Technical Documentation:
Generating Household Wealth and Financial Access Estimates for Local Geographies

September 2014

Introduction

Policymakers, advocates and service providers need local data on financial access and well-being in order to mobilize support for programs and policies that move low-income households into the financial mainstream. However, local-level household financial security data points for key measures of household wealth and financial access are largely unavailable, and stakeholders often have to rely on state-level data for their case making.

CFED is launching the Assets & Opportunity Local Data Center[1] to further improve access to local-level household financial security data. The Local Data Center provides estimates of percentages of unbanked and underbanked households as well as new estimates of household asset poverty and liquid asset poverty at the city, county and metropolitan levels. CFED contracted Dr. Jon Haveman[2] to develop the estimates, and several expert advisors assisted with the development of the models.[3] The purpose of this memo is to describe the estimation methodology and the estimates it produced.

Measures Included in the Estimation

Since 2002, CFED has used household financial data from the most up-to-date iteration of the Census Bureau's Survey of Income and Program Participation (SIPP) [4] Assets and Liabilities supplement to generate national and state-level estimates of asset and liquid asset poverty. For the past several years, these estimates have been published annually; they are the cornerstone of CFED's *Assets & Opportunity Scorecard*. CFED uses the following definitions for these measures:

- **Asset Poverty**: Households without sufficient net worth to subsist at the federal poverty level for three months in the absence of income.
- **Liquid Asset Poverty**: Households without sufficient liquid assets to subsist at the federal poverty level for three months in the absence of income. Liquid assets include: interest earning assets held in banking or other institutions, equity in stocks and mutual funds shares, equity in IRA and KEOGH accounts, equity in 401(k) and thrift savings accounts, and equity in other assets.

Working with Dr. Haveman, CFED has also produced asset poverty estimates at the local level, building from the Local Asset Poverty Index (LAPI) methodology developed by Steve Wertheim.[5] CFED has used LAPI estimates in its *Local Assets & Opportunity Profiles*, the first of which was published in early 2010. CFED began publishing national and state-level liquid asset poverty estimates in its *2012 Assets & Opportunity Scorecard* but, prior to the launch of the Local Data Center, had not generated local estimates of liquid asset poverty.

Similarly, the Federal Deposit Insurance Corporation (FDIC) issues a bi-annual survey of household banking habits. This survey is issued as a supplement to the annual Current Population Survey (CPS), carried out by the Census Bureau. Using data obtained from this survey, the FDIC has released reports and data on the country's unbanked and underbanked populations in 2009 and 2011.[6] These data are produced at the national, state, and larger metropolitan statistical area (MSA) levels. At the time of the publication of this memo, the 2011 FDIC data were the most recent data available. The FDIC uses the following definitions of unbanked and underbanked:[7]

- **Unbanked:** Households that would answer "No" to the following question: "Do you or does anyone in your household currently have a checking or savings account?"
- **Underbanked:** Households that have a checking or savings account, but still utilize alternative financial services. Specifically, underbanked households have used non-bank money orders, non-bank check-cashing services, payday loans, rent-to-own agreements, or pawn shops at least once in the past year, or refund anticipation loans at least once in the past five years.

In 2011, the U.S. Treasury Department contracted CFED and Dr. Haveman to generate estimates of the banked status of households at every U.S. Census geographic level down to the census tract based on the *2009 FDIC National Survey of Unbanked and Underbanked Households*. These estimates were calculated to assist the Treasury Department's BankOn USA initiative and its stakeholders in identifying the size and needs of unbanked and underbanked populations.[8]

Estimation Methodology

CFED contracted Dr. Haveman to develop a standard estimation procedure that would produce estimates of the banked and asset poor status of households at the city, county and metro area levels.[9] The first step involved developing a model to identify household demographic and financial characteristics that that were strong predictors of households' banked and asset poverty status in the FDIC and SIPP survey data. Once the models where refined and their predictive power was verified, local data from the American Community Survey (ACS) are inserted into the model as inputs and used to generate estimates of banked and asset poor status for smaller geographies.

