



Financial Health and Wealth Dashboard: A Local Picture of Residents' Financial Well-Being

Technical Appendix

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The Financial Health and Wealth dashboard provides a detailed picture of financial well-being in the United States using multiple metrics derived from data sources including administrative credit bureau data, the American Community Survey (ACS), and the Survey of Income and Program Participation (SIPP). This technical appendix details the metric definitions, data sources, and methodological decisions made when building the dashboard. We have released data every two years since 2019, when data are available (e.g., 2019, 2021, 2023). For some metrics when data for every two years are not available, we generate data for the latest year possible.

We published an earlier version of this tool in October 2022. The associated feature updates the data from that tool and presents new measures of financial well-being by race and ethnicity. Since the dashboard provides data over time from 2019 to 2023, all the years from 2012–22 use 2010 PUMA, and all the years after and including 2022 use 2022 PUMA. PUMA maps have been updated since 2022. More information can be found on the Census Bureau website.¹

Metric Definitions

The following are definitions of all the metrics in the dashboard and their data sources.

- *Residents with delinquent debt:* Share of residents with a credit record who have debt that is at least 60 days past due, including delinquent debt, derogatory debt, and debt in collections. Delinquent debt is debt more than 60 days past due but less than 180 days late. Derogatory debt is debt more than 180 days late. Debt in collections is debt that has been turned over by the lender to a collection agency (2019, 2021, and 2023 credit bureau data).
- *Student loan holders with delinquent student loan debts:* Share of residents with student loans who have delinquent student loan debt. Delinquent student loan debt is debt that is at least 60 days past due. The student loan delinquency rate has been lower since March 2020, which could be related to the pause in federal student loan repayment authorized in the Coronavirus Aid, Relief, and Economic Security Act² during the COVID-19 pandemic. The pause ended on September 1, 2023 (2019, 2021, and 2023 credit bureau data)
- *Low-income households with housing-cost burden:* Low-income households are defined as households with annual incomes below \$50,000. Renters and homeowners who pay more than 30 percent of their income on housing are considered “cost burdened.” For renters, housing costs include rent and utilities. For homeowners, housing costs include mortgage payments or similar property debts, real estate taxes, home insurance costs, and utilities (2019, 2021, and 2023 ACS data).

- *Housing with high utility burden*: Share of households that pay more than 10 percent of their income on utility bills including electricity, water, gas, and heating fuel cost. These households are considered “utility burdened” (2019, 2021, and 2023 ACS).
- *Households with at least \$2,000 in emergency savings (estimated)*: Share of households with nonretirement savings greater than or equal to \$2,000. Savings data at the local level are not available, so we used machine learning to estimate these values. We consider the following nonretirement savings as sources of emergency savings: government securities, checking accounts, savings accounts, money market accounts, certificates of deposit, municipal and corporate bonds, stocks, and mutual funds. We chose \$2,000 as a measure of emergency savings because other studies have used the same amount to gauge a family’s ability to meet unexpected financial needs (Deevy et al. 2021; estimated using machine learning based on 2020 and 2023 SIPP and 2019 and 2022 ACS data).
- *Low-income households who receive the EITC*: Share of households below 200 percent of the federal poverty level who receive EITC (2019, 2021, and 2022 [SOI Tax Stats](#), individual income tax statistics; ZIP code data from IRS and ACS data)
- *Median credit score*: Median VantageScore credit score among residents with a credit record (2019, 2021, and 2023 credit bureau data).
- *Mortgage holders who had a foreclosure in the past two years*: Share of residents with a mortgage who have a foreclosure on their record from the past two years. Only residents with a mortgage are considered in this metric. The mortgage delinquency rate has been lower since March 2020, which could be related to mortgage forbearance for homeowners authorized in the Coronavirus Aid, Relief, and Economic Security Act³ during the COVID-19 pandemic (2019, 2021, and 2023 credit bureau data).
- *Residents with health insurance coverage*: Share of people with health insurance (2019, 2021, and 2023 ACS data).
- *Median net worth (estimated)*: 50th percentile (median) amounts of household net worth. Net worth is the sum of asset values minus the sum of liabilities for a household (estimated using machine learning based on 2020 and 2023 SIPP and 2019 and 2022 ACS data).
- *Workers with any employer-based retirement plans (estimated)*: Share of adults in the labor force employed or unemployed who had any employer-based retirement plan provided through their employer or business. Plans include defined-benefit pension, cash balance plan, 401k, 403b,

