Note: If we were interested in a specific state, we could save download time and disk space by downloading only that state. See the directory link for 5_year_by_state in Figure 5.12.

Step 4. Access and Analyze the Data

Now that we have the files we need, we can access the data using the 5-year macro program described in Step 1. The 5-Year Macro SAS program needs to be edited to reflect the file paths of our unzipped files. The macro program accesses the geography, estimate, and margin of error data and creates a single table for all geographies from the ACS Summary File. The final data set we create for our analysis includes all tracts (as separate rows) and the estimate and margin of error variables of interest for computing our measure (see Figure 5.14).

STUSAB	LOGRECNO	STATE	TRACT	SEQUENCE	B17001e2	B17001m2	B17001e31	B17001m31	B09001e1	B09001m1
al	1762	1	20100	48	199	129	1811	248	456	126
al	1763	1	20200	48	483	210	1531	252	478	115
al	1764	1	20300	48	337	177	2799	364	701	198
al	1765	1	20400	48	125	97	4438	479	1075	230
al	1766	1	20500	48	998	622	9322	857	2852	349
al	1767	1	20600	48	237	151	3493	406	957	230
al	1768	1	20700	48	573	241	2450	337	758	175
al	1769	1	20801	48	446	244	2579	311	818	187
al	1770	1	20802	48	1639	495	9094	692	2900	382
al	1771	1	20900	48	594	341	5318	581	1487	244
al	1772	1	21000	48	436	193	2449	350	709	152
al	1773	1	21100	48	630	205	2617	322	662	149

With the final data set complete, we begin constructing our measure by computing the poverty rate for each tract. Recall that Table B17001, line 2 (variable B17001e2) is the sum of those living below poverty. Table B17001, line 31 (variable B17001e31) is the sum of those living at or above poverty (see Figure 5.14, above). Therefore, the percentage of residents in a census tract who are living below poverty is calculated as: Percentage in Poverty = B17001e2 / (B17001e2 + B17001e31) (see Figure 5.15).

SAS code:

PCTPOVERTY = B17001e2 / (B17001e2 + B17001e31) *100;

STUSAB	LOGRECNO	STATE	TRACT	SEQUENCE	B17001e2	B17001e31	PCTPOVERTY
al	1834	1	953000	48	369	1108	25.0
al	1835	1	953100	48	1129	1769	39.0
al	1836	1	953200	48	850	3156	21.2
al	1837	1	953300	48	310	1481	17.3
al	1838	1	953400	48	715	1954	26.8
al	1839	1	953500	48	355	941	27.4
al	1840	1	200	48	1199	1835	39.5
al	1841	1	300	48	1101	1408	43.9
al	1842	1	400	48	1145	1566	42.2
al	1843	1	500	48	755	689	52.3
al	1844	1	600	48	845	663	56.0
al	1845	1	700	48	900	1711	34.5
al	1846	1	800	48	268	722	27.1

Source: Author's analysis of data from the U.S. Census Bureau, American Community Survey Summary File.

Next, we create a variable that will identify the number of children who live in tracts with poverty rates at or above 30 percent. We assign a value of zero to a variable when the poverty rate in the tract is below 30 percent. If the poverty rate in the tract is 30 percent or greater, the variable is equal to the child population of that tract. Recall that table B09001 line 1 (B09001e1) is the total population under 18 years (see Figure 5.16). The number of children who live in high-poverty tracts is computed as follows:

SAS code:

NUMCHILD = 0;

If PCTPOVERTY > = 30 then NUMCHILD = B09001e1;

Figure	5.16. Calcı 2016	ulatin	g the I	Number o	of Childr	en in Higł	n-Poverty	y Census 1	racts:
STUSAB	LOGRECNO	STATE	TRACT	SEQUENCE	B17001e2	B17001e31	B09001e1	PCTPOVERTY	NUMCHILD
al	1834	1	953000	48	369	1108	337	25.0	0
al	1835	1	953100	48	1129	1769	872	39.0	872
al	1836	1	953200	48	850	3156	993	21.2	0
al	1837	1	953300	48	310	1481	402	17.3	0
al	1838	1	953400	48	715	1954	602	26.8	0
al	1839	1	953500	48	355	941	240	27.4	0
al	1840	1	200	48	1199	1835	518	39.5	518
al	1841	1	300	48	1101	1408	588	43.9	588
al	1842	1	400	48	1145	1566	660	42.2	660
al	1843	1	500	48	755	689	359	52.3	359
al	1844	1	600	48	845	663	383	56.0	383
al	1845	1	700	48	900	1711	629	34.5	629
al	1846	1	800	48	268	722	238	27.1	0
al	1847	1	900	48	768	2989	882	20.4	0
al	1848	1	1000	48	589	5519	1232	9.6	0
al	1849	1	1100	48	772	6240	1762	11.0	0
al	1850	1	1201	48	757	2270	495	25.0	0

Note: High-poverty is defined as a poverty rate at or above 30 percent. Source: Author's analysis of data from the U.S. Census Bureau, American Community Survey Summary File.

The tract-level totals can be summed to larger levels of geography such as states or the entire United States. When we sum our variables by state, we create a new data set where the observations are the United States, the 50 states, the District of Columbia, and Puerto Rico. Our NUMCHILD variable reflects the number of children in the state (or the nation) who live in high-poverty tracts. The last step is to calculate the percentage of children living in high-poverty tracts for each of these areas.