In order to provide the best possible estimates, we use separate methods for different geographies, depending on the availability of data. The following methods are used for the specified geographies:

1. **Data from FDIC and SIPP Surveys:** As described above, data on household banking status for the United States, all 50 individual states and the District of Columbia, and the nation's 71 largest MSAs[10] are available from the *2011 FDIC National Survey of Unbanked and Underbanked Households*. For the *2014 Assets & Opportunity Scorecard* CFED produced national and state-level estimates of asset and liquid asset poverty from the SIPP's 2008 Panel, Wave 10.[11] In these instances, the data published by the FDIC and in the *Scorecard* are included in the Local Data Center as a location's estimate.

2. **Estimates based on 2008-2012 American Community Survey (ACS) Public Use Microdata Sample (PUMS):** Although the Census Bureau's annual ACS does not collect information regarding household wealth and the banking activities of its respondents, we are able to identify predictors of asset poverty and banking status using regression analysis based on information in the FDIC and SIPP surveys (see Table A1 for the full list of regressors). These regression results are then used to estimate banking and asset poverty status for individual households among survey respondents in the 2008-2012 ACS Public Use Microdata Sample (PUMS). Data from PUMS are released for Public Use Microdata Areas (PUMAs), which are statistical geographic areas with a population of 100,000. From these household level estimates of asset poverty banking status, we are able to provide regional estimates for MSAs, counties and select cities that

are larger than 100,000 in population. When the size of the geography allows for its application, this estimation model is preferred relative to method 3, due to the greater precision of its estimates.

3. **Estimates based on the 2008-2012 American Community Survey (ACS) FactFinder Regional Summary Files**: As the Census Bureau does not release microdata for geographies with populations smaller than 100,000 residents, an alternative data source is required to calculate the estimations for these geographies. For MSAs and counties with fewer than 100,000 residents, most cities (or Census places), and geographies that don't map cleanly to PUMA boundaries,[12] five-year ACS summary estimates available through the Census Bureau's American FactFinder website were used to estimate the percentage of unbanked and asset poor households (see Table A2 for the full list of regressors). While this estimation approach does allow for analysis at a more granular geographic level than would otherwise be possible, the summary file data provide only a single cumulative value for each geography rather than the more precise household-level estimates that result from method 2.

Table 1: Summary of Data Sources and Methods for Different Geographies

Measure	Methodology/Data Source	Geography
Asset Poverty and Liquid Asset Poverty	1. SIPP Survey Data	• United States • AP: 46 States (excluding AK, ND, NH, SD and WY) • LAP: 48 States (excluding AK, SD and WY)
	2. Estimates based on ACS PUMS	• Smaller States (AK, SD and WY) and District of Columbia • Larger MSAs • Larger Counties • Family Assets Count Year 1 partner cities (Boston, Chicago, Houston, Miami, Sacramento)[13]
	3. Estimates based on ACS FactFinder Summary Files	• Smaller MSAs • Smaller Counties • Other Cities/Census "Places"
Unbanked and Underbanked	1. FDIC Survey Data	• United States • 50 States and District of Columbia • 71 largest MSAs
	2. Estimates based on ACS PUMS	• Larger MSAs • Larger Counties
	3. Estimates based on ACS FactFinder Summary Files	• Smaller MSAs • Smaller Counties • All Cities/Census "Places"

Identifying Correlates

As detailed in the previous section, estimation methods 2 and 3 – used for geographies not published by the FDIC or in the Scorecard – are generated through a series of regressions that include independent variables correlated with a household's banked or asset poor status. Where past estimates generated by Dr. Haveman were the result of two regressions each (differentiating by a location's distinction as urban or rural), the inclusion of asset poverty and liquid asset poverty in the model required a different method of analysis. This time, for the ACS PUMS estimates, each of the four measures was run through four distinct regressions, with these regressions providing separate estimates for homeowners and renters, in addition to urban or rural households. Separating populations by housing tenure and urban status allowed for a more nuanced analysis of the data as the predictors of asset poverty, liquid asset poverty and banked status are different for urban and rural households and for households that own their homes versus those that don't. For the estimates generated using FactFinder summary data, two regression models—one for rural households and one for urban households—were used.