503b, or Thrift Savings Plan, IRA, or Keogh accounts (estimated using machine learning based on 2020 and 2023 SIPP and 2019 and 2022 ACS data).

- *Homeownership rate*: Share of households who are homeowners (2019, 2021, and 2023 ACS data).
- *Median home value among homeowners*: 50th percentile values of owner-occupied housing units. Only households with positive home values (not zero or negative values) are considered when calculating the median home value (2019, 2021, and 2023 ACS data).

In the dashboard, we present data for all the metrics above at the geographic level of PUMAs defined by the US Census Bureau.⁴ The map breaks are determined using the Jenks Natural Breaks method.⁵ We also show data for all of these metrics at the national and state levels and the city level for select cities, where data are available. A list of the select cities can be found in the “Select Cities” section.

In addition, we also disaggregate data by racial and ethnic communities for all of the metrics for the nation, states, and select cities. We use the abbreviation AAPI for Asian American Pacific Islander. We use the term Hispanic to refer to people of Hispanic or Latino origin to align with how the data were collected. We recognize that this term may not be the preferred identifier for many, and we remain committed to using inclusive language whenever possible.

Specifically, we report values for Hispanic households, non-Hispanic AAPI households, non-Hispanic Black households, non-Hispanic other race(s) households, and non-Hispanic white households.⁶ We also report values for households of color by aggregating Hispanic, non-Hispanic AAPI, non-Hispanic Black, and non-Hispanic other races. For all the metrics that used credit bureau data, we report values for communities that are majority (more than 50 percent) Hispanic, majority non-Hispanic AAPI, majority non-Hispanic Black, majority non-Hispanic other races, and majority non-Hispanic white, when data are available. We also report values for communities of color when we aggregate Hispanic, non-Hispanic AAPI, non-Hispanic Black, and non-Hispanic other races. We define a community as residents with the same zip code. Data are not available when the sample size is too small or when a zip code does not have a majority (more than 50 percent) of residents in any racial or ethnic group.

Users can search for cities or zip codes to locate a PUMA and see these metrics. Among more than 41,000 zip codes in the US, about 200 zip codes are not linked to PUMAs in the dashboard. These 200 zip codes either cover public places or are areas with no recorded population.

Select Cities

In the dashboard, we reported metrics for the following 285 US cities and places when data were available. Some metrics are unavailable in selected cities. We included all the cities listed in the IPUMS ACS data when data were available. The cities were selected where the sum of data errors for the PUMA-city crosswalk is less than 30 percent, based on IPUMS's data.¹

Abilene, TX	Fremont, CA	Palm Bay, FL
Akron, OH	Fresno, CA	Palm Coast, FL
Albany, NY	Fullerton, CA	Palmdale, CA
Albuquerque, NM	Gainesville, FL	Pasadena, CA
Alexandria, VA	Garden Grove, CA	Pasadena, TX
Alhambra, CA	Gilbert, AZ	Paterson, NJ
Allentown, PA	Glendale, AZ	Philadelphia, PA
Amarillo, TX	Glendale, CA	Phoenix, AZ
Anaheim, CA	Grand Rapids, MI	Pittsburg, CA
Anchorage, AK	Greeley, CO	Pittsburgh, PA
Ann Arbor, MI	Green Bay, WI	Plano, TX
Antioch, CA	Greensboro, NC	Pomona, CA
Arlington, VA	Hammond, IN	Pompano Beach, FL
Arvada, CO	Hampton, VA	Port St. Lucie, FL
Athens-Clarke County, GA	Hartford, CT	Portland, OR
Atlanta, GA	Hawthorne, CA	Portsmouth, VA
Augusta-Richmond County, GA	Hayward, CA	Providence, RI
Aurora, CO	Henderson, NV	Provo, UT
Austin, TX	Hialeah, FL	Pueblo, CO
Avondale, AZ	Hillsboro, OR	Quincy, MA
Bakersfield, CA	Houston, TX	Rancho Cucamonga, CA
Baltimore, MD	Huntington Beach, CA	Reno, NV
Baton Rouge, LA	Indianapolis, IN	Richmond, VA
Beaumont, TX	Inglewood, CA	Riverside, CA
Bellevue, WA	Irvine, CA	Roanoke, VA
Bellingham, WA	Jackson, MS	Rochester, MN
	Jacksonville, FL	