To calculate the percentage of children in each state and the nation living in high-poverty tracts, we divide the number of children who live in high-poverty tracts (NUMCHILD) by the total population of children (B09001e1) (see Table 5.1).

SAS code:

PCTCHILD = NUMCHILD / B09001e1*100;

According to the 2012–2016 ACS 5-year estimates, a total of 9.4 million children under 18 years of age lived in a high-poverty neighborhood, representing 13 percent of all children in the United States.

Table 5.1. Number and Percentage of Children Living in High-Poverty Census Tracts by State: 2012-2016

State	B17001e2	B17001e31	B09001e1	PCTPOVERTY	NUMCHILD	PCTCHILD
United States	46,932,225	263,697,420	73,612,438	15.1	9,448,167	12.8
Alabama	868,666	3,851,926	1,105,189	18.4	178,052	16.1
Alaska	72,826	646,238	187,616	10.1	10,148	5.4
Arizona	1,165,636	5,407,887	1,619,618	17.7	372,624	23
Arkansas	542,431	2,338,973	707,234	18.8	112,970	16
California	6,004,257	31,908,887	9,140,283	15.8	1,385,724	15.2
Colorado	637,938	4,603,119	1,246,181	12.2	71,076	5.7
Connecticut	360,464	3,119,208	773,652	10.4	70,880	9.2
Delaware	109,448	799,525	204,192	12	7,684	3.8
District of Columbia	112,060	512,894	114,685	17.9	30,396	26.5
Florida	3,139,258	16,375,076	4,066,276	16.1	500,585	12.3
Georgia	1,746,894	8,082,162	2,495,175	17.8	399,602	16
Hawaii	148,577	1,227,351	308,216	10.8	16,719	5.4
Idaho	244,585	1,359,784	431,320	15.2	19,932	4.6
Illinois	1,753,731	10,794,807	2,990,629	14	336,198	11.2
Indiana	957,694	5,431,232	1,581,992	15	190,892	12.1
Iowa	369,828	2.635.980	727,514	12.3	23,598	3.2
Kansas	373,162	2.443.029	721.347	13.3	57,950	8
Kentucky	804,139	3.471.063	1.014.190	18.8	161.324	15.9
Louisiana	889.570	3.625.055	1.114.022	19.7	231,234	20.8
Maine	174,405	1,120,041	259.501	13.5	13.351	5.1
Maryland	576,835	5.242.728	1.347.810	9.9	64.433	4.8
Massachusetts	740,836	5,765,193	1,390,552	11.4	108,138	7.8
Michigan	1 575 066	8 108 799	2,227,763	163	376 431	16.9
Minnesota	577 196	4 749 823	1 282 098	10.5	69.041	54
Mississinni	645 553	2 247 538	732 235	22.3	189,066	25.8
Missouri	897,755	4.978.611	1.395.124	15.3	138.044	9.9
Montana	148 677	849 637	225 020	14.9	19 906	8.8
Nebraska	227.021	1.600.170	467.601	12.4	35,743	7.6
Nevada	417.257	2,381,286	664.632	14.9	76,599	11.5
New Hampshire	109 690	1 175 747	266 979	85	5 255	2
New Jersey	949 341	7 789 717	2,009,813	10.9	183 102	91
New Mexico	426 814	1 615 200	501 750	20.9	112 317	22.4
New York	2 967 564	16 218 498	4 226 409	15.5	765 921	18.1
North Carolina	1 631 704	8 053 807	2,287,826	16.8	287 088	12.5
North Dakota	79 314	631 041	167 717	11.2	8 665	52
Ohio	1 732 839	9 534 661	2,639,860	15.4	351 173	13.3
Oklahoma	621,155	3,138,895	952,325	16.5	115.631	12.1
Oregon	614 223	3 291 163	861 395	15.7	56 196	65
Pennsylvania	1 647 762	10 721 909	2 704 268	13.7	325 988	12.1
Rhode Island	140 161	873 755	212 406	13.8	31 531	14.8
South Carolina	806.422	3 886 844	1 085 779	17.0	137 943	12.7
South Dakota	115 300	707 034	209.615	17.2	23 176	11.1
Tennessee	1 100 169	5 286 582	1 494 925	172	218 833	14.6
Texas	4 397 307	21 936 698	7 132 476	167	1 197 938	16.8
Litah	338 808	2 562 657	905 196	10.7	28 761	3.2
Vermont	69,608	531 865	121 691	11.7	1 168	5.2
Virginia	09,075	7 130 228	1 865 556	11.0	01.426	1 4 9
Washington	883 254	6 056 366	1,603,556	11.4	88 039	4.5
West Virginia	318.060	1 474 749	370 9/9	12.7	35 707	0.4
Wisconsin	712 472	4 890 902	1 301 400	17.7	112 202	9.4
Wyoming	65 762	502 191	128 844	12.7	1 767	0.0
Puerto Rico	1 577 075	1 010 652	767 406	45.1	647 275	\$4.2
i dento ideo	1,577,075	1,212,055	707,400	45.1	047,275	04.5

Note: High-poverty is defined as a poverty rate at or above 30 percent. The U.S. totals exclude data for Puerto Rico.

Source: Author's analysis of data from the U.S. Census Bureau, American Community Survey Summary File.