To identify potential covariates, we first looked to the 2011 analysis of local unbanked and underbanked households undertaken for the BankOn initiative. We also drew upon CFED's past asset poverty estimation work, as well as Dr. Haveman's previous work generating Local Asset Poverty Index (LAPI) estimations, and found considerable overlap between the two. Much like unbanked or underbanked status, likelihood of being asset or liquid asset poor is correlated with age, income level, race and ethnicity, and education level, among other factors. As development of the model progressed and estimates were fine-tuned, additional correlates were added, including citizenship and primary language spoken at home.

A detailed list of all covariates included in the regressions is provided in Appendix A.

Estimation Process

This section details the estimation process used for each of the sources indicated above.

1. **FDIC and SIPP Survey Data**
    a. These data were sourced directly from the FDIC and SIPP survey results, and are reproduced as published.

2. **Estimates Based on ACS PUMS**
    a. From the FDIC and SIPP microdata, construct the set of independent variables (see Table A1) and the applicable dependent variables.
    b. Run the regression specifications indicated above separately for each indicator, selecting the model of best fit.
    c. Obtain the 5-year merged ACS data (2008-2012) for households from the Census website.
    d. Construct covariates that are analogous to those built using the FDIC and SIPP microdata.
    e. Use the coefficients from the regressions based on FDIC and SIPP data to estimate unbanked and underbanked status for each household in the sample.
    f. Aggregate over households, weighting by the household weight, to obtain estimates for the proportion of asset poor, liquid asset poor, unbanked and underbanked for each geography.

3. **Estimates Based on ACS FactFinder Summary Files**
    a. From the FDIC and SIPP microdata, construct the set of correlates (see Table A2) and the applicable dependent variables.
    b. Run the regression specifications indicated above separately for each indicator, selecting the model of best fit.
    c. Obtain the 5-year merged ACS regional summary data (2008-2012) from the Census website.
    d. Extract summary variables that are analogous to those constructed from the FDIC and SIPP microdata.
    e. Use the coefficients from the regressions using FDIC and SIPP data to estimate asset poor, liquid asset poor, unbanked and underbanked status for each geography.

Regression Specifications

As detailed previously, limitations inherent to the data used in each method of analysis resulted in the need for unique regression specifications at different geographic levels. The distinctions between these methods are as follows:

- **ACS PUMS Data:** The model for estimating statistics from the ACS PUMS data comprises four separate regressions, and generates estimates for: urban home owners, rural home owners, urban renters, and rural renters. For each category, the regression specification producing estimates that most closely fit the survey data is used. In 2011, all estimates derived from the ACS PUMS data were generated using a linear, Ordinary Least Squares (OLS) probability model. After expanding the model to include estimates of asset poor status, we found that, in many cases, OLS failed to provide as good a fit as other models. In these instances, logit and probit modeling was used.
- **ACS FactFinder Data:** The model for estimating statistics from the ACS FactFinder comprises two separate regressions, and generates estimates for: urban and rural residence. Like with the PUMS analysis, the regression specification that most closely matches the survey data is used in each instance. The framework used to generate estimates derived from FactFinder summary data is OLS.

Appendix C includes a table detailing the specification used in each regression with comparisons of the final estimates from each model to the corresponding national-level survey data.

Appendix A: Regression Covariates

Table A1: ACS PUMS Model Regressors	
Income Variables	**Age of Household Head**
Income: $10,000 to $14,999	Age: 25-34
Income: $15,000 to $19,999	Age: 35-44
Income: $20,000 to $24,999	Age: 45-54
Income: $25,000 to $29,999	Age: 55-59
Income: $30,000 to $34,999	Age: 60-64
Income: $35,000 to $39,999	Age: 65-74
Income: $40,000 to $49,999	Age: 75-84
Income: $50,000 to $59,999	Age: 85+
Income: $60,000 to $74,999	**Race of Household Head**
Income: $75,000 to $99,999	Black
Income: $100,000 to $149,000	Latino
Income: $150,000 or More	Native American
Household Characteristics	Asian
Spanish Only Spoken At Home	**Educational Attainment of Household Head**
Female Headed Household	High School Grad
Married Couple	Some College
Children Present	Bachelor's Degree
Domestic Partnership	Advanced Degree
Single Parent	**Additional Education Controls/Interactions**
Female Single Parent	Single parent with at least some college education
Citizenship Status	Female single parent with at least some college education
Non-citizen	Variables that control for educational attainment across age, as education may make a bigger difference for younger householders than older householders.
Naturalized citizen	
Household Size	
1 person in Household	**Variables Omitted from the Regressions**
2 People in Household	Income: Less than $10,000
3 People in Household	7+ People in Household
4 People in Household	Age < 25
5 People in Household	Race: White & Other
6 People in Household	Education: Less than High School Diploma
	Citizenship Status: Citizen