¹ City data is based on the crosswalk between PUMAs and cities, and cities are referred to as places in IPUMS's publications based on Census Bureau's place definitions. Based on IPUMS's publication on 2020 PUMA match summary by 2020 large place, the sum of errors equals omission errors (percentage of city population not in PUMAs) plus commission error (percentage of PUMAs population not in city). Only cities with less than 30 of the sum of errors were included, although not all data points are available for all cities in all the years. For detailed data and description, please check out IPUMS website, 2020 PUMA Match Summary by 2020 Large Place, column N: <https://usa.ipums.org/usa/volii/cities.shtml#place-puma>.

Bend, OR	Jersey City, NJ	Rochester, NY
Berkeley, CA	Kansas City, KS	Rockford, IL
Billings, MT	Kansas City, MO	Roseville, CA
Birmingham, AL	Kent, WA	Round Rock, TX
Bloomington, IL	Killeen, TX	Sacramento, CA
Bloomington, MN	Knoxville, TN	Salinas, CA
Boca Raton, FL	Lancaster, CA	Salt Lake City, UT
Boston, MA	Lansing, MI	San Angelo, TX
Boulder, CO	Laredo, TX	San Antonio, TX
Bridgeport, CT	Las Cruces, NM	San Buenaventura, CA
Brockton, MA	Las Vegas, NV	San Diego, CA
Brooklyn Park, MN	Lawrence, KS	San Francisco, CA
Brownsville, TX	Lawrence, MA	San Jose, CA
Buffalo, NY	Lawton, OK	Sandy Springs, GA
Burbank, CA	Lee's Summit, MO	Santa Ana, CA
Cambridge, MA	Lewisville, TX	Santa Clara, CA
Cape Coral, FL	Lexington-Fayette, KY	Santa Clarita, CA
Carlsbad, CA	Lincoln, NE	Santa Monica, CA
Carmel, IN	Little Rock, AR	Santa Rosa, CA
Carson, CA	Livermore, CA	Seattle, WA
Cedar Rapids, IA	Long Beach, CA	Shreveport, LA
Chandler, AZ	Longmont, CO	Simi Valley, CA
Charlotte, NC	Los Angeles, CA	Sioux Falls, SD
Chattanooga, TN	Louisville/Jefferson County, KY	South Bend, IN
Chesapeake, VA	Lowell, MA	Spokane Valley, WA
Chicago, IL	Lubbock, TX	Spokane, WA
Chico, CA	Lynn, MA	Springfield, MA
Chula Vista, CA	Macon-Bibb County, GA	St. Louis, MO
Cincinnati, OH	Manchester, NH	St. Paul, MN
Citrus Heights, CA	McAllen, TX	St. Petersburg, FL
Clarksville, TN	McKinney, TX	Sterling Heights, MI
Cleveland, OH	Memphis, TN	Stockton, CA
Clovis, CA	Menifee, CA	Sunnyvale, CA
Colorado Springs, CO	Mesa, AZ	Surprise, AZ
Columbia, MD	Metairie, LA	Syracuse, NY
Columbia, MO	Miami Beach, FL	Tacoma, WA
Columbus, GA	Miami, FL	Tampa, FL
Columbus, OH	Midland, TX	Temecula, CA
Coral Springs, FL	Milpitas, CA	Tempe, AZ
Corpus Christi, TX	Milwaukee, WI	The Woodlands, TX
Dallas, TX	Minneapolis, MN	Thousand Oaks, CA
Dayton, OH	Mission Viejo, CA	Toledo, OH
Deerfield Beach, FL		