Table A2: ACS FactFinder Model Regressors	
Income Variables	**Age of Household Head**
Income: $10,000 to $14,999	Age: 25-34
Income: $15,000 to $19,999	Age: 35-44
Income: $20,000 to $24,999	Age: 45-54
Income: $25,000 to $29,999	Age: 55-59
Income: $30,000 to $34,999	Age: 60-64
Income: $35,000 to $39,999	Age: 65-74
Income: $40,000 to $49,999	Age: 75-84
Income: $50,000 to $59,999	Age: 85+
Income: $60,000 to $74,999	**Race of Household Head**
Income: $75,000 to $99,999	Black
Income: $100,000 to $149,000	Latino
Income: $150,000 or More	Native American
Household Characteristics	Asian
Spanish Only Spoken At Home	**Educational Attainment of Household Head**
Female Headed Household	High School Grad
Married Couple	Some College
Children Present	Bachelor's Degree
Domestic Partnership	Advanced Degree
Single Parent	**Interactions**
Female Single Parent	Variables that account for the interaction between home ownership and race, home ownership and age, and age and education.
Household Size	
1 person in household	
2 People in Household	**Variables Omitted from the Regressions**
3 People in Household	Income: Less than $10,000
4 People in Household	7+ People in Household
5 People in Household	Age < 25
6 People in Household	Race: White & Other
	Education: less than high school diploma

Appendix B: Comparison of Estimation Methodology Results by State

Table B1: Asset Poverty Estimates			
State	**SIPP Survey Data**	**Estimate (ACS PUMS Model)**	**Estimate (ACS FactFinder Model)**
Alabama	24.3%	22.8%	26.4%
Alaska	-	20.1%	21.8%
Arizona	32.0%	22.7%	23.7%
Arkansas	29.0%	23.8%	27.9%
California	29.2%	25.4%	25.1%
Colorado	23.9%	21.1%	19.8%
Connecticut	30.2%	20.0%	17.3%
Delaware	18.9%	19.2%	19.7%
District of Columbia	-	31.0%	27.1%
Florida	27.3%	21.9%	23.9%
Georgia	32.3%	24.8%	26.7%
Hawaii	16.5%	21.6%	20.1%
Idaho	29.6%	20.4%	22.1%
Illinois	23.5%	21.5%	21.7%
Indiana	23.8%	21.1%	23.0%
Iowa	21.7%	18.9%	20.9%
Kansas	22.9%	21.0%	21.7%
Kentucky	21.4%	22.2%	24.9%
Louisiana	23.6%	24.5%	28.9%
Maine	20.3%	18.8%	20.4%
Maryland	23.0%	20.4%	19.0%
Massachusetts	24.2%	21.1%	17.6%
Michigan	25.1%	20.1%	21.6%
Minnesota	22.0%	18.3%	18.2%
Mississippi	30.4%	24.2%	29.2%
Missouri	21.6%	21.6%	23.2%
Montana	23.0%	19.9%	22.2%
Nebraska	18.5%	20.9%	22.3%
Nevada	42.8%	25.7%	26.8%
New Hampshire	-	16.7%	15.9%
New Jersey	24.2%	20.6%	19.1%
New Mexico	23.4%	22.7%	26.2%
New York	32.9%	26.1%	25.4%
North Carolina	25.1%	23.4%	25.9%
North Dakota	-	20.5%	23.5%
Ohio	23.7%	22.1%	23.4%
Oklahoma	20.3%	22.8%	25.4%
Oregon	27.8%	22.5%	22.1%
Pennsylvania	21.0%	20.1%	21.1%
Rhode Island	19.2%	23.9%	22.4%
South Carolina	16.9%	22.9%	25.9%
South Dakota	-	20.9%	23.2%
Tennessee	25.2%	22.7%	25.3%
Texas	23.8%	25.1%	27.6%
Utah	23.0%	20.2%	19.0%
Vermont	26.7%	17.2%	18.1%
Virginia	17.4%	20.1%	19.6%
Washington	25.3%	21.1%	20.3%
West Virginia	18.3%	19.1%	22.8%
Wisconsin	22.5%	20.7%	22.0%
Wyoming	-	18.5%	20.6%
Note: In Alaska, the District of Columbia, South Dakota and Wyoming, there are too few observations in the SIPP to generate reliable estimates. In New Hampshire and North Dakota, the margin of error of SIPP's asset poverty estimate was too great to publish.			

Table B2: Liquid Asset Poverty Estimates			
State	**SIPP Survey Data**	**Estimate (ACS PUMS Model)**	**Estimate (ACS FactFinder Model)**
Alabama	62.7%	43.4%	41.9%
Alaska	-	33.7%	31.6%
Arizona	45.7%	41.0%	37.4%
Arkansas	51.9%	44.6%	44.1%
California	45.9%	42.3%	37.5%
Colorado	39.2%	35.2%	30.4%
Connecticut	39.3%	33.7%	26.4%
Delaware	32.0%	35.9%	31.3%
District of Columbia	-	40.9%	31.1%
Florida	48.7%	42.7%	38.0%
Georgia	55.8%	43.2%	39.6%
Hawaii	29.0%	36.5%	31.7%
Idaho	45.5%	38.6%	37.4%
Illinois	38.3%	38.2%	32.9%
Indiana	43.2%	39.1%	37.5%
Iowa	26.2%	35.6%	35.3%
Kansas	35.4%	37.4%	34.9%
Kentucky	52.2%	42.2%	41.0%
Louisiana	49.9%	45.2%	43.4%
Maine	46.6%	36.1%	37.3%
Maryland	34.8%	34.5%	27.2%
Massachusetts	35.3%	33.9%	26.4%
Michigan	38.8%	38.3%	35.5%
Minnesota	27.8%	32.6%	29.9%
Mississippi	61.9%	47.6%	45.7%
Missouri	38.9%	39.2%	37.4%
Montana	42.3%	37.4%	37.8%
Nebraska	25.4%	37.0%	35.6%
Nevada	55.6%	43.0%	41.1%
New Hampshire	21.1%	30.4%	28.0%
New Jersey	40.2%	35.4%	28.6%
New Mexico	44.4%	46.5%	41.5%
New York	44.7%	41.3%	36.1%
North Carolina	51.5%	42.0%	40.0%
North Dakota	30.9%	35.7%	36.7%
Ohio	44.7%	39.3%	37.3%
Oklahoma	49.1%	42.0%	40.4%
Oregon	36.3%	38.0%	35.2%
Pennsylvania	36.4%	37.2%	34.4%
Rhode Island	38.7%	38.6%	34.2%
South Carolina	47.3%	43.1%	40.8%
South Dakota	-	37.3%	37.7%
Tennessee	50.0%	42.0%	40.5%
Texas	49.8%	45.1%	41.4%
Utah	31.7%	35.2%	30.6%
Vermont	27.0%	33.2%	34.0%
Virginia	36.5%	35.3%	30.0%
Washington	32.5%	35.1%	31.4%
West Virginia	48.6%	41.1%	41.3%
Wisconsin	34.1%	36.5%	35.4%
Wyoming	-	34.9%	33.8%
Note: In Alaska, the District of Columbia, South Dakota and Wyoming, there are too few observations in the SIPP to generate reliable estimates.			