Deltona, FL	Mobile, AL	Topeka, KS
Denver, CO	Modesto, CA	Torrance, CA
Des Moines, IA	Montgomery, AL	Tracy, CA
Detroit, MI	Moreno Valley, CA	Trenton, NJ
Doral, FL	Mount Pleasant, SC	Tucson, AZ
Downey, CA	Mountain View, CA	Tuscaloosa, AL
Duluth, MN	Murfreesboro, TN	Tyler, TX
Durham, NC	Nashua, NH	Urban Honolulu, HI
East Los Angeles, CA	Nashville-Davidson, TN	Vacaville, CA
Edinburg, TX	New Bedford, MA	Vallejo, CA
El Monte, CA	New Haven, CT	Victorville, CA
El Paso, TX	New Orleans, LA	Virginia Beach, VA
Elizabeth, NJ	New York, NY	Visalia, CA
Elk Grove, CA	Newark, NJ	Waco, TX
Erie, PA	Newport News, VA	Warren, MI
Escondido, CA	Norfolk, VA	Washington, DC
Everett, WA	Norman, OK	Waterbury, CT
Fairfield, CA	North Las Vegas, NV	West Jordan, UT
Fall River, MA	Norwalk, CA	West Valley City, UT
Fargo, ND	Norwalk, CT	Wichita Falls, TX
Fayetteville, AR	Oakland, CA	Wilmington, NC
Fayetteville, NC	Olathe, KS	Winston-Salem, NC
Flint, MI	Omaha, NE	Worcester, MA
Fontana, CA	Ontario, CA	Yakima, WA
Fort Collins, CO	Orange, CA	Yonkers, NY
Fort Lauderdale, FL	Oxnard, CA	Yuma, AZ
Fort Wayne, IN		

Data Sources and Methodology

Credit Bureau Data

We used credit bureau data to generate credit metrics, including *median credit score*. The credit metrics are derived from a random sample of deidentified, consumer-level records from a major credit bureau. The credit bureau data are from August 2019, February and August 2021, and August 2023. The August 2019 and February 2021 credit records cover 5 million consumers, which is a 2 percent sample of all

consumers. Since August 2021, we have doubled the sample size to 10 million consumers, which is a 4 percent sample of all consumers.

The credit bureau data do not include information about race, so metrics for race and ethnicity are based on the racial makeup of zip codes within the geographic area (nation, state, city). Specifically, we determined which communities are majority white based on credit records for people who live in zip codes where most residents are white (more than 50 percent of the population is white). And we determined which communities are majority communities of color based on credit records for people who live in zip codes where most residents are people of color (more than 50 percent of the population is AAPI, American Indian or Alaska Native, Black, Hispanic, another race other than white, or multiracial). Using the same definition, we also created statistics for other races and ethnicities when data were available. Data for specific racial groups or communities of color are not reported because no zip codes are predominantly made up of one racial or ethnic group. Credit metrics are reported when they are based on at least 50 people.

American Community Survey (ACS)

The ACS is a household survey of demographic, social, economic, and housing characteristics administered by the US Census Bureau on a rolling basis. Survey responses are pooled from all twelve months in a year to create an annual dataset. We generated five metrics directly from the ACS: *homeownership rates*, *median home values*, *low-income households that are housing-cost burdened*, *housing with high utility burden*, and *residents with health insurance*. The survey does not include information about liquid assets or net worth, but it does contain many important variables that overlap with the SIPP including demographics, income, and home value that can predict wealth.