Table B3: Unbanked Estimates			
State	**FDIC Survey Data**	**Estimate (ACS PUMS Model)**	**Estimate (ACS FactFinder Model)**
Alabama	10.2%	9.2%	10.9%
Alaska	5.2%	5.4%	7.0%
Arizona	11.6%	8.2%	9.3%
Arkansas	12.3%	8.8%	10.9%
California	7.8%	8.8%	10.7%
Colorado	5.4%	6.3%	6.7%
Connecticut	5.3%	6.4%	5.2%
Delaware	6.7%	6.2%	6.4%
District of Columbia	10.9%	10.5%	10.3%
Florida	7.3%	8.0%	9.3%
Georgia	11.5%	9.3%	11.1%
Hawaii	3.8%	5.3%	6.7%
Idaho	5.7%	5.9%	7.5%
Illinois	7.6%	7.0%	7.7%
Indiana	7.8%	6.5%	8.2%
Iowa	4.4%	4.8%	6.5%
Kansas	7.1%	6.0%	7.2%
Kentucky	9.9%	7.7%	9.3%
Louisiana	11.5%	10.1%	12.4%
Maine	3.7%	4.8%	5.8%
Maryland	5.6%	5.9%	5.7%
Massachusetts	4.9%	6.0%	5.6%
Michigan	7.7%	6.5%	7.6%
Minnesota	4.1%	4.7%	5.5%
Mississippi	15.1%	11.4%	12.9%
Missouri	9.5%	6.6%	8.3%
Montana	4.8%	5.0%	7.1%
Nebraska	3.7%	5.6%	7.4%
Nevada	7.5%	8.4%	12.0%
New Hampshire	1.9%	3.6%	3.9%
New Jersey	6.6%	6.7%	6.8%
New Mexico	11.5%	10.5%	10.4%
New York	9.6%	8.8%	10.7%
North Carolina	9.3%	8.6%	10.3%
North Dakota	5.3%	4.4%	7.7%
Ohio	8.8%	6.9%	8.8%
Oklahoma	10.9%	7.9%	9.7%
Oregon	4.3%	6.2%	7.9%
Pennsylvania	6.1%	6.1%	7.3%
Rhode Island	7.0%	7.4%	9.2%
South Carolina	9.3%	9.2%	10.6%
South Dakota	4.4%	5.3%	7.6%
Tennessee	10.9%	7.9%	9.9%
Texas	12.8%	10.2%	11.7%
Utah	2.8%	5.3%	6.0%
Vermont	3.4%	4.0%	4.6%
Virginia	6.6%	6.1%	6.4%
Washington	4.5%	5.7%	6.9%
West Virginia	9.5%	6.5%	8.0%
Wisconsin	4.5%	5.5%	7.3%
Wyoming	5.8%	4.6%	6.4%

Table B4: Underbanked Estimates			
State	**FDIC Survey Data**	**Estimate (ACS PUMS Model)**	**Estimate (ACS FactFinder Model)**
Alabama	28.8%	23.6%	24.0%
Alaska	20.2%	22.2%	21.6%
Arizona	20.5%	21.0%	21.5%
Arkansas	28.1%	23.2%	23.3%
California	18.0%	20.4%	20.7%
Colorado	16.1%	20.3%	20.4%
Connecticut	15.2%	19.0%	19.5%
Delaware	15.5%	21.5%	21.8%
District of Columbia	22.3%	23.3%	23.6%
Florida	21.1%	21.0%	21.9%
Georgia	26.8%	24.1%	24.6%
Hawaii	20.0%	20.0%	16.8%
Idaho	19.0%	21.5%	21.8%
Illinois	17.7%	20.8%	21.5%
Indiana	19.1%	21.5%	22.2%
Iowa	17.2%	20.4%	20.9%
Kansas	19.7%	21.2%	21.4%
Kentucky	21.5%	22.2%	22.3%
Louisiana	27.2%	24.5%	24.9%
Maine	19.0%	20.5%	21.0%
Maryland	21.2%	21.8%	21.7%
Massachusetts	14.1%	18.7%	19.2%
Michigan	17.3%	21.4%	22.2%
Minnesota	12.6%	19.5%	20.4%
Mississippi	23.6%	25.5%	25.5%
Missouri	20.6%	21.7%	22.2%
Montana	22.0%	21.4%	21.3%
Nebraska	17.8%	21.1%	21.4%
Nevada	31.2%	22.1%	22.4%
New Hampshire	12.5%	19.5%	19.8%
New Jersey	19.4%	19.1%	19.8%
New Mexico	23.6%	22.0%	21.9%
New York	19.4%	20.5%	21.7%
North Carolina	21.7%	23.1%	23.5%
North Dakota	18.0%	21.2%	21.2%
Ohio	19.3%	21.6%	22.2%
Oklahoma	23.2%	22.5%	22.5%
Oregon	14.4%	21.0%	21.0%
Pennsylvania	18.0%	20.4%	21.2%
Rhode Island	17.8%	19.8%	20.7%
South Carolina	20.6%	23.7%	24.1%
South Dakota	22.0%	21.2%	21.5%
Tennessee	18.1%	22.7%	23.0%
Texas	27.2%	22.4%	22.8%
Utah	21.0%	21.2%	21.4%
Vermont	17.4%	20.4%	20.6%
Virginia	16.7%	21.2%	21.4%
Washington	19.4%	20.3%	20.3%
West Virginia	19.2%	21.1%	21.4%
Wisconsin	14.2%	20.9%	21.4%
Wyoming	21.1%	21.6%	21.0%

Appendix C Regression Specifications

Table C1: ACS PUMS Mode Regression Options	
Specification	**Regressors**
Specification 1	Household Income + Household Size
Specification 2 (1+)	Household Characteristics (Spanish Only Spoken At Home, Female Headed Household, Married Couple, Domestic Partnership) + Citizenship Status
Specification 3 (2+)	Age of Household Head
Specification 4 (3+)	Race of Household Head
Specification 5 (4+)	Educational Attainment of Household Head
Specification 6 (5+)	Single Parent, Female Single Parent, Single parent with at least some college educations, Female single parent with at least some college education
Specification 7 (6+)	Variables that control for educational attainment across age

Regressions are run including just Specification 1, Specification 1 and Specification 2, Specification 1, 2, and 3, and so on. Fitted values are calculated for each of the statistics from each of the 7 specifications. The final specification chosen is based on an evaluation of the summary statistics indicated above. The specification chosen is sometimes a judgment call. If a specification has a higher MSE and a lower maximum absolute deviation, it may be chosen over one with a lower MSE.

Table C2: ACS PUMS Regressions and Result Comparisons						
Variable	**Tenure**	**Urban/Rural**	**Type**	**Specification**	**Survey Data**	**Estimate**
APOV	Own	Urban	Logit	7	10.0	9.1
APOV	Own	Rural	Linear	7	8.6	8.9
APOV	Rent	Urban	Linear	6	56.9	53.9
APOV	Rent	Rural	Linear	6	57.0	55.7
				Overall Results:	25.4	23.9
L-APOV	Own	Urban	Logit	7	28.7	26.4
L-APOV	Own	Rural	Linear	7	36.4	33.8
L-APOV	Rent	Urban	Probit	5	66.8	63.4
L-APOV	Rent	Rural	Logit	7	71.0	69.8
				Overall Results:	43.3	40.2
Unbanked	Own	Urban	Logit	7	2.5	2.1
Unbanked	Own	Rural	Logit	5	4.4	3.6
Unbanked	Rent	Urban	Logit	7	18.1	17.2
Unbanked	Rent	Rural	Linear	7	22.0	18.4
				Overall Results:	8.2	7.6
Underbanked	Own	Urban	Linear	7	17.0	17.0
Underbanked	Own	Rural	Linear	7	20.7	19.7
Underbanked	Rent	Urban	Linear	7	29.0	18.1
Underbanked	Rent	Rural	Logit	7	31.6	30.5
				Overall Results:	All: 21.7	21.3

Table C3: ACS FactFinder Model Specification Options	
Specification	**Regressors**
Specification 1	Household Income
Specification 2 (1+)	Age of Household Head
Specification 3 (2+)	Race of Household Head
Specification 4 (3+)	Educational Attainment of Household Head
Specification 5 (4+)	Household Size
Specification 6 (5+)	Household Characteristics (Married Couple, Female Headed Household, Domestic Partnership, Single Parent, Female Single Parent)
Specification 7 (6+)	Interactions between homeownership and race of household head (white x homeownership is omitted)
Specification 8 (7+)	Interactions between homeownership and educational attainment of household head (own x less than high school is omitted)
Specification 9 (8+)	Interactions between homeownership and age of household head
Specification 10 (9+)	Interactions between age and educational attainment of household head

Regressions are run including just Specification 1, Specification 1 and Specification 2, Specifications 1, 2, and 3, and so on. Fitted values are calculated for each of the statistics from each of the 10 specifications. The final specification chosen is based on an evaluation of the summary statistics indicated above. The specification chosen is sometimes a judgment call. If a specification has a higher MSE and a lower maximum absolute deviation, it may be chosen over one with a lower MSE.