For *homeownership rates*, we calculated the share of households who own an owner-occupied home relative to all the households for each PUMA. For the median home value, we limited the sample to homeowners who occupy their home and computed the median home value for households with a home within each PUMA.

For *low-income households that are housing-cost burdened*, we calculated the share of *low-income households with housing-cost burden* relative to all low-income households. We defined households with annual household incomes below \$50,000 as low-income households, and we considered renters and homeowners. If any housing-related costs are more than 30 percent of a household's income, that household is considered housing-cost burdened. For renters, housing costs are rent, utilities (water,

electricity, gas), and fuels (oil, coal, kerosene, wood, etc.). For homeowners, housing costs are the sum of payments for mortgages, deeds of trust, contracts to purchase, or similar debts on the property (including payments for the first mortgage, second mortgage, home equity loans, and other junior mortgages); real estate taxes; fire, hazard, and flood insurance on the property; utilities (electricity, gas, and water and sewer); and fuels (oil, coal, kerosene, wood, etc.).

For *housing with high utility burden*: we estimated the share of households that pay more than 10 percent of their total household income on utility bills including electricity, water, gas, and heating fuel cost. These households are considered “utility burdened.”

For *residents with health insurance*, we calculated the share of *residents with health insurance* relative to all residents. This metric was calculated at the individual level, not at the household level.

The US Census Bureau receives more than 2 million responses to the survey each year, which makes it a useful data source for estimates for small geographic areas. PUMS data provide PUMAs, which are Census-generated, nonoverlapping, and state-partitioned geographic areas that contain 100,000 or more people each. PUMAs are drawn based on population, so some are larger than entire counties while others in densely populated areas like New York or Chicago are much smaller. In these cases, PUMAs can be thought of as large neighborhoods.

We also use the ACS 2019–23 five-year data to tabulate the racial composition at the PUMA, city, state, and national level, including the percentages of non-Hispanic Asian, non-Hispanic Black, Hispanic, and non-Hispanic white populations.

Survey of Income and Program Participation

SIPP is a household survey of demographic, economic, and government program participation information administered by the US Census Bureau. The survey is nationally representative and is statistically reliable for some, but not all, states. The SIPP is an important source of information about assets, and its questionnaire asks detailed questions about retirement accounts, interest-earning assets, other income-generating assets, and other assets.

We constructed liquid assets and net worth at the household-level from about a dozen individual questions about assets. Liquid assets include transaction accounts and interest-earning accounts such as checking accounts, savings accounts, certificates of deposit, money market accounts, government securities, municipal and corporate bonds, mutual funds, and stocks. Net worth is the sum of asset values minus the sum of liabilities for a household. We constructed access to a retirement account at

the individual level and limited the analysis to individuals in the labor force. Individuals have access to a retirement account if they have access to a 401(k) or similar account, a pension, or an IRA Keogh plan.

Statistics of Income Tax Stats, Individual Income Tax Statistics, and ZIP Code Data from the IRS

The IRS SOI division provides statistics derived from tax returns at the tax unit level. From the ZIP code data, we can approximate the number of households (based on the number of returns from the tax data) that receive EITC each year at the zip code level. Then using the geographic crosswalk from zip code to PUMA based on the Geocorr 2022 from the Missouri Census Data Center,⁷ we estimate the number of households who receive EITC by PUMA. Additionally, using the city information from IPUMS ACS, we estimate the number of households who receive EITC at each major city, at all states, and nationally. We use the SOI Tax Stats data to estimate the share of low-income households who receive EITC. SOI tax data provides direct information on the numerator, which is the number of households who are EITC recipients. To estimate the denominator, the number of households eligible for EITC, we use 200 percent federal poverty level as the threshold, which is also the common threshold used in the literature. Using ACS, we estimate the number of households living below 200 percent federal poverty level by PUMA, city, state, and nationally. Given the numerator from the SOI and the denominator from the ACS, we have our estimates.

Machine Learning Models

We developed a mass imputation approach to estimate median net worth, households with emergency savings above \$2,000, and workers with any employer-based retirement plans. Although all three outcomes can be measured at the state level, data at the local levels are not widely available and state-level estimates can be imprecise. We used machine learning to predict if a household has at least \$2,000 in liquid assets, the amount of household net worth, and if an adult in the labor force has access to a workplace retirement account and then aggregated results to the PUMA level. We used the 2020 data from the 2018 SIPP and 2020 SIPP, and 2023 data from the 2020 SIPP, 2021 SIPP, 2022 SIPP, and 2023 SIPP to train the machine learning models. Based on the models, we estimated median households net worth, the proportion of households with at least \$2,000 of emergency savings, and the proportion of adult workers with access to a workplace retirement account in the 2019 one-year ACS and 2022 one-year ACS. Emergency savings, which is the sum of liquid assets in checking accounts, stocks, bonds,

and other liquid savings accounts, can indicate households' resilience and ability to bounce back from financial shocks. Households with liquid assets above \$2,000 are considered to have sufficient emergency savings. Net worth, which is calculated as total assets minus total debt, can provide an overview of households' economic well-being and their ability to pursue new opportunities. Adults in the labor force have a retirement account if they have a 401(k) or similar account, pension, or IRA Keogh.

We used detailed wealth data and socioeconomic information from SIPP to train machine learning models. The models' predictors include socioeconomic and financial variables from SIPP. The models' outcomes are an indicator for liquid assets, amount of net worth, and indicator for having a retirement account. Taking the models as given, we then predicted all three outcomes on the ACS and then estimated the liquid assets⁸ and net worth for all households and retirement accounts for adults in the labor force. The ACS has more granular geographic information than SIPP but lacks detailed asset outcomes. The ACS sample covers all PUMAs. We report estimates for all three outcomes at the PUMA, state, and national levels and for select cities.

Our general approach was to leverage the detailed variables in the SIPP to impute values in the ACS, which contains enough households for detailed geographic estimates. The approach of using a smaller, more detailed survey to impute variables on a larger, less detailed dataset was also employed by Blumenstock and colleagues (2015) to impute wealth in administrative cell phone metadata in Rwanda.

Data are reported at the national, state, city, and PUMA levels for all 50 states and Washington, DC. Imputed asset metrics (median net worth and emergency savings) are not reported when the sample size is less than 50 or the coefficient of variation is more than 0.4. Cities with sums of errors exceeding 30 percent for the PUMA-city crosswalk are suppressed.

Notes

¹ "Public Use Microdata Areas (PUMAs)," US Census Bureau, last updated July 11, 2022, <https://www.census.gov/programs-surveys/geography/guidance/geo-areas/pumas.html>.

² Coronavirus Aid, Relief, and Economic Security (CARES) Act, S. B. 3548, 116th Cong., 2nd Sess. (March 19, 2020), <https://www.congress.gov/bill/116th-congress/senate-bill/3548/text>.

- ³ CARES Act. S. B. 3548, 116th Cong., 2nd Sess. (March 19, 2020).
- ⁴ “Public Use Microdata Areas (PUMAS),” US Census Bureau.
- ⁵ “Data Classification Methods,” ArcGIS Pro, Esri, accessed July 27, 2022, <http://pro.arcgis.com/en/pro-app/help/mapping/layer-properties/data-classification-methods.htm>.
- ⁶ The race or ethnicity of the household is based on the race or ethnicity of the head of the household.
- ⁷ “Geocorr 2022: Geographic Correspondence Engine,” Version 1.8, Missouri Census Data Center, last updated October 2022, <https://mcdc.missouri.edu/applications/geocorr2022.html>.
- ⁸ We first calculated the total amount of household liquid assets. Then we identified households with liquid assets above \$2,000 as having sufficient emergency savings.

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For more information on this project, see our Financial Health and Wealth Dashboard at <https://apps.urban.org/features/financial-health-wealth-dashboard>.

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