Table C2: FactFinder Regressions and Result Comparisons					
Variable	**Urban/Rural**	**Type**	**Specification**	**Value**	**Estimate**
APOV	Urban	Linear	6	26.6	25.9
APOV	Rural	Linear	10	23.8	23.9
L-APOV	Urban	Linear	10	43.3	39.1
L-APOV	Rural	Linear	2	42.2	42.7
Unbanked	Urban	Linear	9	7.8	8.5
Unbanked	Rural	Linear	3	8.9	9.6
Underbanked	Urban	Linear	5	19.4	20.0
Underbanked	Rural	Linear	9	22.0	20.0

Notes:

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[1] The Assets & Opportunity Local Data Center is made possible with funding from Citi Community Development.
[2] Dr. Jon Haveman is a principal at Marin Economic Consulting, LLC, a private consultancy based in Marin County, California. Dr. Haveman received his Ph.D in Economics from the University of Michigan, and has been producing data on economic well-being in the United States for over 20 years. Prior to joining Marin Economic Consulting, Dr. Haveman was the Chief Economist at the Bay Area Council Economic Institute, a founding principal at Beacon Economics, and the Director of the Economy Program at the Public Policy Institute of California.
[3] CFED thanks Diana Elliott from the Pew Charitable Trusts, Tatjana Meschede from Brandeis University's Heller School for Social Policy and Management, Nicholas Nagle from the University of Tennessee, and Caroline Ratcliffe from the Urban Institute for their guidance and expertise during the methodology development process.
[4] The Census Bureau's Survey of Income and Program Participation (SIPP) is a national panel survey with a sample that includes over 40,000 households and is designed to be representative at the state level. The SIPP's relatively large sample size makes it the only data source that is large enough to provide data on wealth and assets at the state level. Following recent budgetary strife, the collection and configuration of the SIPP has been re-engineered, with the initial release of the updated SIPP expected early in 2015.
[5] For more on the Wertheim and EARN's LAPI methodology, visit http://www.earn.org/static/uploads/files/LAPI_methodology.pdf.
[6] Available at http://economicinclusion.gov.
[7] 2011 FDIC National Survey of Unbanked and Underbanked Households. (Washington, DC: Federal Deposit Insurance Corporation, 2012), 4, Note 2.
[8] The 2011 local unbanked and underbanked estimates were made available through an interactive tool at http://joinbankon.org. As the estimation methodology has been updated from 2011, however, the new estimates are not directly comparable to those previous figures, and cannot be used to track changes in the unbanked or underbanked rate over time at any geographic level. For more information on the methodology used to generate the previous estimates, please visit http://joinbankon.org/resources/methodology.
[9] To increase the reliability of the estimates, geographies with fewer than 1,000 households are excluded and estimates were not produced for census tracts.
[10] A table of the 71 metropolitan statistical areas included in the *2011 FDIC National Survey of Unbanked and Underbanked Households* is available at http://economicinclusion.gov/surveys/2011household/documents/appendix/2011-MSA-Summary-Unbanked.pdf.
[11] For more information on CFED's methodology for producing the state-level SIPP estimates, also done under contract with Marin Economic Consulting, see http://assetsandopportunity.org/scorecard/about/methodology/sipp/.
[12] If an MSA or county constitutes less than 75% of the population in the PUMA in which it is located, the FactFinder methodology is used to produce the estimate.
[13] Family Assets Count, a project of CFED in partnership with Citi Community Development, empowers decision makers and advocates to expand financial security for vulnerable families in major cities across the United States. The campaign will work intensively in ten cities to inform data-driven programs and policies that move families into economic resilience. Partners in Boston, Chicago, Houston, Miami, and Sacramento have already begun efforts, with an additional five cities to join in 2015. For more on Family Assets Count, please visit http://familyassetscount.org.